
pandas: powerful Python data analysis toolkit

Release 0.16.1

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Binary Installers: <http://pypi.python.org/pypi/pandas>

Source Repository: <http://github.com/pydata/pandas>

Issues & Ideas: <https://github.com/pydata/pandas/issues>

Q&A Support: <http://stackoverflow.com/questions/tagged/pandas>

Developer Mailing List: <http://groups.google.com/group/pydata>

pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, **real world** data analysis in Python. Additionally, it has the broader goal of becoming **the most powerful and flexible open source data analysis / manipulation tool available in any language**. It is already well on its way toward this goal.

pandas is well suited for many different kinds of data:

- Tabular data with heterogeneously-typed columns, as in an SQL table or Excel spreadsheet
- Ordered and unordered (not necessarily fixed-frequency) time series data.
- Arbitrary matrix data (homogeneously typed or heterogeneous) with row and column labels
- Any other form of observational / statistical data sets. The data actually need not be labeled at all to be placed into a pandas data structure

The two primary data structures of pandas, *Series* (1-dimensional) and *DataFrame* (2-dimensional), handle the vast majority of typical use cases in finance, statistics, social science, and many areas of engineering. For R users, *DataFrame* provides everything that R’s *data.frame* provides and much more. pandas is built on top of NumPy and is intended to integrate well within a scientific computing environment with many other 3rd party libraries.

Here are just a few of the things that pandas does well:

- Easy handling of **missing data** (represented as NaN) in floating point as well as non-floating point data
- Size mutability: columns can be **inserted and deleted** from *DataFrame* and higher dimensional objects
- Automatic and explicit **data alignment**: objects can be explicitly aligned to a set of labels, or the user can simply ignore the labels and let *Series*, *DataFrame*, etc. automatically align the data for you in computations
- Powerful, flexible **group by** functionality to perform split-apply-combine operations on data sets, for both aggregating and transforming data
- Make it **easy to convert** ragged, differently-indexed data in other Python and NumPy data structures into *DataFrame* objects
- Intelligent label-based **slicing, fancy indexing**, and **subsetting** of large data sets
- Intuitive **merging** and **joining** data sets
- Flexible **reshaping** and pivoting of data sets
- **Hierarchical** labeling of axes (possible to have multiple labels per tick)
- Robust IO tools for loading data from **flat files** (CSV and delimited), Excel files, databases, and saving / loading data from the ultrafast **HDF5 format**
- **Time series**-specific functionality: date range generation and frequency conversion, moving window statistics, moving window linear regressions, date shifting and lagging, etc.

Many of these principles are here to address the shortcomings frequently experienced using other languages / scientific research environments. For data scientists, working with data is typically divided into multiple stages: munging and cleaning data, analyzing / modeling it, then organizing the results of the analysis into a form suitable for plotting or tabular display. pandas is the ideal tool for all of these tasks.

Some other notes

- pandas is **fast**. Many of the low-level algorithmic bits have been extensively tweaked in [Cython](#) code. However, as with anything else generalization usually sacrifices performance. So if you focus on one feature for your application you may be able to create a faster specialized tool.
- pandas is a dependency of [statsmodels](#), making it an important part of the statistical computing ecosystem in Python.
- pandas has been used extensively in production in financial applications.

Note: This documentation assumes general familiarity with NumPy. If you haven't used NumPy much or at all, do invest some time in [learning about NumPy](#) first.

See the package overview for more detail about what's in the library.

WHAT'S NEW

These are new features and improvements of note in each release.

1.1 v0.16.1 (May 11, 2015)

This is a minor bug-fix release from 0.16.0 and includes a a large number of bug fixes along several new features, enhancements, and performance improvements. We recommend that all users upgrade to this version.

Highlights include:

- Support for a `CategoricalIndex`, a category based index, see [here](#)
- New section on how-to-contribute to *pandas*, see [here](#)
- Revised “Merge, join, and concatenate” documentation, including graphical examples to make it easier to understand each operations, see [here](#)
- New method `sample` for drawing random samples from Series, DataFrames and Panels. See [here](#)
- The default `Index` printing has changed to a more uniform format, see [here](#)
- `BusinessHour` `datetime`-offset is now supported, see [here](#)
- Further enhancement to the `.str` accessor to make string operations easier, see [here](#)

What's new in v0.16.1

- Enhancements
 - `CategoricalIndex`
 - `Sample`
 - String Methods Enhancements
 - Other Enhancements
- API changes
 - Deprecations
- Index Representation
- Performance Improvements
- Bug Fixes

Warning: In pandas 0.17.0, the sub-package `pandas.io.data` will be removed in favor of a separately installable package. See [here for details](#) (GH8961)

1.1.1 Enhancements

CategoricalIndex

We introduce a `CategoricalIndex`, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a `Categorical` (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a `DataFrame`/`Series` with a `category` dtype would convert this to regular object-based `Index`.

```
In [1]: df = DataFrame({'A' : np.arange(6),
...:                  'B' : Series(list('aabbca')).astype('category',
...:                                                    categories=list('cab'))
...:                  })
...:
```

```
In [2]: df
```

```
Out[2]:
   A  B
0  0  a
1  1  a
2  2  b
3  3  b
4  4  c
5  5  a
```

```
In [3]: df.dtypes
```

```
Out[3]:
A      int32
B    category
dtype: object
```

```
In [4]: df.B.cat.categories
```

```
Out[4]: Index([u'c', u'a', u'b'], dtype='object')
```

setting the index, will create create a `CategoricalIndex`

```
In [5]: df2 = df.set_index('B')
```

```
In [6]: df2.index
```

```
Out[6]: CategoricalIndex([u'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'c', u'a', u'b'], ordered=True)
```

indexing with `__getitem__/.iloc/.loc/.ix` works similarly to an `Index` with duplicates. The indexers **MUST** be in the category or the operation will raise.

```
In [7]: df2.loc['a']
```

```
Out[7]:
A
B
a  0
a  1
a  5
```

and preserves the `CategoricalIndex`

```
In [8]: df2.loc['a'].index
```

```
Out[8]: CategoricalIndex([u'a', u'a', u'a'], categories=[u'c', u'a', u'b'], ordered=False, name=u'B')
```

sorting will order by the order of the categories

```
In [9]: df2.sort_index()
```

```
Out[9]:
```

```
      A
B
c    4
a    0
a    1
a    5
b    2
b    3
```

groupby operations on the index will preserve the index nature as well

```
In [10]: df2.groupby(level=0).sum()
```

```
Out[10]:
```

```
      A
B
c    4
a    6
b    5
```

```
In [11]: df2.groupby(level=0).sum().index
```

```
Out[11]: CategoricalIndex([u'c', u'a', u'b'], categories=[u'c', u'a', u'b'], ordered=False, name=u'B')
```

reindexing operations, will return a resulting index based on the type of the passed indexer, meaning that passing a list will return a plain-old-Index; indexing with a Categorical will return a CategoricalIndex, indexed according to the categories of the PASSED Categorical dtype. This allows one to arbitrarily index these even with values NOT in the categories, similarly to how you can reindex ANY pandas index.

```
In [12]: df2.reindex(['a', 'e'])
```

```
Out[12]:
```

```
      A
B
a    0
a    1
a    5
e  NaN
```

```
In [13]: df2.reindex(['a', 'e']).index
```

```
Out[13]: Index([u'a', u'a', u'a', u'e'], dtype='object', name=u'B')
```

```
In [14]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde')))
```

```
Out[14]:
```

```
      A
B
a    0
a    1
a    5
e  NaN
```

```
In [15]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde'))).index
```

```
Out[15]: CategoricalIndex([u'a', u'a', u'a', u'e'], categories=[u'a', u'b', u'c', u'd', u'e'], ordered=False, name=u'B')
```

See the *documentation* for more. ([GH7629](#), [GH10038](#), [GH10039](#))

Sample

Series, DataFrames, and Panels now have a new method: `sample()`. The method accepts a specific number of rows or columns to return, or a fraction of the total number of rows or columns. It also has options for sampling with or without replacement, for passing in a column for weights for non-uniform sampling, and for setting seed values to facilitate replication. (GH2419)

```
In [16]: example_series = Series([0,1,2,3,4,5])

# When no arguments are passed, returns 1
In [17]: example_series.sample()
Out[17]:
2      2
dtype: int64

# One may specify either a number of rows:
In [18]: example_series.sample(n=3)
Out[18]:
4      4
2      2
5      5
dtype: int64

# Or a fraction of the rows:
In [19]: example_series.sample(frac=0.5)
Out[19]:
0      0
4      4
3      3
dtype: int64

# weights are accepted.
In [20]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [21]: example_series.sample(n=3, weights=example_weights)
Out[21]:
5      5
2      2
3      3
dtype: int64

# weights will also be normalized if they do not sum to one,
# and missing values will be treated as zeros.
In [22]: example_weights2 = [0.5, 0, 0, 0, None, np.nan]

In [23]: example_series.sample(n=1, weights=example_weights2)
Out[23]:
0      0
dtype: int64
```

When applied to a DataFrame, one may pass the name of a column to specify sampling weights when sampling from rows.

```
In [24]: df = DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})

In [25]: df.sample(n=3, weights='weight_column')
Out[25]:
   col1  weight_column
1      8            0.4
```

```

2      7      0.1
0      9      0.5

```

String Methods Enhancements

Continuing from v0.16.0, the following enhancements make string operations easier and more consistent with standard python string operations.

- Added StringMethods (`.str` accessor) to Index ([GH9068](#))

The `.str` accessor is now available for both Series and Index.

```
In [26]: idx = Index([' jack', 'jill ', ' jesse ', 'frank'])
```

```
In [27]: idx.str.strip()
```

```
Out[27]: Index([u'jack', u'jill', u'jesse', u'frank'], dtype='object')
```

One special case for the `.str` accessor on Index is that if a string method returns `bool`, the `.str` accessor will return a `np.array` instead of a boolean Index ([GH8875](#)). This enables the following expression to work naturally:

```
In [28]: idx = Index(['a1', 'a2', 'b1', 'b2'])
```

```
In [29]: s = Series(range(4), index=idx)
```

```
In [30]: s
```

```
Out[30]:
```

```

a1    0
a2    1
b1    2
b2    3
dtype: int64

```

```
In [31]: idx.str.startswith('a')
```

```
Out[31]: array([ True,  True, False, False], dtype=bool)
```

```
In [32]: s[s.index.str.startswith('a')]
```

```
Out[32]:
```

```

a1    0
a2    1
dtype: int64

```

- The following new methods are accesible via `.str` accessor to apply the function to each values. ([GH9766](#), [GH9773](#), [GH10031](#), [GH10045](#), [GH10052](#))

		Methods		
<code>capitalize()</code>	<code>swapcase()</code>	<code>normalize()</code>	<code>partition()</code>	<code>rpartition()</code>
<code>index()</code>	<code>rindex()</code>	<code>translate()</code>		

- `split` now takes `expand` keyword to specify whether to expand dimensionality. `return_type` is deprecated. ([GH9847](#))

```
In [33]: s = Series(['a,b', 'a,c', 'b,c'])
```

```
# return Series
```

```
In [34]: s.str.split(',')
```

```
Out[34]:
```

```

0    [a, b]
1    [a, c]

```

```
2      [b, c]
dtype: object

# return DataFrame
In [35]: s.str.split(',', expand=True)
Out[35]:
   0 1
0  a b
1  a c
2  b c

In [36]: idx = Index(['a,b', 'a,c', 'b,c'])

# return Index
In [37]: idx.str.split(',')
Out[37]: Index([[u'a', u'b'], [u'a', u'c'], [u'b', u'c']], dtype='object')

# return MultiIndex
In [38]: idx.str.split(',', expand=True)
Out[38]:
MultiIndex(levels=[[u'a', u'b'], [u'b', u'c']],
            labels=[[0, 0, 1], [0, 1, 1]])
```

- Improved `extract` and `get_dummies` methods for `Index.str` (GH9980)

Other Enhancements

- `BusinessHour` offset is now supported, which represents business hours starting from 09:00 - 17:00 on `BusinessDay` by default. See [Here](#) for details. (GH7905)

```
In [39]: from pandas.tseries.offsets import BusinessHour
```

```
In [40]: Timestamp('2014-08-01 09:00') + BusinessHour()
```

```
Out[40]: Timestamp('2014-08-01 10:00:00')
```

```
In [41]: Timestamp('2014-08-01 07:00') + BusinessHour()
```

```
Out[41]: Timestamp('2014-08-01 10:00:00')
```

```
In [42]: Timestamp('2014-08-01 16:30') + BusinessHour()
```

```
Out[42]: Timestamp('2014-08-04 09:30:00')
```

- `DataFrame.diff` now takes an `axis` parameter that determines the direction of differencing (GH9727)
- Allow `clip`, `clip_lower`, and `clip_upper` to accept array-like arguments as thresholds (This is a regression from 0.11.0). These methods now have an `axis` parameter which determines how the Series or DataFrame will be aligned with the threshold(s). (GH6966)
- `DataFrame.mask()` and `Series.mask()` now support same keywords as `where` (GH8801)
- `drop` function can now accept `errors` keyword to suppress `ValueError` raised when any of label does not exist in the target data. (GH6736)

```
In [43]: df = DataFrame(np.random.randn(3, 3), columns=['A', 'B', 'C'])
```

```
In [44]: df.drop(['A', 'X'], axis=1, errors='ignore')
```

```
Out[44]:
```

```
      B      C
0 -0.064034 -1.282782
```

```
1 -1.071357  0.441153
2  0.583787  0.221471
```

- Add support for separating years and quarters using dashes, for example 2014-Q1. (GH9688)
- Allow conversion of values with dtype `datetime64` or `timedelta64` to strings using `astype(str)` (GH9757)
- `get_dummies` function now accepts `sparse` keyword. If set to `True`, the return `DataFrame` is sparse, e.g. `SparseDataFrame`. (GH8823)
- `Period` now accepts `datetime64` as value input. (GH9054)
- Allow `timedelta` string conversion when leading zero is missing from time definition, ie `0:00:00` vs `00:00:00`. (GH9570)
- Allow `Panel.shift` with `axis='items'` (GH9890)
- Trying to write an excel file now raises `NotImplementedError` if the `DataFrame` has a `MultiIndex` instead of writing a broken Excel file. (GH9794)
- Allow `Categorical.add_categories` to accept `Series` or `np.array`. (GH9927)
- Add/delete `str/dt/cat` accessors dynamically from `__dir__`. (GH9910)
- Add `normalize` as a `dt` accessor method. (GH10047)
- `DataFrame` and `Series` now have `_constructor_expanddim` property as overridable constructor for one higher dimensionality data. This should be used only when it is really needed, see [here](#)
- `pd.lib.infer_dtype` now returns `'bytes'` in Python 3 where appropriate. (GH10032)

1.1.2 API changes

- When passing in an `ax` to `df.plot(..., ax=ax)`, the `sharex` kwarg will now default to `False`. The result is that the visibility of `xlabels` and `xticklabels` will not anymore be changed. You have to do that by yourself for the right axes in your figure or set `sharex=True` explicitly (but this changes the visible for all axes in the figure, not only the one which is passed in!). If pandas creates the subplots itself (e.g. no passed in `ax` kwarg), then the default is still `sharex=True` and the visibility changes are applied.
- `assign()` now inserts new columns in alphabetical order. Previously the order was arbitrary. (GH9777)
- By default, `read_csv` and `read_table` will now try to infer the compression type based on the file extension. Set `compression=None` to restore the previous behavior (no decompression). (GH9770)

Deprecations

- `Series.str.split`'s `return_type` keyword was removed in favor of `expand` (GH9847)

1.1.3 Index Representation

The string representation of `Index` and its sub-classes have now been unified. These will show a single-line display if there are few values; a wrapped multi-line display for a lot of values (but less than `display.max_seq_items`; if lots of items (`> display.max_seq_items`) will show a truncated display (the head and tail of the data). The formatting for `MultiIndex` is unchanged (a multi-line wrapped display). The display width responds to the option `display.max_seq_items`, which is defaulted to 100. (GH6482)

Previous Behavior

```
In [2]: pd.Index(range(4),name='foo')
Out[2]: Int64Index([0, 1, 2, 3], dtype='int64')

In [3]: pd.Index(range(104),name='foo')
Out[3]: Int64Index([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103], dtype='int64', name='foo')

In [4]: pd.date_range('20130101',periods=4,name='foo',tz='US/Eastern')
Out[4]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-01-04 00:00:00-05:00]
Length: 4, Freq: D, Timezone: US/Eastern

In [5]: pd.date_range('20130101',periods=104,name='foo',tz='US/Eastern')
Out[5]:
<class 'pandas.tseries.index.DatetimeIndex'>
[2013-01-01 00:00:00-05:00, ..., 2013-04-14 00:00:00-04:00]
Length: 104, Freq: D, Timezone: US/Eastern
```

New Behavior

```
In [45]: pd.set_option('display.width', 80)

In [46]: pd.Index(range(4), name='foo')
Out[46]: Int64Index([0, 1, 2, 3], dtype='int64', name=u'foo')

In [47]: pd.Index(range(30), name='foo')
Out[47]:
Int64Index([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
            17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29],
            dtype='int64', name=u'foo')

In [48]: pd.Index(range(104), name='foo')
Out[48]:
Int64Index([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9,
            ...,
            94, 95, 96, 97, 98, 99, 100, 101, 102, 103],
            dtype='int64', name=u'foo', length=104)

In [49]: pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd'], ordered=True, name='foobar')
Out[49]: CategoricalIndex([u'a', u'bb', u'ccc', u'dddd'], categories=[u'a', u'bb', u'ccc', u'dddd'],

In [50]: pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd']*10, ordered=True, name='foobar')
Out[50]:
CategoricalIndex([u'a', u'bb', u'ccc', u'dddd', u'a', u'bb', u'ccc', u'dddd',
                  u'a', u'bb', u'ccc', u'dddd', u'a', u'bb', u'ccc', u'dddd',
                  u'a', u'bb', u'ccc', u'dddd', u'a', u'bb', u'ccc', u'dddd',
                  u'a', u'bb', u'ccc', u'dddd', u'a', u'bb', u'ccc', u'dddd'],
                  categories=[u'a', u'bb', u'ccc', u'dddd'], ordered=True, name=u'foobar', dtype='cat

In [51]: pd.CategoricalIndex(['a', 'bb', 'ccc', 'dddd']*100, ordered=True, name='foobar')
Out[51]:
CategoricalIndex([u'a', u'bb', u'ccc', u'dddd', u'a', u'bb', u'ccc', u'dddd',
                  u'a', u'bb',
                  ...,
                  u'ccc', u'dddd', u'a', u'bb', u'ccc', u'dddd', u'a', u'bb',
                  u'ccc', u'dddd'],
                  categories=[u'a', u'bb', u'ccc', u'dddd'], ordered=True, name=u'foobar', dtype='cat
```

```

In [52]: pd.date_range('20130101', periods=4, name='foo', tz='US/Eastern')
Out[52]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
              '2013-01-03 00:00:00-05:00', '2013-01-04 00:00:00-05:00'],
              dtype='datetime64[ns]', name=u'foo', freq='D', tz='US/Eastern')

In [53]: pd.date_range('20130101', periods=25, freq='D')
Out[53]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
              '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
              '2013-01-09', '2013-01-10', '2013-01-11', '2013-01-12',
              '2013-01-13', '2013-01-14', '2013-01-15', '2013-01-16',
              '2013-01-17', '2013-01-18', '2013-01-19', '2013-01-20',
              '2013-01-21', '2013-01-22', '2013-01-23', '2013-01-24',
              '2013-01-25'],
              dtype='datetime64[ns]', freq='D', tz=None)

In [54]: pd.date_range('20130101', periods=104, name='foo', tz='US/Eastern')
Out[54]:
DatetimeIndex(['2013-01-01 00:00:00-05:00', '2013-01-02 00:00:00-05:00',
              '2013-01-03 00:00:00-05:00', '2013-01-04 00:00:00-05:00',
              '2013-01-05 00:00:00-05:00', '2013-01-06 00:00:00-05:00',
              '2013-01-07 00:00:00-05:00', '2013-01-08 00:00:00-05:00',
              '2013-01-09 00:00:00-05:00', '2013-01-10 00:00:00-05:00',
              ...,
              '2013-04-05 00:00:00-04:00', '2013-04-06 00:00:00-04:00',
              '2013-04-07 00:00:00-04:00', '2013-04-08 00:00:00-04:00',
              '2013-04-09 00:00:00-04:00', '2013-04-10 00:00:00-04:00',
              '2013-04-11 00:00:00-04:00', '2013-04-12 00:00:00-04:00',
              '2013-04-13 00:00:00-04:00', '2013-04-14 00:00:00-04:00'],
              dtype='datetime64[ns]', name=u'foo', length=104, freq='D', tz='US/Eastern')

```

1.1.4 Performance Improvements

- Improved csv write performance with mixed dtypes, including datetimes by up to 5x ([GH9940](#))
- Improved csv write performance generally by 2x ([GH9940](#))
- Improved the performance of `pd.lib.max_len_string_array` by 5-7x ([GH10024](#))

1.1.5 Bug Fixes

- Bug where labels did not appear properly in the legend of `DataFrame.plot()`, passing `label=` arguments works, and Series indices are no longer mutated. ([GH9542](#))
- Bug in json serialization causing a segfault when a frame had zero length. ([GH9805](#))
- Bug in `read_csv` where missing trailing delimiters would cause segfault. ([GH5664](#))
- Bug in retaining index name on appending ([GH9862](#))
- Bug in `scatter_matrix` draws unexpected axis ticklabels ([GH5662](#))
- Fixed bug in `StataWriter` resulting in changes to input `DataFrame` upon save ([GH9795](#)).
- Bug in `transform` causing length mismatch when null entries were present and a fast aggregator was being used ([GH9697](#))

- Bug in `equals` causing false negatives when block order differed ([GH9330](#))
- Bug in grouping with multiple `pd.Grouper` where one is non-time based ([GH10063](#))
- Bug in `read_sql_table` error when reading postgres table with timezone ([GH7139](#))
- Bug in `DataFrame` slicing may not retain metadata ([GH9776](#))
- Bug where `TimedeltaIndex` were not properly serialized in fixed `HDFStore` ([GH9635](#))
- Bug with `TimedeltaIndex` constructor ignoring name when given another `TimedeltaIndex` as data ([GH10025](#)).
- Bug in `DataFrameFormatter._get_formatted_index` with not applying `max_colwidth` to the `DataFrame` index ([GH7856](#))
- Bug in `.loc` with a read-only `ndarray` data source ([GH10043](#))
- Bug in `groupby.apply()` that would raise if a passed user defined function either returned only `None` (for all input). ([GH9685](#))
- Always use temporary files in `pytables` tests ([GH9992](#))
- Bug in plotting continuously using `secondary_y` may not show legend properly. ([GH9610](#), [GH9779](#))
- Bug in `DataFrame.plot(kind="hist")` results in `TypeError` when `DataFrame` contains non-numeric columns ([GH9853](#))
- Bug where repeated plotting of `DataFrame` with a `DatetimeIndex` may raise `TypeError` ([GH9852](#))
- Bug in `setup.py` that would allow an incompat cython version to build ([GH9827](#))
- Bug in plotting `secondary_y` incorrectly attaches `right_ax` property to secondary axes specifying itself recursively. ([GH9861](#))
- Bug in `Series.quantile` on empty `Series` of type `Datetime` or `Timedelta` ([GH9675](#))
- Bug in `where` causing incorrect results when upcasting was required ([GH9731](#))
- Bug in `FloatArrayFormatter` where decision boundary for displaying “small” floats in decimal format is off by one order of magnitude for a given `display.precision` ([GH9764](#))
- Fixed bug where `DataFrame.plot()` raised an error when both `color` and `style` keywords were passed and there was no color symbol in the style strings ([GH9671](#))
- Not showing a `DeprecationWarning` on combining list-likes with an `Index` ([GH10083](#))
- Bug in `read_csv` and `read_table` when using `skip_rows` parameter if blank lines are present. ([GH9832](#))
- Bug in `read_csv()` interprets `index_col=True` as 1 ([GH9798](#))
- Bug in index equality comparisons using `==` failing on `Index/MultiIndex` type incompatibility ([GH9785](#))
- Bug in which `SparseDataFrame` could not take `nan` as a column name ([GH8822](#))
- Bug in `to_msgpack` and `read_msgpack` `zlib` and `blosc` compression support ([GH9783](#))
- Bug `GroupBy.size` doesn’t attach index name properly if grouped by `TimeGrouper` ([GH9925](#))
- Bug causing an exception in slice assignments because `length_of_indexer` returns wrong results ([GH9995](#))
- Bug in `csv` parser causing lines with initial whitespace plus one non-space character to be skipped. ([GH9710](#))
- Bug in `C` `csv` parser causing spurious `NaNs` when data started with newline followed by whitespace. ([GH10022](#))
- Bug causing elements with a null group to spill into the final group when grouping by a `Categorical` ([GH9603](#))

- Bug where `.iloc` and `.loc` behavior is not consistent on empty dataframes (GH9964)
- Bug in invalid attribute access on a `TimedeltaIndex` incorrectly raised `ValueError` instead of `AttributeError` (GH9680)
- Bug in unequal comparisons between categorical data and a scalar, which was not in the categories (e.g. `Series(Categorical(list("abc")), ordered=True) > "d"`). This returned `False` for all elements, but now raises a `TypeError`. Equality comparisons also now return `False` for `==` and `True` for `!=`. (GH9848)
- Bug in `DataFrame.__setitem__` when right hand side is a dictionary (GH9874)
- Bug in where when `dtype` is `datetime64/timedelta64`, but `dtype` of other is not (GH9804)
- Bug in `MultiIndex.sortlevel()` results in unicode level name breaks (GH9856)
- Bug in which `groupby.transform` incorrectly enforced output dtypes to match input dtypes. (GH9807)
- Bug in `DataFrame` constructor when `columns` parameter is set, and `data` is an empty list (GH9939)
- Bug in bar plot with `log=True` raises `TypeError` if all values are less than 1 (GH9905)
- Bug in horizontal bar plot ignores `log=True` (GH9905)
- Bug in `PyTables` queries that did not return proper results using the index (GH8265, GH9676)
- Bug where dividing a dataframe containing values of type `Decimal` by another `Decimal` would raise. (GH9787)
- Bug where using `DataFrames` `asfreq` would remove the name of the index. (GH9885)
- Bug causing extra index point when `resample` BM/BQ (GH9756)
- Changed caching in `AbstractHolidayCalendar` to be at the instance level rather than at the class level as the latter can result in unexpected behaviour. (GH9552)
- Fixed latex output for multi-indexed dataframes (GH9778)
- Bug causing an exception when setting an empty range using `DataFrame.loc` (GH9596)
- Bug in hiding ticklabels with subplots and shared axes when adding a new plot to an existing grid of axes (GH9158)
- Bug in `transform` and `filter` when grouping on a categorical variable (GH9921)
- Bug in `transform` when groups are equal in number and `dtype` to the input index (GH9700)
- Google BigQuery connector now imports dependencies on a per-method basis.(GH9713)
- Updated BigQuery connector to no longer use deprecated `oauth2client.tools.run()` (GH8327)
- Bug in subclassed `DataFrame`. It may not return the correct class, when slicing or subsetting it. (GH9632)
- Bug in `.median()` where non-float null values are not handled correctly (GH10040)
- Bug in `Series.fillna()` where it raises if a numerically convertible string is given (GH10092)

1.2 v0.16.0 (March 22, 2015)

This is a major release from 0.15.2 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- `DataFrame.assign` method, see [here](#)
- `Series.to_coo/from_coo` methods to interact with `scipy.sparse`, see [here](#)
- Backwards incompatible change to `Timedelta` to conform the `.seconds` attribute with `datetime.timedelta`, see [here](#)
- Changes to the `.loc` slicing API to conform with the behavior of `.ix` see [here](#)
- Changes to the default for ordering in the `Categorical` constructor, see [here](#)
- Enhancement to the `.str` accessor to make string operations easier, see [here](#)
- The `pandas.tools.rplot`, `pandas.sandbox.qtpandas` and `pandas.rpy` modules are deprecated. We refer users to external packages like [seaborn](#), [pandas-qt](#) and [rpy2](#) for similar or equivalent functionality, see [here](#)

Check the [API Changes](#) and [deprecations](#) before updating.

What's new in v0.16.0

- New features
 - `DataFrame.Assign`
 - Interaction with `scipy.sparse`
 - String Methods Enhancements
 - Other enhancements
- Backwards incompatible API changes
 - Changes in `Timedelta`
 - Indexing Changes
 - Categorical Changes
 - Other API Changes
 - Deprecations
 - Removal of prior version deprecations/changes
- Performance Improvements
- Bug Fixes

1.2.1 New features

DataFrame Assign

Inspired by `dplyr`'s `mutate` verb, `DataFrame` has a new `assign()` method. The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the `DataFrame`. The new values are inserted, and the entire `DataFrame` (with all original and new columns) is returned.

```
In [1]: iris = read_csv('data/iris.data')
```

```
In [2]: iris.head()
```

```
Out[2]:
```

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

```
In [3]: iris.assign(sepal_ratio=iris['SepalWidth'] / iris['SepalLength']).head()
Out[3]:
```

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name	sepal_ratio
0	5.1	3.5	1.4	0.2	Iris-setosa	0.686275
1	4.9	3.0	1.4	0.2	Iris-setosa	0.612245
2	4.7	3.2	1.3	0.2	Iris-setosa	0.680851
3	4.6	3.1	1.5	0.2	Iris-setosa	0.673913
4	5.0	3.6	1.4	0.2	Iris-setosa	0.720000

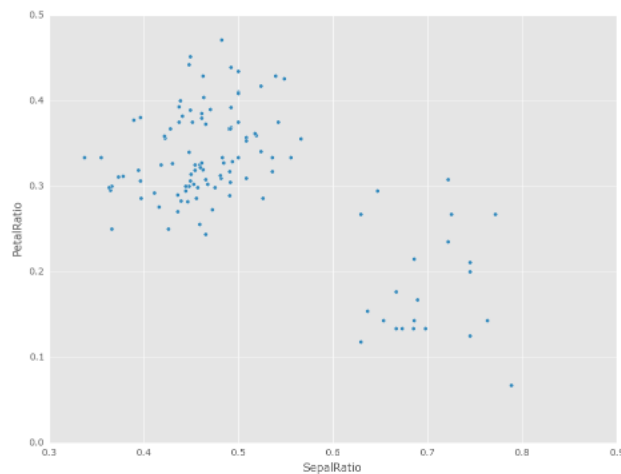
Above was an example of inserting a precomputed value. We can also pass in a function to be evaluated.

```
In [4]: iris.assign(sepal_ratio = lambda x: (x['SepalWidth'] /
...:                                         x['SepalLength'])).head()
Out[4]:
```

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name	sepal_ratio
0	5.1	3.5	1.4	0.2	Iris-setosa	0.686275
1	4.9	3.0	1.4	0.2	Iris-setosa	0.612245
2	4.7	3.2	1.3	0.2	Iris-setosa	0.680851
3	4.6	3.1	1.5	0.2	Iris-setosa	0.673913
4	5.0	3.6	1.4	0.2	Iris-setosa	0.720000

The power of `assign` comes when used in chains of operations. For example, we can limit the DataFrame to just those with a Sepal Length greater than 5, calculate the ratio, and plot

```
In [5]: (iris.query('SepalLength > 5')
...:      .assign(SepalRatio = lambda x: x.SepalWidth / x.SepalLength,
...:              PetalRatio = lambda x: x.PetalWidth / x.PetalLength)
...:      .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0xa332d80c>
```



See the [documentation](#) for more. (GH9229)

Interaction with `scipy.sparse`

Added `SparseSeries.to_coo()` and `SparseSeries.from_coo()` methods (GH8048) for converting to and from `scipy.sparse.coo_matrix` instances (see [here](#)). For example, given a `SparseSeries` with `MultiIndex` we can convert to a `scipy.sparse.coo_matrix` by specifying the row and column labels as index levels:

```
In [6]: from numpy import nan

In [7]: s = Series([3.0, nan, 1.0, 3.0, nan, nan])

In [8]: s.index = MultiIndex.from_tuples([(1, 2, 'a', 0),
....:                                   (1, 2, 'a', 1),
....:                                   (1, 1, 'b', 0),
....:                                   (1, 1, 'b', 1),
....:                                   (2, 1, 'b', 0),
....:                                   (2, 1, 'b', 1)],
....:                                   names=['A', 'B', 'C', 'D'])

In [9]: s
Out[9]:
A B C D
1 2 a 0    3
      1 NaN
      1 b 0    1
      1    3
2 1 b 0 NaN
      1 NaN
dtype: float64

# SparseSeries
In [10]: ss = s.to_sparse()

In [11]: ss
Out[11]:
A B C D
1 2 a 0    3
      1 NaN
      1 b 0    1
      1    3
2 1 b 0 NaN
      1 NaN
dtype: float64
BlockIndex
Block locations: array([0, 2])
Block lengths: array([1, 2])

In [12]: A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
....:                                column_levels=['C', 'D'],
....:                                sort_labels=False)
....:

In [13]: A
Out[13]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
      with 3 stored elements in COOrdinate format>

In [14]: A.todense()
Out[14]:
matrix([[ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  1.,  3.],
        [ 0.,  0.,  0.,  0.]])

In [15]: rows
```

```
Out[15]: [(1L, 2L), (1L, 1L), (2L, 1L)]
```

```
In [16]: columns
```

```
Out[16]: [('a', 0L), ('a', 1L), ('b', 0L), ('b', 1L)]
```

The `from_coo` method is a convenience method for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`:

```
In [17]: from scipy import sparse
```

```
In [18]: A = sparse.coo_matrix((([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
.....:                          shape=(3, 4))
.....:
```

```
In [19]: A
```

```
Out[19]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
      with 3 stored elements in COOrdinate format>
```

```
In [20]: A.todense()
```

```
Out[20]:
matrix([[ 0.,  0.,  1.,  2.],
        [ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  0.,  0.]])
```

```
In [21]: ss = SparseSeries.from_coo(A)
```

```
In [22]: ss
```

```
Out[22]:
0 2 1
  3 2
1 0 3
dtype: float64
BlockIndex
Block locations: array([0])
Block lengths: array([3])
```

String Methods Enhancements

- Following new methods are accessible via `.str` accessor to apply the function to each values. This is intended to make it more consistent with standard methods on strings. ([GH9282](#), [GH9352](#), [GH9386](#), [GH9387](#), [GH9439](#))

Methods				
<code>isalnum()</code>	<code>isalpha()</code>	<code>isdigit()</code>	<code>isdigit()</code>	<code>isspace()</code>
<code>islower()</code>	<code>isupper()</code>	<code>istitle()</code>	<code>isnumeric()</code>	<code>isdecimal()</code>
<code>find()</code>	<code>rfind()</code>	<code>ljust()</code>	<code>rjust()</code>	<code>zfill()</code>

```
In [23]: s = Series(['abcd', '3456', 'EFGH'])
```

```
In [24]: s.str.isalpha()
```

```
Out[24]:
0    True
1   False
2    True
dtype: bool
```

```
In [25]: s.str.find('ab')
```

```
Out[25]:
0      0
1     -1
2     -1
dtype: int64
```

- `Series.str.pad()` and `Series.str.center()` now accept `fillchar` option to specify filling character (GH9352)

```
In [26]: s = Series(['12', '300', '25'])
```

```
In [27]: s.str.pad(5, fillchar='_')
```

```
Out[27]:
0      __12
1     __300
2     __25
dtype: object
```

- Added `Series.str.slice_replace()`, which previously raised `NotImplementedError` (GH8888)

```
In [28]: s = Series(['ABCD', 'EFGH', 'IJK'])
```

```
In [29]: s.str.slice_replace(1, 3, 'X')
```

```
Out[29]:
0      AXD
1      EXH
2       IX
dtype: object
```

```
# replaced with empty char
```

```
In [30]: s.str.slice_replace(0, 1)
```

```
Out[30]:
0      BCD
1      FGH
2       JK
dtype: object
```

Other enhancements

- Reindex now supports `method='nearest'` for frames or series with a monotonic increasing or decreasing index (GH9258):

```
In [31]: df = pd.DataFrame({'x': range(5)})
```

```
In [32]: df.reindex([0.2, 1.8, 3.5], method='nearest')
```

```
Out[32]:
      x
0.2  0
1.8  2
3.5  4
```

This method is also exposed by the lower level `Index.get_indexer` and `Index.get_loc` methods.

- The `read_excel()` function's `sheetname` argument now accepts a list and `None`, to get multiple or all sheets respectively. If more than one sheet is specified, a dictionary is returned. (GH9450)

```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
```

```
pd.read_excel('path_to_file.xls', sheetname=['Sheet1', 3])
```

- Allow Stata files to be read incrementally with an iterator; support for long strings in Stata files. See the docs [here](#) (GH9493:).
- Paths beginning with ~ will now be expanded to begin with the user's home directory (GH9066)
- Added time interval selection in `get_data_yahoo` (GH9071)
- Added `Timestamp.to_datetime64()` to complement `Timedelta.to_timedelta64()` (GH9255)
- `tseries.frequencies.to_offset()` now accepts `Timedelta` as input (GH9064)
- Lag parameter was added to the autocorrelation method of `Series`, defaults to lag-1 autocorrelation (GH9192)
- `Timedelta` will now accept `nanoseconds` keyword in constructor (GH9273)
- SQL code now safely escapes table and column names (GH8986)
- Added auto-complete for `Series.str.<tab>`, `Series.dt.<tab>` and `Series.cat.<tab>` (GH9322)
- `Index.get_indexer` now supports `method='pad'` and `method='backfill'` even for any target array, not just monotonic targets. These methods also work for monotonic decreasing as well as monotonic increasing indexes (GH9258).
- `Index.asof` now works on all index types (GH9258).
- A `verbose` argument has been augmented in `io.read_excel()`, defaults to `False`. Set to `True` to print sheet names as they are parsed. (GH9450)
- Added `days_in_month` (compatibility alias `daysinmonth`) property to `Timestamp`, `DatetimeIndex`, `Period`, `PeriodIndex`, and `Series.dt` (GH9572)
- Added `decimal` option in `to_csv` to provide formatting for non-',' decimal separators (GH781)
- Added `normalize` option for `Timestamp` to normalized to midnight (GH8794)
- Added example for `DataFrame` import to R using HDF5 file and `rhdf5` library. See the [documentation](#) for more (GH9636).

1.2.2 Backwards incompatible API changes

Changes in Timedelta

In v0.15.0 a new scalar type `Timedelta` was introduced, that is a sub-class of `datetime.timedelta`. Mentioned [here](#) was a notice of an API change w.r.t. the `.seconds` accessor. The intent was to provide a user-friendly set of accessors that give the 'natural' value for that unit, e.g. if you had a `Timedelta('1 day, 10:11:12')`, then `.seconds` would return 12. However, this is at odds with the definition of `datetime.timedelta`, which defines `.seconds` as `10 * 3600 + 11 * 60 + 12 == 36672`.

So in v0.16.0, we are restoring the API to match that of `datetime.timedelta`. Further, the component values are still available through the `.components` accessor. This affects the `.seconds` and `.microseconds` accessors, and removes the `.hours`, `.minutes`, `.milliseconds` accessors. These changes affect `TimedeltaIndex` and the `Series .dt` accessor as well. (GH9185, GH9139)

Previous Behavior

```
In [2]: t = pd.Timedelta('1 day, 10:11:12.100123')
```

```
In [3]: t.days
Out[3]: 1
```

```
In [4]: t.seconds
```

```
Out[4]: 12
```

```
In [5]: t.microseconds
Out[5]: 123
```

New Behavior

```
In [33]: t = pd.Timedelta('1 day, 10:11:12.100123')
```

```
In [34]: t.days
Out[34]: 1L
```

```
In [35]: t.seconds
Out[35]: 36672L
```

```
In [36]: t.microseconds
Out[36]: 100123L
```

Using `.components` allows the full component access

```
In [37]: t.components
Out[37]: Components(days=1L, hours=10L, minutes=11L, seconds=12L, milliseconds=100L, microseconds=123L)
```

```
In [38]: t.components.seconds
Out[38]: 12L
```

Indexing Changes

The behavior of a small sub-set of edge cases for using `.loc` have changed ([GH8613](#)). Furthermore we have improved the content of the error messages that are raised:

- Slicing with `.loc` where the start and/or stop bound is not found in the index is now allowed; this previously would raise a `KeyError`. This makes the behavior the same as `.ix` in this case. This change is only for slicing, not when indexing with a single label.

```
In [39]: df = DataFrame(np.random.randn(5,4),
.....:                  columns=list('ABCD'),
.....:                  index=date_range('20130101', periods=5))
.....:
```

```
In [40]: df
Out[40]:
```

	A	B	C	D
2013-01-01	-0.744471	0.758527	1.729689	-0.964980
2013-01-02	-0.845696	-1.340896	1.846883	-1.328865
2013-01-03	1.682706	-1.717693	0.888782	0.228440
2013-01-04	0.901805	1.171216	0.520260	-1.197071
2013-01-05	-1.066969	-0.303421	-0.858447	0.306996

```
In [41]: s = Series(range(5), [-2,-1,1,2,3])
```

```
In [42]: s
Out[42]:
-2    0
-1    1
1     2
2     3
```

```

3      4
dtype: int64

```

Previous Behavior

```

In [4]: df.loc['2013-01-02':'2013-01-10']
KeyError: 'stop bound [2013-01-10] is not in the [index]'

```

```

In [6]: s.loc[-10:3]
KeyError: 'start bound [-10] is not the [index]'

```

New Behavior

```

In [43]: df.loc['2013-01-02':'2013-01-10']
Out[43]:

```

	A	B	C	D
2013-01-02	-0.845696	-1.340896	1.846883	-1.328865
2013-01-03	1.682706	-1.717693	0.888782	0.228440
2013-01-04	0.901805	1.171216	0.520260	-1.197071
2013-01-05	-1.066969	-0.303421	-0.858447	0.306996

```

In [44]: s.loc[-10:3]
Out[44]:
-2      0
-1      1
1       2
2       3
3       4
dtype: int64

```

- Allow slicing with float-like values on an integer index for `.ix`. Previously this was only enabled for `.loc`:

Previous Behavior

```

In [8]: s.ix[-1.0:2]
TypeError: the slice start value [-1.0] is not a proper indexer for this index type (Int64Index)

```

New Behavior

```

In [45]: s.ix[-1.0:2]
Out[45]:
-1      1
1       2
2       3
dtype: int64

```

- Provide a useful exception for indexing with an invalid type for that index when using `.loc`. For example trying to use `.loc` on an index of type `DatetimeIndex` or `PeriodIndex` or `TimedeltaIndex`, with an integer (or a float).

Previous Behavior

```

In [4]: df.loc[2:3]
KeyError: 'start bound [2] is not the [index]'

```

New Behavior

```

In [4]: df.loc[2:3]
TypeError: Cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with <type 'int'>

```

Categorical Changes

In prior versions, `Categoricals` that had an unspecified ordering (meaning no `ordered` keyword was passed) were defaulted as ordered `Categoricals`. Going forward, the `ordered` keyword in the `Categorical` constructor will default to `False`. Ordering must now be explicit.

Furthermore, previously you *could* change the `ordered` attribute of a `Categorical` by just setting the attribute, e.g. `cat.ordered=True`; This is now deprecated and you should use `cat.as_ordered()` or `cat.as_unordered()`. These will by default return a **new** object and not modify the existing object. (GH9347, GH9190)

Previous Behavior

```
In [3]: s = Series([0,1,2], dtype='category')
```

```
In [4]: s
Out[4]:
0    0
1    1
2    2
dtype: category
Categories (3, int64): [0 < 1 < 2]
```

```
In [5]: s.cat.ordered
Out[5]: True
```

```
In [6]: s.cat.ordered = False
```

```
In [7]: s
Out[7]:
0    0
1    1
2    2
dtype: category
Categories (3, int64): [0, 1, 2]
```

New Behavior

```
In [46]: s = Series([0,1,2], dtype='category')
```

```
In [47]: s
Out[47]:
0    0
1    1
2    2
dtype: category
Categories (3, int64): [0, 1, 2]
```

```
In [48]: s.cat.ordered
Out[48]: False
```

```
In [49]: s = s.cat.as_ordered()
```

```
In [50]: s
Out[50]:
0    0
1    1
2    2
dtype: category
```

```
Categories (3, int64): [0 < 1 < 2]
```

```
In [51]: s.cat.ordered
Out[51]: True
```

```
# you can set in the constructor of the Categorical
```

```
In [52]: s = Series(Categorical([0,1,2],ordered=True))
```

```
In [53]: s
Out[53]:
0    0
1    1
2    2
dtype: category
Categories (3, int64): [0 < 1 < 2]
```

```
In [54]: s.cat.ordered
Out[54]: True
```

For ease of creation of series of categorical data, we have added the ability to pass keywords when calling `.astype()`. These are passed directly to the constructor.

```
In [55]: s = Series(["a","b","c","a"]).astype('category',ordered=True)
```

```
In [56]: s
Out[56]:
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a < b < c]
```

```
In [57]: s = Series(["a","b","c","a"]).astype('category',categories=list('abcdef'),ordered=False)
```

```
In [58]: s
Out[58]:
0    a
1    b
2    c
3    a
dtype: category
Categories (6, object): [a, b, c, d, e, f]
```

Other API Changes

- `Index.duplicated` now returns `np.array(dtype=bool)` rather than `Index(dtype=object)` containing `bool` values. (GH8875)
- `DataFrame.to_json` now returns accurate type serialisation for each column for frames of mixed dtype (GH9037)

Previously data was coerced to a common dtype before serialisation, which for example resulted in integers being serialised to floats:

```
In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1.0,"1":2.0}}'
```

Now each column is serialised using its correct dtype:

```
In [2]: pd.DataFrame({'i': [1,2], 'f': [3.0, 4.2]}).to_json()
Out[2]: '{"f":{"0":3.0,"1":4.2},"i":{"0":1,"1":2}}'
```

- `DatetimeIndex`, `PeriodIndex` and `TimedeltaIndex.summary` now output the same format. (GH9116)
- `TimedeltaIndex.freqstr` now output the same string format as `DatetimeIndex`. (GH9116)
- Bar and horizontal bar plots no longer add a dashed line along the info axis. The prior style can be achieved with matplotlib's `axhline` or `axvline` methods (GH9088).
- Series accessors `.dt`, `.cat` and `.str` now raise `AttributeError` instead of `TypeError` if the series does not contain the appropriate type of data (GH9617). This follows Python's built-in exception hierarchy more closely and ensures that tests like `hasattr(s, 'cat')` are consistent on both Python 2 and 3.
- Series now supports bitwise operation for integral types (GH9016). Previously even if the input dtypes were integral, the output dtype was coerced to `bool`.

Previous Behavior

```
In [2]: pd.Series([0,1,2,3], list('abcd')) | pd.Series([4,4,4,4], list('abcd'))
Out[2]:
a    True
b    True
c    True
d    True
dtype: bool
```

New Behavior. If the input dtypes are integral, the output dtype is also integral and the output values are the result of the bitwise operation.

```
In [2]: pd.Series([0,1,2,3], list('abcd')) | pd.Series([4,4,4,4], list('abcd'))
Out[2]:
a    4
b    5
c    6
d    7
dtype: int64
```

- During division involving a Series or DataFrame, `0/0` and `0//0` now give `np.nan` instead of `np.inf`. (GH9144, GH8445)

Previous Behavior

```
In [2]: p = pd.Series([0, 1])
```

```
In [3]: p / 0
Out[3]:
0    inf
1    inf
dtype: float64
```

```
In [4]: p // 0
Out[4]:
0    inf
1    inf
dtype: float64
```

New Behavior

```
In [59]: p = pd.Series([0, 1])
```

```
In [60]: p / 0
Out[60]:
0      NaN
1      inf
dtype: float64
```

```
In [61]: p // 0
Out[61]:
0      NaN
1      inf
dtype: float64
```

- `Series.values_counts` and `Series.describe` for categorical data will now put NaN entries at the end. (GH9443)
- `Series.describe` for categorical data will now give counts and frequencies of 0, not NaN, for unused categories (GH9443)
- Due to a bug fix, looking up a partial string label with `DatetimeIndex.asof` now includes values that match the string, even if they are after the start of the partial string label (GH9258).

Old behavior:

```
In [4]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[4]: Timestamp('2000-01-31 00:00:00')
```

Fixed behavior:

```
In [62]: pd.to_datetime(['2000-01-31', '2000-02-28']).asof('2000-02')
Out[62]: Timestamp('2000-02-28 00:00:00')
```

To reproduce the old behavior, simply add more precision to the label (e.g., use `2000-02-01` instead of `2000-02`).

Deprecations

- The `rplot` trellis plotting interface is deprecated and will be removed in a future version. We refer to external packages like `seaborn` for similar but more refined functionality (GH3445). The documentation includes some examples how to convert your existing code using `rplot` to `seaborn`: [rplot docs](#).
- The `pandas.sandbox.qtpandas` interface is deprecated and will be removed in a future version. We refer users to the external package `pandas-qt`. (GH9615)
- The `pandas.rpy` interface is deprecated and will be removed in a future version. Similar functionality can be accessed thru the `rpy2` project (GH9602)
- Adding `DatetimeIndex/PeriodIndex` to another `DatetimeIndex/PeriodIndex` is being deprecated as a set-operation. This will be changed to a `TypeError` in a future version. `.union()` should be used for the union set operation. (GH9094)
- Subtracting `DatetimeIndex/PeriodIndex` from another `DatetimeIndex/PeriodIndex` is being deprecated as a set-operation. This will be changed to an actual numeric subtraction yielding a `TimeDeltaIndex` in a future version. `.difference()` should be used for the differencing set operation. (GH9094)

Removal of prior version deprecations/changes

- `DataFrame.pivot_table` and `crosstab`'s `rows` and `cols` keyword arguments were removed in favor of `index` and `columns` (GH6581)
- `DataFrame.to_excel` and `DataFrame.to_csv` `cols` keyword argument was removed in favor of `columns` (GH6581)
- Removed `convert_dummies` in favor of `get_dummies` (GH6581)
- Removed `value_range` in favor of `describe` (GH6581)

1.2.3 Performance Improvements

- Fixed a performance regression for `.loc` indexing with an array or list-like (GH9126;).
- `DataFrame.to_json` 30x performance improvement for mixed dtype frames. (GH9037)
- Performance improvements in `MultiIndex.duplicated` by working with labels instead of values (GH9125)
- Improved the speed of `nunique` by calling `unique` instead of `value_counts` (GH9129, GH7771)
- Performance improvement of up to 10x in `DataFrame.count` and `DataFrame.dropna` by taking advantage of homogeneous/heterogeneous dtypes appropriately (GH9136)
- Performance improvement of up to 20x in `DataFrame.count` when using a `MultiIndex` and the `level` keyword argument (GH9163)
- Performance and memory usage improvements in `merge` when key space exceeds `int64` bounds (GH9151)
- Performance improvements in multi-key `groupby` (GH9429)
- Performance improvements in `MultiIndex.sortlevel` (GH9445)
- Performance and memory usage improvements in `DataFrame.duplicated` (GH9398)
- Cythonized `Period` (GH9440)
- Decreased memory usage on `to_hdf` (GH9648)

1.2.4 Bug Fixes

- Changed `.to_html` to remove leading/trailing spaces in table body (GH4987)
- Fixed issue using `read_csv` on s3 with Python 3 (GH9452)
- Fixed compatibility issue in `DatetimeIndex` affecting architectures where `numpy.int_` defaults to `numpy.int32` (GH8943)
- Bug in Panel indexing with an object-like (GH9140)
- Bug in the returned `Series.dt.components` index was reset to the default index (GH9247)
- Bug in `Categorical.__getitem__`/`__setitem__` with listlike input getting incorrect results from indexer coercion (GH9469)
- Bug in partial setting with a `DatetimeIndex` (GH9478)
- Bug in `groupby` for integer and `datetime64` columns when applying an aggregator that caused the value to be changed when the number was sufficiently large (GH9311, GH6620)

- Fixed bug in `to_sql` when mapping a `Timestamp` object column (datetime column with timezone info) to the appropriate sqlalchemy type (GH9085).
- Fixed bug in `to_sql` `dtype` argument not accepting an instantiated SQLAlchemy type (GH9083).
- Bug in `.loc` partial setting with a `np.datetime64` (GH9516)
- Incorrect dtypes inferred on datetimelike looking Series & on `.xs` slices (GH9477)
- Items in `Categorical.unique()` (and `s.unique()` if `s` is of dtype `category`) now appear in the order in which they are originally found, not in sorted order (GH9331). This is now consistent with the behavior for other dtypes in pandas.
- Fixed bug on big endian platforms which produced incorrect results in `StataReader` (GH8688).
- Bug in `MultiIndex.has_duplicates` when having many levels causes an indexer overflow (GH9075, GH5873)
- Bug in `pivot` and `unstack` where nan values would break index alignment (GH4862, GH7401, GH7403, GH7405, GH7466, GH9497)
- Bug in left join on multi-index with `sort=True` or null values (GH9210).
- Bug in `MultiIndex` where inserting new keys would fail (GH9250).
- Bug in `groupby` when key space exceeds `int64` bounds (GH9096).
- Bug in `unstack` with `TimedeltaIndex` or `DatetimeIndex` and nulls (GH9491).
- Bug in `rank` where comparing floats with tolerance will cause inconsistent behaviour (GH8365).
- Fixed character encoding bug in `read_stata` and `StataReader` when loading data from a URL (GH9231).
- Bug in adding offsets. `Nano` to other offsets raises `TypeError` (GH9284)
- Bug in `DatetimeIndex` iteration, related to (GH8890), fixed in (GH9100)
- Bugs in `resample` around DST transitions. This required fixing offset classes so they behave correctly on DST transitions. (GH5172, GH8744, GH8653, GH9173, GH9468).
- Bug in binary operator method (eg `.mul()`) alignment with integer levels (GH9463).
- Bug in `boxplot`, `scatter` and `hexbin` plot may show an unnecessary warning (GH8877)
- Bug in `subplot` with `layout` kw may show unnecessary warning (GH9464)
- Bug in using grouper functions that need passed thru arguments (e.g. `axis`), when using wrapped function (e.g. `fillna`), (GH9221)
- `DataFrame` now properly supports simultaneous `copy` and `dtype` arguments in constructor (GH9099)
- Bug in `read_csv` when using `skiprows` on a file with CR line endings with the `c` engine. (GH9079)
- `isnull` now detects `NaT` in `PeriodIndex` (GH9129)
- Bug in `groupby.nth()` with a multiple column `groupby` (GH8979)
- Bug in `DataFrame.where` and `Series.where` coerce numerics to string incorrectly (GH9280)
- Bug in `DataFrame.where` and `Series.where` raise `ValueError` when string list-like is passed. (GH9280)
- Accessing `Series.str` methods on with non-string values now raises `TypeError` instead of producing incorrect results (GH9184)
- Bug in `DatetimeIndex.__contains__` when index has duplicates and is not monotonic increasing (GH9512)

- Fixed division by zero error for `Series.kurt()` when all values are equal (GH9197)
- Fixed issue in the `xlsxwriter` engine where it added a default ‘General’ format to cells if no other format was applied. This prevented other row or column formatting being applied. (GH9167)
- Fixes issue with `index_col=False` when `usecols` is also specified in `read_csv`. (GH9082)
- Bug where `wide_to_long` would modify the input stubnames list (GH9204)
- Bug in `to_sql` not storing float64 values using double precision. (GH9009)
- `SparseSeries` and `SparsePanel` now accept zero argument constructors (same as their non-sparse counterparts) (GH9272).
- Regression in merging `Categorical` and `object` dtypes (GH9426)
- Bug in `read_csv` with buffer overflows with certain malformed input files (GH9205)
- Bug in `groupby` `MultiIndex` with missing pair (GH9049, GH9344)
- Fixed bug in `Series.groupby` where grouping on `MultiIndex` levels would ignore the `sort` argument (GH9444)
- Fix bug in `DataFrame.Groupby` where `sort=False` is ignored in the case of `Categorical` columns. (GH8868)
- Fixed bug with reading CSV files from Amazon S3 on python 3 raising a `TypeError` (GH9452)
- Bug in the Google BigQuery reader where the ‘`jobComplete`’ key may be present but `False` in the query results (GH8728)
- Bug in `Series.values_counts` with excluding `NaN` for categorical type `Series` with `dropna=True` (GH9443)
- Fixed missing `numeric_only` option for `DataFrame.std/var/sem` (GH9201)
- Support constructing `Panel` or `Panel4D` with scalar data (GH8285)
- `Series` text representation disconnected from `max_rows/max_columns` (GH7508).
- `Series` number formatting inconsistent when truncated (GH8532).

Previous Behavior

```
In [2]: pd.options.display.max_rows = 10
In [3]: s = pd.Series([1,1,1,1,1,1,1,1,1,1,0.9999,1,1]*10)
In [4]: s
Out[4]:
0      1
1      1
2      1
...
127    0.9999
128    1.0000
129    1.0000
Length: 130, dtype: float64
```

New Behavior

```
0      1.0000
1      1.0000
2      1.0000
3      1.0000
4      1.0000
...
```

```

125    1.0000
126    1.0000
127    0.9999
128    1.0000
129    1.0000
dtype: float64

```

- A Spurious SettingWithCopy Warning was generated when setting a new item in a frame in some cases (GH8730)

The following would previously report a SettingWithCopy Warning.

```

In [1]: df1 = DataFrame({'x': Series(['a', 'b', 'c']), 'y': Series(['d', 'e', 'f'])})

In [2]: df2 = df1[['x']]

In [3]: df2['y'] = ['g', 'h', 'i']

```

1.3 v0.15.2 (December 12, 2014)

This is a minor release from 0.15.1 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. A small number of API changes were necessary to fix existing bugs. We recommend that all users upgrade to this version.

- *Enhancements*
- *API Changes*
- *Performance Improvements*
- *Bug Fixes*

1.3.1 API changes

- Indexing in MultiIndex beyond lex-sort depth is now supported, though a lexically sorted index will have a better performance. (GH2646)

```

In [1]: df = pd.DataFrame({'jim':[0, 0, 1, 1],
...:                      'joe':['x', 'x', 'z', 'y'],
...:                      'jolie':np.random.rand(4)}).set_index(['jim', 'joe'])
...:

```

```

In [2]: df
Out[2]:
           jolie
jim joe
0    x    0.751953
    x    0.561512
1    z    0.572214
    y    0.740693

```

```

In [3]: df.index.lexsort_depth
Out[3]: 1

```

```

# in prior versions this would raise a KeyError
# will now show a PerformanceWarning

```

```
In [4]: df.loc[(1, 'z')]
Out[4]:
           jolie
jim joe
1    z    0.572214

# lexically sorting
In [5]: df2 = df.sortlevel()

In [6]: df2
Out[6]:
           jolie
jim joe
0    x    0.751953
      x    0.561512
1    y    0.740693
      z    0.572214

In [7]: df2.index.lexsort_depth
Out[7]: 2

In [8]: df2.loc[(1, 'z')]
Out[8]:
           jolie
jim joe
1    z    0.572214
```

- Bug in `unique` of `Series` with `category` dtype, which returned all categories regardless whether they were “used” or not (see [GH8559](#) for the discussion). Previous behaviour was to return all categories:

```
In [3]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [4]: cat
Out[4]:
[a, b, a]
Categories (3, object): [a < b < c]

In [5]: cat.unique()
Out[5]: array(['a', 'b', 'c'], dtype=object)
```

Now, only the categories that do effectively occur in the array are returned:

```
In [9]: cat = pd.Categorical(['a', 'b', 'a'], categories=['a', 'b', 'c'])

In [10]: cat.unique()
Out[10]: array(['a', 'b'], dtype=object)
```

- `Series.all` and `Series.any` now support the `level` and `skipna` parameters. `Series.all`, `Series.any`, `Index.all`, and `Index.any` no longer support the `out` and `keepdims` parameters, which existed for compatibility with `ndarray`. Various index types no longer support the `all` and `any` aggregation functions and will now raise `TypeError`. ([GH8302](#)).
- Allow equality comparisons of `Series` with a categorical dtype and object dtype; previously these would raise `TypeError` ([GH8938](#))
- Bug in `NDFrame`: conflicting attribute/column names now behave consistently between getting and setting. Previously, when both a column and attribute named `y` existed, `data.y` would return the attribute, while `data.y = z` would update the column ([GH8994](#))

```
In [11]: data = pd.DataFrame({'x':[1, 2, 3]})
```

```
In [12]: data.y = 2
```

```
In [13]: data['y'] = [2, 4, 6]
```

```
In [14]: data
```

```
Out[14]:
```

```
   x  y
0  1  2
1  2  4
2  3  6
```

```
# this assignment was inconsistent
```

```
In [15]: data.y = 5
```

Old behavior:

```
In [6]: data.y
```

```
Out[6]: 2
```

```
In [7]: data['y'].values
```

```
Out[7]: array([5, 5, 5])
```

New behavior:

```
In [16]: data.y
```

```
Out[16]: 5
```

```
In [17]: data['y'].values
```

```
Out[17]: array([2, 4, 6], dtype=int64)
```

- `Timestamp('now')` is now equivalent to `Timestamp.now()` in that it returns the local time rather than UTC. Also, `Timestamp('today')` is now equivalent to `Timestamp.today()` and both have `tz` as a possible argument. (GH9000)
- Fix negative step support for label-based slices (GH8753)

Old behavior:

```
In [1]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])
```

```
Out[1]:
```

```
a    0
b    1
c    2
dtype: int64
```

```
In [2]: s.loc['c':'a':-1]
```

```
Out[2]:
```

```
c    2
dtype: int64
```

New behavior:

```
In [18]: s = pd.Series(np.arange(3), ['a', 'b', 'c'])
```

```
In [19]: s.loc['c':'a':-1]
```

```
Out[19]:
```

```
c    2
b    1
```

```
a      0
dtype: int32
```

1.3.2 Enhancements

Categorical enhancements:

- Added ability to export Categorical data to Stata ([GH8633](#)). See [here](#) for limitations of categorical variables exported to Stata data files.
- Added flag `order_categoricals` to `StataReader` and `read_stata` to select whether to order imported categorical data ([GH8836](#)). See [here](#) for more information on importing categorical variables from Stata data files.
- Added ability to export Categorical data to/from HDF5 ([GH7621](#)). Queries work the same as if it was an object array. However, the `category` dtyped data is stored in a more efficient manner. See [here](#) for an example and caveats w.r.t. prior versions of pandas.
- Added support for `searchsorted()` on *Categorical* class ([GH8420](#)).

Other enhancements:

- Added the ability to specify the SQL type of columns when writing a `DataFrame` to a database ([GH8778](#)). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```
from sqlalchemy.types import String
data.to_sql('data_dtype', engine, dtype={'Col_1': String})
```

- `Series.all` and `Series.any` now support the `level` and `skipna` parameters ([GH8302](#)):

```
In [20]: s = pd.Series([False, True, False], index=[0, 0, 1])
```

```
In [21]: s.any(level=0)
```

```
Out[21]:
0      True
1     False
dtype: bool
```

- `Panel` now supports the `all` and `any` aggregation functions. ([GH8302](#)):

```
In [22]: p = pd.Panel(np.random.rand(2, 5, 4) > 0.1)
```

```
In [23]: p.all()
```

```
Out[23]:
      0      1
0  True  False
1  True  False
2 False  False
3  True   True
```

- Added support for `utcfromtimestamp()`, `fromtimestamp()`, and `combine()` on *Timestamp* class ([GH5351](#)).
- Added Google Analytics (*pandas.io.ga*) basic documentation ([GH8835](#)). See [here](#).
- `Timedelta` arithmetic returns `NotImplemented` in unknown cases, allowing extensions by custom classes ([GH8813](#)).
- `Timedelta` now supports arithmetic with `numpy.ndarray` objects of the appropriate dtype (numpy 1.8 or newer only) ([GH8884](#)).

- Added `Timedelta.to_timedelta64()` method to the public API (GH8884).
- Added `gbq.generate_bq_schema()` function to the `gbq` module (GH8325).
- `Series` now works with map objects the same way as generators (GH8909).
- Added context manager to `HDFStore` for automatic closing (GH8791).
- `to_datetime` gains an `exact` keyword to allow for a format to not require an exact match for a provided format string (if its `False`). `exact` defaults to `True` (meaning that exact matching is still the default) (GH8904)
- Added `axvlines` boolean option to `parallel_coordinates` plot function, determines whether vertical lines will be printed, default is `True`
- Added ability to read table footers to `read_html` (GH8552)
- `to_sql` now infers datatypes of non-NA values for columns that contain NA values and have dtype `object` (GH8778).

1.3.3 Performance

- Reduce memory usage when `skiprows` is an integer in `read_csv` (GH8681)
- Performance boost for `to_datetime` conversions with a passed `format=`, and the `exact=False` (GH8904)

1.3.4 Bug Fixes

- Bug in `concat` of `Series` with `category` dtype which were coercing to `object`. (GH8641)
- Bug in `Timestamp-Timestamp` not returning a `Timedelta` type and `datelike-datelike` ops with timezones (GH8865)
- Made consistent a timezone mismatch exception (either `tz` operated with `None` or incompatible timezone), will now return `TypeError` rather than `ValueError` (a couple of edge cases only), (GH8865)
- Bug in using a `pd.Grouper(key=...)` with no level/axis or level only (GH8795, GH8866)
- Report a `TypeError` when invalid/no parameters are passed in a `groupby` (GH8015)
- Bug in packaging pandas with `py2app/cx_Freeze` (GH8602, GH8831)
- Bug in `groupby` signatures that didn't include `*args` or `**kwargs` (GH8733).
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Unclear error message in `csv` parsing when passing `dtype` and `names` and the parsed data is a different data type (GH8833)
- Bug in slicing a multi-index with an empty list and at least one boolean indexer (GH8781)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo (GH8761).
- `Timedelta` kwargs may now be `numpy` ints and floats (GH8757).
- Fixed several outstanding bugs for `Timedelta` arithmetic and comparisons (GH8813, GH5963, GH5436).
- `sql_schema` now generates dialect appropriate `CREATE TABLE` statements (GH8697)
- `slice` string method now takes `step` into account (GH8754)
- Bug in `BlockManager` where setting values with different type would break block integrity (GH8850)

- Bug in `DatetimeIndex` when using `time` object as key (GH8667)
- Bug in `merge` where `how='left'` and `sort=False` would not preserve left frame order (GH7331)
- Bug in `MultiIndex.reindex` where reindexing at level would not reorder labels (GH4088)
- Bug in certain operations with `dateutil` timezones, manifesting with `dateutil` 2.3 (GH8639)
- Regression in `DatetimeIndex` iteration with a Fixed/Local offset timezone (GH8890)
- Bug in `to_datetime` when parsing a nanoseconds using the `%f` format (GH8989)
- `io.data.Options` now raises `RemoteDataError` when no expiry dates are available from Yahoo and when it receives no data from Yahoo (GH8761), (GH8783).
- Fix: The font size was only set on x axis if vertical or the y axis if horizontal. (GH8765)
- Fixed division by 0 when reading big csv files in python 3 (GH8621)
- Bug in outputting a `Multindex` with `to_html, index=False` which would add an extra column (GH8452)
- Imported categorical variables from Stata files retain the ordinal information in the underlying data (GH8836).
- Defined `.size` attribute across `NDFrame` objects to provide compat with `numpy >= 1.9.1`; buggy with `np.array_split` (GH8846)
- Skip testing of histogram plots for `matplotlib <= 1.2` (GH8648).
- Bug where `get_data_google` returned object dtypes (GH3995)
- Bug in `DataFrame.stack(..., dropna=False)` when the `DataFrame`'s columns is a `MultiIndex` whose labels do not reference all its levels. (GH8844)
- Bug in that Option context applied on `__enter__` (GH8514)
- Bug in `resample` that causes a `ValueError` when resampling across multiple days and the last offset is not calculated from the start of the range (GH8683)
- Bug where `DataFrame.plot(kind='scatter')` fails when checking if an `np.array` is in the `DataFrame` (GH8852)
- Bug in `pd.infer_freq/DataFrame.inferred_freq` that prevented proper sub-daily frequency inference when the index contained DST days (GH8772).
- Bug where index name was still used when plotting a series with `use_index=False` (GH8558).
- Bugs when trying to stack multiple columns, when some (or all) of the level names are numbers (GH8584).
- Bug in `MultiIndex` where `__contains__` returns wrong result if index is not lexically sorted or unique (GH7724)
- BUG CSV: fix problem with trailing whitespace in skipped rows, (GH8679), (GH8661), (GH8983)
- Regression in `Timestamp` does not parse 'Z' zone designator for UTC (GH8771)
- Bug in `StataWriter` the produces writes strings with 244 characters irrespective of actual size (GH8969)
- Fixed `ValueError` raised by `cummin/cummax` when `datetime64` Series contains `NaT`. (GH8965)
- Bug in `Datareader` returns object dtype if there are missing values (GH8980)
- Bug in plotting if `sharex` was enabled and index was a timeseries, would show labels on multiple axes (GH3964).
- Bug where passing a unit to the `TimedeltaIndex` constructor applied the to nano-second conversion twice. (GH9011).
- Bug in plotting of a period-like array (GH9012)

1.4 v0.15.1 (November 9, 2014)

This is a minor bug-fix release from 0.15.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- *Enhancements*
- *API Changes*
- *Bug Fixes*

1.4.1 API changes

- `s.dt.hour` and other `.dt` accessors will now return `np.nan` for missing values (rather than previously `-1`), (GH8689)

```
In [1]: s = Series(date_range('20130101', periods=5, freq='D'))
```

```
In [2]: s.iloc[2] = np.nan
```

```
In [3]: s
```

```
Out[3]:
```

```
0    2013-01-01
1    2013-01-02
2             NaT
3    2013-01-04
4    2013-01-05
dtype: datetime64[ns]
```

previous behavior:

```
In [6]: s.dt.hour
```

```
Out[6]:
```

```
0     0
1     0
2    -1
3     0
4     0
dtype: int64
```

current behavior:

```
In [4]: s.dt.hour
```

```
Out[4]:
```

```
0     0
1     0
2    NaN
3     0
4     0
dtype: float64
```

- `groupby` with `as_index=False` will not add erroneous extra columns to result (GH8582):

```
In [5]: np.random.seed(2718281)
```

```
In [6]: df = pd.DataFrame(np.random.randint(0, 100, (10, 2)),
...:                      columns=['jim', 'joe'])
```

```
...:

In [7]: df.head()
Out[7]:
   jim  joe
0   61   81
1   96   49
2   55   65
3   72   51
4   77   12

In [8]: ts = pd.Series(5 * np.random.randint(0, 3, 10))
```

previous behavior:

```
In [4]: df.groupby(ts, as_index=False).max()
Out[4]:
   NaN  jim  joe
0     0   72  83
1     5   77  84
2    10   96  65
```

current behavior:

```
In [9]: df.groupby(ts, as_index=False).max()
Out[9]:
   jim  joe
0   72   83
1   77   84
2   96   65
```

- groupby will not erroneously exclude columns if the column name conflicts with the grouper name (GH8112):

```
In [10]: df = pd.DataFrame({'jim': range(5), 'joe': range(5, 10)})

In [11]: df
Out[11]:
   jim  joe
0     0    5
1     1    6
2     2    7
3     3    8
4     4    9
```

```
In [12]: gr = df.groupby(df['jim'] < 2)
```

previous behavior (excludes 1st column from output):

```
In [4]: gr.apply(sum)
Out[4]:
   joe
jim
False  24
True   11
```

current behavior:

```
In [13]: gr.apply(sum)
Out[13]:
   jim  joe
False  24
True   11
```

```
jim
False    9    24
True     1    11
```

- Support for slicing with monotonic decreasing indexes, even if start or stop is not found in the index (GH7860):

```
In [14]: s = pd.Series(['a', 'b', 'c', 'd'], [4, 3, 2, 1])
```

```
In [15]: s
```

```
Out[15]:
4      a
3      b
2      c
1      d
dtype: object
```

previous behavior:

```
In [8]: s.loc[3.5:1.5]
KeyError: 3.5
```

current behavior:

```
In [16]: s.loc[3.5:1.5]
Out[16]:
3      b
2      c
dtype: object
```

- `io.data.Options` has been fixed for a change in the format of the Yahoo Options page (GH8612), (GH8741)

Note: As a result of a change in Yahoo's option page layout, when an expiry date is given, `Options` methods now return data for a single expiry date. Previously, methods returned all data for the selected month.

The month and year parameters have been undeprecated and can be used to get all options data for a given month.

If an expiry date that is not valid is given, data for the next expiry after the given date is returned.

Option data frames are now saved on the instance as `callsYYMMDD` or `putsYYMMDD`. Previously they were saved as `callsSMMYY` and `putsSMMYY`. The next expiry is saved as `calls` and `puts`.

New features:

- The expiry parameter can now be a single date or a list-like object containing dates.
- A new property `expiry_dates` was added, which returns all available expiry dates.

Current behavior:

```
In [17]: from pandas.io.data import Options
```

```
In [18]: aapl = Options('aapl', 'yahoo')
```

```
In [19]: aapl.get_call_data().iloc[0:5,0:1]
```

```
Out[19]:
```

Strike	Expiry	Type	Symbol	Last
70	2015-05-15	call	AAPL150515C00070000	53.88

```
75      2015-05-15  call  AAPL150515C00075000  52.42
80      2015-05-15  call  AAPL150515C00080000  45.60
85      2015-05-15  call  AAPL150515C00085000  39.80
90      2015-05-15  call  AAPL150515C00090000  37.45
```

```
In [20]: aapl.expiry_dates
```

```
Out [20]:
[datetime.date(2015, 5, 15),
 datetime.date(2015, 5, 22),
 datetime.date(2015, 5, 29),
 datetime.date(2015, 6, 5),
 datetime.date(2015, 6, 12),
 datetime.date(2015, 6, 19),
 datetime.date(2015, 6, 26),
 datetime.date(2015, 7, 17),
 datetime.date(2015, 8, 21),
 datetime.date(2015, 10, 16),
 datetime.date(2016, 1, 15),
 datetime.date(2017, 1, 20)]
```

```
In [21]: aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3]).iloc[0:5,0:1]
```

```
Out [21]:
```

	Strike	Expiry	Type	Symbol	Last
127		2015-05-22	call	AAPL150522C00127000	2.45
		2015-05-29	call	AAPL150529C00127000	2.93
128		2015-05-15	call	AAPL150515C00128000	1.21
		2015-05-22	call	AAPL150522C00128000	1.90
		2015-05-29	call	AAPL150529C00128000	2.38

See the Options documentation in [Remote Data](#)

- pandas now also registers the `datetime64` dtype in matplotlib's units registry to plot such values as dates. This is activated once pandas is imported. In previous versions, plotting an array of `datetime64` values will have resulted in plotted integer values. To keep the previous behaviour, you can do `del matplotlib.units.registry[np.datetime64]` ([GH8614](#)).

1.4.2 Enhancements

- `concat` permits a wider variety of iterables of pandas objects to be passed as the first parameter ([GH8645](#)):

```
In [22]: from collections import deque
```

```
In [23]: df1 = pd.DataFrame([1, 2, 3])
```

```
In [24]: df2 = pd.DataFrame([4, 5, 6])
```

previous behavior:

```
In [7]: pd.concat(deque((df1, df2)))
```

```
TypeError: first argument must be a list-like of pandas objects, you passed an object of type "deque"
```

current behavior:

```
In [25]: pd.concat(deque((df1, df2)))
```

```
Out [25]:
```

```
0
0  1
```

```

1  2
2  3
0  4
1  5
2  6

```

- Represent `MultiIndex` labels with a dtype that utilizes memory based on the level size. In prior versions, the memory usage was a constant 8 bytes per element in each level. In addition, in prior versions, the *reported* memory usage was incorrect as it didn't show the usage for the memory occupied by the underlying data array. (GH8456)

```
In [26]: dfi = DataFrame(1, index=pd.MultiIndex.from_product(['a'], range(1000)), columns=['A'])
```

previous behavior:

```

# this was underreported in prior versions
In [1]: dfi.memory_usage(index=True)
Out[1]:
Index      8000 # took about 24008 bytes in < 0.15.1
A          8000
dtype: int64

```

current behavior:

```

In [27]: dfi.memory_usage(index=True)
Out[27]:
Index      11020
A          8000
dtype: int64

```

- Added Index properties `is_monotonic_increasing` and `is_monotonic_decreasing` (GH8680).
- Added option to select columns when importing Stata files (GH7935)
- Qualify memory usage in `DataFrame.info()` by adding + if it is a lower bound (GH8578)
- Raise errors in certain aggregation cases where an argument such as `numeric_only` is not handled (GH8592).
- Added support for 3-character ISO and non-standard country codes in `io.wb.download()` (GH8482)
- *World Bank data requests* now will warn/raise based on an `errors` argument, as well as a list of hard-coded country codes and the World Bank's JSON response. In prior versions, the error messages didn't look at the World Bank's JSON response. Problem-inducing input were simply dropped prior to the request. The issue was that many good countries were cropped in the hard-coded approach. All countries will work now, but some bad countries will raise exceptions because some edge cases break the entire response. (GH8482)
- Added option to `Series.str.split()` to return a `DataFrame` rather than a `Series` (GH8428)
- Added option to `df.info(null_counts=None|True|False)` to override the default display options and force showing of the null-counts (GH8701)

1.4.3 Bug Fixes

- Bug in unpickling of a `CustomBusinessDay` object (GH8591)
- Bug in coercing `Categorical` to a records array, e.g. `df.to_records()` (GH8626)
- Bug in `Categorical` not created properly with `Series.to_frame()` (GH8626)
- Bug in coercing in `astype` of a `Categorical` of a passed `pd.Categorical` (this now raises `TypeError` correctly), (GH8626)

- Bug in `cut/qcut` when using `Series` and `retbins=True` (GH8589)
- Bug in writing Categorical columns to an SQL database with `to_sql` (GH8624).
- Bug in comparing Categorical of datetime raising when being compared to a scalar datetime (GH8687)
- Bug in selecting from a Categorical with `.iloc` (GH8623)
- Bug in groupby-transform with a Categorical (GH8623)
- Bug in duplicated/drop_duplicates with a Categorical (GH8623)
- Bug in Categorical reflected comparison operator raising if the first argument was a numpy array scalar (e.g. `np.int64`) (GH8658)
- Bug in Panel indexing with a list-like (GH8710)
- Compat issue is `DataFrame.dtypes` when `options.mode.use_inf_as_null` is True (GH8722)
- Bug in `read_csv`, `dialect` parameter would not take a string (:issue: 8703)
- Bug in slicing a multi-index level with an empty-list (GH8737)
- Bug in numeric index operations of add/sub with Float/Index Index with numpy arrays (GH8608)
- Bug in setitem with empty indexer and unwanted coercion of dtypes (GH8669)
- Bug in ix/loc block splitting on setitem (manifests with integer-like dtypes, e.g. `datetime64`) (GH8607)
- Bug when doing label based indexing with integers not found in the index for non-unique but monotonic indexes (GH8680).
- Bug when indexing a `Float64Index` with `np.nan` on numpy 1.7 (GH8980).
- Fix shape attribute for `MultiIndex` (GH8609)
- Bug in `GroupBy` where a name conflict between the grouper and columns would break groupby operations (GH7115, GH8112)
- Fixed a bug where plotting a column `y` and specifying a label would mutate the index name of the original `DataFrame` (GH8494)
- Fix regression in plotting of a `DatetimeIndex` directly with `matplotlib` (GH8614).
- Bug in `date_range` where partially-specified dates would incorporate current date (GH6961)
- Bug in Setting by indexer to a scalar value with a mixed-dtype `Panel4d` was failing (GH8702)
- Bug where `DataReader`'s would fail if one of the symbols passed was invalid. Now returns data for valid symbols and `np.nan` for invalid (GH8494)
- Bug in `get_quote_yahoo` that wouldn't allow non-float return values (GH5229).

1.5 v0.15.0 (October 18, 2014)

This is a major release from 0.14.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Warning: pandas >= 0.15.0 will no longer support compatibility with NumPy versions < 1.7.0. If you want to use the latest versions of pandas, please upgrade to NumPy >= 1.7.0 (GH7711)

- Highlights include:
 - The `Categorical` type was integrated as a first-class pandas type, see [here](#)

- New scalar type `Timedelta`, and a new index type `TimedeltaIndex`, see [here](#)
- New datetimelike properties accessor `.dt` for `Series`, see [Datetimelike Properties](#)
- New `DataFrame` default display for `df.info()` to include memory usage, see [Memory Usage](#)
- `read_csv` will now by default ignore blank lines when parsing, see [here](#)
- API change in using `Indexes` in set operations, see [here](#)
- Enhancements in the handling of timezones, see [here](#)
- A lot of improvements to the rolling and expanding moment functions, see [here](#)
- Internal refactoring of the `Index` class to no longer sub-class `ndarray`, see [Internal Refactoring](#)
- dropping support for `PyTables` less than version 3.0.0, and `numexpr` less than version 2.1 (GH7990)
- Split indexing documentation into [Indexing and Selecting Data](#) and [MultiIndex / Advanced Indexing](#)
- Split out string methods documentation into [Working with Text Data](#)
- Check the [API Changes](#) and [deprecations](#) before updating
- [Other Enhancements](#)
- [Performance Improvements](#)
- [Bug Fixes](#)

Warning: In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications (See the [Internal Refactoring](#))

Warning: The refactorings in `Categorical` changed the two argument constructor from “codes/labels and levels” to “values and levels (now called ‘categories’)”. This can lead to subtle bugs. If you use `Categorical` directly, please audit your code before updating to this pandas version and change it to use the `from_codes()` constructor. See more on `Categorical` [here](#)

1.5.1 New features

Categoricals in Series/DataFrame

`Categorical` can now be included in `Series` and `DataFrames` and gained new methods to manipulate. Thanks to Jan Schulz for much of this API/implementation. (GH3943, GH5313, GH5314, GH7444, GH7839, GH7848, GH7864, GH7914, GH7768, GH8006, GH3678, GH8075, GH8076, GH8143, GH8453, GH8518).

For full docs, see the [categorical introduction](#) and the [API documentation](#).

```
In [1]: df = DataFrame({"id": [1, 2, 3, 4, 5, 6], "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']})
```

```
In [2]: df["grade"] = df["raw_grade"].astype("category")
```

```
In [3]: df["grade"]
```

```
Out[3]:
```

```
0    a
1    b
2    b
3    a
```

```
4     a
5     e
Name: grade, dtype: category
Categories (3, object): [a, b, e]

# Rename the categories
In [4]: df["grade"].cat.categories = ["very good", "good", "very bad"]

# Reorder the categories and simultaneously add the missing categories
In [5]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [6]: df["grade"]
Out[6]:
0     very good
1         good
2         good
3     very good
4     very good
5     very bad
Name: grade, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]

In [7]: df.sort("grade")
Out[7]:
   id raw_grade  grade
5   6         e  very bad
1   2         b    good
2   3         b    good
0   1         a  very good
3   4         a  very good
4   5         a  very good

In [8]: df.groupby("grade").size()
Out[8]:
grade
very bad    1
bad         NaN
medium      NaN
good        2
very good   3
dtype: float64
```

- `pandas.core.group_agg` and `pandas.core.factor_agg` were removed. As an alternative, construct a dataframe and use `df.groupby(<group>).agg(<func>)`.
- Supplying “codes/labels and levels” to the `Categorical` constructor is not supported anymore. Supplying two arguments to the constructor is now interpreted as “values and levels (now called ‘categories’)”. Please change your code to use the `from_codes()` constructor.
- The `Categorical.labels` attribute was renamed to `Categorical.codes` and is read only. If you want to manipulate codes, please use one of the *API methods on Categoricals*.
- The `Categorical.levels` attribute is renamed to `Categorical.categories`.

TimedeltaIndex/Scalar

We introduce a new scalar type `Timedelta`, which is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation,

parsing, and attributes. This type is very similar to how `Timestamp` works for datetimes. It is a nice-API box for the type. See the *docs*. ([GH3009](#), [GH4533](#), [GH8209](#), [GH8187](#), [GH8190](#), [GH7869](#), [GH7661](#), [GH8345](#), [GH8471](#))

Warning: `Timedelta` scalars (and `TimedeltaIndex`) component fields are *not the same* as the component fields on a `datetime.timedelta` object. For example, `.seconds` on a `datetime.timedelta` object returns the total number of seconds combined between hours, minutes and seconds. In contrast, the pandas `Timedelta` breaks out hours, minutes, microseconds and nanoseconds separately.

```
# Timedelta accessor
In [9]: tds = Timedelta('31 days 5 min 3 sec')
```

```
In [10]: tds.minutes
Out[10]: 5L
```

```
In [11]: tds.seconds
Out[11]: 3L
```

```
# datetime.timedelta accessor
# this is 5 minutes * 60 + 3 seconds
In [12]: tds.to_pytimedelta().seconds
Out[12]: 303
```

Note: this is no longer true starting from v0.16.0, where full compatibility with `datetime.timedelta` is introduced. See the [0.16.0 whatsnew entry](#)

Warning: Prior to 0.15.0 `pd.to_timedelta` would return a `Series` for list-like/`Series` input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for `Series` input, and `Timedelta` for scalar input. The arguments to `pd.to_timedelta` are now `(arg, unit='ns', box=True, coerce=False)`, previously were `(arg, box=True, unit='ns')` as these are more logical.

Construct a scalar

```
In [9]: Timedelta('1 days 06:05:01.00003')
Out[9]: Timedelta('1 days 06:05:01.000030')

In [10]: Timedelta('15.5us')
Out[10]: Timedelta('0 days 00:00:00.000015')

In [11]: Timedelta('1 hour 15.5us')
Out[11]: Timedelta('0 days 01:00:00.000015')

# negative Timedeltas have this string repr
# to be more consistent with datetime.timedelta conventions
In [12]: Timedelta('-1us')
Out[12]: Timedelta('-1 days +23:59:59.999999')

# a NaT
In [13]: Timedelta('nan')
Out[13]: NaT
```

Access fields for a `Timedelta`

```
In [14]: td = Timedelta('1 hour 3m 15.5us')

In [15]: td.seconds
Out[15]: 3780L
```

```
In [16]: td.microseconds
Out[16]: 15L
```

```
In [17]: td.nanoseconds
Out[17]: 500L
```

Construct a TimedeltaIndex

```
In [18]: TimedeltaIndex(['1 days', '1 days, 00:00:05',
.....:                  np.timedelta64(2, 'D'), timedelta(days=2, seconds=2)])
.....:
Out[18]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00',
                '2 days 00:00:02'],
               dtype='timedelta64[ns]', freq=None)
```

Constructing a TimedeltaIndex with a regular range

```
In [19]: timedelta_range('1 days', periods=5, freq='D')
Out[19]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]',
                        freq='D')

In [20]: timedelta_range(start='1 days', end='2 days', freq='30T')
Out[20]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
                '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
                '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
                '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
                '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
                '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
                '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
                '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
                '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
                '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
                '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
                '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
                '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
                '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
                '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
                '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
                '2 days 00:00:00'],
               dtype='timedelta64[ns]', freq='30T')
```

You can now use a TimedeltaIndex as the index of a pandas object

```
In [21]: s = Series(np.arange(5),
.....:              index=timedelta_range('1 days', periods=5, freq='s'))
.....:

In [22]: s
Out[22]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
1 days 00:00:03    3
1 days 00:00:04    4
Freq: S, dtype: int32
```

You can select with partial string selections

```
In [23]: s['1 day 00:00:02']
Out[23]: 2
```

```
In [24]: s['1 day':'1 day 00:00:02']
Out[24]:
1 days 00:00:00    0
1 days 00:00:01    1
1 days 00:00:02    2
dtype: int32
```

Finally, the combination of `TimedeltaIndex` with `DatetimeIndex` allow certain combination operations that are `NaT` preserving:

```
In [25]: tdi = TimedeltaIndex(['1 days',pd.NaT,'2 days'])

In [26]: tdi.tolist()
Out[26]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]

In [27]: dti = date_range('20130101',periods=3)

In [28]: dti.tolist()
Out[28]:
[Timestamp('2013-01-01 00:00:00', offset='D'),
 Timestamp('2013-01-02 00:00:00', offset='D'),
 Timestamp('2013-01-03 00:00:00', offset='D')]

In [29]: (dti + tdi).tolist()
Out[29]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]

In [30]: (dti - tdi).tolist()
Out[30]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

- iteration of a Series e.g. `list(Series(...))` of `timedelta64[ns]` would prior to v0.15.0 return `np.timedelta64` for each element. These will now be wrapped in `Timedelta`.

Memory Usage

Implemented methods to find memory usage of a `DataFrame`. See the [FAQ](#) for more. ([GH6852](#)).

A new display option `display.memory_usage` (see [Options and Settings](#)) sets the default behavior of the `memory_usage` argument in the `df.info()` method. By default `display.memory_usage` is `True`.

```
In [31]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
.....:             'complex128', 'object', 'bool']
.....:

In [32]: n = 5000

In [33]: data = dict([(t, np.random.randint(100, size=n).astype(t))
.....:                  for t in dtypes])
.....:

In [34]: df = DataFrame(data)

In [35]: df['categorical'] = df['object'].astype('category')

In [36]: df.info()
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 5000 entries, 0 to 4999
Data columns (total 8 columns):
bool                5000 non-null bool
complex128          5000 non-null complex128
datetime64[ns]      5000 non-null datetime64[ns]
float64             5000 non-null float64
int64               5000 non-null int64
object              5000 non-null object
timedelta64[ns]     5000 non-null timedelta64[ns]
categorical          5000 non-null category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1), object(1), time
memory usage: 303.5+ KB
```

Additionally `memory_usage()` is an available method for a dataframe object which returns the memory usage of each column.

```
In [37]: df.memory_usage(index=True)
```

```
Out[37]:
```

```
Index                40000
bool                  5000
complex128           80000
datetime64[ns]       40000
float64              40000
int64                40000
object               20000
timedelta64[ns]     40000
categorical           5800
dtype: int64
```

.dt accessor

Series has gained an accessor to succinctly return datetime like properties for the *values* of the Series, if its a datetime/period like Series. (GH7207) This will return a Series, indexed like the existing Series. See the [docs](#)

```
# datetime
```

```
In [38]: s = Series(date_range('20130101 09:10:12', periods=4))
```

```
In [39]: s
```

```
Out[39]:
```

```
0    2013-01-01 09:10:12
1    2013-01-02 09:10:12
2    2013-01-03 09:10:12
3    2013-01-04 09:10:12
dtype: datetime64[ns]
```

```
In [40]: s.dt.hour
```

```
Out[40]:
```

```
0     9
1     9
2     9
3     9
dtype: int64
```

```
In [41]: s.dt.second
```

```
Out[41]:
```

```
0    12
1    12
```

```
2    12
3    12
dtype: int64
```

```
In [42]: s.dt.day
Out[42]:
0     1
1     2
2     3
3     4
dtype: int64
```

```
In [43]: s.dt.freq
Out[43]: <Day>
```

This enables nice expressions like this:

```
In [44]: s[s.dt.day==2]
Out[44]:
1    2013-01-02 09:10:12
dtype: datetime64[ns]
```

You can easily produce tz aware transformations:

```
In [45]: stz = s.dt.tz_localize('US/Eastern')
```

```
In [46]: stz
Out[46]:
0    2013-01-01 09:10:12-05:00
1    2013-01-02 09:10:12-05:00
2    2013-01-03 09:10:12-05:00
3    2013-01-04 09:10:12-05:00
dtype: object
```

```
In [47]: stz.dt.tz
Out[47]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [48]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[48]:
0    2013-01-01 04:10:12-05:00
1    2013-01-02 04:10:12-05:00
2    2013-01-03 04:10:12-05:00
3    2013-01-04 04:10:12-05:00
dtype: object
```

The `.dt` accessor works for period and timedelta dtypes.

```
# period
In [49]: s = Series(period_range('20130101', periods=4, freq='D'))

In [50]: s
Out[50]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
dtype: object
```

```
In [51]: s.dt.year
Out[51]:
0      2013
1      2013
2      2013
3      2013
dtype: int64

In [52]: s.dt.day
Out[52]:
0      1
1      2
2      3
3      4
dtype: int64

# timedelta
In [53]: s = Series(timedelta_range('1 day 00:00:05', periods=4, freq='s'))

In [54]: s
Out[54]:
0    1 days 00:00:05
1    1 days 00:00:06
2    1 days 00:00:07
3    1 days 00:00:08
dtype: timedelta64[ns]

In [55]: s.dt.days
Out[55]:
0      1
1      1
2      1
3      1
dtype: int64

In [56]: s.dt.seconds
Out[56]:
0      5
1      6
2      7
3      8
dtype: int64

In [57]: s.dt.components
Out[57]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0      1      0         0         5             0              0              0
1      1      0         0         6             0              0              0
2      1      0         0         7             0              0              0
3      1      0         0         8             0              0              0
```

Timezone handling improvements

- `tz_localize(None)` for tz-aware Timestamp and DatetimeIndex now removes timezone holding local time, previously this resulted in Exception or TypeError ([GH7812](#))

```

In [58]: ts = Timestamp('2014-08-01 09:00', tz='US/Eastern')

In [59]: ts
Out[59]: Timestamp('2014-08-01 09:00:00-0400', tz='US/Eastern')

In [60]: ts.tz_localize(None)
Out[60]: Timestamp('2014-08-01 09:00:00')

In [61]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')

In [62]: didx
Out[62]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
              '2014-08-01 11:00:00-04:00', '2014-08-01 12:00:00-04:00',
              '2014-08-01 13:00:00-04:00', '2014-08-01 14:00:00-04:00',
              '2014-08-01 15:00:00-04:00', '2014-08-01 16:00:00-04:00',
              '2014-08-01 17:00:00-04:00', '2014-08-01 18:00:00-04:00'],
              dtype='datetime64[ns]', freq='H', tz='US/Eastern')

In [63]: didx.tz_localize(None)
Out[63]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
              '2014-08-01 11:00:00', '2014-08-01 12:00:00',
              '2014-08-01 13:00:00', '2014-08-01 14:00:00',
              '2014-08-01 15:00:00', '2014-08-01 16:00:00',
              '2014-08-01 17:00:00', '2014-08-01 18:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)

```

- `tz_localize` now accepts the ambiguous keyword which allows for passing an array of bools indicating whether the date belongs in DST or not, 'NaT' for setting transition times to NaT, 'infer' for inferring DST/non-DST, and 'raise' (default) for an `AmbiguousTimeError` to be raised. See [the docs](#) for more details ([GH7943](#))
- `DataFrame.tz_localize` and `DataFrame.tz_convert` now accepts an optional `level` argument for localizing a specific level of a `MultiIndex` ([GH7846](#))
- `Timestamp.tz_localize` and `Timestamp.tz_convert` now raise `TypeError` in error cases, rather than `Exception` ([GH8025](#))
- a timeseries/index localized to UTC when inserted into a `Series/DataFrame` will preserve the UTC timezone (rather than being a naive `datetime64[ns]`) as object `dtype` ([GH8411](#))
- `Timestamp.__repr__` displays `dateutil.tz.tzoffset` info ([GH7907](#))

Rolling/Expanding Moments improvements

- `rolling_min()`, `rolling_max()`, `rolling_cov()`, and `rolling_corr()` now return objects with all NaN when `len(arg) < min_periods <= window` rather than raising. (This makes all rolling functions consistent in this behavior). ([GH7766](#))

Prior to 0.15.0

```

In [64]: s = Series([10, 11, 12, 13])

In [15]: rolling_min(s, window=10, min_periods=5)
ValueError: min_periods (5) must be <= window (4)

```

New behavior

```
In [65]: rolling_min(s, window=10, min_periods=5)
Out[65]:
0    NaN
1    NaN
2    NaN
3    NaN
dtype: float64
```

- `rolling_max()`, `rolling_min()`, `rolling_sum()`, `rolling_mean()`, `rolling_median()`, `rolling_std()`, `rolling_var()`, `rolling_skew()`, `rolling_kurt()`, `rolling_quantile()`, `rolling_cov()`, `rolling_corr()`, `rolling_corr_pairwise()`, `rolling_window()`, and `rolling_apply()` with `center=True` previously would return a result of the same structure as the input arg with NaN in the final $(\text{window}-1)/2$ entries.

Now the final $(\text{window}-1)/2$ entries of the result are calculated as if the input arg were followed by $(\text{window}-1)/2$ NaN values (or with shrinking windows, in the case of `rolling_apply()`). (GH7925, GH8269)

Prior behavior (note final value is NaN):

```
In [7]: rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[7]:
0     1
1     3
2     6
3    NaN
dtype: float64
```

New behavior (note final value is 5 = `sum([2, 3, NaN])`):

```
In [66]: rolling_sum(Series(range(4)), window=3, min_periods=0, center=True)
Out[66]:
0     1
1     3
2     6
3     5
dtype: float64
```

- `rolling_window()` now normalizes the weights properly in rolling mean mode (`mean=True`) so that the calculated weighted means (e.g. ‘triang’, ‘gaussian’) are distributed about the same means as those calculated without weighting (i.e. ‘boxcar’). See [the note on normalization](#) for further details. (GH7618)

```
In [67]: s = Series([10.5, 8.8, 11.4, 9.7, 9.3])
```

Behavior prior to 0.15.0:

```
In [39]: rolling_window(s, window=3, win_type='triang', center=True)
Out[39]:
0         NaN
1    6.583333
2    6.883333
3    6.683333
4         NaN
dtype: float64
```

New behavior

```
In [68]: rolling_window(s, window=3, win_type='triang', center=True)
Out[68]:
0         NaN
```

```

1      9.875
2     10.325
3     10.025
4         NaN
dtype: float64

```

- Removed `center` argument from all `expanding_*` functions (see [list](#)), as the results produced when `center=True` did not make much sense. (GH7925)
- Added optional `ddof` argument to `expanding_cov()` and `rolling_cov()`. The default value of 1 is backwards-compatible. (GH8279)
- Documented the `ddof` argument to `expanding_var()`, `expanding_std()`, `rolling_var()`, and `rolling_std()`. These functions' support of a `ddof` argument (with a default value of 1) was previously undocumented. (GH8064)
- `ewma()`, `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now interpret `min_periods` in the same manner that the `rolling_*` and `expanding_*` functions do: a given result entry will be NaN if the (expanding, in this case) window does not contain at least `min_periods` values. The previous behavior was to set to NaN the `min_periods` entries starting with the first non-NaN value. (GH7977)

Prior behavior (note values start at index 2, which is `min_periods` after index 0 (the index of the first non-empty value)):

```
In [69]: s = Series([1, None, None, None, 2, 3])
```

```

In [51]: ewma(s, com=3., min_periods=2)
Out[51]:
0      NaN
1      NaN
2     1.000000
3     1.000000
4     1.571429
5     2.189189
dtype: float64

```

New behavior (note values start at index 4, the location of the 2nd (since `min_periods=2`) non-empty value):

```

In [70]: ewma(s, com=3., min_periods=2)
Out[70]:
0      NaN
1      NaN
2      NaN
3      NaN
4     1.759644
5     2.383784
dtype: float64

```

- `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `adjust` argument, just like `ewma()` does, affecting how the weights are calculated. The default value of `adjust` is `True`, which is backwards-compatible. See *Exponentially weighted moment functions* for details. (GH7911)
- `ewma()`, `ewmstd()`, `ewmvol()`, `ewmvar()`, `ewmcov()`, and `ewmcorr()` now have an optional `ignore_na` argument. When `ignore_na=False` (the default), missing values are taken into account in the weights calculation. When `ignore_na=True` (which reproduces the pre-0.15.0 behavior), missing values are ignored in the weights calculation. (GH7543)

```

In [71]: ewma(Series([None, 1., 8.]), com=2.)
Out[71]:
0      NaN

```

```
1    1.0
2    5.2
dtype: float64
```

```
In [72]: ewma(Series([1., None, 8.]), com=2., ignore_na=True) # pre-0.15.0 behavior
```

```
Out[72]:
0    1.0
1    1.0
2    5.2
dtype: float64
```

```
In [73]: ewma(Series([1., None, 8.]), com=2., ignore_na=False) # new default
```

```
Out[73]:
0    1.000000
1    1.000000
2    5.846154
dtype: float64
```

Warning: By default (`ignore_na=False`) the `ewm*` functions' weights calculation in the presence of missing values is different than in pre-0.15.0 versions. To reproduce the pre-0.15.0 calculation of weights in the presence of missing values one must specify explicitly `ignore_na=True`.

- Bug in `expanding_cov()`, `expanding_corr()`, `rolling_cov()`, `rolling_cor()`, `ewmcov()`, and `ewmcorr()` returning results with columns sorted by name and producing an error for non-unique columns; now handles non-unique columns and returns columns in original order (except for the case of two DataFrames with `pairwise=False`, where behavior is unchanged) (GH7542)
- Bug in `rolling_count()` and `expanding_*` functions unnecessarily producing error message for zero-length data (GH8056)
- Bug in `rolling_apply()` and `expanding_apply()` interpreting `min_periods=0` as `min_periods=1` (GH8080)
- Bug in `expanding_std()` and `expanding_var()` for a single value producing a confusing error message (GH7900)
- Bug in `rolling_std()` and `rolling_var()` for a single value producing 0 rather than NaN (GH7900)
- Bug in `ewmstd()`, `ewmvol()`, `ewmvar()`, and `ewmcov()` calculation of de-biasing factors when `bias=False` (the default). Previously an incorrect constant factor was used, based on `adjust=True`, `ignore_na=True`, and an infinite number of observations. Now a different factor is used for each entry, based on the actual weights (analogous to the usual $N/(N-1)$ factor). In particular, for a single point a value of NaN is returned when `bias=False`, whereas previously a value of (approximately) 0 was returned.

For example, consider the following pre-0.15.0 results for `ewmvar(..., bias=False)`, and the corresponding debiasing factors:

```
In [74]: s = Series([1., 2., 0., 4.])
```

```
In [89]: ewmvar(s, com=2., bias=False)
Out[89]:
0    -2.775558e-16
1     3.000000e-01
2     9.556787e-01
3     3.585799e+00
dtype: float64
```

```
In [90]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
Out[90]:
```

```
0    1.25
1    1.25
2    1.25
3    1.25
dtype: float64
```

Note that entry 0 is approximately 0, and the debiasing factors are a constant 1.25. By comparison, the following 0.15.0 results have a NaN for entry 0, and the debiasing factors are decreasing (towards 1.25):

```
In [75]: ewmvar(s, com=2., bias=False)
```

```
Out [75]:
0         NaN
1    0.500000
2    1.210526
3    4.089069
dtype: float64
```

```
In [76]: ewmvar(s, com=2., bias=False) / ewmvar(s, com=2., bias=True)
```

```
Out [76]:
0         NaN
1    2.083333
2    1.583333
3    1.425439
dtype: float64
```

See *Exponentially weighted moment functions* for details. (GH7912)

Improvements in the sql io module

- Added support for a `chunksize` parameter to `to_sql` function. This allows `DataFrame` to be written in chunks and avoid packet-size overflow errors (GH8062).
- Added support for a `chunksize` parameter to `read_sql` function. Specifying this argument will return an iterator through chunks of the query result (GH2908).
- Added support for writing `datetime.date` and `datetime.time` object columns with `to_sql` (GH6932).
- Added support for specifying a `schema` to read from/write to with `read_sql_table` and `to_sql` (GH7441, GH7952). For example:

```
df.to_sql('table', engine, schema='other_schema')
pd.read_sql_table('table', engine, schema='other_schema')
```

- Added support for writing NaN values with `to_sql` (GH2754).
- Added support for writing `datetime64` columns with `to_sql` for all database flavors (GH7103).

1.5.2 Backwards incompatible API changes

Breaking changes

API changes related to `Categorical` (see [here](#) for more details):

- The `Categorical` constructor with two arguments changed from “codes/labels and levels” to “values and levels (now called ‘categories’)”. This can lead to subtle bugs. If you use `Categorical` directly, please audit your code by changing it to use the `from_codes()` constructor.

An old function call like (prior to 0.15.0):

```
pd.Categorical([0,1,0,2,1], levels=['a', 'b', 'c'])
```

will have to adapted to the following to keep the same behaviour:

```
In [2]: pd.Categorical.from_codes([0,1,0,2,1], categories=['a', 'b', 'c'])
Out[2]:
[a, b, a, c, b]
Categories (3, object): [a, b, c]
```

API changes related to the introduction of the Timedelta scalar (see [above](#) for more details):

- Prior to 0.15.0 `to_timedelta()` would return a Series for list-like/Series input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, Series for Series input, and `Timedelta` for scalar input.

For API changes related to the rolling and expanding functions, see detailed overview [above](#).

Other notable API changes:

- Consistency when indexing with `.loc` and a list-like indexer when no values are found.

```
In [77]: df = DataFrame([[ 'a'], [ 'b']], index=[1,2])
```

```
In [78]: df
Out[78]:
0
1  a
2  b
```

In prior versions there was a difference in these two constructs:

- `df.loc[[3]]` would return a frame reindexed by 3 (with all `np.nan` values)
- `df.loc[[3],:]` would raise `KeyError`.

Both will now raise a `KeyError`. The rule is that *at least 1* indexer must be found when using a list-like and `.loc` ([GH7999](#))

Furthermore in prior versions these were also different:

- `df.loc[[1,3]]` would return a frame reindexed by [1,3]
- `df.loc[[1,3],:]` would raise `KeyError`.

Both will now return a frame reindex by [1,3]. E.g.

```
In [79]: df.loc[[1,3]]
Out[79]:
0
1  a
3 NaN
```

```
In [80]: df.loc[[1,3],:]
Out[80]:
0
1  a
3 NaN
```

This can also be seen in multi-axis indexing with a Panel.

```
In [81]: p = Panel(np.arange(2*3*4).reshape(2,3,4),
.....:             items=['ItemA', 'ItemB'],
.....:             major_axis=[1,2,3],
```

```

.....:         minor_axis=['A', 'B', 'C', 'D'])
.....:

In [82]: p
Out[82]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemB
Major_axis axis: 1 to 3
Minor_axis axis: A to D

```

The following would raise `KeyError` prior to 0.15.0:

```

In [83]: p.loc[['ItemA', 'ItemD'], :, 'D']
Out[83]:
   ItemA  ItemD
1      3     NaN
2      7     NaN
3     11     NaN

```

Furthermore, `.loc` will raise `If no values are found in a multi-index with a list-like indexer`:

```

In [84]: s = Series(np.arange(3, dtype='int64'),
.....:               index=MultiIndex.from_product(['A'], ['foo', 'bar', 'baz']),
.....:               names=['one', 'two'])
.....:
.....:         ).sortlevel()
.....:

In [85]: s
Out[85]:
one  two
A    bar    1
     baz    2
     foo    0
dtype: int64

In [86]: try:
.....:     s.loc[['D']]
.....: except KeyError as e:
.....:     print("KeyError: " + str(e))
.....:
KeyError: 'cannot index a multi-index axis with these keys'

```

- Assigning values to `None` now considers the dtype when choosing an ‘empty’ value ([GH7941](#)).

Previously, assigning to `None` in numeric containers changed the dtype to object (or errored, depending on the call). It now uses `NaN`:

```

In [87]: s = Series([1, 2, 3])

In [88]: s.loc[0] = None

In [89]: s
Out[89]:
0    NaN
1      2
2      3
dtype: float64

```

`NaT` is now used similarly for datetime containers.

For object containers, we now preserve `None` values (previously these were converted to `NaN` values).

```
In [90]: s = Series(["a", "b", "c"])
```

```
In [91]: s.loc[0] = None
```

```
In [92]: s
Out[92]:
0      None
1         b
2         c
dtype: object
```

To insert a `NaN`, you must explicitly use `np.nan`. See the [docs](#).

- In prior versions, updating a pandas object inplace would not reflect in other python references to this object. (GH8511, GH5104)

```
In [93]: s = Series([1, 2, 3])
```

```
In [94]: s2 = s
```

```
In [95]: s += 1.5
```

Behavior prior to v0.15.0

```
# the original object
In [5]: s
Out[5]:
0      2.5
1      3.5
2      4.5
dtype: float64

# a reference to the original object
In [7]: s2
Out[7]:
0      1
1      2
2      3
dtype: int64
```

This is now the correct behavior

```
# the original object
In [96]: s
Out[96]:
0      2.5
1      3.5
2      4.5
dtype: float64

# a reference to the original object
In [97]: s2
Out[97]:
0      2.5
1      3.5
2      4.5
dtype: float64
```

- Made both the C-based and Python engines for `read_csv` and `read_table` ignore empty lines in input as well as whitespace-filled lines, as long as `sep` is not whitespace. This is an API change that can be controlled by the keyword parameter `skip_blank_lines`. See [the docs](#) (GH4466)
- A timeseries/index localized to UTC when inserted into a Series/DataFrame will preserve the UTC timezone and inserted as object dtype rather than being converted to a naive `datetime64[ns]` (GH8411).
- Bug in passing a `DatetimeIndex` with a timezone that was not being retained in DataFrame construction from a dict (GH7822)

In prior versions this would drop the timezone, now it retains the timezone, but gives a column of object dtype:

```
In [98]: i = date_range('1/1/2011', periods=3, freq='10s', tz = 'US/Eastern')
```

```
In [99]: i
```

```
Out[99]:
```

```
DatetimeIndex(['2011-01-01 00:00:00-05:00', '2011-01-01 00:00:10-05:00',
               '2011-01-01 00:00:20-05:00'],
              dtype='datetime64[ns]', freq='10S', tz='US/Eastern')
```

```
In [100]: df = DataFrame( {'a' : i } )
```

```
In [101]: df
```

```
Out[101]:
```

```

              a
0  2011-01-01 00:00:00-05:00
1  2011-01-01 00:00:10-05:00
2  2011-01-01 00:00:20-05:00
```

```
In [102]: df.dtypes
```

```
Out[102]:
```

```
a      object
dtype: object
```

Previously this would have yielded a column of `datetime64` dtype, but without timezone info.

The behaviour of assigning a column to an existing dataframe as `df['a'] = i` remains unchanged (this already returned an object column with a timezone).

- When passing multiple levels to `stack()`, it will now raise a `ValueError` when the levels aren't all level names or all level numbers (GH7660). See [Reshaping by stacking and unstacking](#).
- Raise a `ValueError` in `df.to_hdf` with 'fixed' format, if `df` has non-unique columns as the resulting file will be broken (GH7761)
- `SettingWithCopy` raise/warnings (according to the option `mode.chained_assignment`) will now be issued when setting a value on a sliced mixed-dtype DataFrame using chained-assignment. (GH7845, GH7950)

```
In [1]: df = DataFrame(np.arange(0,9), columns=['count'])
```

```
In [2]: df['group'] = 'b'
```

```
In [3]: df.iloc[0:5]['group'] = 'a'
```

```
/usr/local/bin/ipython:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the the caveats in the documentation: <http://pandas.pydata.org/pandas-docs/stable/indexing.html>

- `merge`, `DataFrame.merge`, and `ordered_merge` now return the same type as the left argument ([GH7737](#)).
- Previously an enlargement with a mixed-dtype frame would act unlike `.append` which will preserve dtypes (related [GH2578](#), [GH8176](#)):

```
In [103]: df = DataFrame([[True, 1], [False, 2]],
.....:                  columns=["female", "fitness"])
.....:
```

```
In [104]: df
Out[104]:
   female  fitness
0    True         1
1   False         2
```

```
In [105]: df.dtypes
Out[105]:
female      bool
fitness    int64
dtype: object
```

```
# dtypes are now preserved
In [106]: df.loc[2] = df.loc[1]
```

```
In [107]: df
Out[107]:
   female  fitness
0    True         1
1   False         2
2   False         2
```

```
In [108]: df.dtypes
Out[108]:
female      bool
fitness    int64
dtype: object
```

- `Series.to_csv()` now returns a string when `path=None`, matching the behaviour of `DataFrame.to_csv()` ([GH8215](#)).
- `read_hdf` now raises `IOError` when a file that doesn't exist is passed in. Previously, a new, empty file was created, and a `KeyError` raised ([GH7715](#)).
- `DataFrame.info()` now ends its output with a newline character ([GH8114](#))
- Concatenating no objects will now raise a `ValueError` rather than a bare `Exception`.
- Merge errors will now be sub-classes of `ValueError` rather than raw `Exception` ([GH8501](#))
- `DataFrame.plot` and `Series.plot` keywords are now have consistent orders ([GH8037](#))

Internal Refactoring

In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This change allows very easy sub-classing and creation of new index types. This should be a transparent change with only very limited API implications ([GH5080](#), [GH7439](#), [GH7796](#), [GH8024](#), [GH8367](#), [GH7997](#), [GH8522](#)):

- you may need to unpickle pandas version < 0.15.0 pickles using `pd.read_pickle` rather than `pickle.load`. See [pickle docs](#)
- when plotting with a `PeriodIndex`, the matplotlib internal axes will now be arrays of `Period` rather than a `PeriodIndex` (this is similar to how a `DatetimeIndex` passes arrays of datetimes now)
- `MultiIndex`s will now raise similarly to other pandas objects w.r.t. truth testing, see [here](#) (GH7897).
- When plotting a `DatetimeIndex` directly with matplotlib's `plot` function, the axis labels will no longer be formatted as dates but as integers (the internal representation of a `datetime64`). **UPDATE** This is fixed in 0.15.1, see [here](#).

Deprecations

- The attributes `Categorical.labels` and `levels` attributes are deprecated and renamed to `codes` and `categories`.
- The `outtype` argument to `pd.DataFrame.to_dict` has been deprecated in favor of `orient`. (GH7840)
- The `convert_dummies` method has been deprecated in favor of `get_dummies` (GH8140)
- The `infer_dst` argument in `tz_localize` will be deprecated in favor of `ambiguous` to allow for more flexibility in dealing with DST transitions. Replace `infer_dst=True` with `ambiguous='infer'` for the same behavior (GH7943). See [the docs](#) for more details.
- The top-level `pd.value_range` has been deprecated and can be replaced by `.describe()` (GH8481)
- The `Index` set operations `+` and `-` were deprecated in order to provide these for numeric type operations on certain index types. `+` can be replaced by `.union()` or `|`, and `-` by `.difference()`. Further the method name `Index.diff()` is deprecated and can be replaced by `Index.difference()` (GH8226)

```
# +
Index(['a', 'b', 'c']) + Index(['b', 'c', 'd'])

# should be replaced by
Index(['a', 'b', 'c']).union(Index(['b', 'c', 'd']))

# -
Index(['a', 'b', 'c']) - Index(['b', 'c', 'd'])

# should be replaced by
Index(['a', 'b', 'c']).difference(Index(['b', 'c', 'd']))
```

- The `infer_types` argument to `read_html()` now has no effect and is deprecated (GH7762, GH7032).

Removal of prior version deprecations/changes

- Remove `DataFrame.delevel` method in favor of `DataFrame.reset_index`

1.5.3 Enhancements

Enhancements in the importing/exporting of Stata files:

- Added support for `bool`, `uint8`, `uint16` and `uint32` datatypes in `to_stata` (GH7097, GH7365)
- Added conversion option when importing Stata files (GH8527)

- `DataFrame.to_stata` and `StataWriter` check string length for compatibility with limitations imposed in dta files where fixed-width strings must contain 244 or fewer characters. Attempting to write Stata dta files with strings longer than 244 characters raises a `ValueError`. (GH7858)
- `read_stata` and `StataReader` can import missing data information into a `DataFrame` by setting the argument `convert_missing` to `True`. When using this options, missing values are returned as `StataMissingValue` objects and columns containing missing values have object data type. (GH8045)

Enhancements in the plotting functions:

- Added `layout` keyword to `DataFrame.plot`. You can pass a tuple of `(rows, columns)`, one of which can be `-1` to automatically infer (GH6667, GH8071).
- Allow to pass multiple axes to `DataFrame.plot`, `hist` and `boxplot` (GH5353, GH6970, GH7069)
- Added support for `c`, `colormap` and `colorbar` arguments for `DataFrame.plot` with `kind='scatter'` (GH7780)
- Histogram from `DataFrame.plot` with `kind='hist'` (GH7809), See *the docs*.
- Boxplot from `DataFrame.plot` with `kind='box'` (GH7998), See *the docs*.

Other:

- `read_csv` now has a keyword parameter `float_precision` which specifies which floating-point converter the C engine should use during parsing, see *here* (GH8002, GH8044)
- Added `searchsorted` method to `Series` objects (GH7447)
- `describe()` on mixed-types `DataFrames` is more flexible. Type-based column filtering is now possible via the `include/exclude` arguments. See the *docs* (GH8164).

```
In [109]: df = DataFrame({'catA': ['foo', 'foo', 'bar'] * 8,
.....:                  'catB': ['a', 'b', 'c', 'd'] * 6,
.....:                  'numC': np.arange(24),
.....:                  'numD': np.arange(24.) + .5})
.....:
```

```
In [110]: df.describe(include=["object"])
```

```
Out [110]:
```

	catA	catB
count	24	24
unique	2	4
top	foo	d
freq	16	6

```
In [111]: df.describe(include=["number", "object"], exclude=["float"])
```

```
Out [111]:
```

	catA	catB	numC
count	24	24	24.000000
unique	2	4	NaN
top	foo	d	NaN
freq	16	6	NaN
mean	NaN	NaN	11.500000
std	NaN	NaN	7.071068
min	NaN	NaN	0.000000
25%	NaN	NaN	5.750000
50%	NaN	NaN	11.500000
75%	NaN	NaN	17.250000
max	NaN	NaN	23.000000

Requesting all columns is possible with the shorthand 'all'

```
In [112]: df.describe(include='all')
Out[112]:
```

	catA	catB	numC	numD
count	24	24	24.000000	24.000000
unique	2	4	NaN	NaN
top	foo	d	NaN	NaN
freq	16	6	NaN	NaN
mean	NaN	NaN	11.500000	12.000000
std	NaN	NaN	7.071068	7.071068
min	NaN	NaN	0.000000	0.500000
25%	NaN	NaN	5.750000	6.250000
50%	NaN	NaN	11.500000	12.000000
75%	NaN	NaN	17.250000	17.750000
max	NaN	NaN	23.000000	23.500000

Without those arguments, ‘describe’ will behave as before, including only numerical columns or, if none are, only categorical columns. See also the [docs](#)

- Added `split` as an option to the `orient` argument in `pd.DataFrame.to_dict`. (GH7840)
- The `get_dummies` method can now be used on DataFrames. By default only categorical columns are encoded as 0's and 1's, while other columns are left untouched.

```
In [113]: df = DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
.....:                  'C': [1, 2, 3]})
.....:
```

```
In [114]: pd.get_dummies(df)
Out[114]:
```

	C	A_a	A_b	B_b	B_c
0	1	1	0	0	1
1	2	0	1	0	1
2	3	1	0	1	0

- `PeriodIndex` supports resolution as the same as `DatetimeIndex` (GH7708)
- `pandas.tseries.holiday` has added support for additional holidays and ways to observe holidays (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a list of offsets in Python3 (GH7070)
- `pandas.tseries.holiday.Holiday` now supports a `days_of_week` parameter (GH7070)
- `GroupBy.nth()` now supports selecting multiple `nth` values (GH7910)

```
In [115]: business_dates = date_range(start='4/1/2014', end='6/30/2014', freq='B')
```

```
In [116]: df = DataFrame(1, index=business_dates, columns=['a', 'b'])
```

```
# get the first, 4th, and last date index for each month
```

```
In [117]: df.groupby((df.index.year, df.index.month)).nth([0, 3, -1])
```

```
Out[117]:
```

	a	b
2014-04-01	1	1
2014-04-04	1	1
2014-04-30	1	1
2014-05-01	1	1
2014-05-06	1	1
2014-05-30	1	1
2014-06-02	1	1

```
2014-06-05  1  1
2014-06-30  1  1
```

- `Period` and `PeriodIndex` supports addition/subtraction with `timedelta`-likes ([GH7966](#))

If `Period` `freq` is `D`, `H`, `T`, `S`, `L`, `U`, `N`, `Timedelta`-like can be added if the result can have same `freq`. Otherwise, only the same offsets can be added.

```
In [118]: idx = pd.period_range('2014-07-01 09:00', periods=5, freq='H')
```

```
In [119]: idx
```

```
Out[119]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
            '2014-07-01 12:00', '2014-07-01 13:00'],
            dtype='int64', freq='H')
```

```
In [120]: idx + pd.offsets.Hour(2)
```

```
Out[120]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
            '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='int64', freq='H')
```

```
In [121]: idx + Timedelta('120m')
```

```
Out[121]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
            '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='int64', freq='H')
```

```
In [122]: idx = pd.period_range('2014-07', periods=5, freq='M')
```

```
In [123]: idx
```

```
Out[123]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'], dtype='int64', fr
```

```
In [124]: idx + pd.offsets.MonthEnd(3)
```

```
Out[124]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'], dtype='int64', fr
```

- Added experimental compatibility with `openpyxl` for versions `>= 2.0`. The `DataFrame.to_excel` method engine keyword now recognizes `openpyxl1` and `openpyxl2` which will explicitly require `openpyxl v1` and `v2` respectively, failing if the requested version is not available. The `openpyxl` engine is now a meta-engine that automatically uses whichever version of `openpyxl` is installed. ([GH7177](#))
- `DataFrame.fillna` can now accept a `DataFrame` as a fill value ([GH8377](#))
- Passing multiple levels to `stack()` will now work when multiple level numbers are passed ([GH7660](#)). See *Reshaping by stacking and unstacking*.
- `set_names()`, `set_labels()`, and `set_levels()` methods now take an optional `level` keyword argument to all modification of specific level(s) of a `MultiIndex`. Additionally `set_names()` now accepts a scalar string value when operating on an `Index` or on a specific level of a `MultiIndex` ([GH7792](#))

```
In [125]: idx = MultiIndex.from_product(['a'], range(3), list("pqr"), names=['foo', 'bar', 'ba
```

```
In [126]: idx.set_names('qux', level=0)
```

```
Out[126]:
MultiIndex(levels=[['a'], [0, 1, 2], [u'p', u'q', u'r']],
            labels=[[0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2,
            names=[u'qux', u'bar', u'baz'])
```

```
In [127]: idx.set_names(['qux', 'baz'], level=[0,1])
```

```
Out[127]:
```

```
MultiIndex(levels=[[u'a'], [0, 1, 2], [u'p', u'q', u'r']],
            labels=[[0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2,
            names=[u'qux', u'baz', u'baz']])
```

```
In [128]: idx.set_levels(['a', 'b', 'c'], level='bar')
```

```
Out[128]:
```

```
MultiIndex(levels=[[u'a'], [u'a', u'b', u'c'], [u'p', u'q', u'r']],
            labels=[[0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2,
            names=[u'foo', u'bar', u'baz']])
```

```
In [129]: idx.set_levels(['a', 'b', 'c'], [1, 2, 3], level=[1, 2])
```

```
Out[129]:
```

```
MultiIndex(levels=[[u'a'], [u'a', u'b', u'c'], [1, 2, 3]],
            labels=[[0, 0, 0, 0, 0, 0, 0, 0], [0, 0, 0, 1, 1, 1, 2, 2, 2], [0, 1, 2, 0, 1, 2,
            names=[u'foo', u'bar', u'baz']])
```

- `Index.isin` now supports a `level` argument to specify which index level to use for membership tests (GH7892, GH7890)

```
In [1]: idx = MultiIndex.from_product([[0, 1], ['a', 'b', 'c']])
```

```
In [2]: idx.values
```

```
Out[2]: array([(0, 'a'), (0, 'b'), (0, 'c'), (1, 'a'), (1, 'b'), (1, 'c')], dtype=object)
```

```
In [3]: idx.isin(['a', 'c', 'e'], level=1)
```

```
Out[3]: array([ True, False,  True,  True, False,  True], dtype=bool)
```

- Index now supports duplicated and `drop_duplicates`. (GH4060)

```
In [130]: idx = Index([1, 2, 3, 4, 1, 2])
```

```
In [131]: idx
```

```
Out[131]: Int64Index([1, 2, 3, 4, 1, 2], dtype='int64')
```

```
In [132]: idx.duplicated()
```

```
Out[132]: array([False, False, False, False,  True,  True], dtype=bool)
```

```
In [133]: idx.drop_duplicates()
```

```
Out[133]: Int64Index([1, 2, 3, 4], dtype='int64')
```

- add `copy=True` argument to `pd.concat` to enable pass thru of complete blocks (GH8252)
- Added support for numpy 1.8+ data types (`bool_`, `int_`, `float_`, `string_`) for conversion to R dataframe (GH8400)

1.5.4 Performance

- Performance improvements in `DatetimeIndex.__iter__` to allow faster iteration (GH7683)
- Performance improvements in Period creation (and `PeriodIndex.setitem`) (GH5155)
- Improvements in `Series.transform` for significant performance gains (revised) (GH6496)
- Performance improvements in `StataReader` when reading large files (GH8040, GH8073)
- Performance improvements in `StataWriter` when writing large files (GH8079)
- Performance and memory usage improvements in multi-key `groupby` (GH8128)

- Performance improvements in `groupby .agg` and `.apply` where builtins `max/min` were not mapped to `numpy/cythonized` versions ([GH7722](#))
- Performance improvement in writing to `sql (to_sql)` of up to 50% ([GH8208](#)).
- Performance benchmarking of `groupby` for large value of `ngroups` ([GH6787](#))
- Performance improvement in `CustomBusinessDay`, `CustomBusinessMonth` ([GH8236](#))
- Performance improvement for `MultiIndex.values` for multi-level indexes containing `datetimes` ([GH8543](#))

1.5.5 Bug Fixes

- Bug in `pivot_table`, when using `margins` and a `dict aggfunc` ([GH8349](#))
- Bug in `read_csv` where `squeeze=True` would return a view ([GH8217](#))
- Bug in checking of table name in `read_sql` in certain cases ([GH7826](#)).
- Bug in `DataFrame.groupby` where `Grouper` does not recognize level when frequency is specified ([GH7885](#))
- Bug in multiindexes dtypes getting mixed up when `DataFrame` is saved to SQL table ([GH8021](#))
- Bug in `Series` 0-division with a float and integer operand dtypes ([GH7785](#))
- Bug in `Series.astype("unicode")` not calling `unicode` on the values correctly ([GH7758](#))
- Bug in `DataFrame.as_matrix()` with mixed `datetime64[ns]` and `timedelta64[ns]` dtypes ([GH7778](#))
- Bug in `HDFStore.select_column()` not preserving UTC timezone info when selecting a `DatetimeIndex` ([GH7777](#))
- Bug in `to_datetime` when `format='%Y%m%d'` and `coerce=True` are specified, where previously an object array was returned (rather than a coerced time-series with `NaT`), ([GH7930](#))
- Bug in `DatetimeIndex` and `PeriodIndex` in-place addition and subtraction cause different result from normal one ([GH6527](#))
- Bug in adding and subtracting `PeriodIndex` with `PeriodIndex` raise `TypeError` ([GH7741](#))
- Bug in `combine_first` with `PeriodIndex` data raises `TypeError` ([GH3367](#))
- Bug in multi-index slicing with missing indexers ([GH7866](#))
- Bug in multi-index slicing with various edge cases ([GH8132](#))
- Regression in multi-index indexing with a non-scalar type object ([GH7914](#))
- Bug in `Timestamp` comparisons with `==` and `int64 dtype` ([GH8058](#))
- Bug in `pickles` contains `DateOffset` may raise `AttributeError` when `normalize` attribute is referred internally ([GH7748](#))
- Bug in `Panel` when using `major_xs` and `copy=False` is passed (deprecation warning fails because of missing warnings) ([GH8152](#)).
- Bug in `pickle` deserialization that failed for pre-0.14.1 containers with `dup` items trying to avoid ambiguity when matching block and manager items, when there's only one block there's no ambiguity ([GH7794](#))
- Bug in putting a `PeriodIndex` into a `Series` would convert to `int64 dtype`, rather than object of `Periods` ([GH7932](#))
- Bug in `HDFStore` iteration when passing a `where` ([GH8014](#))

- Bug in `DataFrameGroupby.transform` when transforming with a passed non-sorted key (GH8046, GH8430)
- Bug in repeated timeseries line and area plot may result in `ValueError` or incorrect kind (GH7733)
- Bug in inference in a `MultiIndex` with `datetime.date` inputs (GH7888)
- Bug in `get` where an `IndexError` would not cause the default value to be returned (GH7725)
- Bug in `offsets.apply`, `rollforward` and `rollback` may reset nanosecond (GH7697)
- Bug in `offsets.apply`, `rollforward` and `rollback` may raise `AttributeError` if `Timestamp` has `dateutil.tzinfo` (GH7697)
- Bug in sorting a multi-index frame with a `Float64Index` (GH8017)
- Bug in inconsistent panel setitem with a rhs of a `DataFrame` for alignment (GH7763)
- Bug in `is_superperiod` and `is_subperiod` cannot handle higher frequencies than S (GH7760, GH7772, GH7803)
- Bug in 32-bit platforms with `Series.shift` (GH8129)
- Bug in `PeriodIndex.unique` returns `int64 np.ndarray` (GH7540)
- Bug in `groupby.apply` with a non-affecting mutation in the function (GH8467)
- Bug in `DataFrame.reset_index` which has `MultiIndex` contains `PeriodIndex` or `DatetimeIndex` with `tz` raises `ValueError` (GH7746, GH7793)
- Bug in `DataFrame.plot` with `subplots=True` may draw unnecessary minor xticks and yticks (GH7801)
- Bug in `StataReader` which did not read variable labels in 117 files due to difference between Stata documentation and implementation (GH7816)
- Bug in `StataReader` where strings were always converted to 244 characters-fixed width irrespective of underlying string size (GH7858)
- Bug in `DataFrame.plot` and `Series.plot` may ignore `rot` and `fontsize` keywords (GH7844)
- Bug in `DatetimeIndex.value_counts` doesn't preserve `tz` (GH7735)
- Bug in `PeriodIndex.value_counts` results in `Int64Index` (GH7735)
- Bug in `DataFrame.join` when doing left join on index and there are multiple matches (GH5391)
- Bug in `GroupBy.transform()` where int groups with a transform that didn't preserve the index were incorrectly truncated (GH7972).
- Bug in `groupby` where callable objects without name attributes would take the wrong path, and produce a `DataFrame` instead of a `Series` (GH7929)
- Bug in `groupby` error message when a `DataFrame` grouping column is duplicated (GH7511)
- Bug in `read_html` where the `infer_types` argument forced coercion of date-likes incorrectly (GH7762, GH7032).
- Bug in `Series.str.cat` with an index which was filtered as to not include the first item (GH7857)
- Bug in `Timestamp` cannot parse nanosecond from string (GH7878)
- Bug in `Timestamp` with string offset and `tz` results incorrect (GH7833)
- Bug in `tslib.tz_convert` and `tslib.tz_convert_single` may return different results (GH7798)
- Bug in `DatetimeIndex.intersection` of non-overlapping timestamps with `tz` raises `IndexError` (GH7880)

- Bug in alignment with TimeOps and non-unique indexes (GH8363)
- Bug in `GroupBy.filter()` where fast path vs. slow path made the filter return a non scalar value that appeared valid but wasn't (GH7870).
- Bug in `date_range()/DatetimeIndex()` when the timezone was inferred from input dates yet incorrect times were returned when crossing DST boundaries (GH7835, GH7901).
- Bug in `to_excel()` where a negative sign was being prepended to positive infinity and was absent for negative infinity (GH7949)
- Bug in area plot draws legend with incorrect alpha when `stacked=True` (GH8027)
- Period and PeriodIndex addition/subtraction with `np.timedelta64` results in incorrect internal representations (GH7740)
- Bug in Holiday with no offset or observance (GH7987)
- Bug in `DataFrame.to_latex` formatting when columns or index is a MultiIndex (GH7982).
- Bug in DateOffset around Daylight Savings Time produces unexpected results (GH5175).
- Bug in `DataFrame.shift` where empty columns would throw `ZeroDivisionError` on numpy 1.7 (GH8019)
- Bug in installation where `html_encoding/*.html` wasn't installed and therefore some tests were not running correctly (GH7927).
- Bug in `read_html` where bytes objects were not tested for in `_read` (GH7927).
- Bug in `DataFrame.stack()` when one of the column levels was a datelike (GH8039)
- Bug in broadcasting numpy scalars with DataFrame (GH8116)
- Bug in `pivot_table` performed with nameless index and columns raises `KeyError` (GH8103)
- Bug in `DataFrame.plot(kind='scatter')` draws points and errorbars with different colors when the color is specified by `c` keyword (GH8081)
- Bug in `Float64Index` where `iat` and `at` were not testing and were failing (GH8092).
- Bug in `DataFrame.boxplot()` where y-limits were not set correctly when producing multiple axes (GH7528, GH5517).
- Bug in `read_csv` where line comments were not handled correctly given a custom line terminator or `delim_whitespace=True` (GH8122).
- Bug in `read_html` where empty tables caused a `StopIteration` (GH7575)
- Bug in casting when setting a column in a same-dtype block (GH7704)
- Bug in accessing groups from a `GroupBy` when the original grouper was a tuple (GH8121).
- Bug in `.at` that would accept integer indexers on a non-integer index and do fallback (GH7814)
- Bug with kde plot and NaNs (GH8182)
- Bug in `GroupBy.count` with float32 data type where nan values were not excluded (GH8169).
- Bug with stacked barplots and NaNs (GH8175).
- Bug in resample with non evenly divisible offsets (e.g. '7s') (GH8371)
- Bug in interpolation methods with the `limit` keyword when no values needed interpolating (GH7173).
- Bug where `col_space` was ignored in `DataFrame.to_string()` when `header=False` (GH8230).

- Bug with `DatetimeIndex.asof` incorrectly matching partial strings and returning the wrong date (GH8245).
- Bug in plotting methods modifying the global matplotlib rcParams (GH8242).
- Bug in `DataFrame.__setitem__` that caused errors when setting a dataframe column to a sparse array (GH8131)
- Bug where `Dataframe.boxplot()` failed when entire column was empty (GH8181).
- Bug with messed variables in `radviz` visualization (GH8199).
- Bug in interpolation methods with the `limit` keyword when no values needed interpolating (GH7173).
- Bug where `col_space` was ignored in `DataFrame.to_string()` when `header=False` (GH8230).
- Bug in `to_clipboard` that would clip long column data (GH8305)
- Bug in `DataFrame` terminal display: Setting `max_column/max_rows` to zero did not trigger auto-resizing of dfs to fit terminal width/height (GH7180).
- Bug in OLS where running with “cluster” and “nw_lags” parameters did not work correctly, but also did not throw an error (GH5884).
- Bug in `DataFrame.dropna` that interpreted non-existent columns in the subset argument as the ‘last column’ (GH8303)
- Bug in `Index.intersection` on non-monotonic non-unique indexes (GH8362).
- Bug in masked series assignment where mismatching types would break alignment (GH8387)
- Bug in `NDFrame.equals` gives false negatives with `dtype=object` (GH8437)
- Bug in assignment with indexer where type diversity would break alignment (GH8258)
- Bug in `NDFrame.loc` indexing when row/column names were lost when target was a list/ndarray (GH6552)
- Regression in `NDFrame.loc` indexing when rows/columns were converted to `Float64Index` if target was an empty list/ndarray (GH7774)
- Bug in `Series` that allows it to be indexed by a `DataFrame` which has unexpected results. Such indexing is no longer permitted (GH8444)
- Bug in item assignment of a `DataFrame` with multi-index columns where right-hand-side columns were not aligned (GH7655)
- Suppress `FutureWarning` generated by NumPy when comparing object arrays containing NaN for equality (GH7065)
- Bug in `DataFrame.eval()` where the dtype of the `not` operator (`~`) was not correctly inferred as `bool`.

1.6 v0.14.1 (July 11, 2014)

This is a minor release from 0.14.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
 - New methods `select_dtypes()` to select columns based on the dtype and `sem()` to calculate the standard error of the mean.
 - Support for dateutil timezones (see *docs*).

- Support for ignoring full line comments in the `read_csv()` text parser.
- New documentation section on *Options and Settings*.
- Lots of bug fixes.

- *Enhancements*
- *API Changes*
- *Performance Improvements*
- *Experimental Changes*
- *Bug Fixes*

1.6.1 API changes

- Openpyxl now raises a `ValueError` on construction of the openpyxl writer instead of warning on pandas import (GH7284).
- For `StringMethods.extract`, when no match is found, the result - only containing NaN values - now also has `dtype=object` instead of `float` (GH7242)
- Period objects no longer raise a `TypeError` when compared using `==` with another object that *isn't* a Period. Instead when comparing a Period with another object using `==` if the other object isn't a Period `False` is returned. (GH7376)
- Previously, the behaviour on resetting the time or not in `offsets.apply`, `rollforward` and `rollback` operations differed between offsets. With the support of the `normalize` keyword for all offsets (see below) with a default value of `False` (preserve time), the behaviour changed for certain offsets (`BusinessMonthBegin`, `MonthEnd`, `BusinessMonthEnd`, `CustomBusinessMonthEnd`, `BusinessYearBegin`, `LastWeekOfMonth`, `FY5253Quarter`, `LastWeekOfMonth`, `Easter`):

```
In [6]: from pandas.tseries import offsets

In [7]: d = pd.Timestamp('2014-01-01 09:00')

# old behaviour < 0.14.1
In [8]: d + offsets.MonthEnd()
Out[8]: Timestamp('2014-01-31 00:00:00')
```

Starting from 0.14.1 all offsets preserve time by default. The old behaviour can be obtained with `normalize=True`

```
# new behaviour
In [1]: d + offsets.MonthEnd()
Out[1]: Timestamp('2014-01-31 09:00:00')

In [2]: d + offsets.MonthEnd(normalize=True)
Out[2]: Timestamp('2014-01-31 00:00:00')
```

Note that for the other offsets the default behaviour did not change.

- Add back `#N/A` `N/A` as a default NA value in text parsing, (regression from 0.12) (GH5521)
- Raise a `TypeError` on inplace-setting with a `.where` and a non `np.nan` value as this is inconsistent with a set-item expression like `df[mask] = None` (GH7656)

1.6.2 Enhancements

- Add `dropna` argument to `value_counts` and `nunique` (GH5569).
- Add `select_dtypes()` method to allow selection of columns based on dtype (GH7316). See *the docs*.
- All offsets supports the `normalize` keyword to specify whether `offsets.apply`, `rollforward` and `rollback` resets the time (hour, minute, etc) or not (default `False`, preserves time) (GH7156):

```
In [3]: import pandas.tseries.offsets as offsets
```

```
In [4]: day = offsets.Day()
```

```
In [5]: day.apply(Timestamp('2014-01-01 09:00'))
```

```
Out[5]: Timestamp('2014-01-02 09:00:00')
```

```
In [6]: day = offsets.Day(normalize=True)
```

```
In [7]: day.apply(Timestamp('2014-01-01 09:00'))
```

```
Out[7]: Timestamp('2014-01-02 00:00:00')
```

- `PeriodIndex` is represented as the same format as `DatetimeIndex` (GH7601)
- `StringMethods` now work on empty `Series` (GH7242)
- The file parsers `read_csv` and `read_table` now ignore line comments provided by the parameter `comment`, which accepts only a single character for the C reader. In particular, they allow for comments before file data begins (GH2685)
- Add `NotImplementedError` for simultaneous use of `chunksize` and `nrows` for `read_csv()` (GH6774).
- Tests for basic reading of public S3 buckets now exist (GH7281).
- `read_html` now sports an `encoding` argument that is passed to the underlying parser library. You can use this to read non-ascii encoded web pages (GH7323).
- `read_excel` now supports reading from URLs in the same way that `read_csv` does. (GH6809)
- Support for `dateutil` timezones, which can now be used in the same way as `pytz` timezones across pandas. (GH4688)

```
In [8]: rng = date_range('3/6/2012 00:00', periods=10, freq='D',
...:                    tz='dateutil/Europe/London')
...:
```

```
In [9]: rng.tz
```

```
Out[9]: tzfile('Europe/Belfast')
```

See *the docs*.

- Implemented `sem` (standard error of the mean) operation for `Series`, `DataFrame`, `Panel`, and `Groupby` (GH6897)
- Add `nlargest` and `nsmallest` to the `Series` `groupby` whitelist, which means you can now use these methods on a `SeriesGroupBy` object (GH7053).
- All offsets `apply`, `rollforward` and `rollback` can now handle `np.datetime64`, previously results in `ApplyTypeError` (GH7452)
- `Period` and `PeriodIndex` can contain `NaT` in its values (GH7485)
- Support pickling `Series`, `DataFrame` and `Panel` objects with non-unique labels along *item* axis (index, columns and items respectively) (GH7370).

- Improved inference of datetime/timedelta with mixed null objects. Regression from 0.13.1 in interpretation of an object Index with all null elements ([GH7431](#))

1.6.3 Performance

- Improvements in dtype inference for numeric operations involving yielding performance gains for dtypes: `int64`, `timedelta64`, `datetime64` ([GH7223](#))
- Improvements in `Series.transform` for significant performance gains ([GH6496](#))
- Improvements in `DataFrame.transform` with `ufuncs` and built-in grouper functions for significant performance gains ([GH7383](#))
- Regression in groupby aggregation of `datetime64` dtypes ([GH7555](#))
- Improvements in `MultiIndex.from_product` for large iterables ([GH7627](#))

1.6.4 Experimental

- `pandas.io.data.Options` has a new method, `get_all_data` method, and now consistently returns a multi-indexed `DataFrame`, see *the docs*. ([GH5602](#))
- `io.gbq.read_gbq` and `io.gbq.to_gbq` were refactored to remove the dependency on the Google `bq.py` command line client. This submodule now uses `httplib2` and the Google `apiclient` and `oauth2client` API client libraries which should be more stable and, therefore, reliable than `bq.py`. See *the docs*. ([GH6937](#)).

1.6.5 Bug Fixes

- Bug in `DataFrame.where` with a symmetric shaped frame and a passed other of a `DataFrame` ([GH7506](#))
- Bug in Panel indexing with a multi-index axis ([GH7516](#))
- Regression in datetimelike slice indexing with a duplicated index and non-exact end-points ([GH7523](#))
- Bug in `setitem` with list-of-lists and single vs mixed types ([GH7551](#);))
- Bug in `timeops` with non-aligned Series ([GH7500](#))
- Bug in `timedelta` inference when assigning an incomplete Series ([GH7592](#))
- Bug in `groupby.nth` with a Series and integer-like column name ([GH7559](#))
- Bug in `Series.get` with a boolean accessor ([GH7407](#))
- Bug in `value_counts` where `NaT` did not qualify as missing (`NaN`) ([GH7423](#))
- Bug in `to_timedelta` that accepted invalid units and misinterpreted 'm/h' ([GH7611](#), [GH6423](#))
- Bug in line plot doesn't set correct `xlim` if `secondary_y=True` ([GH7459](#))
- Bug in grouped `hist` and `scatter` plots use old `figsize` default ([GH7394](#))
- Bug in plotting subplots with `DataFrame.plot`, `hist` clears passed `ax` even if the number of subplots is one ([GH7391](#)).
- Bug in plotting subplots with `DataFrame.boxplot` with `by` kw raises `ValueError` if the number of subplots exceeds 1 ([GH7391](#)).
- Bug in subplots displays `ticklabels` and `labels` in different rule ([GH5897](#))

- Bug in `Panel.apply` with a multi-index as an axis (GH7469)
- Bug in `DatetimeIndex.insert` doesn't preserve name and tz (GH7299)
- Bug in `DatetimeIndex.asobject` doesn't preserve name (GH7299)
- Bug in multi-index slicing with datetimelike ranges (strings and Timestamps), (GH7429)
- Bug in `Index.min` and `max` doesn't handle nan and NaT properly (GH7261)
- Bug in `PeriodIndex.min/max` results in int (GH7609)
- Bug in `resample` where `fill_method` was ignored if you passed `how` (GH2073)
- Bug in `TimeGrouper` doesn't exclude column specified by key (GH7227)
- Bug in `DataFrame` and `Series` `bar` and `barh` plot raises `TypeError` when `bottom` and `left` keyword is specified (GH7226)
- Bug in `DataFrame.hist` raises `TypeError` when it contains non numeric column (GH7277)
- Bug in `Index.delete` does not preserve name and `freq` attributes (GH7302)
- Bug in `DataFrame.query()/eval` where local string variables with the @ sign were being treated as temporaries attempting to be deleted (GH7300).
- Bug in `Float64Index` which didn't allow duplicates (GH7149).
- Bug in `DataFrame.replace()` where truthy values were being replaced (GH7140).
- Bug in `StringMethods.extract()` where a single match group `Series` would use the matcher's name instead of the group name (GH7313).
- Bug in `isnull()` when `mode.use_inf_as_null == True` where `isnull` wouldn't test `True` when it encountered an `inf/-inf` (GH7315).
- Bug in `inferred_freq` results in `None` for eastern hemisphere timezones (GH7310)
- Bug in `Easter` returns incorrect date when offset is negative (GH7195)
- Bug in broadcasting with `.div`, integer dtypes and divide-by-zero (GH7325)
- Bug in `CustomBusinessDay.apply` raises `NameError` when `np.datetime64` object is passed (GH7196)
- Bug in `MultiIndex.append`, `concat` and `pivot_table` don't preserve timezone (GH6606)
- Bug in `.loc` with a list of indexers on a single-multi index level (that is not nested) (GH7349)
- Bug in `Series.map` when mapping a dict with tuple keys of different lengths (GH7333)
- Bug all `StringMethods` now work on empty `Series` (GH7242)
- Fix delegation of `read_sql` to `read_sql_query` when query does not contain 'select' (GH7324).
- Bug where a string column name assignment to a `DataFrame` with a `Float64Index` raised a `TypeError` during a call to `np.isnan` (GH7366).
- Bug where `NDFrame.replace()` didn't correctly replace objects with `Period` values (GH7379).
- Bug in `.ix` `getitem` should always return a `Series` (GH7150)
- Bug in multi-index slicing with incomplete indexers (GH7399)
- Bug in multi-index slicing with a step in a sliced level (GH7400)
- Bug where negative indexers in `DatetimeIndex` were not correctly sliced (GH7408)
- Bug where `NaT` wasn't repr'd correctly in a `MultiIndex` (GH7406, GH7409).

- Bug where bool objects were converted to nan in `convert_objects` (GH7416).
- Bug in `quantile` ignoring the `axis` keyword argument (:issue‘7306‘)
- Bug where `nanops._maybe_null_out` doesn’t work with complex numbers (GH7353)
- Bug in several `nanops` functions when `axis==0` for 1-dimensional nan arrays (GH7354)
- Bug where `nanops.nanmedian` doesn’t work when `axis==None` (GH7352)
- Bug where `nanops._has_infs` doesn’t work with many dtypes (GH7357)
- Bug in `StataReader.data` where reading a 0-observation dta failed (GH7369)
- Bug in `StataReader` when reading Stata 13 (117) files containing fixed width strings (GH7360)
- Bug in `StataWriter` where encoding was ignored (GH7286)
- Bug in `DatetimeIndex` comparison doesn’t handle NaT properly (GH7529)
- Bug in passing input with `tzinfo` to some offsets apply, `rollforward` or `rollback` resets `tzinfo` or raises `ValueError` (GH7465)
- Bug in `DatetimeIndex.to_period`, `PeriodIndex.asobject`, `PeriodIndex.to_timestamp` doesn’t preserve name (GH7485)
- Bug in `DatetimeIndex.to_period` and `PeriodIndex.to_timestamp` handle NaT incorrectly (GH7228)
- Bug in `offsets.apply`, `rollforward` and `rollback` may return normal datetime (GH7502)
- Bug in `resample` raises `ValueError` when target contains NaT (GH7227)
- Bug in `Timestamp.tz_localize` resets nanosecond info (GH7534)
- Bug in `DatetimeIndex.asobject` raises `ValueError` when it contains NaT (GH7539)
- Bug in `Timestamp.__new__` doesn’t preserve nanosecond properly (GH7610)
- Bug in `Index.astype(float)` where it would return an object dtype `Index` (GH7464).
- Bug in `DataFrame.reset_index` loses tz (GH3950)
- Bug in `DatetimeIndex.freqstr` raises `AttributeError` when `freq` is `None` (GH7606)
- Bug in `GroupBy.size` created by `TimeGrouper` raises `AttributeError` (GH7453)
- Bug in single column bar plot is misaligned (GH7498).
- Bug in area plot with tz-aware time series raises `ValueError` (GH7471)
- Bug in non-monotonic `Index.union` may preserve name incorrectly (GH7458)
- Bug in `DatetimeIndex.intersection` doesn’t preserve timezone (GH4690)
- Bug in `rolling_var` where a window larger than the array would raise an error (GH7297)
- Bug with last plotted timeseries dictating `xlim` (GH2960)
- Bug with secondary `y` axis not being considered for timeseries `xlim` (GH3490)
- Bug in `Float64Index` assignment with a non scalar indexer (GH7586)
- Bug in `pandas.core.strings.str_contains` does not properly match in a case insensitive fashion when `regex=False` and `case=False` (GH7505)
- Bug in `expanding_cov`, `expanding_corr`, `rolling_cov`, and `rolling_corr` for two arguments with mismatched index (GH7512)
- Bug in `to_sql` taking the boolean column as text column (GH7678)

- Bug in grouped *hist* doesn't handle *rot* kw and *sharex* kw properly ([GH7234](#))
- Bug in `.loc` performing fallback integer indexing with `object` dtype indices ([GH7496](#))
- Bug (regression) in `PeriodIndex` constructor when passed `Series` objects ([GH7701](#)).

1.7 v0.14.0 (May 31 , 2014)

This is a major release from 0.13.1 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

- Highlights include:
 - Officially support Python 3.4
 - SQL interfaces updated to use `sqlalchemy`, See [Here](#).
 - Display interface changes, See [Here](#)
 - MultiIndexing Using Slicers, See [Here](#).
 - Ability to join a singly-indexed `DataFrame` with a multi-indexed `DataFrame`, see [Here](#)
 - More consistency in groupby results and more flexible groupby specifications, See [Here](#)
 - Holiday calendars are now supported in `CustomBusinessDay`, see [Here](#)
 - Several improvements in plotting functions, including: `hexbin`, `area` and `pie` plots, see [Here](#).
 - Performance doc section on I/O operations, See [Here](#)
- *Other Enhancements*
- *API Changes*
- *Text Parsing API Changes*
- *Groupby API Changes*
- *Performance Improvements*
- *Prior Deprecations*
- *Deprecations*
- *Known Issues*
- *Bug Fixes*

Warning: In 0.14.0 all `NDFrame` based containers have undergone significant internal refactoring. Before that each block of homogeneous data had its own labels and extra care was necessary to keep those in sync with the parent container's labels. This should not have any visible user/API behavior changes ([GH6745](#))

1.7.1 API changes

- `read_excel` uses 0 as the default sheet ([GH6573](#))
- `iloc` will now accept out-of-bounds indexers for slices, e.g. a value that exceeds the length of the object being indexed. These will be excluded. This will make pandas conform more with python/numpy indexing of out-of-bounds values. A single indexer that is out-of-bounds and drops the dimensions of the object will still

raise `IndexError` ([GH6296](#), [GH6299](#)). This could result in an empty axis (e.g. an empty `DataFrame` being returned)

```
In [1]: dfl = DataFrame(np.random.randn(5,2), columns=list('AB'))
```

```
In [2]: dfl
```

```
Out[2]:
```

	A	B
0	1.583584	-0.438313
1	-0.402537	-0.780572
2	-0.141685	0.542241
3	0.370966	-0.251642
4	0.787484	1.666563

```
In [3]: dfl.iloc[:,2:3]
```

```
Out[3]:
```

Empty `DataFrame`
Columns: []
Index: [0, 1, 2, 3, 4]

```
In [4]: dfl.iloc[:,1:3]
```

```
Out[4]:
```

	B
0	-0.438313
1	-0.780572
2	0.542241
3	-0.251642
4	1.666563

```
In [5]: dfl.iloc[4:6]
```

```
Out[5]:
```

	A	B
4	0.787484	1.666563

These are out-of-bounds selections

```
dfl.iloc[[4,5,6]]
```

`IndexError`: positional indexers are out-of-bounds

```
dfl.iloc[:,4]
```

`IndexError`: single positional indexer is out-of-bounds

- Slicing with negative start, stop & step values handles corner cases better ([GH6531](#)):
 - `df.iloc[: -len(df)]` is now empty
 - `df.iloc[len(df) : -1]` now enumerates all elements in reverse
- The `DataFrame.interpolate()` keyword `downcast` default has been changed from `infer` to `None`. This is to preserve the original dtype unless explicitly requested otherwise ([GH6290](#)).
- When converting a dataframe to HTML it used to return *Empty DataFrame*. This special case has been removed, instead a header with the column names is returned ([GH6062](#)).
- `Series` and `Index` now internally share more common operations, e.g. `factorize()`, `nunique()`, `value_counts()` are now supported on `Index` types as well. The `Series.weekday` property from is removed from `Series` for API consistency. Using a `DatetimeIndex/PeriodIndex` method on a `Series` will now raise a `TypeError`. ([GH4551](#), [GH4056](#), [GH5519](#), [GH6380](#), [GH7206](#)).
- Add `is_month_start`, `is_month_end`, `is_quarter_start`, `is_quarter_end`,

`is_year_start`, `is_year_end` accessors for `DateTimeIndex` / `Timestamp` which return a boolean array of whether the timestamp(s) are at the start/end of the month/quarter/year defined by the frequency of the `DateTimeIndex` / `Timestamp` (GH4565, GH6998)

- Local variable usage has changed in `pandas.eval()`/`DataFrame.eval()`/`DataFrame.query()` (GH5987). For the `DataFrame` methods, two things have changed
 - Column names are now given precedence over locals
 - Local variables must be referred to explicitly. This means that even if you have a local variable that is *not* a column you must still refer to it with the `'@'` prefix.
 - You can have an expression like `df.query('@a < a')` with no complaints from pandas about ambiguity of the name `a`.
 - The top-level `pandas.eval()` function does not allow you use the `'@'` prefix and provides you with an error message telling you so.
 - `NameResolutionError` was removed because it isn't necessary anymore.
- Define and document the order of column vs index names in query/eval (GH6676)
- `concat` will now concatenate mixed Series and DataFrames using the Series name or numbering columns as needed (GH2385). See *the docs*
- Slicing and advanced/boolean indexing operations on `Index` classes as well as `Index.delete()` and `Index.drop()` methods will no longer change the type of the resulting index (GH6440, GH7040)

```
In [6]: i = pd.Index([1, 2, 3, 'a', 'b', 'c'])
```

```
In [7]: i[[0,1,2]]
```

```
Out[7]: Index([1, 2, 3], dtype='object')
```

```
In [8]: i.drop(['a', 'b', 'c'])
```

```
Out[8]: Int64Index([1, 2, 3], dtype='int64')
```

Previously, the above operation would return `Int64Index`. If you'd like to do this manually, use `Index.astype()`

```
In [9]: i[[0,1,2]].astype(np.int_)
```

```
Out[9]: Int64Index([1, 2, 3], dtype='int32')
```

- `set_index` no longer converts `MultiIndex`s to an `Index` of tuples. For example, the old behavior returned an `Index` in this case (GH6459):

```
# Old behavior, casted MultiIndex to an Index
```

```
In [10]: tuple_ind
```

```
Out[10]: Index([(u'a', u'c'), (u'a', u'd'), (u'b', u'c'), (u'b', u'd')], dtype='object')
```

```
In [11]: df_multi.set_index(tuple_ind)
```

```
Out[11]:
```

	0	1
(a, c)	0.471435	-1.190976
(a, d)	1.432707	-0.312652
(b, c)	-0.720589	0.887163
(b, d)	0.859588	-0.636524

```
# New behavior
```

```
In [12]: mi
```

```
Out[12]:
```

```
MultiIndex(levels=[[u'a', u'b'], [u'c', u'd']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]])
```

```
In [13]: df_multi.set_index(mi)
Out[13]:
```

	0	1
a c	0.471435	-1.190976
d	1.432707	-0.312652
b c	-0.720589	0.887163
d	0.859588	-0.636524

This also applies when passing multiple indices to `set_index`:

```
# Old output, 2-level MultiIndex of tuples
In [14]: df_multi.set_index([df_multi.index, df_multi.index])
Out[14]:
```

	0	1
(a, c) (a, c)	0.471435	-1.190976
(a, d) (a, d)	1.432707	-0.312652
(b, c) (b, c)	-0.720589	0.887163
(b, d) (b, d)	0.859588	-0.636524


```
# New output, 4-level MultiIndex
In [15]: df_multi.set_index([df_multi.index, df_multi.index])
Out[15]:
```

	0	1
a c a c	0.471435	-1.190976
d a d	1.432707	-0.312652
b c b c	-0.720589	0.887163
d b d	0.859588	-0.636524

- `pairwise` keyword was added to the statistical moment functions `rolling_cov`, `rolling_corr`, `ewmcov`, `ewmcorr`, `expanding_cov`, `expanding_corr` to allow the calculation of moving window covariance and correlation matrices (GH4950). See *Computing rolling pairwise covariances and correlations* in the docs.

```
In [16]: df = DataFrame(np.random.randn(10,4), columns=list('ABCD'))

In [17]: covs = rolling_cov(df[['A','B','C']], df[['B','C','D']], 5, pairwise=True)

In [18]: covs[df.index[-1]]
Out[18]:
```

	B	C	D
A	0.128104	0.183628	-0.047358
B	0.856265	0.058945	0.145447
C	0.058945	0.335350	0.390637

- `Series.iteritems()` is now lazy (returns an iterator rather than a list). This was the documented behavior prior to 0.14. (GH6760)
- Added `nunique` and `value_counts` functions to `Index` for counting unique elements. (GH6734)
- `stack` and `unstack` now raise a `ValueError` when the `level` keyword refers to a non-unique item in the `Index` (previously raised a `KeyError`). (GH6738)
- drop unused `order` argument from `Series.sort`; args now are in the same order as `Series.order`; add `na_position` arg to conform to `Series.order` (GH6847)
- default sorting algorithm for `Series.order` is now `quicksort`, to conform with `Series.sort` (and `numpy` defaults)
- add `inplace` keyword to `Series.order/sort` to make them inverses (GH6859)

- `DataFrame.sort` now places NaNs at the beginning or end of the sort according to the `na_position` parameter. (GH3917)
- accept `TextFileReader` in `concat`, which was affecting a common user idiom (GH6583), this was a regression from 0.13.1
- Added `factorize` functions to `Index` and `Series` to get indexer and unique values (GH7090)
- `describe` on a `DataFrame` with a mix of `Timestamp` and string like objects returns a different `Index` (GH7088). Previously the index was unintentionally sorted.
- Arithmetic operations with **only** `bool` dtypes now give a warning indicating that they are evaluated in Python space for `+`, `-`, and `*` operations and raise for all others (GH7011, GH6762, GH7015, GH7210)

```
x = pd.Series(np.random.rand(10) > 0.5)
y = True
x + y # warning generated: should do x | y instead
x / y # this raises because it doesn't make sense
```

```
NotImplementedError: operator '/' not implemented for bool dtypes
```

- In `HDFStore`, `select_as_multiple` will always raise a `KeyError`, when a key or the selector is not found (GH6177)
- `df['col'] = value` and `df.loc[:, 'col'] = value` are now completely equivalent; previously the `.loc` would not necessarily coerce the dtype of the resultant series (GH6149)
- `dtypes` and `ftypes` now return a series with `dtype=object` on empty containers (GH5740)
- `df.to_csv` will now return a string of the CSV data if neither a target path nor a buffer is provided (GH6061)
- `pd.infer_freq()` will now raise a `TypeError` if given an invalid `Series/Index` type (GH6407, GH6463)
- A tuple passed to `DataFrame.sort_index` will be interpreted as the levels of the index, rather than requiring a list of tuple (GH4370)
- all offset operations now return `Timestamp` types (rather than `datetime`), `Business/Week` frequencies were incorrect (GH4069)
- `to_excel` now converts `np.inf` into a string representation, customizable by the `inf_rep` keyword argument (Excel has no native inf representation) (GH6782)
- Replace `pandas.compat.scipy.scoreatpercentile` with `numpy.percentile` (GH6810)
- `.quantile` on a `datetime[ns]` series now returns `Timestamp` instead of `np.datetime64` objects (GH6810)
- change `AssertionError` to `TypeError` for invalid types passed to `concat` (GH6583)
- Raise a `TypeError` when `DataFrame` is passed an iterator as the data argument (GH5357)

1.7.2 Display Changes

- The default way of printing large `DataFrames` has changed. `DataFrames` exceeding `max_rows` and/or `max_columns` are now displayed in a centrally truncated view, consistent with the printing of a `pandas.Series` (GH5603).

In previous versions, a `DataFrame` was truncated once the dimension constraints were reached and an ellipse (...) signaled that part of the data was cut off.

```
In [1]: import pandas as pd

In [2]: import numpy as np

In [3]: pd.options.display.max_rows = 6

In [4]: pd.options.display.max_columns = 6

In [5]: index = pd.DatetimeIndex(start='20010101', freq='D', periods=10)

In [6]: pd.DataFrame(np.arange(10*10).reshape((10,10)), index=index)
Out[6]:
```

	0	1	2	3	4	5	
2001-01-01	0	1	2	3	4	5	...
2001-01-02	10	11	12	13	14	15	...
2001-01-03	20	21	22	23	24	25	...
2001-01-04	30	31	32	33	34	35	...
2001-01-05	40	41	42	43	44	45	...
2001-01-06	50	51	52	53	54	55	...
...	...	...	...	...	...	...	...

```
[10 rows x 10 columns]
```

In the current version, large DataFrames are centrally truncated, showing a preview of head and tail in both dimensions.

```
In [24]: pd.DataFrame(np.arange(10*10).reshape((10,10)), index=index)
Out[24]:
```

	0	1	2	...	7	8	9
2001-01-01	0	1	2	...	7	8	9
2001-01-02	10	11	12	...	17	18	19
2001-01-03	20	21	22	...	27	28	29
...	..	..	..	...	..	..	..
2001-01-08	70	71	72	...	77	78	79
2001-01-09	80	81	82	...	87	88	89
2001-01-10	90	91	92	...	97	98	99

```
[10 rows x 10 columns]
```

- allow option 'truncate' for `display.show_dimensions` to only show the dimensions if the frame is truncated (GH6547).

The default for `display.show_dimensions` will now be `truncate`. This is consistent with how `Series` display length.

```
In [19]: dfd = pd.DataFrame(np.arange(25).reshape(-1,5), index=[0,1,2,3,4], columns=[0,1,2,3,4])

# show dimensions since this is truncated
In [20]: with pd.option_context('display.max_rows', 2, 'display.max_columns', 2,
.....:                          'display.show_dimensions', 'truncate'):
.....:     print(dfd)
.....:
```

	0	...	4
0	0	...	4

```

.. .. .. ..
4  20 ... 24

[5 rows x 5 columns]

# will not show dimensions since it is not truncated
In [21]: with pd.option_context('display.max_rows', 10, 'display.max_columns', 40,
.....:                          'display.show_dimensions', 'truncate'):
.....:     print(dfd)
.....:
   0  1  2  3  4
0  0  1  2  3  4
1  5  6  7  8  9
2 10 11 12 13 14
3 15 16 17 18 19
4 20 21 22 23 24

```

- Regression in the display of a MultiIndexed Series with `display.max_rows` is less than the length of the series ([GH7101](#))
- Fixed a bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the `large_repr` set to 'info' ([GH7105](#))
- The `verbose` keyword in `DataFrame.info()`, which controls whether to shorten the info representation, is now `None` by default. This will follow the global setting in `display.max_info_columns`. The global setting can be overridden with `verbose=True` or `verbose=False`.
- Fixed a bug with the `info` repr not honoring the `display.max_info_columns` setting ([GH6939](#))
- Offset/freq info now in Timestamp `__repr__` ([GH4553](#))

1.7.3 Text Parsing API Changes

`read_csv()/read_table()` will now be noisier w.r.t invalid options rather than falling back to the `PythonParser`.

- Raise `ValueError` when `sep` specified with `delim_whitespace=True` in `read_csv()/read_table()` ([GH6607](#))
- Raise `ValueError` when `engine='c'` specified with unsupported options in `read_csv()/read_table()` ([GH6607](#))
- Raise `ValueError` when fallback to python parser causes options to be ignored ([GH6607](#))
- Produce `ParserWarning` on fallback to python parser when no options are ignored ([GH6607](#))
- Translate `sep='\s+'` to `delim_whitespace=True` in `read_csv()/read_table()` if no other C-unsupported options specified ([GH6607](#))

1.7.4 Groupby API Changes

More consistent behaviour for some groupby methods:

- groupby `head` and `tail` now act more like `filter` rather than an aggregation:

```

In [22]: df = pd.DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [23]: g = df.groupby('A')

```

```
In [24]: g.head(1)  # filters DataFrame
```

```
Out[24]:
```

```
   A  B
0  1  2
2  5  6
```

```
In [25]: g.apply(lambda x: x.head(1))  # used to simply fall-through
```

```
Out[25]:
```

```
   A  B
A
1  0  1  2
5  2  5  6
```

- groupby head and tail respect column selection:

```
In [26]: g[['B']].head(1)
```

```
Out[26]:
```

```
   B
0  2
2  6
```

- groupby nth now reduces by default; filtering can be achieved by passing `as_index=False`. With an optional `dropna` argument to ignore NaN. See [the docs](#).

Reducing

```
In [27]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
```

```
In [28]: g = df.groupby('A')
```

```
In [29]: g.nth(0)
```

```
Out[29]:
```

```
   B
A
1 NaN
5  6
```

```
# this is equivalent to g.first()
```

```
In [30]: g.nth(0, dropna='any')
```

```
Out[30]:
```

```
   B
A
1  4
5  6
```

```
# this is equivalent to g.last()
```

```
In [31]: g.nth(-1, dropna='any')
```

```
Out[31]:
```

```
   B
A
1  4
5  6
```

Filtering

```
In [32]: gf = df.groupby('A', as_index=False)
```

```
In [33]: gf.nth(0)
```

```
Out[33]:
```

```
   A  B
```

```
0  1  NaN
2  5    6
```

```
In [34]: gf.nth(0, dropna='any')
```

```
Out[34]:
```

```
      B
A
1    4
5    6
```

- `groupby` will now not return the grouped column for non-cython functions ([GH5610](#), [GH5614](#), [GH6732](#)), as its already the index

```
In [35]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])
```

```
In [36]: g = df.groupby('A')
```

```
In [37]: g.count()
```

```
Out[37]:
```

```
      B
A
1    1
5    2
```

```
In [38]: g.describe()
```

```
Out[38]:
```

```
              B
A
1 count    1.000000
  mean    4.000000
  std             NaN
  min    4.000000
  25%    4.000000
  50%    4.000000
  75%    4.000000
...
5 mean    7.000000
  std    1.414214
  min    6.000000
  25%    6.500000
  50%    7.000000
  75%    7.500000
  max    8.000000
```

```
[16 rows x 1 columns]
```

- passing `as_index` will leave the grouped column in-place (this is not change in 0.14.0)

```
In [39]: df = DataFrame([[1, np.nan], [1, 4], [5, 6], [5, 8]], columns=['A', 'B'])
```

```
In [40]: g = df.groupby('A', as_index=False)
```

```
In [41]: g.count()
```

```
Out[41]:
```

```
      A  B
0    1  1
1    5  2
```

```
In [42]: g.describe()
```

```
Out[42]:
```

		A	B
0	count	2	1.000000
	mean	1	4.000000
	std	0	NaN
	min	1	4.000000
	25%	1	4.000000
	50%	1	4.000000
	75%	1	4.000000
...	...	...	...
1	mean	5	7.000000
	std	0	1.414214
	min	5	6.000000
	25%	5	6.500000
	50%	5	7.000000
	75%	5	7.500000
	max	5	8.000000

[16 rows x 2 columns]

- Allow specification of a more complex groupby via `pd.Grouper`, such as grouping by a Time and a string field simultaneously. See *the docs*. (GH3794)
- Better propagation/preservation of Series names when performing groupby operations:
 - `SeriesGroupBy.agg` will ensure that the name attribute of the original series is propagated to the result (GH6265).
 - If the function provided to `GroupBy.apply` returns a named series, the name of the series will be kept as the name of the column index of the DataFrame returned by `GroupBy.apply` (GH6124). This facilitates `DataFrame.stack` operations where the name of the column index is used as the name of the inserted column containing the pivoted data.

1.7.5 SQL

The SQL reading and writing functions now support more database flavors through SQLAlchemy (GH2717, GH4163, GH5950, GH6292). All databases supported by SQLAlchemy can be used, such as PostgreSQL, MySQL, Oracle, Microsoft SQL server (see documentation of SQLAlchemy on *included dialects*).

The functionality of providing DBAPI connection objects will only be supported for sqlite3 in the future. The 'mysql' flavor is deprecated.

The new functions `read_sql_query()` and `read_sql_table()` are introduced. The function `read_sql()` is kept as a convenience wrapper around the other two and will delegate to specific function depending on the provided input (database table name or sql query).

In practice, you have to provide a SQLAlchemy engine to the sql functions. To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For an in-memory sqlite database:

```
In [43]: from sqlalchemy import create_engine

# Create your connection.
In [44]: engine = create_engine('sqlite:///memory:')
```

This engine can then be used to write or read data to/from this database:

```
In [45]: df = pd.DataFrame({'A': [1,2,3], 'B': ['a', 'b', 'c']})
```

```
In [46]: df.to_sql('db_table', engine, index=False)
```

You can read data from a database by specifying the table name:

```
In [47]: pd.read_sql_table('db_table', engine)
```

```
Out[47]:
```

```
   A  B
0  1  a
1  2  b
2  3  c
```

or by specifying a sql query:

```
In [48]: pd.read_sql_query('SELECT * FROM db_table', engine)
```

```
Out[48]:
```

```
   A  B
0  1  a
1  2  b
2  3  c
```

Some other enhancements to the sql functions include:

- support for writing the index. This can be controlled with the `index` keyword (default is `True`).
- specify the column label to use when writing the index with `index_label`.
- specify string columns to parse as datetimes with the `parse_dates` keyword in `read_sql_query()` and `read_sql_table()`.

Warning: Some of the existing functions or function aliases have been deprecated and will be removed in future versions. This includes: `tquery`, `uquery`, `read_frame`, `frame_query`, `write_frame`.

Warning: The support for the ‘mysql’ flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines ([GH6900](#)).

1.7.6 MultiIndexing Using Slicers

In 0.14.0 we added a new way to slice multi-indexed objects. You can slice a multi-index by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see [Selection by Label](#), including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of *that* level. You do not need to specify all the *deeper* levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

See [the docs](#) See also issues ([GH6134](#), [GH4036](#), [GH3057](#), [GH2598](#), [GH5641](#), [GH7106](#))

Warning: You should specify all axes in the `.loc` specifier, meaning the indexer for the **index** and for the **columns**. There are some ambiguous cases where the passed indexer could be mis-interpreted as indexing *both* axes, rather than into say the MultiIndex for the rows.

You should do this:

```
df.loc[(slice('A1', 'A3'), .....), :]
```

rather than this:

```
df.loc[(slice('A1', 'A3'), .....)]
```

Warning: You will need to make sure that the selection axes are fully lexsorted!

```
In [49]: def mklbl(prefix, n):
.....:     return ["%s%s" % (prefix, i) for i in range(n)]
.....:
```

```
In [50]: index = MultiIndex.from_product([mklbl('A', 4),
.....:                                   mklbl('B', 2),
.....:                                   mklbl('C', 4),
.....:                                   mklbl('D', 2)])
.....:
```

```
In [51]: columns = MultiIndex.from_tuples([( 'a', 'foo'), ( 'a', 'bar'),
.....:                                     ( 'b', 'foo'), ( 'b', 'bah')],
.....:                                   names=['lv10', 'lv11'])
.....:
```

```
In [52]: df = DataFrame(np.arange(len(index)*len(columns)).reshape((len(index), len(columns))),
.....:                  index=index,
.....:                  columns=columns).sortlevel().sortlevel(axis=1)
.....:
```

```
In [53]: df
```

```
Out[53]:
lv10      a      b
lv11      bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
      D1    5    4    7    6
      C1 D0    9    8   11   10
      D1   13   12   15   14
      C2 D0   17   16   19   18
      D1   21   20   23   22
      C3 D0   25   24   27   26
...
A3 B1 C0 D1  229  228  231  230
      C1 D0  233  232  235  234
      D1  237  236  239  238
      C2 D0  241  240  243  242
      D1  245  244  247  246
      C3 D0  249  248  251  250
      D1  253  252  255  254
```

```
[64 rows x 4 columns]
```

Basic multi-index slicing using slices, lists, and labels.

```
In [54]: df.loc[(slice('A1', 'A3'), slice(None), ['C1', 'C3']), :]
```

```
Out[54]:
```

```
lvl0      a      b
lvl1      bar  foo  bah  foo
A1 B0 C1 D0   73   72   75   74
      D1   77   76   79   78
      C3 D0   89   88   91   90
      D1   93   92   95   94
      B1 C1 D0  105  104  107  106
      D1  109  108  111  110
      C3 D0  121  120  123  122
...
A3 B0 C1 D1  205  204  207  206
      C3 D0  217  216  219  218
      D1  221  220  223  222
      B1 C1 D0  233  232  235  234
      D1  237  236  239  238
      C3 D0  249  248  251  250
      D1  253  252  255  254
```

```
[24 rows x 4 columns]
```

You can use a `pd.IndexSlice` to shortcut the creation of these slices

```
In [55]: idx = pd.IndexSlice
```

```
In [56]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[56]:
```

```
lvl0      a      b
lvl1      foo  foo
A0 B0 C1 D0    8   10
      D1   12   14
      C3 D0   24   26
      D1   28   30
      B1 C1 D0   40   42
      D1   44   46
      C3 D0   56   58
...
A3 B0 C1 D1  204  206
      C3 D0  216  218
      D1  220  222
      B1 C1 D0  232  234
      D1  236  238
      C3 D0  248  250
      D1  252  254
```

```
[32 rows x 2 columns]
```

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```
In [57]: df.loc['A1', (slice(None), 'foo')]
```

```
Out[57]:
```

```
lvl0      a      b
lvl1      foo  foo
B0 C0 D0   64   66
      D1   68   70
      C1 D0   72   74
      D1   76   78
      C2 D0   80   82
```

```
      D1      84      86
C3 D0      88      90
...
B1 C0 D1    100    102
    C1 D0    104    106
      D1    108    110
    C2 D0    112    114
      D1    116    118
    C3 D0    120    122
      D1    124    126
```

[16 rows x 2 columns]

```
In [58]: df.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[58]:
```

```
lvl0      a      b
lvl1      foo      foo
A0 B0 C1 D0      8     10
      D1     12     14
      C3 D0     24     26
      D1     28     30
    B1 C1 D0     40     42
      D1     44     46
      C3 D0     56     58
...
A3 B0 C1 D1    204    206
      C3 D0    216    218
      D1    220    222
    B1 C1 D0    232    234
      D1    236    238
      C3 D0    248    250
      D1    252    254
```

[32 rows x 2 columns]

Using a boolean indexer you can provide selection related to the *values*.

```
In [59]: mask = df[('a', 'foo')] > 200
```

```
In [60]: df.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out[60]:
```

```
lvl0      a      b
lvl1      foo      foo
A3 B0 C1 D1    204    206
      C3 D0    216    218
      D1    220    222
    B1 C1 D0    232    234
      D1    236    238
      C3 D0    248    250
      D1    252    254
```

You can also specify the `axis` argument to `.loc` to interpret the passed slicers on a single axis.

```
In [61]: df.loc(axis=0)[:, :, ['C1', 'C3']]
```

```
Out[61]:
```

```
lvl0      a      b
lvl1      bar      foo      bah      foo
A0 B0 C1 D0      9      8      11      10
      D1     13     12     15     14
```

```

      C3 D0    25    24    27    26
      D1    29    28    31    30
B1 C1 D0    41    40    43    42
      D1    45    44    47    46
      C3 D0    57    56    59    58
...
A3 B0 C1 D1   205   204   207   206
      C3 D0   217   216   219   218
      D1   221   220   223   222
      B1 C1 D0   233   232   235   234
      D1   237   236   239   238
      C3 D0   249   248   251   250
      D1   253   252   255   254

```

```
[32 rows x 4 columns]
```

Furthermore you can *set* the values using these methods

```
In [62]: df2 = df.copy()
```

```
In [63]: df2.loc(axis=0)[:,:,:,['C1','C3']] = -10
```

```
In [64]: df2
```

```
Out[64]:
```

```

lvl0      a      b
lvl1    bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
      D1    5    4    7    6
      C1 D0  -10  -10  -10  -10
      D1  -10  -10  -10  -10
      C2 D0   17   16   19   18
      D1   21   20   23   22
      C3 D0  -10  -10  -10  -10
...
A3 B1 C0 D1   229   228   231   230
      C1 D0  -10  -10  -10  -10
      D1  -10  -10  -10  -10
      C2 D0   241   240   243   242
      D1   245   244   247   246
      C3 D0  -10  -10  -10  -10
      D1  -10  -10  -10  -10

```

```
[64 rows x 4 columns]
```

You can use a right-hand-side of an alignable object as well.

```
In [65]: df2 = df.copy()
```

```
In [66]: df2.loc[idx[:,:,:,['C1','C3']],:] = df2*1000
```

```
In [67]: df2
```

```
Out[67]:
```

```

lvl0      a      b
lvl1    bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
      D1    5    4    7    6
      C1 D0   9000   8000  11000  10000
      D1  13000  12000  15000  14000
      C2 D0    17    16    19    18

```

```
      D1      21      20      23      22
C3 D0  25000  24000  27000  26000
...
A3 B1 C0 D1    229    228    231    230
      C1 D0  233000 232000 235000 234000
      D1  237000 236000 239000 238000
      C2 D0    241    240    243    242
      D1    245    244    247    246
      C3 D0  249000 248000 251000 250000
      D1  253000 252000 255000 254000
```

```
[64 rows x 4 columns]
```

1.7.7 Plotting

- Hexagonal bin plots from `DataFrame.plot` with `kind='hexbin'` ([GH5478](#)), See [the docs](#).
- `DataFrame.plot` and `Series.plot` now supports area plot with specifying `kind='area'` ([GH6656](#)), See [the docs](#)
- Pie plots from `Series.plot` and `DataFrame.plot` with `kind='pie'` ([GH6976](#)), See [the docs](#).
- Plotting with Error Bars is now supported in the `.plot` method of `DataFrame` and `Series` objects ([GH3796](#), [GH6834](#)), See [the docs](#).
- `DataFrame.plot` and `Series.plot` now support a `table` keyword for plotting `matplotlib.Table`, See [the docs](#). The `table` keyword can receive the following values.
 - `False`: Do nothing (default).
 - `True`: Draw a table using the `DataFrame` or `Series` called `plot` method. Data will be transposed to meet `matplotlib`'s default layout.
 - `DataFrame` or `Series`: Draw `matplotlib.table` using the passed data. The data will be drawn as displayed in `print` method (not transposed automatically). Also, helper function `pandas.tools.plotting.table` is added to create a table from `DataFrame` and `Series`, and add it to an `matplotlib.Axes`.
- `plot(legend='reverse')` will now reverse the order of legend labels for most plot kinds. ([GH6014](#))
- Line plot and area plot can be stacked by `stacked=True` ([GH6656](#))
- Following keywords are now acceptable for `DataFrame.plot()` with `kind='bar'` and `kind='barh'`:
 - `width`: Specify the bar width. In previous versions, static value 0.5 was passed to `matplotlib` and it cannot be overwritten. ([GH6604](#))
 - `align`: Specify the bar alignment. Default is `center` (different from `matplotlib`). In previous versions, `pandas` passes `align='edge'` to `matplotlib` and adjust the location to `center` by itself, and it results `align` keyword is not applied as expected. ([GH4525](#))
 - `position`: Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1(right/top-end). Default is 0.5 (center). ([GH6604](#))

Because of the default `align` value changes, coordinates of bar plots are now located on integer values (0.0, 1.0, 2.0 ...). This is intended to make bar plot be located on the same coordinates as line plot. However, bar plot may differs unexpectedly when you manually adjust the bar location or drawing area, such as using `set_xlim`, `set_ylim`, etc. In this cases, please modify your script to meet with new coordinates.

- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A `FutureWarning` is raised to alert that the old `colors` argument will not be supported in a future release. (GH6956)
- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A `FutureWarning` is raised if the old `data` argument is used by name. (GH6956)
- `DataFrame.boxplot()` now supports `layout` keyword (GH6769)
- `DataFrame.boxplot()` has a new keyword argument, `return_type`. It accepts `'dict'`, `'axes'`, or `'both'`, in which case a namedtuple with the matplotlib axes and a dict of matplotlib Lines is returned.

1.7.8 Prior Version Deprecations/Changes

There are prior version deprecations that are taking effect as of 0.14.0.

- Remove `DateRange` in favor of `DatetimeIndex` (GH6816)
- Remove `column` keyword from `DataFrame.sort` (GH4370)
- Remove `precision` keyword from `set_eng_float_format()` (GH395)
- Remove `force_unicode` keyword from `DataFrame.to_string()`, `DataFrame.to_latex()`, and `DataFrame.to_html()`; these function encode in unicode by default (GH2224, GH2225)
- Remove `nanRep` keyword from `DataFrame.to_csv()` and `DataFrame.to_string()` (GH275)
- Remove `unique` keyword from `HDFStore.select_column()` (GH3256)
- Remove `inferTimeRule` keyword from `Timestamp.offset()` (GH391)
- Remove `name` keyword from `get_data_yahoo()` and `get_data_google()` (commit b921d1a)
- Remove `offset` keyword from `DatetimeIndex` constructor (commit 3136390)
- Remove `time_rule` from several rolling-moment statistical functions, such as `rolling_sum()` (GH1042)
- Removed `neg` – boolean operations on numpy arrays in favor of `inv ~`, as this is going to be deprecated in numpy 1.9 (GH6960)

1.7.9 Deprecations

- The `pivot_table()/DataFrame.pivot_table()` and `crosstab()` functions now take arguments `index` and `columns` instead of `rows` and `cols`. A `FutureWarning` is raised to alert that the old `rows` and `cols` arguments will not be supported in a future release (GH5505)
- The `DataFrame.drop_duplicates()` and `DataFrame.duplicated()` methods now take argument `subset` instead of `cols` to better align with `DataFrame.dropna()`. A `FutureWarning` is raised to alert that the old `cols` arguments will not be supported in a future release (GH6680)
- The `DataFrame.to_csv()` and `DataFrame.to_excel()` functions now takes argument `columns` instead of `cols`. A `FutureWarning` is raised to alert that the old `cols` arguments will not be supported in a future release (GH6645)
- Indexers will warn `FutureWarning` when used with a scalar indexer and a non-floating point Index (GH4892, GH6960)

```
# non-floating point indexes can only be indexed by integers / labels
```

```
In [1]: Series(1,np.arange(5))[3.0]
```

```
pandas/core/index.py:469: FutureWarning: scalar indexers for index type Int64Index should
```

```
Out[1]: 1
```

```
In [2]: Series(1,np.arange(5)).iloc[3.0]
pandas/core/index.py:469: FutureWarning: scalar indexers for index type Int64Index should
Out[2]: 1

In [3]: Series(1,np.arange(5)).iloc[3.0:4]
pandas/core/index.py:527: FutureWarning: slice indexers when using iloc should be integer
Out[3]:
     3    1
dtype: int64

# these are Float64Indexes, so integer or floating point is acceptable
In [4]: Series(1,np.arange(5.))[3]
Out[4]: 1

In [5]: Series(1,np.arange(5.))[3.0]
Out[6]: 1
```

- Numpy 1.9 compat w.r.t. deprecation warnings (GH6960)
- `Panel.shift()` now has a function signature that matches `DataFrame.shift()`. The old positional argument `lags` has been changed to a keyword argument `periods` with a default value of 1. A `FutureWarning` is raised if the old argument `lags` is used by name. (GH6910)
- The `order` keyword argument of `factorize()` will be removed. (GH6926).
- Remove the `copy` keyword from `DataFrame.xs()`, `Panel.major_xs()`, `Panel.minor_xs()`. A view will be returned if possible, otherwise a copy will be made. Previously the user could think that `copy=False` would ALWAYS return a view. (GH6894)
- The `parallel_coordinates()` function now takes argument `color` instead of `colors`. A `FutureWarning` is raised to alert that the old `colors` argument will not be supported in a future release. (GH6956)
- The `parallel_coordinates()` and `andrews_curves()` functions now take positional argument `frame` instead of `data`. A `FutureWarning` is raised if the old `data` argument is used by name. (GH6956)
- The support for the ‘mysql’ flavor when using DBAPI connection objects has been deprecated. MySQL will be further supported with SQLAlchemy engines (GH6900).
- The following `io.sql` functions have been deprecated: `tquery`, `uquery`, `read_frame`, `frame_query`, `write_frame`.
- The `percentile_width` keyword argument in `describe()` has been deprecated. Use the `percentiles` keyword instead, which takes a list of percentiles to display. The default output is unchanged.
- The default return type of `boxplot()` will change from a dict to a matplotlib Axes in a future release. You can use the future behavior now by passing `return_type='axes'` to `boxplot`.

1.7.10 Known Issues

- OpenPyXL 2.0.0 breaks backwards compatibility (GH7169)

1.7.11 Enhancements

- `DataFrame` and `Series` will create a `MultiIndex` object if passed a tuples dict, See *the docs* (GH3323)

```
In [68]: Series({'a', 'b'): 1, ('a', 'a'): 0,
.....:          ('a', 'c'): 2, ('b', 'a'): 3, ('b', 'b'): 4})
.....:
Out[68]:
a a    0
  b    1
  c    2
b a    3
  b    4
dtype: int64

In [69]: DataFrame({'a', 'b'): {'(A', 'B)': 1, ('A', 'C'): 2},
.....:          ('a', 'a'): {'(A', 'C)': 3, ('A', 'B)': 4},
.....:          ('a', 'c'): {'(A', 'B)': 5, ('A', 'C)': 6},
.....:          ('b', 'a'): {'(A', 'C)': 7, ('A', 'B)': 8},
.....:          ('b', 'b'): {'(A', 'D)': 9, ('A', 'B)': 10}})
.....:
Out[69]:
      a      b
A B  4  1  5  8  10
C   3  2  6  7  NaN
D  NaN NaN NaN NaN  9
```

- Added the `sym_diff` method to `Index` (GH5543)
- `DataFrame.to_latex` now takes a `longtable` keyword, which if `True` will return a table in a `longtable` environment. (GH6617)
- Add option to turn off escaping in `DataFrame.to_latex` (GH6472)
- `pd.read_clipboard` will, if the keyword `sep` is unspecified, try to detect data copied from a spreadsheet and parse accordingly. (GH6223)
- Joining a singly-indexed `DataFrame` with a multi-indexed `DataFrame` (GH3662)

See *the docs*. Joining multi-index `DataFrames` on both the left and right is not yet supported ATM.

```
In [70]: household = DataFrame(dict(household_id = [1,2,3],
.....:                               male = [0,1,0],
.....:                               wealth = [196087.3,316478.7,294750]),
.....:                               columns = ['household_id', 'male', 'wealth']
.....:                               ).set_index('household_id'))
.....:
```

```
In [71]: household
Out[71]:
      male  wealth
household_id
1         0  196087.3
2         1  316478.7
3         0  294750.0
```

```
In [72]: portfolio = DataFrame(dict(household_id = [1,2,2,3,3,3,4],
.....:                               asset_id = ["n10000301109", "n10000289783", "gb00b03mlx29",
.....:                                              "gb00b03mlx29", "lu0197800237", "n10000289965", np.
.....:                                              "AAB Eastern Europe Equity Fund", "Postbank BioTech F
.....:                               share = [1.0,0.4,0.6,0.15,0.6,0.25,1.0]),
.....:                               columns = ['household_id', 'asset_id', 'name', 'share'])
```

```
.....:                                     ).set_index(['household_id', 'asset_id'])
.....:

In [73]: portfolio
Out[73]:
```

			name	share
household_id	asset_id			
1	nl0000301109		ABN Amro	1.00
2	nl0000289783		Robeco	0.40
	gb00b03mlx29		Royal Dutch Shell	0.60
3	gb00b03mlx29		Royal Dutch Shell	0.15
	lu0197800237	AAB Eastern Europe Equity Fund		0.60
	nl0000289965	Postbank BioTech Fonds		0.25
4	NaN		NaN	1.00

```
In [74]: household.join(portfolio, how='inner')
Out[74]:
```

		male	wealth		name \
household_id	asset_id				
1	nl0000301109	0	196087.3		ABN Amro
2	nl0000289783	1	316478.7		Robeco
	gb00b03mlx29	1	316478.7		Royal Dutch Shell
3	gb00b03mlx29	0	294750.0		Royal Dutch Shell
	lu0197800237	0	294750.0	AAB Eastern Europe Equity Fund	
	nl0000289965	0	294750.0	Postbank BioTech Fonds	

		share
household_id	asset_id	
1	nl0000301109	1.00
2	nl0000289783	0.40
	gb00b03mlx29	0.60
3	gb00b03mlx29	0.15
	lu0197800237	0.60
	nl0000289965	0.25

- `quotechar`, `doublequote`, and `escapechar` can now be specified when using `DataFrame.to_csv` ([GH5414](#), [GH4528](#))
- Partially sort by only the specified levels of a `MultiIndex` with the `sort_remaining` boolean kwarg. ([GH3984](#))
- Added `to_julian_date` to `TimeStamp` and `DatetimeIndex`. The Julian Date is used primarily in astronomy and represents the number of days from noon, January 1, 4713 BC. Because nanoseconds are used to define the time in pandas the actual range of dates that you can use is 1678 AD to 2262 AD. ([GH4041](#))
- `DataFrame.to_stata` will now check data for compatibility with Stata data types and will upcast when needed. When it is not possible to losslessly upcast, a warning is issued ([GH6327](#))
- `DataFrame.to_stata` and `StataWriter` will accept keyword arguments `time_stamp` and `data_label` which allow the time stamp and dataset label to be set when creating a file. ([GH6545](#))
- `pandas.io.gbq` now handles reading unicode strings properly. ([GH5940](#))
- *Holidays Calendars* are now available and can be used with the `CustomBusinessDay` offset ([GH6719](#))
- `Float64Index` is now backed by a `float64` dtype ndarray instead of an object dtype array ([GH6471](#)).
- Implemented `Panel.pct_change` ([GH6904](#))
- Added `how` option to rolling-moment functions to dictate how to handle resampling; `rolling_max()` defaults to max, `rolling_min()` defaults to min, and all others default to mean ([GH6297](#))

- CustomBuisnessMonthBegin and CustomBusinessMonthEnd are now available (GH6866)
- `Series.quantile()` and `DataFrame.quantile()` now accept an array of quantiles.
- `describe()` now accepts an array of percentiles to include in the summary statistics (GH4196)
- `pivot_table` can now accept Grouper by index and columns keywords (GH6913)

```
In [75]: import datetime
```

```
In [76]: df = DataFrame({
.....:     'Branch' : 'A A A A B'.split(),
.....:     'Buyer' : 'Carl Mark Carl Carl Joe Joe'.split(),
.....:     'Quantity': [1, 3, 5, 1, 8, 1],
.....:     'Date' : [datetime.datetime(2013,11,1,13,0), datetime.datetime(2013,9,1,13,5),
.....:               datetime.datetime(2013,10,1,20,0), datetime.datetime(2013,10,2,10,0),
.....:               datetime.datetime(2013,11,1,20,0), datetime.datetime(2013,10,2,10,0)],
.....:     'PayDay' : [datetime.datetime(2013,10,4,0,0), datetime.datetime(2013,10,15,13,5),
.....:                 datetime.datetime(2013,9,5,20,0), datetime.datetime(2013,11,2,10,0),
.....:                 datetime.datetime(2013,10,7,20,0), datetime.datetime(2013,9,5,10,0)]})
.....:
```

```
In [77]: df
```

```
Out[77]:
```

	Branch	Buyer	Date	PayDay	Quantity
0	A	Carl	2013-11-01 13:00:00	2013-10-04 00:00:00	1
1	A	Mark	2013-09-01 13:05:00	2013-10-15 13:05:00	3
2	A	Carl	2013-10-01 20:00:00	2013-09-05 20:00:00	5
3	A	Carl	2013-10-02 10:00:00	2013-11-02 10:00:00	1
4	A	Joe	2013-11-01 20:00:00	2013-10-07 20:00:00	8
5	B	Joe	2013-10-02 10:00:00	2013-09-05 10:00:00	1

```
In [78]: pivot_table(df, index=Grouper(freq='M', key='Date'),
.....:                 columns=Grouper(freq='M', key='PayDay'),
.....:                 values='Quantity', aggfunc=np.sum)
.....:
```

```
Out[78]:
```

PayDay	2013-09-30	2013-10-31	2013-11-30
Date			
2013-09-30	NaN	3	NaN
2013-10-31	6	NaN	1
2013-11-30	NaN	9	NaN

- Arrays of strings can be wrapped to a specified width (`str.wrap`) (GH6999)
- Add `nsmallest()` and `Series.nlargest()` methods to Series, See *the docs* (GH3960)
- `PeriodIndex` fully supports partial string indexing like `DatetimeIndex` (GH7043)

```
In [79]: prng = period_range('2013-01-01 09:00', periods=100, freq='H')
```

```
In [80]: ps = Series(np.random.randn(len(prng)), index=prng)
```

```
In [81]: ps
```

```
Out[81]:
```

2013-01-01 09:00	0.755414
2013-01-01 10:00	0.215269
2013-01-01 11:00	0.841009
2013-01-01 12:00	-1.445810
2013-01-01 13:00	-1.401973
2013-01-01 14:00	-0.100918

```
2013-01-01 15:00    -0.548242
...
2013-01-05 06:00    -0.379811
2013-01-05 07:00     0.702562
2013-01-05 08:00    -0.850346
2013-01-05 09:00     1.176812
2013-01-05 10:00    -0.524336
2013-01-05 11:00     0.700908
2013-01-05 12:00     0.984188
Freq: H, dtype: float64
```

```
In [82]: ps['2013-01-02']
```

```
Out [82]:
```

```
2013-01-02 00:00    -0.208499
2013-01-02 01:00     1.033801
2013-01-02 02:00    -2.400454
2013-01-02 03:00     2.030604
2013-01-02 04:00    -1.142631
2013-01-02 05:00     0.211883
2013-01-02 06:00     0.704721
...
2013-01-02 17:00     0.464392
2013-01-02 18:00    -3.563517
2013-01-02 19:00     1.321106
2013-01-02 20:00     0.152631
2013-01-02 21:00     0.164530
2013-01-02 22:00    -0.430096
2013-01-02 23:00     0.767369
Freq: H, dtype: float64
```

- `read_excel` can now read milliseconds in Excel dates and times with `xlrd >= 0.9.3`. ([GH5945](#))
- `pd.stats.moments.rolling_var` now uses Welford's method for increased numerical stability ([GH6817](#))
- `pd.expanding_apply` and `pd.rolling_apply` now take args and kwargs that are passed on to the func ([GH6289](#))
- `DataFrame.rank()` now has a percentage rank option ([GH5971](#))
- `Series.rank()` now has a percentage rank option ([GH5971](#))
- `Series.rank()` and `DataFrame.rank()` now accept `method='dense'` for ranks without gaps ([GH6514](#))
- Support passing encoding with `xlwt` ([GH3710](#))
- Refactor Block classes removing `Block.items` attributes to avoid duplication in item handling ([GH6745](#), [GH6988](#)).
- Testing statements updated to use specialized asserts ([GH6175](#))

1.7.12 Performance

- Performance improvement when converting `DatetimeIndex` to floating ordinals using `DatetimeConverter` ([GH6636](#))
- Performance improvement for `DataFrame.shift` ([GH5609](#))
- Performance improvement in indexing into a multi-indexed Series ([GH5567](#))
- Performance improvements in single-dtyped indexing ([GH6484](#))

- Improve performance of DataFrame construction with certain offsets, by removing faulty caching (e.g. MonthEnd, BusinessMonthEnd), (GH6479)
- Improve performance of CustomBusinessDay (GH6584)
- improve performance of slice indexing on Series with string keys (GH6341, GH6372)
- Performance improvement for DataFrame.from_records when reading a specified number of rows from an iterable (GH6700)
- Performance improvements in timedelta conversions for integer dtypes (GH6754)
- Improved performance of compatible pickles (GH6899)
- Improve performance in certain reindexing operations by optimizing take_2d (GH6749)
- GroupBy.count() is now implemented in Cython and is much faster for large numbers of groups (GH7016).

1.7.13 Experimental

There are no experimental changes in 0.14.0

1.7.14 Bug Fixes

- Bug in Series ValueError when index doesn't match data (GH6532)
- Prevent segfault due to MultiIndex not being supported in HDFStore table format (GH1848)
- Bug in pd.DataFrame.sort_index where mergesort wasn't stable when ascending=False (GH6399)
- Bug in pd.tseries.frequencies.to_offset when argument has leading zeroes (GH6391)
- Bug in version string gen. for dev versions with shallow clones / install from tarball (GH6127)
- Inconsistent tz parsing Timestamp / to_datetime for current year (GH5958)
- Indexing bugs with reordered indexes (GH6252, GH6254)
- Bug in .xs with a Series multiindex (GH6258, GH5684)
- Bug in conversion of a string types to a DatetimeIndex with a specified frequency (GH6273, GH6274)
- Bug in eval where type-promotion failed for large expressions (GH6205)
- Bug in interpolate with inplace=True (GH6281)
- HDFStore.remove now handles start and stop (GH6177)
- HDFStore.select_as_multiple handles start and stop the same way as select (GH6177)
- HDFStore.select_as_coordinates and select_column works with a where clause that results in filters (GH6177)
- Regression in join of non_unique_indexes (GH6329)
- Issue with groupby agg with a single function and a a mixed-type frame (GH6337)
- Bug in DataFrame.replace() when passing a non-bool to_replace argument (GH6332)
- Raise when trying to align on different levels of a multi-index assignment (GH3738)
- Bug in setting complex dtypes via boolean indexing (GH6345)

- Bug in TimeGrouper/resample when presented with a non-monotonic DatetimeIndex that would return invalid results. (GH4161)
- Bug in index name propagation in TimeGrouper/resample (GH4161)
- TimeGrouper has a more compatible API to the rest of the groupers (e.g. groups was missing) (GH3881)
- Bug in multiple grouping with a TimeGrouper depending on target column order (GH6764)
- Bug in `pd.eval` when parsing strings with possible tokens like `' & '` (GH6351)
- Bug correctly handle placements of `-inf` in Panels when dividing by integer 0 (GH6178)
- `DataFrame.shift` with `axis=1` was raising (GH6371)
- Disabled clipboard tests until release time (run locally with `nosetests -A disabled`) (GH6048).
- Bug in `DataFrame.replace()` when passing a nested dict that contained keys not in the values to be replaced (GH6342)
- `str.match` ignored the `na` flag (GH6609).
- Bug in `take` with duplicate columns that were not consolidated (GH6240)
- Bug in `interpolate` changing dtypes (GH6290)
- Bug in `Series.get`, was using a buggy access method (GH6383)
- Bug in `hdfstore` queries of the form `where=[('date', '>=', datetime(2013,1,1)), ('date', '<=', datetime(2014,1,1))]` (GH6313)
- Bug in `DataFrame.dropna` with duplicate indices (GH6355)
- Regression in chained getitem indexing with embedded list-like from 0.12 (GH6394)
- `Float64Index` with nans not comparing correctly (GH6401)
- `eval/query` expressions with strings containing the `@` character will now work (GH6366).
- Bug in `Series.reindex` when specifying a method with some nan values was inconsistent (noted on a resample) (GH6418)
- Bug in `DataFrame.replace()` where nested dicts were erroneously depending on the order of dictionary keys and values (GH5338).
- Perf issue in concatting with empty objects (GH3259)
- Clarify sorting of `sym_diff` on `Index` objects with NaN values (GH6444)
- Regression in `MultiIndex.from_product` with a `DatetimeIndex` as input (GH6439)
- Bug in `str.extract` when passed a non-default index (GH6348)
- Bug in `str.split` when passed `pat=None` and `n=1` (GH6466)
- Bug in `io.data.DataReader` when passed `"F-F_Momentum_Factor"` and `data_source="famafrench"` (GH6460)
- Bug in `sum` of a `timedelta64[ns]` series (GH6462)
- Bug in `resample` with a timezone and certain offsets (GH6397)
- Bug in `iat/iloc` with duplicate indices on a `Series` (GH6493)
- Bug in `read_html` where nan's were incorrectly being used to indicate missing values in text. Should use the empty string for consistency with the rest of pandas (GH5129).
- Bug in `read_html` tests where redirected invalid URLs would make one test fail (GH6445).

- Bug in multi-axis indexing using `.loc` on non-unique indices ([GH6504](#))
- Bug that caused `_ref_locs` corruption when slice indexing across columns axis of a DataFrame ([GH6525](#))
- Regression from 0.13 in the treatment of numpy `datetime64` non-ns dtypes in Series creation ([GH6529](#))
- `.names` attribute of MultiIndexes passed to `set_index` are now preserved ([GH6459](#)).
- Bug in setitem with a duplicate index and an alignable rhs ([GH6541](#))
- Bug in setitem with `.loc` on mixed integer Indexes ([GH6546](#))
- Bug in `pd.read_stata` which would use the wrong data types and missing values ([GH6327](#))
- Bug in `DataFrame.to_stata` that lead to data loss in certain cases, and could be exported using the wrong data types and missing values ([GH6335](#))
- `StataWriter` replaces missing values in string columns by empty string ([GH6802](#))
- Inconsistent types in Timestamp addition/subtraction ([GH6543](#))
- Bug in preserving frequency across Timestamp addition/subtraction ([GH4547](#))
- Bug in empty list lookup caused `IndexError` exceptions ([GH6536](#), [GH6551](#))
- `Series.quantile` raising on an object dtype ([GH6555](#))
- Bug in `.xs` with a nan in level when dropped ([GH6574](#))
- Bug in `fillna` with `method='bfill/ffill'` and `datetime64[ns]` dtype ([GH6587](#))
- Bug in sql writing with mixed dtypes possibly leading to data loss ([GH6509](#))
- Bug in `Series.pop` ([GH6600](#))
- Bug in `iloc` indexing when positional indexer matched `Int64Index` of the corresponding axis and no re-ordering happened ([GH6612](#))
- Bug in `fillna` with `limit` and `value` specified
- Bug in `DataFrame.to_stata` when columns have non-string names ([GH4558](#))
- Bug in `compat` with `np.compress`, surfaced in ([GH6658](#))
- Bug in binary operations with a rhs of a Series not aligning ([GH6681](#))
- Bug in `DataFrame.to_stata` which incorrectly handles nan values and ignores `with_index` keyword argument ([GH6685](#))
- Bug in `resample` with extra bins when using an evenly divisible frequency ([GH4076](#))
- Bug in consistency of `groupby` aggregation when passing a custom function ([GH6715](#))
- Bug in `resample` when `how=None` resample freq is the same as the axis frequency ([GH5955](#))
- Bug in downcasting inference with empty arrays ([GH6733](#))
- Bug in `obj.blocks` on sparse containers dropping all but the last items of same for dtype ([GH6748](#))
- Bug in unpickling `NaT` (`NaTType`) ([GH4606](#))
- Bug in `DataFrame.replace()` where regex metacharacters were being treated as regexs even when `regex=False` ([GH6777](#)).
- Bug in `timedelta` ops on 32-bit platforms ([GH6808](#))
- Bug in setting a tz-aware index directly via `.index` ([GH6785](#))
- Bug in `expressions.py` where `numexpr` would try to evaluate arithmetic ops ([GH6762](#)).

- Bug in Makefile where it didn't remove Cython generated C files with `make clean` ([GH6768](#))
- Bug with `numpy < 1.7.2` when reading long strings from `HDFStore` ([GH6166](#))
- Bug in `DataFrame._reduce` where non bool-like (0/1) integers were being converted into bools. ([GH6806](#))
- Regression from 0.13 with `fillna` and a Series on datetime-like ([GH6344](#))
- Bug in adding `np.timedelta64` to `DatetimeIndex` with timezone outputs incorrect results ([GH6818](#))
- Bug in `DataFrame.replace()` where changing a dtype through replacement would only replace the first occurrence of a value ([GH6689](#))
- Better error message when passing a frequency of 'MS' in `Period` construction ([GH5332](#))
- Bug in `Series.__unicode__` when `max_rows=None` and the Series has more than 1000 rows. ([GH6863](#))
- Bug in `groupby.get_group` where a datetlike wasn't always accepted ([GH5267](#))
- Bug in `groupBy.get_group` created by `TimeGrouper` raises `AttributeError` ([GH6914](#))
- Bug in `DatetimeIndex.tz_localize` and `DatetimeIndex.tz_convert` converting NaT incorrectly ([GH5546](#))
- Bug in arithmetic operations affecting NaT ([GH6873](#))
- Bug in `Series.str.extract` where the resulting Series from a single group match wasn't renamed to the group name
- Bug in `DataFrame.to_csv` where setting `index=False` ignored the header kwarg ([GH6186](#))
- Bug in `DataFrame.plot` and `Series.plot`, where the legend behave inconsistently when plotting to the same axes repeatedly ([GH6678](#))
- Internal tests for patching `__finalize__` / bug in merge not finalizing ([GH6923](#), [GH6927](#))
- accept `TextFileReader` in `concat`, which was affecting a common user idiom ([GH6583](#))
- Bug in C parser with leading whitespace ([GH3374](#))
- Bug in C parser with `delim_whitespace=True` and `\r`-delimited lines
- Bug in python parser with explicit multi-index in row following column header ([GH6893](#))
- Bug in `Series.rank` and `DataFrame.rank` that caused small floats ($<1e-13$) to all receive the same rank ([GH6886](#))
- Bug in `DataFrame.apply` with functions that used `*args` or `**kwargs` and returned an empty result ([GH6952](#))
- Bug in `sum/mean` on 32-bit platforms on overflows ([GH6915](#))
- Moved `Panel.shift` to `NDFrame.slice_shift` and fixed to respect multiple dtypes. ([GH6959](#))
- Bug in enabling `subplots=True` in `DataFrame.plot` only has single column raises `TypeError`, and `Series.plot` raises `AttributeError` ([GH6951](#))
- Bug in `DataFrame.plot` draws unnecessary axes when enabling `subplots` and `kind=scatter` ([GH6951](#))
- Bug in `read_csv` from a filesystem with non-utf-8 encoding ([GH6807](#))
- Bug in `iloc` when setting / aligning ([GH6766](#))
- Bug causing `UnicodeEncodeError` when `get_dummies` called with unicode values and a prefix ([GH6885](#))
- Bug in timeseries-with-frequency plot cursor display ([GH5453](#))
- Bug surfaced in `groupby.plot` when using a `Float64Index` ([GH7025](#))

- Stopped tests from failing if options data isn't able to be downloaded from Yahoo ([GH7034](#))
- Bug in `parallel_coordinates` and `radviz` where reordering of class column caused possible color/class mismatch ([GH6956](#))
- Bug in `radviz` and `andrews_curves` where multiple values of 'color' were being passed to plotting method ([GH6956](#))
- Bug in `Float64Index.isin()` where containing `nan`s would make indices claim that they contained all the things ([GH7066](#)).
- Bug in `DataFrame.boxplot` where it failed to use the axis passed as the `ax` argument ([GH3578](#))
- Bug in the `XlsxWriter` and `XlwtWriter` implementations that resulted in datetime columns being formatted without the time ([GH7075](#)) were being passed to plotting method
- `read_fwf()` treats `None` in `colspec` like regular python slices. It now reads from the beginning or until the end of the line when `colspec` contains a `None` (previously raised a `TypeError`)
- Bug in cache coherence with chained indexing and slicing; add `_is_view` property to `NDFrame` to correctly predict views; mark `is_copy` on `xs` only if its an actual copy (and not a view) ([GH7084](#))
- Bug in `DatetimeIndex` creation from string ndarray with `dayfirst=True` ([GH5917](#))
- Bug in `MultiIndex.from_arrays` created from `DatetimeIndex` doesn't preserve `freq` and `tz` ([GH7090](#))
- Bug in `unstack` raises `ValueError` when `MultiIndex` contains `PeriodIndex` ([GH4342](#))
- Bug in `boxplot` and `hist` draws unnecessary axes ([GH6769](#))
- Regression in `groupby.nth()` for out-of-bounds indexers ([GH6621](#))
- Bug in `quantile` with datetime values ([GH6965](#))
- Bug in `Dataframe.set_index`, `reindex` and `pivot` don't preserve `DatetimeIndex` and `PeriodIndex` attributes ([GH3950](#), [GH5878](#), [GH6631](#))
- Bug in `MultiIndex.get_level_values` doesn't preserve `DatetimeIndex` and `PeriodIndex` attributes ([GH7092](#))
- Bug in `Groupby` doesn't preserve `tz` ([GH3950](#))
- Bug in `PeriodIndex` partial string slicing ([GH6716](#))
- Bug in the HTML repr of a truncated Series or DataFrame not showing the class name with the `large_repr` set to 'info' ([GH7105](#))
- Bug in `DatetimeIndex` specifying `freq` raises `ValueError` when passed value is too short ([GH7098](#))
- Fixed a bug with the `info` repr not honoring the `display.max_info_columns` setting ([GH6939](#))
- Bug `PeriodIndex` string slicing with out of bounds values ([GH5407](#))
- Fixed a memory error in the hashtable implementation/factorizer on resizing of large tables ([GH7157](#))
- Bug in `isnull` when applied to 0-dimensional object arrays ([GH7176](#))
- Bug in `query/eval` where global constants were not looked up correctly ([GH7178](#))
- Bug in recognizing out-of-bounds positional list indexers with `iloc` and a multi-axis tuple indexer ([GH7189](#))
- Bug in `setitem` with a single value, multi-index and integer indices ([GH7190](#), [GH7218](#))
- Bug in expressions evaluation with reversed ops, showing in series-dataframe ops ([GH7198](#), [GH7192](#))
- Bug in multi-axis indexing with `> 2` ndim and a multi-index ([GH7199](#))

- Fix a bug where invalid eval/query operations would blow the stack ([GH5198](#))

1.8 v0.13.1 (February 3, 2014)

This is a minor release from 0.13.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes. We recommend that all users upgrade to this version.

Highlights include:

- Added `infer_datetime_format` keyword to `read_csv/to_datetime` to allow speedups for homogeneously formatted datetimes.
- Will intelligently limit display precision for datetime/timedelta formats.
- Enhanced Panel `apply()` method.
- Suggested tutorials in new *Tutorials* section.
- Our pandas ecosystem is growing, We now feature related projects in a new *Pandas Ecosystem* section.
- Much work has been taking place on improving the docs, and a new *Contributing* section has been added.
- Even though it may only be of interest to devs, we <3 our new CI status page: [ScatterCI](#).

Warning: 0.13.1 fixes a bug that was caused by a combination of having numpy < 1.8, and doing chained assignment on a string-like array. Please review [the docs](#), chained indexing can have unexpected results and should generally be avoided.

This would previously segfault:

```
In [1]: df = DataFrame(dict(A = np.array(['foo', 'bar', 'bah', 'foo', 'bar'])))
```

```
In [2]: df['A'].iloc[0] = np.nan
```

```
In [3]: df
```

```
Out[3]:
```

```
      A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

The recommended way to do this type of assignment is:

```
In [4]: df = DataFrame(dict(A = np.array(['foo', 'bar', 'bah', 'foo', 'bar'])))
```

```
In [5]: df.ix[0, 'A'] = np.nan
```

```
In [6]: df
```

```
Out[6]:
```

```
      A
0  NaN
1  bar
2  bah
3  foo
4  bar
```

1.8.1 Output Formatting Enhancements

- `df.info()` view now display dtype info per column (GH5682)
- `df.info()` now honors the option `max_info_rows`, to disable null counts for large frames (GH5974)

```
In [7]: max_info_rows = pd.get_option('max_info_rows')

In [8]: df = DataFrame(dict(A = np.random.randn(10),
...:                        B = np.random.randn(10),
...:                        C = date_range('20130101', periods=10)))
...:

In [9]: df.iloc[3:6, [0, 2]] = np.nan

# set to not display the null counts
In [10]: pd.set_option('max_info_rows', 0)

In [11]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 3 columns):
A      float64
B      float64
C      datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 320.0 bytes

# this is the default (same as in 0.13.0)
In [12]: pd.set_option('max_info_rows', max_info_rows)

In [13]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 3 columns):
A      7 non-null float64
B      10 non-null float64
C      7 non-null datetime64[ns]
dtypes: datetime64[ns](1), float64(2)
memory usage: 320.0 bytes
```

- Add `show_dimensions` display option for the new `DataFrame` repr to control whether the dimensions print.

```
In [14]: df = DataFrame([[1, 2], [3, 4]])

In [15]: pd.set_option('show_dimensions', False)

In [16]: df
Out[16]:
   0  1
0  1  2
1  3  4

In [17]: pd.set_option('show_dimensions', True)

In [18]: df
Out[18]:
   0  1
0  1  2
```

```
1 3 4
```

```
[2 rows x 2 columns]
```

- The `ArrayFormatter` for `datetime` and `timedelta64` now intelligently limit precision based on the values in the array ([GH3401](#))

Previously output might look like:

```
   age                today                diff
0 2001-01-01 00:00:00 2013-04-19 00:00:00 4491 days, 00:00:00
1 2004-06-01 00:00:00 2013-04-19 00:00:00 3244 days, 00:00:00
```

Now the output looks like:

```
In [19]: df = DataFrame([ Timestamp('20010101'),
.....:                  Timestamp('20040601') ], columns=['age'])
.....:
```

```
In [20]: df['today'] = Timestamp('20130419')
```

```
In [21]: df['diff'] = df['today']-df['age']
```

```
In [22]: df
```

```
Out[22]:
```

	age	today	diff
0	2001-01-01	2013-04-19	4491 days
1	2004-06-01	2013-04-19	3244 days

```
[2 rows x 3 columns]
```

1.8.2 API changes

- Add `-NaN` and `-nan` to the default set of NA values ([GH5952](#)). See *NA Values*.
- Added `Series.str.get_dummies` vectorized string method ([GH6021](#)), to extract dummy/indicator variables for separated string columns:

```
In [23]: s = Series(['a', 'a|b', np.nan, 'a|c'])
```

```
In [24]: s.str.get_dummies(sep='|')
```

```
Out[24]:
```

	a	b	c
0	1	0	0
1	1	1	0
2	0	0	0
3	1	0	1

```
[4 rows x 3 columns]
```

- Added the `NDFrame.equals()` method to compare if two `NDFrames` are equal have equal axes, dtypes, and values. Added the `array_equivalent` function to compare if two `ndarrays` are equal. NaNs in identical locations are treated as equal. ([GH5283](#)) See also *the docs* for a motivating example.

```
In [25]: df = DataFrame({'col':['foo', 0, np.nan]})
```

```
In [26]: df2 = DataFrame({'col':[np.nan, 0, 'foo']}, index=[2,1,0])
```

```

In [27]: df.equals(df2)
Out[27]: False

In [28]: df.equals(df2.sort())
Out[28]: True

In [29]: import pandas.core.common as com

In [30]: com.array_equivalent(np.array([0, np.nan]), np.array([0, np.nan]))
Out[30]: True

In [31]: np.array_equal(np.array([0, np.nan]), np.array([0, np.nan]))
Out[31]: False

```

- `DataFrame.apply` will use the `reduce` argument to determine whether a `Series` or a `DataFrame` should be returned when the `DataFrame` is empty (GH6007).

Previously, calling `DataFrame.apply` on an empty `DataFrame` would return either a `DataFrame` if there were no columns, or the function being applied would be called with an empty `Series` to guess whether a `Series` or `DataFrame` should be returned:

```

In [32]: def applied_func(col):
....:     print("Apply function being called with: ", col)
....:     return col.sum()
....:

In [33]: empty = DataFrame(columns=['a', 'b'])

In [34]: empty.apply(applied_func)
('Apply function being called with: ', Series([], dtype: float64))
Out[34]:
a    NaN
b    NaN
dtype: float64

```

Now, when `apply` is called on an empty `DataFrame`: if the `reduce` argument is `True` a `Series` will be returned, if it is `False` a `DataFrame` will be returned, and if it is `None` (the default) the function being applied will be called with an empty `Series` to try and guess the return type.

```

In [35]: empty.apply(applied_func, reduce=True)
Out[35]:
a    NaN
b    NaN
dtype: float64

In [36]: empty.apply(applied_func, reduce=False)
Out[36]:
Empty DataFrame
Columns: [a, b]
Index: []

[0 rows x 2 columns]

```

1.8.3 Prior Version Deprecations/Changes

There are no announced changes in 0.13 or prior that are taking effect as of 0.13.1

1.8.4 Deprecations

There are no deprecations of prior behavior in 0.13.1

1.8.5 Enhancements

- `pd.read_csv` and `pd.to_datetime` learned a new `infer_datetime_format` keyword which greatly improves parsing perf in many cases. Thanks to @lexual for suggesting and @danbirken for rapidly implementing. (GH5490, GH6021)

If `parse_dates` is enabled and this flag is set, pandas will attempt to infer the format of the datetime strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by ~5-10x.

```
# Try to infer the format for the index column
df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
                 infer_datetime_format=True)
```

- `date_format` and `datetime_format` keywords can now be specified when writing to excel files (GH4133)
- `MultiIndex.from_product` convenience function for creating a MultiIndex from the cartesian product of a set of iterables (GH6055):

```
In [37]: shades = ['light', 'dark']
```

```
In [38]: colors = ['red', 'green', 'blue']
```

```
In [39]: MultiIndex.from_product([shades, colors], names=['shade', 'color'])
```

```
Out[39]:
```

```
MultiIndex(levels=[[u'dark', u'light'], [u'blue', u'green', u'red']],
            labels=[[1, 1, 1, 0, 0, 0], [2, 1, 0, 2, 1, 0]],
            names=[u'shade', u'color'])
```

- Panel `apply()` will work on non-ufuncs. See *the docs*.

```
In [40]: import pandas.util.testing as tm
```

```
In [41]: panel = tm.makePanel(5)
```

```
In [42]: panel
```

```
Out[42]:
```

```
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D
```

```
In [43]: panel['ItemA']
```

```
Out[43]:
```

	A	B	C	D
2000-01-03	0.952478	-1.239072	-1.409432	-0.014752
2000-01-04	0.988138	0.139683	1.422986	1.272395
2000-01-05	-0.072608	-0.223019	-2.147855	-1.449567
2000-01-06	-0.550603	2.123692	-1.347533	-1.195524
2000-01-07	-0.938153	0.122273	0.363565	-0.591863

```
[5 rows x 4 columns]
```

Specifying an apply that operates on a Series (to return a single element)

```
In [44]: panel.apply(lambda x: x.dtype, axis='items')
Out[44]:
```

	A	B	C	D
2000-01-03	float64	float64	float64	float64
2000-01-04	float64	float64	float64	float64
2000-01-05	float64	float64	float64	float64
2000-01-06	float64	float64	float64	float64
2000-01-07	float64	float64	float64	float64

[5 rows x 4 columns]

A similar reduction type operation

```
In [45]: panel.apply(lambda x: x.sum(), axis='major_axis')
Out[45]:
```

	ItemA	ItemB	ItemC
A	0.379252	-3.696907	3.709335
B	0.923558	0.504242	4.656781
C	-3.118269	-1.545718	3.188329
D	-1.979310	-0.758060	-1.436483

[4 rows x 3 columns]

This is equivalent to

```
In [46]: panel.sum('major_axis')
Out[46]:
```

	ItemA	ItemB	ItemC
A	0.379252	-3.696907	3.709335
B	0.923558	0.504242	4.656781
C	-3.118269	-1.545718	3.188329
D	-1.979310	-0.758060	-1.436483

[4 rows x 3 columns]

A transformation operation that returns a Panel, but is computing the z-score across the major_axis

```
In [47]: result = panel.apply(
.....:     lambda x: (x-x.mean())/x.std(),
.....:     axis='major_axis')
.....:
```

```
In [48]: result
```

```
Out[48]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D
```

```
In [49]: result['ItemA']
```

```
Out[49]:
```

	A	B	C	D
2000-01-03	1.004994	-1.166509	-0.535027	0.350970
2000-01-04	1.045875	-0.036892	1.393532	1.536326
2000-01-05	-0.170198	-0.334055	-1.037810	-0.970374
2000-01-06	-0.718186	1.588611	-0.492880	-0.736422
2000-01-07	-1.162486	-0.051156	0.672185	-0.180500

```
[5 rows x 4 columns]
```

- Panel `apply()` operating on cross-sectional slabs. (GH1148)

```
In [50]: f = lambda x: ((x.T-x.mean(1))/x.std(1)).T
```

```
In [51]: result = panel.apply(f, axis = ['items', 'major_axis'])
```

```
In [52]: result
```

```
Out[52]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC
```

```
In [53]: result.loc[:, :, 'ItemA']
```

```
Out[53]:
```

	A	B	C	D
2000-01-03	0.116579	-0.667845	-1.151538	-0.157547
2000-01-04	0.650448	-1.114910	0.841527	0.760706
2000-01-05	-0.987433	-0.438897	-1.154468	-0.015033
2000-01-06	0.494000	1.060450	-0.775993	-1.140165
2000-01-07	-0.363770	0.013169	0.392036	-1.123913

```
[5 rows x 4 columns]
```

This is equivalent to the following

```
In [54]: result = Panel(dict([ (ax,f(panel.loc[:, :, ax]))
.....:                        for ax in panel.minor_axis ]))
.....:
```

```
In [55]: result
```

```
Out[55]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC
```

```
In [56]: result.loc[:, :, 'ItemA']
```

```
Out[56]:
```

	A	B	C	D
2000-01-03	0.116579	-0.667845	-1.151538	-0.157547
2000-01-04	0.650448	-1.114910	0.841527	0.760706
2000-01-05	-0.987433	-0.438897	-1.154468	-0.015033
2000-01-06	0.494000	1.060450	-0.775993	-1.140165
2000-01-07	-0.363770	0.013169	0.392036	-1.123913

```
[5 rows x 4 columns]
```

1.8.6 Performance

Performance improvements for 0.13.1

- Series `datetime/timedelta` binary operations (GH5801)

- `DataFrame.count/dropna` for `axis=1`
- `Series.str.contains` now has a `regex=False` keyword which can be faster for plain (non-regex) string patterns. ([GH5879](#))
- `Series.str.extract` ([GH5944](#))
- `dtypes/ftypes` methods ([GH5968](#))
- indexing with object dtypes ([GH5968](#))
- `DataFrame.apply` ([GH6013](#))
- Regression in JSON IO ([GH5765](#))
- Index construction from Series ([GH6150](#))

1.8.7 Experimental

There are no experimental changes in 0.13.1

1.8.8 Bug Fixes

See [V0.13.1 Bug Fixes](#) for an extensive list of bugs that have been fixed in 0.13.1.

See the [full release notes](#) or issue tracker on GitHub for a complete list of all API changes, Enhancements and Bug Fixes.

1.9 v0.13.0 (January 3, 2014)

This is a major release from 0.12.0 and includes a number of API changes, several new features and enhancements along with a large number of bug fixes.

Highlights include:

- support for a new index type `Float64Index`, and other Indexing enhancements
- `HDFStore` has a new string based syntax for query specification
- support for new methods of interpolation
- updated `timedelta` operations
- a new string manipulation method `extract`
- Nanosecond support for Offsets
- `isin` for DataFrames

Several experimental features are added, including:

- new `eval/query` methods for expression evaluation
- support for `msgpack` serialization
- an i/o interface to Google's `BigQuery`

There are several new or updated docs sections including:

- [Comparison with SQL](#), which should be useful for those familiar with SQL but still learning pandas.
- [Comparison with R](#), idiom translations from R to pandas.

- *Enhancing Performance*, ways to enhance pandas performance with `eval/query`.

Warning: In 0.13.0 `Series` has internally been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, similar to the rest of the pandas containers. This should be a transparent change with only very limited API implications. See [Internal Refactoring](#)

1.9.1 API changes

- `read_excel` now supports an integer in its `sheetname` argument giving the index of the sheet to read in (GH4301).
- Text parser now treats anything that reads like `inf` (“inf”, “Inf”, “-Inf”, “iNf”, etc.) as infinity. (GH4220, GH4219), affecting `read_table`, `read_csv`, etc.
- pandas now is Python 2/3 compatible without the need for `2to3` thanks to @jtratrner. As a result, pandas now uses iterators more extensively. This also led to the introduction of substantive parts of the Benjamin Peterson’s `six` library into `compat`. (GH4384, GH4375, GH4372)
- `pandas.util.compat` and `pandas.util.py3compat` have been merged into `pandas.compat`. `pandas.compat` now includes many functions allowing 2/3 compatibility. It contains both list and iterator versions of `range`, `filter`, `map` and `zip`, plus other necessary elements for Python 3 compatibility. `lmap`, `lzip`, `lrange` and `lfilter` all produce lists instead of iterators, for compatibility with `numpy`, subscripting and pandas constructors. (GH4384, GH4375, GH4372)
- `Series.get` with negative indexers now returns the same as `[]` (GH4390)
- Changes to how `Index` and `MultiIndex` handle metadata (`levels`, `labels`, and `names`) (GH4039):

```
# previously, you would have set levels or labels directly
index.levels = [[1, 2, 3, 4], [1, 2, 4, 4]]
```

```
# now, you use the set_levels or set_labels methods
index = index.set_levels([[1, 2, 3, 4], [1, 2, 4, 4]])
```

```
# similarly, for names, you can rename the object
# but setting names is not deprecated
index = index.set_names(["bob", "cranberry"])
```

```
# and all methods take an inplace kwarg - but return None
index.set_names(["bob", "cranberry"], inplace=True)
```

- All division with `NDFrame` objects is now *truedivision*, regardless of the future import. This means that operating on pandas objects will by default use *floating point* division, and return a floating point dtype. You can use `//` and `floordiv` to do integer division.

Integer division

```
In [3]: arr = np.array([1, 2, 3, 4])

In [4]: arr2 = np.array([5, 3, 2, 1])

In [5]: arr / arr2
Out[5]: array([0, 0, 1, 4])

In [6]: Series(arr) // Series(arr2)
Out[6]:
0    0
1    0
```

```
2    1
3    4
dtype: int64
```

True Division

```
In [7]: pd.Series(arr) / pd.Series(arr2) # no future import required
Out[7]:
0    0.200000
1    0.666667
2    1.500000
3    4.000000
dtype: float64
```

- Infer and downcast dtype if `downcast='infer'` is passed to `fillna/ffill/bfill` (GH4604)
- `__nonzero__` for all NDFrame objects, will now raise a `ValueError`, this reverts back to (GH1073, GH4633) behavior. See *gotchas* for a more detailed discussion.

This prevents doing boolean comparison on *entire* pandas objects, which is inherently ambiguous. These all will raise a `ValueError`.

```
if df:
    ....
df1 and df2
s1 and s2
```

Added the `.bool()` method to NDFrame objects to facilitate evaluating of single-element boolean Series:

```
In [1]: Series([True]).bool()
Out[1]: True

In [2]: Series([False]).bool()
Out[2]: False

In [3]: DataFrame([[True]]).bool()
Out[3]: True

In [4]: DataFrame([[False]]).bool()
Out[4]: False
```

- All non-Index NDFrames (Series, DataFrame, Panel, Panel4D, SparsePanel, etc.), now support the entire set of arithmetic operators and arithmetic flex methods (add, sub, mul, etc.). `SparsePanel` does not support `pow` or `mod` with non-scalars. (GH3765)
- `Series` and `DataFrame` now have a `mode()` method to calculate the statistical mode(s) by axis/Series. (GH5367)
- Chained assignment will now by default warn if the user is assigning to a copy. This can be changed with the option `mode.chained_assignment`, allowed options are `raise/warn/None`. See *the docs*.

```
In [5]: dfc = DataFrame({'A': ['aaa', 'bbb', 'ccc'], 'B': [1, 2, 3]})

In [6]: pd.set_option('chained_assignment', 'warn')
```

The following warning / exception will show if this is attempted.

```
In [7]: dfc.loc[0]['A'] = 1111
```

```
Traceback (most recent call last)
```

```
...
```

```
SettingWithCopyWarning:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_index,col_indexer] = value instead
```

Here is the correct method of assignment.

```
In [8]: dfc.loc[0, 'A'] = 11
```

```
In [9]: dfc
```

```
Out[9]:
```

```
      A  B
0    11  1
1   bbb  2
2   ccc  3
```

```
[3 rows x 2 columns]
```

- **Panel.reindex** has the following call signature **Panel.reindex(items=None, major_axis=None, minor_axis=None)** to conform with other NDFrame objects. See *Internal Refactoring* for more information.
- **Series.argmax** and **Series.argmin** are now aliased to **Series.idxmax** and **Series.idxmin**. These return the index of the min or max element respectively. Prior to 0.13.0 these would return the position of the min / max element. (GH6214)

1.9.2 Prior Version Deprecations/Changes

These were announced changes in 0.12 or prior that are taking effect as of 0.13.0

- Remove deprecated **Factor** (GH3650)
- Remove deprecated **set_printoptions/reset_printoptions** (GH3046)
- Remove deprecated **_verbose_info** (GH3215)
- Remove deprecated **read_clipboard/to_clipboard/ExcelFile/ExcelWriter** from **pandas.io.parsers** (GH3717) These are available as functions in the main pandas namespace (e.g. **pd.read_clipboard**)
- default for **tupleize_cols** is now **False** for both **to_csv** and **read_csv**. Fair warning in 0.12 (GH3604)
- default for **display.max_seq_len** is now 100 rather than **None**. This activates truncated display ("...") of long sequences in various places. (GH3391)

1.9.3 Deprecations

Deprecated in 0.13.0

- deprecated **iterkv**, which will be removed in a future release (this was an alias of **iteritems** used to bypass 2to3's changes). (GH4384, GH4375, GH4372)
- deprecated the string method **match**, whose role is now performed more idiomatically by **extract**. In a future release, the default behavior of **match** will change to become analogous to **contains**, which returns a boolean indexer. (Their distinction is strictness: **match** relies on **re.match** while **contains** relies on **re.search**.) In this release, the deprecated behavior is the default, but the new behavior is available through the keyword argument **as_indexer=True**.

1.9.4 Indexing API Changes

Prior to 0.13, it was impossible to use a label indexer (`.loc/.ix`) to set a value that was not contained in the index of a particular axis. ([GH2578](#)). See *the docs*

In the `Series` case this is effectively an appending operation

```
In [10]: s = Series([1,2,3])
```

```
In [11]: s
```

```
Out[11]:
0    1
1    2
2    3
dtype: int64
```

```
In [12]: s[5] = 5.
```

```
In [13]: s
```

```
Out[13]:
0    1
1    2
2    3
5    5
dtype: float64
```

```
In [14]: dfi = DataFrame(np.arange(6).reshape(3,2),
.....:                  columns=['A', 'B'])
.....:
```

```
In [15]: dfi
```

```
Out[15]:
   A  B
0  0  1
1  2  3
2  4  5
```

```
[3 rows x 2 columns]
```

This would previously `KeyError`

```
In [16]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']
```

```
In [17]: dfi
```

```
Out[17]:
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
```

```
[3 rows x 3 columns]
```

This is like an `append` operation.

```
In [18]: dfi.loc[3] = 5
```

```
In [19]: dfi
```

```
Out[19]:
   A  B  C
0  0  1  0
```

```
1  2  3  2
2  4  5  4
3  5  5  5
```

```
[4 rows x 3 columns]
```

A Panel setting operation on an arbitrary axis aligns the input to the Panel

```
In [20]: p = pd.Panel(np.arange(16).reshape(2,4,2),
.....:               items=['Item1', 'Item2'],
.....:               major_axis=pd.date_range('2001/1/12', periods=4),
.....:               minor_axis=['A', 'B'], dtype='float64')
.....:
```

```
In [21]: p
Out[21]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to B
```

```
In [22]: p.loc[:, :, 'C'] = Series([30, 32], index=p.items)
```

```
In [23]: p
Out[23]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2001-01-12 00:00:00 to 2001-01-15 00:00:00
Minor_axis axis: A to C
```

```
In [24]: p.loc[:, :, 'C']
Out[24]:
```

	Item1	Item2
2001-01-12	30	32
2001-01-13	30	32
2001-01-14	30	32
2001-01-15	30	32

```
[4 rows x 2 columns]
```

1.9.5 Float64Index API Change

- Added a new index type, `Float64Index`. This will be automatically created when passing floating values in index creation. This enables a pure label-based slicing paradigm that makes `[]`, `ix`, `loc` for scalar indexing and slicing work exactly the same. See [the docs](#), (GH263)

Construction is by default for floating type values.

```
In [25]: index = Index([1.5, 2, 3, 4.5, 5])
```

```
In [26]: index
Out[26]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')
```

```
In [27]: s = Series(range(5), index=index)
```

```
In [28]: s
Out[28]:
1.5    0
2.0    1
3.0    2
4.5    3
5.0    4
dtype: int64
```

Scalar selection for `[]`, `.ix`, `.loc` will always be label based. An integer will match an equal float index (e.g. 3 is equivalent to 3.0)

```
In [29]: s[3]
Out[29]: 2
```

```
In [30]: s.ix[3]
Out[30]: 2
```

```
In [31]: s.loc[3]
Out[31]: 2
```

The only positional indexing is via `iloc`

```
In [32]: s.iloc[3]
Out[32]: 3
```

A scalar index that is not found will raise `KeyError`

Slicing is ALWAYS on the values of the index, for `[]`, `ix`, `loc` and ALWAYS positional with `iloc`

```
In [33]: s[2:4]
Out[33]:
2    1
3    2
dtype: int64
```

```
In [34]: s.ix[2:4]
Out[34]:
2    1
3    2
dtype: int64
```

```
In [35]: s.loc[2:4]
Out[35]:
2    1
3    2
dtype: int64
```

```
In [36]: s.iloc[2:4]
Out[36]:
3.0    2
4.5    3
dtype: int64
```

In float indexes, slicing using floats are allowed

```
In [37]: s[2.1:4.6]
Out[37]:
3.0    2
4.5    3
```

```
dtype: int64
```

```
In [38]: s.loc[2.1:4.6]
Out[38]:
3.0    2
4.5    3
dtype: int64
```

- Indexing on other index types are preserved (and positional fallback for `[]`, `ix`), with the exception, that floating point slicing on indexes on non `Float64Index` will now raise a `TypeError`.

```
In [1]: Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type (Int64Index)

In [1]: Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type (Int64Index)
```

Using a scalar float indexer will be deprecated in a future version, but is allowed for now.

```
In [3]: Series(range(5))[3.0]
Out[3]: 3
```

1.9.6 HDFStore API Changes

- Query Format Changes. A much more string-like query format is now supported. See [the docs](#).

```
In [39]: path = 'test.h5'

In [40]: dfq = DataFrame(randn(10,4),
.....:                  columns=list('ABCD'),
.....:                  index=date_range('20130101', periods=10))
.....:

In [41]: dfq.to_hdf(path, 'dfq', format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```
In [42]: read_hdf(path, 'dfq',
.....:             where="index>Timestamp('20130104') & columns=['A', 'B']")
.....:
Out[42]:
           A         B
2013-01-05 -1.392054  1.153922
2013-01-06 -0.881047  0.295080
2013-01-07 -1.407085  0.126781
2013-01-08 -0.838843  0.553921
2013-01-09  1.529401  0.205455
2013-01-10  0.299071  1.076541

[6 rows x 2 columns]
```

Use an inline column reference

```
In [43]: read_hdf(path, 'dfq',
.....:             where="A>0 or C>0")
.....:
Out[43]:
           A         B         C         D
```

```

2013-01-01  1.126386  0.247112  0.121172  0.298984
2013-01-03  0.581073  2.763844  0.399325  0.668488
2013-01-04 -0.275774  0.500483  0.863065 -1.051628
2013-01-05 -1.392054  1.153922  1.181944  0.391371
2013-01-06 -0.881047  0.295080  1.863801 -1.712274
2013-01-07 -1.407085  0.126781  0.003760 -1.268994
2013-01-09  1.529401  0.205455  0.313013  0.866521
2013-01-10  0.299071  1.076541  0.363177  1.893680

```

```
[8 rows x 4 columns]
```

- the `format` keyword now replaces the `table` keyword; allowed values are `fixed(f)` or `table(t)` the same defaults as prior < 0.13.0 remain, e.g. `put` implies `fixed` format and `append` implies `table` format. This default format can be set as an option by setting `io.hdf.default_format`.

```
In [44]: path = 'test.h5'
```

```
In [45]: df = DataFrame(randn(10,2), columns=['a','b'])
```

```
In [46]: df.to_hdf(path, 'df_table', format='table')
```

```
In [47]: df.to_hdf(path, 'df_table2', append=True)
```

```
In [48]: df.to_hdf(path, 'df_fixed')
```

```
In [49]: with get_store(path) as store:
```

```
.....:     print(store)
```

```
.....:
```

```
<class 'pandas.io.pytables.HDFStore'>
```

```
File path: test.h5
```

```
/df_fixed          frame          (shape->[10,2])
```

```
/df_table          frame_table    (typ->appendable,nrows->10,ncols->2,indexers->[index])
```

```
/df_table2         frame_table    (typ->appendable,nrows->10,ncols->2,indexers->[index])
```

- Significant table writing performance improvements
- handle a passed Series in table format ([GH4330](#))
- can now serialize a `timedelta64[ns]` dtype in a table ([GH3577](#)), See *the docs*.
- added an `is_open` property to indicate if the underlying file handle is open; a closed store will now report 'CLOSED' when viewing the store (rather than raising an error) ([GH4409](#))
- a close of a `HDFStore` now will close that instance of the `HDFStore` but will only close the actual file if the ref count (by PyTables) w.r.t. all of the open handles are 0. Essentially you have a local instance of `HDFStore` referenced by a variable. Once you close it, it will report closed. Other references (to the same file) will continue to operate until they themselves are closed. Performing an action on a closed file will raise `ClosedFileError`

```
In [50]: path = 'test.h5'
```

```
In [51]: df = DataFrame(randn(10,2))
```

```
In [52]: store1 = HDFStore(path)
```

```
In [53]: store2 = HDFStore(path)
```

```
In [54]: store1.append('df',df)
```

```
In [55]: store2.append('df2',df)
```

```
In [56]: store1
Out[56]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
/df          frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])

In [57]: store2
Out[57]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
/df          frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])
/df2         frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])

In [58]: store1.close()

In [59]: store2
Out[59]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
/df          frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])
/df2         frame_table  (typ->appendable,nrows->10,ncols->2,indexers->[index])

In [60]: store2.close()

In [61]: store2
Out[61]:
<class 'pandas.io.pytables.HDFStore'>
File path: test.h5
File is CLOSED
```

- removed the `_quiet` attribute, replace by a `DuplicateWarning` if retrieving duplicate rows from a table ([GH4367](#))
- removed the `warn` argument from `open`. Instead a `PossibleDataLossError` exception will be raised if you try to use `mode='w'` with an `OPEN` file handle ([GH4367](#))
- allow a passed locations array or mask as a `where` condition ([GH4467](#)). See *the docs* for an example.
- add the keyword `dropna=True` to `append` to change whether ALL nan rows are not written to the store (default is `True`, ALL nan rows are NOT written), also settable via the option `io.hdf.dropna_table` ([GH4625](#))
- pass thru store creation arguments; can be used to support in-memory stores

1.9.7 DataFrame repr Changes

The HTML and plain text representations of `DataFrame` now show a truncated view of the table once it exceeds a certain size, rather than switching to the short info view ([GH4886](#), [GH5550](#)). This makes the representation more consistent as small `DataFrames` get larger.

2010-03-29	13.70	13.88	13.39	13.57	158225000	12.98
2010-03-30	13.55	13.64	13.18	13.28	142055200	12.70
	...	...	...	...	...	...

771 rows × 6 columns

To get the info view, call `DataFrame.info()`. If you prefer the info view as the repr for large DataFrames, you can set this by running `set_option('display.large_repr', 'info')`.

1.9.8 Enhancements

- `df.to_clipboard()` learned a new `excel` keyword that let's you paste df data directly into excel (enabled by default). (GH5070).
- `read_html` now raises a `URLError` instead of catching and raising a `ValueError` (GH4303, GH4305)
- Added a test for `read_clipboard()` and `to_clipboard()` (GH4282)
- Clipboard functionality now works with PySide (GH4282)
- Added a more informative error message when plot arguments contain overlapping color and style arguments (GH4402)
- `to_dict` now takes records as a possible outtype. Returns an array of column-keyed dictionaries. (GH4936)
- NaN handling in `get_dummies` (GH4446) with `dummy_na`

```
# previously, nan was erroneously counted as 2 here
# now it is not counted at all
```

```
In [62]: get_dummies([1, 2, np.nan])
```

```
Out[62]:
```

```
   1  2
0  1  0
1  0  1
2  0  0
```

```
[3 rows x 2 columns]
```

```
# unless requested
```

```
In [63]: get_dummies([1, 2, np.nan], dummy_na=True)
```

```
Out[63]:
```

```
   1  2  NaN
0  1  0   0
1  0  1   0
2  0  0   1
```

```
[3 rows x 3 columns]
```

- `timedelta64[ns]` operations. See [the docs](#).

Warning: Most of these operations require `numpy >= 1.7`

Using the new top-level `to_timedelta`, you can convert a scalar or array from the standard `timedelta` format (produced by `to_csv`) into a `timedelta` type (`np.timedelta64` in nanoseconds).

```
In [64]: to_timedelta('1 days 06:05:01.00003')
```

```
Out[64]: Timedelta('1 days 06:05:01.000030')
```

```
In [65]: to_timedelta('15.5us')
```

```
Out[65]: Timedelta('0 days 00:00:00.000015')
```

```
In [66]: to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
```

```
Out[66]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], dtype='timedelta64[ns]', freq=None)
```

```
In [67]: to_timedelta(np.arange(5), unit='s')
```

```
Out[67]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'], dtype='timedelta64[ns]', freq=None)
```

```
In [68]: to_timedelta(np.arange(5), unit='d')
```

```
Out[68]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype='timedelta64[ns]', freq=None)
```

A Series of dtype `timedelta64[ns]` can now be divided by another `timedelta64[ns]` object, or astyped to yield a `float64` dtype Series. This is frequency conversion. See [the docs](#) for the docs.

```
In [69]: from datetime import timedelta
```

```
In [70]: td = Series(date_range('20130101', periods=4)) - Series(date_range('20121201', periods=4))
```

```
In [71]: td[2] += np.timedelta64(timedelta(minutes=5, seconds=3))
```

```
In [72]: td[3] = np.nan
```

```
In [73]: td
```

```
Out[73]:
```

```
0    31 days 00:00:00
```

```
1    31 days 00:00:00
```

```
2    31 days 00:05:03
```

```
3                NaT
```

```
dtype: timedelta64[ns]
```

```
# to days
```

```
In [74]: td / np.timedelta64(1, 'D')
```

```
Out[74]:
```

```
0    31.000000
```

```
1    31.000000
```

```
2    31.003507
```

```
3         NaN
```

```
dtype: float64
```

```
In [75]: td.astype('timedelta64[D]')
```

```
Out[75]:
```

```
0     31
```

```
1     31
```

```
2     31
```

```
3    NaN
```

```
dtype: float64
```

```
# to seconds
```

```
In [76]: td / np.timedelta64(1, 's')
```

```
Out[76]:
```

```
0    2678400
```

```
1    2678400
```

```
2    2678703
3         NaN
dtype: float64
```

```
In [77]: td.astype('timedelta64[s]')
```

```
Out[77]:
0    2678400
1    2678400
2    2678703
3         NaN
dtype: float64
```

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series

```
In [78]: td * -1
```

```
Out[78]:
0   -31 days +00:00:00
1   -31 days +00:00:00
2   -32 days +23:54:57
3                NaT
dtype: timedelta64[ns]
```

```
In [79]: td * Series([1,2,3,4])
```

```
Out[79]:
0   31 days 00:00:00
1   62 days 00:00:00
2   93 days 00:15:09
3                NaT
dtype: timedelta64[ns]
```

Absolute `DateOffset` objects can act equivalently to `timedeltas`

```
In [80]: from pandas import offsets
```

```
In [81]: td + offsets.Minute(5) + offsets.Milli(5)
```

```
Out[81]:
0   31 days 00:05:00.005000
1   31 days 00:05:00.005000
2   31 days 00:10:03.005000
3                NaT
dtype: timedelta64[ns]
```

`Fillna` is now supported for `timedeltas`

```
In [82]: td.fillna(0)
```

```
Out[82]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3    0 days 00:00:00
dtype: timedelta64[ns]
```

```
In [83]: td.fillna(timedelta(days=1,seconds=5))
```

```
Out[83]:
0   31 days 00:00:00
1   31 days 00:00:00
2   31 days 00:05:03
3    1 days 00:00:05
dtype: timedelta64[ns]
```

You can do numeric reduction operations on timedeltas.

```
In [84]: td.mean()
Out[84]: Timedelta('31 days 00:01:41')
```

```
In [85]: td.quantile(.1)
Out[85]: Timedelta('31 days 00:00:00')
```

- `plot(kind='kde')` now accepts the optional parameters `bw_method` and `ind`, passed to `scipy.stats.gaussian_kde()` (for `scipy >= 0.11.0`) to set the bandwidth, and to `gkde.evaluate()` to specify the indices at which it is evaluated, respectively. See `scipy` docs. (GH4298)
- `DataFrame` constructor now accepts a `numpy` masked record array (GH3478)
- The new vectorized string method `extract` return regular expression matches more conveniently.

```
In [86]: Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
Out[86]:
0      1
1      2
2     NaN
dtype: object
```

Elements that do not match return `NaN`. Extracting a regular expression with more than one group returns a `DataFrame` with one column per group.

```
In [87]: Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
Out[87]:
      0      1
0     a      1
1     b      2
2    NaN    NaN

[3 rows x 2 columns]
```

Elements that do not match return a row of `NaN`. Thus, a `Series` of messy strings can be *converted* into a like-indexed `Series` or `DataFrame` of cleaned-up or more useful strings, without necessitating `get()` to access tuples or `re.match` objects.

Named groups like

```
In [88]: Series(['a1', 'b2', 'c3']).str.extract(
.....:         '(?P<letter>[ab])(?P<digit>\d)')
.....:
Out[88]:
  letter digit
0      a      1
1      b      2
2    NaN    NaN

[3 rows x 2 columns]
```

and optional groups can also be used.

```
In [89]: Series(['a1', 'b2', '3']).str.extract(
.....:         '(?P<letter>[ab])?(?P<digit>\d)')
.....:
Out[89]:
  letter digit
0      a      1
1      b      2
```

```
2      NaN      3

[3 rows x 2 columns]
```

- `read_stata` now accepts Stata 13 format ([GH4291](#))
- `read_fwf` now infers the column specifications from the first 100 rows of the file if the data has correctly separated and properly aligned columns using the delimiter provided to the function ([GH4488](#)).
- support for nanosecond times as an offset

Warning: These operations require `numpy >= 1.7`

Period conversions in the range of seconds and below were reworked and extended up to nanoseconds. Periods in the nanosecond range are now available.

```
In [90]: date_range('2013-01-01', periods=5, freq='5N')
Out[90]:
DatetimeIndex(['2013-01-01', '2013-01-01', '2013-01-01', '2013-01-01',
                '2013-01-01'],
              dtype='datetime64[ns]', freq='5N', tz=None)
```

or with frequency as offset

```
In [91]: date_range('2013-01-01', periods=5, freq=pd.offsets.Nano(5))
Out[91]:
DatetimeIndex(['2013-01-01', '2013-01-01', '2013-01-01', '2013-01-01',
                '2013-01-01'],
              dtype='datetime64[ns]', freq='5N', tz=None)
```

Timestamps can be modified in the nanosecond range

```
In [92]: t = Timestamp('20130101 09:01:02')

In [93]: t + pd.datetools.Nano(123)
Out[93]: Timestamp('2013-01-01 09:01:02.000000123')
```

- A new method, `isin` for DataFrames, which plays nicely with boolean indexing. The argument to `isin`, what we're comparing the DataFrame to, can be a DataFrame, Series, dict, or array of values. See [the docs](#) for more.

To get the rows where any of the conditions are met:

```
In [94]: dfi = DataFrame({'A': [1, 2, 3, 4], 'B': ['a', 'b', 'f', 'n']})

In [95]: dfi
Out[95]:
   A  B
0  1  a
1  2  b
2  3  f
3  4  n

[4 rows x 2 columns]

In [96]: other = DataFrame({'A': [1, 3, 3, 7], 'B': ['e', 'f', 'f', 'e']})

In [97]: mask = dfi.isin(other)

In [98]: mask
```

```
Out[98]:
      A      B
0  True  False
1  False False
2   True   True
3  False  False

[4 rows x 2 columns]

In [99]: dfi[mask.any(1)]
Out[99]:
      A  B
0    1  a
2    3  f

[2 rows x 2 columns]
```

- Series now supports a `to_frame` method to convert it to a single-column DataFrame (GH5164)
- All R datasets listed here <http://stat.ethz.ch/R-manual/R-devel/library/datasets/html/00Index.html> can now be loaded into Pandas objects

```
# note that pandas.rpy was deprecated in v0.16.0
import pandas.rpy.common as com
com.load_data('Titanic')
```

- `tz_localize` can infer a fall daylight savings transition based on the structure of the unlocalized data (GH4230), see *the docs*
- `DatetimeIndex` is now in the API documentation, see *the docs*
- `json_normalize()` is a new method to allow you to create a flat table from semi-structured JSON data. See *the docs* (GH1067)
- Added PySide support for the `qtpandas DataFrameModel` and `DataFrameWidget`.
- Python csv parser now supports `usecols` (GH4335)
- Frequencies gained several new offsets:
 - `LastWeekOfMonth` (GH4637)
 - `FY5253`, and `FY5253Quarter` (GH4511)
- `DataFrame` has a new `interpolate` method, similar to `Series` (GH4434, GH1892)

```
In [100]: df = DataFrame({'A': [1, 2.1, np.nan, 4.7, 5.6, 6.8],
.....:                  'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})
.....:

In [101]: df.interpolate()
Out[101]:
      A      B
0  1.0   0.25
1  2.1   1.50
2  3.4   2.75
3  4.7   4.00
4  5.6  12.20
5  6.8  14.40

[6 rows x 2 columns]
```

Additionally, the method argument to `interpolate` has been expanded to include `'nearest'`, `'zero'`, `'slinear'`, `'quadratic'`, `'cubic'`, `'barycentric'`, `'krogh'`, `'piecewise_polynomial'`, `'pchip'`, `'polynomial'`, `'spline'`. The new methods require `scipy`. Consult the [Scipy reference guide](#) and [documentation](#) for more information about when the various methods are appropriate. See [the docs](#).

`Interpolate` now also accepts a `limit` keyword argument. This works similar to `fillna`'s `limit`:

```
In [102]: ser = Series([1, 3, np.nan, np.nan, np.nan, 11])
```

```
In [103]: ser.interpolate(limit=2)
```

```
Out[103]:
0      1
1      3
2      5
3      7
4     NaN
5     11
dtype: float64
```

- Added `wide_to_long` panel data convenience function. See [the docs](#).

```
In [104]: np.random.seed(123)
```

```
In [105]: df = pd.DataFrame({"A1970" : {0 : "a", 1 : "b", 2 : "c"},
.....:                      "A1980" : {0 : "d", 1 : "e", 2 : "f"},
.....:                      "B1970" : {0 : 2.5, 1 : 1.2, 2 : .7},
.....:                      "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1},
.....:                      "X"      : dict(zip(range(3), np.random.randn(3)))
.....:                      })
```

```
In [106]: df["id"] = df.index
```

```
In [107]: df
```

```
Out[107]:
   A1970 A1980 B1970 B1980      X  id
0     a     d   2.5    3.2 -1.085631  0
1     b     e   1.2    1.3  0.997345  1
2     c     f   0.7    0.1  0.282978  2
```

```
[3 rows x 6 columns]
```

```
In [108]: wide_to_long(df, ["A", "B"], i="id", j="year")
```

```
Out[108]:
      X  A    B
id year
0  1970 -1.085631  a  2.5
1  1970  0.997345  b  1.2
2  1970  0.282978  c  0.7
0  1980 -1.085631  d  3.2
1  1980  0.997345  e  1.3
2  1980  0.282978  f  0.1
```

```
[6 rows x 3 columns]
```

- `to_csv` now takes a `date_format` keyword argument that specifies how output datetime objects should be formatted. Datetimes encountered in the index, columns, and values will all have this formatting applied. ([GH4313](#))

- `DataFrame.plot` will scatter plot `x` versus `y` by passing `kind='scatter'` (GH2215)
- Added support for Google Analytics v3 API segment IDs that also supports v2 IDs. (GH5271)

1.9.9 Experimental

- The new `eval()` function implements expression evaluation using `numexpr` behind the scenes. This results in large speedups for complicated expressions involving large `DataFrames`/`Series`. For example,

```
In [109]: nrows, ncols = 20000, 100

In [110]: df1, df2, df3, df4 = [DataFrame(randn(nrows, ncols))
.....:                             for _ in range(4)]
.....:

# eval with NumExpr backend
In [111]: %timeit pd.eval('df1 + df2 + df3 + df4')
100 loops, best of 3: 14.2 ms per loop

# pure Python evaluation
In [112]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 23.4 ms per loop
```

For more details, see the [the docs](#)

- Similar to `pandas.eval`, `DataFrame` has a new `DataFrame.eval` method that evaluates an expression in the context of the `DataFrame`. For example,

```
In [113]: df = DataFrame(randn(10, 2), columns=['a', 'b'])

In [114]: df.eval('a + b')
Out[114]:
0    -0.685204
1     1.589745
2     0.325441
3    -1.784153
4    -0.432893
5     0.171850
6     1.895919
7     3.065587
8    -0.092759
9     1.391365
dtype: float64
```

- `query()` method has been added that allows you to select elements of a `DataFrame` using a natural query syntax nearly identical to Python syntax. For example,

```
In [115]: n = 20

In [116]: df = DataFrame(np.random.randint(n, size=(n, 3)), columns=['a', 'b', 'c'])

In [117]: df.query('a < b < c')
Out[117]:
   a  b  c
11  1  5  8
15  8 16 19

[2 rows x 3 columns]
```

selects all the rows of `df` where `a < b < c` evaluates to `True`. For more details see the [the docs](#).

- `pd.read_msgpack()` and `pd.to_msgpack()` are now a supported method of serialization of arbitrary pandas (and python objects) in a lightweight portable binary format. See [the docs](#)

Warning: Since this is an EXPERIMENTAL LIBRARY, the storage format may not be stable until a future release.

```
In [118]: df = DataFrame(np.random.rand(5,2), columns=list('AB'))
```

```
In [119]: df.to_msgpack('foo.msg')
```

```
In [120]: pd.read_msgpack('foo.msg')
```

```
Out[120]:
```

	A	B
0	0.251082	0.017357
1	0.347915	0.929879
2	0.546233	0.203368
3	0.064942	0.031722
4	0.355309	0.524575

```
[5 rows x 2 columns]
```

```
In [121]: s = Series(np.random.rand(5), index=date_range('20130101', periods=5))
```

```
In [122]: pd.to_msgpack('foo.msg', df, s)
```

```
In [123]: pd.read_msgpack('foo.msg')
```

```
Out[123]:
```

	A	B
0	0.251082	0.017357
1	0.347915	0.929879
2	0.546233	0.203368
3	0.064942	0.031722
4	0.355309	0.524575


```
[5 rows x 2 columns], 2013-01-01    0.022321
2013-01-02    0.227025
2013-01-03    0.383282
2013-01-04    0.193225
2013-01-05    0.110977
Freq: D, dtype: float64]
```

You can pass `iterator=True` to iterator over the unpacked results

```
In [124]: for o in pd.read_msgpack('foo.msg', iterator=True):
.....:     print o
.....:
```

	A	B
0	0.251082	0.017357
1	0.347915	0.929879
2	0.546233	0.203368
3	0.064942	0.031722
4	0.355309	0.524575

```
[5 rows x 2 columns]
2013-01-01    0.022321
2013-01-02    0.227025
2013-01-03    0.383282
```

```
2013-01-04    0.193225
2013-01-05    0.110977
Freq: D, dtype: float64
```

- `pandas.io.gbq` provides a simple way to extract from, and load data into, Google's BigQuery Data Sets by way of pandas DataFrames. BigQuery is a high performance SQL-like database service, useful for performing ad-hoc queries against extremely large datasets. *See the docs*

```
from pandas.io import gbq

# A query to select the average monthly temperatures in the
# in the year 2000 across the USA. The dataset,
# publicdata:samples.gsod, is available on all BigQuery accounts,
# and is based on NOAA gsod data.

query = """SELECT station_number as STATION,
month as MONTH, AVG(mean_temp) as MEAN_TEMP
FROM publicdata:samples.gsod
WHERE YEAR = 2000
GROUP BY STATION, MONTH
ORDER BY STATION, MONTH ASC"""

# Fetch the result set for this query

# Your Google BigQuery Project ID
# To find this, see your dashboard:
# https://code.google.com/apis/console/b/0/?noredirect
projectid = xxxxxxxxx;

df = gbq.read_gbq(query, project_id = projectid)

# Use pandas to process and reshape the dataset

df2 = df.pivot(index='STATION', columns='MONTH', values='MEAN_TEMP')
df3 = pandas.concat([df2.min(), df2.mean(), df2.max()],
                    axis=1, keys=["Min Tem", "Mean Temp", "Max Temp"])
```

The resulting DataFrame is:

```
> df3
```

	Min Tem	Mean Temp	Max Temp
MONTH			
1	-53.336667	39.827892	89.770968
2	-49.837500	43.685219	93.437932
3	-77.926087	48.708355	96.099998
4	-82.892858	55.070087	97.317240
5	-92.378261	61.428117	102.042856
6	-77.703334	65.858888	102.900000
7	-87.821428	68.169663	106.510714
8	-89.431999	68.614215	105.500000
9	-86.611112	63.436935	107.142856
10	-78.209677	56.880838	92.103333
11	-50.125000	48.861228	94.996428
12	-50.332258	42.286879	94.396774

Warning: To use this module, you will need a BigQuery account. See <https://cloud.google.com/products/big-query> for details.
As of 10/10/13, there is a bug in Google's API preventing result sets from being larger than 100,000 rows. A patch is scheduled for the week of 10/14/13.

1.9.10 Internal Refactoring

In 0.13.0 there is a major refactor primarily to subclass `Series` from `NDFrame`, which is the base class currently for `DataFrame` and `Panel`, to unify methods and behaviors. `Series` formerly subclassed directly from `ndarray`. (GH4080, GH3862, GH816)

Warning: There are two potential incompatibilities from < 0.13.0

- Using certain numpy functions would previously return a `Series` if passed a `Series` as an argument. This seems only to affect `np.ones_like`, `np.empty_like`, `np.diff` and `np.where`. These now return `ndarrays`.

```
In [125]: s = Series([1,2,3,4])
```

Numpy Usage

```
In [126]: np.ones_like(s)
Out[126]: array([1, 1, 1, 1], dtype=int64)
```

```
In [127]: np.diff(s)
Out[127]: array([1, 1, 1], dtype=int64)
```

```
In [128]: np.where(s>1,s,np.nan)
Out[128]: array([ nan,  2.,  3.,  4.])
```

Pandonic Usage

```
In [129]: Series(1,index=s.index)
Out[129]:
0    1
1    1
2    1
3    1
dtype: int64
```

```
In [130]: s.diff()
Out[130]:
0    NaN
1     1
2     1
3     1
dtype: float64
```

```
In [131]: s.where(s>1)
Out[131]:
0    NaN
1     2
2     3
3     4
dtype: float64
```

- Passing a `Series` directly to a cython function expecting an `ndarray` type will no longer work directly, you must pass `Series.values`, See [Enhancing Performance](#)
- `Series(0.5)` would previously return the scalar `0.5`, instead this will return a 1-element `Series`
- This change breaks `ipy2<=2.3.8`. an Issue has been opened against `ipy2` and a workaround is detailed in [GH5698](#). Thanks @JanSchulz.

- Pickle compatibility is preserved for pickles created prior to 0.13. These must be unpickled with `pd.read_pickle`, see [Pickling](#).
- Refactor of `series.py/frame.py/panel.py` to move common code to `generic.py`
 - added `_setup_axes` to created generic `NDFrame` structures
 - moved methods
 - * `from_axes`, `_wrap_array`, `axes`, `ix`, `loc`, `iloc`, `shape`, `empty`, `swapaxes`, `transpose`, `pop`

- * `__iter__`, `keys`, `__contains__`, `__len__`, `__neg__`, `__invert__`
- * `convert_objects`, `as_blocks`, `as_matrix`, `values`
- * `__getstate__`, `__setstate__` (compat remains in frame/panel)
- * `__getattr__`, `__setattr__`
- * `_indexed_same`, `reindex_like`, `align`, `where`, `mask`
- * `fillna`, `replace` (Series `replace` is now consistent with `DataFrame`)
- * `filter` (also added `axis` argument to selectively filter on a different axis)
- * `reindex`, `reindex_axis`, `take`
- * `truncate` (moved to become part of `NDFrame`)

- These are API changes which make `Panel` more consistent with `DataFrame`
 - `swapaxes` on a `Panel` with the same axes specified now return a copy
 - support attribute access for setting
 - `filter` supports the same API as the original `DataFrame` `filter`
- `Reindex` called with no arguments will now return a copy of the input object
- `TimeSeries` is now an alias for `Series`. the property `is_time_series` can be used to distinguish (if desired)
- Refactor of Sparse objects to use `BlockManager`
 - Created a new block type in internals, `SparseBlock`, which can hold multi-dtypes and is non-consolidatable. `SparseSeries` and `SparseDataFrame` now inherit more methods from there hierarchy (`Series/DataFrame`), and no longer inherit from `SparseArray` (which instead is the object of the `SparseBlock`)
 - Sparse suite now supports integration with non-sparse data. Non-float sparse data is supportable (partially implemented)
 - Operations on sparse structures within `DataFrames` should preserve sparseness, merging type operations will convert to dense (and back to sparse), so might be somewhat inefficient
 - enable `setitem` on `SparseSeries` for boolean/integer/slices
 - `SparsePanels` implementation is unchanged (e.g. not using `BlockManager`, needs work)
- added `ftypes` method to `Series/DataFrame`, similar to `dtypes`, but indicates if the underlying is sparse/dense (as well as the dtype)
- All `NDFrame` objects can now use `__finalize__()` to specify various values to propagate to new objects from an existing one (e.g. `name` in `Series` will follow more automatically now)
- Internal type checking is now done via a suite of generated classes, allowing `isinstance(value, klass)` without having to directly import the class, courtesy of @jtratner
- Bug in `Series` update where the parent frame is not updating its cache based on changes ([GH4080](#)) or types ([GH3217](#)), `fillna` ([GH3386](#))
- Indexing with dtype conversions fixed ([GH4463](#), [GH4204](#))
- Refactor `Series.reindex` to `core/generic.py` ([GH4604](#), [GH4618](#)), allow `method=` in reindexing on a `Series` to work
- `Series.copy` no longer accepts the `order` parameter and is now consistent with `NDFrame` `copy`

- Refactor `rename` methods to `core/generic.py`; fixes `Series.rename` for (GH4605), and adds `rename` with the same signature for `Panel`
- Refactor `clip` methods to `core/generic.py` (GH4798)
- Refactor of `_get_numeric_data/_get_bool_data` to `core/generic.py`, allowing `Series/Panel` functionality
- `Series` (for index) / `Panel` (for items) now allow attribute access to its elements (GH1903)

```
In [132]: s = Series([1,2,3],index=list('abc'))
```

```
In [133]: s.b
```

```
Out[133]: 2
```

```
In [134]: s.a = 5
```

```
In [135]: s
```

```
Out[135]:
```

```
a    5
```

```
b    2
```

```
c    3
```

```
dtype: int64
```

1.9.11 Bug Fixes

See *V0.13.0 Bug Fixes* for an extensive list of bugs that have been fixed in 0.13.0.

See the *full release notes* or issue tracker on GitHub for a complete list of all API changes, Enhancements and Bug Fixes.

1.10 v0.12.0 (July 24, 2013)

This is a major release from 0.11.0 and includes several new features and enhancements along with a large number of bug fixes.

Highlights include a consistent I/O API naming scheme, routines to read html, write multi-indexes to csv files, read & write STATA data files, read & write JSON format files, Python 3 support for `HDFStore`, filtering of groupby expressions via `filter`, and a revamped `replace` routine that accepts regular expressions.

1.10.1 API changes

- The I/O API is now much more consistent with a set of top level reader functions accessed like `pd.read_csv()` that generally return a pandas object.

- `read_csv`
- `read_excel`
- `read_hdf`
- `read_sql`
- `read_json`
- `read_html`
- `read_stata`

```
- read_clipboard
```

The corresponding writer functions are object methods that are accessed like `df.to_csv()`

```
- to_csv
- to_excel
- to_hdf
- to_sql
- to_json
- to_html
- to_stata
- to_clipboard
```

- Fix modulo and integer division on Series,DataFrames to act similiary to float dtypes to return `np.nan` or `np.inf` as appropriate (GH3590). This correct a numpy bug that treats integer and float dtypes differently.

```
In [1]: p = DataFrame({ 'first' : [4,5,8], 'second' : [0,0,3] })
```

```
In [2]: p % 0
```

```
Out[2]:
```

	first	second
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN

```
[3 rows x 2 columns]
```

```
In [3]: p % p
```

```
Out[3]:
```

	first	second
0	0	NaN
1	0	NaN
2	0	0

```
[3 rows x 2 columns]
```

```
In [4]: p / p
```

```
Out[4]:
```

	first	second
0	1	NaN
1	1	NaN
2	1	1

```
[3 rows x 2 columns]
```

```
In [5]: p / 0
```

```
Out[5]:
```

	first	second
0	inf	NaN
1	inf	NaN
2	inf	inf

```
[3 rows x 2 columns]
```

- Add `squeeze` keyword to `groupby` to allow reduction from `DataFrame` -> `Series` if groups are unique. This is a Regression from 0.10.1. We are reverting back to the prior behavior. This means `groupby` will return the same shaped objects whether the groups are unique or not. Revert this issue ([GH2893](#)) with ([GH3596](#)).

```
In [6]: df2 = DataFrame([{"val1": 1, "val2": 20}, {"val1": 1, "val2": 19},
...:                    {"val1": 1, "val2": 27}, {"val1": 1, "val2": 12}])
...:
```

```
In [7]: def func(dataf):
...:     return dataf["val2"] - dataf["val2"].mean()
...:
```

```
# squeezing the result frame to a series (because we have unique groups)
```

```
In [8]: df2.groupby("val1", squeeze=True).apply(func)
```

```
Out[8]:
```

```
0    0.5
1   -0.5
2    7.5
3   -7.5
```

```
Name: 1, dtype: float64
```

```
# no squeezing (the default, and behavior in 0.10.1)
```

```
In [9]: df2.groupby("val1").apply(func)
```

```
Out[9]:
```

```
val2    0    1    2    3
val1
1      0.5 -0.5  7.5 -7.5
```

```
[1 rows x 4 columns]
```

- Raise on `iloc` when boolean indexing with a label based indexer mask e.g. a boolean `Series`, even with integer labels, will raise. Since `iloc` is purely positional based, the labels on the `Series` are not alignable ([GH3631](#))

This case is rarely used, and there are plenty of alternatives. This preserves the `iloc` API to be *purely* positional based.

```
In [10]: df = DataFrame(lrange(5), list('ABCDE'), columns=['a'])
```

```
In [11]: mask = (df.a%2 == 0)
```

```
In [12]: mask
```

```
Out[12]:
```

```
A    True
B   False
C    True
D   False
E    True
```

```
Name: a, dtype: bool
```

```
# this is what you should use
```

```
In [13]: df.loc[mask]
```

```
Out[13]:
```

```
   a
A  0
C  2
E  4
```

```
[3 rows x 1 columns]
```

```
# this will work as well
In [14]: df.iloc[mask.values]
Out[14]:
      a
A    0
C    2
E    4
```

```
[3 rows x 1 columns]
```

`df.iloc[mask]` will raise a `ValueError`

- The `raise_on_error` argument to plotting functions is removed. Instead, plotting functions raise a `TypeError` when the dtype of the object is `object` to remind you to avoid object arrays whenever possible and thus you should cast to an appropriate numeric dtype if you need to plot something.
- Add `colormap` keyword to `DataFrame` plotting methods. Accepts either a matplotlib colormap object (ie, `matplotlib.cm.jet`) or a string name of such an object (ie, `'jet'`). The colormap is sampled to select the color for each column. Please see [Colormaps](#) for more information. (GH3860)
- `DataFrame.interpolate()` is now deprecated. Please use `DataFrame.fillna()` and `DataFrame.replace()` instead. (GH3582, GH3675, GH3676)
- the `method` and `axis` arguments of `DataFrame.replace()` are deprecated
- `DataFrame.replace` 's `infer_types` parameter is removed and now performs conversion by default. (GH3907)
- Add the keyword `allow_duplicates` to `DataFrame.insert` to allow a duplicate column to be inserted if `True`, default is `False` (same as prior to 0.12) (GH3679)
- Implement `__nonzero__` for `NDFrame` objects (GH3691, GH3696)
- IO api

- added top-level function `read_excel` to replace the following. The original API is deprecated and will be removed in a future version

```
from pandas.io.parsers import ExcelFile
xls = ExcelFile('path_to_file.xls')
xls.parse('Sheet1', index_col=None, na_values=['NA'])
```

With

```
import pandas as pd
pd.read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

- added top-level function `read_sql` that is equivalent to the following

```
from pandas.io.sql import read_frame
read_frame(...)
```

- `DataFrame.to_html` and `DataFrame.to_latex` now accept a path for their first argument (GH3702)
- Do not allow astypes on `datetime64[ns]` except to `object`, and `timedelta64[ns]` to `object/int` (GH3425)
- The behavior of `datetime64` dtypes has changed with respect to certain so-called reduction operations (GH3726). The following operations now raise a `TypeError` when performed on a `Series` and return an *empty* `Series` when performed on a `DataFrame` similar to performing these operations on, for example, a `DataFrame` of slice objects:
 - `sum`, `prod`, `mean`, `std`, `var`, `skew`, `kurt`, `corr`, and `cov`

- `read_html` now defaults to `None` when reading, and falls back on `bs4` + `html5lib` when `lxml` fails to parse. a list of parsers to try until success is also valid
- The internal pandas class hierarchy has changed (slightly). The previous `PandasObject` now is called `PandasContainer` and a new `PandasObject` has become the baseclass for `PandasContainer` as well as `Index`, `Categorical`, `GroupBy`, `SparseList`, and `SparseArray` (+ their base classes). Currently, `PandasObject` provides string methods (from `StringMixin`). ([GH4090](#), [GH4092](#))
- New `StringMixin` that, given a `__unicode__` method, gets python 2 and python 3 compatible string methods (`__str__`, `__bytes__`, and `__repr__`). Plus string safety throughout. Now employed in many places throughout the pandas library. ([GH4090](#), [GH4092](#))

1.10.2 I/O Enhancements

- `pd.read_html()` can now parse HTML strings, files or urls and return `DataFrames`, courtesy of [@cpcloud](#). ([GH3477](#), [GH3605](#), [GH3606](#), [GH3616](#)). It works with a *single* parser backend: `BeautifulSoup4` + `html5lib` *See the docs*

You can use `pd.read_html()` to read the output from `DataFrame.to_html()` like so

```
In [15]: df = DataFrame({'a': range(3), 'b': list('abc')})
```

```
In [16]: print(df)
```

```
   a  b
0  0  a
1  1  b
2  2  c
```

```
[3 rows x 2 columns]
```

```
In [17]: html = df.to_html()
```

```
In [18]: alist = pd.read_html(html, infer_types=True, index_col=0)
```

```
In [19]: print(df == alist[0])
```

```
   a      b
0  True  True
1  True  True
2  True  True
```

```
[3 rows x 2 columns]
```

Note that `alist` here is a Python list so `pd.read_html()` and `DataFrame.to_html()` are not inverses.

- `pd.read_html()` no longer performs hard conversion of date strings ([GH3656](#)).

Warning: You may have to install an older version of `BeautifulSoup4`, *See the installation docs*

- Added module for reading and writing Stata files: `pandas.io.stata` ([GH1512](#)) accessible via `read_stata` top-level function for reading, and `to_stata` `DataFrame` method for writing, *See the docs*
- Added module for reading and writing json format files: `pandas.io.json` accessible via `read_json` top-level function for reading, and `to_json` `DataFrame` method for writing, *See the docs* various issues ([GH1226](#), [GH3804](#), [GH3876](#), [GH3867](#), [GH1305](#))
- `MultiIndex` column support for reading and writing csv format files

- The header option in `read_csv` now accepts a list of the rows from which to read the index.
- The option, `tupleize_cols` can now be specified in both `to_csv` and `read_csv`, to provide compatibility for the pre 0.12 behavior of writing and reading `MultiIndex` columns via a list of tuples. The default in 0.12 is to write lists of tuples and *not* interpret list of tuples as a `MultiIndex` column.

Note: The default behavior in 0.12 remains unchanged from prior versions, but starting with 0.13, the default *to* write and read `MultiIndex` columns will be in the new format. (GH3571, GH1651, GH3141)

- If an `index_col` is not specified (e.g. you don't have an index, or wrote it with `df.to_csv(..., index=False)`), then any names on the columns index will be *lost*.

```
In [20]: from pandas.util.testing import makeCustomDataframe as mkdf
```

```
In [21]: df = mkdf(5,3,r_idx_nlevels=2,c_idx_nlevels=4)
```

```
In [22]: df.to_csv('mi.csv',tupleize_cols=False)
```

```
In [23]: print(open('mi.csv').read())
```

```
C0,,C_10_g0,C_10_g1,C_10_g2
C1,,C_11_g0,C_11_g1,C_11_g2
C2,,C_12_g0,C_12_g1,C_12_g2
C3,,C_13_g0,C_13_g1,C_13_g2
R0,R1,,,
R_10_g0,R_11_g0,R0C0,R0C1,R0C2
R_10_g1,R_11_g1,R1C0,R1C1,R1C2
R_10_g2,R_11_g2,R2C0,R2C1,R2C2
R_10_g3,R_11_g3,R3C0,R3C1,R3C2
R_10_g4,R_11_g4,R4C0,R4C1,R4C2
```

```
In [24]: pd.read_csv('mi.csv',header=[0,1,2,3],index_col=[0,1],tupleize_cols=False)
```

```
Out[24]:
C0          C_10_g0 C_10_g1 C_10_g2
C1          C_11_g0 C_11_g1 C_11_g2
C2          C_12_g0 C_12_g1 C_12_g2
C3          C_13_g0 C_13_g1 C_13_g2
R0      R1
R_10_g0 R_11_g0      R0C0      R0C1      R0C2
R_10_g1 R_11_g1      R1C0      R1C1      R1C2
R_10_g2 R_11_g2      R2C0      R2C1      R2C2
R_10_g3 R_11_g3      R3C0      R3C1      R3C2
R_10_g4 R_11_g4      R4C0      R4C1      R4C2
```

```
[5 rows x 3 columns]
```

- Support for `HDFStore` (via `PyTables 3.0.0`) on Python3
- Iterator support via `read_hdf` that automatically opens and closes the store when iteration is finished. This is only for *tables*

```
In [25]: path = 'store_iterator.h5'
```

```
In [26]: DataFrame(randn(10,2)).to_hdf(path,'df',table=True)
```

```
In [27]: for df in read_hdf(path,'df', chunksize=3):
```

```
.....:     print(df)
```

```
.....:
```

```
          0          1
0  1.392665 -0.123497
```

```
1 -0.402761 -0.246604
2 -0.288433 -0.763434
```

```
[3 rows x 2 columns]
      0      1
3  2.069526 -1.203569
4  0.591830  0.841159
5 -0.501083 -0.816561
```

```
[3 rows x 2 columns]
      0      1
6 -0.207082 -0.664112
7  0.580411 -0.965628
8 -0.038605 -0.460478
```

```
[3 rows x 2 columns]
      0      1
9 -0.310458  0.866493
```

```
[1 rows x 2 columns]
```

- `read_csv` will now throw a more informative error message when a file contains no columns, e.g., all newline characters

1.10.3 Other Enhancements

- `DataFrame.replace()` now allows regular expressions on contained Series with object dtype. See the examples section in the regular docs [Replacing via String Expression](#)

For example you can do

```
In [28]: df = DataFrame({'a': list('ab..'), 'b': [1, 2, 3, 4]})
```

```
In [29]: df.replace(regex=r'\s*\.\s*', value=np.nan)
```

```
Out[29]:
```

```
      a  b
0     a  1
1     b  2
2  NaN  3
3  NaN  4
```

```
[4 rows x 2 columns]
```

to replace all occurrences of the string `'.'` with zero or more instances of surrounding whitespace with `NaN`.

Regular string replacement still works as expected. For example, you can do

```
In [30]: df.replace('.', np.nan)
```

```
Out[30]:
```

```
      a  b
0     a  1
1     b  2
2  NaN  3
3  NaN  4
```

```
[4 rows x 2 columns]
```

to replace all occurrences of the string `'.'` with `NaN`.

- `pd.melt()` now accepts the optional parameters `var_name` and `value_name` to specify custom column names of the returned DataFrame.
- `pd.set_option()` now allows N option, value pairs ([GH3667](#)).

Let's say that we had an option 'a.b' and another option 'b.c'. We can set them at the same time:

```
In [31]: pd.get_option('a.b')
Out[31]: 2

In [32]: pd.get_option('b.c')
Out[32]: 3

In [33]: pd.set_option('a.b', 1, 'b.c', 4)

In [34]: pd.get_option('a.b')
Out[34]: 1

In [35]: pd.get_option('b.c')
Out[35]: 4
```

- The `filter` method for group objects returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [36]: sf = Series([1, 1, 2, 3, 3, 3])

In [37]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[37]:
3    3
4    3
5    3
dtype: int64
```

The argument of `filter` must a function that, applied to the group as a whole, returns True or False.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [38]: dff = DataFrame({'A': np.arange(8), 'B': list('aabbbbcc')})

In [39]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[39]:
   A  B
2  2  b
3  3  b
4  4  b
5  5  b

[4 rows x 2 columns]
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [40]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
Out[40]:
   A  B
0 NaN NaN
1 NaN NaN
2  2  b
3  3  b
4  4  b
```

```
5    5    b
6 NaN  NaN
7 NaN  NaN

[8 rows x 2 columns]
```

- Series and DataFrame hist methods now take a `figsize` argument ([GH3834](#))
- DatetimeIndexes no longer try to convert mixed-integer indexes during join operations ([GH3877](#))
- Timestamp.min and Timestamp.max now represent valid Timestamp instances instead of the default date-time.min and datetime.max (respectively), thanks @SleepingPills
- read_html now raises when no tables are found and BeautifulSoup==4.2.0 is detected ([GH4214](#))

1.10.4 Experimental Features

- Added experimental CustomBusinessDay class to support DateOffsets with custom holiday calendars and custom weekmasks. ([GH2301](#))

Note: This uses the `numpy.busdaycalendar` API introduced in Numpy 1.7 and therefore requires Numpy 1.7.0 or newer.

```
In [41]: from pandas.tseries.offsets import CustomBusinessDay

In [42]: from datetime import datetime

# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
In [43]: weekmask_egypt = 'Sun Mon Tue Wed Thu'

# They also observe International Workers' Day so let's
# add that for a couple of years
In [44]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01')]

In [45]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)

In [46]: dt = datetime(2013, 4, 30)

In [47]: print(dt + 2 * bday_egypt)
2013-05-05 00:00:00

In [48]: dts = date_range(dt, periods=5, freq=bday_egypt)

In [49]: print(Series(dts.weekday, dts).map(Series('Mon Tue Wed Thu Fri Sat Sun'.split())))
2013-04-30    Tue
2013-05-02    Thu
2013-05-05    Sun
2013-05-06    Mon
2013-05-07    Tue
Freq: C, dtype: object
```

1.10.5 Bug Fixes

- Plotting functions now raise a `TypeError` before trying to plot anything if the associated objects have a `dtype` of `object` ([GH1818](#), [GH3572](#), [GH3911](#), [GH3912](#)), but they will try to convert object arrays to numeric

arrays if possible so that you can still plot, for example, an object array with floats. This happens before any drawing takes place which eliminates any spurious plots from showing up.

- `fillna` methods now raise a `TypeError` if the `value` parameter is a list or tuple.
- `Series.str` now supports iteration ([GH3638](#)). You can iterate over the individual elements of each string in the `Series`. Each iteration yields a `Series` with either a single character at each index of the original `Series` or `NaN`. For example,

```
In [50]: strs = 'go', 'bow', 'joe', 'slow'
```

```
In [51]: ds = Series(strs)
```

```
In [52]: for s in ds.str:
...:     print(s)
...:
```

```
0    g
1    b
2    j
3    s
```

```
dtype: object
```

```
0    o
1    o
2    o
3    l
```

```
dtype: object
```

```
0    NaN
1     w
2     e
3     o
```

```
dtype: object
```

```
0    NaN
1    NaN
2    NaN
3     w
```

```
dtype: object
```

```
In [53]: s
```

```
Out[53]:
```

```
0    NaN
1    NaN
2    NaN
3     w
```

```
dtype: object
```

```
In [54]: s.dropna().values.item() == 'w'
```

```
Out[54]: True
```

The last element yielded by the iterator will be a `Series` containing the last element of the longest string in the `Series` with all other elements being `NaN`. Here since `'slow'` is the longest string and there are no other strings with the same length `'w'` is the only non-null string in the yielded `Series`.

- `HDFStore`
 - will retain index attributes (`freq,tz,name`) on recreation ([GH3499](#))
 - will warn with a `AttributeConflictWarning` if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
 - support datelike columns with a timezone as `data_columns` ([GH2852](#))

- Non-unique index support clarified ([GH3468](#)).
 - Fix assigning a new index to a duplicate index in a DataFrame would fail ([GH3468](#))
 - Fix construction of a DataFrame with a duplicate index
 - `ref_locs` support to allow duplicative indices across dtypes, allows `iget` support to always find the index (even across dtypes) ([GH2194](#))
 - `applymap` on a DataFrame with a non-unique index now works (removed warning) ([GH2786](#)), and fix ([GH3230](#))
 - Fix `to_csv` to handle non-unique columns ([GH3495](#))
 - Duplicate indexes with `getitem` will return items in the correct order ([GH3455](#), [GH3457](#)) and handle missing elements like unique indices ([GH3561](#))
 - Duplicate indexes with and empty `DataFrame.from_records` will return a correct frame ([GH3562](#))
 - Concat to produce a non-unique columns when duplicates are across dtypes is fixed ([GH3602](#))
 - Allow insert/delete to non-unique columns ([GH3679](#))
 - Non-unique indexing with a slice via `loc` and friends fixed ([GH3659](#))
 - Allow insert/delete to non-unique columns ([GH3679](#))
 - Extend `reindex` to correctly deal with non-unique indices ([GH3679](#))
 - `DataFrame.itertuples()` now works with frames with duplicate column names ([GH3873](#))
 - Bug in non-unique indexing via `iloc` ([GH4017](#)); added `takeable` argument to `reindex` for location-based taking
 - Allow non-unique indexing in series via `.ix/.loc` and `__getitem__` ([GH4246](#))
 - Fixed non-unique indexing memory allocation issue with `.ix/.loc` ([GH4280](#))
- `DataFrame.from_records` did not accept empty recarrays ([GH3682](#))
- `read_html` now correctly skips tests ([GH3741](#))
- Fixed a bug where `DataFrame.replace` with a compiled regular expression in the `to_replace` argument wasn't working ([GH3907](#))
- Improved `network` test decorator to catch `IOError` (and therefore `URLError` as well). Added `with_connectivity_check` decorator to allow explicitly checking a website as a proxy for seeing if there is network connectivity. Plus, new `optional_args` decorator factory for decorators. ([GH3910](#), [GH3914](#))
- Fixed testing issue where too many sockets were open thus leading to a connection reset issue ([GH3982](#), [GH3985](#), [GH4028](#), [GH4054](#))
- Fixed failing tests in `test_yahoo`, `test_google` where symbols were not retrieved but were being accessed ([GH3982](#), [GH3985](#), [GH4028](#), [GH4054](#))
- `Series.hist` will now take the figure from the current environment if one is not passed
- Fixed bug where a 1xN DataFrame would barf on a 1xN mask ([GH4071](#))
- Fixed running of `tox` under python3 where the pickle import was getting rewritten in an incompatible way ([GH4062](#), [GH4063](#))
- Fixed bug where `sharex` and `sharey` were not being passed to `grouped_hist` ([GH4089](#))
- Fixed bug in `DataFrame.replace` where a nested dict wasn't being iterated over when `regex=False` ([GH4115](#))
- Fixed bug in the parsing of microseconds when using the `format` argument in `to_datetime` ([GH4152](#))

- Fixed bug in `PandasAutoDateLocator` where `invert_xaxis` triggered incorrectly `MilliSecondLocator` (GH3990)
- Fixed bug in plotting that wasn't raising on invalid colormap for matplotlib 1.1.1 (GH4215)
- Fixed the legend displaying in `DataFrame.plot(kind='kde')` (GH4216)
- Fixed bug where Index slices weren't carrying the name attribute (GH4226)
- Fixed bug in initializing `DatetimeIndex` with an array of strings in a certain time zone (GH4229)
- Fixed bug where `html5lib` wasn't being properly skipped (GH4265)
- Fixed bug where `get_data_famafrench` wasn't using the correct file edges (GH4281)

See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.11 v0.11.0 (April 22, 2013)

This is a major release from 0.10.1 and includes many new features and enhancements along with a large number of bug fixes. The methods of Selecting Data have had quite a number of additions, and Dtype support is now full-fledged. There are also a number of important API changes that long-time pandas users should pay close attention to.

There is a new section in the documentation, *10 Minutes to Pandas*, primarily geared to new users.

There is a new section in the documentation, *Cookbook*, a collection of useful recipes in pandas (and that we want contributions!).

There are several libraries that are now *Recommended Dependencies*

1.11.1 Selection Choices

Starting in 0.11.0, object selection has had a number of user-requested additions in order to support more explicit location based indexing. Pandas now supports three types of multi-axis indexing.

- `.loc` is strictly label based, will raise `KeyError` when the items are not found, allowed inputs are:
 - A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index. This use is **not** an integer position along the index)
 - A list or array of labels ['a', 'b', 'c']
 - A slice object with labels 'a' : 'f', (note that contrary to usual python slices, **both** the start and the stop are included!)
 - A boolean array

See more at [Selection by Label](#)

- `.iloc` is strictly integer position based (from 0 to `length-1` of the axis), will raise `IndexError` when the requested indicies are out of bounds. Allowed inputs are:
 - An integer e.g. 5
 - A list or array of integers [4, 3, 0]
 - A slice object with ints 1 : 7
 - A boolean array

See more at [Selection by Position](#)

- `.ix` supports mixed integer and label based access. It is primarily label based, but will fallback to integer positional access. `.ix` is the most general and will support any of the inputs to `.loc` and `.iloc`, as well as support for floating point label schemes. `.ix` is especially useful when dealing with mixed positional and label based hierarchical indexes.

As using integer slices with `.ix` have different behavior depending on whether the slice is interpreted as position based or label based, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#) and [Advanced Hierarchical](#).

1.11.2 Selection Deprecations

Starting in version 0.11.0, these methods *may* be deprecated in future versions.

- `irow`
- `icol`
- `iget_value`

See the section [Selection by Position](#) for substitutes.

1.11.3 Dtypes

Numeric dtypes will propagate and can coexist in DataFrames. If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`, then it will be preserved in DataFrame operations. Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```
In [1]: df1 = DataFrame(randn(8, 1), columns = ['A'], dtype = 'float32')
```

```
In [2]: df1
```

```
Out[2]:
```

	A
0	0.245972
1	0.319442
2	1.378512
3	0.292502
4	0.329791
5	1.392047
6	0.769914
7	-2.472300

```
[8 rows x 1 columns]
```

```
In [3]: df1.dtypes
```

```
Out[3]:
```

	dtype
A	float32

```
dtype: object
```

```
In [4]: df2 = DataFrame(dict( A = Series(randn(8), dtype='float16'),
...:                          B = Series(randn(8)),
...:                          C = Series(randn(8), dtype='uint8') ))
...:
```

```
In [5]: df2
```

```
Out[5]:
```

	A	B	C
0	-0.611328	-0.270630	255

```

1  1.044922 -1.685677    0
2  1.503906 -0.440747    0
3 -1.328125 -0.115070    1
4  1.024414 -0.632102    0
5  0.660156 -0.585977    0
6  1.236328 -1.444787    0
7 -2.169922 -0.201135    0

```

```
[8 rows x 3 columns]
```

```
In [6]: df2.dtypes
```

```
Out [6]:
```

```

A    float16
B    float64
C      uint8
dtype: object

```

```
# here you get some upcasting
```

```
In [7]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2
```

```
In [8]: df3
```

```
Out [8]:
```

```

      A      B      C
0 -0.365356 -0.270630 255
1  1.364364 -1.685677    0
2  2.882418 -0.440747    0
3 -1.035623 -0.115070    1
4  1.354205 -0.632102    0
5  2.052203 -0.585977    0
6  2.006243 -1.444787    0
7 -4.642221 -0.201135    0

```

```
[8 rows x 3 columns]
```

```
In [9]: df3.dtypes
```

```
Out [9]:
```

```

A    float32
B    float64
C    float64
dtype: object

```

1.11.4 Dtype Conversion

This is lower-common-denominator upcasting, meaning you get the dtype which can accomodate all of the types

```
In [10]: df3.values.dtype
```

```
Out [10]: dtype('float64')
```

Conversion

```
In [11]: df3.astype('float32').dtypes
```

```
Out [11]:
```

```

A    float32
B    float32
C    float32
dtype: object

```

Mixed Conversion

```
In [12]: df3['D'] = '1.'

In [13]: df3['E'] = '1'

In [14]: df3.convert_objects(convert_numeric=True).dtypes
Out[14]:
A    float32
B    float64
C    float64
D    float64
E      int64
dtype: object

# same, but specific dtype conversion
In [15]: df3['D'] = df3['D'].astype('float16')

In [16]: df3['E'] = df3['E'].astype('int32')

In [17]: df3.dtypes
Out[17]:
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object
```

Forcing Date coercion (and setting NaT when not datelike)

```
In [18]: from datetime import datetime

In [19]: s = Series([datetime(2001,1,1,0,0), 'foo', 1.0, 1,
.....:               Timestamp('20010104'), '20010105'], dtype='O')
.....:

In [20]: s.convert_objects(convert_dates='coerce')
Out[20]:
0    2001-01-01
1           NaT
2           NaT
3           NaT
4    2001-01-04
5    2001-01-05
dtype: datetime64[ns]
```

1.11.5 Dtype Gotchas

Platform Gotchas

Starting in 0.11.0, construction of DataFrame/Series will use default dtypes of `int64` and `float64`, *regardless of platform*. This is not an apparent change from earlier versions of pandas. If you specify dtypes, they *WILL* be respected, however ([GH2837](#))

The following will all result in `int64` dtypes

```
In [21]: DataFrame([1,2], columns=['a']).dtypes
Out[21]:
a    int64
```

```
dtype: object
```

```
In [22]: DataFrame({'a' : [1,2] }).dtypes
```

```
Out[22]:
a      int64
dtype: object
```

```
In [23]: DataFrame({'a' : 1 }, index=range(2)).dtypes
```

```
Out[23]:
a      int64
dtype: object
```

Keep in mind that `DataFrame(np.array([1,2]))` **WILL** result in `int32` on 32-bit platforms!

Upcasting Gotchas

Performing indexing operations on integer type data can easily upcast the data. The dtype of the input data will be preserved in cases where nans are not introduced.

```
In [24]: dfi = df3.astype('int32')
```

```
In [25]: dfi['D'] = dfi['D'].astype('int64')
```

```
In [26]: dfi
```

```
Out[26]:
   A  B   C  D  E
0  0  0 255  1  1
1  1  -1   0  1  1
2  2  0   0  1  1
3 -1  0   1  1  1
4  1  0   0  1  1
5  2  0   0  1  1
6  2 -1   0  1  1
7 -4  0   0  1  1
```

```
[8 rows x 5 columns]
```

```
In [27]: dfi.dtypes
```

```
Out[27]:
A      int32
B      int32
C      int32
D      int64
E      int32
dtype: object
```

```
In [28]: casted = dfi[dfi>0]
```

```
In [29]: casted
```

```
Out[29]:
   A  B   C  D  E
0 NaN NaN 255  1  1
1  1 NaN NaN  1  1
2  2 NaN NaN  1  1
3 NaN NaN   1  1  1
4  1 NaN NaN  1  1
5  2 NaN NaN  1  1
6  2 NaN NaN  1  1
7 NaN NaN NaN  1  1
```

```
[8 rows x 5 columns]
```

```
In [30]: casted.dtypes
```

```
Out[30]:
```

```
A    float64
B    float64
C    float64
D      int64
E      int32
dtype: object
```

While float dtypes are unchanged.

```
In [31]: df4 = df3.copy()
```

```
In [32]: df4['A'] = df4['A'].astype('float32')
```

```
In [33]: df4.dtypes
```

```
Out[33]:
```

```
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object
```

```
In [34]: casted = df4[df4>0]
```

```
In [35]: casted
```

```
Out[35]:
```

	A	B	C	D	E
0	NaN	NaN	255	1	1
1	1.364364	NaN	NaN	1	1
2	2.882418	NaN	NaN	1	1
3	NaN	NaN	1	1	1
4	1.354205	NaN	NaN	1	1
5	2.052203	NaN	NaN	1	1
6	2.006243	NaN	NaN	1	1
7	NaN	NaN	NaN	1	1

```
[8 rows x 5 columns]
```

```
In [36]: casted.dtypes
```

```
Out[36]:
```

```
A    float32
B    float64
C    float64
D    float16
E      int32
dtype: object
```

1.11.6 Datetimes Conversion

Datetime64[ns] columns in a DataFrame (or a Series) allow the use of `np.nan` to indicate a nan value, in addition to the traditional NaT, or not-a-time. This allows convenient nan setting in a generic way. Furthermore datetime64[ns] columns are created by default, when passed datetimelike objects (*this change was introduced in*

0.10.1) (GH2809, GH2810)

```
In [37]: df = DataFrame(randn(6,2),date_range('20010102',periods=6),columns=['A','B'])
```

```
In [38]: df['timestamp'] = Timestamp('20010103')
```

```
In [39]: df
```

```
Out[39]:
```

	A	B	timestamp
2001-01-02	-1.448835	0.153437	2001-01-03
2001-01-03	-1.123570	-0.791498	2001-01-03
2001-01-04	0.105400	1.262401	2001-01-03
2001-01-05	-0.721844	-0.647645	2001-01-03
2001-01-06	-0.830631	0.761823	2001-01-03
2001-01-07	0.597819	1.045558	2001-01-03

```
[6 rows x 3 columns]
```

```
# datetime64[ns] out of the box
```

```
In [40]: df.get_dtype_counts()
```

```
Out[40]:
```

datetime64[ns]	1
float64	2

```
dtype: int64
```

```
# use the traditional nan, which is mapped to NaT internally
```

```
In [41]: df.ix[2:4,['A','timestamp']] = np.nan
```

```
In [42]: df
```

```
Out[42]:
```

	A	B	timestamp
2001-01-02	-1.448835	0.153437	2001-01-03
2001-01-03	-1.123570	-0.791498	2001-01-03
2001-01-04	NaN	1.262401	NaT
2001-01-05	NaN	-0.647645	NaT
2001-01-06	-0.830631	0.761823	2001-01-03
2001-01-07	0.597819	1.045558	2001-01-03

```
[6 rows x 3 columns]
```

Astype conversion on datetime64[ns] to object, implicitly converts NaT to np.nan

```
In [43]: import datetime
```

```
In [44]: s = Series([datetime.datetime(2001, 1, 2, 0, 0) for i in range(3)])
```

```
In [45]: s.dtype
```

```
Out[45]: dtype('<M8[ns]')
```

```
In [46]: s[1] = np.nan
```

```
In [47]: s
```

```
Out[47]:
```

0	2001-01-02
1	NaT
2	2001-01-02

```
dtype: datetime64[ns]
```

```
In [48]: s.dtype
```

```
Out[48]: dtype('<M8[ns]')

In [49]: s = s.astype('O')

In [50]: s
Out[50]:
0    2001-01-02 00:00:00
1                    NaN
2    2001-01-02 00:00:00
dtype: object

In [51]: s.dtype
Out[51]: dtype('O')
```

1.11.7 API changes

- Added `to_series()` method to indices, to facilitate the creation of indexers ([GH3275](#))
- `HDFStore`
 - added the method `select_column` to select a single column from a table as a Series.
 - deprecated the `unique` method, can be replicated by `select_column(key, column).unique()`
 - `min_itemsize` parameter to `append` will now automatically create data_columns for passed keys

1.11.8 Enhancements

- Improved performance of `df.to_csv()` by up to 10x in some cases. ([GH3059](#))
- `Numexpr` is now a *Recommended Dependencies*, to accelerate certain types of numerical and boolean operations
- `Bottleneck` is now a *Recommended Dependencies*, to accelerate certain types of nan operations
- `HDFStore`
 - support `read_hdf/to_hdf` API similar to `read_csv/to_csv`

```
In [52]: df = DataFrame(dict(A=lrange(5), B=lrange(5)))

In [53]: df.to_hdf('store.h5', 'table', append=True)

In [54]: read_hdf('store.h5', 'table', where = ['index>2'])
Out[54]:
   A  B
3  3  3
4  4  4

[2 rows x 2 columns]
```
 - provide dotted attribute access to get from stores, e.g. `store.df == store['df']`
 - new keywords `iterator=boolean`, and `chunksizes=number_in_a_chunk` are provided to support iteration on `select` and `select_as_multiple` ([GH3076](#))
- You can now select timestamps from an *unordered* timeseries similarly to an *ordered* timeseries ([GH2437](#))
- You can now select with a string from a DataFrame with a datelike index, in a similar way to a Series ([GH3070](#))

```
In [55]: idx = date_range("2001-10-1", periods=5, freq='M')
```

```
In [56]: ts = Series(np.random.rand(len(idx)), index=idx)
```

```
In [57]: ts['2001']
```

```
Out[57]:
2001-10-31    0.483450
2001-11-30    0.407530
2001-12-31    0.965096
Freq: M, dtype: float64
```

```
In [58]: df = DataFrame(dict(A = ts))
```

```
In [59]: df['2001']
```

```
Out[59]:
           A
2001-10-31  0.483450
2001-11-30  0.407530
2001-12-31  0.965096

[3 rows x 1 columns]
```

- Squeeze to possibly remove length 1 dimensions from an object.

```
In [60]: p = Panel(randn(3,4,4), items=['ItemA', 'ItemB', 'ItemC'],
.....:               major_axis=date_range('20010102', periods=4),
.....:               minor_axis=['A', 'B', 'C', 'D'])
.....:
```

```
In [61]: p
```

```
Out[61]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2001-01-02 00:00:00 to 2001-01-05 00:00:00
Minor_axis axis: A to D
```

```
In [62]: p.reindex(items=['ItemA']).squeeze()
```

```
Out[62]:
           A           B           C           D
2001-01-02  0.396537  0.534880 -0.488797 -1.539385
2001-01-03 -0.829037  0.306681 -0.331032  1.544977
2001-01-04 -0.621754  1.026208 -0.413106 -1.490869
2001-01-05 -1.253235 -0.538879 -1.487449 -1.426475

[4 rows x 4 columns]
```

```
In [63]: p.reindex(items=['ItemA'], minor=['B']).squeeze()
```

```
Out[63]:
2001-01-02    0.534880
2001-01-03    0.306681
2001-01-04    1.026208
2001-01-05   -0.538879
Freq: D, Name: B, dtype: float64
```

- In `pd.io.data.Options`,
 - Fix bug when trying to fetch data for the current month when already past expiry.

- Now using `lxml` to scrape html instead of `BeautifulSoup` (`lxml` was faster).
- New instance variables for calls and puts are automatically created when a method that creates them is called. This works for current month where the instance variables are simply `calls` and `puts`. Also works for future expiry months and save the instance variable as `callsMMYY` or `putsMMYY`, where `MMYY` are, respectively, the month and year of the option's expiry.
- `Options.get_near_stock_price` now allows the user to specify the month for which to get relevant options data.
- `Options.get_forward_data` now has optional kwargs `near` and `above_below`. This allows the user to specify if they would like to only return forward looking data for options near the current stock price. This just obtains the data from `Options.get_near_stock_price` instead of `Options.get_xxx_data()` (GH2758).
- Cursor coordinate information is now displayed in time-series plots.
- added option `display.max_seq_items` to control the number of elements printed per sequence pprinting it. (GH2979)
- added option `display.chop_threshold` to control display of small numerical values. (GH2739)
- added option `display.max_info_rows` to prevent `verbose_info` from being calculated for frames above 1M rows (configurable). (GH2807, GH2918)
- `value_counts()` now accepts a “normalize” argument, for normalized histograms. (GH2710).
- `DataFrame.from_records` now accepts not only dicts but any instance of the `collections.Mapping` ABC.
- added option `display.mpl_style` providing a sleeker visual style for plots. Based on <https://gist.github.com/huyng/816622> (GH3075).
- Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)
- `to_html()` now accepts an optional “escape” argument to control reserved HTML character escaping (enabled by default) and escapes `&`, in addition to `<` and `>`. (GH2919)

See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.12 v0.10.1 (January 22, 2013)

This is a minor release from 0.10.0 and includes new features, enhancements, and bug fixes. In particular, there is substantial new `HDFStore` functionality contributed by Jeff Reback.

An undesired API breakage with functions taking the `inplace` option has been reverted and deprecation warnings added.

1.12.1 API changes

- Functions taking an `inplace` option return the calling object as before. A deprecation message has been added
- Groupby aggregations `Max/Min` no longer exclude non-numeric data (GH2700)
- Resampling an empty `DataFrame` now returns an empty `DataFrame` instead of raising an exception (GH2640)
- The file reader will now raise an exception when NA values are found in an explicitly specified integer column instead of converting the column to float (GH2631)
- `DatetimeIndex.unique` now returns a `DatetimeIndex` with the same name and
- `timezone` instead of an array (GH2563)

1.12.2 New features

- MySQL support for database (contribution from Dan Allan)

1.12.3 HDFStore

You may need to upgrade your existing data files. Please visit the **compatibility** section in the main docs.

You can designate (and index) certain columns that you want to be able to perform queries on a table, by passing a list to `data_columns`

```
In [1]: store = HDFStore('store.h5')
```

```
In [2]: df = DataFrame(randn(8, 3), index=date_range('1/1/2000', periods=8),
...:                  columns=['A', 'B', 'C'])
...:
```

```
In [3]: df['string'] = 'foo'
```

```
In [4]: df.ix[4:6, 'string'] = np.nan
```

```
In [5]: df.ix[7:9, 'string'] = 'bar'
```

```
In [6]: df['string2'] = 'cool'
```

```
In [7]: df
Out[7]:
```

	A	B	C	string	string2
2000-01-01	-1.601262	-0.256718	0.239369	foo	cool
2000-01-02	0.174122	-1.131794	-1.948006	foo	cool
2000-01-03	0.980347	-0.674429	-0.361633	foo	cool
2000-01-04	-0.761218	1.768215	0.152288	foo	cool
2000-01-05	-0.862613	-0.210968	-0.859278	NaN	cool
2000-01-06	1.498195	0.462413	-0.647604	NaN	cool
2000-01-07	1.511487	-0.727189	-0.342928	foo	cool
2000-01-08	-0.007364	1.427674	0.104020	bar	cool

```
[8 rows x 5 columns]
```

```
# on-disk operations
```

```
In [8]: store.append('df', df, data_columns = ['B', 'C', 'string', 'string2'])
```

```
In [9]: store.select('df', [ 'B > 0', 'string == foo' ])
Out[9]:
```

	A	B	C	string	string2
2000-01-04	-0.761218	1.768215	0.152288	foo	cool

```
[1 rows x 5 columns]
```

```
# this is in-memory version of this type of selection
```

```
In [10]: df[(df.B > 0) & (df.string == 'foo')]
Out[10]:
```

	A	B	C	string	string2
2000-01-04	-0.761218	1.768215	0.152288	foo	cool

```
[1 rows x 5 columns]
```

Retrieving unique values in an indexable or data column.

```
# note that this is deprecated as of 0.14.0
# can be replicated by: store.select_column('df', 'index').unique()
store.unique('df', 'index')
store.unique('df', 'string')
```

You can now store datetime64 in data columns

```
In [11]: df_mixed = df.copy()

In [12]: df_mixed['datetime64'] = Timestamp('20010102')

In [13]: df_mixed.ix[3:4, ['A', 'B']] = np.nan

In [14]: store.append('df_mixed', df_mixed)

In [15]: df_mixed1 = store.select('df_mixed')

In [16]: df_mixed1
Out[16]:
```

	A	B	C	string	string2	datetime64
2000-01-01	-1.601262	-0.256718	0.239369	foo	cool	2001-01-02
2000-01-02	0.174122	-1.131794	-1.948006	foo	cool	2001-01-02
2000-01-03	0.980347	-0.674429	-0.361633	foo	cool	2001-01-02
2000-01-04	NaN	NaN	0.152288	foo	cool	2001-01-02
2000-01-05	-0.862613	-0.210968	-0.859278	NaN	cool	2001-01-02
2000-01-06	1.498195	0.462413	-0.647604	NaN	cool	2001-01-02
2000-01-07	1.511487	-0.727189	-0.342928	foo	cool	2001-01-02
2000-01-08	-0.007364	1.427674	0.104020	bar	cool	2001-01-02

```
[8 rows x 6 columns]

In [17]: df_mixed1.get_dtype_counts()
Out[17]:
datetime64[ns]    1
float64           3
object            2
dtype: int64
```

You can pass columns keyword to select to filter a list of the return columns, this is equivalent to passing a Term('columns', list_of_columns_to_filter)

```
In [18]: store.select('df', columns = ['A', 'B'])
Out[18]:
```

	A	B
2000-01-01	-1.601262	-0.256718
2000-01-02	0.174122	-1.131794
2000-01-03	0.980347	-0.674429
2000-01-04	-0.761218	1.768215
2000-01-05	-0.862613	-0.210968
2000-01-06	1.498195	0.462413
2000-01-07	1.511487	-0.727189
2000-01-08	-0.007364	1.427674

```
[8 rows x 2 columns]
```

HDFStore now serializes multi-index dataframes when appending tables.

```
In [19]: index = MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'],
.....:                             ['one', 'two', 'three']],
```

```

.....:         labels=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
.....:                   [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
.....:         names=['foo', 'bar'])
.....:
In [20]: df = DataFrame(np.random.randn(10, 3), index=index,
.....:                  columns=['A', 'B', 'C'])
.....:

```

```
In [21]: df
```

```

Out[21]:
           A          B          C
foo bar
foo one    2.052171 -1.230963 -0.019240
   two   -1.713238  0.838912 -0.637855
   three  0.215109 -1.515362  1.586924
bar one   -0.447974 -1.573998  0.630925
   two   -0.071659 -1.277640 -0.102206
baz two    0.870302  1.275280 -1.199212
   three  1.060780  1.673018  1.249874
gux one    1.458210 -0.710542  0.825392
   two    1.557329  1.993441 -0.616293
   three  0.150468  0.132104  0.580923

```

```
[10 rows x 3 columns]
```

```
In [22]: store.append('mi', df)
```

```
In [23]: store.select('mi')
```

```

Out[23]:
           A          B          C
foo bar
foo one    2.052171 -1.230963 -0.019240
   two   -1.713238  0.838912 -0.637855
   three  0.215109 -1.515362  1.586924
bar one   -0.447974 -1.573998  0.630925
   two   -0.071659 -1.277640 -0.102206
baz two    0.870302  1.275280 -1.199212
   three  1.060780  1.673018  1.249874
gux one    1.458210 -0.710542  0.825392
   two    1.557329  1.993441 -0.616293
   three  0.150468  0.132104  0.580923

```

```
[10 rows x 3 columns]
```

```
# the levels are automatically included as data columns
```

```
In [24]: store.select('mi', Term('foo=bar'))
```

```

Out[24]:
           A          B          C
foo bar
bar one   -0.447974 -1.573998  0.630925
   two   -0.071659 -1.277640 -0.102206

```

```
[2 rows x 3 columns]
```

Multi-table creation via `append_to_multiple` and selection via `select_as_multiple` can create/select from multiple tables and return a combined result, by using `where` on a selector table.

```
In [25]: df_mt = DataFrame(randn(8, 6), index=date_range('1/1/2000', periods=8),
.....:                    columns=['A', 'B', 'C', 'D', 'E', 'F'])
.....:
```

```
In [26]: df_mt['foo'] = 'bar'
```

```
# you can also create the tables individually
```

```
In [27]: store.append_to_multiple({'df1_mt' : ['A','B'], 'df2_mt' : None }, df_mt, selector = 'df1_mt')
```

```
In [28]: store
```

```
Out[28]:
```

```
<class 'pandas.io.pytables.HDFStore'>
```

```
File path: store.h5
```

```
/df                frame_table    (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,stri
```

```
/df1_mt           frame_table    (typ->appendable,nrows->8,ncols->2,indexers->[index],dc->[A,B])
```

```
/df2_mt           frame_table    (typ->appendable,nrows->8,ncols->5,indexers->[index])
```

```
/df_mixed         frame_table    (typ->appendable,nrows->8,ncols->6,indexers->[index])
```

```
/mi               frame_table    (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[ba
```

```
# individual tables were created
```

```
In [29]: store.select('df1_mt')
```

```
Out[29]:
```

	A	B
2000-01-01	-0.128750	1.445964
2000-01-02	-0.688741	0.228006
2000-01-03	0.932498	-2.200069
2000-01-04	1.298390	1.662964
2000-01-05	-0.462446	-0.112019
2000-01-06	-1.626124	0.982041
2000-01-07	0.942864	2.502156
2000-01-08	0.268766	-1.225092

```
[8 rows x 2 columns]
```

```
In [30]: store.select('df2_mt')
```

```
Out[30]:
```

	C	D	E	F	foo
2000-01-01	-0.431163	0.016640	0.904578	-1.645852	bar
2000-01-02	0.800353	-0.451572	0.831767	0.228760	bar
2000-01-03	1.239198	0.185437	-0.540770	-0.370038	bar
2000-01-04	-0.040863	0.290110	-0.096145	1.717830	bar
2000-01-05	-0.134024	-0.205969	1.348944	-1.198246	bar
2000-01-06	0.059493	-0.460111	-1.565401	-0.025706	bar
2000-01-07	-0.302741	0.261551	-0.066342	0.897097	bar
2000-01-08	0.582752	-1.490764	-0.639757	-0.952750	bar

```
[8 rows x 5 columns]
```

```
# as a multiple
```

```
In [31]: store.select_as_multiple(['df1_mt','df2_mt'], where = [ 'A>0','B>0' ], selector = 'df1_mt')
```

```
Out[31]:
```

	A	B	C	D	E	F	foo
2000-01-04	1.298390	1.662964	-0.040863	0.290110	-0.096145	1.717830	bar
2000-01-07	0.942864	2.502156	-0.302741	0.261551	-0.066342	0.897097	bar

```
[2 rows x 7 columns]
```

Enhancements

- `HDFStore` now can read native PyTables table format tables
- You can pass `nan_rep = 'my_nan_rep'` to `append`, to change the default nan representation on disk (which converts to/from `np.nan`), this defaults to `nan`.
- You can pass `index` to `append`. This defaults to `True`. This will automatically create indices on the *indexables* and *data columns* of the table
- You can pass `chunksize=an integer` to `append`, to change the writing chunksize (default is 50000). This will significantly lower your memory usage on writing.
- You can pass `expectedrows=an integer` to the first `append`, to set the TOTAL number of expected rows that PyTables will expect. This will optimize read/write performance.
- `Select` now supports passing `start` and `stop` to provide selection space limiting in selection.
- Greatly improved ISO8601 (e.g., yyyy-mm-dd) date parsing for file parsers ([GH2698](#))
- Allow `DataFrame.merge` to handle combinatorial sizes too large for 64-bit integer ([GH2690](#))
- `Series` now has unary negation (`-series`) and inversion (`~series`) operators ([GH2686](#))
- `DataFrame.plot` now includes a `logx` parameter to change the x-axis to log scale ([GH2327](#))
- `Series` arithmetic operators can now handle constant and `ndarray` input ([GH2574](#))
- `ExcelFile` now takes a `kind` argument to specify the file type ([GH2613](#))
- A faster implementation for `Series.str` methods ([GH2602](#))

Bug Fixes

- `HDFStore` tables can now store `float32` types correctly (cannot be mixed with `float64` however)
- Fixed Google Analytics prefix when specifying request segment ([GH2713](#)).
- Function to reset Google Analytics token store so users can recover from improperly setup client secrets ([GH2687](#)).
- Fixed `groupby` bug resulting in segfault when passing in `MultiIndex` ([GH2706](#))
- Fixed bug where passing a `Series` with `datetime64` values into `to_datetime` results in bogus output values ([GH2699](#))
- Fixed bug in `pattern` in `HDFStore` expressions when `pattern` is not a valid regex ([GH2694](#))
- Fixed performance issues while aggregating boolean data ([GH2692](#))
- When given a boolean mask key and a `Series` of new values, `Series.__setitem__` will now align the incoming values with the original `Series` ([GH2686](#))
- Fixed `MemoryError` caused by performing counting sort on sorting `MultiIndex` levels with a very large number of combinatorial values ([GH2684](#))
- Fixed bug that causes plotting to fail when the index is a `DatetimeIndex` with a fixed-offset timezone ([GH2683](#))
- Corrected `businessday` subtraction logic when the offset is more than 5 bdays and the starting date is on a weekend ([GH2680](#))
- Fixed C file parser behavior when the file has more columns than data ([GH2668](#))
- Fixed file reader bug that misaligned columns with data in the presence of an implicit column and a specified `usecols` value
- `DataFrames` with numerical or datetime indices are now sorted prior to plotting ([GH2609](#))
- Fixed `DataFrame.from_records` error when passed columns, index, but empty records ([GH2633](#))

- Several bug fixed for Series operations when dtype is datetime64 (GH2689, GH2629, GH2626)

See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.13 v0.10.0 (December 17, 2012)

This is a major release from 0.9.1 and includes many new features and enhancements along with a large number of bug fixes. There are also a number of important API changes that long-time pandas users should pay close attention to.

1.13.1 File parsing new features

The delimited file parsing engine (the guts of `read_csv` and `read_table`) has been rewritten from the ground up and now uses a fraction the amount of memory while parsing, while being 40% or more faster in most use cases (in some cases much faster).

There are also many new features:

- Much-improved Unicode handling via the `encoding` option.
- Column filtering (`usecols`)
- Dtype specification (`dtype` argument)
- Ability to specify strings to be recognized as True/False
- Ability to yield NumPy record arrays (`as_reccarray`)
- High performance `delim_whitespace` option
- Decimal format (e.g. European format) specification
- Easier CSV dialect options: `escapechar`, `lineterminator`, `quotechar`, etc.
- More robust handling of many exceptional kinds of files observed in the wild

1.13.2 API changes

Deprecated DataFrame BINOP TimeSeries special case behavior

The default behavior of binary operations between a DataFrame and a Series has always been to align on the DataFrame's columns and broadcast down the rows, **except** in the special case that the DataFrame contains time series. Since there are now method for each binary operator enabling you to specify how you want to broadcast, we are phasing out this special case (Zen of Python: *Special cases aren't special enough to break the rules*). Here's what I'm talking about:

```
In [1]: import pandas as pd

In [2]: df = pd.DataFrame(np.random.randn(6, 4),
...:                      index=pd.date_range('1/1/2000', periods=6))
...:

In [3]: df
Out[3]:
```

	0	1	2	3
2000-01-01	-0.892402	0.505987	-0.681624	0.850162
2000-01-02	0.586586	1.175843	-0.160391	0.481679
2000-01-03	0.408279	1.641246	0.383888	-1.495227

```
2000-01-04  1.166096 -0.802272 -0.275253  0.517938
2000-01-05 -0.750872  1.216537 -0.910343 -0.606534
2000-01-06 -0.410659  0.264024 -0.069315 -1.814768
```

```
[6 rows x 4 columns]
```

```
# deprecated now
```

```
In [4]: df - df[0]
```

```
Out[4]:
```

```
      0      1      2      3
2000-01-01  0  1.398389  0.210778  1.742564
2000-01-02  0  0.589256 -0.746978 -0.104908
2000-01-03  0  1.232968 -0.024391 -1.903505
2000-01-04  0 -1.968368 -1.441350 -0.648158
2000-01-05  0  1.967410 -0.159471  0.144338
2000-01-06  0  0.674682  0.341344 -1.404109
```

```
[6 rows x 4 columns]
```

```
# Change your code to
```

```
In [5]: df.sub(df[0], axis=0) # align on axis 0 (rows)
```

```
Out[5]:
```

```
      0      1      2      3
2000-01-01  0  1.398389  0.210778  1.742564
2000-01-02  0  0.589256 -0.746978 -0.104908
2000-01-03  0  1.232968 -0.024391 -1.903505
2000-01-04  0 -1.968368 -1.441350 -0.648158
2000-01-05  0  1.967410 -0.159471  0.144338
2000-01-06  0  0.674682  0.341344 -1.404109
```

```
[6 rows x 4 columns]
```

You will get a deprecation warning in the 0.10.x series, and the deprecated functionality will be removed in 0.11 or later.

Altered resample default behavior

The default time series `resample` binning behavior of daily `D` and *higher* frequencies has been changed to `closed='left'`, `label='left'`. Lower frequencies are unaffected. The prior defaults were causing a great deal of confusion for users, especially resampling data to daily frequency (which labeled the aggregated group with the end of the interval: the next day).

Note:

```
In [6]: dates = pd.date_range('1/1/2000', '1/5/2000', freq='4h')
```

```
In [7]: series = Series(np.arange(len(dates)), index=dates)
```

```
In [8]: series
```

```
Out[8]:
```

```
2000-01-01 00:00:00    0
2000-01-01 04:00:00    1
2000-01-01 08:00:00    2
2000-01-01 12:00:00    3
2000-01-01 16:00:00    4
2000-01-01 20:00:00    5
2000-01-02 00:00:00    6
..
2000-01-04 00:00:00   18
```

```
2000-01-04 04:00:00    19
2000-01-04 08:00:00    20
2000-01-04 12:00:00    21
2000-01-04 16:00:00    22
2000-01-04 20:00:00    23
2000-01-05 00:00:00    24
Freq: 4H, dtype: int32
```

```
In [9]: series.resample('D', how='sum')
```

```
Out[9]:
2000-01-01    15
2000-01-02    51
2000-01-03    87
2000-01-04   123
2000-01-05    24
Freq: D, dtype: int32
```

```
# old behavior
```

```
In [10]: series.resample('D', how='sum', closed='right', label='right')
```

```
Out[10]:
2000-01-01     0
2000-01-02    21
2000-01-03    57
2000-01-04    93
2000-01-05   129
Freq: D, dtype: int32
```

- Infinity and negative infinity are no longer treated as NA by `isnull` and `notnull`. That they ever were was a relic of early pandas. This behavior can be re-enabled globally by the `mode.use_inf_as_null` option:

```
In [11]: s = pd.Series([1.5, np.inf, 3.4, -np.inf])
```

```
In [12]: pd.isnull(s)
```

```
Out[12]:
0    False
1    False
2    False
3    False
dtype: bool
```

```
In [13]: s.fillna(0)
```

```
Out[13]:
0    1.500000
1         inf
2    3.400000
3        -inf
dtype: float64
```

```
In [14]: pd.set_option('use_inf_as_null', True)
```

```
In [15]: pd.isnull(s)
```

```
Out[15]:
0    False
1     True
2    False
3     True
dtype: bool
```

```
In [16]: s.fillna(0)
```

```
Out[16]:
```

```
0    1.5
1    0.0
2    3.4
3    0.0
dtype: float64
```

```
In [17]: pd.reset_option('use_inf_as_null')
```

- Methods with the `inplace` option now all return `None` instead of the calling object. E.g. code written like `df = df.fillna(0, inplace=True)` may stop working. To fix, simply delete the unnecessary variable assignment.
- `pandas.merge` no longer sorts the group keys (`sort=False`) by default. This was done for performance reasons: the group-key sorting is often one of the more expensive parts of the computation and is often unnecessary.
- The default column names for a file with no header have been changed to the integers 0 through $N - 1$. This is to create consistency with the `DataFrame` constructor with no columns specified. The v0.9.0 behavior (names `X0, X1, ...`) can be reproduced by specifying `prefix='X'`:

```
In [18]: data= 'a,b,c\n1,Yes,2\n3,No,4'
```

```
In [19]: print(data)
```

```
a,b,c
1,Yes,2
3,No,4
```

```
In [20]: pd.read_csv(StringIO(data), header=None)
```

```
Out[20]:
```

```
   0    1    2
0  a    b    c
1  1  Yes    2
2  3   No    4
```

```
[3 rows x 3 columns]
```

```
In [21]: pd.read_csv(StringIO(data), header=None, prefix='X')
```

```
Out[21]:
```

```
   X0    X1 X2
0  a    b    c
1  1  Yes    2
2  3   No    4
```

```
[3 rows x 3 columns]
```

- Values like `'Yes'` and `'No'` are not interpreted as boolean by default, though this can be controlled by new `true_values` and `false_values` arguments:

```
In [22]: print(data)
```

```
a,b,c
1,Yes,2
3,No,4
```

```
In [23]: pd.read_csv(StringIO(data))
```

```
Out[23]:
```

```
   a    b    c
0  1  Yes    2
```

```
1 3    No 4
```

```
[2 rows x 3 columns]
```

```
In [24]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
```

```
Out[24]:
```

```
   a      b  c
0  1    True  2
1  3   False  4
```

```
[2 rows x 3 columns]
```

- The file parsers will not recognize non-string values arising from a converter function as NA if passed in the `na_values` argument. It's better to do post-processing using the `replace` function instead.
- Calling `fillna` on Series or DataFrame with no arguments is no longer valid code. You must either specify a fill value or an interpolation method:

```
In [25]: s = Series([np.nan, 1., 2., np.nan, 4])
```

```
In [26]: s
```

```
Out[26]:
```

```
0    NaN
1      1
2      2
3    NaN
4      4
dtype: float64
```

```
In [27]: s.fillna(0)
```

```
Out[27]:
```

```
0      0
1      1
2      2
3      0
4      4
dtype: float64
```

```
In [28]: s.fillna(method='pad')
```

```
Out[28]:
```

```
0    NaN
1      1
2      2
3      2
4      4
dtype: float64
```

Convenience methods `ffill` and `bfill` have been added:

```
In [29]: s.fffll()
```

```
Out[29]:
```

```
0    NaN
1      1
2      2
3      2
4      4
dtype: float64
```

- `Series.apply` will now operate on a returned value from the applied function, that is itself a series, and

possibly upcast the result to a DataFrame

```
In [30]: def f(x):
...:     return Series([ x, x**2 ], index = ['x', 'x^2'])
...:
```

```
In [31]: s = Series(np.random.rand(5))
```

```
In [32]: s
Out[32]:
0    0.013135
1    0.909855
2    0.098093
3    0.023540
4    0.141354
dtype: float64
```

```
In [33]: s.apply(f)
Out[33]:
      x      x^2
0  0.013135  0.000173
1  0.909855  0.827836
2  0.098093  0.009622
3  0.023540  0.000554
4  0.141354  0.019981

[5 rows x 2 columns]
```

- New API functions for working with pandas options ([GH2097](#)):

- `get_option` / `set_option` - get/set the value of an option. Partial names are accepted.
- `reset_option` - reset one or more options to their default value. Partial names are accepted.
- `describe_option` - print a description of one or more options. When called with no arguments, print all registered options.

Note: `set_printoptions` / `reset_printoptions` are now deprecated (but functioning), the print options now live under “`display.XYZ`”. For example:

```
In [34]: get_option("display.max_rows")
Out[34]: 15
```

- `to_string()` methods now always return unicode strings ([GH2224](#)).

1.13.3 New features

1.13.4 Wide DataFrame Printing

Instead of printing the summary information, pandas now splits the string representation across multiple rows by default:

```
In [35]: wide_frame = DataFrame(randn(5, 16))

In [36]: wide_frame
Out[36]:
      0      1      2      3      4      5      6  \
0  2.520045  1.570114 -0.360875 -0.880096  0.235532  0.207232 -1.983857
1  0.422194  0.288403 -0.487393 -0.777639  0.055865  1.383381  0.085638
2  0.585174 -0.568825 -0.719412  1.191340 -0.456362  0.089931  0.776079
```

```
3  1.218080 -0.564705 -0.581790  0.286071  0.048725  1.002440  1.276582
4 -0.376280  0.511936 -0.116412 -0.625256 -0.550627  1.261433 -0.552429

      7      8      9      10      11      12      13  \
0 -1.702547 -1.621234 -0.906840  1.014601 -0.475108 -0.358944  1.262942
1  0.246392  0.965887  0.246354 -0.727728 -0.094414 -0.276854  0.158399
2  0.752889 -1.195795 -1.425911 -0.548829  0.774225  0.740501  1.510263
3  0.054399  0.241963 -0.471786  0.314510 -0.059986 -2.069319 -1.115104
4  1.695803 -1.025917 -0.910942  0.426805 -0.131749  0.432600  0.044671

      14      15
0 -0.412451 -0.462580
1 -0.277255  1.331263
2 -1.642511  0.432560
3 -0.369325 -1.502617
4 -0.341265  1.844536

[5 rows x 16 columns]
```

The old behavior of printing out summary information can be achieved via the ‘expand_frame_repr’ print option:

```
In [37]: pd.set_option('expand_frame_repr', False)
```

```
In [38]: wide_frame
```

```
Out[38]:
```

```
      0      1      2      3      4      5      6      7      8      9
0  2.520045  1.570114 -0.360875 -0.880096  0.235532  0.207232 -1.983857 -1.702547 -1.621234 -0.906840
1  0.422194  0.288403 -0.487393 -0.777639  0.055865  1.383381  0.085638  0.246392  0.965887  0.246354
2  0.585174 -0.568825 -0.719412  1.191340 -0.456362  0.089931  0.776079  0.752889 -1.195795 -1.425911
3  1.218080 -0.564705 -0.581790  0.286071  0.048725  1.002440  1.276582  0.054399  0.241963 -0.471786
4 -0.376280  0.511936 -0.116412 -0.625256 -0.550627  1.261433 -0.552429  1.695803 -1.025917 -0.910942

[5 rows x 16 columns]
```

The width of each line can be changed via ‘line_width’ (80 by default):

```
In [39]: pd.set_option('line_width', 40)
```

line_width has been deprecated, use display.width instead (currently both are identical)

```
In [40]: wide_frame
```

```
Out[40]:
```

```
      0      1      2  \
0  2.520045  1.570114 -0.360875
1  0.422194  0.288403 -0.487393
2  0.585174 -0.568825 -0.719412
3  1.218080 -0.564705 -0.581790
4 -0.376280  0.511936 -0.116412

      3      4      5  \
0 -0.880096  0.235532  0.207232
1 -0.777639  0.055865  1.383381
2  1.191340 -0.456362  0.089931
3  0.286071  0.048725  1.002440
4 -0.625256 -0.550627  1.261433

      6      7      8  \
0 -1.983857 -1.702547 -1.621234
```

```

1  0.085638  0.246392  0.965887
2  0.776079  0.752889 -1.195795
3  1.276582  0.054399  0.241963
4 -0.552429  1.695803 -1.025917

      9      10      11  \
0 -0.906840  1.014601 -0.475108
1  0.246354 -0.727728 -0.094414
2 -1.425911 -0.548829  0.774225
3 -0.471786  0.314510 -0.059986
4 -0.910942  0.426805 -0.131749

      12      13      14  \
0 -0.358944  1.262942 -0.412451
1 -0.276854  0.158399 -0.277255
2  0.740501  1.510263 -1.642511
3 -2.069319 -1.115104 -0.369325
4  0.432600  0.044671 -0.341265

      15
0 -0.462580
1  1.331263
2  0.432560
3 -1.502617
4  1.844536

[5 rows x 16 columns]
```

1.13.5 Updated PyTables Support

Docs for PyTables Table format & several enhancements to the api. Here is a taste of what to expect.

```
In [41]: store = HDFStore('store.h5')
```

```
In [42]: df = DataFrame(randn(8, 3), index=date_range('1/1/2000', periods=8),
.....:                  columns=['A', 'B', 'C'])
.....:
```

```
In [43]: df
```

```
Out[43]:
```

	A	B	C
2000-01-01	-2.036047	0.000830	-0.955697
2000-01-02	-0.898872	-0.725411	0.059904
2000-01-03	-0.449644	1.082900	-1.221265
2000-01-04	0.361078	1.330704	0.855932
2000-01-05	-1.216718	1.488887	0.018993
2000-01-06	-0.877046	0.045976	0.437274
2000-01-07	-0.567182	-0.888657	-0.556383
2000-01-08	0.655457	1.117949	-2.782376

```
[8 rows x 3 columns]
```

```
# appending data frames
```

```
In [44]: df1 = df[0:4]
```

```
In [45]: df2 = df[4:]
```

```
In [46]: store.append('df', df1)

In [47]: store.append('df', df2)

In [48]: store
Out[48]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                frame_table   (typ->appendable,nrows->8,ncols->3,indexers->[index])

# selecting the entire store
In [49]: store.select('df')
Out[49]:
```

	A	B	C
2000-01-01	-2.036047	0.000830	-0.955697
2000-01-02	-0.898872	-0.725411	0.059904
2000-01-03	-0.449644	1.082900	-1.221265
2000-01-04	0.361078	1.330704	0.855932
2000-01-05	-1.216718	1.488887	0.018993
2000-01-06	-0.877046	0.045976	0.437274
2000-01-07	-0.567182	-0.888657	-0.556383
2000-01-08	0.655457	1.117949	-2.782376

```

[8 rows x 3 columns]

In [50]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
....:               major_axis=date_range('1/1/2000', periods=5),
....:               minor_axis=['A', 'B', 'C', 'D'])
....:

In [51]: wp
Out[51]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

# storing a panel
In [52]: store.append('wp', wp)

# selecting via A QUERY
In [53]: store.select('wp',
....:   [ Term('major_axis>20000102'), Term('minor_axis', '=', ['A','B']) ])
....:
Out[53]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to B

# removing data from tables
In [54]: store.remove('wp', Term('major_axis>20000103'))
Out[54]: 8

In [55]: store.select('wp')
Out[55]:
```

```
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to D

# deleting a store
In [56]: del store['df']

In [57]: store
Out[57]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/wp                wide_table    (typ->appendable,nrows->12,ncols->2,indexers->[major_axis,minor_axis])
```

Enhancements

- added ability to hierarchical keys

```
In [58]: store.put('foo/bar/bah', df)

In [59]: store.append('food/orange', df)

In [60]: store.append('food/apple', df)

In [61]: store
Out[61]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah      frame          (shape->[8,3])
/food/apple       frame_table    (typ->appendable,nrows->8,ncols->3,indexers->[index])
/food/orange      frame_table    (typ->appendable,nrows->8,ncols->3,indexers->[index])
/wp              wide_table     (typ->appendable,nrows->12,ncols->2,indexers->[major_ax

# remove all nodes under this level
In [62]: store.remove('food')

In [63]: store
Out[63]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/foo/bar/bah      frame          (shape->[8,3])
/wp              wide_table     (typ->appendable,nrows->12,ncols->2,indexers->[major_ax
```

- added mixed-dtype support!

```
In [64]: df['string'] = 'string'

In [65]: df['int']    = 1

In [66]: store.append('df',df)

In [67]: df1 = store.select('df')

In [68]: df1
Out[68]:
```

	A	B	C	string	int
2000-01-01	-2.036047	0.000830	-0.955697	string	1
2000-01-02	-0.898872	-0.725411	0.059904	string	1

```
2000-01-03 -0.449644  1.082900 -1.221265  string    1
2000-01-04  0.361078  1.330704  0.855932  string    1
2000-01-05 -1.216718  1.488887  0.018993  string    1
2000-01-06 -0.877046  0.045976  0.437274  string    1
2000-01-07 -0.567182 -0.888657 -0.556383  string    1
2000-01-08  0.655457  1.117949 -2.782376  string    1
```

```
[8 rows x 5 columns]
```

```
In [69]: df1.get_dtype_counts()
```

```
Out [69]:
```

```
float64    3
```

```
int64       1
```

```
object      1
```

```
dtype: int64
```

- performance improvements on table writing
- support for arbitrarily indexed dimensions
- `SparseSeries` now has a `density` property ([GH2384](#))
- enable `Series.str.strip/lstrip/rstrip` methods to take an input argument to strip arbitrary characters ([GH2411](#))
- implement `value_vars` in `melt` to limit values to certain columns and add `melt` to pandas namespace ([GH2412](#))

Bug Fixes

- added `Term` method of specifying where conditions ([GH1996](#)).
- `del store['df']` now call `store.remove('df')` for store deletion
- deleting of consecutive rows is much faster than before
- `min_itemsize` parameter can be specified in table creation to force a minimum size for indexing columns (the previous implementation would set the column size based on the first append)
- indexing support via `create_table_index` (requires `PyTables >= 2.3`) ([GH698](#)).
- appending on a store would fail if the table was not first created via `put`
- fixed issue with missing attributes after loading a pickled dataframe ([GH2431](#))
- minor change to `select` and `remove`: require a table **ONLY** if `where` is also provided (and not `None`)

Compatibility

0.10 of `HDFStore` is backwards compatible for reading tables created in a prior version of pandas, however, query terms using the prior (undocumented) methodology are unsupported. You must read in the entire file and write it out using the new format to take advantage of the updates.

1.13.6 N Dimensional Panels (Experimental)

Adding experimental support for `Panel4D` and factory functions to create n-dimensional named panels. [Docs](#) for `NDim`. Here is a taste of what to expect.

```
In [70]: p4d = Panel4D(randn(2, 2, 5, 4),
.....:                 labels=['Label1', 'Label2'],
.....:                 items=['Item1', 'Item2'],
.....:                 major_axis=date_range('1/1/2000', periods=5),
```

```

.....:         minor_axis=['A', 'B', 'C', 'D'])
.....:

In [71]: p4d
Out[71]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

```

See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.14 v0.9.1 (November 14, 2012)

This is a bugfix release from 0.9.0 and includes several new features and enhancements along with a large number of bug fixes. The new features include by-column sort order for DataFrame and Series, improved NA handling for the rank method, masking functions for DataFrame, and intraday time-series filtering for DataFrame.

1.14.1 New features

- *Series.sort*, *DataFrame.sort*, and *DataFrame.sort_index* can now be specified in a per-column manner to support multiple sort orders ([GH928](#))

```
In [1]: df = DataFrame(np.random.randint(0, 2, (6, 3)), columns=['A', 'B', 'C'])
```

```
In [2]: df.sort(['A', 'B'], ascending=[1, 0])
```

```
Out[2]:
   A  B  C
2  0  1  1
3  0  1  1
4  0  0  1
0  1  1  0
1  1  0  1
5  1  0  1
```

```
[6 rows x 3 columns]
```

- *DataFrame.rank* now supports additional argument values for the *na_option* parameter so missing values can be assigned either the largest or the smallest rank ([GH1508](#), [GH2159](#))

```
In [3]: df = DataFrame(np.random.randn(6, 3), columns=['A', 'B', 'C'])
```

```
In [4]: df.ix[2:4] = np.nan
```

```
In [5]: df.rank()
```

```
Out[5]:
   A  B  C
0   3  2  1
1   2  1  3
2 NaN NaN NaN
3 NaN NaN NaN
4 NaN NaN NaN
5   1  3  2
```

```
[6 rows x 3 columns]
```

```
In [6]: df.rank(na_option='top')
```

```
Out[6]:
```

	A	B	C
0	6	5	4
1	5	4	6
2	2	2	2
3	2	2	2
4	2	2	2
5	4	6	5

```
[6 rows x 3 columns]
```

```
In [7]: df.rank(na_option='bottom')
```

```
Out[7]:
```

	A	B	C
0	3	2	1
1	2	1	3
2	5	5	5
3	5	5	5
4	5	5	5
5	1	3	2

```
[6 rows x 3 columns]
```

- DataFrame has new *where* and *mask* methods to select values according to a given boolean mask ([GH2109](#), [GH2151](#))

DataFrame currently supports slicing via a boolean vector the same length as the DataFrame (inside the *[]*). The returned DataFrame has the same number of columns as the original, but is sliced on its index.

```
In [8]: df = DataFrame(np.random.randn(5, 3), columns = ['A', 'B', 'C'])
```

```
In [9]: df
```

```
Out[9]:
```

	A	B	C
0	0.706220	-1.130744	-0.690308
1	-0.885387	0.246004	1.986687
2	0.212595	-1.189832	-0.344258
3	0.816335	-1.514102	1.298184
4	0.089527	0.576687	-0.737750

```
[5 rows x 3 columns]
```

```
In [10]: df[df['A'] > 0]
```

```
Out[10]:
```

	A	B	C
0	0.706220	-1.130744	-0.690308
2	0.212595	-1.189832	-0.344258
3	0.816335	-1.514102	1.298184
4	0.089527	0.576687	-0.737750

```
[4 rows x 3 columns]
```

If a DataFrame is sliced with a DataFrame based boolean condition (with the same size as the original DataFrame), then a DataFrame the same size (index and columns) as the original is returned, with

elements that do not meet the boolean condition as *NaN*. This is accomplished via the new method *DataFrame.where*. In addition, *where* takes an optional *other* argument for replacement.

```
In [11]: df[df>0]
Out[11]:
```

	A	B	C
0	0.706220	NaN	NaN
1	NaN	0.246004	1.986687
2	0.212595	NaN	NaN
3	0.816335	NaN	1.298184
4	0.089527	0.576687	NaN

[5 rows x 3 columns]

```
In [12]: df.where(df>0)
Out[12]:
```

	A	B	C
0	0.706220	NaN	NaN
1	NaN	0.246004	1.986687
2	0.212595	NaN	NaN
3	0.816335	NaN	1.298184
4	0.089527	0.576687	NaN

[5 rows x 3 columns]

```
In [13]: df.where(df>0,-df)
Out[13]:
```

	A	B	C
0	0.706220	1.130744	0.690308
1	0.885387	0.246004	1.986687
2	0.212595	1.189832	0.344258
3	0.816335	1.514102	1.298184
4	0.089527	0.576687	0.737750

[5 rows x 3 columns]

Furthermore, *where* now aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via *.ix* (but on the contents rather than the axis labels)

```
In [14]: df2 = df.copy()

In [15]: df2[ df2[1:4] > 0 ] = 3

In [16]: df2
Out[16]:
```

	A	B	C
0	0.706220	-1.130744	-0.690308
1	-0.885387	3.000000	3.000000
2	3.000000	-1.189832	-0.344258
3	3.000000	-1.514102	3.000000
4	0.089527	0.576687	-0.737750

[5 rows x 3 columns]

DataFrame.mask is the inverse boolean operation of *where*.

```
In [17]: df.mask(df<=0)
Out[17]:
```

```
      A      B      C
0  0.706220  NaN  NaN
1      NaN  0.246004  1.986687
2  0.212595  NaN  NaN
3  0.816335  NaN  1.298184
4  0.089527  0.576687  NaN
```

```
[5 rows x 3 columns]
```

- Enable referencing of Excel columns by their column names ([GH1936](#))

```
In [18]: xl = ExcelFile('data/test.xls')
```

```
In [19]: xl.parse('Sheet1', index_col=0, parse_dates=True,
....:             parse_cols='A:D')
```

```
Out [19]:
```

```
      A      B      C
2000-01-03  0.980269  3.685731 -0.364217
2000-01-04  1.047916 -0.041232 -0.161812
2000-01-05  0.498581  0.731168 -0.537677
2000-01-06  1.120202  1.567621  0.003641
2000-01-07 -0.487094  0.571455 -1.611639
2000-01-10  0.836649  0.246462  0.588543
2000-01-11 -0.157161  1.340307  1.195778
```

```
[7 rows x 3 columns]
```

- Added option to disable pandas-style tick locators and formatters using `series.plot(x_compat=True)` or `pandas.plot_params['x_compat'] = True` ([GH2205](#))
- Existing TimeSeries methods `at_time` and `between_time` were added to DataFrame ([GH2149](#))
- DataFrame.dot can now accept ndarrays ([GH2042](#))
- DataFrame.drop now supports non-unique indexes ([GH2101](#))
- Panel.shift now supports negative periods ([GH2164](#))
- DataFrame now support unary `~` operator ([GH2110](#))

1.14.2 API changes

- Upsampling data with a PeriodIndex will result in a higher frequency TimeSeries that spans the original time window

```
In [20]: prng = period_range('2012Q1', periods=2, freq='Q')
```

```
In [21]: s = Series(np.random.randn(len(prng)), prng)
```

```
In [22]: s.resample('M')
```

```
Out [22]:
```

```
2012-01    0.194513
2012-02         NaN
2012-03         NaN
2012-04   -0.854246
2012-05         NaN
2012-06         NaN
Freq: M, dtype: float64
```

- `Period.end_time` now returns the last nanosecond in the time interval (GH2124, GH2125, GH1764)

```
In [23]: p = Period('2012')
```

```
In [24]: p.end_time
```

```
Out[24]: Timestamp('2012-12-31 23:59:59.999999999')
```

- File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)

```
In [25]: data = 'A,B,C\n00001,001,5\n00002,002,6'
```

```
In [26]: read_csv(StringIO(data), converters={'A' : lambda x: x.strip()})
```

```
Out[26]:
```

```
      A  B  C
0  00001  1  5
1  00002  2  6
```

```
[2 rows x 3 columns]
```

See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.15 v0.9.0 (October 7, 2012)

This is a major release from 0.8.1 and includes several new features and enhancements along with a large number of bug fixes. New features include vectorized unicode encoding/decoding for `Series.str`, `to_latex` method to `DataFrame`, more flexible parsing of boolean values, and enabling the download of options data from Yahoo! Finance.

1.15.1 New features

- Add `encode` and `decode` for unicode handling to *vectorized string processing methods* in `Series.str` (GH1706)
- Add `DataFrame.to_latex` method (GH1735)
- Add convenient expanding window equivalents of all `rolling_*` ops (GH1785)
- Add `Options` class to `pandas.io.data` for fetching options data from Yahoo! Finance (GH1748, GH1739)
- More flexible parsing of boolean values (Yes, No, TRUE, FALSE, etc) (GH1691, GH1295)
- Add `level` parameter to `Series.reset_index`
- `TimeSeries.between_time` can now select times across midnight (GH1871)
- `Series` constructor can now handle generator as input (GH1679)
- `DataFrame.dropna` can now take multiple axes (tuple/list) as input (GH924)
- Enable `skip_footer` parameter in `ExcelFile.parse` (GH1843)

1.15.2 API changes

- The default column names when `header=None` and no columns names passed to functions like `read_csv` has changed to be more Pythonic and amenable to attribute access:

```
In [1]: data = '0,0,1\n1,1,0\n0,1,0'
```

```
In [2]: df = read_csv(StringIO(data), header=None)
```

```
In [3]: df
```

```
Out[3]:
```

```
   0  1  2
0  0  0  1
1  1  1  0
2  0  1  0
```

```
[3 rows x 3 columns]
```

- Creating a Series from another Series, passing an index, will cause reindexing to happen inside rather than treating the Series like an ndarray. Technically improper usages like `Series(df[col1], index=df[col2])` that worked before “by accident” (this was never intended) will lead to all NA Series in some cases. To be perfectly clear:

```
In [4]: s1 = Series([1, 2, 3])
```

```
In [5]: s1
```

```
Out[5]:
```

```
0    1
1    2
2    3
dtype: int64
```

```
In [6]: s2 = Series(s1, index=['foo', 'bar', 'baz'])
```

```
In [7]: s2
```

```
Out[7]:
```

```
foo    NaN
bar    NaN
baz    NaN
dtype: float64
```

- Deprecated `day_of_year` API removed from `PeriodIndex`, use `dayofyear` ([GH1723](#))
- Don’t modify NumPy suppress printoption to True at import time
- The internal HDF5 data arrangement for DataFrames has been transposed. Legacy files will still be readable by `HDFStore` ([GH1834](#), [GH1824](#))
- Legacy cruft removed: `pandas.stats.misc.quantileTS`
- Use ISO8601 format for Period repr: monthly, daily, and on down ([GH1776](#))
- Empty DataFrame columns are now created as object dtype. This will prevent a class of `TypeError`s that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) ([GH1783](#))
- Setting parts of DataFrame/Panel using `ix` now aligns input Series/DataFrame ([GH1630](#))
- `first` and `last` methods in `GroupBy` no longer drop non-numeric columns ([GH1809](#))
- Resolved inconsistencies in specifying custom NA values in text parser. `na_values` of type dict no longer override default NAs unless `keep_default_na` is set to false explicitly ([GH1657](#))
- `DataFrame.dot` will not do data alignment, and also work with Series ([GH1915](#))

See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.16 v0.8.1 (July 22, 2012)

This release includes a few new features, performance enhancements, and over 30 bug fixes from 0.8.0. New features include notably NA friendly string processing functionality and a series of new plot types and options.

1.16.1 New features

- Add *vectorized string processing methods* accessible via `Series.str` (GH620)
- Add option to disable adjustment in EWMA (GH1584)
- *Radviz plot* (GH1566)
- *Parallel coordinates plot*
- *Bootstrap plot*
- Per column styles and secondary y-axis plotting (GH1559)
- New datetime converters millisecond plotting (GH1599)
- Add option to disable “sparse” display of hierarchical indexes (GH1538)
- `Series/DataFrame`’s `set_index` method can *append levels* to an existing `Index/MultiIndex` (GH1569, GH1577)

1.16.2 Performance improvements

- Improved implementation of rolling min and max (thanks to [Bottleneck](#) !)
- Add accelerated ‘median’ `GroupBy` option (GH1358)
- Significantly improve the performance of parsing ISO8601-format date strings with `DatetimeIndex` or `to_datetime` (GH1571)
- Improve the performance of `GroupBy` on single-key aggregations and use with Categorical types
- Significant datetime parsing performance improvements

1.17 v0.8.0 (June 29, 2012)

This is a major release from 0.7.3 and includes extensive work on the time series handling and processing infrastructure as well as a great deal of new functionality throughout the library. It includes over 700 commits from more than 20 distinct authors. Most pandas 0.7.3 and earlier users should not experience any issues upgrading, but due to the migration to the NumPy `datetime64` dtype, there may be a number of bugs and incompatibilities lurking. Lingering incompatibilities will be fixed ASAP in a 0.8.1 release if necessary. See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.17.1 Support for non-unique indexes

All objects can now work with non-unique indexes. Data alignment / join operations work according to SQL join semantics (including, if application, index duplication in many-to-many joins)

1.17.2 NumPy datetime64 dtype and 1.6 dependency

Time series data are now represented using NumPy's datetime64 dtype; thus, pandas 0.8.0 now requires at least NumPy 1.6. It has been tested and verified to work with the development version (1.7+) of NumPy as well which includes some significant user-facing API changes. NumPy 1.6 also has a number of bugs having to do with nanosecond resolution data, so I recommend that you steer clear of NumPy 1.6's datetime64 API functions (though limited as they are) and only interact with this data using the interface that pandas provides.

See the end of the 0.8.0 section for a “porting” guide listing potential issues for users migrating legacy codebases from pandas 0.7 or earlier to 0.8.0.

Bug fixes to the 0.7.x series for legacy NumPy < 1.6 users will be provided as they arise. There will be no more further development in 0.7.x beyond bug fixes.

1.17.3 Time series changes and improvements

Note: With this release, legacy scikits.timeseries users should be able to port their code to use pandas.

Note: See [documentation](#) for overview of pandas timeseries API.

- New datetime64 representation **speeds up join operations and data alignment, reduces memory usage**, and improve serialization / deserialization performance significantly over datetime.datetime
- High performance and flexible **resample** method for converting from high-to-low and low-to-high frequency. Supports interpolation, user-defined aggregation functions, and control over how the intervals and result labeling are defined. A suite of high performance Cython/C-based resampling functions (including Open-High-Low-Close) have also been implemented.
- Revamp of *frequency aliases* and support for **frequency shortcuts** like ‘15min’, or ‘1h30min’
- New *DatetimeIndex class* supports both fixed frequency and irregular time series. Replaces now deprecated DateRange class
- New PeriodIndex and Period classes for representing *time spans* and performing **calendar logic**, including the *12 fiscal quarterly frequencies* <timeseries.quarterly>. This is a partial port of, and a substantial enhancement to, elements of the scikits.timeseries codebase. Support for conversion between PeriodIndex and DatetimeIndex
- New Timestamp data type subclasses *datetime.datetime*, providing the same interface while enabling working with nanosecond-resolution data. Also provides *easy time zone conversions*.
- Enhanced support for *time zones*. Add *tz_convert* and *tz_localize* methods to TimeSeries and DataFrame. All timestamps are stored as UTC; Timestamps from DatetimeIndex objects with time zone set will be localized to localtime. Time zone conversions are therefore essentially free. User needs to know very little about pytz library now; only time zone names as strings are required. Time zone-aware timestamps are equal if and only if their UTC timestamps match. Operations between time zone-aware time series with different time zones will result in a UTC-indexed time series.
- Time series **string indexing conveniences** / shortcuts: slice years, year and month, and index values with strings
- Enhanced time series **plotting**; adaptation of scikits.timeseries matplotlib-based plotting code
- New *date_range*, *bdate_range*, and *period_range* *factory functions*
- Robust **frequency inference** function *infer_freq* and *inferred_freq* property of DatetimeIndex, with option to infer frequency on construction of DatetimeIndex

- `to_datetime` function efficiently **parses array of strings** to `DatetimeIndex`. `DatetimeIndex` will parse array or list of strings to `datetime64`
- **Optimized** support for `datetime64-dtype` data in `Series` and `DataFrame` columns
- New `NaT` (Not-a-Time) type to represent **NA** in timestamp arrays
- Optimize `Series.asof` for looking up “**as of**” **values** for arrays of timestamps
- Milli, Micro, Nano date offset objects
- Can index time series with `datetime.time` objects to select all data at particular **time of day** (`TimeSeries.at_time`) or **between two times** (`TimeSeries.between_time`)
- Add *tshift* method for leading/lagging using the frequency (if any) of the index, as opposed to a naive lead/lag using `shift`

1.17.4 Other new features

- New *cut* and *qcut* functions (like R’s `cut` function) for computing a categorical variable from a continuous variable by binning values either into value-based (*cut*) or quantile-based (*qcut*) bins
- Rename `Factor` to `Categorical` and add a number of usability features
- Add *limit* argument to `fillna/reindex`
- More flexible multiple function application in `GroupBy`, and can pass list (name, function) tuples to get result in particular order with given names
- Add flexible *replace* method for efficiently substituting values
- Enhanced *read_csv/read_table* for reading time series data and converting multiple columns to dates
- Add *comments* option to parser functions: `read_csv`, etc.
- Add `:ref:dayfirst<io.dayfirst>` option to parser functions for parsing international DD/MM/YYYY dates
- Allow the user to specify the CSV reader *dialect* to control quoting etc.
- Handling *thousands* separators in `read_csv` to improve integer parsing.
- Enable unstacking of multiple levels in one shot. Alleviate `pivot_table` bugs (empty columns being introduced)
- Move to `klib`-based hash tables for indexing; better performance and less memory usage than Python’s `dict`
- Add `first`, `last`, `min`, `max`, and `prod` optimized `GroupBy` functions
- New *ordered_merge* function
- Add flexible *comparison* instance methods `eq`, `ne`, `lt`, `gt`, etc. to `DataFrame`, `Series`
- Improve *scatter_matrix* plotting function and add histogram or kernel density estimates to diagonal
- Add *‘kde’* plot option for density plots
- Support for converting `DataFrame` to R `data.frame` through `rpy2`
- Improved support for complex numbers in `Series` and `DataFrame`
- Add *pct_change* method to all data structures
- Add `max_colwidth` configuration option for `DataFrame` console output
- *Interpolate* `Series` values using index values
- Can select multiple columns from `GroupBy`

- Add *update* methods to Series/DataFrame for updating values in place
- Add *any* and *all* method to DataFrame

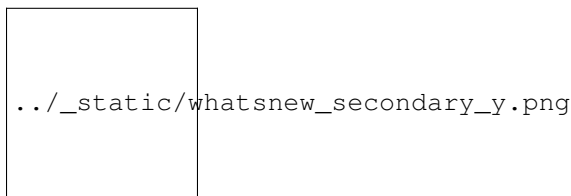
1.17.5 New plotting methods

Series.plot now supports a *secondary_y* option:

```
In [1]: plt.figure()
Out[1]: <matplotlib.figure.Figure at 0xa9d5624c>

In [2]: fx['FR'].plot(style='g')
Out[2]: <matplotlib.axes._subplots.AxesSubplot at 0xa9dbccac>

In [3]: fx['IT'].plot(style='k--', secondary_y=True)
Out[3]: <matplotlib.axes._subplots.AxesSubplot at 0xa9d5652c>
```



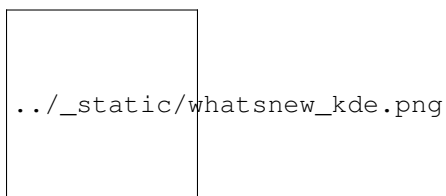
Vytautas Jancauskas, the 2012 GSOC participant, has added many new plot types. For example, 'kde' is a new option:

```
In [4]: s = Series(np.concatenate((np.random.randn(1000),
...:                               np.random.randn(1000) * 0.5 + 3)))
...:
...:

In [5]: plt.figure()
Out[5]: <matplotlib.figure.Figure at 0xa325128c>

In [6]: s.hist(normed=True, alpha=0.2)
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0xa9d78ecc>

In [7]: s.plot(kind='kde')
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0xa9d78ecc>
```



See [the plotting page](#) for much more.

1.17.6 Other API changes

- Deprecation of *offset*, *time_rule*, and *timeRule* arguments names in time series functions. Warnings will be printed until pandas 0.9 or 1.0.

1.17.7 Potential porting issues for pandas <= 0.7.3 users

The major change that may affect you in pandas 0.8.0 is that time series indexes use NumPy's `datetime64` data type instead of `dtype=object` arrays of Python's built-in `datetime.datetime` objects. `DateRange` has been replaced by `DatetimeIndex` but otherwise behaved identically. But, if you have code that converts `DateRange` or `Index` objects that used to contain `datetime.datetime` values to plain NumPy arrays, you may have bugs lurking with code using scalar values because you are handing control over to NumPy:

```
In [8]: import datetime

In [9]: rng = date_range('1/1/2000', periods=10)

In [10]: rng[5]
Out[10]: Timestamp('2000-01-06 00:00:00', offset='D')

In [11]: isinstance(rng[5], datetime.datetime)
Out[11]: True

In [12]: rng_asarray = np.asarray(rng)

In [13]: scalar_val = rng_asarray[5]

In [14]: type(scalar_val)
Out[14]: numpy.datetime64
```

pandas's `Timestamp` object is a subclass of `datetime.datetime` that has nanosecond support (the nanosecond field store the nanosecond value between 0 and 999). It should substitute directly into any code that used `datetime.datetime` values before. Thus, I recommend not casting `DatetimeIndex` to regular NumPy arrays.

If you have code that requires an array of `datetime.datetime` objects, you have a couple of options. First, the `asobject` property of `DatetimeIndex` produces an array of `Timestamp` objects:

```
In [15]: stamp_array = rng.asobject

In [16]: stamp_array
Out[16]:
Index([2000-01-01 00:00:00, 2000-01-02 00:00:00, 2000-01-03 00:00:00,
       2000-01-04 00:00:00, 2000-01-05 00:00:00, 2000-01-06 00:00:00,
       2000-01-07 00:00:00, 2000-01-08 00:00:00, 2000-01-09 00:00:00,
       2000-01-10 00:00:00],
      dtype='object')

In [17]: stamp_array[5]
Out[17]: Timestamp('2000-01-06 00:00:00', offset='D')
```

To get an array of proper `datetime.datetime` objects, use the `to_pydatetime` method:

```
In [18]: dt_array = rng.to_pydatetime()

In [19]: dt_array
Out[19]:
array([datetime.datetime(2000, 1, 1, 0, 0),
       datetime.datetime(2000, 1, 2, 0, 0),
       datetime.datetime(2000, 1, 3, 0, 0),
       datetime.datetime(2000, 1, 4, 0, 0),
       datetime.datetime(2000, 1, 5, 0, 0),
       datetime.datetime(2000, 1, 6, 0, 0),
       datetime.datetime(2000, 1, 7, 0, 0),
```

```
datetime.datetime(2000, 1, 8, 0, 0),
datetime.datetime(2000, 1, 9, 0, 0),
datetime.datetime(2000, 1, 10, 0, 0)], dtype=object)
```

```
In [20]: dt_array[5]
```

```
Out[20]: datetime.datetime(2000, 1, 6, 0, 0)
```

matplotlib knows how to handle `datetime.datetime` but not `Timestamp` objects. While I recommend that you plot time series using `TimeSeries.plot`, you can either use `to_pydatetime` or register a converter for the `Timestamp` type. See [matplotlib documentation](#) for more on this.

Warning: There are bugs in the user-facing API with the nanosecond `datetime64` unit in NumPy 1.6. In particular, the string version of the array shows garbage values, and conversion to `dtype=object` is similarly broken.

```
In [21]: rng = date_range('1/1/2000', periods=10)
```

```
In [22]: rng
```

```
Out[22]:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
              '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
              '2000-01-09', '2000-01-10'],
              dtype='datetime64[ns]', freq='D', tz=None)
```

```
In [23]: np.asarray(rng)
```

```
Out[23]:
array(['2000-01-01T01:00:00.000000000+0100',
       '2000-01-02T01:00:00.000000000+0100',
       '2000-01-03T01:00:00.000000000+0100',
       '2000-01-04T01:00:00.000000000+0100',
       '2000-01-05T01:00:00.000000000+0100',
       '2000-01-06T01:00:00.000000000+0100',
       '2000-01-07T01:00:00.000000000+0100',
       '2000-01-08T01:00:00.000000000+0100',
       '2000-01-09T01:00:00.000000000+0100',
       '2000-01-10T01:00:00.000000000+0100'], dtype='datetime64[ns]')
```

```
In [24]: converted = np.asarray(rng, dtype=object)
```

```
In [25]: converted[5]
```

```
Out[25]: 947116800000000000L
```

Trust me: don't panic. If you are using NumPy 1.6 and restrict your interaction with `datetime64` values to pandas's API you will be just fine. There is nothing wrong with the data-type (a 64-bit integer internally); all of the important data processing happens in pandas and is heavily tested. I strongly recommend that you **do not work directly with `datetime64` arrays in NumPy 1.6** and only use the pandas API.

Support for non-unique indexes: In the latter case, you may have code inside a `try:... catch:` block that failed due to the index not being unique. In many cases it will no longer fail (some method like `append` still check for uniqueness unless disabled). However, all is not lost: you can inspect `index.is_unique` and raise an exception explicitly if it is `False` or go to a different code branch.

1.18 v.0.7.3 (April 12, 2012)

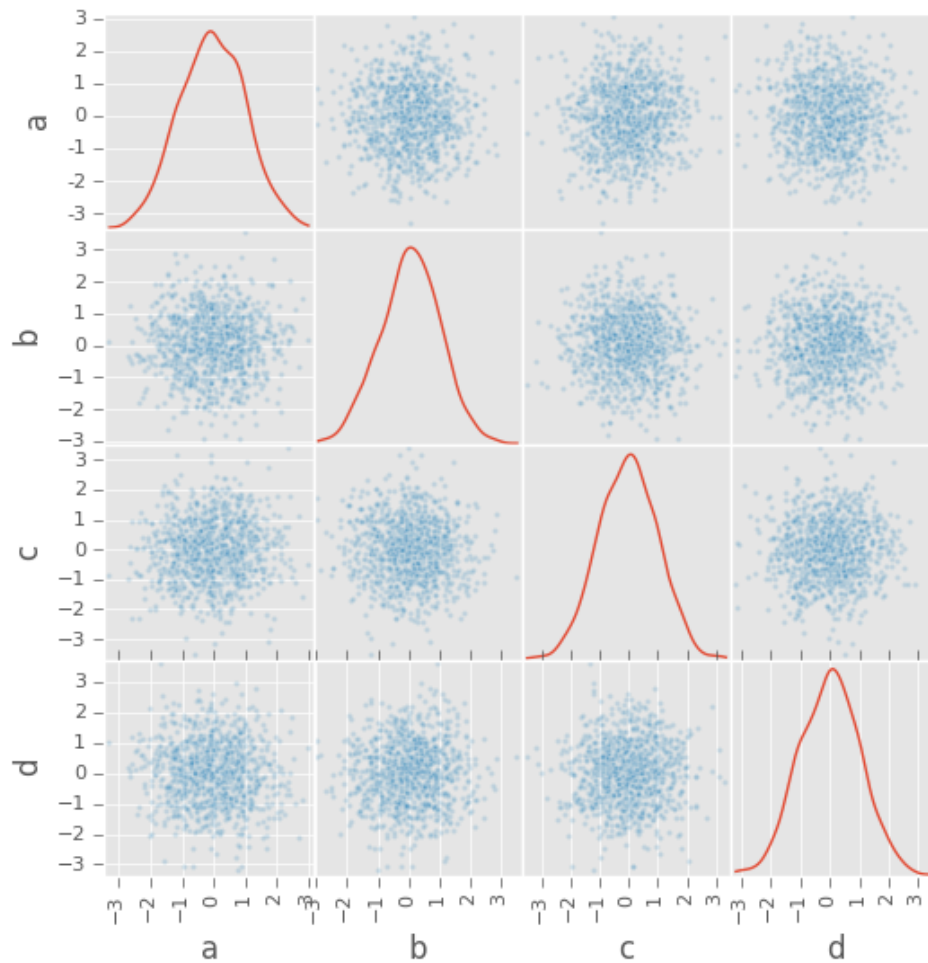
This is a minor release from 0.7.2 and fixes many minor bugs and adds a number of nice new features. There are also a couple of API changes to note; these should not affect very many users, and we are inclined to call them “bug

fixes” even though they do constitute a change in behavior. See the [full release notes](#) or issue tracker on GitHub for a complete list.

1.18.1 New features

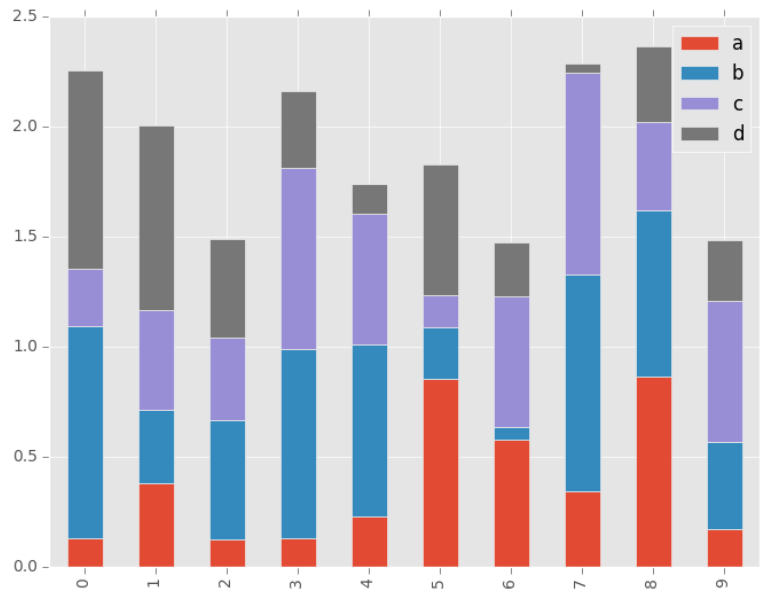
- New *fixed width file reader*, `read_fwf`
- New *scatter_matrix* function for making a scatter plot matrix

```
from pandas.tools.plotting import scatter_matrix
scatter_matrix(df, alpha=0.2)
```

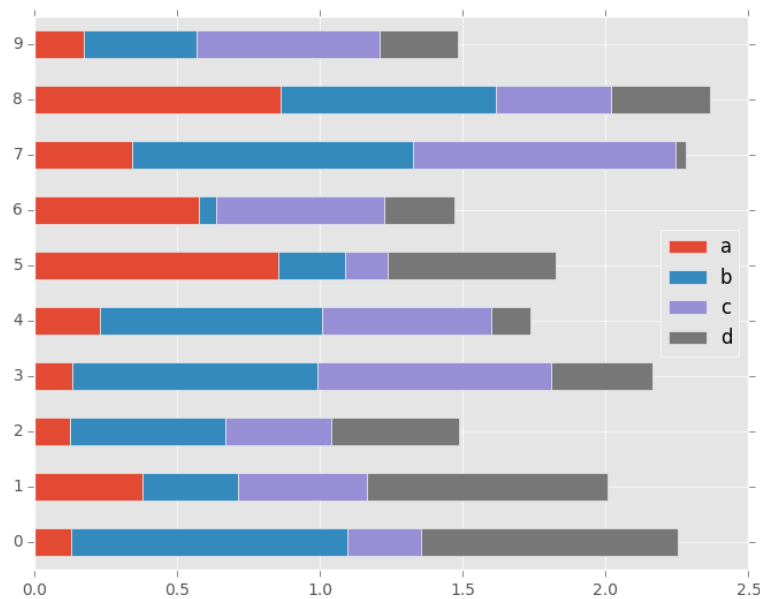


- Add `stacked` argument to Series and DataFrame’s `plot` method for *stacked bar plots*.

```
df.plot(kind='bar', stacked=True)
```



```
df.plot(kind='barh', stacked=True)
```



- Add log x and y *scaling options* to `DataFrame.plot` and `Series.plot`
- Add `kurt` methods to `Series` and `DataFrame` for computing kurtosis

1.18.2 NA Boolean Comparison API Change

Reverted some changes to how NA values (represented typically as `NaN` or `None`) are handled in non-numeric Series:

```
In [1]: series = Series(['Steve', np.nan, 'Joe'])
```

```
In [2]: series == 'Steve'
```

```
Out[2]:
0      True
```

```
1    False
2    False
dtype: bool
```

```
In [3]: series != 'Steve'
Out[3]:
0    False
1     True
2     True
dtype: bool
```

In comparisons, NA / NaN will always come through as `False` except with `!=` which is `True`. *Be very careful* with boolean arithmetic, especially negation, in the presence of NA data. You may wish to add an explicit NA filter into boolean array operations if you are worried about this:

```
In [4]: mask = series == 'Steve'

In [5]: series[mask & series.notnull()]
Out[5]:
0    Steve
dtype: object
```

While propagating NA in comparisons may seem like the right behavior to some users (and you could argue on purely technical grounds that this is the right thing to do), the evaluation was made that propagating NA everywhere, including in numerical arrays, would cause a large amount of problems for users. Thus, a “practicality beats purity” approach was taken. This issue may be revisited at some point in the future.

1.18.3 Other API Changes

When calling `apply` on a grouped Series, the return value will also be a Series, to be more consistent with the `groupby` behavior with DataFrame:

```
In [1]: df = DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
...:                          'foo', 'bar', 'foo', 'foo'],
...:                   'B' : ['one', 'one', 'two', 'three',
...:                          'two', 'two', 'one', 'three'],
...:                   'C' : np.random.randn(8), 'D' : np.random.randn(8)})
...:
```

```
In [2]: df
Out[2]:
```

	A	B	C	D
0	foo	one	0.144909	1.387310
1	bar	one	-1.033812	0.063490
2	foo	two	0.197333	1.437656
3	bar	three	-0.059730	-0.814844
4	foo	two	0.087205	-0.482060
5	bar	two	-1.607906	1.521442
6	foo	one	-1.275249	0.882182
7	foo	three	-0.054460	-0.108020

```
[8 rows x 4 columns]
```

```
In [3]: grouped = df.groupby('A')['C']
```

```
In [4]: grouped.describe()
Out[4]:
```

```
A
bar  count      3.000000
     mean     -0.900483
     std      0.782652
     min     -1.607906
     25%     -1.320859
     50%     -1.033812
     75%     -0.546771
     ...
foo  mean     -0.180052
     std      0.619410
     min     -1.275249
     25%     -0.054460
     50%      0.087205
     75%      0.144909
     max      0.197333
dtype: float64

In [5]: grouped.apply(lambda x: x.order()[-2:]) # top 2 values
Out[5]:
A
bar  1    -1.033812
     3    -0.059730
foo  0     0.144909
     2     0.197333
dtype: float64
```

1.19 v.0.7.2 (March 16, 2012)

This release targets bugs in 0.7.1, and adds a few minor features.

1.19.1 New features

- Add additional tie-breaking methods in `DataFrame.rank` ([GH874](#))
- Add ascending parameter to rank in Series, DataFrame ([GH875](#))
- Add `coerce_float` option to `DataFrame.from_records` ([GH893](#))
- Add `sort_columns` parameter to allow unsorted plots ([GH918](#))
- Enable column access via attributes on `GroupBy` ([GH882](#))
- Can pass dict of values to `DataFrame.fillna` ([GH661](#))
- Can select multiple hierarchical groups by passing list of values in `.ix` ([GH134](#))
- Add `axis` option to `DataFrame.fillna` ([GH174](#))
- Add level keyword to `drop` for dropping values from a level ([GH159](#))

1.19.2 Performance improvements

- Use khash for `Series.value_counts`, add `raw` function to `algorithms.py` ([GH861](#))
- Intercept `__builtin__.sum` in `groupby` ([GH885](#))

1.20 v.0.7.1 (February 29, 2012)

This release includes a few new features and addresses over a dozen bugs in 0.7.0.

1.20.1 New features

- Add `to_clipboard` function to pandas namespace for writing objects to the system clipboard ([GH774](#))
- Add `itertuples` method to DataFrame for iterating through the rows of a dataframe as tuples ([GH818](#))
- Add ability to pass `fill_value` and `method` to DataFrame and Series `align` method ([GH806](#), [GH807](#))
- Add `fill_value` option to `reindex`, `align` methods ([GH784](#))
- Enable `concat` to produce DataFrame from Series ([GH787](#))
- Add `between` method to Series ([GH802](#))
- Add HTML representation hook to DataFrame for the IPython HTML notebook ([GH773](#))
- Support for reading Excel 2007 XML documents using `openpyxl`

1.20.2 Performance improvements

- Improve performance and memory usage of `fillna` on DataFrame
- Can concatenate a list of Series along `axis=1` to obtain a DataFrame ([GH787](#))

1.21 v.0.7.0 (February 9, 2012)

1.21.1 New features

- New unified *merge function* for efficiently performing full gamut of database / relational-algebra operations. Refactored existing join methods to use the new infrastructure, resulting in substantial performance gains ([GH220](#), [GH249](#), [GH267](#))
- New *unified concatenation function* for concatenating Series, DataFrame or Panel objects along an axis. Can form union or intersection of the other axes. Improves performance of `Series.append` and `DataFrame.append` ([GH468](#), [GH479](#), [GH273](#))
- *Can* pass multiple DataFrames to `DataFrame.append` to concatenate (stack) and multiple Series to `Series.append` too
- *Can* pass list of dicts (e.g., a list of JSON objects) to DataFrame constructor ([GH526](#))
- You can now *set multiple columns* in a DataFrame via `__getitem__`, useful for transformation ([GH342](#))
- Handle differently-indexed output values in `DataFrame.apply` ([GH498](#))

```
In [1]: df = DataFrame(randn(10, 4))
```

```
In [2]: df.apply(lambda x: x.describe())
```

```
Out[2]:
```

	0	1	2	3
count	10.000000	10.000000	10.000000	10.000000
mean	0.119046	0.455043	-0.093701	-0.330828
std	0.814006	0.972606	0.948124	0.814913

```
min      -0.964456  -0.790943  -1.921164  -1.578003
25%      -0.512550  -0.462622  -0.683389  -0.934434
50%       0.013691   0.415879  -0.061961  -0.343709
75%       0.616168   1.351857   0.671847   0.150746
max       1.507974   1.755240   1.183075   1.051356
```

```
[8 rows x 4 columns]
```

- *Add* `reorder_levels` method to `Series` and `DataFrame` ([GH534](#))
- *Add* dict-like `get` function to `DataFrame` and `Panel` ([GH521](#))
- *Add* `DataFrame.iterrows` method for efficiently iterating through the rows of a `DataFrame`
- *Add* `DataFrame.to_panel` with code adapted from `LongPanel.to_long`
- *Add* `reindex_axis` method added to `DataFrame`
- *Add* `level` option to binary arithmetic functions on `DataFrame` and `Series`
- *Add* `level` option to the `reindex` and `align` methods on `Series` and `DataFrame` for broadcasting values across a level ([GH542](#), [GH552](#), others)
- *Add* attribute-based item access to `Panel` and add IPython completion ([GH563](#))
- *Add* `logy` option to `Series.plot` for log-scaling on the Y axis
- *Add* `index` and `header` options to `DataFrame.to_string`
- *Can* pass multiple `DataFrames` to `DataFrame.join` to join on index ([GH115](#))
- *Can* pass multiple `Panels` to `Panel.join` ([GH115](#))
- *Added* `justify` argument to `DataFrame.to_string` to allow different alignment of column headers
- *Add* `sort` option to `GroupBy` to allow disabling sorting of the group keys for potential speedups ([GH595](#))
- *Can* pass `MaskedArray` to `Series` constructor ([GH563](#))
- *Add* `Panel` item access via attributes and IPython completion ([GH554](#))
- Implement `DataFrame.lookup`, fancy-indexing analogue for retrieving values given a sequence of row and column labels ([GH338](#))
- *Can* pass a *list of functions* to aggregate with `groupby` on a `DataFrame`, yielding an aggregated result with hierarchical columns ([GH166](#))
- *Can* call `cummin` and `cummax` on `Series` and `DataFrame` to get cumulative minimum and maximum, respectively ([GH647](#))
- `value_range` added as utility function to get min and max of a dataframe ([GH288](#))
- *Added* `encoding` argument to `read_csv`, `read_table`, `to_csv` and `from_csv` for non-ascii text ([GH717](#))
- *Added* `abs` method to pandas objects
- *Added* `crosstab` function for easily computing frequency tables
- *Added* `isin` method to index objects
- *Added* `level` argument to `xs` method of `DataFrame`.

1.21.2 API Changes to integer indexing

One of the potentially riskiest API changes in 0.7.0, but also one of the most important, was a complete review of how **integer indexes** are handled with regard to label-based indexing. Here is an example:

```
In [3]: s = Series(randn(10), index=range(0, 20, 2))
```

```
In [4]: s
```

```
Out[4]:
0    -0.392051
2    -0.189537
4     0.886170
6    -1.125894
8     0.319635
10    0.998222
12    0.091743
14   -2.032047
16   -0.448560
18    0.730510
dtype: float64
```

```
In [5]: s[0]
```

```
Out[5]: -0.39205110783730307
```

```
In [6]: s[2]
```

```
Out[6]: -0.18953739573269113
```

```
In [7]: s[4]
```

```
Out[7]: 0.88617008348573789
```

This is all exactly identical to the behavior before. However, if you ask for a key **not** contained in the Series, in versions 0.6.1 and prior, Series would *fall back* on a location-based lookup. This now raises a `KeyError`:

```
In [2]: s[1]
```

```
KeyError: 1
```

This change also has the same impact on `DataFrame`:

```
In [3]: df = DataFrame(randn(8, 4), index=range(0, 16, 2))
```

```
In [4]: df
```

```

   0      1      2      3
0  0.88427  0.3363 -0.1787  0.03162
2  0.14451 -0.1415  0.2504  0.58374
4 -1.44779 -0.9186 -1.4996  0.27163
6 -0.26598 -2.4184 -0.2658  0.11503
8 -0.58776  0.3144 -0.8566  0.61941
10  0.10940 -0.7175 -1.0108  0.47990
12 -1.16919 -0.3087 -0.6049 -0.43544
14 -0.07337  0.3410  0.0424 -0.16037
```

```
In [5]: df.ix[3]
```

```
KeyError: 3
```

In order to support purely integer-based indexing, the following methods have been added:

Method	Description
<code>Series.iget_value(i)</code>	Retrieve value stored at location <code>i</code>
<code>Series.iget(i)</code>	Alias for <code>iget_value</code>
<code>DataFrame.irow(i)</code>	Retrieve the <code>i</code> -th row
<code>DataFrame.icol(j)</code>	Retrieve the <code>j</code> -th column
<code>DataFrame.iget_value(i, j)</code>	Retrieve the value at row <code>i</code> and column <code>j</code>

1.21.3 API tweaks regarding label-based slicing

Label-based slicing using `ix` now requires that the index be sorted (monotonic) **unless** both the start and endpoint are contained in the index:

```
In [8]: s = Series(randn(6), index=list('gmkaec'))
```

```
In [9]: s
Out[9]:
g    1.269713
m    1.209524
k    2.160843
a    0.533532
e   -2.371548
c    0.562726
dtype: float64
```

Then this is OK:

```
In [10]: s.ix['k':'e']
Out[10]:
k    2.160843
a    0.533532
e   -2.371548
dtype: float64
```

But this is not:

```
In [12]: s.ix['b':'h']
KeyError 'b'
```

If the index had been sorted, the “range selection” would have been possible:

```
In [11]: s2 = s.sort_index()
```

```
In [12]: s2
Out[12]:
a    0.533532
c    0.562726
e   -2.371548
g    1.269713
k    2.160843
m    1.209524
dtype: float64
```

```
In [13]: s2.ix['b':'h']
Out[13]:
c    0.562726
e   -2.371548
g    1.269713
dtype: float64
```

1.21.4 Changes to Series [] operator

As as notational convenience, you can pass a sequence of labels or a label slice to a Series when getting and setting values via [] (i.e. the `__getitem__` and `__setitem__` methods). The behavior will be the same as passing similar input to `ix` **except in the case of integer indexing**:

```
In [14]: s = Series(randn(6), index=list('acegkm'))
```

```
In [15]: s
```

```
Out[15]:
a    2.031757
c    0.851077
e    0.660056
g   -1.662471
k    0.571380
m    0.945588
dtype: float64
```

```
In [16]: s[['m', 'a', 'c', 'e']]
```

```
Out[16]:
m    0.945588
a    2.031757
c    0.851077
e    0.660056
dtype: float64
```

```
In [17]: s['b':'l']
```

```
Out[17]:
c    0.851077
e    0.660056
g   -1.662471
k    0.571380
dtype: float64
```

```
In [18]: s['c':'k']
```

```
Out[18]:
c    0.851077
e    0.660056
g   -1.662471
k    0.571380
dtype: float64
```

In the case of integer indexes, the behavior will be exactly as before (shadowing `ndarray`):

```
In [19]: s = Series(randn(6), index=range(0, 12, 2))
```

```
In [20]: s[[4, 0, 2]]
```

```
Out[20]:
4   -1.263534
0   -0.414691
2    2.108285
dtype: float64
```

```
In [21]: s[1:5]
```

```
Out[21]:
2    2.108285
4   -1.263534
6    2.617801
8    1.967592
```

```
dtype: float64
```

If you wish to do indexing with sequences and slicing on an integer index with label semantics, use `ix`.

1.21.5 Other API Changes

- The deprecated `LongPanel` class has been completely removed
- If `Series.sort` is called on a column of a `DataFrame`, an exception will now be raised. Before it was possible to accidentally mutate a `DataFrame`'s column by doing `df[col].sort()` instead of the side-effect free method `df[col].order()` ([GH316](#))
- Miscellaneous renames and deprecations which will (harmlessly) raise `FutureWarning`
- `drop` added as an optional parameter to `DataFrame.reset_index` ([GH699](#))

1.21.6 Performance improvements

- *Cythonized GroupBy aggregations* no longer presort the data, thus achieving a significant speedup ([GH93](#)). `GroupBy` aggregations with Python functions significantly sped up by clever manipulation of the ndarray data type in Cython ([GH496](#)).
- Better error message in `DataFrame` constructor when passed column labels don't match data ([GH497](#))
- Substantially improve performance of multi-`GroupBy` aggregation when a Python function is passed, reuse ndarray object in Cython ([GH496](#))
- Can store objects indexed by tuples and floats in `HDFStore` ([GH492](#))
- Don't print length by default in `Series.to_string`, add *length* option ([GH489](#))
- Improve Cython code for multi-groupby to aggregate without having to sort the data ([GH93](#))
- Improve `MultiIndex` reindexing speed by storing tuples in the `MultiIndex`, test for backwards unpickling compatibility
- Improve column reindexing performance by using specialized Cython take function
- Further performance tweaking of `Series.__getitem__` for standard use cases
- Avoid `Index` dict creation in some cases (i.e. when getting slices, etc.), regression from prior versions
- Friendlier error message in `setup.py` if `NumPy` not installed
- Use common set of NA-handling operations (sum, mean, etc.) in `Panel` class also ([GH536](#))
- Default name assignment when calling `reset_index` on `DataFrame` with a regular (non-hierarchical) index ([GH476](#))
- Use Cythonized groupers when possible in `Series/DataFrame` stat ops with `level` parameter passed ([GH545](#))
- Ported skiplist data structure to C to speed up `rolling_median` by about 5-10x in most typical use cases ([GH374](#))

1.22 v.0.6.1 (December 13, 2011)

1.22.1 New features

- Can *append single rows* (as `Series`) to a `DataFrame`

- Add Spearman and Kendall rank *correlation* options to `Series.corr` and `DataFrame.corr` (GH428)
- *Added* `get_value` and `set_value` methods to `Series`, `DataFrame`, and `Panel` for very low-overhead access (>2x faster in many cases) to scalar elements (GH437, GH438). `set_value` is capable of producing an enlarged object.
- Add PyQt table widget to sandbox (GH435)
- `DataFrame.align` can *accept Series arguments* and an *axis option* (GH461)
- Implement new *SparseArray* and *SparseList* data structures. `SparseSeries` now derives from `SparseArray` (GH463)
- *Better console printing options* (GH453)
- Implement fast *data ranking* for `Series` and `DataFrame`, fast versions of `scipy.stats.rankdata` (GH428)
- Implement *DataFrame.from_items* alternate constructor (GH444)
- `DataFrame.convert_objects` method for *inferring better dtypes* for object columns (GH302)
- Add *rolling_corr_pairwise* function for computing `Panel` of correlation matrices (GH189)
- Add *margins* option to *pivot_table* for computing subgroup aggregates (GH114)
- Add `Series.from_csv` function (GH482)
- *Can pass* `DataFrame/DataFrame` and `DataFrame/Series` to `rolling_corr/rolling_cov` (GH #462)
- `MultiIndex.get_level_values` can *accept the level name*

1.22.2 Performance improvements

- Improve memory usage of `DataFrame.describe` (do not copy data unnecessarily) (PR #425)
- Optimize scalar value lookups in the general case by 25% or more in `Series` and `DataFrame`
- Fix performance regression in cross-sectional count in `DataFrame`, affecting `DataFrame.dropna` speed
- Column deletion in `DataFrame` copies no data (computes views on blocks) (GH #158)

1.23 v.0.6.0 (November 25, 2011)

1.23.1 New Features

- *Added* `melt` function to `pandas.core.reshape`
- *Added* `level` parameter to `group by` level in `Series` and `DataFrame` descriptive statistics (GH313)
- *Added* `head` and `tail` methods to `Series`, analogous to to `DataFrame` (GH296)
- *Added* `Series.isin` function which checks if each value is contained in a passed sequence (GH289)
- *Added* `float_format` option to `Series.to_string`
- *Added* `skip_footer` (GH291) and `converters` (GH343) options to `read_csv` and `read_table`
- *Added* `drop_duplicates` and `drop_duplicates` functions for removing duplicate `DataFrame` rows and checking for duplicate rows, respectively (GH319)
- *Implemented* operators `&`, `|`, `^`, `-` on `DataFrame` (GH347)
- *Added* `Series.mad`, mean absolute deviation

- *Added* `QuarterEnd` `DateOffset` (GH321)
- *Added* `dot` to `DataFrame` (GH65)
- *Added* `orient` option to `Panel.from_dict` (GH359, GH301)
- *Added* `orient` option to `DataFrame.from_dict`
- *Added* passing list of tuples or list of lists to `DataFrame.from_records` (GH357)
- *Added* multiple levels to `groupby` (GH103)
- *Allow* multiple columns in `by` argument of `DataFrame.sort_index` (GH92, GH362)
- *Added* fast `get_value` and `put_value` methods to `DataFrame` (GH360)
- *Added* `cov` instance methods to `Series` and `DataFrame` (GH194, GH362)
- *Added* `kind='bar'` option to `DataFrame.plot` (GH348)
- *Added* `idxmin` and `idxmax` to `Series` and `DataFrame` (GH286)
- *Added* `read_clipboard` function to parse `DataFrame` from clipboard (GH300)
- *Added* `nunique` function to `Series` for counting unique elements (GH297)
- *Made* `DataFrame` constructor use `Series` name if no columns passed (GH373)
- *Support* regular expressions in `read_table/read_csv` (GH364)
- *Added* `DataFrame.to_html` for writing `DataFrame` to HTML (GH387)
- *Added* support for `MaskedArray` data in `DataFrame`, masked values converted to `NaN` (GH396)
- *Added* `DataFrame.boxplot` function (GH368)
- *Can* pass extra args, `kwds` to `DataFrame.apply` (GH376)
- *Implement* `DataFrame.join` with vector on argument (GH312)
- *Added* legend boolean flag to `DataFrame.plot` (GH324)
- *Can* pass multiple levels to `stack` and `unstack` (GH370)
- *Can* pass multiple values columns to `pivot_table` (GH381)
- *Use* `Series` name in `GroupBy` for result index (GH363)
- *Added* `raw` option to `DataFrame.apply` for performance if only need `ndarray` (GH309)
- *Added* proper, tested weighted least squares to standard and panel OLS (GH303)

1.23.2 Performance Enhancements

- VBENCH Cythonized `cache_readonly`, resulting in substantial micro-performance enhancements throughout the codebase (GH361)
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations with 3-5x better performance than `np.apply_along_axis` (GH309)
- VBENCH Improved performance of `MultiIndex.from_tuples`
- VBENCH Special Cython matrix iterator for applying arbitrary reduction operations
- VBENCH + DOCUMENT Add `raw` option to `DataFrame.apply` for getting better performance when
- VBENCH Faster cythonized count by level in `Series` and `DataFrame` (GH341)

- VBENCH? Significant GroupBy performance enhancement with multiple keys with many “empty” combinations
- VBENCH New Cython vectorized function `map_infer` speeds up `Series.apply` and `Series.map` significantly when passed elementwise Python function, motivated by (GH355)
- VBENCH Significantly improved performance of `Series.order`, which also makes `np.unique` called on a Series faster (GH327)
- VBENCH Vastly improved performance of GroupBy on axes with a MultiIndex (GH299)

1.24 v.0.5.0 (October 24, 2011)

1.24.1 New Features

- *Added* `DataFrame.align` method with standard join options
- *Added* `parse_dates` option to `read_csv` and `read_table` methods to optionally try to parse dates in the index columns
- *Added* `nrows`, `chunksize`, and `iterator` arguments to `read_csv` and `read_table`. The last two return a new `TextParser` class capable of lazily iterating through chunks of a flat file (GH242)
- *Added* ability to join on multiple columns in `DataFrame.join` (GH214)
- Added private `_get_duplicates` function to `Index` for identifying duplicate values more easily (ENH5c)
- *Added* column attribute access to `DataFrame`.
- *Added* Python tab completion hook for `DataFrame` columns. (GH233, GH230)
- *Implemented* `Series.describe` for Series containing objects (GH241)
- *Added* inner join option to `DataFrame.join` when joining on key(s) (GH248)
- *Implemented* selecting `DataFrame` columns by passing a list to `__getitem__` (GH253)
- *Implemented* `&` and `|` to intersect / union `Index` objects, respectively (GH261)
- *Added* `pivot_table` convenience function to pandas namespace (GH234)
- *Implemented* `Panel.rename_axis` function (GH243)
- `DataFrame` will show index level names in console output (GH334)
- *Implemented* `Panel.take`
- *Added* `set_eng_float_format` for alternate `DataFrame` floating point string formatting (ENH61)
- *Added* convenience `set_index` function for creating a `DataFrame` index from its existing columns
- *Implemented* groupby hierarchical index level name (GH223)
- *Added* support for different delimiters in `DataFrame.to_csv` (GH244)
- TODO: DOCS ABOUT TAKE METHODS

1.24.2 Performance Enhancements

- VBENCH Major performance improvements in file parsing functions `read_csv` and `read_table`
- VBENCH Added Cython function for converting tuples to `ndarray` very fast. Speeds up many MultiIndex-related operations

- VBENCH Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance (GH211)
- VBENCH Improved speed of `DataFrame.xs` on mixed-type DataFrame objects by about 5x, regression from 0.3.0 (GH215)
- VBENCH With new `DataFrame.align` method, speeding up binary operations between differently-indexed DataFrame objects by 10-25%.
- VBENCH Significantly sped up conversion of nested dict into DataFrame (GH212)
- VBENCH Significantly speed up DataFrame `__repr__` and `count` on large mixed-type DataFrame objects

1.25 v0.4.3 through v0.4.1 (September 25 - October 9, 2011)

1.25.1 New Features

- Added Python 3 support using 2to3 (GH200)
- *Added* name attribute to Series, now prints as part of `Series.__repr__`
- *Added* instance methods `isnull` and `notnull` to Series (GH209, GH203)
- *Added* `Series.align` method for aligning two series with choice of join method (ENH56)
- *Added* method `get_level_values` to `MultiIndex` (GH188)
- Set values in mixed-type DataFrame objects via `.ix` indexing attribute (GH135)
- Added new DataFrame *methods* `get_dtype_counts` and property `dtypes` (ENHdc)
- Added *ignore_index* option to `DataFrame.append` to stack DataFrames (ENH1b)
- `read_csv` tries to *sniff* delimiters using `csv.Sniffer` (GH146)
- `read_csv` can *read* multiple columns into a `MultiIndex`; DataFrame's `to_csv` method writes out a corresponding `MultiIndex` (GH151)
- `DataFrame.rename` has a new `copy` parameter to *rename* a DataFrame in place (ENHed)
- *Enable* unstacking by name (GH142)
- *Enable* `sortlevel` to work by level (GH141)

1.25.2 Performance Enhancements

- Altered binary operations on differently-indexed `SparseSeries` objects to use the integer-based (dense) alignment logic which is faster with a larger number of blocks (GH205)
- Wrote faster Cython data alignment / merging routines resulting in substantial speed increases
- Improved performance of `isnull` and `notnull`, a regression from v0.3.0 (GH187)
- Refactored code related to `DataFrame.join` so that intermediate aligned copies of the data in each DataFrame argument do not need to be created. Substantial performance increases result (GH176)
- Substantially improved performance of generic `Index.intersection` and `Index.union`
- Implemented `BlockManager.take` resulting in significantly faster take performance on mixed-type DataFrame objects (GH104)
- Improved performance of `Series.sort_index`

- Significant groupby performance enhancement: removed unnecessary integrity checks in DataFrame internals that were slowing down slicing operations to retrieve groups
- Optimized `_ensure_index` function resulting in performance savings in type-checking Index objects
- Wrote fast time series merging / joining methods in Cython. Will be integrated later into `DataFrame.join` and related functions

INSTALLATION

The easiest way for the majority of users to install pandas is to install it as part of the [Anaconda](#) distribution, a cross platform distribution for data analysis and scientific computing. This is the recommended installation method for most users.

Instructions for installing from source, [PyPI](#), various Linux distributions, or a [development version](#) are also provided.

2.1 Python version support

Officially Python 2.6, 2.7, 3.2, 3.3, and 3.4.

2.2 Installing pandas

2.2.1 Trying out pandas, no installation required!

The easiest way to start experimenting with pandas doesn't involve installing pandas at all.

[Wakari](#) is a free service that provides a hosted [IPython Notebook](#) service in the cloud.

Simply create an account, and have access to pandas from within your browser via an [IPython Notebook](#) in a few minutes.

2.2.2 Installing pandas with Anaconda

Installing pandas and the rest of the [NumPy](#) and [SciPy](#) stack can be a little difficult for inexperienced users.

The simplest way to install not only pandas, but Python and the most popular packages that make up the [SciPy](#) stack ([IPython](#), [NumPy](#), [Matplotlib](#), ...) is with [Anaconda](#), a cross-platform (Linux, Mac OS X, Windows) Python distribution for data analytics and scientific computing.

After running a simple installer, the user will have access to pandas and the rest of the [SciPy](#) stack without needing to install anything else, and without needing to wait for any software to be compiled.

Installation instructions for [Anaconda](#) can be found [here](#).

A full list of the packages available as part of the [Anaconda](#) distribution can be found [here](#).

An additional advantage of installing with Anaconda is that you don't require admin rights to install it, it will install in the user's home directory, and this also makes it trivial to delete Anaconda at a later date (just delete that folder).

2.2.3 Installing pandas with Miniconda

The previous section outlined how to get pandas installed as part of the [Anaconda](#) distribution. However this approach means you will install well over one hundred packages and involves downloading the installer which is a few hundred megabytes in size.

If you want to have more control on which packages, or have a limited internet bandwidth, then installing pandas with [Miniconda](#) may be a better solution.

[Conda](#) is the package manager that the [Anaconda](#) distribution is built upon. It is a package manager that is both cross-platform and language agnostic (it can play a similar role to a pip and virtualenv combination).

[Miniconda](#) allows you to create a minimal self contained Python installation, and then use the [Conda](#) command to install additional packages.

First you will need [Conda](#) to be installed and downloading and running the [Miniconda](#) will do this for you. The installer [can be found here](#)

The next step is to create a new conda environment (these are analogous to a virtualenv but they also allow you to specify precisely which Python version to install also). Run the following commands from a terminal window:

```
conda create -n name_of_my_env python
```

This will create a minimal environment with only Python installed in it. To put your self inside this environment run:

```
source activate name_of_my_env
```

On Windows the command is:

```
activate name_of_my_env
```

The final step required is to install pandas. This can be done with the following command:

```
conda install pandas
```

To install a specific pandas version:

```
conda install pandas=0.13.1
```

To install other packages, IPython for example:

```
conda install ipython
```

To install the full [Anaconda](#) distribution:

```
conda install anaconda
```

If you require any packages that are available to pip but not conda, simply install pip, and use pip to install these packages:

```
conda install pip
pip install django
```

2.2.4 Installing from PyPI

pandas can be installed via pip from [PyPI](#).

```
pip install pandas
```

This will likely require the installation of a number of dependencies, including NumPy, will require a compiler to compile required bits of code, and can take a few minutes to complete.

2.2.5 Installing using your Linux distribution's package manager.

Distribution	Status	Download / Repository Link	Install method
Debian	stable	official Debian repository	<code>sudo apt-get install python-pandas</code>
Debian & Ubuntu	unstable (latest packages)	NeuroDebian	<code>sudo apt-get install python-pandas</code>
Ubuntu	stable	official Ubuntu repository	<code>sudo apt-get install python-pandas</code>
Ubuntu	unstable (daily builds)	PythonXY PPA ; activate by: <code>sudo add-apt-repository ppa:pythonxy/pythonxy-devel</code> & <code>sudo apt-get update</code>	<code>sudo apt-get install python-pandas</code>
Open-Suse & Fedora	stable	OpenSuse Repository	<code>zypper in python-pandas</code>

2.2.6 Installing from source

See the [contributing documentation](#) for complete instructions on building from the git source tree. Further, see *creating a development environment* if you wish to create a *pandas* development environment.

2.2.7 Running the test suite

pandas is equipped with an exhaustive set of unit tests covering about 97% of the codebase as of this writing. To run it on your machine to verify that everything is working (and you have all of the dependencies, soft and hard, installed), make sure you have *nose* and run:

```
$ nosetests pandas
.....S.....
.....
.....
.....
.....
.....
.....
.....
.....S.....
....
-----
Ran 818 tests in 21.631s

OK (SKIP=2)
```

2.3 Dependencies

- NumPy: 1.7.0 or higher
- python-dateutil 1.5 or higher
- pytz
 - Needed for time zone support

2.3.1 Recommended Dependencies

- **numexpr**: for accelerating certain numerical operations. **numexpr** uses multiple cores as well as smart chunking and caching to achieve large speedups. If installed, must be Version 2.1 or higher.
- **bottleneck**: for accelerating certain types of nan evaluations. **bottleneck** uses specialized cython routines to achieve large speedups.

Note: You are highly encouraged to install these libraries, as they provide large speedups, especially if working with large data sets.

2.3.2 Optional Dependencies

- **Cython**: Only necessary to build development version. Version 0.19.1 or higher.
- **SciPy**: miscellaneous statistical functions
- **PyTables**: necessary for HDF5-based storage. Version 3.0.0 or higher required, Version 3.2.0 or higher highly recommended.
- **SQLAlchemy**: for SQL database support. Version 0.8.1 or higher recommended.
- **matplotlib**: for plotting
- **statsmodels**
 - Needed for parts of `pandas.stats`
- **openpyxl, xlrd/xlwt**
 - openpyxl version 1.6.1 or higher, but lower than 2.0.0
 - Needed for Excel I/O
- **XlsxWriter**
 - Alternative Excel writer.
- **boto**: necessary for Amazon S3 access.
- **'blosc <<https://pypi.python.org/pypi/blosc>>'**: for msgpack compression using **blosc**
- One of **PyQt4**, **PySide**, **pygtk**, **xsel**, or **xclip**: necessary to use `read_clipboard()`. Most package managers on Linux distributions will have xclip and/or xsel immediately available for installation.
- Google's **python-gflags** and **google-api-python-client**
 - Needed for `gbq`
- **setuptools**
 - Needed for `gbq` (specifically, it utilizes `pkg_resources`)

- **httplib2**

- Needed for gbq
- One of the following combinations of libraries is needed to use the top-level `read_html()` function:
 - BeautifulSoup4 and `html5lib` (Any recent version of `html5lib` is okay.)
 - BeautifulSoup4 and `lxml`
 - BeautifulSoup4 and `html5lib` and `lxml`
 - Only `lxml`, although see *HTML reading gotchas* for reasons as to why you should probably **not** take this approach.

Warning:

- if you install BeautifulSoup4 you must install either `lxml` or `html5lib` or both. `read_html()` will **not** work with *only* BeautifulSoup4 installed.
- You are highly encouraged to read *HTML reading gotchas*. It explains issues surrounding the installation and usage of the above three libraries
- **You may need to install an older version of BeautifulSoup4:**
 - * Versions 4.2.1, 4.1.3 and 4.0.2 have been confirmed for 64 and 32-bit Ubuntu/Debian
- Additionally, if you're using `Anaconda` you should definitely read *the gotchas about HTML parsing libraries*

Note:

- if you're on a system with `apt-get` you can do

```
sudo apt-get build-dep python-lxml
```

to get the necessary dependencies for installation of `lxml`. This will prevent further headaches down the line.

Note: Without the optional dependencies, many useful features will not work. Hence, it is highly recommended that you install these. A packaged distribution like `Enthought Canopy` may be worth considering.

CONTRIBUTING TO PANDAS

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 - Review your code
 - Finally, make the Pull Request
 - Delete your merged branch (optional)

3.1 Where to start?

All contributions, bug reports, bug fixes, documentation improvements, enhancements and ideas are welcome.

If you are simply looking to start working with the *pandas* codebase, navigate to the [GitHub “issues” tab](#) and start looking through interesting issues. There are a number of issues listed under [Docs](#) and [Difficulty Novice](#) where you could start out.

Or maybe through using *pandas* you have an idea of you own or are looking for something in the documentation and thinking ‘this can be improved’...you can do something about it!

Feel free to ask questions on [mailing list](#)

3.2 Bug Reports/Enhancement Requests

Bug reports are an important part of making *pandas* more stable. Having a complete bug report will allow others to reproduce the bug and provide insight into fixing. Since many versions of *pandas* are supported, knowing version information will also identify improvements made since previous versions. Often trying the bug-producing code out on the *master* branch is a worthwhile exercise to confirm the bug still exists. It is also worth searching existing bug reports and pull requests to see if the issue has already been reported and/or fixed.

Bug reports must:

1. Include a short, self-contained Python snippet reproducing the problem. You can have the code formatted nicely by using [GitHub Flavored Markdown](#):

```
```python
>>> from pandas import DataFrame
>>> df = DataFrame(...)
...
```
```

2. Include the full version string of *pandas* and its dependencies. In recent (>0.12) versions of *pandas* you can use a built in function:

```
>>> from pandas.util.print_versions import show_versions
>>> show_versions()
```

and in 0.13.1 onwards:

```
>>> pd.show_versions()
```

3. Explain why the current behavior is wrong/not desired and what you expect instead.

The issue will then show up to the *pandas* community and be open to comments/ideas from others.

3.3 Working with the code

Now that you have an issue you want to fix, enhancement to add, or documentation to improve, you need to learn how to work with GitHub and the *pandas* code base.

3.3.1 Version Control, Git, and GitHub

To the new user, working with Git is one of the more daunting aspects of contributing to *pandas*. It can very quickly become overwhelming, but sticking to the guidelines below will make the process straightforward and will work without much trouble. As always, if you are having difficulties please feel free to ask for help.

The code is hosted on [GitHub](#). To contribute you will need to sign up for a [free GitHub account](#). We use [Git](#) for version control to allow many people to work together on the project.

Some great resources for learning git:

- the [GitHub help pages](#).

- the [NumPy's documentation](#).
- Matthew Brett's [Pydagogue](#).

3.3.2 Getting Started with Git

[GitHub](#) has [instructions](#) for installing git, setting up your SSH key, and configuring git. All these steps need to be completed before working seamlessly with your local repository and GitHub.

3.3.3 Forking

You will need your own fork to work on the code. Go to the [pandas project page](#) and hit the *fork* button. You will want to clone your fork to your machine:

```
git clone git@github.com:your-user-name/pandas.git pandas-yourname
cd pandas-yourname
git remote add upstream git://github.com/pydata/pandas.git
```

This creates the directory *pandas-yourname* and connects your repository to the upstream (main project) *pandas* repository.

The testing suite will run automatically on Travis-CI once your Pull Request is submitted. However, if you wish to run the test suite on a branch prior to submitting the Pull Request, then Travis-CI needs to be hooked up to your GitHub repository. Instructions are for doing so are [here](#).

3.3.4 Creating a Branch

You want your master branch to reflect only production-ready code, so create a feature branch for making your changes. For example:

```
git branch shiny-new-feature
git checkout shiny-new-feature
```

The above can be simplified to:

```
git checkout -b shiny-new-feature
```

This changes your working directory to the shiny-new-feature branch. Keep any changes in this branch specific to one bug or feature so it is clear what the branch brings to *pandas*. You can have many shiny-new-features and switch in between them using the git checkout command.

To update this branch, you need to retrieve the changes from the master branch:

```
git fetch upstream
git rebase upstream/master
```

This will replay your commits on top of the latest pandas git master. If this leads to merge conflicts, you must resolve these before submitting your Pull Request. If you have uncommitted changes, you will need to *stash* them prior to updating. This will effectively store your changes and they can be reapplied after updating.

3.3.5 Creating a Development Environment

An easy way to create a *pandas* development environment is as follows.

- Install either *Install Anaconda* or *Install miniconda*

- Make sure that you have *cloned the repository*
- `cd` to the pandas source directory

Tell conda to create a new environment, named `pandas_dev`, or any name you would like for this environment by running:

```
conda create -n pandas_dev --file ci/requirements_dev.txt
```

For a python 3 environment

```
conda create -n pandas_dev python=3 --file ci/requirements_dev.txt
```

If you are on windows, then you will need to install the compiler linkages:

```
conda install -n pandas_dev libpython
```

This will create the new environment, and not touch any of your existing environments, nor any existing python installation. It will install all of the basic dependencies of *pandas*, as well as the development and testing tools. If you would like to install other dependencies, you can install them as follows:

```
conda install -n pandas_dev -c pandas pytables scipy
```

To install *all* pandas dependencies you can do the following:

```
conda install -n pandas_dev -c pandas --file ci/requirements_all.txt
```

To work in this environment, activate it as follows:

```
activate pandas_dev
```

At which point, the prompt will change to indicate you are in the new development environment.

Note: The above syntax is for windows environments. To work on macosx/linux, use:

```
source activate pandas_dev
```

To view your environments:

```
conda info -e
```

To return to you home root environment:

```
deactivate
```

See the full conda docs [here](#).

At this point you can easily do an *in-place* install, as detailed in the next section.

3.3.6 Making changes

Before making your code changes, it is often necessary to build the code that was just checked out. There are two primary methods of doing this.

1. The best way to develop *pandas* is to build the C extensions in-place by running:

```
python setup.py build_ext --inplace
```

If you startup the Python interpreter in the *pandas* source directory you will call the built C extensions

2. Another very common option is to do a develop install of *pandas*:

```
python setup.py develop
```

This makes a symbolic link that tells the Python interpreter to import *pandas* from your development directory. Thus, you can always be using the development version on your system without being inside the clone directory.

3.4 Contributing to the documentation

If you're not the developer type, contributing to the documentation is still of huge value. You don't even have to be an expert on *pandas* to do so! Something as simple as rewriting small passages for clarity as you reference the docs is a simple but effective way to contribute. The next person to read that passage will be in your debt!

Actually, there are sections of the docs that are worse off by being written by experts. If something in the docs doesn't make sense to you, updating the relevant section after you figure it out is a simple way to ensure it will help the next person.

Documentation:

- [About the pandas documentation](#)
- [How to build the pandas documentation](#)
 - [Requirements](#)
 - [Building the documentation](#)
 - [Built Master Branch Documentation](#)

3.4.1 About the pandas documentation

The documentation is written in **reStructuredText**, which is almost like writing in plain English, and built using [Sphinx](#). The Sphinx Documentation has an excellent [introduction to reST](#). Review the Sphinx docs to perform more complex changes to the documentation as well.

Some other important things to know about the docs:

- The *pandas* documentation consists of two parts: the docstrings in the code itself and the docs in this folder `pandas/doc/`.

The docstrings provide a clear explanation of the usage of the individual functions, while the documentation in this folder consists of tutorial-like overviews per topic together with some other information (what's new, installation, etc).

- The docstrings follow the **Numpy Docstring Standard** which is used widely in the Scientific Python community. This standard specifies the format of the different sections of the docstring. See [this document](#) for a detailed explanation, or look at some of the existing functions to extend it in a similar manner.
- The tutorials make heavy use of the [ipython directive](#) sphinx extension. This directive lets you put code in the documentation which will be run during the doc build. For example:

```
.. ipython:: python

    x = 2
    x**3
```

will be rendered as

```
In [1]: x = 2
```

```
In [2]: x**3
Out[2]: 8
```

This means that almost all code examples in the docs are always run (and the output saved) during the doc build. This way, they will always be up to date, but it makes the doc building a bit more complex.

3.4.2 How to build the pandas documentation

Requirements

To build the *pandas* docs there are some extra requirements: you will need to have `sphinx` and `ipython` installed. `numpydoc` is used to parse the docstrings that follow the Numpy Docstring Standard (see above), but you don't need to install this because a local copy of `numpydoc` is included in the *pandas* source code.

It is easiest to *create a development environment*, then install:

```
conda install -n pandas_dev sphinx ipython
```

Furthermore, it is recommended to have all [optional dependencies](#) installed. This is not strictly necessary, but be aware that you will see some error messages. Because all the code in the documentation is executed during the doc build, the examples using this optional dependencies will generate errors. Run `pd.show_versions()` to get an overview of the installed version of all dependencies.

Warning: Sphinx version $\geq$ 1.2.2 or the older 1.1.3 is required.

Building the documentation

So how do you build the docs? Navigate to your local the folder `pandas/doc/` directory in the console and run:

```
python make.py html
```

And then you can find the html output in the folder `pandas/doc/build/html/`.

The first time it will take quite a while, because it has to run all the code examples in the documentation and build all generated docstring pages. In subsequent evocations, sphinx will try to only build the pages that have been modified.

If you want to do a full clean build, do:

```
python make.py clean
python make.py build
```

Starting with 0.13.1 you can tell `make.py` to compile only a single section of the docs, greatly reducing the turn-around time for checking your changes. You will be prompted to delete `.rst` files that aren't required. This is okay since the prior version can be checked out from git, but make sure to not commit the file deletions.

```
#omit autosummary and API section
python make.py clean
python make.py --no-api

# compile the docs with only a single
# section, that which is in indexing.rst
python make.py clean
python make.py --single indexing
```

For comparison, a full documentation build may take 10 minutes. a `-no-api` build may take 3 minutes and a single section may take 15 seconds. However, subsequent builds only process portions you changed. Now, open the following file in a web browser to see the full documentation you just built:

`pandas/docs/build/html/index.html`

And you'll have the satisfaction of seeing your new and improved documentation!

Built Master Branch Documentation

When pull-requests are merged into the pandas *master* branch, the main parts of the documentation are also built by Travis-CI. These docs are then hosted [here](#).

3.5 Contributing to the code base

Code Base:

- [Code Standards](#)
- [Test-driven Development/Writing Code](#)
 - [Writing tests](#)
 - [Running the test suite](#)
 - [Running the performance test suite](#)
- [Documenting your code](#)

3.5.1 Code Standards

pandas uses the [PEP8](#) standard. There are several tools to ensure you abide by this standard.

We've written a tool to check that your commits are PEP8 great, `pip install pep8radius`. Look at PEP8 fixes in your branch vs master with:

```
pep8radius master --diff` and make these changes with `pep8radius master --diff --in-place`
```

Alternatively, use [flake8](#) tool for checking the style of your code. Additional standards are outlined on the [code style wiki page](#).

Please try to maintain backward-compatibility. *Pandas* has lots of users with lots of existing code, so don't break it if at all possible. If you think breakage is required clearly state why as part of the Pull Request. Also, be careful when changing method signatures and add deprecation warnings where needed.

3.5.2 Test-driven Development/Writing Code

Pandas is serious about testing and strongly encourages individuals to embrace [Test-driven Development \(TDD\)](#). This development process “relies on the repetition of a very short development cycle: first the developer writes an (initially failing) automated test case that defines a desired improvement or new function, then produces the minimum amount of code to pass that test.” So, before actually writing any code, you should write your tests. Often the test can be taken from the original GitHub issue. However, it is always worth considering additional use cases and writing corresponding tests.

Adding tests is one of the most common requests after code is pushed to *pandas*. It is worth getting in the habit of writing tests ahead of time so this is never an issue.

Like many packages, *pandas* uses the [Nose testing system](#) and the convenient extensions in [numpy.testing](#).

Writing tests

All tests should go into the *tests* subdirectory of the specific package. There are probably many examples already there and looking to these for inspiration is suggested. If you test requires working with files or network connectivity there is more information on the [testing page](#) of the wiki.

The `pandas.util.testing` module has many special `assert` functions that make it easier to make statements about whether Series or DataFrame objects are equivalent. The easiest way to verify that your code is correct is to explicitly construct the result you expect, then compare the actual result to the expected correct result:

```
def test_pivot(self):
    data = {
        'index' : ['A', 'B', 'C', 'C', 'B', 'A'],
        'columns' : ['One', 'One', 'One', 'Two', 'Two', 'Two'],
        'values' : [1., 2., 3., 3., 2., 1.]
    }

    frame = DataFrame(data)
    pivoted = frame.pivot(index='index', columns='columns', values='values')

    expected = DataFrame({
        'One' : {'A' : 1., 'B' : 2., 'C' : 3.},
        'Two' : {'A' : 1., 'B' : 2., 'C' : 3.}
    })

    assert_frame_equal(pivoted, expected)
```

Running the test suite

The tests can then be run directly inside your git clone (without having to install *pandas*) by typing::

```
nosetests pandas
```

The tests suite is exhaustive and takes around 20 minutes to run. Often it is worth running only a subset of tests first around your changes before running the entire suite. This is done using one of the following constructs:

```
nosetests pandas/tests/[test-module].py
nosetests pandas/tests/[test-module].py:[TestClass]
nosetests pandas/tests/[test-module].py:[TestClass].[test_method]
```

Running the performance test suite

Performance matters and it is worth considering that your code has not introduced performance regressions. Currently *pandas* uses the [vbench library](#) to enable easy monitoring of the performance of critical *pandas* operations. These benchmarks are all found in the `pandas/vb_suite` directory. *vbench* currently only works on python2.

To install *vbench*:

```
pip install git+https://github.com/pydata/vbench
```

Vbench also requires *sqlalchemy*, *gitpython*, and *psutil* which can all be installed using *pip*. If you need to run a benchmark, change your directory to the *pandas* root and run:

```
./test_perf.sh -b master -t HEAD
```

This will checkout the master revision and run the suite on both master and your commit. Running the full test suite can take up to one hour and use up to 3GB of RAM. Usually it is sufficient to past a subset of the results in to the Pull Request to show that the committed changes do not cause unexpected performance regressions.

You can run specific benchmarks using the `-r` flag which takes a regular expression.

See the [performance testing wiki](#) for information on how to write a benchmark.

3.5.3 Documenting your code

Changes should be reflected in the release notes located in `doc/source/whatsnew/vx.y.z.txt`. This file contains an ongoing change log for each release. Add an entry to this file to document your fix, enhancement or (unavoidable) breaking change. Make sure to include the GitHub issue number when adding your entry.

If your code is an enhancement, it is most likely necessary to add usage examples to the existing documentation. This can be done following the section regarding documentation.

3.6 Contributing your changes to *pandas*

3.6.1 Committing your code

Keep style fixes to a separate commit to make your PR more readable.

Once you've made changes, you can see them by typing:

```
git status
```

If you've created a new file, it is not being tracked by git. Add it by typing

```
git add path/to/file-to-be-added.py
```

Doing 'git status' again should give something like

```
# On branch shiny-new-feature
#
#       modified:   /relative/path/to/file-you-added.py
#
```

Finally, commit your changes to your local repository with an explanatory message. *Pandas* uses a convention for commit message prefixes and layout. Here are some common prefixes along with general guidelines for when to use them:

- ENH: Enhancement, new functionality
- BUG: Bug fix
- DOC: Additions/updates to documentation
- TST: Additions/updates to tests
- BLD: Updates to the build process/scripts
- PERF: Performance improvement
- CLN: Code cleanup

The following defines how a commit message should be structured. Please reference the relevant GitHub issues in your commit message using *GH1234* or *#1234*. Either style is fine, but the former is generally preferred:

- a subject line with < 80 chars.
- One blank line.
- Optionally, a commit message body.

Now you can commit your changes in your local repository:

```
git commit -m
```

If you have multiple commits, it is common to want to combine them into one commit, often referred to as “squashing” or “rebasing”. This is a common request by package maintainers when submitting a Pull Request as it maintains a more compact commit history. To rebase your commits:

```
git rebase -i HEAD~#
```

Where # is the number of commits you want to combine. Then you can pick the relevant commit message and discard others.

3.6.2 Pushing your changes

When you want your changes to appear publicly on your GitHub page, push your forked feature branch’s commits

```
git push origin shiny-new-feature
```

Here *origin* is the default name given to your remote repository on GitHub. You can see the remote repositories

```
git remote -v
```

If you added the upstream repository as described above you will see something like

```
origin  git@github.com:yourname/pandas.git (fetch)
origin  git@github.com:yourname/pandas.git (push)
upstream      git://github.com/pydata/pandas.git (fetch)
upstream      git://github.com/pydata/pandas.git (push)
```

Now your code is on GitHub, but it is not yet a part of the *pandas* project. For that to happen, a Pull Request needs to be submitted on GitHub.

3.6.3 Review your code

When you’re ready to ask for a code review, you will file a Pull Request. Before you do, again make sure you’ve followed all the guidelines outlined in this document regarding code style, tests, performance tests, and documentation. You should also double check your branch changes against the branch it was based off of:

1. Navigate to your repository on GitHub—<https://github.com/your-user-name/pandas>.
2. Click on *Branches*.
3. Click on the *Compare* button for your feature branch.
4. Select the *base* and *compare* branches, if necessary. This will be *master* and *shiny-new-feature*, respectively.

3.6.4 Finally, make the Pull Request

If everything looks good you are ready to make a Pull Request. A Pull Request is how code from a local repository becomes available to the GitHub community and can be looked at and eventually merged into the master version. This Pull Request and its associated changes will eventually be committed to the master branch and available in the next release. To submit a Pull Request:

1. Navigate to your repository on GitHub.
2. Click on the *Pull Request* button.
3. You can then click on *Commits* and *Files Changed* to make sure everything looks okay one last time.
4. Write a description of your changes in the *Preview Discussion* tab.
5. Click *Send Pull Request*.

This request then appears to the repository maintainers, and they will review the code. If you need to make more changes, you can make them in your branch, push them to GitHub, and the pull request will be automatically updated. Pushing them to GitHub again is done by:

```
git push -f origin shiny-new-feature
```

This will automatically update your Pull Request with the latest code and restart the Travis-CI tests.

3.6.5 Delete your merged branch (optional)

Once your feature branch is accepted into upstream, you'll probably want to get rid of the branch. First, merge upstream master into your branch so git knows it is safe to delete your branch

```
git fetch upstream
git checkout master
git merge upstream/master
```

Then you can just do:

```
git branch -d shiny-new-feature
```

Make sure you use a lower-case -d, or else git won't warn you if your feature branch has not actually been merged.

The branch will still exist on GitHub, so to delete it there do

```
git push origin --delete shiny-new-feature
```


FREQUENTLY ASKED QUESTIONS (FAQ)

4.1 DataFrame memory usage

As of pandas version 0.15.0, the memory usage of a dataframe (including the index) is shown when accessing the `info` method of a dataframe. A configuration option, `display.memory_usage` (see [Options and Settings](#)), specifies if the dataframe's memory usage will be displayed when invoking the `df.info()` method.

For example, the memory usage of the dataframe below is shown when calling `df.info()`:

```
In [1]: dtypes = ['int64', 'float64', 'datetime64[ns]', 'timedelta64[ns]',
...:             'complex128', 'object', 'bool']
...:
```

```
In [2]: n = 5000
```

```
In [3]: data = dict([(t, np.random.randint(100, size=n).astype(t))
...:                 for t in dtypes])
...:
```

```
In [4]: df = DataFrame(data)
```

```
In [5]: df['categorical'] = df['object'].astype('category')
```

```
In [6]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5000 entries, 0 to 4999
Data columns (total 8 columns):
bool                5000 non-null bool
complex128          5000 non-null complex128
datetime64[ns]      5000 non-null datetime64[ns]
float64             5000 non-null float64
int64               5000 non-null int64
object              5000 non-null object
timedelta64[ns]     5000 non-null timedelta64[ns]
categorical         5000 non-null category
dtypes: bool(1), category(1), complex128(1), datetime64[ns](1), float64(1), int64(1), object(1), timedelta64[ns](1)
memory usage: 303.5+ KB
```

The + symbol indicates that the true memory usage could be higher, because pandas does not count the memory used by values in columns with `dtype=object`.

By default the display option is set to `True` but can be explicitly overridden by passing the `memory_usage` argument when invoking `df.info()`.

The memory usage of each column can be found by calling the `memory_usage` method. This returns a Series with

an index represented by column names and memory usage of each column shown in bytes. For the dataframe above, the memory usage of each column and the total memory usage of the dataframe can be found with the `memory_usage` method:

```
In [7]: df.memory_usage()
Out[7]:
bool                5000
complex128          80000
datetime64[ns]      40000
float64             40000
int64               40000
object              20000
timedelta64[ns]     40000
categorical          5800
dtype: int64

# total memory usage of dataframe
In [8]: df.memory_usage().sum()
Out[8]: 270800
```

By default the memory usage of the dataframe's index is not shown in the returned Series, the memory usage of the index can be shown by passing the `index=True` argument:

```
In [9]: df.memory_usage(index=True)
Out[9]:
Index                40000
bool                 5000
complex128           80000
datetime64[ns]       40000
float64              40000
int64                40000
object               20000
timedelta64[ns]      40000
categorical           5800
dtype: int64
```

The memory usage displayed by the `info` method utilizes the `memory_usage` method to determine the memory usage of a dataframe while also formatting the output in human-readable units (base-2 representation; i.e., 1KB = 1024 bytes).

See also *Categorical Memory Usage*.

4.2 Adding Features to your pandas Installation

pandas is a powerful tool and already has a plethora of data manipulation operations implemented, most of them are very fast as well. It's very possible however that certain functionality that would make your life easier is missing. In that case you have several options:

1. Open an issue on [Github](#), explain your need and the sort of functionality you would like to see implemented.
2. Fork the repo, Implement the functionality yourself and open a PR on Github.
3. Write a method that performs the operation you are interested in and Monkey-patch the pandas class as part of your IPython profile startup or PYTHONSTARTUP file.

For example, here is an example of adding an `just_foo_cols()` method to the dataframe class:

```
import pandas as pd
def just_foo_cols(self):
    """Get a list of column names containing the string 'foo'

    """
    return [x for x in self.columns if 'foo' in x]

pd.DataFrame.just_foo_cols = just_foo_cols # monkey-patch the DataFrame class
df = pd.DataFrame([list(range(4))], columns=["A", "foo", "foozball", "bar"])
df.just_foo_cols()
del pd.DataFrame.just_foo_cols # you can also remove the new method
```

Monkey-patching is usually frowned upon because it makes your code less portable and can cause subtle bugs in some circumstances. Monkey-patching existing methods is usually a bad idea in that respect. When used with proper care, however, it's a very useful tool to have.

4.3 Migrating from `scikits.timeseries` to `pandas >= 0.8.0`

Starting with `pandas 0.8.0`, users of `scikits.timeseries` should have all of the features that they need to migrate their code to use `pandas`. Portions of the `scikits.timeseries` codebase for implementing calendar logic and timespan frequency conversions (but **not** resampling, that has all been implemented from scratch from the ground up) have been ported to the `pandas` codebase.

The `scikits.timeseries` notions of `Date` and `DateArray` are responsible for implementing calendar logic:

```
In [16]: dt = ts.Date('Q', '1984Q3')

# sic
In [17]: dt
Out[17]: <Q-DEC : 1984Q1>

In [18]: dt.asfreq('D', 'start')
Out[18]: <D : 01-Jan-1984>

In [19]: dt.asfreq('D', 'end')
Out[19]: <D : 31-Mar-1984>

In [20]: dt + 3
Out[20]: <Q-DEC : 1984Q4>
```

`Date` and `DateArray` from `scikits.timeseries` have been reincarnated in `pandas Period` and `PeriodIndex`:

```
In [10]: pnow('D') # scikits.timeseries.now()
Out[10]: Period('2015-05-11', 'D')

In [11]: Period(year=2007, month=3, day=15, freq='D')
Out[11]: Period('2007-03-15', 'D')

In [12]: p = Period('1984Q3')

In [13]: p
Out[13]: Period('1984Q3', 'Q-DEC')

In [14]: p.asfreq('D', 'start')
Out[14]: Period('1984-07-01', 'D')

In [15]: p.asfreq('D', 'end')
```

```

Out[15]: Period('1984-09-30', 'D')

In [16]: (p + 3).asfreq('T') + 6 * 60 + 30
Out[16]: Period('1985-07-01 06:29', 'T')

In [17]: rng = period_range('1990', '2010', freq='A')

In [18]: rng
Out[18]:
PeriodIndex(['1990', '1991', '1992', '1993', '1994', '1995', '1996', '1997',
            '1998', '1999', '2000', '2001', '2002', '2003', '2004', '2005',
            '2006', '2007', '2008', '2009', '2010'],
            dtype='int64', freq='A-DEC')

In [19]: rng.asfreq('B', 'end') - 3
Out[19]:
PeriodIndex(['1990-12-26', '1991-12-26', '1992-12-28', '1993-12-28',
            '1994-12-27', '1995-12-26', '1996-12-26', '1997-12-26',
            '1998-12-28', '1999-12-28', '2000-12-26', '2001-12-26',
            '2002-12-26', '2003-12-26', '2004-12-28', '2005-12-27',
            '2006-12-26', '2007-12-26', '2008-12-26', '2009-12-28',
            '2010-12-28'],
            dtype='int64', freq='B')

```

| scikits.timeseries | pandas | Notes |
|--------------------|--------------|---|
| Date | Period | A span of time, from yearly through to secondly |
| DateArray | PeriodIndex | An array of timespans |
| convert | resample | Frequency conversion in scikits.timeseries |
| convert_to_annual | pivot_annual | currently supports up to daily frequency, see GH736 |

4.3.1 PeriodIndex / DateArray properties and functions

The scikits.timeseries DateArray had a number of information properties. Here are the pandas equivalents:

| scikits.timeseries | pandas | Notes |
|----------------------------|------------------------------------|-------|
| get_steps | np.diff(idx.values) | |
| has_missing_dates | not idx.is_full | |
| is_full | idx.is_full | |
| is_valid | idx.is_monotonic and idx.is_unique | |
| is_chronological | is_monotonic | |
| arr.sort_chronologically() | idx.order() | |

4.3.2 Frequency conversion

Frequency conversion is implemented using the `resample` method on `TimeSeries` and `DataFrame` objects (multiple time series). `resample` also works on panels (3D). Here is some code that resamples daily data to monthly:

```

In [20]: rng = period_range('Jan-2000', periods=50, freq='M')

In [21]: data = Series(np.random.randn(50), index=rng)

In [22]: data
Out[22]:
2000-01    1.544821
2000-02   -1.708552

```

```

2000-03    1.545458
2000-04   -0.735738
2000-05   -0.649091
2000-06   -0.403878
2000-07   -2.474932
...
2003-08    1.034493
2003-09    1.269838
2003-10    0.606166
2003-11   -0.827409
2003-12   -0.943863
2004-01    1.041569
2004-02    0.701815
Freq: M, dtype: float64

```

```
In [23]: data.resample('A', how=np.mean)
```

```
Out [23]:
```

```

2000    0.102447
2001   -0.204847
2002    0.210840
2003    0.300564
2004    0.871692
Freq: A-DEC, dtype: float64

```

4.3.3 Plotting

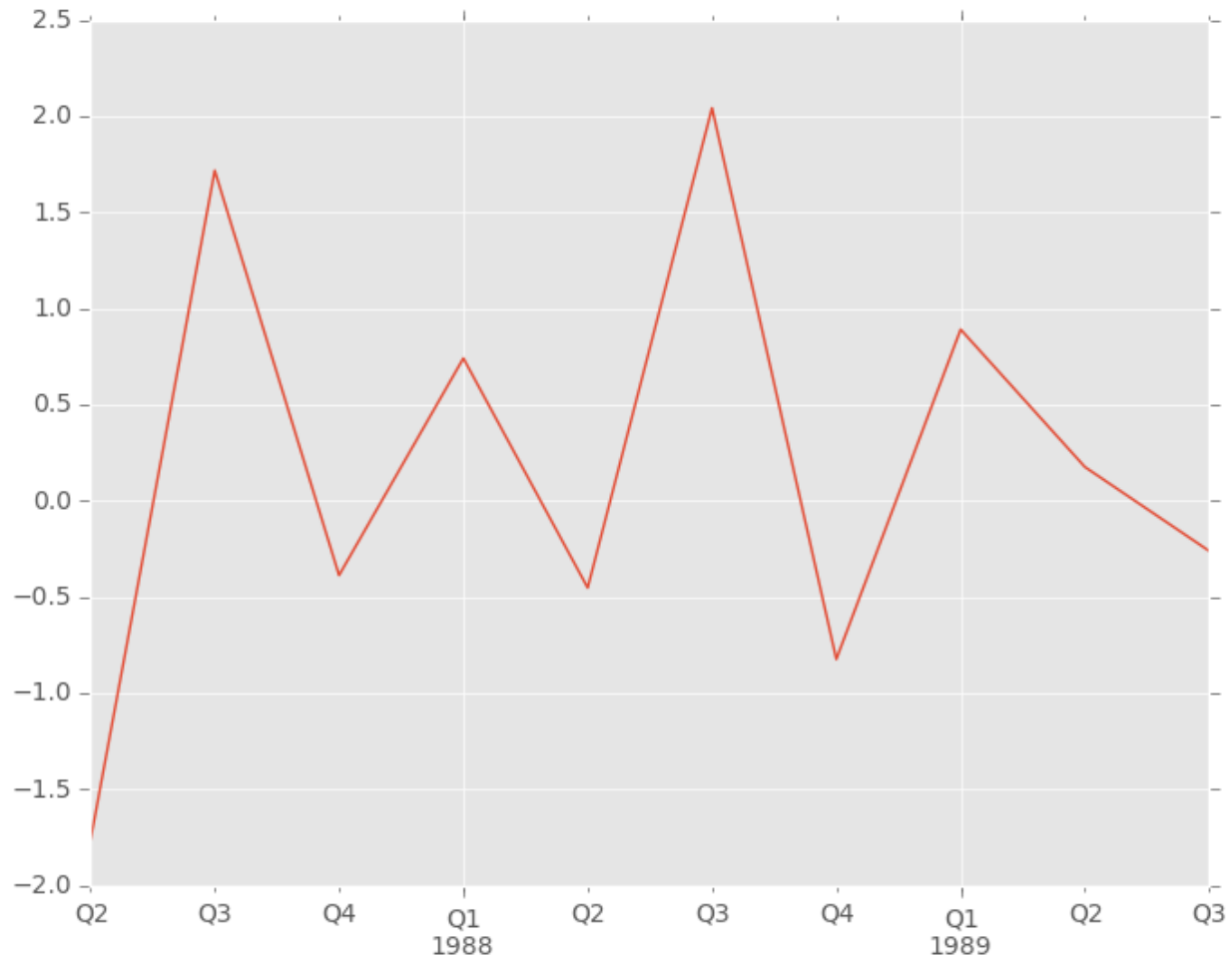
Much of the plotting functionality of `scikits.timeseries` has been ported and adopted to pandas's data structures. For example:

```
In [24]: rng = period_range('1987Q2', periods=10, freq='Q-DEC')
```

```
In [25]: data = Series(np.random.randn(10), index=rng)
```

```
In [26]: plt.figure(); data.plot()
```

```
Out [26]: <matplotlib.axes._subplots.AxesSubplot at 0xa18186cc>
```



4.3.4 Converting to and from period format

Use the `to_timestamp` and `to_period` instance methods.

4.3.5 Treatment of missing data

Unlike `scikits.timeseries`, pandas data structures are not based on NumPy's `MaskedArray` object. Missing data is represented as `NaN` in numerical arrays and either as `None` or `NaN` in non-numerical arrays. Implementing a version of pandas's data structures that use `MaskedArray` is possible but would require the involvement of a dedicated maintainer. Active pandas developers are not interested in this.

4.3.6 Resampling with timestamps and periods

`resample` has a `kind` argument which allows you to resample time series with a `DatetimeIndex` to `PeriodIndex`:

```
In [27]: rng = date_range('1/1/2000', periods=200, freq='D')
```

```
In [28]: data = Series(np.random.randn(200), index=rng)
```

```
In [29]: data[:10]
```

```

Out[29]:
2000-01-01    -0.197661
2000-01-02     0.507155
2000-01-03    -0.493913
2000-01-04    -0.994339
2000-01-05    -0.581662
2000-01-06    -0.855251
2000-01-07    -0.256469
2000-01-08    -0.454868
2000-01-09     0.519612
2000-01-10     0.764490
Freq: D, dtype: float64

In [30]: data.index
Out[30]:
DatetimeIndex(['2000-01-01', '2000-01-02', '2000-01-03', '2000-01-04',
               '2000-01-05', '2000-01-06', '2000-01-07', '2000-01-08',
               '2000-01-09', '2000-01-10',
               ...,
               '2000-07-09', '2000-07-10', '2000-07-11', '2000-07-12',
               '2000-07-13', '2000-07-14', '2000-07-15', '2000-07-16',
               '2000-07-17', '2000-07-18'],
              dtype='datetime64[ns]', length=200, freq='D', tz=None)

```

```
In [31]: data.resample('M', kind='period')
```

```

Out[31]:
2000-01    -0.226155
2000-02     0.056704
2000-03    -0.132553
2000-04    -0.064003
2000-05     0.233736
2000-06    -0.301008
2000-07    -0.584631
Freq: M, dtype: float64

```

Similarly, resampling from periods to timestamps is possible with an optional interval ('start' or 'end') convention:

```

In [32]: rng = period_range('Jan-2000', periods=50, freq='M')

In [33]: data = Series(np.random.randn(50), index=rng)

In [34]: resampled = data.resample('A', kind='timestamp', convention='end')

In [35]: resampled.index
Out[35]:
DatetimeIndex(['2000-12-31', '2001-12-31', '2002-12-31', '2003-12-31',
               '2004-12-31'],
              dtype='datetime64[ns]', freq='A-DEC', tz=None)

```

4.4 Byte-Ordering Issues

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. To deal with this issue you should convert the underlying NumPy array to the native system byte order *before* passing it to Series/DataFrame/Panel constructors using something similar to the following:

```
In [36]: x = np.array(list(range(10)), '>i4') # big endian
In [37]: newx = x.byteswap().newbyteorder() # force native byteorder
In [38]: s = Series(newx)
```

See the NumPy documentation on [byte order](#) for more details.

4.5 Visualizing Data in Qt applications

Warning: The `qt` support is **deprecated and will be removed in a future version**. We refer users to the external package `pandas-qt`.

There is experimental support for visualizing DataFrames in PyQt4 and PySide applications. At the moment you can display and edit the values of the cells in the DataFrame. Qt will take care of displaying just the portion of the DataFrame that is currently visible and the edits will be immediately saved to the underlying DataFrame

To demonstrate this we will create a simple PySide application that will switch between two editable DataFrames. For this will use the `DataFrameModel` class that handles the access to the DataFrame, and the `DataFrameWidget`, which is just a thin layer around the `QTableView`.

```
import numpy as np
import pandas as pd
from pandas.sandbox.qtpandas import DataFrameModel, DataFrameWidget
from PySide import QtGui, QtCore

# Or if you use PyQt4:
# from PyQt4 import QtGui, QtCore

class MainWidget(QtGui.QWidget):
    def __init__(self, parent=None):
        super(MainWidget, self).__init__(parent)

        # Create two DataFrames
        self.df1 = pd.DataFrame(np.arange(9).reshape(3, 3),
                                columns=['foo', 'bar', 'baz'])
        self.df2 = pd.DataFrame({
            'int': [1, 2, 3],
            'float': [1.5, 2.5, 3.5],
            'string': ['a', 'b', 'c'],
            'nan': [np.nan, np.nan, np.nan]
        }, index=['AAA', 'BBB', 'CCC'],
            columns=['int', 'float', 'string', 'nan'])

        # Create the widget and set the first DataFrame
        self.widget = DataFrameWidget(self.df1)

        # Create the buttons for changing DataFrames
        self.button_first = QtGui.QPushButton('First')
        self.button_first.clicked.connect(self.on_first_click)
        self.button_second = QtGui.QPushButton('Second')
        self.button_second.clicked.connect(self.on_second_click)

        # Set the layout
        vbox = QtGui.QVBoxLayout()
```

```
vbox.addWidget(self.widget)
hbox = QtGui.QHBoxLayout()
hbox.addWidget(self.button_first)
hbox.addWidget(self.button_second)
vbox.addLayout(hbox)
self.setLayout(vbox)

def on_first_click(self):
    '''Sets the first DataFrame'''
    self.widget.setDataFrame(self.df1)

def on_second_click(self):
    '''Sets the second DataFrame'''
    self.widget.setDataFrame(self.df2)

if __name__ == '__main__':
    import sys

    # Initialize the application
    app = QtGui.QApplication(sys.argv)
    mw = MainWidget()
    mw.show()
    app.exec_()
```


PACKAGE OVERVIEW

pandas consists of the following things

- A set of labeled array data structures, the primary of which are Series/TimeSeries and DataFrame
- Index objects enabling both simple axis indexing and multi-level / hierarchical axis indexing
- An integrated group by engine for aggregating and transforming data sets
- Date range generation (date_range) and custom date offsets enabling the implementation of customized frequencies
- Input/Output tools: loading tabular data from flat files (CSV, delimited, Excel 2003), and saving and loading pandas objects from the fast and efficient PyTables/HDF5 format.
- Memory-efficient “sparse” versions of the standard data structures for storing data that is mostly missing or mostly constant (some fixed value)
- Moving window statistics (rolling mean, rolling standard deviation, etc.)
- Static and moving window linear and [panel regression](#)

5.1 Data structures at a glance

| Dimen-
sions | Name | Description |
|-----------------|-----------------|---|
| 1 | Series | 1D labeled homogeneously-typed array |
| 1 | Time-
Series | Series with index containing datetimes |
| 2 | DataFrame | General 2D labeled, size-mutable tabular structure with potentially heterogeneously-typed columns |
| 3 | Panel | General 3D labeled, also size-mutable array |

5.1.1 Why more than 1 data structure?

The best way to think about the pandas data structures is as flexible containers for lower dimensional data. For example, DataFrame is a container for Series, and Panel is a container for DataFrame objects. We would like to be able to insert and remove objects from these containers in a dictionary-like fashion.

Also, we would like sensible default behaviors for the common API functions which take into account the typical orientation of time series and cross-sectional data sets. When using ndarrays to store 2- and 3-dimensional data, a burden is placed on the user to consider the orientation of the data set when writing functions; axes are considered more or less equivalent (except when C- or Fortran-contiguosness matters for performance). In pandas, the axes are intended to lend more semantic meaning to the data; i.e., for a particular data set there is likely to be a “right” way to

orient the data. The goal, then, is to reduce the amount of mental effort required to code up data transformations in downstream functions.

For example, with tabular data (DataFrame) it is more semantically helpful to think of the **index** (the rows) and the **columns** rather than axis 0 and axis 1. And iterating through the columns of the DataFrame thus results in more readable code:

```
for col in df.columns:
    series = df[col]
    # do something with series
```

5.2 Mutability and copying of data

All pandas data structures are value-mutable (the values they contain can be altered) but not always size-mutable. The length of a Series cannot be changed, but, for example, columns can be inserted into a DataFrame. However, the vast majority of methods produce new objects and leave the input data untouched. In general, though, we like to **favor immutability** where sensible.

5.3 Getting Support

The first stop for pandas issues and ideas is the [Github Issue Tracker](#). If you have a general question, pandas community experts can answer through [Stack Overflow](#).

Longer discussions occur on the [developer mailing list](#), and commercial support inquiries for Lambda Foundry should be sent to: support@lambdafoundry.com

5.4 Credits

pandas development began at [AQR Capital Management](#) in April 2008. It was open-sourced at the end of 2009. AQR continued to provide resources for development through the end of 2011, and continues to contribute bug reports today.

Since January 2012, [Lambda Foundry](#), has been providing development resources, as well as commercial support, training, and consulting for pandas.

pandas is only made possible by a group of people around the world like you who have contributed new code, bug reports, fixes, comments and ideas. A complete list can be found [on Github](#).

5.5 Development Team

pandas is a part of the PyData project. The PyData Development Team is a collection of developers focused on the improvement of Python's data libraries. The core team that coordinates development can be found [on Github](#). If you're interested in contributing, please visit the [project website](#).

5.6 License

```
=====
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=====
```

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AQR Capital Management began pandas development in 2008. Development was led by Wes McKinney. AQR released the source under this license in 2009. Wes is now an employee of Lambda Foundry, and remains the pandas project lead.

The PyData Development Team is the collection of developers of the PyData project. This includes all of the PyData sub-projects, including pandas. The core team that coordinates development on GitHub can be found here: <http://github.com/pydata>.

Full credits for pandas contributors can be found in the documentation.

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10 MINUTES TO PANDAS

This is a short introduction to pandas, geared mainly for new users. You can see more complex recipes in the *Cookbook*. Customarily, we import as follows

```
In [1]: import pandas as pd
In [2]: import numpy as np
In [3]: import matplotlib.pyplot as plt
```

6.1 Object Creation

See the *Data Structure Intro section*

Creating a `Series` by passing a list of values, letting pandas create a default integer index:

```
In [4]: s = pd.Series([1,3,5,np.nan,6,8])

In [5]: s
Out[5]:
0      1
1      3
2      5
3     NaN
4      6
5      8
dtype: float64
```

Creating a `DataFrame` by passing a numpy array, with a datetime index and labeled columns:

```
In [6]: dates = pd.date_range('20130101', periods=6)

In [7]: dates
Out[7]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D', tz=None)

In [8]: df = pd.DataFrame(np.random.randn(6,4), index=dates, columns=list('ABCD'))

In [9]: df
Out[9]:
```

| | A | B | C | D |
|--|---|---|---|---|
|--|---|---|---|---|

```
2013-01-01    0.469112 -0.282863 -1.509059 -1.135632
2013-01-02    1.212112 -0.173215  0.119209 -1.044236
2013-01-03   -0.861849 -2.104569 -0.494929  1.071804
2013-01-04    0.721555 -0.706771 -1.039575  0.271860
2013-01-05   -0.424972  0.567020  0.276232 -1.087401
2013-01-06   -0.673690  0.113648 -1.478427  0.524988
```

Creating a DataFrame by passing a dict of objects that can be converted to series-like.

```
In [10]: df2 = pd.DataFrame({ 'A' : 1.,
.....:                      'B' : pd.Timestamp('20130102'),
.....:                      'C' : pd.Series(1,index=list(range(4)),dtype='float32'),
.....:                      'D' : np.array([3] * 4,dtype='int32'),
.....:                      'E' : pd.Categorical(["test","train","test","train"]),
.....:                      'F' : 'foo' })
.....:
```

```
In [11]: df2
```

```
Out[11]:
```

| | A | B | C | D | E | F |
|---|---|------------|---|---|-------|-----|
| 0 | 1 | 2013-01-02 | 1 | 3 | test | foo |
| 1 | 1 | 2013-01-02 | 1 | 3 | train | foo |
| 2 | 1 | 2013-01-02 | 1 | 3 | test | foo |
| 3 | 1 | 2013-01-02 | 1 | 3 | train | foo |

Having specific *dtypes*

```
In [12]: df2.dtypes
```

```
Out[12]:
```

| | |
|---|----------------|
| A | float64 |
| B | datetime64[ns] |
| C | float32 |
| D | int32 |
| E | category |
| F | object |

dtype: object

If you're using IPython, tab completion for column names (as well as public attributes) is automatically enabled. Here's a subset of the attributes that will be completed:

```
In [13]: df2.<TAB>
df2.A                df2.boxplot
df2.abs              df2.C
df2.add              df2.clip
df2.add_prefix      df2.clip_lower
df2.add_suffix      df2.clip_upper
df2.align            df2.columns
df2.all              df2.combine
df2.any              df2.combineAdd
df2.append           df2.combine_first
df2.apply            df2.combineMult
df2.applymap         df2.compound
df2.as_blocks        df2.consolidate
df2.asfreq           df2.convert_objects
df2.as_matrix        df2.copy
df2.astype           df2.corr
df2.at               df2.corrwith
df2.at_time          df2.count
df2.axes             df2.cov
```

```

df2.B          df2.cummax
df2.between_time df2.cummin
df2.bfill      df2.cumprod
df2.blocks     df2.cumsum
df2.bool       df2.D

```

As you can see, the columns A, B, C, and D are automatically tab completed. E is there as well; the rest of the attributes have been truncated for brevity.

6.2 Viewing Data

See the *Basics section*

See the top & bottom rows of the frame

```

In [14]: df.head()
Out[14]:
           A          B          C          D
2013-01-01  0.469112 -0.282863 -1.509059 -1.135632
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401

```

```

In [15]: df.tail(3)
Out[15]:
           A          B          C          D
2013-01-04  0.721555 -0.706771 -1.039575  0.271860
2013-01-05 -0.424972  0.567020  0.276232 -1.087401
2013-01-06 -0.673690  0.113648 -1.478427  0.524988

```

Display the index, columns, and the underlying numpy data

```

In [16]: df.index
Out[16]:
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
                '2013-01-05', '2013-01-06'],
              dtype='datetime64[ns]', freq='D', tz=None)

```

```

In [17]: df.columns
Out[17]: Index([u'A', u'B', u'C', u'D'], dtype='object')

```

```

In [18]: df.values
Out[18]:
array([[ 0.4691, -0.2829, -1.5091, -1.1356],
       [ 1.2121, -0.1732,  0.1192, -1.0442],
       [-0.8618, -2.1046, -0.4949,  1.0718],
       [ 0.7216, -0.7068, -1.0396,  0.2719],
       [-0.425 ,  0.567 ,  0.2762, -1.0874],
       [-0.6737,  0.1136, -1.4784,  0.525 ]])

```

Describe shows a quick statistic summary of your data

```

In [19]: df.describe()
Out[19]:
           A          B          C          D
count  6.000000  6.000000  6.000000  6.000000

```

```
mean    0.073711 -0.431125 -0.687758 -0.233103
std     0.843157  0.922818  0.779887  0.973118
min    -0.861849 -2.104569 -1.509059 -1.135632
25%    -0.611510 -0.600794 -1.368714 -1.076610
50%     0.022070 -0.228039 -0.767252 -0.386188
75%     0.658444  0.041933 -0.034326  0.461706
max     1.212112  0.567020  0.276232  1.071804
```

Transposing your data

```
In [20]: df.T
```

```
Out [20]:
```

| | 2013-01-01 | 2013-01-02 | 2013-01-03 | 2013-01-04 | 2013-01-05 | 2013-01-06 |
|---|------------|------------|------------|------------|------------|------------|
| A | 0.469112 | 1.212112 | -0.861849 | 0.721555 | -0.424972 | -0.673690 |
| B | -0.282863 | -0.173215 | -2.104569 | -0.706771 | 0.567020 | 0.113648 |
| C | -1.509059 | 0.119209 | -0.494929 | -1.039575 | 0.276232 | -1.478427 |
| D | -1.135632 | -1.044236 | 1.071804 | 0.271860 | -1.087401 | 0.524988 |

Sorting by an axis

```
In [21]: df.sort_index(axis=1, ascending=False)
```

```
Out [21]:
```

| | D | C | B | A |
|------------|-----------|-----------|-----------|-----------|
| 2013-01-01 | -1.135632 | -1.509059 | -0.282863 | 0.469112 |
| 2013-01-02 | -1.044236 | 0.119209 | -0.173215 | 1.212112 |
| 2013-01-03 | 1.071804 | -0.494929 | -2.104569 | -0.861849 |
| 2013-01-04 | 0.271860 | -1.039575 | -0.706771 | 0.721555 |
| 2013-01-05 | -1.087401 | 0.276232 | 0.567020 | -0.424972 |
| 2013-01-06 | 0.524988 | -1.478427 | 0.113648 | -0.673690 |

Sorting by values

```
In [22]: df.sort(columns='B')
```

```
Out [22]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |
| 2013-01-04 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |
| 2013-01-01 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2013-01-06 | -0.673690 | 0.113648 | -1.478427 | 0.524988 |
| 2013-01-05 | -0.424972 | 0.567020 | 0.276232 | -1.087401 |

6.3 Selection

Note: While standard Python / Numpy expressions for selecting and setting are intuitive and come in handy for interactive work, for production code, we recommend the optimized pandas data access methods, `.at`, `.iat`, `.loc`, `.iloc` and `.ix`.

See the indexing documentation [Indexing and Seleccion Data](#) and [MultiIndex / Advanced Indexing](#)

6.3.1 Getting

Selecting a single column, which yields a `Series`, equivalent to `df.A`

```
In [23]: df['A']
Out[23]:
2013-01-01    0.469112
2013-01-02    1.212112
2013-01-03   -0.861849
2013-01-04    0.721555
2013-01-05   -0.424972
2013-01-06   -0.673690
Freq: D, Name: A, dtype: float64
```

Selecting via `[]`, which slices the rows.

```
In [24]: df[0:3]
Out[24]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2013-01-01 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |

```
In [25]: df['20130102':'20130104']
Out[25]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |
| 2013-01-04 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |

6.3.2 Selection by Label

See more in *Selection by Label*

For getting a cross section using a label

```
In [26]: df.loc[dates[0]]
Out[26]:
A    0.469112
B   -0.282863
C   -1.509059
D   -1.135632
Name: 2013-01-01 00:00:00, dtype: float64
```

Selecting on a multi-axis by label

```
In [27]: df.loc[:, ['A', 'B']]
Out[27]:
```

| | A | B |
|------------|-----------|-----------|
| 2013-01-01 | 0.469112 | -0.282863 |
| 2013-01-02 | 1.212112 | -0.173215 |
| 2013-01-03 | -0.861849 | -2.104569 |
| 2013-01-04 | 0.721555 | -0.706771 |
| 2013-01-05 | -0.424972 | 0.567020 |
| 2013-01-06 | -0.673690 | 0.113648 |

Showing label slicing, both endpoints are *included*

```
In [28]: df.loc['20130102':'20130104', ['A', 'B']]
Out[28]:
```

| | A | B |
|------------|----------|-----------|
| 2013-01-02 | 1.212112 | -0.173215 |

```
2013-01-03 -0.861849 -2.104569
2013-01-04  0.721555 -0.706771
```

Reduction in the dimensions of the returned object

```
In [29]: df.loc['20130102', ['A', 'B']]
Out[29]:
A    1.212112
B   -0.173215
Name: 2013-01-02 00:00:00, dtype: float64
```

For getting a scalar value

```
In [30]: df.loc[dates[0], 'A']
Out[30]: 0.46911229990718628
```

For getting fast access to a scalar (equiv to the prior method)

```
In [31]: df.at[dates[0], 'A']
Out[31]: 0.46911229990718628
```

6.3.3 Selection by Position

See more in *Selection by Position*

Select via the position of the passed integers

```
In [32]: df.iloc[3]
Out[32]:
A    0.721555
B   -0.706771
C   -1.039575
D    0.271860
Name: 2013-01-04 00:00:00, dtype: float64
```

By integer slices, acting similar to numpy/python

```
In [33]: df.iloc[3:5, 0:2]
Out[33]:
           A          B
2013-01-04  0.721555 -0.706771
2013-01-05 -0.424972  0.567020
```

By lists of integer position locations, similar to the numpy/python style

```
In [34]: df.iloc[[1, 2, 4], [0, 2]]
Out[34]:
           A          C
2013-01-02  1.212112  0.119209
2013-01-03 -0.861849 -0.494929
2013-01-05 -0.424972  0.276232
```

For slicing rows explicitly

```
In [35]: df.iloc[1:3, :]
Out[35]:
           A          B          C          D
2013-01-02  1.212112 -0.173215  0.119209 -1.044236
2013-01-03 -0.861849 -2.104569 -0.494929  1.071804
```

For slicing columns explicitly

```
In [36]: df.iloc[:,1:3]
Out[36]:
```

| | B | C |
|------------|-----------|-----------|
| 2013-01-01 | -0.282863 | -1.509059 |
| 2013-01-02 | -0.173215 | 0.119209 |
| 2013-01-03 | -2.104569 | -0.494929 |
| 2013-01-04 | -0.706771 | -1.039575 |
| 2013-01-05 | 0.567020 | 0.276232 |
| 2013-01-06 | 0.113648 | -1.478427 |

For getting a value explicitly

```
In [37]: df.iloc[1,1]
Out[37]: -0.17321464905330858
```

For getting fast access to a scalar (equiv to the prior method)

```
In [38]: df.iat[1,1]
Out[38]: -0.17321464905330858
```

6.3.4 Boolean Indexing

Using a single column's values to select data.

```
In [39]: df[df.A > 0]
Out[39]:
```

| | A | B | C | D |
|------------|----------|-----------|-----------|-----------|
| 2013-01-01 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2013-01-04 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |

A where operation for getting.

```
In [40]: df[df > 0]
Out[40]:
```

| | A | B | C | D |
|------------|----------|----------|----------|----------|
| 2013-01-01 | 0.469112 | NaN | NaN | NaN |
| 2013-01-02 | 1.212112 | NaN | 0.119209 | NaN |
| 2013-01-03 | NaN | NaN | NaN | 1.071804 |
| 2013-01-04 | 0.721555 | NaN | NaN | 0.271860 |
| 2013-01-05 | NaN | 0.567020 | 0.276232 | NaN |
| 2013-01-06 | NaN | 0.113648 | NaN | 0.524988 |

Using the `isin()` method for filtering:

```
In [41]: df2 = df.copy()
In [42]: df2['E']=['one', 'one','two','three','four','three']
In [43]: df2
```

```
Out[43]:
```

| | A | B | C | D | E |
|------------|-----------|-----------|-----------|-----------|-------|
| 2013-01-01 | 0.469112 | -0.282863 | -1.509059 | -1.135632 | one |
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 | one |
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 | two |
| 2013-01-04 | 0.721555 | -0.706771 | -1.039575 | 0.271860 | three |
| 2013-01-05 | -0.424972 | 0.567020 | 0.276232 | -1.087401 | four |

```
2013-01-06 -0.673690  0.113648 -1.478427  0.524988  three
```

```
In [44]: df2[df2['E'].isin(['two', 'four'])]
```

```
Out[44]:
```

| | A | B | C | D | E |
|------------|-----------|-----------|-----------|-----------|------|
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 | two |
| 2013-01-05 | -0.424972 | 0.567020 | 0.276232 | -1.087401 | four |

6.3.5 Setting

Setting a new column automatically aligns the data by the indexes

```
In [45]: s1 = pd.Series([1,2,3,4,5,6],index=pd.date_range('20130102',periods=6))
```

```
In [46]: s1
```

```
Out[46]:
```

```
2013-01-02    1
2013-01-03    2
2013-01-04    3
2013-01-05    4
2013-01-06    5
2013-01-07    6
Freq: D, dtype: int64
```

```
In [47]: df['F'] = s1
```

Setting values by label

```
In [48]: df.at[dates[0], 'A'] = 0
```

Setting values by position

```
In [49]: df.iat[0,1] = 0
```

Setting by assigning with a numpy array

```
In [50]: df.loc[:, 'D'] = np.array([5] * len(df))
```

The result of the prior setting operations

```
In [51]: df
```

```
Out[51]:
```

| | A | B | C | D | F |
|------------|-----------|-----------|-----------|---|-----|
| 2013-01-01 | 0.000000 | 0.000000 | -1.509059 | 5 | NaN |
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | 5 | 1 |
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 5 | 2 |
| 2013-01-04 | 0.721555 | -0.706771 | -1.039575 | 5 | 3 |
| 2013-01-05 | -0.424972 | 0.567020 | 0.276232 | 5 | 4 |
| 2013-01-06 | -0.673690 | 0.113648 | -1.478427 | 5 | 5 |

A where operation with setting.

```
In [52]: df2 = df.copy()
```

```
In [53]: df2[df2 > 0] = -df2
```

```
In [54]: df2
```

```
Out[54]:
```

| | A | B | C | D | F |
|--|---|---|---|---|---|
|--|---|---|---|---|---|

```

2013-01-01  0.000000  0.000000 -1.509059 -5 NaN
2013-01-02 -1.212112 -0.173215 -0.119209 -5 -1
2013-01-03 -0.861849 -2.104569 -0.494929 -5 -2
2013-01-04 -0.721555 -0.706771 -1.039575 -5 -3
2013-01-05 -0.424972 -0.567020 -0.276232 -5 -4
2013-01-06 -0.673690 -0.113648 -1.478427 -5 -5

```

6.4 Missing Data

pandas primarily uses the value `np.nan` to represent missing data. It is by default not included in computations. See the *Missing Data section*

Reindexing allows you to change/add/delete the index on a specified axis. This returns a copy of the data.

```
In [55]: df1 = df.reindex(index=dates[0:4], columns=list(df.columns) + ['E'])
```

```
In [56]: df1.loc[dates[0]:dates[1], 'E'] = 1
```

```
In [57]: df1
```

```
Out [57]:
```

| | A | B | C | D | F | E |
|------------|-----------|-----------|-----------|---|-----|-----|
| 2013-01-01 | 0.000000 | 0.000000 | -1.509059 | 5 | NaN | 1 |
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | 5 | 1 | 1 |
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 5 | 2 | NaN |
| 2013-01-04 | 0.721555 | -0.706771 | -1.039575 | 5 | 3 | NaN |

To drop any rows that have missing data.

```
In [58]: df1.dropna(how='any')
```

```
Out [58]:
```

| | A | B | C | D | F | E |
|------------|----------|-----------|----------|---|---|---|
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | 5 | 1 | 1 |

Filling missing data

```
In [59]: df1.fillna(value=5)
```

```
Out [59]:
```

| | A | B | C | D | F | E |
|------------|-----------|-----------|-----------|---|---|---|
| 2013-01-01 | 0.000000 | 0.000000 | -1.509059 | 5 | 5 | 1 |
| 2013-01-02 | 1.212112 | -0.173215 | 0.119209 | 5 | 1 | 1 |
| 2013-01-03 | -0.861849 | -2.104569 | -0.494929 | 5 | 2 | 5 |
| 2013-01-04 | 0.721555 | -0.706771 | -1.039575 | 5 | 3 | 5 |

To get the boolean mask where values are nan

```
In [60]: pd.isnull(df1)
```

```
Out [60]:
```

| | A | B | C | D | F | E |
|------------|-------|-------|-------|-------|-------|-------|
| 2013-01-01 | False | False | False | False | True | False |
| 2013-01-02 | False | False | False | False | False | False |
| 2013-01-03 | False | False | False | False | False | True |
| 2013-01-04 | False | False | False | False | False | True |

6.5 Operations

See the *Basic section on Binary Ops*

6.5.1 Stats

Operations in general *exclude* missing data.

Performing a descriptive statistic

```
In [61]: df.mean()
Out [61]:
A    -0.004474
B    -0.383981
C    -0.687758
D     5.000000
F     3.000000
dtype: float64
```

Same operation on the other axis

```
In [62]: df.mean(1)
Out [62]:
2013-01-01    0.872735
2013-01-02    1.431621
2013-01-03    0.707731
2013-01-04    1.395042
2013-01-05    1.883656
2013-01-06    1.592306
Freq: D, dtype: float64
```

Operating with objects that have different dimensionality and need alignment. In addition, pandas automatically broadcasts along the specified dimension.

```
In [63]: s = pd.Series([1,3,5,np.nan,6,8],index=dates).shift(2)
```

```
In [64]: s
Out [64]:
2013-01-01    NaN
2013-01-02    NaN
2013-01-03     1
2013-01-04     3
2013-01-05     5
2013-01-06    NaN
Freq: D, dtype: float64
```

```
In [65]: df.sub(s,axis='index')
Out [65]:
```

| | A | B | C | D | F |
|------------|-----------|-----------|-----------|-----|-----|
| 2013-01-01 | NaN | NaN | NaN | NaN | NaN |
| 2013-01-02 | NaN | NaN | NaN | NaN | NaN |
| 2013-01-03 | -1.861849 | -3.104569 | -1.494929 | 4 | 1 |
| 2013-01-04 | -2.278445 | -3.706771 | -4.039575 | 2 | 0 |
| 2013-01-05 | -5.424972 | -4.432980 | -4.723768 | 0 | -1 |
| 2013-01-06 | NaN | NaN | NaN | NaN | NaN |

6.5.2 Apply

Applying functions to the data

```
In [66]: df.apply(np.cumsum)
Out [66]:
```

| | A | B | C | D | F |
|------------|-----------|-----------|-----------|----|-----|
| 2013-01-01 | 0.000000 | 0.000000 | -1.509059 | 5 | NaN |
| 2013-01-02 | 1.212112 | -0.173215 | -1.389850 | 10 | 1 |
| 2013-01-03 | 0.350263 | -2.277784 | -1.884779 | 15 | 3 |
| 2013-01-04 | 1.071818 | -2.984555 | -2.924354 | 20 | 6 |
| 2013-01-05 | 0.646846 | -2.417535 | -2.648122 | 25 | 10 |
| 2013-01-06 | -0.026844 | -2.303886 | -4.126549 | 30 | 15 |

```
In [67]: df.apply(lambda x: x.max() - x.min())
Out[67]:
A    2.073961
B    2.671590
C    1.785291
D     0.000000
F    4.000000
dtype: float64
```

6.5.3 Histogramming

See more at *Histogramming and Discretization*

```
In [68]: s = pd.Series(np.random.randint(0,7,size=10))
```

```
In [69]: s
Out[69]:
0     4
1     2
2     1
3     2
4     6
5     4
6     4
7     6
8     4
9     4
dtype: int32
```

```
In [70]: s.value_counts()
Out[70]:
4     5
6     2
2     2
1     1
dtype: int64
```

6.5.4 String Methods

Series is equipped with a set of string processing methods in the *str* attribute that make it easy to operate on each element of the array, as in the code snippet below. Note that pattern-matching in *str* generally uses [regular expressions](#) by default (and in some cases always uses them). See more at *Vectorized String Methods*.

```
In [71]: s = pd.Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])
```

```
In [72]: s.str.lower()
Out[72]:
```

```
0      a
1      b
2      c
3    aaba
4    baca
5     NaN
6    caba
7     dog
8     cat
dtype: object
```

6.6 Merge

6.6.1 Concat

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

See the [Merging section](#)

Concatenating pandas objects together with `concat()`:

```
In [73]: df = pd.DataFrame(np.random.randn(10, 4))
```

```
In [74]: df
```

```
Out[74]:
```

| | 0 | 1 | 2 | 3 |
|---|-----------|-----------|-----------|-----------|
| 0 | -0.548702 | 1.467327 | -1.015962 | -0.483075 |
| 1 | 1.637550 | -1.217659 | -0.291519 | -1.745505 |
| 2 | -0.263952 | 0.991460 | -0.919069 | 0.266046 |
| 3 | -0.709661 | 1.669052 | 1.037882 | -1.705775 |
| 4 | -0.919854 | -0.042379 | 1.247642 | -0.009920 |
| 5 | 0.290213 | 0.495767 | 0.362949 | 1.548106 |
| 6 | -1.131345 | -0.089329 | 0.337863 | -0.945867 |
| 7 | -0.932132 | 1.956030 | 0.017587 | -0.016692 |
| 8 | -0.575247 | 0.254161 | -1.143704 | 0.215897 |
| 9 | 1.193555 | -0.077118 | -0.408530 | -0.862495 |

```
# break it into pieces
```

```
In [75]: pieces = [df[:3], df[3:7], df[7:]]
```

```
In [76]: pd.concat(pieces)
```

```
Out[76]:
```

| | 0 | 1 | 2 | 3 |
|---|-----------|-----------|-----------|-----------|
| 0 | -0.548702 | 1.467327 | -1.015962 | -0.483075 |
| 1 | 1.637550 | -1.217659 | -0.291519 | -1.745505 |
| 2 | -0.263952 | 0.991460 | -0.919069 | 0.266046 |
| 3 | -0.709661 | 1.669052 | 1.037882 | -1.705775 |
| 4 | -0.919854 | -0.042379 | 1.247642 | -0.009920 |
| 5 | 0.290213 | 0.495767 | 0.362949 | 1.548106 |
| 6 | -1.131345 | -0.089329 | 0.337863 | -0.945867 |
| 7 | -0.932132 | 1.956030 | 0.017587 | -0.016692 |
| 8 | -0.575247 | 0.254161 | -1.143704 | 0.215897 |
| 9 | 1.193555 | -0.077118 | -0.408530 | -0.862495 |

6.6.2 Join

SQL style merges. See the *Database style joining*

```
In [77]: left = pd.DataFrame({'key': ['foo', 'foo'], 'lval': [1, 2]})
```

```
In [78]: right = pd.DataFrame({'key': ['foo', 'foo'], 'rval': [4, 5]})
```

```
In [79]: left
```

```
Out[79]:
   key  lval
0  foo     1
1  foo     2
```

```
In [80]: right
```

```
Out[80]:
   key  rval
0  foo     4
1  foo     5
```

```
In [81]: pd.merge(left, right, on='key')
```

```
Out[81]:
   key  lval  rval
0  foo     1     4
1  foo     1     5
2  foo     2     4
3  foo     2     5
```

6.6.3 Append

Append rows to a dataframe. See the *Appending*

```
In [82]: df = pd.DataFrame(np.random.randn(8, 4), columns=['A', 'B', 'C', 'D'])
```

```
In [83]: df
```

```
Out[83]:
   A         B         C         D
0  1.346061  1.511763  1.627081 -0.990582
1 -0.441652  1.211526  0.268520  0.024580
2 -1.577585  0.396823 -0.105381 -0.532532
3  1.453749  1.208843 -0.080952 -0.264610
4 -0.727965 -0.589346  0.339969 -0.693205
5 -0.339355  0.593616  0.884345  1.591431
6  0.141809  0.220390  0.435589  0.192451
7 -0.096701  0.803351  1.715071 -0.708758
```

```
In [84]: s = df.iloc[3]
```

```
In [85]: df.append(s, ignore_index=True)
```

```
Out[85]:
   A         B         C         D
0  1.346061  1.511763  1.627081 -0.990582
1 -0.441652  1.211526  0.268520  0.024580
2 -1.577585  0.396823 -0.105381 -0.532532
3  1.453749  1.208843 -0.080952 -0.264610
4 -0.727965 -0.589346  0.339969 -0.693205
5 -0.339355  0.593616  0.884345  1.591431
```

```
6  0.141809  0.220390  0.435589  0.192451
7 -0.096701  0.803351  1.715071 -0.708758
8  1.453749  1.208843 -0.080952 -0.264610
```

6.7 Grouping

By “group by” we are referring to a process involving one or more of the following steps

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

See the *Grouping section*

```
In [86]: df = pd.DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
....:                             'foo', 'bar', 'foo', 'foo'],
....:                      'B' : ['one', 'one', 'two', 'three',
....:                             'two', 'two', 'one', 'three'],
....:                      'C' : np.random.randn(8),
....:                      'D' : np.random.randn(8)})
....:
```

```
In [87]: df
Out[87]:
```

| | A | B | C | D |
|---|-----|-------|-----------|-----------|
| 0 | foo | one | -1.202872 | -0.055224 |
| 1 | bar | one | -1.814470 | 2.395985 |
| 2 | foo | two | 1.018601 | 1.552825 |
| 3 | bar | three | -0.595447 | 0.166599 |
| 4 | foo | two | 1.395433 | 0.047609 |
| 5 | bar | two | -0.392670 | -0.136473 |
| 6 | foo | one | 0.007207 | -0.561757 |
| 7 | foo | three | 1.928123 | -1.623033 |

Grouping and then applying a function `sum` to the resulting groups.

```
In [88]: df.groupby('A').sum()
Out[88]:
```

| | C | D |
|-----|-----------|----------|
| A | | |
| bar | -2.802588 | 2.42611 |
| foo | 3.146492 | -0.63958 |

Grouping by multiple columns forms a hierarchical index, which we then apply the function.

```
In [89]: df.groupby(['A', 'B']).sum()
Out[89]:
```

| | | C | D |
|-----|-------|-----------|-----------|
| A | B | | |
| bar | one | -1.814470 | 2.395985 |
| | three | -0.595447 | 0.166599 |
| | two | -0.392670 | -0.136473 |
| foo | one | -1.195665 | -0.616981 |
| | three | 1.928123 | -1.623033 |
| | two | 2.414034 | 1.600434 |

6.8 Reshaping

See the sections on *Hierarchical Indexing* and *Reshaping*.

6.8.1 Stack

```
In [90]: tuples = list(zip(*[['bar', 'bar', 'baz', 'baz',
.....:                       'foo', 'foo', 'qux', 'qux'],
.....:                       ['one', 'two', 'one', 'two',
.....:                       'one', 'two', 'one', 'two']]))
.....:
```

```
In [91]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])
```

```
In [92]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])
```

```
In [93]: df2 = df[:4]
```

```
In [94]: df2
```

```
Out[94]:
```

| | | A | B |
|-------|--------|-----------|-----------|
| first | second | | |
| bar | one | 0.029399 | -0.542108 |
| | two | 0.282696 | -0.087302 |
| baz | one | -1.575170 | 1.771208 |
| | two | 0.816482 | 1.100230 |

The `stack()` method “compresses” a level in the DataFrame’s columns.

```
In [95]: stacked = df2.stack()
```

```
In [96]: stacked
```

```
Out[96]:
```

| first | second | |
|-------|--------|-------------|
| bar | one | A 0.029399 |
| | | B -0.542108 |
| | two | A 0.282696 |
| | | B -0.087302 |
| baz | one | A -1.575170 |
| | | B 1.771208 |
| | two | A 0.816482 |
| | | B 1.100230 |

dtype: float64

With a “stacked” DataFrame or Series (having a MultiIndex as the index), the inverse operation of `stack()` is `unstack()`, which by default unstacks the **last level**:

```
In [97]: stacked.unstack()
```

```
Out[97]:
```

| | | A | B |
|-------|--------|-----------|-----------|
| first | second | | |
| bar | one | 0.029399 | -0.542108 |
| | two | 0.282696 | -0.087302 |
| baz | one | -1.575170 | 1.771208 |
| | two | 0.816482 | 1.100230 |

```
In [98]: stacked.unstack(1)
```

```
Out[98]:
second      one      two
first
bar  A  0.029399  0.282696
     B -0.542108 -0.087302
baz   A -1.575170  0.816482
     B  1.771208  1.100230
```

```
In [99]: stacked.unstack(0)
Out[99]:
first      bar      baz
second
one   A  0.029399 -1.575170
      B -0.542108  1.771208
two   A  0.282696  0.816482
      B -0.087302  1.100230
```

6.8.2 Pivot Tables

See the section on *Pivot Tables*.

```
In [100]: df = pd.DataFrame({'A' : ['one', 'one', 'two', 'three'] * 3,
.....:                      'B' : ['A', 'B', 'C'] * 4,
.....:                      'C' : ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 2,
.....:                      'D' : np.random.randn(12),
.....:                      'E' : np.random.randn(12)})
.....:
```

```
In [101]: df
Out[101]:
   A  B  C      D      E
0  one A  foo  1.418757 -0.179666
1  one B  foo -1.879024  1.291836
2  two C  foo  0.536826 -0.009614
3  three A bar  1.006160  0.392149
4   one B bar -0.029716  0.264599
5   one C bar -1.146178 -0.057409
6  two A  foo  0.100900 -1.425638
7  three B foo -1.035018  1.024098
8   one C  foo  0.314665 -0.106062
9   one A  bar -0.773723  1.824375
10 two B  bar -1.170653  0.595974
11 three C bar  0.648740  1.167115
```

We can produce pivot tables from this data very easily:

```
In [102]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
Out[102]:
C      bar      foo
A  B
one A -0.773723  1.418757
   B -0.029716 -1.879024
   C -1.146178  0.314665
three A  1.006160      NaN
     B      NaN -1.035018
     C  0.648740      NaN
two  A      NaN  0.100900
```

```

B -1.170653      NaN
C      NaN    0.536826

```

6.9 Time Series

pandas has simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications. See the *Time Series section*

```
In [103]: rng = pd.date_range('1/1/2012', periods=100, freq='S')
```

```
In [104]: ts = pd.Series(np.random.randint(0, 500, len(rng)), index=rng)
```

```
In [105]: ts.resample('5Min', how='sum')
```

```

Out[105]:
2012-01-01    25083
Freq: 5T, dtype: int32

```

Time zone representation

```
In [106]: rng = pd.date_range('3/6/2012 00:00', periods=5, freq='D')
```

```
In [107]: ts = pd.Series(np.random.randn(len(rng)), rng)
```

```
In [108]: ts
```

```

Out[108]:
2012-03-06    0.464000
2012-03-07    0.227371
2012-03-08   -0.496922
2012-03-09    0.306389
2012-03-10   -2.290613
Freq: D, dtype: float64

```

```
In [109]: ts_utc = ts.tz_localize('UTC')
```

```
In [110]: ts_utc
```

```

Out[110]:
2012-03-06 00:00:00+00:00    0.464000
2012-03-07 00:00:00+00:00    0.227371
2012-03-08 00:00:00+00:00   -0.496922
2012-03-09 00:00:00+00:00    0.306389
2012-03-10 00:00:00+00:00   -2.290613
Freq: D, dtype: float64

```

Convert to another time zone

```
In [111]: ts_utc.tz_convert('US/Eastern')
```

```

Out[111]:
2012-03-05 19:00:00-05:00    0.464000
2012-03-06 19:00:00-05:00    0.227371
2012-03-07 19:00:00-05:00   -0.496922
2012-03-08 19:00:00-05:00    0.306389
2012-03-09 19:00:00-05:00   -2.290613
Freq: D, dtype: float64

```

Converting between time span representations

```
In [112]: rng = pd.date_range('1/1/2012', periods=5, freq='M')
```

```
In [113]: ts = pd.Series(np.random.randn(len(rng)), index=rng)
```

```
In [114]: ts
```

```
Out[114]:
2012-01-31    -1.134623
2012-02-29    -1.561819
2012-03-31    -0.260838
2012-04-30     0.281957
2012-05-31     1.523962
Freq: M, dtype: float64
```

```
In [115]: ps = ts.to_period()
```

```
In [116]: ps
```

```
Out[116]:
2012-01    -1.134623
2012-02    -1.561819
2012-03    -0.260838
2012-04     0.281957
2012-05     1.523962
Freq: M, dtype: float64
```

```
In [117]: ps.to_timestamp()
```

```
Out[117]:
2012-01-01    -1.134623
2012-02-01    -1.561819
2012-03-01    -0.260838
2012-04-01     0.281957
2012-05-01     1.523962
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```
In [118]: prng = pd.period_range('1990Q1', '2000Q4', freq='Q-NOV')
```

```
In [119]: ts = pd.Series(np.random.randn(len(prng)), prng)
```

```
In [120]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
```

```
In [121]: ts.head()
```

```
Out[121]:
1990-03-01 09:00    -0.902937
1990-06-01 09:00     0.068159
1990-09-01 09:00    -0.057873
1990-12-01 09:00    -0.368204
1991-03-01 09:00    -1.144073
Freq: H, dtype: float64
```

6.10 Categoricals

Since version 0.15, pandas can include categorical data in a DataFrame. For full docs, see the [categorical introduction](#) and the [API documentation](#).

```
In [122]: df = pd.DataFrame({"id": [1, 2, 3, 4, 5, 6], "raw_grade": ['a', 'b', 'b', 'a', 'a', 'e']})
```

Convert the raw grades to a categorical data type.

```
In [123]: df["grade"] = df["raw_grade"].astype("category")
```

```
In [124]: df["grade"]
```

```
Out[124]:
0      a
1      b
2      b
3      a
4      a
5      e
Name: grade, dtype: category
Categories (3, object): [a, b, e]
```

Rename the categories to more meaningful names (assigning to `Series.cat.categories` is inplace!)

```
In [125]: df["grade"].cat.categories = ["very good", "good", "very bad"]
```

Reorder the categories and simultaneously add the missing categories (methods under `Series.cat` return a new `Series` per default).

```
In [126]: df["grade"] = df["grade"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"])
```

```
In [127]: df["grade"]
```

```
Out[127]:
0      very good
1           good
2           good
3      very good
4      very good
5      very bad
Name: grade, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]
```

Sorting is per order in the categories, not lexical order.

```
In [128]: df.sort("grade")
```

```
Out[128]:
   id raw_grade  grade
5   6         e  very bad
1   2         b    good
2   3         b    good
0   1         a  very good
3   4         a  very good
4   5         a  very good
```

Grouping by a categorical column shows also empty categories.

```
In [129]: df.groupby("grade").size()
```

```
Out[129]:
grade
very bad    1
bad         NaN
medium      NaN
good        2
very good   3
dtype: float64
```

6.11 Plotting

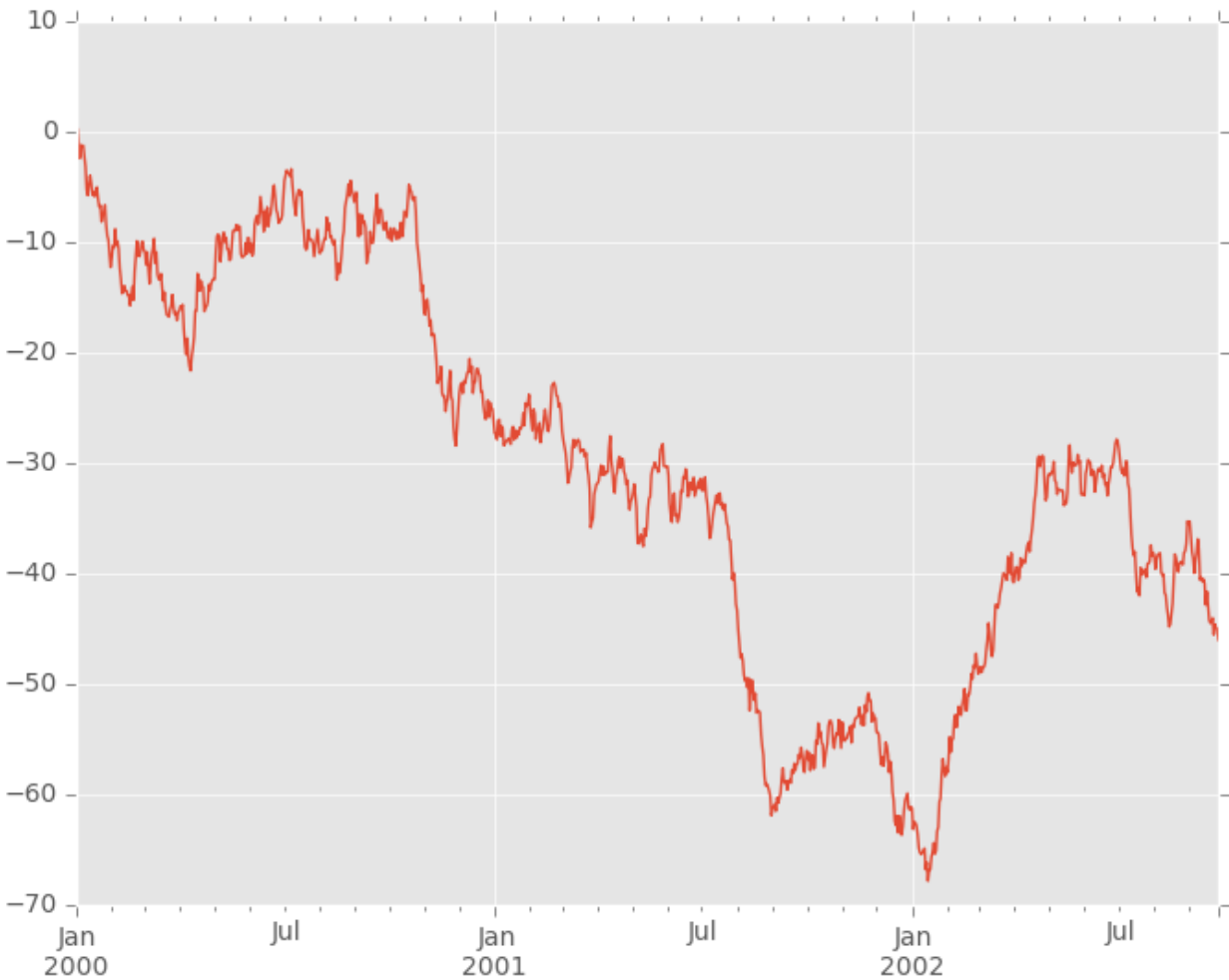
Plotting docs.

```
In [130]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
```

```
In [131]: ts = ts.cumsum()
```

```
In [132]: ts.plot()
```

```
Out[132]: <matplotlib.axes._subplots.AxesSubplot at 0xaf64808c>
```



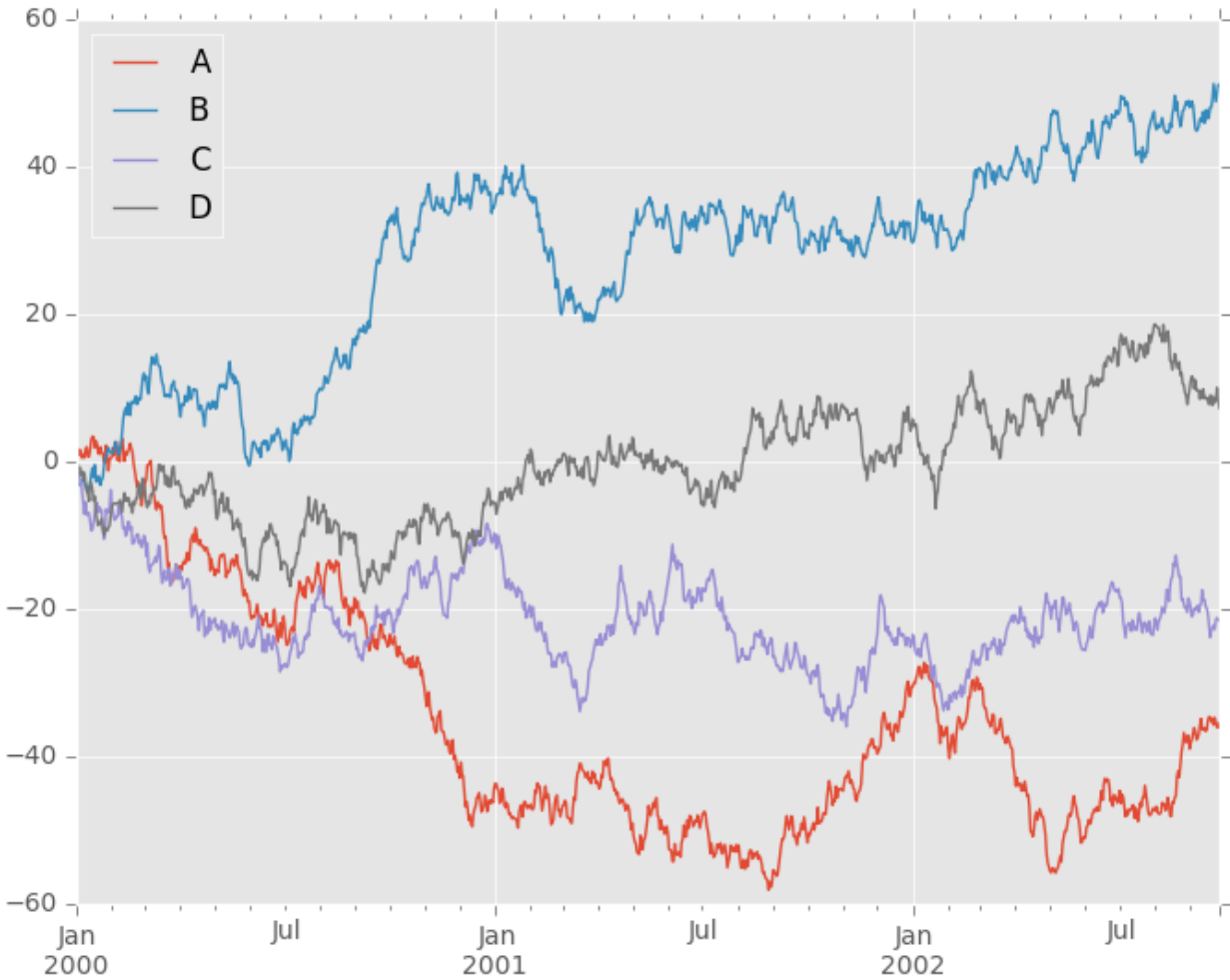
On `DataFrame`, `plot()` is a convenience to plot all of the columns with labels:

```
In [133]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
.....:                      columns=['A', 'B', 'C', 'D'])
.....:
```

```
In [134]: df = df.cumsum()
```

```
In [135]: plt.figure(); df.plot(); plt.legend(loc='best')
```

```
Out[135]: <matplotlib.legend.Legend at 0xaf5cb62c>
```



6.12 Getting Data In/Out

6.12.1 CSV

Writing to a csv file

```
In [136]: df.to_csv('foo.csv')
```

Reading from a csv file

```
In [137]: pd.read_csv('foo.csv')
```

```
Out[137]:
```

| | Unnamed: 0 | A | B | C | D |
|----|------------|-----------|-----------|-----------|-----------|
| 0 | 2000-01-01 | 0.266457 | -0.399641 | -0.219582 | 1.186860 |
| 1 | 2000-01-02 | -1.170732 | -0.345873 | 1.653061 | -0.282953 |
| 2 | 2000-01-03 | -1.734933 | 0.530468 | 2.060811 | -0.515536 |
| 3 | 2000-01-04 | -1.555121 | 1.452620 | 0.239859 | -1.156896 |
| 4 | 2000-01-05 | 0.578117 | 0.511371 | 0.103552 | -2.428202 |
| 5 | 2000-01-06 | 0.478344 | 0.449933 | -0.741620 | -1.962409 |
| 6 | 2000-01-07 | 1.235339 | -0.091757 | -1.543861 | -1.084753 |
| .. | ... | ... | ... | ... | ... |

```
993 2002-09-20 -10.628548 -9.153563 -7.883146 28.313940
994 2002-09-21 -10.390377 -8.727491 -6.399645 30.914107
995 2002-09-22 -8.985362 -8.485624 -4.669462 31.367740
996 2002-09-23 -9.558560 -8.781216 -4.499815 30.518439
997 2002-09-24 -9.902058 -9.340490 -4.386639 30.105593
998 2002-09-25 -10.216020 -9.480682 -3.933802 29.758560
999 2002-09-26 -11.856774 -10.671012 -3.216025 29.369368
```

```
[1000 rows x 5 columns]
```

6.12.2 HDF5

Reading and writing to *HDFStores*

Writing to a HDF5 Store

```
In [138]: df.to_hdf('foo.h5', 'df')
```

Reading from a HDF5 Store

```
In [139]: pd.read_hdf('foo.h5', 'df')
```

```
Out[139]:
```

| | A | B | C | D |
|------------|------------|------------|-----------|-----------|
| 2000-01-01 | 0.266457 | -0.399641 | -0.219582 | 1.186860 |
| 2000-01-02 | -1.170732 | -0.345873 | 1.653061 | -0.282953 |
| 2000-01-03 | -1.734933 | 0.530468 | 2.060811 | -0.515536 |
| 2000-01-04 | -1.555121 | 1.452620 | 0.239859 | -1.156896 |
| 2000-01-05 | 0.578117 | 0.511371 | 0.103552 | -2.428202 |
| 2000-01-06 | 0.478344 | 0.449933 | -0.741620 | -1.962409 |
| 2000-01-07 | 1.235339 | -0.091757 | -1.543861 | -1.084753 |
| ... | ... | ... | ... | ... |
| 2002-09-20 | -10.628548 | -9.153563 | -7.883146 | 28.313940 |
| 2002-09-21 | -10.390377 | -8.727491 | -6.399645 | 30.914107 |
| 2002-09-22 | -8.985362 | -8.485624 | -4.669462 | 31.367740 |
| 2002-09-23 | -9.558560 | -8.781216 | -4.499815 | 30.518439 |
| 2002-09-24 | -9.902058 | -9.340490 | -4.386639 | 30.105593 |
| 2002-09-25 | -10.216020 | -9.480682 | -3.933802 | 29.758560 |
| 2002-09-26 | -11.856774 | -10.671012 | -3.216025 | 29.369368 |

```
[1000 rows x 4 columns]
```

6.12.3 Excel

Reading and writing to *MS Excel*

Writing to an excel file

```
In [140]: df.to_excel('foo.xlsx', sheet_name='Sheet1')
```

Reading from an excel file

```
In [141]: pd.read_excel('foo.xlsx', 'Sheet1', index_col=None, na_values=['NA'])
```

```
Out[141]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.266457 | -0.399641 | -0.219582 | 1.186860 |
| 2000-01-02 | -1.170732 | -0.345873 | 1.653061 | -0.282953 |
| 2000-01-03 | -1.734933 | 0.530468 | 2.060811 | -0.515536 |

```
2000-01-04   -1.555121    1.452620    0.239859   -1.156896
2000-01-05    0.578117    0.511371    0.103552   -2.428202
2000-01-06    0.478344    0.449933   -0.741620   -1.962409
2000-01-07    1.235339   -0.091757   -1.543861   -1.084753
...          ...          ...          ...          ...
2002-09-20  -10.628548   -9.153563   -7.883146   28.313940
2002-09-21  -10.390377   -8.727491   -6.399645   30.914107
2002-09-22   -8.985362   -8.485624   -4.669462   31.367740
2002-09-23   -9.558560   -8.781216   -4.499815   30.518439
2002-09-24   -9.902058   -9.340490   -4.386639   30.105593
2002-09-25  -10.216020   -9.480682   -3.933802   29.758560
2002-09-26 -11.856774 -10.671012   -3.216025   29.369368
```

```
[1000 rows x 4 columns]
```

6.13 Gotchas

If you are trying an operation and you see an exception like:

```
>>> if pd.Series([False, True, False]):
    print("I was true")
Traceback
...
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

See [Comparisons](#) for an explanation and what to do.

See [Gotchas](#) as well.

TUTORIALS

This is a guide to many pandas tutorials, geared mainly for new users.

7.1 Internal Guides

pandas own *10 Minutes to pandas*

More complex recipes are in the *Cookbook*

7.2 pandas Cookbook

The goal of this cookbook (by [Julia Evans](#)) is to give you some concrete examples for getting started with pandas. These are examples with real-world data, and all the bugs and weirdness that that entails.

Here are links to the v0.1 release. For an up-to-date table of contents, see the [pandas-cookbook GitHub repository](#). To run the examples in this tutorial, you'll need to clone the GitHub repository and get IPython Notebook running. See [How to use this cookbook](#).

- [A quick tour of the IPython Notebook](#): Shows off IPython's awesome tab completion and magic functions.
- [Chapter 1](#): Reading your data into pandas is pretty much the easiest thing. Even when the encoding is wrong!
- [Chapter 2](#): It's not totally obvious how to select data from a pandas dataframe. Here we explain the basics (how to take slices and get columns)
- [Chapter 3](#): Here we get into serious slicing and dicing and learn how to filter dataframes in complicated ways, really fast.
- [Chapter 4](#): Groupby/aggregate is seriously my favorite thing about pandas and I use it all the time. You should probably read this.
- [Chapter 5](#): Here you get to find out if it's cold in Montreal in the winter (spoiler: yes). Web scraping with pandas is fun! Here we combine dataframes.
- [Chapter 6](#): Strings with pandas are great. It has all these vectorized string operations and they're the best. We will turn a bunch of strings containing "Snow" into vectors of numbers in a trice.
- [Chapter 7](#): Cleaning up messy data is never a joy, but with pandas it's easier.
- [Chapter 8](#): Parsing Unix timestamps is confusing at first but it turns out to be really easy.

7.3 Lessons for New pandas Users

For more resources, please visit the main [repository](#).

- **01 - Lesson:** - Importing libraries - Creating data sets - Creating data frames - Reading from CSV - Exporting to CSV - Finding maximums - Plotting data
- **02 - Lesson:** - Reading from TXT - Exporting to TXT - Selecting top/bottom records - Descriptive statistics - Grouping/sorting data
- **03 - Lesson:** - Creating functions - Reading from EXCEL - Exporting to EXCEL - Outliers - Lambda functions - Slice and dice data
- **04 - Lesson:** - Adding/deleting columns - Index operations
- **05 - Lesson:** - Stack/Unstack/Transpose functions
- **06 - Lesson:** - GroupBy function
- **07 - Lesson:** - Ways to calculate outliers
- **08 - Lesson:** - Read from Microsoft SQL databases
- **09 - Lesson:** - Export to CSV/EXCEL/TXT
- **10 - Lesson:** - Converting between different kinds of formats
- **11 - Lesson:** - Combining data from various sources

7.4 Practical data analysis with Python

This [guide](#) is a comprehensive introduction to the data analysis process using the Python data ecosystem and an interesting open dataset. There are four sections covering selected topics as follows:

- [Munging Data](#)
- [Aggregating Data](#)
- [Visualizing Data](#)
- [Time Series](#)

7.5 Excel charts with pandas, vincent and xlsxwriter

- [Using Pandas and XlsxWriter to create Excel charts](#)

7.6 Various Tutorials

- [Wes McKinney's \(pandas BDFL\) blog](#)
- [Statistical analysis made easy in Python with SciPy and pandas DataFrames](#), by Randal Olson
- [Statistical Data Analysis in Python](#), tutorial videos, by Christopher Fonnesbeck from SciPy 2013
- [Financial analysis in python](#), by Thomas Wiecki
- [Intro to pandas data structures](#), by Greg Reda

- [Pandas and Python: Top 10](#), by Manish Amde
- [Pandas Tutorial](#), by Mikhail Semeniuk

COOKBOOK

This is a repository for *short and sweet* examples and links for useful pandas recipes. We encourage users to add to this documentation.

Adding interesting links and/or inline examples to this section is a great *First Pull Request*.

Simplified, condensed, new-user friendly, in-line examples have been inserted where possible to augment the Stack-Overflow and GitHub links. Many of the links contain expanded information, above what the in-line examples offer.

Pandas (pd) and Numpy (np) are the only two abbreviated imported modules. The rest are kept explicitly imported for newer users.

These examples are written for python 3.4. Minor tweaks might be necessary for earlier python versions.

8.1 Idioms

These are some neat pandas idioms

if-then/if-then-else on one column, and assignment to another one or more columns:

```
In [1]: df = pd.DataFrame(
...:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]})
...:
Out[1]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 4 | 10 | 100 |
| 1 | 5 | 20 | 50 |
| 2 | 6 | 30 | -30 |
| 3 | 7 | 40 | -50 |

8.1.1 if-then...

An if-then on one column

```
In [2]: df.ix[df.AAA >= 5, 'BBB'] = -1; df
Out[2]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 4 | 10 | 100 |
| 1 | 5 | -1 | 50 |
| 2 | 6 | -1 | -30 |
| 3 | 7 | -1 | -50 |

An if-then with assignment to 2 columns:

```
In [3]: df.ix[df.AAA >= 5, ['BBB', 'CCC']] = 555; df
Out[3]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 4 | 10 | 100 |
| 1 | 5 | 555 | 555 |
| 2 | 6 | 555 | 555 |
| 3 | 7 | 555 | 555 |

Add another line with different logic, to do the -else

```
In [4]: df.ix[df.AAA < 5, ['BBB', 'CCC']] = 2000; df
Out[4]:
```

| | AAA | BBB | CCC |
|---|-----|------|------|
| 0 | 4 | 2000 | 2000 |
| 1 | 5 | 555 | 555 |
| 2 | 6 | 555 | 555 |
| 3 | 7 | 555 | 555 |

Or use pandas where after you've set up a mask

```
In [5]: df_mask = pd.DataFrame({'AAA' : [True] * 4, 'BBB' : [False] * 4, 'CCC' : [True, False] * 2})

In [6]: df.where(df_mask, -1000)
Out[6]:
```

| | AAA | BBB | CCC |
|---|-----|-------|-------|
| 0 | 4 | -1000 | 2000 |
| 1 | 5 | -1000 | -1000 |
| 2 | 6 | -1000 | 555 |
| 3 | 7 | -1000 | -1000 |

if-then-else using numpy's where()

```
In [7]: df = pd.DataFrame(
...:     {'AAA' : [4, 5, 6, 7], 'BBB' : [10, 20, 30, 40], 'CCC' : [100, 50, -30, -50]})
...: df
Out[7]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 4 | 10 | 100 |
| 1 | 5 | 20 | 50 |
| 2 | 6 | 30 | -30 |
| 3 | 7 | 40 | -50 |

```
In [8]: df['logic'] = np.where(df['AAA'] > 5, 'high', 'low'); df
Out[8]:
```

| | AAA | BBB | CCC | logic |
|---|-----|-----|-----|-------|
| 0 | 4 | 10 | 100 | low |
| 1 | 5 | 20 | 50 | low |
| 2 | 6 | 30 | -30 | high |
| 3 | 7 | 40 | -50 | high |

8.1.2 Splitting

Split a frame with a boolean criterion

```
In [9]: df = pd.DataFrame(
...:     {'AAA' : [4, 5, 6, 7], 'BBB' : [10, 20, 30, 40], 'CCC' : [100, 50, -30, -50]})
...: df
Out[9]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 4 | 10 | 100 |
| 1 | 5 | 20 | 50 |
| 2 | 6 | 30 | -30 |
| 3 | 7 | 40 | -50 |

```
In [10]: dflow = df[df.AAA <= 5]
```

```
In [11]: dfhigh = df[df.AAA > 5]
```

```
In [12]: dflow; dfhigh
```

```
Out[12]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 2 | 6 | 30 | -30 |
| 3 | 7 | 40 | -50 |

8.1.3 Building Criteria

Select with multi-column criteria

```
In [13]: df = pd.DataFrame(
.....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]})
.....:
```

```
Out[13]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 4 | 10 | 100 |
| 1 | 5 | 20 | 50 |
| 2 | 6 | 30 | -30 |
| 3 | 7 | 40 | -50 |

...and (without assignment returns a Series)

```
In [14]: newseries = df.loc[(df['BBB'] < 25) & (df['CCC'] >= -40), 'AAA']; newseries
```

```
Out[14]:
```

| | |
|---|---|
| 0 | 4 |
| 1 | 5 |

Name: AAA, dtype: int64

...or (without assignment returns a Series)

```
In [15]: newseries = df.loc[(df['BBB'] > 25) | (df['CCC'] >= -40), 'AAA']; newseries;
```

...or (with assignment modifies the DataFrame.)

```
In [16]: df.loc[(df['BBB'] > 25) | (df['CCC'] >= 75), 'AAA'] = 0.1; df
```

```
Out[16]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 0.1 | 10 | 100 |
| 1 | 5.0 | 20 | 50 |
| 2 | 0.1 | 30 | -30 |
| 3 | 0.1 | 40 | -50 |

Select rows with data closest to certain value using argsort

```
In [17]: df = pd.DataFrame(
.....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]})
.....:
```

```
Out[17]:
```

```
   AAA  BBB  CCC
0     4   10  100
1     5   20   50
2     6   30  -30
3     7   40  -50
```

```
In [18]: aValue = 43.0
```

```
In [19]: df.ix[(df.CCC-aValue).abs().argsort()]
```

```
Out[19]:
   AAA  BBB  CCC
1     5   20   50
0     4   10  100
2     6   30  -30
3     7   40  -50
```

Dynamically reduce a list of criteria using a binary operators

```
In [20]: df = pd.DataFrame(
.....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]})
.....: df
```

```
Out[20]:
   AAA  BBB  CCC
0     4   10  100
1     5   20   50
2     6   30  -30
3     7   40  -50
```

```
In [21]: Crit1 = df.AAA <= 5.5
```

```
In [22]: Crit2 = df.BBB == 10.0
```

```
In [23]: Crit3 = df.CCC > -40.0
```

One could hard code:

```
In [24]: AllCrit = Crit1 & Crit2 & Crit3
```

...Or it can be done with a list of dynamically built criteria

```
In [25]: CritList = [Crit1,Crit2,Crit3]
```

```
In [26]: AllCrit = functools.reduce(lambda x,y: x & y, CritList)
```

```
In [27]: df[AllCrit]
```

```
Out[27]:
   AAA  BBB  CCC
0     4   10  100
```

8.2 Selection

8.2.1 DataFrames

The *indexing* docs.

Using both row labels and value conditionals

```
In [28]: df = pd.DataFrame(
.....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}; df
.....:
```

```
Out[28]:
   AAA  BBB  CCC
0     4   10  100
1     5   20   50
2     6   30  -30
3     7   40  -50
```

```
In [29]: df[(df.AAA <= 6) & (df.index.isin([0,2,4]))]
```

```
Out[29]:
   AAA  BBB  CCC
0     4   10  100
2     6   30  -30
```

Use loc for label-oriented slicing and iloc positional slicing

```
In [30]: data = {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}
```

```
In [31]: df = pd.DataFrame(data=data, index=['foo', 'bar', 'boo', 'kar']); df
```

```
Out[31]:
   AAA  BBB  CCC
foo     4   10  100
bar     5   20   50
boo     6   30  -30
kar     7   40  -50
```

There are 2 explicit slicing methods, with a third general case

1. Positional-oriented (Python slicing style : exclusive of end)
2. Label-oriented (Non-Python slicing style : inclusive of end)
3. General (Either slicing style : depends on if the slice contains labels or positions)

```
In [32]: df.loc['bar':'kar'] #Label
```

```
Out[32]:
   AAA  BBB  CCC
bar     5   20   50
boo     6   30  -30
kar     7   40  -50
```

```
#Generic
```

```
In [33]: df.ix[0:3] #Same as .iloc[0:3]
```

```
Out[33]:
   AAA  BBB  CCC
foo     4   10  100
bar     5   20   50
boo     6   30  -30
```

```
In [34]: df.ix['bar':'kar'] #Same as .loc['bar':'kar']
```

```
Out[34]:
   AAA  BBB  CCC
bar     5   20   50
boo     6   30  -30
kar     7   40  -50
```

Ambiguity arises when an index consists of integers with a non-zero start or non-unit increment.

```
In [35]: df2 = pd.DataFrame(data=data, index=[1,2,3,4]); #Note index starts at 1.
```

```
In [36]: df2.iloc[1:3] #Position-oriented
```

```
Out[36]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 2 | 5 | 20 | 50 |
| 3 | 6 | 30 | -30 |

```
In [37]: df2.loc[1:3] #Label-oriented
```

```
Out[37]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 1 | 4 | 10 | 100 |
| 2 | 5 | 20 | 50 |
| 3 | 6 | 30 | -30 |

```
In [38]: df2.ix[1:3] #General, will mimic loc (label-oriented)
```

```
Out[38]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 1 | 4 | 10 | 100 |
| 2 | 5 | 20 | 50 |
| 3 | 6 | 30 | -30 |

```
In [39]: df2.ix[0:3] #General, will mimic iloc (position-oriented), as loc[0:3] would raise a KeyError
```

```
Out[39]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 1 | 4 | 10 | 100 |
| 2 | 5 | 20 | 50 |
| 3 | 6 | 30 | -30 |

Using inverse operator (~) to take the complement of a mask

```
In [40]: df = pd.DataFrame(  
.....:     {'AAA' : [4,5,6,7], 'BBB' : [10,20,30,40], 'CCC' : [100,50,-30,-50]}); df  
.....:
```

```
Out[40]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 0 | 4 | 10 | 100 |
| 1 | 5 | 20 | 50 |
| 2 | 6 | 30 | -30 |
| 3 | 7 | 40 | -50 |

```
In [41]: df[~((df.AAA <= 6) & (df.index.isin([0,2,4])))]
```

```
Out[41]:
```

| | AAA | BBB | CCC |
|---|-----|-----|-----|
| 1 | 5 | 20 | 50 |
| 3 | 7 | 40 | -50 |

8.2.2 Panels

Extend a panel frame by transposing, adding a new dimension, and transposing back to the original dimensions

```
In [42]: rng = pd.date_range('1/1/2013', periods=100, freq='D')
```

```
In [43]: data = np.random.randn(100, 4)
```

```
In [44]: cols = ['A', 'B', 'C', 'D']
```

```
In [45]: df1, df2, df3 = pd.DataFrame(data, rng, cols), pd.DataFrame(data, rng, cols), pd.DataFrame(data, rng, cols)

In [46]: pf = pd.Panel({'df1':df1,'df2':df2,'df3':df3});pf
Out[46]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 4 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to D

#Assignment using Transpose (pandas < 0.15)
In [47]: pf = pf.transpose(2,0,1)

In [48]: pf['E'] = pd.DataFrame(data, rng, cols)

In [49]: pf = pf.transpose(1,2,0);pf
Out[49]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 5 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to E

#Direct assignment (pandas > 0.15)
In [50]: pf.loc[:, :, 'F'] = pd.DataFrame(data, rng, cols);pf
Out[50]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 100 (major_axis) x 6 (minor_axis)
Items axis: df1 to df3
Major_axis axis: 2013-01-01 00:00:00 to 2013-04-10 00:00:00
Minor_axis axis: A to F
```

Mask a panel by using `np.where` and then reconstructing the panel with the new masked values

8.2.3 New Columns

Efficiently and dynamically creating new columns using `applymap`

```
In [51]: df = pd.DataFrame(
.....:     {'AAA' : [1,2,1,3], 'BBB' : [1,1,2,2], 'CCC' : [2,1,3,1]})
.....:
Out[51]:
   AAA  BBB  CCC
0    1    1    2
1    2    1    1
2    1    2    3
3    3    2    1

In [52]: source_cols = df.columns # or some subset would work too.

In [53]: new_cols = [str(x) + "_cat" for x in source_cols]

In [54]: categories = {1 : 'Alpha', 2 : 'Beta', 3 : 'Charlie' }

In [55]: df[new_cols] = df[source_cols].applymap(categories.get);df
Out[55]:
   AAA  BBB  CCC  AAA_cat  BBB_cat  CCC_cat
```

| | | | | | | |
|---|---|---|---|---------|-------|---------|
| 0 | 1 | 1 | 2 | Alpha | Alpha | Beta |
| 1 | 2 | 1 | 1 | Beta | Alpha | Alpha |
| 2 | 1 | 2 | 3 | Alpha | Beta | Charlie |
| 3 | 3 | 2 | 1 | Charlie | Beta | Alpha |

Keep other columns when using min() with groupby

```
In [56]: df = pd.DataFrame(
.....:     {'AAA' : [1,1,1,2,2,2,3,3], 'BBB' : [2,1,3,4,5,1,2,3]})
.....:
Out[56]:
```

| | AAA | BBB |
|---|-----|-----|
| 0 | 1 | 2 |
| 1 | 1 | 1 |
| 2 | 1 | 3 |
| 3 | 2 | 4 |
| 4 | 2 | 5 |
| 5 | 2 | 1 |
| 6 | 3 | 2 |
| 7 | 3 | 3 |

Method 1 : idxmin() to get the index of the mins

```
In [57]: df.loc[df.groupby("AAA")["BBB"].idxmin()]
Out[57]:
```

| | AAA | BBB |
|---|-----|-----|
| 1 | 1 | 1 |
| 5 | 2 | 1 |
| 6 | 3 | 2 |

Method 2 : sort then take first of each

```
In [58]: df.sort("BBB").groupby("AAA", as_index=False).first()
Out[58]:
```

| | AAA | BBB |
|---|-----|-----|
| 0 | 1 | 1 |
| 1 | 2 | 1 |
| 2 | 3 | 2 |

Notice the same results, with the exception of the index.

8.3 MultiIndexing

The *multindexing* docs.

Creating a multi-index from a labeled frame

```
In [59]: df = pd.DataFrame({'row' : [0,1,2],
.....:                      'One_X' : [1.1,1.1,1.1],
.....:                      'One_Y' : [1.2,1.2,1.2],
.....:                      'Two_X' : [1.11,1.11,1.11],
.....:                      'Two_Y' : [1.22,1.22,1.22]})
.....:
Out[59]:
```

| | One_X | One_Y | Two_X | Two_Y | row |
|---|-------|-------|-------|-------|-----|
| 0 | 1.1 | 1.2 | 1.11 | 1.22 | 0 |
| 1 | 1.1 | 1.2 | 1.11 | 1.22 | 1 |
| 2 | 1.1 | 1.2 | 1.11 | 1.22 | 2 |

```
# As Labelled Index
In [60]: df = df.set_index('row');df
Out[60]:
      One_X  One_Y  Two_X  Two_Y
row
0         1.1    1.2   1.11   1.22
1         1.1    1.2   1.11   1.22
2         1.1    1.2   1.11   1.22

# With Heirarchical Columns
In [61]: df.columns = pd.MultiIndex.from_tuples([tuple(c.split('_')) for c in df.columns]);df
Out[61]:
      One      Two
      X      Y      X      Y
row
0     1.1  1.2  1.11  1.22
1     1.1  1.2  1.11  1.22
2     1.1  1.2  1.11  1.22

# Now stack & Reset
In [62]: df = df.stack(0).reset_index(1);df
Out[62]:
      level_1      X      Y
row
0         One  1.10  1.20
0         Two  1.11  1.22
1         One  1.10  1.20
1         Two  1.11  1.22
2         One  1.10  1.20
2         Two  1.11  1.22

# And fix the labels (Notice the label 'level_1' got added automatically)
In [63]: df.columns = ['Sample', 'All_X', 'All_Y'];df
Out[63]:
      Sample  All_X  All_Y
row
0         One  1.10  1.20
0         Two  1.11  1.22
1         One  1.10  1.20
1         Two  1.11  1.22
2         One  1.10  1.20
2         Two  1.11  1.22
```

8.3.1 Arithmetic

Performing arithmetic with a multi-index that needs broadcasting

```
In [64]: cols = pd.MultiIndex.from_tuples([ (x,y) for x in ['A','B','C'] for y in ['O','I']])

In [65]: df = pd.DataFrame(np.random.randn(2,6), index=['n','m'], columns=cols); df
Out[65]:
      A      B      C
      O      I      O      I      O      I
n  1.920906 -0.388231 -2.314394  0.665508  0.402562  0.399555
m -1.765956  0.850423  0.388054  0.992312  0.744086 -0.739776
```

```
In [66]: df = df.div(df['C'],level=1); df
Out[66]:
```

| | A | | B | | C | |
|---|-----------|-----------|-----------|-----------|---|---|
| | O | I | O | I | O | I |
| n | 4.771702 | -0.971660 | -5.749162 | 1.665625 | 1 | 1 |
| m | -2.373321 | -1.149568 | 0.521518 | -1.341367 | 1 | 1 |

8.3.2 Slicing

Slicing a multi-index with xs

```
In [67]: coords = [('AA','one'),('AA','six'),('BB','one'),('BB','two'),('BB','six')]
```

```
In [68]: index = pd.MultiIndex.from_tuples(coords)
```

```
In [69]: df = pd.DataFrame([11,22,33,44,55],index,['MyData']); df
```

```
Out[69]:
```

| | MyData |
|--------|--------|
| AA one | 11 |
| six | 22 |
| BB one | 33 |
| two | 44 |
| six | 55 |

To take the cross section of the 1st level and 1st axis the index:

```
In [70]: df.xs('BB',level=0,axis=0) #Note : level and axis are optional, and default to zero
```

```
Out[70]:
```

| | MyData |
|-----|--------|
| one | 33 |
| two | 44 |
| six | 55 |

...and now the 2nd level of the 1st axis.

```
In [71]: df.xs('six',level=1,axis=0)
```

```
Out[71]:
```

| | MyData |
|----|--------|
| AA | 22 |
| BB | 55 |

Slicing a multi-index with xs, method #2

```
In [72]: index = list(itertools.product(['Ada','Quinn','Violet'],['Comp','Math','Sci']))
```

```
In [73]: headr = list(itertools.product(['Exams','Labs'],['I','II']))
```

```
In [74]: indx = pd.MultiIndex.from_tuples(index,names=['Student','Course'])
```

```
In [75]: cols = pd.MultiIndex.from_tuples(headr) #Notice these are un-named
```

```
In [76]: data = [[70+x+y+(x*y)%3 for x in range(4)] for y in range(9)]
```

```
In [77]: df = pd.DataFrame(data,indx,cols); df
```

```
Out[77]:
```

| | | Exams | | Labs | |
|---------|--------|-------|----|------|----|
| | | I | II | I | II |
| Student | Course | | | | |

| | | | | | |
|--------|------|----|----|----|----|
| Ada | Comp | 70 | 71 | 72 | 73 |
| | Math | 71 | 73 | 75 | 74 |
| | Sci | 72 | 75 | 75 | 75 |
| Quinn | Comp | 73 | 74 | 75 | 76 |
| | Math | 74 | 76 | 78 | 77 |
| | Sci | 75 | 78 | 78 | 78 |
| Violet | Comp | 76 | 77 | 78 | 79 |
| | Math | 77 | 79 | 81 | 80 |
| | Sci | 78 | 81 | 81 | 81 |

```
In [78]: All = slice(None)
```

```
In [79]: df.loc['Violet']
```

```
Out[79]:
```

| | Exams | | Labs | |
|--------|-------|----|------|----|
| | I | II | I | II |
| Course | | | | |
| Comp | 76 | 77 | 78 | 79 |
| Math | 77 | 79 | 81 | 80 |
| Sci | 78 | 81 | 81 | 81 |

```
In [80]: df.loc[(All, 'Math'), All]
```

```
Out[80]:
```

| | | Exams | | Labs | |
|---------|--------|-------|----|------|----|
| | | I | II | I | II |
| Student | Course | | | | |
| Ada | Math | 71 | 73 | 75 | 74 |
| Quinn | Math | 74 | 76 | 78 | 77 |
| Violet | Math | 77 | 79 | 81 | 80 |

```
In [81]: df.loc[(slice('Ada', 'Quinn'), 'Math'), All]
```

```
Out[81]:
```

| | | Exams | | Labs | |
|---------|--------|-------|----|------|----|
| | | I | II | I | II |
| Student | Course | | | | |
| Ada | Math | 71 | 73 | 75 | 74 |
| Quinn | Math | 74 | 76 | 78 | 77 |

```
In [82]: df.loc[(All, 'Math'), ('Exams')]
```

```
Out[82]:
```

| | | I | II |
|---------|--------|----|----|
| Student | Course | | |
| Ada | Math | 71 | 73 |
| Quinn | Math | 74 | 76 |
| Violet | Math | 77 | 79 |

```
In [83]: df.loc[(All, 'Math'), (All, 'II')]
```

```
Out[83]:
```

| | | Exams | Labs |
|---------|--------|-------|------|
| | | II | II |
| Student | Course | | |
| Ada | Math | 73 | 74 |
| Quinn | Math | 76 | 77 |
| Violet | Math | 79 | 80 |

Setting portions of a multi-index with xs

8.3.3 Sorting

Sort by specific column or an ordered list of columns, with a multi-index

```
In [84]: df.sort(('Labs', 'II'), ascending=False)
```

```
Out [84]:
```

| Student | Course | Exams | | Labs | |
|---------|--------|-------|----|------|----|
| | | I | II | I | II |
| Violet | Sci | 78 | 81 | 81 | 81 |
| | Math | 77 | 79 | 81 | 80 |
| | Comp | 76 | 77 | 78 | 79 |
| Quinn | Sci | 75 | 78 | 78 | 78 |
| | Math | 74 | 76 | 78 | 77 |
| | Comp | 73 | 74 | 75 | 76 |
| Ada | Sci | 72 | 75 | 75 | 75 |
| | Math | 71 | 73 | 75 | 74 |
| | Comp | 70 | 71 | 72 | 73 |

Partial Selection, the need for sortedness;

8.3.4 Levels

Prepending a level to a multiindex

Flatten Hierarchical columns

8.3.5 panelnd

The *panelnd* docs.

Construct a 5D panelnd

8.4 Missing Data

The *missing data* docs.

Fill forward a reversed timeseries

```
In [85]: df = pd.DataFrame(np.random.randn(6,1), index=pd.date_range('2013-08-01', periods=6, freq='D'))
```

```
In [86]: df.ix[3, 'A'] = np.nan
```

```
In [87]: df
```

```
Out [87]:
```

| | A |
|------------|-----------|
| 2013-08-01 | -1.054874 |
| 2013-08-02 | -0.179642 |
| 2013-08-05 | 0.639589 |
| 2013-08-06 | NaN |
| 2013-08-07 | 1.906684 |
| 2013-08-08 | 0.104050 |

```
In [88]: df.reindex(df.index[::-1]).ffill()
```

```
Out [88]:
```

```

                A
2013-08-08    0.104050
2013-08-07    1.906684
2013-08-06    1.906684
2013-08-05    0.639589
2013-08-02   -0.179642
2013-08-01   -1.054874

```

cumsum reset at NaN values

8.4.1 Replace

Using replace with backrefs

8.5 Grouping

The *grouping* docs.

Basic grouping with apply

Unlike `agg`, `apply`'s callable is passed a sub-DataFrame which gives you access to all the columns

```

In [89]: df = pd.DataFrame({'animal': 'cat dog cat fish dog cat cat'.split(),
    ....:                   'size': list('SSMMMLL'),
    ....:                   'weight': [8, 10, 11, 1, 20, 12, 12],
    ....:                   'adult' : [False] * 5 + [True] * 2}); df
Out[89]:

```

| | adult | animal | size | weight |
|---|-------|--------|------|--------|
| 0 | False | cat | S | 8 |
| 1 | False | dog | S | 10 |
| 2 | False | cat | M | 11 |
| 3 | False | fish | M | 1 |
| 4 | False | dog | M | 20 |
| 5 | True | cat | L | 12 |
| 6 | True | cat | L | 12 |

#List the size of the animals with the highest weight.

```

In [90]: df.groupby('animal').apply(lambda subf: subf['size'][subf['weight'].idxmax()])

```

```

Out[90]:
animal
cat      L
dog      M
fish     M
dtype: object

```

Using `get_group`

```

In [91]: gb = df.groupby(['animal'])

```

```

In [92]: gb.get_group('cat')

```

```

Out[92]:
   adult animal size  weight
0  False    cat   S      8
2  False    cat   M     11

```

```
5   True    cat    L      12
6   True    cat    L      12
```

Apply to different items in a group

```
In [93]: def GrowUp(x):
.....:     avg_weight = sum(x[x['size'] == 'S'].weight * 1.5)
.....:     avg_weight += sum(x[x['size'] == 'M'].weight * 1.25)
.....:     avg_weight += sum(x[x['size'] == 'L'].weight)
.....:     avg_weight /= len(x)
.....:     return pd.Series(['L', avg_weight, True], index=['size', 'weight', 'adult'])
.....:
```

```
In [94]: expected_df = gb.apply(GrowUp)
```

```
In [95]: expected_df
```

```
Out[95]:
      size  weight adult
animal
cat      L  12.4375  True
dog      L  20.0000  True
fish     L   1.2500  True
```

Expanding Apply

```
In [96]: S = pd.Series([i / 100.0 for i in range(1,11)])
```

```
In [97]: def CumRet(x,y):
.....:     return x * (1 + y)
.....:
```

```
In [98]: def Red(x):
.....:     return functools.reduce(CumRet, x, 1.0)
.....:
```

```
In [99]: pd.expanding_apply(S, Red)
```

```
Out[99]:
0    1.010000
1    1.030200
2    1.061106
3    1.103550
4    1.158728
5    1.228251
6    1.314229
7    1.419367
8    1.547110
9    1.701821
dtype: float64
```

Replacing some values with mean of the rest of a group

```
In [100]: df = pd.DataFrame({'A' : [1, 1, 2, 2], 'B' : [1, -1, 1, 2]})
```

```
In [101]: gb = df.groupby('A')
```

```
In [102]: def replace(g):
.....:     mask = g < 0
.....:     g.loc[mask] = g[~mask].mean()
.....:     return g
```

```

.....:

In [103]: gb.transform(replace)
Out[103]:
   B
0  1
1  1
2  1
3  2

```

Sort groups by aggregated data

```

In [104]: df = pd.DataFrame({'code': ['foo', 'bar', 'baz'] * 2,
.....:                      'data': [0.16, -0.21, 0.33, 0.45, -0.59, 0.62],
.....:                      'flag': [False, True] * 3})
.....:

In [105]: code_groups = df.groupby('code')

In [106]: agg_n_sort_order = code_groups[['data']].transform(sum).sort('data')

In [107]: sorted_df = df.ix[agg_n_sort_order.index]

In [108]: sorted_df
Out[108]:
   code  data  flag
1  bar -0.21  True
4  bar -0.59 False
0  foo  0.16 False
3  foo  0.45  True
2  baz  0.33 False
5  baz  0.62  True

```

Create multiple aggregated columns

```

In [109]: rng = pd.date_range(start="2014-10-07", periods=10, freq='2min')

In [110]: ts = pd.Series(data = list(range(10)), index = rng)

In [111]: def MyCust(x):
.....:     if len(x) > 2:
.....:         return x[1] * 1.234
.....:     return pd.NaT
.....:

In [112]: mhc = {'Mean' : np.mean, 'Max' : np.max, 'Custom' : MyCust}

In [113]: ts.resample("5min", how = mhc)
Out[113]:
               Max Custom  Mean
2014-10-07 00:00:00    2  1.234    1.0
2014-10-07 00:05:00    4   NaN    3.5
2014-10-07 00:10:00    7  7.404    6.0
2014-10-07 00:15:00    9   NaN    8.5

In [114]: ts
Out[114]:
2014-10-07 00:00:00    0
2014-10-07 00:02:00    1

```

```
2014-10-07 00:04:00    2
2014-10-07 00:06:00    3
2014-10-07 00:08:00    4
2014-10-07 00:10:00    5
2014-10-07 00:12:00    6
2014-10-07 00:14:00    7
2014-10-07 00:16:00    8
2014-10-07 00:18:00    9
Freq: 2T, dtype: int64
```

Create a value counts column and reassign back to the DataFrame

```
In [115]: df = pd.DataFrame({'Color': 'Red Red Red Blue'.split(),
.....:                      'Value': [100, 150, 50, 50]}); df
.....:
Out[115]:
   Color  Value
0    Red   100
1    Red   150
2    Red    50
3   Blue    50
```

```
In [116]: df['Counts'] = df.groupby(['Color']).transform(len)
```

```
In [117]: df
Out[117]:
   Color  Value  Counts
0    Red   100      3
1    Red   150      3
2    Red    50      3
3   Blue    50      1
```

Shift groups of the values in a column based on the index

```
In [118]: df = pd.DataFrame(
.....:     {'line_race': [10, 10, 8, 10, 10, 8],
.....:      'beyer': [99, 102, 103, 103, 88, 100]},
.....:      index=[u'Last Gunfighter', u'Last Gunfighter', u'Last Gunfighter',
.....:               u'Paynter', u'Paynter', u'Paynter']); df
.....:
Out[118]:
                beyer  line_race
Last Gunfighter     99         10
Last Gunfighter    102         10
Last Gunfighter    103          8
Paynter             103         10
Paynter              88         10
Paynter             100          8
```

```
In [119]: df['beyer_shifted'] = df.groupby(level=0)['beyer'].shift(1)
```

```
In [120]: df
Out[120]:
                beyer  line_race  beyer_shifted
Last Gunfighter     99         10           NaN
Last Gunfighter    102         10            99
Last Gunfighter    103          8           102
Paynter             103         10           NaN
Paynter              88         10           103
```

Paynter 100 8 88

Select row with maximum value from each group

```
In [121]: df = pd.DataFrame({'host': ['other', 'other', 'that', 'this', 'this'],
.....:                      'service': ['mail', 'web', 'mail', 'mail', 'web'],
.....:                      'no': [1, 2, 1, 2, 1]})
.....:                      .set_index(['host', 'service'])
```

```
In [122]: mask = df.groupby(level=0).agg('idxmax')
```

```
In [123]: df_count = df.loc[mask['no']].reset_index()
```

```
In [124]: df_count
```

```
Out[124]:
   host service  no
0  other     web   2
1   that    mail   1
2   this    mail   2
```

Grouping like Python's `itertools.groupby`

```
In [125]: df = pd.DataFrame([0, 1, 0, 1, 1, 1, 0, 1, 1], columns=['A'])
```

```
In [126]: df.A.groupby((df.A != df.A.shift()).cumsum()).groups
```

```
Out[126]: {1: [0L], 2: [1L], 3: [2L], 4: [3L, 4L, 5L], 5: [6L], 6: [7L, 8L]}
```

```
In [127]: df.A.groupby((df.A != df.A.shift()).cumsum()).cumsum()
```

```
Out[127]:
0    0
1    1
2    0
3    1
4    2
5    3
6    0
7    1
8    2
dtype: int64
```

8.5.1 Expanding Data

Alignment and to-date

Rolling Computation window based on values instead of counts

Rolling Mean by Time Interval

8.5.2 Splitting

Splitting a frame

Create a list of dataframes, split using a delineation based on logic included in rows.

```
In [128]: df = pd.DataFrame(data={'Case' : ['A', 'A', 'A', 'B', 'A', 'A', 'B', 'A', 'A'],
.....:                           'Data' : np.random.randn(9)})
.....:
```

```
In [129]: dfs = list(zip(*df.groupby(pd.rolling_median((1*(df['Case']=='B')).cumsum(),3,True))))[-1]
```

```
In [130]: dfs[0]
```

```
Out[130]:
```

| | Case | Data |
|---|------|-----------|
| 0 | A | 0.174068 |
| 1 | A | -0.439461 |
| 2 | A | -0.741343 |
| 3 | B | -0.079673 |

```
In [131]: dfs[1]
```

```
Out[131]:
```

| | Case | Data |
|---|------|-----------|
| 4 | A | -0.922875 |
| 5 | A | 0.303638 |
| 6 | B | -0.917368 |

```
In [132]: dfs[2]
```

```
Out[132]:
```

| | Case | Data |
|---|------|-----------|
| 7 | A | -1.624062 |
| 8 | A | -0.758514 |

8.5.3 Pivot

The *Pivot* docs.

Partial sums and subtotals

```
In [133]: df = pd.DataFrame(data={'Province' : ['ON','QC','BC','AL','AL','MN','ON'],
.....:                               'City' : ['Toronto','Montreal','Vancouver','Calgary','Edmonton','Windsor'],
.....:                               'Sales' : [13,6,16,8,4,3,1]})
.....:
```

```
In [134]: table = pd.pivot_table(df,values=['Sales'],index=['Province'],columns=['City'],aggfunc=np.sum)
```

```
In [135]: table.stack('City')
```

```
Out[135]:
```

| Province | City | Sales |
|----------|-----------|-------|
| AL | All | 12 |
| | Calgary | 8 |
| | Edmonton | 4 |
| | Winnipeg | 3 |
| BC | All | 16 |
| | Vancouver | 16 |
| MN | All | 3 |
| | Winnipeg | 3 |
| ON | All | 13 |
| | Calgary | 8 |
| | Edmonton | 4 |
| | Montreal | 6 |
| | Toronto | 13 |
| | Vancouver | 16 |
| QC | All | 6 |
| | Windsor | 1 |
| W | All | 3 |
| | Winnipeg | 3 |

```
[20 rows x 1 columns]
```

Frequency table like `plyr` in R

```
In [136]: grades = [48,99,75,80,42,80,72,68,36,78]
```

```
In [137]: df = pd.DataFrame( {'ID': ["x%d" % r for r in range(10)],
.....:                      'Gender': ['F', 'M', 'F', 'M', 'F', 'M', 'F', 'M', 'M', 'M'],
.....:                      'ExamYear': ['2007', '2007', '2007', '2008', '2008', '2008', '2008', '2009', '2009', '2009'],
.....:                      'Class': ['algebra', 'stats', 'bio', 'algebra', 'algebra', 'stats', 'stats', 'algebra', 'algebra', 'stats'],
.....:                      'Participated': ['yes', 'yes', 'yes', 'yes', 'no', 'yes', 'yes', 'yes', 'yes', 'yes'],
.....:                      'Passed': ['yes' if x > 50 else 'no' for x in grades],
.....:                      'Employed': [True, True, True, False, False, False, False, True, True, False],
.....:                      'Grade': grades})
```

```
In [138]: df.groupby('ExamYear').agg({'Participated': lambda x: x.value_counts()['yes'],
.....:                               'Passed': lambda x: sum(x == 'yes'),
.....:                               'Employed': lambda x: sum(x),
.....:                               'Grade': lambda x: sum(x) / len(x)})
```

```
Out[138]:
```

| | Grade | Employed | Participated | Passed |
|----------|-------|----------|--------------|--------|
| ExamYear | | | | |
| 2007 | 74 | 3 | 3 | 2 |
| 2008 | 68 | 0 | 3 | 3 |
| 2009 | 60 | 2 | 3 | 2 |

8.5.4 Apply

Rolling Apply to Organize - Turning embedded lists into a multi-index frame

```
In [139]: df = pd.DataFrame(data={'A': [[2,4,8,16],[100,200],[10,20,30]], 'B': [['a','b','c'],['jjj',
```

```
In [140]: def SeriesFromSubList(aList):
.....:     return pd.Series(aList)
.....:
```

```
In [141]: df_orgz = pd.concat(dict([(ind,row.apply(SeriesFromSubList)) for ind,row in df.iterrows()])
```

Rolling Apply with a DataFrame returning a Series

Rolling Apply to multiple columns where function calculates a Series before a Scalar from the Series is returned

```
In [142]: df = pd.DataFrame(data=np.random.randn(2000,2)/10000,
.....:                      index=pd.date_range('2001-01-01',periods=2000),
.....:                      columns=['A','B']); df
```

```
Out[142]:
```

| | A | B |
|------------|-----------|-----------|
| 2001-01-01 | -0.000056 | -0.000059 |
| 2001-01-02 | -0.000107 | -0.000168 |
| 2001-01-03 | 0.000040 | 0.000061 |
| 2001-01-04 | 0.000039 | 0.000182 |
| 2001-01-05 | 0.000071 | -0.000067 |
| 2001-01-06 | 0.000024 | 0.000031 |
| 2001-01-07 | 0.000012 | -0.000021 |
| ... | ... | ... |
| 2006-06-17 | 0.000129 | 0.000094 |
| 2006-06-18 | 0.000059 | 0.000216 |

```
2006-06-19 -0.000069  0.000283
2006-06-20  0.000089  0.000084
2006-06-21  0.000075  0.000041
2006-06-22 -0.000037 -0.000011
2006-06-23 -0.000070 -0.000048
```

```
[2000 rows x 2 columns]
```

```
In [143]: def gm(aDF, Const):
.....:     v = (((aDF.A+aDF.B)+1).cumprod()-1)*Const
.....:     return (aDF.index[0],v.iloc[-1])
.....:
```

```
In [144]: S = pd.Series(dict([ gm(df.iloc[i:min(i+51,len(df)-1)],5) for i in range(len(df)-50) ])); S
```

```
Out[144]:
```

```
2001-01-01    -0.003108
2001-01-02    -0.001787
2001-01-03     0.000204
2001-01-04    -0.000166
2001-01-05    -0.002148
2001-01-06    -0.001831
2001-01-07    -0.001663
```

```
...
```

```
2006-04-28    -0.009152
2006-04-29    -0.006728
2006-04-30    -0.005840
2006-05-01    -0.003650
2006-05-02    -0.003801
2006-05-03    -0.004272
2006-05-04    -0.003839
```

```
dtype: float64
```

Rolling apply with a DataFrame returning a Scalar

Rolling Apply to multiple columns where function returns a Scalar (Volume Weighted Average Price)

```
In [145]: rng = pd.date_range(start = '2014-01-01',periods = 100)
```

```
In [146]: df = pd.DataFrame({'Open' : np.random.randn(len(rng)),
.....:                      'Close' : np.random.randn(len(rng)),
.....:                      'Volume' : np.random.randint(100,2000,len(rng))}, index=rng); df
.....:
```

```
Out[146]:
```

| | Close | Open | Volume |
|------------|-----------|-----------|--------|
| 2014-01-01 | 1.550590 | 0.458513 | 1371 |
| 2014-01-02 | -0.818812 | -0.508850 | 1433 |
| 2014-01-03 | 1.160619 | 0.257610 | 645 |
| 2014-01-04 | 0.081521 | -1.773393 | 878 |
| 2014-01-05 | 1.083284 | -0.560676 | 1143 |
| 2014-01-06 | -0.518721 | 0.284174 | 1088 |
| 2014-01-07 | 0.140661 | 1.146889 | 1722 |
| ... | ... | ... | ... |
| 2014-04-04 | 0.458193 | -0.669474 | 1768 |
| 2014-04-05 | 0.108502 | -1.616315 | 836 |
| 2014-04-06 | 1.418082 | -1.294906 | 694 |
| 2014-04-07 | 0.486530 | 1.171647 | 796 |
| 2014-04-08 | 0.181885 | 0.501639 | 265 |
| 2014-04-09 | -0.707238 | -0.361868 | 1293 |
| 2014-04-10 | 1.211432 | 1.564429 | 1088 |

```
[100 rows x 3 columns]
```

```
In [147]: def vwap(bars): return ((bars.Close*bars.Volume).sum()/bars.Volume.sum()).round(2)
```

```
In [148]: window = 5
```

```
In [149]: s = pd.concat([ (pd.Series(vwap(df.iloc[i:i+window]), index=[df.index[i+window]])) for i in range(df.index[0], df.index[-1]-window+1, window)])
Out[149]:
```

```
2014-01-06    0.55
2014-01-07    0.06
2014-01-08    0.32
2014-01-09    0.03
2014-01-10    0.08
2014-01-11   -0.50
2014-01-12   -0.26
...
2014-04-04    0.36
2014-04-05    0.48
2014-04-06    0.54
2014-04-07    0.46
2014-04-08    0.45
2014-04-09    0.53
2014-04-10    0.15
dtype: float64
```

8.6 Timeseries

Between times

Using indexer between time

Constructing a datetime range that excludes weekends and includes only certain times

Vectorized Lookup

Turn a matrix with hours in columns and days in rows into a continuous row sequence in the form of a time series.

How to rearrange a python pandas DataFrame?

Dealing with duplicates when reindexing a timeseries to a specified frequency

Calculate the first day of the month for each entry in a DatetimeIndex

```
In [150]: dates = pd.date_range('2000-01-01', periods=5)
```

```
In [151]: dates.to_period(freq='M').to_timestamp()
```

```
Out[151]:
DatetimeIndex(['2000-01-01', '2000-01-01', '2000-01-01', '2000-01-01',
               '2000-01-01'],
              dtype='datetime64[ns]', freq=None, tz=None)
```

8.6.1 Resampling

The *Resample* docs.

TimeGrouping of values grouped across time

TimeGrouping #2

Using TimeGrouper and another grouping to create subgroups, then apply a custom function

Resampling with custom periods

Resample intraday frame without adding new days

Resample minute data

Resample with groupby

8.7 Merge

The *Concat* docs. The *Join* docs.

Append two dataframes with overlapping index (emulate R rbind)

```
In [152]: rng = pd.date_range('2000-01-01', periods=6)
```

```
In [153]: df1 = pd.DataFrame(np.random.randn(6, 3), index=rng, columns=['A', 'B', 'C'])
```

```
In [154]: df2 = df1.copy()
```

ignore_index is needed in pandas < v0.13, and depending on df construction

```
In [155]: df = df1.append(df2, ignore_index=True); df
```

```
Out[155]:
```

| | A | B | C |
|----|-----------|-----------|-----------|
| 0 | -0.174202 | -0.477257 | 0.239870 |
| 1 | -0.654455 | -1.411456 | -1.778457 |
| 2 | 0.351578 | 0.307871 | -0.286865 |
| 3 | 0.565398 | -0.185821 | 0.937593 |
| 4 | 0.446473 | 0.566368 | 0.721476 |
| 5 | 1.710685 | -0.667054 | -0.651191 |
| 6 | -0.174202 | -0.477257 | 0.239870 |
| 7 | -0.654455 | -1.411456 | -1.778457 |
| 8 | 0.351578 | 0.307871 | -0.286865 |
| 9 | 0.565398 | -0.185821 | 0.937593 |
| 10 | 0.446473 | 0.566368 | 0.721476 |
| 11 | 1.710685 | -0.667054 | -0.651191 |

Self Join of a DataFrame

```
In [156]: df = pd.DataFrame(data={'Area' : ['A'] * 5 + ['C'] * 2,  
.....:                          'Bins' : [110] * 2 + [160] * 3 + [40] * 2,  
.....:                          'Test_0' : [0, 1, 0, 1, 2, 0, 1],  
.....:                          'Data' : np.random.randn(7)});df
```

```
Out[156]:
```

| | Area | Bins | Data | Test_0 |
|---|------|------|-----------|--------|
| 0 | A | 110 | -0.399974 | 0 |
| 1 | A | 110 | -1.519206 | 1 |
| 2 | A | 160 | 1.678487 | 0 |
| 3 | A | 160 | 0.005345 | 1 |
| 4 | A | 160 | -0.534461 | 2 |
| 5 | C | 40 | 0.255077 | 0 |
| 6 | C | 40 | 1.093310 | 1 |

```
In [157]: df['Test_1'] = df['Test_0'] - 1
```

```
In [158]: pd.merge(df, df, left_on=['Bins', 'Area', 'Test_0'], right_on=['Bins', 'Area', 'Test_1'], suffixes=('_L', '_R'))
```

```
Out[158]:
```

| | Area | Bins | Data_L | Test_0_L | Test_1_L | Data_R | Test_0_R | Test_1_R |
|---|------|------|-----------|----------|----------|-----------|----------|----------|
| 0 | A | 110 | -0.399974 | 0 | -1 | -1.519206 | 1 | 0 |
| 1 | A | 160 | 1.678487 | 0 | -1 | 0.005345 | 1 | 0 |
| 2 | A | 160 | 0.005345 | 1 | 0 | -0.534461 | 2 | 1 |
| 3 | C | 40 | 0.255077 | 0 | -1 | 1.093310 | 1 | 0 |

How to set the index and join

KDB like asof join

Join with a criteria based on the values

8.8 Plotting

The *Plotting* docs.

Make Matplotlib look like R

Setting x-axis major and minor labels

Plotting multiple charts in an ipython notebook

Creating a multi-line plot

Plotting a heatmap

Annotate a time-series plot

Annotate a time-series plot #2

Generate Embedded plots in excel files using Pandas, Vincent and xlsxwriter

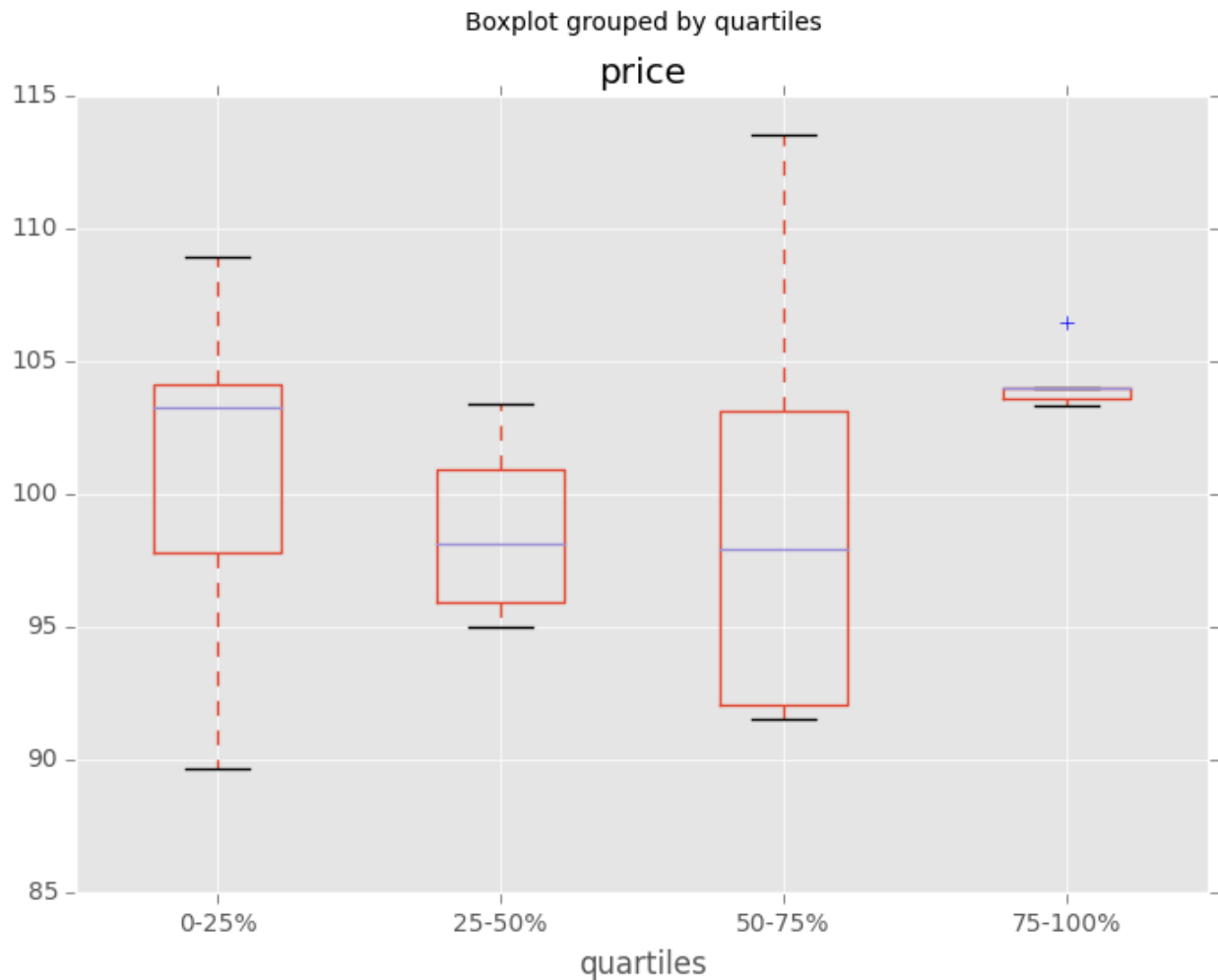
Boxplot for each quartile of a stratifying variable

```
In [159]: df = pd.DataFrame(
.....:     {'stratifying_var': np.random.uniform(0, 100, 20),
.....:      'price': np.random.normal(100, 5, 20)})
.....:
```

```
In [160]: df['quartiles'] = pd.qcut(
.....:     df['stratifying_var'],
.....:     4,
.....:     labels=['0-25%', '25-50%', '50-75%', '75-100%'])
.....:
```

```
In [161]: df.boxplot(column='price', by='quartiles')
```

```
Out[161]: <matplotlib.axes._subplots.AxesSubplot at 0xa920408c>
```



8.9 Data In/Out

Performance comparison of SQL vs HDF5

8.9.1 CSV

The *CSV* docs

`read_csv` in action

appending to a csv

how to read in multiple files, appending to create a single dataframe

Reading a csv chunk-by-chunk

Reading only certain rows of a csv chunk-by-chunk

Reading the first few lines of a frame

Reading a file that is compressed but not by `gzip/bz2` (the native compressed formats which `read_csv` understands). This example shows a WinZipped file, but is a general application of opening the file within a context manager and using that handle to read. [See here](#)

[Inferring dtypes from a file](#)

[Dealing with bad lines](#)

[Dealing with bad lines II](#)

[Reading CSV with Unix timestamps and converting to local timezone](#)

[Write a multi-row index CSV without writing duplicates](#)

[Parsing date components in multi-columns is faster with a format](#)

```
In [30]: i = pd.date_range('20000101', periods=10000)
```

```
In [31]: df = pd.DataFrame(dict(year = i.year, month = i.month, day = i.day))
```

```
In [32]: df.head()
```

```
Out[32]:
```

| | day | month | year |
|---|-----|-------|------|
| 0 | 1 | 1 | 2000 |
| 1 | 2 | 1 | 2000 |
| 2 | 3 | 1 | 2000 |
| 3 | 4 | 1 | 2000 |
| 4 | 5 | 1 | 2000 |

```
In [33]: %timeit pd.to_datetime(df.year*10000+df.month*100+df.day, format='%Y%m%d')
100 loops, best of 3: 7.08 ms per loop
```

simulate combining into a string, then parsing

```
In [34]: ds = df.apply(lambda x: "%04d%02d%02d" % (x['year'], x['month'], x['day']), axis=1)
```

```
In [35]: ds.head()
```

```
Out[35]:
```

| | |
|---|----------|
| 0 | 20000101 |
| 1 | 20000102 |
| 2 | 20000103 |
| 3 | 20000104 |
| 4 | 20000105 |

```
dtype: object
```

```
In [36]: %timeit pd.to_datetime(ds)
1 loops, best of 3: 488 ms per loop
```

8.9.2 SQL

The *SQL* docs

[Reading from databases with SQL](#)

8.9.3 Excel

The *Excel* docs

[Reading from a filelike handle](#) [Reading HTML tables from a server that cannot handle the default request header](#)

8.9.4 HDFStore

The *HDFStores* docs

Simple Queries with a Timestamp Index

Managing heterogeneous data using a linked multiple table hierarchy

Merging on-disk tables with millions of rows

Avoiding inconsistencies when writing to a store from multiple processes/threads

De-duplicating a large store by chunks, essentially a recursive reduction operation. Shows a function for taking in data from csv file and creating a store by chunks, with date parsing as well. [See here](#)

Creating a store chunk-by-chunk from a csv file

Appending to a store, while creating a unique index

Large Data work flows

Reading in a sequence of files, then providing a global unique index to a store while appending

Groupby on a HDFStore with low group density

Groupby on a HDFStore with high group density

Hierarchical queries on a HDFStore

Counting with a HDFStore

Troubleshoot HDFStore exceptions

Setting min_itemsize with strings

Using ptrepack to create a completely-sorted-index on a store

Storing Attributes to a group node

```
In [162]: df = pd.DataFrame(np.random.randn(8,3))

In [163]: store = pd.HDFStore('test.h5')

In [164]: store.put('df',df)

# you can store an arbitrary python object via pickle
In [165]: store.get_storer('df').attrs.my_attribute = dict(A = 10)

In [166]: store.get_storer('df').attrs.my_attribute
Out[166]: {'A': 10}
```

8.9.5 Binary Files

pandas readily accepts numpy record arrays, if you need to read in a binary file consisting of an array of C structs. For example, given this C program in a file called `main.c` compiled with `gcc main.c -std=gnu99` on a 64-bit machine,

```
#include <stdio.h>
#include <stdint.h>

typedef struct _Data
{
    int32_t count;
```

```

    double avg;
    float scale;
} Data;

int main(int argc, const char *argv[])
{
    size_t n = 10;
    Data d[n];

    for (int i = 0; i < n; ++i)
    {
        d[i].count = i;
        d[i].avg = i + 1.0;
        d[i].scale = (float) i + 2.0f;
    }

    FILE *file = fopen("binary.dat", "wb");
    fwrite(&d, sizeof(Data), n, file);
    fclose(file);

    return 0;
}

```

the following Python code will read the binary file 'binary.dat' into a pandas DataFrame, where each element of the struct corresponds to a column in the frame:

```

names = 'count', 'avg', 'scale'

# note that the offsets are larger than the size of the type because of
# struct padding
offsets = 0, 8, 16
formats = 'i4', 'f8', 'f4'
dt = np.dtype({'names': names, 'offsets': offsets, 'formats': formats},
              align=True)
df = pd.DataFrame(np.fromfile('binary.dat', dt))

```

Note: The offsets of the structure elements may be different depending on the architecture of the machine on which the file was created. Using a raw binary file format like this for general data storage is not recommended, as it is not cross platform. We recommend either HDF5 or msgpack, both of which are supported by pandas' IO facilities.

8.10 Computation

Numerical integration (sample-based) of a time series

8.11 Timedeltas

The *Timedeltas* docs.

Using timedeltas

```
In [167]: s = pd.Series(pd.date_range('2012-1-1', periods=3, freq='D'))
```

```
In [168]: s - s.max()
```

```
Out[168]:
0    -2 days
1    -1 days
2     0 days
dtype: timedelta64[ns]

In [169]: s.max() - s
Out[169]:
0     2 days
1     1 days
2     0 days
dtype: timedelta64[ns]

In [170]: s - datetime.datetime(2011,1,1,3,5)
Out[170]:
0    364 days 20:55:00
1    365 days 20:55:00
2    366 days 20:55:00
dtype: timedelta64[ns]

In [171]: s + datetime.timedelta(minutes=5)
Out[171]:
0    2012-01-01 00:05:00
1    2012-01-02 00:05:00
2    2012-01-03 00:05:00
dtype: datetime64[ns]

In [172]: datetime.datetime(2011,1,1,3,5) - s
Out[172]:
0    -365 days +03:05:00
1    -366 days +03:05:00
2    -367 days +03:05:00
dtype: timedelta64[ns]

In [173]: datetime.timedelta(minutes=5) + s
Out[173]:
0    2012-01-01 00:05:00
1    2012-01-02 00:05:00
2    2012-01-03 00:05:00
dtype: datetime64[ns]
```

Adding and subtracting deltas and dates

```
In [174]: deltas = pd.Series([ datetime.timedelta(days=i) for i in range(3) ])

In [175]: df = pd.DataFrame(dict(A = s, B = deltas)); df
Out[175]:
      A      B
0 2012-01-01 0 days
1 2012-01-02 1 days
2 2012-01-03 2 days

In [176]: df['New Dates'] = df['A'] + df['B'];

In [177]: df['Delta'] = df['A'] - df['New Dates']; df
Out[177]:
      A      B  New Dates  Delta
0 2012-01-01 0 days 2012-01-01 0 days
```

```
1 2012-01-02 1 days 2012-01-03 -1 days
2 2012-01-03 2 days 2012-01-05 -2 days
```

```
In [178]: df.dtypes
Out[178]:
A          datetime64[ns]
B          timedelta64[ns]
New Dates   datetime64[ns]
Delta       timedelta64[ns]
dtype: object
```

Another example

Values can be set to NaT using np.nan, similar to datetime

```
In [179]: y = s - s.shift(); y
Out[179]:
0          NaT
1    1 days
2    1 days
dtype: timedelta64[ns]
```

```
In [180]: y[1] = np.nan; y
Out[180]:
0          NaT
1          NaT
2    1 days
dtype: timedelta64[ns]
```

8.12 Aliasing Axis Names

To globally provide aliases for axis names, one can define these 2 functions:

```
In [181]: def set_axis_alias(cls, axis, alias):
.....:     if axis not in cls._AXIS_NUMBERS:
.....:         raise Exception("invalid axis [%s] for alias [%s]" % (axis, alias))
.....:     cls._AXIS_ALIASES[alias] = axis
.....:

In [182]: def clear_axis_alias(cls, axis, alias):
.....:     if axis not in cls._AXIS_NUMBERS:
.....:         raise Exception("invalid axis [%s] for alias [%s]" % (axis, alias))
.....:     cls._AXIS_ALIASES.pop(alias, None)
.....:

In [183]: set_axis_alias(pd.DataFrame, 'columns', 'myaxis2')

In [184]: df2 = pd.DataFrame(np.random.randn(3,2), columns=['c1', 'c2'], index=['i1', 'i2', 'i3'])

In [185]: df2.sum(axis='myaxis2')
Out[185]:
i1    0.239786
i2    0.259018
i3    0.163470
dtype: float64

In [186]: clear_axis_alias(pd.DataFrame, 'columns', 'myaxis2')
```

8.13 Creating Example Data

To create a dataframe from every combination of some given values, like R's `expand.grid()` function, we can create a dict where the keys are column names and the values are lists of the data values:

```
In [187]: def expand_grid(data_dict):
.....:     rows = itertools.product(*data_dict.values())
.....:     return pd.DataFrame.from_records(rows, columns=data_dict.keys())
.....:
```

```
In [188]: df = expand_grid(
.....:     {'height': [60, 70],
.....:      'weight': [100, 140, 180],
.....:      'sex': ['Male', 'Female']})
.....:
```

```
In [189]: df
```

```
Out[189]:
```

| | sex | weight | height |
|----|--------|--------|--------|
| 0 | Male | 100 | 60 |
| 1 | Male | 100 | 70 |
| 2 | Male | 140 | 60 |
| 3 | Male | 140 | 70 |
| 4 | Male | 180 | 60 |
| 5 | Male | 180 | 70 |
| 6 | Female | 100 | 60 |
| 7 | Female | 100 | 70 |
| 8 | Female | 140 | 60 |
| 9 | Female | 140 | 70 |
| 10 | Female | 180 | 60 |
| 11 | Female | 180 | 70 |

INTRO TO DATA STRUCTURES

We'll start with a quick, non-comprehensive overview of the fundamental data structures in pandas to get you started. The fundamental behavior about data types, indexing, and axis labeling / alignment apply across all of the objects. To get started, import numpy and load pandas into your namespace:

```
In [1]: import numpy as np

# will use a lot in examples
In [2]: randn = np.random.randn

In [3]: from pandas import *
```

Here is a basic tenet to keep in mind: **data alignment is intrinsic**. The link between labels and data will not be broken unless done so explicitly by you.

We'll give a brief intro to the data structures, then consider all of the broad categories of functionality and methods in separate sections.

When using pandas, we recommend the following import convention:

```
import pandas as pd
```

9.1 Series

Warning: In 0.13.0 `Series` has internally been refactored to no longer sub-class `ndarray` but instead subclass `NDFrame`, similarly to the rest of the pandas containers. This should be a transparent change with only very limited API implications (See the *Internal Refactoring*)

`Series` is a one-dimensional labeled array capable of holding any data type (integers, strings, floating point numbers, Python objects, etc.). The axis labels are collectively referred to as the **index**. The basic method to create a `Series` is to call:

```
>>> s = Series(data, index=index)
```

Here, `data` can be many different things:

- a Python dict
- an `ndarray`
- a scalar value (like 5)

The passed **index** is a list of axis labels. Thus, this separates into a few cases depending on what **data** is:

From `ndarray`

If data is an ndarray, **index** must be the same length as **data**. If no index is passed, one will be created having values `[0, ..., len(data) - 1]`.

```
In [4]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])
```

```
In [5]: s
Out[5]:
a    -2.783
b     0.426
c    -0.650
d     1.146
e    -0.663
dtype: float64
```

```
In [6]: s.index
Out[6]: Index([u'a', u'b', u'c', u'd', u'e'], dtype='object')
```

```
In [7]: Series(randn(5))
Out[7]:
0     0.294
1    -0.405
2     1.167
3     0.842
4     0.540
dtype: float64
```

Note: Starting in v0.8.0, pandas supports non-unique index values. If an operation that does not support duplicate index values is attempted, an exception will be raised at that time. The reason for being lazy is nearly all performance-based (there are many instances in computations, like parts of GroupBy, where the index is not used).

From dict

If data is a dict, if **index** is passed the values in data corresponding to the labels in the index will be pulled out. Otherwise, an index will be constructed from the sorted keys of the dict, if possible.

```
In [8]: d = {'a' : 0., 'b' : 1., 'c' : 2.}
```

```
In [9]: Series(d)
Out[9]:
a     0
b     1
c     2
dtype: float64
```

```
In [10]: Series(d, index=['b', 'c', 'd', 'a'])
Out[10]:
b     1
c     2
d    NaN
a     0
dtype: float64
```

Note: NaN (not a number) is the standard missing data marker used in pandas

From scalar value If data is a scalar value, an index must be provided. The value will be repeated to match the length of **index**

```
In [11]: Series(5., index=['a', 'b', 'c', 'd', 'e'])
Out[11]:
a      5
b      5
c      5
d      5
e      5
dtype: float64
```

9.1.1 Series is ndarray-like

Series acts very similarly to a `ndarray`, and is a valid argument to most NumPy functions. However, things like slicing also slice the index.

```
In [12]: s[0]
Out[12]: -2.7827595933769937
```

```
In [13]: s[:3]
Out[13]:
a    -2.783
b     0.426
c    -0.650
dtype: float64
```

```
In [14]: s[s > s.median()]
Out[14]:
b     0.426
d     1.146
dtype: float64
```

```
In [15]: s[[4, 3, 1]]
Out[15]:
e    -0.663
d     1.146
b     0.426
dtype: float64
```

```
In [16]: np.exp(s)
Out[16]:
a     0.062
b     1.532
c     0.522
d     3.147
e     0.515
dtype: float64
```

We will address array-based indexing in a separate [section](#).

9.1.2 Series is dict-like

A Series is like a fixed-size dict in that you can get and set values by index label:

```
In [17]: s['a']
Out[17]: -2.7827595933769937
```

```
In [18]: s['e'] = 12.
```

```
In [19]: s
Out[19]:
a    -2.783
b     0.426
c    -0.650
d     1.146
e    12.000
dtype: float64
```

```
In [20]: 'e' in s
Out[20]: True
```

```
In [21]: 'f' in s
Out[21]: False
```

If a label is not contained, an exception is raised:

```
>>> s['f']
KeyError: 'f'
```

Using the `get` method, a missing label will return `None` or specified default:

```
In [22]: s.get('f')
```

```
In [23]: s.get('f', np.nan)
Out[23]: nan
```

See also the [section on attribute access](#).

9.1.3 Vectorized operations and label alignment with Series

When doing data analysis, as with raw NumPy arrays looping through Series value-by-value is usually not necessary. Series can be also be passed into most NumPy methods expecting an ndarray.

```
In [24]: s + s
Out[24]:
a    -5.566
b     0.853
c    -1.301
d     2.293
e    24.000
dtype: float64
```

```
In [25]: s * 2
Out[25]:
a    -5.566
b     0.853
c    -1.301
d     2.293
e    24.000
dtype: float64
```

```
In [26]: np.exp(s)
Out[26]:
a     0.062
b     1.532
c     0.522
```

```
d          3.147
e    162754.791
dtype: float64
```

A key difference between Series and ndarray is that operations between Series automatically align the data based on label. Thus, you can write computations without giving consideration to whether the Series involved have the same labels.

```
In [27]: s[1:] + s[:-1]
Out[27]:
a      NaN
b      0.853
c     -1.301
d      2.293
e      NaN
dtype: float64
```

The result of an operation between unaligned Series will have the **union** of the indexes involved. If a label is not found in one Series or the other, the result will be marked as missing NaN. Being able to write code without doing any explicit data alignment grants immense freedom and flexibility in interactive data analysis and research. The integrated data alignment features of the pandas data structures set pandas apart from the majority of related tools for working with labeled data.

Note: In general, we chose to make the default result of operations between differently indexed objects yield the **union** of the indexes in order to avoid loss of information. Having an index label, though the data is missing, is typically important information as part of a computation. You of course have the option of dropping labels with missing data via the **dropna** function.

9.1.4 Name attribute

Series can also have a name attribute:

```
In [28]: s = Series(np.random.randn(5), name='something')

In [29]: s
Out[29]:
0      0.541
1     -1.175
2      0.129
3      0.043
4     -0.429
Name: something, dtype: float64

In [30]: s.name
Out[30]: 'something'
```

The Series `name` will be assigned automatically in many cases, in particular when taking 1D slices of DataFrame as you will see below.

9.2 DataFrame

DataFrame is a 2-dimensional labeled data structure with columns of potentially different types. You can think of it like a spreadsheet or SQL table, or a dict of Series objects. It is generally the most commonly used pandas object. Like Series, DataFrame accepts many different kinds of input:

- Dict of 1D ndarrays, lists, dicts, or Series
- 2-D numpy.ndarray
- [Structured or record ndarray](#)
- A Series
- Another DataFrame

Along with the data, you can optionally pass **index** (row labels) and **columns** (column labels) arguments. If you pass an index and / or columns, you are guaranteeing the index and / or columns of the resulting DataFrame. Thus, a dict of Series plus a specific index will discard all data not matching up to the passed index.

If axis labels are not passed, they will be constructed from the input data based on common sense rules.

9.2.1 From dict of Series or dicts

The result **index** will be the **union** of the indexes of the various Series. If there are any nested dicts, these will be first converted to Series. If no columns are passed, the columns will be the sorted list of dict keys.

```
In [31]: d = {'one' : Series([1., 2., 3.], index=['a', 'b', 'c']),
....:        'two' : Series([1., 2., 3., 4.], index=['a', 'b', 'c', 'd'])}
....:
```

```
In [32]: df = DataFrame(d)
```

```
In [33]: df
```

```
Out[33]:
```

| | one | two |
|---|-----|-----|
| a | 1 | 1 |
| b | 2 | 2 |
| c | 3 | 3 |
| d | NaN | 4 |

```
In [34]: DataFrame(d, index=['d', 'b', 'a'])
```

```
Out[34]:
```

| | one | two |
|---|-----|-----|
| d | NaN | 4 |
| b | 2 | 2 |
| a | 1 | 1 |

```
In [35]: DataFrame(d, index=['d', 'b', 'a'], columns=['two', 'three'])
```

```
Out[35]:
```

| | two | three |
|---|-----|-------|
| d | 4 | NaN |
| b | 2 | NaN |
| a | 1 | NaN |

The row and column labels can be accessed respectively by accessing the **index** and **columns** attributes:

Note: When a particular set of columns is passed along with a dict of data, the passed columns override the keys in the dict.

```
In [36]: df.index
```

```
Out[36]: Index([u'a', u'b', u'c', u'd'], dtype='object')
```

```
In [37]: df.columns
```

```
Out[37]: Index([u'one', u'two'], dtype='object')
```

9.2.2 From dict of ndarrays / lists

The ndarrays must all be the same length. If an index is passed, it must clearly also be the same length as the arrays. If no index is passed, the result will be `range(n)`, where `n` is the array length.

```
In [38]: d = {'one' : [1., 2., 3., 4.],
.....:       'two' : [4., 3., 2., 1.]}
.....:
```

```
In [39]: DataFrame(d)
```

```
Out[39]:
   one  two
0    1    4
1    2    3
2    3    2
3    4    1
```

```
In [40]: DataFrame(d, index=['a', 'b', 'c', 'd'])
```

```
Out[40]:
   one  two
a    1    4
b    2    3
c    3    2
d    4    1
```

9.2.3 From structured or record array

This case is handled identically to a dict of arrays.

```
In [41]: data = np.zeros((2,), dtype=[('A', 'i4'), ('B', 'f4'), ('C', 'a10')])
```

```
In [42]: data[:] = [(1, 2., 'Hello'), (2, 3., "World")]
```

```
In [43]: DataFrame(data)
```

```
Out[43]:
   A  B      C
0  1  2  Hello
1  2  3  World
```

```
In [44]: DataFrame(data, index=['first', 'second'])
```

```
Out[44]:
   A  B      C
first  1  2  Hello
second 2  3  World
```

```
In [45]: DataFrame(data, columns=['C', 'A', 'B'])
```

```
Out[45]:
   C  A  B
0  Hello  1  2
1  World  2  3
```

Note: DataFrame is not intended to work exactly like a 2-dimensional NumPy ndarray.

9.2.4 From a list of dicts

```
In [46]: data2 = [{'a': 1, 'b': 2}, {'a': 5, 'b': 10, 'c': 20}]
```

```
In [47]: DataFrame(data2)
```

```
Out[47]:
```

| | a | b | c |
|---|---|----|-----|
| 0 | 1 | 2 | NaN |
| 1 | 5 | 10 | 20 |

```
In [48]: DataFrame(data2, index=['first', 'second'])
```

```
Out[48]:
```

| | a | b | c |
|--------|---|----|-----|
| first | 1 | 2 | NaN |
| second | 5 | 10 | 20 |

```
In [49]: DataFrame(data2, columns=['a', 'b'])
```

```
Out[49]:
```

| | a | b |
|---|---|----|
| 0 | 1 | 2 |
| 1 | 5 | 10 |

9.2.5 From a dict of tuples

You can automatically create a multi-indexed frame by passing a tuples dictionary

```
In [50]: DataFrame({('a', 'b'): {('A', 'B'): 1, ('A', 'C'): 2},
.....:               ('a', 'a'): {('A', 'C'): 3, ('A', 'B'): 4},
.....:               ('a', 'c'): {('A', 'B'): 5, ('A', 'C'): 6},
.....:               ('b', 'a'): {('A', 'C'): 7, ('A', 'B'): 8},
.....:               ('b', 'b'): {('A', 'D'): 9, ('A', 'B'): 10}})
```

```
Out[50]:
```

| | | a | | | b | |
|---|-----|-----|-----|-----|-----|-----|
| | | a | b | c | a | b |
| A | B | 4 | 1 | 5 | 8 | 10 |
| C | | 3 | 2 | 6 | 7 | NaN |
| D | NaN | NaN | NaN | NaN | NaN | 9 |

9.2.6 From a Series

The result will be a DataFrame with the same index as the input Series, and with one column whose name is the original name of the Series (only if no other column name provided).

Missing Data

Much more will be said on this topic in the [Missing data](#) section. To construct a DataFrame with missing data, use `np.nan` for those values which are missing. Alternatively, you may pass a `numpy.MaskedArray` as the data argument to the DataFrame constructor, and its masked entries will be considered missing.

9.2.7 Alternate Constructors

DataFrame.from_dict

`DataFrame.from_dict` takes a dict of dicts or a dict of array-like sequences and returns a `DataFrame`. It operates like the `DataFrame` constructor except for the `orient` parameter which is `'columns'` by default, but which can be set to `'index'` in order to use the dict keys as row labels. **`DataFrame.from_records`**

`DataFrame.from_records` takes a list of tuples or an ndarray with structured dtype. Works analogously to the normal `DataFrame` constructor, except that index maybe be a specific field of the structured dtype to use as the index. For example:

```
In [51]: data
Out[51]:
array([(1, 2.0, 'Hello'), (2, 3.0, 'World')],
      dtype=[('A', '<i4'), ('B', '<f4'), ('C', 'S10')])
```

```
In [52]: DataFrame.from_records(data, index='C')
```

```
Out[52]:
   A  B
C
Hello 1  2
World 2  3
```

`DataFrame.from_items`

`DataFrame.from_items` works analogously to the form of the dict constructor that takes a sequence of (key, value) pairs, where the keys are column (or row, in the case of `orient='index'`) names, and the value are the column values (or row values). This can be useful for constructing a `DataFrame` with the columns in a particular order without having to pass an explicit list of columns:

```
In [53]: DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])])
```

```
Out[53]:
   A  B
0  1  4
1  2  5
2  3  6
```

If you pass `orient='index'`, the keys will be the row labels. But in this case you must also pass the desired column names:

```
In [54]: DataFrame.from_items([('A', [1, 2, 3]), ('B', [4, 5, 6])],
.....:                        orient='index', columns=['one', 'two', 'three'])
.....:
```

```
Out[54]:
   one  two  three
A     1    2     3
B     4    5     6
```

9.2.8 Column selection, addition, deletion

You can treat a `DataFrame` semantically like a dict of like-indexed `Series` objects. Getting, setting, and deleting columns works with the same syntax as the analogous dict operations:

```
In [55]: df['one']
Out[55]:
a     1
b     2
c     3
d    NaN
Name: one, dtype: float64
```

```
In [56]: df['three'] = df['one'] * df['two']
```

```
In [57]: df['flag'] = df['one'] > 2
```

```
In [58]: df
```

```
Out[58]:
```

| | one | two | three | flag |
|---|-----|-----|-------|-------|
| a | 1 | 1 | 1 | False |
| b | 2 | 2 | 4 | False |
| c | 3 | 3 | 9 | True |
| d | NaN | 4 | NaN | False |

Columns can be deleted or popped like with a dict:

```
In [59]: del df['two']
```

```
In [60]: three = df.pop('three')
```

```
In [61]: df
```

```
Out[61]:
```

| | one | flag |
|---|-----|-------|
| a | 1 | False |
| b | 2 | False |
| c | 3 | True |
| d | NaN | False |

When inserting a scalar value, it will naturally be propagated to fill the column:

```
In [62]: df['foo'] = 'bar'
```

```
In [63]: df
```

```
Out[63]:
```

| | one | flag | foo |
|---|-----|-------|-----|
| a | 1 | False | bar |
| b | 2 | False | bar |
| c | 3 | True | bar |
| d | NaN | False | bar |

When inserting a Series that does not have the same index as the DataFrame, it will be conformed to the DataFrame's index:

```
In [64]: df['one_trunc'] = df['one'][:2]
```

```
In [65]: df
```

```
Out[65]:
```

| | one | flag | foo | one_trunc |
|---|-----|-------|-----|-----------|
| a | 1 | False | bar | 1 |
| b | 2 | False | bar | 2 |
| c | 3 | True | bar | NaN |
| d | NaN | False | bar | NaN |

You can insert raw ndarrays but their length must match the length of the DataFrame's index.

By default, columns get inserted at the end. The `insert` function is available to insert at a particular location in the columns:

```
In [66]: df.insert(1, 'bar', df['one'])
```

```
In [67]: df
```

```
Out[67]:
```

| | one | bar | flag | foo | one_trunc |
|---|-----|-----|-------|-----|-----------|
| a | 1 | 1 | False | bar | 1 |
| b | 2 | 2 | False | bar | 2 |
| c | 3 | 3 | True | bar | NaN |
| d | NaN | NaN | False | bar | NaN |

9.2.9 Assigning New Columns in Method Chains

New in version 0.16.0.

Inspired by `dplyr`'s `mutate` verb, `DataFrame` has an `assign()` method that allows you to easily create new columns that are potentially derived from existing columns.

```
In [68]: iris = read_csv('data/iris.data')
```

```
In [69]: iris.head()
```

```
Out[69]:
```

| | SepalLength | SepalWidth | PetalLength | PetalWidth | Name |
|---|-------------|------------|-------------|------------|-------------|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |

```
In [70]: (iris.assign(sepal_ratio = iris['SepalWidth'] / iris['SepalLength'])
.....:             .head())
.....:
```

```
Out[70]:
```

| | SepalLength | SepalWidth | PetalLength | PetalWidth | Name | sepal_ratio |
|---|-------------|------------|-------------|------------|-------------|-------------|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa | 0.686 |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa | 0.612 |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa | 0.681 |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa | 0.674 |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa | 0.720 |

Above was an example of inserting a precomputed value. We can also pass in a function of one argument to be evaluated on the `DataFrame` being assigned to.

```
In [71]: iris.assign(sepal_ratio = lambda x: (x['SepalWidth'] /
.....:                                         x['SepalLength'])).head()
.....:
```

```
Out[71]:
```

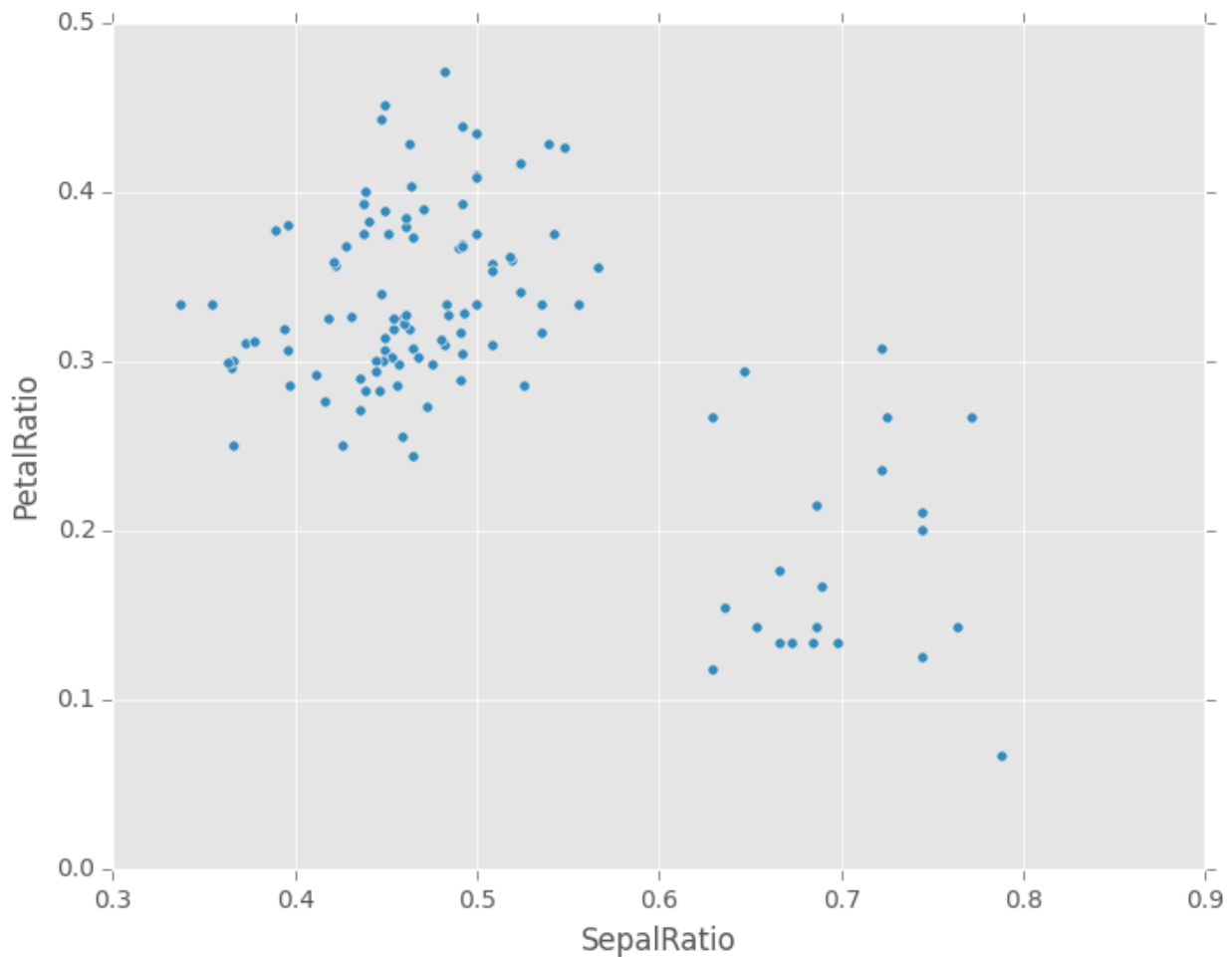
| | SepalLength | SepalWidth | PetalLength | PetalWidth | Name | sepal_ratio |
|---|-------------|------------|-------------|------------|-------------|-------------|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa | 0.686 |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa | 0.612 |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa | 0.681 |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa | 0.674 |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa | 0.720 |

`assign` **always** returns a copy of the data, leaving the original `DataFrame` untouched.

Passing a callable, as opposed to an actual value to be inserted, is useful when you don't have a reference to the `DataFrame` at hand. This is common when using `assign` in chains of operations. For example, we can limit the `DataFrame` to just those observations with a Sepal Length greater than 5, calculate the ratio, and plot:

```
In [72]: (iris.query('SepalLength > 5')
.....:         .assign(SepalRatio = lambda x: x.SepalWidth / x.SepalLength,
.....:                 PetalRatio = lambda x: x.PetalWidth / x.PetalLength))
```

```
.....: .plot(kind='scatter', x='SepalRatio', y='PetalRatio'))
.....:
Out[72]: <matplotlib.axes._subplots.AxesSubplot at 0xa92ff26c>
```



Since a function is passed in, the function is computed on the DataFrame being assigned to. Importantly, this is the DataFrame that's been filtered to those rows with sepal length greater than 5. The filtering happens first, and then the ratio calculations. This is an example where we didn't have a reference to the *filtered* DataFrame available.

The function signature for `assign` is simply `**kwargs`. The keys are the column names for the new fields, and the values are either a value to be inserted (for example, a `Series` or NumPy array), or a function of one argument to be called on the DataFrame. A *copy* of the original DataFrame is returned, with the new values inserted.

Warning: Since the function signature of `assign` is `**kwargs`, a dictionary, the order of the new columns in the resulting DataFrame cannot be guaranteed to match the order you pass in. To make things predictable, items are inserted alphabetically (by key) at the end of the DataFrame.

All expressions are computed first, and then assigned. So you can't refer to another column being assigned in the same call to `assign`. For example:

```
In [73]: # Don't do this, bad reference to `C`
         df.assign(C = lambda x: x['A'] + x['B'],
                  D = lambda x: x['A'] + x['C'])

In [2]: # Instead, break it into two assigns
        (df.assign(C = lambda x: x['A'] + x['B'])
         .assign(D = lambda x: x['A'] + x['C']))
```

9.2.10 Indexing / Selection

The basics of indexing are as follows:

| Operation | Syntax | Result |
|--------------------------------|----------------------------|-----------|
| Select column | <code>df[col]</code> | Series |
| Select row by label | <code>df.loc[label]</code> | Series |
| Select row by integer location | <code>df.iloc[loc]</code> | Series |
| Slice rows | <code>df[5:10]</code> | DataFrame |
| Select rows by boolean vector | <code>df[bool_vec]</code> | DataFrame |

Row selection, for example, returns a Series whose index is the columns of the DataFrame:

```
In [74]: df.loc['b']
Out[74]:
one          2
bar          2
flag        False
foo          bar
one_trunc     2
Name: b, dtype: object
```

```
In [75]: df.iloc[2]
Out[75]:
one          3
bar          3
flag         True
foo          bar
one_trunc    NaN
Name: c, dtype: object
```

For a more exhaustive treatment of more sophisticated label-based indexing and slicing, see the [section on indexing](#). We will address the fundamentals of reindexing / conforming to new sets of labels in the [section on reindexing](#).

9.2.11 Data alignment and arithmetic

Data alignment between DataFrame objects automatically align on **both the columns and the index (row labels)**. Again, the resulting object will have the union of the column and row labels.

```
In [76]: df = DataFrame(randn(10, 4), columns=['A', 'B', 'C', 'D'])
```

```
In [77]: df2 = DataFrame(randn(7, 3), columns=['A', 'B', 'C'])
```

```
In [78]: df + df2
```

```
Out[78]:
```

| | A | B | C | D |
|---|--------|--------|------------|-----|
| 0 | -1.916 | -0.986 | -2.421e+00 | NaN |
| 1 | 0.965 | 1.677 | 3.298e-01 | NaN |
| 2 | -1.662 | 2.197 | -1.917e+00 | NaN |
| 3 | -0.189 | 0.765 | -9.522e-04 | NaN |
| 4 | -1.076 | 0.397 | -1.177e+00 | NaN |
| 5 | 2.810 | -0.179 | -5.705e-01 | NaN |
| 6 | -1.227 | 0.196 | 5.312e-01 | NaN |
| 7 | NaN | NaN | NaN | NaN |
| 8 | NaN | NaN | NaN | NaN |
| 9 | NaN | NaN | NaN | NaN |

When doing an operation between DataFrame and Series, the default behavior is to align the Series **index** on the DataFrame **columns**, thus **broadcasting** row-wise. For example:

```
In [79]: df - df.iloc[0]
```

```
Out[79]:
```

| | A | B | C | D |
|---|-------|-------|-------|--------|
| 0 | 0.000 | 0.000 | 0.000 | 0.000 |
| 1 | 2.386 | 1.358 | 1.223 | -2.107 |
| 2 | 2.105 | 1.700 | 1.327 | -0.689 |
| 3 | 1.874 | 2.718 | 2.382 | -0.760 |
| 4 | 2.199 | 0.966 | 0.826 | 0.093 |
| 5 | 4.997 | 1.197 | 1.330 | -0.285 |
| 6 | 1.263 | 0.578 | 1.071 | -0.525 |
| 7 | 3.463 | 0.632 | 1.063 | -0.443 |
| 8 | 2.680 | 3.163 | 1.298 | -1.818 |
| 9 | 1.304 | 0.196 | 3.590 | -0.867 |

In the special case of working with time series data, if the Series is a TimeSeries (which it will be automatically if the index contains datetime objects), and the DataFrame index also contains dates, the broadcasting will be column-wise:

```
In [80]: index = date_range('1/1/2000', periods=8)
```

```
In [81]: df = DataFrame(randn(8, 3), index=index, columns=list('ABC'))
```

```
In [82]: df
```

```
Out[82]:
```

| | A | B | C |
|------------|--------|--------|--------|
| 2000-01-01 | 0.063 | -0.028 | 0.444 |
| 2000-01-02 | -0.269 | -1.578 | 1.850 |
| 2000-01-03 | 0.638 | -0.557 | -0.071 |
| 2000-01-04 | -0.511 | 0.156 | -1.076 |
| 2000-01-05 | 1.664 | -0.438 | -0.077 |
| 2000-01-06 | 0.029 | 0.179 | 1.740 |
| 2000-01-07 | -0.729 | -0.898 | -0.314 |
| 2000-01-08 | -0.048 | -0.876 | 0.169 |

```
In [83]: type(df['A'])
```

```
Out[83]: pandas.core.series.Series
```

```
In [84]: df - df['A']
```

```
Out[84]:
```

| | A | B | C |
|------------|---|--------|-------|
| 2000-01-01 | 0 | -0.091 | 0.381 |

```

2000-01-02    0 -1.309    2.119
2000-01-03    0 -1.195   -0.709
2000-01-04    0  0.668   -0.564
2000-01-05    0 -2.101   -1.741
2000-01-06    0  0.150    1.711
2000-01-07    0 -0.169    0.415
2000-01-08    0 -0.828    0.217

```

Warning:

```
df - df['A']
```

is now deprecated and will be removed in a future release. The preferred way to replicate this behavior is

```
df.sub(df['A'], axis=0)
```

For explicit control over the matching and broadcasting behavior, see the section on *flexible binary operations*.

Operations with scalars are just as you would expect:

```
In [85]: df * 5 + 2
```

```
Out[85]:
```

```

          A          B          C
2000-01-01  2.314  1.858  4.218
2000-01-02  0.656 -5.888 11.251
2000-01-03  5.190 -0.783  1.644
2000-01-04 -0.557  2.781 -3.378
2000-01-05 10.318 -0.189  1.613
2000-01-06  2.146  2.895 10.700
2000-01-07 -1.645 -2.490  0.429
2000-01-08  1.760 -2.378  2.846

```

```
In [86]: 1 / df
```

```
Out[86]:
```

```

          A          B          C
2000-01-01 15.948 -35.193  2.255
2000-01-02 -3.721  -0.634  0.540
2000-01-03  1.567  -1.797 -14.039
2000-01-04 -1.955   6.398  -0.930
2000-01-05  0.601  -2.285 -12.936
2000-01-06 34.257   5.586   0.575
2000-01-07 -1.372  -1.114  -3.183
2000-01-08 -20.802  -1.142   5.913

```

```
In [87]: df ** 4
```

```
Out[87]:
```

```

          A          B          C
2000-01-01 1.546e-05  6.519e-07  3.871e-02
2000-01-02 5.219e-03  6.195e+00  1.172e+01
2000-01-03 1.657e-01  9.598e-02  2.574e-05
2000-01-04 6.841e-02  5.966e-04  1.339e+00
2000-01-05 7.660e+00  3.671e-02  3.571e-05
2000-01-06 7.261e-07  1.027e-03  9.168e+00
2000-01-07 2.825e-01  6.503e-01  9.747e-03
2000-01-08 5.341e-06  5.878e-01  8.178e-04

```

Boolean operators work as well:

```
In [88]: df1 = DataFrame({'a' : [1, 0, 1], 'b' : [0, 1, 1] }, dtype=bool)
```

```
In [89]: df2 = DataFrame({'a' : [0, 1, 1], 'b' : [1, 1, 0] }, dtype=bool)
```

```
In [90]: df1 & df2
```

```
Out[90]:
```

| | a | b |
|---|-------|-------|
| 0 | False | False |
| 1 | False | True |
| 2 | True | False |

```
In [91]: df1 | df2
```

```
Out[91]:
```

| | a | b |
|---|------|------|
| 0 | True | True |
| 1 | True | True |
| 2 | True | True |

```
In [92]: df1 ^ df2
```

```
Out[92]:
```

| | a | b |
|---|-------|-------|
| 0 | True | True |
| 1 | True | False |
| 2 | False | True |

```
In [93]: -df1
```

```
Out[93]:
```

| | a | b |
|---|-------|-------|
| 0 | False | True |
| 1 | True | False |
| 2 | False | False |

9.2.12 Transposing

To transpose, access the `T` attribute (also the `transpose` function), similar to an `ndarray`:

```
# only show the first 5 rows
```

```
In [94]: df[:5].T
```

```
Out[94]:
```

| | 2000-01-01 | 2000-01-02 | 2000-01-03 | 2000-01-04 | 2000-01-05 |
|---|------------|------------|------------|------------|------------|
| A | 0.063 | -0.269 | 0.638 | -0.511 | 1.664 |
| B | -0.028 | -1.578 | -0.557 | 0.156 | -0.438 |
| C | 0.444 | 1.850 | -0.071 | -1.076 | -0.077 |

9.2.13 DataFrame interoperability with NumPy functions

Elementwise NumPy ufuncs (`log`, `exp`, `sqrt`, ...) and various other NumPy functions can be used with no issues on `DataFrame`, assuming the data within are numeric:

```
In [95]: np.exp(df)
```

```
Out[95]:
```

| | A | B | C |
|------------|-------|-------|-------|
| 2000-01-01 | 1.065 | 0.972 | 1.558 |
| 2000-01-02 | 0.764 | 0.206 | 6.361 |
| 2000-01-03 | 1.893 | 0.573 | 0.931 |
| 2000-01-04 | 0.600 | 1.169 | 0.341 |

```
2000-01-05    5.278    0.646    0.926
2000-01-06    1.030    1.196    5.698
2000-01-07    0.482    0.407    0.730
2000-01-08    0.953    0.417    1.184
```

```
In [96]: np.asarray(df)
Out[96]:
array([[ 0.0627, -0.0284,  0.4436],
       [-0.2688, -1.5776,  1.8502],
       [ 0.6381, -0.5566, -0.0712],
       [-0.5114,  0.1563, -1.0756],
       [ 1.6636, -0.4377, -0.0773],
       [ 0.0292,  0.179 ,  1.7401],
       [-0.729 , -0.898 , -0.3142],
       [-0.0481, -0.8756,  0.1691]])
```

The dot method on DataFrame implements matrix multiplication:

```
In [97]: df.T.dot(df)
Out[97]:
```

| | A | B | C |
|---|--------|--------|--------|
| A | 4.047 | -0.039 | 0.178 |
| B | -0.039 | 4.621 | -2.581 |
| C | 0.178 | -2.581 | 7.943 |

Similarly, the dot method on Series implements dot product:

```
In [98]: s1 = Series(np.arange(5,10))

In [99]: s1.dot(s1)
Out[99]: 255
```

DataFrame is not intended to be a drop-in replacement for ndarray as its indexing semantics are quite different in places from a matrix.

9.2.14 Console display

Very large DataFrames will be truncated to display them in the console. You can also get a summary using `info()`. (Here I am reading a CSV version of the **baseball** dataset from the **plyr** R package):

```
In [100]: baseball = read_csv('data/baseball.csv')

In [101]: print(baseball)
```

| | id | player | year | stint | ... | hbp | sh | sf | gidp |
|----|-------|-----------|------|-------|-----|-----|----|----|------|
| 0 | 88641 | womacto01 | 2006 | 2 | ... | 0 | 3 | 0 | 0 |
| 1 | 88643 | schilcu01 | 2006 | 1 | ... | 0 | 0 | 0 | 0 |
| .. | ... | ... | ... | ... | ... | .. | .. | .. | ... |
| 98 | 89533 | aloumo01 | 2007 | 1 | ... | 2 | 0 | 3 | 13 |
| 99 | 89534 | alomasa02 | 2007 | 1 | ... | 0 | 0 | 0 | 0 |

```
[100 rows x 23 columns]

In [102]: baseball.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 100 entries, 0 to 99
Data columns (total 23 columns):
id          100 non-null int64
player      100 non-null object
```

```
year      100 non-null int64
stint     100 non-null int64
team      100 non-null object
lg        100 non-null object
g         100 non-null int64
ab        100 non-null int64
r         100 non-null int64
h         100 non-null int64
X2b       100 non-null int64
X3b       100 non-null int64
hr        100 non-null int64
rbi       100 non-null float64
sb        100 non-null float64
cs        100 non-null float64
bb        100 non-null int64
so        100 non-null float64
ibb       100 non-null float64
hbp       100 non-null float64
sh        100 non-null float64
sf        100 non-null float64
gidp      100 non-null float64
dtypes: float64(9), int64(11), object(3)
memory usage: 17.6+ KB
```

However, using `to_string` will return a string representation of the DataFrame in tabular form, though it won't always fit the console width:

```
In [103]: print(baseball.iloc[-20:, :12].to_string())
```

| | id | player | year | stint | team | lg | g | ab | r | h | X2b | X3b |
|----|-------|-----------|------|-------|------|----|-----|-----|----|-----|-----|-----|
| 80 | 89474 | finlest01 | 2007 | 1 | COL | NL | 43 | 94 | 9 | 17 | 3 | 0 |
| 81 | 89480 | embreal01 | 2007 | 1 | OAK | AL | 4 | 0 | 0 | 0 | 0 | 0 |
| 82 | 89481 | edmonji01 | 2007 | 1 | SLN | NL | 117 | 365 | 39 | 92 | 15 | 2 |
| 83 | 89482 | easleda01 | 2007 | 1 | NYN | NL | 76 | 193 | 24 | 54 | 6 | 0 |
| 84 | 89489 | delgaca01 | 2007 | 1 | NYN | NL | 139 | 538 | 71 | 139 | 30 | 0 |
| 85 | 89493 | cormirh01 | 2007 | 1 | CIN | NL | 6 | 0 | 0 | 0 | 0 | 0 |
| 86 | 89494 | coninje01 | 2007 | 2 | NYN | NL | 21 | 41 | 2 | 8 | 2 | 0 |
| 87 | 89495 | coninje01 | 2007 | 1 | CIN | NL | 80 | 215 | 23 | 57 | 11 | 1 |
| 88 | 89497 | clemero02 | 2007 | 1 | NYA | AL | 2 | 2 | 0 | 1 | 0 | 0 |
| 89 | 89498 | claytro01 | 2007 | 2 | BOS | AL | 8 | 6 | 1 | 0 | 0 | 0 |
| 90 | 89499 | claytro01 | 2007 | 1 | TOR | AL | 69 | 189 | 23 | 48 | 14 | 0 |
| 91 | 89501 | cirilje01 | 2007 | 2 | ARI | NL | 28 | 40 | 6 | 8 | 4 | 0 |
| 92 | 89502 | cirilje01 | 2007 | 1 | MIN | AL | 50 | 153 | 18 | 40 | 9 | 2 |
| 93 | 89521 | bondsba01 | 2007 | 1 | SFN | NL | 126 | 340 | 75 | 94 | 14 | 0 |
| 94 | 89523 | biggicr01 | 2007 | 1 | HOU | NL | 141 | 517 | 68 | 130 | 31 | 3 |
| 95 | 89525 | benitar01 | 2007 | 2 | FLO | NL | 34 | 0 | 0 | 0 | 0 | 0 |
| 96 | 89526 | benitar01 | 2007 | 1 | SFN | NL | 19 | 0 | 0 | 0 | 0 | 0 |
| 97 | 89530 | ausmubr01 | 2007 | 1 | HOU | NL | 117 | 349 | 38 | 82 | 16 | 3 |
| 98 | 89533 | aloumo01 | 2007 | 1 | NYN | NL | 87 | 328 | 51 | 112 | 19 | 1 |
| 99 | 89534 | alomasa02 | 2007 | 1 | NYN | NL | 8 | 22 | 1 | 3 | 1 | 0 |

New since 0.10.0, wide DataFrames will now be printed across multiple rows by default:

```
In [104]: DataFrame(randn(3, 12))
```

```
Out[104]:
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | \ |
|---|-----------|-----------|-----------|-----------|-----------|-----------|-----------|---|
| 0 | 1.225021 | -0.528620 | 0.448676 | 0.619107 | -1.199110 | -0.949097 | 2.169523 | |
| 1 | -1.753617 | 0.992384 | -0.505601 | -0.599848 | 0.133585 | 0.008836 | -1.767710 | |
| 2 | -0.461585 | -1.321106 | 1.745476 | 1.445100 | 0.991037 | -0.860733 | -0.870661 | |

```

      7      8      9      10      11
0  0.302230  0.919516  0.657436  0.262574 -0.804798
1  0.700112 -0.020773 -0.302481  0.347869  0.179123
2 -0.117845 -0.046266  2.095649 -0.524324 -0.610555

```

You can change how much to print on a single row by setting the `display.width` option:

```
In [105]: set_option('display.width', 40) # default is 80
```

```
In [106]: DataFrame(randn(3, 12))
```

```

Out[106]:
      0      1      2  \
0 -1.280951  1.472585 -1.001914
1  0.130529 -1.603771 -0.128830
2 -1.084566 -0.515272  1.367586

      3      4      5  \
0  1.044770 -0.050668 -0.013289
1 -1.869301 -0.232977 -0.139801
2  0.963500  0.224105 -0.020051

      6      7      8  \
0 -0.291893  2.029038 -1.117195
1 -1.083341 -0.357234 -0.818199
2  0.524663  0.351081 -1.574209

      9      10      11
0  1.598577 -0.397325  0.151653
1 -0.886885  1.238885 -1.639274
2 -0.486856 -0.545888 -0.927076

```

You can also disable this feature via the `expand_frame_repr` option. This will print the table in one block.

9.2.15 DataFrame column attribute access and IPython completion

If a `DataFrame` column label is a valid Python variable name, the column can be accessed like attributes:

```
In [107]: df = DataFrame({'foo1' : np.random.randn(5),
.....:                  'foo2' : np.random.randn(5)})
.....:
```

```
In [108]: df
```

```

Out[108]:
      foo1      foo2
0  0.909160  1.360298
1 -0.667763 -1.603624
2 -0.101656 -1.648929
3  1.189682  0.145121
4 -0.090648 -2.536359

```

```
In [109]: df.foo1
```

```

Out[109]:
0    0.909160
1   -0.667763
2   -0.101656
3    1.189682
4   -0.090648
Name: foo1, dtype: float64

```

The columns are also connected to the [IPython](#) completion mechanism so they can be tab-completed:

```
In [5]: df.fo<TAB>
df.foo1 df.foo2
```

9.3 Panel

Panel is a somewhat less-used, but still important container for 3-dimensional data. The term [panel data](#) is derived from econometrics and is partially responsible for the name pandas: pan(el)-da(ta)-s. The names for the 3 axes are intended to give some semantic meaning to describing operations involving panel data and, in particular, econometric analysis of panel data. However, for the strict purposes of slicing and dicing a collection of DataFrame objects, you may find the axis names slightly arbitrary:

- **items**: axis 0, each item corresponds to a DataFrame contained inside
- **major_axis**: axis 1, it is the **index** (rows) of each of the DataFrames
- **minor_axis**: axis 2, it is the **columns** of each of the DataFrames

Construction of Panels works about like you would expect:

9.3.1 From 3D ndarray with optional axis labels

```
In [110]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
.....:               major_axis=date_range('1/1/2000', periods=5),
.....:               minor_axis=['A', 'B', 'C', 'D'])
.....:

In [111]: wp
Out[111]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

9.3.2 From dict of DataFrame objects

```
In [112]: data = {'Item1' : DataFrame(randn(4, 3)),
.....:           'Item2' : DataFrame(randn(4, 2))}
.....:

In [113]: Panel(data)
Out[113]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 4 (major_axis) x 3 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
```

Note that the values in the dict need only be **convertible to DataFrame**. Thus, they can be any of the other valid inputs to DataFrame as per above.

One helpful factory method is `Panel.from_dict`, which takes a dictionary of DataFrames as above, and the following named parameters:

| Parameter | Default | Description |
|-----------|---------|---|
| intersect | False | drops elements whose indices do not align |
| orient | items | use minor to use DataFrames' columns as panel items |

For example, compare to the construction above:

```
In [114]: Panel.from_dict(data, orient='minor')
Out[114]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 2 (minor_axis)
Items axis: 0 to 2
Major_axis axis: 0 to 3
Minor_axis axis: Item1 to Item2
```

Orient is especially useful for mixed-type DataFrames. If you pass a dict of DataFrame objects with mixed-type columns, all of the data will get upcasted to `dtype=object` unless you pass `orient='minor'`:

```
In [115]: df = DataFrame({'a': ['foo', 'bar', 'baz'],
.....:                  'b': np.random.randn(3)})
.....:
```

```
In [116]: df
Out[116]:
      a      b
0  foo -1.264356
1  bar -0.497629
2  baz  1.789719
```

```
In [117]: data = {'item1': df, 'item2': df}
```

```
In [118]: panel = Panel.from_dict(data, orient='minor')
```

```
In [119]: panel['a']
Out[119]:
      item1 item2
0    foo    foo
1    bar    bar
2    baz    baz
```

```
In [120]: panel['b']
Out[120]:
      item1      item2
0 -1.264356 -1.264356
1 -0.497629 -0.497629
2  1.789719  1.789719
```

```
In [121]: panel['b'].dtypes
Out[121]:
item1    float64
item2    float64
dtype: object
```

Note: Unfortunately Panel, being less commonly used than Series and DataFrame, has been slightly neglected feature-wise. A number of methods and options available in DataFrame are not available in Panel. This will get worked on, of course, in future releases. And faster if you join me in working on the codebase.

9.3.3 From DataFrame using `to_panel` method

This method was introduced in v0.7 to replace `LongPanel.to_long`, and converts a `DataFrame` with a two-level index to a `Panel`.

```
In [122]: midx = MultiIndex(levels=[['one', 'two'], ['x', 'y']], labels=[[1,1,0,0],[1,0,1,0]])
```

```
In [123]: df = DataFrame({'A' : [1, 2, 3, 4], 'B': [5, 6, 7, 8]}, index=midx)
```

```
In [124]: df.to_panel()
```

```
Out[124]:
```

```
<class 'pandas.core.panel.Panel'>
```

```
Dimensions: 2 (items) x 2 (major_axis) x 2 (minor_axis)
```

```
Items axis: A to B
```

```
Major_axis axis: one to two
```

```
Minor_axis axis: x to y
```

9.3.4 Item selection / addition / deletion

Similar to `DataFrame` functioning as a dict of `Series`, `Panel` is like a dict of `DataFrames`:

```
In [125]: wp['Item1']
```

```
Out[125]:
```

```
          A          B          C          D
2000-01-01  0.835993 -0.621868 -0.173710 -0.174326
2000-01-02 -0.354356  2.090183 -0.736019 -1.250412
2000-01-03 -0.581326 -0.244477  0.917119  0.611695
2000-01-04 -1.576078 -0.528562 -0.704643 -0.481453
2000-01-05  1.085093 -1.229749  2.295679 -1.016910
```

```
In [126]: wp['Item3'] = wp['Item1'] / wp['Item2']
```

The API for insertion and deletion is the same as for `DataFrame`. And as with `DataFrame`, if the item is a valid python identifier, you can access it as an attribute and tab-complete it in IPython.

9.3.5 Transposing

A `Panel` can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

```
In [127]: wp.transpose(2, 0, 1)
```

```
Out[127]:
```

```
<class 'pandas.core.panel.Panel'>
```

```
Dimensions: 4 (items) x 3 (major_axis) x 5 (minor_axis)
```

```
Items axis: A to D
```

```
Major_axis axis: Item1 to Item3
```

```
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
```

9.3.6 Indexing / Selection

| Operation | Syntax | Result |
|--|-------------------------------|------------------------|
| Select item | <code>wp[item]</code> | <code>DataFrame</code> |
| Get slice at <code>major_axis</code> label | <code>wp.major_xs(val)</code> | <code>DataFrame</code> |
| Get slice at <code>minor_axis</code> label | <code>wp.minor_xs(val)</code> | <code>DataFrame</code> |

For example, using the earlier example data, we could do:

```
In [128]: wp['Item1']
Out[128]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.835993 | -0.621868 | -0.173710 | -0.174326 |
| 2000-01-02 | -0.354356 | 2.090183 | -0.736019 | -1.250412 |
| 2000-01-03 | -0.581326 | -0.244477 | 0.917119 | 0.611695 |
| 2000-01-04 | -1.576078 | -0.528562 | -0.704643 | -0.481453 |
| 2000-01-05 | 1.085093 | -1.229749 | 2.295679 | -1.016910 |

```
In [129]: wp.major_xs(wp.major_axis[2])
Out[129]:
```

| | Item1 | Item2 | Item3 |
|---|-----------|-----------|-----------|
| A | -0.581326 | -1.271582 | 0.457167 |
| B | -0.244477 | -0.861256 | 0.283861 |
| C | 0.917119 | -0.597879 | -1.533955 |
| D | 0.611695 | -0.118700 | -5.153265 |

```
In [130]: wp.minor_axis
Out[130]: Index([u'A', u'B', u'C', u'D'], dtype='object')
```

```
In [131]: wp.minor_xs('C')
Out[131]:
```

| | Item1 | Item2 | Item3 |
|------------|-----------|-----------|-----------|
| 2000-01-01 | -0.173710 | 2.381645 | -0.072937 |
| 2000-01-02 | -0.736019 | -2.413161 | 0.305002 |
| 2000-01-03 | 0.917119 | -0.597879 | -1.533955 |
| 2000-01-04 | -0.704643 | -1.536019 | 0.458746 |
| 2000-01-05 | 2.295679 | 0.181524 | 12.646732 |

9.3.7 Squeezing

Another way to change the dimensionality of an object is to squeeze a 1-len object, similar to `wp['Item1']`

```
In [132]: wp.reindex(items=['Item1']).squeeze()
Out[132]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.835993 | -0.621868 | -0.173710 | -0.174326 |
| 2000-01-02 | -0.354356 | 2.090183 | -0.736019 | -1.250412 |
| 2000-01-03 | -0.581326 | -0.244477 | 0.917119 | 0.611695 |
| 2000-01-04 | -1.576078 | -0.528562 | -0.704643 | -0.481453 |
| 2000-01-05 | 1.085093 | -1.229749 | 2.295679 | -1.016910 |

```
In [133]: wp.reindex(items=['Item1'], minor=['B']).squeeze()
Out[133]:
```

| | |
|------------|-----------|
| 2000-01-01 | -0.621868 |
| 2000-01-02 | 2.090183 |
| 2000-01-03 | -0.244477 |
| 2000-01-04 | -0.528562 |
| 2000-01-05 | -1.229749 |

```
Freq: D, Name: B, dtype: float64
```

9.3.8 Conversion to DataFrame

A Panel can be represented in 2D form as a hierarchically indexed DataFrame. See the section *hierarchical indexing* for more on this. To convert a Panel to a DataFrame, use the `to_frame` method:

```
In [134]: panel = Panel(np.random.randn(3, 5, 4), items=['one', 'two', 'three'],
.....:                 major_axis=date_range('1/1/2000', periods=5),
.....:                 minor_axis=['a', 'b', 'c', 'd'])
.....:
```

```
In [135]: panel.to_frame()
```

```
Out[135]:
```

| | | one | two | three |
|------------|-------|-----------|-----------|-----------|
| major | minor | | | |
| 2000-01-01 | a | 0.445900 | -1.286198 | -1.023189 |
| | b | -0.574496 | -0.407154 | 0.591682 |
| | c | 0.872979 | 0.068084 | -0.008919 |
| | d | 0.297255 | -2.157051 | -0.415572 |
| 2000-01-02 | a | -1.022617 | -0.443982 | -0.772683 |
| | b | 1.091870 | -0.881639 | -0.516197 |
| | c | 1.831444 | 0.851834 | 0.626655 |
| | d | 1.271808 | -1.352515 | 0.269623 |
| 2000-01-03 | a | -0.472876 | 0.228761 | 1.709250 |
| | b | -0.279340 | 0.416858 | -0.830728 |
| | c | 0.495966 | 0.301709 | -0.290244 |
| | d | 0.367858 | 0.569010 | -1.588782 |
| 2000-01-04 | a | -1.530917 | -0.047619 | 0.639406 |
| | b | -0.285890 | 0.413370 | 1.055533 |
| | c | 0.943062 | 0.573056 | -0.260898 |
| | d | 1.361752 | -0.154419 | -0.289725 |
| 2000-01-05 | a | 0.210373 | 0.987044 | 0.279621 |
| | b | -1.945608 | 0.063191 | 0.454423 |
| | c | 2.532409 | 0.439086 | -0.065750 |
| | d | 0.373819 | 1.657475 | 1.465709 |

9.4 Panel4D (Experimental)

Panel4D is a 4-Dimensional named container very much like a `Panel`, but having 4 named dimensions. It is intended as a test bed for more N-Dimensional named containers.

- **labels**: axis 0, each item corresponds to a `Panel` contained inside
- **items**: axis 1, each item corresponds to a `DataFrame` contained inside
- **major_axis**: axis 2, it is the **index** (rows) of each of the `DataFrames`
- **minor_axis**: axis 3, it is the **columns** of each of the `DataFrames`

Panel4D is a sub-class of `Panel`, so most methods that work on `Panels` are applicable to `Panel4D`. The following methods are disabled:

- `join` , `to_frame` , `to_excel` , `to_sparse` , `groupby`

Construction of `Panel4D` works in a very similar manner to a `Panel`

9.4.1 From 4D ndarray with optional axis labels

```
In [136]: p4d = Panel4D(randn(2, 2, 5, 4),
.....:                  labels=['Label1', 'Label2'],
.....:                  items=['Item1', 'Item2'],
.....:                  major_axis=date_range('1/1/2000', periods=5),
.....:                  minor_axis=['A', 'B', 'C', 'D'])
.....:

In [137]: p4d
Out[137]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

9.4.2 From dict of Panel objects

```
In [138]: data = { 'Label1' : Panel({ 'Item1' : DataFrame(randn(4, 3)) }),
.....:             'Label2' : Panel({ 'Item2' : DataFrame(randn(4, 2)) }) }
.....:

In [139]: Panel4D(data)
Out[139]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 4 (major_axis) x 3 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 0 to 3
Minor_axis axis: 0 to 2
```

Note that the values in the dict need only be **convertible to Panels**. Thus, they can be any of the other valid inputs to Panel as per above.

9.4.3 Slicing

Slicing works in a similar manner to a Panel. `[]` slices the first dimension. `.ix` allows you to slice arbitrarily and get back lower dimensional objects

```
In [140]: p4d['Label1']
Out[140]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

4D -> Panel

```
In [141]: p4d.ix[:, :, :, 'A']
Out[141]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 5 (minor_axis)
Items axis: Label1 to Label2
```

```
Major_axis axis: Item1 to Item2
Minor_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
```

4D -> DataFrame

```
In [142]: p4d.ix[:, :, 0, 'A']
Out[142]:
          Label1    Label2
Item1  1.127489  0.015494
Item2 -1.650400  0.130533
```

4D -> Series

```
In [143]: p4d.ix[:, 0, 0, 'A']
Out[143]:
Label1    1.127489
Label2    0.015494
Name: A, dtype: float64
```

9.4.4 Transposing

A Panel4D can be rearranged using its `transpose` method (which does not make a copy by default unless the data are heterogeneous):

```
In [144]: p4d.transpose(3, 2, 1, 0)
Out[144]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 4 (labels) x 5 (items) x 2 (major_axis) x 2 (minor_axis)
Labels axis: A to D
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: Item1 to Item2
Minor_axis axis: Label1 to Label2
```

9.5 PanelND (Experimental)

PanelND is a module with a set of factory functions to enable a user to construct N-dimensional named containers like Panel4D, with a custom set of axis labels. Thus a domain-specific container can easily be created.

The following creates a Panel5D. A new panel type object must be sliceable into a lower dimensional object. Here we slice to a Panel4D.

```
In [145]: from pandas.core import panelnd

In [146]: Panel5D = panelnd.create_nd_panel_factory(
.....:     klass_name = 'Panel5D',
.....:     orders = [ 'cool', 'labels', 'items', 'major_axis', 'minor_axis'],
.....:     slices = { 'labels' : 'labels', 'items' : 'items',
.....:                 'major_axis' : 'major_axis', 'minor_axis' : 'minor_axis' },
.....:     slicer = Panel4D,
.....:     aliases = { 'major' : 'major_axis', 'minor' : 'minor_axis' },
.....:     stat_axis = 2)
.....:

In [147]: p5d = Panel5D(dict(C1 = p4d))
```

```
In [148]: p5d
Out[148]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 1 (cool) x 2 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Cool axis: C1 to C1
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

# print a slice of our 5D
In [149]: p5d.ix['C1', :, :, 0:3, :]
Out[149]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 2 (labels) x 2 (items) x 3 (major_axis) x 4 (minor_axis)
Labels axis: Label1 to Label2
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to D

# transpose it
In [150]: p5d.transpose(1,2,3,4,0)
Out[150]:
<class 'pandas.core.panelnd.Panel5D'>
Dimensions: 2 (cool) x 2 (labels) x 5 (items) x 4 (major_axis) x 1 (minor_axis)
Cool axis: Label1 to Label2
Labels axis: Item1 to Item2
Items axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Major_axis axis: A to D
Minor_axis axis: C1 to C1

# look at the shape & dim
In [151]: p5d.shape
Out[151]: (1, 2, 2, 5, 4)

In [152]: p5d.ndim
Out[152]: 5
```


ESSENTIAL BASIC FUNCTIONALITY

Here we discuss a lot of the essential functionality common to the pandas data structures. Here's how to create some of the objects used in the examples from the previous section:

```
In [1]: index = date_range('1/1/2000', periods=8)

In [2]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [3]: df = DataFrame(randn(8, 3), index=index,
...:                   columns=['A', 'B', 'C'])
...:
...:

In [4]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
...:               major_axis=date_range('1/1/2000', periods=5),
...:               minor_axis=['A', 'B', 'C', 'D'])
...:
...:
```

10.1 Head and Tail

To view a small sample of a Series or DataFrame object, use the `head()` and `tail()` methods. The default number of elements to display is five, but you may pass a custom number.

```
In [5]: long_series = Series(randn(1000))

In [6]: long_series.head()
Out[6]:
0    -0.305384
1    -0.479195
2     0.095031
3    -0.270099
4    -0.707140
dtype: float64

In [7]: long_series.tail(3)
Out[7]:
997     0.588446
998     0.026465
999    -1.728222
dtype: float64
```

10.2 Attributes and the raw ndarray(s)

pandas objects have a number of attributes enabling you to access the metadata

- **shape**: gives the axis dimensions of the object, consistent with ndarray
- Axis labels
 - **Series**: *index* (only axis)
 - **DataFrame**: *index* (rows) and *columns*
 - **Panel**: *items*, *major_axis*, and *minor_axis*

Note, these attributes can be safely assigned to!

```
In [8]: df[:2]
```

```
Out [8]:
```

| | A | B | C |
|------------|----------|-----------|-----------|
| 2000-01-01 | 0.187483 | -1.933946 | 0.377312 |
| 2000-01-02 | 0.734122 | 2.141616 | -0.011225 |

```
In [9]: df.columns = [x.lower() for x in df.columns]
```

```
In [10]: df
```

```
Out [10]:
```

| | a | b | c |
|------------|-----------|-----------|-----------|
| 2000-01-01 | 0.187483 | -1.933946 | 0.377312 |
| 2000-01-02 | 0.734122 | 2.141616 | -0.011225 |
| 2000-01-03 | 0.048869 | -1.360687 | -0.479010 |
| 2000-01-04 | -0.859661 | -0.231595 | -0.527750 |
| 2000-01-05 | -1.296337 | 0.150680 | 0.123836 |
| 2000-01-06 | 0.571764 | 1.555563 | -0.823761 |
| 2000-01-07 | 0.535420 | -1.032853 | 1.469725 |
| 2000-01-08 | 1.304124 | 1.449735 | 0.203109 |

To get the actual data inside a data structure, one need only access the **values** property:

```
In [11]: s.values
```

```
Out [11]: array([ 0.1122,  0.8717, -0.8161, -0.7849,  1.0307])
```

```
In [12]: df.values
```

```
Out [12]:
```

```
array([[ 0.1875, -1.9339,  0.3773],
       [ 0.7341,  2.1416, -0.0112],
       [ 0.0489, -1.3607, -0.479 ],
       [-0.8597, -0.2316, -0.5278],
       [-1.2963,  0.1507,  0.1238],
       [ 0.5718,  1.5556, -0.8238],
       [ 0.5354, -1.0329,  1.4697],
       [ 1.3041,  1.4497,  0.2031]])
```

```
In [13]: wp.values
```

```
Out [13]:
```

```
array([[[-1.032 ,  0.9698, -0.9627,  1.3821],
        [-0.9388,  0.6691, -0.4336, -0.2736],
        [ 0.6804, -0.3084, -0.2761, -1.8212],
        [-1.9936, -1.9274, -2.0279,  1.625 ],
        [ 0.5511,  3.0593,  0.4553, -0.0307]],

       [[ 0.9357,  1.0612, -2.1079,  0.1999],
```

```
[ 0.3236, -0.6416, -0.5875,  0.0539],
[ 0.1949, -0.382 ,  0.3186,  2.0891],
[-0.7283, -0.0903, -0.7482,  1.3189],
[-2.0298,  0.7927,  0.461 , -0.5427]]])
```

If a DataFrame or Panel contains homogeneously-typed data, the ndarray can actually be modified in-place, and the changes will be reflected in the data structure. For heterogeneous data (e.g. some of the DataFrame's columns are not all the same dtype), this will not be the case. The values attribute itself, unlike the axis labels, cannot be assigned to.

Note: When working with heterogeneous data, the dtype of the resulting ndarray will be chosen to accommodate all of the data involved. For example, if strings are involved, the result will be of object dtype. If there are only floats and integers, the resulting array will be of float dtype.

10.3 Accelerated operations

pandas has support for accelerating certain types of binary numerical and boolean operations using the `numexpr` library (starting in 0.11.0) and the `bottleneck` libraries.

These libraries are especially useful when dealing with large data sets, and provide large speedups. `numexpr` uses smart chunking, caching, and multiple cores. `bottleneck` is a set of specialized cython routines that are especially fast when dealing with arrays that have nans.

Here is a sample (using 100 column x 100,000 row DataFrames):

| Operation | 0.11.0 (ms) | Prior Version (ms) | Ratio to Prior |
|-----------|-------------|--------------------|----------------|
| df1 > df2 | 13.32 | 125.35 | 0.1063 |
| df1 * df2 | 21.71 | 36.63 | 0.5928 |
| df1 + df2 | 22.04 | 36.50 | 0.6039 |

You are highly encouraged to install both libraries. See the section [Recommended Dependencies](#) for more installation info.

10.4 Flexible binary operations

With binary operations between pandas data structures, there are two key points of interest:

- Broadcasting behavior between higher- (e.g. DataFrame) and lower-dimensional (e.g. Series) objects.
- Missing data in computations

We will demonstrate how to manage these issues independently, though they can be handled simultaneously.

10.4.1 Matching / broadcasting behavior

DataFrame has the methods `add()`, `sub()`, `mul()`, `div()` and related functions `radd()`, `rsub()`, ... for carrying out binary operations. For broadcasting behavior, Series input is of primary interest. Using these functions, you can use to either match on the *index* or *columns* via the **axis** keyword:

```
In [14]: df = DataFrame({'one' : Series(randn(3), index=['a', 'b', 'c']),
.....:                  'two' : Series(randn(4), index=['a', 'b', 'c', 'd']),
.....:                  'three' : Series(randn(3), index=['b', 'c', 'd'])})
.....:
```

```
In [15]: df
Out[15]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| a | -0.626544 | NaN | -0.351587 |
| b | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |
| d | NaN | 1.124472 | -1.101558 |

```
In [16]: row = df.ix[1]
```

```
In [17]: column = df['two']
```

```
In [18]: df.sub(row, axis='columns')
Out[18]:
```

| | one | three | two |
|---|-----------|----------|-----------|
| a | -0.487650 | NaN | -1.487837 |
| b | 0.000000 | 0.000000 | 0.000000 |
| c | 0.150512 | 0.639504 | -1.585038 |
| d | NaN | 1.301762 | -2.237808 |

```
In [19]: df.sub(row, axis=1)
Out[19]:
```

| | one | three | two |
|---|-----------|----------|-----------|
| a | -0.487650 | NaN | -1.487837 |
| b | 0.000000 | 0.000000 | 0.000000 |
| c | 0.150512 | 0.639504 | -1.585038 |
| d | NaN | 1.301762 | -2.237808 |

```
In [20]: df.sub(column, axis='index')
Out[20]:
```

| | one | three | two |
|---|-----------|-----------|-----|
| a | -0.274957 | NaN | 0 |
| b | -1.275144 | -1.313539 | 0 |
| c | 0.460406 | 0.911003 | 0 |
| d | NaN | 2.226031 | 0 |

```
In [21]: df.sub(column, axis=0)
Out[21]:
```

| | one | three | two |
|---|-----------|-----------|-----|
| a | -0.274957 | NaN | 0 |
| b | -1.275144 | -1.313539 | 0 |
| c | 0.460406 | 0.911003 | 0 |
| d | NaN | 2.226031 | 0 |

Furthermore you can align a level of a multi-indexed DataFrame with a Series.

```
In [22]: dfmi = df.copy()
```

```
In [23]: dfmi.index = MultiIndex.from_tuples([(1, 'a'), (1, 'b'), (1, 'c'), (2, 'a')],
.....:                                     names=['first', 'second'])
.....:
```

```
In [24]: dfmi.sub(column, axis=0, level='second')
Out[24]:
```

| | | one | three | two |
|---|--------------|-----------|-----------|----------|
| 1 | first second | | | |
| | a | -0.274957 | NaN | 0.000000 |
| | b | -1.275144 | -1.313539 | 0.000000 |
| | c | 0.460406 | 0.911003 | 0.000000 |

```
2      a      NaN    1.476060 -0.749971
```

With Panel, describing the matching behavior is a bit more difficult, so the arithmetic methods instead (and perhaps confusingly?) give you the option to specify the *broadcast axis*. For example, suppose we wished to demean the data over a particular axis. This can be accomplished by taking the mean over an axis and broadcasting over the same axis:

```
In [25]: major_mean = wp.mean(axis='major')
```

```
In [26]: major_mean
```

```
Out[26]:
```

| | Item1 | Item2 |
|---|-----------|-----------|
| A | -0.546569 | -0.260774 |
| B | 0.492478 | 0.147993 |
| C | -0.649010 | -0.532794 |
| D | 0.176307 | 0.623812 |

```
In [27]: wp.sub(major_mean, axis='major')
```

```
Out[27]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D
```

And similarly for `axis="items"` and `axis="minor"`.

Note: I could be convinced to make the **axis** argument in the DataFrame methods match the broadcasting behavior of Panel. Though it would require a transition period so users can change their code...

10.4.2 Missing data / operations with fill values

In Series and DataFrame (though not yet in Panel), the arithmetic functions have the option of inputting a *fill_value*, namely a value to substitute when at most one of the values at a location are missing. For example, when adding two DataFrame objects, you may wish to treat NaN as 0 unless both DataFrames are missing that value, in which case the result will be NaN (you can later replace NaN with some other value using `fillna` if you wish).

```
In [28]: df
```

```
Out[28]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| a | -0.626544 | NaN | -0.351587 |
| b | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |
| d | NaN | 1.124472 | -1.101558 |

```
In [29]: df2
```

```
Out[29]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| a | -0.626544 | 1.000000 | -0.351587 |
| b | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |
| d | NaN | 1.124472 | -1.101558 |

```
In [30]: df + df2
```

```
Out[30]:
```

| | one | three | two |
|---|-----------|-------|-----------|
| a | -1.253088 | NaN | -0.703174 |

```
b -0.277789 -0.354579  2.272499
c  0.023235  0.924429 -0.897577
d           NaN  2.248945 -2.203116
```

```
In [31]: df.add(df2, fill_value=0)
```

```
Out[31]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| a | -1.253088 | 1.000000 | -0.703174 |
| b | -0.277789 | -0.354579 | 2.272499 |
| c | 0.023235 | 0.924429 | -0.897577 |
| d | NaN | 2.248945 | -2.203116 |

10.4.3 Flexible Comparisons

Starting in v0.8, pandas introduced binary comparison methods `eq`, `ne`, `lt`, `gt`, `le`, and `ge` to Series and DataFrame whose behavior is analogous to the binary arithmetic operations described above:

```
In [32]: df.gt(df2)
```

```
Out[32]:
```

| | one | three | two |
|---|-------|-------|-------|
| a | False | False | False |
| b | False | False | False |
| c | False | False | False |
| d | False | False | False |

```
In [33]: df2.ne(df)
```

```
Out[33]:
```

| | one | three | two |
|---|-------|-------|-------|
| a | False | True | False |
| b | False | False | False |
| c | False | False | False |
| d | True | False | False |

These operations produce a pandas object the same type as the left-hand-side input that if of dtype `bool`. These boolean objects can be used in indexing operations, see [here](#)

10.4.4 Boolean Reductions

You can apply the reductions: `empty`, `any()`, `all()`, and `bool()` to provide a way to summarize a boolean result.

```
In [34]: (df>0).all()
```

```
Out[34]:
```

| | one | three | two |
|-------|-------|-------|-----|
| one | False | | |
| three | False | | |
| two | False | | |

dtype: bool

```
In [35]: (df>0).any()
```

```
Out[35]:
```

| | one | three | two |
|-------|------|-------|-----|
| one | True | | |
| three | True | | |
| two | True | | |

dtype: bool

You can reduce to a final boolean value.

```
In [36]: (df>0).any().any()
Out[36]: True
```

You can test if a pandas object is empty, via the `empty` property.

```
In [37]: df.empty
Out[37]: False
```

```
In [38]: DataFrame(columns=list('ABC')).empty
Out[38]: True
```

To evaluate single-element pandas objects in a boolean context, use the method `bool()`:

```
In [39]: Series([True]).bool()
Out[39]: True
```

```
In [40]: Series([False]).bool()
Out[40]: False
```

```
In [41]: DataFrame([[True]]).bool()
Out[41]: True
```

```
In [42]: DataFrame([[False]]).bool()
Out[42]: False
```

Warning: You might be tempted to do the following:

```
>>> if df:
...     ...
```

Or

```
>>> df and df2
```

These both will raise as you are trying to compare multiple values.

```
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

See *gotchas* for a more detailed discussion.

10.4.5 Comparing if objects are equivalent

Often you may find there is more than one way to compute the same result. As a simple example, consider `df+df` and `df*2`. To test that these two computations produce the same result, given the tools shown above, you might imagine using `(df+df == df*2).all()`. But in fact, this expression is False:

```
In [43]: df+df == df*2
Out[43]:
```

```
   one  three  two
a  True  False  True
b  True   True  True
c  True   True  True
d False   True  True
```

```
In [44]: (df+df == df*2).all()
Out[44]:
one      False
```

```
three    False
two      True
dtype: bool
```

Notice that the boolean DataFrame `df+df == df*2` contains some False values! That is because NaNs do not compare as equals:

```
In [45]: np.nan == np.nan
Out[45]: False
```

So, as of v0.13.1, NDFrames (such as Series, DataFrames, and Panels) have an `equals()` method for testing equality, with NaNs in corresponding locations treated as equal.

```
In [46]: (df+df).equals(df*2)
Out[46]: True
```

Note that the Series or DataFrame index needs to be in the same order for equality to be True:

```
In [47]: df1 = DataFrame({'col': ['foo', 0, np.nan]})

In [48]: df2 = DataFrame({'col': [np.nan, 0, 'foo']}, index=[2,1,0])

In [49]: df1.equals(df2)
Out[49]: False

In [50]: df1.equals(df2.sort())
Out[50]: True
```

10.4.6 Combining overlapping data sets

A problem occasionally arising is the combination of two similar data sets where values in one are preferred over the other. An example would be two data series representing a particular economic indicator where one is considered to be of “higher quality”. However, the lower quality series might extend further back in history or have more complete data coverage. As such, we would like to combine two DataFrame objects where missing values in one DataFrame are conditionally filled with like-labeled values from the other DataFrame. The function implementing this operation is `combine_first()`, which we illustrate:

```
In [51]: df1 = DataFrame({'A' : [1., np.nan, 3., 5., np.nan],
.....:                  'B' : [np.nan, 2., 3., np.nan, 6.]})
.....:

In [52]: df2 = DataFrame({'A' : [5., 2., 4., np.nan, 3., 7.],
.....:                  'B' : [np.nan, np.nan, 3., 4., 6., 8.]})
.....:

In [53]: df1
Out[53]:
   A  B
0  1 NaN
1 NaN 2
2  3  3
3  5 NaN
4 NaN 6

In [54]: df2
Out[54]:
   A  B
0  5 NaN
1  2 NaN
2  4  3
3 NaN 4
4 NaN 6
5  3  6
6  7  8
```

```

0    5 NaN
1    2 NaN
2    4    3
3 NaN    4
4    3    6
5    7    8

```

```
In [55]: df1.combine_first(df2)
```

```
Out[55]:
```

```

   A    B
0  1 NaN
1  2    2
2  3    3
3  5    4
4  3    6
5  7    8

```

10.4.7 General DataFrame Combine

The `combine_first()` method above calls the more general DataFrame method `combine()`. This method takes another DataFrame and a combiner function, aligns the input DataFrame and then passes the combiner function pairs of Series (i.e., columns whose names are the same).

So, for instance, to reproduce `combine_first()` as above:

```
In [56]: combiner = lambda x, y: np.where(isnull(x), y, x)
```

```
In [57]: df1.combine(df2, combiner)
```

```
Out[57]:
```

```

   A    B
0  1 NaN
1  2    2
2  3    3
3  5    4
4  3    6
5  7    8

```

10.5 Descriptive statistics

A large number of methods for computing descriptive statistics and other related operations on *Series*, *DataFrame*, and *Panel*. Most of these are aggregations (hence producing a lower-dimensional result) like `sum()`, `mean()`, and `quantile()`, but some of them, like `cumsum()` and `cumprod()`, produce an object of the same size. Generally speaking, these methods take an **axis** argument, just like `ndarray.{sum, std, ...}`, but the axis can be specified by name or integer:

- **Series:** no axis argument needed
- **DataFrame:** “index” (axis=0, default), “columns” (axis=1)
- **Panel:** “items” (axis=0), “major” (axis=1, default), “minor” (axis=2)

For example:

```
In [58]: df
```

```
Out[58]:
```

```

one    three    two

```

```
a -0.626544      NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d      NaN  1.124472 -1.101558
```

```
In [59]: df.mean(0)
```

```
Out[59]:
```

```
one      -0.251274
three     0.469799
two      -0.191421
dtype: float64
```

```
In [60]: df.mean(1)
```

```
Out[60]:
```

```
a   -0.489066
b    0.273355
c    0.008348
d    0.011457
dtype: float64
```

All such methods have a `skipna` option signaling whether to exclude missing data (`True` by default):

```
In [61]: df.sum(0, skipna=False)
```

```
Out[61]:
```

```
one      NaN
three     NaN
two     -0.765684
dtype: float64
```

```
In [62]: df.sum(axis=1, skipna=True)
```

```
Out[62]:
```

```
a   -0.978131
b    0.820066
c    0.025044
d    0.022914
dtype: float64
```

Combined with the broadcasting / arithmetic behavior, one can describe various statistical procedures, like standardization (rendering data zero mean and standard deviation 1), very concisely:

```
In [63]: ts_stand = (df - df.mean()) / df.std()
```

```
In [64]: ts_stand.std()
```

```
Out[64]:
```

```
one      1
three     1
two       1
dtype: float64
```

```
In [65]: xs_stand = df.sub(df.mean(1), axis=0).div(df.std(1), axis=0)
```

```
In [66]: xs_stand.std(1)
```

```
Out[66]:
```

```
a      1
b      1
c      1
d      1
dtype: float64
```

Note that methods like `cumsum()` and `cumprod()` preserve the location of NA values:

```
In [67]: df.cumsum()
Out[67]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| a | -0.626544 | NaN | -0.351587 |
| b | -0.765438 | -0.177289 | 0.784662 |
| c | -0.753821 | 0.284925 | 0.335874 |
| d | NaN | 1.409398 | -0.765684 |

Here is a quick reference summary table of common functions. Each also takes an optional `level` parameter which applies only if the object has a *hierarchical index*.

| Function | Description |
|-----------------------|-------------------------------------|
| <code>count</code> | Number of non-null observations |
| <code>sum</code> | Sum of values |
| <code>mean</code> | Mean of values |
| <code>mad</code> | Mean absolute deviation |
| <code>median</code> | Arithmetic median of values |
| <code>min</code> | Minimum |
| <code>max</code> | Maximum |
| <code>mode</code> | Mode |
| <code>abs</code> | Absolute Value |
| <code>prod</code> | Product of values |
| <code>std</code> | Unbiased standard deviation |
| <code>var</code> | Unbiased variance |
| <code>sem</code> | Unbiased standard error of the mean |
| <code>skew</code> | Unbiased skewness (3rd moment) |
| <code>kurt</code> | Unbiased kurtosis (4th moment) |
| <code>quantile</code> | Sample quantile (value at %) |
| <code>cumsum</code> | Cumulative sum |
| <code>cumprod</code> | Cumulative product |
| <code>cummax</code> | Cumulative maximum |
| <code>cummin</code> | Cumulative minimum |

Note that by chance some NumPy methods, like `mean`, `std`, and `sum`, will exclude NAs on Series input by default:

```
In [68]: np.mean(df['one'])
Out[68]: -0.25127365175839511

In [69]: np.mean(df['one'].values)
Out[69]: nan
```

Series also has a method `nunique()` which will return the number of unique non-null values:

```
In [70]: series = Series(randn(500))

In [71]: series[20:500] = np.nan

In [72]: series[10:20] = 5

In [73]: series.nunique()
Out[73]: 11
```

10.5.1 Summarizing data: describe

There is a convenient `describe()` function which computes a variety of summary statistics about a Series or the columns of a DataFrame (excluding NAs of course):

```
In [74]: series = Series(randn(1000))
```

```
In [75]: series[::2] = np.nan
```

```
In [76]: series.describe()
```

```
Out[76]:
count      500.000000
mean       -0.039663
std         1.069371
min        -3.463789
25%        -0.731101
50%        -0.058918
75%         0.672758
max         3.120271
dtype: float64
```

```
In [77]: frame = DataFrame(randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])
```

```
In [78]: frame.ix[::2] = np.nan
```

```
In [79]: frame.describe()
```

```
Out[79]:
```

| | a | b | c | d | e |
|-------|------------|------------|------------|------------|------------|
| count | 500.000000 | 500.000000 | 500.000000 | 500.000000 | 500.000000 |
| mean | 0.000954 | -0.044014 | 0.075936 | -0.003679 | 0.020751 |
| std | 1.005133 | 0.974882 | 0.967432 | 1.004732 | 0.963812 |
| min | -3.010899 | -2.782760 | -3.401252 | -2.944925 | -3.794127 |
| 25% | -0.682900 | -0.681161 | -0.528190 | -0.663503 | -0.615717 |
| 50% | -0.001651 | -0.006279 | 0.040098 | -0.003378 | 0.006282 |
| 75% | 0.656439 | 0.632852 | 0.717919 | 0.687214 | 0.653423 |
| max | 3.007143 | 2.627688 | 2.702490 | 2.850852 | 3.072117 |

You can select specific percentiles to include in the output:

```
In [80]: series.describe(percentiles=[.05, .25, .75, .95])
```

```
Out[80]:
count      500.000000
mean       -0.039663
std         1.069371
min        -3.463789
5%         -1.741334
25%        -0.731101
50%        -0.058918
75%         0.672758
95%         1.854383
max         3.120271
dtype: float64
```

By default, the median is always included.

For a non-numerical Series object, `describe()` will give a simple summary of the number of unique values and most frequently occurring values:

```
In [81]: s = Series(['a', 'a', 'b', 'b', 'a', 'a', np.nan, 'c', 'd', 'a'])
```

```
In [82]: s.describe()
```

```
Out[82]:
count      9
unique      4
top         a
freq        5
dtype: object
```

Note that on a mixed-type DataFrame object, `describe()` will restrict the summary to include only numerical columns or, if none are, only categorical columns:

```
In [83]: frame = DataFrame({'a': ['Yes', 'Yes', 'No', 'No'], 'b': range(4)})
```

```
In [84]: frame.describe()
```

```
Out[84]:
           b
count  4.000000
mean   1.500000
std    1.290994
min    0.000000
25%    0.750000
50%    1.500000
75%    2.250000
max    3.000000
```

This behaviour can be controlled by providing a list of types as `include/exclude` arguments. The special value `all` can also be used:

```
In [85]: frame.describe(include=['object'])
```

```
Out[85]:
           a
count      4
unique      2
top        No
freq        2
```

```
In [86]: frame.describe(include=['number'])
```

```
Out[86]:
           b
count  4.000000
mean   1.500000
std    1.290994
min    0.000000
25%    0.750000
50%    1.500000
75%    2.250000
max    3.000000
```

```
In [87]: frame.describe(include='all')
```

```
Out[87]:
           a           b
count      4  4.000000
unique      2         NaN
top        No         NaN
freq        2         NaN
mean      NaN  1.500000
std      NaN  1.290994
```

```
min      NaN    0.000000
25%      NaN    0.750000
50%      NaN    1.500000
75%      NaN    2.250000
max      NaN    3.000000
```

That feature relies on *select_dtypes*. Refer to there for details about accepted inputs.

10.5.2 Index of Min/Max Values

The `idxmin()` and `idxmax()` functions on Series and DataFrame compute the index labels with the minimum and maximum corresponding values:

```
In [88]: s1 = Series(randn(5))
```

```
In [89]: s1
```

```
Out[89]:
0    -0.872725
1     1.522411
2     0.080594
3    -1.676067
4     0.435804
dtype: float64
```

```
In [90]: s1.idxmin(), s1.idxmax()
```

```
Out[90]: (3, 1)
```

```
In [91]: df1 = DataFrame(randn(5,3), columns=['A', 'B', 'C'])
```

```
In [92]: df1
```

```
Out[92]:
      A         B         C
0  0.445734 -1.649461  0.169660
1  1.246181  0.131682 -2.001988
2 -1.273023  0.870502  0.214583
3  0.088452 -0.173364  1.207466
4  0.546121  0.409515 -0.310515
```

```
In [93]: df1.idxmin(axis=0)
```

```
Out[93]:
A    2
B    0
C    1
dtype: int64
```

```
In [94]: df1.idxmax(axis=1)
```

```
Out[94]:
0    A
1    A
2    B
3    C
4    A
dtype: object
```

When there are multiple rows (or columns) matching the minimum or maximum value, `idxmin()` and `idxmax()` return the first matching index:

```
In [95]: df3 = DataFrame([2, 1, 1, 3, np.nan], columns=['A'], index=list('edcba'))
```

```
In [96]: df3
```

```
Out[96]:
```

```
   A
e   2
d   1
c   1
b   3
a  NaN
```

```
In [97]: df3['A'].idxmin()
```

```
Out[97]: 'd'
```

Note: `idxmin` and `idxmax` are called `argmin` and `argmax` in NumPy.

10.5.3 Value counts (histogramming) / Mode

The `value_counts()` Series method and top-level function computes a histogram of a 1D array of values. It can also be used as a function on regular arrays:

```
In [98]: data = np.random.randint(0, 7, size=50)
```

```
In [99]: data
```

```
Out[99]:
```

```
array([5, 3, 2, 2, 1, 4, 0, 4, 0, 2, 0, 6, 4, 1, 6, 3, 3, 0, 2, 1, 0, 5, 5,
       3, 6, 1, 5, 6, 2, 0, 0, 6, 3, 3, 5, 0, 4, 3, 3, 3, 0, 6, 1, 3, 5, 5,
       0, 4, 0, 6])
```

```
In [100]: s = Series(data)
```

```
In [101]: s.value_counts()
```

```
Out[101]:
```

```
0    11
3    10
6     7
5     7
4     5
2     5
1     5
dtype: int64
```

```
In [102]: value_counts(data)
```

```
Out[102]:
```

```
0    11
3    10
6     7
5     7
4     5
2     5
1     5
dtype: int64
```

Similarly, you can get the most frequently occurring value(s) (the mode) of the values in a Series or DataFrame:

```
In [103]: s5 = Series([1, 1, 3, 3, 3, 5, 5, 7, 7, 7])

In [104]: s5.mode()
Out[104]:
0      3
1      7
dtype: int64

In [105]: df5 = DataFrame({"A": np.random.randint(0, 7, size=50),
.....:                    "B": np.random.randint(-10, 15, size=50)})
.....:

In [106]: df5.mode()
Out[106]:
   A  B
0  1 -5
```

10.5.4 Discretization and quantiling

Continuous values can be discretized using the `cut()` (bins based on values) and `qcut()` (bins based on sample quantiles) functions:

```
In [107]: arr = np.random.randn(20)

In [108]: factor = cut(arr, 4)

In [109]: factor
Out[109]:
[(-0.645, 0.336], (-2.61, -1.626], (-1.626, -0.645], (-1.626, -0.645], (-1.626, -0.645], ..., (0.336, 1.316]]
Length: 20
Categories (4, object): [(-2.61, -1.626] < (-1.626, -0.645] < (-0.645, 0.336] < (0.336, 1.316]]

In [110]: factor = cut(arr, [-5, -1, 0, 1, 5])

In [111]: factor
Out[111]:
[(-1, 0], (-5, -1], (-1, 0], (-5, -1], (-1, 0], ..., (0, 1], (1, 5], (0, 1], (0, 1], (-5, -1]]
Length: 20
Categories (4, object): [(-5, -1] < (-1, 0] < (0, 1] < (1, 5]]
```

`qcut()` computes sample quantiles. For example, we could slice up some normally distributed data into equal-size quantiles like so:

```
In [112]: arr = np.random.randn(30)

In [113]: factor = qcut(arr, [0, .25, .5, .75, 1])

In [114]: factor
Out[114]:
[(-0.139, 1.00736], (1.00736, 1.976], (1.00736, 1.976], [-1.0705, -0.439], [-1.0705, -0.439], ..., (1.00736, 1.976]]
Length: 30
Categories (4, object): [[-1.0705, -0.439] < (-0.439, -0.139] < (-0.139, 1.00736] < (1.00736, 1.976]]

In [115]: value_counts(factor)
Out[115]:
(1.00736, 1.976]      8
[-1.0705, -0.439]     8
```

```
(-0.139, 1.00736]      7
(-0.439, -0.139]      7
dtype: int64
```

We can also pass infinite values to define the bins:

```
In [116]: arr = np.random.randn(20)
```

```
In [117]: factor = cut(arr, [-np.inf, 0, np.inf])
```

```
In [118]: factor
```

```
Out[118]:
[(-inf, 0], (0, inf], (0, inf], (0, inf], (-inf, 0], ..., (-inf, 0], (0, inf], (-inf, 0], (-inf, 0],
Length: 20
Categories (2, object): [(-inf, 0] < (0, inf]]
```

10.6 Function application

Arbitrary functions can be applied along the axes of a DataFrame or Panel using the `apply()` method, which, like the descriptive statistics methods, take an optional `axis` argument:

```
In [119]: df.apply(np.mean)
```

```
Out[119]:
one      -0.251274
three     0.469799
two      -0.191421
dtype: float64
```

```
In [120]: df.apply(np.mean, axis=1)
```

```
Out[120]:
a      -0.489066
b       0.273355
c       0.008348
d       0.011457
dtype: float64
```

```
In [121]: df.apply(lambda x: x.max() - x.min())
```

```
Out[121]:
one      0.638161
three    1.301762
two      2.237808
dtype: float64
```

```
In [122]: df.apply(np.cumsum)
```

```
Out[122]:
      one      three      two
a -0.626544      NaN -0.351587
b -0.765438 -0.177289  0.784662
c -0.753821  0.284925  0.335874
d      NaN  1.409398 -0.765684
```

```
In [123]: df.apply(np.exp)
```

```
Out[123]:
      one      three      two
a  0.534436      NaN  0.703570
b  0.870320  0.837537  3.115063
```

```
c  1.011685  1.587586  0.638401
d           NaN  3.078592  0.332353
```

Depending on the return type of the function passed to `apply()`, the result will either be of lower dimension or the same dimension.

`apply()` combined with some cleverness can be used to answer many questions about a data set. For example, suppose we wanted to extract the date where the maximum value for each column occurred:

```
In [124]: tsdf = DataFrame(randn(1000, 3), columns=['A', 'B', 'C'],
.....:                    index=date_range('1/1/2000', periods=1000))
.....:
```

```
In [125]: tsdf.apply(lambda x: x.idxmax())
```

```
Out[125]:
A    2001-04-27
B    2002-06-02
C    2000-04-02
dtype: datetime64[ns]
```

You may also pass additional arguments and keyword arguments to the `apply()` method. For instance, consider the following function you would like to apply:

```
def subtract_and_divide(x, sub, divide=1):
    return (x - sub) / divide
```

You may then apply this function as follows:

```
df.apply(subtract_and_divide, args=(5,), divide=3)
```

Another useful feature is the ability to pass Series methods to carry out some Series operation on each column or row:

```
In [126]: tsdf
```

```
Out[126]:
```

| | A | B | C |
|------------|-----------|-----------|-----------|
| 2000-01-01 | 1.796883 | -0.930690 | 3.542846 |
| 2000-01-02 | -1.242888 | -0.695279 | -1.000884 |
| 2000-01-03 | -0.720299 | 0.546303 | -0.082042 |
| 2000-01-04 | NaN | NaN | NaN |
| 2000-01-05 | NaN | NaN | NaN |
| 2000-01-06 | NaN | NaN | NaN |
| 2000-01-07 | NaN | NaN | NaN |
| 2000-01-08 | -0.527402 | 0.933507 | 0.129646 |
| 2000-01-09 | -0.338903 | -1.265452 | -1.969004 |
| 2000-01-10 | 0.532566 | 0.341548 | 0.150493 |

```
In [127]: tsdf.apply(Series.interpolate)
```

```
Out[127]:
```

| | A | B | C |
|------------|-----------|-----------|-----------|
| 2000-01-01 | 1.796883 | -0.930690 | 3.542846 |
| 2000-01-02 | -1.242888 | -0.695279 | -1.000884 |
| 2000-01-03 | -0.720299 | 0.546303 | -0.082042 |
| 2000-01-04 | -0.681720 | 0.623743 | -0.039704 |
| 2000-01-05 | -0.643140 | 0.701184 | 0.002633 |
| 2000-01-06 | -0.604561 | 0.778625 | 0.044971 |
| 2000-01-07 | -0.565982 | 0.856066 | 0.087309 |
| 2000-01-08 | -0.527402 | 0.933507 | 0.129646 |
| 2000-01-09 | -0.338903 | -1.265452 | -1.969004 |
| 2000-01-10 | 0.532566 | 0.341548 | 0.150493 |

Finally, `apply()` takes an argument `raw` which is `False` by default, which converts each row or column into a `Series` before applying the function. When set to `True`, the passed function will instead receive an `ndarray` object, which has positive performance implications if you do not need the indexing functionality.

See also:

The section on [GroupBy](#) demonstrates related, flexible functionality for grouping by some criterion, applying, and combining the results into a `Series`, `DataFrame`, etc.

10.6.1 Applying elementwise Python functions

Since not all functions can be vectorized (accept NumPy arrays and return another array or value), the methods `applymap()` on `DataFrame` and analogously `map()` on `Series` accept any Python function taking a single value and returning a single value. For example:

```
In [128]: df4
```

```
Out[128]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| a | -0.626544 | NaN | -0.351587 |
| b | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |
| d | NaN | 1.124472 | -1.101558 |

```
In [129]: f = lambda x: len(str(x))
```

```
In [130]: df4['one'].map(f)
```

```
Out[130]:
```

| | |
|---|----|
| a | 14 |
| b | 15 |
| c | 15 |
| d | 3 |

Name: one, dtype: int64

```
In [131]: df4.applymap(f)
```

```
Out[131]:
```

| | one | three | two |
|---|-----|-------|-----|
| a | 14 | 3 | 15 |
| b | 15 | 15 | 11 |
| c | 15 | 14 | 15 |
| d | 3 | 13 | 14 |

`Series.map()` has an additional feature which is that it can be used to easily “link” or “map” values defined by a secondary series. This is closely related to *merging/joining functionality*:

```
In [132]: s = Series(['six', 'seven', 'six', 'seven', 'six'],
.....:               index=['a', 'b', 'c', 'd', 'e'])
.....:
```

```
In [133]: t = Series({'six' : 6., 'seven' : 7.})
```

```
In [134]: s
```

```
Out[134]:
```

| | |
|---|-------|
| a | six |
| b | seven |
| c | six |
| d | seven |
| e | six |

dtype: object

```
In [135]: s.map(t)
Out[135]:
a      6
b      7
c      6
d      7
e      6
dtype: float64
```

10.6.2 Applying with a Panel

Applying with a Panel will pass a Series to the applied function. If the applied function returns a Series, the result of the application will be a Panel. If the applied function reduces to a scalar, the result of the application will be a DataFrame.

Note: Prior to 0.13.1 apply on a Panel would only work on ufuncs (e.g. np.sum/np.max).

```
In [136]: import pandas.util.testing as tm

In [137]: panel = tm.makePanel(5)

In [138]: panel
Out[138]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [139]: panel['ItemA']
Out[139]:
```

| | A | B | C | D |
|------------|-----------|-----------|----------|-----------|
| 2000-01-03 | 0.330418 | 1.893177 | 0.801111 | 0.528154 |
| 2000-01-04 | 1.761200 | 0.170247 | 0.445614 | -0.029371 |
| 2000-01-05 | 0.567133 | -0.916844 | 1.453046 | -0.631117 |
| 2000-01-06 | -0.251020 | 0.835024 | 2.430373 | -0.172441 |
| 2000-01-07 | 1.020099 | 1.259919 | 0.653093 | -1.020485 |

A transformational apply.

```
In [140]: result = panel.apply(lambda x: x*2, axis='items')

In [141]: result
Out[141]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D

In [142]: result['ItemA']
Out[142]:
```

| | A | B | C | D |
|------------|----------|-----------|----------|-----------|
| 2000-01-03 | 0.660836 | 3.786354 | 1.602222 | 1.056308 |
| 2000-01-04 | 3.522400 | 0.340494 | 0.891228 | -0.058742 |
| 2000-01-05 | 1.134266 | -1.833689 | 2.906092 | -1.262234 |

```
2000-01-06 -0.502039  1.670047  4.860747 -0.344882
2000-01-07  2.040199  2.519838  1.306185 -2.040969
```

A reduction operation.

```
In [143]: panel.apply(lambda x: x.dtype, axis='items')
```

```
Out[143]:
```

| | A | B | C | D |
|------------|---------|---------|---------|---------|
| 2000-01-03 | float64 | float64 | float64 | float64 |
| 2000-01-04 | float64 | float64 | float64 | float64 |
| 2000-01-05 | float64 | float64 | float64 | float64 |
| 2000-01-06 | float64 | float64 | float64 | float64 |
| 2000-01-07 | float64 | float64 | float64 | float64 |

A similar reduction type operation

```
In [144]: panel.apply(lambda x: x.sum(), axis='major_axis')
```

```
Out[144]:
```

| | ItemA | ItemB | ItemC |
|---|-----------|-----------|-----------|
| A | 3.427831 | -2.581431 | 0.840809 |
| B | 3.241522 | -1.409935 | -1.114512 |
| C | 5.783237 | 0.319672 | -0.431906 |
| D | -1.325260 | -2.914834 | 0.857043 |

This last reduction is equivalent to

```
In [145]: panel.sum('major_axis')
```

```
Out[145]:
```

| | ItemA | ItemB | ItemC |
|---|-----------|-----------|-----------|
| A | 3.427831 | -2.581431 | 0.840809 |
| B | 3.241522 | -1.409935 | -1.114512 |
| C | 5.783237 | 0.319672 | -0.431906 |
| D | -1.325260 | -2.914834 | 0.857043 |

A transformation operation that returns a Panel, but is computing the z-score across the major_axis.

```
In [146]: result = panel.apply(
.....:     lambda x: (x-x.mean())/x.std(),
.....:     axis='major_axis')
.....:
```

```
In [147]: result
```

```
Out[147]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 5 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: A to D
```

```
In [148]: result['ItemA']
```

```
Out[148]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-03 | -0.469761 | 1.156225 | -0.441347 | 1.341731 |
| 2000-01-04 | 1.422763 | -0.444015 | -0.882647 | 0.398661 |
| 2000-01-05 | -0.156654 | -1.453694 | 0.367936 | -0.619210 |
| 2000-01-06 | -1.238841 | 0.173423 | 1.581149 | 0.156654 |
| 2000-01-07 | 0.442494 | 0.568061 | -0.625091 | -1.277837 |

Apply can also accept multiple axes in the axis argument. This will pass a DataFrame of the cross-section to the applied function.

```
In [149]: f = lambda x: ((x.T-x.mean(1))/x.std(1)).T
In [150]: result = panel.apply(f, axis = ['items','major_axis'])

In [151]: result
Out[151]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [152]: result.loc[:, :, 'ItemA']
Out[152]:
```

| | A | B | C | D |
|------------|-----------|----------|-----------|-----------|
| 2000-01-03 | 0.864236 | 1.132969 | 0.557316 | 0.575106 |
| 2000-01-04 | 0.795745 | 0.652527 | 0.534808 | -0.070674 |
| 2000-01-05 | -0.310864 | 0.558627 | 1.086688 | -1.051477 |
| 2000-01-06 | -0.001065 | 0.832460 | 0.846006 | 0.043602 |
| 2000-01-07 | 1.128946 | 1.152469 | -0.218186 | -0.891680 |

This is equivalent to the following

```
In [153]: result = Panel(dict([ (ax,f(panel.loc[:, :, ax]))
.....:                          for ax in panel.minor_axis ]))
.....:

In [154]: result
Out[154]:
<class 'pandas.core.panel.Panel'>
Dimensions: 4 (items) x 5 (major_axis) x 3 (minor_axis)
Items axis: A to D
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-07 00:00:00
Minor_axis axis: ItemA to ItemC

In [155]: result.loc[:, :, 'ItemA']
Out[155]:
```

| | A | B | C | D |
|------------|-----------|----------|-----------|-----------|
| 2000-01-03 | 0.864236 | 1.132969 | 0.557316 | 0.575106 |
| 2000-01-04 | 0.795745 | 0.652527 | 0.534808 | -0.070674 |
| 2000-01-05 | -0.310864 | 0.558627 | 1.086688 | -1.051477 |
| 2000-01-06 | -0.001065 | 0.832460 | 0.846006 | 0.043602 |
| 2000-01-07 | 1.128946 | 1.152469 | -0.218186 | -0.891680 |

10.7 Reindexing and altering labels

`reindex()` is the fundamental data alignment method in pandas. It is used to implement nearly all other features relying on label-alignment functionality. To *reindex* means to conform the data to match a given set of labels along a particular axis. This accomplishes several things:

- Reorders the existing data to match a new set of labels
- Inserts missing value (NA) markers in label locations where no data for that label existed
- If specified, **fill** data for missing labels using logic (highly relevant to working with time series data)

Here is a simple example:

```
In [156]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])
```

```
In [157]: s
```

```
Out[157]:
a    -1.010924
b    -0.672504
c    -1.139222
d     0.354653
e     0.563622
dtype: float64
```

```
In [158]: s.reindex(['e', 'b', 'f', 'd'])
```

```
Out[158]:
e     0.563622
b    -0.672504
f         NaN
d     0.354653
dtype: float64
```

Here, the `f` label was not contained in the Series and hence appears as `NaN` in the result.

With a `DataFrame`, you can simultaneously reindex the index and columns:

```
In [159]: df
```

```
Out[159]:
      one      three      two
a -0.626544      NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d         NaN  1.124472 -1.101558
```

```
In [160]: df.reindex(index=['c', 'f', 'b'], columns=['three', 'two', 'one'])
```

```
Out[160]:
      three      two      one
c  0.462215 -0.448789  0.011617
f         NaN      NaN      NaN
b -0.177289  1.136249 -0.138894
```

For convenience, you may utilize the `reindex_axis()` method, which takes the labels and a keyword `axis` parameter.

Note that the `Index` objects containing the actual axis labels can be **shared** between objects. So if we have a `Series` and a `DataFrame`, the following can be done:

```
In [161]: rs = s.reindex(df.index)
```

```
In [162]: rs
```

```
Out[162]:
a    -1.010924
b    -0.672504
c    -1.139222
d     0.354653
dtype: float64
```

```
In [163]: rs.index is df.index
```

```
Out[163]: True
```

This means that the reindexed Series's index is the same Python object as the `DataFrame`'s index.

See also:

MultiIndex / Advanced Indexing is an even more concise way of doing reindexing.

Note: When writing performance-sensitive code, there is a good reason to spend some time becoming a reindexing ninja: **many operations are faster on pre-aligned data**. Adding two unaligned DataFrames internally triggers a reindexing step. For exploratory analysis you will hardly notice the difference (because `reindex` has been heavily optimized), but when CPU cycles matter sprinkling a few explicit `reindex` calls here and there can have an impact.

10.7.1 Reindexing to align with another object

You may wish to take an object and reindex its axes to be labeled the same as another object. While the syntax for this is straightforward albeit verbose, it is a common enough operation that the `reindex_like()` method is available to make this simpler:

```
In [164]: df2
Out[164]:
```

| | one | two |
|---|-----------|-----------|
| a | -0.626544 | -0.351587 |
| b | -0.138894 | 1.136249 |
| c | 0.011617 | -0.448789 |

```
In [165]: df3
Out[165]:
```

| | one | two |
|---|-----------|-----------|
| a | -0.375270 | -0.463545 |
| b | 0.112379 | 1.024292 |
| c | 0.262891 | -0.560746 |

```
In [166]: df.reindex_like(df2)
Out[166]:
```

| | one | two |
|---|-----------|-----------|
| a | -0.626544 | -0.351587 |
| b | -0.138894 | 1.136249 |
| c | 0.011617 | -0.448789 |

10.7.2 Aligning objects with each other with `align`

The `align()` method is the fastest way to simultaneously align two objects. It supports a `join` argument (related to *joining and merging*):

- `join='outer'`: take the union of the indexes (default)
- `join='left'`: use the calling object's index
- `join='right'`: use the passed object's index
- `join='inner'`: intersect the indexes

It returns a tuple with both of the reindexed Series:

```
In [167]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])
In [168]: s1 = s[:4]
In [169]: s2 = s[1:]
In [170]: s1.align(s2)
Out[170]:
```

```
(a   -0.365106
b    1.092702
c   -1.481449
d    1.781190
e         NaN
dtype: float64, a         NaN
b    1.092702
c   -1.481449
d    1.781190
e   -0.031543
dtype: float64)
```

```
In [171]: s1.align(s2, join='inner')
```

```
Out[171]:
(b    1.092702
c   -1.481449
d    1.781190
dtype: float64, b    1.092702
c   -1.481449
d    1.781190
dtype: float64)
```

```
In [172]: s1.align(s2, join='left')
```

```
Out[172]:
(a   -0.365106
b    1.092702
c   -1.481449
d    1.781190
dtype: float64, a         NaN
b    1.092702
c   -1.481449
d    1.781190
dtype: float64)
```

For DataFrames, the join method will be applied to both the index and the columns by default:

```
In [173]: df.align(df2, join='inner')
```

```
Out[173]:
(
  one      two
a -0.626544 -0.351587
b -0.138894  1.136249
c  0.011617 -0.448789,
  one      two
a -0.626544 -0.351587
b -0.138894  1.136249
c  0.011617 -0.448789)
```

You can also pass an axis option to only align on the specified axis:

```
In [174]: df.align(df2, join='inner', axis=0)
```

```
Out[174]:
(
  one      three      two
a -0.626544      NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789,
  one      two
a -0.626544 -0.351587
b -0.138894  1.136249
c  0.011617 -0.448789)
```

If you pass a Series to `DataFrame.align()`, you can choose to align both objects either on the DataFrame's index or columns using the `axis` argument:

```
In [175]: df.align(df2.ix[0], axis=1)
Out[175]:
(
   one      three      two
a -0.626544      NaN -0.351587
b -0.138894 -0.177289  1.136249
c  0.011617  0.462215 -0.448789
d      NaN  1.124472 -1.101558, one      -0.626544
three      NaN
two      -0.351587
Name: a, dtype: float64)
```

10.7.3 Filling while reindexing

`reindex()` takes an optional parameter `method` which is a filling method chosen from the following table:

| Method | Action |
|------------------|-----------------------------------|
| pad / ffill | Fill values forward |
| bfill / backfill | Fill values backward |
| nearest | Fill from the nearest index value |

We illustrate these fill methods on a simple Series:

```
In [176]: rng = date_range('1/3/2000', periods=8)
```

```
In [177]: ts = Series(randn(8), index=rng)
```

```
In [178]: ts2 = ts[[0, 3, 6]]
```

```
In [179]: ts
Out[179]:
2000-01-03    0.480993
2000-01-04    0.604244
2000-01-05   -0.487265
2000-01-06    1.990533
2000-01-07    0.327007
2000-01-08    1.053639
2000-01-09   -2.927808
2000-01-10    0.082065
Freq: D, dtype: float64
```

```
In [180]: ts2
Out[180]:
2000-01-03    0.480993
2000-01-06    1.990533
2000-01-09   -2.927808
dtype: float64
```

```
In [181]: ts2.reindex(ts.index)
Out[181]:
2000-01-03    0.480993
2000-01-04         NaN
2000-01-05         NaN
2000-01-06    1.990533
2000-01-07         NaN
2000-01-08         NaN
```

```
2000-01-09    -2.927808
2000-01-10         NaN
Freq: D, dtype: float64
```

```
In [182]: ts2.reindex(ts.index, method='ffill')
```

```
Out[182]:
2000-01-03    0.480993
2000-01-04    0.480993
2000-01-05    0.480993
2000-01-06    1.990533
2000-01-07    1.990533
2000-01-08    1.990533
2000-01-09   -2.927808
2000-01-10   -2.927808
Freq: D, dtype: float64
```

```
In [183]: ts2.reindex(ts.index, method='bfill')
```

```
Out[183]:
2000-01-03    0.480993
2000-01-04    1.990533
2000-01-05    1.990533
2000-01-06    1.990533
2000-01-07   -2.927808
2000-01-08   -2.927808
2000-01-09   -2.927808
2000-01-10         NaN
Freq: D, dtype: float64
```

```
In [184]: ts2.reindex(ts.index, method='nearest')
```

```
Out[184]:
2000-01-03    0.480993
2000-01-04    0.480993
2000-01-05    1.990533
2000-01-06    1.990533
2000-01-07    1.990533
2000-01-08   -2.927808
2000-01-09   -2.927808
2000-01-10   -2.927808
Freq: D, dtype: float64
```

These methods require that the indexes are **ordered** increasing or decreasing.

Note that the same result could have been achieved using *fillna* (except for `method='nearest'`) or *interpolate*:

```
In [185]: ts2.reindex(ts.index).fillna(method='ffill')
```

```
Out[185]:
2000-01-03    0.480993
2000-01-04    0.480993
2000-01-05    0.480993
2000-01-06    1.990533
2000-01-07    1.990533
2000-01-08    1.990533
2000-01-09   -2.927808
2000-01-10   -2.927808
Freq: D, dtype: float64
```

`reindex()` will raise a `ValueError` if the index is not monotonic increasing or decreasing. `fillna()` and `interpolate()` will not make any checks on the order of the index.

10.7.4 Dropping labels from an axis

A method closely related to `reindex` is the `drop()` function. It removes a set of labels from an axis:

```
In [186]: df
Out[186]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| a | -0.626544 | NaN | -0.351587 |
| b | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |
| d | NaN | 1.124472 | -1.101558 |

```
In [187]: df.drop(['a', 'd'], axis=0)
Out[187]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| b | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |

```
In [188]: df.drop(['one'], axis=1)
Out[188]:
```

| | three | two |
|---|-----------|-----------|
| a | NaN | -0.351587 |
| b | -0.177289 | 1.136249 |
| c | 0.462215 | -0.448789 |
| d | 1.124472 | -1.101558 |

Note that the following also works, but is a bit less obvious / clean:

```
In [189]: df.reindex(df.index.difference(['a', 'd']))
Out[189]:
```

| | one | three | two |
|---|-----------|-----------|-----------|
| b | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |

10.7.5 Renaming / mapping labels

The `rename()` method allows you to relabel an axis based on some mapping (a dict or Series) or an arbitrary function.

```
In [190]: s
Out[190]:
```

| | |
|---|-----------|
| a | -0.365106 |
| b | 1.092702 |
| c | -1.481449 |
| d | 1.781190 |
| e | -0.031543 |

dtype: float64

```
In [191]: s.rename(str.upper)
Out[191]:
```

| | |
|---|-----------|
| A | -0.365106 |
| B | 1.092702 |
| C | -1.481449 |
| D | 1.781190 |
| E | -0.031543 |

dtype: float64

If you pass a function, it must return a value when called with any of the labels (and must produce a set of unique values). But if you pass a dict or Series, it need only contain a subset of the labels as keys:

```
In [192]: df.rename(columns={'one' : 'foo', 'two' : 'bar'},
.....:               index={'a' : 'apple', 'b' : 'banana', 'd' : 'durian'})
.....:
Out[192]:
```

| | foo | three | bar |
|--------|-----------|-----------|-----------|
| apple | -0.626544 | NaN | -0.351587 |
| banana | -0.138894 | -0.177289 | 1.136249 |
| c | 0.011617 | 0.462215 | -0.448789 |
| durian | NaN | 1.124472 | -1.101558 |

The `rename()` method also provides an `inplace` named parameter that is by default `False` and copies the underlying data. Pass `inplace=True` to rename the data in place. The `Panel` class has a related `rename_axis()` class which can rename any of its three axes.

10.8 Iteration

Because `Series` is array-like, basic iteration produces the values. Other data structures follow the dict-like convention of iterating over the “keys” of the objects. In short:

- **Series:** values
- **DataFrame:** column labels
- **Panel:** item labels

Thus, for example:

```
In [193]: for col in df:
.....:     print(col)
.....:
one
three
two
```

10.8.1 iteritems

Consistent with the dict-like interface, `iteritems()` iterates through key-value pairs:

- **Series:** (index, scalar value) pairs
- **DataFrame:** (column, `Series`) pairs
- **Panel:** (item, `DataFrame`) pairs

For example:

```
In [194]: for item, frame in wp.iteritems():
.....:     print(item)
.....:     print(frame)
.....:
Item1
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | -1.032011 | 0.969818 | -0.962723 | 1.382083 |
| 2000-01-02 | -0.938794 | 0.669142 | -0.433567 | -0.273610 |
| 2000-01-03 | 0.680433 | -0.308450 | -0.276099 | -1.821168 |
| 2000-01-04 | -1.993606 | -1.927385 | -2.027924 | 1.624972 |
| 2000-01-05 | 0.551135 | 3.059267 | 0.455264 | -0.030740 |

```
Item2
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.935716 | 1.061192 | -2.107852 | 0.199905 |
| 2000-01-02 | 0.323586 | -0.641630 | -0.587514 | 0.053897 |
| 2000-01-03 | 0.194889 | -0.381994 | 0.318587 | 2.089075 |
| 2000-01-04 | -0.728293 | -0.090255 | -0.748199 | 1.318931 |
| 2000-01-05 | -2.029766 | 0.792652 | 0.461007 | -0.542749 |

10.8.2 iterrows

New in v0.7 is the ability to iterate efficiently through rows of a DataFrame with `iterrows()`. It returns an iterator yielding each index value along with a Series containing the data in each row:

```
In [195]: for row_index, row in df2.iterrows():
.....:     print('%s\n%s' % (row_index, row))
.....:

a
one    -0.626544
two    -0.351587
Name: a, dtype: float64
b
one    -0.138894
two     1.136249
Name: b, dtype: float64
c
one     0.011617
two    -0.448789
Name: c, dtype: float64
```

For instance, a contrived way to transpose the DataFrame would be:

```
In [196]: df2 = DataFrame({'x': [1, 2, 3], 'y': [4, 5, 6]})

In [197]: print(df2)
   x  y
0  1  4
1  2  5
2  3  6

In [198]: print(df2.T)
   0  1  2
x  1  2  3
y  4  5  6

In [199]: df2_t = DataFrame(dict((idx, values) for idx, values in df2.iterrows()))

In [200]: print(df2_t)
   0  1  2
x  1  2  3
y  4  5  6
```

Note: `iterrows` does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
In [201]: df_iter = DataFrame([[1, 1.0]], columns=['x', 'y'])

In [202]: row = next(df_iter.iterrows())[1]
```

```
In [203]: print(row['x'].dtype)
float64

In [204]: print(df_iter['x'].dtype)
int64
```

10.8.3 itertuples

The `itertuples()` method will return an iterator yielding a tuple for each row in the DataFrame. The first element of the tuple will be the row's corresponding index value, while the remaining values are the row values proper.

For instance,

```
In [205]: for r in df2.itertuples():
.....:     print(r)
.....:
(0, 1, 4)
(1, 2, 5)
(2, 3, 6)
```

10.8.4 .dt accessor

Series has an accessor to succinctly return datetime like properties for the *values* of the Series, if its a date-time/period like Series. This will return a Series, indexed like the existing Series.

```
# datetime
In [206]: s = Series(date_range('20130101 09:10:12', periods=4))
```

```
In [207]: s
Out[207]:
0    2013-01-01 09:10:12
1    2013-01-02 09:10:12
2    2013-01-03 09:10:12
3    2013-01-04 09:10:12
dtype: datetime64[ns]
```

```
In [208]: s.dt.hour
Out[208]:
0     9
1     9
2     9
3     9
dtype: int64
```

```
In [209]: s.dt.second
Out[209]:
0    12
1    12
2    12
3    12
dtype: int64
```

```
In [210]: s.dt.day
Out[210]:
0     1
```

```
1    2
2    3
3    4
dtype: int64
```

This enables nice expressions like this:

```
In [211]: s[s.dt.day==2]
Out[211]:
1    2013-01-02 09:10:12
dtype: datetime64[ns]
```

You can easily produces tz aware transformations:

```
In [212]: stz = s.dt.tz_localize('US/Eastern')
```

```
In [213]: stz
Out[213]:
0    2013-01-01 09:10:12-05:00
1    2013-01-02 09:10:12-05:00
2    2013-01-03 09:10:12-05:00
3    2013-01-04 09:10:12-05:00
dtype: object
```

```
In [214]: stz.dt.tz
Out[214]: <DstTzInfo 'US/Eastern' LMT-1 day, 19:04:00 STD>
```

You can also chain these types of operations:

```
In [215]: s.dt.tz_localize('UTC').dt.tz_convert('US/Eastern')
Out[215]:
0    2013-01-01 04:10:12-05:00
1    2013-01-02 04:10:12-05:00
2    2013-01-03 04:10:12-05:00
3    2013-01-04 04:10:12-05:00
dtype: object
```

The `.dt` accessor works for period and timedelta dtypes.

```
# period
In [216]: s = Series(period_range('20130101', periods=4, freq='D'))
```

```
In [217]: s
Out[217]:
0    2013-01-01
1    2013-01-02
2    2013-01-03
3    2013-01-04
dtype: object
```

```
In [218]: s.dt.year
Out[218]:
0    2013
1    2013
2    2013
3    2013
dtype: int64
```

```
In [219]: s.dt.day
```

```

Out[219]:
0    1
1    2
2    3
3    4
dtype: int64

# timedelta
In [220]: s = Series(timedelta_range('1 day 00:00:05', periods=4, freq='s'))

In [221]: s
Out[221]:
0    1 days 00:00:05
1    1 days 00:00:06
2    1 days 00:00:07
3    1 days 00:00:08
dtype: timedelta64[ns]

In [222]: s.dt.days
Out[222]:
0    1
1    1
2    1
3    1
dtype: int64

In [223]: s.dt.seconds
Out[223]:
0    5
1    6
2    7
3    8
dtype: int64

In [224]: s.dt.components
Out[224]:
   days  hours  minutes  seconds  milliseconds  microseconds  nanoseconds
0     1     0         0         5             0              0             0
1     1     0         0         6             0              0             0
2     1     0         0         7             0              0             0
3     1     0         0         8             0              0             0

```

Note: `Series.dt` will raise a `TypeError` if you access with a non-datetime-like values

10.9 Vectorized string methods

`Series` is equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the `Series`'s `str` attribute and generally have names matching the equivalent (scalar) built-in string methods. For example:

```

In [225]: s = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [226]: s.str.lower()
Out[226]:
0      a

```

```
1      b
2      c
3    aaba
4    baca
5     NaN
6    caba
7     dog
8     cat
dtype: object
```

Powerful pattern-matching methods are provided as well, but note that pattern-matching generally uses [regular expressions](#) by default (and in some cases always uses them).

Please see [Vectorized String Methods](#) for a complete description.

10.10 Sorting by index and value

There are two obvious kinds of sorting that you may be interested in: sorting by label and sorting by actual values. The primary method for sorting axis labels (indexes) across data structures is the `sort_index()` method.

```
In [227]: unsorted_df = df.reindex(index=['a', 'd', 'c', 'b'],
.....:                               columns=['three', 'two', 'one'])
.....:
```

```
In [228]: unsorted_df.sort_index()
```

```
Out[228]:
      three      two      one
a      NaN -0.351587 -0.626544
b -0.177289  1.136249 -0.138894
c  0.462215 -0.448789  0.011617
d  1.124472 -1.101558      NaN
```

```
In [229]: unsorted_df.sort_index(ascending=False)
```

```
Out[229]:
      three      two      one
d  1.124472 -1.101558      NaN
c  0.462215 -0.448789  0.011617
b -0.177289  1.136249 -0.138894
a      NaN -0.351587 -0.626544
```

```
In [230]: unsorted_df.sort_index(axis=1)
```

```
Out[230]:
      one      three      two
a -0.626544      NaN -0.351587
d      NaN  1.124472 -1.101558
c  0.011617  0.462215 -0.448789
b -0.138894 -0.177289  1.136249
```

`DataFrame.sort_index()` can accept an optional `by` argument for `axis=0` which will use an arbitrary vector or a column name of the `DataFrame` to determine the sort order:

```
In [231]: df1 = DataFrame({'one': [2, 1, 1, 1], 'two': [1, 3, 2, 4], 'three': [5, 4, 3, 2]})
```

```
In [232]: df1.sort_index(by='two')
```

```
Out[232]:
      one  three  two
0      2      5    1
```

```
2    1    3    2
1    1    4    3
3    1    2    4
```

The `by` argument can take a list of column names, e.g.:

```
In [233]: df1[['one', 'two', 'three']].sort_index(by=['one', 'two'])
```

```
Out[233]:
   one  two  three
2    1    2     3
1    1    3     4
3    1    4     2
0    2    1     5
```

Series has the method `order()` (analogous to R's `order` function) which sorts by value, with special treatment of NA values via the `na_position` argument:

```
In [234]: s[2] = np.nan
```

```
In [235]: s.order()
```

```
Out[235]:
0      A
3    Aaba
1      B
4    Baca
6    CABA
8    cat
7    dog
2    NaN
5    NaN
dtype: object
```

```
In [236]: s.order(na_position='first')
```

```
Out[236]:
2    NaN
5    NaN
0      A
3    Aaba
1      B
4    Baca
6    CABA
8    cat
7    dog
dtype: object
```

Note: `Series.sort()` sorts a Series by value in-place. This is to provide compatibility with NumPy methods which expect the `ndarray.sort` behavior. `Series.order()` returns a copy of the sorted data.

Series has the `searchsorted()` method, which works similar to `numpy.ndarray.searchsorted()`.

```
In [237]: ser = Series([1, 2, 3])
```

```
In [238]: ser.searchsorted([0, 3])
```

```
Out[238]: array([0, 2])
```

```
In [239]: ser.searchsorted([0, 4])
```

```
Out[239]: array([0, 3])
```

```
In [240]: ser.searchsorted([1, 3], side='right')
Out[240]: array([1, 3])

In [241]: ser.searchsorted([1, 3], side='left')
Out[241]: array([0, 2])

In [242]: ser = Series([3, 1, 2])

In [243]: ser.searchsorted([0, 3], sorter=np.argsort(ser))
Out[243]: array([0, 2])
```

10.10.1 smallest / largest values

New in version 0.14.0.

Series has the `nsmallest()` and `nlargest()` methods which return the smallest or largest n values. For a large Series this can be much faster than sorting the entire Series and calling `head(n)` on the result.

```
In [244]: s = Series(np.random.permutation(10))
```

```
In [245]: s
```

```
Out[245]:
0    7
1    5
2    4
3    6
4    1
5    8
6    9
7    2
8    0
9    3
dtype: int32
```

```
In [246]: s.order()
```

```
Out[246]:
8    0
4    1
7    2
9    3
2    4
1    5
3    6
0    7
5    8
6    9
dtype: int32
```

```
In [247]: s.nsmallest(3)
```

```
Out[247]:
8    0
4    1
7    2
dtype: int32
```

```
In [248]: s.nlargest(3)
```

```
Out[248]:
```

```
6      9
5      8
0      7
dtype: int32
```

10.10.2 Sorting by a multi-index column

You must be explicit about sorting when the column is a multi-index, and fully specify all levels to `by`.

```
In [249]: df1.columns = MultiIndex.from_tuples([('a', 'one'), ('a', 'two'), ('b', 'three')])
```

```
In [250]: df1.sort_index(by=('a', 'two'))
```

```
Out[250]:
```

| | a | b |
|---|---------|-------|
| | one two | three |
| 3 | 1 2 | 4 |
| 2 | 1 3 | 2 |
| 1 | 1 4 | 3 |
| 0 | 2 5 | 1 |

10.11 Copying

The `copy()` method on pandas objects copies the underlying data (though not the axis indexes, since they are immutable) and returns a new object. Note that **it is seldom necessary to copy objects**. For example, there are only a handful of ways to alter a DataFrame *in-place*:

- Inserting, deleting, or modifying a column
- Assigning to the `index` or `columns` attributes
- For homogeneous data, directly modifying the values via the `values` attribute or advanced indexing

To be clear, no pandas methods have the side effect of modifying your data; almost all methods return new objects, leaving the original object untouched. If data is modified, it is because you did so explicitly.

10.12 dtypes

The main types stored in pandas objects are `float`, `int`, `bool`, `datetime64[ns]`, `timedelta[ns]` and `object`. In addition these dtypes have item sizes, e.g. `int64` and `int32`. A convenient `dtypes` attribute for DataFrames returns a Series with the data type of each column.

```
In [251]: dft = DataFrame(dict( A = np.random.rand(3),
.....:                          B = 1,
.....:                          C = 'foo',
.....:                          D = Timestamp('20010102'),
.....:                          E = Series([1.0]*3).astype('float32'),
.....:                          F = False,
.....:                          G = Series([1]*3, dtype='int8')))
.....:
```

```
In [252]: dft
```

```
Out[252]:
```

| | A | B | C | D | E | F | G |
|--|---|---|---|---|---|---|---|
|--|---|---|---|---|---|---|---|

```
0  0.028931  1  foo 2001-01-02  1  False  1
1  0.936706  1  foo 2001-01-02  1  False  1
2  0.831782  1  foo 2001-01-02  1  False  1
```

```
In [253]: dft.dtypes
```

```
Out[253]:
A          float64
B          int64
C          object
D    datetime64[ns]
E          float32
F          bool
G          int8
dtype: object
```

On a Series use the `dtype` attribute.

```
In [254]: dft['A'].dtype
```

```
Out[254]: dtype('float64')
```

If a pandas object contains data multiple dtypes *IN A SINGLE COLUMN*, the dtype of the column will be chosen to accommodate all of the data types (object is the most general).

```
# these ints are coerced to floats
```

```
In [255]: Series([1, 2, 3, 4, 5, 6.])
```

```
Out[255]:
0    1
1    2
2    3
3    4
4    5
5    6
dtype: float64
```

```
# string data forces an ``object`` dtype
```

```
In [256]: Series([1, 2, 3, 6., 'foo'])
```

```
Out[256]:
0    1
1    2
2    3
3    6
4  foo
dtype: object
```

The method `get_dtype_counts()` will return the number of columns of each type in a DataFrame:

```
In [257]: dft.get_dtype_counts()
```

```
Out[257]:
bool          1
datetime64[ns] 1
float32        1
float64        1
int64          1
int8           1
object         1
dtype: int64
```

Numeric dtypes will propagate and can coexist in DataFrames (starting in v0.11.0). If a dtype is passed (either directly via the `dtype` keyword, a passed `ndarray`, or a passed `Series`, then it will be preserved in DataFrame operations.

Furthermore, different numeric dtypes will **NOT** be combined. The following example will give you a taste.

```
In [258]: df1 = DataFrame(randn(8, 1), columns = ['A'], dtype = 'float32')
```

```
In [259]: df1
```

```
Out[259]:
```

```
      A
0  1.213978
1 -0.505425
2  0.254678
3 -0.744834
4  0.647650
5  0.822993
6  1.778703
7 -1.543048
```

```
In [260]: df1.dtypes
```

```
Out[260]:
```

```
A      float32
dtype: object
```

```
In [261]: df2 = DataFrame(dict( A = Series(randn(8), dtype='float16'),
.....:                          B = Series(randn(8)),
.....:                          C = Series(np.array(randn(8), dtype='uint8')) ))
.....:
```

```
In [262]: df2
```

```
Out[262]:
```

```
      A      B      C
0 -0.123230 -1.508174    0
1  2.240234 -0.502623    0
2 -0.143799  0.529008    0
3 -2.884766  0.590536    1
4  0.027588  0.296947    0
5 -1.150391  0.007045  255
6  0.246460  0.707877    1
7 -0.455078  0.950661    0
```

```
In [263]: df2.dtypes
```

```
Out[263]:
```

```
A      float16
B      float64
C         uint8
dtype: object
```

10.12.1 defaults

By default integer types are `int64` and float types are `float64`, *REGARDLESS* of platform (32-bit or 64-bit). The following will all result in `int64` dtypes.

```
In [264]: DataFrame([1, 2], columns=['a']).dtypes
```

```
Out[264]:
```

```
a      int64
dtype: object
```

```
In [265]: DataFrame({'a': [1, 2]}).dtypes
```

```
Out[265]:
```

```
a      int64
dtype: object
```

```
In [266]: DataFrame({'a': 1 }, index=list(range(2))).dtypes
Out[266]:
a      int64
dtype: object
```

Numpy, however will choose *platform-dependent* types when creating arrays. The following **WILL** result in `int32` on 32-bit platform.

```
In [267]: frame = DataFrame(np.array([1, 2]))
```

10.12.2 upcasting

Types can potentially be *upcasted* when combined with other types, meaning they are promoted from the current type (say `int` to `float`)

```
In [268]: df3 = df1.reindex_like(df2).fillna(value=0.0) + df2
```

```
In [269]: df3
Out[269]:
```

| | A | B | C |
|---|-----------|-----------|-----|
| 0 | 1.090748 | -1.508174 | 0 |
| 1 | 1.734810 | -0.502623 | 0 |
| 2 | 0.110879 | 0.529008 | 0 |
| 3 | -3.629600 | 0.590536 | 1 |
| 4 | 0.675238 | 0.296947 | 0 |
| 5 | -0.327398 | 0.007045 | 255 |
| 6 | 2.025163 | 0.707877 | 1 |
| 7 | -1.998126 | 0.950661 | 0 |

```
In [270]: df3.dtypes
Out[270]:
A      float32
B      float64
C      float64
dtype: object
```

The `values` attribute on a `DataFrame` return the *lower-common-denominator* of the dtypes, meaning the dtype that can accommodate **ALL** of the types in the resulting homogeneous dtyped numpy array. This can force some *upcasting*.

```
In [271]: df3.values.dtype
Out[271]: dtype('float64')
```

10.12.3 astype

You can use the `astype()` method to explicitly convert dtypes from one to another. These will by default return a copy, even if the dtype was unchanged (pass `copy=False` to change this behavior). In addition, they will raise an exception if the `astype` operation is invalid.

Upcasting is always according to the **numpy** rules. If two different dtypes are involved in an operation, then the more *general* one will be used as the result of the operation.

```
In [272]: df3
Out[272]:
```

| | A | B | C |
|---|-----------|-----------|-----|
| 0 | 1.090748 | -1.508174 | 0 |
| 1 | 1.734810 | -0.502623 | 0 |
| 2 | 0.110879 | 0.529008 | 0 |
| 3 | -3.629600 | 0.590536 | 1 |
| 4 | 0.675238 | 0.296947 | 0 |
| 5 | -0.327398 | 0.007045 | 255 |
| 6 | 2.025163 | 0.707877 | 1 |
| 7 | -1.998126 | 0.950661 | 0 |

```
In [273]: df3.dtypes
```

```
Out[273]:
```

```
A    float32
B    float64
C    float64
dtype: object
```

```
# conversion of dtypes
```

```
In [274]: df3.astype('float32').dtypes
```

```
Out[274]:
```

```
A    float32
B    float32
C    float32
dtype: object
```

10.12.4 object conversion

`convert_objects()` is a method to try to force conversion of types from the `object` dtype to other types. To force conversion of specific types that are *number like*, e.g. could be a string that represents a number, pass `convert_numeric=True`. This will force strings and numbers alike to be numbers if possible, otherwise they will be set to `np.nan`.

```
In [275]: df3['D'] = '1.'
```

```
In [276]: df3['E'] = '1'
```

```
In [277]: df3.convert_objects(convert_numeric=True).dtypes
```

```
Out[277]:
```

```
A    float32
B    float64
C    float64
D    float64
E    int64
dtype: object
```

```
# same, but specific dtype conversion
```

```
In [278]: df3['D'] = df3['D'].astype('float16')
```

```
In [279]: df3['E'] = df3['E'].astype('int32')
```

```
In [280]: df3.dtypes
```

```
Out[280]:
```

```
A    float32
B    float64
C    float64
D    float16
```

```
E      int32
dtype: object
```

To force conversion to `datetime64[ns]`, pass `convert_dates='coerce'`. This will convert any datetime-like object to dates, forcing other values to `NaT`. This might be useful if you are reading in data which is mostly dates, but occasionally has non-dates intermixed and you want to represent as missing.

```
In [281]: s = Series([datetime(2001,1,1,0,0),
.....:               'foo', 1.0, 1, Timestamp('20010104'),
.....:               '20010105'], dtype='O')
.....:
```

```
In [282]: s
Out[282]:
0      2001-01-01 00:00:00
1                      foo
2                      1
3                      1
4      2001-01-04 00:00:00
5      20010105
dtype: object
```

```
In [283]: s.convert_objects(convert_dates='coerce')
Out[283]:
0      2001-01-01
1           NaT
2           NaT
3           NaT
4      2001-01-04
5      2001-01-05
dtype: datetime64[ns]
```

In addition, `convert_objects()` will attempt the *soft* conversion of any *object* dtypes, meaning that if all the objects in a Series are of the same type, the Series will have that dtype.

10.12.5 gotchas

Performing selection operations on integer type data can easily upcast the data to floating. The dtype of the input data will be preserved in cases where nans are not introduced (starting in 0.11.0) See also *integer na gotchas*

```
In [284]: dfi = df3.astype('int32')
```

```
In [285]: dfi['E'] = 1
```

```
In [286]: dfi
Out[286]:
   A  B  C  D  E
0  1 -1  0  1  1
1  1  0  0  1  1
2  0  0  0  1  1
3 -3  0  1  1  1
4  0  0  0  1  1
5  0  0 255  1  1
6  2  0  1  1  1
7 -1  0  0  1  1
```

```
In [287]: dfi.dtypes
```

```
Out[287]:
A      int32
B      int32
C      int32
D      int32
E      int64
dtype: object
```

```
In [288]: casted = dfi[dfi>0]
```

```
In [289]: casted
```

```
Out[289]:
   A  B  C  D  E
0   1 NaN NaN 1  1
1   1 NaN NaN 1  1
2 NaN NaN NaN 1  1
3 NaN NaN  1  1  1
4 NaN NaN NaN 1  1
5 NaN NaN 255 1  1
6   2 NaN  1  1  1
7 NaN NaN NaN 1  1
```

```
In [290]: casted.dtypes
```

```
Out[290]:
A      float64
B      float64
C      float64
D      int32
E      int64
dtype: object
```

While float dtypes are unchanged.

```
In [291]: dfa = df3.copy()
```

```
In [292]: dfa['A'] = dfa['A'].astype('float32')
```

```
In [293]: dfa.dtypes
```

```
Out[293]:
A      float32
B      float64
C      float64
D      float16
E      int32
dtype: object
```

```
In [294]: casted = dfa[df2>0]
```

```
In [295]: casted
```

```
Out[295]:
   A      B  C  D  E
0   NaN   NaN NaN NaN NaN
1  1.734810 NaN NaN NaN NaN
2   NaN  0.529008 NaN NaN NaN
3   NaN  0.590536  1 NaN NaN
4  0.675238  0.296947 NaN NaN NaN
5   NaN  0.007045 255 NaN NaN
6  2.025163  0.707877  1 NaN NaN
```

```
7          NaN    0.950661    NaN    NaN    NaN
```

```
In [296]: casted.dtypes
```

```
Out[296]:
A    float32
B    float64
C    float64
D    float16
E    float64
dtype: object
```

10.13 Selecting columns based on dtype

New in version 0.14.1.

The `select_dtypes()` method implements subsetting of columns based on their dtype.

First, let's create a `DataFrame` with a slew of different dtypes:

```
In [297]: df = DataFrame({'string': list('abc'),
.....:                  'int64': list(range(1, 4)),
.....:                  'uint8': np.arange(3, 6).astype('u1'),
.....:                  'float64': np.arange(4.0, 7.0),
.....:                  'bool1': [True, False, True],
.....:                  'bool2': [False, True, False],
.....:                  'dates': pd.date_range('now', periods=3).values,
.....:                  'category': pd.Categorical(list("ABC"))})
.....:
```

```
In [298]: df['tdeltas'] = df.dates.diff()
```

```
In [299]: df['uint64'] = np.arange(3, 6).astype('u8')
```

```
In [300]: df['other_dates'] = pd.date_range('20130101', periods=3).values
```

```
In [301]: df
```

```
Out[301]:
   bool1  bool2  category  dates  float64  int64  string \
0   True  False         A  2015-05-11 11:00:20.785134    4    1      a
1  False   True         B  2015-05-12 11:00:20.785134    5    2      b
2   True  False         C  2015-05-13 11:00:20.785134    6    3      c

   uint8  tdeltas  uint64  other_dates
0      3      NaT      3  2013-01-01
1      4    1 days      4  2013-01-02
2      5    1 days      5  2013-01-03
```

`select_dtypes()` has two parameters `include` and `exclude` that allow you to say “give me the columns WITH these dtypes” (`include`) and/or “give the columns WITHOUT these dtypes” (`exclude`).

For example, to select `bool` columns

```
In [302]: df.select_dtypes(include=[bool])
```

```
Out[302]:
   bool1  bool2
0   True  False
```

```
1 False    True
2  True    False
```

You can also pass the name of a dtype in the `numpy` dtype hierarchy:

```
In [303]: df.select_dtypes(include=['bool'])
```

```
Out[303]:
   bool1  bool2
0   True  False
1  False   True
2   True  False
```

`select_dtypes()` also works with generic dtypes as well.

For example, to select all numeric and boolean columns while excluding unsigned integers

```
In [304]: df.select_dtypes(include=['number', 'bool'], exclude=['unsignedinteger'])
```

```
Out[304]:
   bool1  bool2  float64  int64  tdelat
0   True  False         4     1     NaT
1  False   True         5     2    1 days
2   True  False         6     3    1 days
```

To select string columns you must use the `object` dtype:

```
In [305]: df.select_dtypes(include=['object'])
```

```
Out[305]:
   string
0       a
1       b
2       c
```

To see all the child dtypes of a generic dtype like `numpy.number` you can define a function that returns a tree of child dtypes:

```
In [306]: def subdtypes(dtype):
.....:     subs = dtype.__subclasses__()
.....:     if not subs:
.....:         return dtype
.....:     return [dtype, [subdtypes(dt) for dt in subs]]
.....:
```

All `numpy` dtypes are subclasses of `numpy.generic`:

```
In [307]: subdtypes(np.generic)
```

```
Out[307]:
[numpy.generic,
 [ [numpy.number,
    [ [numpy.integer,
      [ [numpy.signedinteger,
        [numpy.int8,
         numpy.int16,
         numpy.int32,
         numpy.int32,
         numpy.int64,
         numpy.timedelta64]],
       [numpy.unsignedinteger,
        [numpy.uint8,
         numpy.uint16,
         numpy.uint32,
```

```
        numpy.uint32,
        numpy.uint64]]]],
[numpy.inexact,
 [[numpy.floating,
   [numpy.float16, numpy.float32, numpy.float64, numpy.float96]],
  [numpy.complexfloating,
   [numpy.complex64, numpy.complex128, numpy.complex192]]]]],
[numpy.flexible,
 [[numpy.character, [numpy.string_, numpy.unicode_]],
  [numpy.void, [numpy.core.records.record]]]],
numpy.bool_,
numpy.datetime64,
numpy.object_]]
```

Note: Pandas also defines an additional `category` dtype, which is not integrated into the normal numpy hierarchy and won't show up with the above function.

Note: The `include` and `exclude` parameters must be non-string sequences.

WORKING WITH TEXT DATA

Series and Index are equipped with a set of string processing methods that make it easy to operate on each element of the array. Perhaps most importantly, these methods exclude missing/NA values automatically. These are accessed via the `str` attribute and generally have names matching the equivalent (scalar) built-in string methods:

```
In [1]: s = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])
```

```
In [2]: s.str.lower()
```

```
Out[2]:
0      a
1      b
2      c
3    aaba
4    baca
5     NaN
6    caba
7     dog
8     cat
dtype: object
```

```
In [3]: s.str.upper()
```

```
Out[3]:
0      A
1      B
2      C
3    AABA
4    BACA
5     NaN
6    CABA
7     DOG
8     CAT
dtype: object
```

```
In [4]: s.str.len()
```

```
Out[4]:
0      1
1      1
2      1
3      4
4      4
5     NaN
6      4
7      3
8      3
dtype: float64
```

```
In [5]: idx = Index([' jack', 'jill ', ' jesse ', 'frank'])
In [6]: idx.str.strip()
Out[6]: Index([u'jack', u'jill', u'jesse', u'frank'], dtype='object')
In [7]: idx.str.lstrip()
Out[7]: Index([u'jack', u'jill ', u'jesse ', u'frank'], dtype='object')
In [8]: idx.str.rstrip()
Out[8]: Index([u' jack', u'jill', u' jesse', u'frank'], dtype='object')
```

The string methods on Index are especially useful for cleaning up or transforming DataFrame columns. For instance, you may have columns with leading or trailing whitespace:

```
In [9]: df = DataFrame(randn(3, 2), columns=[' Column A ', ' Column B '],
...:                  index=range(3))
...:

In [10]: df
Out[10]:
   Column A  Column B
0    0.017428  0.039049
1   -2.240248  0.847859
2   -1.342107  0.368828
```

Since `df.columns` is an Index object, we can use the `.str` accessor

```
In [11]: df.columns.str.strip()
Out[11]: Index([u'Column A', u'Column B'], dtype='object')

In [12]: df.columns.str.lower()
Out[12]: Index([u' column a ', u' column b '], dtype='object')
```

These string methods can then be used to clean up the columns as needed. Here we are removing leading and trailing whitespaces, lowercasing all names, and replacing any remaining whitespaces with underscores:

```
In [13]: df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_')

In [14]: df
Out[14]:
   column_a  column_b
0    0.017428  0.039049
1   -2.240248  0.847859
2   -1.342107  0.368828
```

11.1 Splitting and Replacing Strings

Methods like `split` return a Series of lists:

```
In [15]: s2 = Series(['a_b_c', 'c_d_e', np.nan, 'f_g_h'])

In [16]: s2.str.split('_')
Out[16]:
0    [a, b, c]
1    [c, d, e]
2         NaN
```

```
3      [f, g, h]
dtype: object
```

Elements in the split lists can be accessed using `get` or `[]` notation:

```
In [17]: s2.str.split('_').str.get(1)
Out[17]:
0      b
1      d
2     NaN
3      g
dtype: object
```

```
In [18]: s2.str.split('_').str[1]
Out[18]:
0      b
1      d
2     NaN
3      g
dtype: object
```

Easy to expand this to return a DataFrame using `expand`.

```
In [19]: s2.str.split('_', expand=True)
Out[19]:
   0  1  2
0  a  b  c
1  c  d  e
2 NaN NaN NaN
3  f  g  h
```

Methods like `replace` and `findall` take [regular expressions](#), too:

```
In [20]: s3 = Series(['A', 'B', 'C', 'Aaba', 'Baca',
.....:               '', np.nan, 'CABA', 'dog', 'cat'])
.....:
```

```
In [21]: s3
Out[21]:
0      A
1      B
2      C
3  Aaba
4  Baca
5
6     NaN
7  CABA
8   dog
9   cat
dtype: object
```

```
In [22]: s3.str.replace('^.a|dog', 'XX-XX ', case=False)
Out[22]:
0      A
1      B
2      C
3  XX-XX ba
4  XX-XX ca
5
```

```
6          NaN
7    XX-XX BA
8      XX-XX
9    XX-XX t
dtype: object
```

Some caution must be taken to keep regular expressions in mind! For example, the following code will cause trouble because of the regular expression meaning of \$:

```
# Consider the following badly formatted financial data
In [23]: dollars = Series(['12', '-$10', '$10,000'])
```

```
# This does what you'd naively expect:
```

```
In [24]: dollars.str.replace('$', '')
Out[24]:
0          12
1         -10
2    10,000
dtype: object
```

```
# But this doesn't:
```

```
In [25]: dollars.str.replace('-$', '-')
Out[25]:
0          12
1         -$10
2    $10,000
dtype: object
```

```
# We need to escape the special character (for >1 len patterns)
```

```
In [26]: dollars.str.replace(r'\-$', '-')
Out[26]:
0          12
1         -10
2    $10,000
dtype: object
```

11.2 Indexing with `.str`

You can use `[]` notation to directly index by position locations. If you index past the end of the string, the result will be a NaN.

```
In [27]: s = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan,
.....:              'CABA', 'dog', 'cat'])
.....:
```

```
In [28]: s.str[0]
```

```
Out[28]:
0    A
1    B
2    C
3    A
4    B
5    NaN
6    C
7    d
8    c
```

```
dtype: object
```

```
In [29]: s.str[1]
```

```
Out[29]:
```

```
0    NaN
1    NaN
2    NaN
3     a
4     a
5    NaN
6     A
7     o
8     a
```

```
dtype: object
```

11.3 Extracting Substrings

The method `extract` (introduced in version 0.13) accepts [regular expressions](#) with match groups. Extracting a regular expression with one group returns a Series of strings.

```
In [30]: Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
```

```
Out[30]:
```

```
0     1
1     2
2    NaN
```

```
dtype: object
```

Elements that do not match return NaN. Extracting a regular expression with more than one group returns a DataFrame with one column per group.

```
In [31]: Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
```

```
Out[31]:
```

```
   0  1
0  a  1
1  b  2
2 NaN NaN
```

Elements that do not match return a row filled with NaN. Thus, a Series of messy strings can be “converted” into a like-indexed Series or DataFrame of cleaned-up or more useful strings, without necessitating `get()` to access tuples or `re.match` objects.

The results dtype always is object, even if no match is found and the result only contains NaN.

Named groups like

```
In [32]: Series(['a1', 'b2', 'c3']).str.extract('(?(P<letter>[ab])(?P<digit>\d)')
```

```
Out[32]:
```

```
   letter digit
0     a      1
1     b      2
2    NaN    NaN
```

and optional groups like

```
In [33]: Series(['a1', 'b2', '3']).str.extract('(?(P<letter>[ab])?(?P<digit>\d)')
```

```
Out[33]:
```

```
   letter digit
```

```
0      a      1
1      b      2
2    NaN      3
```

can also be used.

11.3.1 Testing for Strings that Match or Contain a Pattern

You can check whether elements contain a pattern:

```
In [34]: pattern = r'[a-z][0-9]'
```

```
In [35]: Series(['1', '2', '3a', '3b', '03c']).str.contains(pattern)
Out[35]:
0    False
1    False
2    False
3    False
4    False
dtype: bool
```

or match a pattern:

```
In [36]: Series(['1', '2', '3a', '3b', '03c']).str.match(pattern, as_indexer=True)
Out[36]:
0    False
1    False
2    False
3    False
4    False
dtype: bool
```

The distinction between `match` and `contains` is strictness: `match` relies on strict `re.match`, while `contains` relies on `re.search`.

Warning: In previous versions, `match` was for *extracting* groups, returning a not-so-convenient Series of tuples. The new method `extract` (described in the previous section) is now preferred. This old, deprecated behavior of `match` is still the default. As demonstrated above, use the new behavior by setting `as_indexer=True`. In this mode, `match` is analogous to `contains`, returning a boolean Series. The new behavior will become the default behavior in a future release.

Methods like `match`, `contains`, `startswith`, and `endswith` take an extra `na` argument so missing values can be considered True or False:

```
In [37]: s4 = Series(['A', 'B', 'C', 'Aaba', 'Baca', np.nan, 'CABA', 'dog', 'cat'])

In [38]: s4.str.contains('A', na=False)
Out[38]:
0     True
1    False
2    False
3     True
4    False
5    False
6     True
7    False
8    False
dtype: bool
```

11.3.2 Creating Indicator Variables

You can extract dummy variables from string columns. For example if they are separated by a ' | ':

```
In [39]: s = Series(['a', 'a|b', np.nan, 'a|c'])
```

```
In [40]: s.str.get_dummies(sep='|')
```

```
Out[40]:
   a  b  c
0  1  0  0
1  1  1  0
2  0  0  0
3  1  0  1
```

See also `get_dummies()`.

11.4 Method Summary

| Method | Description |
|------------------------------|---|
| <code>cat()</code> | Concatenate strings |
| <code>split()</code> | Split strings on delimiter |
| <code>get()</code> | Index into each element (retrieve i-th element) |
| <code>join()</code> | Join strings in each element of the Series with passed separator |
| <code>contains()</code> | Return boolean array if each string contains pattern/regex |
| <code>replace()</code> | Replace occurrences of pattern/regex with some other string |
| <code>repeat()</code> | Duplicate values (<code>s.str.repeat(3)</code> equivalent to <code>x * 3</code>) |
| <code>pad()</code> | Add whitespace to left, right, or both sides of strings |
| <code>center()</code> | Equivalent to <code>str.center</code> |
| <code>ljust()</code> | Equivalent to <code>str.ljust</code> |
| <code>rjust()</code> | Equivalent to <code>str.rjust</code> |
| <code>zfill()</code> | Equivalent to <code>str.zfill</code> |
| <code>wrap()</code> | Split long strings into lines with length less than a given width |
| <code>slice()</code> | Slice each string in the Series |
| <code>slice_replace()</code> | Replace slice in each string with passed value |
| <code>count()</code> | Count occurrences of pattern |
| <code>startswith()</code> | Equivalent to <code>str.startswith(pat)</code> for each element |
| <code>endswith()</code> | Equivalent to <code>str.endswith(pat)</code> for each element |
| <code>findall()</code> | Compute list of all occurrences of pattern/regex for each string |
| <code>match()</code> | Call <code>re.match</code> on each element, returning matched groups as list |
| <code>extract()</code> | Call <code>re.match</code> on each element, as <code>match</code> does, but return matched groups as strings for convenience. |
| <code>len()</code> | Compute string lengths |
| <code>strip()</code> | Equivalent to <code>str.strip</code> |
| <code>rstrip()</code> | Equivalent to <code>str.rstrip</code> |
| <code>lstrip()</code> | Equivalent to <code>str.lstrip</code> |
| <code>partition()</code> | Equivalent to <code>str.partition</code> |
| <code>rpartition()</code> | Equivalent to <code>str.rpartition</code> |
| <code>lower()</code> | Equivalent to <code>str.lower</code> |
| <code>upper()</code> | Equivalent to <code>str.upper</code> |
| <code>find()</code> | Equivalent to <code>str.find</code> |
| <code>rfind()</code> | Equivalent to <code>str.rfind</code> |
| <code>index()</code> | Equivalent to <code>str.index</code> |
| <code>rindex()</code> | Equivalent to <code>str.rindex</code> |

Continued on next page

Table 11.1 – continued from previous page

| Method | Description |
|---------------------------|--|
| <code>capitalize()</code> | Equivalent to <code>str.capitalize</code> |
| <code>swapcase()</code> | Equivalent to <code>str.swapcase</code> |
| <code>normalize()</code> | Return Unicode normal form. Equivalent to <code>unicodedata.normalize</code> |
| <code>translate()</code> | Equivalent to <code>str.translate</code> |
| <code>isalnum()</code> | Equivalent to <code>str.isalnum</code> |
| <code>isalpha()</code> | Equivalent to <code>str.isalpha</code> |
| <code>isdigit()</code> | Equivalent to <code>str.isdigit</code> |
| <code>isspace()</code> | Equivalent to <code>str.isspace</code> |
| <code>islower()</code> | Equivalent to <code>str.islower</code> |
| <code>isupper()</code> | Equivalent to <code>str.isupper</code> |
| <code>istitle()</code> | Equivalent to <code>str.istitle</code> |
| <code>isnumeric()</code> | Equivalent to <code>str.isnumeric</code> |
| <code>isdecimal()</code> | Equivalent to <code>str.isdecimal</code> |

OPTIONS AND SETTINGS

12.1 Overview

pandas has an options system that lets you customize some aspects of its behaviour, display-related options being those the user is most likely to adjust.

Options have a full “dotted-style”, case-insensitive name (e.g. `display.max_rows`). You can get/set options directly as attributes of the top-level `options` attribute:

```
In [1]: import pandas as pd

In [2]: pd.options.display.max_rows
Out[2]: 15

In [3]: pd.options.display.max_rows = 999

In [4]: pd.options.display.max_rows
Out[4]: 999
```

There is also an API composed of 5 relevant functions, available directly from the `pandas` namespace:

- `get_option()` / `set_option()` - get/set the value of a single option.
- `reset_option()` - reset one or more options to their default value.
- `describe_option()` - print the descriptions of one or more options.
- `option_context()` - execute a codeblock with a set of options that revert to prior settings after execution.

Note: developers can check out `pandas/core/config.py` for more info.

All of the functions above accept a regexp pattern (`re.search` style) as an argument, and so passing in a substring will work - as long as it is unambiguous :

```
In [5]: pd.get_option("display.max_rows")
Out[5]: 999

In [6]: pd.set_option("display.max_rows", 101)

In [7]: pd.get_option("display.max_rows")
Out[7]: 101

In [8]: pd.set_option("max_r", 102)

In [9]: pd.get_option("display.max_rows")
Out[9]: 102
```

The following will **not work** because it matches multiple option names, e.g. `display.max_colwidth`, `display.max_rows`, `display.max_columns`:

```
In [10]: try:
.....:     pd.get_option("column")
.....: except KeyError as e:
.....:     print(e)
.....:
'Pattern matched multiple keys'
```

Note: Using this form of shorthand may cause your code to break if new options with similar names are added in future versions.

You can get a list of available options and their descriptions with `describe_option`. When called with no argument `describe_option` will print out the descriptions for all available options.

12.2 Getting and Setting Options

As described above, `get_option()` and `set_option()` are available from the pandas namespace. To change an option, call `set_option('option regex', new_value)`

```
In [11]: pd.get_option('mode.sim_interactive')
Out[11]: False

In [12]: pd.set_option('mode.sim_interactive', True)

In [13]: pd.get_option('mode.sim_interactive')
Out[13]: True
```

Note: that the option 'mode.sim_interactive' is mostly used for debugging purposes.

All options also have a default value, and you can use `reset_option` to do just that:

```
In [14]: pd.get_option("display.max_rows")
Out[14]: 60

In [15]: pd.set_option("display.max_rows", 999)

In [16]: pd.get_option("display.max_rows")
Out[16]: 999

In [17]: pd.reset_option("display.max_rows")

In [18]: pd.get_option("display.max_rows")
Out[18]: 60
```

It's also possible to reset multiple options at once (using a regex):

```
In [19]: pd.reset_option("^display")
height has been deprecated.
```

`line_width` has been deprecated, use `display.width` instead (currently both are identical)

`option_context` context manager has been exposed through the top-level API, allowing you to execute code with given option values. Option values are restored automatically when you exit the *with* block:

```
In [20]: with pd.option_context("display.max_rows",10,"display.max_columns", 5):
.....:     print(pd.get_option("display.max_rows"))
.....:     print(pd.get_option("display.max_columns"))
.....:
10
5

In [21]: print(pd.get_option("display.max_rows"))
60

In [22]: print(pd.get_option("display.max_columns"))
20
```

12.3 Setting Startup Options in python/ipython Environment

Using startup scripts for the python/ipython environment to import pandas and set options makes working with pandas more efficient. To do this, create a .py or .ipy script in the startup directory of the desired profile. An example where the startup folder is in a default ipython profile can be found at:

```
$IPYTHONDIR/profile_default/startup
```

More information can be found in the [ipython documentation](#). An example startup script for pandas is displayed below:

```
import pandas as pd
pd.set_option('display.max_rows', 999)
pd.set_option('precision', 5)
```

12.4 Frequently Used Options

The following is a walkthrough of the more frequently used display options.

`display.max_rows` and `display.max_columns` sets the maximum number of rows and columns displayed when a frame is pretty-printed. Truncated lines are replaced by an ellipsis.

```
In [23]: df=pd.DataFrame(np.random.randn(7,2))
```

```
In [24]: pd.set_option('max_rows', 7)
```

```
In [25]: df
```

```
Out[25]:
   0         1
0  0.469112 -0.282863
1 -1.509059 -1.135632
2  1.212112 -0.173215
3  0.119209 -1.044236
4 -0.861849 -2.104569
5 -0.494929  1.071804
6  0.721555 -0.706771
```

```
In [26]: pd.set_option('max_rows', 5)
```

```
In [27]: df
```

```
Out[27]:
```

```
      0      1
0  0.469112 -0.282863
1 -1.509059 -1.135632
..      ...      ...
5 -0.494929  1.071804
6  0.721555 -0.706771
```

```
[7 rows x 2 columns]
```

```
In [28]: pd.reset_option('max_rows')
```

`display.expand_frame_repr` allows for the the representation of dataframes to stretch across pages, wrapped over the full column vs row-wise.

```
In [29]: df=pd.DataFrame(np.random.randn(5,10))
```

```
In [30]: pd.set_option('expand_frame_repr', True)
```

```
In [31]: df
```

```
Out[31]:
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | \ |
|---|-----------|-----------|-----------|-----------|-----------|-----------|-----------|---|
| 0 | -1.039575 | 0.271860 | -0.424972 | 0.567020 | 0.276232 | -1.087401 | -0.673690 | |
| 1 | 0.404705 | 0.577046 | -1.715002 | -1.039268 | -0.370647 | -1.157892 | -1.344312 | |
| 2 | 1.643563 | -1.469388 | 0.357021 | -0.674600 | -1.776904 | -0.968914 | -1.294524 | |
| 3 | -0.013960 | -0.362543 | -0.006154 | -0.923061 | 0.895717 | 0.805244 | -1.206412 | |
| 4 | -1.170299 | -0.226169 | 0.410835 | 0.813850 | 0.132003 | -0.827317 | -0.076467 | |

| | 7 | 8 | 9 |
|---|-----------|-----------|-----------|
| 0 | 0.113648 | -1.478427 | 0.524988 |
| 1 | 0.844885 | 1.075770 | -0.109050 |
| 2 | 0.413738 | 0.276662 | -0.472035 |
| 3 | 2.565646 | 1.431256 | 1.340309 |
| 4 | -1.187678 | 1.130127 | -1.436737 |

```
In [32]: pd.set_option('expand_frame_repr', False)
```

```
In [33]: df
```

```
Out[33]:
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|
| 0 | -1.039575 | 0.271860 | -0.424972 | 0.567020 | 0.276232 | -1.087401 | -0.673690 | 0.113648 | -1.478427 | 0.524988 |
| 1 | 0.404705 | 0.577046 | -1.715002 | -1.039268 | -0.370647 | -1.157892 | -1.344312 | 0.844885 | 1.075770 | -0.109050 |
| 2 | 1.643563 | -1.469388 | 0.357021 | -0.674600 | -1.776904 | -0.968914 | -1.294524 | 0.413738 | 0.276662 | -0.472035 |
| 3 | -0.013960 | -0.362543 | -0.006154 | -0.923061 | 0.895717 | 0.805244 | -1.206412 | 2.565646 | 1.431256 | 1.340309 |
| 4 | -1.170299 | -0.226169 | 0.410835 | 0.813850 | 0.132003 | -0.827317 | -0.076467 | -1.187678 | 1.130127 | -1.436737 |

```
In [34]: pd.reset_option('expand_frame_repr')
```

`display.large_repr` lets you select whether to display dataframes that exceed `max_columns` or `max_rows` as a truncated frame, or as a summary.

```
In [35]: df=pd.DataFrame(np.random.randn(10,10))
```

```
In [36]: pd.set_option('max_rows', 5)
```

```
In [37]: pd.set_option('large_repr', 'truncate')
```

```
In [38]: df
```

```
Out[38]:
```

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | \ |
|--|---|---|---|---|---|---|---|---|
|--|---|---|---|---|---|---|---|---|

```

0  -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466
1   0.545952 -1.219217 -1.226825  0.769804 -1.281247 -0.727707 -0.121306
..      ...      ...      ...      ...      ...      ...      ...
8  -2.484478 -0.281461  0.030711  0.109121  1.126203 -0.977349  1.474071
9  -1.071357  0.441153  2.353925  0.583787  0.221471 -0.744471  0.758527

```

```

          7          8          9
0  -2.006747 -0.410001 -0.078638
1  -0.097883  0.695775  0.341734
..      ...      ...      ...
8  -0.064034 -1.282782  0.781836
9   1.729689 -0.964980 -0.845696

```

```
[10 rows x 10 columns]
```

```
In [39]: pd.set_option('large_repr', 'info')
```

```
In [40]: df
```

```

Out[40]:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0      10 non-null float64
1      10 non-null float64
2      10 non-null float64
3      10 non-null float64
4      10 non-null float64
5      10 non-null float64
6      10 non-null float64
7      10 non-null float64
8      10 non-null float64
9      10 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes

```

```
In [41]: pd.reset_option('large_repr')
```

```
In [42]: pd.reset_option('max_rows')
```

`display.max_columnwidth` sets the maximum width of columns. Cells of this length or longer will be truncated with an ellipsis.

```

In [43]: df=pd.DataFrame(np.array([[ 'foo', 'bar', 'bim', 'uncomfortably long string'],
.....:                             ['horse', 'cow', 'banana', 'apple']]))
.....:

```

```
In [44]: pd.set_option('max_colwidth', 40)
```

```
In [45]: df
```

```

Out[45]:
      0      1      2      3
0  foo bar  bim  uncomfortably long string
1 horse cow banana                apple

```

```
In [46]: pd.set_option('max_colwidth', 6)
```

```
In [47]: df
```

```
Out[47]:
```

```
      0      1      2      3
0   foo bar   bim un...
1  horse cow  ba...  apple
```

```
In [48]: pd.reset_option('max_colwidth')
```

`display.max_info_columns` sets a threshold for when by-column info will be given.

```
In [49]: df=pd.DataFrame(np.random.randn(10,10))
```

```
In [50]: pd.set_option('max_info_columns', 11)
```

```
In [51]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0      10 non-null float64
1      10 non-null float64
2      10 non-null float64
3      10 non-null float64
4      10 non-null float64
5      10 non-null float64
6      10 non-null float64
7      10 non-null float64
8      10 non-null float64
9      10 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes
```

```
In [52]: pd.set_option('max_info_columns', 5)
```

```
In [53]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Columns: 10 entries, 0 to 9
dtypes: float64(10)
memory usage: 880.0 bytes
```

```
In [54]: pd.reset_option('max_info_columns')
```

`display.max_info_rows: df.info()` will usually show null-counts for each column. For large frames this can be quite slow. `max_info_rows` and `max_info_cols` limit this null check only to frames with smaller dimensions than specified. Note that you can specify the option `df.info(null_counts=True)` to override on showing a particular frame.

```
In [55]: df=pd.DataFrame(np.random.choice([0,1,np.nan],size=(10,10)))
```

```
In [56]: df
```

```
Out[56]:
      0      1      2      3      4      5      6      7      8      9
0     0      1      1      0      1      1      0  NaN      1  NaN
1     1  NaN      0      0      1      1  NaN      1      0      1
2  NaN  NaN  NaN      1      1      0  NaN      0      1  NaN
3     0      1      1  NaN      0  NaN      1  NaN  NaN      0
4     0      1      0      0      1      0      0  NaN      0      0
5     0  NaN      1  NaN  NaN  NaN  NaN      0      1  NaN
6     0      1      0      0  NaN      1  NaN  NaN      0  NaN
7     0  NaN      1      1  NaN      1      1      1      1  NaN
8     0      0  NaN      0  NaN      1      0      0  NaN  NaN
```

```
9 NaN NaN    0 NaN NaN NaN    0    1    1 NaN
```

```
In [57]: pd.set_option('max_info_rows', 11)
```

```
In [58]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0      8 non-null float64
1      5 non-null float64
2      8 non-null float64
3      7 non-null float64
4      5 non-null float64
5      7 non-null float64
6      6 non-null float64
7      6 non-null float64
8      8 non-null float64
9      3 non-null float64
dtypes: float64(10)
memory usage: 880.0 bytes
```

```
In [59]: pd.set_option('max_info_rows', 5)
```

```
In [60]: df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10 entries, 0 to 9
Data columns (total 10 columns):
0      float64
1      float64
2      float64
3      float64
4      float64
5      float64
6      float64
7      float64
8      float64
9      float64
dtypes: float64(10)
memory usage: 880.0 bytes
```

```
In [61]: pd.reset_option('max_info_rows')
```

display.precision sets the output display precision. This is only a suggestion.

```
In [62]: df=pd.DataFrame(np.random.randn(5,5))
```

```
In [63]: pd.set_option('precision',7)
```

```
In [64]: df
Out[64]:
```

| | 0 | 1 | 2 | 3 | 4 |
|---|-----------|-----------|-----------|-----------|----------|
| 0 | -2.049028 | 2.846612 | -1.208049 | -0.450392 | 2.423905 |
| 1 | 0.121108 | 0.266916 | 0.843826 | -0.222540 | 2.021981 |
| 2 | -0.716789 | -2.224485 | -1.061137 | -0.232825 | 0.430793 |
| 3 | -0.665478 | 1.829807 | -1.406509 | 1.078248 | 0.322774 |
| 4 | 0.200324 | 0.890024 | 0.194813 | 0.351633 | 0.448881 |

```
In [65]: pd.set_option('precision',4)
```

```
In [66]: df
```

```
Out[66]:
```

| | 0 | 1 | 2 | 3 | 4 |
|---|--------|--------|--------|--------|-------|
| 0 | -2.049 | 2.847 | -1.208 | -0.450 | 2.424 |
| 1 | 0.121 | 0.267 | 0.844 | -0.223 | 2.022 |
| 2 | -0.717 | -2.224 | -1.061 | -0.233 | 0.431 |
| 3 | -0.665 | 1.830 | -1.407 | 1.078 | 0.323 |
| 4 | 0.200 | 0.890 | 0.195 | 0.352 | 0.449 |

`display.chop_threshold` sets at what level pandas rounds to zero when it displays a Series of DataFrame. Note, this does not effect the precision at which the number is stored.

```
In [67]: df=pd.DataFrame(np.random.randn(6,6))
```

```
In [68]: pd.set_option('chop_threshold', 0)
```

```
In [69]: df
```

```
Out[69]:
```

| | 0 | 1 | 2 | 3 | 4 | 5 |
|---|--------|--------|--------|--------|--------|--------|
| 0 | -0.198 | 0.966 | -1.523 | -0.117 | 0.296 | -1.048 |
| 1 | 1.641 | 1.906 | 2.772 | 0.089 | -1.144 | -0.633 |
| 2 | 0.925 | -0.006 | -0.820 | -0.601 | -1.039 | 0.825 |
| 3 | -0.824 | -0.338 | -0.928 | -0.840 | 0.249 | -0.109 |
| 4 | 0.432 | -0.461 | 0.337 | -3.208 | -1.536 | 0.410 |
| 5 | -0.673 | -0.741 | -0.111 | -2.673 | 0.864 | 0.061 |

```
In [70]: pd.set_option('chop_threshold', .5)
```

```
In [71]: df
```

```
Out[71]:
```

| | 0 | 1 | 2 | 3 | 4 | 5 |
|---|--------|--------|--------|--------|--------|--------|
| 0 | 0.000 | 0.966 | -1.523 | 0.000 | 0.000 | -1.048 |
| 1 | 1.641 | 1.906 | 2.772 | 0.000 | -1.144 | -0.633 |
| 2 | 0.925 | 0.000 | -0.820 | -0.601 | -1.039 | 0.825 |
| 3 | -0.824 | 0.000 | -0.928 | -0.840 | 0.000 | 0.000 |
| 4 | 0.000 | 0.000 | 0.000 | -3.208 | -1.536 | 0.000 |
| 5 | -0.673 | -0.741 | 0.000 | -2.673 | 0.864 | 0.000 |

```
In [72]: pd.reset_option('chop_threshold')
```

`display.colheader_justify` controls the justification of the headers. Options are 'right', and 'left'.

```
In [73]: df=pd.DataFrame(np.array([np.random.randn(6), np.random.randint(1,9,6)*.1, np.zeros(6)]).T,
```

```
In [74]: pd.set_option('colheader_justify', 'right')
```

```
In [75]: df
```

```
Out[75]:
```

| | A | B | C |
|---|--------|-----|---|
| 0 | 0.933 | 0.3 | 0 |
| 1 | 0.289 | 0.2 | 0 |
| 2 | 1.325 | 0.2 | 0 |
| 3 | 0.589 | 0.7 | 0 |
| 4 | 0.531 | 0.1 | 0 |
| 5 | -1.199 | 0.7 | 0 |

```
In [76]: pd.set_option('colheader_justify', 'left')
```

```
In [77]: df
```

```
Out[77]:
```

```
   A      B  C
0  0.933  0.3  0
1  0.289  0.2  0
2  1.325  0.2  0
3  0.589  0.7  0
4  0.531  0.1  0
5 -1.199  0.7  0
```

```
In [78]: pd.reset_option('colheader_justify')
```

12.5 List of Options

| Option | Default | Function |
|----------------------------|----------|---|
| display.chop_threshold | None | If set to a float value, all float values smaller then the given threshold will be displayed as 0 |
| display.colheader_justify | right | Controls the justification of column headers. used by DataFrameFormatter. |
| display.column_space | 12 | No description available. |
| display.date_dayfirst | False | When True, prints and parses dates with the day first, eg 20/01/2005 |
| display.date_yearfirst | False | When True, prints and parses dates with the year first, eg 2005/01/20 |
| display.encoding | UTF-8 | Defaults to the detected encoding of the console. Specifies the encoding to be used for string |
| display.expand_frame_repr | True | Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, m |
| display.float_format | None | The callable should accept a floating point number and return a string with the desired form |
| display.height | 60 | Deprecated. Use <i>display.max_rows</i> instead. |
| display.large_repr | truncate | For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a tru |
| display.line_width | 80 | Deprecated. Use <i>display.width</i> instead. |
| display.max_columns | 20 | max_rows and max_columns are used in <i>__repr__()</i> methods to decide if <i>to_string()</i> or <i>info</i> |
| display.max_colwidth | 50 | The maximum width in characters of a column in the repr of a pandas data structure. Whe |
| display.max_info_columns | 100 | max_info_columns is used in DataFrame.info method to decide if per column information |
| display.max_info_rows | 1690785 | df.info() will usually show null-counts for each column. For large frames this can be quite |
| display.max_rows | 60 | This sets the maximum number of rows pandas should output when printing out various ou |
| display.max_seq_items | 100 | when pretty-printing a long sequence, no more then <i>max_seq_items</i> will be printed. If item |
| display.memory_usage | True | This specifies if the memory usage of a DataFrame should be displayed when the df.info() |
| display.mpl_style | None | Setting this to 'default' will modify the rcParams used by matplotlib to give plots a more p |
| display.multi_sparse | True | "Sparsify" MultiIndex display (don't display repeated elements in outer levels within grou |
| display.notebook_repr_html | True | When True, IPython notebook will use html representation for pandas objects (if it is avail |
| display.pprint_nest_depth | 3 | Controls the number of nested levels to process when pretty-printing |
| display.precision | 7 | Floating point output precision (number of significant digits). This is only a suggestion |
| display.show_dimensions | truncate | Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, on |
| display.width | 80 | Width of the display in characters. In case python/IPython is running in a terminal this can |
| io.excel.xls.writer | xlwt | The default Excel writer engine for 'xls' files. |
| io.excel.xlsm.writer | openpyxl | The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default |
| io.excel.xlsx.writer | openpyxl | The default Excel writer engine for 'xlsx' files. |
| io.hdf.default_format | None | default format writing format, if None, then put will default to 'fixed' and append will defa |
| io.hdf.dropna_table | True | drop ALL nan rows when appending to a table |
| mode.chained_assignment | warn | Raise an exception, warn, or no action if trying to use chained assignment, The default is v |
| mode.sim_interactive | False | Whether to simulate interactive mode for purposes of testing |
| mode.use_inf_as_null | False | True means treat None, NaN, -INF, INF as null (old way), False means None and NaN are |

12.6 Number Formatting

pandas also allows you to set how numbers are displayed in the console. This option is not set through the `set_options` API.

Use the `set_eng_float_format` function to alter the floating-point formatting of pandas objects to produce a particular format.

For instance:

```
In [79]: import numpy as np
```

```
In [80]: pd.set_eng_float_format(accuracy=3, use_eng_prefix=True)
```

```
In [81]: s = pd.Series(np.random.randn(5), index=['a', 'b', 'c', 'd', 'e'])
```

```
In [82]: s/1.e3
```

```
Out[82]:  
a    -236.866u  
b     846.974u  
c    -685.597u  
d     609.099u  
e    -303.961u  
dtype: float64
```

```
In [83]: s/1.e6
```

```
Out[83]:  
a    -236.866n  
b     846.974n  
c    -685.597n  
d     609.099n  
e    -303.961n  
dtype: float64
```

INDEXING AND SELECTING DATA

The axis labeling information in pandas objects serves many purposes:

- Identifies data (i.e. provides *metadata*) using known indicators, important for analysis, visualization, and interactive console display
- Enables automatic and explicit data alignment
- Allows intuitive getting and setting of subsets of the data set

In this section, we will focus on the final point: namely, how to slice, dice, and generally get and set subsets of pandas objects. The primary focus will be on Series and DataFrame as they have received more development attention in this area. Expect more work to be invested in higher-dimensional data structures (including Panel) in the future, especially in label-based advanced indexing.

Note: The Python and NumPy indexing operators `[]` and attribute operator `.` provide quick and easy access to pandas data structures across a wide range of use cases. This makes interactive work intuitive, as there's little new to learn if you already know how to deal with Python dictionaries and NumPy arrays. However, since the type of the data to be accessed isn't known in advance, directly using standard operators has some optimization limits. For production code, we recommended that you take advantage of the optimized pandas data access methods exposed in this chapter.

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See [Returning a View versus Copy](#)

Warning: In 0.15.0 `Index` has internally been refactored to no longer subclass `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This should be a transparent change with only very limited API implications (See the [Internal Refactoring](#))

See the [MultiIndex / Advanced Indexing](#) for `MultiIndex` and more advanced indexing documentation.

See the [cookbook](#) for some advanced strategies

13.1 Different Choices for Indexing

New in version 0.11.0.

Object selection has had a number of user-requested additions in order to support more explicit location based indexing. pandas now supports three types of multi-axis indexing.

- `.loc` is primarily label based, but may also be used with a boolean array. `.loc` will raise `KeyError` when the items are not found. Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index. This use is **not** an integer position along the index)
- A list or array of labels ['a', 'b', 'c']
- A slice object with labels 'a' : 'f', (note that contrary to usual python slices, **both** the start and the stop are included!)
- A boolean array

See more at [Selection by Label](#)

- `.iloc` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array. `.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing. (this conforms with python/numpy *slice* semantics). Allowed inputs are:
 - An integer e.g. 5
 - A list or array of integers [4, 3, 0]
 - A slice object with ints 1 : 7
 - A boolean array

See more at [Selection by Position](#)

- `.ix` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type. `.ix` is the most general and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#) and [Advanced Hierarchical](#).

Getting values from an object with multi-axes selection uses the following notation (using `.loc` as an example, but applies to `.iloc` and `.ix` as well). Any of the axes accessors may be the null slice `:`. Axes left out of the specification are assumed to be `:`. (e.g. `p.loc['a']` is equiv to `p.loc['a', :, :]`)

| Object Type | Indexers |
|-------------|--|
| Series | <code>s.loc[indexer]</code> |
| DataFrame | <code>df.loc[row_indexer, column_indexer]</code> |
| Panel | <code>p.loc[item_indexer, major_indexer, minor_indexer]</code> |

13.2 Deprecations

Beginning with version 0.11.0, it's recommended that you transition away from the following methods as they *may* be deprecated in future versions.

- `irow`
- `icol`
- `iget_value`

See the section [Selection by Position](#) for substitutes.

13.3 Basics

As mentioned when introducing the data structures in the *last section*, the primary function of indexing with `[]` (a.k.a. `__getitem__` for those familiar with implementing class behavior in Python) is selecting out lower-dimensional slices. Thus,

| Object Type | Selection | Return Value Type |
|-------------|------------------------------|---|
| Series | <code>series[label]</code> | scalar value |
| DataFrame | <code>frame[colname]</code> | Series corresponding to colname |
| Panel | <code>panel[itemname]</code> | DataFrame corresponding to the itemname |

Here we construct a simple time series data set to use for illustrating the indexing functionality:

```
In [1]: dates = date_range('1/1/2000', periods=8)
```

```
In [2]: df = DataFrame(randn(8, 4), index=dates, columns=['A', 'B', 'C', 'D'])
```

```
In [3]: df
```

```
Out[3]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 2000-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2000-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |
| 2000-01-04 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |
| 2000-01-05 | -0.424972 | 0.567020 | 0.276232 | -1.087401 |
| 2000-01-06 | -0.673690 | 0.113648 | -1.478427 | 0.524988 |
| 2000-01-07 | 0.404705 | 0.577046 | -1.715002 | -1.039268 |
| 2000-01-08 | -0.370647 | -1.157892 | -1.344312 | 0.844885 |

```
In [4]: panel = Panel({'one' : df, 'two' : df - df.mean()})
```

```
In [5]: panel
```

```
Out[5]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 8 (major_axis) x 4 (minor_axis)
Items axis: one to two
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-08 00:00:00
Minor_axis axis: A to D
```

Note: None of the indexing functionality is time series specific unless specifically stated.

Thus, as per above, we have the most basic indexing using `[]`:

```
In [6]: s = df['A']
```

```
In [7]: s[dates[5]]
```

```
Out[7]: -0.67368970808837025
```

```
In [8]: panel['two']
```

```
Out[8]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.409571 | 0.113086 | -0.610826 | -0.936507 |
| 2000-01-02 | 1.152571 | 0.222735 | 1.017442 | -0.845111 |
| 2000-01-03 | -0.921390 | -1.708620 | 0.403304 | 1.270929 |
| 2000-01-04 | 0.662014 | -0.310822 | -0.141342 | 0.470985 |
| 2000-01-05 | -0.484513 | 0.962970 | 1.174465 | -0.888276 |
| 2000-01-06 | -0.733231 | 0.509598 | -0.580194 | 0.724113 |
| 2000-01-07 | 0.345164 | 0.972995 | -0.816769 | -0.840143 |

```
2000-01-08 -0.430188 -0.761943 -0.446079 1.044010
```

You can pass a list of columns to `[]` to select columns in that order. If a column is not contained in the DataFrame, an exception will be raised. Multiple columns can also be set in this manner:

```
In [9]: df
Out[9]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 2000-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2000-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |
| 2000-01-04 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |
| 2000-01-05 | -0.424972 | 0.567020 | 0.276232 | -1.087401 |
| 2000-01-06 | -0.673690 | 0.113648 | -1.478427 | 0.524988 |
| 2000-01-07 | 0.404705 | 0.577046 | -1.715002 | -1.039268 |
| 2000-01-08 | -0.370647 | -1.157892 | -1.344312 | 0.844885 |

```
In [10]: df[['B', 'A']] = df[['A', 'B']]
```

```
In [11]: df
Out[11]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | -0.282863 | 0.469112 | -1.509059 | -1.135632 |
| 2000-01-02 | -0.173215 | 1.212112 | 0.119209 | -1.044236 |
| 2000-01-03 | -2.104569 | -0.861849 | -0.494929 | 1.071804 |
| 2000-01-04 | -0.706771 | 0.721555 | -1.039575 | 0.271860 |
| 2000-01-05 | 0.567020 | -0.424972 | 0.276232 | -1.087401 |
| 2000-01-06 | 0.113648 | -0.673690 | -1.478427 | 0.524988 |
| 2000-01-07 | 0.577046 | 0.404705 | -1.715002 | -1.039268 |
| 2000-01-08 | -1.157892 | -0.370647 | -1.344312 | 0.844885 |

You may find this useful for applying a transform (in-place) to a subset of the columns.

13.4 Attribute Access

You may access an index on a Series, column on a DataFrame, and a item on a Panel directly as an attribute:

```
In [12]: sa = Series([1,2,3],index=list('abc'))
```

```
In [13]: dfa = df.copy()
```

```
In [14]: sa.b
```

```
Out[14]: 2
```

```
In [15]: dfa.A
```

```
Out[15]:
```

| | |
|------------|-----------|
| 2000-01-01 | -0.282863 |
| 2000-01-02 | -0.173215 |
| 2000-01-03 | -2.104569 |
| 2000-01-04 | -0.706771 |
| 2000-01-05 | 0.567020 |
| 2000-01-06 | 0.113648 |
| 2000-01-07 | 0.577046 |
| 2000-01-08 | -1.157892 |

Freq: D, Name: A, dtype: float64

```
In [16]: panel.one
```

Out[16]:

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 2000-01-02 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2000-01-03 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |
| 2000-01-04 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |
| 2000-01-05 | -0.424972 | 0.567020 | 0.276232 | -1.087401 |
| 2000-01-06 | -0.673690 | 0.113648 | -1.478427 | 0.524988 |
| 2000-01-07 | 0.404705 | 0.577046 | -1.715002 | -1.039268 |
| 2000-01-08 | -0.370647 | -1.157892 | -1.344312 | 0.844885 |

You can use attribute access to modify an existing element of a Series or column of a DataFrame, but be careful; if you try to use attribute access to create a new column, it fails silently, creating a new attribute rather than a new column.

In [17]: `sa.a = 5`

In [18]: `sa`

Out[18]:

```
a      5
b      2
c      3
dtype: int64
```

In [19]: `dfa.A = list(range(len(dfa.index)))` *# ok if A already exists*

In [20]: `dfa`

Out[20]:

| | A | B | C | D |
|------------|---|-----------|-----------|-----------|
| 2000-01-01 | 0 | 0.469112 | -1.509059 | -1.135632 |
| 2000-01-02 | 1 | 1.212112 | 0.119209 | -1.044236 |
| 2000-01-03 | 2 | -0.861849 | -0.494929 | 1.071804 |
| 2000-01-04 | 3 | 0.721555 | -1.039575 | 0.271860 |
| 2000-01-05 | 4 | -0.424972 | 0.276232 | -1.087401 |
| 2000-01-06 | 5 | -0.673690 | -1.478427 | 0.524988 |
| 2000-01-07 | 6 | 0.404705 | -1.715002 | -1.039268 |
| 2000-01-08 | 7 | -0.370647 | -1.344312 | 0.844885 |

In [21]: `dfa['A'] = list(range(len(dfa.index)))` *# use this form to create a new column*

In [22]: `dfa`

Out[22]:

| | A | B | C | D |
|------------|---|-----------|-----------|-----------|
| 2000-01-01 | 0 | 0.469112 | -1.509059 | -1.135632 |
| 2000-01-02 | 1 | 1.212112 | 0.119209 | -1.044236 |
| 2000-01-03 | 2 | -0.861849 | -0.494929 | 1.071804 |
| 2000-01-04 | 3 | 0.721555 | -1.039575 | 0.271860 |
| 2000-01-05 | 4 | -0.424972 | 0.276232 | -1.087401 |
| 2000-01-06 | 5 | -0.673690 | -1.478427 | 0.524988 |
| 2000-01-07 | 6 | 0.404705 | -1.715002 | -1.039268 |
| 2000-01-08 | 7 | -0.370647 | -1.344312 | 0.844885 |

Warning:

- You can use this access only if the index element is a valid python identifier, e.g. `s.1` is not allowed. See [here for an explanation of valid identifiers](#).
- The attribute will not be available if it conflicts with an existing method name, e.g. `s.min` is not allowed.
- Similarly, the attribute will not be available if it conflicts with any of the following list: `index`, `major_axis`, `minor_axis`, `items`, `labels`.
- In any of these cases, standard indexing will still work, e.g. `s['1']`, `s['min']`, and `s['index']` will access the corresponding element or column.
- The `Series/Panel` accesses are available starting in 0.13.0.

If you are using the IPython environment, you may also use tab-completion to see these accessible attributes.

You can also assign a dict to a row of a DataFrame:

```
In [23]: x = pd.DataFrame({'x': [1, 2, 3], 'y': [3, 4, 5]})
```

```
In [24]: x.iloc[1] = dict(x=9, y=99)
```

```
In [25]: x
```

```
Out[25]:
```

| | x | y |
|---|---|----|
| 0 | 1 | 3 |
| 1 | 9 | 99 |
| 2 | 3 | 5 |

13.5 Slicing ranges

The most robust and consistent way of slicing ranges along arbitrary axes is described in the *Selection by Position* section detailing the `.iloc` method. For now, we explain the semantics of slicing using the `[]` operator.

With `Series`, the syntax works exactly as with an `ndarray`, returning a slice of the values and the corresponding labels:

```
In [26]: s[:5]
```

```
Out[26]:
```

| | |
|------------|-----------|
| 2000-01-01 | -0.282863 |
| 2000-01-02 | -0.173215 |
| 2000-01-03 | -2.104569 |
| 2000-01-04 | -0.706771 |
| 2000-01-05 | 0.567020 |

Freq: D, Name: A, dtype: float64

```
In [27]: s[::2]
```

```
Out[27]:
```

| | |
|------------|-----------|
| 2000-01-01 | -0.282863 |
| 2000-01-03 | -2.104569 |
| 2000-01-05 | 0.567020 |
| 2000-01-07 | 0.577046 |

Freq: 2D, Name: A, dtype: float64

```
In [28]: s[::-1]
```

```
Out[28]:
```

| | |
|------------|-----------|
| 2000-01-08 | -1.157892 |
| 2000-01-07 | 0.577046 |
| 2000-01-06 | 0.113648 |
| 2000-01-05 | 0.567020 |
| 2000-01-04 | -0.706771 |

```

2000-01-03    -2.104569
2000-01-02    -0.173215
2000-01-01    -0.282863
Freq: -1D, Name: A, dtype: float64

```

Note that setting works as well:

```
In [29]: s2 = s.copy()
```

```
In [30]: s2[:5] = 0
```

```
In [31]: s2
```

```

Out [31]:
2000-01-01    0.000000
2000-01-02    0.000000
2000-01-03    0.000000
2000-01-04    0.000000
2000-01-05    0.000000
2000-01-06    0.113648
2000-01-07    0.577046
2000-01-08   -1.157892
Freq: D, Name: A, dtype: float64

```

With DataFrame, slicing inside of `[]` **slices the rows**. This is provided largely as a convenience since it is such a common operation.

```
In [32]: df[:3]
```

```

Out [32]:
           A           B           C           D
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804

```

```
In [33]: df[::-1]
```

```

Out [33]:
           A           B           C           D
2000-01-08 -1.157892 -0.370647 -1.344312  0.844885
2000-01-07  0.577046  0.404705 -1.715002 -1.039268
2000-01-06  0.113648 -0.673690 -1.478427  0.524988
2000-01-05  0.567020 -0.424972  0.276232 -1.087401
2000-01-04 -0.706771  0.721555 -1.039575  0.271860
2000-01-03 -2.104569 -0.861849 -0.494929  1.071804
2000-01-02 -0.173215  1.212112  0.119209 -1.044236
2000-01-01 -0.282863  0.469112 -1.509059 -1.135632

```

13.6 Selection By Label

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See [Returning a View versus Copy](#)

Warning:

`.loc` is strict when you present slicers that are not compatible (or convertible) with the index type. For example using integers in a `DatetimeIndex`. These will raise a `TypeError`.

```
In [34]: df1 = DataFrame(np.random.randn(5,4), columns=list('ABCD'), index=date_range('20130101',pe
```

```
In [35]: df1
```

```
Out[35]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2013-01-01 | 1.075770 | -0.109050 | 1.643563 | -1.469388 |
| 2013-01-02 | 0.357021 | -0.674600 | -1.776904 | -0.968914 |
| 2013-01-03 | -1.294524 | 0.413738 | 0.276662 | -0.472035 |
| 2013-01-04 | -0.013960 | -0.362543 | -0.006154 | -0.923061 |
| 2013-01-05 | 0.895717 | 0.805244 | -1.206412 | 2.565646 |

```
In [4]: df1.loc[2:3]
```

```
TypeError: cannot do slice indexing on <class 'pandas.tseries.index.DatetimeIndex'> with these inde
```

String likes in slicing *can* be convertible to the type of the index and lead to natural slicing.

```
In [36]: df1.loc['20130102':'20130104']
```

```
Out[36]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2013-01-02 | 0.357021 | -0.674600 | -1.776904 | -0.968914 |
| 2013-01-03 | -1.294524 | 0.413738 | 0.276662 | -0.472035 |
| 2013-01-04 | -0.013960 | -0.362543 | -0.006154 | -0.923061 |

pandas provides a suite of methods in order to have **purely label based indexing**. This is a strict inclusion based protocol. **At least 1** of the labels for which you ask, must be in the index or a `KeyError` will be raised! When slicing, the start bound is *included*, **AND** the stop bound is *included*. Integers are valid labels, but they refer to the label **and not the position**.

The `.loc` attribute is the primary access method. The following are valid inputs:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index. This use is **not** an integer position along the index)
- A list or array of labels ['a', 'b', 'c']
- A slice object with labels 'a' : 'f' (note that contrary to usual python slices, **both** the start and the stop are included!)
- A boolean array

```
In [37]: s1 = Series(np.random.randn(6), index=list('abcdef'))
```

```
In [38]: s1
```

```
Out[38]:
```

```
a    1.431256
b    1.340309
c   -1.170299
d   -0.226169
e    0.410835
f    0.813850
dtype: float64
```

```
In [39]: s1.loc['c':]
```

```
Out[39]:
```

```
c    -1.170299
d    -0.226169
e     0.410835
f     0.813850
dtype: float64
```

```
In [40]: s1.loc['b']
Out[40]: 1.3403088497993827
```

Note that setting works as well:

```
In [41]: s1.loc['c':] = 0
```

```
In [42]: s1
Out[42]:
a    1.431256
b    1.340309
c    0.000000
d    0.000000
e    0.000000
f    0.000000
dtype: float64
```

With a DataFrame

```
In [43]: df1 = DataFrame(np.random.randn(6,4),
.....:                  index=list('abcdef'),
.....:                  columns=list('ABCD'))
.....:
```

```
In [44]: df1
Out[44]:
      A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
c  1.024180  0.569605  0.875906 -2.211372
d  0.974466 -2.006747 -0.410001 -0.078638
e  0.545952 -1.219217 -1.226825  0.769804
f -1.281247 -0.727707 -0.121306 -0.097883
```

```
In [45]: df1.loc[['a','b','d'],:]
Out[45]:
      A         B         C         D
a  0.132003 -0.827317 -0.076467 -1.187678
b  1.130127 -1.436737 -1.413681  1.607920
d  0.974466 -2.006747 -0.410001 -0.078638
```

Accessing via label slices

```
In [46]: df1.loc['d':,'A':'C']
Out[46]:
      A         B         C
d  0.974466 -2.006747 -0.410001
e  0.545952 -1.219217 -1.226825
f -1.281247 -0.727707 -0.121306
```

For getting a cross section using a label (equiv to `df.xs('a')`)

```
In [47]: df1.loc['a']
Out[47]:
A    0.132003
B   -0.827317
C   -0.076467
D   -1.187678
Name: a, dtype: float64
```

For getting values with a boolean array

```
In [48]: df1.loc['a']>0
Out[48]:
A    True
B   False
C   False
D   False
Name: a, dtype: bool
```

```
In [49]: df1.loc[:,df1.loc['a']>0]
Out[49]:
      A
a  0.132003
b  1.130127
c  1.024180
d  0.974466
e  0.545952
f -1.281247
```

For getting a value explicitly (equiv to deprecated `df.get_value('a', 'A')`)

```
# this is also equivalent to ``df1.at['a', 'A']``
In [50]: df1.loc['a', 'A']
Out[50]: 0.13200317033032927
```

13.7 Selection By Position

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See [Returning a View versus Copy](#)

pandas provides a suite of methods in order to get **purely integer based indexing**. The semantics follow closely python and numpy slicing. These are 0-based indexing. When slicing, the start bounds is *included*, while the upper bound is *excluded*. Trying to use a non-integer, even a **valid** label will raise a `IndexError`.

The `.iloc` attribute is the primary access method. The following are valid inputs:

- An integer e.g. 5
- A list or array of integers [4, 3, 0]
- A slice object with ints 1:7
- A boolean array

```
In [51]: s1 = Series(np.random.randn(5), index=list(range(0,10,2)))
```

```
In [52]: s1
Out[52]:
```

```

0    0.695775
2    0.341734
4    0.959726
6   -1.110336
8   -0.619976
dtype: float64

```

```
In [53]: s1.iloc[:3]
```

```

Out[53]:
0    0.695775
2    0.341734
4    0.959726
dtype: float64

```

```
In [54]: s1.iloc[3]
```

```
Out[54]: -1.1103361028911667
```

Note that setting works as well:

```
In [55]: s1.iloc[:3] = 0
```

```
In [56]: s1
```

```

Out[56]:
0    0.000000
2    0.000000
4    0.000000
6   -1.110336
8   -0.619976
dtype: float64

```

With a DataFrame

```

In [57]: df1 = DataFrame(np.random.randn(6,4),
.....:                  index=list(range(0,12,2)),
.....:                  columns=list(range(0,8,2)))
.....:

```

```
In [58]: df1
```

```

Out[58]:
      0         2         4         6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161
6 -0.826591 -0.345352  1.314232  0.690579
8  0.995761  2.396780  0.014871  3.357427
10 -0.317441 -1.236269  0.896171 -0.487602

```

Select via integer slicing

```
In [59]: df1.iloc[:3]
```

```

Out[59]:
      0         2         4         6
0  0.149748 -0.732339  0.687738  0.176444
2  0.403310 -0.154951  0.301624 -2.179861
4 -1.369849 -0.954208  1.462696 -1.743161

```

```
In [60]: df1.iloc[1:5,2:4]
```

```

Out[60]:
      4         6
2  0.301624 -2.179861
4  1.462696 -1.743161

```

```
2  0.301624 -2.179861
4  1.462696 -1.743161
6  1.314232  0.690579
8  0.014871  3.357427
```

Select via integer list

```
In [61]: df1.iloc[[1,3,5],[1,3]]
Out[61]:
```

| | 2 | 6 |
|----|-----------|-----------|
| 2 | -0.154951 | -2.179861 |
| 6 | -0.345352 | 0.690579 |
| 10 | -1.236269 | -0.487602 |

For slicing rows explicitly (equiv to deprecated `df.irow(slice(1,3))`).

```
In [62]: df1.iloc[1:3,:]
Out[62]:
```

| | 0 | 2 | 4 | 6 |
|---|-----------|-----------|----------|-----------|
| 2 | 0.403310 | -0.154951 | 0.301624 | -2.179861 |
| 4 | -1.369849 | -0.954208 | 1.462696 | -1.743161 |

For slicing columns explicitly (equiv to deprecated `df.icol(slice(1,3))`).

```
In [63]: df1.iloc[:,1:3]
Out[63]:
```

| | 2 | 4 |
|----|-----------|----------|
| 0 | -0.732339 | 0.687738 |
| 2 | -0.154951 | 0.301624 |
| 4 | -0.954208 | 1.462696 |
| 6 | -0.345352 | 1.314232 |
| 8 | 2.396780 | 0.014871 |
| 10 | -1.236269 | 0.896171 |

For getting a scalar via integer position (equiv to deprecated `df.get_value(1,1)`)

```
# this is also equivalent to `df1.iat[1,1]`
In [64]: df1.iloc[1,1]
Out[64]: -0.15495077442490321
```

For getting a cross section using an integer position (equiv to `df.xs(1)`)

```
In [65]: df1.iloc[1]
Out[65]:
```

| | |
|---|-----------|
| 0 | 0.403310 |
| 2 | -0.154951 |
| 4 | 0.301624 |
| 6 | -2.179861 |

Name: 2, dtype: float64

Out of range slice indexes are handled gracefully just as in Python/Numpy.

```
# these are allowed in python/numpy.
# Only works in Pandas starting from v0.14.0.
In [66]: x = list('abcdef')

In [67]: x
Out[67]: ['a', 'b', 'c', 'd', 'e', 'f']

In [68]: x[4:10]
```

```
Out[68]: ['e', 'f']
```

```
In [69]: x[8:10]
```

```
Out[69]: []
```

```
In [70]: s = Series(x)
```

```
In [71]: s
```

```
Out[71]:
```

```
0    a
1    b
2    c
3    d
4    e
5    f
dtype: object
```

```
In [72]: s.iloc[4:10]
```

```
Out[72]:
```

```
4    e
5    f
dtype: object
```

```
In [73]: s.iloc[8:10]
```

```
Out[73]: Series([], dtype: object)
```

Note: Prior to v0.14.0, `iloc` would not accept out of bounds indexers for slices, e.g. a value that exceeds the length of the object being indexed.

Note that this could result in an empty axis (e.g. an empty DataFrame being returned)

```
In [74]: df1 = DataFrame(np.random.randn(5,2), columns=list('AB'))
```

```
In [75]: df1
```

```
Out[75]:
```

```
      A      B
0 -0.082240 -2.182937
1  0.380396  0.084844
2  0.432390  1.519970
3 -0.493662  0.600178
4  0.274230  0.132885
```

```
In [76]: df1.iloc[:,2:3]
```

```
Out[76]:
```

```
Empty DataFrame
Columns: []
Index: [0, 1, 2, 3, 4]
```

```
In [77]: df1.iloc[:,1:3]
```

```
Out[77]:
```

```
      B
0 -2.182937
1  0.084844
2  1.519970
3  0.600178
4  0.132885
```

```
In [78]: df1.iloc[4:6]
```

```
Out[78]:
```

| | A | B |
|---|---------|----------|
| 4 | 0.27423 | 0.132885 |

A single indexer that is out of bounds will raise an `IndexError`. A list of indexers where any element is out of bounds will raise an `IndexError`

```
df1.iloc[[4,5,6]]
IndexError: positional indexers are out-of-bounds

df1.iloc[:,4]
IndexError: single positional indexer is out-of-bounds
```

13.8 Selecting Random Samples

A random selection of rows or columns from a Series, DataFrame, or Panel with the `sample()` method. The method will sample rows by default, and accepts a specific number of rows/columns to return, or a fraction of rows.

```
In [79]: s = Series([0,1,2,3,4,5])

# When no arguments are passed, returns 1 row.
In [80]: s.sample()
Out[80]:
3      3
dtype: int64

# One may specify either a number of rows:
In [81]: s.sample(n=3)
Out[81]:
5      5
1      1
0      0
dtype: int64

# Or a fraction of the rows:
In [82]: s.sample(frac=0.5)
Out[82]:
1      1
3      3
0      0
dtype: int64
```

By default, `sample` will return each row at most once, but one can also sample with replacement using the `replace` option:

```
In [83]: s = Series([0,1,2,3,4,5])

# Without replacement (default):
In [84]: s.sample(n=6, replace=False)
Out[84]:
0      0
5      5
4      4
3      3
2      2
1      1
```

```
dtype: int64
```

```
# With replacement:
In [85]: s.sample(n=6, replace=True)
Out[85]:
3      3
4      4
1      1
0      0
4      4
0      0
dtype: int64
```

By default, each row has an equal probability of being selected, but if you want rows to have different probabilities, you can pass the `sample` function sampling weights as `weights`. These weights can be a list, a numpy array, or a Series, but they must be of the same length as the object you are sampling. Missing values will be treated as a weight of zero, and inf values are not allowed. If weights do not sum to 1, they will be re-normalized by dividing all weights by the sum of the weights. For example:

```
In [86]: s = Series([0,1,2,3,4,5])

In [87]: example_weights = [0, 0, 0.2, 0.2, 0.2, 0.4]

In [88]: s.sample(n=3, weights=example_weights)
Out[88]:
4      4
5      5
3      3
dtype: int64

# Weights will be re-normalized automatically
In [89]: example_weights2 = [0.5, 0, 0, 0, 0, 0]

In [90]: s.sample(n=1, weights=example_weights2)
Out[90]:
0      0
dtype: int64
```

When applied to a DataFrame, you can use a column of the DataFrame as sampling weights (provided you are sampling rows and not columns) by simply passing the name of the column as a string.

```
In [91]: df2 = DataFrame({'col1':[9,8,7,6], 'weight_column':[0.5, 0.4, 0.1, 0]})

In [92]: df2.sample(n = 3, weights = 'weight_column')
Out[92]:
   col1  weight_column
2      7             0.1
0      9             0.5
1      8             0.4
```

`sample` also allows users to sample columns instead of rows using the `axis` argument.

```
In [93]: df3 = DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})

In [94]: df3.sample(n=1, axis=1)
Out[94]:
   col2
0      2
1      3
```

2 4

Finally, one can also set a seed for sample's random number generator using the `random_state` argument, which will accept either an integer (as a seed) or a numpy `RandomState` object.

```
In [95]: df4 = DataFrame({'col1':[1,2,3], 'col2':[2,3,4]})
```

```
# With a given seed, the sample will always draw the same rows.
```

```
In [96]: df4.sample(n=2, random_state=2)
```

```
Out[96]:
```

| | col1 | col2 |
|---|------|------|
| 2 | 3 | 4 |
| 1 | 2 | 3 |

```
In [97]: df4.sample(n=2, random_state=2)
```

```
Out[97]:
```

| | col1 | col2 |
|---|------|------|
| 2 | 3 | 4 |
| 1 | 2 | 3 |

13.9 Setting With Enlargement

New in version 0.13.

The `.loc/.ix/[]` operations can perform enlargement when setting a non-existent key for that axis.

In the `Series` case this is effectively an appending operation

```
In [98]: se = Series([1,2,3])
```

```
In [99]: se
```

```
Out[99]:
```

| | |
|---|---|
| 0 | 1 |
| 1 | 2 |
| 2 | 3 |

dtype: int64

```
In [100]: se[5] = 5.
```

```
In [101]: se
```

```
Out[101]:
```

| | |
|---|---|
| 0 | 1 |
| 1 | 2 |
| 2 | 3 |
| 5 | 5 |

dtype: float64

A `DataFrame` can be enlarged on either axis via `.loc`

```
In [102]: dfi = DataFrame(np.arange(6).reshape(3,2),
.....:                    columns=['A', 'B'])
.....:
```

```
In [103]: dfi
```

```
Out[103]:
```

| | A | B |
|---|---|---|
| 0 | 0 | 1 |

```
1  2  3
2  4  5
```

```
In [104]: dfi.loc[:, 'C'] = dfi.loc[:, 'A']
```

```
In [105]: dfi
```

```
Out[105]:
```

```
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
```

This is like an append operation on the DataFrame.

```
In [106]: dfi.loc[3] = 5
```

```
In [107]: dfi
```

```
Out[107]:
```

```
   A  B  C
0  0  1  0
1  2  3  2
2  4  5  4
3  5  5  5
```

13.10 Fast scalar value getting and setting

Since indexing with `[]` must handle a lot of cases (single-label access, slicing, boolean indexing, etc.), it has a bit of overhead in order to figure out what you're asking for. If you only want to access a scalar value, the fastest way is to use the `at` and `iat` methods, which are implemented on all of the data structures.

Similarly to `loc`, `at` provides **label** based scalar lookups, while, `iat` provides **integer** based lookups analogously to `iloc`

```
In [108]: s.iat[5]
```

```
Out[108]: 5
```

```
In [109]: df.at[dates[5], 'A']
```

```
Out[109]: 0.11364840968888545
```

```
In [110]: df.iat[3, 0]
```

```
Out[110]: -0.70677113363008437
```

You can also set using these same indexers.

```
In [111]: df.at[dates[5], 'E'] = 7
```

```
In [112]: df.iat[3, 0] = 7
```

`at` may enlarge the object in-place as above if the indexer is missing.

```
In [113]: df.at[dates[-1]+1, 0] = 7
```

```
In [114]: df
```

```
Out[114]:
```

| | A | B | C | D | E | 0 |
|------------|-----------|----------|-----------|-----------|-----|-----|
| 2000-01-01 | -0.282863 | 0.469112 | -1.509059 | -1.135632 | NaN | NaN |
| 2000-01-02 | -0.173215 | 1.212112 | 0.119209 | -1.044236 | NaN | NaN |

```
2000-01-03 -2.104569 -0.861849 -0.494929 1.071804 NaN NaN
2000-01-04 7.000000 0.721555 -1.039575 0.271860 NaN NaN
2000-01-05 0.567020 -0.424972 0.276232 -1.087401 NaN NaN
2000-01-06 0.113648 -0.673690 -1.478427 0.524988 7 NaN
2000-01-07 0.577046 0.404705 -1.715002 -1.039268 NaN NaN
2000-01-08 -1.157892 -0.370647 -1.344312 0.844885 NaN NaN
2000-01-09 NaN NaN NaN NaN NaN 7
```

13.11 Boolean indexing

Another common operation is the use of boolean vectors to filter the data. The operators are: `|` for or, `&` for and, and `~` for not. These **must** be grouped by using parentheses.

Using a boolean vector to index a Series works exactly as in a numpy ndarray:

```
In [115]: s = Series(range(-3, 4))
```

```
In [116]: s
```

```
Out[116]:
0    -3
1    -2
2    -1
3     0
4     1
5     2
6     3
dtype: int32
```

```
In [117]: s[s > 0]
```

```
Out[117]:
4     1
5     2
6     3
dtype: int32
```

```
In [118]: s[(s < -1) | (s > 0.5)]
```

```
Out[118]:
0    -3
1    -2
4     1
5     2
6     3
dtype: int32
```

```
In [119]: s[~(s < 0)]
```

```
Out[119]:
3     0
4     1
5     2
6     3
dtype: int32
```

You may select rows from a DataFrame using a boolean vector the same length as the DataFrame's index (for example, something derived from one of the columns of the DataFrame):

```
In [120]: df[df['A'] > 0]
Out[120]:
```

| | A | B | C | D | E | 0 |
|------------|----------|-----------|-----------|-----------|-----|-----|
| 2000-01-04 | 7.000000 | 0.721555 | -1.039575 | 0.271860 | NaN | NaN |
| 2000-01-05 | 0.567020 | -0.424972 | 0.276232 | -1.087401 | NaN | NaN |
| 2000-01-06 | 0.113648 | -0.673690 | -1.478427 | 0.524988 | 7 | NaN |
| 2000-01-07 | 0.577046 | 0.404705 | -1.715002 | -1.039268 | NaN | NaN |

List comprehensions and map method of Series can also be used to produce more complex criteria:

```
In [121]: df2 = DataFrame({'a' : ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
.....:                  'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
.....:                  'c' : randn(7)})
.....:
```

```
# only want 'two' or 'three'
```

```
In [122]: criterion = df2['a'].map(lambda x: x.startswith('t'))
```

```
In [123]: df2[criterion]
Out[123]:
```

| | a | b | c |
|---|-------|---|-----------|
| 2 | two | y | 1.450520 |
| 3 | three | x | 0.206053 |
| 4 | two | y | -0.251905 |

```
# equivalent but slower
```

```
In [124]: df2[[x.startswith('t') for x in df2['a']]]
```

```
Out[124]:
```

| | a | b | c |
|---|-------|---|-----------|
| 2 | two | y | 1.450520 |
| 3 | three | x | 0.206053 |
| 4 | two | y | -0.251905 |

```
# Multiple criteria
```

```
In [125]: df2[criterion & (df2['b'] == 'x')]
```

```
Out[125]:
```

| | a | b | c |
|---|-------|---|----------|
| 3 | three | x | 0.206053 |

Note, with the choice methods *Selection by Label*, *Selection by Position*, and *Advanced Indexing* you may select along more than one axis using boolean vectors combined with other indexing expressions.

```
In [126]: df2.loc[criterion & (df2['b'] == 'x'), 'b':'c']
```

```
Out[126]:
```

| | b | c |
|---|---|----------|
| 3 | x | 0.206053 |

13.12 Indexing with isin

Consider the `isin` method of Series, which returns a boolean vector that is true wherever the Series elements exist in the passed list. This allows you to select rows where one or more columns have values you want:

```
In [127]: s = Series(np.arange(5), index=np.arange(5)[::-1], dtype='int64')
```

```
In [128]: s
```

```
Out[128]:
```

| | |
|---|---|
| 4 | 0 |
|---|---|

```
3    1
2    2
1    3
0    4
dtype: int64
```

```
In [129]: s.isin([2, 4, 6])
Out[129]:
4    False
3    False
2     True
1    False
0     True
dtype: bool
```

```
In [130]: s[s.isin([2, 4, 6])]
Out[130]:
2    2
0    4
dtype: int64
```

The same method is available for `Index` objects and is useful for the cases when you don't know which of the sought labels are in fact present:

```
In [131]: s[s.index.isin([2, 4, 6])]
Out[131]:
4    0
2    2
dtype: int64
```

```
# compare it to the following
In [132]: s[[2, 4, 6]]
Out[132]:
2    2
4    0
6   NaN
dtype: float64
```

In addition to that, `MultiIndex` allows selecting a separate level to use in the membership check:

```
In [133]: s_mi = Series(np.arange(6),
.....:                  index=pd.MultiIndex.from_product([[0, 1], ['a', 'b', 'c']]))
.....:
```

```
In [134]: s_mi
Out[134]:
0  a    0
   b    1
   c    2
1  a    3
   b    4
   c    5
dtype: int32
```

```
In [135]: s_mi.iloc[s_mi.index.isin([(1, 'a'), (2, 'b'), (0, 'c')])]
Out[135]:
0  c    2
1  a    3
dtype: int32
```

```
In [136]: s_mi.iloc[s_mi.index.isin(['a', 'c', 'e'], level=1)]
Out[136]:
0  a    0
   c    2
1  a    3
   c    5
dtype: int32
```

DataFrame also has an `isin` method. When calling `isin`, pass a set of values as either an array or dict. If values is an array, `isin` returns a DataFrame of booleans that is the same shape as the original DataFrame, with True wherever the element is in the sequence of values.

```
In [137]: df = DataFrame({'vals': [1, 2, 3, 4], 'ids': ['a', 'b', 'f', 'n'],
.....:                  'ids2': ['a', 'n', 'c', 'n']})
.....:
```

```
In [138]: values = ['a', 'b', 1, 3]
```

```
In [139]: df.isin(values)
```

```
Out[139]:
   ids  ids2  vals
0  True  True  True
1  True False False
2 False False  True
3 False False False
```

Oftentimes you'll want to match certain values with certain columns. Just make values a dict where the key is the column, and the value is a list of items you want to check for.

```
In [140]: values = {'ids': ['a', 'b'], 'vals': [1, 3]}
```

```
In [141]: df.isin(values)
```

```
Out[141]:
   ids  ids2  vals
0  True False  True
1  True False False
2 False False  True
3 False False False
```

Combine DataFrame's `isin` with the `any()` and `all()` methods to quickly select subsets of your data that meet a given criteria. To select a row where each column meets its own criterion:

```
In [142]: values = {'ids': ['a', 'b'], 'ids2': ['a', 'c'], 'vals': [1, 3]}
```

```
In [143]: row_mask = df.isin(values).all(1)
```

```
In [144]: df[row_mask]
```

```
Out[144]:
   ids ids2  vals
0   a    a     1
```

13.13 The `where()` Method and Masking

Selecting values from a Series with a boolean vector generally returns a subset of the data. To guarantee that selection output has the same shape as the original data, you can use the `where` method in Series and DataFrame.

To return only the selected rows

```
In [145]: s[s > 0]
Out[145]:
3    1
2    2
1    3
0    4
dtype: int64
```

To return a Series of the same shape as the original

```
In [146]: s.where(s > 0)
Out[146]:
4    NaN
3     1
2     2
1     3
0     4
dtype: float64
```

Selecting values from a DataFrame with a boolean criterion now also preserves input data shape. `where` is used under the hood as the implementation. Equivalent is `df.where(df < 0)`

```
In [147]: df[df < 0]
Out[147]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | NaN | NaN | -0.863838 | NaN |
| 2000-01-02 | -1.048089 | -0.025747 | -0.988387 | NaN |
| 2000-01-03 | NaN | NaN | NaN | -0.055758 |
| 2000-01-04 | NaN | -0.489682 | NaN | -0.034571 |
| 2000-01-05 | -2.484478 | -0.281461 | NaN | NaN |
| 2000-01-06 | NaN | -0.977349 | NaN | -0.064034 |
| 2000-01-07 | -1.282782 | NaN | -1.071357 | NaN |
| 2000-01-08 | NaN | NaN | NaN | -0.744471 |

In addition, `where` takes an optional `other` argument for replacement of values where the condition is False, in the returned copy.

```
In [148]: df.where(df < 0, -df)
Out[148]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | -1.266143 | -0.299368 | -0.863838 | -0.408204 |
| 2000-01-02 | -1.048089 | -0.025747 | -0.988387 | -0.094055 |
| 2000-01-03 | -1.262731 | -1.289997 | -0.082423 | -0.055758 |
| 2000-01-04 | -0.536580 | -0.489682 | -0.369374 | -0.034571 |
| 2000-01-05 | -2.484478 | -0.281461 | -0.030711 | -0.109121 |
| 2000-01-06 | -1.126203 | -0.977349 | -1.474071 | -0.064034 |
| 2000-01-07 | -1.282782 | -0.781836 | -1.071357 | -0.441153 |
| 2000-01-08 | -2.353925 | -0.583787 | -0.221471 | -0.744471 |

You may wish to set values based on some boolean criteria. This can be done intuitively like so:

```
In [149]: s2 = s.copy()

In [150]: s2[s2 < 0] = 0

In [151]: s2
Out[151]:
4    0
3    1
```

```
2    2
1    3
0    4
dtype: int64
```

```
In [152]: df2 = df.copy()
```

```
In [153]: df2[df2 < 0] = 0
```

```
In [154]: df2
```

```
Out [154]:
```

| | A | B | C | D |
|------------|----------|----------|----------|----------|
| 2000-01-01 | 1.266143 | 0.299368 | 0.000000 | 0.408204 |
| 2000-01-02 | 0.000000 | 0.000000 | 0.000000 | 0.094055 |
| 2000-01-03 | 1.262731 | 1.289997 | 0.082423 | 0.000000 |
| 2000-01-04 | 0.536580 | 0.000000 | 0.369374 | 0.000000 |
| 2000-01-05 | 0.000000 | 0.000000 | 0.030711 | 0.109121 |
| 2000-01-06 | 1.126203 | 0.000000 | 1.474071 | 0.000000 |
| 2000-01-07 | 0.000000 | 0.781836 | 0.000000 | 0.441153 |
| 2000-01-08 | 2.353925 | 0.583787 | 0.221471 | 0.000000 |

By default, `where` returns a modified copy of the data. There is an optional parameter `inplace` so that the original data can be modified without creating a copy:

```
In [155]: df_orig = df.copy()
```

```
In [156]: df_orig.where(df > 0, -df, inplace=True);
```

```
In [157]: df_orig
```

```
Out [157]:
```

| | A | B | C | D |
|------------|----------|----------|----------|----------|
| 2000-01-01 | 1.266143 | 0.299368 | 0.863838 | 0.408204 |
| 2000-01-02 | 1.048089 | 0.025747 | 0.988387 | 0.094055 |
| 2000-01-03 | 1.262731 | 1.289997 | 0.082423 | 0.055758 |
| 2000-01-04 | 0.536580 | 0.489682 | 0.369374 | 0.034571 |
| 2000-01-05 | 2.484478 | 0.281461 | 0.030711 | 0.109121 |
| 2000-01-06 | 1.126203 | 0.977349 | 1.474071 | 0.064034 |
| 2000-01-07 | 1.282782 | 0.781836 | 1.071357 | 0.441153 |
| 2000-01-08 | 2.353925 | 0.583787 | 0.221471 | 0.744471 |

alignment

Furthermore, `where` aligns the input boolean condition (ndarray or DataFrame), such that partial selection with setting is possible. This is analogous to partial setting via `.ix` (but on the contents rather than the axis labels)

```
In [158]: df2 = df.copy()
```

```
In [159]: df2[ df2[1:4] > 0 ] = 3
```

```
In [160]: df2
```

```
Out [160]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | 1.266143 | 0.299368 | -0.863838 | 0.408204 |
| 2000-01-02 | -1.048089 | -0.025747 | -0.988387 | 3.000000 |
| 2000-01-03 | 3.000000 | 3.000000 | 3.000000 | -0.055758 |
| 2000-01-04 | 3.000000 | -0.489682 | 3.000000 | -0.034571 |
| 2000-01-05 | -2.484478 | -0.281461 | 0.030711 | 0.109121 |
| 2000-01-06 | 1.126203 | -0.977349 | 1.474071 | -0.064034 |
| 2000-01-07 | -1.282782 | 0.781836 | -1.071357 | 0.441153 |

```
2000-01-08    2.353925    0.583787    0.221471   -0.744471
```

New in version 0.13.

Where can also accept `axis` and `level` parameters to align the input when performing the where.

```
In [161]: df2 = df.copy()
```

```
In [162]: df2.where(df2>0,df2['A'],axis='index')
```

```
Out[162]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|----------|
| 2000-01-01 | 1.266143 | 0.299368 | 1.266143 | 0.408204 |
| 2000-01-02 | -1.048089 | -1.048089 | -1.048089 | 0.094055 |
| 2000-01-03 | 1.262731 | 1.289997 | 0.082423 | 1.262731 |
| 2000-01-04 | 0.536580 | 0.536580 | 0.369374 | 0.536580 |
| 2000-01-05 | -2.484478 | -2.484478 | 0.030711 | 0.109121 |
| 2000-01-06 | 1.126203 | 1.126203 | 1.474071 | 1.126203 |
| 2000-01-07 | -1.282782 | 0.781836 | -1.282782 | 0.441153 |
| 2000-01-08 | 2.353925 | 0.583787 | 0.221471 | 2.353925 |

This is equivalent (but faster than) the following.

```
In [163]: df2 = df.copy()
```

```
In [164]: df.apply(lambda x, y: x.where(x>0,y), y=df['A'])
```

```
Out[164]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|----------|
| 2000-01-01 | 1.266143 | 0.299368 | 1.266143 | 0.408204 |
| 2000-01-02 | -1.048089 | -1.048089 | -1.048089 | 0.094055 |
| 2000-01-03 | 1.262731 | 1.289997 | 0.082423 | 1.262731 |
| 2000-01-04 | 0.536580 | 0.536580 | 0.369374 | 0.536580 |
| 2000-01-05 | -2.484478 | -2.484478 | 0.030711 | 0.109121 |
| 2000-01-06 | 1.126203 | 1.126203 | 1.474071 | 1.126203 |
| 2000-01-07 | -1.282782 | 0.781836 | -1.282782 | 0.441153 |
| 2000-01-08 | 2.353925 | 0.583787 | 0.221471 | 2.353925 |

mask

mask is the inverse boolean operation of where.

```
In [165]: s.mask(s >= 0)
```

```
Out[165]:
```

| | |
|---|-----|
| 4 | NaN |
| 3 | NaN |
| 2 | NaN |
| 1 | NaN |
| 0 | NaN |

dtype: float64

```
In [166]: df.mask(df >= 0)
```

```
Out[166]:
```

| | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| 2000-01-01 | NaN | NaN | -0.863838 | NaN |
| 2000-01-02 | -1.048089 | -0.025747 | -0.988387 | NaN |
| 2000-01-03 | NaN | NaN | NaN | -0.055758 |
| 2000-01-04 | NaN | -0.489682 | NaN | -0.034571 |
| 2000-01-05 | -2.484478 | -0.281461 | NaN | NaN |
| 2000-01-06 | NaN | -0.977349 | NaN | -0.064034 |
| 2000-01-07 | -1.282782 | NaN | -1.071357 | NaN |
| 2000-01-08 | NaN | NaN | NaN | -0.744471 |

13.14 The `query()` Method (Experimental)

New in version 0.13.

`DataFrame` objects have a `query()` method that allows selection using an expression.

You can get the value of the frame where column `b` has values between the values of columns `a` and `c`. For example:

```
In [167]: n = 10
```

```
In [168]: df = DataFrame(rand(n, 3), columns=list('abc'))
```

```
In [169]: df
```

```
Out[169]:
```

| | a | b | c |
|---|----------|----------|----------|
| 0 | 0.191519 | 0.622109 | 0.437728 |
| 1 | 0.785359 | 0.779976 | 0.272593 |
| 2 | 0.276464 | 0.801872 | 0.958139 |
| 3 | 0.875933 | 0.357817 | 0.500995 |
| 4 | 0.683463 | 0.712702 | 0.370251 |
| 5 | 0.561196 | 0.503083 | 0.013768 |
| 6 | 0.772827 | 0.882641 | 0.364886 |
| 7 | 0.615396 | 0.075381 | 0.368824 |
| 8 | 0.933140 | 0.651378 | 0.397203 |
| 9 | 0.788730 | 0.316836 | 0.568099 |

```
# pure python
```

```
In [170]: df[(df.a < df.b) & (df.b < df.c)]
```

```
Out[170]:
```

| | a | b | c |
|---|----------|----------|----------|
| 2 | 0.276464 | 0.801872 | 0.958139 |

```
# query
```

```
In [171]: df.query('(a < b) & (b < c)')
```

```
Out[171]:
```

| | a | b | c |
|---|----------|----------|----------|
| 2 | 0.276464 | 0.801872 | 0.958139 |

Do the same thing but fall back on a named index if there is no column with the name `a`.

```
In [172]: df = DataFrame(randint(n / 2, size=(n, 2)), columns=list('bc'))
```

```
In [173]: df.index.name = 'a'
```

```
In [174]: df
```

```
Out[174]:
```

| a | b | c |
|---|---|---|
| 0 | 2 | 3 |
| 1 | 4 | 1 |
| 2 | 4 | 0 |
| 3 | 4 | 1 |
| 4 | 1 | 4 |
| 5 | 1 | 4 |
| 6 | 0 | 1 |
| 7 | 0 | 0 |
| 8 | 4 | 0 |
| 9 | 4 | 2 |

```
In [175]: df.query('a < b and b < c')
Out[175]:
   b  c
a
0  2  3
```

If instead you don't want to or cannot name your index, you can use the name `index` in your query expression:

```
In [176]: df = DataFrame(randint(n, size=(n, 2)), columns=list('bc'))

In [177]: df
Out[177]:
   b  c
0  3  1
1  2  5
2  2  5
3  6  7
4  4  3
5  5  6
6  4  6
7  2  4
8  2  7
9  9  7
```

```
In [178]: df.query('index < b < c')
Out[178]:
   b  c
1  2  5
3  6  7
```

Note: If the name of your index overlaps with a column name, the column name is given precedence. For example,

```
In [179]: df = DataFrame({'a': randint(5, size=5)})

In [180]: df.index.name = 'a'

In [181]: df.query('a > 2') # uses the column 'a', not the index
Out[181]:
   a
a
0  3
3  4
```

You can still use the index in a query expression by using the special identifier `'index'`:

```
In [182]: df.query('index > 2')
Out[182]:
   a
a
3  4
4  1
```

If for some reason you have a column named `index`, then you can refer to the index as `ilevel_0` as well, but at this point you should consider renaming your columns to something less ambiguous.

13.14.1 MultiIndex query() Syntax

You can also use the levels of a DataFrame with a MultiIndex as if they were columns in the frame:

```
In [183]: import pandas.util.testing as tm

In [184]: n = 10

In [185]: colors = tm.choice(['red', 'green'], size=n)

In [186]: foods = tm.choice(['eggs', 'ham'], size=n)

In [187]: colors
Out[187]:
array(['red', 'green', 'red', 'green', 'red', 'green', 'red', 'green',
       'green', 'green'],
      dtype='<S5')

In [188]: foods
Out[188]:
array(['ham', 'eggs', 'ham', 'ham', 'ham', 'eggs', 'eggs', 'eggs', 'ham',
       'eggs'],
      dtype='<S4')

In [189]: index = MultiIndex.from_arrays([colors, foods], names=['color', 'food'])

In [190]: df = DataFrame(randn(n, 2), index=index)

In [191]: df
Out[191]:
```

| | | 0 | 1 |
|-------|------|-----------|-----------|
| color | food | | |
| red | ham | 0.157622 | -0.293555 |
| green | eggs | 0.111560 | 0.597679 |
| red | ham | -1.270093 | 0.120949 |
| green | ham | -0.193898 | 1.804172 |
| red | ham | -0.234694 | 0.939908 |
| green | eggs | -0.171520 | -0.153055 |
| red | eggs | -0.363095 | -0.067318 |
| green | eggs | 1.444721 | 0.325771 |
| | ham | -0.855732 | -0.697595 |
| | eggs | -0.276134 | -1.258759 |

```

In [192]: df.query('color == "red"')
Out[192]:
```

| | | 0 | 1 |
|-------|------|-----------|-----------|
| color | food | | |
| red | ham | 0.157622 | -0.293555 |
| | ham | -1.270093 | 0.120949 |
| | ham | -0.234694 | 0.939908 |
| | eggs | -0.363095 | -0.067318 |

If the levels of the MultiIndex are unnamed, you can refer to them using special names:

```
In [193]: df.index.names = [None, None]

In [194]: df
Out[194]:
```

| | | 0 | 1 |
|--|--|---|---|
|--|--|---|---|

```
red    ham    0.157622 -0.293555
green  eggs    0.111560  0.597679
red    ham   -1.270093  0.120949
green  ham   -0.193898  1.804172
red    ham   -0.234694  0.939908
green  eggs  -0.171520 -0.153055
red    eggs  -0.363095 -0.067318
green  eggs   1.444721  0.325771
        ham   -0.855732 -0.697595
        eggs  -0.276134 -1.258759
```

```
In [195]: df.query('ilevel_0 == "red"')
```

```
Out[195]:
```

| | 0 | 1 |
|---------|-----------|-----------|
| red ham | 0.157622 | -0.293555 |
| ham | -1.270093 | 0.120949 |
| ham | -0.234694 | 0.939908 |
| eggs | -0.363095 | -0.067318 |

The convention is `ilevel_0`, which means “index level 0” for the 0th level of the index.

13.14.2 `query()` Use Cases

A use case for `query()` is when you have a collection of `DataFrame` objects that have a subset of column names (or index levels/names) in common. You can pass the same query to both frames *without* having to specify which frame you’re interested in querying

```
In [196]: df = DataFrame(rand(n, 3), columns=list('abc'))
```

```
In [197]: df
```

```
Out[197]:
```

| | a | b | c |
|---|----------|----------|----------|
| 0 | 0.972113 | 0.046532 | 0.917354 |
| 1 | 0.158930 | 0.943383 | 0.763162 |
| 2 | 0.053878 | 0.254082 | 0.927973 |
| 3 | 0.838312 | 0.156925 | 0.690776 |
| 4 | 0.366946 | 0.937473 | 0.613365 |
| 5 | 0.699350 | 0.502946 | 0.711111 |
| 6 | 0.134386 | 0.828932 | 0.742846 |
| 7 | 0.457034 | 0.079103 | 0.373047 |
| 8 | 0.933636 | 0.418725 | 0.234212 |
| 9 | 0.572485 | 0.572111 | 0.416893 |

```
In [198]: df2 = DataFrame(rand(n + 2, 3), columns=df.columns)
```

```
In [199]: df2
```

```
Out[199]:
```

| | a | b | c |
|---|----------|----------|----------|
| 0 | 0.625883 | 0.220362 | 0.622059 |
| 1 | 0.477672 | 0.974342 | 0.772985 |
| 2 | 0.027139 | 0.221022 | 0.120328 |
| 3 | 0.175274 | 0.429462 | 0.657769 |
| 4 | 0.565899 | 0.569035 | 0.654196 |
| 5 | 0.368558 | 0.952385 | 0.196770 |
| 6 | 0.849930 | 0.960458 | 0.381118 |
| 7 | 0.330936 | 0.260923 | 0.665491 |
| 8 | 0.181795 | 0.376800 | 0.014259 |

```
9    0.339135  0.401351  0.467574
10   0.652106  0.997192  0.517462
11   0.403612  0.058447  0.045196
```

```
In [200]: expr = '0.0 <= a <= c <= 0.5'
```

```
In [201]: map(lambda frame: frame.query(expr), [df, df2])
```

```
Out[201]:
```

```
[Empty DataFrame
 Columns: [a, b, c]
 Index: [],
      a      b      c
2  0.027139  0.221022  0.120328
9  0.339135  0.401351  0.467574]
```

13.14.3 query() Python versus pandas Syntax Comparison

Full numpy-like syntax

```
In [202]: df = DataFrame(randint(n, size=(n, 3)), columns=list('abc'))
```

```
In [203]: df
```

```
Out[203]:
```

```
   a  b  c
0  5  3  8
1  8  8  1
2  3  6  8
3  9  1  5
4  8  4  1
5  1  1  2
6  3  4  2
7  1  9  4
8  0  0  2
9  1  2  5
```

```
In [204]: df.query('(a < b) & (b < c)')
```

```
Out[204]:
```

```
   a  b  c
2  3  6  8
9  1  2  5
```

```
In [205]: df[(df.a < df.b) & (df.b < df.c)]
```

```
Out[205]:
```

```
   a  b  c
2  3  6  8
9  1  2  5
```

Slightly nicer by removing the parentheses (by binding making comparison operators bind tighter than `&/|`)

```
In [206]: df.query('a < b & b < c')
```

```
Out[206]:
```

```
   a  b  c
2  3  6  8
9  1  2  5
```

Use English instead of symbols

```
In [207]: df.query('a < b and b < c')
```

```
Out[207]:
```

```
   a  b  c
2  3  6  8
9  1  2  5
```

Pretty close to how you might write it on paper

```
In [208]: df.query('a < b < c')
```

```
Out[208]:
```

```
   a  b  c
2  3  6  8
9  1  2  5
```

13.14.4 The `in` and `not in` operators

`query()` also supports special use of Python's `in` and `not in` comparison operators, providing a succinct syntax for calling the `isin` method of a `Series` or `DataFrame`.

```
# get all rows where columns "a" and "b" have overlapping values
```

```
In [209]: df = DataFrame({'a': list('aabbccddeeff'), 'b': list('aaaabbbbcccc'),
.....:                  'c': randint(5, size=12), 'd': randint(9, size=12)})
.....:
```

```
In [210]: df
```

```
Out[210]:
```

| | a | b | c | d |
|----|---|---|---|---|
| 0 | a | a | 1 | 7 |
| 1 | a | a | 0 | 0 |
| 2 | b | a | 0 | 2 |
| 3 | b | a | 2 | 8 |
| 4 | c | b | 0 | 4 |
| 5 | c | b | 0 | 8 |
| 6 | d | b | 1 | 3 |
| 7 | d | b | 1 | 2 |
| 8 | e | c | 4 | 4 |
| 9 | e | c | 3 | 7 |
| 10 | f | c | 2 | 7 |
| 11 | f | c | 0 | 0 |

```
In [211]: df.query('a in b')
```

```
Out[211]:
```

| | a | b | c | d |
|---|---|---|---|---|
| 0 | a | a | 1 | 7 |
| 1 | a | a | 0 | 0 |
| 2 | b | a | 0 | 2 |
| 3 | b | a | 2 | 8 |
| 4 | c | b | 0 | 4 |
| 5 | c | b | 0 | 8 |

```
# How you'd do it in pure Python
```

```
In [212]: df[df.a.isin(df.b)]
```

```
Out[212]:
```

| | a | b | c | d |
|---|---|---|---|---|
| 0 | a | a | 1 | 7 |
| 1 | a | a | 0 | 0 |
| 2 | b | a | 0 | 2 |
| 3 | b | a | 2 | 8 |
| 4 | c | b | 0 | 4 |

```
5 c b 0 8
```

```
In [213]: df.query('a not in b')
```

```
Out[213]:
   a b c d
6 d b 1 3
7 d b 1 2
8 e c 4 4
9 e c 3 7
10 f c 2 7
11 f c 0 0
```

```
# pure Python
```

```
In [214]: df[~df.a.isin(df.b)]
```

```
Out[214]:
   a b c d
6 d b 1 3
7 d b 1 2
8 e c 4 4
9 e c 3 7
10 f c 2 7
11 f c 0 0
```

You can combine this with other expressions for very succinct queries:

```
# rows where cols a and b have overlapping values and col c's values are less than col d's
```

```
In [215]: df.query('a in b and c < d')
```

```
Out[215]:
   a b c d
0 a a 1 7
2 b a 0 2
3 b a 2 8
4 c b 0 4
5 c b 0 8
```

```
# pure Python
```

```
In [216]: df[df.b.isin(df.a) & (df.c < df.d)]
```

```
Out[216]:
   a b c d
0 a a 1 7
2 b a 0 2
3 b a 2 8
4 c b 0 4
5 c b 0 8
6 d b 1 3
7 d b 1 2
9 e c 3 7
10 f c 2 7
```

Note: Note that `in` and `not in` are evaluated in Python, since `numexpr` has no equivalent of this operation. However, **only the `in/not in` expression itself** is evaluated in vanilla Python. For example, in the expression

```
df.query('a in b + c + d')
```

`(b + c + d)` is evaluated by `numexpr` and *then* the `in` operation is evaluated in plain Python. In general, any operations that can be evaluated using `numexpr` will be.

13.14.5 Special use of the == operator with list objects

Comparing a list of values to a column using ==/!= works similarly to in/not in

```
In [217]: df.query('b == ["a", "b", "c"]')
```

```
Out[217]:
```

| | a | b | c | d |
|----|---|---|---|---|
| 0 | a | a | 1 | 7 |
| 1 | a | a | 0 | 0 |
| 2 | b | a | 0 | 2 |
| 3 | b | a | 2 | 8 |
| 4 | c | b | 0 | 4 |
| 5 | c | b | 0 | 8 |
| 6 | d | b | 1 | 3 |
| 7 | d | b | 1 | 2 |
| 8 | e | c | 4 | 4 |
| 9 | e | c | 3 | 7 |
| 10 | f | c | 2 | 7 |
| 11 | f | c | 0 | 0 |

```
# pure Python
```

```
In [218]: df[df.b.isin(["a", "b", "c"])]
```

```
Out[218]:
```

| | a | b | c | d |
|----|---|---|---|---|
| 0 | a | a | 1 | 7 |
| 1 | a | a | 0 | 0 |
| 2 | b | a | 0 | 2 |
| 3 | b | a | 2 | 8 |
| 4 | c | b | 0 | 4 |
| 5 | c | b | 0 | 8 |
| 6 | d | b | 1 | 3 |
| 7 | d | b | 1 | 2 |
| 8 | e | c | 4 | 4 |
| 9 | e | c | 3 | 7 |
| 10 | f | c | 2 | 7 |
| 11 | f | c | 0 | 0 |

```
In [219]: df.query('c == [1, 2]')
```

```
Out[219]:
```

| | a | b | c | d |
|----|---|---|---|---|
| 0 | a | a | 1 | 7 |
| 3 | b | a | 2 | 8 |
| 6 | d | b | 1 | 3 |
| 7 | d | b | 1 | 2 |
| 10 | f | c | 2 | 7 |

```
In [220]: df.query('c != [1, 2]')
```

```
Out[220]:
```

| | a | b | c | d |
|----|---|---|---|---|
| 1 | a | a | 0 | 0 |
| 2 | b | a | 0 | 2 |
| 4 | c | b | 0 | 4 |
| 5 | c | b | 0 | 8 |
| 8 | e | c | 4 | 4 |
| 9 | e | c | 3 | 7 |
| 11 | f | c | 0 | 0 |

```
# using in/not in
```

```
In [221]: df.query('[1, 2] in c')
```

```
Out[221]:
```

```
   a  b  c  d
0  a  a  1  7
3  b  a  2  8
6  d  b  1  3
7  d  b  1  2
10 f  c  2  7
```

```
In [222]: df.query('[1, 2] not in c')
```

```
Out[222]:
```

```
   a  b  c  d
1  a  a  0  0
2  b  a  0  2
4  c  b  0  4
5  c  b  0  8
8  e  c  4  4
9  e  c  3  7
11 f  c  0  0
```

```
# pure Python
```

```
In [223]: df[df.c.isin([1, 2])]
```

```
Out[223]:
```

```
   a  b  c  d
0  a  a  1  7
3  b  a  2  8
6  d  b  1  3
7  d  b  1  2
10 f  c  2  7
```

13.14.6 Boolean Operators

You can negate boolean expressions with the word `not` or the `~` operator.

```
In [224]: df = DataFrame(rand(n, 3), columns=list('abc'))
```

```
In [225]: df['bools'] = rand(len(df)) > 0.5
```

```
In [226]: df.query('~bools')
```

```
Out[226]:
```

```
   a         b         c  bools
0  0.395827  0.035597  0.171689  False
2  0.582329  0.898831  0.435002  False
3  0.078368  0.224708  0.697626  False
5  0.877177  0.221076  0.287379  False
6  0.993264  0.861585  0.108845  False
```

```
In [227]: df.query('not bools')
```

```
Out[227]:
```

```
   a         b         c  bools
0  0.395827  0.035597  0.171689  False
2  0.582329  0.898831  0.435002  False
3  0.078368  0.224708  0.697626  False
5  0.877177  0.221076  0.287379  False
6  0.993264  0.861585  0.108845  False
```

```
In [228]: df.query('not bools') == df[~df.bools]
```

```
Out[228]:
```

```
      a      b      c bools
0  True  True  True   True
2  True  True  True   True
3  True  True  True   True
5  True  True  True   True
6  True  True  True   True
```

Of course, expressions can be arbitrarily complex too

```
# short query syntax
```

```
In [229]: shorter = df.query('a < b < c and (not bools) or bools > 2')
```

```
# equivalent in pure Python
```

```
In [230]: longer = df[(df.a < df.b) & (df.b < df.c) & (~df.bools) | (df.bools > 2)]
```

```
In [231]: shorter
```

```
Out[231]:
```

| | a | b | c | bools |
|---|----------|----------|----------|-------|
| 3 | 0.078368 | 0.224708 | 0.697626 | False |

```
In [232]: longer
```

```
Out[232]:
```

| | a | b | c | bools |
|---|----------|----------|----------|-------|
| 3 | 0.078368 | 0.224708 | 0.697626 | False |

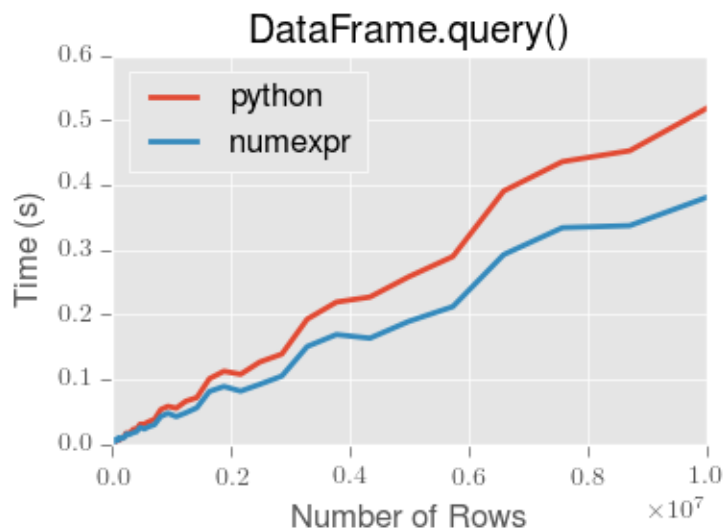
```
In [233]: shorter == longer
```

```
Out[233]:
```

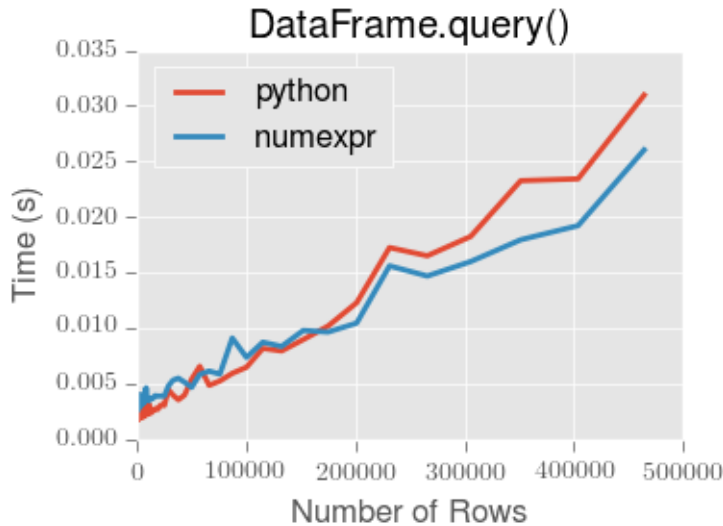
| | a | b | c | bools |
|---|------|------|------|-------|
| 3 | True | True | True | True |

13.14.7 Performance of query()

`DataFrame.query()` using `numexpr` is slightly faster than Python for large frames



Note: You will only see the performance benefits of using the `numexpr` engine with `DataFrame.query()` if your frame has more than approximately 200,000 rows



This plot was created using a DataFrame with 3 columns each containing floating point values generated using `numpy.random.randn()`.

13.15 Duplicate Data

If you want to identify and remove duplicate rows in a DataFrame, there are two methods that will help: `duplicated` and `drop_duplicates`. Each takes as an argument the columns to use to identify duplicated rows.

- `duplicated` returns a boolean vector whose length is the number of rows, and which indicates whether a row is duplicated.
- `drop_duplicates` removes duplicate rows.

By default, the first observed row of a duplicate set is considered unique, but each method has a `take_last` parameter that indicates the last observed row should be taken instead.

```
In [234]: df2 = DataFrame({'a' : ['one', 'one', 'two', 'three', 'two', 'one', 'six'],
.....:                  'b' : ['x', 'y', 'y', 'x', 'y', 'x', 'x'],
.....:                  'c' : np.random.randn(7)})
.....:
```

```
In [235]: df2.duplicated(['a', 'b'])
```

```
Out[235]:
```

```
0    False
1    False
2    False
3    False
4     True
5     True
6    False
dtype: bool
```

```
In [236]: df2.drop_duplicates(['a', 'b'])
```

```
Out[236]:
```

```
   a  b      c
0  one x  0.932713
```

```
1    one  y -0.393510
2    two  y -0.548454
3  three  x  1.130736
6    six  x -1.233298
```

```
In [237]: df2.drop_duplicates(['a','b'], take_last=True)
```

```
Out[237]:
      a  b      c
1    one  y -0.393510
3  three  x  1.130736
4    two  y -0.447217
5    one  x  1.043921
6    six  x -1.233298
```

An alternative way to drop duplicates on the index is `.groupby(level=0)` combined with `first()` or `last()`.

```
In [238]: df3 = df2.set_index('b')
```

```
In [239]: df3
```

```
Out[239]:
      a      c
b
x    one  0.932713
y    one -0.393510
y    two -0.548454
x  three  1.130736
y    two -0.447217
x    one  1.043921
x    six -1.233298
```

```
In [240]: df3.groupby(level=0).first()
```

```
Out[240]:
      a      c
b
x    one  0.932713
y    one -0.393510
```

```
# a bit more verbose
```

```
In [241]: df3.reset_index().drop_duplicates(subset='b', take_last=False).set_index('b')
```

```
Out[241]:
      a      c
b
x    one  0.932713
y    one -0.393510
```

13.16 Dictionary-like `get()` method

Each of `Series`, `DataFrame`, and `Panel` have a `get` method which can return a default value.

```
In [242]: s = Series([1,2,3], index=['a','b','c'])
```

```
In [243]: s.get('a')                                # equivalent to s['a']
```

```
Out[243]: 1
```

```
In [244]: s.get('x', default=-1)
```

```
Out[244]: -1
```

13.17 The `select()` Method

Another way to extract slices from an object is with the `select` method of `Series`, `DataFrame`, and `Panel`. This method should be used only when there is no more direct way. `select` takes a function which operates on labels along `axis` and returns a boolean. For instance:

```
In [245]: df.select(lambda x: x == 'A', axis=1)
Out[245]:
```

```
      A
2000-01-01  0.454389
2000-01-02  0.036249
2000-01-03  0.378125
2000-01-04  0.075871
2000-01-05 -0.677097
2000-01-06  1.482845
2000-01-07  0.272681
2000-01-08 -0.459059
```

13.18 The `lookup()` Method

Sometimes you want to extract a set of values given a sequence of row labels and column labels, and the `lookup` method allows for this and returns a numpy array. For instance,

```
In [246]: dflookup = DataFrame(np.random.rand(20,4), columns = ['A','B','C','D'])
```

```
In [247]: dflookup.lookup(list(range(0,10,2)), ['B','C','A','B','D'])
Out[247]: array([ 0.012 ,  0.3551,  0.3261,  0.4702,  0.3107])
```

13.19 Index objects

The pandas `Index` class and its subclasses can be viewed as implementing an *ordered multiset*. Duplicates are allowed. However, if you try to convert an `Index` object with duplicate entries into a `set`, an exception will be raised.

`Index` also provides the infrastructure necessary for lookups, data alignment, and reindexing. The easiest way to create an `Index` directly is to pass a list or other sequence to `Index`:

```
In [248]: index = Index(['e', 'd', 'a', 'b'])
```

```
In [249]: index
```

```
Out[249]: Index([u'e', u'd', u'a', u'b'], dtype='object')
```

```
In [250]: 'd' in index
```

```
Out[250]: True
```

You can also pass a name to be stored in the index:

```
In [251]: index = Index(['e', 'd', 'a', 'b'], name='something')
```

```
In [252]: index.name
```

```
Out[252]: 'something'
```

The name, if set, will be shown in the console display:

```
In [253]: index = Index(list(range(5)), name='rows')

In [254]: columns = Index(['A', 'B', 'C'], name='cols')

In [255]: df = DataFrame(np.random.randn(5, 3), index=index, columns=columns)

In [256]: df
Out[256]:
cols          A          B          C
rows
0      0.603791  0.388713  0.544331
1     -0.152978  1.929541  0.202138
2      0.024972  0.117533 -0.184740
3      1.054144 -0.736061 -0.785352
4     -1.362549 -0.063514  0.487562

In [257]: df['A']
Out[257]:
rows
0      0.603791
1     -0.152978
2      0.024972
3      1.054144
4     -1.362549
Name: A, dtype: float64
```

13.19.1 Setting metadata

New in version 0.13.0. Indexes are “mostly immutable”, but it is possible to set and change their metadata, like the index name (or, for MultiIndex, levels and labels).

You can use the `rename`, `set_names`, `set_levels`, and `set_labels` to set these attributes directly. They default to returning a copy; however, you can specify `inplace=True` to have the data change in place.

See *Advanced Indexing* for usage of MultiIndexes.

```
In [258]: ind = Index([1, 2, 3])

In [259]: ind.rename("apple")
Out[259]: Int64Index([1, 2, 3], dtype='int64', name=u'apple')

In [260]: ind
Out[260]: Int64Index([1, 2, 3], dtype='int64')

In [261]: ind.set_names(["apple"], inplace=True)

In [262]: ind.name = "bob"

In [263]: ind
Out[263]: Int64Index([1, 2, 3], dtype='int64', name=u'bob')
```

New in version 0.15.0.

`set_names`, `set_levels`, and `set_labels` also take an optional *level* argument

```
In [264]: index = MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])

In [265]: index
```

```

Out[265]:
MultiIndex(levels=[[0, 1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
            names=[u'first', u'second'])

In [266]: index.levels[1]
Out[266]: Index([u'one', u'two'], dtype='object', name=u'second')

In [267]: index.set_levels(["a", "b"], level=1)
Out[267]:
MultiIndex(levels=[[0, 1, 2], [u'a', u'b']],
            labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
            names=[u'first', u'second'])

```

13.19.2 Set operations on Index objects

Warning: In 0.15.0, the set operations `+` and `-` were deprecated in order to provide these for numeric type operations on certain index types. `+` can be replaced by `.union()` or `|`, and `-` by `.difference()`.

The two main operations are `union` (`|`), `intersection` (`&`). These can be directly called as instance methods or used via overloaded operators. Difference is provided via the `.difference()` method.

```

In [268]: a = Index(['c', 'b', 'a'])

In [269]: b = Index(['c', 'e', 'd'])

In [270]: a | b
Out[270]: Index([u'a', u'b', u'c', u'd', u'e'], dtype='object')

In [271]: a & b
Out[271]: Index([u'c'], dtype='object')

In [272]: a.difference(b)
Out[272]: Index([u'a', u'b'], dtype='object')

```

Also available is the `sym_diff` (`^`) operation, which returns elements that appear in either `idx1` or `idx2` but not both. This is equivalent to the Index created by `idx1.difference(idx2).union(idx2.difference(idx1))`, with duplicates dropped.

```

In [273]: idx1 = Index([1, 2, 3, 4])

In [274]: idx2 = Index([2, 3, 4, 5])

In [275]: idx1.sym_diff(idx2)
Out[275]: Int64Index([1, 5], dtype='int64')

In [276]: idx1 ^ idx2
Out[276]: Int64Index([1, 5], dtype='int64')

```

13.20 Set / Reset Index

Occasionally you will load or create a data set into a DataFrame and want to add an index after you've already done so. There are a couple of different ways.

13.20.1 Set an index

`DataFrame` has a `set_index` method which takes a column name (for a regular `Index`) or a list of column names (for a `MultiIndex`), to create a new, indexed `DataFrame`:

```
In [277]: data
```

```
Out[277]:
```

| | a | b | c | d |
|---|-----|-----|---|---|
| 0 | bar | one | z | 1 |
| 1 | bar | two | y | 2 |
| 2 | foo | one | x | 3 |
| 3 | foo | two | w | 4 |

```
In [278]: indexed1 = data.set_index('c')
```

```
In [279]: indexed1
```

```
Out[279]:
```

| c | a | b | d |
|---|-----|-----|---|
| z | bar | one | 1 |
| y | bar | two | 2 |
| x | foo | one | 3 |
| w | foo | two | 4 |

```
In [280]: indexed2 = data.set_index(['a', 'b'])
```

```
In [281]: indexed2
```

```
Out[281]:
```

| | | c | d |
|-----|-----|---|---|
| a | b | | |
| bar | one | z | 1 |
| | two | y | 2 |
| foo | one | x | 3 |
| | two | w | 4 |

The `append` keyword option allow you to keep the existing index and append the given columns to a `MultiIndex`:

```
In [282]: frame = data.set_index('c', drop=False)
```

```
In [283]: frame = frame.set_index(['a', 'b'], append=True)
```

```
In [284]: frame
```

```
Out[284]:
```

| | | | c | d |
|---|-----|-----|---|---|
| c | a | b | | |
| z | bar | one | z | 1 |
| y | bar | two | y | 2 |
| x | foo | one | x | 3 |
| w | foo | two | w | 4 |

Other options in `set_index` allow you not drop the index columns or to add the index in-place (without creating a new object):

```
In [285]: data.set_index('c', drop=False)
```

```
Out[285]:
```

| | a | b | c | d |
|---|-----|-----|---|---|
| c | | | | |
| z | bar | one | z | 1 |
| y | bar | two | y | 2 |

```
x  foo  one  x  3
w  foo  two  w  4
```

```
In [286]: data.set_index(['a', 'b'], inplace=True)
```

```
In [287]: data
```

```
Out[287]:
```

| | | c | d |
|-----|-----|---|---|
| a | b | | |
| bar | one | z | 1 |
| | two | y | 2 |
| foo | one | x | 3 |
| | two | w | 4 |

13.20.2 Reset the index

As a convenience, there is a new function on DataFrame called `reset_index` which transfers the index values into the DataFrame's columns and sets a simple integer index. This is the inverse operation to `set_index`

```
In [288]: data
```

```
Out[288]:
```

| | | c | d |
|-----|-----|---|---|
| a | b | | |
| bar | one | z | 1 |
| | two | y | 2 |
| foo | one | x | 3 |
| | two | w | 4 |

```
In [289]: data.reset_index()
```

```
Out[289]:
```

| | a | b | c | d |
|---|-----|-----|---|---|
| 0 | bar | one | z | 1 |
| 1 | bar | two | y | 2 |
| 2 | foo | one | x | 3 |
| 3 | foo | two | w | 4 |

The output is more similar to a SQL table or a record array. The names for the columns derived from the index are the ones stored in the `names` attribute.

You can use the `level` keyword to remove only a portion of the index:

```
In [290]: frame
```

```
Out[290]:
```

| | | c | d |
|---|-----|-----|-----|
| c | a | b | |
| z | bar | one | z 1 |
| y | bar | two | y 2 |
| x | foo | one | x 3 |
| w | foo | two | w 4 |

```
In [291]: frame.reset_index(level=1)
```

```
Out[291]:
```

| | | a | c | d |
|---|-----|-----|---|---|
| c | b | | | |
| z | one | bar | z | 1 |
| y | two | bar | y | 2 |
| x | one | foo | x | 3 |
| w | two | foo | w | 4 |

`reset_index` takes an optional parameter `drop` which if true simply discards the index, instead of putting index values in the DataFrame's columns.

Note: The `reset_index` method used to be called `delevel` which is now deprecated.

13.20.3 Adding an ad hoc index

If you create an index yourself, you can just assign it to the `index` field:

```
data.index = index
```

13.21 Returning a view versus a copy

When setting values in a pandas object, care must be taken to avoid what is called `chained indexing`. Here is an example.

```
In [292]: dfmi = DataFrame([list('abcd'),
.....:                     list('efgh'),
.....:                     list('ijkl'),
.....:                     list('mnop')],
.....:                     columns=MultiIndex.from_product([['one', 'two'],
.....:                                                         ['first', 'second']]))
.....:
```

```
In [293]: dfmi
```

```
Out[293]:
```

| | one | | two | |
|---|-------|--------|-------|--------|
| | first | second | first | second |
| 0 | a | b | c | d |
| 1 | e | f | g | h |
| 2 | i | j | k | l |
| 3 | m | n | o | p |

Compare these two access methods:

```
In [294]: dfmi['one']['second']
```

```
Out[294]:
```

| | |
|---|---|
| 0 | b |
| 1 | f |
| 2 | j |
| 3 | n |

Name: second, dtype: object

```
In [295]: dfmi.loc[:, ('one', 'second')]
```

```
Out[295]:
```

| | |
|---|---|
| 0 | b |
| 1 | f |
| 2 | j |
| 3 | n |

Name: (one, second), dtype: object

These both yield the same results, so which should you use? It is instructive to understand the order of operations on these and why method 2 (`.loc`) is much preferred over method 1 (chained `[]`)

`dfmi['one']` selects the first level of the columns and returns a data frame that is singly-indexed. Then another python operation `dfmi_with_one['second']` selects the series indexed by 'second' happens. This is indicated by the variable `dfmi_with_one` because pandas sees these operations as separate events. e.g. separate calls to `__getitem__`, so it has to treat them as linear operations, they happen one after another.

Contrast this to `df.loc[:, ('one', 'second')]` which passes a nested tuple of `(slice(None), ('one', 'second'))` to a single call to `__getitem__`. This allows pandas to deal with this as a single entity. Furthermore this order of operations *can* be significantly faster, and allows one to index *both* axes if so desired.

13.21.1 Why does the assignment when using chained indexing fail!

So, why does this show the `SettingWithCopy` warning / and possibly not work when you do chained indexing and assignment:

```
dfmi['one']['second'] = value
```

Since the chained indexing is 2 calls, it is possible that either call may return a **copy** of the data because of the way it is sliced. Thus when setting, you are actually setting a **copy**, and not the original frame data. It is impossible for pandas to figure this out because there are 2 separate python operations that are not connected.

The `SettingWithCopy` warning is a 'heuristic' to detect this (meaning it tends to catch most cases but is simply a lightweight check). Figuring this out for real is way complicated.

The `.loc` operation is a single python operation, and thus can select a slice (which still may be a copy), but allows pandas to assign that slice back into the frame after it is modified, thus setting the values as you would think.

The reason for having the `SettingWithCopy` warning is this. Sometimes when you slice an array you will simply get a view back, which means you can set it no problem. However, even a single dtyped array can generate a copy if it is sliced in a particular way. A multi-dtyped DataFrame (meaning it has say `float` and `object` data), will almost always yield a copy. Whether a view is created is dependent on the memory layout of the array.

13.21.2 Evaluation order matters

Furthermore, in chained expressions, the order may determine whether a copy is returned or not. If an expression will set values on a copy of a slice, then a `SettingWithCopy` exception will be raised (this raise/warn behavior is new starting in 0.13.0)

You can control the action of a chained assignment via the option `mode.chained_assignment`, which can take the values `['raise', 'warn', None]`, where showing a warning is the default.

```
In [296]: dfb = DataFrame({'a' : ['one', 'one', 'two',
.....:                        'three', 'two', 'one', 'six'],
.....:                  'c' : np.arange(7)})
.....:
```

```
# This will show the SettingWithCopyWarning
# but the frame values will be set
```

```
In [297]: dfb['c'][dfb.a.str.startswith('o')] = 42
```

This however is operating on a copy and will not work.

```
>>> pd.set_option('mode.chained_assignment', 'warn')
>>> dfb[dfb.a.str.startswith('o')]['c'] = 42
Traceback (most recent call last):
...
SettingWithCopyWarning:
```

A value is trying to be set on a copy of a slice from a DataFrame.
Try using `.loc[row_index,col_indexer] = value` instead

A chained assignment can also crop up in setting in a mixed dtype frame.

Note: These setting rules apply to all of `.loc/.iloc/.ix`

This is the correct access method

```
In [298]: dfc = DataFrame({'A': ['aaa', 'bbb', 'ccc'], 'B': [1, 2, 3]})
```

```
In [299]: dfc.loc[0, 'A'] = 11
```

```
In [300]: dfc
```

```
Out[300]:
```

| | A | B |
|---|-----|---|
| 0 | 11 | 1 |
| 1 | bbb | 2 |
| 2 | ccc | 3 |

This *can* work at times, but is not guaranteed, and so should be avoided

```
In [301]: dfc = dfc.copy()
```

```
In [302]: dfc['A'][0] = 111
```

```
In [303]: dfc
```

```
Out[303]:
```

| | A | B |
|---|-----|---|
| 0 | 111 | 1 |
| 1 | bbb | 2 |
| 2 | ccc | 3 |

This will **not** work at all, and so should be avoided

```
>>> pd.set_option('mode.chained_assignment', 'raise')
```

```
>>> dfc.loc[0]['A'] = 1111
```

```
Traceback (most recent call last)
```

```
...
```

```
SettingWithCopyException:
```

```
A value is trying to be set on a copy of a slice from a DataFrame.  
Try using .loc[row_index,col_indexer] = value instead
```

Warning: The chained assignment warnings / exceptions are aiming to inform the user of a possibly invalid assignment. There may be false positives; situations where a chained assignment is inadvertently reported.

MULTIINDEX / ADVANCED INDEXING

This section covers indexing with a `MultiIndex` and more advanced indexing features.

See the [Indexing and Selecting Data](#) for general indexing documentation.

Warning: Whether a copy or a reference is returned for a setting operation, may depend on the context. This is sometimes called `chained assignment` and should be avoided. See [Returning a View versus Copy](#)

Warning: In 0.15.0 `Index` has internally been refactored to no longer sub-class `ndarray` but instead subclass `PandasObject`, similarly to the rest of the pandas objects. This should be a transparent change with only very limited API implications (See the [Internal Refactoring](#))

See the [cookbook](#) for some advanced strategies

14.1 Hierarchical indexing (MultiIndex)

Hierarchical / Multi-level indexing is very exciting as it opens the door to some quite sophisticated data analysis and manipulation, especially for working with higher dimensional data. In essence, it enables you to store and manipulate data with an arbitrary number of dimensions in lower dimensional data structures like `Series` (1d) and `DataFrame` (2d).

In this section, we will show what exactly we mean by “hierarchical” indexing and how it integrates with the all of the pandas indexing functionality described above and in prior sections. Later, when discussing [group by](#) and [pivoting and reshaping data](#), we’ll show non-trivial applications to illustrate how it aids in structuring data for analysis.

See the [cookbook](#) for some advanced strategies

14.1.1 Creating a MultiIndex (hierarchical index) object

The `MultiIndex` object is the hierarchical analogue of the standard `Index` object which typically stores the axis labels in pandas objects. You can think of `MultiIndex` an array of tuples where each tuple is unique. A `MultiIndex` can be created from a list of arrays (using `MultiIndex.from_arrays`), an array of tuples (using `MultiIndex.from_tuples`), or a crossed set of iterables (using `MultiIndex.from_product`). The `Index` constructor will attempt to return a `MultiIndex` when it is passed a list of tuples. The following examples demo different ways to initialize `MultiIndexes`.

```
In [1]: arrays = [['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux'],
...:             ['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two']]
...:
```

```
In [2]: tuples = list(zip(*arrays))
```

```
In [3]: tuples
Out[3]:
[('bar', 'one'),
 ('bar', 'two'),
 ('baz', 'one'),
 ('baz', 'two'),
 ('foo', 'one'),
 ('foo', 'two'),
 ('qux', 'one'),
 ('qux', 'two')]

In [4]: index = MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [5]: index
Out[5]:
MultiIndex(levels=[[u'bar', u'baz', u'foo', u'qux'], [u'one', u'two']],
            labels=[[0, 0, 1, 1, 2, 2, 3, 3], [0, 1, 0, 1, 0, 1, 0, 1]],
            names=[u'first', u'second'])

In [6]: s = Series(randn(8), index=index)

In [7]: s
Out[7]:
first second
bar    one    0.469112
      two   -0.282863
baz    one   -1.509059
      two   -1.135632
foo    one    1.212112
      two   -0.173215
qux    one    0.119209
      two   -1.044236
dtype: float64
```

When you want every pairing of the elements in two iterables, it can be easier to use the `MultiIndex.from_product` function:

```
In [8]: iterables = [['bar', 'baz', 'foo', 'qux'], ['one', 'two']]

In [9]: MultiIndex.from_product(iterables, names=['first', 'second'])
Out[9]:
MultiIndex(levels=[[u'bar', u'baz', u'foo', u'qux'], [u'one', u'two']],
            labels=[[0, 0, 1, 1, 2, 2, 3, 3], [0, 1, 0, 1, 0, 1, 0, 1]],
            names=[u'first', u'second'])
```

As a convenience, you can pass a list of arrays directly into `Series` or `DataFrame` to construct a `MultiIndex` automatically:

```
In [10]: arrays = [np.array(['bar', 'bar', 'baz', 'baz', 'foo', 'foo', 'qux', 'qux']),
.....:              np.array(['one', 'two', 'one', 'two', 'one', 'two', 'one', 'two'])]
.....:

In [11]: s = Series(randn(8), index=arrays)

In [12]: s
Out[12]:
bar one   -0.861849
     two   -2.104569
baz one   -0.494929
```

```

two      1.071804
foo one   0.721555
two     -0.706771
qux one  -1.039575
two      0.271860
dtype: float64

```

```
In [13]: df = DataFrame(randn(8, 4), index=arrays)
```

```
In [14]: df
```

```

Out[14]:
           0          1          2          3
bar one -0.424972  0.567020  0.276232 -1.087401
      two -0.673690  0.113648 -1.478427  0.524988
baz one  0.404705  0.577046 -1.715002 -1.039268
      two -0.370647 -1.157892 -1.344312  0.844885
foo one  1.075770 -0.109050  1.643563 -1.469388
      two  0.357021 -0.674600 -1.776904 -0.968914
qux one -1.294524  0.413738  0.276662 -0.472035
      two -0.013960 -0.362543 -0.006154 -0.923061

```

All of the `MultiIndex` constructors accept a `names` argument which stores string names for the levels themselves. If no names are provided, `None` will be assigned:

```
In [15]: df.index.names
```

```
Out[15]: FrozenList([None, None])
```

This index can back any axis of a pandas object, and the number of **levels** of the index is up to you:

```
In [16]: df = DataFrame(randn(3, 8), index=['A', 'B', 'C'], columns=index)
```

```
In [17]: df
```

```

Out[17]:
first      bar      baz      foo      qux \
second     one     two     one     two     one     two     one
A      0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.170299
B      0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127
C     -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466

first
second      two
A      -0.226169
B      -1.436737
C      -2.006747

```

```
In [18]: DataFrame(randn(6, 6), index=index[:6], columns=index[:6])
```

```

Out[18]:
first      bar      baz      foo
second     one     two     one     two     one     two
first second
bar   one -0.410001 -0.078638  0.545952 -1.219217 -1.226825  0.769804
      two -1.281247 -0.727707 -0.121306 -0.097883  0.695775  0.341734
baz   one  0.959726 -1.110336 -0.619976  0.149748 -0.732339  0.687738
      two  0.176444  0.403310 -0.154951  0.301624 -2.179861 -1.369849
foo   one -0.954208  1.462696 -1.743161 -0.826591 -0.345352  1.314232
      two  0.690579  0.995761  2.396780  0.014871  3.357427 -0.317441

```

We’ve “sparsified” the higher levels of the indexes to make the console output a bit easier on the eyes.

It’s worth keeping in mind that there’s nothing preventing you from using tuples as atomic labels on an axis:

```
In [19]: Series(randn(8), index=tuples)
```

```
Out[19]:
(bar, one)    -1.236269
(bar, two)     0.896171
(baz, one)    -0.487602
(baz, two)    -0.082240
(foo, one)    -2.182937
(foo, two)     0.380396
(qux, one)     0.084844
(qux, two)     0.432390
dtype: float64
```

The reason that the `MultiIndex` matters is that it can allow you to do grouping, selection, and reshaping operations as we will describe below and in subsequent areas of the documentation. As you will see in later sections, you can find yourself working with hierarchically-indexed data without creating a `MultiIndex` explicitly yourself. However, when loading data from a file, you may wish to generate your own `MultiIndex` when preparing the data set.

Note that how the index is displayed by be controlled using the `multi_sparse` option in `pandas.set_printoptions`:

```
In [20]: pd.set_option('display.multi_sparse', False)
```

```
In [21]: df
```

```
Out[21]:
first      bar      bar      baz      baz      foo      foo      qux  \
second      one      two      one      two      one      two      one
A      0.895717  0.805244 -1.206412  2.565646  1.431256  1.340309 -1.170299
B      0.410835  0.813850  0.132003 -0.827317 -0.076467 -1.187678  1.130127
C     -1.413681  1.607920  1.024180  0.569605  0.875906 -2.211372  0.974466

first      qux
second      two
A      -0.226169
B     -1.436737
C     -2.006747
```

```
In [22]: pd.set_option('display.multi_sparse', True)
```

14.1.2 Reconstructing the level labels

The method `get_level_values` will return a vector of the labels for each location at a particular level:

```
In [23]: index.get_level_values(0)
```

```
Out[23]: Index([u'bar', u'bar', u'baz', u'baz', u'foo', u'foo', u'qux', u'qux'], dtype='object', name=0)
```

```
In [24]: index.get_level_values('second')
```

```
Out[24]: Index([u'one', u'two', u'one', u'two', u'one', u'two', u'one', u'two'], dtype='object', name=second)
```

14.1.3 Basic indexing on axis with MultiIndex

One of the important features of hierarchical indexing is that you can select data by a “partial” label identifying a subgroup in the data. **Partial** selection “drops” levels of the hierarchical index in the result in a completely analogous way to selecting a column in a regular `DataFrame`:

```
In [25]: df['bar']
```

```
Out[25]:
second      one      two
A      0.895717  0.805244
B      0.410835  0.813850
C     -1.413681  1.607920
```

```
In [26]: df['bar', 'one']
```

```
Out[26]:
A      0.895717
B      0.410835
C     -1.413681
Name: (bar, one), dtype: float64
```

```
In [27]: df['bar']['one']
```

```
Out[27]:
A      0.895717
B      0.410835
C     -1.413681
Name: one, dtype: float64
```

```
In [28]: s['qux']
```

```
Out[28]:
one    -1.039575
two     0.271860
dtype: float64
```

See *Cross-section with hierarchical index* for how to select on a deeper level.

14.1.4 Data alignment and using `reindex`

Operations between differently-indexed objects having `MultiIndex` on the axes will work as you expect; data alignment will work the same as an `Index` of tuples:

```
In [29]: s + s[:-2]
```

```
Out[29]:
bar one    -1.723698
    two    -4.209138
baz one    -0.989859
    two     2.143608
foo one     1.443110
    two    -1.413542
qux one         NaN
    two         NaN
dtype: float64
```

```
In [30]: s + s[:, :2]
```

```
Out[30]:
bar one    -1.723698
    two         NaN
baz one    -0.989859
    two         NaN
foo one     1.443110
    two         NaN
qux one    -2.079150
    two         NaN
dtype: float64
```

`reindex` can be called with another `MultiIndex` or even a list or array of tuples:

```
In [31]: s.reindex(index[:3])
```

```
Out[31]:
first second
bar  one    -0.861849
      two    -2.104569
baz   one    -0.494929
dtype: float64
```

```
In [32]: s.reindex([('foo', 'two'), ('bar', 'one'), ('qux', 'one'), ('baz', 'one')])
```

```
Out[32]:
foo two    -0.706771
bar  one    -0.861849
qux  one    -1.039575
baz  one    -0.494929
dtype: float64
```

14.2 Advanced indexing with hierarchical index

Syntactically integrating `MultiIndex` in advanced indexing with `.loc/.ix` is a bit challenging, but we’ve made every effort to do so. for example the following works as you would expect:

```
In [33]: df = df.T
```

```
In [34]: df
```

```
Out[34]:
              A          B          C
first second
bar  one    0.895717  0.410835 -1.413681
      two    0.805244  0.813850  1.607920
baz   one   -1.206412  0.132003  1.024180
      two    2.565646 -0.827317  0.569605
foo   one    1.431256 -0.076467  0.875906
      two    1.340309 -1.187678 -2.211372
qux   one   -1.170299  1.130127  0.974466
      two   -0.226169 -1.436737 -2.006747
```

```
In [35]: df.loc['bar']
```

```
Out[35]:
              A          B          C
second
one    0.895717  0.410835 -1.413681
two    0.805244  0.813850  1.607920
```

```
In [36]: df.loc['bar', 'two']
```

```
Out[36]:
A    0.805244
B    0.813850
C    1.607920
Name: (bar, two), dtype: float64
```

“Partial” slicing also works quite nicely.

```
In [37]: df.loc['baz':'foo']
```

```
Out[37]:
              A          B          C
```

```

first second
baz  one  -1.206412  0.132003  1.024180
     two   2.565646 -0.827317  0.569605
foo   one   1.431256 -0.076467  0.875906
     two   1.340309 -1.187678 -2.211372

```

You can slice with a ‘range’ of values, by providing a slice of tuples.

```
In [38]: df.loc[('baz', 'two'):( 'qux', 'one')]
```

```
Out[38]:
```

| | | A | B | C |
|-------|--------|-----------|-----------|-----------|
| first | second | | | |
| baz | two | 2.565646 | -0.827317 | 0.569605 |
| foo | one | 1.431256 | -0.076467 | 0.875906 |
| | two | 1.340309 | -1.187678 | -2.211372 |
| qux | one | -1.170299 | 1.130127 | 0.974466 |

```
In [39]: df.loc[('baz', 'two'):'foo']
```

```
Out[39]:
```

| | | A | B | C |
|-------|--------|----------|-----------|-----------|
| first | second | | | |
| baz | two | 2.565646 | -0.827317 | 0.569605 |
| foo | one | 1.431256 | -0.076467 | 0.875906 |
| | two | 1.340309 | -1.187678 | -2.211372 |

Passing a list of labels or tuples works similar to reindexing:

```
In [40]: df.ix[[('bar', 'two'), ('qux', 'one')]]
```

```
Out[40]:
```

| | | A | B | C |
|-------|--------|-----------|----------|----------|
| first | second | | | |
| bar | two | 0.805244 | 0.813850 | 1.607920 |
| qux | one | -1.170299 | 1.130127 | 0.974466 |

14.2.1 Using slicers

New in version 0.14.0.

In 0.14.0 we added a new way to slice multi-indexed objects. You can slice a multi-index by providing multiple indexers.

You can provide any of the selectors as if you are indexing by label, see [Selection by Label](#), including slices, lists of labels, labels, and boolean indexers.

You can use `slice(None)` to select all the contents of *that* level. You do not need to specify all the *deeper* levels, they will be implied as `slice(None)`.

As usual, **both sides** of the slicers are included as this is label indexing.

Warning: You should specify all axes in the `.loc` specifier, meaning the indexer for the **index** and for the **columns**. There are some ambiguous cases where the passed indexer could be mis-interpreted as indexing *both* axes, rather than into say the MultiIndex for the rows.

You should do this:

```
df.loc[(slice('A1', 'A3'), .....), :]
```

rather than this:

```
df.loc[(slice('A1', 'A3'), .....)]
```

Warning: You will need to make sure that the selection axes are fully lexsorted!

```
In [41]: def mklbl(prefix, n):
.....:     return ["%s%s" % (prefix, i) for i in range(n)]
.....:
```

```
In [42]: miindex = MultiIndex.from_product([mklbl('A', 4),
.....:                                     mklbl('B', 2),
.....:                                     mklbl('C', 4),
.....:                                     mklbl('D', 2)])
.....:
```

```
In [43]: micolumns = MultiIndex.from_tuples([( 'a', 'foo'), ( 'a', 'bar'),
.....:                                       ( 'b', 'foo'), ( 'b', 'bah')],
.....:                                       names=['lv10', 'lv11'])
.....:
```

```
In [44]: dfmi = DataFrame(np.arange(len(miindex)*len(micolumns)).reshape((len(miindex), len(micolumns)),
.....:                                                                    index=miindex,
.....:                                                                    columns=micolumns).sortlevel().sortlevel(axis=1)
.....:
```

```
In [45]: dfmi
```

```
Out[45]:
lv10      a      b
lv11      bar  foo  bah  foo
A0 B0 C0 D0    1    0    3    2
      D1    5    4    7    6
      C1 D0    9    8   11   10
      D1   13   12   15   14
      C2 D0   17   16   19   18
      D1   21   20   23   22
      C3 D0   25   24   27   26
...
A3 B1 C0 D1  229  228  231  230
      C1 D0  233  232  235  234
      D1   237  236  239  238
      C2 D0  241  240  243  242
      D1   245  244  247  246
      C3 D0  249  248  251  250
      D1   253  252  255  254
```

```
[64 rows x 4 columns]
```

Basic multi-index slicing using slices, lists, and labels.

```
In [46]: dfmi.loc[(slice('A1','A3'),slice(None), ['C1','C3']),:]
```

```
Out[46]:
```

| lvl0 | | | | a | | b | |
|------|----|----|----|-----|-----|-----|-----|
| lvl1 | | | | bar | foo | bah | foo |
| A1 | B0 | C1 | D0 | 73 | 72 | 75 | 74 |
| | | | D1 | 77 | 76 | 79 | 78 |
| | | C3 | D0 | 89 | 88 | 91 | 90 |
| | | | D1 | 93 | 92 | 95 | 94 |
| | B1 | C1 | D0 | 105 | 104 | 107 | 106 |
| | | | D1 | 109 | 108 | 111 | 110 |
| | | C3 | D0 | 121 | 120 | 123 | 122 |
| ... | | | | ... | ... | ... | ... |
| A3 | B0 | C1 | D1 | 205 | 204 | 207 | 206 |
| | | C3 | D0 | 217 | 216 | 219 | 218 |
| | | | D1 | 221 | 220 | 223 | 222 |
| | B1 | C1 | D0 | 233 | 232 | 235 | 234 |
| | | | D1 | 237 | 236 | 239 | 238 |
| | | C3 | D0 | 249 | 248 | 251 | 250 |
| | | | D1 | 253 | 252 | 255 | 254 |

```
[24 rows x 4 columns]
```

You can use a `pd.IndexSlice` to have a more natural syntax using `:` rather than using `slice(None)`

```
In [47]: idx = pd.IndexSlice
```

```
In [48]: dfmi.loc[idx[:, :, ['C1','C3']],idx[:, 'foo']]
```

```
Out[48]:
```

| lvl0 | | | | a | | b | |
|------|----|----|----|-----|-----|---|--|
| lvl1 | | | | foo | foo | | |
| A0 | B0 | C1 | D0 | 8 | 10 | | |
| | | | D1 | 12 | 14 | | |
| | | C3 | D0 | 24 | 26 | | |
| | | | D1 | 28 | 30 | | |
| | B1 | C1 | D0 | 40 | 42 | | |
| | | | D1 | 44 | 46 | | |
| | | C3 | D0 | 56 | 58 | | |
| ... | | | | ... | ... | | |
| A3 | B0 | C1 | D1 | 204 | 206 | | |
| | | C3 | D0 | 216 | 218 | | |
| | | | D1 | 220 | 222 | | |
| | B1 | C1 | D0 | 232 | 234 | | |
| | | | D1 | 236 | 238 | | |
| | | C3 | D0 | 248 | 250 | | |
| | | | D1 | 252 | 254 | | |

```
[32 rows x 2 columns]
```

It is possible to perform quite complicated selections using this method on multiple axes at the same time.

```
In [49]: dfmi.loc['A1', (slice(None), 'foo')]
```

```
Out[49]:
```

| lvl0 | | | | a | | b | |
|------|----|----|----|-----|-----|---|--|
| lvl1 | | | | foo | foo | | |
| B0 | C0 | D0 | | 64 | 66 | | |
| | | | D1 | 68 | 70 | | |
| | C1 | D0 | | 72 | 74 | | |
| | | | D1 | 76 | 78 | | |
| | C2 | D0 | | 80 | 82 | | |

```
      D1      84      86
C3 D0      88      90
...
B1 C0 D1    100    102
    C1 D0    104    106
      D1    108    110
    C2 D0    112    114
      D1    116    118
    C3 D0    120    122
      D1    124    126
```

[16 rows x 2 columns]

```
In [50]: dfmi.loc[idx[:, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out [50]:
```

```
lvl0      a      b
lvl1      foo    foo
A0 B0 C1 D0      8     10
      D1     12     14
      C3 D0     24     26
      D1     28     30
    B1 C1 D0     40     42
      D1     44     46
      C3 D0     56     58
...
A3 B0 C1 D1    204    206
      C3 D0    216    218
      D1    220    222
    B1 C1 D0    232    234
      D1    236    238
      C3 D0    248    250
      D1    252    254
```

[32 rows x 2 columns]

Using a boolean indexer you can provide selection related to the *values*.

```
In [51]: mask = dfmi[('a', 'foo')] > 200
```

```
In [52]: dfmi.loc[idx[mask, :, ['C1', 'C3']], idx[:, 'foo']]
```

```
Out [52]:
```

```
lvl0      a      b
lvl1      foo    foo
A3 B0 C1 D1    204    206
      C3 D0    216    218
      D1    220    222
    B1 C1 D0    232    234
      D1    236    238
      C3 D0    248    250
      D1    252    254
```

You can also specify the `axis` argument to `.loc` to interpret the passed slicers on a single axis.

```
In [53]: dfmi.loc(axis=0)[:, :, ['C1', 'C3']]
```

```
Out [53]:
```

```
lvl0      a      b
lvl1      bar    foo    bah    foo
A0 B0 C1 D0      9      8     11     10
      D1     13     12     15     14
```

```

      C3 D0    25    24    27    26
         D1    29    28    31    30
B1 C1 D0    41    40    43    42
         D1    45    44    47    46
      C3 D0    57    56    59    58
...
A3 B0 C1 D1   205   204   207   206
      C3 D0   217   216   219   218
         D1   221   220   223   222
B1 C1 D0   233   232   235   234
         D1   237   236   239   238
      C3 D0   249   248   251   250
         D1   253   252   255   254

```

```
[32 rows x 4 columns]
```

Furthermore you can *set* the values using these methods

```
In [54]: df2 = dfmi.copy()
```

```
In [55]: df2.loc(axis=0)[:,:,:,['C1','C3']] = -10
```

```
In [56]: df2
```

```
Out[56]:
```

```

lvl0      a      b
lvl1    bar  foo  bah  foo
A0 B0 C0 D0     1     0     3     2
         D1     5     4     7     6
      C1 D0   -10   -10   -10   -10
         D1   -10   -10   -10   -10
      C2 D0    17    16    19    18
         D1    21    20    23    22
      C3 D0   -10   -10   -10   -10
...
A3 B1 C0 D1   229   228   231   230
      C1 D0   -10   -10   -10   -10
         D1   -10   -10   -10   -10
      C2 D0   241   240   243   242
         D1   245   244   247   246
      C3 D0   -10   -10   -10   -10
         D1   -10   -10   -10   -10

```

```
[64 rows x 4 columns]
```

You can use a right-hand-side of an alignable object as well.

```
In [57]: df2 = dfmi.copy()
```

```
In [58]: df2.loc[idx[:,:,:,['C1','C3']],:] = df2*1000
```

```
In [59]: df2
```

```
Out[59]:
```

```

lvl0      a      b
lvl1    bar  foo  bah  foo
A0 B0 C0 D0     1     0     3     2
         D1     5     4     7     6
      C1 D0   9000   8000  11000  10000
         D1  13000  12000  15000  14000
      C2 D0     17     16     19     18

```

```
      D1      21      20      23      22
C3 D0  25000  24000  27000  26000
...
A3 B1 C0 D1    229    228    231    230
      C1 D0  233000  232000  235000  234000
      D1  237000  236000  239000  238000
      C2 D0    241    240    243    242
      D1    245    244    247    246
      C3 D0  249000  248000  251000  250000
      D1  253000  252000  255000  254000
```

```
[64 rows x 4 columns]
```

14.2.2 Cross-section

The `xs` method of `DataFrame` additionally takes a `level` argument to make selecting data at a particular level of a `MultiIndex` easier.

```
In [60]: df
```

```
Out [60]:
```

| | | A | B | C |
|-------|--------|-----------|-----------|-----------|
| first | second | | | |
| bar | one | 0.895717 | 0.410835 | -1.413681 |
| | two | 0.805244 | 0.813850 | 1.607920 |
| baz | one | -1.206412 | 0.132003 | 1.024180 |
| | two | 2.565646 | -0.827317 | 0.569605 |
| foo | one | 1.431256 | -0.076467 | 0.875906 |
| | two | 1.340309 | -1.187678 | -2.211372 |
| qux | one | -1.170299 | 1.130127 | 0.974466 |
| | two | -0.226169 | -1.436737 | -2.006747 |

```
In [61]: df.xs('one', level='second')
```

```
Out [61]:
```

| | A | B | C |
|-------|-----------|-----------|-----------|
| first | | | |
| bar | 0.895717 | 0.410835 | -1.413681 |
| baz | -1.206412 | 0.132003 | 1.024180 |
| foo | 1.431256 | -0.076467 | 0.875906 |
| qux | -1.170299 | 1.130127 | 0.974466 |

```
# using the slicers (new in 0.14.0)
```

```
In [62]: df.loc[(slice(None), 'one'), :]
```

```
Out [62]:
```

| | | A | B | C |
|-------|--------|-----------|-----------|-----------|
| first | second | | | |
| bar | one | 0.895717 | 0.410835 | -1.413681 |
| baz | one | -1.206412 | 0.132003 | 1.024180 |
| foo | one | 1.431256 | -0.076467 | 0.875906 |
| qux | one | -1.170299 | 1.130127 | 0.974466 |

You can also select on the columns with `xs()`, by providing the `axis` argument

```
In [63]: df = df.T
```

```
In [64]: df.xs('one', level='second', axis=1)
```

```
Out [64]:
```

| first | bar | baz | foo | qux |
|-------|-----|-----|-----|-----|
|-------|-----|-----|-----|-----|

```
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

using the slicers (new in 0.14.0)

```
In [65]: df.loc[:, (slice(None), 'one')]
```

```
Out[65]:
first      bar      baz      foo      qux
second    one      one      one      one
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

`xs()` also allows selection with multiple keys

```
In [66]: df.xs(('one', 'bar'), level=('second', 'first'), axis=1)
```

```
Out[66]:
first      bar
second    one
A      0.895717
B      0.410835
C     -1.413681
```

using the slicers (new in 0.14.0)

```
In [67]: df.loc[:, ('bar', 'one')]
```

```
Out[67]:
A      0.895717
B      0.410835
C     -1.413681
Name: (bar, one), dtype: float64
```

New in version 0.13.0.

You can pass `drop_level=False` to `xs()` to retain the level that was selected

```
In [68]: df.xs('one', level='second', axis=1, drop_level=False)
```

```
Out[68]:
first      bar      baz      foo      qux
second    one      one      one      one
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

versus the result with `drop_level=True` (the default value)

```
In [69]: df.xs('one', level='second', axis=1, drop_level=True)
```

```
Out[69]:
first      bar      baz      foo      qux
A      0.895717 -1.206412  1.431256 -1.170299
B      0.410835  0.132003 -0.076467  1.130127
C     -1.413681  1.024180  0.875906  0.974466
```

14.2.3 Advanced reindexing and alignment

The parameter `level` has been added to the `reindex` and `align` methods of pandas objects. This is useful to broadcast values across a level. For instance:

```
In [70]: midx = MultiIndex(levels=[['zero', 'one'], ['x', 'y']],
.....:                      labels=[[1,1,0,0],[1,0,1,0]])
.....:
```

```
In [71]: df = DataFrame(randn(4,2), index=midx)
```

```
In [72]: df
```

```
Out[72]:
```

| | | 0 | 1 |
|------|---|----------|-----------|
| one | y | 1.519970 | -0.493662 |
| | x | 0.600178 | 0.274230 |
| zero | y | 0.132885 | -0.023688 |
| | x | 2.410179 | 1.450520 |

```
In [73]: df2 = df.mean(level=0)
```

```
In [74]: df2
```

```
Out[74]:
```

| | 0 | 1 |
|------|----------|-----------|
| zero | 1.271532 | 0.713416 |
| one | 1.060074 | -0.109716 |

```
In [75]: df2.reindex(df.index, level=0)
```

```
Out[75]:
```

| | | 0 | 1 |
|------|---|----------|-----------|
| one | y | 1.060074 | -0.109716 |
| | x | 1.060074 | -0.109716 |
| zero | y | 1.271532 | 0.713416 |
| | x | 1.271532 | 0.713416 |

```
# aligning
```

```
In [76]: df_aligned, df2_aligned = df.align(df2, level=0)
```

```
In [77]: df_aligned
```

```
Out[77]:
```

| | | 0 | 1 |
|------|---|----------|-----------|
| one | y | 1.519970 | -0.493662 |
| | x | 0.600178 | 0.274230 |
| zero | y | 0.132885 | -0.023688 |
| | x | 2.410179 | 1.450520 |

```
In [78]: df2_aligned
```

```
Out[78]:
```

| | | 0 | 1 |
|------|---|----------|-----------|
| one | y | 1.060074 | -0.109716 |
| | x | 1.060074 | -0.109716 |
| zero | y | 1.271532 | 0.713416 |
| | x | 1.271532 | 0.713416 |

14.2.4 Swapping levels with `swaplevel()`

The `swaplevel` function can switch the order of two levels:

```
In [79]: df[:5]
```

```
Out[79]:
```

| | | 0 | 1 |
|-----|---|----------|-----------|
| one | y | 1.519970 | -0.493662 |

```

      x  0.600178  0.274230
zero y  0.132885 -0.023688
      x  2.410179  1.450520

```

```
In [80]: df[:5].swaplevel(0, 1, axis=0)
```

```
Out [80]:
```

| | 0 | 1 |
|--------|----------|-----------|
| y one | 1.519970 | -0.493662 |
| x one | 0.600178 | 0.274230 |
| y zero | 0.132885 | -0.023688 |
| x zero | 2.410179 | 1.450520 |

14.2.5 Reordering levels with `reorder_levels()`

The `reorder_levels` function generalizes the `swaplevel` function, allowing you to permute the hierarchical index levels in one step:

```
In [81]: df[:5].reorder_levels([1,0], axis=0)
```

```
Out [81]:
```

| | 0 | 1 |
|--------|----------|-----------|
| y one | 1.519970 | -0.493662 |
| x one | 0.600178 | 0.274230 |
| y zero | 0.132885 | -0.023688 |
| x zero | 2.410179 | 1.450520 |

14.3 The need for sortedness with `MultiIndex`

Caveat emptor: the present implementation of `MultiIndex` requires that the labels be sorted for some of the slicing / indexing routines to work correctly. You can think about breaking the axis into unique groups, where at the hierarchical level of interest, each distinct group shares a label, but no two have the same label. However, the `MultiIndex` does not enforce this: **you are responsible for ensuring that things are properly sorted**. There is an important new method `sortlevel` to sort an axis within a `MultiIndex` so that its labels are grouped and sorted by the original ordering of the associated factor at that level. Note that this does not necessarily mean the labels will be sorted lexicographically!

```
In [82]: import random; random.shuffle(tuples)
```

```
In [83]: s = Series(randn(8), index=MultiIndex.from_tuples(tuples))
```

```
In [84]: s
```

```
Out [84]:
```

| | |
|---------|-----------|
| bar two | 0.206053 |
| foo two | -0.251905 |
| bar one | -2.213588 |
| qux two | 1.063327 |
| foo one | 1.266143 |
| baz two | 0.299368 |
| one | -0.863838 |
| qux one | 0.408204 |

dtype: float64

```
In [85]: s.sortlevel(0)
```

```
Out [85]:
```

| | |
|---------|-----------|
| bar one | -2.213588 |
|---------|-----------|

```
      two    0.206053
baz one  -0.863838
      two    0.299368
foo one   1.266143
      two  -0.251905
qux one   0.408204
      two   1.063327
dtype: float64
```

```
In [86]: s.sortlevel(1)
```

```
Out[86]:
bar one  -2.213588
baz one  -0.863838
foo one   1.266143
qux one   0.408204
bar two   0.206053
baz two   0.299368
foo two  -0.251905
qux two   1.063327
dtype: float64
```

Note, you may also pass a level name to `sortlevel` if the MultiIndex levels are named.

```
In [87]: s.index.set_names(['L1', 'L2'], inplace=True)
```

```
In [88]: s.sortlevel(level='L1')
```

```
Out[88]:
L1  L2
bar one  -2.213588
      two   0.206053
baz one  -0.863838
      two   0.299368
foo one   1.266143
      two  -0.251905
qux one   0.408204
      two   1.063327
dtype: float64
```

```
In [89]: s.sortlevel(level='L2')
```

```
Out[89]:
L1  L2
bar one  -2.213588
baz one  -0.863838
foo one   1.266143
qux one   0.408204
bar two   0.206053
baz two   0.299368
foo two  -0.251905
qux two   1.063327
dtype: float64
```

Some indexing will work even if the data are not sorted, but will be rather inefficient and will also return a copy of the data rather than a view:

```
In [90]: s['qux']
```

```
Out[90]:
L2
two    1.063327
one    0.408204
```

```
dtype: float64
```

```
In [91]: s.sortlevel(1)['qux']
Out[91]:
L2
one      0.408204
two      1.063327
dtype: float64
```

On higher dimensional objects, you can sort any of the other axes by level if they have a MultiIndex:

```
In [92]: df.T.sortlevel(1, axis=1)
Out[92]:
```

| | zero | one | zero | one |
|---|----------|----------|-----------|-----------|
| | x | x | y | y |
| 0 | 2.410179 | 0.600178 | 0.132885 | 1.519970 |
| 1 | 1.450520 | 0.274230 | -0.023688 | -0.493662 |

The MultiIndex object has code to **explicitly check the sort depth**. Thus, if you try to index at a depth at which the index is not sorted, it will raise an exception. Here is a concrete example to illustrate this:

```
In [93]: tuples = [('a', 'a'), ('a', 'b'), ('b', 'a'), ('b', 'b')]
```

```
In [94]: idx = MultiIndex.from_tuples(tuples)
```

```
In [95]: idx.lexsort_depth
Out[95]: 2
```

```
In [96]: reordered = idx[[1, 0, 3, 2]]
```

```
In [97]: reordered.lexsort_depth
Out[97]: 1
```

```
In [98]: s = Series(randn(4), index=reordered)
```

```
In [99]: s.ix['a':'a']
Out[99]:
a b    -1.048089
a    -0.025747
dtype: float64
```

However:

```
>>> s.ix[('a', 'b'):(('b', 'a'))]
Traceback (most recent call last)
...
KeyError: Key length (3) was greater than MultiIndex lexsort depth (2)
```

14.4 Take Methods

Similar to numpy ndarrays, pandas Index, Series, and DataFrame also provides the `take` method that retrieves elements along a given axis at the given indices. The given indices must be either a list or an ndarray of integer index positions. `take` will also accept negative integers as relative positions to the end of the object.

```
In [100]: index = Index(randint(0, 1000, 10))
```

```
In [101]: index
```

```
Out[101]: Int64Index([214, 502, 712, 567, 786, 175, 993, 133, 758, 329], dtype='int64')

In [102]: positions = [0, 9, 3]

In [103]: index[positions]
Out[103]: Int64Index([214, 329, 567], dtype='int64')

In [104]: index.take(positions)
Out[104]: Int64Index([214, 329, 567], dtype='int64')

In [105]: ser = Series(randn(10))

In [106]: ser.iloc[positions]
Out[106]:
0    -0.179666
9     1.824375
3     0.392149
dtype: float64

In [107]: ser.take(positions)
Out[107]:
0    -0.179666
9     1.824375
3     0.392149
dtype: float64
```

For DataFrames, the given indices should be a 1d list or ndarray that specifies row or column positions.

```
In [108]: frm = DataFrame(randn(5, 3))

In [109]: frm.take([1, 4, 3])
Out[109]:
      0         1         2
1 -1.237881  0.106854 -1.276829
4  0.629675 -1.425966  1.857704
3  0.979542 -1.633678  0.615855

In [110]: frm.take([0, 2], axis=1)
Out[110]:
      0         2
0  0.595974  0.601544
1 -1.237881 -1.276829
2 -0.767101  1.499591
3  0.979542  0.615855
4  0.629675  1.857704
```

It is important to note that the `take` method on pandas objects are not intended to work on boolean indices and may return unexpected results.

```
In [111]: arr = randn(10)

In [112]: arr.take([False, False, True, True])
Out[112]: array([-1.1935, -1.1935,  0.6775,  0.6775])

In [113]: arr[[0, 1]]
Out[113]: array([-1.1935,  0.6775])

In [114]: ser = Series(randn(10))
```

```
In [115]: ser.take([False, False, True, True])
Out[115]:
0    0.233141
0    0.233141
1   -0.223540
1   -0.223540
dtype: float64
```

```
In [116]: ser.ix[[0, 1]]
Out[116]:
0    0.233141
1   -0.223540
dtype: float64
```

Finally, as a small note on performance, because the `take` method handles a narrower range of inputs, it can offer performance that is a good deal faster than fancy indexing.

14.5 CategoricalIndex

New in version 0.16.1.

We introduce a `CategoricalIndex`, a new type of index object that is useful for supporting indexing with duplicates. This is a container around a `Categorical` (introduced in v0.15.0) and allows efficient indexing and storage of an index with a large number of duplicated elements. Prior to 0.16.1, setting the index of a `DataFrame`/`Series` with a `category` dtype would convert this to regular object-based `Index`.

```
In [117]: df = DataFrame({'A' : np.arange(6),
.....:                  'B' : Series(list('aabbca')).astype('category',
.....:                                                    categories=list('cab'))
.....:                  })
.....:
```

```
In [118]: df
Out[118]:
   A  B
0  0  a
1  1  a
2  2  b
3  3  b
4  4  c
5  5  a
```

```
In [119]: df.dtypes
Out[119]:
A      int32
B    category
dtype: object
```

```
In [120]: df.B.cat.categories
Out[120]: Index([u'c', u'a', u'b'], dtype='object')
```

Setting the index, will create create a `CategoricalIndex`

```
In [121]: df2 = df.set_index('B')

In [122]: df2.index
Out[122]: CategoricalIndex([u'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'c', u'a', u'b'], order=)
```

Indexing with `__getitem__/.iloc/.loc/.ix` works similarly to an `Index` with duplicates. The indexers **MUST** be in the category or the operation will raise.

```
In [123]: df2.loc['a']
```

```
Out[123]:
```

```
      A
B
a    0
a    1
a    5
```

These **PRESERVE** the `CategoricalIndex`

```
In [124]: df2.loc['a'].index
```

```
Out[124]: CategoricalIndex([u'a', u'a', u'a'], categories=[u'c', u'a', u'b'], ordered=False, name=u'B')
```

Sorting will order by the order of the categories

```
In [125]: df2.sort_index()
```

```
Out[125]:
```

```
      A
B
c    4
a    0
a    1
a    5
b    2
b    3
```

Groupby operations on the index will preserve the index nature as well

```
In [126]: df2.groupby(level=0).sum()
```

```
Out[126]:
```

```
      A
B
c    4
a    6
b    5
```

```
In [127]: df2.groupby(level=0).sum().index
```

```
Out[127]: CategoricalIndex([u'c', u'a', u'b'], categories=[u'c', u'a', u'b'], ordered=False, name=u'B')
```

Reindexing operations, will return a resulting index based on the type of the passed indexer, meaning that passing a list will return a plain-old-`Index`; indexing with a `Categorical` will return a `CategoricalIndex`, indexed according to the categories of the **PASSED** `Categorical` dtype. This allows one to arbitrarily index these even with values **NOT** in the categories, similarly to how you can reindex ANY pandas index.

```
In [128]: df2.reindex(['a', 'e'])
```

```
Out[128]:
```

```
      A
B
a    0
a    1
a    5
e  NaN
```

```
In [129]: df2.reindex(['a', 'e']).index
```

```
Out[129]: Index([u'a', u'a', u'a', u'e'], dtype='object', name=u'B')
```

```
In [130]: df2.reindex(pd.Categorical(['a', 'e'], categories=list('abcde')))
```

```
Out[130]:
```

```
      A
B
a    0
a    1
a    5
e  NaN
```

```
In [131]: df2.reindex(pd.Categorical(['a','e'],categories=list('abcde'))).index
```

```
Out[131]: CategoricalIndex([u'a', u'a', u'a', u'e'], categories=[u'a', u'b', u'c', u'd', u'e'], order=)
```

Warning: Reshaping and Comparison operations on a CategoricalIndex must have the same categories or a TypeError will be raised.

```
In [10]: df3 = DataFrame({'A' : np.arange(6),
                        'B' : Series(list('aabbca')).astype('category',
                                                           categories=list('abc'))
                        }).set_index('B')
```

```
In [11]: df3.index
```

```
Out[11]: CategoricalIndex([u'a', u'a', u'b', u'b', u'c', u'a'], categories=[u'a', u'b', u'c'], order=)
```

```
In [12]: pd.concat([df2,df3])
```

```
TypeError: categories must match existing categories when appending
```

14.6 Float64Index

Note: As of 0.14.0, Float64Index is backed by a native float64 dtype array. Prior to 0.14.0, Float64Index was backed by an object dtype array. Using a float64 dtype in the backend speeds up arithmetic operations by about 30x and boolean indexing operations on the Float64Index itself are about 2x as fast.

New in version 0.13.0.

By default a Float64Index will be automatically created when passing floating, or mixed-integer-floating values in index creation. This enables a pure label-based slicing paradigm that makes `[]`, `ix`, `loc` for scalar indexing and slicing work exactly the same.

```
In [132]: indexf = Index([1.5, 2, 3, 4.5, 5])
```

```
In [133]: indexf
```

```
Out[133]: Float64Index([1.5, 2.0, 3.0, 4.5, 5.0], dtype='float64')
```

```
In [134]: sf = Series(range(5),index=indexf)
```

```
In [135]: sf
```

```
Out[135]:
```

```
1.5    0
2.0    1
3.0    2
4.5    3
5.0    4
dtype: int32
```

Scalar selection for `[]`, `.ix`, `.loc` will always be label based. An integer will match an equal float index (e.g. 3 is

equivalent to `3.0`)

```
In [136]: sf[3]
Out[136]: 2
```

```
In [137]: sf[3.0]
Out[137]: 2
```

```
In [138]: sf.ix[3]
Out[138]: 2
```

```
In [139]: sf.ix[3.0]
Out[139]: 2
```

```
In [140]: sf.loc[3]
Out[140]: 2
```

```
In [141]: sf.loc[3.0]
Out[141]: 2
```

The only positional indexing is via `iloc`

```
In [142]: sf.iloc[3]
Out[142]: 3
```

A scalar index that is not found will raise `KeyError`

Slicing is ALWAYS on the values of the index, for `[]`, `ix`, `loc` and ALWAYS positional with `iloc`

```
In [143]: sf[2:4]
Out[143]:
2    1
3    2
dtype: int32
```

```
In [144]: sf.ix[2:4]
Out[144]:
2    1
3    2
dtype: int32
```

```
In [145]: sf.loc[2:4]
Out[145]:
2    1
3    2
dtype: int32
```

```
In [146]: sf.iloc[2:4]
Out[146]:
3.0    2
4.5    3
dtype: int32
```

In float indexes, slicing using floats is allowed

```
In [147]: sf[2.1:4.6]
Out[147]:
3.0    2
4.5    3
dtype: int32
```

```
In [148]: sf.loc[2.1:4.6]
Out[148]:
3.0      2
4.5      3
dtype: int32
```

In non-float indexes, slicing using floats will raise a `TypeError`

```
In [1]: Series(range(5))[3.5]
TypeError: the label [3.5] is not a proper indexer for this index type (Int64Index)

In [1]: Series(range(5))[3.5:4.5]
TypeError: the slice start [3.5] is not a proper indexer for this index type (Int64Index)
```

Using a scalar float indexer will be deprecated in a future version, but is allowed for now.

```
In [3]: Series(range(5))[3.0]
Out[3]: 3
```

Here is a typical use-case for using this type of indexing. Imagine that you have a somewhat irregular `timedelta`-like indexing scheme, but the data is recorded as floats. This could for example be millisecond offsets.

```
In [149]: dfir = concat([DataFrame(randn(5,2),
.....:                          index=np.arange(5) * 250.0,
.....:                          columns=list('AB')),
.....:                  DataFrame(randn(6,2),
.....:                          index=np.arange(4,10) * 250.1,
.....:                          columns=list('AB'))])
.....:
```

```
In [150]: dfir
Out[150]:
```

| | A | B |
|--------|-----------|-----------|
| 0.0 | 0.997289 | -1.693316 |
| 250.0 | -0.179129 | -1.598062 |
| 500.0 | 0.936914 | 0.912560 |
| 750.0 | -1.003401 | 1.632781 |
| 1000.0 | -0.724626 | 0.178219 |
| 1000.4 | 0.310610 | -0.108002 |
| 1250.5 | -0.974226 | -1.147708 |
| 1500.6 | -2.281374 | 0.760010 |
| 1750.7 | -0.742532 | 1.533318 |
| 2000.8 | 2.495362 | -0.432771 |
| 2250.9 | -0.068954 | 0.043520 |

Selection operations then will always work on a value basis, for all selection operators.

```
In [151]: dfir[0:1000.4]
Out[151]:
```

| | A | B |
|--------|-----------|-----------|
| 0.0 | 0.997289 | -1.693316 |
| 250.0 | -0.179129 | -1.598062 |
| 500.0 | 0.936914 | 0.912560 |
| 750.0 | -1.003401 | 1.632781 |
| 1000.0 | -0.724626 | 0.178219 |
| 1000.4 | 0.310610 | -0.108002 |

```
In [152]: dfir.loc[0:1001, 'A']
Out[152]:
```

```
0.0      0.997289
250.0    -0.179129
500.0     0.936914
750.0    -1.003401
1000.0   -0.724626
1000.4    0.310610
Name: A, dtype: float64
```

```
In [153]: dfir.loc[1000.4]
Out[153]:
A    0.310610
B   -0.108002
Name: 1000.4, dtype: float64
```

You could then easily pick out the first 1 second (1000 ms) of data then.

```
In [154]: dfir[0:1000]
Out[154]:
```

| | A | B |
|------|-----------|-----------|
| 0 | 0.997289 | -1.693316 |
| 250 | -0.179129 | -1.598062 |
| 500 | 0.936914 | 0.912560 |
| 750 | -1.003401 | 1.632781 |
| 1000 | -0.724626 | 0.178219 |

Of course if you need integer based selection, then use `iloc`

```
In [155]: dfir.iloc[0:5]
Out[155]:
```

| | A | B |
|------|-----------|-----------|
| 0 | 0.997289 | -1.693316 |
| 250 | -0.179129 | -1.598062 |
| 500 | 0.936914 | 0.912560 |
| 750 | -1.003401 | 1.632781 |
| 1000 | -0.724626 | 0.178219 |

COMPUTATIONAL TOOLS

15.1 Statistical functions

15.1.1 Percent Change

Series, DataFrame, and Panel all have a method `pct_change` to compute the percent change over a given number of periods (using `fill_method` to fill NA/null values *before* computing the percent change).

```
In [1]: ser = pd.Series(np.random.randn(8))
```

```
In [2]: ser.pct_change()
```

```
Out[2]:
0      NaN
1   -1.602976
2    4.334938
3   -0.247456
4   -2.067345
5   -1.142903
6   -1.688214
7   -9.759729
dtype: float64
```

```
In [3]: df = pd.DataFrame(np.random.randn(10, 4))
```

```
In [4]: df.pct_change(periods=3)
```

```
Out[4]:
      0      1      2      3
0     NaN     NaN     NaN     NaN
1     NaN     NaN     NaN     NaN
2     NaN     NaN     NaN     NaN
3 -0.218320 -1.054001  1.987147 -0.510183
4 -0.439121 -1.816454  0.649715 -4.822809
5 -0.127833 -3.042065 -5.866604 -1.776977
6 -2.596833 -1.959538 -2.111697 -3.798900
7 -0.117826 -2.169058  0.036094 -0.067696
8  2.492606 -1.357320 -1.205802 -1.558697
9 -1.012977  2.324558 -1.003744 -0.371806
```

15.1.2 Covariance

The Series object has a method `cov` to compute covariance between series (excluding NA/null values).

```
In [5]: s1 = pd.Series(np.random.randn(1000))
```

```
In [6]: s2 = pd.Series(np.random.randn(1000))
```

```
In [7]: s1.cov(s2)
```

```
Out[7]: 0.00068010881743109993
```

Analogously, `DataFrame` has a method `cov` to compute pairwise covariances among the series in the `DataFrame`, also excluding NA/null values.

Note: Assuming the missing data are missing at random this results in an estimate for the covariance matrix which is unbiased. However, for many applications this estimate may not be acceptable because the estimated covariance matrix is not guaranteed to be positive semi-definite. This could lead to estimated correlations having absolute values which are greater than one, and/or a non-invertible covariance matrix. See [Estimation of covariance matrices](#) for more details.

```
In [8]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])
```

```
In [9]: frame.cov()
```

```
Out[9]:
```

| | a | b | c | d | e |
|---|-----------|-----------|-----------|-----------|-----------|
| a | 1.000882 | -0.003177 | -0.002698 | -0.006889 | 0.031912 |
| b | -0.003177 | 1.024721 | 0.000191 | 0.009212 | 0.000857 |
| c | -0.002698 | 0.000191 | 0.950735 | -0.031743 | -0.005087 |
| d | -0.006889 | 0.009212 | -0.031743 | 1.002983 | -0.047952 |
| e | 0.031912 | 0.000857 | -0.005087 | -0.047952 | 1.042487 |

`DataFrame.cov` also supports an optional `min_periods` keyword that specifies the required minimum number of observations for each column pair in order to have a valid result.

```
In [10]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])
```

```
In [11]: frame.ix[:5, 'a'] = np.nan
```

```
In [12]: frame.ix[5:10, 'b'] = np.nan
```

```
In [13]: frame.cov()
```

```
Out[13]:
```

| | a | b | c |
|---|-----------|-----------|----------|
| a | 1.210090 | -0.430629 | 0.018002 |
| b | -0.430629 | 1.240960 | 0.347188 |
| c | 0.018002 | 0.347188 | 1.301149 |

```
In [14]: frame.cov(min_periods=12)
```

```
Out[14]:
```

| | a | b | c |
|---|----------|----------|----------|
| a | 1.210090 | NaN | 0.018002 |
| b | NaN | 1.240960 | 0.347188 |
| c | 0.018002 | 0.347188 | 1.301149 |

15.1.3 Correlation

Several methods for computing correlations are provided:

| Method name | Description |
|-------------------|---------------------------------------|
| pearson (default) | Standard correlation coefficient |
| kendall | Kendall Tau correlation coefficient |
| spearman | Spearman rank correlation coefficient |

All of these are currently computed using pairwise complete observations.

Note: Please see the *caveats* associated with this method of calculating correlation matrices in the *covariance section*.

```
In [15]: frame = pd.DataFrame(np.random.randn(1000, 5), columns=['a', 'b', 'c', 'd', 'e'])
```

```
In [16]: frame.ix[:,2] = np.nan
```

```
# Series with Series
```

```
In [17]: frame['a'].corr(frame['b'])
```

```
Out[17]: 0.013479040400098794
```

```
In [18]: frame['a'].corr(frame['b'], method='spearman')
```

```
Out[18]: -0.0072898851595406388
```

```
# Pairwise correlation of DataFrame columns
```

```
In [19]: frame.corr()
```

```
Out[19]:
```

| | a | b | c | d | e |
|---|-----------|-----------|-----------|-----------|-----------|
| a | 1.000000 | 0.013479 | -0.049269 | -0.042239 | -0.028525 |
| b | 0.013479 | 1.000000 | -0.020433 | -0.011139 | 0.005654 |
| c | -0.049269 | -0.020433 | 1.000000 | 0.018587 | -0.054269 |
| d | -0.042239 | -0.011139 | 0.018587 | 1.000000 | -0.017060 |
| e | -0.028525 | 0.005654 | -0.054269 | -0.017060 | 1.000000 |

Note that non-numeric columns will be automatically excluded from the correlation calculation.

Like `cov`, `corr` also supports the optional `min_periods` keyword:

```
In [20]: frame = pd.DataFrame(np.random.randn(20, 3), columns=['a', 'b', 'c'])
```

```
In [21]: frame.ix[:5, 'a'] = np.nan
```

```
In [22]: frame.ix[5:10, 'b'] = np.nan
```

```
In [23]: frame.corr()
```

```
Out[23]:
```

| | a | b | c |
|---|-----------|-----------|----------|
| a | 1.000000 | -0.076520 | 0.160092 |
| b | -0.076520 | 1.000000 | 0.135967 |
| c | 0.160092 | 0.135967 | 1.000000 |

```
In [24]: frame.corr(min_periods=12)
```

```
Out[24]:
```

| | a | b | c |
|---|----------|----------|----------|
| a | 1.000000 | NaN | 0.160092 |
| b | NaN | 1.000000 | 0.135967 |
| c | 0.160092 | 0.135967 | 1.000000 |

A related method `corrwith` is implemented on `DataFrame` to compute the correlation between like-labeled `Series` contained in different `DataFrame` objects.

```
In [25]: index = ['a', 'b', 'c', 'd', 'e']
```

```
In [26]: columns = ['one', 'two', 'three', 'four']

In [27]: df1 = pd.DataFrame(np.random.randn(5, 4), index=index, columns=columns)

In [28]: df2 = pd.DataFrame(np.random.randn(4, 4), index=index[:4], columns=columns)

In [29]: df1.corrwith(df2)
Out[29]:
one      -0.125501
two      -0.493244
three     0.344056
four      0.004183
dtype: float64

In [30]: df2.corrwith(df1, axis=1)
Out[30]:
a      -0.675817
b       0.458296
c       0.190809
d      -0.186275
e           NaN
dtype: float64
```

15.1.4 Data ranking

The rank method produces a data ranking with ties being assigned the mean of the ranks (by default) for the group:

```
In [31]: s = pd.Series(np.random.randn(5), index=list('abcde'))

In [32]: s['d'] = s['b'] # so there's a tie

In [33]: s.rank()
Out[33]:
a      5.0
b      2.5
c      1.0
d      2.5
e      4.0
dtype: float64
```

rank is also a DataFrame method and can rank either the rows (axis=0) or the columns (axis=1). NaN values are excluded from the ranking.

```
In [34]: df = pd.DataFrame(np.random.randn(10, 6))

In [35]: df[4] = df[2][:5] # some ties

In [36]: df
Out[36]:
```

| | 0 | 1 | 2 | 3 | 4 | 5 |
|---|-----------|-----------|-----------|-----------|-----------|-----------|
| 0 | -0.904948 | -1.163537 | -1.457187 | 0.135463 | -1.457187 | 0.294650 |
| 1 | -0.976288 | -0.244652 | -0.748406 | -0.999601 | -0.748406 | -0.800809 |
| 2 | 0.401965 | 1.460840 | 1.256057 | 1.308127 | 1.256057 | 0.876004 |
| 3 | 0.205954 | 0.369552 | -0.669304 | 0.038378 | -0.669304 | 1.140296 |
| 4 | -0.477586 | -0.730705 | -1.129149 | -0.601463 | -1.129149 | -0.211196 |
| 5 | -1.092970 | -0.689246 | 0.908114 | 0.204848 | NaN | 0.463347 |
| 6 | 0.376892 | 0.959292 | 0.095572 | -0.593740 | NaN | -0.069180 |

```

7 -1.002601  1.957794 -0.120708  0.094214      NaN -1.467422
8 -0.547231  0.664402 -0.519424 -0.073254      NaN -1.263544
9 -0.250277 -0.237428 -1.056443  0.419477      NaN  1.375064

```

```
In [37]: df.rank(1)
```

```
Out[37]:
```

```

   0  1  2  3  4  5
0  4  3  1.5  5  1.5  6
1  2  6  4.5  1  4.5  3
2  1  6  3.5  5  3.5  2
3  4  5  1.5  3  1.5  6
4  5  3  1.5  4  1.5  6
5  1  2  5.0  3  NaN  4
6  4  5  3.0  1  NaN  2
7  2  5  3.0  4  NaN  1
8  2  5  3.0  4  NaN  1
9  2  3  1.0  4  NaN  5

```

`rank` optionally takes a parameter `ascending` which by default is `true`; when `false`, data is reverse-ranked, with larger values assigned a smaller rank.

`rank` supports different tie-breaking methods, specified with the `method` parameter:

- `average` : average rank of tied group
- `min` : lowest rank in the group
- `max` : highest rank in the group
- `first` : ranks assigned in the order they appear in the array

15.2 Moving (rolling) statistics / moments

For working with time series data, a number of functions are provided for computing common *moving* or *rolling* statistics. Among these are count, sum, mean, median, correlation, variance, covariance, standard deviation, skewness, and kurtosis. All of these methods are in the `pandas` namespace, but otherwise they can be found in `pandas.stats.moments`.

| Function | Description |
|-------------------------------|---------------------------------|
| <code>rolling_count</code> | Number of non-null observations |
| <code>rolling_sum</code> | Sum of values |
| <code>rolling_mean</code> | Mean of values |
| <code>rolling_median</code> | Arithmetic median of values |
| <code>rolling_min</code> | Minimum |
| <code>rolling_max</code> | Maximum |
| <code>rolling_std</code> | Unbiased standard deviation |
| <code>rolling_var</code> | Unbiased variance |
| <code>rolling_skew</code> | Unbiased skewness (3rd moment) |
| <code>rolling_kurt</code> | Unbiased kurtosis (4th moment) |
| <code>rolling_quantile</code> | Sample quantile (value at %) |
| <code>rolling_apply</code> | Generic apply |
| <code>rolling_cov</code> | Unbiased covariance (binary) |
| <code>rolling_corr</code> | Correlation (binary) |
| <code>rolling_window</code> | Moving window function |

Generally these methods all have the same interface. The binary operators (e.g. `rolling_corr`) take two Series or DataFrames. Otherwise, they all accept the following arguments:

- `window`: size of moving window
- `min_periods`: threshold of non-null data points to require (otherwise result is NA)
- `freq`: optionally specify a *frequency string* or *DateOffset* to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument `time_rule` was used instead of `freq` that referred to the legacy time rule constants
- `how`: optionally specify method for down or re-sampling. Default is `min` for `rolling_min`, `max` for `rolling_max`, `median` for `rolling_median`, and `mean` for all other rolling functions. See `DataFrame.resample()`'s `how` argument for more information.

These functions can be applied to `ndarrays` or `Series` objects:

```
In [38]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
```

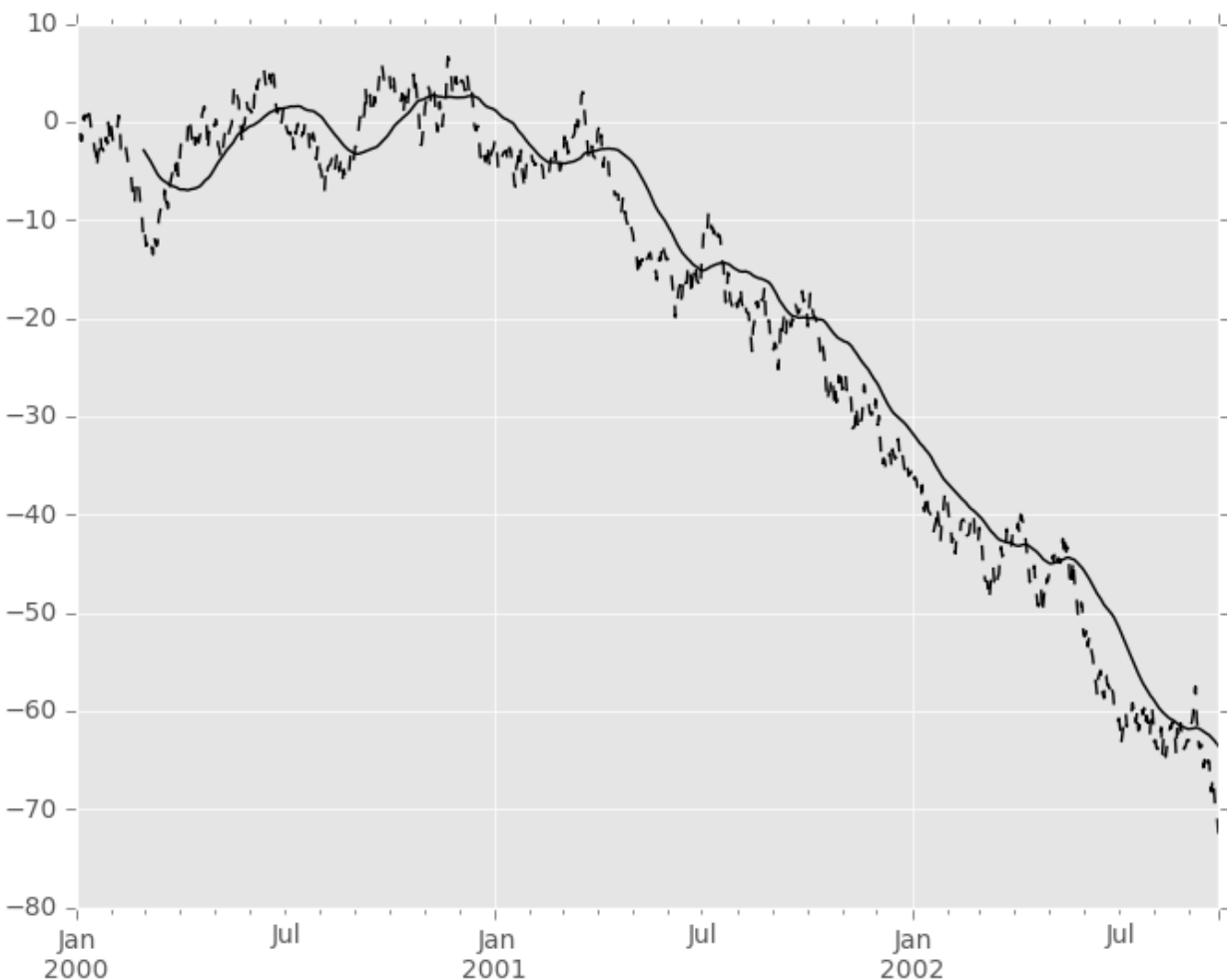
```
In [39]: ts = ts.cumsum()
```

```
In [40]: ts.plot(style='k--')
```

```
Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0xaa1c31cc>
```

```
In [41]: rolling_mean(ts, 60).plot(style='k')
```

```
Out[41]: <matplotlib.axes._subplots.AxesSubplot at 0xaa1c31cc>
```



They can also be applied to `DataFrame` objects. This is really just syntactic sugar for applying the moving window

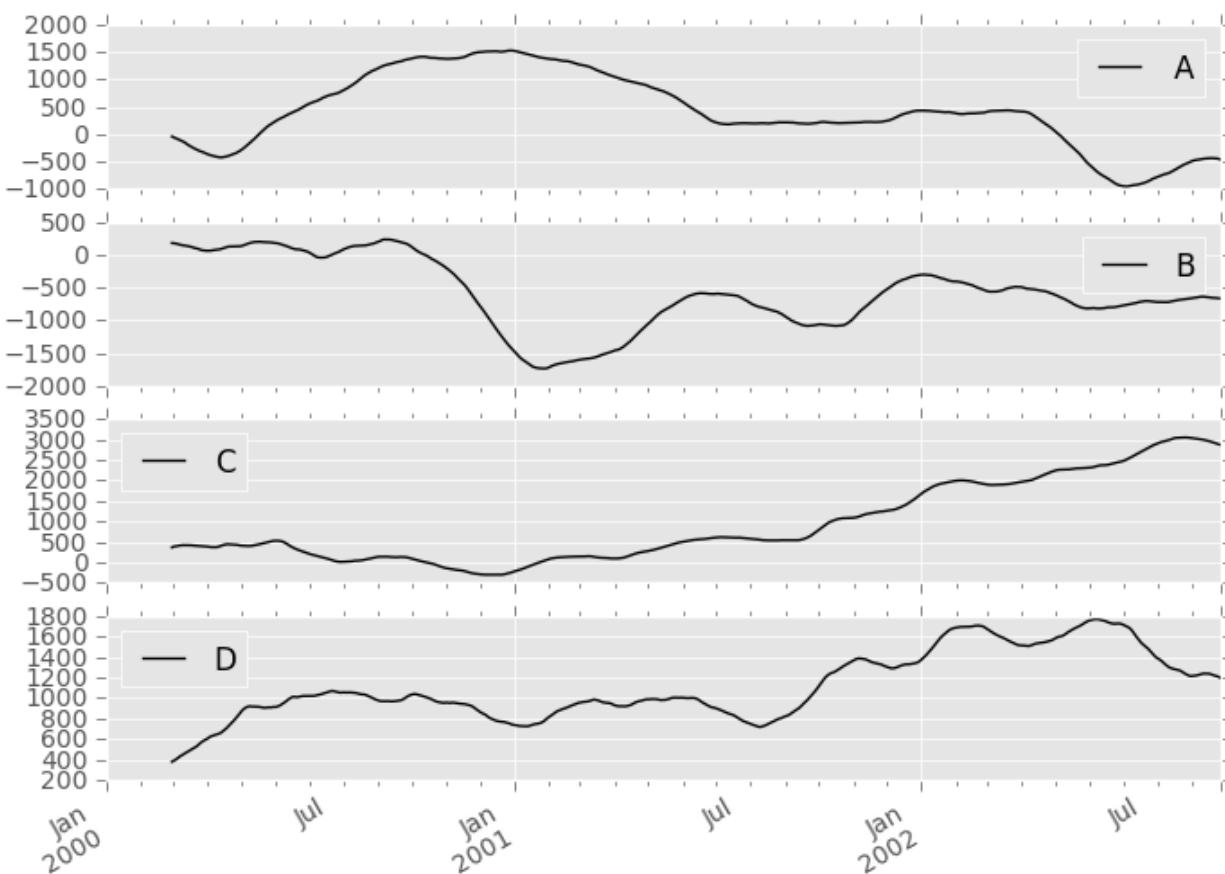
operator to all of the DataFrame's columns:

```
In [42]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index,
.....:                    columns=['A', 'B', 'C', 'D'])
.....:
```

```
In [43]: df = df.cumsum()
```

```
In [44]: rolling_sum(df, 60).plot(subplots=True)
```

```
Out[44]:
array([<matplotlib.axes._subplots.AxesSubplot object at 0xab2fd60c>,
      <matplotlib.axes._subplots.AxesSubplot object at 0xab33f5cc>,
      <matplotlib.axes._subplots.AxesSubplot object at 0xab3ad3ac>,
      <matplotlib.axes._subplots.AxesSubplot object at 0xab297fcc>], dtype=object)
```

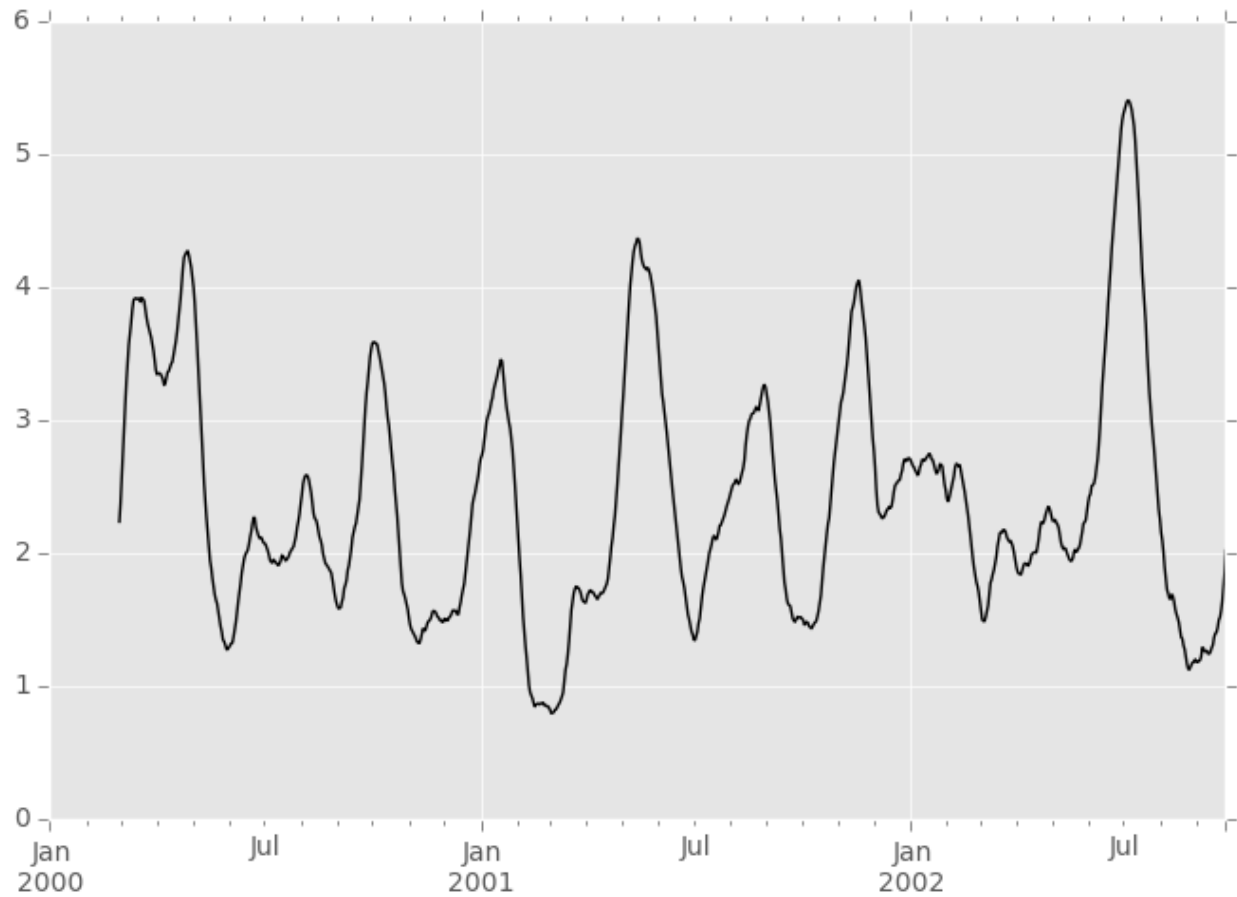


The `rolling_apply` function takes an extra `func` argument and performs generic rolling computations. The `func` argument should be a single function that produces a single value from an ndarray input. Suppose we wanted to compute the mean absolute deviation on a rolling basis:

```
In [45]: mad = lambda x: np.fabs(x - x.mean()).mean()
```

```
In [46]: rolling_apply(ts, 60, mad).plot(style='k')
```

```
Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0xabfabcec>
```



The `rolling_window` function performs a generic rolling window computation on the input data. The weights used in the window are specified by the `win_type` keyword. The list of recognized types are:

- `boxcar`
- `triang`
- `blackman`
- `hamming`
- `bartlett`
- `parzen`
- `bohman`
- `blackmanharris`
- `nuttall`
- `barthann`
- `kaiser` (needs `beta`)
- `gaussian` (needs `std`)
- `general_gaussian` (needs `power`, `width`)
- `slepian` (needs `width`).

```
In [47]: ser = pd.Series(np.random.randn(10), index=pd.date_range('1/1/2000', periods=10))
```

```
In [48]: rolling_window(ser, 5, 'triang')
```

```
Out[48]:
```

```
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05    -1.037870
2000-01-06    -0.767705
2000-01-07    -0.383197
2000-01-08    -0.395513
2000-01-09    -0.558440
2000-01-10    -0.672416
Freq: D, dtype: float64
```

Note that the boxcar window is equivalent to `rolling_mean`.

```
In [49]: rolling_window(ser, 5, 'boxcar')
```

```
Out[49]:
```

```
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64
```

```
In [50]: rolling_mean(ser, 5)
```

```
Out[50]:
```

```
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05   -0.841164
2000-01-06   -0.779948
2000-01-07   -0.565487
2000-01-08   -0.502815
2000-01-09   -0.553755
2000-01-10   -0.472211
Freq: D, dtype: float64
```

For some windowing functions, additional parameters must be specified:

```
In [51]: rolling_window(ser, 5, 'gaussian', std=0.1)
```

```
Out[51]:
```

```
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05   -1.309989
2000-01-06   -1.153000
2000-01-07    0.606382
2000-01-08   -0.681101
2000-01-09   -0.289724
```

```
2000-01-10    -0.996632
Freq: D, dtype: float64
```

By default the labels are set to the right edge of the window, but a `center` keyword is available so the labels can be set at the center. This keyword is available in other rolling functions as well.

```
In [52]: rolling_window(ser, 5, 'boxcar')
```

```
Out [52]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03      NaN
2000-01-04      NaN
2000-01-05    -0.841164
2000-01-06    -0.779948
2000-01-07    -0.565487
2000-01-08    -0.502815
2000-01-09    -0.553755
2000-01-10    -0.472211
Freq: D, dtype: float64
```

```
In [53]: rolling_window(ser, 5, 'boxcar', center=True)
```

```
Out [53]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03    -0.841164
2000-01-04    -0.779948
2000-01-05    -0.565487
2000-01-06    -0.502815
2000-01-07    -0.553755
2000-01-08    -0.472211
2000-01-09      NaN
2000-01-10      NaN
Freq: D, dtype: float64
```

```
In [54]: rolling_mean(ser, 5, center=True)
```

```
Out [54]:
2000-01-01      NaN
2000-01-02      NaN
2000-01-03    -0.841164
2000-01-04    -0.779948
2000-01-05    -0.565487
2000-01-06    -0.502815
2000-01-07    -0.553755
2000-01-08    -0.472211
2000-01-09      NaN
2000-01-10      NaN
Freq: D, dtype: float64
```

Note: In rolling sum mode (`mean=False`) there is no normalization done to the weights. Passing custom weights of `[1, 1, 1]` will yield a different result than passing weights of `[2, 2, 2]`, for example. When passing a `win_type` instead of explicitly specifying the weights, the weights are already normalized so that the largest weight is 1.

In contrast, the nature of the rolling mean calculation (`mean=True`) is such that the weights are normalized with respect to each other. Weights of `[1, 1, 1]` and `[2, 2, 2]` yield the same result.

15.2.1 Binary rolling moments

`rolling_cov` and `rolling_corr` can compute moving window statistics about two `Series` or any combination of `DataFrame/Series` or `DataFrame/DataFrame`. Here is the behavior in each case:

- two `Series`: compute the statistic for the pairing.
- `DataFrame/Series`: compute the statistics for each column of the `DataFrame` with the passed `Series`, thus returning a `DataFrame`.
- `DataFrame/DataFrame`: by default compute the statistic for matching column names, returning a `DataFrame`. If the keyword argument `pairwise=True` is passed then computes the statistic for each pair of columns, returning a `Panel` whose items are the dates in question (see [the next section](#)).

For example:

```
In [55]: df2 = df[:20]
```

```
In [56]: rolling_corr(df2, df2['B'], window=5)
```

```
Out[56]:
```

| | A | B | C | D |
|------------|-----------|-----|-----------|-----------|
| 2000-01-01 | NaN | NaN | NaN | NaN |
| 2000-01-02 | NaN | NaN | NaN | NaN |
| 2000-01-03 | NaN | NaN | NaN | NaN |
| 2000-01-04 | NaN | NaN | NaN | NaN |
| 2000-01-05 | -0.262853 | 1 | 0.334449 | 0.193380 |
| 2000-01-06 | -0.083745 | 1 | -0.521587 | -0.556126 |
| 2000-01-07 | -0.292940 | 1 | -0.658532 | -0.458128 |
| ... | ... | .. | ... | ... |
| 2000-01-14 | 0.519499 | 1 | -0.687277 | 0.192822 |
| 2000-01-15 | 0.048982 | 1 | 0.167669 | -0.061463 |
| 2000-01-16 | 0.217190 | 1 | 0.167564 | -0.326034 |
| 2000-01-17 | 0.641180 | 1 | -0.164780 | -0.111487 |
| 2000-01-18 | 0.130422 | 1 | 0.322833 | 0.632383 |
| 2000-01-19 | 0.317278 | 1 | 0.384528 | 0.813656 |
| 2000-01-20 | 0.293598 | 1 | 0.159538 | 0.742381 |

```
[20 rows x 4 columns]
```

15.2.2 Computing rolling pairwise covariances and correlations

In financial data analysis and other fields it's common to compute covariance and correlation matrices for a collection of time series. Often one is also interested in moving-window covariance and correlation matrices. This can be done by passing the `pairwise` keyword argument, which in the case of `DataFrame` inputs will yield a `Panel` whose items are the dates in question. In the case of a single `DataFrame` argument the `pairwise` argument can even be omitted:

Note: Missing values are ignored and each entry is computed using the pairwise complete observations. Please see the [covariance section](#) for *caveats* associated with this method of calculating covariance and correlation matrices.

```
In [57]: covs = rolling_cov(df[['B', 'C', 'D']], df[['A', 'B', 'C']], 50, pairwise=True)
```

```
In [58]: covs[df.index[-50]]
```

```
Out[58]:
```

| | A | B | C |
|---|----------|----------|----------|
| B | 2.667506 | 1.671711 | 1.938634 |

```
C 8.513843  1.938634  10.556436
D -7.714737 -1.434529 -7.082653
```

```
In [59]: correls = rolling_corr(df, 50)
```

```
In [60]: correls[df.index[-50]]
```

```
Out[60]:
```

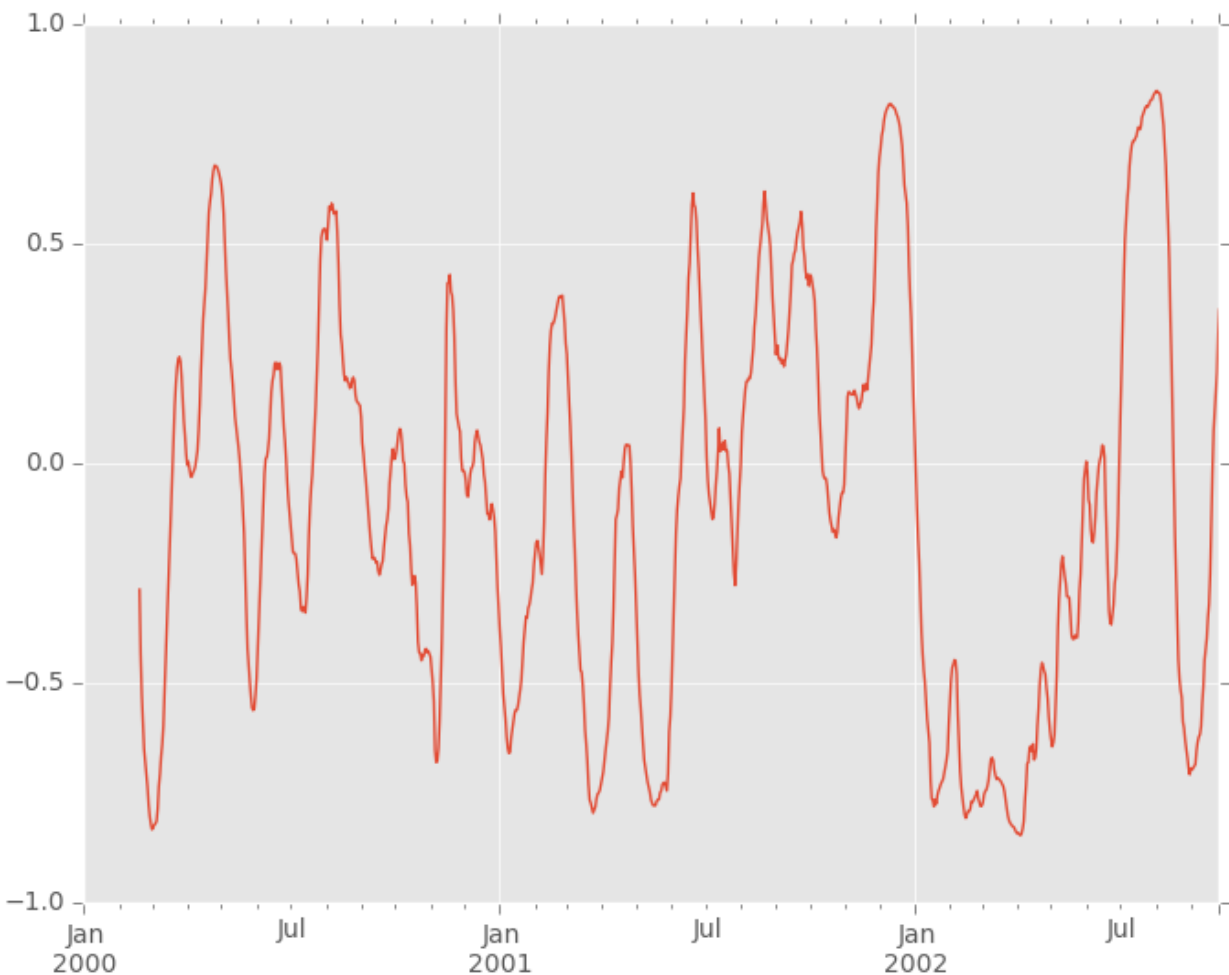
| | A | B | C | D |
|---|-----------|-----------|-----------|-----------|
| A | 1.000000 | 0.604221 | 0.767429 | -0.776170 |
| B | 0.604221 | 1.000000 | 0.461484 | -0.381148 |
| C | 0.767429 | 0.461484 | 1.000000 | -0.748863 |
| D | -0.776170 | -0.381148 | -0.748863 | 1.000000 |

Note: Prior to version 0.14 this was available through `rolling_corr_pairwise` which is now simply syntactic sugar for calling `rolling_corr(..., pairwise=True)` and deprecated. This is likely to be removed in a future release.

You can efficiently retrieve the time series of correlations between two columns using `ix` indexing:

```
In [61]: correls.ix[:, 'A', 'C'].plot()
```

```
Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0xa99abacc>
```



15.3 Expanding window moment functions

A common alternative to rolling statistics is to use an *expanding* window, which yields the value of the statistic with all the data available up to that point in time. As these calculations are a special case of rolling statistics, they are implemented in pandas such that the following two calls are equivalent:

```
In [62]: rolling_mean(df, window=len(df), min_periods=1)[:5]
Out [62]:
```

| | A | B | C | D |
|------------|-----------|----------|----------|-----------|
| 2000-01-01 | -1.388345 | 3.317290 | 0.344542 | -0.036968 |
| 2000-01-02 | -1.123132 | 3.622300 | 1.675867 | 0.595300 |
| 2000-01-03 | -0.628502 | 3.626503 | 2.455240 | 1.060158 |
| 2000-01-04 | -0.768740 | 3.888917 | 2.451354 | 1.281874 |
| 2000-01-05 | -0.824034 | 4.108035 | 2.556112 | 1.140723 |

```
In [63]: expanding_mean(df)[:5]
Out [63]:
```

| | A | B | C | D |
|------------|-----------|----------|----------|-----------|
| 2000-01-01 | -1.388345 | 3.317290 | 0.344542 | -0.036968 |
| 2000-01-02 | -1.123132 | 3.622300 | 1.675867 | 0.595300 |
| 2000-01-03 | -0.628502 | 3.626503 | 2.455240 | 1.060158 |
| 2000-01-04 | -0.768740 | 3.888917 | 2.451354 | 1.281874 |
| 2000-01-05 | -0.824034 | 4.108035 | 2.556112 | 1.140723 |

Like the `rolling_` functions, the following methods are included in the pandas namespace or can be located in `pandas.stats.moments`.

| Function | Description |
|---------------------------------|---------------------------------|
| <code>expanding_count</code> | Number of non-null observations |
| <code>expanding_sum</code> | Sum of values |
| <code>expanding_mean</code> | Mean of values |
| <code>expanding_median</code> | Arithmetic median of values |
| <code>expanding_min</code> | Minimum |
| <code>expanding_max</code> | Maximum |
| <code>expanding_std</code> | Unbiased standard deviation |
| <code>expanding_var</code> | Unbiased variance |
| <code>expanding_skew</code> | Unbiased skewness (3rd moment) |
| <code>expanding_kurt</code> | Unbiased kurtosis (4th moment) |
| <code>expanding_quantile</code> | Sample quantile (value at %) |
| <code>expanding_apply</code> | Generic apply |
| <code>expanding_cov</code> | Unbiased covariance (binary) |
| <code>expanding_corr</code> | Correlation (binary) |

Aside from not having a `window` parameter, these functions have the same interfaces as their `rolling_` counterpart. Like above, the parameters they all accept are:

- `min_periods`: threshold of non-null data points to require. Defaults to minimum needed to compute statistic. No NaNs will be output once `min_periods` non-null data points have been seen.
- `freq`: optionally specify a *frequency string* or *DateOffset* to pre-conform the data to. Note that prior to pandas v0.8.0, a keyword argument `time_rule` was used instead of `freq` that referred to the legacy time rule constants

Note: The output of the `rolling_` and `expanding_` functions do not return a NaN if there are at least `min_periods` non-null values in the current window. This differs from `cumsum`, `cumprod`, `cummax`, and `cummin`, which return NaN in the output wherever a NaN is encountered in the input.

An expanding window statistic will be more stable (and less responsive) than its rolling window counterpart as the increasing window size decreases the relative impact of an individual data point. As an example, here is the `expanding_mean` output for the previous time series dataset:

```
In [64]: ts.plot(style='k--')
Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0xa9409d0c>

In [65]: expanding_mean(ts).plot(style='k')
Out[65]: <matplotlib.axes._subplots.AxesSubplot at 0xa9409d0c>
```



15.4 Exponentially weighted moment functions

A related set of functions are exponentially weighted versions of several of the above statistics. A number of expanding EW (exponentially weighted) functions are provided:

| Function | Description |
|----------------------|------------------------------|
| <code>ewma</code> | EW moving average |
| <code>ewmvar</code> | EW moving variance |
| <code>ewmstd</code> | EW moving standard deviation |
| <code>ewmcorr</code> | EW moving correlation |
| <code>ewmcov</code> | EW moving covariance |

In general, a weighted moving average is calculated as

$$y_t = \frac{\sum_{i=0}^t w_i x_{t-i}}{\sum_{i=0}^t w_i},$$

where x_t is the input at y_t is the result.

The EW functions support two variants of exponential weights: The default, `adjust=True`, uses the weights $w_i = (1 - \alpha)^i$. When `adjust=False` is specified, moving averages are calculated as

$$\begin{aligned} y_0 &= x_0 \\ y_t &= (1 - \alpha)y_{t-1} + \alpha x_t, \end{aligned}$$

which is equivalent to using weights

$$w_i = \begin{cases} \alpha(1 - \alpha)^i & \text{if } i < t \\ (1 - \alpha)^i & \text{if } i = t. \end{cases}$$

Note: These equations are sometimes written in terms of $\alpha' = 1 - \alpha$, e.g.

$$y_t = \alpha' y_{t-1} + (1 - \alpha') x_t.$$

One must have $0 < \alpha \leq 1$, but rather than pass α directly, it's easier to think about either the **span**, **center of mass** (**com**) or **halflife** of an EW moment:

$$\alpha = \begin{cases} \frac{2}{s+1}, & s = \text{span} \\ \frac{1}{1+c}, & c = \text{center of mass} \\ 1 - \exp^{\frac{\log 0.5}{h}}, & h = \text{half life} \end{cases}$$

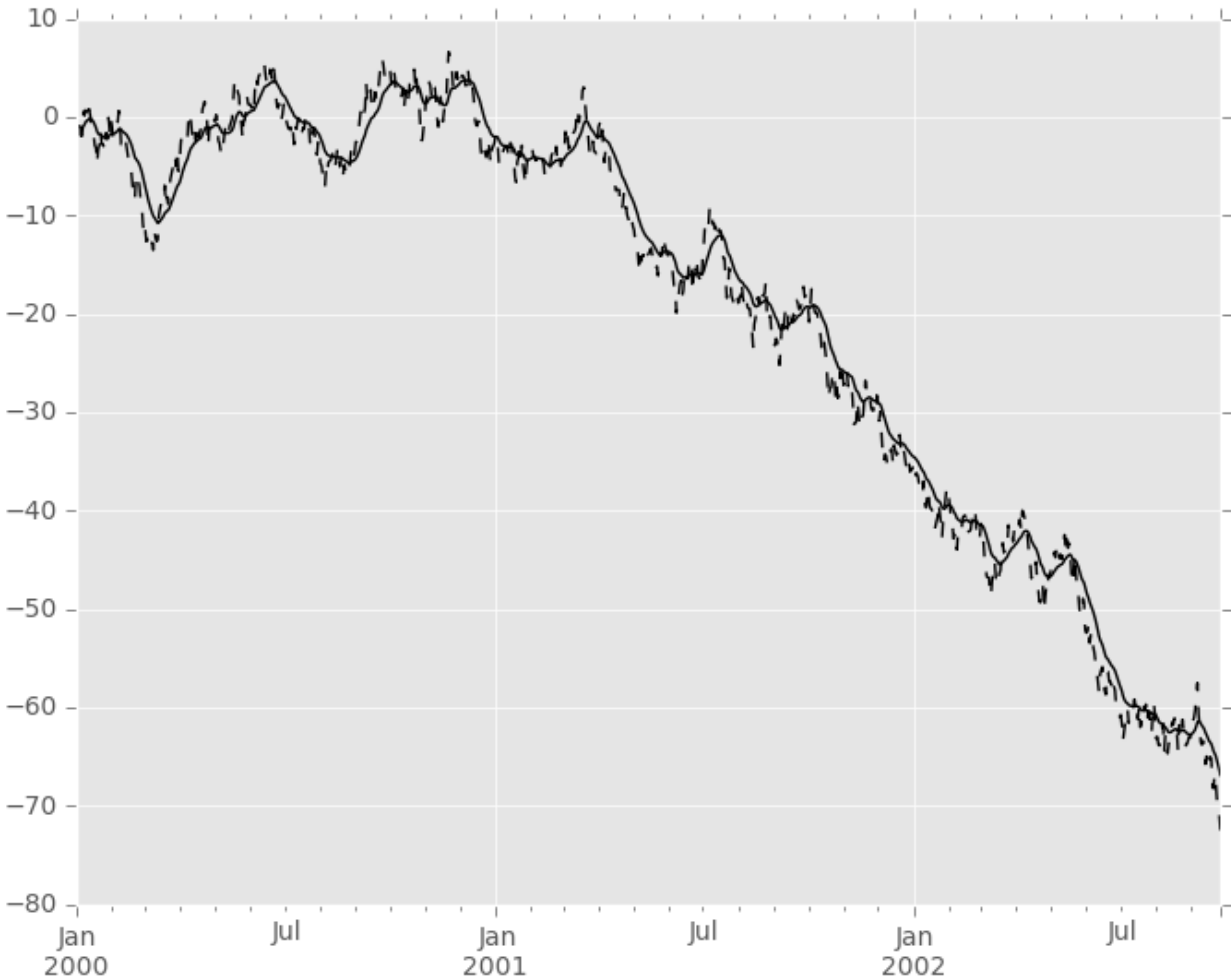
One must specify precisely one of the three to the EW functions. **Span** corresponds to what is commonly called a “20-day EW moving average” for example. **Center of mass** has a more physical interpretation. For example, **span** = 20 corresponds to **com** = 9.5. **Halflife** is the period of time for the exponential weight to reduce to one half.

Here is an example for a univariate time series:

```
In [66]: plt.close('all')

In [67]: ts.plot(style='k--')
Out[67]: <matplotlib.axes._subplots.AxesSubplot at 0xa9a47c4c>

In [68]: ewma(ts, span=20).plot(style='k')
Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0xa9a47c4c>
```



All the EW functions have a `min_periods` argument, which has the same meaning it does for all the `expanding_` and `rolling_` functions: no output values will be set until at least `min_periods` non-null values are encountered in the (expanding) window. (This is a change from versions prior to 0.15.0, in which the `min_periods` argument affected only the `min_periods` consecutive entries starting at the first non-null value.)

All the EW functions also have an `ignore_na` argument, which determines how intermediate null values affect the calculation of the weights. When `ignore_na=False` (the default), weights are calculated based on absolute positions, so that intermediate null values affect the result. When `ignore_na=True` (which reproduces the behavior in versions prior to 0.15.0), weights are calculated by ignoring intermediate null values. For example, assuming `adjust=True`, if `ignore_na=False`, the weighted average of 3, NaN, 5 would be calculated as

$$\frac{(1 - \alpha)^2 \cdot 3 + 1 \cdot 5}{(1 - \alpha)^2 + 1}$$

Whereas if `ignore_na=True`, the weighted average would be calculated as

$$\frac{(1 - \alpha) \cdot 3 + 1 \cdot 5}{(1 - \alpha) + 1}.$$

The `ewmvar`, `ewmstd`, and `ewmcov` functions have a `bias` argument, specifying whether the result should contain biased or unbiased statistics. For example, if `bias=True`, `ewmvar(x)` is calculated as `ewmvar(x) = ewma(x**2) - ewma(x)**2`; whereas if `bias=False` (the default), the biased variance statistics are scaled

by debiasing factors

$$\frac{\left(\sum_{i=0}^t w_i\right)^2}{\left(\sum_{i=0}^t w_i\right)^2 - \sum_{i=0}^t w_i^2}.$$

(For $w_i = 1$, this reduces to the usual $N/(N - 1)$ factor, with $N = t + 1$.) See http://en.wikipedia.org/wiki/Weighted_arithmetic_mean#Weighted_sample_variance for further details.

WORKING WITH MISSING DATA

In this section, we will discuss missing (also referred to as NA) values in pandas.

Note: The choice of using NaN internally to denote missing data was largely for simplicity and performance reasons. It differs from the MaskedArray approach of, for example, `scikits.timeseries`. We are hopeful that NumPy will soon be able to provide a native NA type solution (similar to R) performant enough to be used in pandas.

See the *cookbook* for some advanced strategies

16.1 Missing data basics

16.1.1 When / why does data become missing?

Some might quibble over our usage of *missing*. By “missing” we simply mean **null** or “not present for whatever reason”. Many data sets simply arrive with missing data, either because it exists and was not collected or it never existed. For example, in a collection of financial time series, some of the time series might start on different dates. Thus, values prior to the start date would generally be marked as missing.

In pandas, one of the most common ways that missing data is **introduced** into a data set is by reindexing. For example

```
In [1]: df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f', 'h'],
...:                      columns=['one', 'two', 'three'])
...:
```

```
In [2]: df['four'] = 'bar'
```

```
In [3]: df['five'] = df['one'] > 0
```

```
In [4]: df
```

```
Out[4]:
```

| | one | two | three | four | five |
|---|-----------|-----------|-----------|------|-------|
| a | 0.469112 | -0.282863 | -1.509059 | bar | True |
| c | -1.135632 | 1.212112 | -0.173215 | bar | False |
| e | 0.119209 | -1.044236 | -0.861849 | bar | True |
| f | -2.104569 | -0.494929 | 1.071804 | bar | False |
| h | 0.721555 | -0.706771 | -1.039575 | bar | True |

```
In [5]: df2 = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
```

```
In [6]: df2
```

```
Out[6]:
```

| | one | two | three | four | five |
|--|-----|-----|-------|------|------|
|--|-----|-----|-------|------|------|

```
a  0.469112 -0.282863 -1.509059  bar  True
b         NaN         NaN         NaN  NaN  NaN
c -1.135632  1.212112 -0.173215  bar  False
d         NaN         NaN         NaN  NaN  NaN
e  0.119209 -1.044236 -0.861849  bar  True
f -2.104569 -0.494929  1.071804  bar  False
g         NaN         NaN         NaN  NaN  NaN
h  0.721555 -0.706771 -1.039575  bar  True
```

16.1.2 Values considered “missing”

As data comes in many shapes and forms, pandas aims to be flexible with regard to handling missing data. While NaN is the default missing value marker for reasons of computational speed and convenience, we need to be able to easily detect this value with data of different types: floating point, integer, boolean, and general object. In many cases, however, the Python None will arise and we wish to also consider that “missing” or “null”.

Prior to version v0.10.0 inf and -inf were also considered to be “null” in computations. This is no longer the case by default; use the `mode.use_inf_as_null` option to recover it. To make detecting missing values easier (and across different array dtypes), pandas provides the `isnull()` and `notnull()` functions, which are also methods on Series objects:

```
In [7]: df2['one']
Out[7]:
a    0.469112
b         NaN
c   -1.135632
d         NaN
e    0.119209
f   -2.104569
g         NaN
h    0.721555
Name: one, dtype: float64
```

```
In [8]: isnull(df2['one'])
Out[8]:
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool
```

```
In [9]: df2['four'].notnull()
Out[9]:
a     True
b    False
c     True
d    False
e     True
f     True
g    False
h     True
Name: four, dtype: bool
```

Summary: NaN and None (in object arrays) are considered missing by the `isnull` and `notnull` functions. `inf` and `-inf` are no longer considered missing by default.

16.2 Datetimes

For `datetime64[ns]` types, `NaT` represents missing values. This is a pseudo-native sentinel value that can be represented by numpy in a singular dtype (`datetime64[ns]`). pandas objects provide intercompatibility between `NaT` and `NaN`.

```
In [10]: df2 = df.copy()
```

```
In [11]: df2['timestamp'] = Timestamp('20120101')
```

```
In [12]: df2
```

```
Out[12]:
```

| | one | two | three | four | five | timestamp |
|---|-----------|-----------|-----------|------|-------|------------|
| a | 0.469112 | -0.282863 | -1.509059 | bar | True | 2012-01-01 |
| c | -1.135632 | 1.212112 | -0.173215 | bar | False | 2012-01-01 |
| e | 0.119209 | -1.044236 | -0.861849 | bar | True | 2012-01-01 |
| f | -2.104569 | -0.494929 | 1.071804 | bar | False | 2012-01-01 |
| h | 0.721555 | -0.706771 | -1.039575 | bar | True | 2012-01-01 |

```
In [13]: df2.ix[['a', 'c', 'h'], ['one', 'timestamp']] = np.nan
```

```
In [14]: df2
```

```
Out[14]:
```

| | one | two | three | four | five | timestamp |
|---|-----------|-----------|-----------|------|-------|------------|
| a | NaN | -0.282863 | -1.509059 | bar | True | NaT |
| c | NaN | 1.212112 | -0.173215 | bar | False | NaT |
| e | 0.119209 | -1.044236 | -0.861849 | bar | True | 2012-01-01 |
| f | -2.104569 | -0.494929 | 1.071804 | bar | False | 2012-01-01 |
| h | NaN | -0.706771 | -1.039575 | bar | True | NaT |

```
In [15]: df2.get_dtype_counts()
```

```
Out[15]:
```

| | |
|----------------|---|
| bool | 1 |
| datetime64[ns] | 1 |
| float64 | 3 |
| object | 1 |
| dtype: int64 | |

16.3 Inserting missing data

You can insert missing values by simply assigning to containers. The actual missing value used will be chosen based on the dtype.

For example, numeric containers will always use `NaN` regardless of the missing value type chosen:

```
In [16]: s = pd.Series([1, 2, 3])
```

```
In [17]: s.loc[0] = None
```

```
In [18]: s
```

```
Out[18]:
```

| | |
|---|-----|
| 0 | NaN |
|---|-----|

```
1      2
2      3
dtype: float64
```

Likewise, datetime containers will always use NaT.

For object containers, pandas will use the value given:

```
In [19]: s = pd.Series(["a", "b", "c"])
```

```
In [20]: s.loc[0] = None
```

```
In [21]: s.loc[1] = np.nan
```

```
In [22]: s
```

```
Out[22]:
0      None
1      NaN
2         c
dtype: object
```

16.4 Calculations with missing data

Missing values propagate naturally through arithmetic operations between pandas objects.

```
In [23]: a
```

```
Out[23]:
      one      two
a      NaN -0.282863
c      NaN  1.212112
e  0.119209 -1.044236
f -2.104569 -0.494929
h -2.104569 -0.706771
```

```
In [24]: b
```

```
Out[24]:
      one      two      three
a      NaN -0.282863 -1.509059
c      NaN  1.212112 -0.173215
e  0.119209 -1.044236 -0.861849
f -2.104569 -0.494929  1.071804
h      NaN -0.706771 -1.039575
```

```
In [25]: a + b
```

```
Out[25]:
      one  three      two
a      NaN   NaN -0.565727
c      NaN   NaN  2.424224
e  0.238417   NaN -2.088472
f -4.209138   NaN -0.989859
h      NaN   NaN -1.413542
```

The descriptive statistics and computational methods discussed in the *data structure overview* (and listed [here](#) and [here](#)) are all written to account for missing data. For example:

- When summing data, NA (missing) values will be treated as zero
- If the data are all NA, the result will be NA

- Methods like **cumsum** and **cumprod** ignore NA values, but preserve them in the resulting arrays

```
In [26]: df
Out[26]:
```

| | one | two | three |
|---|-----------|-----------|-----------|
| a | NaN | -0.282863 | -1.509059 |
| c | NaN | 1.212112 | -0.173215 |
| e | 0.119209 | -1.044236 | -0.861849 |
| f | -2.104569 | -0.494929 | 1.071804 |
| h | NaN | -0.706771 | -1.039575 |

```
In [27]: df['one'].sum()
Out[27]: -1.9853605075978744
```

```
In [28]: df.mean(1)
Out[28]:
```

| | |
|---|-----------|
| a | -0.895961 |
| c | 0.519449 |
| e | -0.595625 |
| f | -0.509232 |
| h | -0.873173 |

dtype: float64

```
In [29]: df.cumsum()
Out[29]:
```

| | one | two | three |
|---|-----------|-----------|-----------|
| a | NaN | -0.282863 | -1.509059 |
| c | NaN | 0.929249 | -1.682273 |
| e | 0.119209 | -0.114987 | -2.544122 |
| f | -1.985361 | -0.609917 | -1.472318 |
| h | NaN | -1.316688 | -2.511893 |

16.4.1 NA values in GroupBy

NA groups in GroupBy are automatically excluded. This behavior is consistent with R, for example.

16.5 Cleaning / filling missing data

pandas objects are equipped with various data manipulation methods for dealing with missing data.

16.5.1 Filling missing values: fillna

The **fillna** function can “fill in” NA values with non-null data in a couple of ways, which we illustrate:

Replace NA with a scalar value

```
In [30]: df2
Out[30]:
```

| | one | two | three | four | five | timestamp |
|---|-----------|-----------|-----------|------|-------|------------|
| a | NaN | -0.282863 | -1.509059 | bar | True | NaT |
| c | NaN | 1.212112 | -0.173215 | bar | False | NaT |
| e | 0.119209 | -1.044236 | -0.861849 | bar | True | 2012-01-01 |
| f | -2.104569 | -0.494929 | 1.071804 | bar | False | 2012-01-01 |
| h | NaN | -0.706771 | -1.039575 | bar | True | NaT |

```
In [31]: df2.fillna(0)
Out[31]:
```

| | one | two | three | four | five | timestamp |
|---|-----------|-----------|-----------|------|-------|------------|
| a | 0.000000 | -0.282863 | -1.509059 | bar | True | 1970-01-01 |
| c | 0.000000 | 1.212112 | -0.173215 | bar | False | 1970-01-01 |
| e | 0.119209 | -1.044236 | -0.861849 | bar | True | 2012-01-01 |
| f | -2.104569 | -0.494929 | 1.071804 | bar | False | 2012-01-01 |
| h | 0.000000 | -0.706771 | -1.039575 | bar | True | 1970-01-01 |

```
In [32]: df2['four'].fillna('missing')
Out[32]:
```

| | |
|---|-----|
| a | bar |
| c | bar |
| e | bar |
| f | bar |
| h | bar |

Name: four, dtype: object

Fill gaps forward or backward

Using the same filling arguments as *reindexing*, we can propagate non-null values forward or backward:

```
In [33]: df
Out[33]:
```

| | one | two | three |
|---|-----------|-----------|-----------|
| a | NaN | -0.282863 | -1.509059 |
| c | NaN | 1.212112 | -0.173215 |
| e | 0.119209 | -1.044236 | -0.861849 |
| f | -2.104569 | -0.494929 | 1.071804 |
| h | NaN | -0.706771 | -1.039575 |

```
In [34]: df.fillna(method='pad')
Out[34]:
```

| | | | |
|---|-----------|-----------|-----------|
| a | NaN | -0.282863 | -1.509059 |
| c | NaN | 1.212112 | -0.173215 |
| e | 0.119209 | -1.044236 | -0.861849 |
| f | -2.104569 | -0.494929 | 1.071804 |
| h | -2.104569 | -0.706771 | -1.039575 |

Limit the amount of filling

If we only want consecutive gaps filled up to a certain number of data points, we can use the *limit* keyword:

```
In [35]: df
Out[35]:
```

| | one | two | three |
|---|-----|-----------|-----------|
| a | NaN | -0.282863 | -1.509059 |
| c | NaN | 1.212112 | -0.173215 |
| e | NaN | NaN | NaN |
| f | NaN | NaN | NaN |
| h | NaN | -0.706771 | -1.039575 |

```
In [36]: df.fillna(method='pad', limit=1)
Out[36]:
```

| | one | two | three |
|---|-----|-----------|-----------|
| a | NaN | -0.282863 | -1.509059 |
| c | NaN | 1.212112 | -0.173215 |
| e | NaN | 1.212112 | -0.173215 |

```
f NaN NaN NaN
h NaN -0.706771 -1.039575
```

To remind you, these are the available filling methods:

| Method | Action |
|------------------|----------------------|
| pad / ffill | Fill values forward |
| bfill / backfill | Fill values backward |

With time series data, using pad/ffill is extremely common so that the “last known value” is available at every time point.

The `ffill()` function is equivalent to `fillna(method='ffill')` and `bfill()` is equivalent to `fillna(method='bfill')`

16.5.2 Filling with a PandasObject

New in version 0.12.

You can also fillna using a dict or Series that is alignable. The labels of the dict or index of the Series must match the columns of the frame you wish to fill. The use case of this is to fill a DataFrame with the mean of that column.

```
In [37]: dff = pd.DataFrame(np.random.randn(10,3), columns=list('ABC'))
```

```
In [38]: dff.iloc[3:5,0] = np.nan
```

```
In [39]: dff.iloc[4:6,1] = np.nan
```

```
In [40]: dff.iloc[5:8,2] = np.nan
```

```
In [41]: dff
```

```
Out[41]:
```

| | A | B | C |
|---|-----------|-----------|-----------|
| 0 | 0.271860 | -0.424972 | 0.567020 |
| 1 | 0.276232 | -1.087401 | -0.673690 |
| 2 | 0.113648 | -1.478427 | 0.524988 |
| 3 | NaN | 0.577046 | -1.715002 |
| 4 | NaN | NaN | -1.157892 |
| 5 | -1.344312 | NaN | NaN |
| 6 | -0.109050 | 1.643563 | NaN |
| 7 | 0.357021 | -0.674600 | NaN |
| 8 | -0.968914 | -1.294524 | 0.413738 |
| 9 | 0.276662 | -0.472035 | -0.013960 |

```
In [42]: dff.fillna(dff.mean())
```

```
Out[42]:
```

| | A | B | C |
|---|-----------|-----------|-----------|
| 0 | 0.271860 | -0.424972 | 0.567020 |
| 1 | 0.276232 | -1.087401 | -0.673690 |
| 2 | 0.113648 | -1.478427 | 0.524988 |
| 3 | -0.140857 | 0.577046 | -1.715002 |
| 4 | -0.140857 | -0.401419 | -1.157892 |
| 5 | -1.344312 | -0.401419 | -0.293543 |
| 6 | -0.109050 | 1.643563 | -0.293543 |
| 7 | 0.357021 | -0.674600 | -0.293543 |
| 8 | -0.968914 | -1.294524 | 0.413738 |
| 9 | 0.276662 | -0.472035 | -0.013960 |

```
In [43]: dff.fillna(dff.mean()['B':'C'])
Out[43]:
```

| | A | B | C |
|---|-----------|-----------|-----------|
| 0 | 0.271860 | -0.424972 | 0.567020 |
| 1 | 0.276232 | -1.087401 | -0.673690 |
| 2 | 0.113648 | -1.478427 | 0.524988 |
| 3 | NaN | 0.577046 | -1.715002 |
| 4 | NaN | -0.401419 | -1.157892 |
| 5 | -1.344312 | -0.401419 | -0.293543 |
| 6 | -0.109050 | 1.643563 | -0.293543 |
| 7 | 0.357021 | -0.674600 | -0.293543 |
| 8 | -0.968914 | -1.294524 | 0.413738 |
| 9 | 0.276662 | -0.472035 | -0.013960 |

New in version 0.13.

Same result as above, but is aligning the ‘fill’ value which is a Series in this case.

```
In [44]: dff.where(notnull(dff), dff.mean(), axis='columns')
Out[44]:
```

| | A | B | C |
|---|-----------|-----------|-----------|
| 0 | 0.271860 | -0.424972 | 0.567020 |
| 1 | 0.276232 | -1.087401 | -0.673690 |
| 2 | 0.113648 | -1.478427 | 0.524988 |
| 3 | -0.140857 | 0.577046 | -1.715002 |
| 4 | -0.140857 | -0.401419 | -1.157892 |
| 5 | -1.344312 | -0.401419 | -0.293543 |
| 6 | -0.109050 | 1.643563 | -0.293543 |
| 7 | 0.357021 | -0.674600 | -0.293543 |
| 8 | -0.968914 | -1.294524 | 0.413738 |
| 9 | 0.276662 | -0.472035 | -0.013960 |

16.5.3 Dropping axis labels with missing data: dropna

You may wish to simply exclude labels from a data set which refer to missing data. To do this, use the **dropna** method:

```
In [45]: df
Out[45]:
```

| | one | two | three |
|---|-----|-----------|-----------|
| a | NaN | -0.282863 | -1.509059 |
| c | NaN | 1.212112 | -0.173215 |
| e | NaN | 0.000000 | 0.000000 |
| f | NaN | 0.000000 | 0.000000 |
| h | NaN | -0.706771 | -1.039575 |

```
In [46]: df.dropna(axis=0)
Out[46]:
```

Empty DataFrame
Columns: [one, two, three]
Index: []

```
In [47]: df.dropna(axis=1)
Out[47]:
```

| | two | three |
|---|-----------|-----------|
| a | -0.282863 | -1.509059 |
| c | 1.212112 | -0.173215 |
| e | 0.000000 | 0.000000 |
| f | 0.000000 | 0.000000 |

```
h -0.706771 -1.039575
```

```
In [48]: df['one'].dropna()
```

```
Out[48]: Series([], Name: one, dtype: float64)
```

`Series.dropna` is a simpler method as it only has one axis to consider. `DataFrame.dropna` has considerably more options than `Series.dropna`, which can be examined *in the API*.

16.5.4 Interpolation

New in version 0.13.0: `interpolate()`, and `interpolate()` have revamped interpolation methods and functionality.

Both `Series` and `Dataframe` objects have an `interpolate` method that, by default, performs linear interpolation at missing datapoints.

```
In [49]: ts
```

```
Out[49]:
```

```
2000-01-31    0.469112
2000-02-29         NaN
2000-03-31         NaN
2000-04-28         NaN
2000-05-31         NaN
2000-06-30         NaN
2000-07-31         NaN
...
2007-10-31   -3.305259
2007-11-30   -5.485119
2007-12-31   -6.854968
2008-01-31   -7.809176
2008-02-29   -6.346480
2008-03-31   -8.089641
2008-04-30   -8.916232
Freq: BM, dtype: float64
```

```
In [50]: ts.count()
```

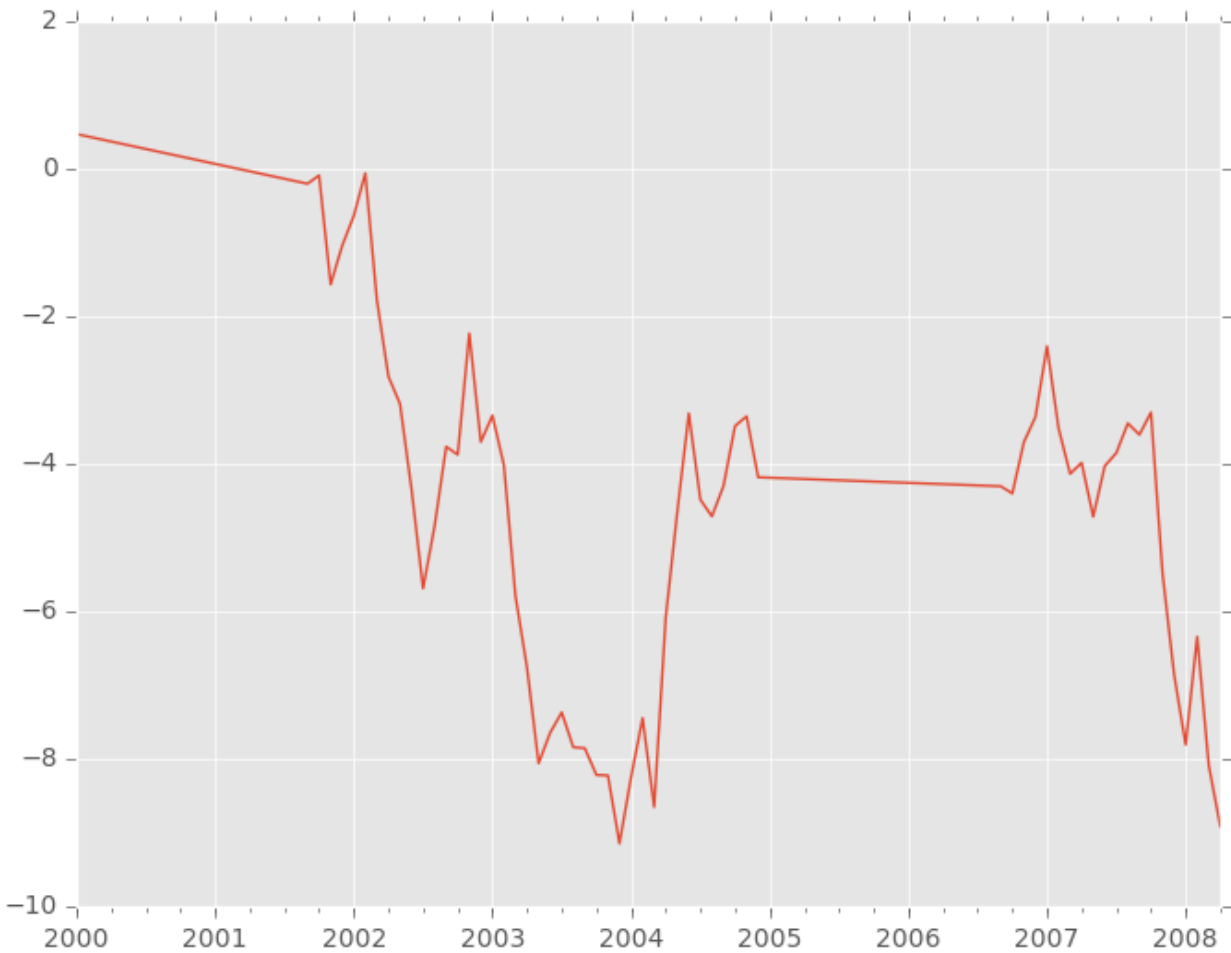
```
Out[50]: 61
```

```
In [51]: ts.interpolate().count()
```

```
Out[51]: 100
```

```
In [52]: ts.interpolate().plot()
```

```
Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x9b4cae8c>
```



Index aware interpolation is available via the `method` keyword:

In [53]: `ts2`

Out [53]:

```
2000-01-31    0.469112
2000-02-29         NaN
2002-07-31   -5.689738
2005-01-31         NaN
2008-04-30   -8.916232
dtype: float64
```

In [54]: `ts2.interpolate()`

Out [54]:

```
2000-01-31    0.469112
2000-02-29   -2.610313
2002-07-31   -5.689738
2005-01-31   -7.302985
2008-04-30   -8.916232
dtype: float64
```

In [55]: `ts2.interpolate(method='time')`

Out [55]:

```
2000-01-31    0.469112
2000-02-29    0.273272
2002-07-31   -5.689738
```

```
2005-01-31    -7.095568
2008-04-30    -8.916232
dtype: float64
```

For a floating-point index, use `method='values'`:

```
In [56]: ser
Out[56]:
0      0
1     NaN
10     10
dtype: float64
```

```
In [57]: ser.interpolate()
Out[57]:
0      0
1      5
10     10
dtype: float64
```

```
In [58]: ser.interpolate(method='values')
Out[58]:
0      0
1      1
10     10
dtype: float64
```

You can also interpolate with a DataFrame:

```
In [59]: df = pd.DataFrame({'A': [1, 2.1, np.nan, 4.7, 5.6, 6.8],
.....:                      'B': [.25, np.nan, np.nan, 4, 12.2, 14.4]})
.....:
```

```
In [60]: df
Out[60]:
   A      B
0  1.0  0.25
1  2.1   NaN
2  NaN   NaN
3  4.7  4.00
4  5.6 12.20
5  6.8 14.40
```

```
In [61]: df.interpolate()
Out[61]:
   A      B
0  1.0  0.25
1  2.1  1.50
2  3.4  2.75
3  4.7  4.00
4  5.6 12.20
5  6.8 14.40
```

The `method` argument gives access to fancier interpolation methods. If you have `scipy` installed, you can set pass the name of a 1-d interpolation routine to `method`. You'll want to consult the full [scipy interpolation documentation](#) and reference [guide](#) for details. The appropriate interpolation method will depend on the type of data you are working with. For example, if you are dealing with a time series that is growing at an increasing rate, `method='quadratic'` may be appropriate. If you have values approximating a cumulative distribution function, then `method='pchip'` should work well.

Warning: These methods require `scipy`.

```
In [62]: df.interpolate(method='barycentric')
```

```
Out[62]:
```

| | A | B |
|---|------|--------|
| 0 | 1.00 | 0.250 |
| 1 | 2.10 | -7.660 |
| 2 | 3.53 | -4.515 |
| 3 | 4.70 | 4.000 |
| 4 | 5.60 | 12.200 |
| 5 | 6.80 | 14.400 |

```
In [63]: df.interpolate(method='pchip')
```

```
Out[63]:
```

| | A | B |
|---|----------|-----------|
| 0 | 1.000000 | 0.250000 |
| 1 | 2.100000 | 1.130135 |
| 2 | 3.429309 | 2.337586 |
| 3 | 4.700000 | 4.000000 |
| 4 | 5.600000 | 12.200000 |
| 5 | 6.800000 | 14.400000 |

When interpolating via a polynomial or spline approximation, you must also specify the degree or order of the approximation:

```
In [64]: df.interpolate(method='spline', order=2)
```

```
Out[64]:
```

| | A | B |
|---|----------|-----------|
| 0 | 1.000000 | 0.250000 |
| 1 | 2.100000 | -0.428598 |
| 2 | 3.404545 | 1.206900 |
| 3 | 4.700000 | 4.000000 |
| 4 | 5.600000 | 12.200000 |
| 5 | 6.800000 | 14.400000 |

```
In [65]: df.interpolate(method='polynomial', order=2)
```

```
Out[65]:
```

| | A | B |
|---|----------|-----------|
| 0 | 1.000000 | 0.250000 |
| 1 | 2.100000 | -4.161538 |
| 2 | 3.547059 | -2.911538 |
| 3 | 4.700000 | 4.000000 |
| 4 | 5.600000 | 12.200000 |
| 5 | 6.800000 | 14.400000 |

Compare several methods:

```
In [66]: np.random.seed(2)
```

```
In [67]: ser = pd.Series(np.arange(1, 10.1, .25)**2 + np.random.randn(37))
```

```
In [68]: bad = np.array([4, 13, 14, 15, 16, 17, 18, 20, 29])
```

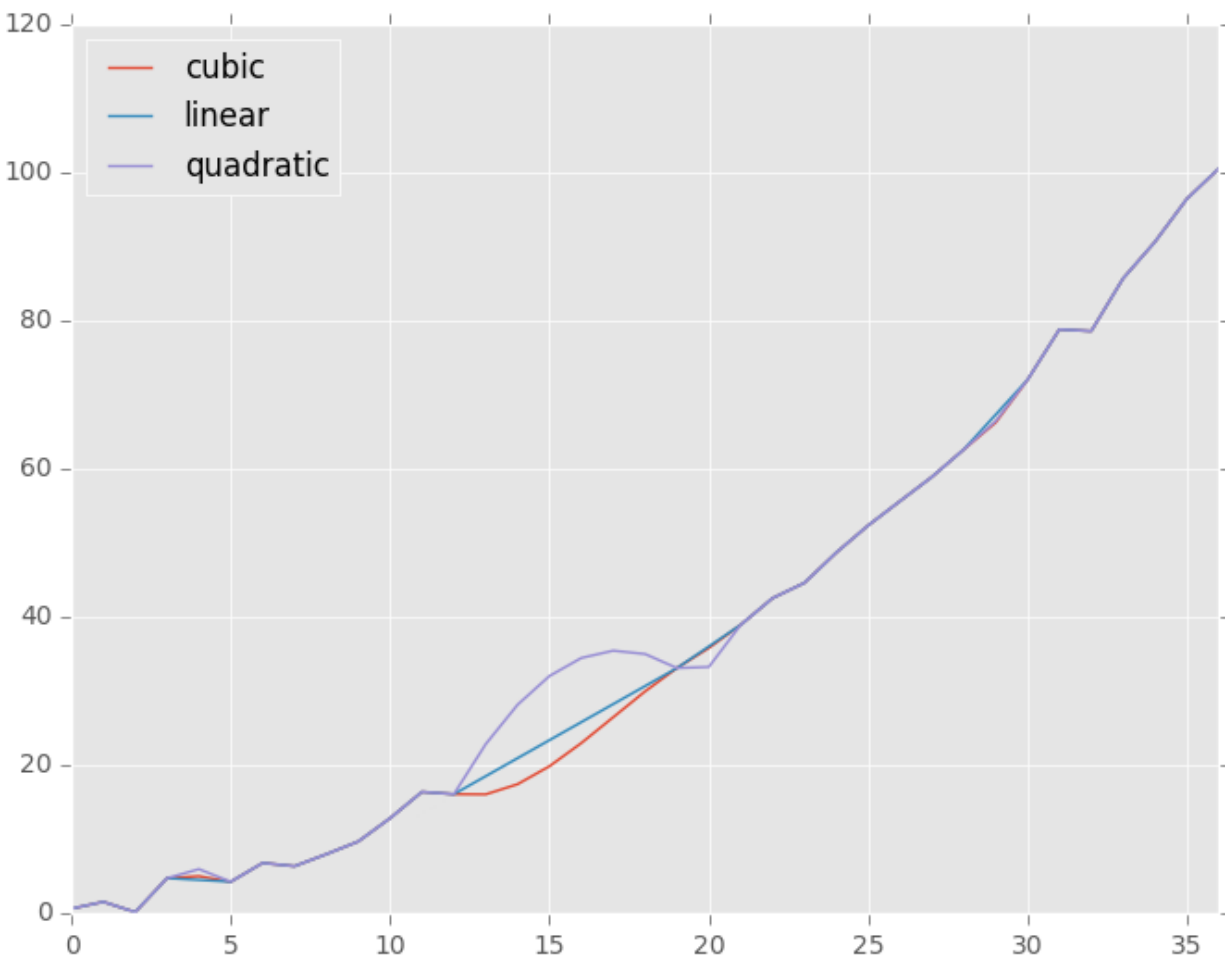
```
In [69]: ser[bad] = np.nan
```

```
In [70]: methods = ['linear', 'quadratic', 'cubic']
```

```
In [71]: df = pd.DataFrame({m: ser.interpolate(method=m) for m in methods})
```

```
In [72]: df.plot()
```

```
Out [72]: <matplotlib.axes._subplots.AxesSubplot at 0x9b4d294c>
```



Another use case is interpolation at *new* values. Suppose you have 100 observations from some distribution. And let's suppose that you're particularly interested in what's happening around the middle. You can mix pandas' `reindex` and `interpolate` methods to interpolate at the new values.

```
In [73]: ser = pd.Series(np.sort(np.random.uniform(size=100)))
```

```
# interpolate at new_index
```

```
In [74]: new_index = ser.index | Index([49.25, 49.5, 49.75, 50.25, 50.5, 50.75])
```

```
In [75]: interp_s = ser.reindex(new_index).interpolate(method='pchip')
```

```
In [76]: interp_s[49:51]
```

```
Out [76]:
```

```
49.00    0.471410
49.25    0.476841
49.50    0.481780
49.75    0.485998
50.00    0.489266
50.25    0.491814
50.50    0.493995
50.75    0.495763
```

```
51.00      0.497074
dtype: float64
```

Like other pandas fill methods, `interpolate` accepts a `limit` keyword argument. Use this to limit the number of consecutive interpolations, keeping NaN values for interpolations that are too far from the last valid observation:

```
In [77]: ser = pd.Series([1, 3, np.nan, np.nan, np.nan, 11])
```

```
In [78]: ser.interpolate(limit=2)
```

```
Out[78]:
0      1
1      3
2      5
3      7
4     NaN
5     11
dtype: float64
```

16.5.5 Replacing Generic Values

Often times we want to replace arbitrary values with other values. New in v0.8 is the `replace` method in `Series/DataFrame` that provides an efficient yet flexible way to perform such replacements.

For a `Series`, you can replace a single value or a list of values by another value:

```
In [79]: ser = pd.Series([0., 1., 2., 3., 4.])
```

```
In [80]: ser.replace(0, 5)
```

```
Out[80]:
0      5
1      1
2      2
3      3
4      4
dtype: float64
```

You can replace a list of values by a list of other values:

```
In [81]: ser.replace([0, 1, 2, 3, 4], [4, 3, 2, 1, 0])
```

```
Out[81]:
0      4
1      3
2      2
3      1
4      0
dtype: float64
```

You can also specify a mapping dict:

```
In [82]: ser.replace({0: 10, 1: 100})
```

```
Out[82]:
0      10
1     100
2      2
3      3
4      4
dtype: float64
```

For a DataFrame, you can specify individual values by column:

```
In [83]: df = pd.DataFrame({'a': [0, 1, 2, 3, 4], 'b': [5, 6, 7, 8, 9]})
```

```
In [84]: df.replace({'a': 0, 'b': 5}, 100)
```

```
Out[84]:
```

| | a | b |
|---|-----|-----|
| 0 | 100 | 100 |
| 1 | 1 | 6 |
| 2 | 2 | 7 |
| 3 | 3 | 8 |
| 4 | 4 | 9 |

Instead of replacing with specified values, you can treat all given values as missing and interpolate over them:

```
In [85]: ser.replace([1, 2, 3], method='pad')
```

```
Out[85]:
```

| | |
|---|---|
| 0 | 0 |
| 1 | 0 |
| 2 | 0 |
| 3 | 0 |
| 4 | 4 |

dtype: float64

16.5.6 String/Regular Expression Replacement

Note: Python strings prefixed with the `r` character such as `r'hello world'` are so-called “raw” strings. They have different semantics regarding backslashes than strings without this prefix. Backslashes in raw strings will be interpreted as an escaped backslash, e.g., `r'\'` == `'\\'`. You should [read about them](#) if this is unclear.

Replace the `'.'` with `nan` (`str -> str`)

```
In [86]: d = {'a': list(range(4)), 'b': list('ab..'), 'c': ['a', 'b', np.nan, 'd']}
```

```
In [87]: df = pd.DataFrame(d)
```

```
In [88]: df.replace('.', np.nan)
```

```
Out[88]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | a | a |
| 1 | 1 | b | b |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

Now do it with a regular expression that removes surrounding whitespace (`regex -> regex`)

```
In [89]: df.replace(r'\s*\.\s*', np.nan, regex=True)
```

```
Out[89]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | a | a |
| 1 | 1 | b | b |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

Replace a few different values (`list -> list`)

```
In [90]: df.replace(['a', '.'], ['b', np.nan])
```

```
Out[90]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | b | b |
| 1 | 1 | b | b |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

list of regex -> list of regex

```
In [91]: df.replace([r'\.', r'(a)'], ['dot', '\1stuff'], regex=True)
```

```
Out[91]:
```

| | a | b | c |
|---|---|--------|--------|
| 0 | 0 | {stuff | {stuff |
| 1 | 1 | b | b |
| 2 | 2 | dot | NaN |
| 3 | 3 | dot | d |

Only search in column 'b' (dict -> dict)

```
In [92]: df.replace({'b': '.'}, {'b': np.nan})
```

```
Out[92]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | a | a |
| 1 | 1 | b | b |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

Same as the previous example, but use a regular expression for searching instead (dict of regex -> dict)

```
In [93]: df.replace({'b': r'\s*\.\s*'}, {'b': np.nan}, regex=True)
```

```
Out[93]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | a | a |
| 1 | 1 | b | b |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

You can pass nested dictionaries of regular expressions that use `regex=True`

```
In [94]: df.replace({'b': {'b': r''}}, regex=True)
```

```
Out[94]:
```

| | a | b | c |
|---|---|---|-----|
| 0 | 0 | a | a |
| 1 | 1 | b | b |
| 2 | 2 | . | NaN |
| 3 | 3 | . | d |

or you can pass the nested dictionary like so

```
In [95]: df.replace(regex={'b': {r'\s*\.\s*': np.nan}})
```

```
Out[95]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | a | a |
| 1 | 1 | b | b |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

You can also use the group of a regular expression match when replacing (dict of regex -> dict of regex), this works for lists as well

```
In [96]: df.replace({'b': r'\s*(\.)\s*'}, {'b': r'\1ty'}, regex=True)
Out[96]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | a | a |
| 1 | 1 | b | b |
| 2 | 2 | .ty | NaN |
| 3 | 3 | .ty | d |

You can pass a list of regular expressions, of which those that match will be replaced with a scalar (list of regex -> regex)

```
In [97]: df.replace([r'\s*\.\s*', r'a|b'], np.nan, regex=True)
Out[97]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | NaN | NaN |
| 1 | 1 | NaN | NaN |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

All of the regular expression examples can also be passed with the `to_replace` argument as the `regex` argument. In this case the `value` argument must be passed explicitly by name or `regex` must be a nested dictionary. The previous example, in this case, would then be

```
In [98]: df.replace(regex=[r'\s*\.\s*', r'a|b'], value=np.nan)
Out[98]:
```

| | a | b | c |
|---|---|-----|-----|
| 0 | 0 | NaN | NaN |
| 1 | 1 | NaN | NaN |
| 2 | 2 | NaN | NaN |
| 3 | 3 | NaN | d |

This can be convenient if you do not want to pass `regex=True` every time you want to use a regular expression.

Note: Anywhere in the above `replace` examples that you see a regular expression a compiled regular expression is valid as well.

16.5.7 Numeric Replacement

Similar to `DataFrame.fillna`

```
In [99]: df = pd.DataFrame(np.random.randn(10, 2))
In [100]: df[np.random.rand(df.shape[0]) > 0.5] = 1.5
In [101]: df.replace(1.5, np.nan)
Out[101]:
```

| | 0 | 1 |
|---|-----------|-----------|
| 0 | -0.844214 | -1.021415 |
| 1 | 0.432396 | -0.323580 |
| 2 | 0.423825 | 0.799180 |
| 3 | 1.262614 | 0.751965 |
| 4 | NaN | NaN |
| 5 | NaN | NaN |
| 6 | -0.498174 | -1.060799 |
| 7 | 0.591667 | -0.183257 |
| 8 | 1.019855 | -1.482465 |
| 9 | NaN | NaN |

Replacing more than one value via lists works as well

```
In [102]: df00 = df.values[0, 0]

In [103]: df.replace([1.5, df00], [np.nan, 'a'])
Out[103]:
```

| | 0 | 1 |
|---|------------|-----------|
| 0 | a | -1.021415 |
| 1 | 0.4323957 | -0.323580 |
| 2 | 0.4238247 | 0.799180 |
| 3 | 1.262614 | 0.751965 |
| 4 | NaN | NaN |
| 5 | NaN | NaN |
| 6 | -0.4981742 | -1.060799 |
| 7 | 0.5916665 | -0.183257 |
| 8 | 1.019855 | -1.482465 |
| 9 | NaN | NaN |

```
In [104]: df[1].dtype
Out[104]: dtype('float64')
```

You can also operate on the DataFrame in place

```
In [105]: df.replace(1.5, np.nan, inplace=True)
```

Warning: When replacing multiple bool or datetime64 objects, the first argument to replace (to_replace) must match the type of the value being replaced type. For example,

```
s = pd.Series([True, False, True])
s.replace({'a string': 'new value', True: False}) # raises

TypeError: Cannot compare types 'ndarray(dtype=bool)' and 'str'
```

will raise a `TypeError` because one of the dict keys is not of the correct type for replacement. However, when replacing a *single* object such as,

```
In [106]: s = pd.Series([True, False, True])

In [107]: s.replace('a string', 'another string')
Out[107]:
```

| | |
|---|-------|
| 0 | True |
| 1 | False |
| 2 | True |

```
dtype: bool
```

the original `NDFrame` object will be returned untouched. We’re working on unifying this API, but for backwards compatibility reasons we cannot break the latter behavior. See [GH6354](#) for more details.

16.6 Missing data casting rules and indexing

While pandas supports storing arrays of integer and boolean type, these types are not capable of storing missing data. Until we can switch to using a native NA type in NumPy, we’ve established some “casting rules” when reindexing will cause missing data to be introduced into, say, a `Series` or `DataFrame`. Here they are:

| data type | Cast to |
|-----------|---------|
| integer | float |
| boolean | object |
| float | no cast |
| object | no cast |

For example:

```
In [108]: s = pd.Series(np.random.randn(5), index=[0, 2, 4, 6, 7])
```

```
In [109]: s > 0
```

```
Out[109]:
0      True
2      True
4      True
6      True
7      True
dtype: bool
```

```
In [110]: (s > 0).dtype
```

```
Out[110]: dtype('bool')
```

```
In [111]: crit = (s > 0).reindex(list(range(8)))
```

```
In [112]: crit
```

```
Out[112]:
0      True
1      NaN
2      True
3      NaN
4      True
5      NaN
6      True
7      True
dtype: object
```

```
In [113]: crit.dtype
```

```
Out[113]: dtype('O')
```

Ordinarily NumPy will complain if you try to use an object array (even if it contains boolean values) instead of a boolean array to get or set values from an ndarray (e.g. selecting values based on some criteria). If a boolean vector contains NAs, an exception will be generated:

```
In [114]: reindexed = s.reindex(list(range(8))).fillna(0)
```

```
In [115]: reindexed[crit]
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-115-2da204ed1ac7> in <module>()
----> 1 reindexed[crit]

/home/joris/scipy/pandas/pandas/core/series.pyc in __getitem__(self, key)
    554         key = list(key)
    555
--> 556         if is_bool_indexer(key):
    557             key = check_bool_indexer(self.index, key)
    558

/home/joris/scipy/pandas/pandas/core/common.pyc in is_bool_indexer(key)
```

```
2126         if not lib.is_bool_array(key):
2127             if isnull(key).any():
-> 2128                 raise ValueError('cannot index with vector containing '
2129                                     'NA / NaN values')
2130         return False
```

ValueError: cannot index with vector containing NA / NaN values

However, these can be filled in using **fillna** and it will work fine:

```
In [116]: reindexed[crit.fillna(False)]
```

```
Out[116]:
0    0.126504
2    0.696198
4    0.697416
6    0.601516
7    0.003659
dtype: float64
```

```
In [117]: reindexed[crit.fillna(True)]
```

```
Out[117]:
0    0.126504
1    0.000000
2    0.696198
3    0.000000
4    0.697416
5    0.000000
6    0.601516
7    0.003659
dtype: float64
```

GROUP BY: SPLIT-APPLY-COMBINE

By “group by” we are referring to a process involving one or more of the following steps

- **Splitting** the data into groups based on some criteria
- **Applying** a function to each group independently
- **Combining** the results into a data structure

Of these, the split step is the most straightforward. In fact, in many situations you may wish to split the data set into groups and do something with those groups yourself. In the apply step, we might wish to one of the following:

- **Aggregation:** computing a summary statistic (or statistics) about each group. Some examples:
 - Compute group sums or means
 - Compute group sizes / counts
- **Transformation:** perform some group-specific computations and return a like-indexed. Some examples:
 - Standardizing data (zscore) within group
 - Filling NAs within groups with a value derived from each group
- **Filtration:** discard some groups, according to a group-wise computation that evaluates True or False. Some examples:
 - Discarding data that belongs to groups with only a few members
 - Filtering out data based on the group sum or mean
- Some combination of the above: GroupBy will examine the results of the apply step and try to return a sensibly combined result if it doesn’t fit into either of the above two categories

Since the set of object instance method on pandas data structures are generally rich and expressive, we often simply want to invoke, say, a DataFrame function on each group. The name GroupBy should be quite familiar to those who have used a SQL-based tool (or `itertools`), in which you can write code like:

```
SELECT Column1, Column2, mean(Column3), sum(Column4)
FROM SomeTable
GROUP BY Column1, Column2
```

We aim to make operations like this natural and easy to express using pandas. We’ll address each area of GroupBy functionality then provide some non-trivial examples / use cases.

See the [cookbook](#) for some advanced strategies

17.1 Splitting an object into groups

pandas objects can be split on any of their axes. The abstract definition of grouping is to provide a mapping of labels to group names. To create a GroupBy object (more on what the GroupBy object is later), you do the following:

```
>>> grouped = obj.groupby(key)
>>> grouped = obj.groupby(key, axis=1)
>>> grouped = obj.groupby([key1, key2])
```

The mapping can be specified many different ways:

- A Python function, to be called on each of the axis labels
- A list or NumPy array of the same length as the selected axis
- A dict or Series, providing a label $\rightarrow$ group name mapping
- For DataFrame objects, a string indicating a column to be used to group. Of course `df.groupby('A')` is just syntactic sugar for `df.groupby(df['A'])`, but it makes life simpler
- A list of any of the above things

Collectively we refer to the grouping objects as the **keys**. For example, consider the following DataFrame:

```
In [1]: df = DataFrame({'A' : ['foo', 'bar', 'foo', 'bar',
...:                          'foo', 'bar', 'foo', 'foo'],
...:                   'B' : ['one', 'one', 'two', 'three',
...:                          'two', 'two', 'one', 'three'],
...:                   'C' : randn(8), 'D' : randn(8)})
...:
```

```
In [2]: df
```

```
Out[2]:
```

| | A | B | C | D |
|---|-----|-------|-----------|-----------|
| 0 | foo | one | 0.469112 | -0.861849 |
| 1 | bar | one | -0.282863 | -2.104569 |
| 2 | foo | two | -1.509059 | -0.494929 |
| 3 | bar | three | -1.135632 | 1.071804 |
| 4 | foo | two | 1.212112 | 0.721555 |
| 5 | bar | two | -0.173215 | -0.706771 |
| 6 | foo | one | 0.119209 | -1.039575 |
| 7 | foo | three | -1.044236 | 0.271860 |

We could naturally group by either the A or B columns or both:

```
In [3]: grouped = df.groupby('A')
```

```
In [4]: grouped = df.groupby(['A', 'B'])
```

These will split the DataFrame on its index (rows). We could also split by the columns:

```
In [5]: def get_letter_type(letter):
...:     if letter.lower() in 'aeiou':
...:         return 'vowel'
...:     else:
...:         return 'consonant'
...:
```

```
In [6]: grouped = df.groupby(get_letter_type, axis=1)
```

Starting with 0.8, pandas Index objects now supports duplicate values. If a non-unique index is used as the group key in a groupby operation, all values for the same index value will be considered to be in one group and thus the output of aggregation functions will only contain unique index values:

```
In [7]: lst = [1, 2, 3, 1, 2, 3]

In [8]: s = Series([1, 2, 3, 10, 20, 30], lst)

In [9]: grouped = s.groupby(level=0)

In [10]: grouped.first()
Out[10]:
1      1
2      2
3      3
dtype: int64

In [11]: grouped.last()
Out[11]:
1     10
2     20
3     30
dtype: int64

In [12]: grouped.sum()
Out[12]:
1     11
2     22
3     33
dtype: int64
```

Note that **no splitting occurs** until it's needed. Creating the GroupBy object only verifies that you've passed a valid mapping.

Note: Many kinds of complicated data manipulations can be expressed in terms of GroupBy operations (though can't be guaranteed to be the most efficient). You can get quite creative with the label mapping functions.

17.1.1 GroupBy object attributes

The `groups` attribute is a dict whose keys are the computed unique groups and corresponding values being the axis labels belonging to each group. In the above example we have:

```
In [13]: df.groupby('A').groups
Out[13]: {'bar': [1L, 3L, 5L], 'foo': [0L, 2L, 4L, 6L, 7L]}

In [14]: df.groupby(get_letter_type, axis=1).groups
Out[14]: {'consonant': ['B', 'C', 'D'], 'vowel': ['A']}
```

Calling the standard Python `len` function on the GroupBy object just returns the length of the groups dict, so it is largely just a convenience:

```
In [15]: grouped = df.groupby(['A', 'B'])

In [16]: grouped.groups
Out[16]:
{('bar', 'one'): [1L],
 ('bar', 'three'): [3L],
```

```
('bar', 'two'): [5L],
('foo', 'one'): [0L, 6L],
('foo', 'three'): [7L],
('foo', 'two'): [2L, 4L]}
```

```
In [17]: len(grouped)
Out[17]: 6
```

By default the group keys are sorted during the groupby operation. You may however pass `sort=False` for potential speedups:

```
In [18]: df2 = DataFrame({'X' : ['B', 'B', 'A', 'A'], 'Y' : [1, 2, 3, 4]})
```

```
In [19]: df2.groupby(['X'], sort=True).sum()
Out[19]:
      Y
X
A    7
B    3
```

```
In [20]: df2.groupby(['X'], sort=False).sum()
Out[20]:
      Y
X
B    3
A    7
```

GroupBy will tab complete column names (and other attributes)

```
In [21]: df
Out[21]:
      gender  height  weight
2000-01-01  male  42.849980  157.500553
2000-01-02  male  49.607315  177.340407
2000-01-03  male  56.293531  171.524640
2000-01-04  female  48.421077  144.251986
2000-01-05  male  46.556882  152.526206
2000-01-06  female  68.448851  168.272968
2000-01-07  male  70.757698  136.431469
2000-01-08  female  58.909500  176.499753
2000-01-09  female  76.435631  174.094104
2000-01-10  male  45.306120  177.540920
```

```
In [22]: gb = df.groupby('gender')
```

```
In [23]: gb.<TAB>
gb.agg      gb.boxplot      gb.cummin      gb.describe      gb.filter      gb.get_group      gb.height      gb
gb.aggregate  gb.count      gb.cumprod      gb.dtype      gb.first      gb.groups      gb.hist      gb
gb.apply      gb.cummax      gb.cumsum      gb.fillna      gb.gender      gb.head      gb.indices      gb
```

17.1.2 GroupBy with MultiIndex

With *hierarchically-indexed data*, it's quite natural to group by one of the levels of the hierarchy.

```
In [24]: s
Out[24]:
first  second
```

```

bar    one    -0.575247
      two     0.254161
baz    one    -1.143704
      two     0.215897
foo    one     1.193555
      two    -0.077118
qux    one    -0.408530
      two    -0.862495
dtype: float64

```

```
In [25]: grouped = s.groupby(level=0)
```

```
In [26]: grouped.sum()
```

```

Out[26]:
first
bar    -0.321085
baz    -0.927807
foo     1.116437
qux    -1.271025
dtype: float64

```

If the MultiIndex has names specified, these can be passed instead of the level number:

```
In [27]: s.groupby(level='second').sum()
```

```

Out[27]:
second
one    -0.933926
two    -0.469555
dtype: float64

```

The aggregation functions such as `sum` will take the level parameter directly. Additionally, the resulting index will be named according to the chosen level:

```
In [28]: s.sum(level='second')
```

```

Out[28]:
second
one    -0.933926
two    -0.469555
dtype: float64

```

Also as of v0.6, grouping with multiple levels is supported.

```
In [29]: s
```

```

Out[29]:
first second third
bar    doo    one    1.346061
      two    1.511763
baz    bee    one    1.627081
      two   -0.990582
foo    bop    one   -0.441652
      two    1.211526
qux    bop    one    0.268520
      two    0.024580
dtype: float64

```

```
In [30]: s.groupby(level=['first', 'second']).sum()
```

```

Out[30]:
first second
bar    doo    2.857824

```

```
baz    bee      0.636499
foo    bop      0.769873
qux    bop      0.293100
dtype: float64
```

More on the `sum` function and aggregation later.

17.1.3 DataFrame column selection in GroupBy

Once you have created the `GroupBy` object from a `DataFrame`, for example, you might want to do something different for each of the columns. Thus, using `[]` similar to getting a column from a `DataFrame`, you can do:

```
In [31]: grouped = df.groupby(['A'])
```

```
In [32]: grouped_C = grouped['C']
```

```
In [33]: grouped_D = grouped['D']
```

This is mainly syntactic sugar for the alternative and much more verbose:

```
In [34]: df['C'].groupby(df['A'])
Out[34]: <pandas.core.groupby.SeriesGroupBy object at 0xa0ccb0cc>
```

Additionally this method avoids recomputing the internal grouping information derived from the passed key.

17.2 Iterating through groups

With the `GroupBy` object in hand, iterating through the grouped data is very natural and functions similarly to `itertools.groupby`:

```
In [35]: grouped = df.groupby('A')
```

```
In [36]: for name, group in grouped:
.....:     print(name)
.....:     print(group)
.....:
```

```
bar
   A      B      C      D
1 bar  one -0.042379 -0.089329
3 bar three -0.009920 -0.945867
5 bar  two  0.495767  1.956030
foo
   A      B      C      D
0 foo  one -0.919854 -1.131345
2 foo  two  1.247642  0.337863
4 foo  two  0.290213 -0.932132
6 foo  one  0.362949  0.017587
7 foo three  1.548106 -0.016692
```

In the case of grouping by multiple keys, the group name will be a tuple:

```
In [37]: for name, group in df.groupby(['A', 'B']):
.....:     print(name)
.....:     print(group)
.....:
('bar', 'one')
```

```

      A      B      C      D
1  bar  one -0.042379 -0.089329
('bar', 'three')
      A      B      C      D
3  bar  three -0.00992 -0.945867
('bar', 'two')
      A      B      C      D
5  bar  two  0.495767  1.95603
('foo', 'one')
      A      B      C      D
0  foo  one -0.919854 -1.131345
6  foo  one  0.362949  0.017587
('foo', 'three')
      A      B      C      D
7  foo  three  1.548106 -0.016692
('foo', 'two')
      A      B      C      D
2  foo  two  1.247642  0.337863
4  foo  two  0.290213 -0.932132

```

It's standard Python-fu but remember you can unpack the tuple in the for loop statement if you wish: `for (k1, k2), group in grouped:`.

17.3 Selecting a group

A single group can be selected using `GroupBy.get_group()`:

```

In [38]: grouped.get_group('bar')
Out[38]:
      A      B      C      D
1  bar  one -0.042379 -0.089329
3  bar  three -0.009920 -0.945867
5  bar  two  0.495767  1.956030

```

Or for an object grouped on multiple columns:

```

In [39]: df.groupby(['A', 'B']).get_group(('bar', 'one'))
Out[39]:
      A      B      C      D
1  bar  one -0.042379 -0.089329

```

17.4 Aggregation

Once the `GroupBy` object has been created, several methods are available to perform a computation on the grouped data.

An obvious one is aggregation via the `aggregate` or equivalently `agg` method:

```

In [40]: grouped = df.groupby('A')
In [41]: grouped.aggregate(np.sum)
Out[41]:
      C      D
A
bar  0.443469  0.920834

```

```
foo    2.529056 -1.724719
```

```
In [42]: grouped = df.groupby(['A', 'B'])
```

```
In [43]: grouped.aggregate(np.sum)
```

```
Out[43]:
```

| | | C | D |
|-----|-------|-----------|-----------|
| A | B | | |
| bar | one | -0.042379 | -0.089329 |
| | three | -0.009920 | -0.945867 |
| | two | 0.495767 | 1.956030 |
| foo | one | -0.556905 | -1.113758 |
| | three | 1.548106 | -0.016692 |
| | two | 1.537855 | -0.594269 |

As you can see, the result of the aggregation will have the group names as the new index along the grouped axis. In the case of multiple keys, the result is a *MultiIndex* by default, though this can be changed by using the `as_index` option:

```
In [44]: grouped = df.groupby(['A', 'B'], as_index=False)
```

```
In [45]: grouped.aggregate(np.sum)
```

```
Out[45]:
```

| | A | B | C | D |
|---|-----|-------|-----------|-----------|
| 0 | bar | one | -0.042379 | -0.089329 |
| 1 | bar | three | -0.009920 | -0.945867 |
| 2 | bar | two | 0.495767 | 1.956030 |
| 3 | foo | one | -0.556905 | -1.113758 |
| 4 | foo | three | 1.548106 | -0.016692 |
| 5 | foo | two | 1.537855 | -0.594269 |

```
In [46]: df.groupby('A', as_index=False).sum()
```

```
Out[46]:
```

| | A | C | D |
|---|-----|----------|-----------|
| 0 | bar | 0.443469 | 0.920834 |
| 1 | foo | 2.529056 | -1.724719 |

Note that you could use the `reset_index` `DataFrame` function to achieve the same result as the column names are stored in the resulting `MultiIndex`:

```
In [47]: df.groupby(['A', 'B']).sum().reset_index()
```

```
Out[47]:
```

| | A | B | C | D |
|---|-----|-------|-----------|-----------|
| 0 | bar | one | -0.042379 | -0.089329 |
| 1 | bar | three | -0.009920 | -0.945867 |
| 2 | bar | two | 0.495767 | 1.956030 |
| 3 | foo | one | -0.556905 | -1.113758 |
| 4 | foo | three | 1.548106 | -0.016692 |
| 5 | foo | two | 1.537855 | -0.594269 |

Another simple aggregation example is to compute the size of each group. This is included in `GroupBy` as the `size` method. It returns a `Series` whose index are the group names and whose values are the sizes of each group.

```
In [48]: grouped.size()
```

```
Out[48]:
```

| A | B | |
|-----|-------|---|
| bar | one | 1 |
| | three | 1 |
| | two | 1 |

```
foo one      2
    three    1
    two      2
dtype: int64
```

```
In [49]: grouped.describe()
```

```
Out[49]:
```

| | | C | D |
|-----|-------|-----------|-----------|
| 0 | count | 1.000000 | 1.000000 |
| | mean | -0.042379 | -0.089329 |
| | std | NaN | NaN |
| | min | -0.042379 | -0.089329 |
| | 25% | -0.042379 | -0.089329 |
| | 50% | -0.042379 | -0.089329 |
| | 75% | -0.042379 | -0.089329 |
| ... | ... | ... | ... |
| 5 | mean | 0.768928 | -0.297134 |
| | std | 0.677005 | 0.898022 |
| | min | 0.290213 | -0.932132 |
| | 25% | 0.529570 | -0.614633 |
| | 50% | 0.768928 | -0.297134 |
| | 75% | 1.008285 | 0.020364 |
| | max | 1.247642 | 0.337863 |

```
[48 rows x 2 columns]
```

Note: Aggregation functions **will not** return the groups that you are aggregating over if they are named *columns*, when `as_index=True`, the default. The grouped columns will be the **indices** of the returned object.

Passing `as_index=False` **will** return the groups that you are aggregating over, if they are named *columns*.

Aggregating functions are ones that reduce the dimension of the returned objects, for example: `mean`, `sum`, `size`, `count`, `std`, `var`, `sem`, `describe`, `first`, `last`, `nth`, `min`, `max`. This is what happens when you do for example `DataFrame.sum()` and get back a `Series`.

`nth` can act as a reducer *or* a filter, see [here](#)

17.4.1 Applying multiple functions at once

With grouped `Series` you can also pass a list or dict of functions to do aggregation with, outputting a `DataFrame`:

```
In [50]: grouped = df.groupby('A')
```

```
In [51]: grouped['C'].agg([np.sum, np.mean, np.std])
```

```
Out[51]:
```

| | sum | mean | std |
|-----|----------|----------|----------|
| A | | | |
| bar | 0.443469 | 0.147823 | 0.301765 |
| foo | 2.529056 | 0.505811 | 0.966450 |

If a dict is passed, the keys will be used to name the columns. Otherwise the function's name (stored in the function object) will be used.

```
In [52]: grouped['D'].agg({'result1' : np.sum,
    ....:                  'result2' : np.mean})
    ....:
```

```
Out[52]:
```

```
      result2  result1
A
bar  0.306945  0.920834
foo -0.344944 -1.724719
```

On a grouped DataFrame, you can pass a list of functions to apply to each column, which produces an aggregated result with a hierarchical index:

```
In [53]: grouped.agg([np.sum, np.mean, np.std])
Out[53]:
```

| | C | | | D | | |
|-----|----------|----------|----------|-----------|-----------|----------|
| | sum | mean | std | sum | mean | std |
| A | | | | | | |
| bar | 0.443469 | 0.147823 | 0.301765 | 0.920834 | 0.306945 | 1.490982 |
| foo | 2.529056 | 0.505811 | 0.966450 | -1.724719 | -0.344944 | 0.645875 |

Passing a dict of functions has different behavior by default, see the next section.

17.4.2 Applying different functions to DataFrame columns

By passing a dict to `aggregate` you can apply a different aggregation to the columns of a DataFrame:

```
In [54]: grouped.agg({'C' : np.sum,
.....:               'D' : lambda x: np.std(x, ddof=1)})
.....:
Out[54]:
```

| | C | D |
|-----|----------|----------|
| A | | |
| bar | 0.443469 | 1.490982 |
| foo | 2.529056 | 0.645875 |

The function names can also be strings. In order for a string to be valid it must be either implemented on `GroupBy` or available via *dispatching*:

```
In [55]: grouped.agg({'C' : 'sum', 'D' : 'std'})
Out[55]:
```

| | C | D |
|-----|----------|----------|
| A | | |
| bar | 0.443469 | 1.490982 |
| foo | 2.529056 | 0.645875 |

17.4.3 Cython-optimized aggregation functions

Some common aggregations, currently only `sum`, `mean`, `std`, and `sem`, have optimized Cython implementations:

```
In [56]: df.groupby('A').sum()
Out[56]:
```

| | C | D |
|-----|----------|-----------|
| A | | |
| bar | 0.443469 | 0.920834 |
| foo | 2.529056 | -1.724719 |

```
In [57]: df.groupby(['A', 'B']).mean()
Out[57]:
```

| | | C | D |
|-----|-----|-----------|-----------|
| A | B | | |
| bar | one | -0.042379 | -0.089329 |

```

three -0.009920 -0.945867
two    0.495767  1.956030
foo one -0.278452 -0.556879
three  1.548106 -0.016692
two    0.768928 -0.297134

```

Of course `sum` and `mean` are implemented on pandas objects, so the above code would work even without the special versions via dispatching (see below).

17.5 Transformation

The `transform` method returns an object that is indexed the same (same size) as the one being grouped. Thus, the passed transform function should return a result that is the same size as the group chunk. For example, suppose we wished to standardize the data within each group:

```

In [58]: index = date_range('10/1/1999', periods=1100)

In [59]: ts = Series(np.random.normal(0.5, 2, 1100), index)

In [60]: ts = rolling_mean(ts, 100, 100).dropna()

In [61]: ts.head()
Out[61]:
2000-01-08    0.779333
2000-01-09    0.778852
2000-01-10    0.786476
2000-01-11    0.782797
2000-01-12    0.798110
Freq: D, dtype: float64

In [62]: ts.tail()
Out[62]:
2002-09-30    0.660294
2002-10-01    0.631095
2002-10-02    0.673601
2002-10-03    0.709213
2002-10-04    0.719369
Freq: D, dtype: float64

In [63]: key = lambda x: x.year

In [64]: zscore = lambda x: (x - x.mean()) / x.std()

In [65]: transformed = ts.groupby(key).transform(zscore)

```

We would expect the result to now have mean 0 and standard deviation 1 within each group, which we can easily check:

```

# Original Data
In [66]: grouped = ts.groupby(key)

In [67]: grouped.mean()
Out[67]:
2000    0.442441
2001    0.526246
2002    0.459365

```

```
dtype: float64
```

```
In [68]: grouped.std()
```

```
Out[68]:
```

```
2000    0.131752
```

```
2001    0.210945
```

```
2002    0.128753
```

```
dtype: float64
```

```
# Transformed Data
```

```
In [69]: grouped_trans = transformed.groupby(key)
```

```
In [70]: grouped_trans.mean()
```

```
Out[70]:
```

```
2000   -1.250934e-16
```

```
2001   -4.291848e-16
```

```
2002    2.404815e-17
```

```
dtype: float64
```

```
In [71]: grouped_trans.std()
```

```
Out[71]:
```

```
2000    1
```

```
2001    1
```

```
2002    1
```

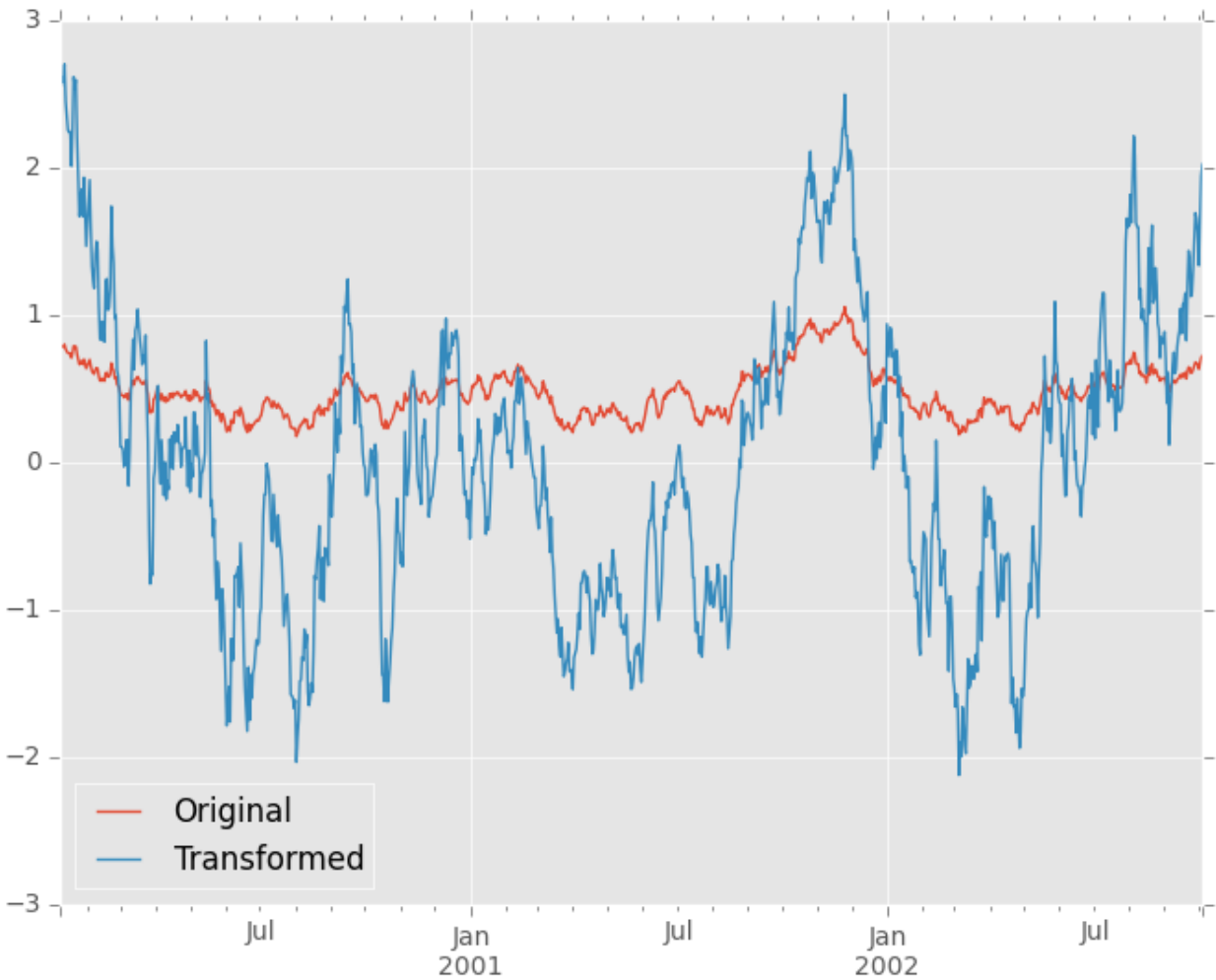
```
dtype: float64
```

We can also visually compare the original and transformed data sets.

```
In [72]: compare = DataFrame({'Original': ts, 'Transformed': transformed})
```

```
In [73]: compare.plot()
```

```
Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0xa0e2426c>
```



Another common data transform is to replace missing data with the group mean.

In [74]: data_df

Out[74]:

| | A | B | C |
|-----|-----------|-----------|-----------|
| 0 | 1.539708 | -1.166480 | 0.533026 |
| 1 | 1.302092 | -0.505754 | NaN |
| 2 | -0.371983 | 1.104803 | -0.651520 |
| 3 | -1.309622 | 1.118697 | -1.161657 |
| 4 | -1.924296 | 0.396437 | 0.812436 |
| 5 | 0.815643 | 0.367816 | -0.469478 |
| 6 | -0.030651 | 1.376106 | -0.645129 |
| ... | ... | ... | ... |
| 993 | 0.012359 | 0.554602 | -1.976159 |
| 994 | 0.042312 | -1.628835 | 1.013822 |
| 995 | -0.093110 | 0.683847 | -0.774753 |
| 996 | -0.185043 | 1.438572 | NaN |
| 997 | -0.394469 | -0.642343 | 0.011374 |
| 998 | -1.174126 | 1.857148 | NaN |
| 999 | 0.234564 | 0.517098 | 0.393534 |

[1000 rows x 3 columns]

```
In [75]: countries = np.array(['US', 'UK', 'GR', 'JP'])
```

```
In [76]: key = countries[np.random.randint(0, 4, 1000)]
```

```
In [77]: grouped = data_df.groupby(key)
```

```
# Non-NA count in each group
```

```
In [78]: grouped.count()
```

```
Out[78]:
```

| | A | B | C |
|----|-----|-----|-----|
| GR | 209 | 217 | 189 |
| JP | 240 | 255 | 217 |
| UK | 216 | 231 | 193 |
| US | 239 | 250 | 217 |

```
In [79]: f = lambda x: x.fillna(x.mean())
```

```
In [80]: transformed = grouped.transform(f)
```

We can verify that the group means have not changed in the transformed data and that the transformed data contains no NAs.

```
In [81]: grouped_trans = transformed.groupby(key)
```

```
In [82]: grouped.mean() # original group means
```

```
Out[82]:
```

| | A | B | C |
|----|-----------|-----------|-----------|
| GR | -0.098371 | -0.015420 | 0.068053 |
| JP | 0.069025 | 0.023100 | -0.077324 |
| UK | 0.034069 | -0.052580 | -0.116525 |
| US | 0.058664 | -0.020399 | 0.028603 |

```
In [83]: grouped_trans.mean() # transformation did not change group means
```

```
Out[83]:
```

| | A | B | C |
|----|-----------|-----------|-----------|
| GR | -0.098371 | -0.015420 | 0.068053 |
| JP | 0.069025 | 0.023100 | -0.077324 |
| UK | 0.034069 | -0.052580 | -0.116525 |
| US | 0.058664 | -0.020399 | 0.028603 |

```
In [84]: grouped.count() # original has some missing data points
```

```
Out[84]:
```

| | A | B | C |
|----|-----|-----|-----|
| GR | 209 | 217 | 189 |
| JP | 240 | 255 | 217 |
| UK | 216 | 231 | 193 |
| US | 239 | 250 | 217 |

```
In [85]: grouped_trans.count() # counts after transformation
```

```
Out[85]:
```

| | A | B | C |
|----|-----|-----|-----|
| GR | 228 | 228 | 228 |
| JP | 267 | 267 | 267 |
| UK | 247 | 247 | 247 |
| US | 258 | 258 | 258 |

```
In [86]: grouped_trans.size() # Verify non-NA count equals group size
```

```
Out[86]:
```

```
GR      228
JP      267
UK      247
US      258
dtype: int64
```

Note: Some functions when applied to a `groupby` object will automatically transform the input, returning an object of the same shape as the original. Passing `as_index=False` will not affect these transformation methods.

For example: `fillna`, `ffill`, `bfill`, `shift`.

```
In [87]: grouped.fffll()
Out[87]:
```

| | A | B | C |
|-----|-----------|-----------|-----------|
| 0 | 1.539708 | -1.166480 | 0.533026 |
| 1 | 1.302092 | -0.505754 | 0.533026 |
| 2 | -0.371983 | 1.104803 | -0.651520 |
| 3 | -1.309622 | 1.118697 | -1.161657 |
| 4 | -1.924296 | 0.396437 | 0.812436 |
| 5 | 0.815643 | 0.367816 | -0.469478 |
| 6 | -0.030651 | 1.376106 | -0.645129 |
| .. | ... | ... | ... |
| 993 | 0.012359 | 0.554602 | -1.976159 |
| 994 | 0.042312 | -1.628835 | 1.013822 |
| 995 | -0.093110 | 0.683847 | -0.774753 |
| 996 | -0.185043 | 1.438572 | -0.774753 |
| 997 | -0.394469 | -0.642343 | 0.011374 |
| 998 | -1.174126 | 1.857148 | -0.774753 |
| 999 | 0.234564 | 0.517098 | 0.393534 |

```
[1000 rows x 3 columns]
```

17.6 Filtration

New in version 0.12.

The `filter` method returns a subset of the original object. Suppose we want to take only elements that belong to groups with a group sum greater than 2.

```
In [88]: sf = Series([1, 1, 2, 3, 3, 3])
In [89]: sf.groupby(sf).filter(lambda x: x.sum() > 2)
Out[89]:
```

| | |
|---|---|
| 3 | 3 |
| 4 | 3 |
| 5 | 3 |

```
dtype: int64
```

The argument of `filter` must be a function that, applied to the group as a whole, returns `True` or `False`.

Another useful operation is filtering out elements that belong to groups with only a couple members.

```
In [90]: dff = DataFrame({'A': np.arange(8), 'B': list('aabbbbcc')})
In [91]: dff.groupby('B').filter(lambda x: len(x) > 2)
Out[91]:
```

```
      A  B
2  2  b
3  3  b
4  4  b
5  5  b
```

Alternatively, instead of dropping the offending groups, we can return a like-indexed objects where the groups that do not pass the filter are filled with NaNs.

```
In [92]: dff.groupby('B').filter(lambda x: len(x) > 2, dropna=False)
```

```
Out [92]:
      A  B
0 NaN NaN
1 NaN NaN
2  2  b
3  3  b
4  4  b
5  5  b
6 NaN NaN
7 NaN NaN
```

For dataframes with multiple columns, filters should explicitly specify a column as the filter criterion.

```
In [93]: dff['C'] = np.arange(8)
```

```
In [94]: dff.groupby('B').filter(lambda x: len(x['C']) > 2)
```

```
Out [94]:
      A  B  C
2  2  b  2
3  3  b  3
4  4  b  4
5  5  b  5
```

Note: Some functions when applied to a groupby object will act as a **filter** on the input, returning a reduced shape of the original (and potentially eliminating groups), but with the index unchanged. Passing `as_index=False` will not affect these transformation methods.

For example: `head`, `tail`.

```
In [95]: dff.groupby('B').head(2)
```

```
Out [95]:
      A  B  C
0  0  a  0
1  1  a  1
2  2  b  2
3  3  b  3
6  6  c  6
7  7  c  7
```

17.7 Dispatching to instance methods

When doing an aggregation or transformation, you might just want to call an instance method on each data group. This is pretty easy to do by passing lambda functions:

```
In [96]: grouped = df.groupby('A')
```

```
In [97]: grouped.agg(lambda x: x.std())
Out[97]:
```

| | C | D |
|-----|----------|----------|
| A | | |
| bar | 0.301765 | 1.490982 |
| foo | 0.966450 | 0.645875 |

But, it's rather verbose and can be untidy if you need to pass additional arguments. Using a bit of metaprogramming cleverness, GroupBy now has the ability to “dispatch” method calls to the groups:

```
In [98]: grouped.std()
Out[98]:
```

| | C | D |
|-----|----------|----------|
| A | | |
| bar | 0.301765 | 1.490982 |
| foo | 0.966450 | 0.645875 |

What is actually happening here is that a function wrapper is being generated. When invoked, it takes any passed arguments and invokes the function with any arguments on each group (in the above example, the `std` function). The results are then combined together much in the style of `agg` and `transform` (it actually uses `apply` to infer the grouping, documented next). This enables some operations to be carried out rather succinctly:

```
In [99]: tsdf = DataFrame(randn(1000, 3),
.....:                    index=date_range('1/1/2000', periods=1000),
.....:                    columns=['A', 'B', 'C'])
.....:
```

```
In [100]: tsdf.ix[::2] = np.nan
```

```
In [101]: grouped = tsdf.groupby(lambda x: x.year)
```

```
In [102]: grouped.fillna(method='pad')
Out[102]:
```

| | A | B | C |
|------------|-----------|-----------|-----------|
| 2000-01-01 | NaN | NaN | NaN |
| 2000-01-02 | -0.353501 | -0.080957 | -0.876864 |
| 2000-01-03 | -0.353501 | -0.080957 | -0.876864 |
| 2000-01-04 | 0.050976 | 0.044273 | -0.559849 |
| 2000-01-05 | 0.050976 | 0.044273 | -0.559849 |
| 2000-01-06 | 0.030091 | 0.186460 | -0.680149 |
| 2000-01-07 | 0.030091 | 0.186460 | -0.680149 |
| ... | ... | ... | ... |
| 2002-09-20 | 2.310215 | 0.157482 | -0.064476 |
| 2002-09-21 | 2.310215 | 0.157482 | -0.064476 |
| 2002-09-22 | 0.005011 | 0.053897 | -1.026922 |
| 2002-09-23 | 0.005011 | 0.053897 | -1.026922 |
| 2002-09-24 | -0.456542 | -1.849051 | 1.559856 |
| 2002-09-25 | -0.456542 | -1.849051 | 1.559856 |
| 2002-09-26 | 1.123162 | 0.354660 | 1.128135 |

```
[1000 rows x 3 columns]
```

In this example, we chopped the collection of time series into yearly chunks then independently called *fillna* on the groups.

New in version 0.14.1.

The `nlargest` and `nsmallest` methods work on Series style groupbys:

```
In [103]: s = Series([9, 8, 7, 5, 19, 1, 4.2, 3.3])
```

```
In [104]: g = Series(list('abababab'))
```

```
In [105]: gb = s.groupby(g)
```

```
In [106]: gb.nlargest(3)
```

```
Out[106]:
a  4    19.0
   0     9.0
   2     7.0
b  1     8.0
   3     5.0
   7     3.3
dtype: float64
```

```
In [107]: gb.nsmallest(3)
```

```
Out[107]:
a  6     4.2
   2     7.0
   0     9.0
b  5     1.0
   7     3.3
   3     5.0
dtype: float64
```

17.8 Flexible apply

Some operations on the grouped data might not fit into either the aggregate or transform categories. Or, you may simply want GroupBy to infer how to combine the results. For these, use the `apply` function, which can be substituted for both `aggregate` and `transform` in many standard use cases. However, `apply` can handle some exceptional use cases, for example:

```
In [108]: df
```

```
Out[108]:
   A      B      C      D
0  foo   one -0.919854 -1.131345
1  bar   one -0.042379 -0.089329
2  foo   two  1.247642  0.337863
3  bar  three -0.009920 -0.945867
4  foo   two  0.290213 -0.932132
5  bar   two  0.495767  1.956030
6  foo   one  0.362949  0.017587
7  foo  three  1.548106 -0.016692
```

```
In [109]: grouped = df.groupby('A')
```

```
# could also just call .describe()
```

```
In [110]: grouped['C'].apply(lambda x: x.describe())
```

```
Out[110]:
A
bar  count      3.000000
     mean      0.147823
     std      0.301765
     min     -0.042379
     25%     -0.026149
```

```

50%      -0.009920
75%       0.242924
...
foo mean    0.505811
   std     0.966450
   min    -0.919854
   25%     0.290213
   50%     0.362949
   75%     1.247642
   max     1.548106
dtype: float64

```

The dimension of the returned result can also change:

```
In [111]: grouped = df.groupby('A')['C']
```

```
In [112]: def f(group):
.....:     return DataFrame({'original' : group,
.....:                      'demeaned' : group - group.mean()})
.....:
```

```
In [113]: grouped.apply(f)
```

```
Out[113]:
   demeaned  original
0 -1.425665 -0.919854
1 -0.190202 -0.042379
2  0.741831  1.247642
3 -0.157743 -0.009920
4 -0.215598  0.290213
5  0.347944  0.495767
6 -0.142862  0.362949
7  1.042295  1.548106

```

`apply` on a `Series` can operate on a returned value from the applied function, that is itself a series, and possibly upcast the result to a `DataFrame`

```
In [114]: def f(x):
.....:     return Series([ x, x**2 ], index = ['x', 'x^s'])
.....:
```

```
In [115]: s
```

```
Out[115]:
0    9.0
1    8.0
2    7.0
3    5.0
4   19.0
5    1.0
6    4.2
7    3.3
dtype: float64

```

```
In [116]: s.apply(f)
```

```
Out[116]:
      x      x^s
0  9.0   81.00
1  8.0   64.00
2  7.0   49.00
3  5.0   25.00

```

```
4  19.0   361.00
5   1.0     1.00
6   4.2    17.64
7   3.3    10.89
```

Note: `apply` can act as a reducer, transformer, *or* filter function, depending on exactly what is passed to `apply`. So depending on the path taken, and exactly what you are grouping. Thus the grouped columns(s) may be included in the output as well as set the indices.

Warning: In the current implementation `apply` calls `func` twice on the first group to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if `func` has side-effects, as they will take effect twice for the first group.

```
In [117]: d = DataFrame({"a":["x", "y"], "b":[1,2]})
```

```
In [118]: def identity(df):
.....:     print df
.....:     return df
.....:
```

```
In [119]: d.groupby("a").apply(identity)
```

```
  a  b
0  x  1
  a  b
0  x  1
  a  b
1  y  2
```

```
Out[119]:
```

```
  a  b
0  x  1
1  y  2
```

17.9 Other useful features

17.9.1 Automatic exclusion of “nuisance” columns

Again consider the example DataFrame we’ve been looking at:

```
In [120]: df
```

```
Out[120]:
```

| | A | B | C | D |
|---|-----|-------|-----------|-----------|
| 0 | foo | one | -0.919854 | -1.131345 |
| 1 | bar | one | -0.042379 | -0.089329 |
| 2 | foo | two | 1.247642 | 0.337863 |
| 3 | bar | three | -0.009920 | -0.945867 |
| 4 | foo | two | 0.290213 | -0.932132 |
| 5 | bar | two | 0.495767 | 1.956030 |
| 6 | foo | one | 0.362949 | 0.017587 |
| 7 | foo | three | 1.548106 | -0.016692 |

Supposed we wished to compute the standard deviation grouped by the A column. There is a slight problem, namely that we don’t care about the data in column B. We refer to this as a “nuisance” column. If the passed aggregation

function can't be applied to some columns, the troublesome columns will be (silently) dropped. Thus, this does not pose any problems:

```
In [121]: df.groupby('A').std()
Out[121]:
```

| | C | D |
|-----|----------|----------|
| A | | |
| bar | 0.301765 | 1.490982 |
| foo | 0.966450 | 0.645875 |

17.9.2 NA group handling

If there are any NaN values in the grouping key, these will be automatically excluded. So there will never be an “NA group”. This was not the case in older versions of pandas, but users were generally discarding the NA group anyway (and supporting it was an implementation headache).

17.9.3 Grouping with ordered factors

Categorical variables represented as instance of pandas's `Categorical` class can be used as group keys. If so, the order of the levels will be preserved:

```
In [122]: data = Series(np.random.randn(100))
In [123]: factor = qcut(data, [0, .25, .5, .75, 1.])
In [124]: data.groupby(factor).mean()
Out[124]:
```

| | |
|-------------------|-----------|
| [-2.617, -0.684] | -1.331461 |
| (-0.684, -0.0232] | -0.272816 |
| (-0.0232, 0.541] | 0.263607 |
| (0.541, 2.369] | 1.166038 |

dtype: float64

17.9.4 Grouping with a Grouper specification

You may need to specify a bit more data to properly group. You can use the `pd.Grouper` to provide this local control.

```
In [125]: import datetime as DT
In [126]: df = DataFrame({
.....:     'Branch' : 'A A A A A A B'.split(),
.....:     'Buyer' : 'Carl Mark Carl Carl Joe Joe Joe Carl'.split(),
.....:     'Quantity': [1,3,5,1,8,1,9,3],
.....:     'Date' : [
.....:         DT.datetime(2013,1,1,13,0),
.....:         DT.datetime(2013,1,1,13,5),
.....:         DT.datetime(2013,10,1,20,0),
.....:         DT.datetime(2013,10,2,10,0),
.....:         DT.datetime(2013,10,1,20,0),
.....:         DT.datetime(2013,10,2,10,0),
.....:         DT.datetime(2013,12,2,12,0),
.....:         DT.datetime(2013,12,2,14,0),
.....:     ]})
```

```
.....:

In [127]: df
Out[127]:
```

| | Branch | Buyer | Date | Quantity |
|---|--------|-------|---------------------|----------|
| 0 | A | Carl | 2013-01-01 13:00:00 | 1 |
| 1 | A | Mark | 2013-01-01 13:05:00 | 3 |
| 2 | A | Carl | 2013-10-01 20:00:00 | 5 |
| 3 | A | Carl | 2013-10-02 10:00:00 | 1 |
| 4 | A | Joe | 2013-10-01 20:00:00 | 8 |
| 5 | A | Joe | 2013-10-02 10:00:00 | 1 |
| 6 | A | Joe | 2013-12-02 12:00:00 | 9 |
| 7 | B | Carl | 2013-12-02 14:00:00 | 3 |

Groupby a specific column with the desired frequency. This is like resampling.

```
In [128]: df.groupby([pd.Grouper(freq='1M',key='Date'),'Buyer']).sum()
Out[128]:
```

| Date | Buyer | Quantity |
|------------|-------|----------|
| 2013-01-31 | Carl | 1 |
| | Mark | 3 |
| 2013-10-31 | Carl | 6 |
| | Joe | 9 |
| 2013-12-31 | Carl | 3 |
| | Joe | 9 |

You have an ambiguous specification in that you have a named index and a column that could be potential groupers.

```
In [129]: df = df.set_index('Date')

In [130]: df['Date'] = df.index + pd.offsets.MonthEnd(2)

In [131]: df.groupby([pd.Grouper(freq='6M',key='Date'),'Buyer']).sum()
Out[131]:
```

| Date | Buyer | Quantity |
|------------|-------|----------|
| 2013-02-28 | Carl | 1 |
| | Mark | 3 |
| 2014-02-28 | Carl | 9 |
| | Joe | 18 |

```
In [132]: df.groupby([pd.Grouper(freq='6M',level='Date'),'Buyer']).sum()
Out[132]:
```

| Date | Buyer | Quantity |
|------------|-------|----------|
| 2013-01-31 | Carl | 1 |
| | Mark | 3 |
| 2014-01-31 | Carl | 9 |
| | Joe | 18 |

17.9.5 Taking the first rows of each group

Just like for a DataFrame or Series you can call head and tail on a groupby:

```
In [133]: df = DataFrame([[1, 2], [1, 4], [5, 6]], columns=['A', 'B'])

In [134]: df
```

```
Out[134]:
```

```
   A  B
0  1  2
1  1  4
2  5  6
```

```
In [135]: g = df.groupby('A')
```

```
In [136]: g.head(1)
```

```
Out[136]:
```

```
   A  B
0  1  2
2  5  6
```

```
In [137]: g.tail(1)
```

```
Out[137]:
```

```
   A  B
1  1  4
2  5  6
```

This shows the first or last n rows from each group.

Warning: Before 0.14.0 this was implemented with a fall-through apply, so the result would incorrectly respect the `as_index` flag:

```
>>> g.head(1): # was equivalent to g.apply(lambda x: x.head(1))
```

```
   A  B
A
1  0  1  2
5  2  5  6
```

17.9.6 Taking the nth row of each group

To select from a DataFrame or Series the nth item, use the `nth` method. This is a reduction method, and will return a single row (or no row) per group if you pass an int for n:

```
In [138]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
```

```
In [139]: g = df.groupby('A')
```

```
In [140]: g.nth(0)
```

```
Out[140]:
```

```
   B
A
1 NaN
5  6
```

```
In [141]: g.nth(-1)
```

```
Out[141]:
```

```
   B
A
1  4
5  6
```

```
In [142]: g.nth(1)
```

```
Out[142]:
```

```
      B
A
1    4
```

If you want to select the *nth* not-null item, use the `dropna` kwarg. For a `DataFrame` this should be either `'any'` or `'all'` just like you would pass to `dropna`, for a `Series` this just needs to be truthy.

```
# nth(0) is the same as g.first()
```

```
In [143]: g.nth(0, dropna='any')
```

```
Out[143]:
```

```
      B
A
1    4
5    6
```

```
In [144]: g.first()
```

```
Out[144]:
```

```
      B
A
1    4
5    6
```

```
# nth(-1) is the same as g.last()
```

```
In [145]: g.nth(-1, dropna='any') # NaNs denote group exhausted when using dropna
```

```
Out[145]:
```

```
      B
A
1    4
5    6
```

```
In [146]: g.last()
```

```
Out[146]:
```

```
      B
A
1    4
5    6
```

```
In [147]: g.B.nth(0, dropna=True)
```

```
Out[147]:
```

```
A
1    4
5    6
Name: B, dtype: float64
```

As with other methods, passing `as_index=False`, will achieve a filtration, which returns the grouped row.

```
In [148]: df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
```

```
In [149]: g = df.groupby('A', as_index=False)
```

```
In [150]: g.nth(0)
```

```
Out[150]:
```

```
   A  B
0  1 NaN
2  5   6
```

```
In [151]: g.nth(-1)
```

```
Out[151]:
   A  B
```

```
1  1  4
2  5  6
```

You can also select multiple rows from each group by specifying multiple `nth` values as a list of ints.

```
In [152]: business_dates = date_range(start='4/1/2014', end='6/30/2014', freq='B')
```

```
In [153]: df = DataFrame(1, index=business_dates, columns=['a', 'b'])
```

```
# get the first, 4th, and last date index for each month
```

```
In [154]: df.groupby((df.index.year, df.index.month)).nth([0, 3, -1])
```

```
Out[154]:
```

| | a | b |
|------------|---|---|
| 2014-04-01 | 1 | 1 |
| 2014-04-04 | 1 | 1 |
| 2014-04-30 | 1 | 1 |
| 2014-05-01 | 1 | 1 |
| 2014-05-06 | 1 | 1 |
| 2014-05-30 | 1 | 1 |
| 2014-06-02 | 1 | 1 |
| 2014-06-05 | 1 | 1 |
| 2014-06-30 | 1 | 1 |

17.9.7 Enumerate group items

New in version 0.13.0.

To see the order in which each row appears within its group, use the `cumcount` method:

```
In [155]: df = pd.DataFrame(list('aaabba'), columns=['A'])
```

```
In [156]: df
```

```
Out[156]:
```

| | A |
|---|---|
| 0 | a |
| 1 | a |
| 2 | a |
| 3 | b |
| 4 | b |
| 5 | a |

```
In [157]: df.groupby('A').cumcount()
```

```
Out[157]:
```

| | |
|---|---|
| 0 | 0 |
| 1 | 1 |
| 2 | 2 |
| 3 | 0 |
| 4 | 1 |
| 5 | 3 |

dtype: int64

```
In [158]: df.groupby('A').cumcount(ascending=False) # kward only
```

```
Out[158]:
```

| | |
|---|---|
| 0 | 3 |
| 1 | 2 |
| 2 | 1 |
| 3 | 1 |
| 4 | 0 |

```
5      0
dtype: int64
```

17.9.8 Plotting

Groupby also works with some plotting methods. For example, suppose we suspect that some features in a DataFrame may differ by group, in this case, the values in column 1 where the group is “B” are 3 higher on average.

```
In [159]: np.random.seed(1234)
```

```
In [160]: df = DataFrame(np.random.randn(50, 2))
```

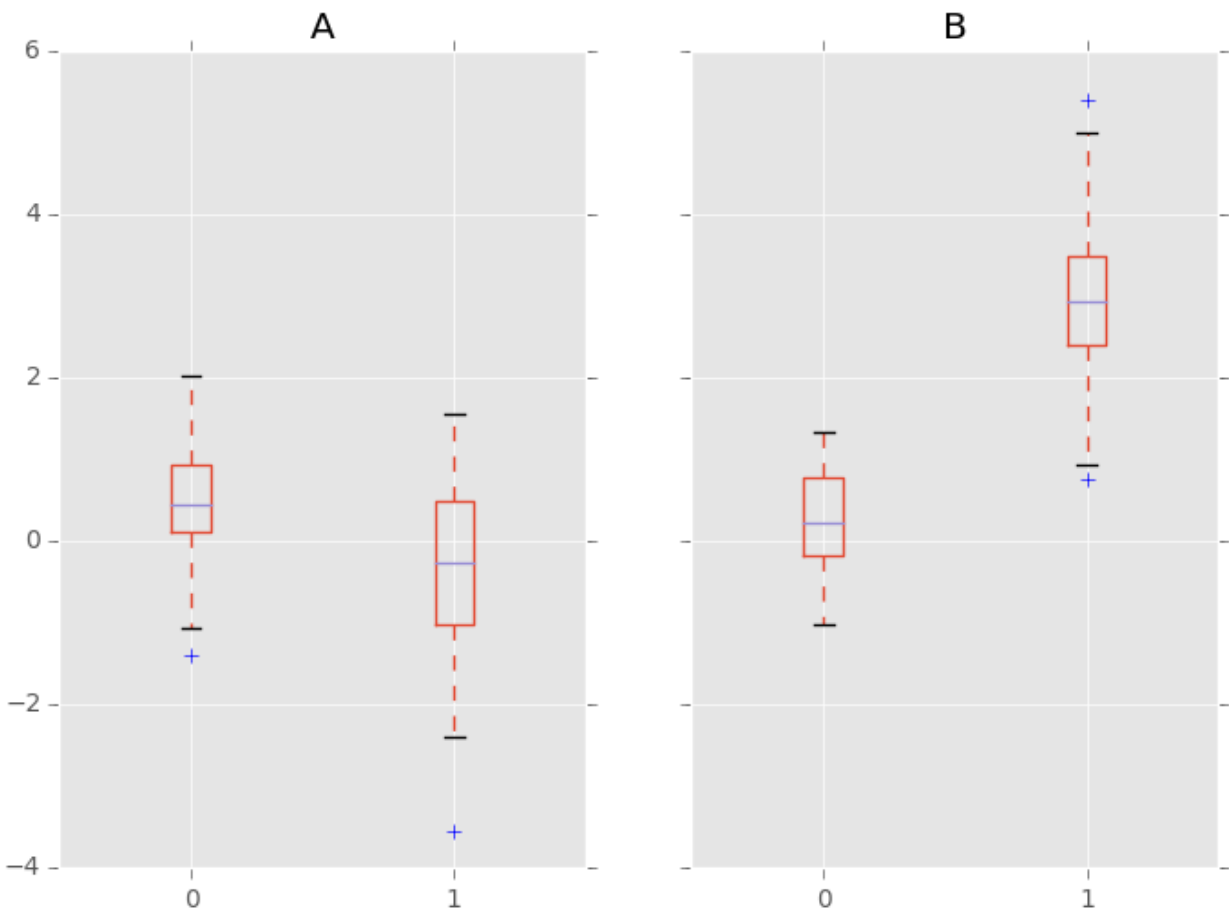
```
In [161]: df['g'] = np.random.choice(['A', 'B'], size=50)
```

```
In [162]: df.loc[df['g'] == 'B', 1] += 3
```

We can easily visualize this with a boxplot:

```
In [163]: df.groupby('g').boxplot()
```

```
Out[163]: OrderedDict([('A', {'boxes': [matplotlib.lines.Line2D object at 0xa18745ec], <matplotlib.lines.Line2D object at 0xa18745ec>}, ('B', {'boxes': [matplotlib.lines.Line2D object at 0xa18745ec], <matplotlib.lines.Line2D object at 0xa18745ec>})])
```



The result of calling `boxplot` is a dictionary whose keys are the values of our grouping column `g` (“A” and “B”). The values of the resulting dictionary can be controlled by the `return_type` keyword of `boxplot`. See the [visualization documentation](#) for more.

Warning: For historical reasons, `df.groupby("g").boxplot()` is not equivalent to `df.boxplot(by="g")`. See [here](#) for an explanation.

17.10 Examples

17.10.1 Regrouping by factor

Regroup columns of a DataFrame according to their sum, and sum the aggregated ones.

```
In [164]: df = pd.DataFrame({'a': [1, 0, 0], 'b': [0, 1, 0], 'c': [1, 0, 0], 'd': [2, 3, 4]})
```

```
In [165]: df
```

```
Out[165]:
   a  b  c  d
0  1  0  1  2
1  0  1  0  3
2  0  0  0  4
```

```
In [166]: df.groupby(df.sum(), axis=1).sum()
```

```
Out[166]:
   1  9
0  2  2
1  1  3
2  0  4
```

17.10.2 Returning a Series to propagate names

Group DataFrame columns, compute a set of metrics and return a named Series. The Series name is used as the name for the column index. This is especially useful in conjunction with reshaping operations such as stacking in which the column index name will be used as the name of the inserted column:

```
In [167]: df = pd.DataFrame({
.....:     'a': [0, 0, 0, 0, 1, 1, 1, 1, 2, 2, 2, 2],
.....:     'b': [0, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 1],
.....:     'c': [1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0],
.....:     'd': [0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1],
.....: })
```

```
In [168]: def compute_metrics(x):
.....:     result = {'b_sum': x['b'].sum(), 'c_mean': x['c'].mean()}
.....:     return pd.Series(result, name='metrics')
.....:
```

```
In [169]: result = df.groupby('a').apply(compute_metrics)
```

```
In [170]: result
```

```
Out[170]:
metrics  b_sum  c_mean
a
0         2     0.5
1         2     0.5
2         2     0.5
```

```
In [171]: result.stack()
Out[171]:
a  metrics
0  b_sum      2.0
   c_mean      0.5
1  b_sum      2.0
   c_mean      0.5
2  b_sum      2.0
   c_mean      0.5
dtype: float64
```

MERGE, JOIN, AND CONCATENATE

pandas provides various facilities for easily combining together Series, DataFrame, and Panel objects with various kinds of set logic for the indexes and relational algebra functionality in the case of join / merge-type operations.

18.1 Concatenating objects

The `concat` function (in the main pandas namespace) does all of the heavy lifting of performing concatenation operations along an axis while performing optional set logic (union or intersection) of the indexes (if any) on the other axes. Note that I say “if any” because there is only a single possible axis of concatenation for Series.

Before diving into all of the details of `concat` and what it can do, here is a simple example:

```
In [1]: df1 = DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
...:                    'B': ['B0', 'B1', 'B2', 'B3'],
...:                    'C': ['C0', 'C1', 'C2', 'C3'],
...:                    'D': ['D0', 'D1', 'D2', 'D3']},
...:                    index=[0, 1, 2, 3])
...:

In [2]: df2 = DataFrame({'A': ['A4', 'A5', 'A6', 'A7'],
...:                    'B': ['B4', 'B5', 'B6', 'B7'],
...:                    'C': ['C4', 'C5', 'C6', 'C7'],
...:                    'D': ['D4', 'D5', 'D6', 'D7']},
...:                    index=[4, 5, 6, 7])
...:

In [3]: df3 = DataFrame({'A': ['A8', 'A9', 'A10', 'A11'],
...:                    'B': ['B8', 'B9', 'B10', 'B11'],
...:                    'C': ['C8', 'C9', 'C10', 'C11'],
...:                    'D': ['D8', 'D9', 'D10', 'D11']},
...:                    index=[8, 9, 10, 11])
...:

In [4]: frames = [df1, df2, df3]

In [5]: result = concat(frames)
```

| df1 | | | | | Result | | | | |
|-----|-----|-----|-----|-----|--------|-----|-----|-----|-----|
| | A | B | C | D | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 |
| df2 | | | | | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | 8 | A8 | B8 | C8 | D8 |
| 7 | A7 | B7 | C7 | D7 | 9 | A9 | B9 | C9 | D9 |
| df3 | | | | | 10 | A10 | B10 | C10 | D10 |
| | A | B | C | D | 11 | A11 | B11 | C11 | D11 |
| 8 | A8 | B8 | C8 | D8 | | | | | |
| 9 | A9 | B9 | C9 | D9 | | | | | |
| 10 | A10 | B10 | C10 | D10 | | | | | |
| 11 | A11 | B11 | C11 | D11 | | | | | |

Like its sibling function on ndarrays, `numpy.concatenate`, `pandas.concat` takes a list or dict of homogeneously-typed objects and concatenates them with some configurable handling of “what to do with the other axes”:

```
concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False,
       keys=None, levels=None, names=None, verify_integrity=False)
```

- `objs`: list or dict of Series, DataFrame, or Panel objects. If a dict is passed, the sorted keys will be used as the `keys` argument, unless it is passed, in which case the values will be selected (see below)
- `axis`: {0, 1, ...}, default 0. The axis to concatenate along
- `join`: {'inner', 'outer'}, default 'outer'. How to handle indexes on other axis(es). Outer for union and inner for intersection
- `join_axes`: list of Index objects. Specific indexes to use for the other $n - 1$ axes instead of performing inner/outer set logic
- `keys`: sequence, default None. Construct hierarchical index using the passed keys as the outermost level. If multiple levels passed, should contain tuples.
- `levels`: list of sequences, default None. If keys passed, specific levels to use for the resulting MultiIndex. Otherwise they will be inferred from the keys
- `names`: list, default None. Names for the levels in the resulting hierarchical index
- `verify_integrity`: boolean, default False. Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation
- `ignore_index`: boolean, default False. If True, do not use the index values on the concatenation axis. The resulting axis will be labeled 0, ..., $n - 1$. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information.

Without a little bit of context and example many of these arguments don't make much sense. Let's take the above example. Suppose we wanted to associate specific keys with each of the pieces of the chopped up DataFrame. We can do this using the `keys` argument:

```
In [6]: result = concat(frames, keys=['x', 'y', 'z'])
```

| df1 | | | | | Result | | | | | |
|-----|-----|-----|-----|-----|--------|----|-----|-----|-----|-----|
| | A | B | C | D | | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | x | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | | 3 | A3 | B3 | C3 | D3 |
| df2 | | | | | y | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | z | 8 | A8 | B8 | C8 | D8 |
| 7 | A7 | B7 | C7 | D7 | | 9 | A9 | B9 | C9 | D9 |
| df3 | | | | | | 10 | A10 | B10 | C10 | D10 |
| | A | B | C | D | | 11 | A11 | B11 | C11 | D11 |
| 8 | A8 | B8 | C8 | D8 | | | | | | |
| 9 | A9 | B9 | C9 | D9 | | | | | | |
| 10 | A10 | B10 | C10 | D10 | | | | | | |
| 11 | A11 | B11 | C11 | D11 | | | | | | |

As you can see (if you've read the rest of the documentation), the resulting object's index has a *hierarchical index*. This means that we can now do stuff like select out each chunk by key:

```
In [7]: result.ix['y']
Out[7]:
```

| | A | B | C | D |
|---|----|----|----|----|
| 4 | A4 | B4 | C4 | D4 |
| 5 | A5 | B5 | C5 | D5 |
| 6 | A6 | B6 | C6 | D6 |
| 7 | A7 | B7 | C7 | D7 |

It's not a stretch to see how this can be very useful. More detail on this functionality below.

Note: It is worth noting however, that `concat` (and therefore `append`) makes a full copy of the data, and that constantly reusing this function can create a significant performance hit. If you need to use the operation over several datasets, use a list comprehension.

```
frames = [ process_your_file(f) for f in files ]
result = pd.concat(frames)
```

18.1.1 Set logic on the other axes

When gluing together multiple DataFrames (or Panels or...), for example, you have a choice of how to handle the other axes (other than the one being concatenated). This can be done in three ways:

- Take the (sorted) union of them all, `join='outer'`. This is the default option as it results in zero information loss.

- Take the intersection, `join='inner'`.
- Use a specific index (in the case of `DataFrame`) or indexes (in the case of `Panel` or future higher dimensional objects), i.e. the `join_axes` argument

Here is a example of each of these methods. First, the default `join='outer'` behavior:

```
In [8]: df4 = DataFrame({'B': ['B2', 'B3', 'B6', 'B7'],
...:                    'D': ['D2', 'D3', 'D6', 'D7'],
...:                    'F': ['F2', 'F3', 'F6', 'F7']},
...:                    index=[2, 3, 6, 7])
...:
```

```
In [9]: result = concat([df1, df4], axis=1)
```

| df1 | | | | | df4 | | | | Result | | | | | | | |
|-----|----|----|----|----|-----|----|----|----|--------|-----|-----|-----|-----|-----|-----|-----|
| | A | B | C | D | | B | D | F | | A | B | C | D | B | D | F |
| 0 | A0 | B0 | C0 | D0 | 2 | B2 | D2 | F2 | 0 | A0 | B0 | C0 | D0 | NaN | NaN | NaN |
| 1 | A1 | B1 | C1 | D1 | 3 | B3 | D3 | F3 | 1 | A1 | B1 | C1 | D1 | NaN | NaN | NaN |
| 2 | A2 | B2 | C2 | D2 | 6 | B6 | D6 | F6 | 2 | A2 | B2 | C2 | D2 | B2 | D2 | F2 |
| 3 | A3 | B3 | C3 | D3 | 7 | B7 | D7 | F7 | 3 | A3 | B3 | C3 | D3 | B3 | D3 | F3 |
| | | | | | | | | | 6 | NaN | NaN | NaN | NaN | B6 | D6 | F6 |
| | | | | | | | | | 7 | NaN | NaN | NaN | NaN | B7 | D7 | F7 |

Note that the row indexes have been unioned and sorted. Here is the same thing with `join='inner'`:

```
In [10]: result = concat([df1, df4], axis=1, join='inner')
```

| df1 | | | | | df4 | | | | Result | | | | | | | |
|-----|----|----|----|----|-----|----|----|----|--------|----|----|----|----|----|----|----|
| | A | B | C | D | | B | D | F | | A | B | C | D | B | D | F |
| 0 | A0 | B0 | C0 | D0 | 2 | B2 | D2 | F2 | 2 | A2 | B2 | C2 | D2 | B2 | D2 | F2 |
| 1 | A1 | B1 | C1 | D1 | 3 | B3 | D3 | F3 | 3 | A3 | B3 | C3 | D3 | B3 | D3 | F3 |
| 2 | A2 | B2 | C2 | D2 | 6 | B6 | D6 | F6 | | | | | | | | |
| 3 | A3 | B3 | C3 | D3 | 7 | B7 | D7 | F7 | | | | | | | | |

Lastly, suppose we just wanted to reuse the *exact index* from the original `DataFrame`:

```
In [11]: result = concat([df1, df4], axis=1, join_axes=[df1.index])
```

| df1 | | | | | df4 | | | | Result | | | | | | | |
|-----|----|----|----|----|-----|----|----|----|--------|----|----|----|----|-----|-----|-----|
| | A | B | C | D | | B | D | F | | A | B | C | D | B | D | F |
| 0 | A0 | B0 | C0 | D0 | 2 | B2 | D2 | F2 | 0 | A0 | B0 | C0 | D0 | NaN | NaN | NaN |
| 1 | A1 | B1 | C1 | D1 | 3 | B3 | D3 | F3 | 1 | A1 | B1 | C1 | D1 | NaN | NaN | NaN |
| 2 | A2 | B2 | C2 | D2 | 6 | B6 | D6 | F6 | 2 | A2 | B2 | C2 | D2 | B2 | D2 | F2 |
| 3 | A3 | B3 | C3 | D3 | 7 | B7 | D7 | F7 | 3 | A3 | B3 | C3 | D3 | B3 | D3 | F3 |

18.1.2 Concatenating using `append`

A useful shortcut to `concat` are the `append` instance methods on `Series` and `DataFrame`. These methods actually predated `concat`. They concatenate along `axis=0`, namely the index:

```
In [12]: result = df1.append(df2)
```

| df1 | | | | | Result | | | | |
|-----|----|----|----|----|--------|----|----|----|----|
| | A | B | C | D | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 |
| df2 | | | | | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | | | | | |
| 7 | A7 | B7 | C7 | D7 | | | | | |

In the case of `DataFrame`, the indexes must be disjoint but the columns do not need to be:

```
In [13]: result = df1.append(df4)
```

| df1 | | | | | Result | | | | | |
|-----|----|----|----|----|--------|-----|-----|-----|----|-----|
| | A | B | C | D | | A | B | C | D | F |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 | NaN |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 | NaN |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 | NaN |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 | NaN |
| df4 | | | | | 2 | NaN | B2 | NaN | D2 | F2 |
| | B | D | F | 3 | NaN | B3 | NaN | D3 | F3 | |
| 2 | B2 | D2 | F2 | 6 | NaN | B6 | NaN | D6 | F6 | |
| 3 | B3 | D3 | F3 | 7 | NaN | B7 | NaN | D7 | F7 | |
| 6 | B6 | D6 | F6 | | | | | | | |
| 7 | B7 | D7 | F7 | | | | | | | |

append may take multiple objects to concatenate:

```
In [14]: result = df1.append([df2, df3])
```

| df1 | | | | | Result | | | | |
|-----|-----|-----|-----|-----|--------|-----|-----|-----|-----|
| | A | B | C | D | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 |
| df2 | | | | | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | 8 | A8 | B8 | C8 | D8 |
| 7 | A7 | B7 | C7 | D7 | 9 | A9 | B9 | C9 | D9 |
| df3 | | | | | 10 | A10 | B10 | C10 | D10 |
| | A | B | C | D | 11 | A11 | B11 | C11 | D11 |
| 8 | A8 | B8 | C8 | D8 | | | | | |
| 9 | A9 | B9 | C9 | D9 | | | | | |
| 10 | A10 | B10 | C10 | D10 | | | | | |
| 11 | A11 | B11 | C11 | D11 | | | | | |

Note: Unlike *list.append* method, which appends to the original list and returns nothing, append here **does not** modify df1 and returns its copy with df2 appended.

18.1.3 Ignoring indexes on the concatenation axis

For DataFrames which don't have a meaningful index, you may wish to append them and ignore the fact that they may have overlapping indexes:

To do this, use the `ignore_index` argument:

```
In [15]: result = concat([df1, df4], ignore_index=True)
```

| df1 | | | | | Result | | | | | |
|-----|----|----|----|----|--------|-----|-----|-----|----|-----|
| | A | B | C | D | | A | B | C | D | F |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 | NaN |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 | NaN |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 | NaN |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 | NaN |
| df4 | | | | | 4 | NaN | B2 | NaN | D2 | F2 |
| | B | D | F | | 5 | NaN | B3 | NaN | D3 | F3 |
| 2 | B2 | D2 | F2 | 6 | NaN | B6 | NaN | D6 | F6 | |
| 3 | B3 | D3 | F3 | 7 | NaN | B7 | NaN | D7 | F7 | |
| 6 | B6 | D6 | F6 | | | | | | | |
| 7 | B7 | D7 | F7 | | | | | | | |

This is also a valid argument to `DataFrame.append`:

```
In [16]: result = df1.append(df4, ignore_index=True)
```

| df1 | | | | | Result | | | | | |
|-----|----|----|----|----|--------|-----|-----|-----|----|-----|
| | A | B | C | D | | A | B | C | D | F |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 | NaN |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 | NaN |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 | NaN |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 | NaN |
| df4 | | | | | 4 | NaN | B2 | NaN | D2 | F2 |
| | B | D | F | | 5 | NaN | B3 | NaN | D3 | F3 |
| 2 | B2 | D2 | F2 | 6 | NaN | B6 | NaN | D6 | F6 | |
| 3 | B3 | D3 | F3 | 7 | NaN | B7 | NaN | D7 | F7 | |
| 6 | B6 | D6 | F6 | | | | | | | |
| 7 | B7 | D7 | F7 | | | | | | | |

18.1.4 Concatenating with mixed ndims

You can concatenate a mix of Series and DataFrames. The Series will be transformed to DataFrames with the column name as the name of the Series.

```
In [17]: s1 = Series(['X0', 'X1', 'X2', 'X3'], name='X')
```

```
In [18]: result = concat([df1, s1], axis=1)
```

| df1 | | | | | s1 | | Result | | | | | |
|-----|----|----|----|----|----|----|--------|----|----|----|----|----|
| | A | B | C | D | | X | | A | B | C | D | X |
| 0 | A0 | B0 | C0 | D0 | 0 | X0 | 0 | A0 | B0 | C0 | D0 | X0 |
| 1 | A1 | B1 | C1 | D1 | 1 | X1 | 1 | A1 | B1 | C1 | D1 | X1 |
| 2 | A2 | B2 | C2 | D2 | 2 | X2 | 2 | A2 | B2 | C2 | D2 | X2 |
| 3 | A3 | B3 | C3 | D3 | 3 | X3 | 3 | A3 | B3 | C3 | D3 | X3 |

If unnamed Series are passed they will be numbered consecutively.

```
In [19]: s2 = Series(['_0', '_1', '_2', '_3'])
```

```
In [20]: result = concat([df1, s2, s2, s2], axis=1)
```

| df1 | | | | | s2 | | Result | | | | | | | |
|-----|----|----|----|----|----|----|--------|----|----|----|----|----|----|----|
| | A | B | C | D | | | | A | B | C | D | 0 | 1 | 2 |
| 0 | A0 | B0 | C0 | D0 | 0 | _0 | 0 | A0 | B0 | C0 | D0 | _0 | _0 | _0 |
| 1 | A1 | B1 | C1 | D1 | 1 | _1 | 1 | A1 | B1 | C1 | D1 | _1 | _1 | _1 |
| 2 | A2 | B2 | C2 | D2 | 2 | _2 | 2 | A2 | B2 | C2 | D2 | _2 | _2 | _2 |
| 3 | A3 | B3 | C3 | D3 | 3 | _3 | 3 | A3 | B3 | C3 | D3 | _3 | _3 | _3 |

Passing ignore_index=True will drop all name references.

```
In [21]: result = concat([df1, s1], axis=1, ignore_index=True)
```

| df1 | | | | | s1 | | Result | | | | | |
|-----|----|----|----|----|----|----|--------|----|----|----|----|----|
| | A | B | C | D | | X | | 0 | 1 | 2 | 3 | 4 |
| 0 | A0 | B0 | C0 | D0 | 0 | X0 | 0 | A0 | B0 | C0 | D0 | X0 |
| 1 | A1 | B1 | C1 | D1 | 1 | X1 | 1 | A1 | B1 | C1 | D1 | X1 |
| 2 | A2 | B2 | C2 | D2 | 2 | X2 | 2 | A2 | B2 | C2 | D2 | X2 |
| 3 | A3 | B3 | C3 | D3 | 3 | X3 | 3 | A3 | B3 | C3 | D3 | X3 |

18.1.5 More concatenating with group keys

Let's consider a variation on the first example presented:

```
In [22]: result = concat(frames, keys=['x', 'y', 'z'])
```

| df1 | | | | | Result | | | | | |
|-----|-----|-----|-----|-----|--------|-----|-----|-----|-----|-----|
| | A | B | C | D | x | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | | 3 | A3 | B3 | C3 | D3 |
| df2 | | | | | | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | | 8 | A8 | B8 | C8 | D8 |
| 7 | A7 | B7 | C7 | D7 | | 9 | A9 | B9 | C9 | D9 |
| df3 | | | | | | 10 | A10 | B10 | C10 | D10 |
| | A | B | C | D | 11 | A11 | B11 | C11 | D11 | |
| 8 | A8 | B8 | C8 | D8 | | | | | | |
| 9 | A9 | B9 | C9 | D9 | | | | | | |
| 10 | A10 | B10 | C10 | D10 | | | | | | |
| 11 | A11 | B11 | C11 | D11 | | | | | | |

You can also pass a dict to `concat` in which case the dict keys will be used for the `keys` argument (unless other keys are specified):

```
In [23]: pieces = {'x': df1, 'y': df2, 'z': df3}
```

```
In [24]: result = concat(pieces)
```

| df1 | | | | | Result | | | | | |
|-----|-----|-----|-----|-----|--------|----|-----|-----|-----|-----|
| | A | B | C | D | | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | x | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | | 3 | A3 | B3 | C3 | D3 |
| df2 | | | | | y | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | z | 8 | A8 | B8 | C8 | D8 |
| 7 | A7 | B7 | C7 | D7 | | 9 | A9 | B9 | C9 | D9 |
| df3 | | | | | | 10 | A10 | B10 | C10 | D10 |
| | A | B | C | D | | 11 | A11 | B11 | C11 | D11 |
| 8 | A8 | B8 | C8 | D8 | | | | | | |
| 9 | A9 | B9 | C9 | D9 | | | | | | |
| 10 | A10 | B10 | C10 | D10 | | | | | | |
| 11 | A11 | B11 | C11 | D11 | | | | | | |

```
In [25]: result = concat(pieces, keys=['z', 'y'])
```

| df1 | | | | | Result | | | | | |
|-----|-----|-----|-----|-----|--------|----|-----|-----|-----|-----|
| | A | B | C | D | z | 8 | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | | | A8 | B8 | C8 | D8 |
| 1 | A1 | B1 | C1 | D1 | | | A9 | B9 | C9 | D9 |
| 2 | A2 | B2 | C2 | D2 | | | A10 | B10 | C10 | D10 |
| 3 | A3 | B3 | C3 | D3 | z | 11 | A11 | B11 | C11 | D11 |
| df2 | | | | | y | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | y | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | y | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | y | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | | | | | | |
| 7 | A7 | B7 | C7 | D7 | | | | | | |
| df3 | | | | | | | | | | |
| | A | B | C | D | | | | | | |
| 8 | A8 | B8 | C8 | D8 | | | | | | |
| 9 | A9 | B9 | C9 | D9 | | | | | | |
| 10 | A10 | B10 | C10 | D10 | | | | | | |
| 11 | A11 | B11 | C11 | D11 | | | | | | |

The MultiIndex created has levels that are constructed from the passed keys and the index of the DataFrame pieces:

```
In [26]: result.index.levels
Out[26]: FrozenList([[u'z', u'y'], [4, 5, 6, 7, 8, 9, 10, 11]])
```

If you wish to specify other levels (as will occasionally be the case), you can do so using the `levels` argument:

```
In [27]: result = concat(pieces, keys=['x', 'y', 'z'],
.....:                  levels=[['z', 'y', 'x', 'w']],
.....:                  names=['group_key'])
.....:
```

| df1 | | | | | Result | | | | | |
|-----|-----|-----|-----|-----|--------|----|-----|-----|-----|-----|
| | A | B | C | D | | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | x | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | | 3 | A3 | B3 | C3 | D3 |
| df2 | | | | | y | 4 | A4 | B4 | C4 | D4 |
| | A | B | C | D | | 5 | A5 | B5 | C5 | D5 |
| 4 | A4 | B4 | C4 | D4 | | 6 | A6 | B6 | C6 | D6 |
| 5 | A5 | B5 | C5 | D5 | | 7 | A7 | B7 | C7 | D7 |
| 6 | A6 | B6 | C6 | D6 | z | 8 | A8 | B8 | C8 | D8 |
| 7 | A7 | B7 | C7 | D7 | | 9 | A9 | B9 | C9 | D9 |
| df3 | | | | | | 10 | A10 | B10 | C10 | D10 |
| | A | B | C | D | | 11 | A11 | B11 | C11 | D11 |
| 8 | A8 | B8 | C8 | D8 | | | | | | |
| 9 | A9 | B9 | C9 | D9 | | | | | | |
| 10 | A10 | B10 | C10 | D10 | | | | | | |
| 11 | A11 | B11 | C11 | D11 | | | | | | |

```
In [28]: result.index.levels
```

```
Out[28]: FrozenList([[u'z', u'y', u'x', u'w'], [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11]])
```

Yes, this is fairly esoteric, but is actually necessary for implementing things like GroupBy where the order of a categorical variable is meaningful.

18.1.6 Appending rows to a DataFrame

While not especially efficient (since a new object must be created), you can append a single row to a DataFrame by passing a Series or dict to `append`, which returns a new DataFrame as above.

```
In [29]: s2 = Series(['X0', 'X1', 'X2', 'X3'], index=['A', 'B', 'C', 'D'])
```

```
In [30]: result = df1.append(s2, ignore_index=True)
```

| df1 | | | | | Result | | | | |
|-----|----|----|----|----|--------|----|----|----|----|
| | A | B | C | D | | A | B | C | D |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 |
| s2 | | | | | 4 | X0 | X1 | X2 | X3 |
| | A | | | X0 | | | | | |
| | B | | | X1 | | | | | |
| | C | | | X2 | | | | | |
| | D | | | X3 | | | | | |

You should use `ignore_index` with this method to instruct `DataFrame` to discard its index. If you wish to preserve the index, you should construct an appropriately-indexed `DataFrame` and append or concatenate those objects.

You can also pass a list of dicts or Series:

```
In [31]: dicts = [{'A': 1, 'B': 2, 'C': 3, 'X': 4},
.....:           {'A': 5, 'B': 6, 'C': 7, 'Y': 8}]
.....:

In [32]: result = df1.append(dicts, ignore_index=True)
```

| df1 | | | | | Result | | | | | | |
|-------|----|----|----|-----|--------|----|----|----|-----|-----|-----|
| | A | B | C | D | | A | B | C | D | X | Y |
| 0 | A0 | B0 | C0 | D0 | 0 | A0 | B0 | C0 | D0 | NaN | NaN |
| 1 | A1 | B1 | C1 | D1 | 1 | A1 | B1 | C1 | D1 | NaN | NaN |
| 2 | A2 | B2 | C2 | D2 | 2 | A2 | B2 | C2 | D2 | NaN | NaN |
| 3 | A3 | B3 | C3 | D3 | 3 | A3 | B3 | C3 | D3 | NaN | NaN |
| dicts | | | | | 4 | 1 | 2 | 3 | NaN | 4.0 | NaN |
| | A | B | C | X | 5 | 5 | 6 | 7 | NaN | NaN | 8.0 |
| 0 | 1 | 2 | 3 | 4.0 | | | | | | | |
| 1 | 5 | 6 | 7 | NaN | | | | | | | |

18.2 Database-style DataFrame joining/merging

pandas has full-featured, **high performance** in-memory join operations idiomatically very similar to relational databases like SQL. These methods perform significantly better (in some cases well over an order of magnitude better) than other open source implementations (like `base::merge.data.frame` in R). The reason for this is careful algorithmic design and internal layout of the data in `DataFrame`.

See the [cookbook](#) for some advanced strategies.

Users who are familiar with SQL but new to pandas might be interested in a [comparison with SQL](#).

pandas provides a single function, `merge`, as the entry point for all standard database join operations between `DataFrame` objects:

```
merge(left, right, how='inner', on=None, left_on=None, right_on=None,
      left_index=False, right_index=False, sort=True,
      suffixes=('_x', '_y'), copy=True)
```

Here's a description of what each argument is for:

- `left`: A `DataFrame` object
- `right`: Another `DataFrame` object
- `on`: Columns (names) to join on. Must be found in both the left and right `DataFrame` objects. If not passed and `left_index` and `right_index` are `False`, the intersection of the columns in the `DataFrames` will be inferred to be the join keys
- `left_on`: Columns from the left `DataFrame` to use as keys. Can either be column names or arrays with length equal to the length of the `DataFrame`
- `right_on`: Columns from the right `DataFrame` to use as keys. Can either be column names or arrays with length equal to the length of the `DataFrame`
- `left_index`: If `True`, use the index (row labels) from the left `DataFrame` as its join key(s). In the case of a `DataFrame` with a `MultiIndex` (hierarchical), the number of levels must match the number of join keys from the right `DataFrame`
- `right_index`: Same usage as `left_index` for the right `DataFrame`
- `how`: One of `'left'`, `'right'`, `'outer'`, `'inner'`. Defaults to `inner`. See below for more detailed description of each method
- `sort`: Sort the result `DataFrame` by the join keys in lexicographical order. Defaults to `True`, setting to `False` will improve performance substantially in many cases
- `suffixes`: A tuple of string suffixes to apply to overlapping columns. Defaults to `('_x', '_y')`.
- `copy`: Always copy data (default `True`) from the passed `DataFrame` objects, even when reindexing is not necessary. Cannot be avoided in many cases but may improve performance / memory usage. The cases where copying can be avoided are somewhat pathological but this option is provided nonetheless.

The return type will be the same as `left`. If `left` is a `DataFrame` and `right` is a subclass of `DataFrame`, the return type will still be `DataFrame`.

`merge` is a function in the pandas namespace, and it is also available as a `DataFrame` instance method, with the calling `DataFrame` being implicitly considered the left object in the join.

The related `DataFrame.join` method, uses `merge` internally for the index-on-index and index-on-column(s) joins, but *joins on indexes* by default rather than trying to join on common columns (the default behavior for `merge`). If you are joining on index, you may wish to use `DataFrame.join` to save yourself some typing.

18.2.1 Brief primer on merge methods (relational algebra)

Experienced users of relational databases like SQL will be familiar with the terminology used to describe join operations between two SQL-table like structures (`DataFrame` objects). There are several cases to consider which are very important to understand:

- **one-to-one** joins: for example when joining two `DataFrame` objects on their indexes (which must contain unique values)
- **many-to-one** joins: for example when joining an index (unique) to one or more columns in a `DataFrame`

- **many-to-many** joins: joining columns on columns.

Note: When joining columns on columns (potentially a many-to-many join), any indexes on the passed DataFrame objects **will be discarded**.

It is worth spending some time understanding the result of the **many-to-many** join case. In SQL / standard relational algebra, if a key combination appears more than once in both tables, the resulting table will have the **Cartesian product** of the associated data. Here is a very basic example with one unique key combination:

```
In [33]: left = DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
.....:                  'A': ['A0', 'A1', 'A2', 'A3'],
.....:                  'B': ['B0', 'B1', 'B2', 'B3']})
.....:

In [34]: right = DataFrame({'key': ['K0', 'K1', 'K2', 'K3'],
.....:                    'C': ['C0', 'C1', 'C2', 'C3'],
.....:                    'D': ['D0', 'D1', 'D2', 'D3']})
.....:

In [35]: result = merge(left, right, on='key')
```

| left | | | | right | | | | Result | | | | | |
|------|----|----|-----|-------|----|----|-----|--------|----|----|-----|----|----|
| | A | B | key | | C | D | key | | A | B | key | C | D |
| 0 | A0 | B0 | K0 | 0 | C0 | D0 | K0 | 0 | A0 | B0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K1 | 1 | C1 | D1 | K1 | 1 | A1 | B1 | K1 | C1 | D1 |
| 2 | A2 | B2 | K2 | 2 | C2 | D2 | K2 | 2 | A2 | B2 | K2 | C2 | D2 |
| 3 | A3 | B3 | K3 | 3 | C3 | D3 | K3 | 3 | A3 | B3 | K3 | C3 | D3 |

Here is a more complicated example with multiple join keys:

```
In [36]: left = DataFrame({'key1': ['K0', 'K0', 'K1', 'K2'],
.....:                  'key2': ['K0', 'K1', 'K0', 'K1'],
.....:                  'A': ['A0', 'A1', 'A2', 'A3'],
.....:                  'B': ['B0', 'B1', 'B2', 'B3']})
.....:

In [37]: right = DataFrame({'key1': ['K0', 'K1', 'K1', 'K2'],
.....:                    'key2': ['K0', 'K0', 'K0', 'K0'],
.....:                    'C': ['C0', 'C1', 'C2', 'C3'],
.....:                    'D': ['D0', 'D1', 'D2', 'D3']})
.....:

In [38]: result = merge(left, right, on=['key1', 'key2'])
```

| left | | | | | right | | | | | Result | | | | | | |
|------|----|----|------|------|-------|----|----|------|------|--------|----|----|------|------|----|----|
| | A | B | key1 | key2 | | C | D | key1 | key2 | | A | B | key1 | key2 | C | D |
| 0 | A0 | B0 | K0 | K0 | 0 | C0 | D0 | K0 | K0 | 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | 1 | C1 | D1 | K1 | K0 | 1 | A2 | B2 | K1 | K0 | C1 | D1 |
| 2 | A2 | B2 | K1 | K0 | 2 | C2 | D2 | K1 | K0 | 2 | A2 | B2 | K1 | K0 | C2 | D2 |
| 3 | A3 | B3 | K2 | K1 | 3 | C3 | D3 | K2 | K0 | | | | | | | |

The `how` argument to `merge` specifies how to determine which keys are to be included in the resulting table. If a key combination **does not appear** in either the left or right tables, the values in the joined table will be NA. Here is a summary of the `how` options and their SQL equivalent names:

| Merge method | SQL Join Name | Description |
|--------------|------------------|---|
| left | LEFT OUTER JOIN | Use keys from left frame only |
| right | RIGHT OUTER JOIN | Use keys from right frame only |
| outer | FULL OUTER JOIN | Use union of keys from both frames |
| inner | INNER JOIN | Use intersection of keys from both frames |

```
In [39]: result = merge(left, right, how='left', on=['key1', 'key2'])
```

| left | | | | | right | | | | | Result | | | | | | |
|------|----|----|------|------|-------|----|----|------|------|--------|----|----|------|------|-----|-----|
| | A | B | key1 | key2 | | C | D | key1 | key2 | | A | B | key1 | key2 | C | D |
| 0 | A0 | B0 | K0 | K0 | 0 | C0 | D0 | K0 | K0 | 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | 1 | C1 | D1 | K1 | K0 | 1 | A1 | B1 | K0 | K1 | NaN | NaN |
| 2 | A2 | B2 | K1 | K0 | 2 | C2 | D2 | K1 | K0 | 2 | A2 | B2 | K1 | K0 | C1 | D1 |
| 3 | A3 | B3 | K2 | K1 | 3 | C3 | D3 | K2 | K0 | 3 | A2 | B2 | K1 | K0 | C2 | D2 |
| | | | | | | | | | | 4 | A3 | B3 | K2 | K1 | NaN | NaN |

```
In [40]: result = merge(left, right, how='right', on=['key1', 'key2'])
```

| left | | | | | right | | | | | Result | | | | | | |
|------|----|----|------|------|-------|----|----|------|------|--------|-----|-----|------|------|----|----|
| | A | B | key1 | key2 | | C | D | key1 | key2 | | A | B | key1 | key2 | C | D |
| 0 | A0 | B0 | K0 | K0 | 0 | C0 | D0 | K0 | K0 | 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | 1 | C1 | D1 | K1 | K0 | 1 | A2 | B2 | K1 | K0 | C1 | D1 |
| 2 | A2 | B2 | K1 | K0 | 2 | C2 | D2 | K1 | K0 | 2 | A2 | B2 | K1 | K0 | C2 | D2 |
| 3 | A3 | B3 | K2 | K1 | 3 | C3 | D3 | K2 | K0 | 3 | NaN | NaN | K2 | K0 | C3 | D3 |

```
In [41]: result = merge(left, right, how='outer', on=['key1', 'key2'])
```

| left | | | | | right | | | | | Result | | | | | | |
|------|----|----|------|------|-------|----|----|------|------|--------|-----|-----|------|------|-----|-----|
| | | | | | | | | | | | A | B | key1 | key2 | C | D |
| | A | B | key1 | key2 | | C | D | key1 | key2 | 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 0 | A0 | B0 | K0 | K0 | 0 | C0 | D0 | K0 | K0 | 1 | A1 | B1 | K0 | K1 | NaN | NaN |
| 1 | A1 | B1 | K0 | K1 | 1 | C1 | D1 | K1 | K0 | 2 | A2 | B2 | K1 | K0 | C1 | D1 |
| 2 | A2 | B2 | K1 | K0 | 2 | C2 | D2 | K1 | K0 | 3 | A2 | B2 | K1 | K0 | C2 | D2 |
| 3 | A3 | B3 | K2 | K1 | 3 | C3 | D3 | K2 | K0 | 4 | A3 | B3 | K2 | K1 | NaN | NaN |
| | | | | | | | | | | 5 | NaN | NaN | K2 | K0 | C3 | D3 |

```
In [42]: result = merge(left, right, how='inner', on=['key1', 'key2'])
```

| left | | | | | right | | | | | Result | | | | | | |
|------|----|----|------|------|-------|----|----|------|------|--------|----|----|------|------|----|----|
| | A | B | key1 | key2 | | C | D | key1 | key2 | | A | B | key1 | key2 | C | D |
| 0 | A0 | B0 | K0 | K0 | 0 | C0 | D0 | K0 | K0 | 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | 1 | C1 | D1 | K1 | K0 | 1 | A2 | B2 | K1 | K0 | C1 | D1 |
| 2 | A2 | B2 | K1 | K0 | 2 | C2 | D2 | K1 | K0 | 2 | A2 | B2 | K1 | K0 | C2 | D2 |
| 3 | A3 | B3 | K2 | K1 | 3 | C3 | D3 | K2 | K0 | | | | | | | |

18.2.2 Joining on index

`DataFrame.join` is a convenient method for combining the columns of two potentially differently-indexed DataFrames into a single result DataFrame. Here is a very basic example:

```
In [43]: left = DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                    'B': ['B0', 'B1', 'B2']},
.....:                    index=['K0', 'K1', 'K2'])
.....:
```

```
In [44]: right = DataFrame({'C': ['C0', 'C2', 'C3'],
.....:                     'D': ['D0', 'D2', 'D3']},
.....:                     index=['K0', 'K2', 'K3'])
.....:
```

```
In [45]: result = left.join(right)
```

| left | | | right | | | Result | | | | |
|------|----|----|-------|----|----|--------|----|----|-----|-----|
| | A | B | | C | D | | A | B | C | D |
| K0 | A0 | B0 | K0 | C0 | D0 | K0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | K2 | C2 | D2 | K1 | A1 | B1 | NaN | NaN |
| K2 | A2 | B2 | K3 | C3 | D3 | K2 | A2 | B2 | C2 | D2 |

```
In [46]: result = left.join(right, how='outer')
```

| left | | | right | | | Result | | | | |
|------|----|----|-------|----|----|--------|-----|-----|-----|-----|
| | A | B | | C | D | | A | B | C | D |
| K0 | A0 | B0 | K0 | C0 | D0 | K0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | K2 | C2 | D2 | K1 | A1 | B1 | NaN | NaN |
| K2 | A2 | B2 | K3 | C3 | D3 | K2 | A2 | B2 | C2 | D2 |
| | | | | | | K3 | NaN | NaN | C3 | D3 |

```
In [47]: result = left.join(right, how='inner')
```

| left | | | right | | | Result | | | | |
|------|----|----|-------|----|----|--------|----|----|----|----|
| | A | B | | C | D | | A | B | C | D |
| K0 | A0 | B0 | K0 | C0 | D0 | K0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | K2 | C2 | D2 | K2 | A2 | B2 | C2 | D2 |
| K2 | A2 | B2 | K3 | C3 | D3 | | | | | |

The data alignment here is on the indexes (row labels). This same behavior can be achieved using `merge` plus additional arguments instructing it to use the indexes:

```
In [48]: result = merge(left, right, left_index=True, right_index=True, how='outer')
```

| left | | | right | | | Result | | | | |
|------|----|----|-------|----|----|--------|-----|-----|-----|-----|
| | A | B | | C | D | | A | B | C | D |
| K0 | A0 | B0 | K0 | C0 | D0 | K0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | K2 | C2 | D2 | K1 | A1 | B1 | NaN | NaN |
| K2 | A2 | B2 | K3 | C3 | D3 | K2 | A2 | B2 | C2 | D2 |
| | | | | | | K3 | NaN | NaN | C3 | D3 |

```
In [49]: result = merge(left, right, left_index=True, right_index=True, how='inner');
```

| left | | | right | | | Result | | | | |
|------|----|----|-------|----|----|--------|----|----|----|----|
| | A | B | | C | D | | A | B | C | D |
| K0 | A0 | B0 | K0 | C0 | D0 | K0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | K2 | C2 | D2 | K2 | A2 | B2 | C2 | D2 |
| K2 | A2 | B2 | K3 | C3 | D3 | | | | | |

18.2.3 Joining key columns on an index

`join` takes an optional `on` argument which may be a column or multiple column names, which specifies that the passed DataFrame is to be aligned on that column in the DataFrame. These two function calls are completely equivalent:

```
left.join(right, on=key_or_keys)
merge(left, right, left_on=key_or_keys, right_index=True,
      how='left', sort=False)
```

Obviously you can choose whichever form you find more convenient. For many-to-one joins (where one of the DataFrame's is already indexed by the join key), using `join` may be more convenient. Here is a simple example:

```
In [50]: left = DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
.....:                   'B': ['B0', 'B1', 'B2', 'B3'],
.....:                   'key': ['K0', 'K1', 'K0', 'K1']})
.....:
```

```
In [51]: right = DataFrame({'C': ['C0', 'C1'],
.....:                    'D': ['D0', 'D1']},
.....:                   index=['K0', 'K1'])
.....:
```

```
In [52]: result = left.join(right, on='key')
```

| left | | | | right | | | Result | | | | | |
|------|----|----|-----|-------|----|----|--------|----|----|-----|----|----|
| | A | B | key | | C | D | | A | B | key | C | D |
| 0 | A0 | B0 | K0 | | | | 0 | A0 | B0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K1 | K0 | C0 | D0 | 1 | A1 | B1 | K1 | C1 | D1 |
| 2 | A2 | B2 | K0 | K1 | C1 | D1 | 2 | A2 | B2 | K0 | C0 | D0 |
| 3 | A3 | B3 | K1 | | | | 3 | A3 | B3 | K1 | C1 | D1 |

```
In [53]: result = merge(left, right, left_on='key', right_index=True,
.....:                  how='left', sort=False);
.....:
```

| left | | | | right | | | Result | | | | | |
|------|----|----|-----|-------|----|----|--------|----|----|-----|----|----|
| | A | B | key | | C | D | | A | B | key | C | D |
| 0 | A0 | B0 | K0 | | | | 0 | A0 | B0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K1 | K0 | C0 | D0 | 1 | A1 | B1 | K1 | C1 | D1 |
| 2 | A2 | B2 | K0 | K1 | C1 | D1 | 2 | A2 | B2 | K0 | C0 | D0 |
| 3 | A3 | B3 | K1 | | | | 3 | A3 | B3 | K1 | C1 | D1 |

the passed DataFrame must have a MultiIndex:

```
In [54]: left = DataFrame({'A': ['A0', 'A1', 'A2', 'A3'],
.....:                   'B': ['B0', 'B1', 'B2', 'B3'],
.....:                   'key1': ['K0', 'K0', 'K1', 'K2'],
```

To join on multiple keys,

```

.....:         'key2': ['K0', 'K1', 'K0', 'K1'])
.....:
In [55]: index = MultiIndex.from_tuples([('K0', 'K0'), ('K1', 'K0'),
.....:                                   ('K2', 'K0'), ('K2', 'K1')])
.....:
In [56]: right = DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                      'D': ['D0', 'D1', 'D2', 'D3']},
.....:                      index=index)
.....:

```

Now this can be joined by passing the two key column names:

```
In [57]: result = left.join(right, on=['key1', 'key2'])
```

| left | | | | | right | | | | Result | | | | | | |
|------|----|----|------|------|-------|----|----|----|--------|----|----|------|------|-----|-----|
| | A | B | key1 | key2 | | | C | D | | A | B | key1 | key2 | C | D |
| 0 | A0 | B0 | K0 | K0 | K0 | K0 | C0 | D0 | 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | K1 | K0 | C1 | D1 | 1 | A1 | B1 | K0 | K1 | NaN | NaN |
| 2 | A2 | B2 | K1 | K0 | K2 | K0 | C2 | D2 | 2 | A2 | B2 | K1 | K0 | C1 | D1 |
| 3 | A3 | B3 | K2 | K1 | K2 | K1 | C3 | D3 | 3 | A3 | B3 | K2 | K1 | C3 | D3 |

The default for `DataFrame.join` is to perform a left join (essentially a “VLOOKUP” operation, for Excel users), which uses only the keys found in the calling `DataFrame`. Other join types, for example inner join, can be just as easily performed:

```
In [58]: result = left.join(right, on=['key1', 'key2'], how='inner')
```

| left | | | | | right | | | | Result | | | | | | |
|------|----|----|------|------|-------|----|----|----|--------|----|----|------|------|----|----|
| | A | B | key1 | key2 | | | C | D | | A | B | key1 | key2 | C | D |
| 0 | A0 | B0 | K0 | K0 | K0 | K0 | C0 | D0 | 0 | A0 | B0 | K0 | K0 | C0 | D0 |
| 1 | A1 | B1 | K0 | K1 | K1 | K0 | C1 | D1 | | | | | | | |
| 2 | A2 | B2 | K1 | K0 | K2 | K0 | C2 | D2 | 2 | A2 | B2 | K1 | K0 | C1 | D1 |
| 3 | A3 | B3 | K2 | K1 | K2 | K1 | C3 | D3 | 3 | A3 | B3 | K2 | K1 | C3 | D3 |

As you can see, this drops any rows where there was no match.

18.2.4 Joining a single Index to a Multi-index

New in version 0.14.0.

You can join a singly-indexed `DataFrame` with a level of a multi-indexed `DataFrame`. The level will match on the name of the index of the singly-indexed frame against a level name of the multi-indexed frame.

```
In [59]: left = DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                    'B': ['B0', 'B1', 'B2']},
```

```

.....:             index=Index(['K0', 'K1', 'K2'], name='key'))
.....:

In [60]: index = MultiIndex.from_tuples([('K0', 'Y0'), ('K1', 'Y1'),
.....:                                  ('K2', 'Y2'), ('K2', 'Y3')],
.....:                                  names=['key', 'Y'])
.....:

In [61]: right = DataFrame({'C': ['C0', 'C1', 'C2', 'C3'],
.....:                     'D': ['D0', 'D1', 'D2', 'D3']},
.....:                     index=index)
.....:

In [62]: result = left.join(right, how='inner')

```

| left | | | right | | | | Result | | | | | | |
|------|----|----|-------|----|----|----|--------|----|----|----|----|----|--|
| | A | B | | | C | D | | | A | B | C | D | |
| K0 | A0 | B0 | K0 | Y0 | C0 | D0 | K0 | Y0 | A0 | B0 | C0 | D0 | |
| K1 | A1 | B1 | K1 | Y1 | C1 | D1 | K1 | Y1 | A1 | B1 | C1 | D1 | |
| K2 | A2 | B2 | K2 | Y2 | C2 | D2 | K2 | Y2 | A2 | B2 | C2 | D2 | |
| | | | K2 | Y3 | C3 | D3 | K2 | Y3 | A2 | B2 | C3 | D3 | |

This is equivalent but less verbose and more memory efficient / faster than this.

```

In [63]: result = merge(left.reset_index(), right.reset_index(),
.....:                  on=['key'], how='inner').set_index(['key', 'Y'])
.....:

```

| left | | | right | | | | Result | | | | | |
|------|----|----|-------|----|----|----|--------|----|----|----|----|----|
| | A | B | | | C | D | | | A | B | C | D |
| K0 | A0 | B0 | K0 | Y0 | C0 | D0 | K0 | Y0 | A0 | B0 | C0 | D0 |
| K1 | A1 | B1 | K1 | Y1 | C1 | D1 | K1 | Y1 | A1 | B1 | C1 | D1 |
| K2 | A2 | B2 | K2 | Y2 | C2 | D2 | K2 | Y2 | A2 | B2 | C2 | D2 |
| | | | K2 | Y3 | C3 | D3 | K2 | Y3 | A2 | B2 | C3 | D3 |

18.2.5 Joining with two multi-indexes

This is not Implemented via `join` at-the-moment, however it can be done using the following.

```

In [64]: index = MultiIndex.from_tuples([('K0', 'X0'), ('K0', 'X1'),
.....:                                  ('K1', 'X2')],
.....:                                  names=['key', 'X'])
.....:

In [65]: left = DataFrame({'A': ['A0', 'A1', 'A2'],
.....:                     'B': ['B0', 'B1', 'B2']},

```

```

.....:         index=index)
.....:
In [66]: result = merge(left.reset_index(), right.reset_index(),
.....:                  on=['key'], how='inner').set_index(['key', 'X', 'Y'])
.....:

```

| left | | | | right | | | | Result | | | | | | | |
|------|----|----|----|-------|----|----|----|--------|----|----|----|----|----|----|--|
| | | A | B | | | C | D | | | | A | B | C | D | |
| K0 | X0 | A0 | B0 | K0 | Y0 | C0 | D0 | K0 | X0 | Y0 | A0 | B0 | C0 | D0 | |
| K0 | X1 | A1 | B1 | K1 | Y1 | C1 | D1 | K0 | X1 | Y0 | A1 | B1 | C0 | D0 | |
| K1 | X2 | A2 | B2 | K2 | Y2 | C2 | D2 | K1 | X2 | Y1 | A2 | B2 | C1 | D1 | |
| | | | | K2 | Y3 | C3 | D3 | | | | | | | | |

18.2.6 Overlapping value columns

The merge `suffixes` argument takes a tuple of list of strings to append to overlapping column names in the input DataFrames to disambiguate the result columns:

```

In [67]: left = DataFrame({'k': ['K0', 'K1', 'K2'], 'v': [1, 2, 3]})
In [68]: right = DataFrame({'k': ['K0', 'K0', 'K3'], 'v': [4, 5, 6]})
In [69]: result = merge(left, right, on='k')

```

| left | | | right | | | Result | | | |
|------|----|---|-------|----|---|--------|----|-----|-----|
| | k | v | | k | v | | k | v_x | v_y |
| 0 | K0 | 1 | 0 | K0 | 4 | 0 | K0 | 1 | 4 |
| 1 | K1 | 2 | 1 | K0 | 5 | 1 | K0 | 1 | 5 |
| 2 | K2 | 3 | 2 | K3 | 6 | | | | |

```

In [70]: result = merge(left, right, on='k', suffixes=['_l', '_r'])

```

| left | | | right | | | Result | | | |
|------|----|---|-------|----|---|--------|----|-----|-----|
| | k | v | | k | v | | k | v_l | v_r |
| 0 | K0 | 1 | 0 | K0 | 4 | 0 | K0 | 1 | 4 |
| 1 | K1 | 2 | 1 | K0 | 5 | 1 | K0 | 1 | 5 |
| 2 | K2 | 3 | 2 | K3 | 6 | | | | |

`DataFrame.join` has `lsuffix` and `rsuffix` arguments which behave similarly.

```
In [71]: left = left.set_index('k')
In [72]: right = right.set_index('k')
In [73]: result = left.join(right, lsuffix='_l', rsuffix='_r')
```

| left | | right | | Result | |
|------|---|-------|---|--------|-------|
| | v | | v | | |
| K0 | 1 | K0 | 4 | v_l | v_r |
| K1 | 2 | K0 | 5 | K0 | 1 4.0 |
| K2 | 3 | K3 | 6 | K0 | 1 5.0 |
| | | | | K1 | 2 NaN |
| | | | | K2 | 3 NaN |

18.2.7 Joining multiple DataFrame or Panel objects

A list or tuple of DataFrames can also be passed to `DataFrame.join` to join them together on their indexes. The same is true for `Panel.join`.

```
In [74]: right2 = DataFrame({'v': [7, 8, 9]}, index=['K1', 'K1', 'K2'])
In [75]: result = left.join([right, right2])
```

| left | | right | | right2 | | Result | | | |
|------|---|-------|---|--------|---|--------|-----|-----|-----|
| | v | | v | | v | | v_x | v_y | v |
| K0 | 1 | K0 | 4 | K1 | 7 | K0 | 1.0 | 4.0 | NaN |
| K1 | 2 | K0 | 5 | K1 | 8 | K0 | 1.0 | 5.0 | NaN |
| K2 | 3 | K3 | 6 | K2 | 9 | K1 | 2.0 | NaN | 7.0 |
| | | | | | | K1 | 2.0 | NaN | 8.0 |
| | | | | | | K2 | 3.0 | NaN | 9.0 |
| | | | | | | K3 | NaN | 6.0 | NaN |

18.2.8 Merging Ordered Data

New in v0.8.0 is the `ordered_merge` function for combining time series and other ordered data. In particular it has an optional `fill_method` keyword to fill/interpolate missing data:

```
In [76]: left = DataFrame({'k': ['K0', 'K1', 'K1', 'K2'],
.....:                   'lv': [1, 2, 3, 4],
.....:                   's': ['a', 'b', 'c', 'd']})
.....:
In [77]: right = DataFrame({'k': ['K1', 'K2', 'K4'],
.....:                     'rv': [1, 2, 3]})
```

```
.....:
```

```
In [78]: result = ordered_merge(left, right, fill_method='ffill', left_by='s')
```

| left | | | | Result | | | | |
|------|----|----|---|--------|----|-----|---|-----|
| | k | lv | s | | k | lv | s | rv |
| 0 | K0 | 1 | a | 0 | K0 | 1.0 | a | NaN |
| 1 | K1 | 2 | b | 1 | K1 | 1.0 | a | 1.0 |
| 2 | K1 | 3 | c | 2 | K2 | 1.0 | a | 2.0 |
| 3 | K2 | 4 | d | 3 | K4 | 1.0 | a | 3.0 |
| | | | | 4 | K1 | 2.0 | b | 1.0 |
| | | | | 5 | K2 | 2.0 | b | 2.0 |
| | | | | 6 | K4 | 2.0 | b | 3.0 |
| | | | | 7 | K1 | 3.0 | c | 1.0 |
| | | | | 8 | K2 | 3.0 | c | 2.0 |
| | | | | 9 | K4 | 3.0 | c | 3.0 |
| | | | | 10 | K1 | NaN | d | 1.0 |
| | | | | 11 | K2 | 4.0 | d | 2.0 |
| | | | | 12 | K4 | 4.0 | d | 3.0 |

18.2.9 Merging together values within Series or DataFrame columns

Another fairly common situation is to have two like-indexed (or similarly indexed) Series or DataFrame objects and wanting to “patch” values in one object from values for matching indices in the other. Here is an example:

```
In [79]: df1 = DataFrame([[nan, 3., 5.], [-4.6, np.nan, nan],
.....:                  [nan, 7., nan]])
.....:
```

```
In [80]: df2 = DataFrame([[-42.6, np.nan, -8.2], [-5., 1.6, 4]],
.....:                  index=[1, 2])
.....:
```

For this, use the `combine_first` method:

```
In [81]: result = df1.combine_first(df2)
```

| df1 | | | | df2 | | | | Result | | | |
|-----|------|-----|-----|-----|-------|-----|------|--------|------|-----|------|
| | 0 | 1 | 2 | | 0 | 1 | 2 | | 0 | 1 | 2 |
| 0 | NaN | 3.0 | 5.0 | | | | | 0 | NaN | 3.0 | 5.0 |
| 1 | -4.6 | NaN | NaN | 1 | -42.6 | NaN | -8.2 | 1 | -4.6 | NaN | -8.2 |
| 2 | NaN | 7.0 | NaN | 2 | -5.0 | 1.6 | 4.0 | 2 | -5.0 | 7.0 | 4.0 |

Note that this method only takes values from the right DataFrame if they are missing in the left DataFrame. A related method, `update`, alters non-NA values inplace:

```
In [82]: df1.update(df2)
```

| df1 | | | | df2 | | | | Result | | | |
|-----|------|-----|-----|-----|-------|-----|------|--------|-------|-----|------|
| | 0 | 1 | 2 | | 0 | 1 | 2 | | 0 | 1 | 2 |
| 0 | NaN | 3.0 | 5.0 | 1 | -42.6 | NaN | -8.2 | 0 | NaN | 3.0 | 5.0 |
| 1 | -4.6 | NaN | NaN | 2 | -5.0 | 1.6 | 4.0 | 1 | -42.6 | NaN | -8.2 |
| 2 | NaN | 7.0 | NaN | | | | | 2 | -5.0 | 1.6 | 4.0 |

RESHAPING AND PIVOT TABLES

19.1 Reshaping by pivoting DataFrame objects

Data is often stored in CSV files or databases in so-called “stacked” or “record” format:

```
In [1]: df
Out[1]:
```

| | date | variable | value |
|----|------------|----------|-----------|
| 0 | 2000-01-03 | A | 0.469112 |
| 1 | 2000-01-04 | A | -0.282863 |
| 2 | 2000-01-05 | A | -1.509059 |
| 3 | 2000-01-03 | B | -1.135632 |
| 4 | 2000-01-04 | B | 1.212112 |
| 5 | 2000-01-05 | B | -0.173215 |
| 6 | 2000-01-03 | C | 0.119209 |
| 7 | 2000-01-04 | C | -1.044236 |
| 8 | 2000-01-05 | C | -0.861849 |
| 9 | 2000-01-03 | D | -2.104569 |
| 10 | 2000-01-04 | D | -0.494929 |
| 11 | 2000-01-05 | D | 1.071804 |

For the curious here is how the above DataFrame was created:

```
import pandas.util.testing as tm; tm.N = 3
def unpivot(frame):
    N, K = frame.shape
    data = {'value' : frame.values.ravel('F'),
           'variable' : np.asarray(frame.columns).repeat(N),
           'date' : np.tile(np.asarray(frame.index), K)}
    return pd.DataFrame(data, columns=['date', 'variable', 'value'])
df = unpivot(tm.makeTimeDataFrame())
```

To select out everything for variable A we could do:

```
In [2]: df[df['variable'] == 'A']
Out[2]:
```

| | date | variable | value |
|---|------------|----------|-----------|
| 0 | 2000-01-03 | A | 0.469112 |
| 1 | 2000-01-04 | A | -0.282863 |
| 2 | 2000-01-05 | A | -1.509059 |

But suppose we wish to do time series operations with the variables. A better representation would be where the columns are the unique variables and an index of dates identifies individual observations. To reshape the data into this form, use the `pivot` function:

```
In [3]: df.pivot(index='date', columns='variable', values='value')
Out[3]:
variable          A          B          C          D
date
2000-01-03  0.469112 -1.135632  0.119209 -2.104569
2000-01-04 -0.282863  1.212112 -1.044236 -0.494929
2000-01-05 -1.509059 -0.173215 -0.861849  1.071804
```

If the `values` argument is omitted, and the input `DataFrame` has more than one column of values which are not used as column or index inputs to `pivot`, then the resulting “pivoted” `DataFrame` will have *hierarchical columns* whose toplevel level indicates the respective value column:

```
In [4]: df['value2'] = df['value'] * 2

In [5]: pivoted = df.pivot('date', 'variable')
```

```
In [6]: pivoted
Out[6]:
```

| variable | value | | | | value2 | | \ |
|------------|-----------|-----------|-----------|-----------|-----------|-----------|---|
| | A | B | C | D | A | B | |
| date | | | | | | | |
| 2000-01-03 | 0.469112 | -1.135632 | 0.119209 | -2.104569 | 0.938225 | -2.271265 | |
| 2000-01-04 | -0.282863 | 1.212112 | -1.044236 | -0.494929 | -0.565727 | 2.424224 | |
| 2000-01-05 | -1.509059 | -0.173215 | -0.861849 | 1.071804 | -3.018117 | -0.346429 | |

| variable | C | | D |
|------------|-----------|-----------|---|
| | | | |
| date | | | |
| 2000-01-03 | 0.238417 | -4.209138 | |
| 2000-01-04 | -2.088472 | -0.989859 | |
| 2000-01-05 | -1.723698 | 2.143608 | |

You of course can then select subsets from the pivoted `DataFrame`:

```
In [7]: pivoted['value2']
Out[7]:
```

| variable | A | B | C | D |
|------------|-----------|-----------|-----------|-----------|
| date | | | | |
| 2000-01-03 | 0.938225 | -2.271265 | 0.238417 | -4.209138 |
| 2000-01-04 | -0.565727 | 2.424224 | -2.088472 | -0.989859 |
| 2000-01-05 | -3.018117 | -0.346429 | -1.723698 | 2.143608 |

Note that this returns a view on the underlying data in the case where the data are homogeneously-typed.

19.2 Reshaping by stacking and unstacking

Closely related to the `pivot` function are the related `stack` and `unstack` functions currently available on `Series` and `DataFrame`. These functions are designed to work together with `MultiIndex` objects (see the section on *hierarchical indexing*). Here are essentially what these functions do:

- `stack`: “pivot” a level of the (possibly hierarchical) column labels, returning a `DataFrame` with an index with a new inner-most level of row labels.
- `unstack`: inverse operation from `stack`: “pivot” a level of the (possibly hierarchical) row index to the column axis, producing a reshaped `DataFrame` with a new inner-most level of column labels.

The clearest way to explain is by example. Let’s take a prior example data set from the hierarchical indexing section:

```
In [8]: tuples = list(zip(*(['bar', 'bar', 'baz', 'baz',
...:                        'foo', 'foo', 'qux', 'qux'],
...:                        ['one', 'two', 'one', 'two',
...:                        'one', 'two', 'one', 'two'])))
...:

In [9]: index = pd.MultiIndex.from_tuples(tuples, names=['first', 'second'])

In [10]: df = pd.DataFrame(np.random.randn(8, 2), index=index, columns=['A', 'B'])

In [11]: df2 = df[:4]

In [12]: df2
Out[12]:
```

| | | A | B |
|-------|--------|-----------|-----------|
| first | second | | |
| bar | one | 0.721555 | -0.706771 |
| | two | -1.039575 | 0.271860 |
| baz | one | -0.424972 | 0.567020 |
| | two | 0.276232 | -1.087401 |

The `stack` function “compresses” a level in the `DataFrame`’s columns to produce either:

- A `Series`, in the case of a simple column `Index`
- A `DataFrame`, in the case of a `MultiIndex` in the columns

If the columns have a `MultiIndex`, you can choose which level to stack. The stacked level becomes the new lowest level in a `MultiIndex` on the columns:

```
In [13]: stacked = df2.stack()
```

```
In [14]: stacked
```

```
Out[14]:
```

| first | second | | |
|-------|--------|---|-----------|
| bar | one | A | 0.721555 |
| | | B | -0.706771 |
| | two | A | -1.039575 |
| | | B | 0.271860 |
| baz | one | A | -0.424972 |
| | | B | 0.567020 |
| | two | A | 0.276232 |
| | | B | -1.087401 |

```
dtype: float64
```

With a “stacked” `DataFrame` or `Series` (having a `MultiIndex` as the `index`), the inverse operation of `stack` is `unstack`, which by default unstacks the **last level**:

```
In [15]: stacked.unstack()
```

```
Out[15]:
```

| | | A | B |
|-------|--------|-----------|-----------|
| first | second | | |
| bar | one | 0.721555 | -0.706771 |
| | two | -1.039575 | 0.271860 |
| baz | one | -0.424972 | 0.567020 |
| | two | 0.276232 | -1.087401 |

```
In [16]: stacked.unstack(1)
```

```
Out[16]:
```

| second | one | two |
|--------|-----|-----|
|--------|-----|-----|

```
first
bar   A   0.721555 -1.039575
      B  -0.706771   0.271860
baz   A  -0.424972   0.276232
      B   0.567020 -1.087401
```

```
In [17]: stacked.unstack(0)
Out[17]:
first      bar      baz
second
one   A   0.721555 -0.424972
      B  -0.706771   0.567020
two   A  -1.039575   0.276232
      B   0.271860 -1.087401
```

If the indexes have names, you can use the level names instead of specifying the level numbers:

```
In [18]: stacked.unstack('second')
Out[18]:
second      one      two
first
bar   A   0.721555 -1.039575
      B  -0.706771   0.271860
baz   A  -0.424972   0.276232
      B   0.567020 -1.087401
```

Notice that the `stack` and `unstack` methods implicitly sort the index levels involved. Hence a call to `stack` and then `unstack`, or viceversa, will result in a **sorted** copy of the original DataFrame or Series:

```
In [19]: index = pd.MultiIndex.from_product([[2,1], ['a', 'b']])
In [20]: df = pd.DataFrame(np.random.randn(4), index=index, columns=['A'])
In [21]: df
Out[21]:
           A
2 a -0.370647
  b -1.157892
1 a -1.344312
  b  0.844885

In [22]: all(df.unstack().stack() == df.sort())
Out[22]: True
```

while the above code will raise a `TypeError` if the call to `sort` is removed.

19.2.1 Multiple Levels

You may also stack or unstack more than one level at a time by passing a list of levels, in which case the end result is as if each level in the list were processed individually.

```
In [23]: columns = pd.MultiIndex.from_tuples([
.....:     ('A', 'cat', 'long'), ('B', 'cat', 'long'),
.....:     ('A', 'dog', 'short'), ('B', 'dog', 'short')
.....: ],
.....: names=['exp', 'animal', 'hair_length']
.....: )
.....:
```

```
In [24]: df = pd.DataFrame(np.random.randn(4, 4), columns=columns)
```

```
In [25]: df
```

```
Out [25]:
```

| | | A | B | A | B |
|-------------|--------|-----------|-----------|-----------|-----------|
| exp | animal | cat | cat | dog | dog |
| hair_length | | long | long | short | short |
| 0 | | 1.075770 | -0.109050 | 1.643563 | -1.469388 |
| 1 | | 0.357021 | -0.674600 | -1.776904 | -0.968914 |
| 2 | | -1.294524 | 0.413738 | 0.276662 | -0.472035 |
| 3 | | -0.013960 | -0.362543 | -0.006154 | -0.923061 |

```
In [26]: df.stack(level=['animal', 'hair_length'])
```

```
Out [26]:
```

| exp | | | A | B |
|-----|--------|-------------|-----------|-----------|
| | animal | hair_length | | |
| 0 | cat | long | 1.075770 | -0.109050 |
| | dog | short | 1.643563 | -1.469388 |
| 1 | cat | long | 0.357021 | -0.674600 |
| | dog | short | -1.776904 | -0.968914 |
| 2 | cat | long | -1.294524 | 0.413738 |
| | dog | short | 0.276662 | -0.472035 |
| 3 | cat | long | -0.013960 | -0.362543 |
| | dog | short | -0.006154 | -0.923061 |

The list of levels can contain either level names or level numbers (but not a mixture of the two).

```
# df.stack(level=['animal', 'hair_length'])
# from above is equivalent to:
```

```
In [27]: df.stack(level=[1, 2])
```

```
Out [27]:
```

| exp | | | A | B |
|-----|--------|-------------|-----------|-----------|
| | animal | hair_length | | |
| 0 | cat | long | 1.075770 | -0.109050 |
| | dog | short | 1.643563 | -1.469388 |
| 1 | cat | long | 0.357021 | -0.674600 |
| | dog | short | -1.776904 | -0.968914 |
| 2 | cat | long | -1.294524 | 0.413738 |
| | dog | short | 0.276662 | -0.472035 |
| 3 | cat | long | -0.013960 | -0.362543 |
| | dog | short | -0.006154 | -0.923061 |

19.2.2 Missing Data

These functions are intelligent about handling missing data and do not expect each subgroup within the hierarchical index to have the same set of labels. They also can handle the index being unsorted (but you can make it sorted by calling `sortlevel`, of course). Here is a more complex example:

```
In [28]: columns = pd.MultiIndex.from_tuples([('A', 'cat'), ('B', 'dog'),
.....:                                     ('B', 'cat'), ('A', 'dog')],
.....:                                     names=['exp', 'animal'])
```

```
In [29]: index = pd.MultiIndex.from_product([('bar', 'baz', 'foo', 'qux'),
.....:                                     ('one', 'two')],
.....:                                     names=['first', 'second'])
```

```
.....:

In [30]: df = pd.DataFrame(np.random.randn(8, 4), index=index, columns=columns)

In [31]: df2 = df.ix[[0, 1, 2, 4, 5, 7]]

In [32]: df2
Out[32]:
```

| | | A | B | | A |
|-------|--------|-----------|-----------|-----------|-----------|
| exp | animal | cat | dog | cat | dog |
| first | second | | | | |
| bar | one | 0.895717 | 0.805244 | -1.206412 | 2.565646 |
| | two | 1.431256 | 1.340309 | -1.170299 | -0.226169 |
| baz | one | 0.410835 | 0.813850 | 0.132003 | -0.827317 |
| foo | one | -1.413681 | 1.607920 | 1.024180 | 0.569605 |
| | two | 0.875906 | -2.211372 | 0.974466 | -2.006747 |
| qux | two | -1.226825 | 0.769804 | -1.281247 | -0.727707 |

As mentioned above, `stack` can be called with a `level` argument to select which level in the columns to stack:

```
In [33]: df2.stack('exp')
Out[33]:
```

| animal | | cat | dog |
|--------|--------|-----|-----------|
| first | second | exp | |
| bar | one | A | 0.895717 |
| | | B | -1.206412 |
| | two | A | 1.431256 |
| | | B | -1.170299 |
| baz | one | A | 0.410835 |
| | | B | 0.132003 |
| foo | one | A | -1.413681 |
| | | B | 1.024180 |
| | two | A | 0.875906 |
| | | B | 0.974466 |
| qux | two | A | -1.226825 |
| | | B | -1.281247 |

```
In [34]: df2.stack('animal')
Out[34]:
```

| exp | | A | B |
|-------|--------|--------|-----------|
| first | second | animal | |
| bar | one | cat | 0.895717 |
| | | dog | 2.565646 |
| | two | cat | 1.431256 |
| | | dog | -0.226169 |
| baz | one | cat | 0.410835 |
| | | dog | -0.827317 |
| foo | one | cat | -1.413681 |
| | | dog | 0.569605 |
| | two | cat | 0.875906 |
| | | dog | -2.006747 |
| qux | two | cat | -1.226825 |
| | | dog | -0.727707 |

19.2.3 With a MultiIndex

Unstacking when the columns are a `MultiIndex` is also careful about doing the right thing:

```
In [35]: df[:3].unstack(0)
```

```
Out[35]:
```

```
exp          A          B          A \
animal      cat          dog          dog
first      bar      baz      bar      baz      bar      baz      bar
second
one      0.895717  0.410835  0.805244  0.81385 -1.206412  0.132003  2.565646
two      1.431256      NaN  1.340309      NaN -1.170299      NaN -0.226169
```

```
exp
animal
first      baz
second
one      -0.827317
two      NaN
```

```
In [36]: df2.unstack(1)
```

```
Out[36]:
```

```
exp          A          B          A \
animal      cat          dog          dog
second      one      two      one      two      one      two      one
first
bar      0.895717  1.431256  0.805244  1.340309 -1.206412 -1.170299  2.565646
baz      0.410835      NaN  0.813850      NaN  0.132003      NaN -0.827317
foo     -1.413681  0.875906  1.607920 -2.211372  1.024180  0.974466  0.569605
qux      NaN -1.226825      NaN  0.769804      NaN -1.281247      NaN
```

```
exp
animal
second      two
first
bar      -0.226169
baz      NaN
foo     -2.006747
qux     -0.727707
```

19.3 Reshaping by Melt

The `melt()` function is useful to massage a DataFrame into a format where one or more columns are identifier variables, while all other columns, considered measured variables, are “unpivoted” to the row axis, leaving just two non-identifier columns, “variable” and “value”. The names of those columns can be customized by supplying the `var_name` and `value_name` parameters.

For instance,

```
In [37]: cheese = pd.DataFrame({'first' : ['John', 'Mary'],
.....:                          'last'  : ['Doe', 'Bo'],
.....:                          'height': [5.5, 6.0],
.....:                          'weight': [130, 150]})
.....:
```

```
In [38]: cheese
```

```
Out[38]:
```

```
   first  height last  weight
0  John     5.5  Doe    130
1  Mary     6.0  Bo   150
```

```
In [39]: pd.melt(cheese, id_vars=['first', 'last'])
```

```
Out[39]:
```

| | first | last | variable | value |
|---|-------|------|----------|-------|
| 0 | John | Doe | height | 5.5 |
| 1 | Mary | Bo | height | 6.0 |
| 2 | John | Doe | weight | 130.0 |
| 3 | Mary | Bo | weight | 150.0 |

```
In [40]: pd.melt(cheese, id_vars=['first', 'last'], var_name='quantity')
```

```
Out[40]:
```

| | first | last | quantity | value |
|---|-------|------|----------|-------|
| 0 | John | Doe | height | 5.5 |
| 1 | Mary | Bo | height | 6.0 |
| 2 | John | Doe | weight | 130.0 |
| 3 | Mary | Bo | weight | 150.0 |

Another way to transform is to use the `wide_to_long` panel data convenience function.

```
In [41]: dft = pd.DataFrame({"A1970" : {0 : "a", 1 : "b", 2 : "c"},
.....:                      "A1980" : {0 : "d", 1 : "e", 2 : "f"},
.....:                      "B1970" : {0 : 2.5, 1 : 1.2, 2 : .7},
.....:                      "B1980" : {0 : 3.2, 1 : 1.3, 2 : .1},
.....:                      "X"      : dict(zip(range(3), np.random.randn(3)))
.....:                      })
.....:
```

```
In [42]: dft["id"] = dft.index
```

```
In [43]: dft
```

```
Out[43]:
```

| | A1970 | A1980 | B1970 | B1980 | X | id |
|---|-------|-------|-------|-------|-----------|----|
| 0 | a | d | 2.5 | 3.2 | -0.121306 | 0 |
| 1 | b | e | 1.2 | 1.3 | -0.097883 | 1 |
| 2 | c | f | 0.7 | 0.1 | 0.695775 | 2 |

```
In [44]: pd.wide_to_long(dft, ["A", "B"], i="id", j="year")
```

```
Out[44]:
```

| | | X | A | B |
|----|------|-----------|---|-----|
| id | year | | | |
| 0 | 1970 | -0.121306 | a | 2.5 |
| 1 | 1970 | -0.097883 | b | 1.2 |
| 2 | 1970 | 0.695775 | c | 0.7 |
| 0 | 1980 | -0.121306 | d | 3.2 |
| 1 | 1980 | -0.097883 | e | 1.3 |
| 2 | 1980 | 0.695775 | f | 0.1 |

19.4 Combining with stats and GroupBy

It should be no shock that combining `pivot / stack / unstack` with `GroupBy` and the basic `Series` and `DataFrame` statistical functions can produce some very expressive and fast data manipulations.

```
In [45]: df
```

```
Out[45]:
```

| exp | | A | B | | A |
|--------|--------|-----|-----|-----|-----|
| animal | | cat | dog | cat | dog |
| first | second | | | | |

```

bar   one      0.895717  0.805244 -1.206412  2.565646
      two      1.431256  1.340309 -1.170299 -0.226169
baz   one      0.410835  0.813850  0.132003 -0.827317
      two     -0.076467 -1.187678  1.130127 -1.436737
foo   one     -1.413681  1.607920  1.024180  0.569605
      two      0.875906 -2.211372  0.974466 -2.006747
qux   one     -0.410001 -0.078638  0.545952 -1.219217
      two     -1.226825  0.769804 -1.281247 -0.727707

```

```
In [46]: df.stack().mean(1).unstack()
```

```
Out[46]:
```

```

animal      cat      dog
first second
bar   one   -0.155347  1.685445
      two    0.130479  0.557070
baz   one    0.271419 -0.006733
      two    0.526830 -1.312207
foo   one   -0.194750  1.088763
      two    0.925186 -2.109060
qux   one    0.067976 -0.648927
      two   -1.254036  0.021048

```

```
# same result, another way
```

```
In [47]: df.groupby(level=1, axis=1).mean()
```

```
Out[47]:
```

```

animal      cat      dog
first second
bar   one   -0.155347  1.685445
      two    0.130479  0.557070
baz   one    0.271419 -0.006733
      two    0.526830 -1.312207
foo   one   -0.194750  1.088763
      two    0.925186 -2.109060
qux   one    0.067976 -0.648927
      two   -1.254036  0.021048

```

```
In [48]: df.stack().groupby(level=1).mean()
```

```
Out[48]:
```

```

exp      A      B
second
one      0.071448  0.455513
two     -0.424186 -0.204486

```

```
In [49]: df.mean().unstack(0)
```

```
Out[49]:
```

```

exp      A      B
animal
cat      0.060843  0.018596
dog     -0.413580  0.232430

```

19.5 Pivot tables and cross-tabulations

The function `pandas.pivot_table` can be used to create spreadsheet-style pivot tables. See the *cookbook* for some advanced strategies

It takes a number of arguments

- `data`: A DataFrame object
- `values`: a column or a list of columns to aggregate
- `index`: a column, Grouper, array which has the same length as `data`, or list of them. Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.
- `columns`: a column, Grouper, array which has the same length as `data`, or list of them. Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.
- `aggfunc`: function to use for aggregation, defaulting to `numpy.mean`

Consider a data set like this:

```
In [50]: import datetime
```

```
In [51]: df = pd.DataFrame({'A': ['one', 'one', 'two', 'three'] * 6,  
.....:                    'B': ['A', 'B', 'C'] * 8,  
.....:                    'C': ['foo', 'foo', 'foo', 'bar', 'bar', 'bar'] * 4,  
.....:                    'D': np.random.randn(24),  
.....:                    'E': np.random.randn(24),  
.....:                    'F': [datetime.datetime(2013, i, 1) for i in range(1, 13)] +  
.....:                        [datetime.datetime(2013, i, 15) for i in range(1, 13)]})  
.....:
```

```
In [52]: df
```

```
Out [52]:
```

| | A | B | C | D | E | F |
|----|-------|----|-----|-----------|-----------|------------|
| 0 | one | A | foo | 0.341734 | -0.317441 | 2013-01-01 |
| 1 | one | B | foo | 0.959726 | -1.236269 | 2013-02-01 |
| 2 | two | C | foo | -1.110336 | 0.896171 | 2013-03-01 |
| 3 | three | A | bar | -0.619976 | -0.487602 | 2013-04-01 |
| 4 | one | B | bar | 0.149748 | -0.082240 | 2013-05-01 |
| 5 | one | C | bar | -0.732339 | -2.182937 | 2013-06-01 |
| 6 | two | A | foo | 0.687738 | 0.380396 | 2013-07-01 |
| .. | ... | .. | ... | ... | ... | ... |
| 17 | one | C | bar | -0.345352 | 0.206053 | 2013-06-15 |
| 18 | two | A | foo | 1.314232 | -0.251905 | 2013-07-15 |
| 19 | three | B | foo | 0.690579 | -2.213588 | 2013-08-15 |
| 20 | one | C | foo | 0.995761 | 1.063327 | 2013-09-15 |
| 21 | one | A | bar | 2.396780 | 1.266143 | 2013-10-15 |
| 22 | two | B | bar | 0.014871 | 0.299368 | 2013-11-15 |
| 23 | three | C | bar | 3.357427 | -0.863838 | 2013-12-15 |

```
[24 rows x 6 columns]
```

We can produce pivot tables from this data very easily:

```
In [53]: pd.pivot_table(df, values='D', index=['A', 'B'], columns=['C'])
```

```
Out [53]:
```

| | | bar | foo |
|-------|---|-----------|-----------|
| A | B | | |
| one | A | 1.120915 | -0.514058 |
| | B | -0.338421 | 0.002759 |
| | C | -0.538846 | 0.699535 |
| three | A | -1.181568 | NaN |
| | B | NaN | 0.433512 |
| | C | 0.588783 | NaN |
| two | A | NaN | 1.000985 |
| | B | 0.158248 | NaN |
| | C | NaN | 0.176180 |

```
In [54]: pd.pivot_table(df, values='D', index=['B'], columns=['A', 'C'], aggfunc=np.sum)
```

```
Out[54]:
```

| | one | foo | three | bar | foo | two | bar | foo |
|---|-----------|-----------|-----------|-----|----------|----------|-----|----------|
| A | 2.241830 | -1.028115 | -2.363137 | | NaN | | NaN | 2.001971 |
| B | -0.676843 | 0.005518 | | NaN | 0.867024 | 0.316495 | | NaN |
| C | -1.077692 | 1.399070 | 1.177566 | | NaN | | NaN | 0.352360 |

```
In [55]: pd.pivot_table(df, values=['D', 'E'], index=['B'], columns=['A', 'C'], aggfunc=np.sum)
```

```
Out[55]:
```

| | D | | | | | | E \ | |
|---|-----------|-----------|-----------|-----|----------|----------|-----|----------|
| | one | foo | three | bar | foo | two | bar | foo |
| A | 2.241830 | -1.028115 | -2.363137 | | NaN | | NaN | 2.001971 |
| B | -0.676843 | 0.005518 | | NaN | 0.867024 | 0.316495 | | NaN |
| C | -1.077692 | 1.399070 | 1.177566 | | NaN | | NaN | 0.352360 |

| | foo | bar | three | bar | foo | two | bar | foo |
|---|-----------|-----------|-------|-----------|-----------|-----|----------|-----|
| A | -0.043211 | 1.922577 | | NaN | | NaN | 0.128491 | |
| B | -1.103384 | | NaN | -2.128743 | -0.194294 | | NaN | |
| C | 1.495717 | -0.263660 | | NaN | | NaN | 0.872482 | |

The result object is a DataFrame having potentially hierarchical indexes on the rows and columns. If the values column name is not given, the pivot table will include all of the data that can be aggregated in an additional level of hierarchy in the columns:

```
In [56]: pd.pivot_table(df, index=['A', 'B'], columns=['C'])
```

```
Out[56]:
```

| | | D | | E | |
|-------|---|-----------|-----------|-----------|-----------|
| | | bar | foo | bar | foo |
| one | A | 1.120915 | -0.514058 | 1.393057 | -0.021605 |
| | B | -0.338421 | 0.002759 | 0.684140 | -0.551692 |
| | C | -0.538846 | 0.699535 | -0.988442 | 0.747859 |
| three | A | -1.181568 | | NaN | 0.961289 |
| | B | | NaN | 0.433512 | |
| | C | 0.588783 | | NaN | -0.131830 |
| two | A | | NaN | 1.000985 | |
| | B | 0.158248 | | NaN | -0.097147 |
| | C | | NaN | 0.176180 | |

Also, you can use Grouper for index and columns keywords. For detail of Grouper, see [Grouping with a Grouper specification](#).

```
In [57]: pd.pivot_table(df, values='D', index=Grouper(freq='M', key='F'), columns='C')
```

```
Out[57]:
```

| | bar | foo |
|------------|-----------|-----------|
| 2013-01-31 | NaN | -0.514058 |
| 2013-02-28 | NaN | 0.002759 |
| 2013-03-31 | NaN | 0.176180 |
| 2013-04-30 | -1.181568 | NaN |
| 2013-05-31 | -0.338421 | NaN |

```
2013-06-30 -0.538846      NaN
2013-07-31      NaN  1.000985
2013-08-31      NaN  0.433512
2013-09-30      NaN  0.699535
2013-10-31  1.120915      NaN
2013-11-30  0.158248      NaN
2013-12-31  0.588783      NaN
```

You can render a nice output of the table omitting the missing values by calling `to_string` if you wish:

```
In [58]: table = pd.pivot_table(df, index=['A', 'B'], columns=['C'])
```

```
In [59]: print(table.to_string(na_rep=''))
```

| | | D | | E | |
|-------|---|-----------|-----------|-----------|-----------|
| C | | bar | foo | bar | foo |
| one | A | 1.120915 | -0.514058 | 1.393057 | -0.021605 |
| | B | -0.338421 | 0.002759 | 0.684140 | -0.551692 |
| | C | -0.538846 | 0.699535 | -0.988442 | 0.747859 |
| three | A | -1.181568 | | 0.961289 | |
| | B | | 0.433512 | | -1.064372 |
| | C | 0.588783 | | -0.131830 | |
| two | A | | 1.000985 | | 0.064245 |
| | B | 0.158248 | | -0.097147 | |
| | C | | 0.176180 | | 0.436241 |

Note that `pivot_table` is also available as an instance method on `DataFrame`.

19.5.1 Cross tabulations

Use the `crosstab` function to compute a cross-tabulation of two (or more) factors. By default `crosstab` computes a frequency table of the factors unless an array of values and an aggregation function are passed.

It takes a number of arguments

- `index`: array-like, values to group by in the rows
- `columns`: array-like, values to group by in the columns
- `values`: array-like, optional, array of values to aggregate according to the factors
- `aggfunc`: function, optional, If no values array is passed, computes a frequency table
- `rownames`: sequence, default `None`, must match number of row arrays passed
- `colnames`: sequence, default `None`, if passed, must match number of column arrays passed
- `margins`: boolean, default `False`, Add row/column margins (subtotals)

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified

For example:

```
In [60]: foo, bar, dull, shiny, one, two = 'foo', 'bar', 'dull', 'shiny', 'one', 'two'
```

```
In [61]: a = np.array([foo, foo, bar, bar, foo, foo], dtype=object)
```

```
In [62]: b = np.array([one, one, two, one, two, one], dtype=object)
```

```
In [63]: c = np.array([dull, dull, shiny, dull, dull, shiny], dtype=object)
```

```
In [64]: pd.crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
```

```
Out[64]:
```

```
b      one      two
c  dull shiny dull shiny
a
bar    1      0      0      1
foo    2      1      1      0
```

19.5.2 Adding margins (partial aggregates)

If you pass `margins=True` to `pivot_table`, special All columns and rows will be added with partial group aggregates across the categories on the rows and columns:

```
In [65]: df.pivot_table(index=['A', 'B'], columns='C', margins=True, aggfunc=np.std)
```

```
Out[65]:
```

| C | | D | | | E | | |
|-------|---|----------|----------|----------|----------|----------|----------|
| | | bar | foo | All | bar | foo | All |
| one | A | 1.804346 | 1.210272 | 1.569879 | 0.179483 | 0.418374 | 0.858005 |
| | B | 0.690376 | 1.353355 | 0.898998 | 1.083825 | 0.968138 | 1.101401 |
| | C | 0.273641 | 0.418926 | 0.771139 | 1.689271 | 0.446140 | 1.422136 |
| three | A | 0.794212 | NaN | 0.794212 | 2.049040 | NaN | 2.049040 |
| | B | NaN | 0.363548 | 0.363548 | NaN | 1.625237 | 1.625237 |
| | C | 3.915454 | NaN | 3.915454 | 1.035215 | NaN | 1.035215 |
| two | A | NaN | 0.442998 | 0.442998 | NaN | 0.447104 | 0.447104 |
| | B | 0.202765 | NaN | 0.202765 | 0.560757 | NaN | 0.560757 |
| | C | NaN | 1.819408 | 1.819408 | NaN | 0.650439 | 0.650439 |
| All | | 1.556686 | 0.952552 | 1.246608 | 1.250924 | 0.899904 | 1.059389 |

19.6 Tiling

The `cut` function computes groupings for the values of the input array and is often used to transform continuous variables to discrete or categorical variables:

```
In [66]: ages = np.array([10, 15, 13, 12, 23, 25, 28, 59, 60])
```

```
In [67]: pd.cut(ages, bins=3)
```

```
Out[67]:
```

```
[(9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (9.95, 26.667], (26.667, 43.333], (26.667, 43.333], (43.333, 60]]
Categories (3, object): [(9.95, 26.667] < (26.667, 43.333] < (43.333, 60]]
```

If the `bins` keyword is an integer, then equal-width bins are formed. Alternatively we can specify custom bin-edges:

```
In [68]: pd.cut(ages, bins=[0, 18, 35, 70])
```

```
Out[68]:
```

```
[(0, 18], (0, 18], (0, 18], (0, 18], (18, 35], (18, 35], (18, 35], (35, 70], (35, 70]]
Categories (3, object): [(0, 18] < (18, 35] < (35, 70]]
```

19.7 Computing indicator / dummy variables

To convert a categorical variable into a “dummy” or “indicator” DataFrame, for example a column in a DataFrame (a Series) which has k distinct values, can derive a DataFrame containing k columns of 1s and 0s:

```
In [69]: df = pd.DataFrame({'key': list('bbacab'), 'data1': range(6)})
```

```
In [70]: pd.get_dummies(df['key'])
```

```
Out[70]:
```

| | a | b | c |
|---|---|---|---|
| 0 | 0 | 1 | 0 |
| 1 | 0 | 1 | 0 |
| 2 | 1 | 0 | 0 |
| 3 | 0 | 0 | 1 |
| 4 | 1 | 0 | 0 |
| 5 | 0 | 1 | 0 |

Sometimes it's useful to prefix the column names, for example when merging the result with the original DataFrame:

```
In [71]: dummies = pd.get_dummies(df['key'], prefix='key')
```

```
In [72]: dummies
```

```
Out[72]:
```

| | key_a | key_b | key_c |
|---|-------|-------|-------|
| 0 | 0 | 1 | 0 |
| 1 | 0 | 1 | 0 |
| 2 | 1 | 0 | 0 |
| 3 | 0 | 0 | 1 |
| 4 | 1 | 0 | 0 |
| 5 | 0 | 1 | 0 |

```
In [73]: df[['data1']].join(dummies)
```

```
Out[73]:
```

| | data1 | key_a | key_b | key_c |
|---|-------|-------|-------|-------|
| 0 | 0 | 0 | 1 | 0 |
| 1 | 1 | 0 | 1 | 0 |
| 2 | 2 | 1 | 0 | 0 |
| 3 | 3 | 0 | 0 | 1 |
| 4 | 4 | 1 | 0 | 0 |
| 5 | 5 | 0 | 1 | 0 |

This function is often used along with discretization functions like `cut`:

```
In [74]: values = np.random.randn(10)
```

```
In [75]: values
```

```
Out[75]:
```

```
array([ 0.4082, -1.0481, -0.0257, -0.9884,  0.0941,  1.2627,  1.29   ,
        0.0824, -0.0558,  0.5366])
```

```
In [76]: bins = [0, 0.2, 0.4, 0.6, 0.8, 1]
```

```
In [77]: pd.get_dummies(pd.cut(values, bins))
```

```
Out[77]:
```

| | (0, 0.2] | (0.2, 0.4] | (0.4, 0.6] | (0.6, 0.8] | (0.8, 1] |
|---|----------|------------|------------|------------|----------|
| 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 |
| 4 | 1 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 |
| 7 | 1 | 0 | 0 | 0 | 0 |
| 8 | 0 | 0 | 0 | 0 | 0 |

```
9          0          0          1          0          0
```

See also `Series.str.get_dummies`.

New in version 0.15.0.

`get_dummies()` also accepts a `DataFrame`. By default all categorical variables (categorical in the statistical sense, those with *object* or *categorical* dtype) are encoded as dummy variables.

```
In [78]: df = pd.DataFrame({'A': ['a', 'b', 'a'], 'B': ['c', 'c', 'b'],
.....:                    'C': [1, 2, 3]})
.....:
```

```
In [79]: pd.get_dummies(df)
```

```
Out[79]:
   C  A_a  A_b  B_b  B_c
0  1    1    0    0    1
1  2    0    1    0    1
2  3    1    0    1    0
```

All non-object columns are included untouched in the output.

You can control the columns that are encoded with the `columns` keyword.

```
In [80]: pd.get_dummies(df, columns=['A'])
```

```
Out[80]:
   B  C  A_a  A_b
0  c  1    1    0
1  c  2    0    1
2  b  3    1    0
```

Notice that the `B` column is still included in the output, it just hasn't been encoded. You can drop `B` before calling `get_dummies` if you don't want to include it in the output.

As with the `Series` version, you can pass values for the `prefix` and `prefix_sep`. By default the column name is used as the prefix, and `'_'` as the prefix separator. You can specify `prefix` and `prefix_sep` in 3 ways

- string: Use the same value for `prefix` or `prefix_sep` for each column to be encoded
- list: Must be the same length as the number of columns being encoded.
- dict: Mapping column name to prefix

```
In [81]: simple = pd.get_dummies(df, prefix='new_prefix')
```

```
In [82]: simple
```

```
Out[82]:
   C  new_prefix_a  new_prefix_b  new_prefix_b  new_prefix_c
0  1              1              0              0              1
1  2              0              1              0              1
2  3              1              0              1              0
```

```
In [83]: from_list = pd.get_dummies(df, prefix=['from_A', 'from_B'])
```

```
In [84]: from_list
```

```
Out[84]:
   C  from_A_a  from_A_b  from_B_b  from_B_c
0  1          1          0          0          1
1  2          0          1          0          1
2  3          1          0          1          0
```

```
In [85]: from_dict = pd.get_dummies(df, prefix={'B': 'from_B', 'A': 'from_A'})
```

```
In [86]: from_dict
Out[86]:
```

| | C | from_A_a | from_A_b | from_B_b | from_B_c |
|---|---|----------|----------|----------|----------|
| 0 | 1 | 1 | 0 | 0 | 1 |
| 1 | 2 | 0 | 1 | 0 | 1 |
| 2 | 3 | 1 | 0 | 1 | 0 |

19.8 Factorizing values

To encode 1-d values as an enumerated type use `factorize`:

```
In [87]: x = pd.Series(['A', 'A', np.nan, 'B', 3.14, np.inf])
```

```
In [88]: x
Out[88]:
```

| | |
|---|------|
| 0 | A |
| 1 | A |
| 2 | NaN |
| 3 | B |
| 4 | 3.14 |
| 5 | inf |

dtype: object

```
In [89]: labels, uniques = pd.factorize(x)
```

```
In [90]: labels
Out[90]: array([ 0,  0, -1,  1,  2,  3])
```

```
In [91]: uniques
Out[91]: Index([u'A', u'B', 3.14, inf], dtype='object')
```

Note that `factorize` is similar to `numpy.unique`, but differs in its handling of NaN:

Note: The following `numpy.unique` will fail under Python 3 with a `TypeError` because of an ordering bug. See also [Here](#)

```
In [92]: pd.factorize(x, sort=True)
Out[92]:
```

```
(array([ 2,  2, -1,  3,  0,  1]),
 Index([3.14, inf, u'A', u'B'], dtype='object'))
```

```
In [93]: np.unique(x, return_inverse=True)[::-1]
Out[93]: (array([3, 3, 0, 4, 1, 2]), array([nan, 3.14, inf, 'A', 'B'], dtype=object))
```

Note: If you just want to handle one column as a categorical variable (like R's factor), you can use `df["cat_col"] = pd.Categorical(df["col"])` or `df["cat_col"] = df["col"].astype("category")`. For full docs on [Categorical](#), see the [Categorical introduction](#) and the [API documentation](#). This feature was introduced in version 0.15.

TIME SERIES / DATE FUNCTIONALITY

pandas has proven very successful as a tool for working with time series data, especially in the financial data analysis space. With the 0.8 release, we have further improved the time series API in pandas by leaps and bounds. Using the new NumPy `datetime64` dtype, we have consolidated a large number of features from other Python libraries like `scikits.timeseries` as well as created a tremendous amount of new functionality for manipulating time series data.

In working with time series data, we will frequently seek to:

- generate sequences of fixed-frequency dates and time spans
- conform or convert time series to a particular frequency
- compute “relative” dates based on various non-standard time increments (e.g. 5 business days before the last business day of the year), or “roll” dates forward or backward

pandas provides a relatively compact and self-contained set of tools for performing the above tasks.

Create a range of dates:

```
# 72 hours starting with midnight Jan 1st, 2011
In [1]: rng = date_range('1/1/2011', periods=72, freq='H')

In [2]: rng[:5]
Out[2]:
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-01 01:00:00',
                '2011-01-01 02:00:00', '2011-01-01 03:00:00',
                '2011-01-01 04:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

Index pandas objects with dates:

```
In [3]: ts = Series(randn(len(rng)), index=rng)

In [4]: ts.head()
Out[4]:
2011-01-01 00:00:00    0.469112
2011-01-01 01:00:00   -0.282863
2011-01-01 02:00:00   -1.509059
2011-01-01 03:00:00   -1.135632
2011-01-01 04:00:00    1.212112
Freq: H, dtype: float64
```

Change frequency and fill gaps:

```
# to 45 minute frequency and forward fill
In [5]: converted = ts.asfreq('45Min', method='pad')
```

```
In [6]: converted.head()
Out[6]:
2011-01-01 00:00:00    0.469112
2011-01-01 00:45:00    0.469112
2011-01-01 01:30:00   -0.282863
2011-01-01 02:15:00   -1.509059
2011-01-01 03:00:00   -1.135632
Freq: 45T, dtype: float64
```

Resample:

```
# Daily means
In [7]: ts.resample('D', how='mean')
Out[7]:
2011-01-01    -0.319569
2011-01-02    -0.337703
2011-01-03     0.117258
Freq: D, dtype: float64
```

20.1 Time Stamps vs. Time Spans

Time-stamped data is the most basic type of timeseries data that associates values with points in time. For pandas objects it means using the points in time to create the index

```
In [8]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]

In [9]: ts = Series(np.random.randn(3), dates)

In [10]: type(ts.index)
Out[10]: pandas.tseries.index.DatetimeIndex

In [11]: ts
Out[11]:
2012-05-01    -0.410001
2012-05-02    -0.078638
2012-05-03     0.545952
dtype: float64
```

However, in many cases it is more natural to associate things like change variables with a time span instead.

For example:

```
In [12]: periods = PeriodIndex([Period('2012-01'), Period('2012-02'),
.....:                          Period('2012-03')])
.....:

In [13]: ts = Series(np.random.randn(3), periods)

In [14]: type(ts.index)
Out[14]: pandas.tseries.period.PeriodIndex

In [15]: ts
Out[15]:
2012-01    -1.219217
2012-02    -1.226825
2012-03     0.769804
Freq: M, dtype: float64
```

Starting with 0.8, pandas allows you to capture both representations and convert between them. Under the hood, pandas represents timestamps using instances of `Timestamp` and sequences of timestamps using instances of `DatetimeIndex`. For regular time spans, pandas uses `Period` objects for scalar values and `PeriodIndex` for sequences of spans. Better support for irregular intervals with arbitrary start and end points are forth-coming in future releases.

20.2 Converting to Timestamps

To convert a Series or list-like object of date-like objects e.g. strings, epochs, or a mixture, you can use the `to_datetime` function. When passed a Series, this returns a Series (with the same index), while a list-like is converted to a `DatetimeIndex`:

```
In [16]: to_datetime(Series(['Jul 31, 2009', '2010-01-10', None]))
Out[16]:
0    2009-07-31
1    2010-01-10
2             NaT
dtype: datetime64[ns]

In [17]: to_datetime(['2005/11/23', '2010.12.31'])
Out[17]: DatetimeIndex(['2005-11-23', '2010-12-31'], dtype='datetime64[ns]', freq=None, tz=None)
```

If you use dates which start with the day first (i.e. European style), you can pass the `dayfirst` flag:

```
In [18]: to_datetime(['04-01-2012 10:00'], dayfirst=True)
Out[18]: DatetimeIndex(['2012-01-04 10:00:00'], dtype='datetime64[ns]', freq=None, tz=None)

In [19]: to_datetime(['14-01-2012', '01-14-2012'], dayfirst=True)
Out[19]: DatetimeIndex(['2012-01-14', '2012-01-14'], dtype='datetime64[ns]', freq=None, tz=None)
```

Warning: You see in the above example that `dayfirst` isn't strict, so if a date can't be parsed with the day being first it will be parsed as if `dayfirst` were `False`.

Note: Specifying a `format` argument will potentially speed up the conversion considerably and on versions later than 0.13.0 explicitly specifying a format string of `'%Y%m%d'` takes a faster path still.

20.2.1 Invalid Data

Pass `coerce=True` to convert invalid data to `NaT` (not a time):

```
In [20]: to_datetime(['2009-07-31', 'asd'])
Out[20]: array(['2009-07-31', 'asd'], dtype=object)

In [21]: to_datetime(['2009-07-31', 'asd'], coerce=True)
Out[21]: DatetimeIndex(['2009-07-31', 'NaT'], dtype='datetime64[ns]', freq=None, tz=None)
```

Take care, `to_datetime` may not act as you expect on mixed data:

```
In [22]: to_datetime([1, '1'])
Out[22]: array([1, '1'], dtype=object)
```

20.2.2 Epoch Timestamps

It's also possible to convert integer or float epoch times. The default unit for these is nanoseconds (since these are how Timestamps are stored). However, often epochs are stored in another unit which can be specified:

Typical epoch stored units

```
In [23]: to_datetime([1349720105, 1349806505, 1349892905,
.....:                1349979305, 1350065705], unit='s')
.....:
```

```
Out [23]:
DatetimeIndex(['2012-10-08 18:15:05', '2012-10-09 18:15:05',
               '2012-10-10 18:15:05', '2012-10-11 18:15:05',
               '2012-10-12 18:15:05'],
              dtype='datetime64[ns]', freq=None, tz=None)
```

```
In [24]: to_datetime([1349720105100, 1349720105200, 1349720105300,
.....:                1349720105400, 1349720105500 ], unit='ms')
.....:
```

```
Out [24]:
DatetimeIndex(['2012-10-08 18:15:05.100000', '2012-10-08 18:15:05.200000',
               '2012-10-08 18:15:05.300000', '2012-10-08 18:15:05.400000',
               '2012-10-08 18:15:05.500000'],
              dtype='datetime64[ns]', freq=None, tz=None)
```

These *work*, but the results may be unexpected.

```
In [25]: to_datetime([1])
```

```
Out [25]: DatetimeIndex(['1970-01-01 00:00:00.000000001'], dtype='datetime64[ns]', freq=None, tz=None)
```

```
In [26]: to_datetime([1, 3.14], unit='s')
```

```
Out [26]: DatetimeIndex(['1970-01-01 00:00:01', '1970-01-01 00:00:03.140000'], dtype='datetime64[ns]',
```

Note: Epoch times will be rounded to the nearest nanosecond.

20.3 Generating Ranges of Timestamps

To generate an index with time stamps, you can use either the DatetimeIndex or Index constructor and pass in a list of datetime objects:

```
In [27]: dates = [datetime(2012, 5, 1), datetime(2012, 5, 2), datetime(2012, 5, 3)]
```

```
In [28]: index = DatetimeIndex(dates)
```

```
In [29]: index # Note the frequency information
```

```
Out [29]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)
```

```
In [30]: index = Index(dates)
```

```
In [31]: index # Automatically converted to DatetimeIndex
```

```
Out [31]: DatetimeIndex(['2012-05-01', '2012-05-02', '2012-05-03'], dtype='datetime64[ns]', freq=None)
```

Practically, this becomes very cumbersome because we often need a very long index with a large number of timestamps. If we need timestamps on a regular frequency, we can use the pandas functions `date_range` and `bdate_range` to create timestamp indexes.

```
In [32]: index = date_range('2000-1-1', periods=1000, freq='M')
```

```
In [33]: index
```

```
Out [33]:
DatetimeIndex(['2000-01-31', '2000-02-29', '2000-03-31', '2000-04-30',
               '2000-05-31', '2000-06-30', '2000-07-31', '2000-08-31',
               '2000-09-30', '2000-10-31',
               ...
               '2082-07-31', '2082-08-31', '2082-09-30', '2082-10-31',
               '2082-11-30', '2082-12-31', '2083-01-31', '2083-02-28',
               '2083-03-31', '2083-04-30'],
              dtype='datetime64[ns]', length=1000, freq='M', tz=None)
```

```
In [34]: index = bdate_range('2012-1-1', periods=250)
```

```
In [35]: index
```

```
Out [35]:
DatetimeIndex(['2012-01-02', '2012-01-03', '2012-01-04', '2012-01-05',
               '2012-01-06', '2012-01-09', '2012-01-10', '2012-01-11',
               '2012-01-12', '2012-01-13',
               ...
               '2012-12-03', '2012-12-04', '2012-12-05', '2012-12-06',
               '2012-12-07', '2012-12-10', '2012-12-11', '2012-12-12',
               '2012-12-13', '2012-12-14'],
              dtype='datetime64[ns]', length=250, freq='B', tz=None)
```

Convenience functions like `date_range` and `bdate_range` utilize a variety of frequency aliases. The default frequency for `date_range` is a **calendar day** while the default for `bdate_range` is a **business day**

```
In [36]: start = datetime(2011, 1, 1)
```

```
In [37]: end = datetime(2012, 1, 1)
```

```
In [38]: rng = date_range(start, end)
```

```
In [39]: rng
```

```
Out [39]:
DatetimeIndex(['2011-01-01', '2011-01-02', '2011-01-03', '2011-01-04',
               '2011-01-05', '2011-01-06', '2011-01-07', '2011-01-08',
               '2011-01-09', '2011-01-10',
               ...
               '2011-12-23', '2011-12-24', '2011-12-25', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30',
               '2011-12-31', '2012-01-01'],
              dtype='datetime64[ns]', length=366, freq='D', tz=None)
```

```
In [40]: rng = bdate_range(start, end)
```

```
In [41]: rng
```

```
Out [41]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14',
               ...
               '2011-12-19', '2011-12-20', '2011-12-21', '2011-12-22',
               '2011-12-23', '2011-12-26', '2011-12-27', '2011-12-28',
               '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', length=260, freq='B', tz=None)
```

`date_range` and `bdate_range` make it easy to generate a range of dates using various combinations of parameters like `start`, `end`, `periods`, and `freq`:

```
In [42]: date_range(start, end, freq='BM')
Out [42]:
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
               '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
               '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
              dtype='datetime64[ns]', freq='BM', tz=None)
```

```
In [43]: date_range(start, end, freq='W')
Out [43]:
DatetimeIndex(['2011-01-02', '2011-01-09', '2011-01-16', '2011-01-23',
               '2011-01-30', '2011-02-06', '2011-02-13', '2011-02-20',
               '2011-02-27', '2011-03-06', '2011-03-13', '2011-03-20',
               '2011-03-27', '2011-04-03', '2011-04-10', '2011-04-17',
               '2011-04-24', '2011-05-01', '2011-05-08', '2011-05-15',
               '2011-05-22', '2011-05-29', '2011-06-05', '2011-06-12',
               '2011-06-19', '2011-06-26', '2011-07-03', '2011-07-10',
               '2011-07-17', '2011-07-24', '2011-07-31', '2011-08-07',
               '2011-08-14', '2011-08-21', '2011-08-28', '2011-09-04',
               '2011-09-11', '2011-09-18', '2011-09-25', '2011-10-02',
               '2011-10-09', '2011-10-16', '2011-10-23', '2011-10-30',
               '2011-11-06', '2011-11-13', '2011-11-20', '2011-11-27',
               '2011-12-04', '2011-12-11', '2011-12-18', '2011-12-25',
               '2012-01-01'],
              dtype='datetime64[ns]', freq='W-SUN', tz=None)
```

```
In [44]: bdate_range(end=end, periods=20)
Out [44]:
DatetimeIndex(['2011-12-05', '2011-12-06', '2011-12-07', '2011-12-08',
               '2011-12-09', '2011-12-12', '2011-12-13', '2011-12-14',
               '2011-12-15', '2011-12-16', '2011-12-19', '2011-12-20',
               '2011-12-21', '2011-12-22', '2011-12-23', '2011-12-26',
               '2011-12-27', '2011-12-28', '2011-12-29', '2011-12-30'],
              dtype='datetime64[ns]', freq='B', tz=None)
```

```
In [45]: bdate_range(start=start, periods=20)
Out [45]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07', '2011-01-10', '2011-01-11', '2011-01-12',
               '2011-01-13', '2011-01-14', '2011-01-17', '2011-01-18',
               '2011-01-19', '2011-01-20', '2011-01-21', '2011-01-24',
               '2011-01-25', '2011-01-26', '2011-01-27', '2011-01-28'],
              dtype='datetime64[ns]', freq='B', tz=None)
```

The start and end dates are strictly inclusive. So it will not generate any dates outside of those dates if specified.

20.4 DatetimeIndex

One of the main uses for `DatetimeIndex` is as an index for pandas objects. The `DatetimeIndex` class contains many timeseries related optimizations:

- A large range of dates for various offsets are pre-computed and cached under the hood in order to make generating subsequent date ranges very fast (just have to grab a slice)
- Fast shifting using the `shift` and `tshift` method on pandas objects

- Unioning of overlapping DatetimeIndex objects with the same frequency is very fast (important for fast data alignment)
- Quick access to date fields via properties such as `year`, `month`, etc.
- Regularization functions like `snap` and very fast `asof` logic

DatetimeIndex objects has all the basic functionality of regular Index objects and a smorgasbord of advanced timeseries-specific methods for easy frequency processing.

See also:

Reindexing methods

Note: While pandas does not force you to have a sorted date index, some of these methods may have unexpected or incorrect behavior if the dates are unsorted. So please be careful.

DatetimeIndex can be used like a regular index and offers all of its intelligent functionality like selection, slicing, etc.

```
In [46]: rng = date_range(start, end, freq='BM')
```

```
In [47]: ts = Series(randn(len(rng)), index=rng)
```

```
In [48]: ts.index
```

```
Out[48]:
```

```
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
                '2011-05-31', '2011-06-30', '2011-07-29', '2011-08-31',
                '2011-09-30', '2011-10-31', '2011-11-30', '2011-12-30'],
               dtype='datetime64[ns]', freq='BM', tz=None)
```

```
In [49]: ts[:5].index
```

```
Out[49]:
```

```
DatetimeIndex(['2011-01-31', '2011-02-28', '2011-03-31', '2011-04-29',
                '2011-05-31'],
               dtype='datetime64[ns]', freq='BM', tz=None)
```

```
In [50]: ts[::2].index
```

```
Out[50]:
```

```
DatetimeIndex(['2011-01-31', '2011-03-31', '2011-05-31', '2011-07-29',
                '2011-09-30', '2011-11-30'],
               dtype='datetime64[ns]', freq='2BM', tz=None)
```

20.4.1 DatetimeIndex Partial String Indexing

You can pass in dates and strings that parse to dates as indexing parameters:

```
In [51]: ts['1/31/2011']
```

```
Out[51]: -1.2812473076599529
```

```
In [52]: ts[datetime(2011, 12, 25):]
```

```
Out[52]:
```

```
2011-12-30    0.687738
```

```
Freq: BM, dtype: float64
```

```
In [53]: ts['10/31/2011':'12/31/2011']
```

```
Out[53]:
```

```
2011-10-31    0.149748
```

```
2011-11-30    -0.732339
2011-12-30     0.687738
Freq: BM, dtype: float64
```

To provide convenience for accessing longer time series, you can also pass in the year or year and month as strings:

```
In [54]: ts['2011']
Out[54]:
2011-01-31    -1.281247
2011-02-28    -0.727707
2011-03-31    -0.121306
2011-04-29    -0.097883
2011-05-31     0.695775
2011-06-30     0.341734
2011-07-29     0.959726
2011-08-31    -1.110336
2011-09-30    -0.619976
2011-10-31     0.149748
2011-11-30    -0.732339
2011-12-30     0.687738
Freq: BM, dtype: float64
```

```
In [55]: ts['2011-6']
Out[55]:
2011-06-30     0.341734
Freq: BM, dtype: float64
```

This type of slicing will work on a `DataFrame` with a `DateTimeIndex` as well. Since the partial string selection is a form of label slicing, the endpoints **will be** included. This would include matching times on an included date. Here's an example:

```
In [56]: dft = DataFrame(randn(100000,1),columns=['A'],index=date_range('20130101',periods=100000,freq='T'))
```

```
In [57]: dft
Out[57]:
```

| | A |
|---------------------|-----------|
| 2013-01-01 00:00:00 | 0.176444 |
| 2013-01-01 00:01:00 | 0.403310 |
| 2013-01-01 00:02:00 | -0.154951 |
| 2013-01-01 00:03:00 | 0.301624 |
| 2013-01-01 00:04:00 | -2.179861 |
| 2013-01-01 00:05:00 | -1.369849 |
| 2013-01-01 00:06:00 | -0.954208 |
| ... | ... |
| 2013-03-11 10:33:00 | -0.293083 |
| 2013-03-11 10:34:00 | -0.059881 |
| 2013-03-11 10:35:00 | 1.252450 |
| 2013-03-11 10:36:00 | 0.046611 |
| 2013-03-11 10:37:00 | 0.059478 |
| 2013-03-11 10:38:00 | -0.286539 |
| 2013-03-11 10:39:00 | 0.841669 |

```
[100000 rows x 1 columns]
```

```
In [58]: dft['2013']
Out[58]:
```

| | A |
|---------------------|----------|
| 2013-01-01 00:00:00 | 0.176444 |
| 2013-01-01 00:01:00 | 0.403310 |

```

2013-01-01 00:02:00 -0.154951
2013-01-01 00:03:00  0.301624
2013-01-01 00:04:00 -2.179861
2013-01-01 00:05:00 -1.369849
2013-01-01 00:06:00 -0.954208
...
2013-03-11 10:33:00 -0.293083
2013-03-11 10:34:00 -0.059881
2013-03-11 10:35:00  1.252450
2013-03-11 10:36:00  0.046611
2013-03-11 10:37:00  0.059478
2013-03-11 10:38:00 -0.286539
2013-03-11 10:39:00  0.841669

```

```
[100000 rows x 1 columns]
```

This starts on the very first time in the month, and includes the last date & time for the month

```
In [59]: dft['2013-1':'2013-2']
```

```
Out [59]:
```

```

                                     A
2013-01-01 00:00:00  0.176444
2013-01-01 00:01:00  0.403310
2013-01-01 00:02:00 -0.154951
2013-01-01 00:03:00  0.301624
2013-01-01 00:04:00 -2.179861
2013-01-01 00:05:00 -1.369849
2013-01-01 00:06:00 -0.954208
...
2013-02-28 23:53:00  0.103114
2013-02-28 23:54:00 -1.303422
2013-02-28 23:55:00  0.451943
2013-02-28 23:56:00  0.220534
2013-02-28 23:57:00 -1.624220
2013-02-28 23:58:00  0.093915
2013-02-28 23:59:00 -1.087454

```

```
[84960 rows x 1 columns]
```

This specifies a stop time **that includes all of the times on the last day**

```
In [60]: dft['2013-1':'2013-2-28']
```

```
Out [60]:
```

```

                                     A
2013-01-01 00:00:00  0.176444
2013-01-01 00:01:00  0.403310
2013-01-01 00:02:00 -0.154951
2013-01-01 00:03:00  0.301624
2013-01-01 00:04:00 -2.179861
2013-01-01 00:05:00 -1.369849
2013-01-01 00:06:00 -0.954208
...
2013-02-28 23:53:00  0.103114
2013-02-28 23:54:00 -1.303422
2013-02-28 23:55:00  0.451943
2013-02-28 23:56:00  0.220534
2013-02-28 23:57:00 -1.624220
2013-02-28 23:58:00  0.093915
2013-02-28 23:59:00 -1.087454

```

```
[84960 rows x 1 columns]
```

This specifies an **exact** stop time (and is not the same as the above)

```
In [61]: dft['2013-1':'2013-2-28 00:00:00']
```

```
Out [61]:
```

```

          A
2013-01-01 00:00:00    0.176444
2013-01-01 00:01:00    0.403310
2013-01-01 00:02:00   -0.154951
2013-01-01 00:03:00    0.301624
2013-01-01 00:04:00   -2.179861
2013-01-01 00:05:00   -1.369849
2013-01-01 00:06:00   -0.954208
...
2013-02-27 23:54:00    0.897051
2013-02-27 23:55:00   -0.309230
2013-02-27 23:56:00    1.944713
2013-02-27 23:57:00    0.369265
2013-02-27 23:58:00    0.053071
2013-02-27 23:59:00   -0.019734
2013-02-28 00:00:00    1.388189
```

```
[83521 rows x 1 columns]
```

We are stopping on the included end-point as it is part of the index

```
In [62]: dft['2013-1-15':'2013-1-15 12:30:00']
```

```
Out [62]:
```

```

          A
2013-01-15 00:00:00    0.501288
2013-01-15 00:01:00   -0.605198
2013-01-15 00:02:00    0.215146
2013-01-15 00:03:00    0.924732
2013-01-15 00:04:00   -2.228519
2013-01-15 00:05:00    1.517331
2013-01-15 00:06:00   -1.188774
...
2013-01-15 12:24:00    1.358314
2013-01-15 12:25:00   -0.737727
2013-01-15 12:26:00    1.838323
2013-01-15 12:27:00   -0.774090
2013-01-15 12:28:00    0.622261
2013-01-15 12:29:00   -0.631649
2013-01-15 12:30:00    0.193284
```

```
[751 rows x 1 columns]
```

Warning: The following selection will raise a `KeyError`; otherwise this selection methodology would be inconsistent with other selection methods in pandas (as this is not a *slice*, nor does it resolve to one)

```
dft['2013-1-15 12:30:00']
```

To select a single row, use `.loc`

```
In [63]: dft.loc['2013-1-15 12:30:00']
Out[63]:
A      0.193284
Name: 2013-01-15 12:30:00, dtype: float64
```

20.4.2 Datetime Indexing

Indexing a `DatetimeIndex` with a partial string depends on the “accuracy” of the period, in other words how specific the interval is in relation to the frequency of the index. In contrast, indexing with datetime objects is exact, because the objects have exact meaning. These also follow the semantics of *including both endpoints*.

These datetime objects are specific hours, minutes, and seconds even though they were not explicitly specified (they are 0).

```
In [64]: dft[datetime(2013, 1, 1):datetime(2013, 2, 28)]
Out[64]:
```

```

A
2013-01-01 00:00:00    0.176444
2013-01-01 00:01:00    0.403310
2013-01-01 00:02:00   -0.154951
2013-01-01 00:03:00    0.301624
2013-01-01 00:04:00   -2.179861
2013-01-01 00:05:00   -1.369849
2013-01-01 00:06:00   -0.954208
...
2013-02-27 23:54:00    0.897051
2013-02-27 23:55:00   -0.309230
2013-02-27 23:56:00    1.944713
2013-02-27 23:57:00    0.369265
2013-02-27 23:58:00    0.053071
2013-02-27 23:59:00   -0.019734
2013-02-28 00:00:00    1.388189
```

```
[83521 rows x 1 columns]
```

With no defaults.

```
In [65]: dft[datetime(2013, 1, 1, 10, 12, 0):datetime(2013, 2, 28, 10, 12, 0)]
Out[65]:
```

```

A
2013-01-01 10:12:00   -0.246733
2013-01-01 10:13:00   -1.429225
2013-01-01 10:14:00   -1.265339
2013-01-01 10:15:00    0.710986
2013-01-01 10:16:00   -0.818200
2013-01-01 10:17:00    0.543542
2013-01-01 10:18:00    1.577713
...
2013-02-28 10:06:00    0.311249
```

```
2013-02-28 10:07:00    2.366080
2013-02-28 10:08:00   -0.490372
2013-02-28 10:09:00    0.373340
2013-02-28 10:10:00    0.638442
2013-02-28 10:11:00    1.330135
2013-02-28 10:12:00   -0.945450
```

```
[83521 rows x 1 columns]
```

20.4.3 Truncating & Fancy Indexing

A `truncate` convenience function is provided that is equivalent to slicing:

```
In [66]: ts.truncate(before='10/31/2011', after='12/31/2011')
Out[66]:
2011-10-31    0.149748
2011-11-30   -0.732339
2011-12-30    0.687738
Freq: BM, dtype: float64
```

Even complicated fancy indexing that breaks the `DatetimeIndex`'s frequency regularity will result in a `DatetimeIndex` (but frequency is lost):

```
In [67]: ts[[0, 2, 6]].index
Out[67]: DatetimeIndex(['2011-01-31', '2011-03-31', '2011-07-29'], dtype='datetime64[ns]', freq=None)
```

20.4.4 Time/Date Components

There are several time/date properties that one can access from `Timestamp` or a collection of timestamps like a `DatetimeIndex`.

| Property | Description |
|-------------------------------|---|
| <code>year</code> | The year of the datetime |
| <code>month</code> | The month of the datetime |
| <code>day</code> | The days of the datetime |
| <code>hour</code> | The hour of the datetime |
| <code>minute</code> | The minutes of the datetime |
| <code>second</code> | The seconds of the datetime |
| <code>microsecond</code> | The microseconds of the datetime |
| <code>nanosecond</code> | The nanoseconds of the datetime |
| <code>date</code> | Returns <code>datetime.date</code> |
| <code>time</code> | Returns <code>datetime.time</code> |
| <code>dayofyear</code> | The ordinal day of year |
| <code>weekofyear</code> | The week ordinal of the year |
| <code>week</code> | The week ordinal of the year |
| <code>dayofweek</code> | The day of the week with Monday=0, Sunday=6 |
| <code>weekday</code> | The day of the week with Monday=0, Sunday=6 |
| <code>quarter</code> | Quarter of the date: Jan=Mar = 1, Apr-Jun = 2, etc. |
| <code>is_month_start</code> | Logical indicating if first day of month (defined by frequency) |
| <code>is_month_end</code> | Logical indicating if last day of month (defined by frequency) |
| <code>is_quarter_start</code> | Logical indicating if first day of quarter (defined by frequency) |
| <code>is_quarter_end</code> | Logical indicating if last day of quarter (defined by frequency) |
| <code>is_year_start</code> | Logical indicating if first day of year (defined by frequency) |
| <code>is_year_end</code> | Logical indicating if last day of year (defined by frequency) |

Furthermore, if you have a `Series` with datetimelike values, then you can access these properties via the `.dt` accessor, see the [docs](#)

20.5 DateOffset objects

In the preceding examples, we created `DatetimeIndex` objects at various frequencies by passing in frequency strings like ‘M’, ‘W’, and ‘BM’ to the `freq` keyword. Under the hood, these frequency strings are being translated into an instance of pandas `DateOffset`, which represents a regular frequency increment. Specific offset logic like “month”, “business day”, or “one hour” is represented in its various subclasses.

| Class name | Description |
|------------------------------|--|
| <code>DateOffset</code> | Generic offset class, defaults to 1 calendar day |
| <code>BDay</code> | business day (weekday) |
| <code>CDay</code> | custom business day (experimental) |
| <code>Week</code> | one week, optionally anchored on a day of the week |
| <code>WeekOfMonth</code> | the x-th day of the y-th week of each month |
| <code>LastWeekOfMonth</code> | the x-th day of the last week of each month |
| <code>MonthEnd</code> | calendar month end |
| <code>MonthBegin</code> | calendar month begin |
| <code>BMonthEnd</code> | business month end |
| <code>BMonthBegin</code> | business month begin |
| <code>CBMonthEnd</code> | custom business month end |
| <code>CBMonthBegin</code> | custom business month begin |
| <code>QuarterEnd</code> | calendar quarter end |
| <code>QuarterBegin</code> | calendar quarter begin |
| <code>BQuarterEnd</code> | business quarter end |
| <code>BQuarterBegin</code> | business quarter begin |
| <code>FY5253Quarter</code> | retail (aka 52-53 week) quarter |
| <code>YearEnd</code> | calendar year end |
| <code>YearBegin</code> | calendar year begin |
| <code>BYearEnd</code> | business year end |
| <code>BYearBegin</code> | business year begin |
| <code>FY5253</code> | retail (aka 52-53 week) year |
| <code>BusinessHour</code> | business hour |
| <code>Hour</code> | one hour |
| <code>Minute</code> | one minute |
| <code>Second</code> | one second |
| <code>Milli</code> | one millisecond |
| <code>Micro</code> | one microsecond |
| <code>Nano</code> | one nanosecond |

The basic `DateOffset` takes the same arguments as `dateutil.relativedelta`, which works like:

```
In [68]: d = datetime(2008, 8, 18, 9, 0)

In [69]: d + relativedelta(months=4, days=5)
Out[69]: datetime.datetime(2008, 12, 23, 9, 0)
```

We could have done the same thing with `DateOffset`:

```
In [70]: from pandas.tseries.offsets import *

In [71]: d + DateOffset(months=4, days=5)
Out[71]: Timestamp('2008-12-23 09:00:00')
```

The key features of a `DateOffset` object are:

- it can be added / subtracted to/from a datetime object to obtain a shifted date
- it can be multiplied by an integer (positive or negative) so that the increment will be applied multiple times
- it has `rollforward` and `rollback` methods for moving a date forward or backward to the next or previous “offset date”

Subclasses of `DateOffset` define the `apply` function which dictates custom date increment logic, such as adding business days:

```
class BDay(DateOffset):  
    """DateOffset increments between business days"""  
    def apply(self, other):  
        ...
```

```
In [72]: d - 5 * BDay()  
Out[72]: Timestamp('2008-08-11 09:00:00')
```

```
In [73]: d + BMonthEnd()  
Out[73]: Timestamp('2008-08-29 09:00:00')
```

The `rollforward` and `rollback` methods do exactly what you would expect:

```
In [74]: d  
Out[74]: datetime.datetime(2008, 8, 18, 9, 0)
```

```
In [75]: offset = BMonthEnd()
```

```
In [76]: offset.rollforward(d)  
Out[76]: Timestamp('2008-08-29 09:00:00')
```

```
In [77]: offset.rollback(d)  
Out[77]: Timestamp('2008-07-31 09:00:00')
```

It’s definitely worth exploring the `pandas.tseries.offsets` module and the various docstrings for the classes.

These operations (`apply`, `rollforward` and `rollback`) preserves time (hour, minute, etc) information by default. To reset time, use `normalize=True` keyword when creating the offset instance. If `normalize=True`, result is normalized after the function is applied.

```
In [78]: day = Day()
```

```
In [79]: day.apply(Timestamp('2014-01-01 09:00'))  
Out[79]: Timestamp('2014-01-02 09:00:00')
```

```
In [80]: day = Day(normalize=True)
```

```
In [81]: day.apply(Timestamp('2014-01-01 09:00'))  
Out[81]: Timestamp('2014-01-02 00:00:00')
```

```
In [82]: hour = Hour()
```

```
In [83]: hour.apply(Timestamp('2014-01-01 22:00'))  
Out[83]: Timestamp('2014-01-01 23:00:00')
```

```
In [84]: hour = Hour(normalize=True)
```

```
In [85]: hour.apply(Timestamp('2014-01-01 22:00'))  
Out[85]: Timestamp('2014-01-01 00:00:00')
```

```
In [86]: hour.apply(Timestamp('2014-01-01 23:00'))
Out[86]: Timestamp('2014-01-02 00:00:00')
```

20.5.1 Parametric offsets

Some of the offsets can be “parameterized” when created to result in different behaviors. For example, the `Week` offset for generating weekly data accepts a `weekday` parameter which results in the generated dates always lying on a particular day of the week:

```
In [87]: d
Out[87]: datetime.datetime(2008, 8, 18, 9, 0)
```

```
In [88]: d + Week()
Out[88]: Timestamp('2008-08-25 09:00:00')
```

```
In [89]: d + Week(weekday=4)
Out[89]: Timestamp('2008-08-22 09:00:00')
```

```
In [90]: (d + Week(weekday=4)).weekday()
Out[90]: 4
```

```
In [91]: d - Week()
Out[91]: Timestamp('2008-08-11 09:00:00')
```

`normalize` option will be effective for addition and subtraction.

```
In [92]: d + Week(normalize=True)
Out[92]: Timestamp('2008-08-25 00:00:00')
```

```
In [93]: d - Week(normalize=True)
Out[93]: Timestamp('2008-08-11 00:00:00')
```

Another example is parameterizing `YearEnd` with the specific ending month:

```
In [94]: d + YearEnd()
Out[94]: Timestamp('2008-12-31 09:00:00')
```

```
In [95]: d + YearEnd(month=6)
Out[95]: Timestamp('2009-06-30 09:00:00')
```

20.5.2 Custom Business Days (Experimental)

The `CDay` or `CustomBusinessDay` class provides a parametric `BusinessDay` class which can be used to create customized business day calendars which account for local holidays and local weekend conventions.

```
In [96]: from pandas.tseries.offsets import CustomBusinessDay
```

```
# As an interesting example, let's look at Egypt where
# a Friday-Saturday weekend is observed.
```

```
In [97]: weekmask_egypt = 'Sun Mon Tue Wed Thu'
```

```
# They also observe International Workers' Day so let's
# add that for a couple of years
```

```
In [98]: holidays = ['2012-05-01', datetime(2013, 5, 1), np.datetime64('2014-05-01')]
```

```
In [99]: bday_egypt = CustomBusinessDay(holidays=holidays, weekmask=weekmask_egypt)

In [100]: dt = datetime(2013, 4, 30)

In [101]: dt + 2 * bday_egypt
Out[101]: Timestamp('2013-05-05 00:00:00')

In [102]: dts = date_range(dt, periods=5, freq=bday_egypt)

In [103]: Series(dts.weekday, dts).map(Series('Mon Tue Wed Thu Fri Sat Sun'.split()))
Out[103]:
2013-04-30    Tue
2013-05-02    Thu
2013-05-05    Sun
2013-05-06    Mon
2013-05-07    Tue
Freq: C, dtype: object
```

As of v0.14 holiday calendars can be used to provide the list of holidays. See the [holiday calendar](#) section for more information.

```
In [104]: from pandas.tseries.holiday import USFederalHolidayCalendar

In [105]: bday_us = CustomBusinessDay(calendar=USFederalHolidayCalendar())

# Friday before MLK Day
In [106]: dt = datetime(2014, 1, 17)

# Tuesday after MLK Day (Monday is skipped because it's a holiday)
In [107]: dt + bday_us
Out[107]: Timestamp('2014-01-21 00:00:00')
```

Monthly offsets that respect a certain holiday calendar can be defined in the usual way.

```
In [108]: from pandas.tseries.offsets import CustomBusinessMonthBegin

In [109]: bmth_us = CustomBusinessMonthBegin(calendar=USFederalHolidayCalendar())

# Skip new years
In [110]: dt = datetime(2013, 12, 17)

In [111]: dt + bmth_us
Out[111]: Timestamp('2014-01-02 00:00:00')

# Define date index with custom offset
In [112]: from pandas import DatetimeIndex

In [113]: DatetimeIndex(start='20100101', end='20120101', freq=bmth_us)
Out[113]:
DatetimeIndex(['2010-01-04', '2010-02-01', '2010-03-01', '2010-04-01',
                '2010-05-03', '2010-06-01', '2010-07-01', '2010-08-02',
                '2010-09-01', '2010-10-01', '2010-11-01', '2010-12-01',
                '2011-01-03', '2011-02-01', '2011-03-01', '2011-04-01',
                '2011-05-02', '2011-06-01', '2011-07-01', '2011-08-01',
                '2011-09-01', '2011-10-03', '2011-11-01', '2011-12-01'],
              dtype='datetime64[ns]', freq='CBMS', tz=None)
```

Note: The frequency string ‘C’ is used to indicate that a CustomBusinessDay DateOffset is used, it is important to note that since CustomBusinessDay is a parameterised type, instances of CustomBusinessDay may differ and this is

not detectable from the 'C' frequency string. The user therefore needs to ensure that the 'C' frequency string is used consistently within the user's application.

Note: This uses the `numpy.busdaycalendar` API introduced in Numpy 1.7 and therefore requires Numpy 1.7.0 or newer.

Warning: There are known problems with the timezone handling in Numpy 1.7 and users should therefore use this **experimental(!)** feature with caution and at their own risk.
To the extent that the `datetime64` and `busdaycalendar` APIs in Numpy have to change to fix the timezone issues, the behaviour of the `CustomBusinessDay` class may have to change in future versions.

20.5.3 Business Hour

The `BusinessHour` class provides a business hour representation on `BusinessDay`, allowing to use specific start and end times.

By default, `BusinessHour` uses 9:00 - 17:00 as business hours. Adding `BusinessHour` will increment `Timestamp` by hourly. If target `Timestamp` is out of business hours, move to the next business hour then increment it. If the result exceeds the business hours end, remaining is added to the next business day.

```
In [114]: bh = BusinessHour()

In [115]: bh
Out[115]: <BusinessHour: BH=09:00-17:00>

# 2014-08-01 is Friday
In [116]: Timestamp('2014-08-01 10:00').weekday()
Out[116]: 4

In [117]: Timestamp('2014-08-01 10:00') + bh
Out[117]: Timestamp('2014-08-01 11:00:00')

# Below example is the same as Timestamp('2014-08-01 09:00') + bh
In [118]: Timestamp('2014-08-01 08:00') + bh
Out[118]: Timestamp('2014-08-01 10:00:00')

# If the results is on the end time, move to the next business day
In [119]: Timestamp('2014-08-01 16:00') + bh
Out[119]: Timestamp('2014-08-04 09:00:00')

# Remainings are added to the next day
In [120]: Timestamp('2014-08-01 16:30') + bh
Out[120]: Timestamp('2014-08-04 09:30:00')

# Adding 2 business hours
In [121]: Timestamp('2014-08-01 10:00') + BusinessHour(2)
Out[121]: Timestamp('2014-08-01 12:00:00')

# Subtracting 3 business hours
In [122]: Timestamp('2014-08-01 10:00') + BusinessHour(-3)
Out[122]: Timestamp('2014-07-31 15:00:00')
```

Also, you can specify start and end time by keywords. Argument must be `str` which has `hour:minute` representation or `datetime.time` instance. Specifying seconds, microseconds and nanoseconds as business hour results in `ValueError`.

```
In [123]: bh = BusinessHour(start='11:00', end=time(20, 0))
```

```
In [124]: bh
```

```
Out[124]: <BusinessHour: BH=11:00-20:00>
```

```
In [125]: Timestamp('2014-08-01 13:00') + bh
```

```
Out[125]: Timestamp('2014-08-01 14:00:00')
```

```
In [126]: Timestamp('2014-08-01 09:00') + bh
```

```
Out[126]: Timestamp('2014-08-01 12:00:00')
```

```
In [127]: Timestamp('2014-08-01 18:00') + bh
```

```
Out[127]: Timestamp('2014-08-01 19:00:00')
```

Passing start time later than end represents midnight business hour. In this case, business hour exceeds midnight and overlap to the next day. Valid business hours are distinguished by whether it started from valid `BusinessDay`.

```
In [128]: bh = BusinessHour(start='17:00', end='09:00')
```

```
In [129]: bh
```

```
Out[129]: <BusinessHour: BH=17:00-09:00>
```

```
In [130]: Timestamp('2014-08-01 17:00') + bh
```

```
Out[130]: Timestamp('2014-08-01 18:00:00')
```

```
In [131]: Timestamp('2014-08-01 23:00') + bh
```

```
Out[131]: Timestamp('2014-08-02 00:00:00')
```

```
# Although 2014-08-02 is Saturday,
```

```
# it is valid because it starts from 08-01 (Friday).
```

```
In [132]: Timestamp('2014-08-02 04:00') + bh
```

```
Out[132]: Timestamp('2014-08-02 05:00:00')
```

```
# Although 2014-08-04 is Monday,
```

```
# it is out of business hours because it starts from 08-03 (Sunday).
```

```
In [133]: Timestamp('2014-08-04 04:00') + bh
```

```
Out[133]: Timestamp('2014-08-04 18:00:00')
```

Applying `BusinessHour.rollforward` and `rollback` to out of business hours results in the next business hour start or previous day's end. Different from other offsets, `BusinessHour.rollforward` may output different results from apply by definition.

This is because one day's business hour end is equal to next day's business hour start. For example, under the default business hours (9:00 - 17:00), there is no gap (0 minutes) between 2014-08-01 17:00 and 2014-08-04 09:00.

```
# This adjusts a Timestamp to business hour edge
```

```
In [134]: BusinessHour().rollback(Timestamp('2014-08-02 15:00'))
```

```
Out[134]: Timestamp('2014-08-01 17:00:00')
```

```
In [135]: BusinessHour().rollforward(Timestamp('2014-08-02 15:00'))
```

```
Out[135]: Timestamp('2014-08-04 09:00:00')
```

```
# It is the same as BusinessHour().apply(Timestamp('2014-08-01 17:00')).
```

```
# And it is the same as BusinessHour().apply(Timestamp('2014-08-04 09:00'))
```

```
In [136]: BusinessHour().apply(Timestamp('2014-08-02 15:00'))
```

```
Out[136]: Timestamp('2014-08-04 10:00:00')
```

```
# BusinessDay results (for reference)
```

```

In [137]: BusinessHour().rollforward(Timestamp('2014-08-02'))
Out[137]: Timestamp('2014-08-04 09:00:00')

# It is the same as BusinessDay().apply(Timestamp('2014-08-01'))
# The result is the same as rollforward because BusinessDay never overlap.
In [138]: BusinessHour().apply(Timestamp('2014-08-02'))
Out[138]: Timestamp('2014-08-04 10:00:00')

```

20.5.4 Offset Aliases

A number of string aliases are given to useful common time series frequencies. We will refer to these aliases as *offset aliases* (referred to as *time rules* prior to v0.8.0).

| Alias | Description |
|-------|--|
| B | business day frequency |
| C | custom business day frequency (experimental) |
| D | calendar day frequency |
| W | weekly frequency |
| M | month end frequency |
| BM | business month end frequency |
| CBM | custom business month end frequency |
| MS | month start frequency |
| BMS | business month start frequency |
| CBMS | custom business month start frequency |
| Q | quarter end frequency |
| BQ | business quarter end frequency |
| QS | quarter start frequency |
| BQS | business quarter start frequency |
| A | year end frequency |
| BA | business year end frequency |
| AS | year start frequency |
| BAS | business year start frequency |
| BH | business hour frequency |
| H | hourly frequency |
| T | minutely frequency |
| S | secondly frequency |
| L | milliseconds |
| U | microseconds |
| N | nanoseconds |

20.5.5 Combining Aliases

As we have seen previously, the alias and the offset instance are fungible in most functions:

```

In [139]: date_range(start, periods=5, freq='B')
Out[139]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',
               '2011-01-07'],
              dtype='datetime64[ns]', freq='B', tz=None)

In [140]: date_range(start, periods=5, freq=BDay())
Out[140]:
DatetimeIndex(['2011-01-03', '2011-01-04', '2011-01-05', '2011-01-06',

```

```
'2011-01-07'],  
dtype='datetime64[ns]', freq='B', tz=None)
```

You can combine together day and intraday offsets:

```
In [141]: date_range(start, periods=10, freq='2h20min')  
Out[141]:  
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-01 02:20:00',  
              '2011-01-01 04:40:00', '2011-01-01 07:00:00',  
              '2011-01-01 09:20:00', '2011-01-01 11:40:00',  
              '2011-01-01 14:00:00', '2011-01-01 16:20:00',  
              '2011-01-01 18:40:00', '2011-01-01 21:00:00'],  
              dtype='datetime64[ns]', freq='140T', tz=None)  
  
In [142]: date_range(start, periods=10, freq='1D10U')  
Out[142]:  
DatetimeIndex(['2011-01-01 00:00:00', '2011-01-02 00:00:00.000010',  
              '2011-01-03 00:00:00.000020', '2011-01-04 00:00:00.000030',  
              '2011-01-05 00:00:00.000040', '2011-01-06 00:00:00.000050',  
              '2011-01-07 00:00:00.000060', '2011-01-08 00:00:00.000070',  
              '2011-01-09 00:00:00.000080', '2011-01-10 00:00:00.000090'],  
              dtype='datetime64[ns]', freq='86400000010U', tz=None)
```

20.5.6 Anchored Offsets

For some frequencies you can specify an anchoring suffix:

| Alias | Description |
|-------------|---|
| W-SUN | weekly frequency (sundays). Same as 'W' |
| W-MON | weekly frequency (mondays) |
| W-TUE | weekly frequency (tuesdays) |
| W-WED | weekly frequency (wednesdays) |
| W-THU | weekly frequency (thursdays) |
| W-FRI | weekly frequency (fridays) |
| W-SAT | weekly frequency (saturdays) |
| (B)Q(S)-DEC | quarterly frequency, year ends in December. Same as 'Q' |
| (B)Q(S)-JAN | quarterly frequency, year ends in January |
| (B)Q(S)-FEB | quarterly frequency, year ends in February |
| (B)Q(S)-MAR | quarterly frequency, year ends in March |
| (B)Q(S)-APR | quarterly frequency, year ends in April |
| (B)Q(S)-MAY | quarterly frequency, year ends in May |
| (B)Q(S)-JUN | quarterly frequency, year ends in June |
| (B)Q(S)-JUL | quarterly frequency, year ends in July |
| (B)Q(S)-AUG | quarterly frequency, year ends in August |
| (B)Q(S)-SEP | quarterly frequency, year ends in September |
| (B)Q(S)-OCT | quarterly frequency, year ends in October |
| (B)Q(S)-NOV | quarterly frequency, year ends in November |
| (B)A(S)-DEC | annual frequency, anchored end of December. Same as 'A' |
| (B)A(S)-JAN | annual frequency, anchored end of January |
| (B)A(S)-FEB | annual frequency, anchored end of February |
| (B)A(S)-MAR | annual frequency, anchored end of March |
| (B)A(S)-APR | annual frequency, anchored end of April |
| (B)A(S)-MAY | annual frequency, anchored end of May |
| (B)A(S)-JUN | annual frequency, anchored end of June |

Continued on next page

Table 20.1 – continued from previous page

| Alias | Description |
|-------------|---|
| (B)A(S)-JUL | annual frequency, anchored end of July |
| (B)A(S)-AUG | annual frequency, anchored end of August |
| (B)A(S)-SEP | annual frequency, anchored end of September |
| (B)A(S)-OCT | annual frequency, anchored end of October |
| (B)A(S)-NOV | annual frequency, anchored end of November |

These can be used as arguments to `date_range`, `bdate_range`, constructors for `DatetimeIndex`, as well as various other timeseries-related functions in pandas.

20.5.7 Legacy Aliases

Note that prior to v0.8.0, time rules had a slightly different look. pandas will continue to support the legacy time rules for the time being but it is strongly recommended that you switch to using the new offset aliases.

| Legacy Time Rule | Offset Alias |
|------------------|--------------|
| WEEKDAY | B |
| EOM | BM |
| W@MON | W-MON |
| W@TUE | W-TUE |
| W@WED | W-WED |
| W@THU | W-THU |
| W@FRI | W-FRI |
| W@SAT | W-SAT |
| W@SUN | W-SUN |
| Q@JAN | BQ-JAN |
| Q@FEB | BQ-FEB |
| Q@MAR | BQ-MAR |
| A@JAN | BA-JAN |
| A@FEB | BA-FEB |
| A@MAR | BA-MAR |
| A@APR | BA-APR |
| A@MAY | BA-MAY |
| A@JUN | BA-JUN |
| A@JUL | BA-JUL |
| A@AUG | BA-AUG |
| A@SEP | BA-SEP |
| A@OCT | BA-OCT |
| A@NOV | BA-NOV |
| A@DEC | BA-DEC |
| min | T |
| ms | L |
| us | U |

As you can see, legacy quarterly and annual frequencies are business quarters and business year ends. Please also note the legacy time rule for milliseconds `ms` versus the new offset alias for month start `MS`. This means that offset alias parsing is case sensitive.

20.5.8 Holidays / Holiday Calendars

Holidays and calendars provide a simple way to define holiday rules to be used with `CustomBusinessDay` or in other analysis that requires a predefined set of holidays. The `AbstractHolidayCalendar` class provides all

the necessary methods to return a list of holidays and only rules need to be defined in a specific holiday calendar class. Further, `start_date` and `end_date` class attributes determine over what date range holidays are generated. These should be overwritten on the `AbstractHolidayCalendar` class to have the range apply to all calendar subclasses. `USFederalHolidayCalendar` is the only calendar that exists and primarily serves as an example for developing other calendars.

For holidays that occur on fixed dates (e.g., US Memorial Day or July 4th) an observance rule determines when that holiday is observed if it falls on a weekend or some other non-observed day. Defined observance rules are:

| Rule | Description |
|-------------------------------------|--|
| <code>nearest_workday</code> | move Saturday to Friday and Sunday to Monday |
| <code>sunday_to_monday</code> | move Sunday to following Monday |
| <code>next_monday_or_tuesday</code> | move Saturday to Monday and Sunday/Monday to Tuesday |
| <code>previous_friday</code> | move Saturday and Sunday to previous Friday |
| <code>next_monday</code> | move Saturday and Sunday to following Monday |

An example of how holidays and holiday calendars are defined:

```
In [143]: from pandas.tseries.holiday import Holiday, USMemorialDay,\n.....:      AbstractHolidayCalendar, nearest_workday, MO\n.....:
```

```
In [144]: class ExampleCalendar(AbstractHolidayCalendar):\n.....:     rules = [\n.....:         USMemorialDay,\n.....:         Holiday('July 4th', month=7, day=4, observance=nearest_workday),\n.....:         Holiday('Columbus Day', month=10, day=1,\n.....:             offset=DateOffset(weekday=MO(2))), #same as 2*Week(weekday=2)\n.....:     ]\n.....:
```

```
In [145]: cal = ExampleCalendar()
```

```
In [146]: cal.holidays(datetime(2012, 1, 1), datetime(2012, 12, 31))
```

```
Out[146]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype='datetime64[ns]', freq=None)
```

Using this calendar, creating an index or doing offset arithmetic skips weekends and holidays (i.e., Memorial Day/July 4th).

```
In [147]: DatetimeIndex(start='7/1/2012', end='7/10/2012',\n.....:     freq=CDay(calendar=cal)).to_pydatetime()\n.....:
```

```
Out[147]:\narray([datetime.datetime(2012, 7, 2, 0, 0),\n      datetime.datetime(2012, 7, 3, 0, 0),\n      datetime.datetime(2012, 7, 5, 0, 0),\n      datetime.datetime(2012, 7, 6, 0, 0),\n      datetime.datetime(2012, 7, 9, 0, 0),\n      datetime.datetime(2012, 7, 10, 0, 0)], dtype=object)
```

```
In [148]: offset = CustomBusinessDay(calendar=cal)
```

```
In [149]: datetime(2012, 5, 25) + offset\nOut[149]: Timestamp('2012-05-29 00:00:00')
```

```
In [150]: datetime(2012, 7, 3) + offset\nOut[150]: Timestamp('2012-07-05 00:00:00')
```

```
In [151]: datetime(2012, 7, 3) + 2 * offset
```

```
Out [151]: Timestamp('2012-07-06 00:00:00')
```

```
In [152]: datetime(2012, 7, 6) + offset
Out [152]: Timestamp('2012-07-09 00:00:00')
```

Ranges are defined by the `start_date` and `end_date` class attributes of `AbstractHolidayCalendar`. The defaults are below.

```
In [153]: AbstractHolidayCalendar.start_date
Out [153]: Timestamp('1970-01-01 00:00:00')
```

```
In [154]: AbstractHolidayCalendar.end_date
Out [154]: Timestamp('2030-12-31 00:00:00')
```

These dates can be overwritten by setting the attributes as `datetime`/`Timestamp`/`string`.

```
In [155]: AbstractHolidayCalendar.start_date = datetime(2012, 1, 1)
```

```
In [156]: AbstractHolidayCalendar.end_date = datetime(2012, 12, 31)
```

```
In [157]: cal.holidays()
Out [157]: DatetimeIndex(['2012-05-28', '2012-07-04', '2012-10-08'], dtype='datetime64[ns]', freq=None)
```

Every calendar class is accessible by name using the `get_calendar` function which returns a holiday class instance. Any imported calendar class will automatically be available by this function. Also, `HolidayCalendarFactory` provides an easy interface to create calendars that are combinations of calendars or calendars with additional rules.

```
In [158]: from pandas.tseries.holiday import get_calendar, HolidayCalendarFactory, \
.....:      USLaborDay
.....:
```

```
In [159]: cal = get_calendar('ExampleCalendar')
```

```
In [160]: cal.rules
Out [160]:
[Holiday: MemorialDay (month=5, day=24, offset=<DateOffset: kwds={'weekday': MO(+1)}>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at 0x9c8c2924>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: kwds={'weekday': MO(+2)}>)]
```

```
In [161]: new_cal = HolidayCalendarFactory('NewExampleCalendar', cal, USLaborDay)
```

```
In [162]: new_cal.rules
Out [162]:
[Holiday: Labor Day (month=9, day=1, offset=<DateOffset: kwds={'weekday': MO(+1)}>),
 Holiday: Columbus Day (month=10, day=1, offset=<DateOffset: kwds={'weekday': MO(+2)}>),
 Holiday: July 4th (month=7, day=4, observance=<function nearest_workday at 0x9c8c2924>),
 Holiday: MemorialDay (month=5, day=24, offset=<DateOffset: kwds={'weekday': MO(+1)}>)]
```

20.6 Time series-related instance methods

20.6.1 Shifting / lagging

One may want to *shift* or *lag* the values in a `TimeSeries` back and forward in time. The method for this is `shift`, which is available on all of the pandas objects.

```
In [163]: ts = ts[:5]
```

```
In [164]: ts.shift(1)
```

```
Out[164]:
2011-01-31      NaN
2011-02-28    -1.281247
2011-03-31    -0.727707
2011-04-29    -0.121306
2011-05-31    -0.097883
Freq: BM, dtype: float64
```

The shift method accepts an freq argument which can accept a DateOffset class or other timedelta-like object or also a *offset alias*:

```
In [165]: ts.shift(5, freq=datetools.bday)
```

```
Out[165]:
2011-02-07    -1.281247
2011-03-07    -0.727707
2011-04-07    -0.121306
2011-05-06    -0.097883
2011-06-07     0.695775
dtype: float64
```

```
In [166]: ts.shift(5, freq='BM')
```

```
Out[166]:
2011-06-30    -1.281247
2011-07-29    -0.727707
2011-08-31    -0.121306
2011-09-30    -0.097883
2011-10-31     0.695775
Freq: BM, dtype: float64
```

Rather than changing the alignment of the data and the index, DataFrame and TimeSeries objects also have a tshift convenience method that changes all the dates in the index by a specified number of offsets:

```
In [167]: ts.tshift(5, freq='D')
```

```
Out[167]:
2011-02-05    -1.281247
2011-03-05    -0.727707
2011-04-05    -0.121306
2011-05-04    -0.097883
2011-06-05     0.695775
dtype: float64
```

Note that with tshift, the leading entry is no longer NaN because the data is not being realigned.

20.6.2 Frequency conversion

The primary function for changing frequencies is the asfreq function. For a DatetimeIndex, this is basically just a thin, but convenient wrapper around reindex which generates a date_range and calls reindex.

```
In [168]: dr = date_range('1/1/2010', periods=3, freq=3 * datetools.bday)
```

```
In [169]: ts = Series(randn(3), index=dr)
```

```
In [170]: ts
```

```
Out[170]:
2010-01-01    -0.659574
```

```
2010-01-06    1.494522
2010-01-11   -0.778425
Freq: 3B, dtype: float64
```

```
In [171]: ts.asfreq(BDay())
```

```
Out [171]:
2010-01-01   -0.659574
2010-01-04         NaN
2010-01-05         NaN
2010-01-06    1.494522
2010-01-07         NaN
2010-01-08         NaN
2010-01-11   -0.778425
Freq: B, dtype: float64
```

`asfreq` provides a further convenience so you can specify an interpolation method for any gaps that may appear after the frequency conversion

```
In [172]: ts.asfreq(BDay(), method='pad')
```

```
Out [172]:
2010-01-01   -0.659574
2010-01-04   -0.659574
2010-01-05   -0.659574
2010-01-06    1.494522
2010-01-07    1.494522
2010-01-08    1.494522
2010-01-11   -0.778425
Freq: B, dtype: float64
```

20.6.3 Filling forward / backward

Related to `asfreq` and `reindex` is the `fillna` function documented in the [missing data section](#).

20.6.4 Converting to Python datetimes

`DatetimeIndex` can be converted to an array of Python native `datetime.datetime` objects using the `to_pydatetime` method.

20.7 Up- and downsampling

With 0.8, pandas introduces simple, powerful, and efficient functionality for performing resampling operations during frequency conversion (e.g., converting secondly data into 5-minutely data). This is extremely common in, but not limited to, financial applications.

See some [cookbook examples](#) for some advanced strategies

```
In [173]: rng = date_range('1/1/2012', periods=100, freq='S')
```

```
In [174]: ts = Series(randint(0, 500, len(rng)), index=rng)
```

```
In [175]: ts.resample('5Min', how='sum')
```

```
Out [175]:
2012-01-01    25103
Freq: 5T, dtype: int32
```

The `resample` function is very flexible and allows you to specify many different parameters to control the frequency conversion and resampling operation.

The `how` parameter can be a function name or numpy array function that takes an array and produces aggregated values:

```
In [176]: ts.resample('5Min') # default is mean
Out[176]:
2012-01-01    251.03
Freq: 5T, dtype: float64
```

```
In [177]: ts.resample('5Min', how='ohlc')
Out[177]:
           open  high  low  close
2012-01-01   308   460    9    205
```

```
In [178]: ts.resample('5Min', how=np.max)
Out[178]:
2012-01-01    460
Freq: 5T, dtype: int32
```

Any function available via *dispatching* can be given to the `how` parameter by name, including `sum`, `mean`, `std`, `sem`, `max`, `min`, `median`, `first`, `last`, `ohlc`.

For downsampling, `closed` can be set to 'left' or 'right' to specify which end of the interval is closed:

```
In [179]: ts.resample('5Min', closed='right')
Out[179]:
2011-12-31 23:55:00    308.000000
2012-01-01 00:00:00    250.454545
Freq: 5T, dtype: float64
```

```
In [180]: ts.resample('5Min', closed='left')
Out[180]:
2012-01-01    251.03
Freq: 5T, dtype: float64
```

For upsampling, the `fill_method` and `limit` parameters can be specified to interpolate over the gaps that are created:

```
# from secondly to every 250 milliseconds
```

```
In [181]: ts[:2].resample('250L')
Out[181]:
2012-01-01 00:00:00    308
2012-01-01 00:00:00.250000    NaN
2012-01-01 00:00:00.500000    NaN
2012-01-01 00:00:00.750000    NaN
2012-01-01 00:00:01    204
Freq: 250L, dtype: float64
```

```
In [182]: ts[:2].resample('250L', fill_method='pad')
Out[182]:
2012-01-01 00:00:00    308
2012-01-01 00:00:00.250000    308
2012-01-01 00:00:00.500000    308
2012-01-01 00:00:00.750000    308
2012-01-01 00:00:01    204
Freq: 250L, dtype: int32
```

```
In [183]: ts[:2].resample('250L', fill_method='pad', limit=2)
```

```
Out[183]:
2012-01-01 00:00:00      308
2012-01-01 00:00:00.250000    308
2012-01-01 00:00:00.500000    308
2012-01-01 00:00:00.750000   NaN
2012-01-01 00:00:01      204
Freq: 250L, dtype: float64
```

Parameters like `label` and `loffset` are used to manipulate the resulting labels. `label` specifies whether the result is labeled with the beginning or the end of the interval. `loffset` performs a time adjustment on the output labels.

```
In [184]: ts.resample('5Min') # by default label='right'
Out[184]:
2012-01-01      251.03
Freq: 5T, dtype: float64
```

```
In [185]: ts.resample('5Min', label='left')
Out[185]:
2012-01-01      251.03
Freq: 5T, dtype: float64
```

```
In [186]: ts.resample('5Min', label='left', loffset='1s')
Out[186]:
2012-01-01 00:00:01      251.03
dtype: float64
```

The `axis` parameter can be set to 0 or 1 and allows you to resample the specified axis for a `DataFrame`.

`kind` can be set to 'timestamp' or 'period' to convert the resulting index to/from time-stamp and time-span representations. By default `resample` retains the input representation.

`convention` can be set to 'start' or 'end' when resampling period data (detail below). It specifies how low frequency periods are converted to higher frequency periods.

Note that 0.8 marks a watershed in the timeseries functionality in pandas. In previous versions, resampling had to be done using a combination of `date_range`, `groupby` with `asof`, and then calling an aggregation function on the grouped object. This was not nearly as convenient or performant as the new pandas timeseries API.

20.8 Time Span Representation

Regular intervals of time are represented by `Period` objects in pandas while sequences of `Period` objects are collected in a `PeriodIndex`, which can be created with the convenience function `period_range`.

20.8.1 Period

A `Period` represents a span of time (e.g., a day, a month, a quarter, etc). It can be created using a frequency alias:

```
In [187]: Period('2012', freq='A-DEC')
Out[187]: Period('2012', 'A-DEC')

In [188]: Period('2012-1-1', freq='D')
Out[188]: Period('2012-01-01', 'D')

In [189]: Period('2012-1-1 19:00', freq='H')
Out[189]: Period('2012-01-01 19:00', 'H')
```

Unlike time stamped data, pandas does not support frequencies at multiples of DateOffsets (e.g., '3Min') for periods. Adding and subtracting integers from periods shifts the period by its own frequency.

```
In [190]: p = Period('2012', freq='A-DEC')
```

```
In [191]: p + 1
Out[191]: Period('2013', 'A-DEC')
```

```
In [192]: p - 3
Out[192]: Period('2009', 'A-DEC')
```

If Period freq is daily or higher (D, H, T, S, L, U, N), offsets and timedelta-like can be added if the result can have the same freq. Otherwise, ValueError will be raised.

```
In [193]: p = Period('2014-07-01 09:00', freq='H')
```

```
In [194]: p + Hour(2)
Out[194]: Period('2014-07-01 11:00', 'H')
```

```
In [195]: p + timedelta(minutes=120)
Out[195]: Period('2014-07-01 11:00', 'H')
```

```
In [196]: p + np.timedelta64(7200, 's')
Out[196]: Period('2014-07-01 11:00', 'H')
```

```
In [1]: p + Minute(5)
Traceback
...
ValueError: Input has different freq from Period(freq=H)
```

If Period has other freqs, only the same offsets can be added. Otherwise, ValueError will be raised.

```
In [197]: p = Period('2014-07', freq='M')
```

```
In [198]: p + MonthEnd(3)
Out[198]: Period('2014-10', 'M')
```

```
In [1]: p + MonthBegin(3)
Traceback
...
ValueError: Input has different freq from Period(freq=M)
```

Taking the difference of Period instances with the same frequency will return the number of frequency units between them:

```
In [199]: Period('2012', freq='A-DEC') - Period('2002', freq='A-DEC')
Out[199]: 10L
```

20.8.2 PeriodIndex and period_range

Regular sequences of Period objects can be collected in a PeriodIndex, which can be constructed using the period_range convenience function:

```
In [200]: prng = period_range('1/1/2011', '1/1/2012', freq='M')
```

```
In [201]: prng
Out[201]:
```

```
PeriodIndex(['2011-01', '2011-02', '2011-03', '2011-04', '2011-05', '2011-06',
            '2011-07', '2011-08', '2011-09', '2011-10', '2011-11', '2011-12',
            '2012-01'],
            dtype='int64', freq='M')
```

The PeriodIndex constructor can also be used directly:

```
In [202]: PeriodIndex(['2011-1', '2011-2', '2011-3'], freq='M')
Out[202]: PeriodIndex(['2011-01', '2011-02', '2011-03'], dtype='int64', freq='M')
```

Just like DatetimeIndex, a PeriodIndex can also be used to index pandas objects:

```
In [203]: ps = Series(randn(len(prng)), prng)
```

```
In [204]: ps
Out[204]:
2011-01    -0.253355
2011-02    -1.426908
2011-03     1.548971
2011-04    -0.088718
2011-05    -1.771348
2011-06    -0.989328
2011-07    -1.584789
2011-08    -0.288786
2011-09    -2.029806
2011-10    -0.761200
2011-11    -1.603608
2011-12     1.756171
2012-01     0.256502
Freq: M, dtype: float64
```

PeriodIndex supports addition and subtraction with the same rule as Period.

```
In [205]: idx = period_range('2014-07-01 09:00', periods=5, freq='H')
```

```
In [206]: idx
Out[206]:
PeriodIndex(['2014-07-01 09:00', '2014-07-01 10:00', '2014-07-01 11:00',
            '2014-07-01 12:00', '2014-07-01 13:00'],
            dtype='int64', freq='H')
```

```
In [207]: idx + Hour(2)
Out[207]:
PeriodIndex(['2014-07-01 11:00', '2014-07-01 12:00', '2014-07-01 13:00',
            '2014-07-01 14:00', '2014-07-01 15:00'],
            dtype='int64', freq='H')
```

```
In [208]: idx = period_range('2014-07', periods=5, freq='M')
```

```
In [209]: idx
Out[209]: PeriodIndex(['2014-07', '2014-08', '2014-09', '2014-10', '2014-11'], dtype='int64', freq='M')
```

```
In [210]: idx + MonthEnd(3)
Out[210]: PeriodIndex(['2014-10', '2014-11', '2014-12', '2015-01', '2015-02'], dtype='int64', freq='M')
```

20.8.3 PeriodIndex Partial String Indexing

You can pass in dates and strings to Series and DataFrame with PeriodIndex, in the same manner as DatetimeIndex. For details, refer to *DatetimeIndex Partial String Indexing*.

```
In [211]: ps['2011-01']
Out[211]: -0.25335528290092818

In [212]: ps[datetime(2011, 12, 25):]
Out[212]:
2011-12    1.756171
2012-01    0.256502
Freq: M, dtype: float64

In [213]: ps['10/31/2011':'12/31/2011']
Out[213]:
2011-10   -0.761200
2011-11   -1.603608
2011-12    1.756171
Freq: M, dtype: float64
```

Passing a string representing a lower frequency than PeriodIndex returns partial sliced data.

```
In [214]: ps['2011']
Out[214]:
2011-01   -0.253355
2011-02   -1.426908
2011-03    1.548971
2011-04   -0.088718
2011-05   -1.771348
2011-06   -0.989328
2011-07   -1.584789
2011-08   -0.288786
2011-09   -2.029806
2011-10   -0.761200
2011-11   -1.603608
2011-12    1.756171
Freq: M, dtype: float64

In [215]: dfp = DataFrame(randn(600,1), columns=['A'],
.....:                    index=period_range('2013-01-01 9:00', periods=600, freq='T'))
.....:

In [216]: dfp
Out[216]:
              A
2013-01-01 09:00  0.020601
2013-01-01 09:01 -0.411719
2013-01-01 09:02  2.079413
2013-01-01 09:03 -1.077911
2013-01-01 09:04  0.099258
2013-01-01 09:05 -0.089851
2013-01-01 09:06  0.711329
...
2013-01-01 18:53 -1.340038
2013-01-01 18:54  1.315461
2013-01-01 18:55  2.396188
2013-01-01 18:56 -0.501527
2013-01-01 18:57 -3.171938
```

```
2013-01-01 18:58    0.142019
2013-01-01 18:59    0.606998
```

```
[600 rows x 1 columns]
```

```
In [217]: dfp['2013-01-01 10H']
Out[217]:
```

```

A
2013-01-01 10:00 -0.745396
2013-01-01 10:01    0.141880
2013-01-01 10:02 -1.077754
2013-01-01 10:03 -1.301174
2013-01-01 10:04 -0.269628
2013-01-01 10:05 -0.456347
2013-01-01 10:06    0.157766
...
2013-01-01 10:53    0.168057
2013-01-01 10:54 -0.214306
2013-01-01 10:55 -0.069739
2013-01-01 10:56 -1.511809
2013-01-01 10:57    0.307021
2013-01-01 10:58    1.449776
2013-01-01 10:59    0.782537
```

```
[60 rows x 1 columns]
```

As with `DatetimeIndex`, the endpoints will be included in the result. The example below slices data starting from 10:00 to 11:59.

```
In [218]: dfp['2013-01-01 10H':'2013-01-01 11H']
Out[218]:
```

```

A
2013-01-01 10:00 -0.745396
2013-01-01 10:01    0.141880
2013-01-01 10:02 -1.077754
2013-01-01 10:03 -1.301174
2013-01-01 10:04 -0.269628
2013-01-01 10:05 -0.456347
2013-01-01 10:06    0.157766
...
2013-01-01 11:53 -0.064395
2013-01-01 11:54    0.350193
2013-01-01 11:55    1.336433
2013-01-01 11:56 -0.438701
2013-01-01 11:57 -0.915841
2013-01-01 11:58    0.294215
2013-01-01 11:59    0.040959
```

```
[120 rows x 1 columns]
```

20.8.4 Frequency Conversion and Resampling with `PeriodIndex`

The frequency of `Period` and `PeriodIndex` can be converted via the `asfreq` method. Let's start with the fiscal year 2011, ending in December:

```
In [219]: p = Period('2011', freq='A-DEC')
```

```
In [220]: p
Out[220]: Period('2011', 'A-DEC')
```

We can convert it to a monthly frequency. Using the `how` parameter, we can specify whether to return the starting or ending month:

```
In [221]: p.asfreq('M', how='start')
Out[221]: Period('2011-01', 'M')
```

```
In [222]: p.asfreq('M', how='end')
Out[222]: Period('2011-12', 'M')
```

The shorthands `'s'` and `'e'` are provided for convenience:

```
In [223]: p.asfreq('M', 's')
Out[223]: Period('2011-01', 'M')
```

```
In [224]: p.asfreq('M', 'e')
Out[224]: Period('2011-12', 'M')
```

Converting to a “super-period” (e.g., annual frequency is a super-period of quarterly frequency) automatically returns the super-period that includes the input period:

```
In [225]: p = Period('2011-12', freq='M')

In [226]: p.asfreq('A-NOV')
Out[226]: Period('2012', 'A-NOV')
```

Note that since we converted to an annual frequency that ends the year in November, the monthly period of December 2011 is actually in the 2012 A-NOV period. Period conversions with anchored frequencies are particularly useful for working with various quarterly data common to economics, business, and other fields. Many organizations define quarters relative to the month in which their fiscal year starts and ends. Thus, first quarter of 2011 could start in 2010 or a few months into 2011. Via anchored frequencies, pandas works for all quarterly frequencies Q-JAN through Q-DEC.

Q-DEC define regular calendar quarters:

```
In [227]: p = Period('2012Q1', freq='Q-DEC')

In [228]: p.asfreq('D', 's')
Out[228]: Period('2012-01-01', 'D')

In [229]: p.asfreq('D', 'e')
Out[229]: Period('2012-03-31', 'D')
```

Q-MAR defines fiscal year end in March:

```
In [230]: p = Period('2011Q4', freq='Q-MAR')

In [231]: p.asfreq('D', 's')
Out[231]: Period('2011-01-01', 'D')

In [232]: p.asfreq('D', 'e')
Out[232]: Period('2011-03-31', 'D')
```

20.9 Converting between Representations

Timestamped data can be converted to PeriodIndex-ed data using `to_period` and vice-versa using `to_timestamp`:

```
In [233]: rng = date_range('1/1/2012', periods=5, freq='M')
```

```
In [234]: ts = Series(randn(len(rng)), index=rng)
```

```
In [235]: ts
```

```
Out[235]:
2012-01-31    -0.016142
2012-02-29     0.865782
2012-03-31     0.246439
2012-04-30    -1.199736
2012-05-31     0.407620
Freq: M, dtype: float64
```

```
In [236]: ps = ts.to_period()
```

```
In [237]: ps
```

```
Out[237]:
2012-01    -0.016142
2012-02     0.865782
2012-03     0.246439
2012-04    -1.199736
2012-05     0.407620
Freq: M, dtype: float64
```

```
In [238]: ps.to_timestamp()
```

```
Out[238]:
2012-01-01    -0.016142
2012-02-01     0.865782
2012-03-01     0.246439
2012-04-01    -1.199736
2012-05-01     0.407620
Freq: MS, dtype: float64
```

Remember that 's' and 'e' can be used to return the timestamps at the start or end of the period:

```
In [239]: ps.to_timestamp('D', how='s')
```

```
Out[239]:
2012-01-01    -0.016142
2012-02-01     0.865782
2012-03-01     0.246439
2012-04-01    -1.199736
2012-05-01     0.407620
Freq: MS, dtype: float64
```

Converting between period and timestamp enables some convenient arithmetic functions to be used. In the following example, we convert a quarterly frequency with year ending in November to 9am of the end of the month following the quarter end:

```
In [240]: prng = period_range('1990Q1', '2000Q4', freq='Q-NOV')
```

```
In [241]: ts = Series(randn(len(prng)), prng)
```

```
In [242]: ts.index = (prng.asfreq('M', 'e') + 1).asfreq('H', 's') + 9
```

```
In [243]: ts.head()
Out[243]:
1990-03-01 09:00    -2.470970
1990-06-01 09:00    -0.929915
1990-09-01 09:00     1.385889
1990-12-01 09:00    -1.830966
1991-03-01 09:00    -0.328505
Freq: H, dtype: float64
```

20.10 Representing out-of-bounds spans

If you have data that is outside of the Timestamp bounds, see *Timestamp limitations*, then you can use a `PeriodIndex` and/or `Series of Periods` to do computations.

```
In [244]: span = period_range('1215-01-01', '1381-01-01', freq='D')
```

```
In [245]: span
Out[245]:
PeriodIndex(['1215-01-01', '1215-01-02', '1215-01-03', '1215-01-04',
            '1215-01-05', '1215-01-06', '1215-01-07', '1215-01-08',
            '1215-01-09', '1215-01-10',
            ...,
            '1380-12-23', '1380-12-24', '1380-12-25', '1380-12-26',
            '1380-12-27', '1380-12-28', '1380-12-29', '1380-12-30',
            '1380-12-31', '1381-01-01'],
            dtype='int64', length=60632, freq='D')
```

To convert from a `int64` based `YYYYMMDD` representation.

```
In [246]: s = Series([20121231, 20141130, 99991231])
```

```
In [247]: s
Out[247]:
0    20121231
1    20141130
2    99991231
dtype: int64
```

```
In [248]: def conv(x):
.....:     return Period(year = x // 10000, month = x//100 % 100, day = x%100, freq='D')
.....:
```

```
In [249]: s.apply(conv)
Out[249]:
0    2012-12-31
1    2014-11-30
2    9999-12-31
dtype: object
```

```
In [250]: s.apply(conv)[2]
Out[250]: Period('9999-12-31', 'D')
```

These can easily be converted to a `PeriodIndex`

```
In [251]: span = PeriodIndex(s.apply(conv))
```

```
In [252]: span
Out[252]: PeriodIndex(['2012-12-31', '2014-11-30', '9999-12-31'], dtype='int64', freq='D')
```

20.11 Time Zone Handling

Pandas provides rich support for working with timestamps in different time zones using `pytz` and `dateutil` libraries. `dateutil` support is new in 0.14.1 and currently only supported for fixed offset and `tzfile` zones. The default library is `pytz`. Support for `dateutil` is provided for compatibility with other applications e.g. if you use `dateutil` in other python packages.

20.11.1 Working with Time Zones

By default, pandas objects are time zone unaware:

```
In [253]: rng = date_range('3/6/2012 00:00', periods=15, freq='D')
```

```
In [254]: rng.tz is None
Out[254]: True
```

To supply the time zone, you can use the `tz` keyword to `date_range` and other functions. `Dateutil` time zone strings are distinguished from `pytz` time zones by starting with `dateutil/`.

- In `pytz` you can find a list of common (and less common) time zones using `from pytz import common_timezones, all_timezones`.
- `dateutil` uses the OS timezones so there isn't a fixed list available. For common zones, the names are the same as `pytz`.

```
# pytz
In [255]: rng_pytz = date_range('3/6/2012 00:00', periods=10, freq='D',
.....:                        tz='Europe/London')
.....:

In [256]: rng_pytz.tz
Out[256]: <DstTzInfo 'Europe/London' LMT-1 day, 23:59:00 STD>

# dateutil
In [257]: rng_dateutil = date_range('3/6/2012 00:00', periods=10, freq='D',
.....:                        tz='dateutil/Europe/London')
.....:

In [258]: rng_dateutil.tz
Out[258]: tzfile('Europe/Belfast')

# dateutil - utc special case
In [259]: rng_utc = date_range('3/6/2012 00:00', periods=10, freq='D',
.....:                        tz=dateutil.tz.tzutc())
.....:

In [260]: rng_utc.tz
Out[260]: tzutc()
```

Note that the UTC timezone is a special case in `dateutil` and should be constructed explicitly as an instance of `dateutil.tz.tzutc`. You can also construct other timezones explicitly first, which gives you more control over which time zone is used:

```
# pytz
In [261]: tz_pytz = pytz.timezone('Europe/London')

In [262]: rng_pytz = date_range('3/6/2012 00:00', periods=10, freq='D',
.....:                          tz=tz_pytz)
.....:

In [263]: rng_pytz.tz == tz_pytz
Out[263]: True

# dateutil
In [264]: tz_dateutil = dateutil.tz.gettz('Europe/London')

In [265]: rng_dateutil = date_range('3/6/2012 00:00', periods=10, freq='D',
.....:                               tz=tz_dateutil)
.....:

In [266]: rng_dateutil.tz == tz_dateutil
Out[266]: True
```

Timestamps, like Python's `datetime.datetime` object can be either time zone naive or time zone aware. Naive time series and `DatetimeIndex` objects can be *localized* using `tz_localize`:

```
In [267]: ts = Series(randn(len(rng)), rng)

In [268]: ts_utc = ts.tz_localize('UTC')

In [269]: ts_utc
Out[269]:
2012-03-06 00:00:00+00:00    0.758606
2012-03-07 00:00:00+00:00    2.190827
2012-03-08 00:00:00+00:00    0.706087
2012-03-09 00:00:00+00:00    1.798831
2012-03-10 00:00:00+00:00    1.228481
2012-03-11 00:00:00+00:00   -0.179494
2012-03-12 00:00:00+00:00    0.634073
2012-03-13 00:00:00+00:00    0.262123
2012-03-14 00:00:00+00:00    1.928233
2012-03-15 00:00:00+00:00    0.322573
2012-03-16 00:00:00+00:00   -0.711113
2012-03-17 00:00:00+00:00    1.444272
2012-03-18 00:00:00+00:00   -0.352268
2012-03-19 00:00:00+00:00    0.213008
2012-03-20 00:00:00+00:00   -0.619340
Freq: D, dtype: float64
```

Again, you can explicitly construct the timezone object first. You can use the `tz_convert` method to convert pandas objects to convert tz-aware data to another time zone:

```
In [270]: ts_utc.tz_convert('US/Eastern')
Out[270]:
2012-03-05 19:00:00-05:00    0.758606
2012-03-06 19:00:00-05:00    2.190827
2012-03-07 19:00:00-05:00    0.706087
2012-03-08 19:00:00-05:00    1.798831
2012-03-09 19:00:00-05:00    1.228481
2012-03-10 19:00:00-05:00   -0.179494
2012-03-11 20:00:00-04:00    0.634073
2012-03-12 20:00:00-04:00    0.262123
```

```

2012-03-13 20:00:00-04:00    1.928233
2012-03-14 20:00:00-04:00    0.322573
2012-03-15 20:00:00-04:00   -0.711113
2012-03-16 20:00:00-04:00    1.444272
2012-03-17 20:00:00-04:00   -0.352268
2012-03-18 20:00:00-04:00    0.213008
2012-03-19 20:00:00-04:00   -0.619340
Freq: D, dtype: float64

```

Warning: Be wary of conversions between libraries. For some zones `pytz` and `dateutil` have different definitions of the zone. This is more of a problem for unusual timezones than for ‘standard’ zones like `US/Eastern`.

Warning: Be aware that a timezone definition across versions of timezone libraries may not be considered equal. This may cause problems when working with stored data that is localized using one version and operated on with a different version. See [here](#) for how to handle such a situation.

Warning: It is incorrect to pass a timezone directly into the `datetime.datetime` constructor (e.g., `datetime.datetime(2011, 1, 1, tz=timezone('US/Eastern'))`). Instead, the `datetime` needs to be localized using the `localize` method on the `timezone`.

Under the hood, all timestamps are stored in UTC. Scalar values from a `DatetimeIndex` with a time zone will have their fields (day, hour, minute) localized to the time zone. However, timestamps with the same UTC value are still considered to be equal even if they are in different time zones:

```

In [271]: rng_eastern = rng_utc.tz_convert('US/Eastern')

In [272]: rng_berlin = rng_utc.tz_convert('Europe/Berlin')

In [273]: rng_eastern[5]
Out[273]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', offset='D')

In [274]: rng_berlin[5]
Out[274]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', offset='D')

In [275]: rng_eastern[5] == rng_berlin[5]
Out[275]: True

```

Like `Series`, `DataFrame`, and `DatetimeIndex`, `Timestamps` can be converted to other time zones using `tz_convert`:

```

In [276]: rng_eastern[5]
Out[276]: Timestamp('2012-03-10 19:00:00-0500', tz='US/Eastern', offset='D')

In [277]: rng_berlin[5]
Out[277]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin', offset='D')

In [278]: rng_eastern[5].tz_convert('Europe/Berlin')
Out[278]: Timestamp('2012-03-11 01:00:00+0100', tz='Europe/Berlin')

```

Localization of `Timestamps` functions just like `DatetimeIndex` and `TimeSeries`:

```

In [279]: rng[5]
Out[279]: Timestamp('2012-03-11 00:00:00', offset='D')

In [280]: rng[5].tz_localize('Asia/Shanghai')
Out[280]: Timestamp('2012-03-11 00:00:00+0800', tz='Asia/Shanghai')

```

Operations between TimeSeries in different time zones will yield UTC TimeSeries, aligning the data on the UTC timestamps:

```
In [281]: eastern = ts_utc.tz_convert('US/Eastern')
```

```
In [282]: berlin = ts_utc.tz_convert('Europe/Berlin')
```

```
In [283]: result = eastern + berlin
```

```
In [284]: result
```

```
Out[284]:
2012-03-06 00:00:00+00:00    1.517212
2012-03-07 00:00:00+00:00    4.381654
2012-03-08 00:00:00+00:00    1.412174
2012-03-09 00:00:00+00:00    3.597662
2012-03-10 00:00:00+00:00    2.456962
2012-03-11 00:00:00+00:00   -0.358988
2012-03-12 00:00:00+00:00    1.268146
2012-03-13 00:00:00+00:00    0.524245
2012-03-14 00:00:00+00:00    3.856466
2012-03-15 00:00:00+00:00    0.645146
2012-03-16 00:00:00+00:00   -1.422226
2012-03-17 00:00:00+00:00    2.888544
2012-03-18 00:00:00+00:00   -0.704537
2012-03-19 00:00:00+00:00    0.426017
2012-03-20 00:00:00+00:00   -1.238679
Freq: D, dtype: float64
```

```
In [285]: result.index
```

```
Out[285]:
DatetimeIndex(['2012-03-06', '2012-03-07', '2012-03-08', '2012-03-09',
               '2012-03-10', '2012-03-11', '2012-03-12', '2012-03-13',
               '2012-03-14', '2012-03-15', '2012-03-16', '2012-03-17',
               '2012-03-18', '2012-03-19', '2012-03-20'],
              dtype='datetime64[ns]', freq='D', tz='UTC')
```

To remove timezone from tz-aware DatetimeIndex, use `tz_localize(None)` or `tz_convert(None)`. `tz_localize(None)` will remove timezone holding local time representations. `tz_convert(None)` will remove timezone after converting to UTC time.

```
In [286]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')
```

```
In [287]: didx
```

```
Out[287]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
               '2014-08-01 11:00:00-04:00', '2014-08-01 12:00:00-04:00',
               '2014-08-01 13:00:00-04:00', '2014-08-01 14:00:00-04:00',
               '2014-08-01 15:00:00-04:00', '2014-08-01 16:00:00-04:00',
               '2014-08-01 17:00:00-04:00', '2014-08-01 18:00:00-04:00'],
              dtype='datetime64[ns]', freq='H', tz='US/Eastern')
```

```
In [288]: didx.tz_localize(None)
```

```
Out[288]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
               '2014-08-01 11:00:00', '2014-08-01 12:00:00',
               '2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

```
In [289]: didx.tz_convert(None)
Out[289]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00',
               '2014-08-01 19:00:00', '2014-08-01 20:00:00',
               '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)

# tz_convert(None) is identical with tz_convert('UTC').tz_localize(None)
In [290]: didx.tz_convert('UCT').tz_localize(None)
Out[290]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00',
               '2014-08-01 19:00:00', '2014-08-01 20:00:00',
               '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

20.11.2 Ambiguous Times when Localizing

In some cases, localize cannot determine the DST and non-DST hours when there are duplicates. This often happens when reading files or database records that simply duplicate the hours. Passing `ambiguous='infer'` (`infer_dst` argument in prior releases) into `tz_localize` will attempt to determine the right offset. Below the top example will fail as it contains ambiguous times and the bottom will infer the right offset.

```
In [291]: rng_hourly = DatetimeIndex(['11/06/2011 00:00', '11/06/2011 01:00',
.....:                               '11/06/2011 01:00', '11/06/2011 02:00',
.....:                               '11/06/2011 03:00'])
.....:
```

This will fail as there are ambiguous times

```
In [292]: rng_hourly.tz_localize('US/Eastern')
```

```
-----
AmbiguousTimeError                                Traceback (most recent call last)
<ipython-input-292-8c5fa6a37f5b> in <module>()
----> 1 rng_hourly.tz_localize('US/Eastern')
```

```
/home/joris/scipy/pandas/pandas/util/decorators.pyc in wrapper(*args, **kwargs)
    86         else:
    87             kwargs[new_arg_name] = new_arg_value
--> 88         return func(*args, **kwargs)
    89     return wrapper
    90     return _deprecate_kwarg
```

```
/home/joris/scipy/pandas/pandas/tseries/index.pyc in tz_localize(self, tz, ambiguous)
   1644
   1645         new_dates = tslib.tz_localize_to_utc(self.asi8, tz,
-> 1646                                           ambiguous=ambiguous)
   1647         new_dates = new_dates.view(_NS_DTYPE)
   1648         return self._shallow_copy(new_dates, tz=tz)
```

```
/home/joris/scipy/pandas/pandas/tslib.so in pandas.tslib.tz_localize_to_utc (pandas/tslib.c:46871)()
```

```
AmbiguousTimeError: Cannot infer dst time from Timestamp('2011-11-06 01:00:00'), try using the 'ambi
```

```
In [293]: rng_hourly_eastern = rng_hourly.tz_localize('US/Eastern', ambiguous='infer')
```

```
In [294]: rng_hourly_eastern.tolist()
```

```
Out [294]:
[Timestamp('2011-11-06 00:00:00-0400', tz='US/Eastern'),
 Timestamp('2011-11-06 01:00:00-0400', tz='US/Eastern'),
 Timestamp('2011-11-06 01:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 02:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 03:00:00-0500', tz='US/Eastern')]
```

In addition to ‘infer’, there are several other arguments supported. Passing an array-like of bools or 0s/1s where True represents a DST hour and False a non-DST hour, allows for distinguishing more than one DST transition (e.g., if you have multiple records in a database each with their own DST transition). Or passing ‘NaT’ will fill in transition times with not-a-time values. These methods are available in the `DatetimeIndex` constructor as well as `tz_localize`.

```
In [295]: rng_hourly_dst = np.array([1, 1, 0, 0, 0])
```

```
In [296]: rng_hourly.tz_localize('US/Eastern', ambiguous=rng_hourly_dst).tolist()
```

```
Out [296]:
[Timestamp('2011-11-06 00:00:00-0400', tz='US/Eastern'),
 Timestamp('2011-11-06 01:00:00-0400', tz='US/Eastern'),
 Timestamp('2011-11-06 01:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 02:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 03:00:00-0500', tz='US/Eastern')]
```

```
In [297]: rng_hourly.tz_localize('US/Eastern', ambiguous='NaT').tolist()
```

```
Out [297]:
[Timestamp('2011-11-06 00:00:00-0400', tz='US/Eastern'),
 NaT,
 NaT,
 Timestamp('2011-11-06 02:00:00-0500', tz='US/Eastern'),
 Timestamp('2011-11-06 03:00:00-0500', tz='US/Eastern')]
```

```
In [298]: didx = DatetimeIndex(start='2014-08-01 09:00', freq='H', periods=10, tz='US/Eastern')
```

```
In [299]: didx
```

```
Out [299]:
DatetimeIndex(['2014-08-01 09:00:00-04:00', '2014-08-01 10:00:00-04:00',
               '2014-08-01 11:00:00-04:00', '2014-08-01 12:00:00-04:00',
               '2014-08-01 13:00:00-04:00', '2014-08-01 14:00:00-04:00',
               '2014-08-01 15:00:00-04:00', '2014-08-01 16:00:00-04:00',
               '2014-08-01 17:00:00-04:00', '2014-08-01 18:00:00-04:00'],
              dtype='datetime64[ns]', freq='H', tz='US/Eastern')
```

```
In [300]: didx.tz_localize(None)
```

```
Out [300]:
DatetimeIndex(['2014-08-01 09:00:00', '2014-08-01 10:00:00',
               '2014-08-01 11:00:00', '2014-08-01 12:00:00',
               '2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```

```
In [301]: didx.tz_convert(None)
```

```
Out [301]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
               '2014-08-01 15:00:00', '2014-08-01 16:00:00',
               '2014-08-01 17:00:00', '2014-08-01 18:00:00',
               ],
              dtype='datetime64[ns]', freq=None)
```

```
'2014-08-01 19:00:00', '2014-08-01 20:00:00',
'2014-08-01 21:00:00', '2014-08-01 22:00:00'],
dtype='datetime64[ns]', freq='H', tz=None)

# tz_convert(None) is identical with tz_convert('UTC').tz_localize(None)
In [302]: didx.tz_convert('UCT').tz_localize(None)
Out[302]:
DatetimeIndex(['2014-08-01 13:00:00', '2014-08-01 14:00:00',
                '2014-08-01 15:00:00', '2014-08-01 16:00:00',
                '2014-08-01 17:00:00', '2014-08-01 18:00:00',
                '2014-08-01 19:00:00', '2014-08-01 20:00:00',
                '2014-08-01 21:00:00', '2014-08-01 22:00:00'],
              dtype='datetime64[ns]', freq='H', tz=None)
```


TIME DELTAS

Note: Starting in v0.15.0, we introduce a new scalar type `Timedelta`, which is a subclass of `datetime.timedelta`, and behaves in a similar manner, but allows compatibility with `np.timedelta64` types as well as a host of custom representation, parsing, and attributes.

Timedeltas are differences in times, expressed in difference units, e.g. days, hours, minutes, seconds. They can be both positive and negative.

21.1 Parsing

You can construct a `Timedelta` scalar through various arguments:

```
# strings
In [1]: Timedelta('1 days')
Out[1]: Timedelta('1 days 00:00:00')

In [2]: Timedelta('1 days 00:00:00')
Out[2]: Timedelta('1 days 00:00:00')

In [3]: Timedelta('1 days 2 hours')
Out[3]: Timedelta('1 days 02:00:00')

In [4]: Timedelta('-1 days 2 min 3us')
Out[4]: Timedelta('-2 days +23:57:59.999997')

# like datetime.timedelta
# note: these MUST be specified as keyword arguments
In [5]: Timedelta(days=1, seconds=1)
Out[5]: Timedelta('1 days 00:00:01')

# integers with a unit
In [6]: Timedelta(1, unit='d')
Out[6]: Timedelta('1 days 00:00:00')

# from a timedelta/np.timedelta64
In [7]: Timedelta(timedelta(days=1, seconds=1))
Out[7]: Timedelta('1 days 00:00:01')

In [8]: Timedelta(np.timedelta64(1, 'ms'))
Out[8]: Timedelta('0 days 00:00:00.001000')

# negative Timedeltas have this string repr
```

```
# to be more consistent with datetime.timedelta conventions
In [9]: Timedelta('-1us')
Out[9]: Timedelta('-1 days +23:59:59.999999')
```

```
# a NaT
In [10]: Timedelta('nan')
Out[10]: NaT
```

```
In [11]: Timedelta('nat')
Out[11]: NaT
```

DateOffsets (Day, Hour, Minute, Second, Milli, Micro, Nano) can also be used in construction.

```
In [12]: Timedelta(Second(2))
Out[12]: Timedelta('0 days 00:00:02')
```

Further, operations among the scalars yield another scalar `Timedelta`

```
In [13]: Timedelta(Day(2)) + Timedelta(Second(2)) + Timedelta('00:00:00.000123')
Out[13]: Timedelta('2 days 00:00:02.000123')
```

21.1.1 to_timedelta

Warning: Prior to 0.15.0 `pd.to_timedelta` would return a `Series` for list-like/`Series` input, and a `np.timedelta64` for scalar input. It will now return a `TimedeltaIndex` for list-like input, `Series` for `Series` input, and `Timedelta` for scalar input.

The arguments to `pd.to_timedelta` are now `(arg, unit='ns', box=True)`, previously were `(arg, box=True, unit='ns')` as these are more logical.

Using the top-level `pd.to_timedelta`, you can convert a scalar, array, list, or `Series` from a recognized `timedelta` format / value into a `Timedelta` type. It will construct `Series` if the input is a `Series`, a scalar if the input is scalar-like, otherwise will output a `TimedeltaIndex`

```
In [14]: to_timedelta('1 days 06:05:01.00003')
Out[14]: Timedelta('1 days 06:05:01.000030')
```

```
In [15]: to_timedelta('15.5us')
Out[15]: Timedelta('0 days 00:00:00.000015')
```

```
In [16]: to_timedelta(['1 days 06:05:01.00003', '15.5us', 'nan'])
Out[16]: TimedeltaIndex(['1 days 06:05:01.000030', '0 days 00:00:00.000015', NaT], dtype='timedelta64[ns]', freq=None)
```

```
In [17]: to_timedelta(np.arange(5), unit='s')
Out[17]: TimedeltaIndex(['00:00:00', '00:00:01', '00:00:02', '00:00:03', '00:00:04'], dtype='timedelta64[ns]', freq=None)
```

```
In [18]: to_timedelta(np.arange(5), unit='d')
Out[18]: TimedeltaIndex(['0 days', '1 days', '2 days', '3 days', '4 days'], dtype='timedelta64[ns]', freq=None)
```

21.2 Operations

You can operate on `Series/DataFrames` and construct `timedelta64[ns]` `Series` through subtraction operations on `datetime64[ns]` `Series`, or `Timestamps`.

```
In [19]: s = Series(date_range('2012-1-1', periods=3, freq='D'))
```

```
In [20]: td = Series([ Timedelta(days=i) for i in range(3) ])
```

```
In [21]: df = DataFrame(dict(A = s, B = td))
```

```
In [22]: df
```

```
Out[22]:
```

| | A | B |
|---|------------|--------|
| 0 | 2012-01-01 | 0 days |
| 1 | 2012-01-02 | 1 days |
| 2 | 2012-01-03 | 2 days |

```
In [23]: df['C'] = df['A'] + df['B']
```

```
In [24]: df
```

```
Out[24]:
```

| | A | B | C |
|---|------------|--------|------------|
| 0 | 2012-01-01 | 0 days | 2012-01-01 |
| 1 | 2012-01-02 | 1 days | 2012-01-03 |
| 2 | 2012-01-03 | 2 days | 2012-01-05 |

```
In [25]: df.dtypes
```

```
Out[25]:
```

| | |
|---|-----------------|
| A | datetime64[ns] |
| B | timedelta64[ns] |
| C | datetime64[ns] |

dtype: object

```
In [26]: s - s.max()
```

```
Out[26]:
```

| | |
|---|---------|
| 0 | -2 days |
| 1 | -1 days |
| 2 | 0 days |

dtype: timedelta64[ns]

```
In [27]: s - datetime(2011,1,1,3,5)
```

```
Out[27]:
```

| | |
|---|-------------------|
| 0 | 364 days 20:55:00 |
| 1 | 365 days 20:55:00 |
| 2 | 366 days 20:55:00 |

dtype: timedelta64[ns]

```
In [28]: s + timedelta(minutes=5)
```

```
Out[28]:
```

| | |
|---|---------------------|
| 0 | 2012-01-01 00:05:00 |
| 1 | 2012-01-02 00:05:00 |
| 2 | 2012-01-03 00:05:00 |

dtype: datetime64[ns]

```
In [29]: s + Minute(5)
```

```
Out[29]:
```

| | |
|---|---------------------|
| 0 | 2012-01-01 00:05:00 |
| 1 | 2012-01-02 00:05:00 |
| 2 | 2012-01-03 00:05:00 |

dtype: datetime64[ns]

```
In [30]: s + Minute(5) + Milli(5)
```

```
Out [30]:
0    2012-01-01 00:05:00.005000
1    2012-01-02 00:05:00.005000
2    2012-01-03 00:05:00.005000
dtype: datetime64[ns]
```

Operations with scalars from a `timedelta64[ns]` series

```
In [31]: y = s - s[0]
```

```
In [32]: y
Out [32]:
0    0 days
1    1 days
2    2 days
dtype: timedelta64[ns]
```

Series of `timedeltas` with `NaT` values are supported

```
In [33]: y = s - s.shift()
```

```
In [34]: y
Out [34]:
0      NaT
1    1 days
2    1 days
dtype: timedelta64[ns]
```

Elements can be set to `NaT` using `np.nan` analogously to datetimes

```
In [35]: y[1] = np.nan
```

```
In [36]: y
Out [36]:
0      NaT
1      NaT
2    1 days
dtype: timedelta64[ns]
```

Operands can also appear in a reversed order (a singular object operated with a Series)

```
In [37]: s.max() - s
Out [37]:
0    2 days
1    1 days
2    0 days
dtype: timedelta64[ns]
```

```
In [38]: datetime(2011,1,1,3,5) - s
Out [38]:
0   -365 days +03:05:00
1   -366 days +03:05:00
2   -367 days +03:05:00
dtype: timedelta64[ns]
```

```
In [39]: timedelta(minutes=5) + s
Out [39]:
0    2012-01-01 00:05:00
1    2012-01-02 00:05:00
```

```
2    2012-01-03 00:05:00
dtype: datetime64[ns]
```

min, max and the corresponding idxmin, idxmax operations are supported on frames

```
In [40]: A = s - Timestamp('20120101') - Timedelta('00:05:05')
```

```
In [41]: B = s - Series(date_range('2012-1-2', periods=3, freq='D'))
```

```
In [42]: df = DataFrame(dict(A=A, B=B))
```

```
In [43]: df
```

```
Out[43]:
```

| | A | B |
|---|-------------------|---------|
| 0 | -1 days +23:54:55 | -1 days |
| 1 | 0 days 23:54:55 | -1 days |
| 2 | 1 days 23:54:55 | -1 days |

```
In [44]: df.min()
```

```
Out[44]:
```

| | A | B |
|---|-------------------|---|
| A | -1 days +23:54:55 | |
| B | -1 days +00:00:00 | |

dtype: timedelta64[ns]

```
In [45]: df.min(axis=1)
```

```
Out[45]:
```

| 0 | -1 days |
|---|---------|
| 1 | -1 days |
| 2 | -1 days |

dtype: timedelta64[ns]

```
In [46]: df.idxmin()
```

```
Out[46]:
```

| A | 0 |
|---|---|
| B | 0 |

dtype: int64

```
In [47]: df.idxmax()
```

```
Out[47]:
```

| A | 2 |
|---|---|
| B | 0 |

dtype: int64

min, max, idxmin, idxmax operations are supported on Series as well. A scalar result will be a Timedelta.

```
In [48]: df.min().max()
```

```
Out[48]: Timedelta('-1 days +23:54:55')
```

```
In [49]: df.min(axis=1).min()
```

```
Out[49]: Timedelta('-1 days +00:00:00')
```

```
In [50]: df.min().idxmax()
```

```
Out[50]: 'A'
```

```
In [51]: df.min(axis=1).idxmin()
```

```
Out[51]: 0
```

You can fillna on timedeltas. Integers will be interpreted as seconds. You can pass a timedelta to get a particular value.

```
In [52]: y.fillna(0)
Out[52]:
0    0 days
1    0 days
2    1 days
dtype: timedelta64[ns]

In [53]: y.fillna(10)
Out[53]:
0    0 days 00:00:10
1    0 days 00:00:10
2    1 days 00:00:00
dtype: timedelta64[ns]

In [54]: y.fillna(Timedelta('-1 days, 00:00:05'))
Out[54]:
0    -1 days +00:00:05
1    -1 days +00:00:05
2     1 days 00:00:00
dtype: timedelta64[ns]
```

You can also negate, multiply and use `abs` on `Timedeltas`

```
In [55]: td1 = Timedelta('-1 days 2 hours 3 seconds')

In [56]: td1
Out[56]: Timedelta('-2 days +21:59:57')

In [57]: -1 * td1
Out[57]: Timedelta('1 days 02:00:03')

In [58]: - td1
Out[58]: Timedelta('1 days 02:00:03')

In [59]: abs(td1)
Out[59]: Timedelta('1 days 02:00:03')
```

21.3 Reductions

Numeric reduction operation for `timedelta64[ns]` will return `Timedelta` objects. As usual `NaT` are skipped during evaluation.

```
In [60]: y2 = Series(to_timedelta(['-1 days +00:00:05', 'nat', '-1 days +00:00:05', '1 days']))

In [61]: y2
Out[61]:
0    -1 days +00:00:05
1              NaT
2    -1 days +00:00:05
3     1 days 00:00:00
dtype: timedelta64[ns]

In [62]: y2.mean()
Out[62]: Timedelta('-1 days +16:00:03.333333')

In [63]: y2.median()
```

```
Out[63]: Timedelta('-1 days +00:00:05')
```

```
In [64]: y2.quantile(.1)
```

```
Out[64]: Timedelta('-1 days +00:00:05')
```

```
In [65]: y2.sum()
```

```
Out[65]: Timedelta('-1 days +00:00:10')
```

21.4 Frequency Conversion

New in version 0.13.

Timedelta Series, TimedeltaIndex, and Timedelta scalars can be converted to other ‘frequencies’ by dividing by another timedelta, or by astyping to a specific timedelta type. These operations yield Series and propagate NaT -> nan. Note that division by the numpy scalar is true division, while astyping is equivalent of floor division.

```
In [66]: td = Series(date_range('20130101', periods=4)) - \
.....:         Series(date_range('20121201', periods=4))
.....:
```

```
In [67]: td[2] += timedelta(minutes=5, seconds=3)
```

```
In [68]: td[3] = np.nan
```

```
In [69]: td
```

```
Out[69]:
```

```
0    31 days 00:00:00
1    31 days 00:00:00
2    31 days 00:05:03
3                NaT
dtype: timedelta64[ns]
```

```
# to days
```

```
In [70]: td / np.timedelta64(1, 'D')
```

```
Out[70]:
```

```
0    31.000000
1    31.000000
2    31.003507
3           NaN
dtype: float64
```

```
In [71]: td.astype('timedelta64[D]')
```

```
Out[71]:
```

```
0     31
1     31
2     31
3     NaN
dtype: float64
```

```
# to seconds
```

```
In [72]: td / np.timedelta64(1, 's')
```

```
Out[72]:
```

```
0    2678400
1    2678400
2    2678703
3           NaN
```

```
dtype: float64
```

```
In [73]: td.astype('timedelta64[s]')
```

```
Out[73]:
```

```
0    2678400
```

```
1    2678400
```

```
2    2678703
```

```
3         NaN
```

```
dtype: float64
```

```
# to months (these are constant months)
```

```
In [74]: td / np.timedelta64(1, 'M')
```

```
Out[74]:
```

```
0    1.018501
```

```
1    1.018501
```

```
2    1.018617
```

```
3         NaN
```

```
dtype: float64
```

Dividing or multiplying a `timedelta64[ns]` Series by an integer or integer Series yields another `timedelta64[ns]` dtypes Series.

```
In [75]: td * -1
```

```
Out[75]:
```

```
0   -31 days +00:00:00
```

```
1   -31 days +00:00:00
```

```
2   -32 days +23:54:57
```

```
3                NaT
```

```
dtype: timedelta64[ns]
```

```
In [76]: td * Series([1,2,3,4])
```

```
Out[76]:
```

```
0    31 days 00:00:00
```

```
1    62 days 00:00:00
```

```
2    93 days 00:15:09
```

```
3                NaT
```

```
dtype: timedelta64[ns]
```

21.5 Attributes

You can access various components of the `Timedelta` or `TimedeltaIndex` directly using the attributes `days`, `seconds`, `microseconds`, `nanoseconds`. These are identical to the values returned by `datetime.timedelta`, in that, for example, the `.seconds` attribute represents the number of seconds ≥ 0 and < 1 day. These are signed according to whether the `Timedelta` is signed.

These operations can also be directly accessed via the `.dt` property of the Series as well.

Note: Note that the attributes are NOT the displayed values of the `Timedelta`. Use `.components` to retrieve the displayed values.

For a Series

```
In [77]: td.dt.days
```

```
Out[77]:
```

```
0     31
```

```
1     31
```

```
2    31
3    NaN
dtype: float64
```

```
In [78]: td.dt.seconds
Out[78]:
0      0
1      0
2    303
3     NaN
dtype: float64
```

You can access the value of the fields for a scalar Timedelta directly.

```
In [79]: tds = Timedelta('31 days 5 min 3 sec')
```

```
In [80]: tds.days
Out[80]: 31L
```

```
In [81]: tds.seconds
Out[81]: 303L
```

```
In [82]: (-tds).seconds
Out[82]: 86097L
```

You can use the `.components` property to access a reduced form of the timedelta. This returns a DataFrame indexed similarly to the Series. These are the *displayed* values of the Timedelta.

```
In [83]: td.dt.components
Out[83]:
```

| | days | hours | minutes | seconds | milliseconds | microseconds | nanoseconds |
|---|------|-------|---------|---------|--------------|--------------|-------------|
| 0 | 31 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 31 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 31 | 0 | 5 | 3 | 0 | 0 | 0 |
| 3 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

```
In [84]: td.dt.components.seconds
Out[84]:
0      0
1      0
2      3
3     NaN
Name: seconds, dtype: float64
```

21.6 TimedeltaIndex

New in version 0.15.0.

To generate an index with time delta, you can use either the `TimedeltaIndex` or the `timedelta_range` constructor.

Using `TimedeltaIndex` you can pass string-like, `Timedelta`, `timedelta`, or `np.timedelta64` objects. Passing `np.nan`/`pd.NaT`/`nat` will represent missing values.

```
In [85]: TimedeltaIndex(['1 days', '1 days, 00:00:05',
.....:                  np.timedelta64(2, 'D'), timedelta(days=2, seconds=2)])
.....:
```

```
Out[85]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:00:05', '2 days 00:00:00',
               '2 days 00:00:02'],
              dtype='timedelta64[ns]', freq=None)
```

Similarly to `date_range`, you can construct regular ranges of a `TimedeltaIndex`:

```
In [86]: timedelta_range(start='1 days', periods=5, freq='D')
Out[86]: TimedeltaIndex(['1 days', '2 days', '3 days', '4 days', '5 days'], dtype='timedelta64[ns]',
                        freq='D')

In [87]: timedelta_range(start='1 days', end='2 days', freq='30T')
Out[87]:
TimedeltaIndex(['1 days 00:00:00', '1 days 00:30:00', '1 days 01:00:00',
               '1 days 01:30:00', '1 days 02:00:00', '1 days 02:30:00',
               '1 days 03:00:00', '1 days 03:30:00', '1 days 04:00:00',
               '1 days 04:30:00', '1 days 05:00:00', '1 days 05:30:00',
               '1 days 06:00:00', '1 days 06:30:00', '1 days 07:00:00',
               '1 days 07:30:00', '1 days 08:00:00', '1 days 08:30:00',
               '1 days 09:00:00', '1 days 09:30:00', '1 days 10:00:00',
               '1 days 10:30:00', '1 days 11:00:00', '1 days 11:30:00',
               '1 days 12:00:00', '1 days 12:30:00', '1 days 13:00:00',
               '1 days 13:30:00', '1 days 14:00:00', '1 days 14:30:00',
               '1 days 15:00:00', '1 days 15:30:00', '1 days 16:00:00',
               '1 days 16:30:00', '1 days 17:00:00', '1 days 17:30:00',
               '1 days 18:00:00', '1 days 18:30:00', '1 days 19:00:00',
               '1 days 19:30:00', '1 days 20:00:00', '1 days 20:30:00',
               '1 days 21:00:00', '1 days 21:30:00', '1 days 22:00:00',
               '1 days 22:30:00', '1 days 23:00:00', '1 days 23:30:00',
               '2 days 00:00:00'],
              dtype='timedelta64[ns]', freq='30T')
```

21.6.1 Using the `TimedeltaIndex`

Similarly to other of the datetime-like indices, `DatetimeIndex` and `PeriodIndex`, you can use `TimedeltaIndex` as the index of pandas objects.

```
In [88]: s = Series(np.arange(100),
.....:              index=timedelta_range('1 days', periods=100, freq='h'))
.....:
```

```
In [89]: s
Out[89]:
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
1 days 05:00:00    5
1 days 06:00:00    6
..
4 days 21:00:00   93
4 days 22:00:00   94
4 days 23:00:00   95
5 days 00:00:00   96
5 days 01:00:00   97
5 days 02:00:00   98
5 days 03:00:00   99
```

```
Freq: H, dtype: int32
```

Selections work similarly, with coercion on string-likes and slices:

```
In [90]: s['1 day':'2 day']
```

```
Out[90]:
```

```
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
1 days 05:00:00    5
1 days 06:00:00    6
..
2 days 17:00:00   41
2 days 18:00:00   42
2 days 19:00:00   43
2 days 20:00:00   44
2 days 21:00:00   45
2 days 22:00:00   46
2 days 23:00:00   47
dtype: int32
```

```
In [91]: s['1 day 01:00:00']
```

```
Out[91]: 1
```

```
In [92]: s[Timedelta('1 day 1h')]
```

```
Out[92]: 1
```

Furthermore you can use partial string selection and the range will be inferred:

```
In [93]: s['1 day':'1 day 5 hours']
```

```
Out[93]:
```

```
1 days 00:00:00    0
1 days 01:00:00    1
1 days 02:00:00    2
1 days 03:00:00    3
1 days 04:00:00    4
1 days 05:00:00    5
dtype: int32
```

21.6.2 Operations

Finally, the combination of `TimedeltaIndex` with `DatetimeIndex` allow certain combination operations that are NaT preserving:

```
In [94]: tdi = TimedeltaIndex(['1 days',pd.NaT,'2 days'])
```

```
In [95]: tdi.tolist()
```

```
Out[95]: [Timedelta('1 days 00:00:00'), NaT, Timedelta('2 days 00:00:00')]
```

```
In [96]: dti = date_range('20130101',periods=3)
```

```
In [97]: dti.tolist()
```

```
Out[97]:
```

```
[Timestamp('2013-01-01 00:00:00', offset='D'),
 Timestamp('2013-01-02 00:00:00', offset='D'),
```

```
Timestamp('2013-01-03 00:00:00', offset='D')]
```

```
In [98]: (dti + tdi).tolist()
Out[98]: [Timestamp('2013-01-02 00:00:00'), NaT, Timestamp('2013-01-05 00:00:00')]
```

```
In [99]: (dti - tdi).tolist()
Out[99]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2013-01-01 00:00:00')]
```

21.6.3 Conversions

Similarly to frequency conversion on a Series above, you can convert these indices to yield another Index.

```
In [100]: tdi / np.timedelta64(1, 's')
Out[100]: Float64Index([86400.0, nan, 172800.0], dtype='float64')
```

```
In [101]: tdi.astype('timedelta64[s]')
Out[101]: Float64Index([86400.0, nan, 172800.0], dtype='float64')
```

Scalars type ops work as well. These can potentially return a *different* type of index.

```
# adding or timedelta and date -> datelike
In [102]: tdi + Timestamp('20130101')
Out[102]: DatetimeIndex(['2013-01-02', 'NaT', '2013-01-03'], dtype='datetime64[ns]', freq=None, tz=None)
```

```
# subtraction of a date and a timedelta -> datelike
# note that trying to subtract a date from a Timedelta will raise an exception
In [103]: (Timestamp('20130101') - tdi).tolist()
Out[103]: [Timestamp('2012-12-31 00:00:00'), NaT, Timestamp('2012-12-30 00:00:00')]
```

```
# timedelta + timedelta -> timedelta
In [104]: tdi + Timedelta('10 days')
Out[104]: TimedeltaIndex(['11 days', NaT, '12 days'], dtype='timedelta64[ns]', freq=None)
```

```
# division can result in a Timedelta if the divisor is an integer
In [105]: tdi / 2
Out[105]: TimedeltaIndex(['0 days 12:00:00', NaT, '1 days 00:00:00'], dtype='timedelta64[ns]', freq=None)
```

```
# or a Float64Index if the divisor is a Timedelta
In [106]: tdi / tdi[0]
Out[106]: Float64Index([1.0, nan, 2.0], dtype='float64')
```

21.7 Resampling

Similar to *timeseries resampling*, we can resample with a TimedeltaIndex.

```
In [107]: s.resample('D')
Out[107]:
1 days    11.5
2 days    35.5
3 days    59.5
4 days    83.5
5 days    97.5
dtype: float64
```

CATEGORICAL DATA

New in version 0.15.

Note: While there was *pandas.Categorical* in earlier versions, the ability to use categorical data in *Series* and *DataFrame* is new.

This is an introduction to pandas categorical data type, including a short comparison with R's *factor*.

Categoricals are a pandas data type, which correspond to categorical variables in statistics: a variable, which can take on only a limited, and usually fixed, number of possible values (*categories*; *levels* in R). Examples are gender, social class, blood types, country affiliations, observation time or ratings via Likert scales.

In contrast to statistical categorical variables, categorical data might have an order (e.g. 'strongly agree' vs 'agree' or 'first observation' vs. 'second observation'), but numerical operations (additions, divisions, ...) are not possible.

All values of categorical data are either in *categories* or *np.nan*. Order is defined by the order of *categories*, not lexical order of the values. Internally, the data structure consists of a *categories* array and an integer array of *codes* which point to the real value in the *categories* array.

The categorical data type is useful in the following cases:

- A string variable consisting of only a few different values. Converting such a string variable to a categorical variable will save some memory, see [here](#).
- The lexical order of a variable is not the same as the logical order ("one", "two", "three"). By converting to a categorical and specifying an order on the categories, sorting and min/max will use the logical order instead of the lexical order, see [here](#).
- As a signal to other python libraries that this column should be treated as a categorical variable (e.g. to use suitable statistical methods or plot types).

See also the [API docs on categoricals](#).

22.1 Object Creation

Categorical *Series* or columns in a *DataFrame* can be created in several ways:

By specifying `dtype="category"` when constructing a *Series*:

```
In [1]: s = Series(["a", "b", "c", "a"], dtype="category")
```

```
In [2]: s
```

```
Out[2]:  
0      a  
1      b
```

```
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]
```

By converting an existing *Series* or column to a category dtype:

```
In [3]: df = DataFrame({"A": ["a", "b", "c", "a"]})
```

```
In [4]: df["B"] = df["A"].astype('category')
```

```
In [5]: df
```

```
Out[5]:
   A  B
0  a  a
1  b  b
2  c  c
3  a  a
```

By using some special functions:

```
In [6]: df = DataFrame({'value': np.random.randint(0, 100, 20)})
```

```
In [7]: labels = [ "{0} - {1}".format(i, i + 9) for i in range(0, 100, 10) ]
```

```
In [8]: df['group'] = pd.cut(df.value, range(0, 105, 10), right=False, labels=labels)
```

```
In [9]: df.head(10)
```

```
Out[9]:
   value  group
0     65  60 - 69
1     49  40 - 49
2     56  50 - 59
3     43  40 - 49
4     43  40 - 49
5     91  90 - 99
6     32  30 - 39
7     87  80 - 89
8     36  30 - 39
9      8   0 - 9
```

See *documentation* for `cut()`.

By passing a `pandas.Categorical` object to a *Series* or assigning it to a *DataFrame*.

```
In [10]: raw_cat = Categorical(["a", "b", "c", "a"], categories=["b", "c", "d"],
.....:                        ordered=False)
.....:
```

```
In [11]: s = Series(raw_cat)
```

```
In [12]: s
```

```
Out[12]:
0    NaN
1     b
2     c
3    NaN
dtype: category
Categories (3, object): [b, c, d]
```

```
In [13]: df = DataFrame({"A": ["a", "b", "c", "a"]})
```

```
In [14]: df["B"] = raw_cat
```

```
In [15]: df
```

```
Out[15]:
```

| | A | B |
|---|---|-----|
| 0 | a | NaN |
| 1 | b | b |
| 2 | c | c |
| 3 | a | NaN |

You can also specify differently ordered categories or make the resulting data ordered, by passing these arguments to `astype()`:

```
In [16]: s = Series(["a", "b", "c", "a"])
```

```
In [17]: s_cat = s.astype("category", categories=["b", "c", "d"], ordered=False)
```

```
In [18]: s_cat
```

```
Out[18]:
```

| | |
|---|-----|
| 0 | NaN |
| 1 | b |
| 2 | c |
| 3 | NaN |

dtype: category
Categories (3, object): [b, c, d]

Categorical data has a specific category *dtype*:

```
In [19]: df.dtypes
```

```
Out[19]:
```

| | |
|---|----------|
| A | object |
| B | category |

dtype: object

Note: In contrast to R's *factor* function, categorical data is not converting input values to strings and categories will end up the same data type as the original values.

Note: In contrast to R's *factor* function, there is currently no way to assign/change labels at creation time. Use *categories* to change the categories after creation time.

To get back to the original Series or *numpy* array, use `Series.astype(original_dtype)` or `np.asarray(categorical)`:

```
In [20]: s = Series(["a", "b", "c", "a"])
```

```
In [21]: s
```

```
Out[21]:
```

| | |
|---|---|
| 0 | a |
| 1 | b |
| 2 | c |
| 3 | a |

dtype: object

```
In [22]: s2 = s.astype('category')
```

```
In [23]: s2
Out[23]:
0      a
1      b
2      c
3      a
dtype: category
Categories (3, object): [a, b, c]
```

```
In [24]: s3 = s2.astype('string')
```

```
In [25]: s3
Out[25]:
0      a
1      b
2      c
3      a
dtype: object
```

```
In [26]: np.asarray(s2)
Out[26]: array(['a', 'b', 'c', 'a'], dtype=object)
```

If you have already *codes* and *categories*, you can use the `from_codes()` constructor to save the factorize step during normal constructor mode:

```
In [27]: splitter = np.random.choice([0,1], 5, p=[0.5,0.5])
```

```
In [28]: s = Series(Categorical.from_codes(splitter, categories=["train", "test"]))
```

22.2 Description

Using `.describe()` on categorical data will produce similar output to a *Series* or *DataFrame* of type string.

```
In [29]: cat = Categorical(["a", "c", "c", np.nan], categories=["b", "a", "c", np.nan])
```

```
In [30]: df = DataFrame({"cat":cat, "s":["a", "c", "c", np.nan]})
```

```
In [31]: df.describe()
Out[31]:
```

| | cat | s |
|--------|-----|---|
| count | 3 | 3 |
| unique | 2 | 2 |
| top | c | c |
| freq | 2 | 2 |

```
In [32]: df["cat"].describe()
```

```
Out[32]:
count      3
unique     2
top        c
freq       2
Name: cat, dtype: object
```

22.3 Working with categories

Categorical data has a *categories* and a *ordered* property, which list their possible values and whether the ordering matters or not. These properties are exposed as `s.cat.categories` and `s.cat.ordered`. If you don't manually specify categories and ordering, they are inferred from the passed in values.

```
In [33]: s = Series(["a", "b", "c", "a"], dtype="category")
```

```
In [34]: s.cat.categories
```

```
Out[34]: Index([u'a', u'b', u'c'], dtype='object')
```

```
In [35]: s.cat.ordered
```

```
Out[35]: False
```

It's also possible to pass in the categories in a specific order:

```
In [36]: s = Series(Categorical(["a", "b", "c", "a"], categories=["c", "b", "a"]))
```

```
In [37]: s.cat.categories
```

```
Out[37]: Index([u'c', u'b', u'a'], dtype='object')
```

```
In [38]: s.cat.ordered
```

```
Out[38]: False
```

Note: New categorical data are NOT automatically ordered. You must explicitly pass `ordered=True` to indicate an ordered `Categorical`.

22.3.1 Renaming categories

Renaming categories is done by assigning new values to the `Series.cat.categories` property or by using the `Categorical.rename_categories()` method:

```
In [39]: s = Series(["a", "b", "c", "a"], dtype="category")
```

```
In [40]: s
```

```
Out[40]:
```

```
0    a
1    b
2    c
3    a
dtype: category
Categories (3, object): [a, b, c]
```

```
In [41]: s.cat.categories = ["Group %s" % g for g in s.cat.categories]
```

```
In [42]: s
```

```
Out[42]:
```

```
0    Group a
1    Group b
2    Group c
3    Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]
```

```
In [43]: s.cat.rename_categories([1,2,3])
```

```
Out[43]:
```

```
0    1
1    2
2    3
3    1
dtype: category
Categories (3, int64): [1, 2, 3]
```

Note: In contrast to R's *factor*, categorical data can have categories of other types than string.

Note: Be aware that assigning new categories is an inplace operations, while most other operation under `Series.cat` per default return a new Series of dtype *category*.

Categories must be unique or a *ValueError* is raised:

```
In [44]: try:
.....:     s.cat.categories = [1,1,1]
.....: except ValueError as e:
.....:     print("ValueError: " + str(e))
.....:
ValueError: Categorical categories must be unique
```

22.3.2 Appending new categories

Appending categories can be done by using the `Categorical.add_categories()` method:

```
In [45]: s = s.cat.add_categories([4])

In [46]: s.cat.categories
Out[46]: Index([u'Group a', u'Group b', u'Group c', 4], dtype='object')

In [47]: s
Out[47]:
0    Group a
1    Group b
2    Group c
3    Group a
dtype: category
Categories (4, object): [Group a, Group b, Group c, 4]
```

22.3.3 Removing categories

Removing categories can be done by using the `Categorical.remove_categories()` method. Values which are removed are replaced by `np.nan`:

```
In [48]: s = s.cat.remove_categories([4])

In [49]: s
Out[49]:
0    Group a
1    Group b
2    Group c
3    Group a
dtype: category
Categories (3, object): [Group a, Group b, Group c]
```

22.3.4 Removing unused categories

Removing unused categories can also be done:

```
In [50]: s = Series(Categorical(["a", "b", "a"], categories=["a", "b", "c", "d"]))
```

```
In [51]: s
```

```
Out[51]:
0    a
1    b
2    a
dtype: category
Categories (4, object): [a, b, c, d]
```

```
In [52]: s.cat.remove_unused_categories()
```

```
Out[52]:
0    a
1    b
2    a
dtype: category
Categories (2, object): [a, b]
```

22.3.5 Setting categories

If you want to do remove and add new categories in one step (which has some speed advantage), or simply set the categories to a predefined scale, use `Categorical.set_categories()`.

```
In [53]: s = Series(["one", "two", "four", "-"], dtype="category")
```

```
In [54]: s
```

```
Out[54]:
0    one
1    two
2    four
3     -
dtype: category
Categories (4, object): [-, four, one, two]
```

```
In [55]: s = s.cat.set_categories(["one", "two", "three", "four"])
```

```
In [56]: s
```

```
Out[56]:
0    one
1    two
2    four
3    NaN
dtype: category
Categories (4, object): [one, two, three, four]
```

Note: Be aware that `Categorical.set_categories()` cannot know whether some category is omitted intentionally or because it is misspelled or (under Python3) due to a type difference (e.g., numpys S1 dtype and python strings). This can result in surprising behaviour!

22.4 Sorting and Order

Warning: The default for construction has changed in v0.16.0 to `ordered=False`, from the prior implicit `ordered=True`

If categorical data is ordered (`s.cat.ordered == True`), then the order of the categories has a meaning and certain operations are possible. If the categorical is unordered, `.min()` / `.max()` will raise a *TypeError*.

```
In [57]: s = Series(Categorical(["a", "b", "c", "a"], ordered=False))

In [58]: s.sort()

In [59]: s = Series(["a", "b", "c", "a"]).astype('category', ordered=True)

In [60]: s.sort()

In [61]: s
Out[61]:
0      a
3      a
1      b
2      c
dtype: category
Categories (3, object): [a < b < c]

In [62]: s.min(), s.max()
Out[62]: ('a', 'c')
```

You can set categorical data to be ordered by using `as_ordered()` or unordered by using `as_unordered()`. These will by default return a *new* object.

```
In [63]: s.cat.as_ordered()
Out[63]:
0      a
3      a
1      b
2      c
dtype: category
Categories (3, object): [a < b < c]

In [64]: s.cat.as_unordered()
Out[64]:
0      a
3      a
1      b
2      c
dtype: category
Categories (3, object): [a, b, c]
```

Sorting will use the order defined by categories, not any lexical order present on the data type. This is even true for strings and numeric data:

```
In [65]: s = Series([1,2,3,1], dtype="category")

In [66]: s = s.cat.set_categories([2,3,1], ordered=True)

In [67]: s
```

```
Out [67]:  
0    1  
1    2  
2    3  
3    1  
dtype: category  
Categories (3, int64): [2 < 3 < 1]
```

```
In [68]: s.sort()
```

```
In [69]: s  
Out [69]:  
1    2  
2    3  
0    1  
3    1  
dtype: category  
Categories (3, int64): [2 < 3 < 1]
```

```
In [70]: s.min(), s.max()  
Out [70]: (2, 1)
```

22.4.1 Reordering

Reordering the categories is possible via the `Categorical.reorder_categories()` and the `Categorical.set_categories()` methods. For `Categorical.reorder_categories()`, all old categories must be included in the new categories and no new categories are allowed. This will necessarily make the sort order the same as the categories order.

```
In [71]: s = Series([1,2,3,1], dtype="category")
```

```
In [72]: s = s.cat.reorder_categories([2,3,1], ordered=True)
```

```
In [73]: s  
Out [73]:  
0    1  
1    2  
2    3  
3    1  
dtype: category  
Categories (3, int64): [2 < 3 < 1]
```

```
In [74]: s.sort()
```

```
In [75]: s  
Out [75]:  
1    2  
2    3  
0    1  
3    1  
dtype: category  
Categories (3, int64): [2 < 3 < 1]
```

```
In [76]: s.min(), s.max()  
Out [76]: (2, 1)
```

Note: Note the difference between assigning new categories and reordering the categories: the first renames categories and therefore the individual values in the *Series*, but if the first position was sorted last, the renamed value will still be sorted last. Reordering means that the way values are sorted is different afterwards, but not that individual values in the *Series* are changed.

Note: If the *Categorical* is not ordered, `Series.min()` and `Series.max()` will raise *TypeError*. Numeric operations like `+`, `-`, `*`, `/` and operations based on them (e.g. “`Series.median()`”, which would need to compute the mean between two values if the length of an array is even) do not work and raise a *TypeError*.

22.4.2 Multi Column Sorting

A categorical dtyped column will participate in a multi-column sort in a similar manner to other columns. The ordering of the categorical is determined by the `categories` of that column.

```
In [77]: dfs = DataFrame({'A' : Categorical(list('bbeebbaa'), categories=['e', 'a', 'b'], ordered=True),
.....:                  'B' : [1,2,1,2,2,1,2,1] })
.....:
```

```
In [78]: dfs.sort(['A', 'B'])
```

```
Out [78]:
```

| | A | B |
|---|---|---|
| 2 | e | 1 |
| 3 | e | 2 |
| 7 | a | 1 |
| 6 | a | 2 |
| 0 | b | 1 |
| 5 | b | 1 |
| 1 | b | 2 |
| 4 | b | 2 |

Reordering the `categories` changes a future sort.

```
In [79]: dfs['A'] = dfs['A'].cat.reorder_categories(['a', 'b', 'e'])
```

```
In [80]: dfs.sort(['A', 'B'])
```

```
Out [80]:
```

| | A | B |
|---|---|---|
| 7 | a | 1 |
| 6 | a | 2 |
| 0 | b | 1 |
| 5 | b | 1 |
| 1 | b | 2 |
| 4 | b | 2 |
| 2 | e | 1 |
| 3 | e | 2 |

22.5 Comparisons

Comparing categorical data with other objects is possible in three cases:

- comparing equality (`==` and `!=`) to a list-like object (list, *Series*, array, ...) of the same length as the categorical data.

- all comparisons (`==`, `!=`, `>`, `>=`, `<`, and `<=`) of categorical data to another categorical Series, when `ordered==True` and the *categories* are the same.
- all comparisons of a categorical data to a scalar.

All other comparisons, especially “non-equality” comparisons of two categoricals with different categories or a categorical with any list-like object, will raise a `TypeError`.

Note: Any “non-equality” comparisons of categorical data with a *Series*, *np.array*, *list* or categorical data with different categories or ordering will raise an *TypeError* because custom categories ordering could be interpreted in two ways: one with taking into account the ordering and one without.

```
In [81]: cat = Series([1,2,3]).astype("category", categories=[3,2,1], ordered=True)

In [82]: cat_base = Series([2,2,2]).astype("category", categories=[3,2,1], ordered=True)

In [83]: cat_base2 = Series([2,2,2]).astype("category", ordered=True)

In [84]: cat
Out[84]:
0    1
1    2
2    3
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [85]: cat_base
Out[85]:
0    2
1    2
2    2
dtype: category
Categories (3, int64): [3 < 2 < 1]

In [86]: cat_base2
Out[86]:
0    2
1    2
2    2
dtype: category
Categories (1, int64): [2]
```

Comparing to a categorical with the same categories and ordering or to a scalar works:

```
In [87]: cat > cat_base
Out[87]:
0    True
1   False
2   False
dtype: bool

In [88]: cat > 2
Out[88]:
0    True
1   False
2   False
dtype: bool
```

Equality comparisons work with any list-like object of same length and scalars:

```
In [89]: cat == cat_base
Out[89]:
0    False
1     True
2    False
dtype: bool

In [90]: cat == np.array([1,2,3])
Out[90]:
0     True
1     True
2     True
dtype: bool

In [91]: cat == 2
Out[91]:
0    False
1     True
2    False
dtype: bool
```

This doesn't work because the categories are not the same:

```
In [92]: try:
.....:     cat > cat_base2
.....: except TypeError as e:
.....:     print("TypeError: " + str(e))
.....:
TypeError: Categoricals can only be compared if 'categories' are the same
```

If you want to do a “non-equality” comparison of a categorical series with a list-like object which is not categorical data, you need to be explicit and convert the categorical data back to the original values:

```
In [93]: base = np.array([1,2,3])

In [94]: try:
.....:     cat > base
.....: except TypeError as e:
.....:     print("TypeError: " + str(e))
.....:
TypeError: Cannot compare a Categorical for op __gt__ with type <type 'numpy.ndarray'>. If you want to
compare values, use 'np.asarray(cat) <op> other'.

In [95]: np.asarray(cat) > base
Out[95]: array([False, False, False], dtype=bool)
```

22.6 Operations

Apart from `Series.min()`, `Series.max()` and `Series.mode()`, the following operations are possible with categorical data:

Series methods like `Series.value_counts()` will use all categories, even if some categories are not present in the data:

```
In [96]: s = Series(Categorical(["a", "b", "c", "c"], categories=["c", "a", "b", "d"]))

In [97]: s.value_counts()
Out[97]:
```

```
c    2
b    1
a    1
d    0
dtype: int64
```

Groupby will also show “unused” categories:

```
In [98]: cats = Categorical(["a", "b", "b", "b", "c", "c", "c"], categories=["a", "b", "c", "d"])
```

```
In [99]: df = DataFrame({"cats":cats, "values":[1,2,2,2,3,4,5]})
```

```
In [100]: df.groupby("cats").mean()
```

```
Out[100]:
      values
cats
a          1
b          2
c          4
d         NaN
```

```
In [101]: cats2 = Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])
```

```
In [102]: df2 = DataFrame({"cats":cats2, "B":["c", "d", "c", "d"], "values":[1,2,3,4]})
```

```
In [103]: df2.groupby(["cats", "B"]).mean()
```

```
Out[103]:
      values
cats B
a    c      1
     d      2
b    c      3
     d      4
c    c     NaN
     d     NaN
```

Pivot tables:

```
In [104]: raw_cat = Categorical(["a", "a", "b", "b"], categories=["a", "b", "c"])
```

```
In [105]: df = DataFrame({"A":raw_cat, "B":["c", "d", "c", "d"], "values":[1,2,3,4]})
```

```
In [106]: pd.pivot_table(df, values='values', index=['A', 'B'])
```

```
Out[106]:
A  B
a  c    1
   d    2
b  c    3
   d    4
c  c   NaN
   d   NaN
Name: values, dtype: float64
```

22.7 Data munging

The optimized pandas data access methods `.loc`, `.iloc`, `.ix`, `.at`, and `.iat`, work as normal. The only difference is the return type (for getting) and that only values already in *categories* can be assigned.

22.7.1 Getting

If the slicing operation returns either a *DataFrame* or a column of type *Series*, the category dtype is preserved.

```
In [107]: idx = Index(["h", "i", "j", "k", "l", "m", "n",])

In [108]: cats = Series(["a", "b", "b", "b", "c", "c", "c"], dtype="category", index=idx)

In [109]: values= [1, 2, 2, 2, 3, 4, 5]

In [110]: df = DataFrame({"cats":cats, "values":values}, index=idx)

In [111]: df.iloc[2:4, :]
Out[111]:
   cats  values
j     b       2
k     b       2

In [112]: df.iloc[2:4, :].dtypes
Out[112]:
cats      category
values    int64
dtype: object

In [113]: df.loc["h":"j", "cats"]
Out[113]:
h     a
i     b
j     b
Name: cats, dtype: category
Categories (3, object): [a, b, c]

In [114]: df.ix["h":"j", 0:1]
Out[114]:
   cats
h     a
i     b
j     b

In [115]: df[df["cats"] == "b"]
Out[115]:
   cats  values
i     b       2
j     b       2
k     b       2
```

An example where the category type is not preserved is if you take one single row: the resulting *Series* is of dtype object:

```
# get the complete "h" row as a Series
In [116]: df.loc["h", :]
Out[116]:
cats      a
values    1
Name: h, dtype: object
```

Returning a single item from categorical data will also return the value, not a categorical of length “1”.

```
In [117]: df.iat[0,0]
Out[117]: 'a'

In [118]: df["cats"].cat.categories = ["x","y","z"]

In [119]: df.at["h","cats"] # returns a string
Out[119]: 'x'
```

Note: This is a difference to R's *factor* function, where `factor(c(1,2,3))[1]` returns a single value *factor*.

To get a single value *Series* of type category pass in a list with a single value:

```
In [120]: df.loc[["h"],"cats"]
Out[120]:
h      x
Name: cats, dtype: category
Categories (3, object): [x, y, z]
```

22.7.2 Setting

Setting values in a categorical column (or *Series*) works as long as the value is included in the *categories*:

```
In [121]: idx = Index(["h","i","j","k","l","m","n"])

In [122]: cats = Categorical(["a","a","a","a","a","a","a"], categories=["a","b"])

In [123]: values = [1,1,1,1,1,1,1]

In [124]: df = DataFrame({"cats":cats,"values":values}, index=idx)

In [125]: df.iloc[2:4,:] = [["b",2],["b",2]]

In [126]: df
Out[126]:
   cats  values
h     a        1
i     a        1
j     b        2
k     b        2
l     a        1
m     a        1
n     a        1

In [127]: try:
.....:     df.iloc[2:4,:] = [["c",3],["c",3]]
.....: except ValueError as e:
.....:     print("ValueError: " + str(e))
.....:
ValueError: cannot setitem on a Categorical with a new category, set the categories first

Setting values by assigning categorical data will also check that the categories match:

In [128]: df.loc["j":"k","cats"] = Categorical(["a","a"], categories=["a","b"])

In [129]: df
Out[129]:
   cats  values
j     a        1
k     a        1
```

```
h    a    1
i    a    1
j    a    2
k    a    2
l    a    1
m    a    1
n    a    1
```

```
In [130]: try:
.....:     df.loc["j":"k", "cats"] = Categorical(["b", "b"], categories=["a", "b", "c"])
.....: except ValueError as e:
.....:     print("ValueError: " + str(e))
.....:
```

ValueError: Cannot set a Categorical with another, without identical categories

Assigning a *Categorical* to parts of a column of other types will use the values:

```
In [131]: df = DataFrame({"a": [1, 1, 1, 1, 1], "b": ["a", "a", "a", "a", "a"]})
```

```
In [132]: df.loc[1:2, "a"] = Categorical(["b", "b"], categories=["a", "b"])
```

```
In [133]: df.loc[2:3, "b"] = Categorical(["b", "b"], categories=["a", "b"])
```

```
In [134]: df
```

```
Out[134]:
```

```
   a  b
0  1  a
1  b  a
2  b  b
3  1  b
4  1  a
```

```
In [135]: df.dtypes
```

```
Out[135]:
```

```
a    object
b    object
dtype: object
```

22.7.3 Merging

You can concat two *DataFrames* containing categorical data together, but the categories of these categoricals need to be the same:

```
In [136]: cat = Series(["a", "b"], dtype="category")
```

```
In [137]: vals = [1, 2]
```

```
In [138]: df = DataFrame({"cats": cat, "vals": vals})
```

```
In [139]: res = pd.concat([df, df])
```

```
In [140]: res
```

```
Out[140]:
```

```
   cats  vals
0     a     1
1     b     2
0     a     1
```

```
1      b      2
```

```
In [141]: res.dtypes
Out[141]:
cats      category
vals      int64
dtype: object
```

In this case the categories are not the same and so an error is raised:

```
In [142]: df_different = df.copy()

In [143]: df_different["cats"].cat.categories = ["c", "d"]

In [144]: try:
.....:     pd.concat([df, df_different])
.....: except ValueError as e:
.....:     print("ValueError: " + str(e))
.....:
ValueError: incompatible categories in categorical concat
```

The same applies to `df.append(df_different)`.

22.8 Getting Data In/Out

New in version 0.15.2.

Writing data (*Series*, *Frames*) to a HDF store that contains a `category` dtype was implemented in 0.15.2. See [here](#) for an example and caveats.

Writing data to and reading data from *Stata* format files was implemented in 0.15.2. See [here](#) for an example and caveats.

Writing to a CSV file will convert the data, effectively removing any information about the categorical (categories and ordering). So if you read back the CSV file you have to convert the relevant columns back to `category` and assign the right categories and categories ordering.

```
In [145]: s = Series(Categorical(['a', 'b', 'b', 'a', 'a', 'd']))

# rename the categories
In [146]: s.cat.categories = ["very good", "good", "bad"]

# reorder the categories and add missing categories
In [147]: s = s.cat.set_categories(["very bad", "bad", "medium", "good", "very good"])

In [148]: df = DataFrame({"cats":s, "vals":[1,2,3,4,5,6]})

In [149]: csv = StringIO()

In [150]: df.to_csv(csv)

In [151]: df2 = pd.read_csv(StringIO(csv.getvalue()))

In [152]: df2.dtypes
Out[152]:
Unnamed: 0      int64
cats          object
```

```
vals          int64
dtype: object

In [153]: df2["cats"]
Out[153]:
0    very good
1         good
2         good
3    very good
4    very good
5         bad
Name: cats, dtype: object

# Redo the category
In [154]: df2["cats"] = df2["cats"].astype("category")

In [155]: df2["cats"].cat.set_categories(["very bad", "bad", "medium", "good", "very good"],
.....:                                inplace=True)
.....:

In [156]: df2.dtypes
Out[156]:
Unnamed: 0      int64
cats          category
vals          int64
dtype: object

In [157]: df2["cats"]
Out[157]:
0    very good
1         good
2         good
3    very good
4    very good
5         bad
Name: cats, dtype: category
Categories (5, object): [very bad, bad, medium, good, very good]
```

The same holds for writing to a SQL database with `to_sql`.

22.9 Missing Data

pandas primarily uses the value *np.nan* to represent missing data. It is by default not included in computations. See the [Missing Data section](#)

There are two ways a *np.nan* can be represented in categorical data: either the value is not available (“missing value”) or *np.nan* is a valid category.

```
In [158]: s = Series(["a", "b", np.nan, "a"], dtype="category")

# only two categories
In [159]: s
Out[159]:
0    a
1    b
2  NaN
```

```
3      a
dtype: category
Categories (2, object): [a, b]
```

```
In [160]: s2 = Series(["a", "b", "c", "a"], dtype="category")
```

```
In [161]: s2.cat.categories = [1, 2, np.nan]
```

```
# three categories, np.nan included
```

```
In [162]: s2
```

```
Out[162]:
```

```
0      1
1      2
2     NaN
3      1
dtype: category
Categories (3, object): [1, 2, NaN]
```

Note: As integer *Series* can't include NaN, the categories were converted to *object*.

Note: Missing value methods like `isnull` and `fillna` will take both missing values as well as *np.nan* categories into account:

```
In [163]: c = Series(["a", "b", np.nan], dtype="category")
```

```
In [164]: c.cat.set_categories(["a", "b", np.nan], inplace=True)
```

```
# will be inserted as a NA category:
```

```
In [165]: c[0] = np.nan
```

```
In [166]: s = Series(c)
```

```
In [167]: s
```

```
Out[167]:
```

```
0     NaN
1      b
2     NaN
dtype: category
Categories (3, object): [a, b, NaN]
```

```
In [168]: pd.isnull(s)
```

```
Out[168]:
```

```
0     True
1    False
2     True
dtype: bool
```

```
In [169]: s.fillna("a")
```

```
Out[169]:
```

```
0      a
1      b
2      a
dtype: category
Categories (3, object): [a, b, NaN]
```

22.9.1 Differences to R's *factor*

The following differences to R's *factor* functions can be observed:

- R's *levels* are named *categories*
- R's *levels* are always of type string, while *categories* in pandas can be of any dtype.
- It's not possible to specify labels at creation time. Use `s.cat.rename_categories(new_labels)` afterwards.
- In contrast to R's *factor* function, using categorical data as the sole input to create a new categorical series will *not* remove unused categories but create a new categorical series which is equal to the passed in one!

22.10 Gotchas

22.10.1 Memory Usage

The memory usage of a `Categorical` is proportional to the number of categories times the length of the data. In contrast, an `object` dtype is a constant times the length of the data.

```
In [170]: s = Series(['foo', 'bar']*1000)
```

```
# object dtype
```

```
In [171]: s.nbytes
```

```
Out[171]: 8000
```

```
# category dtype
```

```
In [172]: s.astype('category').nbytes
```

```
Out[172]: 2008
```

Note: If the number of categories approaches the length of the data, the `Categorical` will use nearly the same or more memory than an equivalent `object` dtype representation.

```
In [173]: s = Series(['foo%04d' % i for i in range(2000)])
```

```
# object dtype
```

```
In [174]: s.nbytes
```

```
Out[174]: 8000
```

```
# category dtype
```

```
In [175]: s.astype('category').nbytes
```

```
Out[175]: 12000
```

22.10.2 Old style constructor usage

In earlier versions than pandas 0.15, a `Categorical` could be constructed by passing in precomputed *codes* (called then *labels*) instead of values with categories. The *codes* were interpreted as pointers to the categories with `-1` as `NaN`. This type of constructor usage is replaced by the special constructor `Categorical.from_codes()`.

Unfortunately, in some special cases, using code which assumes the old style constructor usage will work with the current pandas version, resulting in subtle bugs:

```
>>> cat = Categorical([1,2], [1,2,3])
>>> # old version
>>> cat.get_values()
array([2, 3], dtype=int64)
>>> # new version
>>> cat.get_values()
array([1, 2], dtype=int64)
```

Warning: If you used *Categoricals* with older versions of pandas, please audit your code before upgrading and change your code to use the `from_codes()` constructor.

22.10.3 *Categorical* is not a *numpy* array

Currently, categorical data and the underlying *Categorical* is implemented as a python object and not as a low-level *numpy* array dtype. This leads to some problems.

numpy itself doesn't know about the new *dtype*:

```
In [176]: try:
.....:     np.dtype("category")
.....: except TypeError as e:
.....:     print("TypeError: " + str(e))
.....:
TypeError: data type "category" not understood
```

```
In [177]: dtype = Categorical(["a"]).dtype
```

```
In [178]: try:
.....:     np.dtype(dtype)
.....: except TypeError as e:
.....:     print("TypeError: " + str(e))
.....:
TypeError: data type not understood
```

Dtype comparisons work:

```
In [179]: dtype == np.str_
Out[179]: False
```

```
In [180]: np.str_ == dtype
Out[180]: False
```

To check if a *Series* contains *Categorical* data, with pandas 0.16 or later, use `hasattr(s, 'cat')`:

```
In [181]: hasattr(Series(['a'], dtype='category'), 'cat')
Out[181]: True
```

```
In [182]: hasattr(Series(['a']), 'cat')
Out[182]: False
```

Using *numpy* functions on a *Series* of type *category* should not work as *Categoricals* are not numeric data (even in the case that `.categories` is numeric).

```
In [183]: s = Series(Categorical([1,2,3,4]))
```

```
In [184]: try:
.....:     np.sum(s)
```

```
.....: except TypeError as e:
.....:     print("TypeError: " + str(e))
.....:
```

TypeError: Categorical cannot perform the operation sum

Note: If such a function works, please file a bug at <https://github.com/pydata/pandas!>

22.10.4 dtype in apply

Pandas currently does not preserve the dtype in apply functions: If you apply along rows you get a *Series* of object *dtype* (same as getting a row -> getting one element will return a basic type) and applying along columns will also convert to object.

```
In [185]: df = DataFrame({"a": [1, 2, 3, 4],
.....:                  "b": ["a", "b", "c", "d"],
.....:                  "cats": Categorical([1, 2, 3, 2])})
.....:
```

```
In [186]: df.apply(lambda row: type(row["cats"]), axis=1)
Out[186]:
0    <type 'long'>
1    <type 'long'>
2    <type 'long'>
3    <type 'long'>
dtype: object
```

```
In [187]: df.apply(lambda col: col.dtype, axis=0)
Out[187]:
a      object
b      object
cats   object
dtype: object
```

22.10.5 Categorical Index

New in version 0.16.1.

A new `CategoricalIndex` index type is introduced in version 0.16.1. See the [advanced indexing docs](#) for a more detailed explanation.

Setting the index, will create a `CategoricalIndex`

```
In [188]: cats = Categorical([1, 2, 3, 4], categories=[4, 2, 3, 1])
```

```
In [189]: strings = ["a", "b", "c", "d"]
```

```
In [190]: values = [4, 2, 3, 1]
```

```
In [191]: df = DataFrame({"strings": strings, "values": values}, index=cats)
```

```
In [192]: df.index
```

```
Out[192]: CategoricalIndex([1, 2, 3, 4], categories=[4, 2, 3, 1], ordered=False, dtype='category')
```

```
# This now sorts by the categories order
```

```
In [193]: df.sort_index()
```

```
Out[193]:
  strings  values
4      d      1
2      b      2
3      c      3
1      a      4
```

In previous versions (<0.16.1) there is no index of type `category`, so setting the index to categorical column will convert the categorical data to a “normal” dtype first and therefore remove any custom ordering of the categories.

22.10.6 Side Effects

Constructing a *Series* from a *Categorical* will not copy the input *Categorical*. This means that changes to the *Series* will in most cases change the original *Categorical*:

```
In [194]: cat = Categorical([1,2,3,10], categories=[1,2,3,4,10])
```

```
In [195]: s = Series(cat, name="cat")
```

```
In [196]: cat
```

```
Out[196]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

```
In [197]: s.iloc[0:2] = 10
```

```
In [198]: cat
```

```
Out[198]:
[10, 10, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

```
In [199]: df = DataFrame(s)
```

```
In [200]: df["cat"].cat.categories = [1,2,3,4,5]
```

```
In [201]: cat
```

```
Out[201]:
[5, 5, 3, 5]
Categories (5, int64): [1, 2, 3, 4, 5]
```

Use `copy=True` to prevent such a behaviour or simply don't reuse *Categoricals*:

```
In [202]: cat = Categorical([1,2,3,10], categories=[1,2,3,4,10])
```

```
In [203]: s = Series(cat, name="cat", copy=True)
```

```
In [204]: cat
```

```
Out[204]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

```
In [205]: s.iloc[0:2] = 10
```

```
In [206]: cat
```

```
Out[206]:
[1, 2, 3, 10]
Categories (5, int64): [1, 2, 3, 4, 10]
```

Note: This also happens in some cases when you supply a *numpy* array instead of a *Categorical*: using an int array (e.g. `np.array([1, 2, 3, 4])`) will exhibit the same behaviour, while using a string array (e.g. `np.array(["a", "b", "c", "a"])`) will not.

PLOTTING

We use the standard convention for referencing the matplotlib API:

```
In [1]: import matplotlib.pyplot as plt
```

The plots in this document are made using matplotlib's ggplot style (new in version 1.4):

```
import matplotlib
matplotlib.style.use('ggplot')
```

If your version of matplotlib is 1.3 or lower, you can set `display.mpl_style` to 'default' with `pd.options.display.mpl_style = 'default'` to produce more appealing plots. When set, matplotlib's rcParams are changed (globally!) to nicer-looking settings.

We provide the basics in pandas to easily create decent looking plots. See the *ecosystem* section for visualization libraries that go beyond the basics documented here.

Note: All calls to `np.random` are seeded with 123456.

23.1 Basic Plotting: plot

See the *cookbook* for some advanced strategies

The `plot` method on Series and DataFrame is just a simple wrapper around `plt.plot()`:

```
In [2]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
```

```
In [3]: ts = ts.cumsum()
```

```
In [4]: ts.plot()
```

```
Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0xaf71f64c>
```



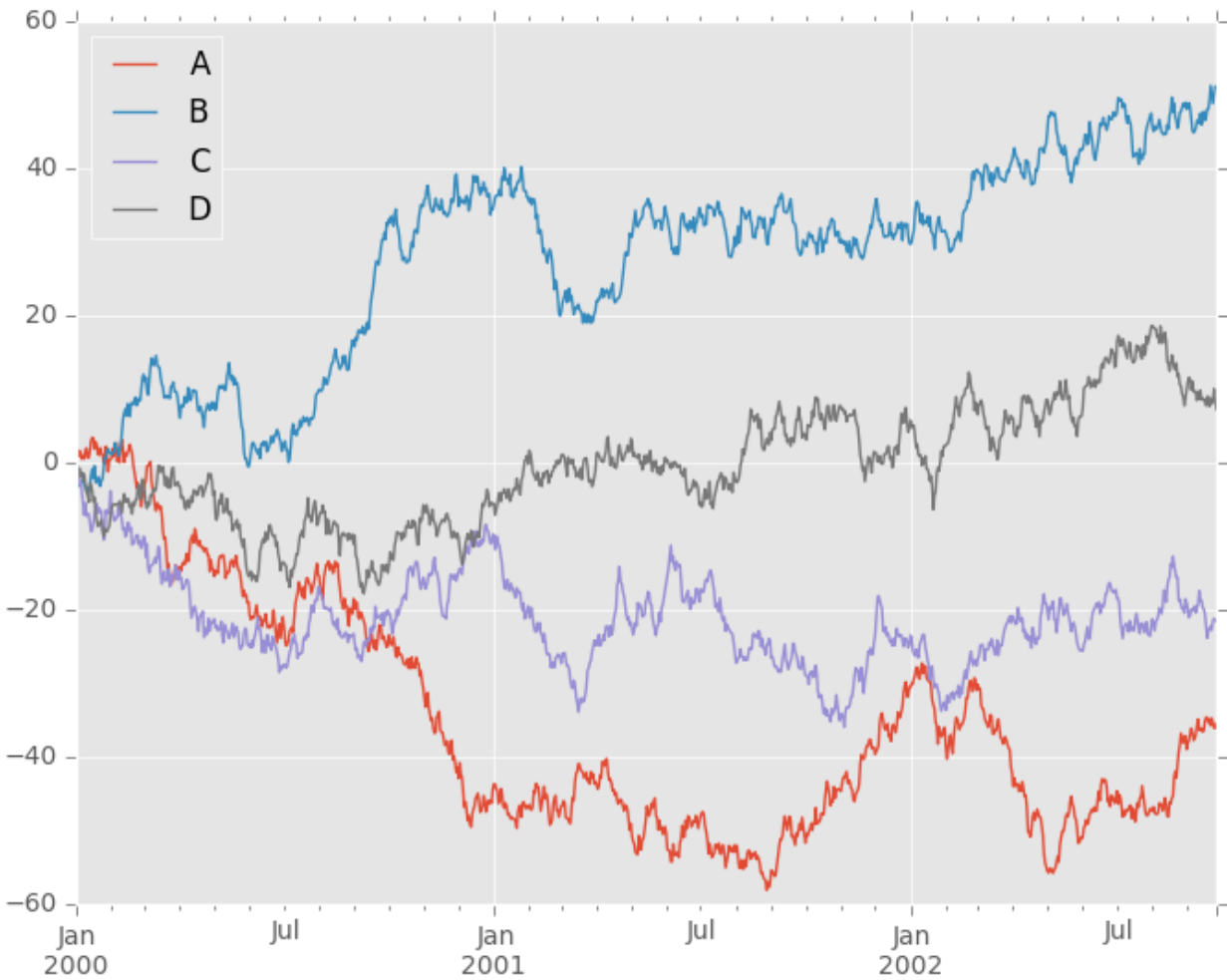
If the index consists of dates, it calls `gcf().autofmt_xdate()` to try to format the x-axis nicely as per above.

On `DataFrame`, `plot()` is a convenience to plot all of the columns with labels:

```
In [5]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))
```

```
In [6]: df = df.cumsum()
```

```
In [7]: plt.figure(); df.plot();
```



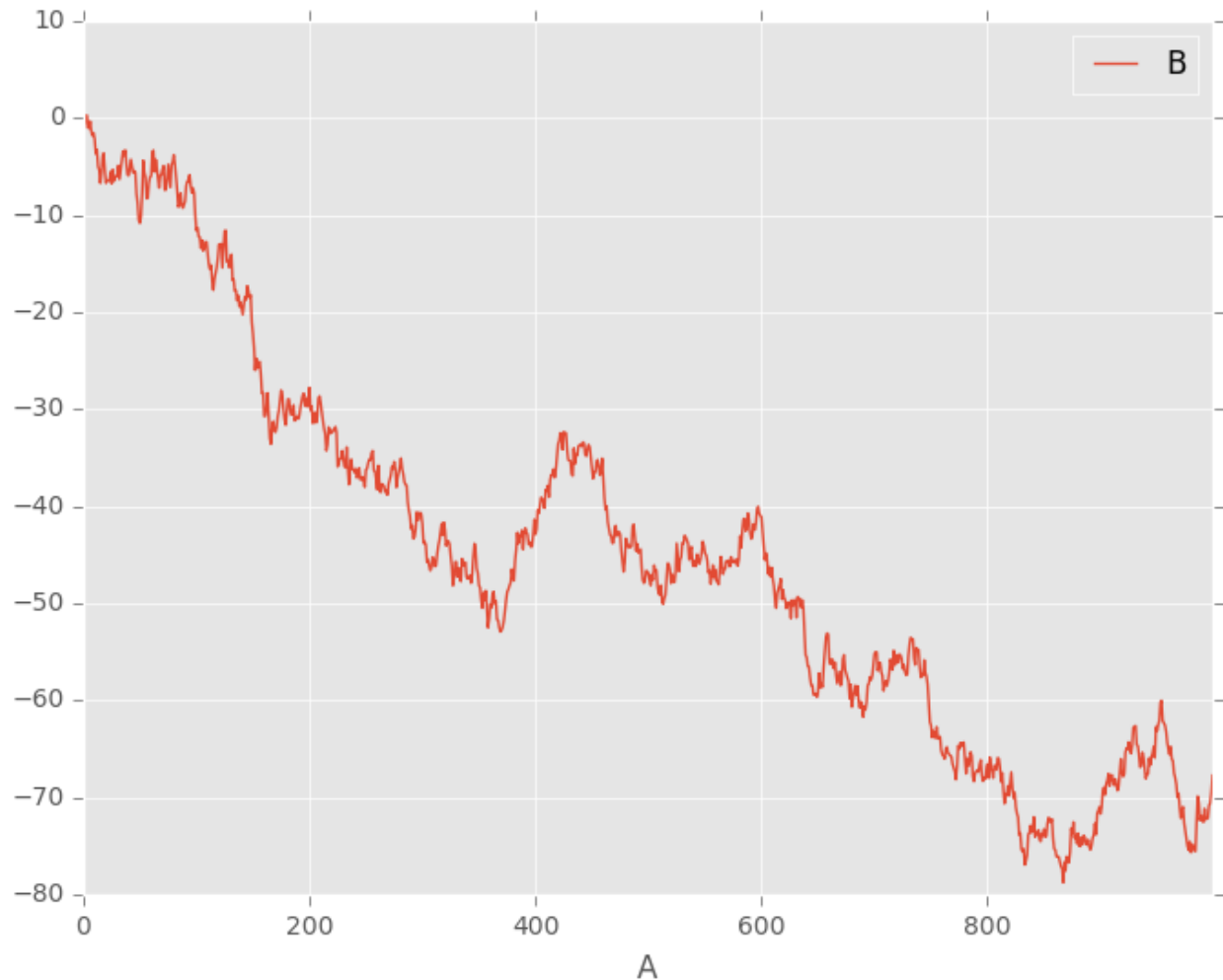
You can plot one column versus another using the `x` and `y` keywords in `plot()`:

```
In [8]: df3 = pd.DataFrame(np.random.randn(1000, 2), columns=['B', 'C']).cumsum()
```

```
In [9]: df3['A'] = pd.Series(list(range(len(df))))
```

```
In [10]: df3.plot(x='A', y='B')
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0xaf66360c>
```



Note: For more formatting and styling options, see [below](#).

23.2 Other Plots

The `kind` keyword argument of `plot()` accepts a handful of values for plots other than the default Line plot. These include:

- `'bar'` or `'barh'` for bar plots
- `'hist'` for histogram
- `'box'` for boxplot
- `'kde'` or `'density'` for density plots
- `'area'` for area plots
- `'scatter'` for scatter plots
- `'hexbin'` for hexagonal bin plots
- `'pie'` for pie plots

In addition to these `kinds`, there are the `DataFrame.hist()`, and `DataFrame.boxplot()` methods, which use a separate interface.

Finally, there are several *plotting functions* in `pandas.tools.plotting` that take a `Series` or `DataFrame` as an argument. These include

- *Scatter Matrix*
- *Andrews Curves*
- *Parallel Coordinates*
- *Lag Plot*
- *Autocorrelation Plot*
- *Bootstrap Plot*
- *RadViz*

Plots may also be adorned with *errorbars* or *tables*.

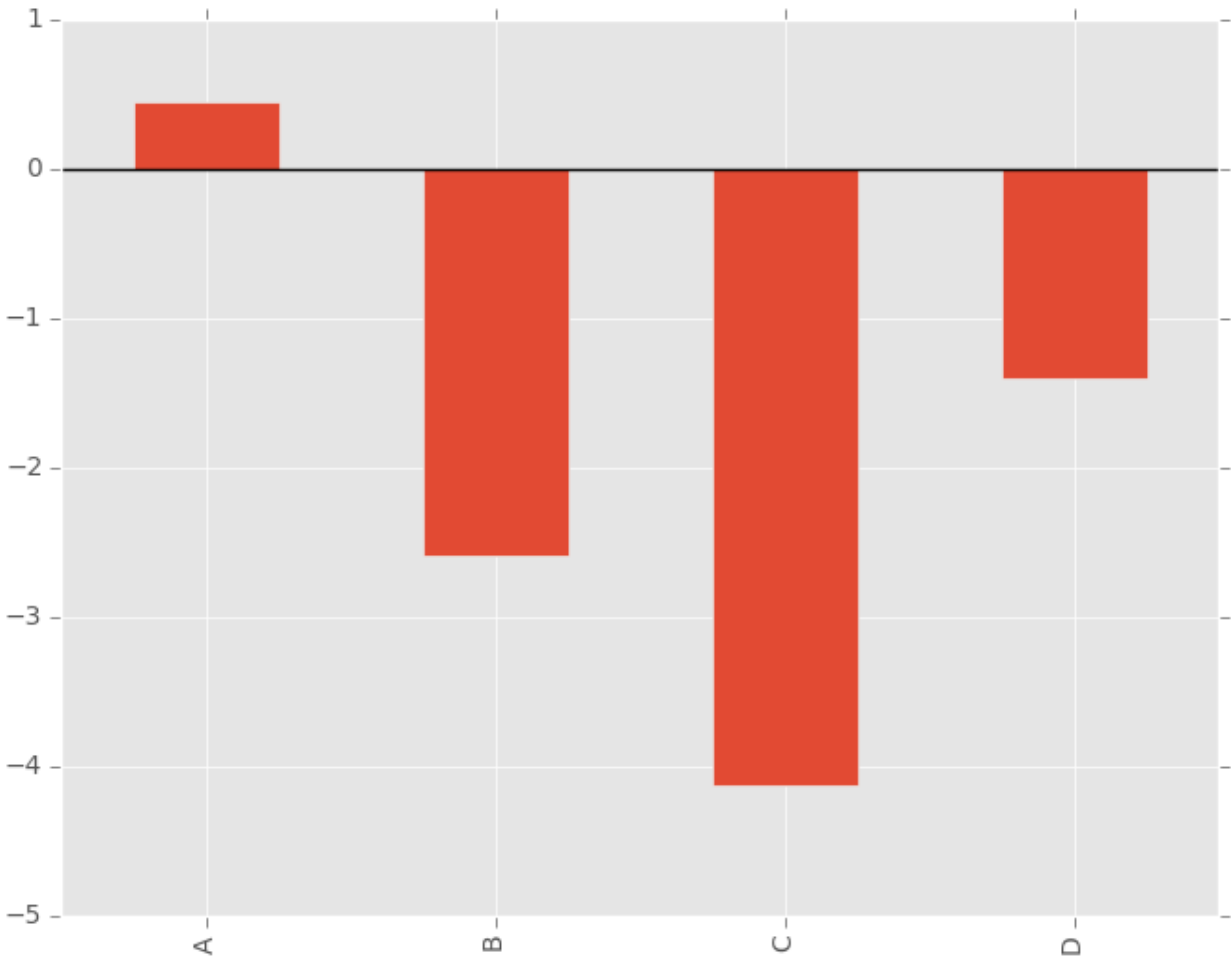
23.2.1 Bar plots

For labeled, non-time series data, you may wish to produce a bar plot:

```
In [11]: plt.figure();
```

```
In [12]: df.ix[5].plot(kind='bar'); plt.axhline(0, color='k')
```

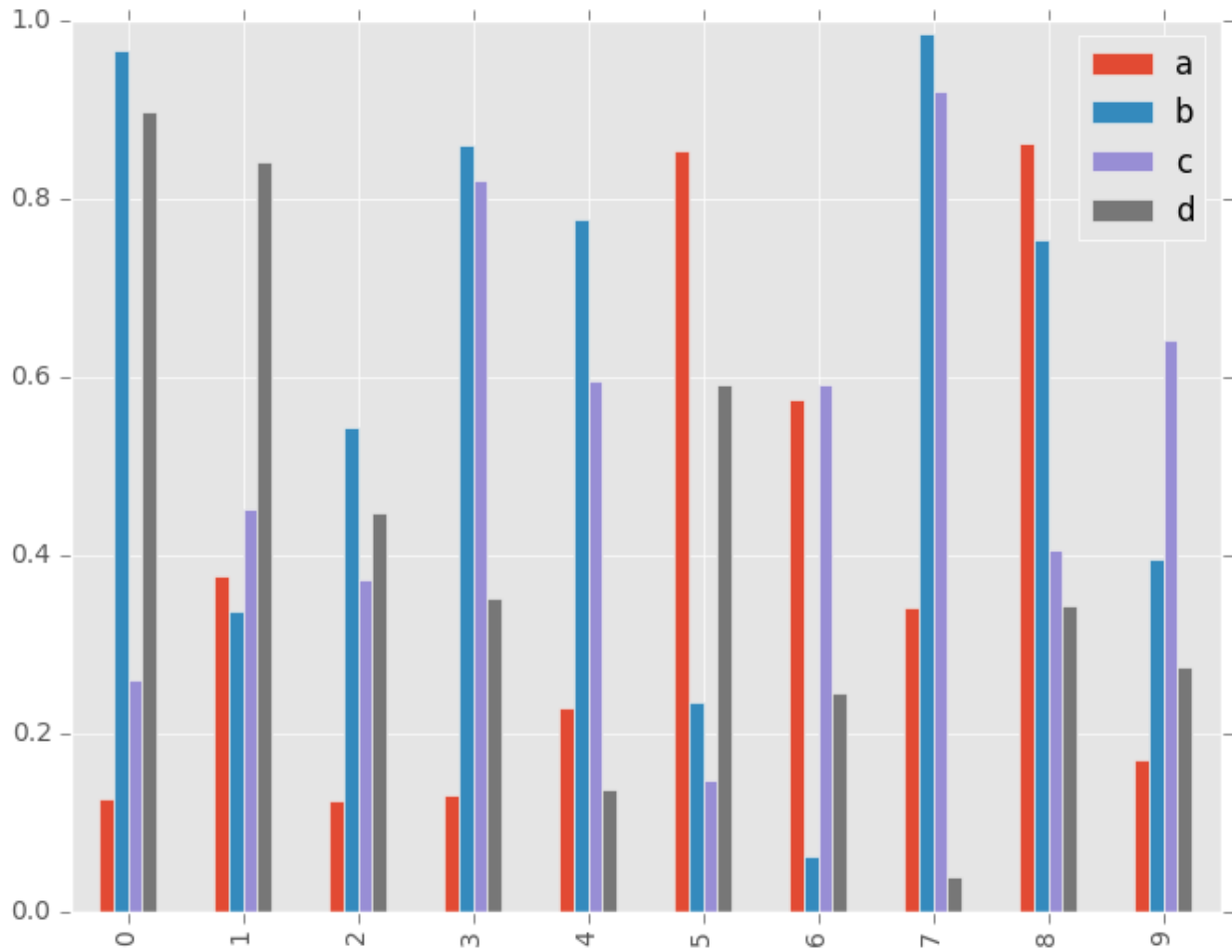
```
Out[12]: <matplotlib.lines.Line2D at 0xaf5cd12c>
```



Calling a `DataFrame`'s `plot()` method with `kind='bar'` produces a multiple bar plot:

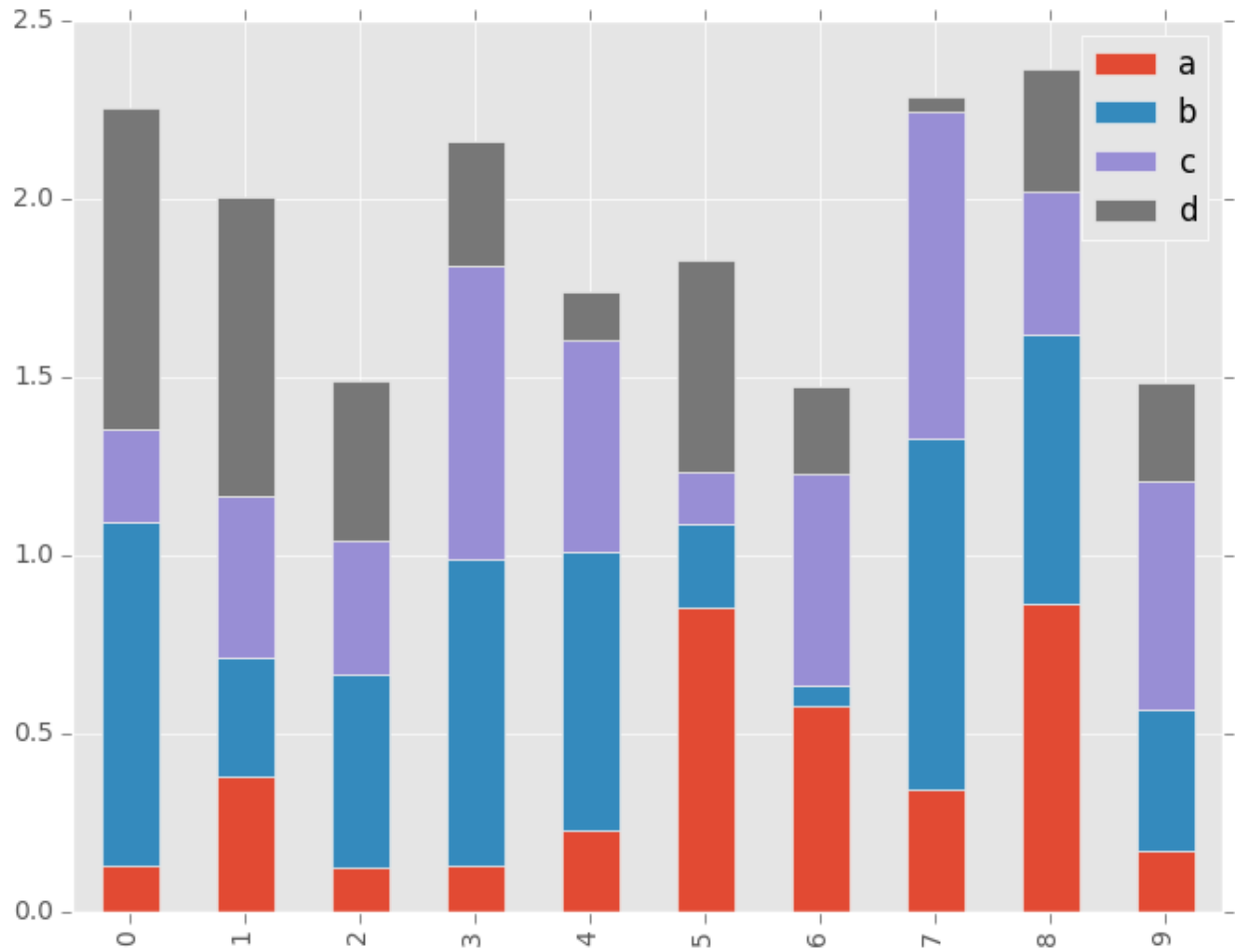
```
In [13]: df2 = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
```

```
In [14]: df2.plot(kind='bar');
```



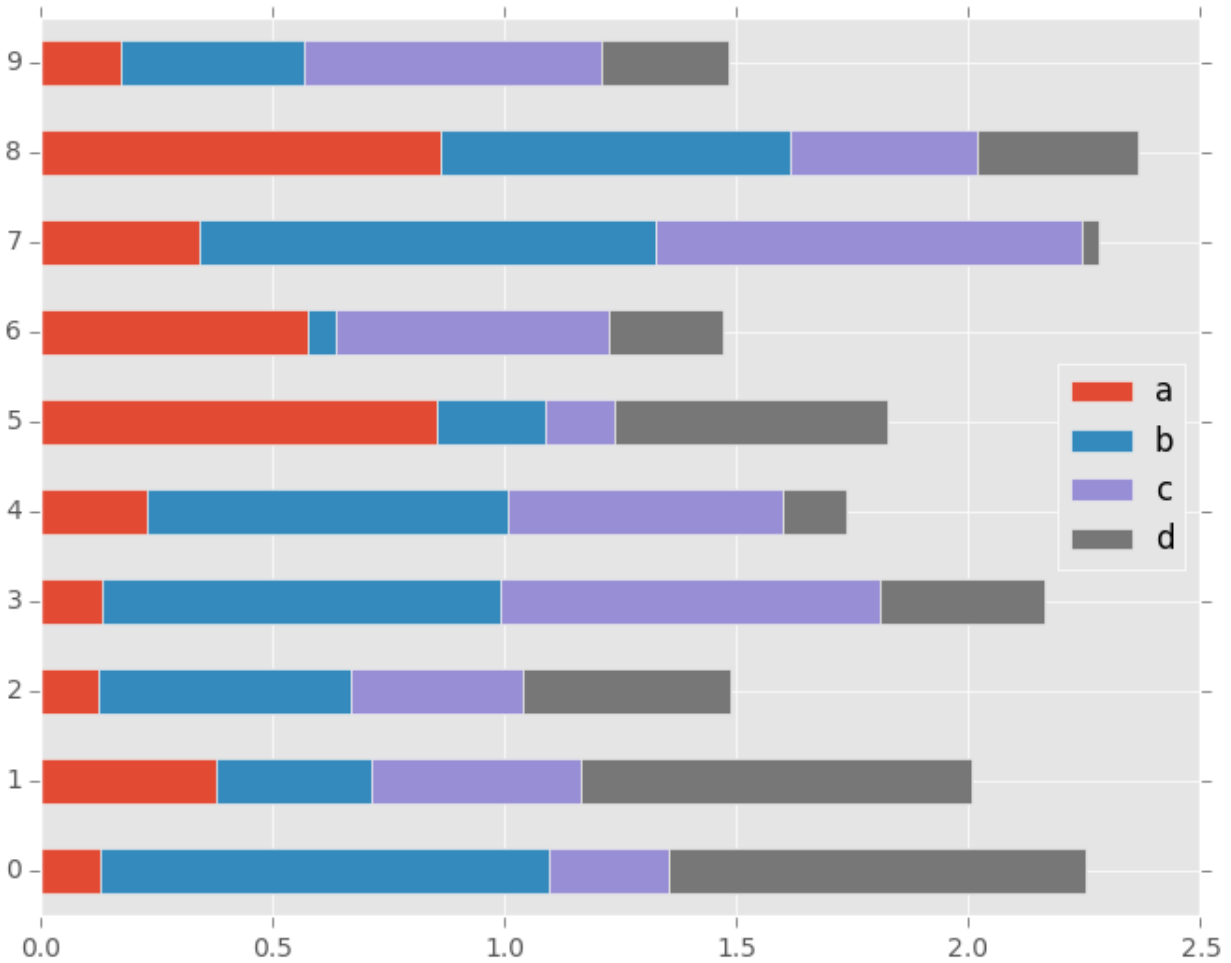
To produce a stacked bar plot, pass `stacked=True`:

```
In [15]: df2.plot(kind='bar', stacked=True);
```



To get horizontal bar plots, pass `kind='barh'`:

```
In [16]: df2.plot(kind='barh', stacked=True);
```



23.2.2 Histograms

New in version 0.15.0.

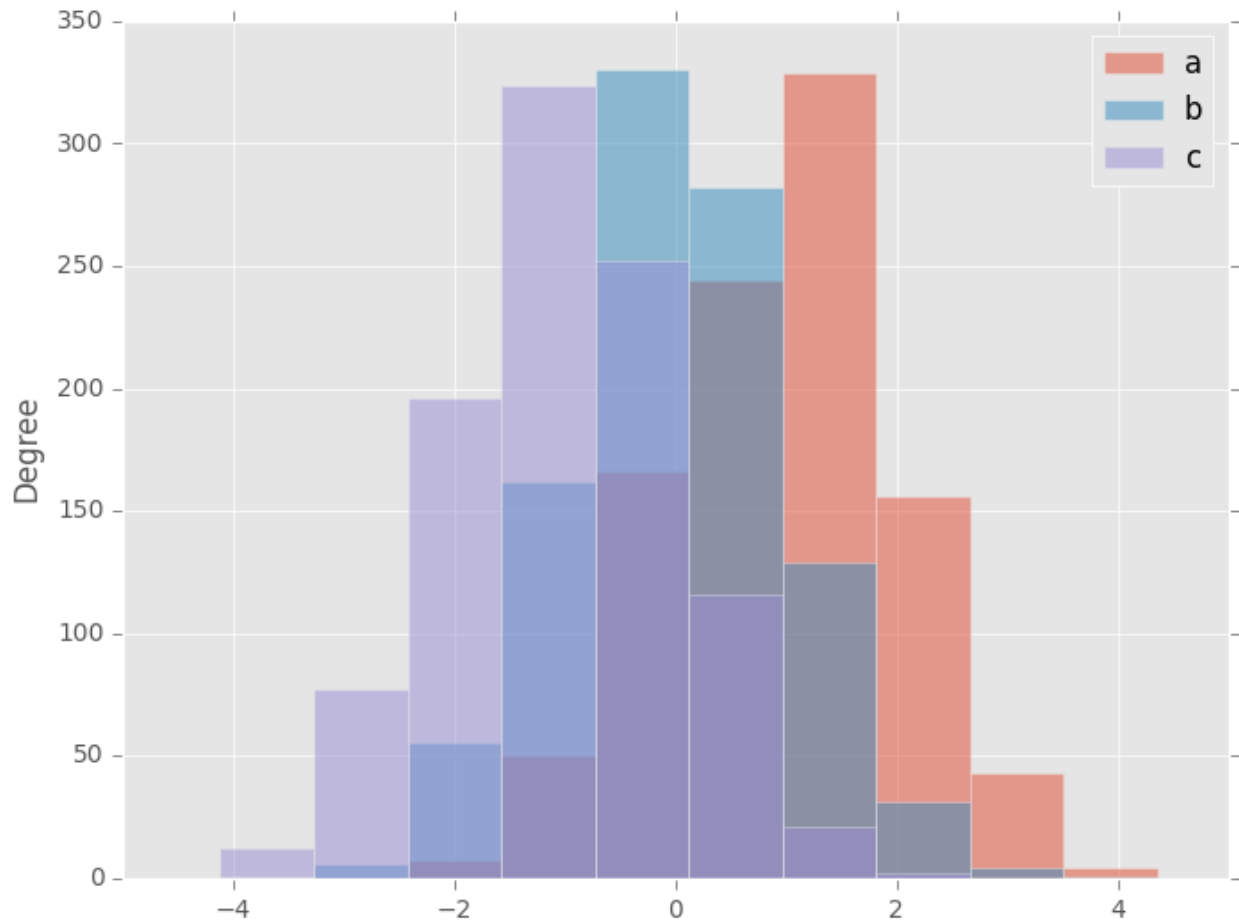
Histogram can be drawn specifying `kind='hist'`.

```
In [17]: df4 = pd.DataFrame({'a': np.random.randn(1000) + 1, 'b': np.random.randn(1000),
.....:                      'c': np.random.randn(1000) - 1}, columns=['a', 'b', 'c'])
.....:
```

```
In [18]: plt.figure();
```

```
In [19]: df4.plot(kind='hist', alpha=0.5)
```

```
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0xaf2132ec>
```

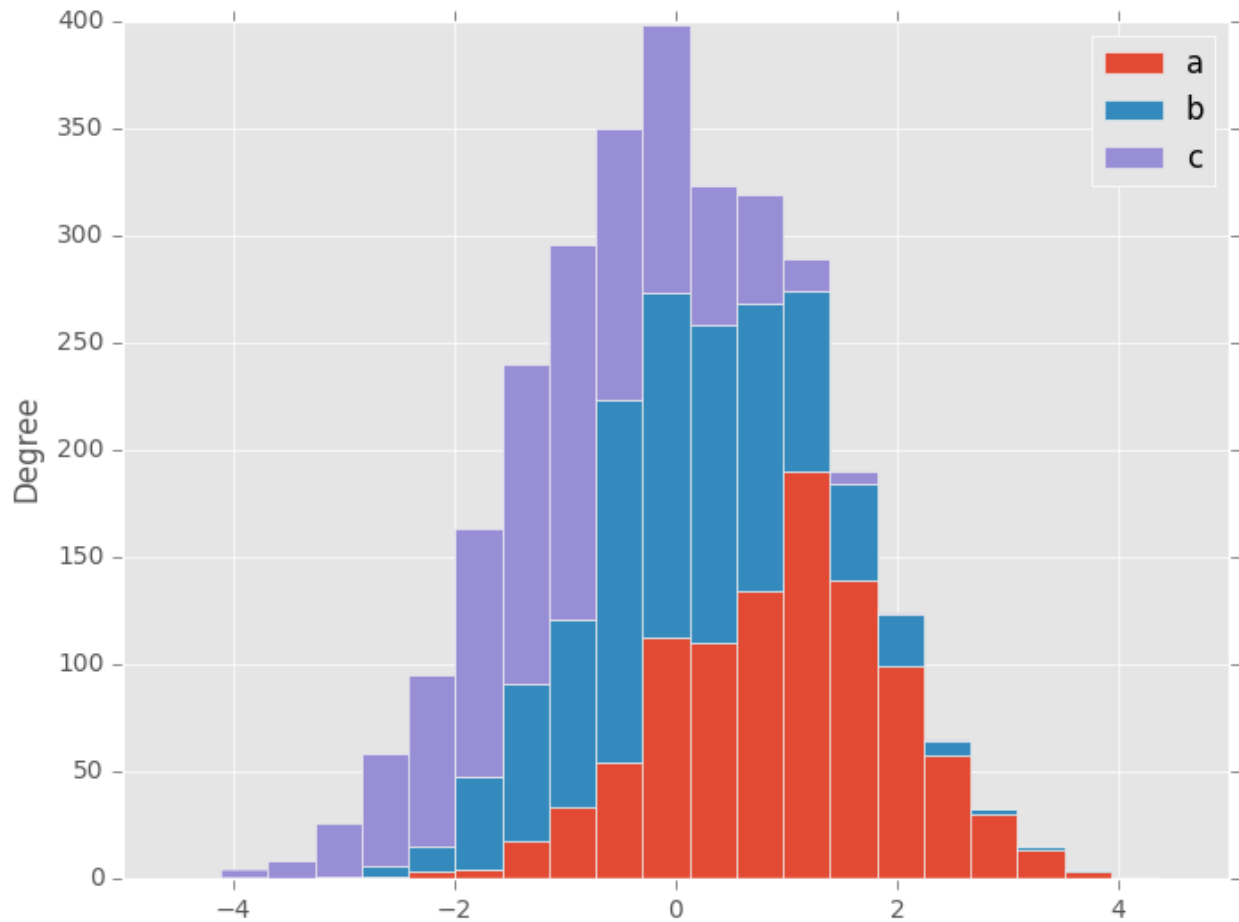


Histogram can be stacked by `stacked=True`. Bin size can be changed by `bins` keyword.

```
In [20]: plt.figure();
```

```
In [21]: df4.plot(kind='hist', stacked=True, bins=20)
```

```
Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0xaf27ed0c>
```

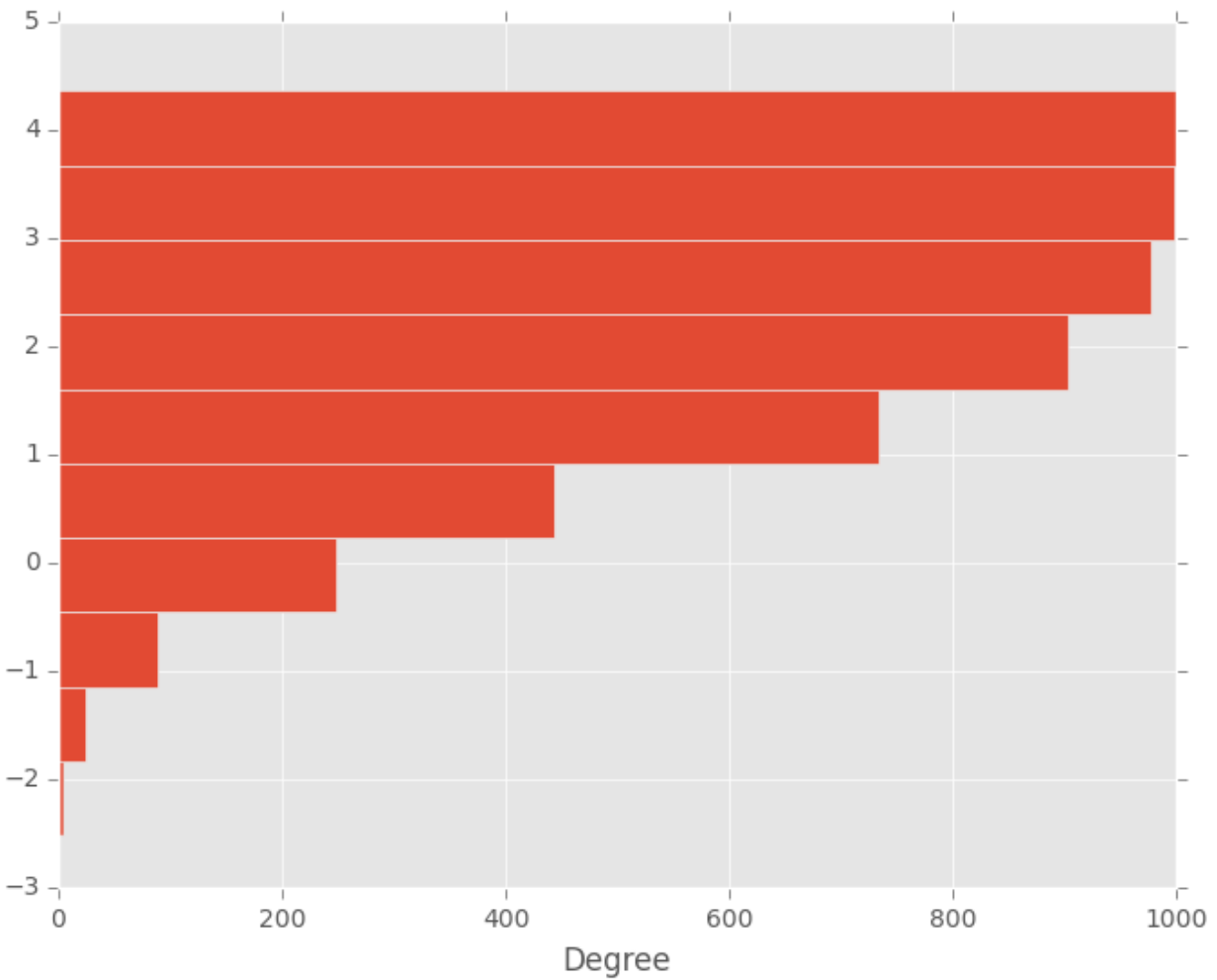


You can pass other keywords supported by matplotlib `hist`. For example, horizontal and cumulative histogram can be drawn by `orientation='horizontal'` and `cumulative=True`.

```
In [22]: plt.figure();
```

```
In [23]: df4['a'].plot(kind='hist', orientation='horizontal', cumulative=True)
```

```
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0xaf29458c>
```



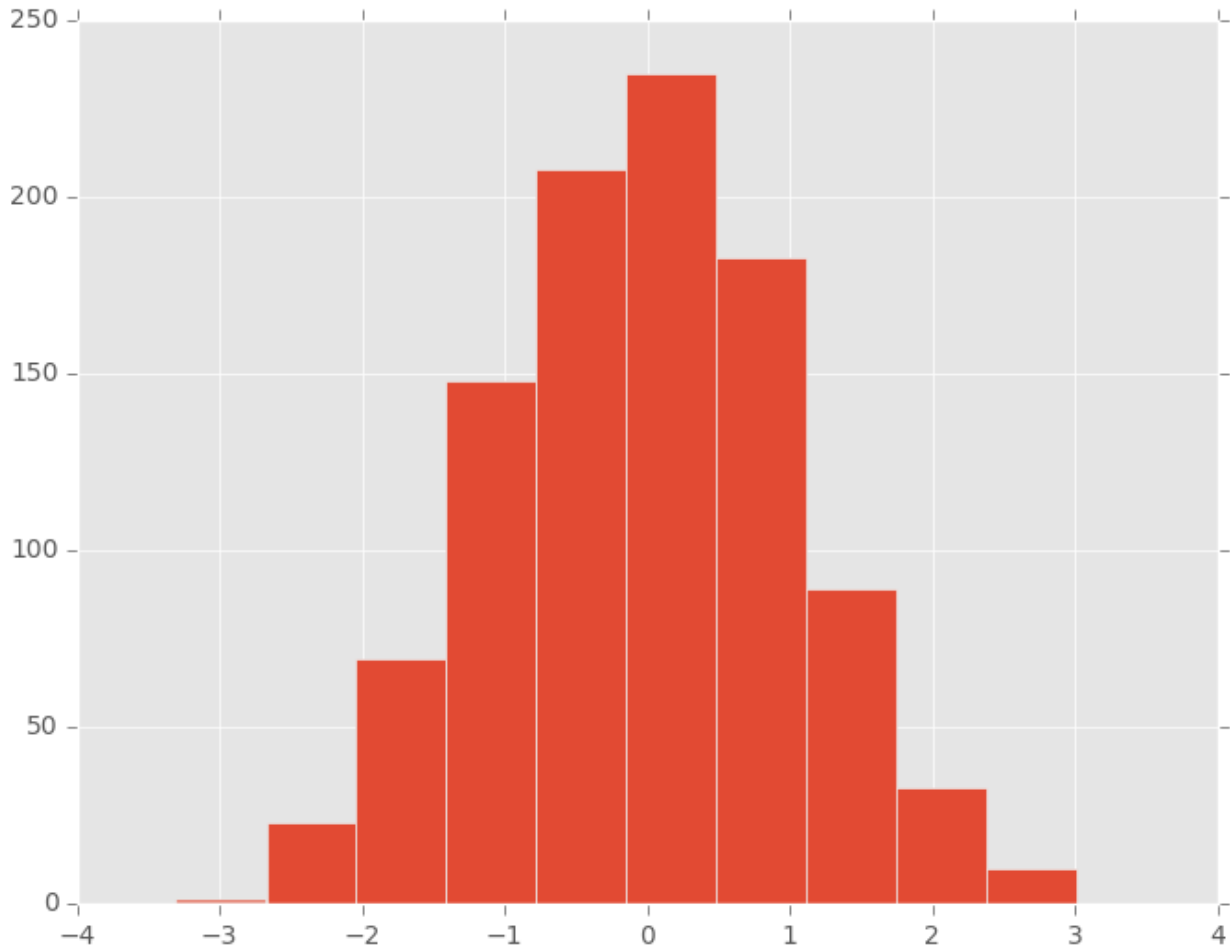
See the [hist](#) method and the [matplotlib hist documentation](#) for more.

The existing interface `DataFrame.hist` to plot histogram still can be used.

```
In [24]: plt.figure();
```

```
In [25]: df['A'].diff().hist()
```

```
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0xaf5b6bac>
```



`DataFrame.hist()` plots the histograms of the columns on multiple subplots:

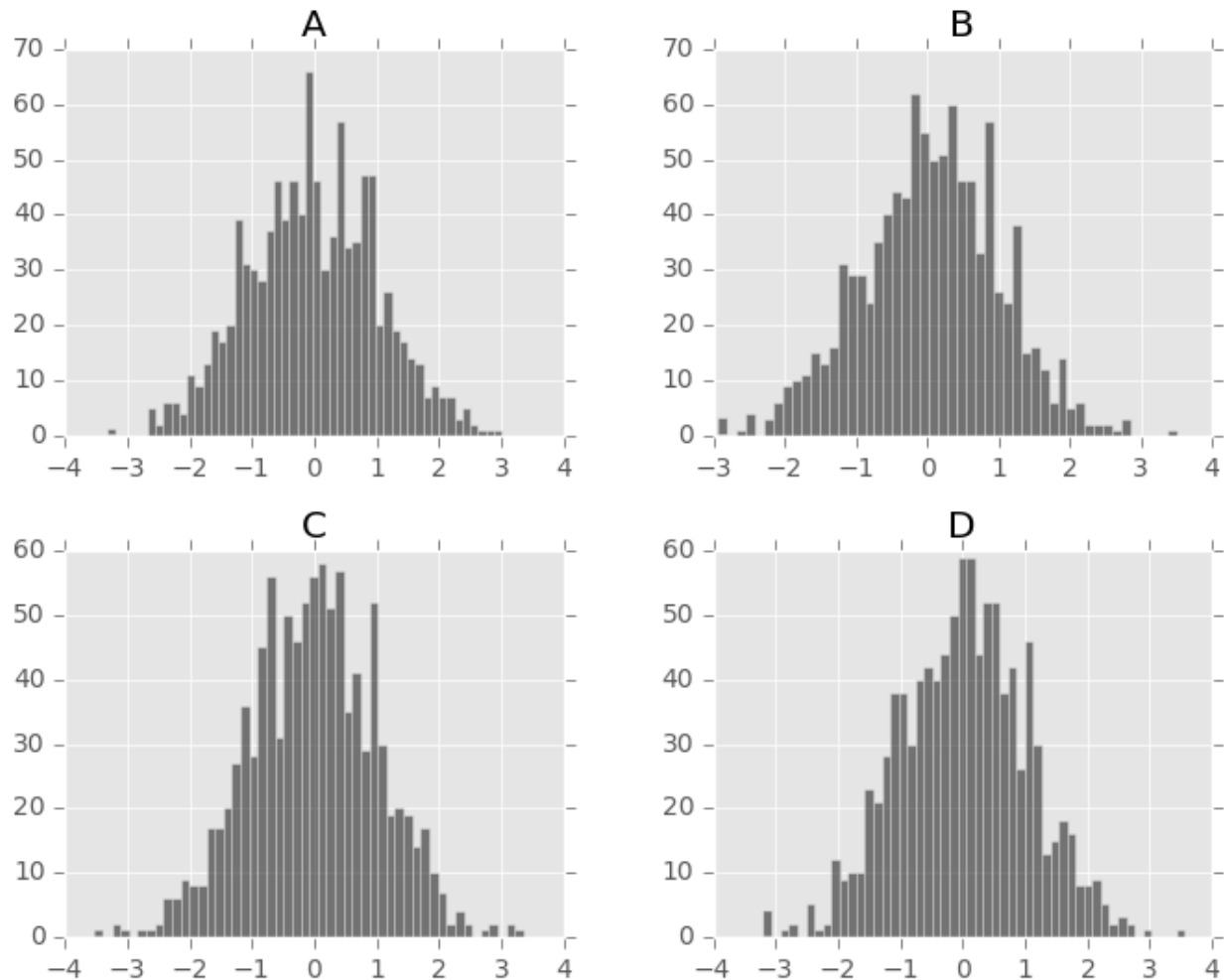
In [26]: `plt.figure()`

Out [26]: `<matplotlib.figure.Figure at 0xb0d67ccc>`

In [27]: `df.diff().hist(color='k', alpha=0.5, bins=50)`

Out [27]:

`array([[<matplotlib.axes._subplots.AxesSubplot object at 0xaf5cb64c>,
 <matplotlib.axes._subplots.AxesSubplot object at 0xaf16990c>],
 [<matplotlib.axes._subplots.AxesSubplot object at 0xaecdea4c>,
 <matplotlib.axes._subplots.AxesSubplot object at 0xaec921cc>]], dtype=object)`



New in version 0.10.0.

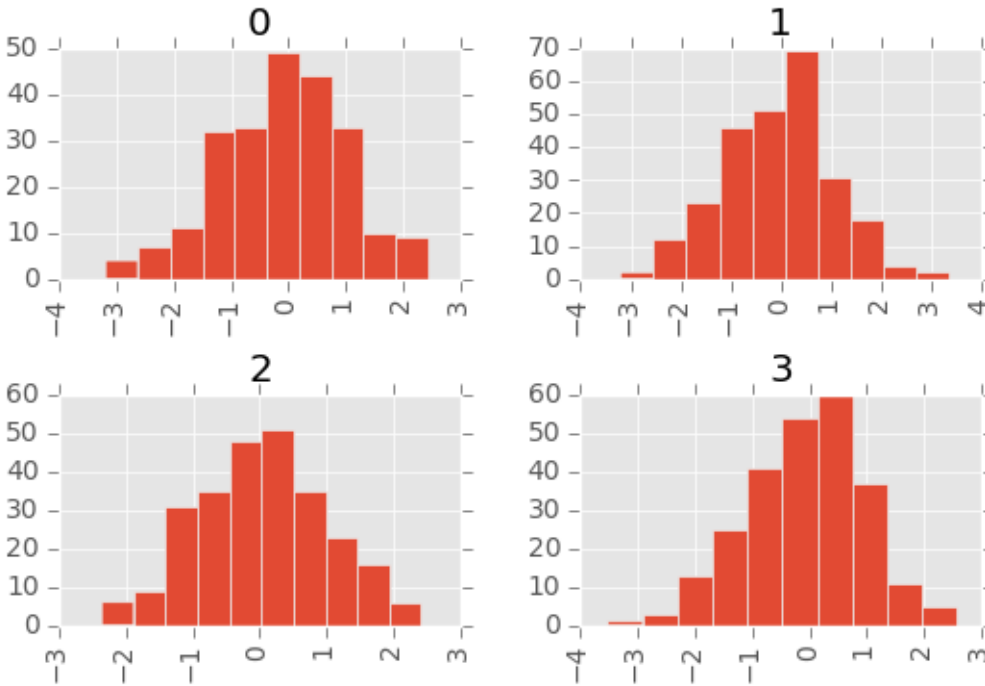
The `by` keyword can be specified to plot grouped histograms:

```
In [28]: data = pd.Series(np.random.randn(1000))
```

```
In [29]: data.hist(by=np.random.randint(0, 4, 1000), figsize=(6, 4))
```

```
Out[29]:
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0xae8bd6c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xae81a16c>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0xae7db1ec>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xae78866c>]], dtype=object)
```



23.2.3 Box Plots

Boxplot can be drawn calling a `Series` and `DataFrame.plot` with `kind='box'`, or `DataFrame.boxplot` to visualize the distribution of values within each column.

New in version 0.15.0.

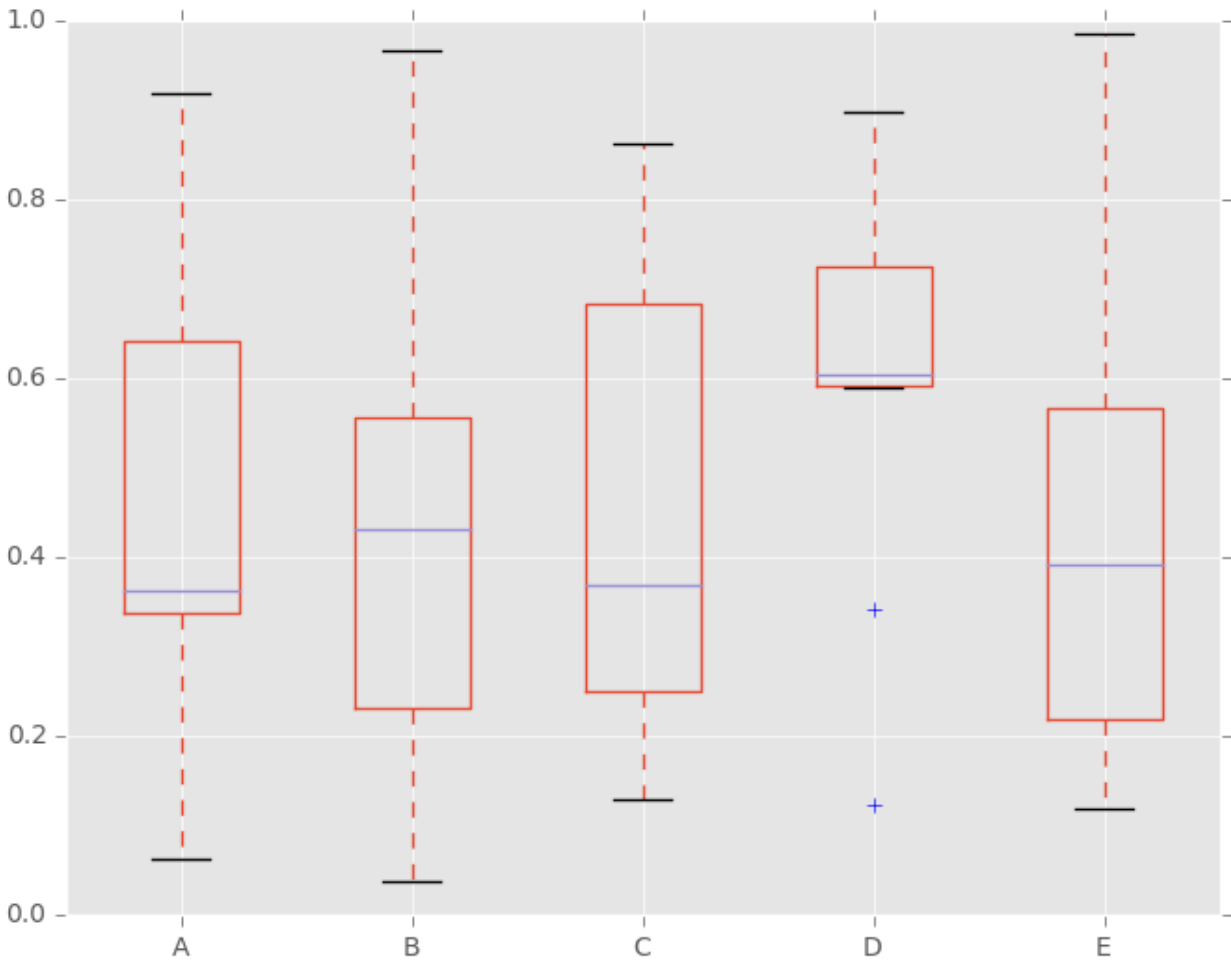
`plot` method now supports `kind='box'` to draw boxplot.

For instance, here is a boxplot representing five trials of 10 observations of a uniform random variable on $[0,1)$.

```
In [30]: df = pd.DataFrame(np.random.rand(10, 5), columns=['A', 'B', 'C', 'D', 'E'])
```

```
In [31]: df.plot(kind='box')
```

```
Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0xae156b2c>
```



Boxplot can be colored by passing `color` keyword. You can pass a dict whose keys are `boxes`, `whiskers`, `medians` and `caps`. If some keys are missing in the dict, default colors are used for the corresponding artists. Also, boxplot has `sym` keyword to specify fliers style.

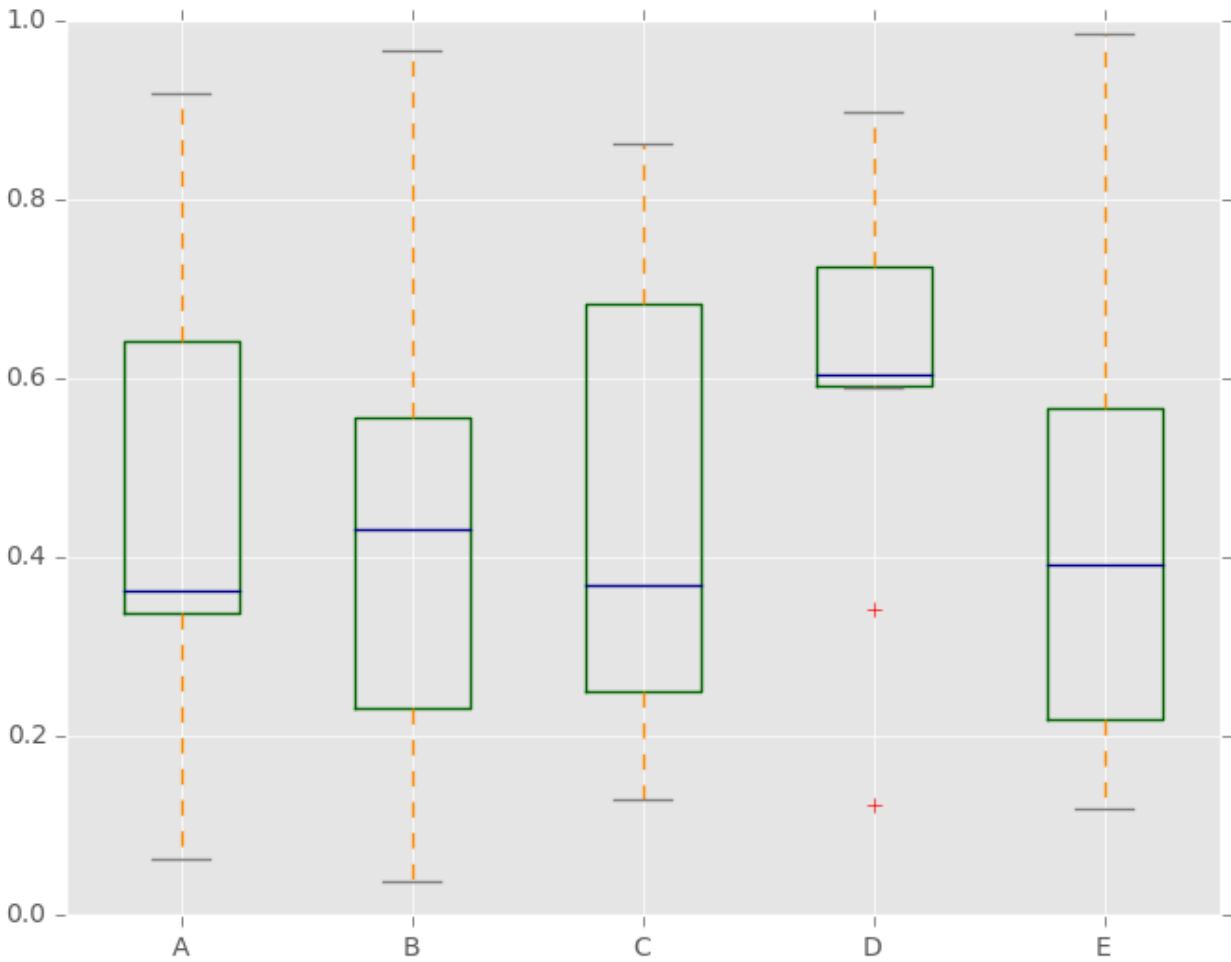
When you pass other type of arguments via `color` keyword, it will be directly passed to matplotlib for all the `boxes`, `whiskers`, `medians` and `caps` colorization.

The colors are applied to every boxes to be drawn. If you want more complicated colorization, you can get each drawn artists by passing `return_type`.

```
In [32]: color = dict(boxes='DarkGreen', whiskers='DarkOrange',
.....:               medians='DarkBlue', caps='Gray')
.....:
```

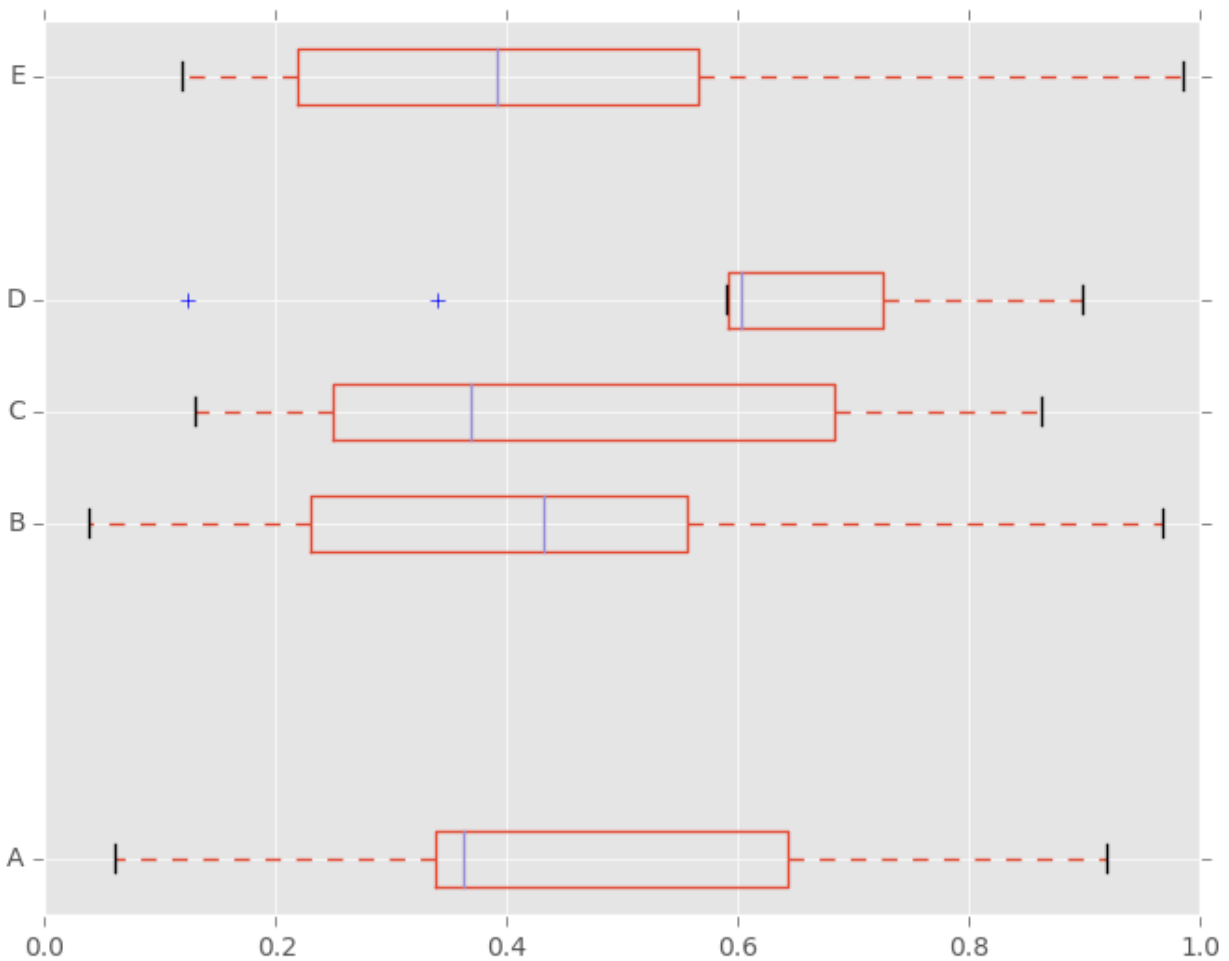
```
In [33]: df.plot(kind='box', color=color, sym='r+')
```

```
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0xadf73fec>
```



Also, you can pass other keywords supported by matplotlib `boxplot`. For example, horizontal and custom-positioned boxplot can be drawn by `vert=False` and `positions` keywords.

```
In [34]: df.plot(kind='box', vert=False, positions=[1, 4, 5, 6, 8])
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0xade97d0c>
```



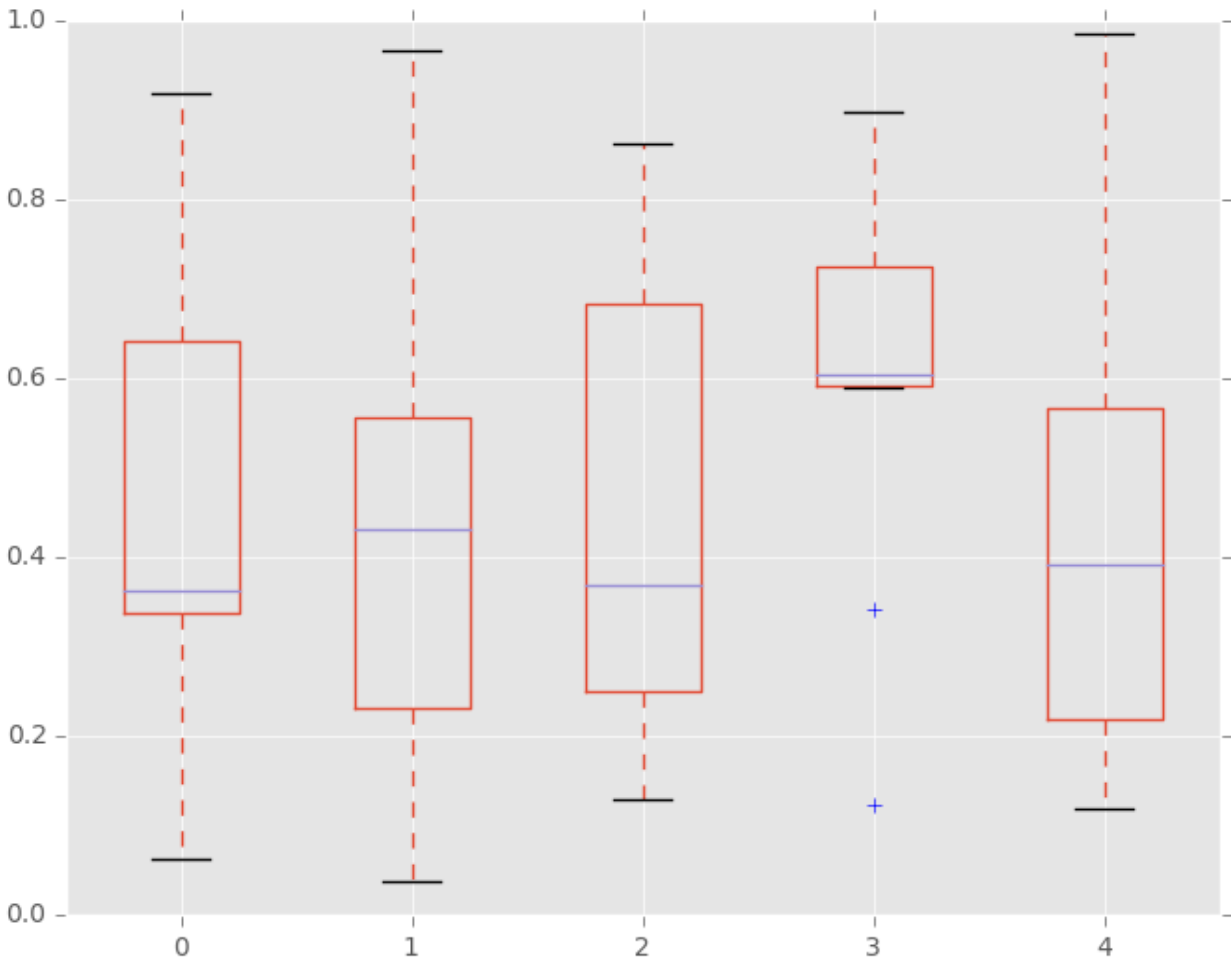
See the `boxplot` method and the [matplotlib boxplot documentation](#) for more.

The existing interface `DataFrame.boxplot` to plot boxplot still can be used.

```
In [35]: df = pd.DataFrame(np.random.rand(10, 5))
```

```
In [36]: plt.figure();
```

```
In [37]: bp = df.boxplot()
```



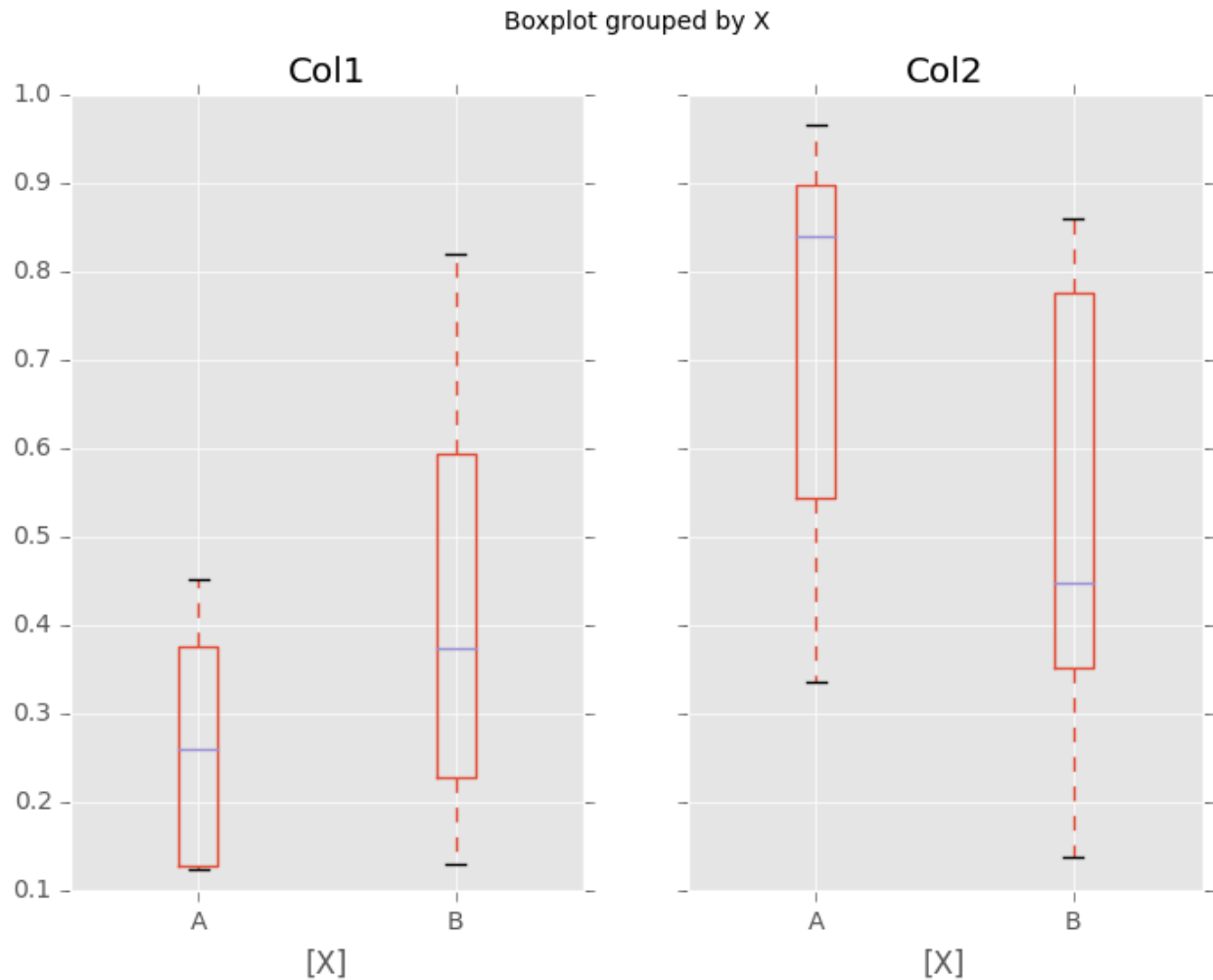
You can create a stratified boxplot using the `by` keyword argument to create groupings. For instance,

```
In [38]: df = pd.DataFrame(np.random.rand(10,2), columns=['Col1', 'Col2'] )
```

```
In [39]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])
```

```
In [40]: plt.figure();
```

```
In [41]: bp = df.boxplot(by='X')
```



You can also pass a subset of columns to plot, as well as group by multiple columns:

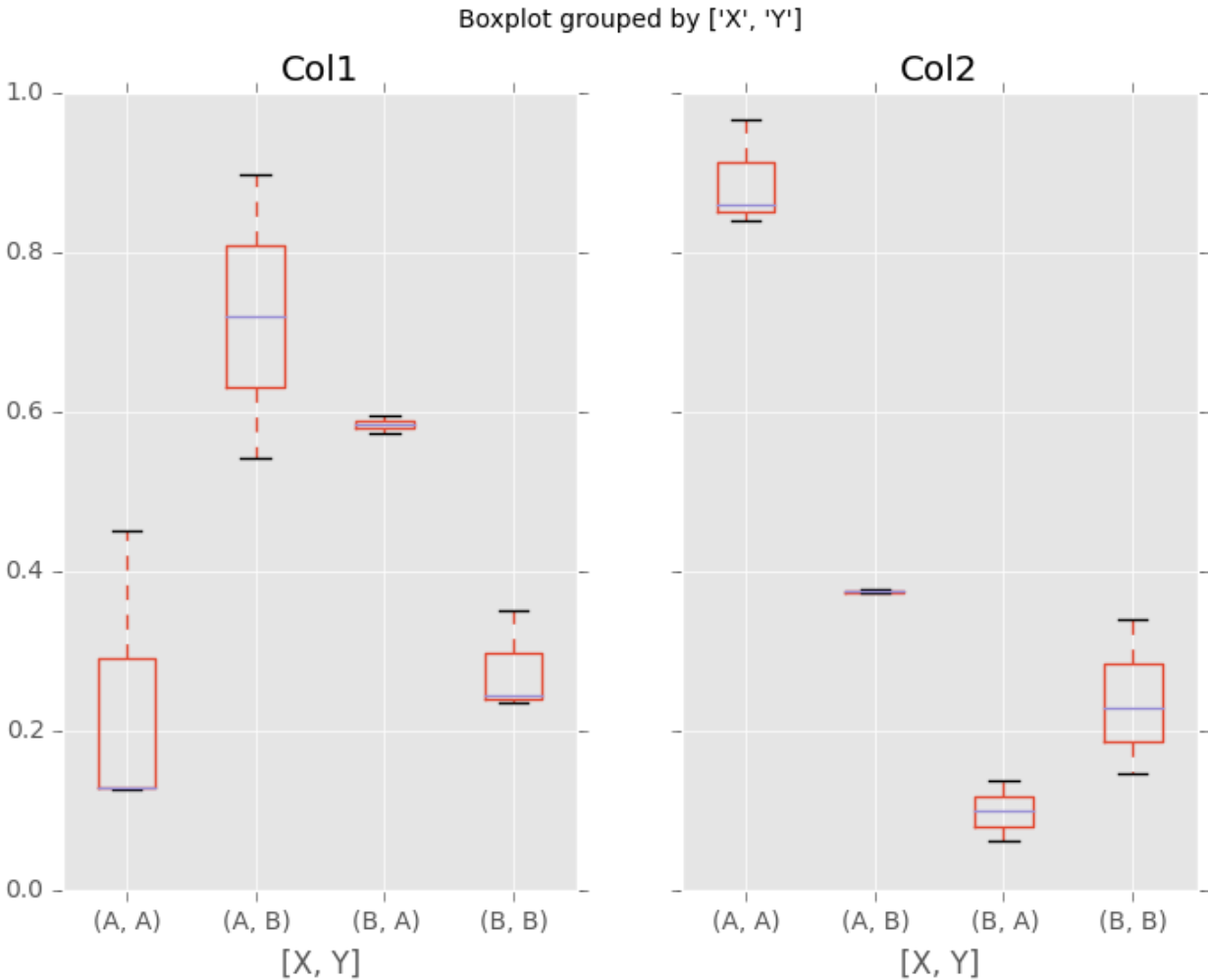
```
In [42]: df = pd.DataFrame(np.random.rand(10,3), columns=['Col1', 'Col2', 'Col3'])
```

```
In [43]: df['X'] = pd.Series(['A','A','A','A','A','B','B','B','B','B'])
```

```
In [44]: df['Y'] = pd.Series(['A','B','A','B','A','B','A','B','A','B'])
```

```
In [45]: plt.figure();
```

```
In [46]: bp = df.boxplot(column=['Col1','Col2'], by=['X','Y'])
```



Basically, plot functions return `matplotlib Axes` as a return value. In `boxplot`, the return type can be changed by argument `return_type`, and whether the subplots is enabled (`subplots=True` in `plot` or `by` is specified in `boxplot`).

When `subplots=False` / `by` is `None`:

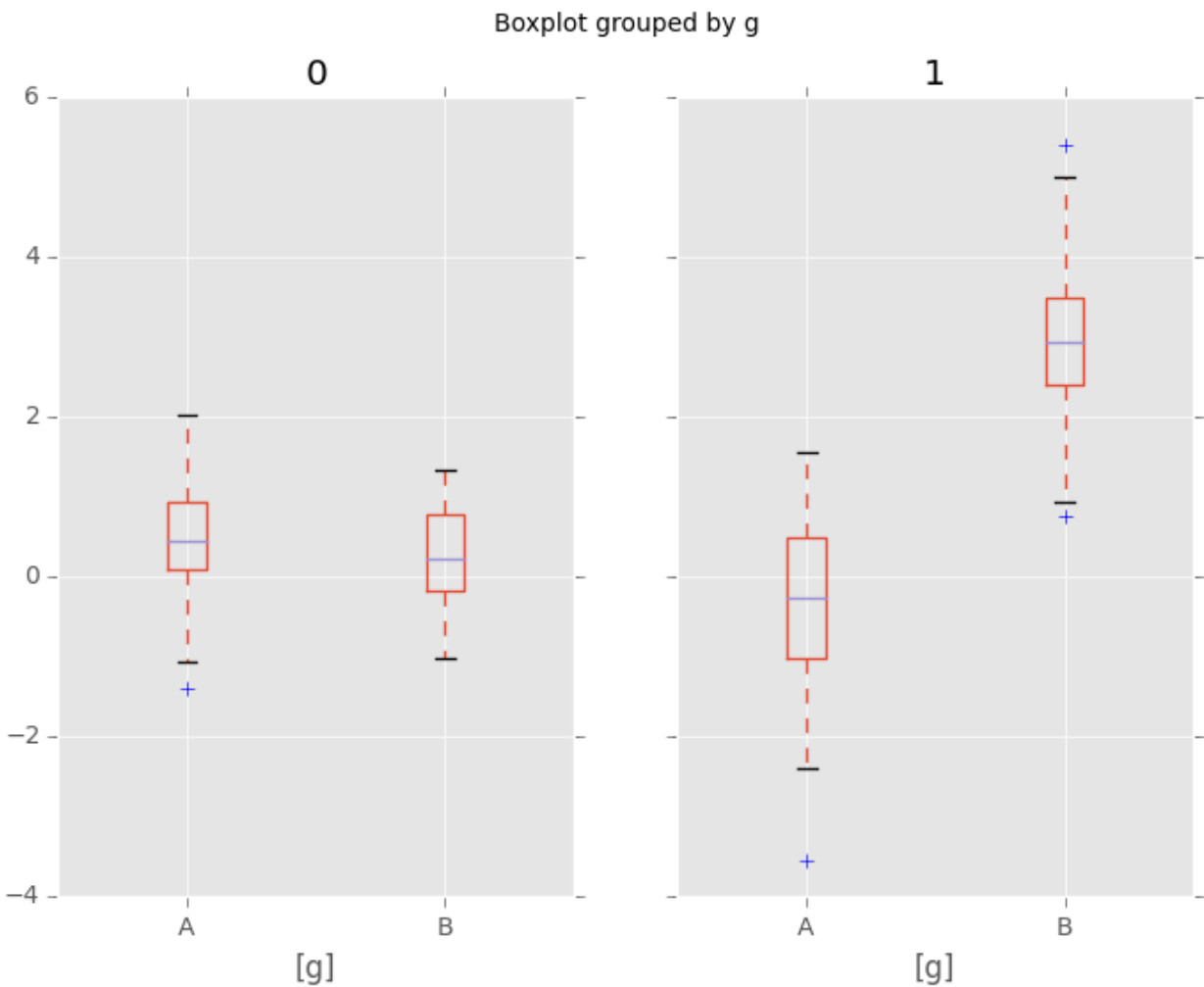
- if `return_type` is `'dict'`, a dictionary containing the `matplotlib Lines` is returned. The keys are “boxes”, “caps”. This is the default of `boxplot` in historical reason. Note that `plot(kind='box')` returns `Axes` as default as the same as other plots.
- if `return_type` is `'axes'`, a `matplotlib Axes` containing the boxplot is returned.
- if `return_type` is `'both'` a namedtuple containing the `matplotlib Axes` and `matplotlib Lines` is returned

When `subplots=True` / `by` is some column of the `DataFrame`:

- A dict of `return_type` is returned, where the keys are the columns of the `DataFrame`. The plot has a facet for each column of the `DataFrame`, with a separate box for each value of `by`.

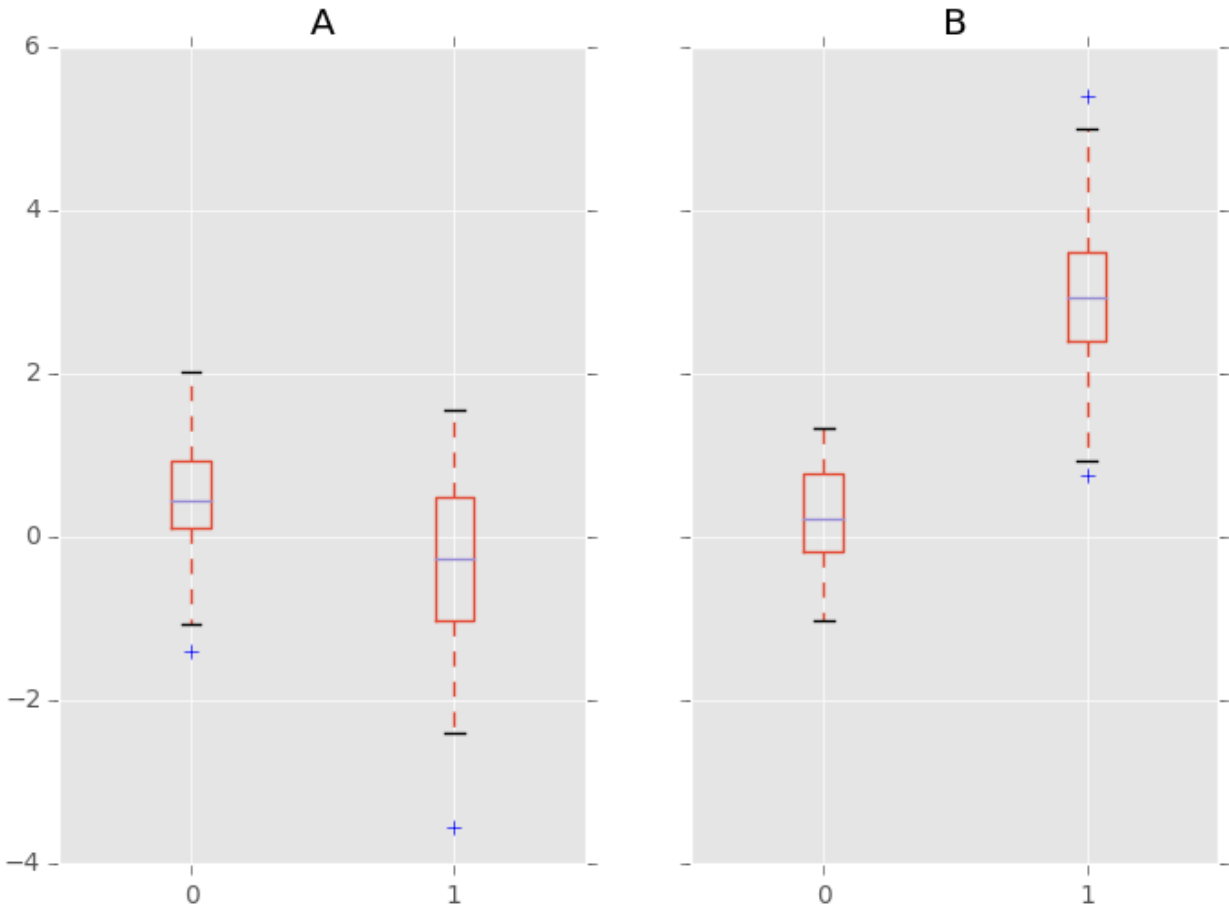
Finally, when calling `boxplot` on a `Groupby` object, a dict of `return_type` is returned, where the keys are the same as the `Groupby` object. The plot has a facet for each key, with each facet containing a box for each column of the `DataFrame`.

```
In [47]: np.random.seed(1234)
In [48]: df_box = pd.DataFrame(np.random.randn(50, 2))
In [49]: df_box['g'] = np.random.choice(['A', 'B'], size=50)
In [50]: df_box.loc[df_box['g'] == 'B', 1] += 3
In [51]: bp = df_box.boxplot(by='g')
```



Compare to:

```
In [52]: bp = df_box.groupby('g').boxplot()
```



23.2.4 Area Plot

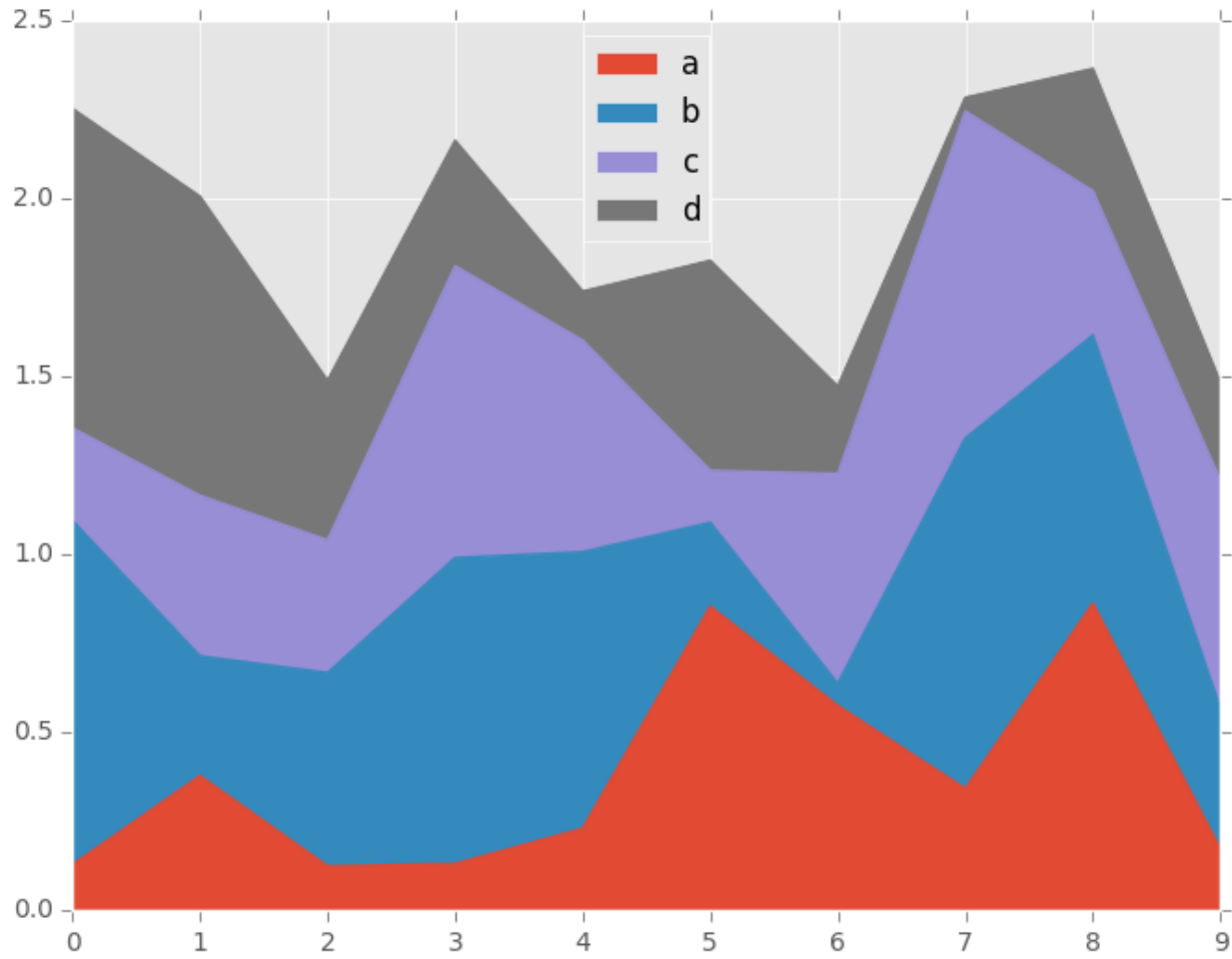
New in version 0.14.

You can create area plots with `Series.plot` and `DataFrame.plot` by passing `kind='area'`. Area plots are stacked by default. To produce stacked area plot, each column must be either all positive or all negative values.

When input data contains *NaN*, it will be automatically filled by 0. If you want to drop or fill by different values, use `dataframe.dropna()` or `dataframe.fillna()` before calling `plot`.

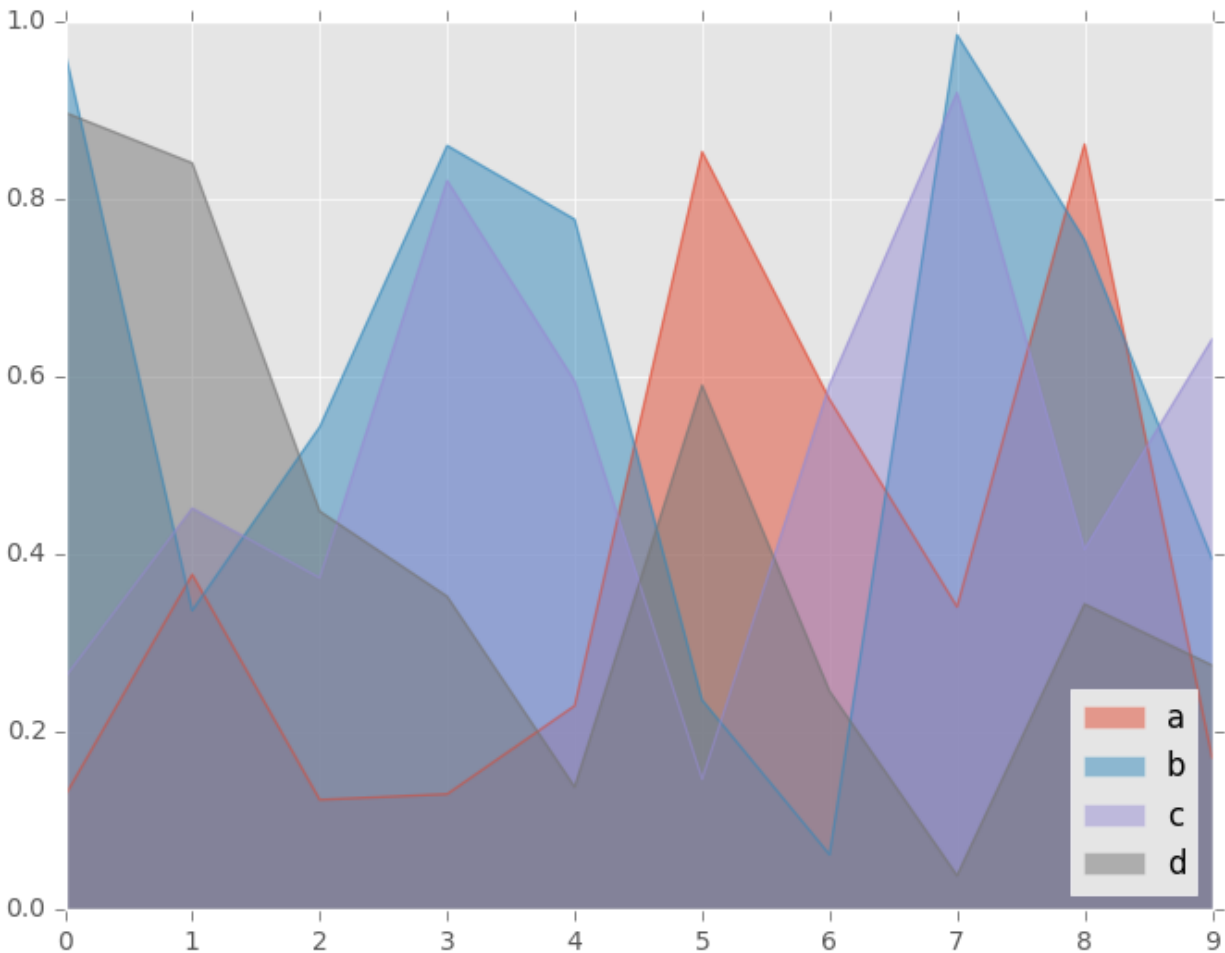
```
In [53]: df = pd.DataFrame(np.random.rand(10, 4), columns=['a', 'b', 'c', 'd'])
```

```
In [54]: df.plot(kind='area');
```



To produce an unstacked plot, pass `stacked=False`. Alpha value is set to 0.5 unless otherwise specified:

```
In [55]: df.plot(kind='area', stacked=False);
```



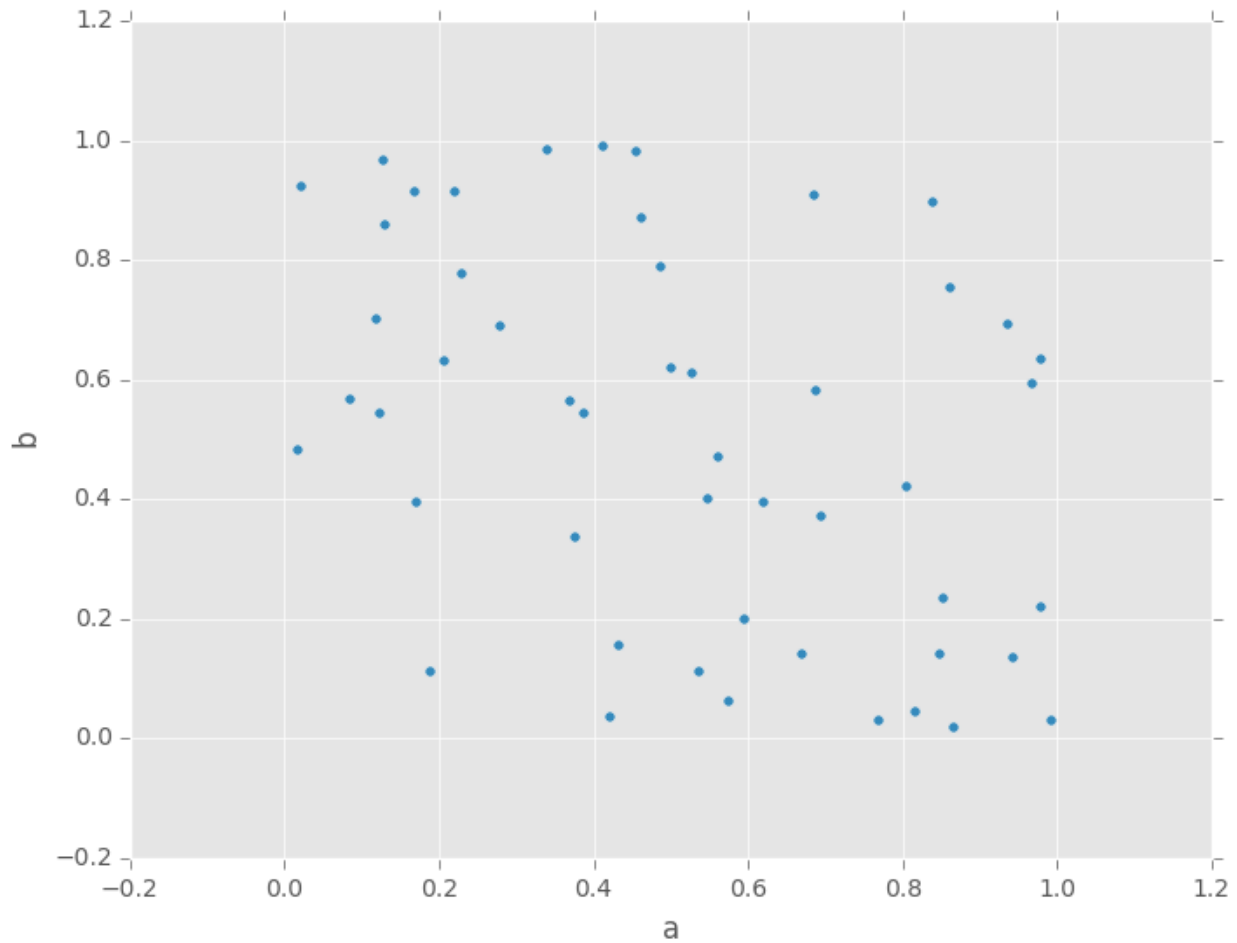
23.2.5 Scatter Plot

New in version 0.13.

You can create scatter plots with `DataFrame.plot` by passing `kind='scatter'`. Scatter plot requires numeric columns for x and y axis. These can be specified by `x` and `y` keywords each.

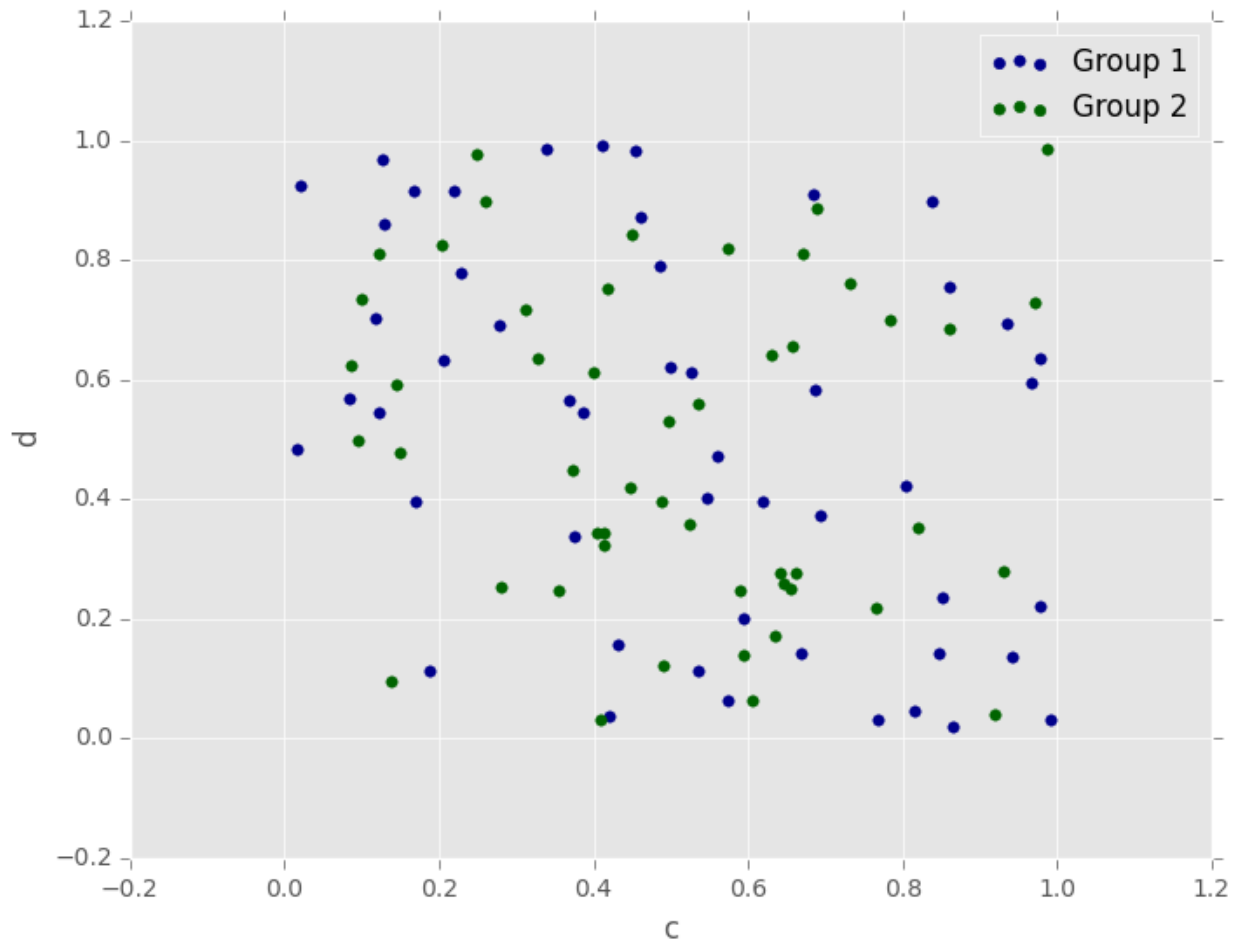
```
In [56]: df = pd.DataFrame(np.random.rand(50, 4), columns=['a', 'b', 'c', 'd'])
```

```
In [57]: df.plot(kind='scatter', x='a', y='b');
```



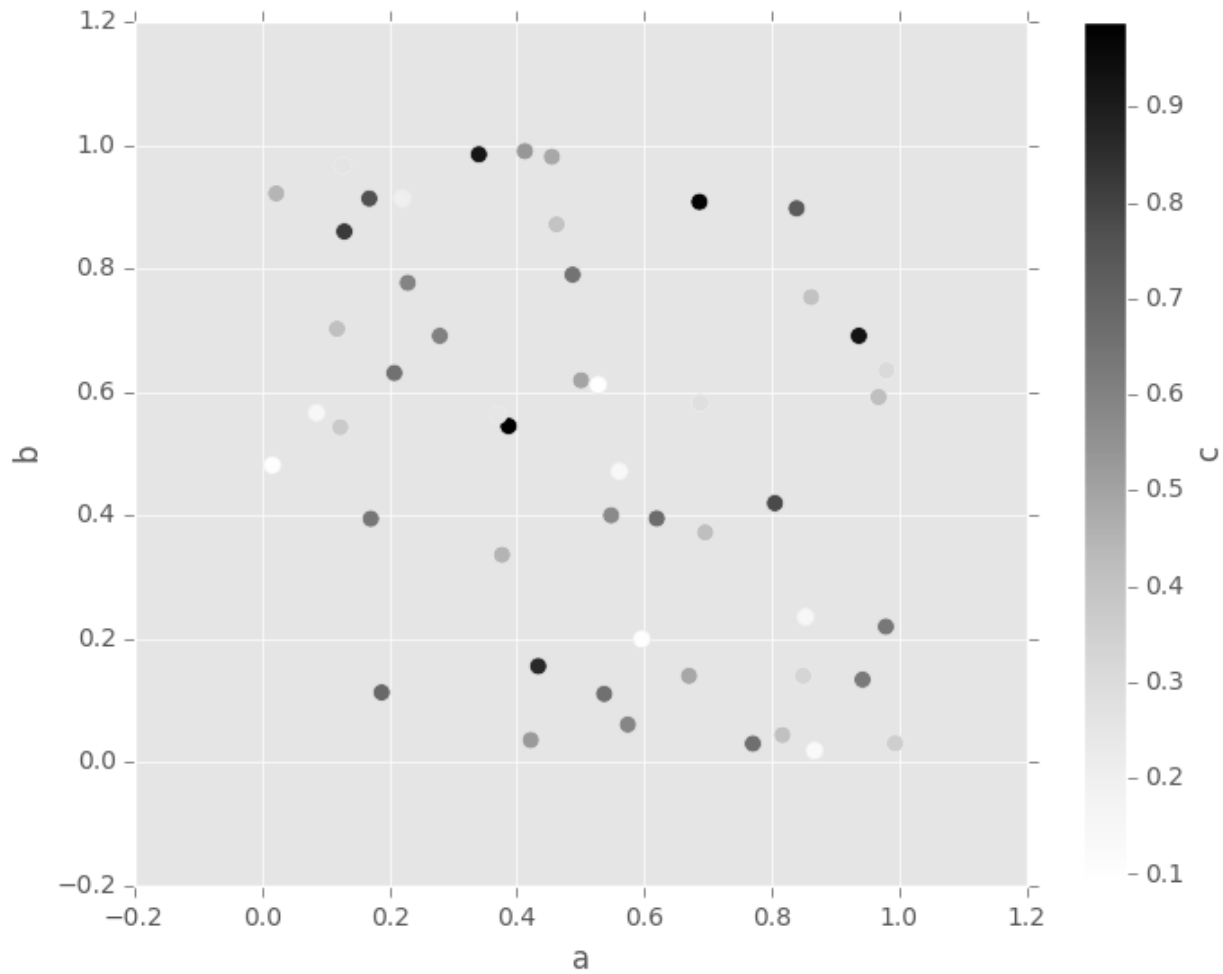
To plot multiple column groups in a single axes, repeat `plot` method specifying target `ax`. It is recommended to specify `color` and `label` keywords to distinguish each groups.

```
In [58]: ax = df.plot(kind='scatter', x='a', y='b',  
.....:               color='DarkBlue', label='Group 1');  
.....:  
  
In [59]: df.plot(kind='scatter', x='c', y='d',  
.....:               color='DarkGreen', label='Group 2', ax=ax);  
.....:
```



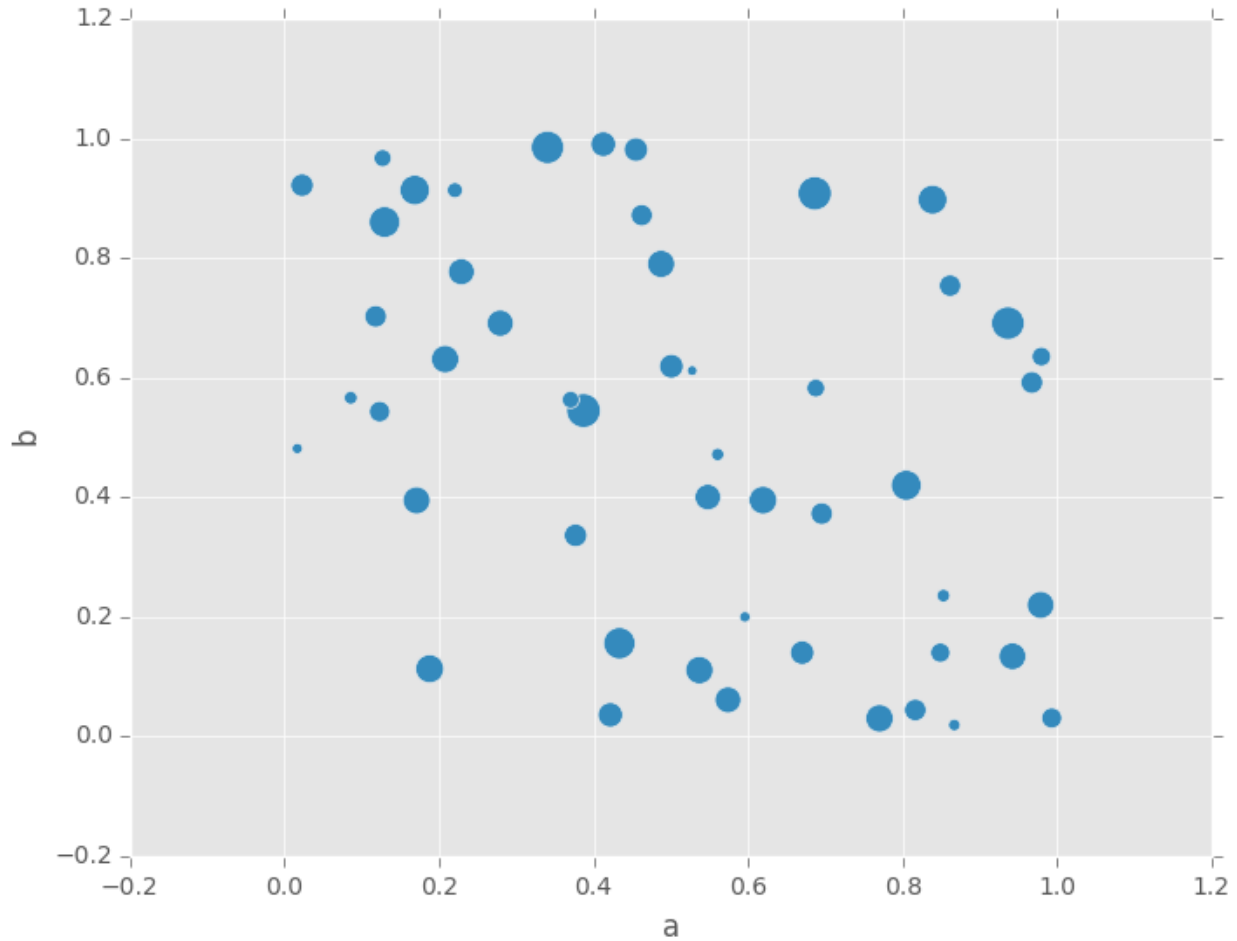
The keyword `c` may be given as the name of a column to provide colors for each point:

```
In [60]: df.plot(kind='scatter', x='a', y='b', c='c', s=50);
```



You can pass other keywords supported by matplotlib `scatter`. Below example shows a bubble chart using a dataframe column values as bubble size.

```
In [61]: df.plot(kind='scatter', x='a', y='b', s=df['c']*200);
```



See the `scatter` method and the [matplotlib scatter documentation](#) for more.

23.2.6 Hexagonal Bin Plot

New in version 0.14.

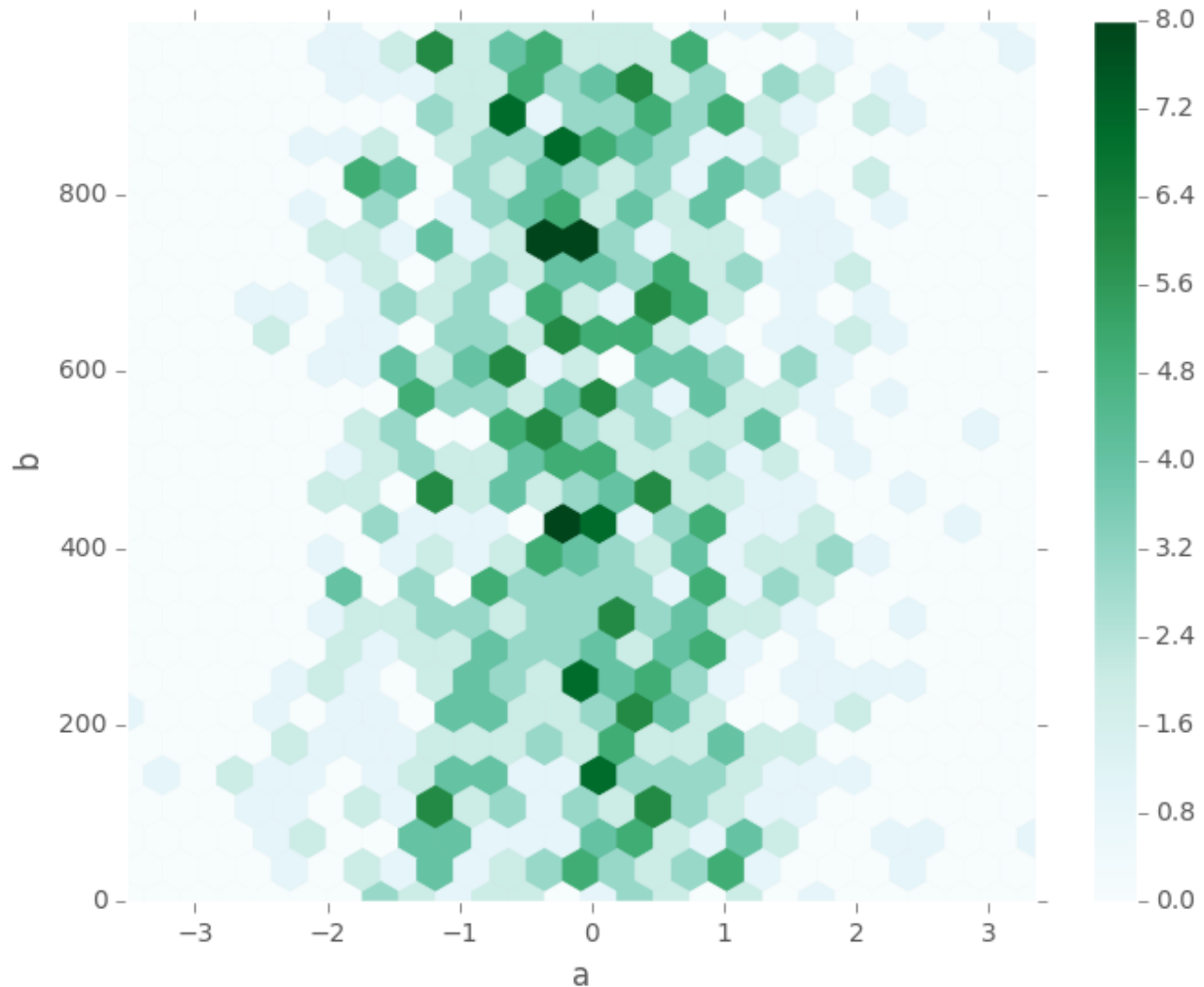
You can create hexagonal bin plots with `DataFrame.plot()` and `kind='hexbin'`. Hexbin plots can be a useful alternative to scatter plots if your data are too dense to plot each point individually.

```
In [62]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])
```

```
In [63]: df['b'] = df['b'] + np.arange(1000)
```

```
In [64]: df.plot(kind='hexbin', x='a', y='b', gridsize=25)
```

```
Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0xad44616c>
```



A useful keyword argument is `gridsize`; it controls the number of hexagons in the x-direction, and defaults to 100. A larger `gridsize` means more, smaller bins.

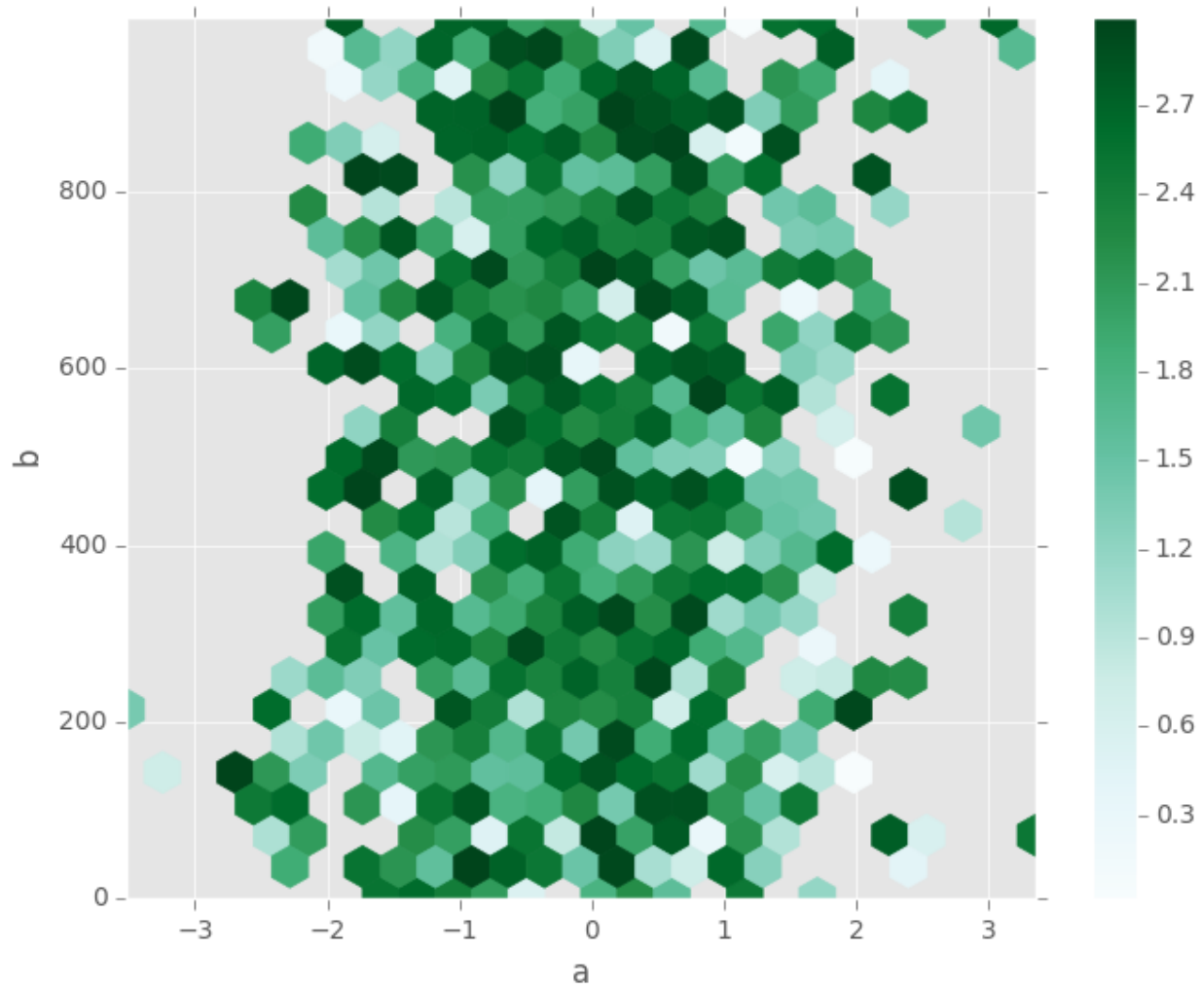
By default, a histogram of the counts around each (x, y) point is computed. You can specify alternative aggregations by passing values to the `C` and `reduce_C_function` arguments. `C` specifies the value at each (x, y) point and `reduce_C_function` is a function of one argument that reduces all the values in a bin to a single number (e.g. mean, max, sum, std). In this example the positions are given by columns `a` and `b`, while the value is given by column `z`. The bins are aggregated with numpy's `max` function.

```
In [65]: df = pd.DataFrame(np.random.randn(1000, 2), columns=['a', 'b'])

In [66]: df['b'] = df['b'] + np.arange(1000)

In [67]: df['z'] = np.random.uniform(0, 3, 1000)

In [68]: df.plot(kind='hexbin', x='a', y='b', C='z', reduce_C_function=np.max,
....:         gridsize=25)
....:
Out[68]: <matplotlib.axes._subplots.AxesSubplot at 0xadad0a0c>
```



See the `hexbin` method and the `matplotlib hexbin` documentation for more.

23.2.7 Pie plot

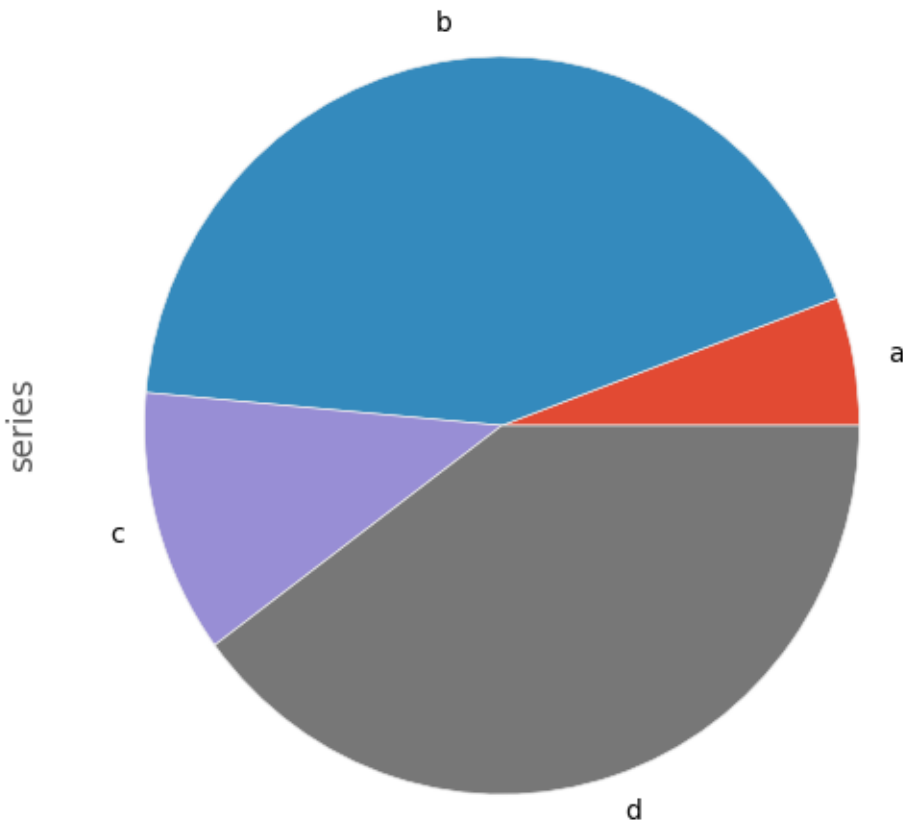
New in version 0.14.

You can create a pie plot with `DataFrame.plot()` or `Series.plot()` with `kind='pie'`. If your data includes any `NaN`, they will be automatically filled with 0. A `ValueError` will be raised if there are any negative values in your data.

```
In [69]: series = pd.Series(3 * np.random.rand(4), index=['a', 'b', 'c', 'd'], name='series')
```

```
In [70]: series.plot(kind='pie', figsize=(6, 6))
```

```
Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0xacd1e5ac>
```



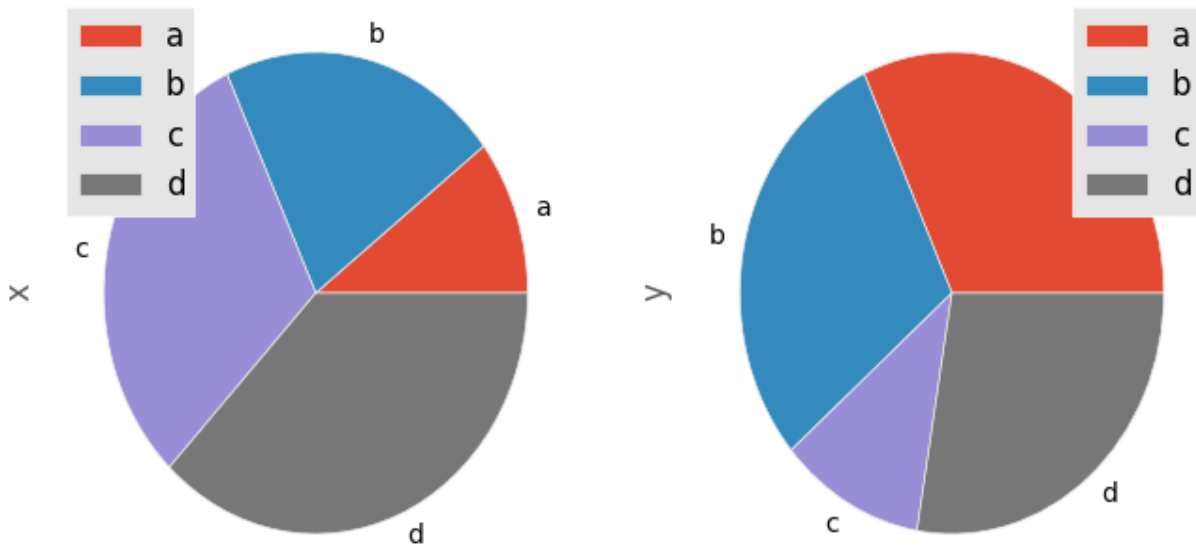
For pie plots it's best to use square figures, one's with an equal aspect ratio. You can create the figure with equal width and height, or force the aspect ratio to be equal after plotting by calling `ax.set_aspect('equal')` on the returned axes object.

Note that pie plot with `DataFrame` requires that you either specify a target column by the `y` argument or `subplots=True`. When `y` is specified, pie plot of selected column will be drawn. If `subplots=True` is specified, pie plots for each column are drawn as subplots. A legend will be drawn in each pie plots by default; specify `legend=False` to hide it.

```
In [71]: df = pd.DataFrame(3 * np.random.rand(4, 2), index=['a', 'b', 'c', 'd'], columns=['x', 'y'])
```

```
In [72]: df.plot(kind='pie', subplots=True, figsize=(8, 4))
```

```
Out[72]: array([<matplotlib.axes._subplots.AxesSubplot object at 0xadaa768c>,
      <matplotlib.axes._subplots.AxesSubplot object at 0xadb0f94c>], dtype=object)
```

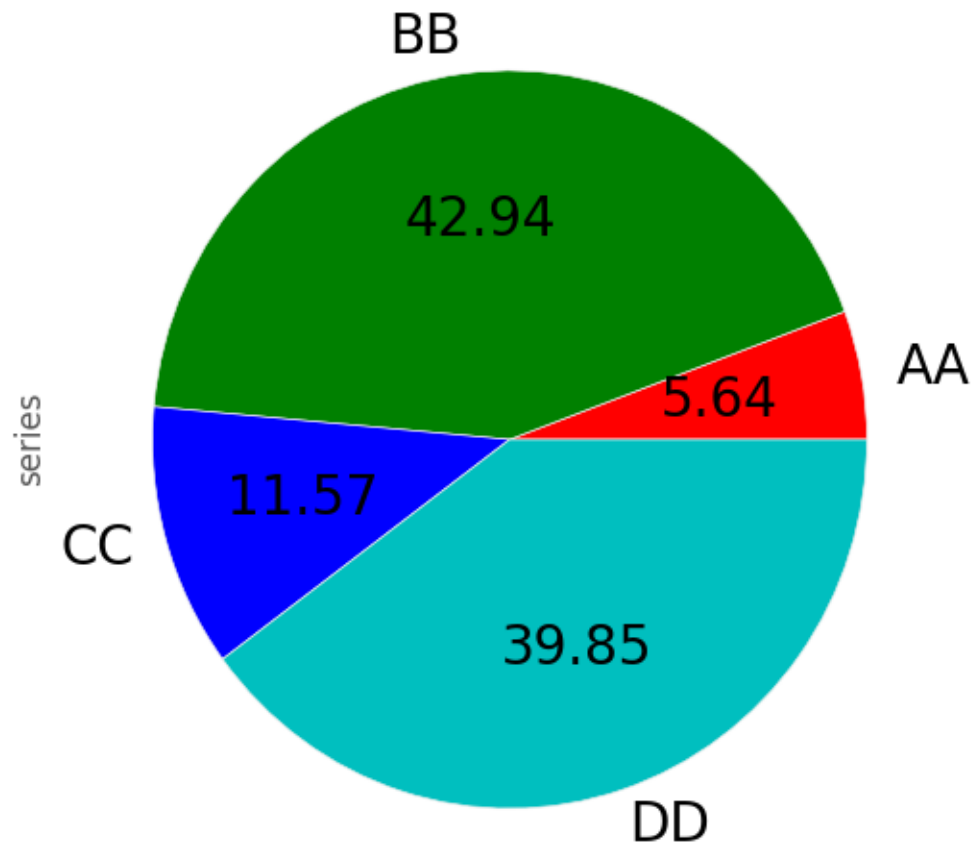


You can use the `labels` and `colors` keywords to specify the labels and colors of each wedge.

Warning: Most pandas plots use the `label` and `color` arguments (note the lack of “s” on those). To be consistent with `matplotlib.pyplot.pie()` you must use `labels` and `colors`.

If you want to hide wedge labels, specify `labels=None`. If `fontsize` is specified, the value will be applied to wedge labels. Also, other keywords supported by `matplotlib.pyplot.pie()` can be used.

```
In [73]: series.plot(kind='pie', labels=['AA', 'BB', 'CC', 'DD'], colors=['r', 'g', 'b', 'c'],
.....:               autopct='%.2f', fontsize=20, figsize=(6, 6))
.....:
Out[73]: <matplotlib.axes._subplots.AxesSubplot at 0xadcf6dac>
```

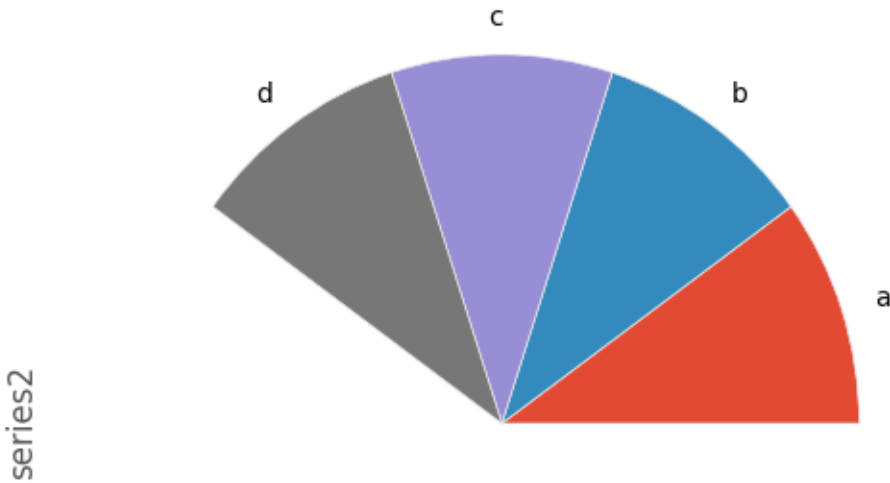


If you pass values whose sum total is less than 1.0, matplotlib draws a semicircle.

```
In [74]: series = pd.Series([0.1] * 4, index=['a', 'b', 'c', 'd'], name='series2')
```

```
In [75]: series.plot(kind='pie', figsize=(6, 6))
```

```
Out[75]: <matplotlib.axes._subplots.AxesSubplot at 0xadce538c>
```



See the [matplotlib pie documentation](#) for more.

23.3 Plotting with Missing Data

Pandas tries to be pragmatic about plotting DataFrames or Series that contain missing data. Missing values are dropped, left out, or filled depending on the plot type.

| Plot Type | NaN Handling |
|----------------|-------------------------|
| Line | Leave gaps at NaNs |
| Line (stacked) | Fill 0's |
| Bar | Fill 0's |
| Scatter | Drop NaNs |
| Histogram | Drop NaNs (column-wise) |
| Box | Drop NaNs (column-wise) |
| Area | Fill 0's |
| KDE | Drop NaNs (column-wise) |
| Hexbin | Drop NaNs |
| Pie | Fill 0's |

If any of these defaults are not what you want, or if you want to be explicit about how missing values are handled, consider using `fillna()` or `dropna()` before plotting.

23.4 Plotting Tools

These functions can be imported from `pandas.tools.plotting` and take a `Series` or `DataFrame` as an argument.

23.4.1 Scatter Matrix Plot

New in version 0.7.3.

You can create a scatter plot matrix using the `scatter_matrix` method in `pandas.tools.plotting`:

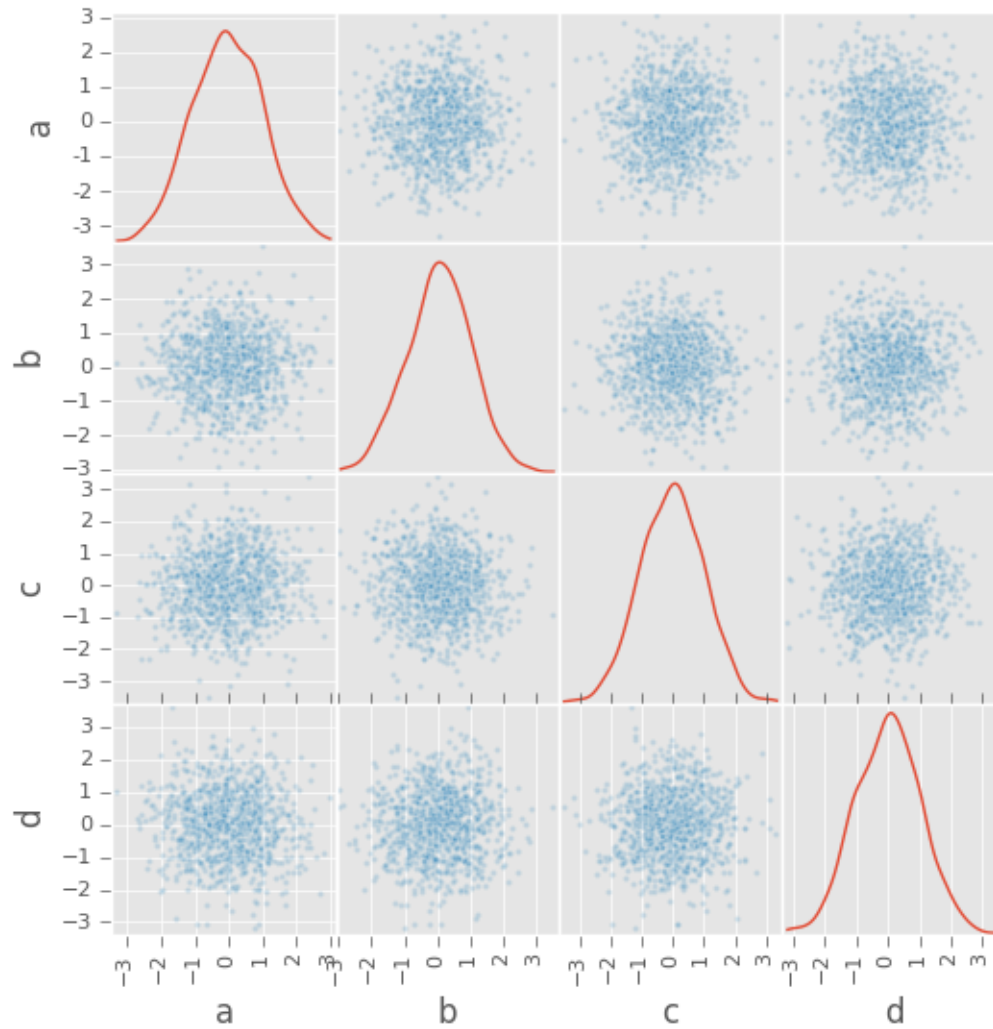
```
In [76]: from pandas.tools.plotting import scatter_matrix
```

```
In [77]: df = pd.DataFrame(np.random.randn(1000, 4), columns=['a', 'b', 'c', 'd'])
```

```
In [78]: scatter_matrix(df, alpha=0.2, figsize=(6, 6), diagonal='kde')
```

```
Out[78]:
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0xad5c94cc>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xac438a0c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad5e02ac>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xac3ac76c>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0xac36b98c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xac31f32c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xac2df22c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad104b0c>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0xad568aec>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad49e10c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad42e28c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad41ea6c>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0xad1dc0ac>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad0cecec>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad38e86c>,
        <matplotlib.axes._subplots.AxesSubplot object at 0xad3bdeac>]], dtype=object)
```



23.4.2 Density Plot

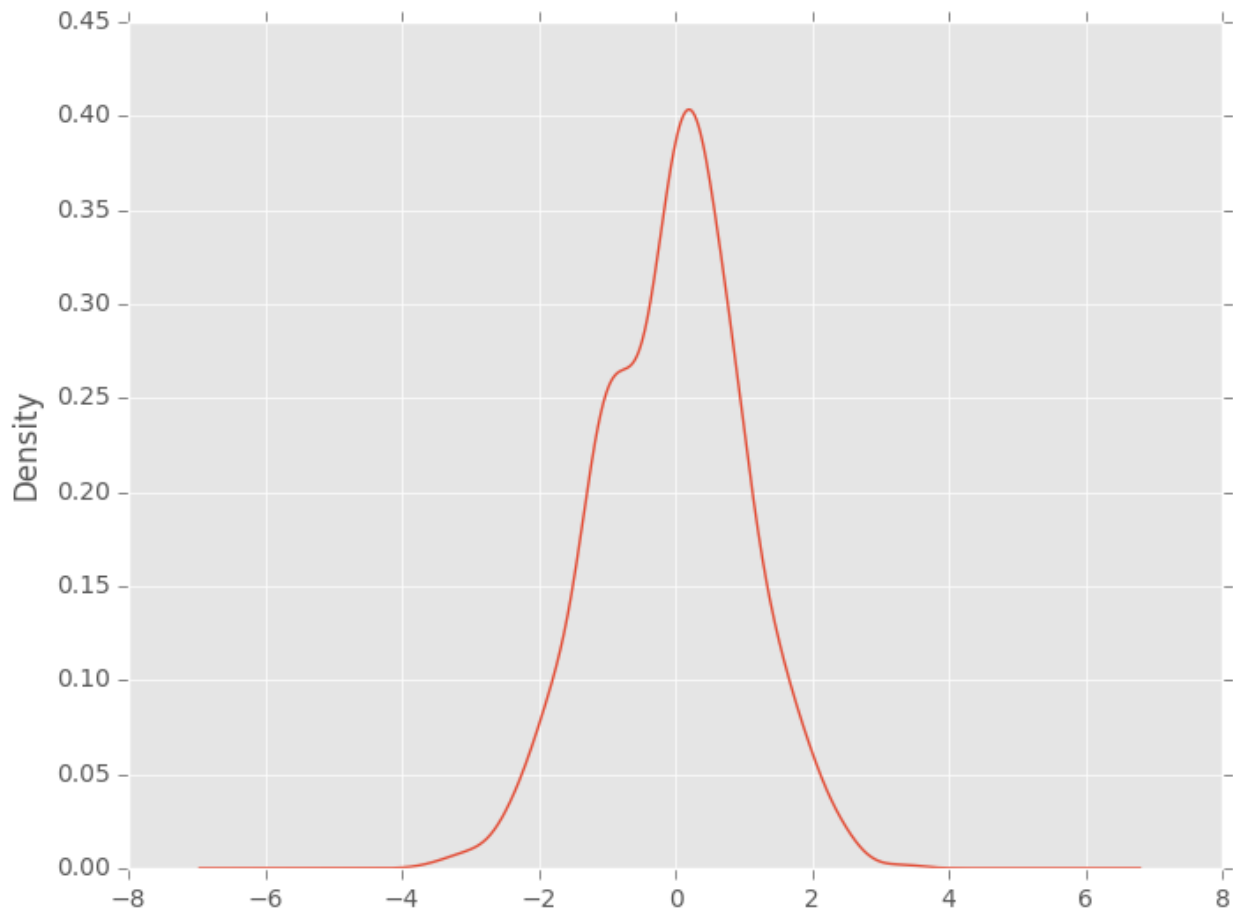
New in version 0.8.0.

You can create density plots using the `Series/DataFrame.plot` and setting `kind='kde'`:

```
In [79]: ser = pd.Series(np.random.randn(1000))
```

```
In [80]: ser.plot(kind='kde')
```

```
Out[80]: <matplotlib.axes._subplots.AxesSubplot at 0xa9af0b2c>
```



23.4.3 Andrews Curves

Andrews curves allow one to plot multivariate data as a large number of curves that are created using the attributes of samples as coefficients for Fourier series. By coloring these curves differently for each class it is possible to visualize data clustering. Curves belonging to samples of the same class will usually be closer together and form larger structures.

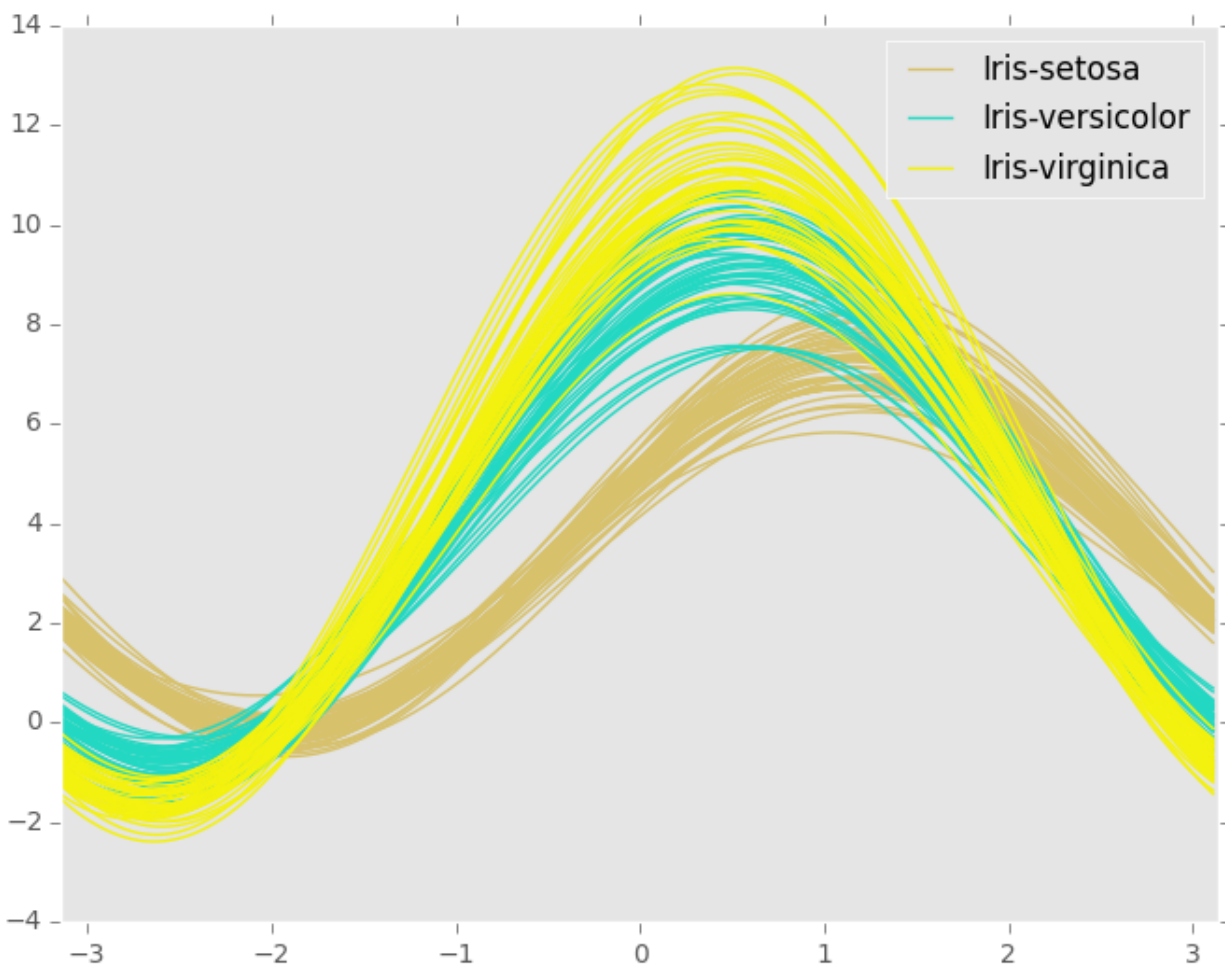
Note: The “Iris” dataset is available [here](#).

```
In [81]: from pandas.tools.plotting import andrews_curves

In [82]: data = pd.read_csv('data/iris.data')

In [83]: plt.figure()
Out[83]: <matplotlib.figure.Figure at 0xa9ca428c>

In [84]: andrews_curves(data, 'Name')
Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0xa9ca472c>
```



23.4.4 Parallel Coordinates

Parallel coordinates is a plotting technique for plotting multivariate data. It allows one to see clusters in data and to estimate other statistics visually. Using parallel coordinates points are represented as connected line segments. Each vertical line represents one attribute. One set of connected line segments represents one data point. Points that tend to cluster will appear closer together.

```
In [85]: from pandas.tools.plotting import parallel_coordinates
```

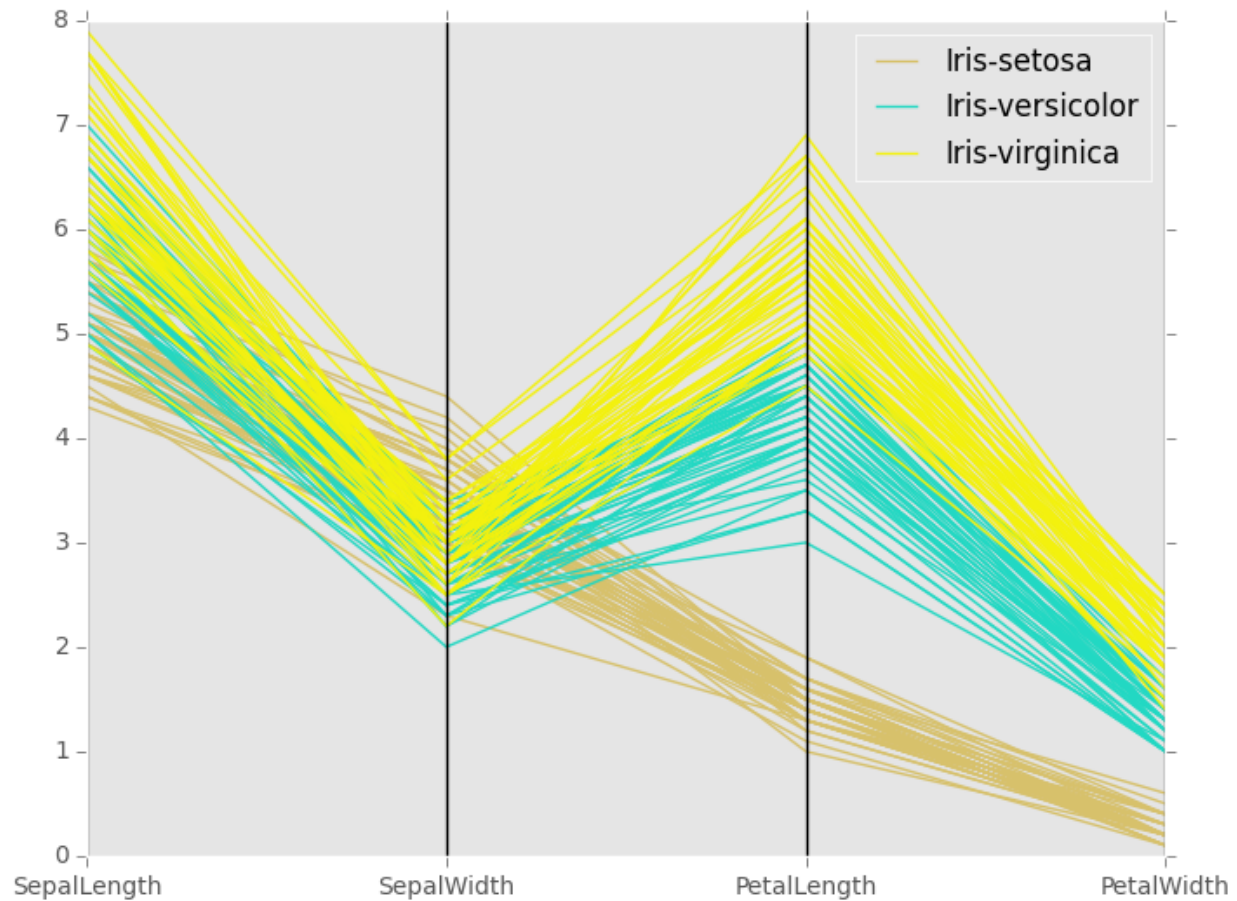
```
In [86]: data = pd.read_csv('data/iris.data')
```

```
In [87]: plt.figure()
```

```
Out[87]: <matplotlib.figure.Figure at 0xa9bfc7ac>
```

```
In [88]: parallel_coordinates(data, 'Name')
```

```
Out[88]: <matplotlib.axes._subplots.AxesSubplot at 0xa9b8170c>
```



23.4.5 Lag Plot

Lag plots are used to check if a data set or time series is random. Random data should not exhibit any structure in the lag plot. Non-random structure implies that the underlying data are not random.

```
In [89]: from pandas.tools.plotting import lag_plot
```

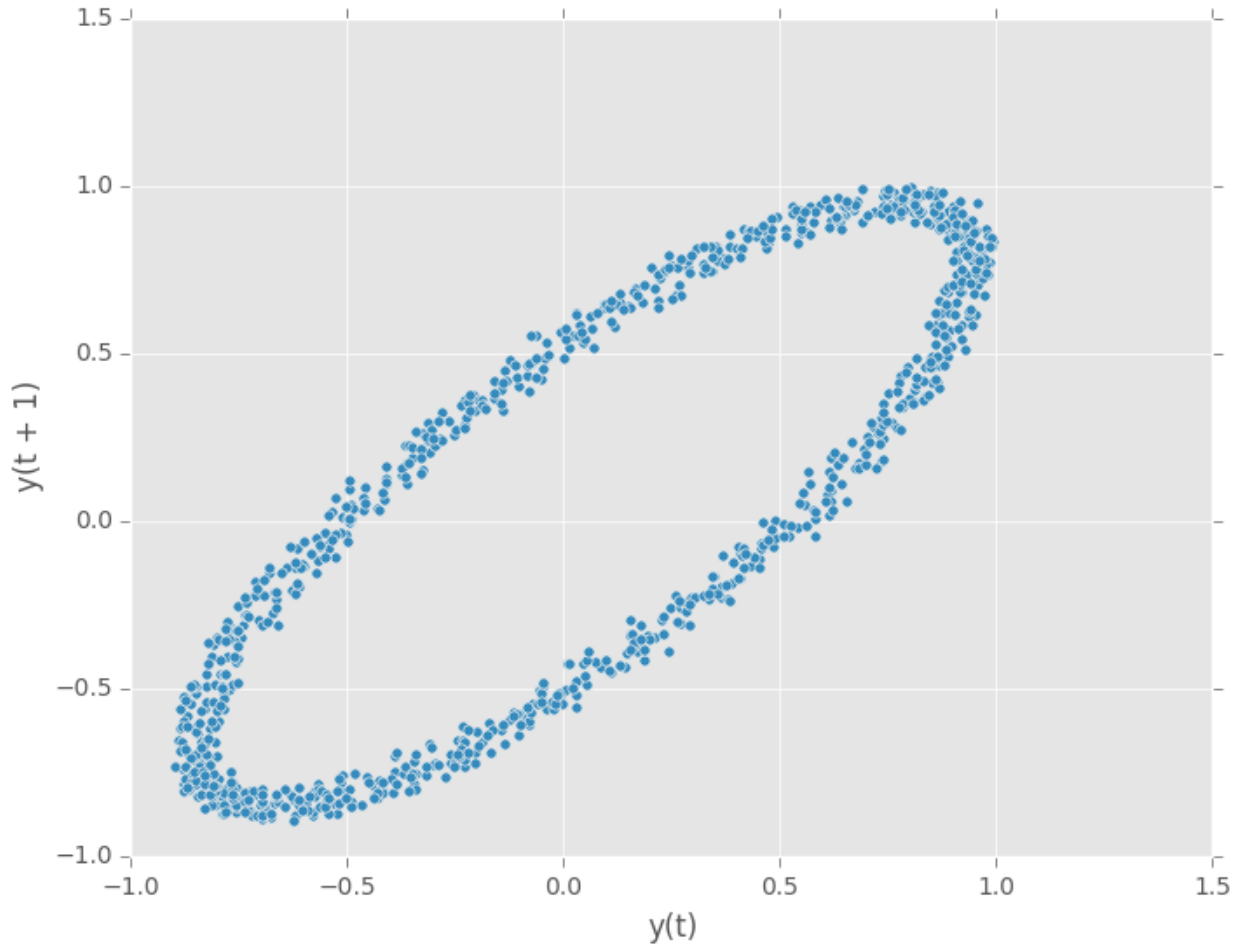
```
In [90]: plt.figure()
```

```
Out[90]: <matplotlib.figure.Figure at 0xa9bcda4c>
```

```
In [91]: data = pd.Series(0.1 * np.random.rand(1000) +
.....:     0.9 * np.sin(np.linspace(-99 * np.pi, 99 * np.pi, num=1000)))
.....:
```

```
In [92]: lag_plot(data)
```

```
Out[92]: <matplotlib.axes._subplots.AxesSubplot at 0xa9bf574c>
```



23.4.6 Autocorrelation Plot

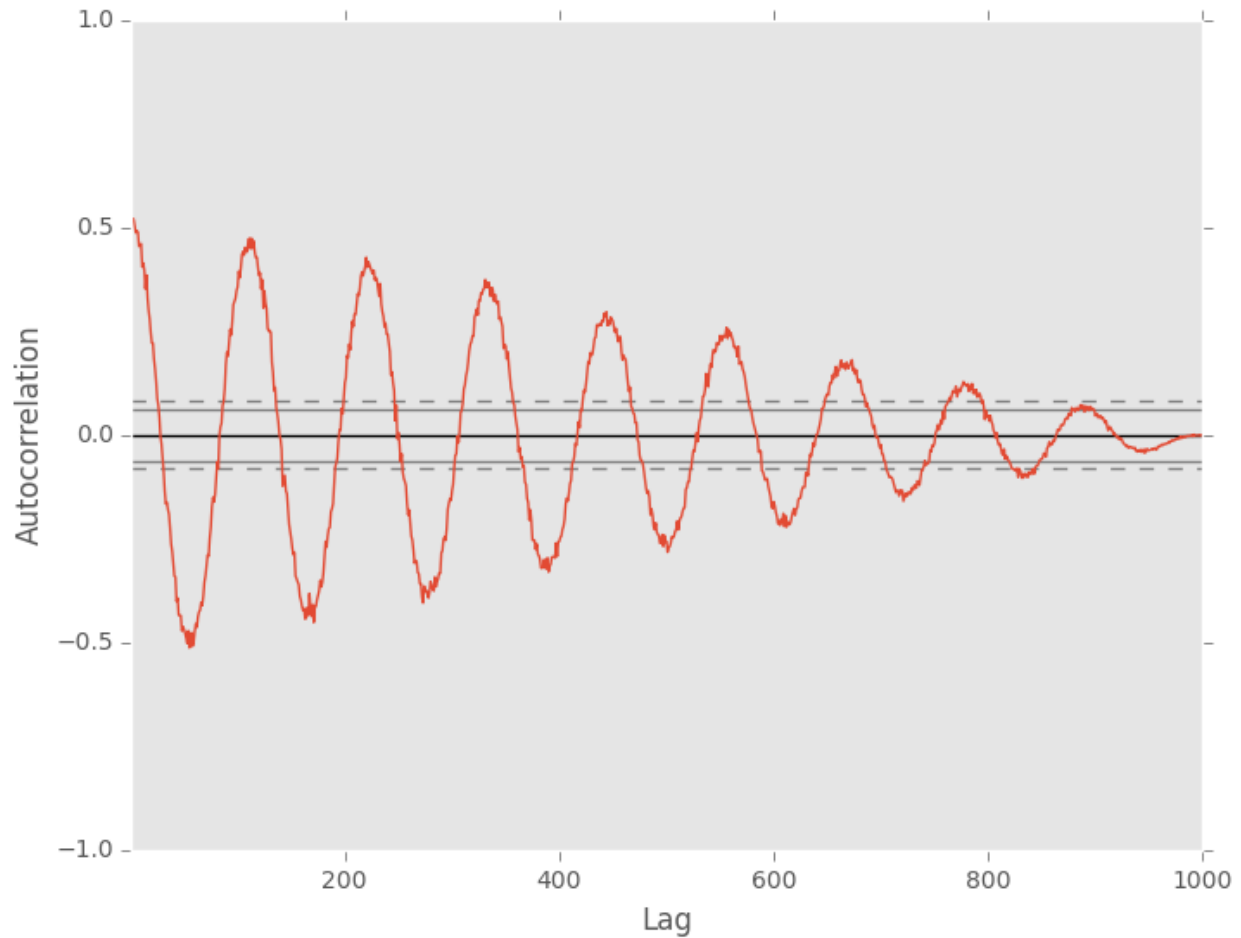
Autocorrelation plots are often used for checking randomness in time series. This is done by computing autocorrelations for data values at varying time lags. If time series is random, such autocorrelations should be near zero for any and all time-lag separations. If time series is non-random then one or more of the autocorrelations will be significantly non-zero. The horizontal lines displayed in the plot correspond to 95% and 99% confidence bands. The dashed line is 99% confidence band.

```
In [93]: from pandas.tools.plotting import autocorrelation_plot

In [94]: plt.figure()
Out[94]: <matplotlib.figure.Figure at 0xa9c3b38c>

In [95]: data = pd.Series(0.7 * np.random.rand(1000) +
.....:     0.3 * np.sin(np.linspace(-9 * np.pi, 9 * np.pi, num=1000)))
.....:

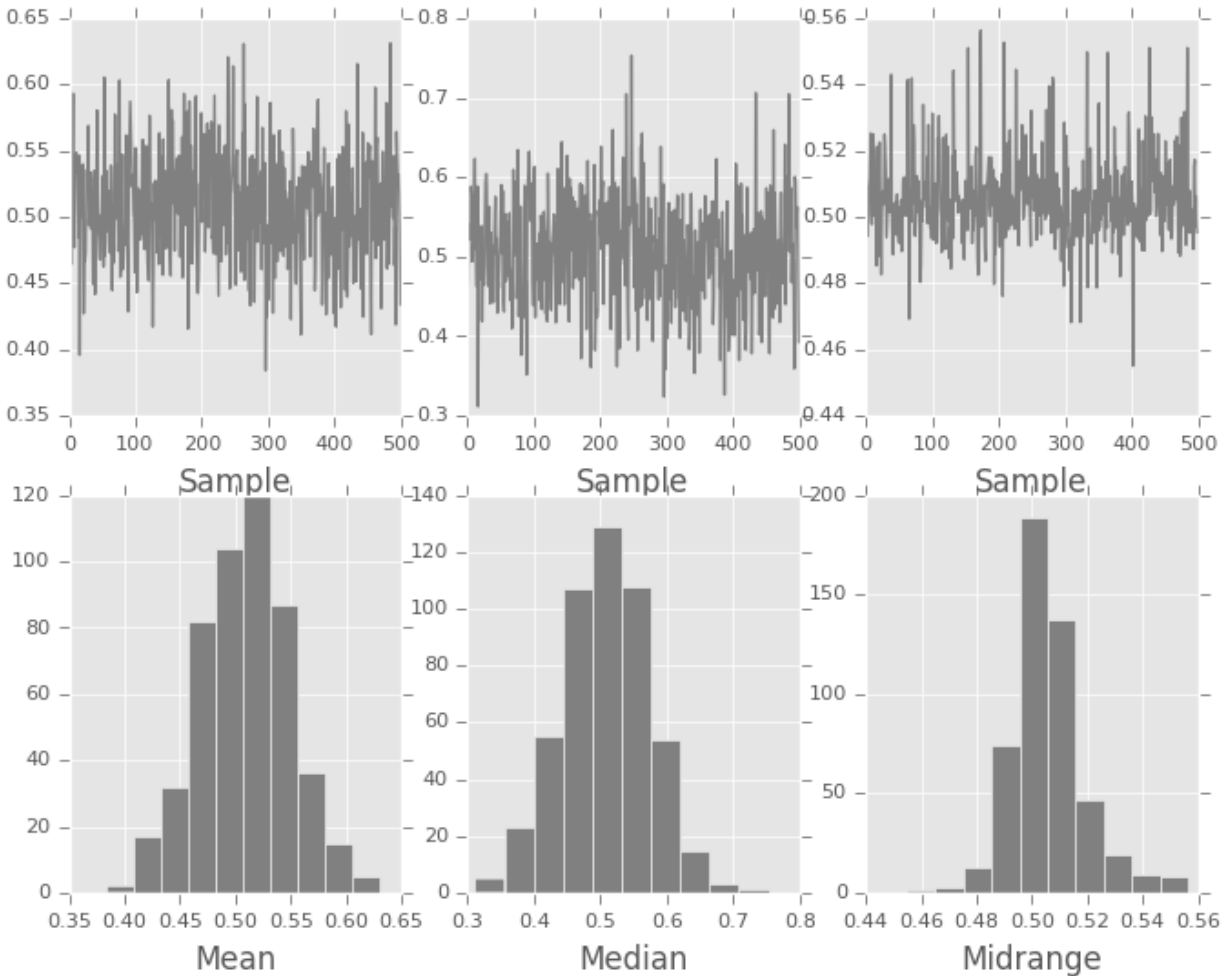
In [96]: autocorrelation_plot(data)
Out[96]: <matplotlib.axes._subplots.AxesSubplot at 0xa99083ac>
```



23.4.7 Bootstrap Plot

Bootstrap plots are used to visually assess the uncertainty of a statistic, such as mean, median, midrange, etc. A random subset of a specified size is selected from a data set, the statistic in question is computed for this subset and the process is repeated a specified number of times. Resulting plots and histograms are what constitutes the bootstrap plot.

```
In [97]: from pandas.tools.plotting import bootstrap_plot
In [98]: data = pd.Series(np.random.rand(1000))
In [99]: bootstrap_plot(data, size=50, samples=500, color='grey')
Out[99]: <matplotlib.figure.Figure at 0xa9c4c34c>
```



23.4.8 RadViz

RadViz is a way of visualizing multi-variate data. It is based on a simple spring tension minimization algorithm. Basically you set up a bunch of points in a plane. In our case they are equally spaced on a unit circle. Each point represents a single attribute. You then pretend that each sample in the data set is attached to each of these points by a spring, the stiffness of which is proportional to the numerical value of that attribute (they are normalized to unit interval). The point in the plane, where our sample settles to (where the forces acting on our sample are at an equilibrium) is where a dot representing our sample will be drawn. Depending on which class that sample belongs to it will be colored differently.

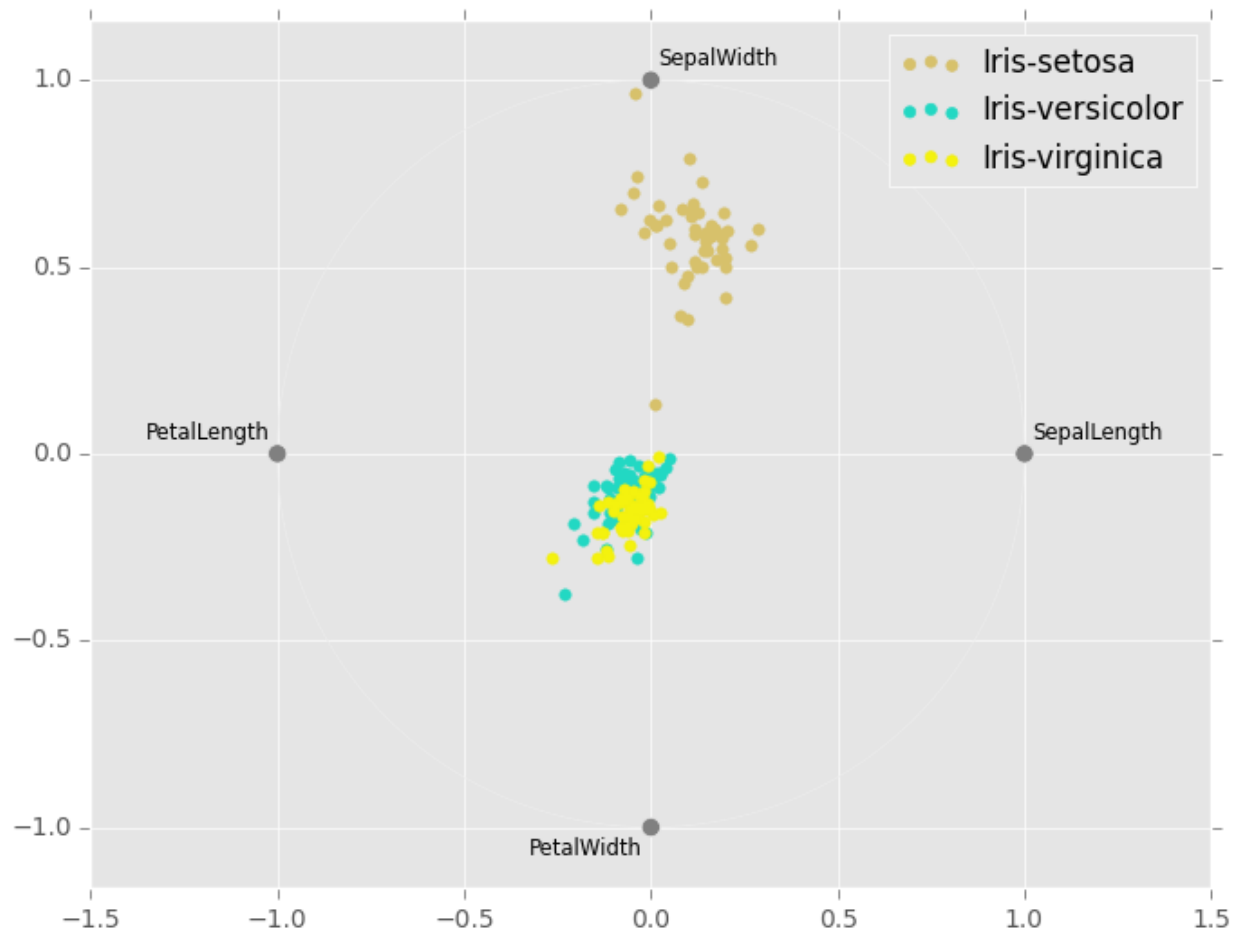
Note: The “Iris” dataset is available [here](#).

```
In [100]: from pandas.tools.plotting import radviz

In [101]: data = pd.read_csv('data/iris.data')

In [102]: plt.figure()
Out[102]: <matplotlib.figure.Figure at 0xa9c4c9cc>

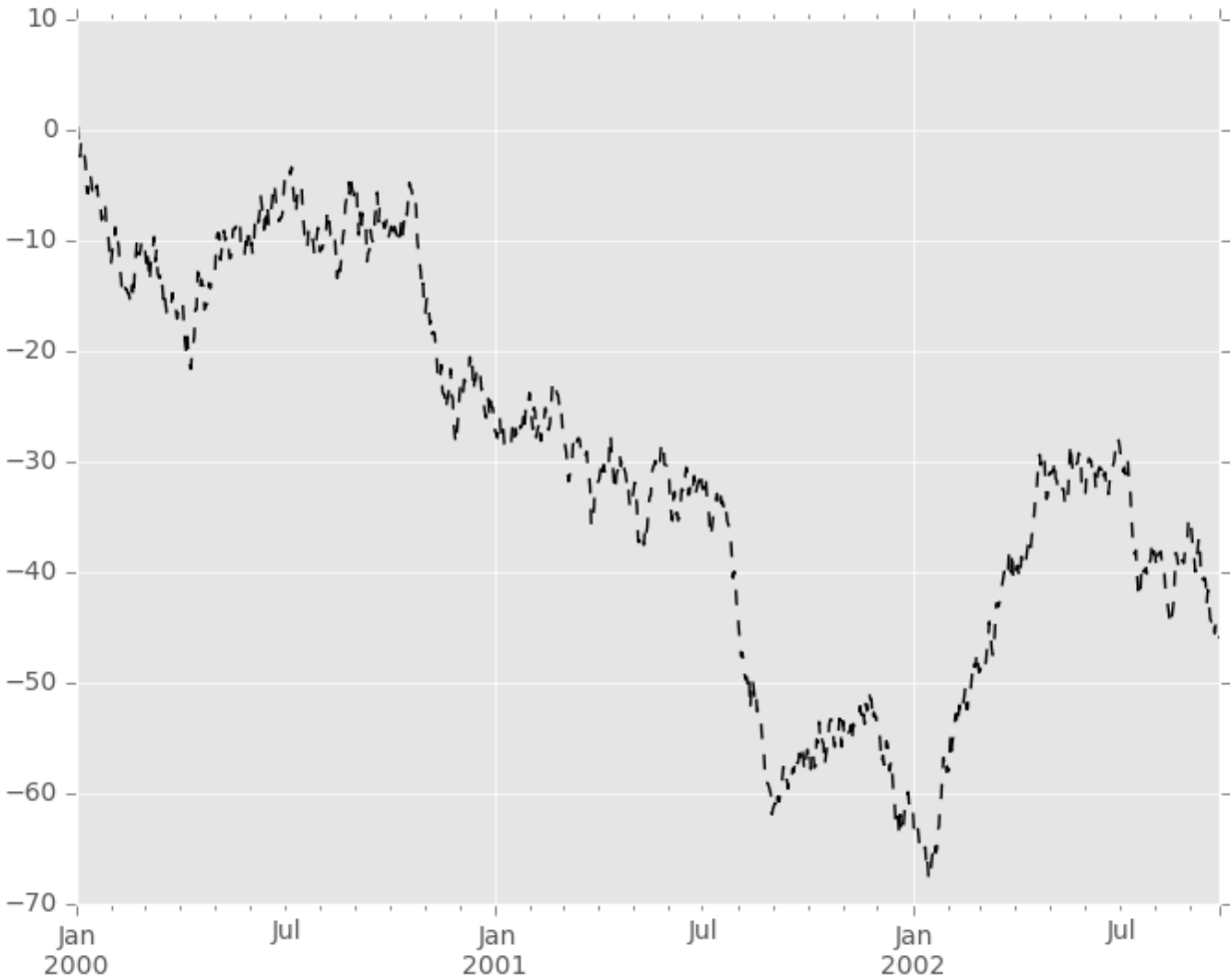
In [103]: radviz(data, 'Name')
Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0xa92014cc>
```



23.5 Plot Formatting

Most plotting methods have a set of keyword arguments that control the layout and formatting of the returned plot:

```
In [104]: plt.figure(); ts.plot(style='k--', label='Series');
```



For each kind of plot (e.g. *line*, *bar*, *scatter*) any additional arguments keywords are passed along to the corresponding matplotlib function (`ax.plot()`, `ax.bar()`, `ax.scatter()`). These can be used to control additional styling, beyond what pandas provides.

23.5.1 Controlling the Legend

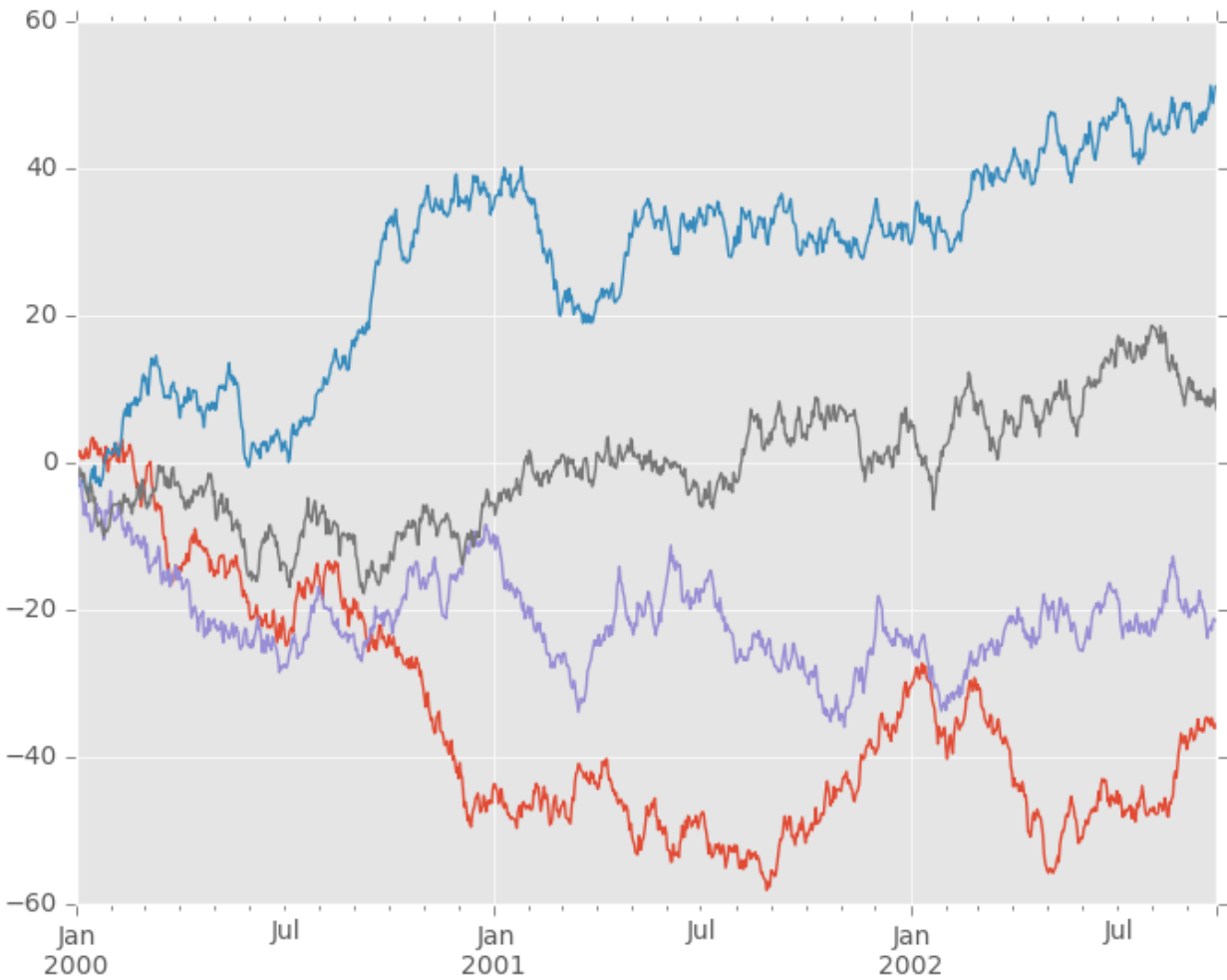
You may set the `legend` argument to `False` to hide the legend, which is shown by default.

```
In [105]: df = pd.DataFrame(np.random.randn(1000, 4), index=ts.index, columns=list('ABCD'))
```

```
In [106]: df = df.cumsum()
```

```
In [107]: df.plot(legend=False)
```

```
Out[107]: <matplotlib.axes._subplots.AxesSubplot at 0xa8d1158c>
```



23.5.2 Scales

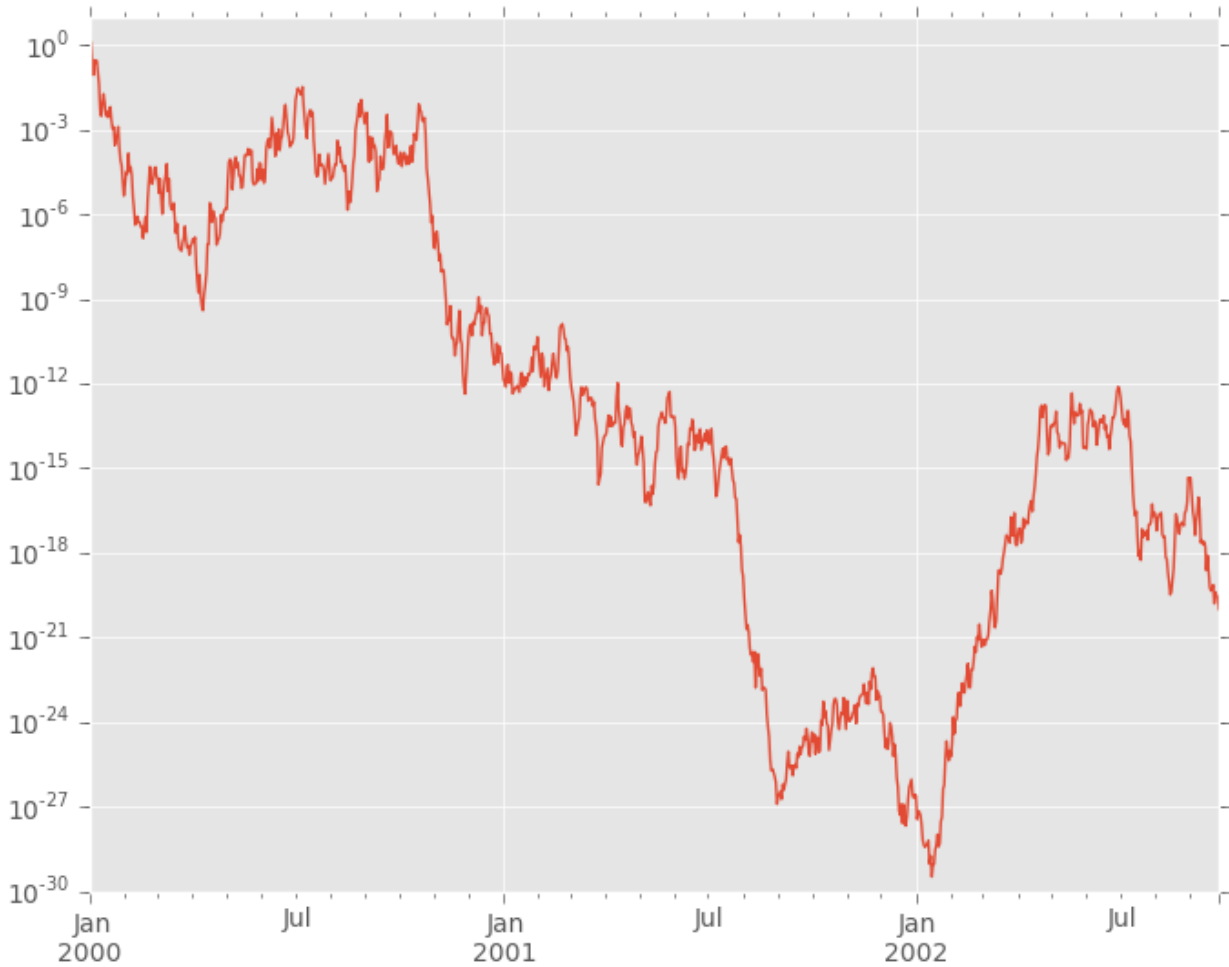
You may pass `logy` to get a log-scale Y axis.

```
In [108]: ts = pd.Series(np.random.randn(1000), index=pd.date_range('1/1/2000', periods=1000))
```

```
In [109]: ts = np.exp(ts.cumsum())
```

```
In [110]: ts.plot(logy=True)
```

```
Out[110]: <matplotlib.axes._subplots.AxesSubplot at 0xa8a5ff4c>
```



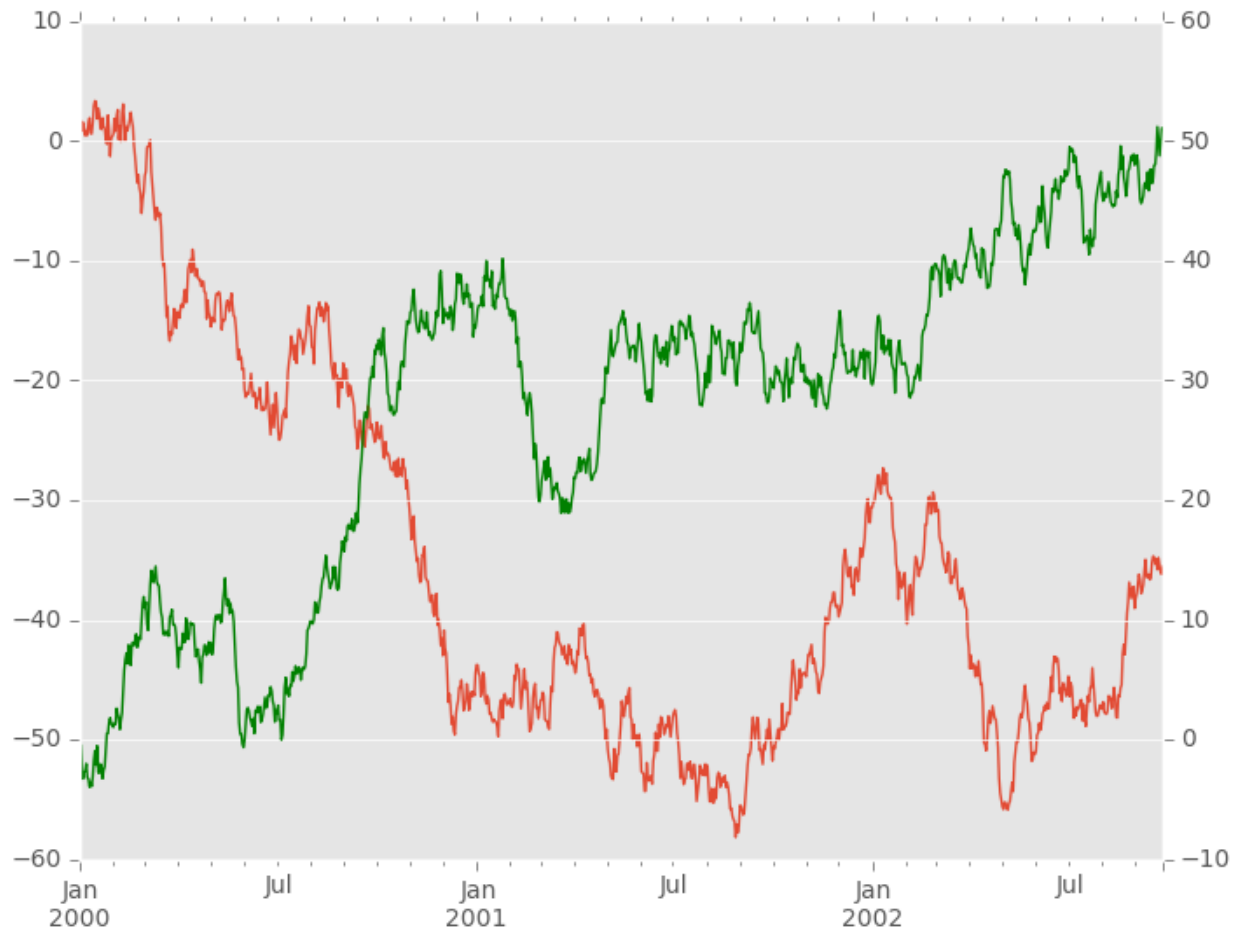
See also the `logx` and `loglog` keyword arguments.

23.5.3 Plotting on a Secondary Y-axis

To plot data on a secondary y-axis, use the `secondary_y` keyword:

```
In [111]: df.A.plot()
Out[111]: <matplotlib.axes._subplots.AxesSubplot at 0xa8dcd38c>

In [112]: df.B.plot(secondary_y=True, style='g')
Out[112]: <matplotlib.axes._subplots.AxesSubplot at 0xa8595e4c>
```



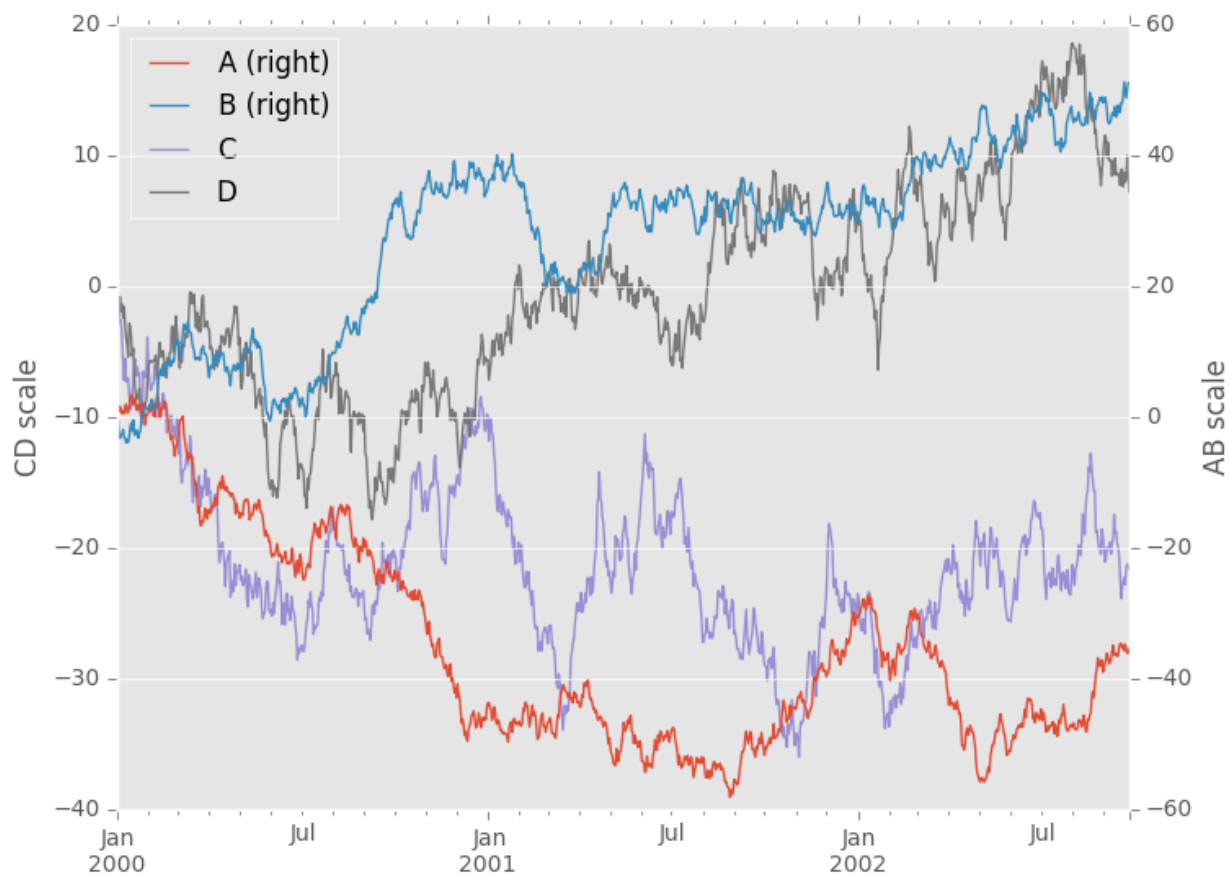
To plot some columns in a DataFrame, give the column names to the `secondary_y` keyword:

```
In [113]: plt.figure()
Out[113]: <matplotlib.figure.Figure at 0xa85a704c>

In [114]: ax = df.plot(secondary_y=['A', 'B'])

In [115]: ax.set_ylabel('CD scale')
Out[115]: <matplotlib.text.Text at 0xa893182c>

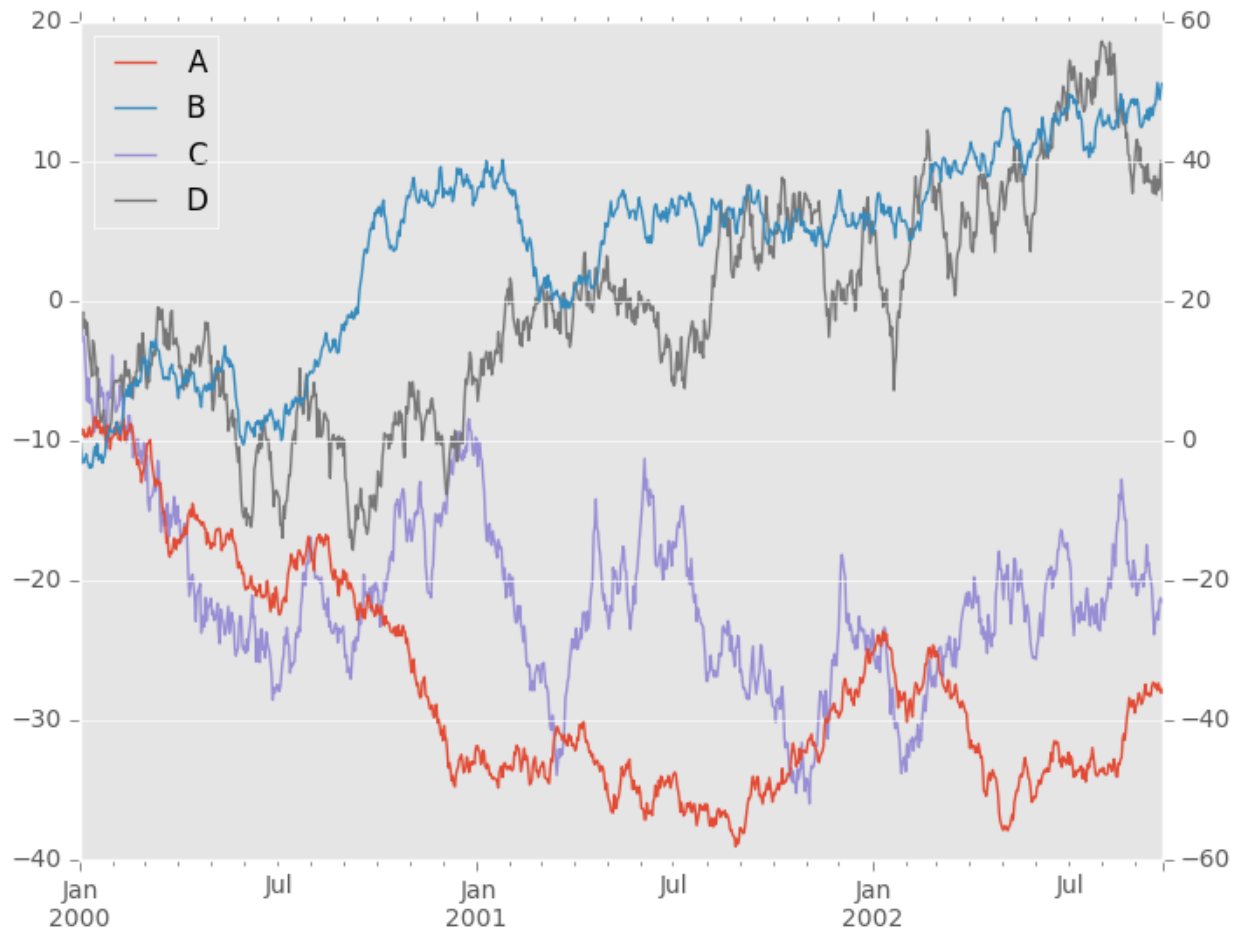
In [116]: ax.right_ax.set_ylabel('AB scale')
Out[116]: <matplotlib.text.Text at 0xa89ba0cc>
```



Note that the columns plotted on the secondary y-axis is automatically marked with “(right)” in the legend. To turn off the automatic marking, use the `mark_right=False` keyword:

```
In [117]: plt.figure()
Out[117]: <matplotlib.figure.Figure at 0xa9c39a2c>

In [118]: df.plot(secondary_y=['A', 'B'], mark_right=False)
Out[118]: <matplotlib.axes._subplots.AxesSubplot at 0xa84eea2c>
```



23.5.4 Suppressing Tick Resolution Adjustment

pandas includes automatic tick resolution adjustment for regular frequency time-series data. For limited cases where pandas cannot infer the frequency information (e.g., in an externally created `twinx`), you can choose to suppress this behavior for alignment purposes.

Here is the default behavior, notice how the x-axis tick labelling is performed:

```
In [119]: plt.figure()
Out[119]: <matplotlib.figure.Figure at 0xa809b4ac>

In [120]: df.A.plot()
Out[120]: <matplotlib.axes._subplots.AxesSubplot at 0xa814c5ac>
```



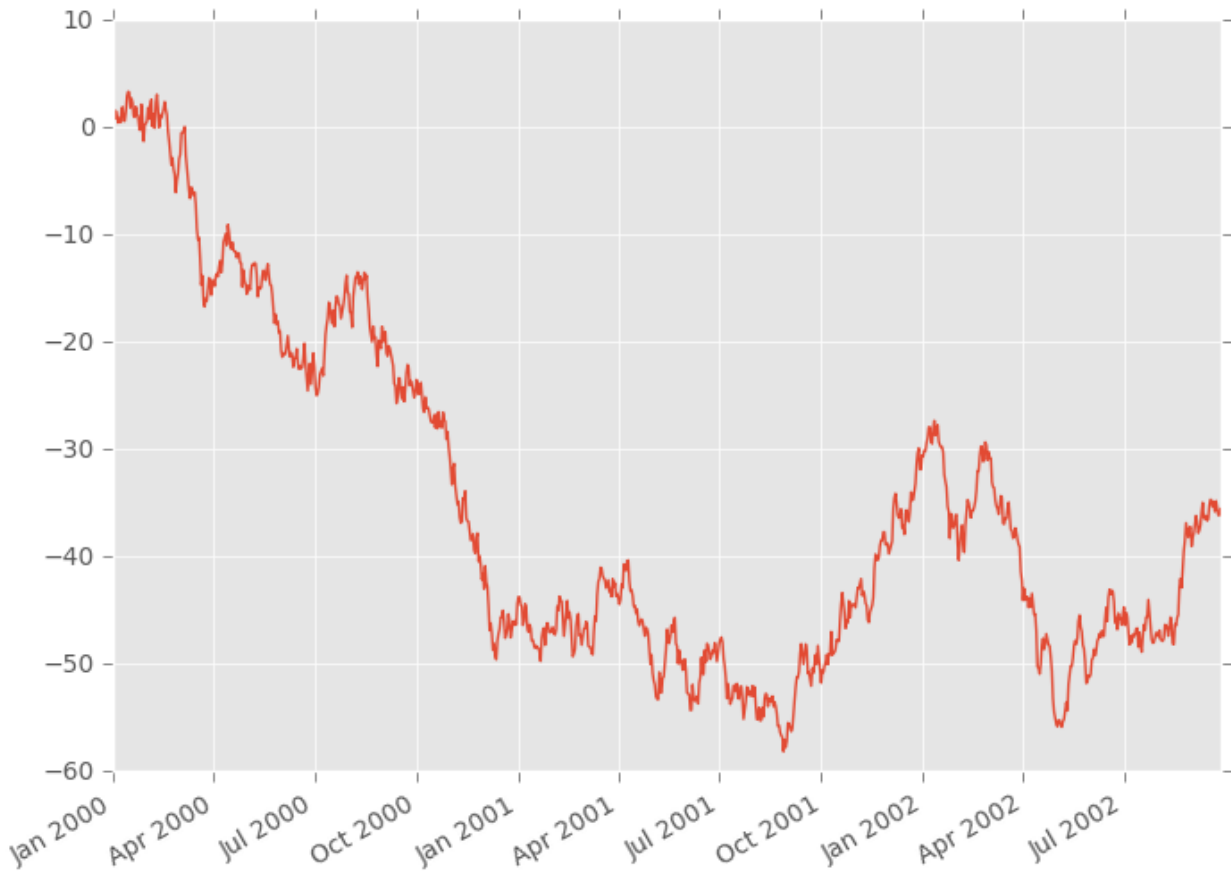
Using the `x_compat` parameter, you can suppress this behavior:

```
In [121]: plt.figure()
```

```
Out[121]: <matplotlib.figure.Figure at 0xa7fd10ec>
```

```
In [122]: df.A.plot(x_compat=True)
```

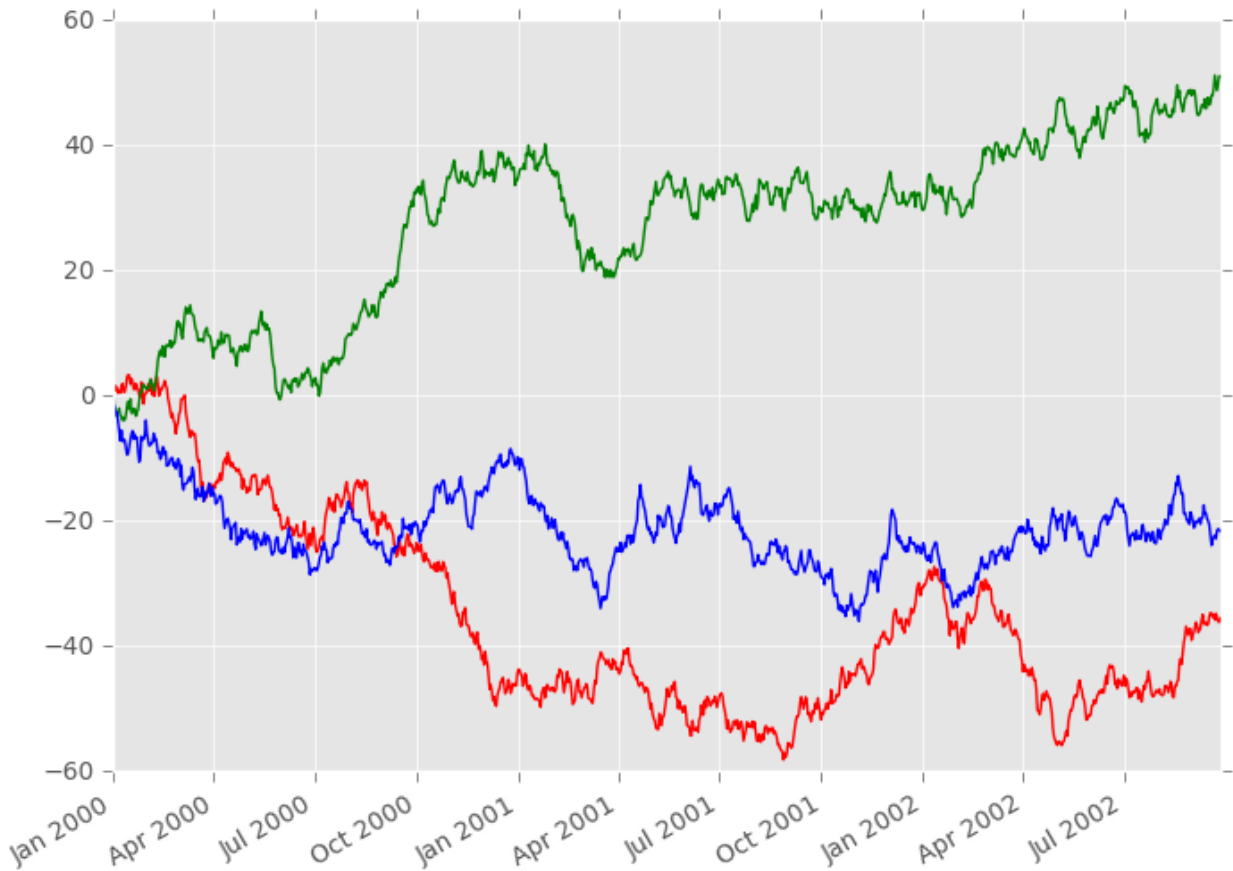
```
Out[122]: <matplotlib.axes._subplots.AxesSubplot at 0xa7fd14ec>
```



If you have more than one plot that needs to be suppressed, the use method in `pandas.plot_params` can be used in a *with* statement:

```
In [123]: plt.figure()
Out[123]: <matplotlib.figure.Figure at 0xa7fb618c>

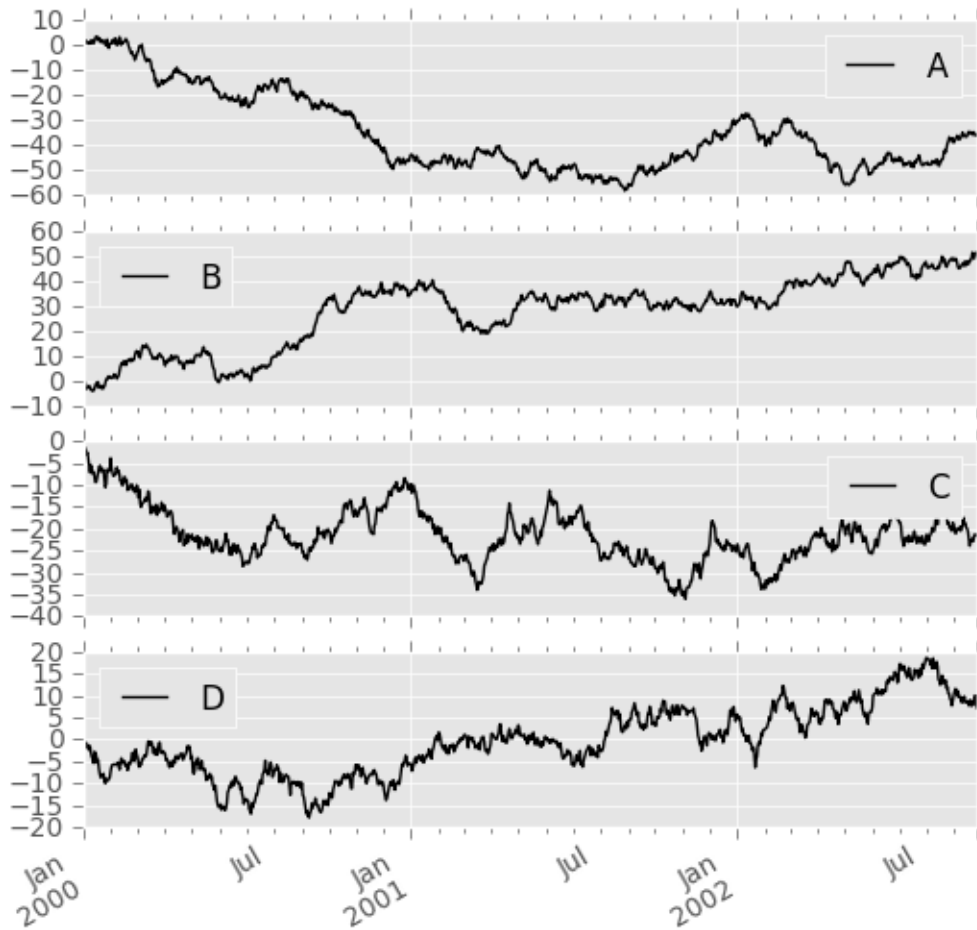
In [124]: with pd.plot_params.use('x_compat', True):
.....:     df.A.plot(color='r')
.....:     df.B.plot(color='g')
.....:     df.C.plot(color='b')
.....:
```



23.5.5 Subplots

Each Series in a DataFrame can be plotted on a different axis with the `subplots` keyword:

```
In [125]: df.plot(subplots=True, figsize=(6, 6));
```

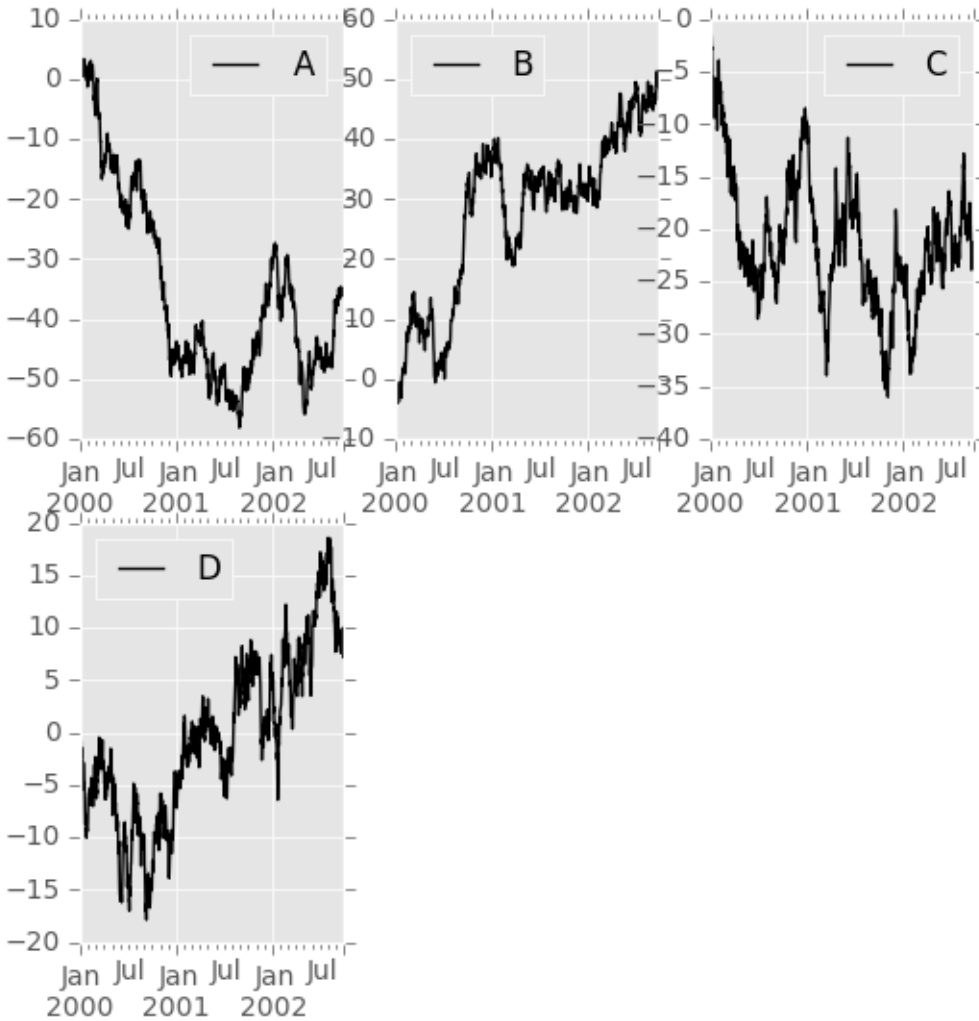


23.5.6 Using Layout and Targetting Multiple Axes

The layout of subplots can be specified by `layout` keyword. It can accept `(rows, columns)`. The `layout` keyword can be used in `hist` and `boxplot` also. If input is invalid, `ValueError` will be raised.

The number of axes which can be contained by `rows x columns` specified by `layout` must be larger than the number of required subplots. If `layout` can contain more axes than required, blank axes are not drawn. Similar to a `numpy` array's `reshape` method, you can use `-1` for one dimension to automatically calculate the number of rows or columns needed, given the other.

```
In [126]: df.plot(subplots=True, layout=(2, 3), figsize=(6, 6), sharex=False);
```



The above example is identical to using

```
In [127]: df.plot(subplots=True, layout=(2, -1), figsize=(6, 6), sharex=False);
```

The required number of columns (3) is inferred from the number of series to plot and the given number of rows (2).

Also, you can pass multiple axes created beforehand as list-like via `ax` keyword. This allows to use more complicated layout. The passed axes must be the same number as the subplots being drawn.

When multiple axes are passed via `ax` keyword, `layout`, `sharex` and `sharey` keywords don't affect to the output. You should explicitly pass `sharex=False` and `sharey=False`, otherwise you will see a warning.

```
In [128]: fig, axes = plt.subplots(4, 4, figsize=(6, 6));
```

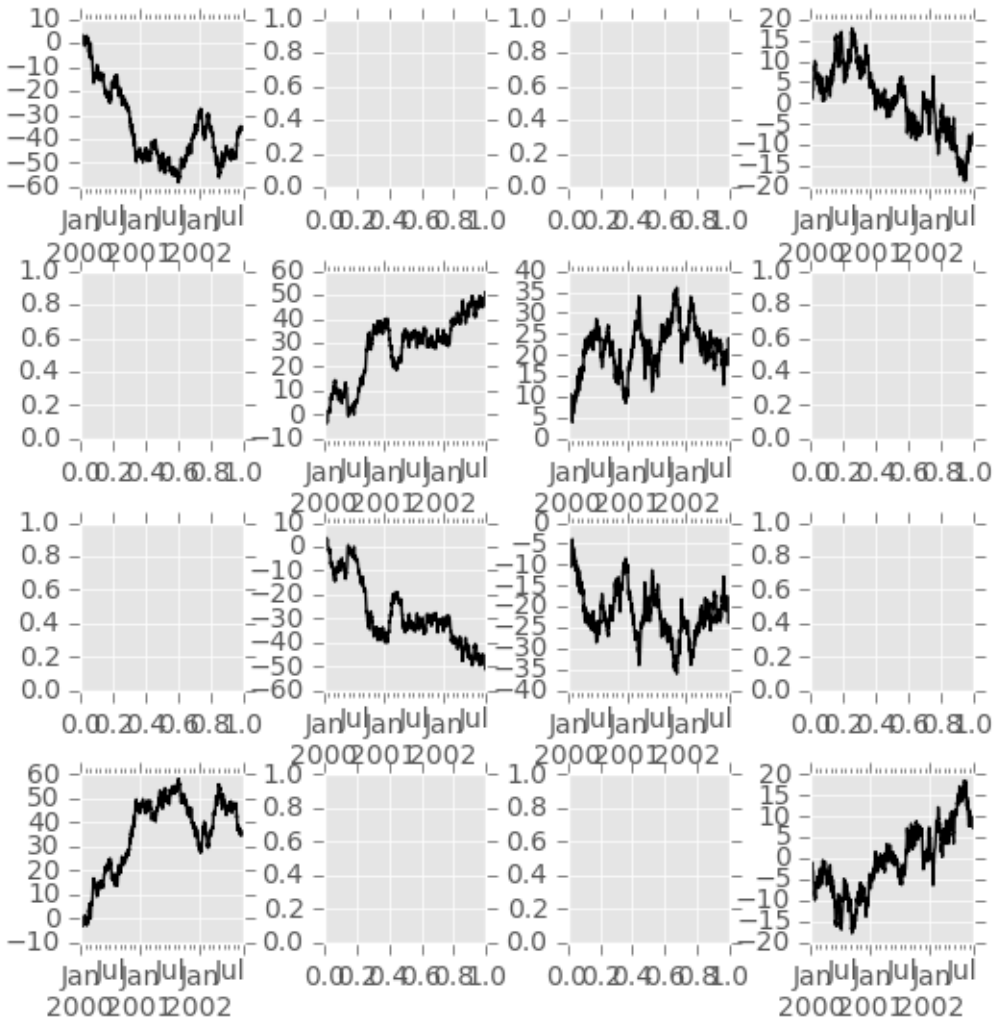
```
In [129]: plt.subplots_adjust(wspace=0.5, hspace=0.5);
```

```
In [130]: target1 = [axes[0][0], axes[1][1], axes[2][2], axes[3][3]]
```

```
In [131]: target2 = [axes[3][0], axes[2][1], axes[1][2], axes[0][3]]
```

```
In [132]: df.plot(subplots=True, ax=target1, legend=False, sharex=False, sharey=False);
```

```
In [133]: (-df).plot(subplots=True, ax=target2, legend=False, sharex=False, sharey=False);
```



Another option is passing an `ax` argument to `Series.plot()` to plot on a particular axis:

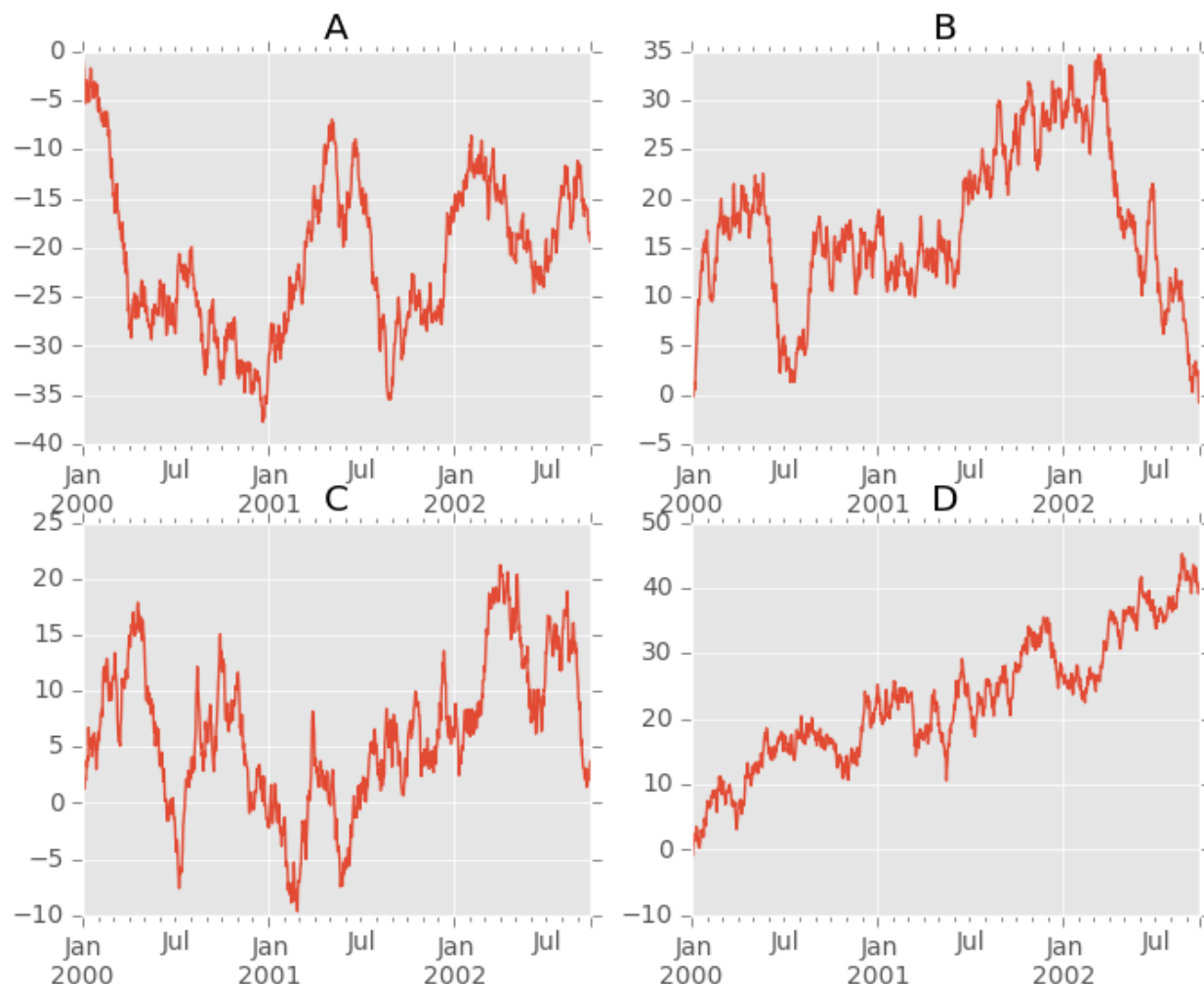
```
In [134]: fig, axes = plt.subplots(nrows=2, ncols=2)
```

```
In [135]: df['A'].plot(ax=axes[0,0]); axes[0,0].set_title('A');
```

```
In [136]: df['B'].plot(ax=axes[0,1]); axes[0,1].set_title('B');
```

```
In [137]: df['C'].plot(ax=axes[1,0]); axes[1,0].set_title('C');
```

```
In [138]: df['D'].plot(ax=axes[1,1]); axes[1,1].set_title('D');
```



23.5.7 Plotting With Error Bars

New in version 0.14.

Plotting with error bars is now supported in the `DataFrame.plot()` and `Series.plot()`

Horizontal and vertical errorbars can be supplied to the `xerr` and `yerr` keyword arguments to `plot()`. The error values can be specified using a variety of formats.

- As a `DataFrame` or dict of errors with column names matching the `columns` attribute of the plotting `DataFrame` or matching the `name` attribute of the `Series`
- As a `str` indicating which of the columns of plotting `DataFrame` contain the error values
- As raw values (list, tuple, or `np.ndarray`). Must be the same length as the plotting `DataFrame/Series`

Asymmetrical error bars are also supported, however raw error values must be provided in this case. For a `M` length `Series`, a `Mx2` array should be provided indicating lower and upper (or left and right) errors. For a `MxN` `DataFrame`, asymmetrical errors should be in a `Mx2xN` array.

Here is an example of one way to easily plot group means with standard deviations from the raw data.

```
# Generate the data
In [139]: ix3 = pd.MultiIndex.from_arrays([[ 'a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'], [ 'foo', 'foo',

In [140]: df3 = pd.DataFrame({'data1': [3, 2, 4, 3, 2, 4, 3, 2], 'data2': [6, 5, 7, 5, 4, 5, 6, 5]}),

# Group by index labels and take the means and standard deviations for each group
In [141]: gp3 = df3.groupby(level=('letter', 'word'))

In [142]: means = gp3.mean()

In [143]: errors = gp3.std()

In [144]: means
Out[144]:
```

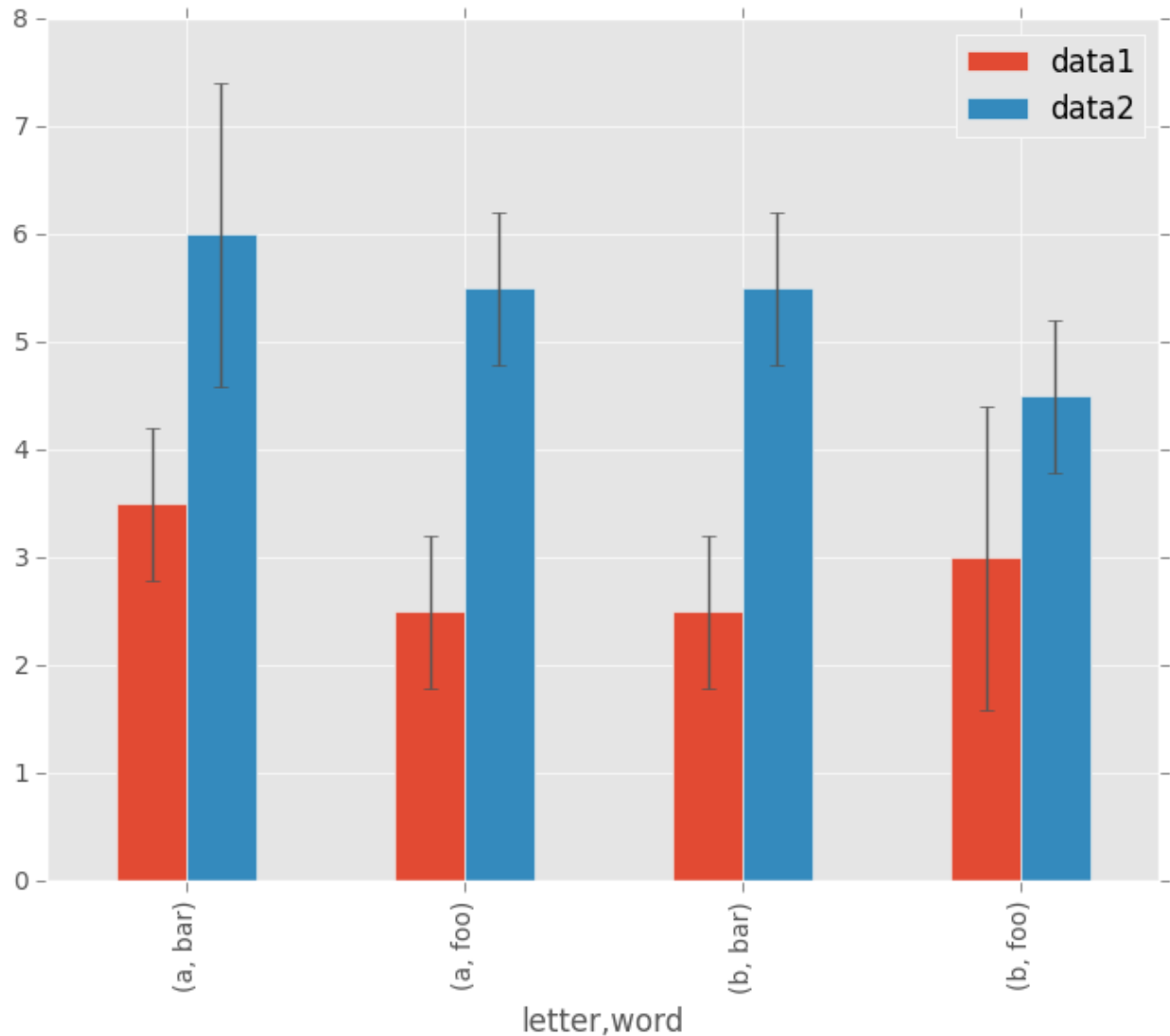
| | | data1 | data2 |
|--------|------|-------|-------|
| letter | word | | |
| a | bar | 3.5 | 6.0 |
| | foo | 2.5 | 5.5 |
| b | bar | 2.5 | 5.5 |
| | foo | 3.0 | 4.5 |

```
In [145]: errors
Out[145]:
```

| | | data1 | data2 |
|--------|------|----------|----------|
| letter | word | | |
| a | bar | 0.707107 | 1.414214 |
| | foo | 0.707107 | 0.707107 |
| b | bar | 0.707107 | 0.707107 |
| | foo | 1.414214 | 0.707107 |

```
# Plot
In [146]: fig, ax = plt.subplots()

In [147]: means.plot(yerr=errors, ax=ax, kind='bar')
Out[147]: <matplotlib.axes._subplots.AxesSubplot at 0xa632ad4c>
```



23.5.8 Plotting Tables

New in version 0.14.

Plotting with matplotlib table is now supported in `DataFrame.plot()` and `Series.plot()` with a `table` keyword. The `table` keyword can accept `bool`, `DataFrame` or `Series`. The simple way to draw a table is to specify `table=True`. Data will be transposed to meet matplotlib's default layout.

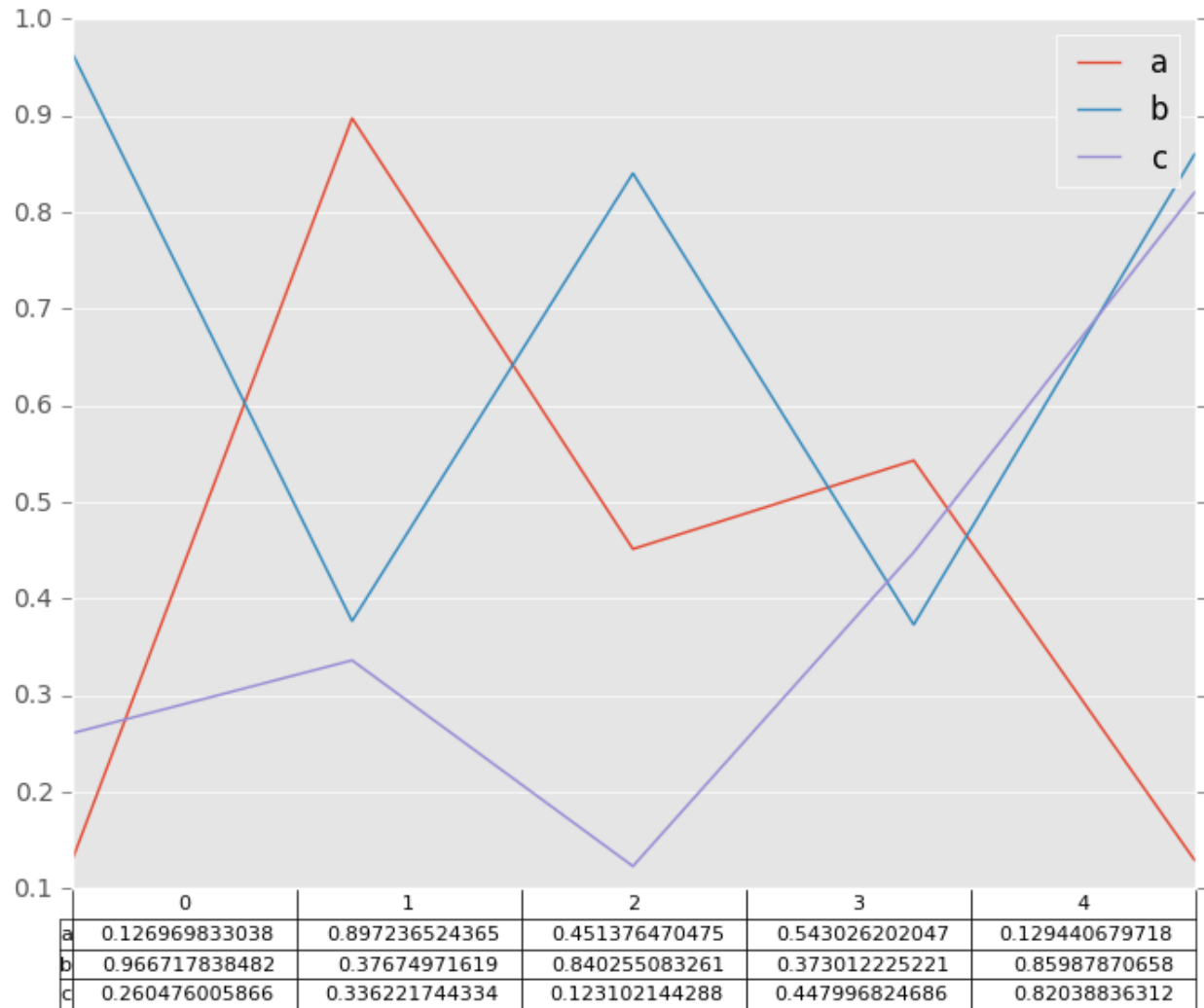
```
In [148]: fig, ax = plt.subplots(1, 1)
```

```
In [149]: df = pd.DataFrame(np.random.rand(5, 3), columns=['a', 'b', 'c'])
```

```
In [150]: ax.get_xaxis().set_visible(False)    # Hide Ticks
```

```
In [151]: df.plot(table=True, ax=ax)
```

```
Out[151]: <matplotlib.axes._subplots.AxesSubplot at 0xa62b17ec>
```



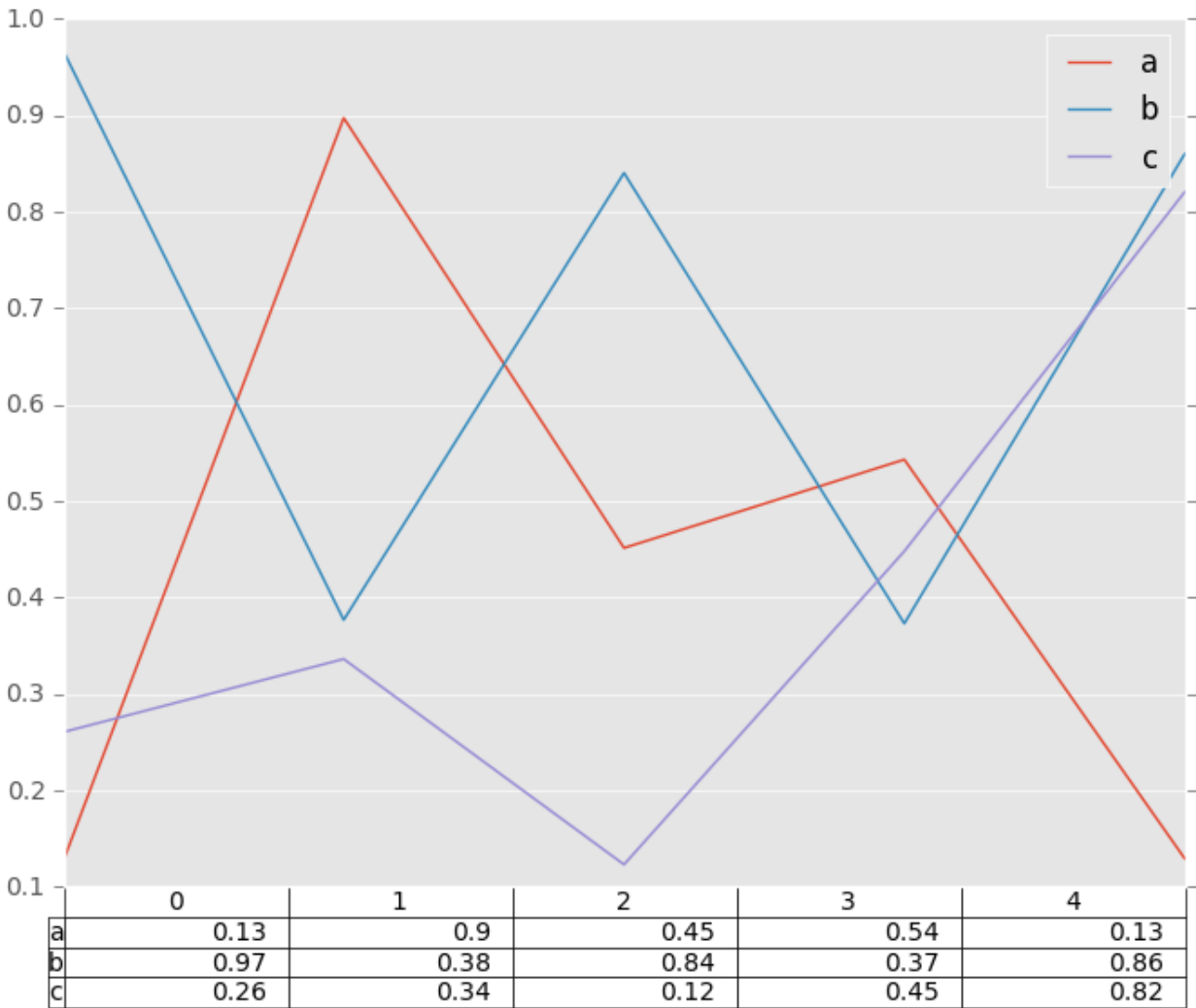
Also, you can pass different `DataFrame` or `Series` for `table` keyword. The data will be drawn as displayed in print method (not transposed automatically). If required, it should be transposed manually as below example.

```
In [152]: fig, ax = plt.subplots(1, 1)
```

```
In [153]: ax.get_xaxis().set_visible(False)    # Hide Ticks
```

```
In [154]: df.plot(table=np.round(df.T, 2), ax=ax)
```

```
Out[154]: <matplotlib.axes._subplots.AxesSubplot at 0xa61cefac>
```



Finally, there is a helper function `pandas.tools.plotting.table` to create a table from `DataFrame` and `Series`, and add it to an `matplotlib.Axes`. This function can accept keywords which `matplotlib` table has.

```
In [155]: from pandas.tools.plotting import table
```

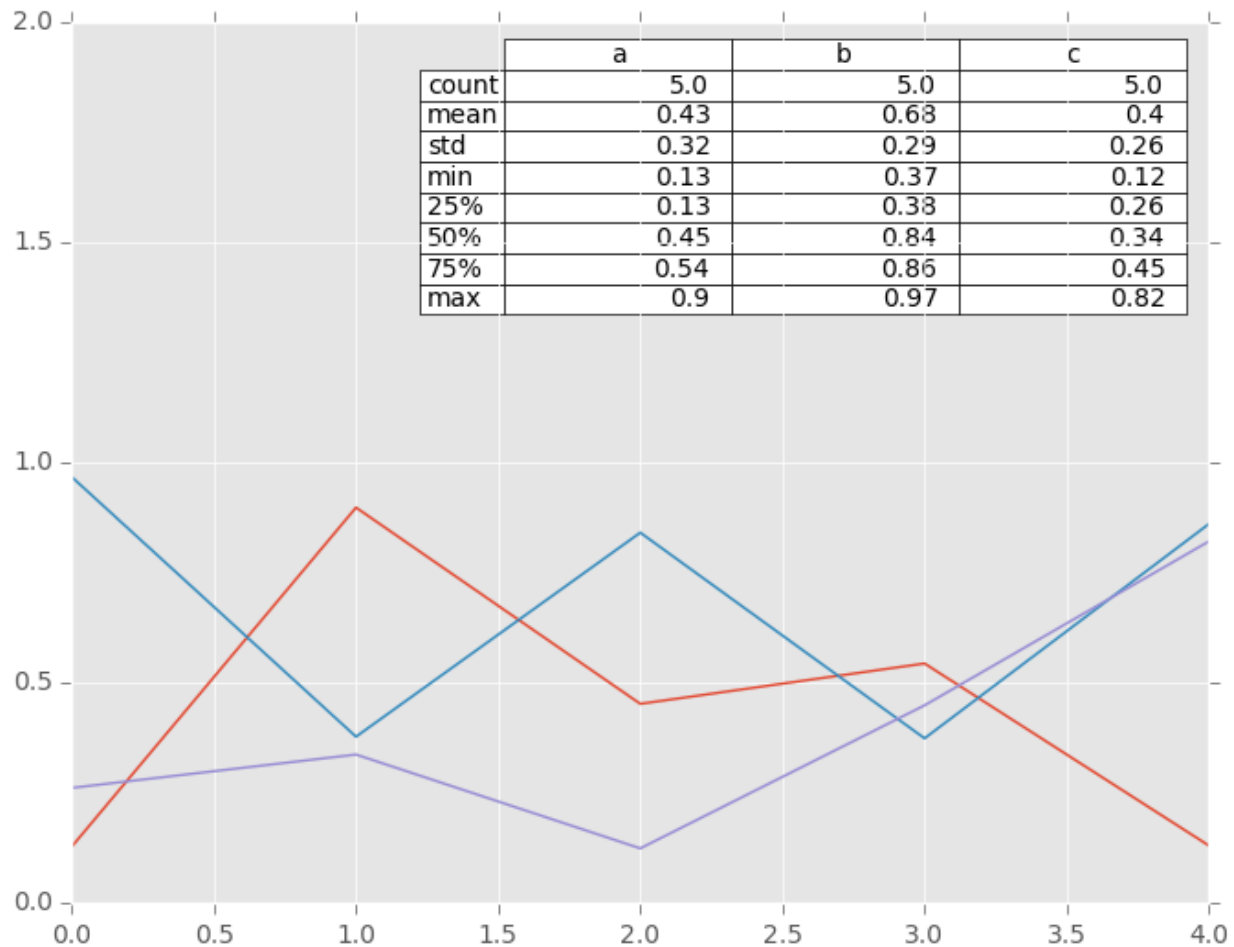
```
In [156]: fig, ax = plt.subplots(1, 1)
```

```
In [157]: table(ax, np.round(df.describe(), 2),
.....:         loc='upper right', colWidths=[0.2, 0.2, 0.2])
.....:
```

```
Out[157]: <matplotlib.table.Table at 0xa5fb3dac>
```

```
In [158]: df.plot(ax=ax, ylim=(0, 2), legend=None)
```

```
Out[158]: <matplotlib.axes._subplots.AxesSubplot at 0xa616fc4c>
```



Note: You can get table instances on the axes using `axes.tables` property for further decorations. See the [matplotlib table documentation](#) for more.

23.5.9 Colormaps

A potential issue when plotting a large number of columns is that it can be difficult to distinguish some series due to repetition in the default colors. To remedy this, DataFrame plotting supports the use of the `colormap=` argument, which accepts either a Matplotlib [colormap](#) or a string that is a name of a colormap registered with Matplotlib. A visualization of the default matplotlib colormaps is available [here](#).

As matplotlib does not directly support colormaps for line-based plots, the colors are selected based on an even spacing determined by the number of columns in the DataFrame. There is no consideration made for background color, so some colormaps will produce lines that are not easily visible.

To use the cubehelix colormap, we can simply pass 'cubehelix' to `colormap=`

```
In [159]: df = pd.DataFrame(np.random.randn(1000, 10), index=ts.index)
```

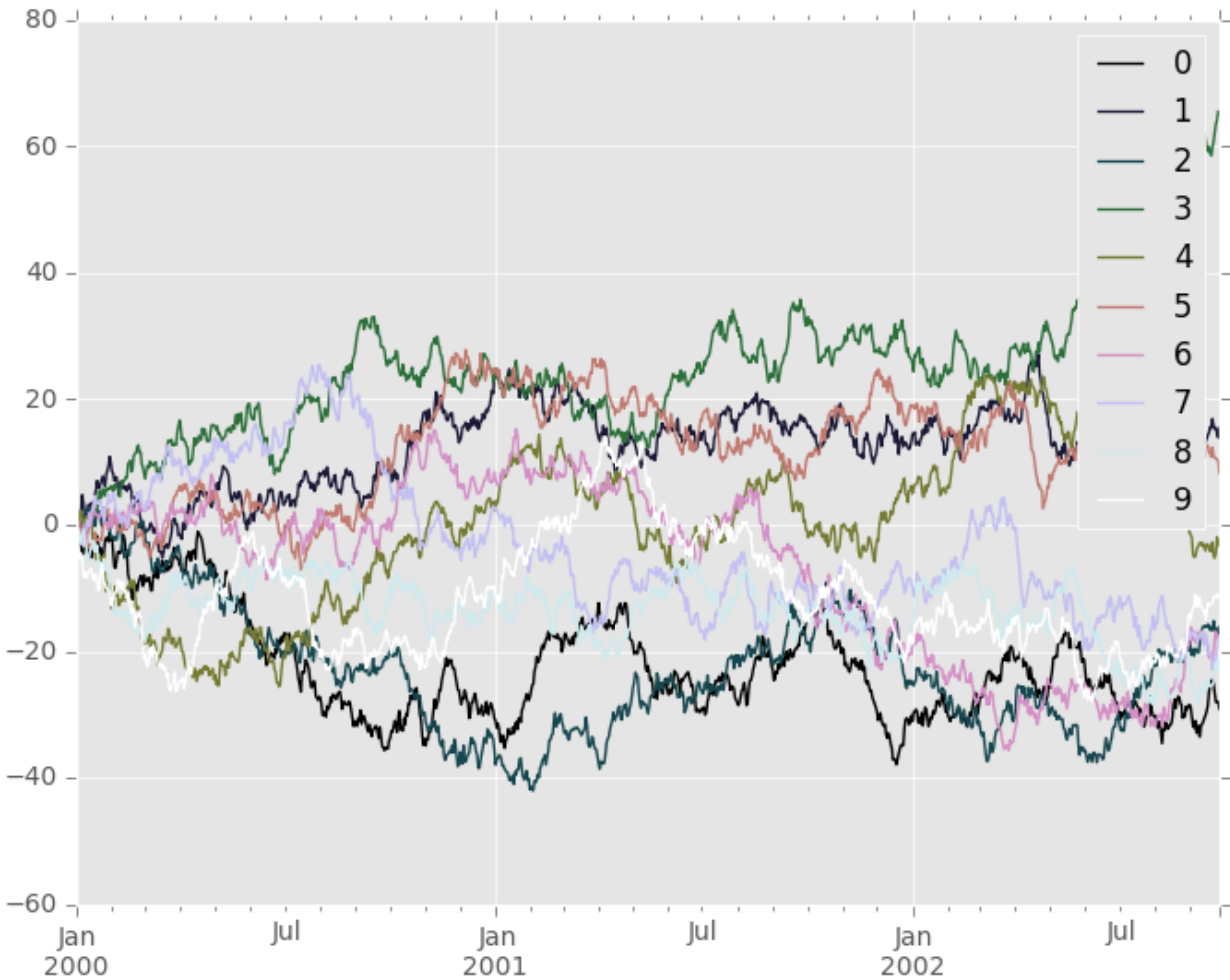
```
In [160]: df = df.cumsum()
```

```
In [161]: plt.figure()
```

```
Out[161]: <matplotlib.figure.Figure at 0xa5f199ac>
```

```
In [162]: df.plot(colormap='cubehelix')
```

```
Out[162]: <matplotlib.axes._subplots.AxesSubplot at 0xa5f239ac>
```



or we can pass the colormap itself

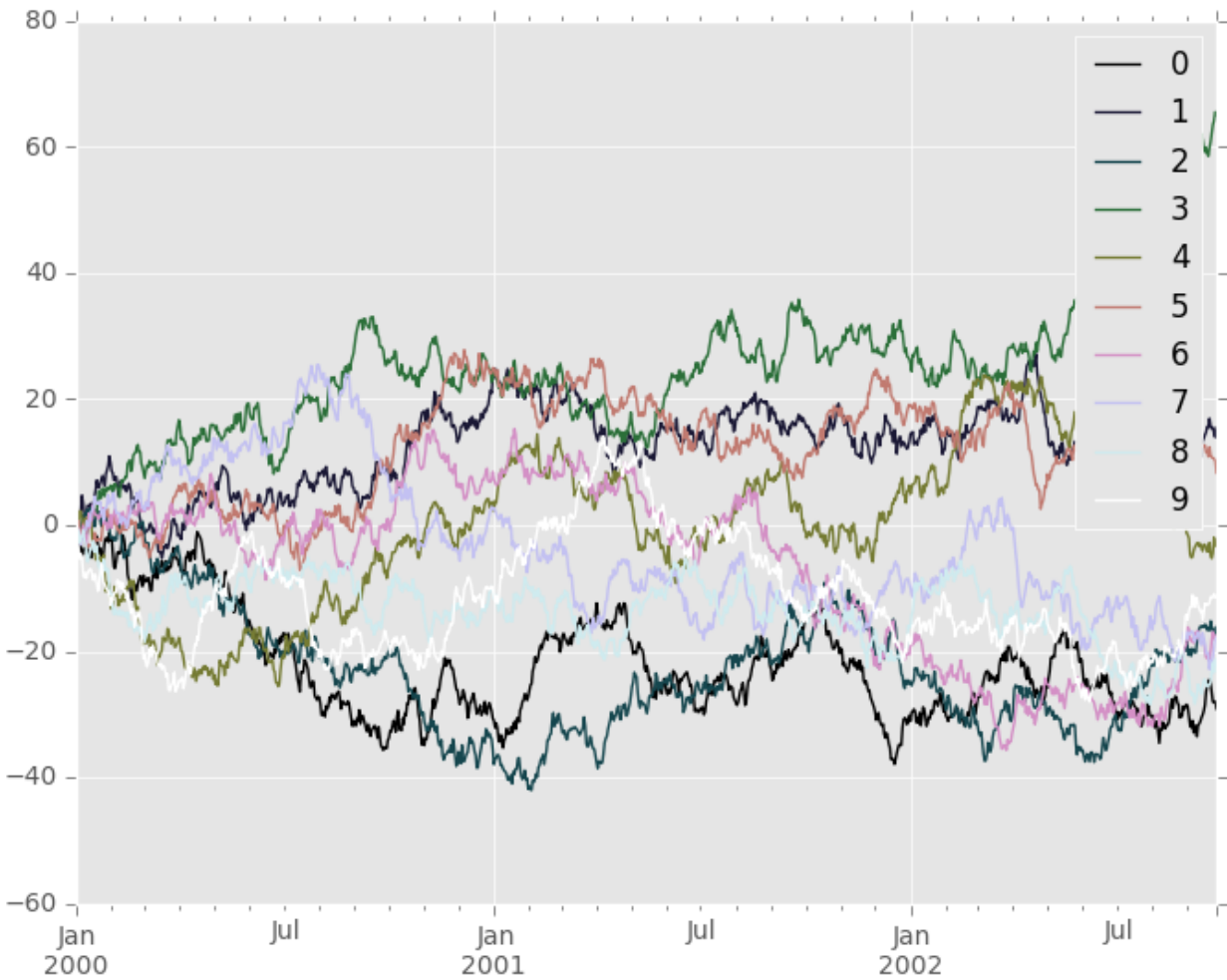
```
In [163]: from matplotlib import cm
```

```
In [164]: plt.figure()
```

```
Out[164]: <matplotlib.figure.Figure at 0xa5e3fb8c>
```

```
In [165]: df.plot(colormap=cm.cubehelix)
```

```
Out[165]: <matplotlib.axes._subplots.AxesSubplot at 0xa5e3362c>
```



Colormaps can also be used other plot types, like bar charts:

```
In [166]: dd = pd.DataFrame(np.random.randn(10, 10)).applymap(abs)
```

```
In [167]: dd = dd.cumsum()
```

```
In [168]: plt.figure()
```

```
Out[168]: <matplotlib.figure.Figure at 0xa557a1cc>
```

```
In [169]: dd.plot(kind='bar', colormap='Greens')
```

```
Out[169]: <matplotlib.axes._subplots.AxesSubplot at 0xa556206c>
```



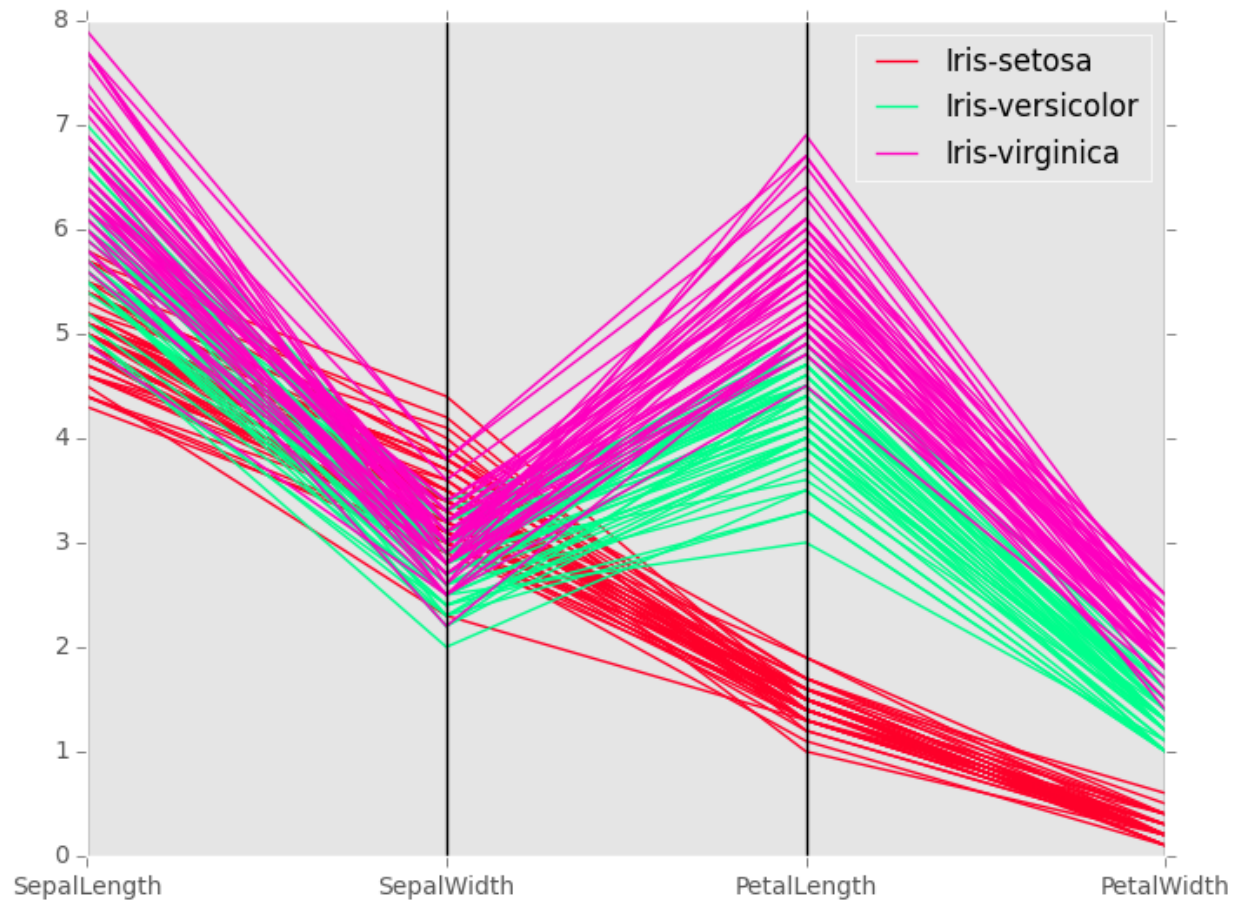
Parallel coordinates charts:

```
In [170]: plt.figure()
```

```
Out[170]: <matplotlib.figure.Figure at 0xa54a748c>
```

```
In [171]: parallel_coordinates(data, 'Name', colormap='gist_rainbow')
```

```
Out[171]: <matplotlib.axes._subplots.AxesSubplot at 0xa54ce48c>
```



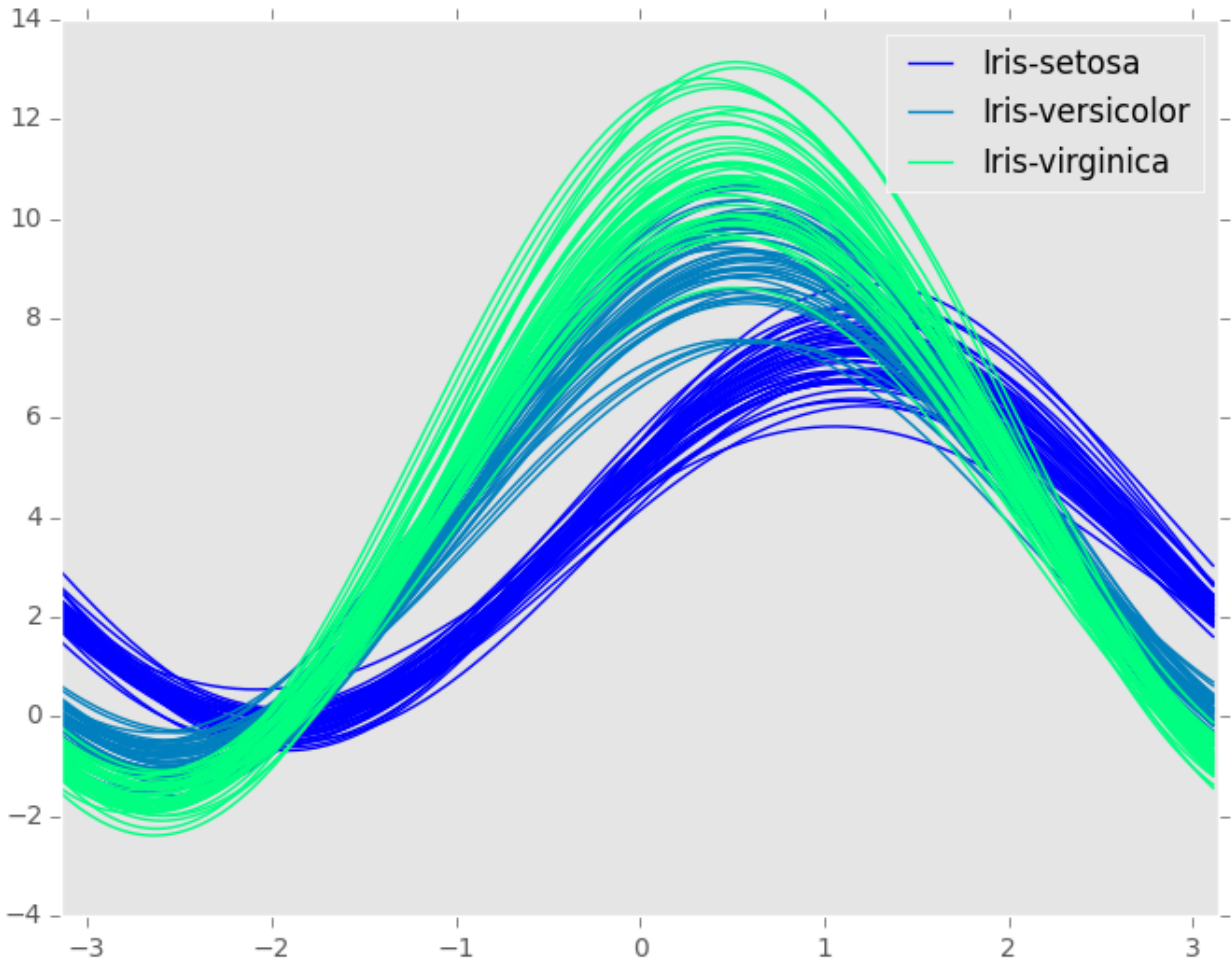
Andrews curves charts:

```
In [172]: plt.figure()
```

```
Out[172]: <matplotlib.figure.Figure at 0xa5066ccc>
```

```
In [173]: andrews_curves(data, 'Name', colormap='winter')
```

```
Out[173]: <matplotlib.axes._subplots.AxesSubplot at 0xa50396ec>
```



23.6 Plotting directly with matplotlib

In some situations it may still be preferable or necessary to prepare plots directly with matplotlib, for instance when a certain type of plot or customization is not (yet) supported by pandas. Series and DataFrame objects behave like arrays and can therefore be passed directly to matplotlib functions without explicit casts.

pandas also automatically registers formatters and locators that recognize date indices, thereby extending date and time support to practically all plot types available in matplotlib. Although this formatting does not provide the same level of refinement you would get when plotting via pandas, it can be faster when plotting a large number of points.

Note: The speed up for large data sets only applies to pandas 0.14.0 and later.

```
In [174]: price = pd.Series(np.random.randn(150).cumsum(),
.....:                     index=pd.date_range('2000-1-1', periods=150, freq='B'))
.....:

In [175]: ma = pd.rolling_mean(price, 20)

In [176]: mstd = pd.rolling_std(price, 20)

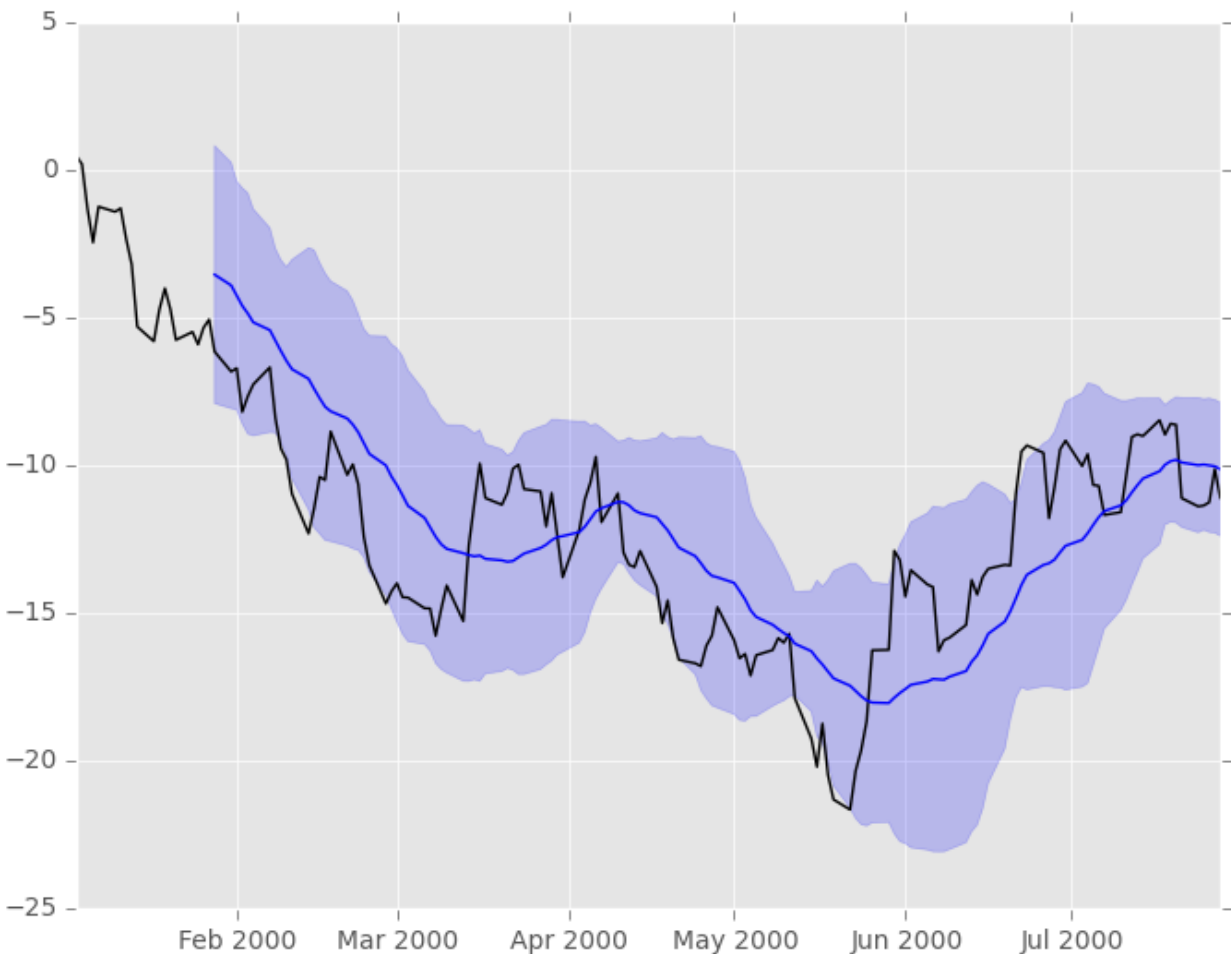
In [177]: plt.figure()
```

```
Out[177]: <matplotlib.figure.Figure at 0xa4cc8c0c>

In [178]: plt.plot(price.index, price, 'k')
Out[178]: [<matplotlib.lines.Line2D at 0xa490cbcc>]

In [179]: plt.plot(ma.index, ma, 'b')
Out[179]: [<matplotlib.lines.Line2D at 0xa493096c>]

In [180]: plt.fill_between(mstd.index, ma-2*mstd, ma+2*mstd, color='b', alpha=0.2)
Out[180]: <matplotlib.collections.PolyCollection at 0xa49360cc>
```



23.7 Trellis plotting interface

Warning: The `rplot` trellis plotting interface is **deprecated and will be removed in a future version**. We refer to external packages like [seaborn](#) for similar but more refined functionality. The docs below include some example on how to convert your existing code to `seaborn`.

Note: The tips data set can be downloaded [here](#). Once you download it execute

```
tips_data = pd.read_csv('tips.csv')
```

from the directory where you downloaded the file.

We import the rplot API:

```
In [181]: import pandas.tools.rplot as rplot
```

23.7.1 Examples

RPlot was an API for producing Trellis plots. These plots allow you to arrange data in a rectangular grid by values of certain attributes. In the example below, data from the tips data set is arranged by the attributes 'sex' and 'smoker'. Since both of those attributes can take on one of two values, the resulting grid has two columns and two rows. A histogram is displayed for each cell of the grid.

```
In [182]: plt.figure()
```

```
Out[182]: <matplotlib.figure.Figure at 0xa4783fec>
```

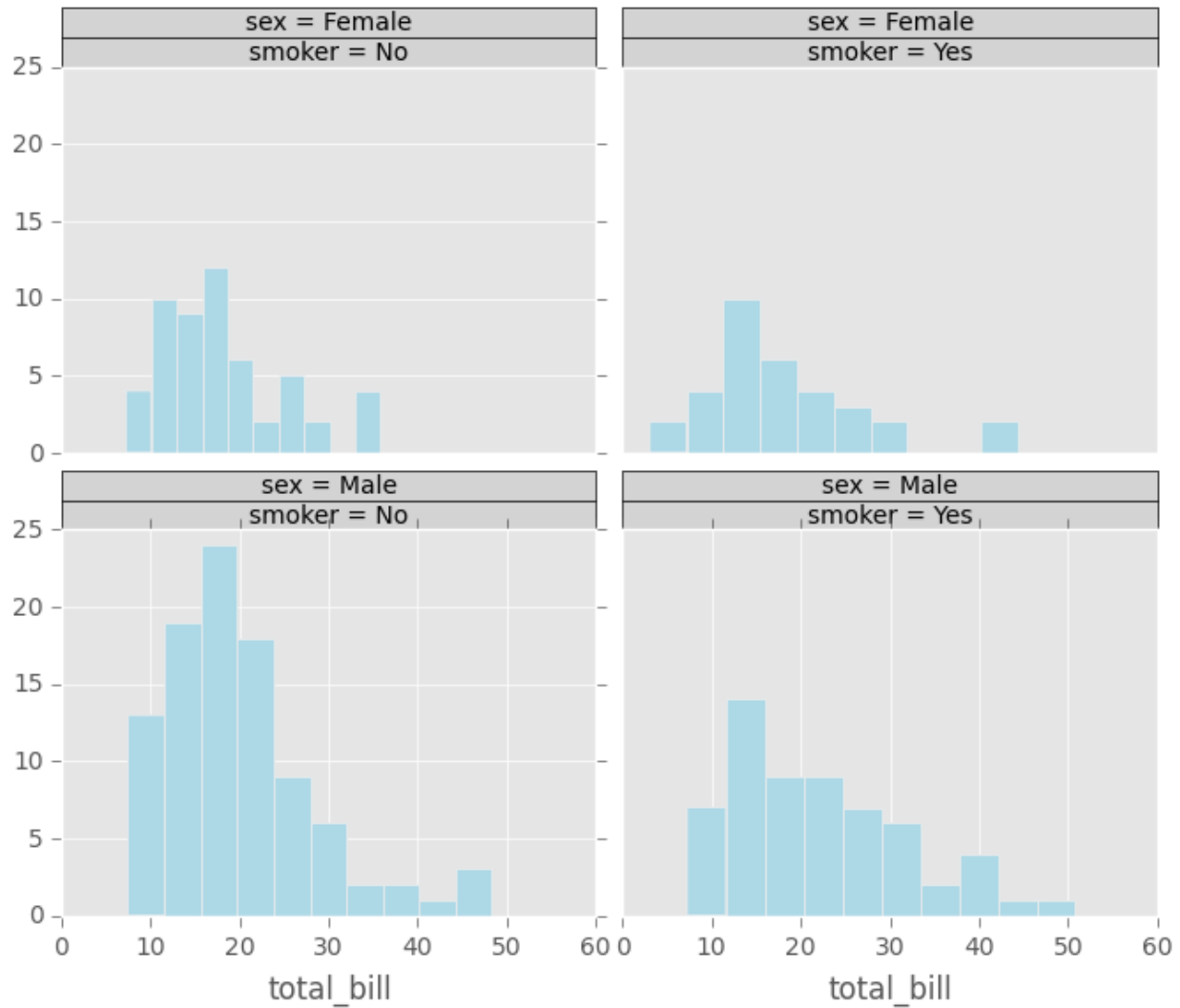
```
In [183]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')
```

```
In [184]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))
```

```
In [185]: plot.add(rplot.GeoHistogram())
```

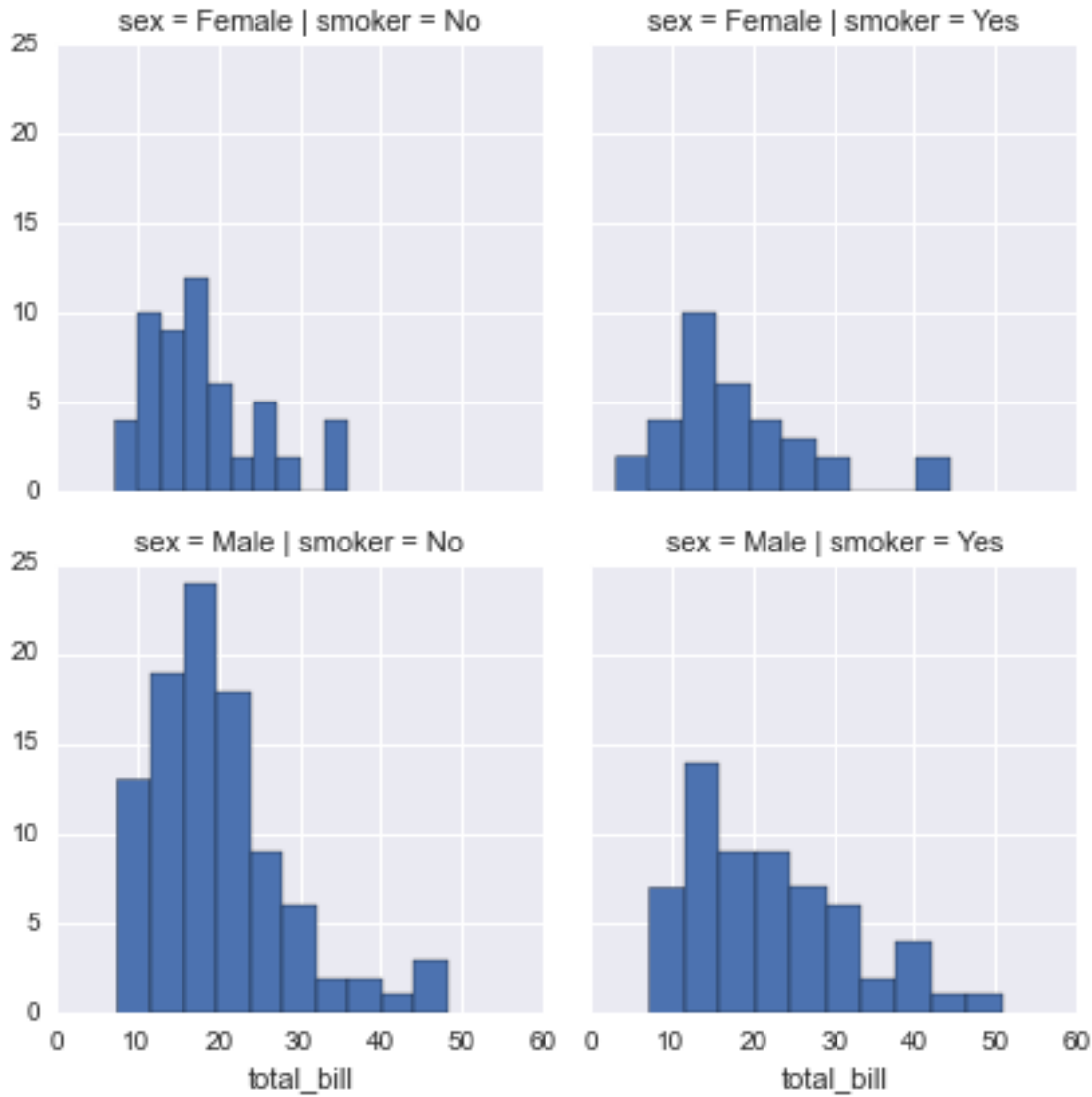
```
In [186]: plot.render(plt.gcf())
```

```
Out[186]: <matplotlib.figure.Figure at 0xa4783fec>
```



A similar plot can be made with seaborn using the FacetGrid object, resulting in the following image:

```
import seaborn as sns
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.hist, "total_bill")
```



Example below is the same as previous except the plot is set to kernel density estimation. A seaborn example is included beneath.

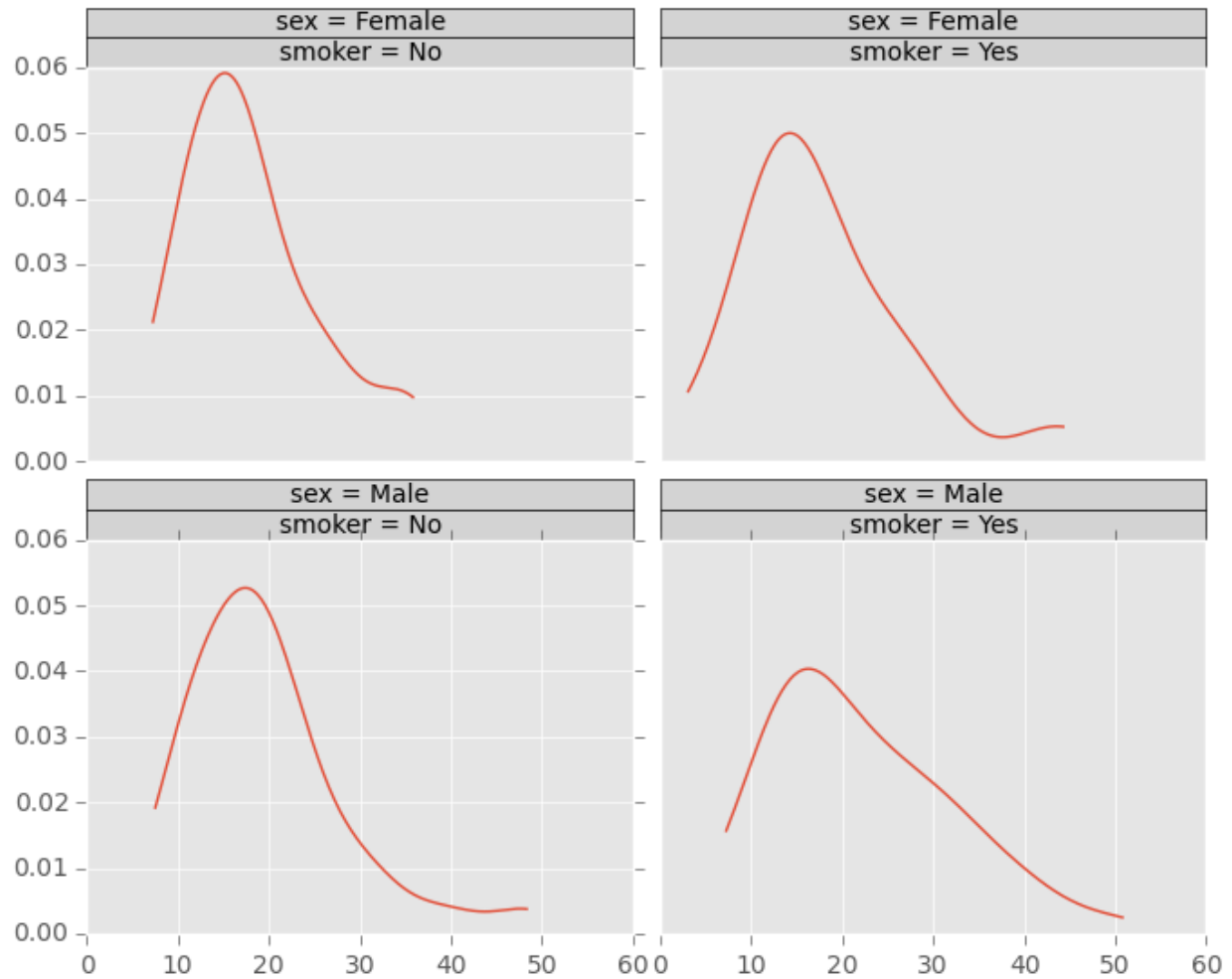
```
In [187]: plt.figure()
Out[187]: <matplotlib.figure.Figure at 0xa4796a4c>

In [188]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

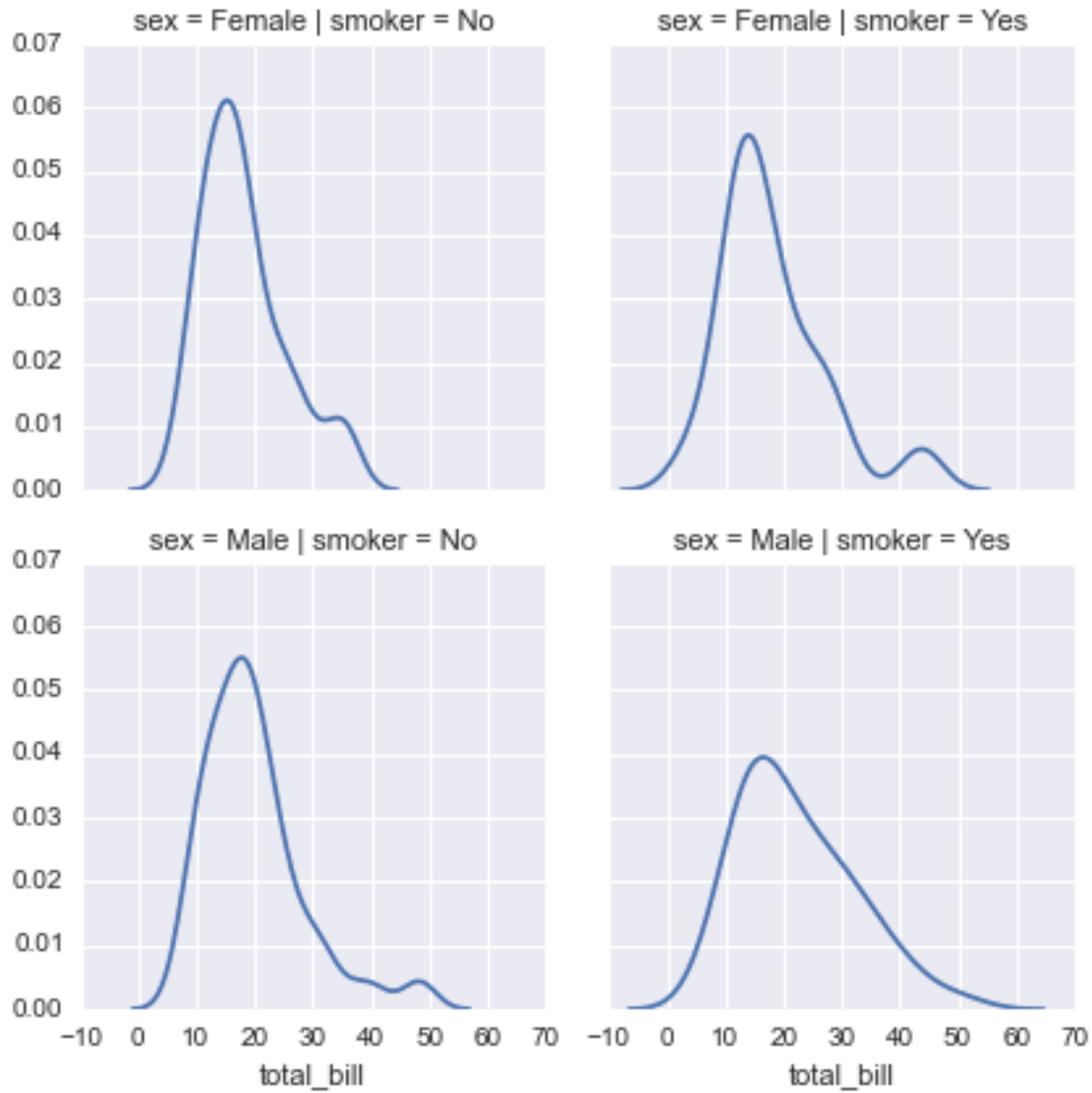
In [189]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [190]: plot.add(rplot.GeoDensity())

In [191]: plot.render(plt.gcf())
Out[191]: <matplotlib.figure.Figure at 0xa4796a4c>
```



```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(sns.kdeplot, "total_bill")
```



The plot below shows that it is possible to have two or more plots for the same data displayed on the same Trellis grid cell.

```
In [192]: plt.figure()
Out[192]: <matplotlib.figure.Figure at 0xa456f5ec>

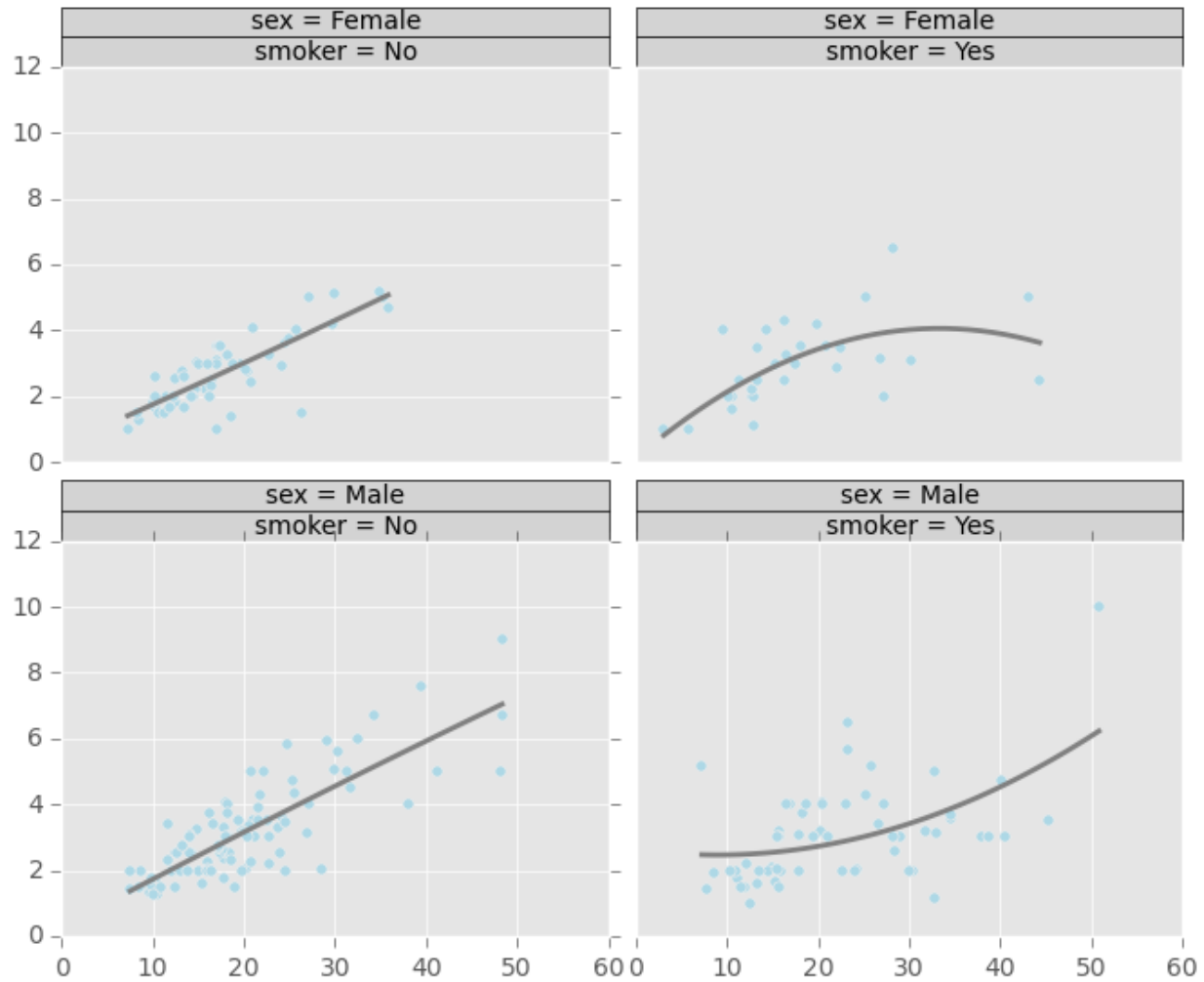
In [193]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [194]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

In [195]: plot.add(rplot.GeoMScatter())

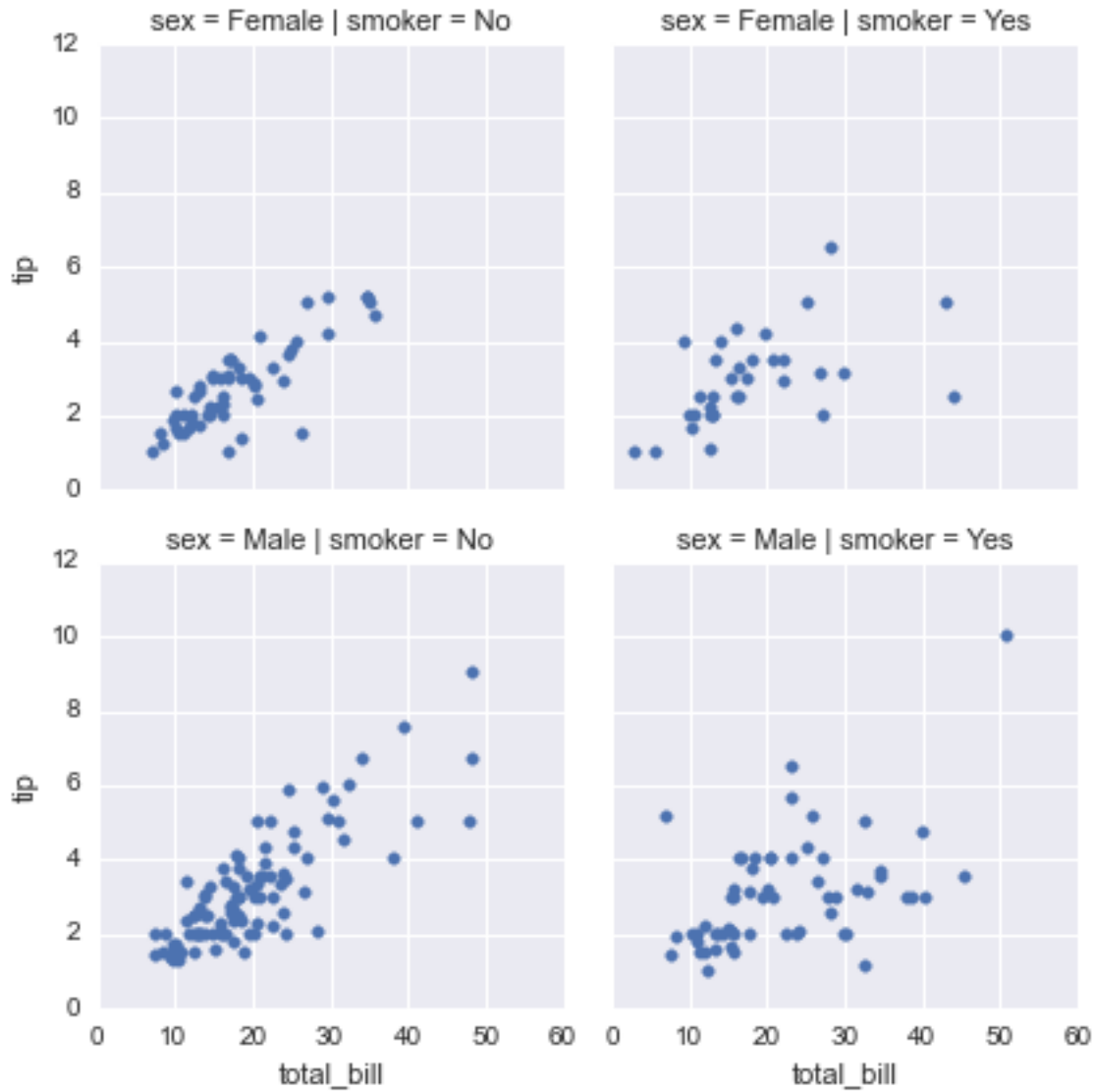
In [196]: plot.add(rplot.GeoMPolyFit(degree=2))

In [197]: plot.render(plt.gcf())
Out[197]: <matplotlib.figure.Figure at 0xa456f5ec>
```



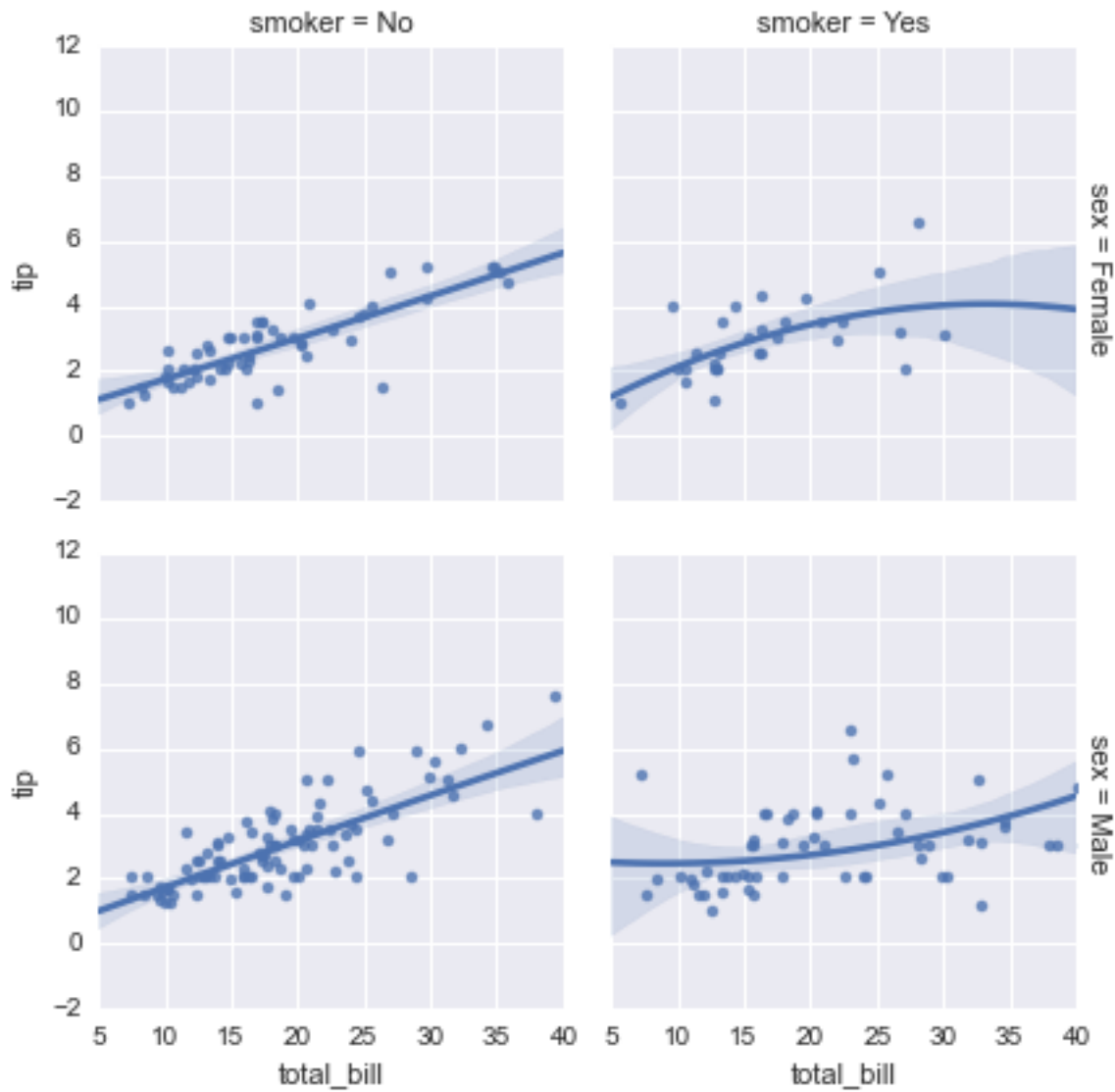
A seaborn equivalent for a simple scatter plot:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
```



and with a regression line, using the dedicated seaborn regplot function:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker", margin_titles=True)
g.map(sns.regplot, "total_bill", "tip", order=2)
```



Below is a similar plot but with 2D kernel density estimation plot superimposed, followed by a seaborn equivalent:

```
In [198]: plt.figure()
Out[198]: <matplotlib.figure.Figure at 0xa3f4a94c>

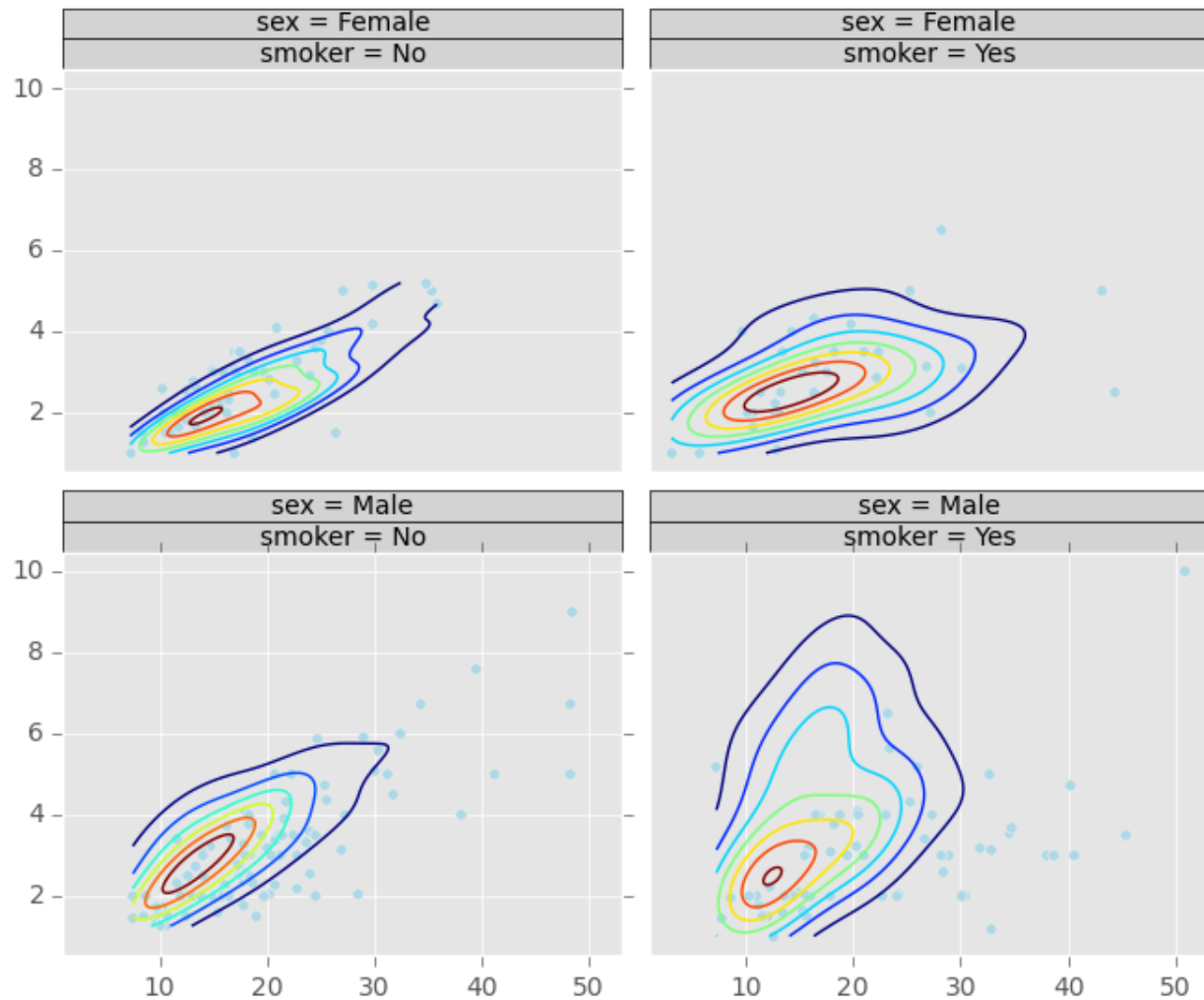
In [199]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [200]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))

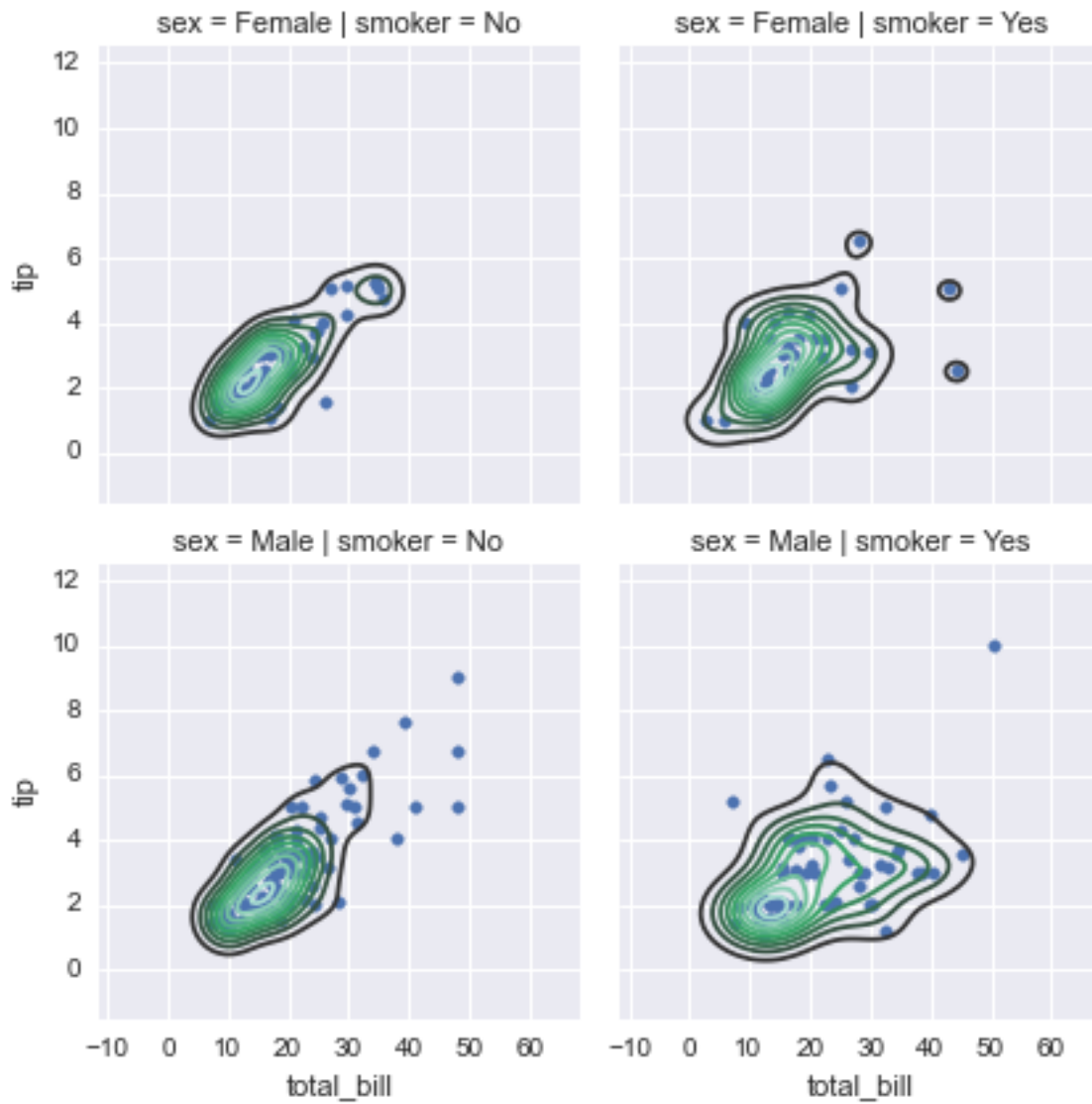
In [201]: plot.add(rplot.GeoMScatter())

In [202]: plot.add(rplot.GeoMDensity2D())

In [203]: plot.render(plt.gcf())
Out[203]: <matplotlib.figure.Figure at 0xa3f4a94c>
```



```
g = sns.FacetGrid(tips_data, row="sex", col="smoker")
g.map(plt.scatter, "total_bill", "tip")
g.map(sns.kdeplot, "total_bill", "tip")
```



It is possible to only use one attribute for grouping data. The example above only uses 'sex' attribute. If the second grouping attribute is not specified, the plots will be arranged in a column.

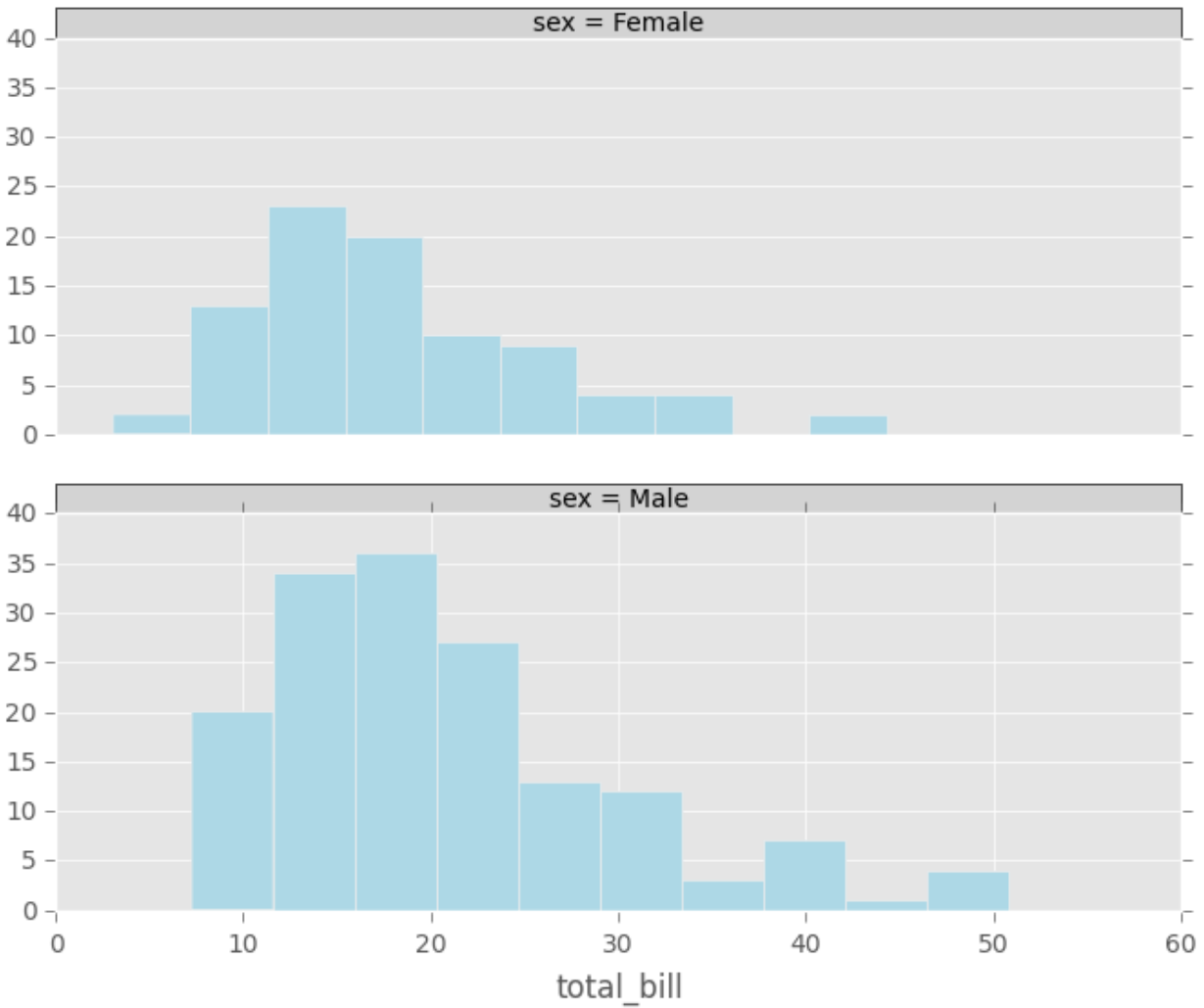
```
In [204]: plt.figure()
Out[204]: <matplotlib.figure.Figure at 0xa40eb4cc>

In [205]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')

In [206]: plot.add(rplot.TrellisGrid(['sex', '.']))

In [207]: plot.add(rplot.GeoHistogram())

In [208]: plot.render(plt.gcf())
Out[208]: <matplotlib.figure.Figure at 0xa40eb4cc>
```



If the first grouping attribute is not specified the plots will be arranged in a row.

```
In [209]: plt.figure()
```

```
Out[209]: <matplotlib.figure.Figure at 0xa3d666cc>
```

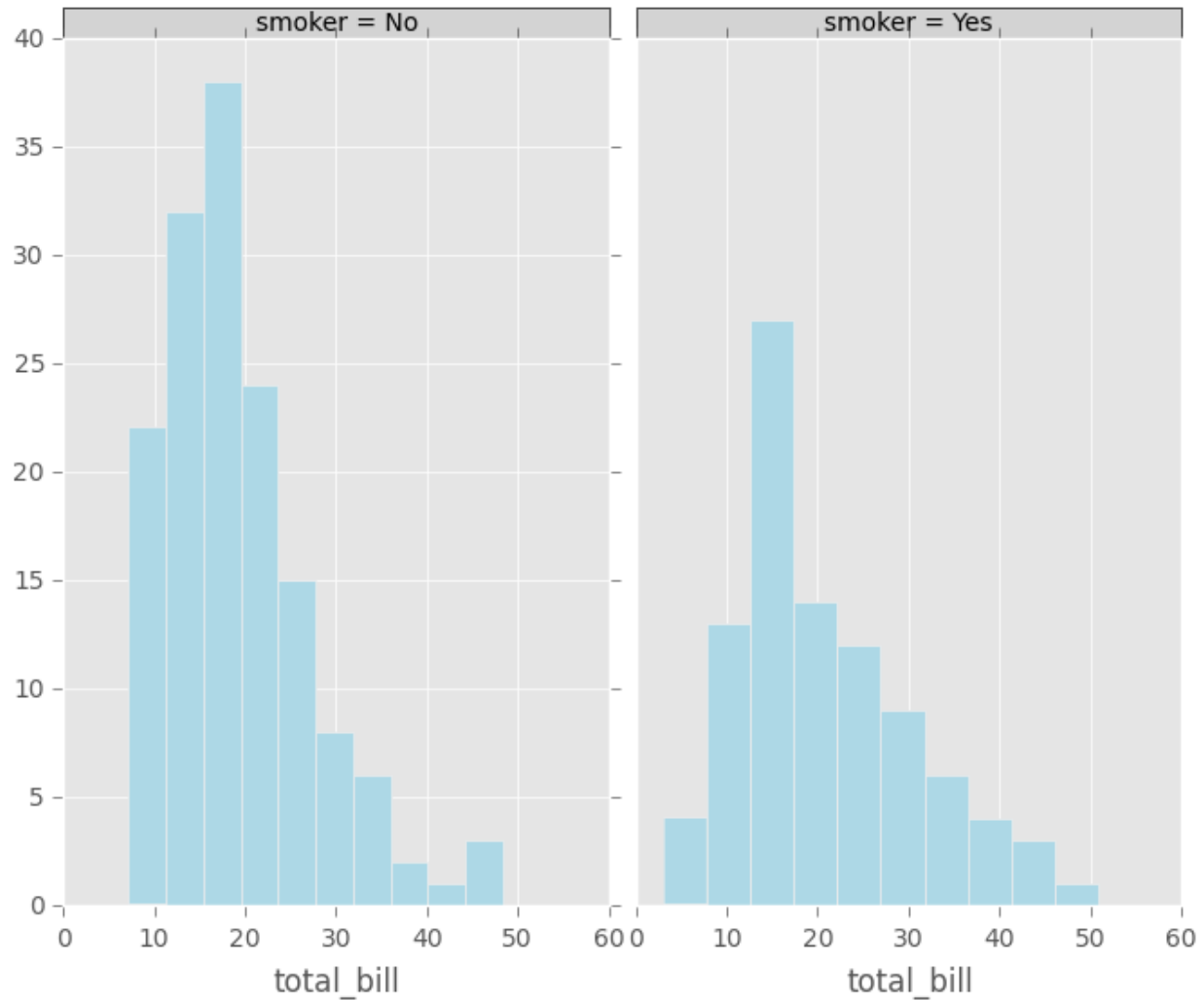
```
In [210]: plot = rplot.RPlot(tips_data, x='total_bill', y='tip')
```

```
In [211]: plot.add(rplot.TrellisGrid(['.', 'smoker']))
```

```
In [212]: plot.add(rplot.GeoHistogram())
```

```
In [213]: plot.render(plt.gcf())
```

```
Out[213]: <matplotlib.figure.Figure at 0xa3d666cc>
```



In seaborn, this can also be done by only specifying one of the `row` and `col` arguments.

In the example below the colour and shape of the scatter plot graphical objects is mapped to 'day' and 'size' attributes respectively. You use scale objects to specify these mappings. The list of scale classes is given below with initialization arguments for quick reference.

```
In [214]: plt.figure()
```

```
Out[214]: <matplotlib.figure.Figure at 0xa3c5c8ec>
```

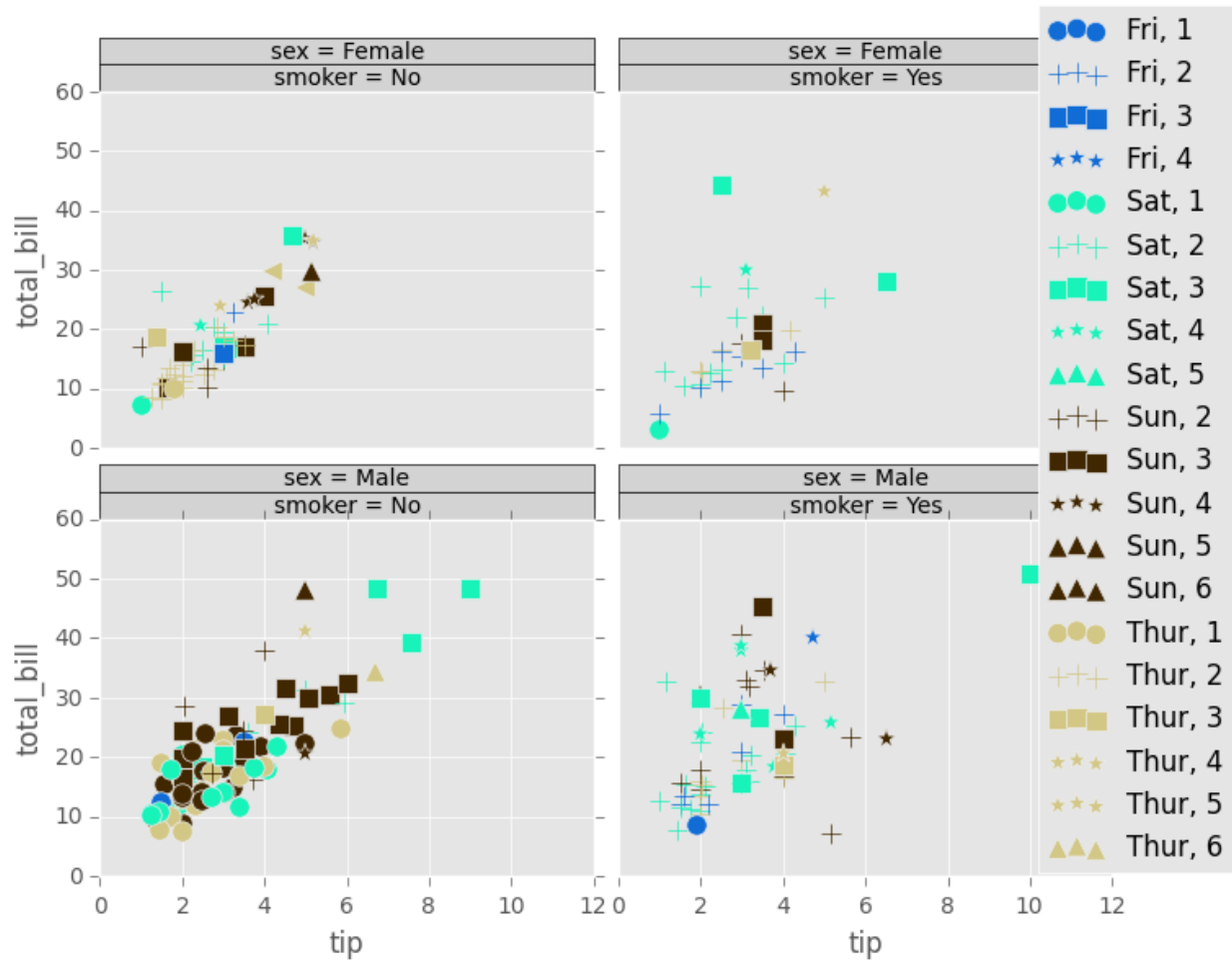
```
In [215]: plot = rplot.RPlot(tips_data, x='tip', y='total_bill')
```

```
In [216]: plot.add(rplot.TrellisGrid(['sex', 'smoker']))
```

```
In [217]: plot.add(rplot.GeoPoint(size=80.0, colour=rplot.ScaleRandomColour('day'), shape=rplot.Sca
```

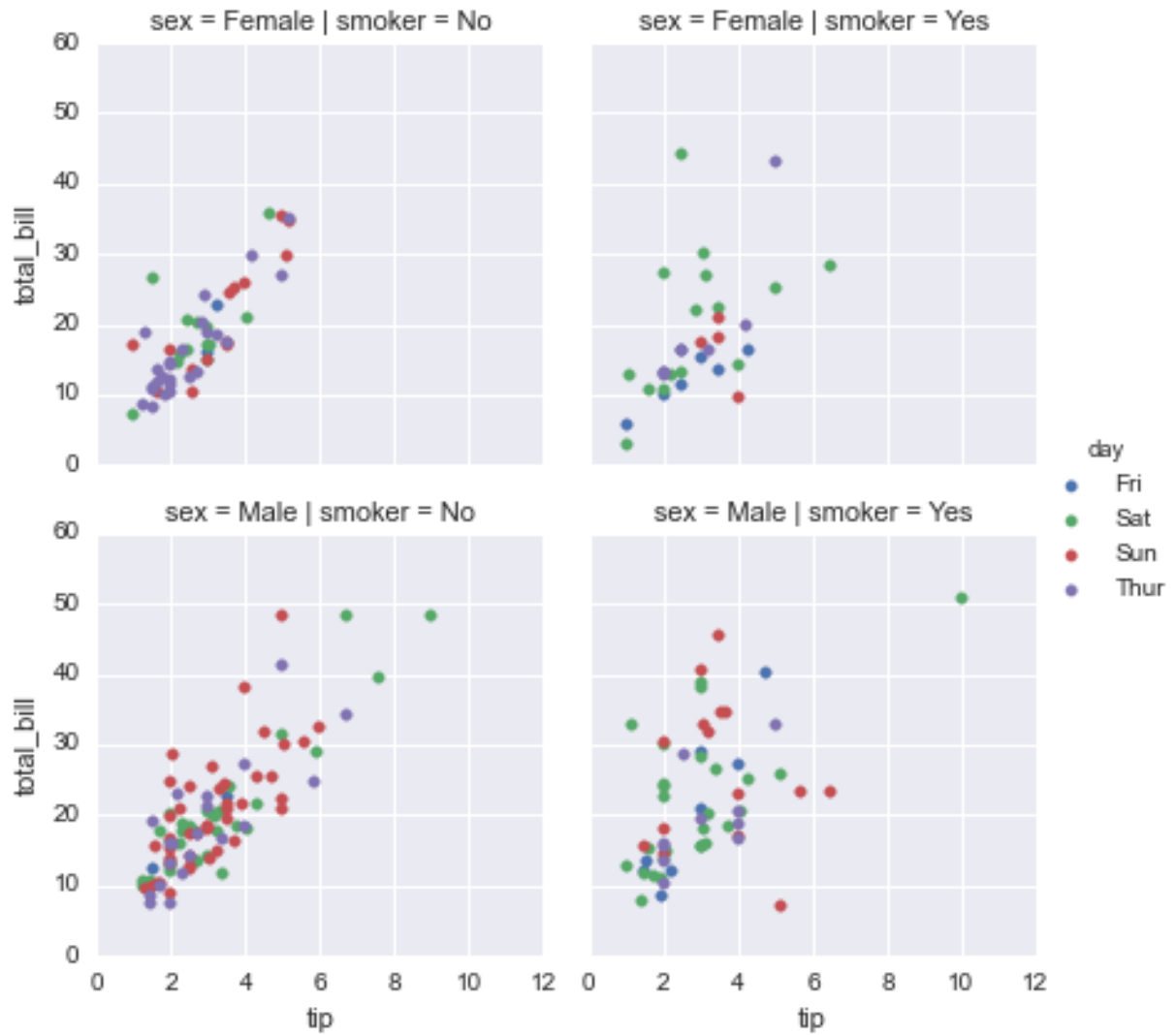
```
In [218]: plot.render(plt.gcf())
```

```
Out[218]: <matplotlib.figure.Figure at 0xa3c5c8ec>
```



This can also be done in `seaborn`, at least for 3 variables:

```
g = sns.FacetGrid(tips_data, row="sex", col="smoker", hue="day")
g.map(plt.scatter, "tip", "total_bill")
g.add_legend()
```



IO TOOLS (TEXT, CSV, HDF5, ...)

The pandas I/O API is a set of top level reader functions accessed like `pd.read_csv()` that generally return a pandas object.

- *read_csv*
- *read_excel*
- *read_hdf*
- *read_sql*
- *read_json*
- *read_msgpack* (experimental)
- *read_html*
- *read_gbq* (experimental)
- *read_stata*
- *read_clipboard*
- *read_pickle*

The corresponding writer functions are object methods that are accessed like `df.to_csv()`

- *to_csv*
- *to_excel*
- *to_hdf*
- *to_sql*
- *to_json*
- *to_msgpack* (experimental)
- *to_html*
- *to_gbq* (experimental)
- *to_stata*
- *to_clipboard*
- *to_pickle*

Here is an informal performance comparison for some of these IO methods.

Note: For examples that use the `StringIO` class, make sure you import it according to your Python version, i.e. `from StringIO import StringIO` for Python 2 and `from io import StringIO` for Python 3.

24.1 CSV & Text files

The two workhorse functions for reading text files (a.k.a. flat files) are `read_csv()` and `read_table()`. They both use the same parsing code to intelligently convert tabular data into a `DataFrame` object. See the [cookbook](#) for some advanced strategies

They can take a number of arguments:

- `filepath_or_buffer`: Either a string path to a file, URL (including http, ftp, and S3 locations), or any object with a `read` method (such as an open file or `StringIO`).
- `sep` or `delimiter`: A delimiter / separator to split fields on. With `sep=None`, `read_csv` will try to infer the delimiter automatically in some cases by “sniffing”. The separator may be specified as a regular expression; for instance you may use `'\s*'` to indicate a pipe plus arbitrary whitespace.
- `delim_whitespace`: Parse whitespace-delimited (spaces or tabs) file (much faster than using a regular expression)
- `compression`: decompress `'gzip'` and `'bz2'` formats on the fly. Set to `'infer'` (the default) to guess a format based on the file extension.
- `dialect`: string or `csv.Dialect` instance to expose more ways to specify the file format
- `dtype`: A data type name or a dict of column name to data type. If not specified, data types will be inferred. (Unsupported with `engine='python'`)
- `header`: row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise `None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. `[0,1,3]`. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True` (the default), so `header=0` denotes the first line of data rather than the first line of the file.
- `skip_blank_lines`: whether to skip over blank lines rather than interpreting them as NaN values
- `skiprows`: A collection of numbers for rows in the file to skip. Can also be an integer to skip the first `n` rows
- `index_col`: column number, column name, or list of column numbers/names, to use as the `index` (row labels) of the resulting `DataFrame`. By default, it will number the rows without using any column, unless there is one more data column than there are headers, in which case the first column is taken as the index.
- `names`: List of column names to use as column names. To replace header existing in file, explicitly pass `header=0`.
- `na_values`: optional list of strings to recognize as NaN (missing values), either in addition to or in lieu of the default set.
- `true_values`: list of strings to recognize as `True`
- `false_values`: list of strings to recognize as `False`
- `keep_default_na`: whether to include the default set of missing values in addition to the ones specified in `na_values`
- `parse_dates`: if `True` then index will be parsed as dates (`False` by default). You can specify more complicated options to parse a subset of columns or a combination of columns into a single date column (list of ints or names, list of lists, or dict) `[1, 2, 3]` -> try parsing columns 1, 2, 3 each as a separate date column `[[1, 3]]` -> combine columns 1 and 3 and parse as a single date column `{ 'foo' : [1, 3] }` -> parse columns 1, 3 as date and call result `'foo'`

- `keep_date_col`: if True, then date component columns passed into `parse_dates` will be retained in the output (False by default).
- `date_parser`: function to use to parse strings into datetime objects. If `parse_dates` is True, it defaults to the very robust `dateutil.parser`. Specifying this implicitly sets `parse_dates` as True. You can also use functions from community supported date converters from `date_converters.py`
- `dayfirst`: if True then uses the DD/MM international/European date format (This is False by default)
- `thousands`: specifies the thousands separator. If not None, this character will be stripped from numeric dtypes. However, if it is the first character in a field, that column will be imported as a string. In the `PythonParser`, if not None, then parser will try to look for it in the output and parse relevant data to numeric dtypes. Because it has to essentially scan through the data again, this causes a significant performance hit so only use if necessary.
- `lineterminator`: string (length 1), default None, Character to break file into lines. Only valid with C parser
- `quotechar`: string, The character to used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.
- `quoting`: int, Controls whether quotes should be recognized. Values are taken from `csv.QUOTE_*` values. Acceptable values are 0, 1, 2, and 3 for `QUOTE_MINIMAL`, `QUOTE_ALL`, `QUOTE_NONE`, and `QUOTE_NONNUMERIC`, respectively.
- `skipinitialspace`: boolean, default False, Skip spaces after delimiter
- `escapechar`: string, to specify how to escape quoted data
- `comment`: Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines, fully commented lines are ignored by the parameter `header` but not by `skiprows`. For example, if `comment='#'`, parsing `#empty n1,2,3na,b,c'` with `header=0` will result in `'1,2,3'` being treated as the header.
- `nrows`: Number of rows to read out of the file. Useful to only read a small portion of a large file
- `iterator`: If True, return a `TextFileReader` to enable reading a file into memory piece by piece
- `chunksize`: An number of rows to be used to “chunk” a file into pieces. Will cause an `TextFileReader` object to be returned. More on this below in the section on [iterating and chunking](#)
- `skip_footer`: number of lines to skip at bottom of file (default 0) (Unsupported with `engine='c'`)
- `converters`: a dictionary of functions for converting values in certain columns, where keys are either integers or column labels
- `encoding`: a string representing the encoding to use for decoding unicode data, e.g. `'utf-8'` or `'latin-1'`. [Full list of Python standard encodings](#)
- `verbose`: show number of NA values inserted in non-numeric columns
- `squeeze`: if True then output with only one column is turned into Series
- `error_bad_lines`: if False then any lines causing an error will be skipped [bad lines](#)
- `usecols`: a subset of columns to return, results in much faster parsing time and lower memory usage.
- `mangle_dupe_cols`: boolean, default True, then duplicate columns will be specified as `'X.0'...'X.N'`, rather than `'X'...'X'`
- `tupleize_cols`: boolean, default False, if False, convert a list of tuples to a multi-index of columns, otherwise, leave the column index as a list of tuples
- `float_precision`: string, default None. Specifies which converter the C engine should use for floating-point values. The options are None for the ordinary converter, 'high' for the high-precision converter, and 'round_trip' for the round-trip converter.

Consider a typical CSV file containing, in this case, some time series data:

```
In [1]: print(open('foo.csv').read())
date,A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

The default for `read_csv` is to create a DataFrame with simple numbered rows:

```
In [2]: pd.read_csv('foo.csv')
Out[2]:
```

| | date | A | B | C |
|---|----------|---|---|---|
| 0 | 20090101 | a | 1 | 2 |
| 1 | 20090102 | b | 3 | 4 |
| 2 | 20090103 | c | 4 | 5 |

In the case of indexed data, you can pass the column number or column name you wish to use as the index:

```
In [3]: pd.read_csv('foo.csv', index_col=0)
Out[3]:
```

| | A | B | C |
|----------|---|---|---|
| date | | | |
| 20090101 | a | 1 | 2 |
| 20090102 | b | 3 | 4 |
| 20090103 | c | 4 | 5 |

```
In [4]: pd.read_csv('foo.csv', index_col='date')
Out[4]:
```

| | A | B | C |
|----------|---|---|---|
| date | | | |
| 20090101 | a | 1 | 2 |
| 20090102 | b | 3 | 4 |
| 20090103 | c | 4 | 5 |

You can also use a list of columns to create a hierarchical index:

```
In [5]: pd.read_csv('foo.csv', index_col=[0, 'A'])
Out[5]:
```

| | | B | C |
|----------|---|---|---|
| date | A | | |
| 20090101 | a | 1 | 2 |
| 20090102 | b | 3 | 4 |
| 20090103 | c | 4 | 5 |

The `dialect` keyword gives greater flexibility in specifying the file format. By default it uses the Excel dialect but you can specify either the dialect name or a `csv.Dialect` instance.

Suppose you had data with unenclosed quotes:

```
In [6]: print(data)
label1,label2,label3
index1,"a,c,e
index2,b,d,f
```

By default, `read_csv` uses the Excel dialect and treats the double quote as the quote character, which causes it to fail when it finds a newline before it finds the closing double quote.

We can get around this using `dialect`

```
In [7]: dia = csv.excel()

In [8]: dia.quoting = csv.QUOTE_NONE

In [9]: pd.read_csv(StringIO(data), dialect=dia)
Out[9]:
```

| | label1 | label2 | label3 |
|--------|--------|--------|--------|
| index1 | "a | c | e |
| index2 | b | d | f |

All of the dialect options can be specified separately by keyword arguments:

```
In [10]: data = 'a,b,c~1,2,3~4,5,6'

In [11]: pd.read_csv(StringIO(data), lineterminator='~')
Out[11]:
```

| | a | b | c |
|---|---|---|---|
| 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 |

Another common dialect option is `skipinitialspace`, to skip any whitespace after a delimiter:

```
In [12]: data = 'a, b, c\n1, 2, 3\n4, 5, 6'

In [13]: print(data)
a, b, c
1, 2, 3
4, 5, 6

In [14]: pd.read_csv(StringIO(data), skipinitialspace=True)
Out[14]:
```

| | a | b | c |
|---|---|---|---|
| 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 |

The parsers make every attempt to “do the right thing” and not be very fragile. Type inference is a pretty big deal. So if a column can be coerced to integer dtype without altering the contents, it will do so. Any non-numeric columns will come through as object dtype as with the rest of pandas objects.

24.1.1 Specifying column data types

Starting with v0.10, you can indicate the data type for the whole DataFrame or individual columns:

```
In [15]: data = 'a,b,c\n1,2,3\n4,5,6\n7,8,9'

In [16]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9

In [17]: df = pd.read_csv(StringIO(data), dtype=object)

In [18]: df
Out[18]:
```

| | a | b | c |
|---|---|---|---|
| 0 | 1 | 2 | 3 |
| 1 | 4 | 5 | 6 |

```
2  7  8  9
```

```
In [19]: df['a'][0]
Out[19]: '1'
```

```
In [20]: df = pd.read_csv(StringIO(data), dtype={'b': object, 'c': np.float64})
```

```
In [21]: df.dtypes
Out[21]:
a      int64
b      object
c    float64
dtype: object
```

Note: The `dtype` option is currently only supported by the C engine. Specifying `dtype` with engine other than `'c'` raises a `ValueError`.

24.1.2 Handling column names

A file may or may not have a header row. pandas assumes the first row should be used as the column names:

```
In [22]: data = 'a,b,c\n1,2,3\n4,5,6\n7,8,9'
```

```
In [23]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9
```

```
In [24]: pd.read_csv(StringIO(data))
Out[24]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9
```

By specifying the `names` argument in conjunction with `header` you can indicate other names to use and whether or not to throw away the header row (if any):

```
In [25]: print(data)
a,b,c
1,2,3
4,5,6
7,8,9
```

```
In [26]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=0)
Out[26]:
   foo  bar  baz
0     1    2    3
1     4    5    6
2     7    8    9
```

```
In [27]: pd.read_csv(StringIO(data), names=['foo', 'bar', 'baz'], header=None)
Out[27]:
   foo bar baz
0    a  b  c
```

```

1  1  2  3
2  4  5  6
3  7  8  9

```

If the header is in a row other than the first, pass the row number to `header`. This will skip the preceding rows:

```
In [28]: data = 'skip this skip it\na,b,c\n1,2,3\n4,5,6\n7,8,9'
```

```
In [29]: pd.read_csv(StringIO(data), header=1)
```

```
Out[29]:
   a  b  c
0  1  2  3
1  4  5  6
2  7  8  9

```

24.1.3 Filtering columns (`usecols`)

The `usecols` argument allows you to select any subset of the columns in a file, either using the column names or position numbers:

```
In [30]: data = 'a,b,c,d\n1,2,3,foo\n4,5,6,bar\n7,8,9,baz'
```

```
In [31]: pd.read_csv(StringIO(data))
```

```
Out[31]:
   a  b  c  d
0  1  2  3  foo
1  4  5  6  bar
2  7  8  9  baz

```

```
In [32]: pd.read_csv(StringIO(data), usecols=['b', 'd'])
```

```
Out[32]:
   b  d
0  2  foo
1  5  bar
2  8  baz

```

```
In [33]: pd.read_csv(StringIO(data), usecols=[0, 2, 3])
```

```
Out[33]:
   a  c  d
0  1  3  foo
1  4  6  bar
2  7  9  baz

```

24.1.4 Ignoring line comments and empty lines

If the `comment` parameter is specified, then completely commented lines will be ignored. By default, completely blank lines will be ignored as well. Both of these are API changes introduced in version 0.15.

```
In [34]: data = '\na,b,c\n \n# commented line\n1,2,3\n4,5,6'
```

```
In [35]: print(data)
```

```
a,b,c
```

```
1,2,3
```

```
4,5,6
```

```
# commented line
```

```
In [36]: pd.read_csv(StringIO(data), comment='#')
```

```
Out[36]:
```

```
   a  b  c
0  1  2  3
1  4  5  6
```

If `skip_blank_lines=False`, then `read_csv` will not ignore blank lines:

```
In [37]: data = 'a,b,c\n\n1,2,3\n\n4,5,6'
```

```
In [38]: pd.read_csv(StringIO(data), skip_blank_lines=False)
```

```
Out[38]:
```

```
   a  b  c
0 NaN NaN NaN
1  1  2  3
2 NaN NaN NaN
3 NaN NaN NaN
4  4  5  6
```

Warning: The presence of ignored lines might create ambiguities involving line numbers; the parameter `header` uses row numbers (ignoring commented/empty lines), while `skiprows` uses line numbers (including commented/empty lines):

```
In [39]: data = '#comment\na,b,c\nA,B,C\n1,2,3'

In [40]: pd.read_csv(StringIO(data), comment='#', header=1)
Out[40]:
   A  B  C
0  1  2  3

In [41]: data = 'A,B,C\n#comment\na,b,c\n1,2,3'

In [42]: pd.read_csv(StringIO(data), comment='#', skiprows=2)
Out[42]:
   a  b  c
0  1  2  3
```

If both `header` and `skiprows` are specified, `header` will be relative to the end of `skiprows`. For example:

```
In [43]: data = '# empty\n# second empty line\n# third empty' \
           'line\nX,Y,Z\n1,2,3\nA,B,C\n1,2.,4.\n5.,NaN,10.0'

In [43]: 'line\nX,Y,Z\n1,2,3\nA,B,C\n1,2.,4.\n5.,NaN,10.0'

In [44]: print(data)
# empty
# second empty line
# third emptyline
X,Y,Z
1,2,3
A,B,C
1,2.,4.
5.,NaN,10.0

In [45]: pd.read_csv(StringIO(data), comment='#', skiprows=4, header=1)
Out[45]:
   A  B  C
0  1  2  4
1  5 NaN 10
```

24.1.5 Dealing with Unicode Data

The `encoding` argument should be used for encoded unicode data, which will result in byte strings being decoded to unicode in the result:

```
In [46]: data = b'word,length\nTr\u00e4umen,7\nGr\u00fc\u00fe,5'.decode('utf8').encode('latin-1')

In [47]: df = pd.read_csv(BytesIO(data), encoding='latin-1')

In [48]: df
Out[48]:
   word  length
0  Tr\u00e4umen      7
1   Gr\u00fc\u00fe      5

In [49]: df['word'][1]
```

```
Out[49]: u'Gr\xfc\xdf'
```

Some formats which encode all characters as multiple bytes, like UTF-16, won't parse correctly at all without specifying the encoding. [Full list of Python standard encodings](#)

24.1.6 Index columns and trailing delimiters

If a file has one more column of data than the number of column names, the first column will be used as the DataFrame's row names:

```
In [50]: data = 'a,b,c\n4,apple,bat,5.7\n8,orange,cow,10'
```

```
In [51]: pd.read_csv(StringIO(data))
```

```
Out[51]:
```

| | a | b | c |
|---|--------|-----|------|
| 4 | apple | bat | 5.7 |
| 8 | orange | cow | 10.0 |

```
In [52]: data = 'index,a,b,c\n4,apple,bat,5.7\n8,orange,cow,10'
```

```
In [53]: pd.read_csv(StringIO(data), index_col=0)
```

```
Out[53]:
```

| | a | b | c |
|-------|--------|-----|------|
| index | | | |
| 4 | apple | bat | 5.7 |
| 8 | orange | cow | 10.0 |

Ordinarily, you can achieve this behavior using the `index_col` option.

There are some exception cases when a file has been prepared with delimiters at the end of each data line, confusing the parser. To explicitly disable the index column inference and discard the last column, pass `index_col=False`:

```
In [54]: data = 'a,b,c\n4,apple,bat,\n8,orange,cow, '
```

```
In [55]: print(data)
```

```
a,b,c
4,apple,bat,
8,orange,cow, 
```

```
In [56]: pd.read_csv(StringIO(data))
```

```
Out[56]:
```

| | a | b | c |
|---|--------|-----|-----|
| 4 | apple | bat | NaN |
| 8 | orange | cow | NaN |

```
In [57]: pd.read_csv(StringIO(data), index_col=False)
```

```
Out[57]:
```

| | a | b | c |
|---|---|--------|-----|
| 0 | 4 | apple | bat |
| 1 | 8 | orange | cow |

24.1.7 Specifying Date Columns

To better facilitate working with datetime data, `read_csv()` and `read_table()` uses the keyword arguments `parse_dates` and `date_parser` to allow users to specify a variety of columns and date/time formats to turn the input text data into datetime objects.

The simplest case is to just pass in `parse_dates=True`:

```
# Use a column as an index, and parse it as dates.
```

```
In [58]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True)
```

```
In [59]: df
```

```
Out[59]:
```

| | A | B | C |
|------------|---|---|---|
| date | | | |
| 2009-01-01 | a | 1 | 2 |
| 2009-01-02 | b | 3 | 4 |
| 2009-01-03 | c | 4 | 5 |

```
# These are python datetime objects
```

```
In [60]: df.index
```

```
Out[60]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', name=u'date', freq='D')
```

It is often the case that we may want to store date and time data separately, or store various date fields separately. the `parse_dates` keyword can be used to specify a combination of columns to parse the dates and/or times from.

You can specify a list of column lists to `parse_dates`, the resulting date columns will be prepended to the output (so as to not affect the existing column order) and the new column names will be the concatenation of the component column names:

```
In [61]: print(open('tmp.csv').read())
```

```
KORD,19990127, 19:00:00, 18:56:00, 0.8100
KORD,19990127, 20:00:00, 19:56:00, 0.0100
KORD,19990127, 21:00:00, 20:56:00, -0.5900
KORD,19990127, 21:00:00, 21:18:00, -0.9900
KORD,19990127, 22:00:00, 21:56:00, -0.5900
KORD,19990127, 23:00:00, 22:56:00, -0.5900
```

```
In [62]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]])
```

```
In [63]: df
```

```
Out[63]:
```

| | | 1_2 | | 1_3 | 0 | 4 |
|---|------------|----------|------------|----------|------|-------|
| 0 | 1999-01-27 | 19:00:00 | 1999-01-27 | 18:56:00 | KORD | 0.81 |
| 1 | 1999-01-27 | 20:00:00 | 1999-01-27 | 19:56:00 | KORD | 0.01 |
| 2 | 1999-01-27 | 21:00:00 | 1999-01-27 | 20:56:00 | KORD | -0.59 |
| 3 | 1999-01-27 | 21:00:00 | 1999-01-27 | 21:18:00 | KORD | -0.99 |
| 4 | 1999-01-27 | 22:00:00 | 1999-01-27 | 21:56:00 | KORD | -0.59 |
| 5 | 1999-01-27 | 23:00:00 | 1999-01-27 | 22:56:00 | KORD | -0.59 |

By default the parser removes the component date columns, but you can choose to retain them via the `keep_date_col` keyword:

```
In [64]: df = pd.read_csv('tmp.csv', header=None, parse_dates=[[1, 2], [1, 3]],
.....:                  keep_date_col=True)
.....:
```

```
In [65]: df
```

```
Out[65]:
```

| | | 1_2 | | 1_3 | 0 | 1 | 2 | \ |
|---|------------|----------|------------|----------|------|----------|----------|---|
| 0 | 1999-01-27 | 19:00:00 | 1999-01-27 | 18:56:00 | KORD | 19990127 | 19:00:00 | |
| 1 | 1999-01-27 | 20:00:00 | 1999-01-27 | 19:56:00 | KORD | 19990127 | 20:00:00 | |
| 2 | 1999-01-27 | 21:00:00 | 1999-01-27 | 20:56:00 | KORD | 19990127 | 21:00:00 | |
| 3 | 1999-01-27 | 21:00:00 | 1999-01-27 | 21:18:00 | KORD | 19990127 | 21:00:00 | |
| 4 | 1999-01-27 | 22:00:00 | 1999-01-27 | 21:56:00 | KORD | 19990127 | 22:00:00 | |
| 5 | 1999-01-27 | 23:00:00 | 1999-01-27 | 22:56:00 | KORD | 19990127 | 23:00:00 | |

```
      3      4
0  18:56:00  0.81
1  19:56:00  0.01
2  20:56:00 -0.59
3  21:18:00 -0.99
4  21:56:00 -0.59
5  22:56:00 -0.59
```

Note that if you wish to combine multiple columns into a single date column, a nested list must be used. In other words, `parse_dates=[1, 2]` indicates that the second and third columns should each be parsed as separate date columns while `parse_dates=[[1, 2]]` means the two columns should be parsed into a single column.

You can also use a dict to specify custom name columns:

```
In [66]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}
```

```
In [67]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec)
```

```
In [68]: df
```

```
Out[68]:
```

| | nominal | | actual | | 0 | 4 |
|---|---------------------|------------|----------|------|-------|---|
| 0 | 1999-01-27 19:00:00 | 1999-01-27 | 18:56:00 | KORD | 0.81 | |
| 1 | 1999-01-27 20:00:00 | 1999-01-27 | 19:56:00 | KORD | 0.01 | |
| 2 | 1999-01-27 21:00:00 | 1999-01-27 | 20:56:00 | KORD | -0.59 | |
| 3 | 1999-01-27 21:00:00 | 1999-01-27 | 21:18:00 | KORD | -0.99 | |
| 4 | 1999-01-27 22:00:00 | 1999-01-27 | 21:56:00 | KORD | -0.59 | |
| 5 | 1999-01-27 23:00:00 | 1999-01-27 | 22:56:00 | KORD | -0.59 | |

It is important to remember that if multiple text columns are to be parsed into a single date column, then a new column is prepended to the data. The `index_col` specification is based off of this new set of columns rather than the original data columns:

```
In [69]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}
```

```
In [70]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
.....:                    index_col=0) #index is the nominal column
.....:
```

```
In [71]: df
```

```
Out[71]:
```

| | | actual | | 0 | 4 |
|---------------------|------------|----------|------|-------|---|
| nominal | | | | | |
| 1999-01-27 19:00:00 | 1999-01-27 | 18:56:00 | KORD | 0.81 | |
| 1999-01-27 20:00:00 | 1999-01-27 | 19:56:00 | KORD | 0.01 | |
| 1999-01-27 21:00:00 | 1999-01-27 | 20:56:00 | KORD | -0.59 | |
| 1999-01-27 21:00:00 | 1999-01-27 | 21:18:00 | KORD | -0.99 | |
| 1999-01-27 22:00:00 | 1999-01-27 | 21:56:00 | KORD | -0.59 | |
| 1999-01-27 23:00:00 | 1999-01-27 | 22:56:00 | KORD | -0.59 | |

Note: `read_csv` has a `fast_path` for parsing datetime strings in iso8601 format, e.g “2000-01-01T00:01:02+00:00” and similar variations. If you can arrange for your data to store datetimes in this format, load times will be significantly faster, ~20x has been observed.

Note: When passing a dict as the `parse_dates` argument, the order of the columns prepended is not guaranteed, because *dict* objects do not impose an ordering on their keys. On Python 2.7+ you may use *collections.OrderedDict* instead of a regular *dict* if this matters to you. Because of this, when using a dict for ‘`parse_dates`’ in conjunction with the `index_col` argument, it’s best to specify `index_col` as a column label rather than as an index on the resulting frame.

24.1.8 Specifying method for floating-point conversion

The parameter `float_precision` can be specified in order to use a specific floating-point converter during parsing with the C engine. The options are the ordinary converter, the high-precision converter, and the round-trip converter (which is guaranteed to round-trip values after writing to a file). For example:

```
In [72]: val = '0.3066101993807095471566981359501369297504425048828125'
```

```
In [73]: data = 'a,b,c\n1,2,{0}'.format(val)
```

```
In [74]: abs(pd.read_csv(StringIO(data), engine='c', float_precision=None)['c'][0] - float(val))
Out[74]: 0.0
```

```
In [75]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='high')['c'][0] - float(val))
Out[75]: 5.5511151231257827e-17
```

```
In [76]: abs(pd.read_csv(StringIO(data), engine='c', float_precision='round_trip')['c'][0] - float(val))
Out[76]: 0.0
```

24.1.9 Date Parsing Functions

Finally, the parser allows you to specify a custom `date_parser` function to take full advantage of the flexibility of the date parsing API:

```
In [77]: import pandas.io.date_converters as conv
```

```
In [78]: df = pd.read_csv('tmp.csv', header=None, parse_dates=date_spec,
.....:                  date_parser=conv.parse_date_time)
.....:
```

```
In [79]: df
```

```
Out[79]:
```

| | nominal | actual | 0 | 4 |
|---|---------------------|---------------------|------|-------|
| 0 | 1999-01-27 19:00:00 | 1999-01-27 18:56:00 | KORD | 0.81 |
| 1 | 1999-01-27 20:00:00 | 1999-01-27 19:56:00 | KORD | 0.01 |
| 2 | 1999-01-27 21:00:00 | 1999-01-27 20:56:00 | KORD | -0.59 |
| 3 | 1999-01-27 21:00:00 | 1999-01-27 21:18:00 | KORD | -0.99 |
| 4 | 1999-01-27 22:00:00 | 1999-01-27 21:56:00 | KORD | -0.59 |
| 5 | 1999-01-27 23:00:00 | 1999-01-27 22:56:00 | KORD | -0.59 |

Pandas will try to call the `date_parser` function in three different ways. If an exception is raised, the next one is tried:

1. `date_parser` is first called with one or more arrays as arguments, as defined using `parse_dates` (e.g., `date_parser(['2013', '2013'], ['1', '2'])`)
2. If #1 fails, `date_parser` is called with all the columns concatenated row-wise into a single array (e.g., `date_parser(['2013 1', '2013 2'])`)
3. If #2 fails, `date_parser` is called once for every row with one or more string arguments from the columns indicated with `parse_dates` (e.g., `date_parser('2013', '1')` for the first row, `date_parser('2013', '2')` for the second, etc.)

Note that performance-wise, you should try these methods of parsing dates in order:

1. Try to infer the format using `infer_datetime_format=True` (see section below)

2. If you know the format, use `pd.to_datetime()`: `date_parser=lambda x: pd.to_datetime(x, format=...)`
3. If you have a really non-standard format, use a custom `date_parser` function. For optimal performance, this should be vectorized, i.e., it should accept arrays as arguments.

You can explore the date parsing functionality in `date_converters.py` and add your own. We would love to turn this module into a community supported set of date/time parsers. To get you started, `date_converters.py` contains functions to parse dual date and time columns, year/month/day columns, and year/month/day/hour/minute/second columns. It also contains a `generic_parser` function so you can curry it with a function that deals with a single date rather than the entire array.

24.1.10 Inferring Datetime Format

If you have `parse_dates` enabled for some or all of your columns, and your datetime strings are all formatted the same way, you may get a large speed up by setting `infer_datetime_format=True`. If set, pandas will attempt to guess the format of your datetime strings, and then use a faster means of parsing the strings. 5-10x parsing speeds have been observed. pandas will fallback to the usual parsing if either the format cannot be guessed or the format that was guessed cannot properly parse the entire column of strings. So in general, `infer_datetime_format` should not have any negative consequences if enabled.

Here are some examples of datetime strings that can be guessed (All representing December 30th, 2011 at 00:00:00)

- “20111230”
- “2011/12/30”
- “20111230 00:00:00”
- “12/30/2011 00:00:00”
- “30/Dec/2011 00:00:00”
- “30/December/2011 00:00:00”

`infer_datetime_format` is sensitive to `dayfirst`. With `dayfirst=True`, it will guess “01/12/2011” to be December 1st. With `dayfirst=False` (default) it will guess “01/12/2011” to be January 12th.

```
# Try to infer the format for the index column
In [80]: df = pd.read_csv('foo.csv', index_col=0, parse_dates=True,
.....:                  infer_datetime_format=True)
.....:
```

```
In [81]: df
Out[81]:
```

| | A | B | C |
|------------|---|---|---|
| date | | | |
| 2009-01-01 | a | 1 | 2 |
| 2009-01-02 | b | 3 | 4 |
| 2009-01-03 | c | 4 | 5 |

24.1.11 International Date Formats

While US date formats tend to be MM/DD/YYYY, many international formats use DD/MM/YYYY instead. For convenience, a `dayfirst` keyword is provided:

```
In [82]: print(open('tmp.csv').read())
date,value,cat
1/6/2000,5,a
```

```
2/6/2000,10,b
3/6/2000,15,c
```

```
In [83]: pd.read_csv('tmp.csv', parse_dates=[0])
```

```
Out[83]:
```

| | date | value | cat |
|---|------------|-------|-----|
| 0 | 2000-01-06 | 5 | a |
| 1 | 2000-02-06 | 10 | b |
| 2 | 2000-03-06 | 15 | c |

```
In [84]: pd.read_csv('tmp.csv', dayfirst=True, parse_dates=[0])
```

```
Out[84]:
```

| | date | value | cat |
|---|------------|-------|-----|
| 0 | 2000-06-01 | 5 | a |
| 1 | 2000-06-02 | 10 | b |
| 2 | 2000-06-03 | 15 | c |

24.1.12 Thousand Separators

For large numbers that have been written with a thousands separator, you can set the `thousands` keyword to a string of length 1 so that integers will be parsed correctly:

By default, numbers with a thousands separator will be parsed as strings

```
In [85]: print(open('tmp.csv').read())
```

```
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
```

```
In [86]: df = pd.read_csv('tmp.csv', sep='|')
```

```
In [87]: df
```

```
Out[87]:
```

| | ID | level | category |
|---|----------|-----------|----------|
| 0 | Patient1 | 123,000 | x |
| 1 | Patient2 | 23,000 | y |
| 2 | Patient3 | 1,234,018 | z |

```
In [88]: df.level.dtype
```

```
Out[88]: dtype('O')
```

The `thousands` keyword allows integers to be parsed correctly

```
In [89]: print(open('tmp.csv').read())
```

```
ID|level|category
Patient1|123,000|x
Patient2|23,000|y
Patient3|1,234,018|z
```

```
In [90]: df = pd.read_csv('tmp.csv', sep='|', thousands=',')
```

```
In [91]: df
```

```
Out[91]:
```

| | ID | level | category |
|---|----------|--------|----------|
| 0 | Patient1 | 123000 | x |
| 1 | Patient2 | 23000 | y |

```
2 Patient3 1234018 z
```

```
In [92]: df.level.dtype
Out[92]: dtype('int64')
```

24.1.13 NA Values

To control which values are parsed as missing values (which are signified by NaN), specify a list of strings in `na_values`. If you specify a number (a float, like 5.0 or an integer like 5), the corresponding equivalent values will also imply a missing value (in this case effectively `[5.0, 5]` are recognized as NaN).

To completely override the default values that are recognized as missing, specify `keep_default_na=False`. The default NaN recognized values are `['-1.#IND', '1.#QNAN', '1.#IND', '-1.#QNAN', '#N/A', 'N/A', 'NA', '#NA', 'NULL', 'NaN', '-NaN', 'nan', '-nan']`.

```
read_csv(path, na_values=[5])
```

the default values, in addition to 5, 5.0 when interpreted as numbers are recognized as NaN

```
read_csv(path, keep_default_na=False, na_values=[""])
```

only an empty field will be NaN

```
read_csv(path, keep_default_na=False, na_values=["NA", "0"])
```

only NA and 0 as strings are NaN

```
read_csv(path, na_values=["Nope"])
```

the default values, in addition to the string "Nope" are recognized as NaN

24.1.14 Infinity

`inf` like values will be parsed as `np.inf` (positive infinity), and `-inf` as `-np.inf` (negative infinity). These will ignore the case of the value, meaning `Inf`, will also be parsed as `np.inf`.

24.1.15 Comments

Sometimes comments or meta data may be included in a file:

```
In [93]: print(open('tmp.csv').read())
ID,level,category
Patient1,123000,x # really unpleasant
Patient2,23000,y # wouldn't take his medicine
Patient3,1234018,z # awesome
```

By default, the parse includes the comments in the output:

```
In [94]: df = pd.read_csv('tmp.csv')
```

```
In [95]: df
Out[95]:
```

| | ID | level | category |
|---|----------|---------|--------------------------------|
| 0 | Patient1 | 123000 | x # really unpleasant |
| 1 | Patient2 | 23000 | y # wouldn't take his medicine |
| 2 | Patient3 | 1234018 | z # awesome |

We can suppress the comments using the `comment` keyword:

```
In [96]: df = pd.read_csv('tmp.csv', comment='#')
```

```
In [97]: df
```

```
Out[97]:
```

| | ID | level | category |
|---|----------|---------|----------|
| 0 | Patient1 | 123000 | x |
| 1 | Patient2 | 23000 | y |
| 2 | Patient3 | 1234018 | z |

24.1.16 Returning Series

Using the `squeeze` keyword, the parser will return output with a single column as a `Series`:

```
In [98]: print(open('tmp.csv').read())
```

```
level
Patient1,123000
Patient2,23000
Patient3,1234018
```

```
In [99]: output = pd.read_csv('tmp.csv', squeeze=True)
```

```
In [100]: output
```

```
Out[100]:
```

| | |
|----------|---------|
| Patient1 | 123000 |
| Patient2 | 23000 |
| Patient3 | 1234018 |

Name: level, dtype: int64

```
In [101]: type(output)
```

```
Out[101]: pandas.core.series.Series
```

24.1.17 Boolean values

The common values `True`, `False`, `TRUE`, and `FALSE` are all recognized as boolean. Sometime you would want to recognize some other values as being boolean. To do this use the `true_values` and `false_values` options:

```
In [102]: data= 'a,b,c\n1,Yes,2\n3,No,4'
```

```
In [103]: print(data)
```

```
a,b,c
1,Yes,2
3,No,4
```

```
In [104]: pd.read_csv(StringIO(data))
```

```
Out[104]:
```

| | a | b | c |
|---|---|-----|---|
| 0 | 1 | Yes | 2 |
| 1 | 3 | No | 4 |

```
In [105]: pd.read_csv(StringIO(data), true_values=['Yes'], false_values=['No'])
```

```
Out[105]:
```

| | a | b | c |
|---|---|-------|---|
| 0 | 1 | True | 2 |
| 1 | 3 | False | 4 |

24.1.18 Handling “bad” lines

Some files may have malformed lines with too few fields or too many. Lines with too few fields will have NA values filled in the trailing fields. Lines with too many will cause an error by default:

```
In [27]: data = 'a,b,c\n1,2,3\n4,5,6,7\n8,9,10'
```

```
In [28]: pd.read_csv(StringIO(data))
```

```
-----
CParserError                                Traceback (most recent call last)
CParserError: Error tokenizing data. C error: Expected 3 fields in line 3, saw 4
```

You can elect to skip bad lines:

```
In [29]: pd.read_csv(StringIO(data), error_bad_lines=False)
```

```
Skipping line 3: expected 3 fields, saw 4
```

```
Out[29]:
```

```
   a  b  c
0  1  2  3
1  8  9 10
```

24.1.19 Quoting and Escape Characters

Quotes (and other escape characters) in embedded fields can be handled in any number of ways. One way is to use backslashes; to properly parse this data, you should pass the `escapechar` option:

```
In [106]: data = 'a,b\n"hello, \\"Bob\\", nice to see you",5'
```

```
In [107]: print(data)
```

```
a,b
"hello, \"Bob\", nice to see you",5
```

```
In [108]: pd.read_csv(StringIO(data), escapechar='\\')
```

```
Out[108]:
```

| | a | b |
|---|--------|--------------------------|
| 0 | hello, | "Bob", nice to see you 5 |

24.1.20 Files with Fixed Width Columns

While `read_csv` reads delimited data, the `read_fwf()` function works with data files that have known and fixed column widths. The function parameters to `read_fwf` are largely the same as `read_csv` with two extra parameters:

- `colspecs`: A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[). String value ‘infer’ can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data. Default behaviour, if not specified, is to infer.
- `widths`: A list of field widths which can be used instead of ‘`colspecs`’ if the intervals are contiguous.

Consider a typical fixed-width data file:

```
In [109]: print(open('bar.csv').read())
```

```
id8141 360.242940 149.910199 11950.7
id1594 444.953632 166.985655 11788.4
id1849 364.136849 183.628767 11806.2
id1230 413.836124 184.375703 11916.8
id1948 502.953953 173.237159 12468.3
```

In order to parse this file into a DataFrame, we simply need to supply the column specifications to the `read_fwf` function along with the file name:

```
#Column specifications are a list of half-intervals
In [110]: colspecs = [(0, 6), (8, 20), (21, 33), (34, 43)]

In [111]: df = pd.read_fwf('bar.csv', colspecs=colspecs, header=None, index_col=0)

In [112]: df
Out[112]:
```

| | 1 | 2 | 3 |
|--------|------------|------------|---------|
| 0 | | | |
| id8141 | 360.242940 | 149.910199 | 11950.7 |
| id1594 | 444.953632 | 166.985655 | 11788.4 |
| id1849 | 364.136849 | 183.628767 | 11806.2 |
| id1230 | 413.836124 | 184.375703 | 11916.8 |
| id1948 | 502.953953 | 173.237159 | 12468.3 |

Note how the parser automatically picks column names X.<column number> when `header=None` argument is specified. Alternatively, you can supply just the column widths for contiguous columns:

```
#Widths are a list of integers
In [113]: widths = [6, 14, 13, 10]

In [114]: df = pd.read_fwf('bar.csv', widths=widths, header=None)

In [115]: df
Out[115]:
```

| | 0 | 1 | 2 | 3 |
|---|--------|------------|------------|---------|
| 0 | id8141 | 360.242940 | 149.910199 | 11950.7 |
| 1 | id1594 | 444.953632 | 166.985655 | 11788.4 |
| 2 | id1849 | 364.136849 | 183.628767 | 11806.2 |
| 3 | id1230 | 413.836124 | 184.375703 | 11916.8 |
| 4 | id1948 | 502.953953 | 173.237159 | 12468.3 |

The parser will take care of extra white spaces around the columns so it's ok to have extra separation between the columns in the file.

New in version 0.13.0.

By default, `read_fwf` will try to infer the file's `colspecs` by using the first 100 rows of the file. It can do it only in cases when the columns are aligned and correctly separated by the provided `delimiter` (default delimiter is whitespace).

```
In [116]: df = pd.read_fwf('bar.csv', header=None, index_col=0)

In [117]: df
Out[117]:
```

| | 1 | 2 | 3 |
|--------|------------|------------|---------|
| 0 | | | |
| id8141 | 360.242940 | 149.910199 | 11950.7 |
| id1594 | 444.953632 | 166.985655 | 11788.4 |
| id1849 | 364.136849 | 183.628767 | 11806.2 |
| id1230 | 413.836124 | 184.375703 | 11916.8 |
| id1948 | 502.953953 | 173.237159 | 12468.3 |

24.1.21 Files with an “implicit” index column

Consider a file with one less entry in the header than the number of data column:

```
In [118]: print(open('foo.csv').read())
A,B,C
20090101,a,1,2
20090102,b,3,4
20090103,c,4,5
```

In this special case, `read_csv` assumes that the first column is to be used as the index of the DataFrame:

```
In [119]: pd.read_csv('foo.csv')
Out[119]:
```

| | A | B | C |
|----------|---|---|---|
| 20090101 | a | 1 | 2 |
| 20090102 | b | 3 | 4 |
| 20090103 | c | 4 | 5 |

Note that the dates weren't automatically parsed. In that case you would need to do as before:

```
In [120]: df = pd.read_csv('foo.csv', parse_dates=True)

In [121]: df.index
Out[121]: DatetimeIndex(['2009-01-01', '2009-01-02', '2009-01-03'], dtype='datetime64[ns]', freq=None)
```

24.1.22 Reading an index with a `MultiIndex`

Suppose you have data indexed by two columns:

```
In [122]: print(open('data/minindex_ex.csv').read())
year,indiv,zit,xit
1977,"A",1.2,.6
1977,"B",1.5,.5
1977,"C",1.7,.8
1978,"A",.2,.06
1978,"B",.7,.2
1978,"C",.8,.3
1978,"D",.9,.5
1978,"E",1.4,.9
1979,"C",.2,.15
1979,"D",.14,.05
1979,"E",.5,.15
1979,"F",1.2,.5
1979,"G",3.4,1.9
1979,"H",5.4,2.7
1979,"I",6.4,1.2
```

The `index_col` argument to `read_csv` and `read_table` can take a list of column numbers to turn multiple columns into a `MultiIndex` for the index of the returned object:

```
In [123]: df = pd.read_csv("data/minindex_ex.csv", index_col=[0,1])

In [124]: df
Out[124]:
```

| | | zit | xit |
|------|---|------|------|
| 1977 | A | 1.20 | 0.60 |
| | B | 1.50 | 0.50 |
| | C | 1.70 | 0.80 |
| 1978 | A | 0.20 | 0.06 |
| | B | 0.70 | 0.20 |

| | | | |
|------|---|------|------|
| | C | 0.80 | 0.30 |
| | D | 0.90 | 0.50 |
| | E | 1.40 | 0.90 |
| 1979 | C | 0.20 | 0.15 |
| | D | 0.14 | 0.05 |
| | E | 0.50 | 0.15 |
| | F | 1.20 | 0.50 |
| | G | 3.40 | 1.90 |
| | H | 5.40 | 2.70 |
| | I | 6.40 | 1.20 |

```
In [125]: df.ix[1978]
```

```
Out[125]:
```

| | zit | xit |
|-------|-----|------|
| indiv | | |
| A | 0.2 | 0.06 |
| B | 0.7 | 0.20 |
| C | 0.8 | 0.30 |
| D | 0.9 | 0.50 |
| E | 1.4 | 0.90 |

24.1.23 Reading columns with a MultiIndex

By specifying list of row locations for the `header` argument, you can read in a `MultiIndex` for the columns. Specifying non-consecutive rows will skip the intervening rows. In order to have the pre-0.13 behavior of tupleizing columns, specify `tupleize_cols=True`.

```
In [126]: from pandas.util.testing import makeCustomDataframe as mkdf
```

```
In [127]: df = mkdf(5,3,r_idx_nlevels=2,c_idx_nlevels=4)
```

```
In [128]: df.to_csv('mi.csv')
```

```
In [129]: print(open('mi.csv').read())
```

```
C0,,C_10_g0,C_10_g1,C_10_g2
C1,,C_11_g0,C_11_g1,C_11_g2
C2,,C_12_g0,C_12_g1,C_12_g2
C3,,C_13_g0,C_13_g1,C_13_g2
R0,R1,,,
R_10_g0,R_11_g0,R0C0,R0C1,R0C2
R_10_g1,R_11_g1,R1C0,R1C1,R1C2
R_10_g2,R_11_g2,R2C0,R2C1,R2C2
R_10_g3,R_11_g3,R3C0,R3C1,R3C2
R_10_g4,R_11_g4,R4C0,R4C1,R4C2
```

```
In [130]: pd.read_csv('mi.csv',header=[0,1,2,3],index_col=[0,1])
```

```
Out[130]:
```

| | | C_10_g0 | C_10_g1 | C_10_g2 |
|---------|---------|---------|---------|---------|
| C0 | | | | |
| C1 | | C_11_g0 | C_11_g1 | C_11_g2 |
| C2 | | C_12_g0 | C_12_g1 | C_12_g2 |
| C3 | | C_13_g0 | C_13_g1 | C_13_g2 |
| R0 | R1 | | | |
| R_10_g0 | R_11_g0 | R0C0 | R0C1 | R0C2 |
| R_10_g1 | R_11_g1 | R1C0 | R1C1 | R1C2 |
| R_10_g2 | R_11_g2 | R2C0 | R2C1 | R2C2 |
| R_10_g3 | R_11_g3 | R3C0 | R3C1 | R3C2 |

```
R_l0_g4 R_l1_g4      R4C0      R4C1      R4C2
```

Starting in 0.13.0, `read_csv` will be able to interpret a more common format of multi-columns indices.

```
In [131]: print(open('mi2.csv').read())
,a,a,a,b,c,c
,q,r,s,t,u,v
one,1,2,3,4,5,6
two,7,8,9,10,11,12

In [132]: pd.read_csv('mi2.csv',header=[0,1],index_col=0)
Out[132]:
```

| | a | | b | c | | |
|-----|---|---|---|----|----|----|
| | q | r | s | t | u | v |
| one | 1 | 2 | 3 | 4 | 5 | 6 |
| two | 7 | 8 | 9 | 10 | 11 | 12 |

Note: If an `index_col` is not specified (e.g. you don't have an index, or wrote it with `df.to_csv(..., index=False)`), then any names on the columns index will be *lost*.

24.1.24 Automatically “sniffing” the delimiter

`read_csv` is capable of inferring delimited (not necessarily comma-separated) files, as pandas uses the `csv.Sniffer` class of the `csv` module. For this, you have to specify `sep=None`.

```
In [133]: print(open('tmp2.csv').read())
:0:1:2:3
0:0.469112299907:-0.282863344329:-1.50905850317:-1.13563237102
1:1.21211202502:-0.173214649053:0.119208711297:-1.04423596628
2:-0.861848963348:-2.10456921889:-0.494929274069:1.07180380704
3:0.721555162244:-0.70677113363:-1.03957498511:0.271859885543
4:-0.424972329789:0.567020349794:0.276232019278:-1.08740069129
5:-0.673689708088:0.113648409689:-1.47842655244:0.524987667115
6:0.40470521868:0.57704598592:-1.71500201611:-1.03926848351
7:-0.370646858236:-1.15789225064:-1.34431181273:0.844885141425
8:1.07576978372:-0.10904997528:1.64356307036:-1.46938795954
9:0.357020564133:-0.67460010373:-1.77690371697:-0.968913812447
```

```
In [134]: pd.read_csv('tmp2.csv', sep=None, engine='python')
Out[134]:
```

| | Unnamed: 0 | 0 | 1 | 2 | 3 |
|---|------------|-----------|-----------|-----------|-----------|
| 0 | 0 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 1 | 1 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2 | 2 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |
| 3 | 3 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |
| 4 | 4 | -0.424972 | 0.567020 | 0.276232 | -1.087401 |
| 5 | 5 | -0.673690 | 0.113648 | -1.478427 | 0.524988 |
| 6 | 6 | 0.404705 | 0.577046 | -1.715002 | -1.039268 |
| 7 | 7 | -0.370647 | -1.157892 | -1.344312 | 0.844885 |
| 8 | 8 | 1.075770 | -0.109050 | 1.643563 | -1.469388 |
| 9 | 9 | 0.357021 | -0.674600 | -1.776904 | -0.968914 |

24.1.25 Iterating through files chunk by chunk

Suppose you wish to iterate through a (potentially very large) file lazily rather than reading the entire file into memory, such as the following:

```
In [135]: print(open('tmp.csv').read())
|0|1|2|3
0|0.469112299907|-0.282863344329|-1.50905850317|-1.13563237102
1|1.21211202502|-0.173214649053|0.119208711297|-1.04423596628
2|-0.861848963348|-2.10456921889|-0.494929274069|1.07180380704
3|0.721555162244|-0.70677113363|-1.03957498511|0.271859885543
4|-0.424972329789|0.567020349794|0.276232019278|-1.08740069129
5|-0.673689708088|0.113648409689|-1.47842655244|0.524987667115
6|0.40470521868|0.57704598592|-1.71500201611|-1.03926848351
7|-0.370646858236|-1.15789225064|-1.34431181273|0.844885141425
8|1.07576978372|-0.10904997528|1.64356307036|-1.46938795954
9|0.357020564133|-0.67460010373|-1.77690371697|-0.968913812447
```

```
In [136]: table = pd.read_table('tmp.csv', sep='|')
```

```
In [137]: table
```

```
Out[137]:
   Unnamed: 0      0      1      2      3
0      0  0.469112 -0.282863 -1.509059 -1.135632
1      1  1.212112 -0.173215  0.119209 -1.044236
2      2 -0.861849 -2.104569 -0.494929  1.071804
3      3  0.721555 -0.706771 -1.039575  0.271860
4      4 -0.424972  0.567020  0.276232 -1.087401
5      5 -0.673690  0.113648 -1.478427  0.524988
6      6  0.404705  0.577046 -1.715002 -1.039268
7      7 -0.370647 -1.157892 -1.344312  0.844885
8      8  1.075770 -0.109050  1.643563 -1.469388
9      9  0.357021 -0.674600 -1.776904 -0.968914
```

By specifying a `chunksize` to `read_csv` or `read_table`, the return value will be an iterable object of type `TextFileReader`:

```
In [138]: reader = pd.read_table('tmp.csv', sep='|', chunksize=4)
```

```
In [139]: reader
```

```
Out[139]: <pandas.io.parsers.TextFileReader at 0xa581768c>
```

```
In [140]: for chunk in reader:
```

```
.....:     print(chunk)
.....:
   Unnamed: 0      0      1      2      3
0      0  0.469112 -0.282863 -1.509059 -1.135632
1      1  1.212112 -0.173215  0.119209 -1.044236
2      2 -0.861849 -2.104569 -0.494929  1.071804
3      3  0.721555 -0.706771 -1.039575  0.271860
   Unnamed: 0      0      1      2      3
0      4 -0.424972  0.567020  0.276232 -1.087401
1      5 -0.673690  0.113648 -1.478427  0.524988
2      6  0.404705  0.577046 -1.715002 -1.039268
3      7 -0.370647 -1.157892 -1.344312  0.844885
   Unnamed: 0      0      1      2      3
0      8  1.075770 -0.109050  1.643563 -1.469388
1      9  0.357021 -0.674600 -1.776904 -0.968914
```

Specifying `iterator=True` will also return the `TextFileReader` object:

```
In [141]: reader = pd.read_table('tmp.csv', sep='|', iterator=True)
```

```
In [142]: reader.get_chunk(5)
```

```
Out[142]:
```

| | Unnamed: 0 | 0 | 1 | 2 | 3 |
|---|------------|-----------|-----------|-----------|-----------|
| 0 | 0 | 0.469112 | -0.282863 | -1.509059 | -1.135632 |
| 1 | 1 | 1.212112 | -0.173215 | 0.119209 | -1.044236 |
| 2 | 2 | -0.861849 | -2.104569 | -0.494929 | 1.071804 |
| 3 | 3 | 0.721555 | -0.706771 | -1.039575 | 0.271860 |
| 4 | 4 | -0.424972 | 0.567020 | 0.276232 | -1.087401 |

24.1.26 Specifying the parser engine

Under the hood pandas uses a fast and efficient parser implemented in C as well as a python implementation which is currently more feature-complete. Where possible pandas uses the C parser (specified as `engine='c'`), but may fall back to python if C-unsupported options are specified. Currently, C-unsupported options include:

- `sep` other than a single character (e.g. regex separators)
- `skip_footer`
- `sep=None` with `delim_whitespace=False`

Specifying any of the above options will produce a `ParserWarning` unless the python engine is selected explicitly using `engine='python'`.

24.1.27 Writing to CSV format

The `Series` and `DataFrame` objects have an instance method `to_csv` which allows storing the contents of the object as a comma-separated-values file. The function takes a number of arguments. Only the first is required.

- `path_or_buf`: A string path to the file to write or a `StringIO`
- `sep`: Field delimiter for the output file (default `','`)
- `na_rep`: A string representation of a missing value (default `''`)
- `float_format`: Format string for floating point numbers
- `cols`: Columns to write (default `None`)
- `header`: Whether to write out the column names (default `True`)
- `index`: whether to write row (index) names (default `True`)
- `index_label`: Column label(s) for index column(s) if desired. If `None` (default), and `header` and `index` are `True`, then the index names are used. (A sequence should be given if the `DataFrame` uses `MultiIndex`).
- `mode`: Python write mode, default `'w'`
- `encoding`: a string representing the encoding to use if the contents are non-ASCII, for python versions prior to 3
- `line_terminator`: Character sequence denoting line end (default `'\n'`)
- `quoting`: Set quoting rules as in `csv` module (default `csv.QUOTE_MINIMAL`)
- `quotechar`: Character used to quote fields (default `'\"'`)
- `doublequote`: Control quoting of `quotechar` in fields (default `True`)

- `escapechar`: Character used to escape `sep` and `quotechar` when appropriate (default `None`)
- `chunksize`: Number of rows to write at a time
- `tupleize_cols`: If `False` (default), write as a list of tuples, otherwise write in an expanded line format suitable for `read_csv`
- `date_format`: Format string for datetime objects

24.1.28 Writing a formatted string

The `DataFrame` object has an instance method `to_string` which allows control over the string representation of the object. All arguments are optional:

- `buf` default `None`, for example a `StringIO` object
- `columns` default `None`, which columns to write
- `col_space` default `None`, minimum width of each column.
- `na_rep` default `NaN`, representation of NA value
- `formatters` default `None`, a dictionary (by column) of functions each of which takes a single argument and returns a formatted string
- `float_format` default `None`, a function which takes a single (float) argument and returns a formatted string; to be applied to floats in the `DataFrame`.
- `sparsify` default `True`, set to `False` for a `DataFrame` with a hierarchical index to print every multiindex key at each row.
- `index_names` default `True`, will print the names of the indices
- `index` default `True`, will print the index (ie, row labels)
- `header` default `True`, will print the column labels
- `justify` default `left`, will print column headers left- or right-justified

The `Series` object also has a `to_string` method, but with only the `buf`, `na_rep`, `float_format` arguments. There is also a `length` argument which, if set to `True`, will additionally output the length of the `Series`.

24.2 JSON

Read and write JSON format files and strings.

24.2.1 Writing JSON

A `Series` or `DataFrame` can be converted to a valid JSON string. Use `to_json` with optional parameters:

- `path_or_buf`: the pathname or buffer to write the output This can be `None` in which case a JSON string is returned
- `orient`:
 - Series :**
 - default is `index`
 - allowed values are `{split, records, index}`

DataFrame

- default is `columns`
- allowed values are `{split, records, index, columns, values}`

The format of the JSON string

| | |
|----------------------|--|
| <code>split</code> | dict like <code>{index -> [index], columns -> [columns], data -> [values]}</code> |
| <code>records</code> | list like <code>[{column -> value}, ... , {column -> value}]</code> |
| <code>index</code> | dict like <code>{index -> {column -> value}}</code> |
| <code>columns</code> | dict like <code>{column -> {index -> value}}</code> |
| <code>values</code> | just the values array |

- `date_format` : string, type of date conversion, 'epoch' for timestamp, 'iso' for ISO8601.
- `double_precision` : The number of decimal places to use when encoding floating point values, default 10.
- `force_ascii` : force encoded string to be ASCII, default True.
- `date_unit` : The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us' or 'ns' for seconds, milliseconds, microseconds and nanoseconds respectively. Default 'ms'.
- `default_handler` : The handler to call if an object cannot otherwise be converted to a suitable format for JSON. Takes a single argument, which is the object to convert, and returns a serializable object.

Note NaN's, NaT's and None will be converted to null and datetime objects will be converted based on the `date_format` and `date_unit` parameters.

```
In [143]: dfj = DataFrame(randn(5, 2), columns=list('AB'))
```

```
In [144]: json = dfj.to_json()
```

```
In [145]: json
```

```
Out[145]: '{"A":{"0":-1.2945235903,"1":0.2766617129,"2":-0.0139597524,"3":-0.0061535699,"4":0.895717...
```

Orient Options

There are a number of different options for the format of the resulting JSON file / string. Consider the following DataFrame and Series:

```
In [146]: dfjo = DataFrame(dict(A=range(1, 4), B=range(4, 7), C=range(7, 10)),
.....:                      columns=list('ABC'), index=list('xyz'))
.....:
```

```
In [147]: dfjo
```

```
Out[147]:
```

```
   A  B  C
x  1  4  7
y  2  5  8
z  3  6  9
```

```
In [148]: sjo = Series(dict(x=15, y=16, z=17), name='D')
```

```
In [149]: sjo
```

```
Out[149]:
x    15
y    16
z    17
Name: D, dtype: int64
```

Column oriented (the default for DataFrame) serializes the data as nested JSON objects with column labels acting as the primary index:

```
In [150]: dfjo.to_json(orient="columns")
Out[150]: '{"A":{"x":1,"y":2,"z":3},"B":{"x":4,"y":5,"z":6},"C":{"x":7,"y":8,"z":9}}'
```

Index oriented (the default for Series) similar to column oriented but the index labels are now primary:

```
In [151]: dfjo.to_json(orient="index")
Out[151]: '{"x":{"A":1,"B":4,"C":7},"y":{"A":2,"B":5,"C":8},"z":{"A":3,"B":6,"C":9}}'
```

```
In [152]: sjo.to_json(orient="index")
Out[152]: '{"x":15,"y":16,"z":17}'
```

Record oriented serializes the data to a JSON array of column -> value records, index labels are not included. This is useful for passing DataFrame data to plotting libraries, for example the JavaScript library d3.js:

```
In [153]: dfjo.to_json(orient="records")
Out[153]: ' [{"A":1,"B":4,"C":7}, {"A":2,"B":5,"C":8}, {"A":3,"B":6,"C":9}] '
```

```
In [154]: sjo.to_json(orient="records")
Out[154]: '[15,16,17]'
```

Value oriented is a bare-bones option which serializes to nested JSON arrays of values only, column and index labels are not included:

```
In [155]: dfjo.to_json(orient="values")
Out[155]: '[[1,4,7],[2,5,8],[3,6,9]]'
```

Split oriented serializes to a JSON object containing separate entries for values, index and columns. Name is also included for Series:

```
In [156]: dfjo.to_json(orient="split")
Out[156]: '{"columns":["A","B","C"],"index":["x","y","z"],"data":[[1,4,7],[2,5,8],[3,6,9]]}'
```

```
In [157]: sjo.to_json(orient="split")
Out[157]: '{"name":"D","index":["x","y","z"],"data":[15,16,17]}'
```

Note: Any orient option that encodes to a JSON object will not preserve the ordering of index and column labels during round-trip serialization. If you wish to preserve label ordering use the *split* option as it uses ordered containers.

Date Handling

Writing in ISO date format

```
In [158]: dfd = DataFrame(randn(5, 2), columns=list('AB'))
```

```
In [159]: dfd['date'] = Timestamp('20130101')
```

```
In [160]: dfd = dfd.sort_index(1, ascending=False)
```

```
In [161]: json = dfd.to_json(date_format='iso')
```

```
In [162]: json
```

```
Out[162]: '{"date":{"0":"2013-01-01T00:00:00.000Z","1":"2013-01-01T00:00:00.000Z","2":"2013-01-01T00:00:00.000Z","3":"2013-01-01T00:00:00.000Z","4":"2013-01-01T00:00:00.000Z"},"A":{"0":0.123456789012345678,"1":0.234567890123456789,"2":0.345678901234567890,"3":0.456789012345678901,"4":0.567890123456789012},"B":{"0":0.678901234567890123,"1":0.789012345678901234,"2":0.890123456789012345,"3":0.901234567890123456,"4":0.012345678901234567}}
```

Writing in ISO date format, with microseconds

```
In [163]: json = dfd.to_json(date_format='iso', date_unit='us')
```

```
In [164]: json
```

```
Out [164]: '{"date":{"0":"2013-01-01T00:00:00.000000Z","1":"2013-01-01T00:00:00.000000Z","2":"2013-01-01T00:00:00.000000Z","3":"2013-01-01T00:00:00.000000Z","4":"2013-01-01T00:00:00.000000Z"},"B":1}'
```

Epoch timestamps, in seconds

```
In [165]: json = dfd.to_json(date_format='epoch', date_unit='s')
```

```
In [166]: json
```

```
Out [166]: '{"date":{"0":1356998400,"1":1356998400,"2":1356998400,"3":1356998400,"4":1356998400},"B":1}'
```

Writing to a file, with a date index and a date column

```
In [167]: dfj2 = dfj.copy()
```

```
In [168]: dfj2['date'] = Timestamp('20130101')
```

```
In [169]: dfj2['ints'] = list(range(5))
```

```
In [170]: dfj2['bools'] = True
```

```
In [171]: dfj2.index = date_range('20130101', periods=5)
```

```
In [172]: dfj2.to_json('test.json')
```

```
In [173]: open('test.json').read()
```

```
Out [173]: '{"A":{"1356998400000":-1.2945235903,"1357084800000":0.2766617129,"1357171200000":-0.0139512945235903,"1357257600000":0.2766617129,"1357344000000":-0.0139512945235903},"B":1}'
```

Fallback Behavior

If the JSON serializer cannot handle the container contents directly it will fallback in the following manner:

- if a `toDict` method is defined by the unrecognised object then that will be called and its returned dict will be JSON serialized.
- if a `default_handler` has been passed to `to_json` that will be called to convert the object.
- otherwise an attempt is made to convert the object to a dict by parsing its contents. However if the object is complex this will often fail with an `OverflowError`.

Your best bet when encountering `OverflowError` during serialization is to specify a `default_handler`. For example `timedelta` can cause problems:

```
In [141]: from datetime import timedelta
```

```
In [142]: dftd = DataFrame([timedelta(23), timedelta(seconds=5), 42])
```

```
In [143]: dftd.to_json()
```

```
-----
OverflowError                                Traceback (most recent call last)
OverflowError: Maximum recursion level reached
```

which can be dealt with by specifying a simple `default_handler`:

```
In [174]: dftd.to_json(default_handler=str)
```

```
Out [174]: '{"0":{"0":1987200000,"1":5000,"2":42}}'
```

```
In [175]: def my_handler(obj):
.....:     return obj.total_seconds()
.....:
```

24.2.2 Reading JSON

Reading a JSON string to pandas object can take a number of parameters. The parser will try to parse a `DataFrame` if `typ` is not supplied or is `None`. To explicitly force `Series` parsing, pass `typ=series`

- `filepath_or_buffer` : a **VALID** JSON string or file handle / `StringIO`. The string could be a URL. Valid URL schemes include `http`, `ftp`, `S3`, and `file`. For file URLs, a host is expected. For instance, a local file could be `file://localhost/path/to/table.json`
- `typ` : type of object to recover (series or frame), default 'frame'
- `orient` :

Series :

- default is `index`
- allowed values are `{split, records, index}`

DataFrame

- default is `columns`
- allowed values are `{split, records, index, columns, values}`

The format of the JSON string

| | |
|----------------------|--|
| <code>split</code> | dict like {index -> [index], columns -> [columns], data -> [values]} |
| <code>records</code> | list like [{column -> value}, ... , {column -> value}] |
| <code>index</code> | dict like {index -> {column -> value}} |
| <code>columns</code> | dict like {column -> {index -> value}} |
| <code>values</code> | just the values array |

- `dtype` : if `True`, infer dtypes, if a dict of column to dtype, then use those, if `False`, then don't infer dtypes at all, default is `True`, apply only to the data
- `convert_axes` : boolean, try to convert the axes to the proper dtypes, default is `True`
- `convert_dates` : a list of columns to parse for dates; If `True`, then try to parse date-like columns, default is `True`
- `keep_default_dates` : boolean, default `True`. If parsing dates, then parse the default date-like columns
- `numpy` : direct decoding to numpy arrays. default is `False`; Supports numeric data only, although labels may be non-numeric. Also note that the JSON ordering **MUST** be the same for each term if `numpy=True`
- `precise_float` : boolean, default `False`. Set to enable usage of higher precision (`strtod`) function when decoding string to double values. Default (`False`) is to use fast but less precise builtin functionality
- `date_unit` : string, the timestamp unit to detect if converting dates. Default `None`. By default the timestamp precision will be detected, if this is not desired then pass one of 's', 'ms', 'us' or 'ns' to force timestamp precision to seconds, milliseconds, microseconds or nanoseconds respectively.

The parser will raise one of `ValueError`/`TypeError`/`AssertionError` if the JSON is not parseable.

If a non-default `orient` was used when encoding to JSON be sure to pass the same option here so that decoding produces sensible results, see [Orient Options](#) for an overview.

Data Conversion

The default of `convert_axes=True`, `dtype=True`, and `convert_dates=True` will try to parse the axes, and all of the data into appropriate types, including dates. If you need to override specific dtypes, pass a dict to `dtype`. `convert_axes` should only be set to `False` if you need to preserve string-like numbers (e.g. '1', '2') in an axes.

Note: Large integer values may be converted to dates if `convert_dates=True` and the data and / or column labels appear 'date-like'. The exact threshold depends on the `date_unit` specified.

Warning: When reading JSON data, automatic coercing into dtypes has some quirks:

- an index can be reconstructed in a different order from serialization, that is, the returned order is not guaranteed to be the same as before serialization
- a column that was `float` data will be converted to `integer` if it can be done safely, e.g. a column of 1.
- `bool` columns will be converted to `integer` on reconstruction

Thus there are times where you may want to specify specific dtypes via the `dtype` keyword argument.

Reading from a JSON string:

```
In [176]: pd.read_json(json)
```

```
Out[176]:
```

| | A | B | date |
|---|-----------|-----------|------------|
| 0 | -1.206412 | 2.565646 | 2013-01-01 |
| 1 | 1.431256 | 1.340309 | 2013-01-01 |
| 2 | -1.170299 | -0.226169 | 2013-01-01 |
| 3 | 0.410835 | 0.813850 | 2013-01-01 |
| 4 | 0.132003 | -0.827317 | 2013-01-01 |

Reading from a file:

```
In [177]: pd.read_json('test.json')
```

```
Out[177]:
```

| | A | B | bools | date | ints |
|------------|-----------|-----------|-------|------------|------|
| 2013-01-01 | -1.294524 | 0.413738 | True | 2013-01-01 | 0 |
| 2013-01-02 | 0.276662 | -0.472035 | True | 2013-01-01 | 1 |
| 2013-01-03 | -0.013960 | -0.362543 | True | 2013-01-01 | 2 |
| 2013-01-04 | -0.006154 | -0.923061 | True | 2013-01-01 | 3 |
| 2013-01-05 | 0.895717 | 0.805244 | True | 2013-01-01 | 4 |

Don't convert any data (but still convert axes and dates):

```
In [178]: pd.read_json('test.json', dtype=object).dtypes
```

```
Out[178]:
```

| | |
|--------|--------|
| A | object |
| B | object |
| bools | object |
| date | object |
| ints | object |
| dtype: | object |

Specify dtypes for conversion:

```
In [179]: pd.read_json('test.json', dtype={'A' : 'float32', 'bools' : 'int8'}).dtypes
```

```
Out[179]:
```

| | |
|-------|----------------|
| A | float32 |
| B | float64 |
| bools | int8 |
| date | datetime64[ns] |

```
ints          int64
dtype: object
```

Preserve string indices:

```
In [180]: si = DataFrame(np.zeros((4, 4)),
.....:                  columns=list(range(4)),
.....:                  index=[str(i) for i in range(4)])
.....:
```

```
In [181]: si
```

```
Out[181]:
   0  1  2  3
0  0  0  0  0
1  0  0  0  0
2  0  0  0  0
3  0  0  0  0
```

```
In [182]: si.index
```

```
Out[182]: Index([u'0', u'1', u'2', u'3'], dtype='object')
```

```
In [183]: si.columns
```

```
Out[183]: Int64Index([0, 1, 2, 3], dtype='int64')
```

```
In [184]: json = si.to_json()
```

```
In [185]: sij = pd.read_json(json, convert_axes=False)
```

```
In [186]: sij
```

```
Out[186]:
   0  1  2  3
0  0  0  0  0
1  0  0  0  0
2  0  0  0  0
3  0  0  0  0
```

```
In [187]: sij.index
```

```
Out[187]: Index([u'0', u'1', u'2', u'3'], dtype='object')
```

```
In [188]: sij.columns
```

```
Out[188]: Index([u'0', u'1', u'2', u'3'], dtype='object')
```

Dates written in nanoseconds need to be read back in nanoseconds:

```
In [189]: json = dfj2.to_json(date_unit='ns')
```

```
# Try to parse timestamps as milliseconds -> Won't Work
```

```
In [190]: dfju = pd.read_json(json, date_unit='ms')
```

```
In [191]: dfju
```

```
Out[191]:
              A          B bools          date  ints
1.356998e+18 -1.294524  0.413738   True  1356998400000000000  0
1.357085e+18  0.276662 -0.472035   True  1356998400000000000  1
1.357171e+18 -0.013960 -0.362543   True  1356998400000000000  2
1.357258e+18 -0.006154 -0.923061   True  1356998400000000000  3
1.357344e+18  0.895717  0.805244   True  1356998400000000000  4
```

```
# Let pandas detect the correct precision
```

```
In [192]: dfju = pd.read_json(json)
```

```
In [193]: dfju
```

```
Out[193]:
```

| | A | B | bools | date | ints |
|------------|-----------|-----------|-------|------------|------|
| 2013-01-01 | -1.294524 | 0.413738 | True | 2013-01-01 | 0 |
| 2013-01-02 | 0.276662 | -0.472035 | True | 2013-01-01 | 1 |
| 2013-01-03 | -0.013960 | -0.362543 | True | 2013-01-01 | 2 |
| 2013-01-04 | -0.006154 | -0.923061 | True | 2013-01-01 | 3 |
| 2013-01-05 | 0.895717 | 0.805244 | True | 2013-01-01 | 4 |

```
# Or specify that all timestamps are in nanoseconds
```

```
In [194]: dfju = pd.read_json(json, date_unit='ns')
```

```
In [195]: dfju
```

```
Out[195]:
```

| | A | B | bools | date | ints |
|------------|-----------|-----------|-------|------------|------|
| 2013-01-01 | -1.294524 | 0.413738 | True | 2013-01-01 | 0 |
| 2013-01-02 | 0.276662 | -0.472035 | True | 2013-01-01 | 1 |
| 2013-01-03 | -0.013960 | -0.362543 | True | 2013-01-01 | 2 |
| 2013-01-04 | -0.006154 | -0.923061 | True | 2013-01-01 | 3 |
| 2013-01-05 | 0.895717 | 0.805244 | True | 2013-01-01 | 4 |

The Numpy Parameter

Note: This supports numeric data only. Index and columns labels may be non-numeric, e.g. strings, dates etc.

If `numpy=True` is passed to `read_json` an attempt will be made to sniff an appropriate dtype during deserialization and to subsequently decode directly to numpy arrays, bypassing the need for intermediate Python objects.

This can provide speedups if you are deserialising a large amount of numeric data:

```
In [196]: randfloats = np.random.uniform(-100, 1000, 10000)
```

```
In [197]: randfloats.shape = (1000, 10)
```

```
In [198]: dffloats = DataFrame(randfloats, columns=list('ABCDEFGHIJ'))
```

```
In [199]: jsonfloats = dffloats.to_json()
```

```
In [200]: timeit read_json(jsonfloats)
100 loops, best of 3: 11.1 ms per loop
```

```
In [201]: timeit read_json(jsonfloats, numpy=True)
100 loops, best of 3: 7.06 ms per loop
```

The speedup is less noticeable for smaller datasets:

```
In [202]: jsonfloats = dffloats.head(100).to_json()
```

```
In [203]: timeit read_json(jsonfloats)
100 loops, best of 3: 4.49 ms per loop
```

```
In [204]: timeit read_json(jsonfloats, numpy=True)
100 loops, best of 3: 3.45 ms per loop
```

Warning: Direct numpy decoding makes a number of assumptions and may fail or produce unexpected output if these assumptions are not satisfied:

- data is numeric.
- data is uniform. The dtype is sniffed from the first value decoded. A `ValueError` may be raised, or incorrect output may be produced if this condition is not satisfied.
- labels are ordered. Labels are only read from the first container, it is assumed that each subsequent row / column has been encoded in the same order. This should be satisfied if the data was encoded using `to_json` but may not be the case if the JSON is from another source.

24.2.3 Normalization

New in version 0.13.0.

pandas provides a utility function to take a dict or list of dicts and *normalize* this semi-structured data into a flat table.

```
In [205]: from pandas.io.json import json_normalize
```

```
In [206]: data = [{'state': 'Florida',
.....:             'shortname': 'FL',
.....:             'info': {
.....:                 'governor': 'Rick Scott'
.....:             }},
.....:             {'counties': [{'name': 'Dade', 'population': 12345},
.....:                             {'name': 'Broward', 'population': 40000},
.....:                             {'name': 'Palm Beach', 'population': 60000}]}],
.....:             {'state': 'Ohio',
.....:             'shortname': 'OH',
.....:             'info': {
.....:                 'governor': 'John Kasich'
.....:             }},
.....:             {'counties': [{'name': 'Summit', 'population': 1234},
.....:                             {'name': 'Cuyahoga', 'population': 1337}]}]}
```

```
In [207]: json_normalize(data, 'counties', ['state', 'shortname', ['info', 'governor']])
```

```
Out[207]:
```

| | name | population | info.governor | state | shortname |
|---|------------|------------|---------------|---------|-----------|
| 0 | Dade | 12345 | Rick Scott | Florida | FL |
| 1 | Broward | 40000 | Rick Scott | Florida | FL |
| 2 | Palm Beach | 60000 | Rick Scott | Florida | FL |
| 3 | Summit | 1234 | John Kasich | Ohio | OH |
| 4 | Cuyahoga | 1337 | John Kasich | Ohio | OH |

24.3 HTML

24.3.1 Reading HTML Content

Warning: We **highly encourage** you to read the *HTML parsing gotchas* regarding the issues surrounding the BeautifulSoup4/html5lib/lxml parsers.

New in version 0.12.0.

The top-level `read_html()` function can accept an HTML string/file/URL and will parse HTML tables into list of pandas DataFrames. Let's look at a few examples.

Note: `read_html` returns a list of DataFrame objects, even if there is only a single table contained in the HTML content

Read a URL with no options

```
In [208]: url = 'http://www.fdic.gov/bank/individual/failed/banklist.html'
```

```
In [209]: dfs = read_html(url)
```

```
In [210]: dfs
```

```
Out[210]:
```

| | Bank Name | City | ST | CERT | \ |
|-----|--|-------------|-----|-------|---|
| 0 | Edgebrook Bank | Chicago | IL | 57772 | |
| 1 | Doral BankEn Espanol | San Juan | PR | 32102 | |
| 2 | Capitol City Bank & Trust Company | Atlanta | GA | 33938 | |
| 3 | Highland Community Bank | Chicago | IL | 20290 | |
| 4 | First National Bank of Crestview | Crestview | FL | 17557 | |
| 5 | Northern Star Bank | Mankato | MN | 34983 | |
| 6 | Frontier Bank, FSB D/B/A El Paseo Bank | Palm Desert | CA | 34738 | |
| .. | ... | ... | ... | ... | |
| 532 | Hamilton Bank, NAEspanol | Miami | FL | 24382 | |
| 533 | Sinclair National Bank | Gravette | AR | 34248 | |
| 534 | Superior Bank, FSB | Hinsdale | IL | 32646 | |
| 535 | Malta National Bank | Malta | OH | 6629 | |
| 536 | First Alliance Bank & Trust Co. | Manchester | NH | 34264 | |
| 537 | National State Bank of Metropolis | Metropolis | IL | 3815 | |
| 538 | Bank of Honolulu | Honolulu | HI | 21029 | |

| | Acquiring Institution | Closing Date | \ |
|-----|-------------------------------------|-------------------|---|
| 0 | Republic Bank of Chicago | May 8, 2015 | |
| 1 | Banco Popular de Puerto Rico | February 27, 2015 | |
| 2 | First-Citizens Bank & Trust Company | February 13, 2015 | |
| 3 | United Fidelity Bank, fsb | January 23, 2015 | |
| 4 | First NBC Bank | January 16, 2015 | |
| 5 | BankVista | December 19, 2014 | |
| 6 | Bank of Southern California, N.A. | November 7, 2014 | |
| .. | ... | ... | |
| 532 | Israel Discount Bank of New York | January 11, 2002 | |
| 533 | Delta Trust & Bank | September 7, 2001 | |
| 534 | Superior Federal, FSB | July 27, 2001 | |
| 535 | North Valley Bank | May 3, 2001 | |
| 536 | Southern New Hampshire Bank & Trust | February 2, 2001 | |
| 537 | Banterra Bank of Marion | December 14, 2000 | |
| 538 | Bank of the Orient | October 13, 2000 | |

| | Updated Date | Loss Share | Type Agreement | Terminated | Termination Date |
|-----|----------------|------------|----------------|------------|------------------|
| 0 | May 8, 2015 | NaN | NaN | NaN | NaN |
| 1 | April 21, 2015 | NaN | NaN | NaN | NaN |
| 2 | April 21, 2015 | none | NaN | NaN | NaN |
| 3 | April 21, 2015 | none | NaN | NaN | NaN |
| 4 | April 21, 2015 | none | NaN | NaN | NaN |
| 5 | March 26, 2015 | none | NaN | NaN | NaN |
| 6 | March 26, 2015 | none | NaN | NaN | NaN |
| .. | ... | ... | ... | ... | ... |
| 532 | June 5, 2012 | none | NaN | NaN | NaN |

```

533 February 10, 2004      none      NaN      NaN
534 August 19, 2014      none      NaN      NaN
535 November 18, 2002     none      NaN      NaN
536 February 18, 2003     none      NaN      NaN
537 March 17, 2005        none      NaN      NaN
538 March 17, 2005        none      NaN      NaN

```

```
[539 rows x 10 columns]
```

Note: The data from the above URL changes every Monday so the resulting data above and the data below may be slightly different.

Read in the content of the file from the above URL and pass it to `read_html` as a string

```

In [211]: with open(file_path, 'r') as f:
.....:     dfs = read_html(f.read())
.....:

```

```
In [212]: dfs
```

```

Out[212]:
[
      Bank Name      City  ST  CERT  \
0  Banks of Wisconsin d/b/a Bank of Kenosha  Kenosha  WI  35386
1      Central Arizona Bank  Scottsdale  AZ  34527
2      Sunrise Bank  Valdosta  GA  58185
3  Pisgah Community Bank  Asheville  NC  58701
4  Douglas County Bank  Douglasville  GA  21649
5      Parkway Bank  Lenoir  NC  57158
6  Chipola Community Bank  Marianna  FL  58034
..      ...      ...  ..  ...
499  Hamilton Bank, NAE n Espanol  Miami  FL  24382
500  Sinclair National Bank  Gravette  AR  34248
501  Superior Bank, FSB  Hinsdale  IL  32646
502  Malta National Bank  Malta  OH  6629
503  First Alliance Bank & Trust Co.  Manchester  NH  34264
504  National State Bank of Metropolis  Metropolis  IL  3815
505  Bank of Honolulu  Honolulu  HI  21029

      Acquiring Institution      Closing Date      Updated Date
0  North Shore Bank, FSB  May 31, 2013  May 31, 2013
1  Western State Bank  May 14, 2013  May 20, 2013
2  Synovus Bank  May 10, 2013  May 21, 2013
3  Capital Bank, N.A.  May 10, 2013  May 14, 2013
4  Hamilton State Bank  April 26, 2013  May 16, 2013
5  CertusBank, National Association  April 26, 2013  May 17, 2013
6  First Federal Bank of Florida  April 19, 2013  May 16, 2013
..      ...      ...      ...
499  Israel Discount Bank of New York  January 11, 2002  June 5, 2012
500  Delta Trust & Bank  September 7, 2001  February 10, 2004
501  Superior Federal, FSB  July 27, 2001  June 5, 2012
502  North Valley Bank  May 3, 2001  November 18, 2002
503  Southern New Hampshire Bank & Trust  February 2, 2001  February 18, 2003
504  Banterra Bank of Marion  December 14, 2000  March 17, 2005
505  Bank of the Orient  October 13, 2000  March 17, 2005

[506 rows x 7 columns]

```

You can even pass in an instance of `StringIO` if you so desire

```
In [213]: with open(file_path, 'r') as f:
.....:     sio = StringIO(f.read())
.....:
```

```
In [214]: dfs = read_html(sio)
```

```
In [215]: dfs
```

```
Out[215]:
```

```
[
  Bank Name      City  ST  CERT  \
0  Banks of Wisconsin d/b/a Bank of Kenosha  Kenosha  WI  35386
1      Central Arizona Bank  Scottsdale  AZ  34527
2      Sunrise Bank  Valdosta  GA  58185
3  Pisgah Community Bank  Asheville  NC  58701
4  Douglas County Bank  Douglasville  GA  21649
5      Parkway Bank  Lenoir  NC  57158
6  Chipola Community Bank  Marianna  FL  58034
..      ...      ...  ..  ...
499  Hamilton Bank, NAE  Miami  FL  24382
500  Sinclair National Bank  Gravette  AR  34248
501  Superior Bank, FSB  Hinsdale  IL  32646
502  Malta National Bank  Malta  OH  6629
503  First Alliance Bank & Trust Co.  Manchester  NH  34264
504  National State Bank of Metropolis  Metropolis  IL  3815
505  Bank of Honolulu  Honolulu  HI  21029

  Acquiring Institution  Closing Date  Updated Date
0  North Shore Bank, FSB  May 31, 2013  May 31, 2013
1  Western State Bank  May 14, 2013  May 20, 2013
2  Synovus Bank  May 10, 2013  May 21, 2013
3  Capital Bank, N.A.  May 10, 2013  May 14, 2013
4  Hamilton State Bank  April 26, 2013  May 16, 2013
5  CertusBank, National Association  April 26, 2013  May 17, 2013
6  First Federal Bank of Florida  April 19, 2013  May 16, 2013
..      ...      ...  ...
499  Israel Discount Bank of New York  January 11, 2002  June 5, 2012
500  Delta Trust & Bank  September 7, 2001  February 10, 2004
501  Superior Federal, FSB  July 27, 2001  June 5, 2012
502  North Valley Bank  May 3, 2001  November 18, 2002
503  Southern New Hampshire Bank & Trust  February 2, 2001  February 18, 2003
504  Banterra Bank of Marion  December 14, 2000  March 17, 2005
505  Bank of the Orient  October 13, 2000  March 17, 2005

[506 rows x 7 columns]
```

Note: The following examples are not run by the IPython evaluator due to the fact that having so many network-accessing functions slows down the documentation build. If you spot an error or an example that doesn't run, please do not hesitate to report it over on [pandas GitHub issues page](#).

Read a URL and match a table that contains specific text

```
match = 'Metcalf Bank'
df_list = read_html(url, match=match)
```

Specify a header row (by default `<th>` elements are used to form the column index); if specified, the header row is taken from the data minus the parsed header elements (`<th>` elements).

```
dfs = read_html(url, header=0)
```

Specify an index column

```
dfs = read_html(url, index_col=0)
```

Specify a number of rows to skip

```
dfs = read_html(url, skiprows=0)
```

Specify a number of rows to skip using a list (`xrange` (Python 2 only) works as well)

```
dfs = read_html(url, skiprows=range(2))
```

Don't infer numeric and date types

```
dfs = read_html(url, infer_types=False)
```

Specify an HTML attribute

```
dfs1 = read_html(url, attrs={'id': 'table'})
dfs2 = read_html(url, attrs={'class': 'sortable'})
print(np.array_equal(dfs1[0], dfs2[0])) # Should be True
```

Use some combination of the above

```
dfs = read_html(url, match='Metcalfe Bank', index_col=0)
```

Read in pandas `to_html` output (with some loss of floating point precision)

```
df = DataFrame(randn(2, 2))
s = df.to_html(float_format='{0:.40g}'.format)
dfin = read_html(s, index_col=0)
```

The `lxml` backend will raise an error on a failed parse if that is the only parser you provide (if you only have a single parser you can provide just a string, but it is considered good practice to pass a list with one string if, for example, the function expects a sequence of strings)

```
dfs = read_html(url, 'Metcalfe Bank', index_col=0, flavor=['lxml'])
```

or

```
dfs = read_html(url, 'Metcalfe Bank', index_col=0, flavor='lxml')
```

However, if you have `bs4` and `html5lib` installed and pass `None` or `['lxml', 'bs4']` then the parse will most likely succeed. Note that *as soon as a parse succeeds, the function will return*.

```
dfs = read_html(url, 'Metcalfe Bank', index_col=0, flavor=['lxml', 'bs4'])
```

24.3.2 Writing to HTML files

`DataFrame` objects have an instance method `to_html` which renders the contents of the `DataFrame` as an HTML table. The function arguments are as in the method `to_string` described above.

Note: Not all of the possible options for `DataFrame.to_html` are shown here for brevity's sake. See `to_html()` for the full set of options.

```
In [216]: df = DataFrame(randn(2, 2))
```

```
In [217]: df
```

```
Out[217]:
```

| | 0 | 1 |
|---|-----------|----------|
| 0 | -0.184744 | 0.496971 |
| 1 | -0.856240 | 1.857977 |

```
In [218]: print(df.to_html()) # raw html
```

```
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

HTML:

The columns argument will limit the columns shown

```
In [219]: print(df.to_html(columns=[0]))
```

```
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.184744</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.856240</td>
    </tr>
  </tbody>
</table>
```

HTML:

`float_format` takes a Python callable to control the precision of floating point values

In [220]: `print(df.to_html(float_format='{0:.10f}'.format))`

```
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>-0.1847438576</td>
      <td>0.4969711327</td>
    </tr>
    <tr>
      <th>1</th>
      <td>-0.8562396763</td>
      <td>1.8579766508</td>
    </tr>
  </tbody>
</table>
```

HTML:

`bold_rows` will make the row labels bold by default, but you can turn that off

In [221]: `print(df.to_html(bold_rows=False))`

```
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
      <th>1</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <td>0</td>
      <td>-0.184744</td>
      <td>0.496971</td>
    </tr>
    <tr>
      <td>1</td>
      <td>-0.856240</td>
      <td>1.857977</td>
    </tr>
  </tbody>
</table>
```

The `classes` argument provides the ability to give the resulting HTML table CSS classes. Note that these classes are *appended* to the existing 'dataframe' class.

In [222]: `print(df.to_html(classes=['awesome_table_class', 'even_more_awesome_class']))`

```
<table border="1" class="dataframe awesome_table_class even_more_awesome_class">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>0</th>
```

```
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<th>0</th>
<td>-0.184744</td>
<td>0.496971</td>
</tr>
<tr>
<th>1</th>
<td>-0.856240</td>
<td>1.857977</td>
</tr>
</tbody>
</table>
```

Finally, the `escape` argument allows you to control whether the “<”, “>” and “&” characters escaped in the resulting HTML (by default it is `True`). So to get the HTML without escaped characters pass `escape=False`

```
In [223]: df = DataFrame({'a': list('&<>'), 'b': randn(3)})
```

Escaped:

```
In [224]: print(df.to_html())
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>a</th>
      <th>b</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>0</th>
      <td>&amp;lt;</td>
      <td>-0.474063</td>
    </tr>
    <tr>
      <th>1</th>
      <td>&lt;</td>
      <td>-0.230305</td>
    </tr>
    <tr>
      <th>2</th>
      <td>&gt;</td>
      <td>-0.400654</td>
    </tr>
  </tbody>
</table>
```

Not escaped:

```
In [225]: print(df.to_html(escape=False))
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
```

```

        <th>a</th>
        <th>b</th>
    </tr>
</thead>
<tbody>
    <tr>
        <th>0</th>
        <td>&</td>
        <td>-0.474063</td>
    </tr>
    <tr>
        <th>1</th>
        <td><</td>
        <td>-0.230305</td>
    </tr>
    <tr>
        <th>2</th>
        <td>></td>
        <td>-0.400654</td>
    </tr>
</tbody>
</table>

```

Note: Some browsers may not show a difference in the rendering of the previous two HTML tables.

24.4 Excel files

The `read_excel()` method can read Excel 2003 (`.xls`) and Excel 2007 (`.xlsx`) files using the `xlrd` Python module and use the same parsing code as the above to convert tabular data into a `DataFrame`. See the [cookbook](#) for some advanced strategies

24.4.1 Reading Excel Files

New in version 0.16.

`read_excel` can read more than one sheet, by setting `sheetname` to either a list of sheet names, a list of sheet positions, or `None` to read all sheets.

New in version 0.13.

Sheets can be specified by sheet index or sheet name, using an integer or string, respectively.

New in version 0.12.

`ExcelFile` has been moved to the top level namespace.

There are two approaches to reading an excel file. The `read_excel` function and the `ExcelFile` class. `read_excel` is for reading one file with file-specific arguments (ie. identical data formats across sheets). `ExcelFile` is for reading one file with sheet-specific arguments (ie. various data formats across sheets). Choosing the approach is largely a question of code readability and execution speed.

Equivalent class and function approaches to read a single sheet:

```

# using the ExcelFile class
xls = pd.ExcelFile('path_to_file.xls')
data = xls.parse('Sheet1', index_col=None, na_values=['NA'])

```

```
# using the read_excel function
data = read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

Equivalent class and function approaches to read multiple sheets:

```
data = {}
# For when Sheet1's format differs from Sheet2
xls = pd.ExcelFile('path_to_file.xls')
data['Sheet1'] = xls.parse('Sheet1', index_col=None, na_values=['NA'])
data['Sheet2'] = xls.parse('Sheet2', index_col=1)

# For when Sheet1's format is identical to Sheet2
data = read_excel('path_to_file.xls', ['Sheet1', 'Sheet2'], index_col=None, na_values=['NA'])
```

Specifying Sheets

Note: The second argument is `sheetname`, not to be confused with `ExcelFile.sheet_names`

Note: An `ExcelFile`'s attribute `sheet_names` provides access to a list of sheets.

- The arguments `sheetname` allows specifying the sheet or sheets to read.
- The default value for `sheetname` is 0, indicating to read the first sheet
- Pass a string to refer to the name of a particular sheet in the workbook.
- Pass an integer to refer to the index of a sheet. Indices follow Python convention, beginning at 0.
- Pass a list of either strings or integers, to return a dictionary of specified sheets.
- Pass a `None` to return a dictionary of all available sheets.

```
# Returns a DataFrame
read_excel('path_to_file.xls', 'Sheet1', index_col=None, na_values=['NA'])
```

Using the sheet index:

```
# Returns a DataFrame
read_excel('path_to_file.xls', 0, index_col=None, na_values=['NA'])
```

Using all default values:

```
# Returns a DataFrame
read_excel('path_to_file.xls')
```

Using `None` to get all sheets:

```
# Returns a dictionary of DataFrames
read_excel('path_to_file.xls', sheetname=None)
```

Using a list to get multiple sheets:

```
# Returns the 1st and 4th sheet, as a dictionary of DataFrames.
read_excel('path_to_file.xls', sheetname=['Sheet1', 3])
```

Parsing Specific Columns

It is often the case that users will insert columns to do temporary computations in Excel and you may not want to read in those columns. `read_excel` takes a `parse_cols` keyword to allow you to specify a subset of columns to parse.

If `parse_cols` is an integer, then it is assumed to indicate the last column to be parsed.

```
read_excel('path_to_file.xls', 'Sheet1', parse_cols=2)
```

If `parse_cols` is a list of integers, then it is assumed to be the file column indices to be parsed.

```
read_excel('path_to_file.xls', 'Sheet1', parse_cols=[0, 2, 3])
```

Cell Converters

It is possible to transform the contents of Excel cells via the `converters` option. For instance, to convert a column to boolean:

```
read_excel('path_to_file.xls', 'Sheet1', converters={'MyBools': bool})
```

This options handles missing values and treats exceptions in the converters as missing data. Transformations are applied cell by cell rather than to the column as a whole, so the array dtype is not guaranteed. For instance, a column of integers with missing values cannot be transformed to an array with integer dtype, because NaN is strictly a float. You can manually mask missing data to recover integer dtype:

```
cfun = lambda x: int(x) if x else -1
read_excel('path_to_file.xls', 'Sheet1', converters={'MyInts': cfun})
```

24.4.2 Writing Excel Files

To write a DataFrame object to a sheet of an Excel file, you can use the `to_excel` instance method. The arguments are largely the same as `to_csv` described above, the first argument being the name of the excel file, and the optional second argument the name of the sheet to which the DataFrame should be written. For example:

```
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

Files with a `.xls` extension will be written using `xlwt` and those with a `.xlsx` extension will be written using `xlsxwriter` (if available) or `openpyxl`.

The DataFrame will be written in a way that tries to mimic the REPL output. One difference from 0.12.0 is that the `index_label` will be placed in the second row instead of the first. You can get the previous behaviour by setting the `merge_cells` option in `to_excel()` to `False`:

```
df.to_excel('path_to_file.xlsx', index_label='label', merge_cells=False)
```

The Panel class also has a `to_excel` instance method, which writes each DataFrame in the Panel to a separate sheet.

In order to write separate DataFrames to separate sheets in a single Excel file, one can pass an `ExcelWriter`.

```
with ExcelWriter('path_to_file.xlsx') as writer:
    df1.to_excel(writer, sheet_name='Sheet1')
    df2.to_excel(writer, sheet_name='Sheet2')
```

Note: Wringing a little more performance out of `read_excel` Internally, Excel stores all numeric data as floats. Because this can produce unexpected behavior when reading in data, pandas defaults to trying to convert integers to floats if it doesn't lose information (`1.0 --> 1`). You can pass `convert_float=False` to disable this behavior, which may give a slight performance improvement.

24.4.3 Excel writer engines

New in version 0.13.

pandas chooses an Excel writer via two methods:

1. the `engine` keyword argument
2. the filename extension (via the default specified in config options)

By default, pandas uses the `XlsxWriter` for `.xlsx` and `openpyxl` for `.xlsm` files and `xlwt` for `.xls` files. If you have multiple engines installed, you can set the default engine through *setting the config options* `io.excel.xlsx.writer` and `io.excel.xls.writer`. pandas will fall back on `openpyxl` for `.xlsx` files if `Xlsxwriter` is not available.

To specify which writer you want to use, you can pass an engine keyword argument to `to_excel` and to `ExcelWriter`. The built-in engines are:

- `openpyxl`: This includes stable support for OpenPyxl 1.6.1 up to but not including 2.0.0, and experimental support for OpenPyxl 2.0.0 and later.
- `xlsxwriter`
- `xlwt`

```
# By setting the 'engine' in the DataFrame and Panel 'to_excel()' methods.
df.to_excel('path_to_file.xlsx', sheet_name='Sheet1', engine='xlsxwriter')
```

```
# By setting the 'engine' in the ExcelWriter constructor.
writer = ExcelWriter('path_to_file.xlsx', engine='xlsxwriter')
```

```
# Or via pandas configuration.
from pandas import options
options.io.excel.xlsx.writer = 'xlsxwriter'

df.to_excel('path_to_file.xlsx', sheet_name='Sheet1')
```

24.5 Clipboard

A handy way to grab data is to use the `read_clipboard` method, which takes the contents of the clipboard buffer and passes them to the `read_table` method. For instance, you can copy the following text to the clipboard (CTRL-C on many operating systems):

```
A B C
x 1 4 p
y 2 5 q
z 3 6 r
```

And then import the data directly to a `DataFrame` by calling:

```
clipdf = pd.read_clipboard()
```

```
In [226]: clipdf
```

```
Out[226]:
   A  B  C
x  1  4  p
y  2  5  q
z  3  6  r
```

The `to_clipboard` method can be used to write the contents of a DataFrame to the clipboard. Following which you can paste the clipboard contents into other applications (CTRL-V on many operating systems). Here we illustrate writing a DataFrame into clipboard and reading it back.

```
In [227]: df=pd.DataFrame(randn(5,3))
```

```
In [228]: df
```

```
Out[228]:
```

	0	1	2
0	-0.288267	-0.084905	0.004772
1	1.382989	0.343635	-1.253994
2	-0.124925	0.212244	0.496654
3	0.525417	1.238640	-1.210543
4	-1.175743	-0.172372	-0.734129

```
In [229]: df.to_clipboard()
```

```
In [230]: pd.read_clipboard()
```

```
Out[230]:
```

	0	1	2
0	-0.288267	-0.084905	0.004772
1	1.382989	0.343635	-1.253994
2	-0.124925	0.212244	0.496654
3	0.525417	1.238640	-1.210543
4	-1.175743	-0.172372	-0.734129

We can see that we got the same content back, which we had earlier written to the clipboard.

Note: You may need to install `xclip` or `xsel` (with `gtk` or `PyQt4` modules) on Linux to use these methods.

24.6 Pickling

All pandas objects are equipped with `to_pickle` methods which use Python's `cPickle` module to save data structures to disk using the pickle format.

```
In [231]: df
```

```
Out[231]:
```

	0	1	2
0	-0.288267	-0.084905	0.004772
1	1.382989	0.343635	-1.253994
2	-0.124925	0.212244	0.496654
3	0.525417	1.238640	-1.210543
4	-1.175743	-0.172372	-0.734129

```
In [232]: df.to_pickle('foo.pkl')
```

The `read_pickle` function in the pandas namespace can be used to load any pickled pandas object (or any other pickled object) from file:

```
In [233]: read_pickle('foo.pkl')
```

```
Out[233]:
```

	0	1	2
0	-0.288267	-0.084905	0.004772
1	1.382989	0.343635	-1.253994
2	-0.124925	0.212244	0.496654

```
3  0.525417  1.238640 -1.210543
4 -1.175743 -0.172372 -0.734129
```

Warning: Loading pickled data received from untrusted sources can be unsafe.
See: <http://docs.python.org/2.7/library/pickle.html>

Warning: Several internal refactorings, 0.13 (*Series Refactoring*), and 0.15 (*Index Refactoring*), preserve compatibility with pickles created prior to these versions. However, these must be read with `pd.read_pickle`, rather than the default `python pickle.load`. See [this question](#) for a detailed explanation.

Note: These methods were previously `pd.save` and `pd.load`, prior to 0.12.0, and are now deprecated.

24.7 msgpack (experimental)

New in version 0.13.0.

Starting in 0.13.0, pandas is supporting the `msgpack` format for object serialization. This is a lightweight portable binary format, similar to binary JSON, that is highly space efficient, and provides good performance both on the writing (serialization), and reading (deserialization).

Warning: This is a very new feature of pandas. We intend to provide certain optimizations in the io of the `msgpack` data. Since this is marked as an **EXPERIMENTAL LIBRARY**, the storage format may not be stable until a future release.

```
In [234]: df = DataFrame(np.random.rand(5,2), columns=list('AB'))
```

```
In [235]: df.to_msgpack('foo.msg')
```

```
In [236]: pd.read_msgpack('foo.msg')
```

```
Out[236]:
```

	A	B
0	0.154336	0.710999
1	0.398096	0.765220
2	0.586749	0.293052
3	0.290293	0.710783
4	0.988593	0.062106

```
In [237]: s = Series(np.random.rand(5), index=date_range('20130101', periods=5))
```

You can pass a list of objects and you will receive them back on deserialization.

```
In [238]: pd.to_msgpack('foo.msg', df, 'foo', np.array([1,2,3]), s)
```

```
In [239]: pd.read_msgpack('foo.msg')
```

```
Out[239]:
```

	A	B
0	0.154336	0.710999
1	0.398096	0.765220
2	0.586749	0.293052
3	0.290293	0.710783
4	0.988593	0.062106
2013-01-01	0.690810	
2013-01-02	0.235907	
2013-01-03	0.712756	

```
2013-01-04    0.119599
2013-01-05    0.023493
Freq: D, dtype: float64]
```

You can pass `iterator=True` to iterate over the unpacked results

```
In [240]: for o in pd.read_msgpack('foo.msg', iterator=True):
.....:     print o
.....:
           A          B
0  0.154336  0.710999
1  0.398096  0.765220
2  0.586749  0.293052
3  0.290293  0.710783
4  0.988593  0.062106
foo
[1 2 3]
2013-01-01    0.690810
2013-01-02    0.235907
2013-01-03    0.712756
2013-01-04    0.119599
2013-01-05    0.023493
Freq: D, dtype: float64
```

You can pass `append=True` to the writer to append to an existing pack

```
In [241]: df.to_msgpack('foo.msg', append=True)

In [242]: pd.read_msgpack('foo.msg')
Out[242]:
[           A          B
0  0.154336  0.710999
1  0.398096  0.765220
2  0.586749  0.293052
3  0.290293  0.710783
4  0.988593  0.062106, u'foo', array([1, 2, 3]), 2013-01-01    0.690810
2013-01-02    0.235907
2013-01-03    0.712756
2013-01-04    0.119599
2013-01-05    0.023493
Freq: D, dtype: float64,           A          B
0  0.154336  0.710999
1  0.398096  0.765220
2  0.586749  0.293052
3  0.290293  0.710783
4  0.988593  0.062106]
```

Unlike other io methods, `to_msgpack` is available on both a per-object basis, `df.to_msgpack()` and using the top-level `pd.to_msgpack(...)` where you can pack arbitrary collections of python lists, dicts, scalars, while intermixing pandas objects.

```
In [243]: pd.to_msgpack('foo2.msg', { 'dict' : [ { 'df' : df }, { 'string' : 'foo' }, { 'scalar' : 1 } ])

In [244]: pd.read_msgpack('foo2.msg')
Out[244]:
{u'dict': ({u'df':           A          B
0  0.154336  0.710999
1  0.398096  0.765220
2  0.586749  0.293052
```


Objects can be written to the file just like adding key-value pairs to a dict:

```
In [249]: np.random.seed(1234)

In [250]: index = date_range('1/1/2000', periods=8)

In [251]: s = Series(randn(5), index=['a', 'b', 'c', 'd', 'e'])

In [252]: df = DataFrame(randn(8, 3), index=index,
.....:                  columns=['A', 'B', 'C'])
.....:

In [253]: wp = Panel(randn(2, 5, 4), items=['Item1', 'Item2'],
.....:               major_axis=date_range('1/1/2000', periods=5),
.....:               minor_axis=['A', 'B', 'C', 'D'])
.....:

# store.put('s', s) is an equivalent method
In [254]: store['s'] = s

In [255]: store['df'] = df

In [256]: store['wp'] = wp

# the type of stored data
In [257]: store.root.wp._v_attrs.pandas_type
Out[257]: 'wide'

In [258]: store
Out[258]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df          frame          (shape->[8,3])
/s           series         (shape->[5])
/wp          wide           (shape->[2,5,4])
```

In a current or later Python session, you can retrieve stored objects:

```
# store.get('df') is an equivalent method
In [259]: store['df']
Out[259]:
```

	A	B	C
2000-01-01	0.887163	0.859588	-0.636524
2000-01-02	0.015696	-2.242685	1.150036
2000-01-03	0.991946	0.953324	-2.021255
2000-01-04	-0.334077	0.002118	0.405453
2000-01-05	0.289092	1.321158	-1.546906
2000-01-06	-0.202646	-0.655969	0.193421
2000-01-07	0.553439	1.318152	-0.469305
2000-01-08	0.675554	-1.817027	-0.183109

```
# dotted (attribute) access provides get as well
In [260]: store.df
Out[260]:
```

	A	B	C
2000-01-01	0.887163	0.859588	-0.636524
2000-01-02	0.015696	-2.242685	1.150036
2000-01-03	0.991946	0.953324	-2.021255
2000-01-04	-0.334077	0.002118	0.405453

```
2000-01-05    0.289092    1.321158   -1.546906
2000-01-06   -0.202646   -0.655969    0.193421
2000-01-07    0.553439    1.318152   -0.469305
2000-01-08    0.675554   -1.817027   -0.183109
```

Deletion of the object specified by the key

```
# store.remove('wp') is an equivalent method
In [261]: del store['wp']
```

```
In [262]: store
Out[262]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                frame          (shape->[8,3])
/s                 series         (shape->[5])
```

Closing a Store, Context Manager

```
In [263]: store.close()
```

```
In [264]: store
Out[264]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
File is CLOSED
```

```
In [265]: store.is_open
Out[265]: False
```

```
# Working with, and automatically closing the store with the context
# manager
In [266]: with HDFStore('store.h5') as store:
.....:     store.keys()
.....:
```

24.8.1 Read/Write API

HDFStore supports an top-level API using `read_hdf` for reading and `to_hdf` for writing, similar to how `read_csv` and `to_csv` work. (new in 0.11.0)

```
In [267]: df_t1 = DataFrame(dict(A=list(range(5)), B=list(range(5))))
```

```
In [268]: df_t1.to_hdf('store_t1.h5', 'table', append=True)
```

```
In [269]: read_hdf('store_t1.h5', 'table', where = ['index>2'])
Out[269]:
   A  B
3  3  3
4  4  4
```

24.8.2 Fixed Format

Note: This was prior to 0.13.0 the `Storer` format.

The examples above show storing using `put`, which write the HDF5 to PyTables in a fixed array format, called the fixed format. These types of stores are **not** appendable once written (though you can simply remove them and rewrite). Nor are they **queryable**; they must be retrieved in their entirety. They also do not support dataframes with non-unique column names. The fixed format stores offer very fast writing and slightly faster reading than table stores. This format is specified by default when using `put` or `to_hdf` or by `format='fixed'` or `format='f'`

Warning: A fixed format will raise a `TypeError` if you try to retrieve using a `where`.

```
DataFrame(randn(10,2)).to_hdf('test_fixed.h5','df')

pd.read_hdf('test_fixed.h5','df',where='index>5')
TypeError: cannot pass a where specification when reading a fixed format.
this store must be selected in its entirety
```

24.8.3 Table Format

`HDFStore` supports another PyTables format on disk, the table format. Conceptually a table is shaped very much like a `DataFrame`, with rows and columns. A table may be appended to in the same or other sessions. In addition, delete & query type operations are supported. This format is specified by `format='table'` or `format='t'` to append or `put` or `to_hdf`

New in version 0.13.

This format can be set as an option as well `pd.set_option('io.hdf.default_format','table')` to enable `put`/`append`/`to_hdf` to by default store in the table format.

```
In [270]: store = HDFStore('store.h5')

In [271]: df1 = df[0:4]

In [272]: df2 = df[4:]

# append data (creates a table automatically)
In [273]: store.append('df', df1)

In [274]: store.append('df', df2)

In [275]: store
Out[275]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])

# select the entire object
In [276]: store.select('df')
Out[276]:
```

	A	B	C
2000-01-01	0.887163	0.859588	-0.636524
2000-01-02	0.015696	-2.242685	1.150036
2000-01-03	0.991946	0.953324	-2.021255
2000-01-04	-0.334077	0.002118	0.405453
2000-01-05	0.289092	1.321158	-1.546906
2000-01-06	-0.202646	-0.655969	0.193421
2000-01-07	0.553439	1.318152	-0.469305
2000-01-08	0.675554	-1.817027	-0.183109

```
# the type of stored data
In [277]: store.root.df._v_attrs.pandas_type
Out[277]: 'frame_table'
```

Note: You can also create a table by passing `format='table'` or `format='t'` to a put operation.

24.8.4 Hierarchical Keys

Keys to a store can be specified as a string. These can be in a hierarchical path-name like format (e.g. `foo/bar/bah`), which will generate a hierarchy of sub-stores (or Groups in PyTables parlance). Keys can be specified with out the leading `'/'` and are ALWAYS absolute (e.g. `'foo'` refers to `'/foo'`). Removal operations can remove everything in the sub-store and BELOW, so be *careful*.

```
In [278]: store.put('foo/bar/bah', df)

In [279]: store.append('food/orange', df)

In [280]: store.append('food/apple', df)

In [281]: store
Out[281]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/bar/bah       frame        (shape->[8,3])
/food/apple        frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/food/orange       frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])

# a list of keys are returned
In [282]: store.keys()
Out[282]: ['/df', '/food/apple', '/food/orange', '/foo/bar/bah']

# remove all nodes under this level
In [283]: store.remove('food')

In [284]: store
Out[284]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
/df                frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/foo/bar/bah       frame        (shape->[8,3])
```

24.8.5 Storing Mixed Types in a Table

Storing mixed-dtype data is supported. Strings are stored as a fixed-width using the maximum size of the appended column. Subsequent appends will truncate strings at this length.

Passing `min_itemsize={'values': size}` as a parameter to append will set a larger minimum for the string columns. Storing floats, strings, ints, bools, `datetime64` are currently supported. For string columns, passing `nan_rep = 'nan'` to append will change the default nan representation on disk (which converts to/from `np.nan`), this defaults to `nan`.

```
In [285]: df_mixed = DataFrame({'A' : randn(8),
.....:                        'B' : randn(8),
```

```

.....:                                     'C' : np.array(randn(8),dtype='float32'),
.....:                                     'string' : 'string',
.....:                                     'int' : 1,
.....:                                     'bool' : True,
.....:                                     'datetime64' : Timestamp('20010102'),
.....:                                     index=list(range(8))
.....:

```

```
In [286]: df_mixed.ix[3:5,['A', 'B', 'string', 'datetime64']] = np.nan
```

```
In [287]: store.append('df_mixed', df_mixed, min_itemsize = {'values': 50})
```

```
In [288]: df_mixed1 = store.select('df_mixed')
```

```
In [289]: df_mixed1
```

```
Out[289]:
```

	A	B	C	bool	datetime64	int	string
0	0.704721	-1.152659	-0.430096	True	2001-01-02	1	string
1	-0.785435	0.631979	0.767369	True	2001-01-02	1	string
2	0.462060	0.039513	0.984920	True	2001-01-02	1	string
3	NaN	NaN	0.270836	True	NaT	1	NaN
4	NaN	NaN	1.391986	True	NaT	1	NaN
5	NaN	NaN	0.079842	True	NaT	1	NaN
6	2.007843	0.152631	-0.399965	True	2001-01-02	1	string
7	0.226963	0.164530	-1.027851	True	2001-01-02	1	string

```
In [290]: df_mixed1.get_dtype_counts()
```

```
Out[290]:
bool                1
datetime64[ns]      1
float32              1
float64             2
int64               1
object              1
dtype: int64
```

```
# we have provided a minimum string column size
```

```
In [291]: store.root.df_mixed.table
```

```
Out[291]:
/df_mixed/table (Table(8,)) ''
description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(2,), dflt=0.0, pos=1),
  "values_block_1": Float32Col(shape=(1,), dflt=0.0, pos=2),
  "values_block_2": Int64Col(shape=(1,), dflt=0, pos=3),
  "values_block_3": Int64Col(shape=(1,), dflt=0, pos=4),
  "values_block_4": BoolCol(shape=(1,), dflt=False, pos=5),
  "values_block_5": StringCol(itemsizes=50, shape=(1,), dflt='', pos=6)}
byteorder := 'little'
chunkshape := (689,)
autoindex := True
colindexes := {
  "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

24.8.6 Storing Multi-Index DataFrames

Storing multi-index dataframes as tables is very similar to storing/selecting from homogeneous index DataFrames.

```
In [292]: index = MultiIndex(levels=[['foo', 'bar', 'baz', 'qux'],
.....:                             ['one', 'two', 'three']],
.....:                       labels=[[0, 0, 0, 1, 1, 2, 2, 3, 3, 3],
.....:                              [0, 1, 2, 0, 1, 1, 2, 0, 1, 2]],
.....:                       names=['foo', 'bar'])
.....:
```

```
In [293]: df_mi = DataFrame(np.random.randn(10, 3), index=index,
.....:                      columns=['A', 'B', 'C'])
.....:
```

```
In [294]: df_mi
```

```
Out[294]:
```

		A	B	C
foo	bar			
foo	one	-0.584718	0.816594	-0.081947
	two	-0.344766	0.528288	-1.068989
	three	-0.511881	0.291205	0.566534
bar	one	0.503592	0.285296	0.484288
	two	1.363482	-0.781105	-0.468018
baz	two	1.224574	-1.281108	0.875476
	three	-1.710715	-0.450765	0.749164
qux	one	-0.203933	-0.182175	0.680656
	two	-1.818499	0.047072	0.394844
	three	-0.248432	-0.617707	-0.682884

```
In [295]: store.append('df_mi', df_mi)
```

```
In [296]: store.select('df_mi')
```

```
Out[296]:
```

		A	B	C
foo	bar			
foo	one	-0.584718	0.816594	-0.081947
	two	-0.344766	0.528288	-1.068989
	three	-0.511881	0.291205	0.566534
bar	one	0.503592	0.285296	0.484288
	two	1.363482	-0.781105	-0.468018
baz	two	1.224574	-1.281108	0.875476
	three	-1.710715	-0.450765	0.749164
qux	one	-0.203933	-0.182175	0.680656
	two	-1.818499	0.047072	0.394844
	three	-0.248432	-0.617707	-0.682884

```
# the levels are automatically included as data columns
```

```
In [297]: store.select('df_mi', 'foo=bar')
```

```
Out[297]:
```

		A	B	C
foo	bar			
bar	one	0.503592	0.285296	0.484288
	two	1.363482	-0.781105	-0.468018

24.8.7 Querying a Table

Warning: This query capabilities have changed substantially starting in 0.13.0. Queries from prior version are accepted (with a `DeprecationWarning`) printed if its not string-like.

`select` and `delete` operations have an optional criterion that can be specified to select/delete only a subset of the data. This allows one to have a very large on-disk table and retrieve only a portion of the data.

A query is specified using the `Term` class under the hood, as a boolean expression.

- `index` and `columns` are supported indexers of a `DataFrame`
- `major_axis`, `minor_axis`, and `items` are supported indexers of the `Panel`
- if `data_columns` are specified, these can be used as additional indexers

Valid comparison operators are:

- `=`, `==`, `!=`, `>`, `>=`, `<`, `<=`

Valid boolean expressions are combined with:

- `|` : or
- `&` : and
- `( and )` : for grouping

These rules are similar to how boolean expressions are used in pandas for indexing.

Note:

- `=` will be automatically expanded to the comparison operator `==`
 - `~` is the not operator, but can only be used in very limited circumstances
 - If a list/tuple of expressions is passed they will be combined via `&`
-

The following are valid expressions:

- `'index>=date'`
- `"columns=['A', 'D']"`
- `"columns in ['A', 'D']"`
- `'columns=A'`
- `'columns==A'`
- `"~(columns=['A', 'B'])"`
- `'index>df.index[3] & string="bar"'`
- `'(index>df.index[3] & index<=df.index[6]) | string="bar"'`
- `"ts>=Timestamp('2012-02-01')"`
- `"major_axis>=20130101"`

The indexers are on the left-hand side of the sub-expression:

- `columns`, `major_axis`, `ts`

The right-hand side of the sub-expression (after a comparison operator) can be:

- functions that will be evaluated, e.g. `Timestamp('2012-02-01')`
- strings, e.g. `"bar"`
- date-like, e.g. `20130101`, or `"20130101"`
- lists, e.g. `"['A', 'B']"`
- variables that are defined in the local names space, e.g. `date`

Note: Passing a string to a query by interpolating it into the query expression is not recommended. Simply assign the string of interest to a variable and use that variable in an expression. For example, do this

```
string = "HolyMoly"
store.select('df', 'index == string')
```

instead of this

```
string = "HolyMoly"
store.select('df', 'index == %s' % string)
```

The latter will **not** work and will raise a `SyntaxError`. Note that there's a single quote followed by a double quote in the string variable.

If you *must* interpolate, use the `'%r'` format specifier

```
store.select('df', 'index == %r' % string)
```

which will quote string.

Here are some examples:

```
In [298]: dfq = DataFrame(randn(10,4), columns=list('ABCD'), index=date_range('20130101', periods=10))
```

```
In [299]: store.append('dfq', dfq, format='table', data_columns=True)
```

Use boolean expressions, with in-line function evaluation.

```
In [300]: store.select('dfq', "index>Timestamp('20130104') & columns=['A', 'B']")
```

```
Out[300]:
```

	A	B
2013-01-05	1.210384	0.797435
2013-01-06	-0.850346	1.176812
2013-01-07	0.984188	-0.121728
2013-01-08	0.796595	-0.474021
2013-01-09	-0.804834	-2.123620
2013-01-10	0.334198	0.536784

Use and inline column reference

```
In [301]: store.select('dfq', where="A>0 or C>0")
```

```
Out[301]:
```

	A	B	C	D
2013-01-01	0.436258	-1.703013	0.393711	-0.479324
2013-01-02	-0.299016	0.694103	0.678630	0.239556
2013-01-03	0.151227	0.816127	1.893534	0.639633
2013-01-04	-0.962029	-2.085266	1.930247	-1.735349
2013-01-05	1.210384	0.797435	-0.379811	0.702562
2013-01-07	0.984188	-0.121728	2.365769	0.496143
2013-01-08	0.796595	-0.474021	-0.056696	1.357797
2013-01-10	0.334198	0.536784	-0.743830	-0.320204

Works with a Panel as well.

```
In [302]: store.append('wp', wp)
```

```
In [303]: store
```

```
Out[303]:
<class 'pandas.io.pytables.HDFStore'>
File path: store.h5
```

```

/df                frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df_mi             frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[A,B,C])
/df_mixed          frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfq               frame_table  (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C])
/foo/bar/bah       frame        (shape->[8,3])
/wp                wide_table   (typ->appendable,nrows->20,ncols->2,indexers->[major_axis,minor_axis])

```

```
In [304]: store.select('wp', "major_axis>Timestamp('20000102') & minor_axis=['A', 'B']")
```

```
Out[304]:
```

```

<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 3 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to B

```

The `columns` keyword can be supplied to select a list of columns to be returned, this is equivalent to passing a `'columns=list_of_columns_to_filter'`:

```
In [305]: store.select('df', "columns=['A', 'B']")
```

```
Out[305]:
```

	A	B
2000-01-01	0.887163	0.859588
2000-01-02	0.015696	-2.242685
2000-01-03	0.991946	0.953324
2000-01-04	-0.334077	0.002118
2000-01-05	0.289092	1.321158
2000-01-06	-0.202646	-0.655969
2000-01-07	0.553439	1.318152
2000-01-08	0.675554	-1.817027

start and stop parameters can be specified to limit the total search space. These are in terms of the total number of rows in a table.

```
# this is effectively what the storage of a Panel looks like
```

```
In [306]: wp.to_frame()
```

```
Out[306]:
```

		Item1	Item2
major	minor		
2000-01-01	A	1.058969	0.215269
	B	-0.397840	0.841009
	C	0.337438	-1.445810
	D	1.047579	-1.401973
2000-01-02	A	1.045938	-0.100918
	B	0.863717	-0.548242
	C	-0.122092	-0.144620
...	...	...	...
2000-01-04	B	0.036142	0.307969
	C	-2.074978	-0.208499
	D	0.247792	1.033801
2000-01-05	A	-0.897157	-2.400454
	B	-0.136795	2.030604
	C	0.018289	-1.142631
	D	0.755414	0.211883

```
[20 rows x 2 columns]
```

```
# limiting the search
```

```
In [307]: store.select('wp',"major_axis>20000102 & minor_axis=['A','B']",
.....:                  start=0, stop=10)
```

```
.....:
Out[307]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 1 (major_axis) x 2 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-03 00:00:00 to 2000-01-03 00:00:00
Minor_axis axis: A to B
```

Note: `select` will raise a `ValueError` if the query expression has an unknown variable reference. Usually this means that you are trying to select on a column that is **not** a `data_column`.

`select` will raise a `SyntaxError` if the query expression is not valid.

Using `timedelta64[ns]`

New in version 0.13.

Beginning in 0.13.0, you can store and query using the `timedelta64[ns]` type. Terms can be specified in the format: `<float>(<unit>)`, where float may be signed (and fractional), and unit can be `D`, `s`, `ms`, `us`, `ns` for the `timedelta`. Here's an example:

Warning: This requires `numpy >= 1.7`

```
In [308]: from datetime import timedelta
```

```
In [309]: dftd = DataFrame(dict(A = Timestamp('20130101'), B = [ Timestamp('20130101') + timedelta(d
```

```
In [310]: dftd['C'] = dftd['A']-dftd['B']
```

```
In [311]: dftd
```

```
Out[311]:
```

	A	B	C
0	2013-01-01 2013-01-01 00:00:10	-1 days +23:59:50	
1	2013-01-01 2013-01-02 00:00:10	-2 days +23:59:50	
2	2013-01-01 2013-01-03 00:00:10	-3 days +23:59:50	
3	2013-01-01 2013-01-04 00:00:10	-4 days +23:59:50	
4	2013-01-01 2013-01-05 00:00:10	-5 days +23:59:50	
5	2013-01-01 2013-01-06 00:00:10	-6 days +23:59:50	
6	2013-01-01 2013-01-07 00:00:10	-7 days +23:59:50	
7	2013-01-01 2013-01-08 00:00:10	-8 days +23:59:50	
8	2013-01-01 2013-01-09 00:00:10	-9 days +23:59:50	
9	2013-01-01 2013-01-10 00:00:10	-10 days +23:59:50	

```
In [312]: store.append('dftd',dftd,data_columns=True)
```

```
In [313]: store.select('dftd',"C<'-3.5D'")
```

```
Out[313]:
```

	A	B	C
4	2013-01-01 2013-01-05 00:00:10	-5 days +23:59:50	
5	2013-01-01 2013-01-06 00:00:10	-6 days +23:59:50	
6	2013-01-01 2013-01-07 00:00:10	-7 days +23:59:50	
7	2013-01-01 2013-01-08 00:00:10	-8 days +23:59:50	
8	2013-01-01 2013-01-09 00:00:10	-9 days +23:59:50	
9	2013-01-01 2013-01-10 00:00:10	-10 days +23:59:50	

24.8.8 Indexing

You can create/modify an index for a table with `create_table_index` after data is already in the table (after and append/put operation). Creating a table index is **highly** encouraged. This will speed your queries a great deal when you use a `select` with the indexed dimension as the `where`.

Note: Indexes are automatically created (starting 0.10.1) on the indexables and any data columns you specify. This behavior can be turned off by passing `index=False` to `append`.

```
# we have automagically already created an index (in the first section)
In [314]: i = store.root.df.table.cols.index.index

In [315]: i.optlevel, i.kind
Out[315]: (6, 'medium')

# change an index by passing new parameters
In [316]: store.create_table_index('df', optlevel=9, kind='full')

In [317]: i = store.root.df.table.cols.index.index

In [318]: i.optlevel, i.kind
Out[318]: (9, 'full')
```

See [here](#) for how to create a completely-sorted-index (CSI) on an existing store.

24.8.9 Query via Data Columns

You can designate (and index) certain columns that you want to be able to perform queries (other than the *indexable* columns, which you can always query). For instance say you want to perform this common operation, on-disk, and return just the frame that matches this query. You can specify `data_columns = True` to force all columns to be `data_columns`

```
In [319]: df_dc = df.copy()

In [320]: df_dc['string'] = 'foo'

In [321]: df_dc.ix[4:6, 'string'] = np.nan

In [322]: df_dc.ix[7:9, 'string'] = 'bar'

In [323]: df_dc['string2'] = 'cool'

In [324]: df_dc.ix[1:3, ['B', 'C']] = 1.0

In [325]: df_dc
Out[325]:
```

	A	B	C	string	string2
2000-01-01	0.887163	0.859588	-0.636524	foo	cool
2000-01-02	0.015696	1.000000	1.000000	foo	cool
2000-01-03	0.991946	1.000000	1.000000	foo	cool
2000-01-04	-0.334077	0.002118	0.405453	foo	cool
2000-01-05	0.289092	1.321158	-1.546906	NaN	cool
2000-01-06	-0.202646	-0.655969	0.193421	NaN	cool
2000-01-07	0.553439	1.318152	-0.469305	foo	cool
2000-01-08	0.675554	-1.817027	-0.183109	bar	cool

```
# on-disk operations
In [326]: store.append('df_dc', df_dc, data_columns = ['B', 'C', 'string', 'string2'])

In [327]: store.select('df_dc', [ Term('B>0') ])
Out[327]:
```

	A	B	C	string	string2
2000-01-01	0.887163	0.859588	-0.636524	foo	cool
2000-01-02	0.015696	1.000000	1.000000	foo	cool
2000-01-03	0.991946	1.000000	1.000000	foo	cool
2000-01-04	-0.334077	0.002118	0.405453	foo	cool
2000-01-05	0.289092	1.321158	-1.546906	NaN	cool
2000-01-07	0.553439	1.318152	-0.469305	foo	cool

```
# getting creative
In [328]: store.select('df_dc', 'B > 0 & C > 0 & string == foo')
Out[328]:
```

	A	B	C	string	string2
2000-01-02	0.015696	1.000000	1.000000	foo	cool
2000-01-03	0.991946	1.000000	1.000000	foo	cool
2000-01-04	-0.334077	0.002118	0.405453	foo	cool

```
# this is in-memory version of this type of selection
In [329]: df_dc[(df_dc.B > 0) & (df_dc.C > 0) & (df_dc.string == 'foo')]
Out[329]:
```

	A	B	C	string	string2
2000-01-02	0.015696	1.000000	1.000000	foo	cool
2000-01-03	0.991946	1.000000	1.000000	foo	cool
2000-01-04	-0.334077	0.002118	0.405453	foo	cool

```
# we have automagically created this index and the B/C/string/string2
# columns are stored separately as ``PyTables`` columns
In [330]: store.root.df_dc.table
Out[330]:
```

```
/df_dc/table (Table(8,)) ''
description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": Float64Col(shape=(1,), dflt=0.0, pos=1),
  "B": Float64Col(shape=(), dflt=0.0, pos=2),
  "C": Float64Col(shape=(), dflt=0.0, pos=3),
  "string": StringCol(itemsizes=3, shape=(), dflt='', pos=4),
  "string2": StringCol(itemsizes=4, shape=(), dflt='', pos=5)}
byteorder := 'little'
chunkshape := (1680,)
autoindex := True
colindexes := {
  "index": Index(6, medium, shuffle, zlib(1)).is_csi=False,
  "C": Index(6, medium, shuffle, zlib(1)).is_csi=False,
  "B": Index(6, medium, shuffle, zlib(1)).is_csi=False,
  "string2": Index(6, medium, shuffle, zlib(1)).is_csi=False,
  "string": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

There is some performance degradation by making lots of columns into *data columns*, so it is up to the user to designate these. In addition, you cannot change data columns (nor indexables) after the first append/put operation (Of course you can simply read in the data and create a new table!)

24.8.10 Iterator

Starting in 0.11.0, you can pass, `iterator=True` or `chunksize=number_in_a_chunk` to select and `select_as_multiple` to return an iterator on the results. The default is 50,000 rows returned in a chunk.

```
In [331]: for df in store.select('df', chunksize=3):
.....:     print(df)
.....:
```

	A	B	C
2000-01-01	0.887163	0.859588	-0.636524
2000-01-02	0.015696	-2.242685	1.150036
2000-01-03	0.991946	0.953324	-2.021255
	A	B	C
2000-01-04	-0.334077	0.002118	0.405453
2000-01-05	0.289092	1.321158	-1.546906
2000-01-06	-0.202646	-0.655969	0.193421
	A	B	C
2000-01-07	0.553439	1.318152	-0.469305
2000-01-08	0.675554	-1.817027	-0.183109

Note: New in version 0.12.0.

You can also use the iterator with `read_hdf` which will open, then automatically close the store when finished iterating.

```
for df in read_hdf('store.h5', 'df', chunksize=3):
    print(df)
```

Note, that the `chunksize` keyword applies to the **source** rows. So if you are doing a query, then the `chunksize` will subdivide the total rows in the table and the query applied, returning an iterator on potentially unequal sized chunks.

Here is a recipe for generating a query and using it to create equal sized return chunks.

```
In [332]: dfreq = DataFrame({'number': np.arange(1,11)})
```

```
In [333]: dfreq
```

```
Out[333]:
```

	number
0	1
1	2
2	3
3	4
4	5
5	6
6	7
7	8
8	9
9	10

```
In [334]: store.append('dfreq', dfreq, data_columns=['number'])
```

```
In [335]: def chunks(l, n):
```

```
.....:     return [l[i:i+n] for i in range(0, len(l), n)]
.....:
```

```
In [336]: evens = [2,4,6,8,10]
```

```
In [337]: coordinates = store.select_as_coordinates('dfreq', 'number=evens')
```

```
In [338]: for c in chunks(coordinates, 2):
.....:     print store.select('dfeq', where=c)
.....:
number
1      2
3      4
number
5      6
7      8
number
9     10
```

24.8.11 Advanced Queries

Select a Single Column

To retrieve a single indexable or data column, use the method `select_column`. This will, for example, enable you to get the index very quickly. These return a `Series` of the result, indexed by the row number. These do not currently accept the `where` selector.

```
In [339]: store.select_column('df_dc', 'index')
Out[339]:
0    2000-01-01
1    2000-01-02
2    2000-01-03
3    2000-01-04
4    2000-01-05
5    2000-01-06
6    2000-01-07
7    2000-01-08
dtype: datetime64[ns]
```

```
In [340]: store.select_column('df_dc', 'string')
Out[340]:
0    foo
1    foo
2    foo
3    foo
4    NaN
5    NaN
6    foo
7    bar
dtype: object
```

Selecting coordinates

Sometimes you want to get the coordinates (a.k.a the index locations) of your query. This returns an `Int64Index` of the resulting locations. These coordinates can also be passed to subsequent `where` operations.

```
In [341]: df_coord = DataFrame(np.random.randn(1000,2), index=date_range('20000101', periods=1000))

In [342]: store.append('df_coord', df_coord)

In [343]: c = store.select_as_coordinates('df_coord', 'index>20020101')

In [344]: c.summary()
Out[344]: u'Int64Index: 268 entries, 732 to 999'
```

```
In [345]: store.select('df_coord', where=c)
```

```
Out[345]:
```

	0	1
2002-01-02	-0.667994	-0.368175
2002-01-03	0.020119	-0.823208
2002-01-04	-0.165481	0.720866
2002-01-05	1.295919	-0.527767
2002-01-06	-0.463393	-0.150792
2002-01-07	-1.139341	-0.954387
2002-01-08	0.051837	-0.147048
...	...	...
2002-09-20	0.058626	-0.489107
2002-09-21	-0.356873	-0.437071
2002-09-22	-0.243534	-0.093778
2002-09-23	-0.615983	0.414649
2002-09-24	0.202096	-0.297561
2002-09-25	0.681661	0.538311
2002-09-26	-0.614051	0.769058

```
[268 rows x 2 columns]
```

Selecting using a where mask

Sometime your query can involve creating a list of rows to select. Usually this mask would be a resulting index from an indexing operation. This example selects the months of a datetimeindex which are 5.

```
In [346]: df_mask = DataFrame(np.random.randn(1000,2), index=date_range('20000101', periods=1000))
```

```
In [347]: store.append('df_mask', df_mask)
```

```
In [348]: c = store.select_column('df_mask', 'index')
```

```
In [349]: where = c[DatetimeIndex(c).month==5].index
```

```
In [350]: store.select('df_mask', where=where)
```

```
Out[350]:
```

	0	1
2000-05-01	-0.098554	-0.280782
2000-05-02	0.739851	1.627182
2000-05-03	0.030132	-0.145601
2000-05-04	0.227530	1.048856
2000-05-05	1.773939	1.116887
2000-05-06	1.081251	1.509416
2000-05-07	-0.498694	-0.913155
...	...	...
2002-05-25	-0.497252	0.348099
2002-05-26	-1.287350	-1.488122
2002-05-27	-0.726220	0.507747
2002-05-28	0.189871	0.980528
2002-05-29	0.555156	0.369371
2002-05-30	-0.637441	-3.434819
2002-05-31	-0.070283	-0.278044

```
[93 rows x 2 columns]
```

Storer Object

If you want to inspect the stored object, retrieve via `get_storer`. You could use this programmatically to say get the number of rows in an object.

```
In [351]: store.get_storer('df_dc').nrows
Out[351]: 8
```

24.8.12 Multiple Table Queries

New in 0.10.1 are the methods `append_to_multiple` and `select_as_multiple`, that can perform appending/selecting from multiple tables at once. The idea is to have one table (call it the selector table) that you index most/all of the columns, and perform your queries. The other table(s) are data tables with an index matching the selector table's index. You can then perform a very fast query on the selector table, yet get lots of data back. This method is similar to having a very wide table, but enables more efficient queries.

The `append_to_multiple` method splits a given single DataFrame into multiple tables according to `d`, a dictionary that maps the table names to a list of 'columns' you want in that table. If `None` is used in place of a list, that table will have the remaining unspecified columns of the given DataFrame. The argument `selector` defines which table is the selector table (which you can make queries from). The argument `dropna` will drop rows from the input DataFrame to ensure tables are synchronized. This means that if a row for one of the tables being written to is entirely `np.NaN`, that row will be dropped from all tables.

If `dropna` is `False`, **THE USER IS RESPONSIBLE FOR SYNCHRONIZING THE TABLES**. Remember that entirely `np.NaN` rows are not written to the HDFStore, so if you choose to call `dropna=False`, some tables may have more rows than others, and therefore `select_as_multiple` may not work or it may return unexpected results.

```
In [352]: df_mt = DataFrame(randn(8, 6), index=date_range('1/1/2000', periods=8),
.....:                      columns=['A', 'B', 'C', 'D', 'E', 'F'])
.....:
```

```
In [353]: df_mt['foo'] = 'bar'
```

```
In [354]: df_mt.ix[1, ('A', 'B')] = np.nan
```

```
# you can also create the tables individually
```

```
In [355]: store.append_to_multiple({'df1_mt': ['A', 'B'], 'df2_mt': None },
.....:                             df_mt, selector='df1_mt')
.....:
```

```
In [356]: store
```

```
Out[356]:
```

```
<class 'pandas.io.pytables.HDFStore'>
```

```
File path: store.h5
```

/df	frame_table	(typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt	frame_table	(typ->appendable,nrows->7,ncols->2,indexers->[index],dc->[A,B])
/df2_mt	frame_table	(typ->appendable,nrows->7,ncols->5,indexers->[index])
/df_coord	frame_table	(typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc	frame_table	(typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,st])
/df_mask	frame_table	(typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi	frame_table	(typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[A,B,C])
/df_mixed	frame_table	(typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfeq	frame_table	(typ->appendable,nrows->10,ncols->1,indexers->[index],dc->[numbe])
/dfq	frame_table	(typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C])
/dftd	frame_table	(typ->appendable,nrows->10,ncols->3,indexers->[index],dc->[A,B,C])
/foo/bar/bah	frame	(shape->[8,3])
/wp	wide_table	(typ->appendable,nrows->20,ncols->2,indexers->[major_axis,minor_axis])

```
# individual tables were created
```

```
In [357]: store.select('df1_mt')
```

Out [357]:

	A	B
2000-01-01	-0.816310	1.282296
2000-01-03	0.684353	-1.755306
2000-01-04	-1.315814	1.455079
2000-01-05	-0.027564	0.046757
2000-01-06	-0.416244	-0.821168
2000-01-07	0.665090	1.084344
2000-01-08	0.607460	0.790907

In [358]: store.select('df2_mt')

Out [358]:

	C	D	E	F	foo
2000-01-01	-1.521825	-0.428670	-1.550209	0.826839	bar
2000-01-03	1.236974	-1.328279	0.662291	1.894976	bar
2000-01-04	-0.746478	0.851039	1.415686	-0.929096	bar
2000-01-05	-1.452287	1.575492	-0.197377	-0.219901	bar
2000-01-06	1.190342	2.115021	0.148762	1.073931	bar
2000-01-07	-0.709897	-2.022441	0.714697	0.318215	bar
2000-01-08	0.852225	0.096696	-0.379903	0.929313	bar

as a multiple

In [359]: store.select_as_multiple(['df1_mt', 'df2_mt'], where=['A>0', 'B>0'],
: selector = 'df1_mt')

Out [359]:

	A	B	C	D	E	F	foo
2000-01-07	0.66509	1.084344	-0.709897	-2.022441	0.714697	0.318215	bar
2000-01-08	0.60746	0.790907	0.852225	0.096696	-0.379903	0.929313	bar

24.8.13 Delete from a Table

You can delete from a table selectively by specifying a `where`. In deleting rows, it is important to understand the PyTables deletes rows by erasing the rows, then **moving** the following data. Thus deleting can potentially be a very expensive operation depending on the orientation of your data. This is especially true in higher dimensional objects (Panel and Panel4D). To get optimal performance, it's worthwhile to have the dimension you are deleting be the first of the indexables.

Data is ordered (on the disk) in terms of the `indexables`. Here's a simple use case. You store panel-type data, with dates in the `major_axis` and ids in the `minor_axis`. The data is then interleaved like this:

- **date_1**
 - id_1
 - id_2
 - .
 - id_n
- **date_2**
 - id_1
 - .
 - id_n

It should be clear that a delete operation on the `major_axis` will be fairly quick, as one chunk is removed, then the following data moved. On the other hand a delete operation on the `minor_axis` will be very expensive. In this case it would almost certainly be faster to rewrite the table using a `where` that selects all but the missing data.

```
# returns the number of rows deleted
In [360]: store.remove('wp', 'major_axis>20000102' )
Out[360]: 12

In [361]: store.select('wp')
Out[361]:
<class 'pandas.core.panel.Panel'>
Dimensions: 2 (items) x 2 (major_axis) x 4 (minor_axis)
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-02 00:00:00
Minor_axis axis: A to D
```

Please note that HDF5 **DOES NOT RECLAIM SPACE** in the h5 files automatically. Thus, repeatedly deleting (or removing nodes) and adding again **WILL TEND TO INCREASE THE FILE SIZE**. To *clean* the file, use `ptrepack` (see below).

24.8.14 Compression

`PyTables` allows the stored data to be compressed. This applies to all kinds of stores, not just tables.

- Pass `complevel=int` for a compression level (1-9, with 0 being no compression, and the default)
- Pass `complib=lib` where `lib` is any of `zlib`, `bzip2`, `lzo`, `blosc` for whichever compression library you prefer.

`HDFStore` will use the file based compression scheme if no overriding `complib` or `complevel` options are provided. `blosc` offers very fast compression, and is my most used. Note that `lzo` and `bzip2` may not be installed (by Python) by default.

Compression for all objects within the file

- `store_compressed = HDFStore('store_compressed.h5', complevel=9, complib='blosc')`

Or on-the-fly compression (this only applies to tables). You can turn off file compression for a specific table by passing `complevel=0`

- `store.append('df', df, complib='zlib', complevel=5)`

ptrepack

`PyTables` offers better write performance when tables are compressed after they are written, as opposed to turning on compression at the very beginning. You can use the supplied `PyTables` utility `ptrepack`. In addition, `ptrepack` can change compression levels after the fact.

- `ptrepack --chunkshape=auto --propindexes --complevel=9 --complib=blosc in.h5 out.h5`

Furthermore `ptrepack in.h5 out.h5` will *repack* the file to allow you to reuse previously deleted space. Alternatively, one can simply remove the file and write again, or use the `copy` method.

24.8.15 Notes & Caveats

- Once a table is created its items (Panel) / columns (DataFrame) are fixed; only exactly the same columns can be appended

- If a row has `np.nan` for **EVERY COLUMN** (having a `nan` in a string, or a `NaT` in a datetime-like column counts as having a value), then those rows **WILL BE DROPPED IMPLICITLY**. This limitation *may* be addressed in the future.
- `HDFStore` is **not-threadsafe for writing**. The underlying `PyTables` only supports concurrent reads (via threading or processes). If you need reading and writing *at the same time*, you need to serialize these operations in a single thread in a single process. You will corrupt your data otherwise. See the issue (:2397) for more information.
- If you use locks to manage write access between multiple processes, you may want to use `fsync()` before releasing write locks. For convenience you can use `store.flush(fsyntax=True)` to do this for you.
- `PyTables` only supports fixed-width string columns in tables. The sizes of a string based indexing column (e.g. `columns` or `minor_axis`) are determined as the maximum size of the elements in that axis or by passing the parameter
- Be aware that timezones (e.g., `pytz.timezone('US/Eastern')`) are not necessarily equal across timezone versions. So if data is localized to a specific timezone in the `HDFStore` using one version of a timezone library and that data is updated with another version, the data will be converted to UTC since these timezones are not considered equal. Either use the same version of timezone library or use `tz_convert` with the updated timezone definition.

Warning: `PyTables` will show a `NaturalNameWarning` if a column name cannot be used as an attribute selector. Generally identifiers that have spaces, start with numbers, or `_`, or have `-` embedded are not considered *natural*. These types of identifiers cannot be used in a `where` clause and are generally a bad idea.

24.8.16 DataTypes

`HDFStore` will map an object dtype to the `PyTables` underlying dtype. This means the following types are known to work:

- `floating`: `float64`, `float32`, `float16` (using `np.nan` to represent invalid values)
- `integer`: `int64`, `int32`, `int8`, `uint64`, `uint32`, `uint8`
- `bool`
- `datetime64[ns]` (using `NaT` to represent invalid values)
- `object`: strings (using `np.nan` to represent invalid values)

Currently, unicode and datetime columns (represented with a dtype of `object`), **WILL FAIL**. In addition, even though a column may look like a `datetime64[ns]`, if it contains `np.nan`, this **WILL FAIL**. You can try to convert datetimelike columns to proper `datetime64[ns]` columns, that possibly contain `NaT` to represent invalid values. (Some of these issues have been addressed and these conversion may not be necessary in future versions of pandas)

```
In [362]: import datetime

In [363]: df = DataFrame(dict(datelike=Series([datetime.datetime(2001, 1, 1),
.....:                                     datetime.datetime(2001, 1, 2), np.nan])))
.....:

In [364]: df
Out[364]:
   datelike
0 2001-01-01
1 2001-01-02
2          NaT
```

```
In [365]: df.dtypes
Out[365]:
datelike    datetime64[ns]
dtype: object

# to convert
In [366]: df['datelike'] = Series(df['datelike'].values, dtype='M8[ns]')

In [367]: df
Out[367]:
      datelike
0 2001-01-01
1 2001-01-02
2         NaT

In [368]: df.dtypes
Out[368]:
datelike    datetime64[ns]
dtype: object
```

24.8.17 Categorical Data

New in version 0.15.2.

Writing data to a `HDFStore` that contains a `category` dtype was implemented in 0.15.2. Queries work the same as if it was an object array. However, the `category` typed data is stored in a more efficient manner.

```
In [369]: dfcat = DataFrame({ 'A' : Series(list('aabbcdaba')).astype('category'),
.....:                        'B' : np.random.randn(8) })
.....:
```

```
In [370]: dfcat
Out[370]:
   A      B
0  a  0.811031
1  a -0.356817
2  b  1.047085
3  b  0.664705
4  c -0.086919
5  d  0.416905
6  b -0.764381
7  a -0.287229
```

```
In [371]: dfcat.dtypes
Out[371]:
A    category
B    float64
dtype: object
```

```
In [372]: cstore = pd.HDFStore('cats.h5', mode='w')
```

```
In [373]: cstore.append('dfcat', dfcat, format='table', data_columns=['A'])
```

```
In [374]: result = cstore.select('dfcat', where="A in ['b','c']")
```

```
In [375]: result
Out[375]:
```

```

      A      B
2  b  1.047085
3  b  0.664705
4  c -0.086919
6  b -0.764381

```

```
In [376]: result.dtypes
```

```
Out[376]:
```

```

A      category
B      float64
dtype: object

```

Warning: The format of the `Categorical` is readable by prior versions of pandas (< 0.15.2), but will retrieve the data as an integer based column (e.g. the codes). However, the categories *can* be retrieved but require the user to select them manually using the explicit meta path.

The data is stored like so:

```
In [377]: cstore
```

```
Out[377]:
```

```
<class 'pandas.io.pytables.HDFStore'>
```

```
File path: cats.h5
```

```
/dfcat                                     frame_table  (typ->appendable,nrows->8,ncols->2,indexers->[index],dc-
```

```
/dfcat/meta/A/meta                         series_table (typ->appendable,nrows->4,ncols->1,indexers->[index],dc-
```

```
# to get the categories
```

```
In [378]: cstore.select('dfcat/meta/A/meta')
```

```
Out[378]:
```

```

0      a
1      b
2      c
3      d
dtype: object

```

24.8.18 String Columns

min_itemsize

The underlying implementation of `HDFStore` uses a fixed column width (`itemsizes`) for string columns. A string column `itemsize` is calculated as the maximum of the length of data (for that column) that is passed to the `HDFStore`, **in the first append**. Subsequent appends, may introduce a string for a column **larger** than the column can hold, an `Exception` will be raised (otherwise you could have a silent truncation of these columns, leading to loss of information). In the future we may relax this and allow a user-specified truncation to occur.

Pass `min_itemsize` on the first table creation to a-priori specify the minimum length of a particular string column. `min_itemsize` can be an integer, or a dict mapping a column name to an integer. You can pass values as a key to allow all *indexables* or *data_columns* to have this `min_itemsize`.

Starting in 0.11.0, passing a `min_itemsize` dict will cause all passed columns to be created as *data_columns* automatically.

Note: If you are not passing any *data_columns*, then the `min_itemsize` will be the maximum of the length of any string passed

```
In [379]: dfs = DataFrame(dict(A = 'foo', B = 'bar'), index=list(range(5)))
```

```
In [380]: dfs
Out[380]:
   A    B
0  foo  bar
1  foo  bar
2  foo  bar
3  foo  bar
4  foo  bar

# A and B have a size of 30
In [381]: store.append('dfs', dfs, min_itemsize = 30)

In [382]: store.get_storer('dfs').table
Out[382]:
/dfs/table (Table(5,)) ''
description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": StringCol(itemsizes=30, shape=(2,), dflt='', pos=1)}
byteorder := 'little'
chunkshape := (963,)
autoindex := True
colindexes := {
  "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}

# A is created as a data_column with a size of 30
# B is size is calculated
In [383]: store.append('dfs2', dfs, min_itemsize = { 'A' : 30 })

In [384]: store.get_storer('dfs2').table
Out[384]:
/dfs2/table (Table(5,)) ''
description := {
  "index": Int64Col(shape=(), dflt=0, pos=0),
  "values_block_0": StringCol(itemsizes=3, shape=(1,), dflt='', pos=1),
  "A": StringCol(itemsizes=30, shape=(), dflt='', pos=2)}
byteorder := 'little'
chunkshape := (1598,)
autoindex := True
colindexes := {
  "A": Index(6, medium, shuffle, zlib(1)).is_csi=False,
  "index": Index(6, medium, shuffle, zlib(1)).is_csi=False}
```

nan_rep

String columns will serialize a `np.nan` (a missing value) with the `nan_rep` string representation. This defaults to the string value `nan`. You could inadvertently turn an actual `nan` value into a missing value.

```
In [385]: dfss = DataFrame(dict(A = ['foo', 'bar', 'nan']))

In [386]: dfss
Out[386]:
   A
0  foo
1  bar
2  nan

In [387]: store.append('dfss', dfss)

In [388]: store.select('dfss')
```

```

Out[388]:
      A
0  foo
1  bar
2  NaN

# here you need to specify a different nan rep
In [389]: store.append('dfss2', dfss, nan_rep='_nan_')

In [390]: store.select('dfss2')
Out[390]:
      A
0  foo
1  bar
2  nan

```

24.8.19 External Compatibility

HDFStore writes table format objects in specific formats suitable for producing loss-less round trips to pandas objects. For external compatibility, HDFStore can read native PyTables format tables.

It is possible to write an HDFStore object that can easily be imported into R using the rhdf5 library ([Package website](#)). Create a table format store like this:

```

In [391]: np.random.seed(1)

In [392]: df_for_r = pd.DataFrame({"first": np.random.rand(100),
.....:                           "second": np.random.rand(100),
.....:                           "class": np.random.randint(0, 2, (100,))},
.....:                           index=range(100))
.....:

In [393]: df_for_r.head()
Out[393]:
   class  first  second
0      0  0.417022  0.326645
1      0  0.720324  0.527058
2      1  0.000114  0.885942
3      1  0.302333  0.357270
4      1  0.146756  0.908535

In [394]: store_export = HDFStore('export.h5')

In [395]: store_export.append('df_for_r', df_for_r, data_columns=df_dc.columns)

In [396]: store_export
Out[396]:
<class 'pandas.io.pytables.HDFStore'>
File path: export.h5
/df_for_r          frame_table  (typ->appendable,nrows->100,ncols->3,indexers->[index])

```

In R this file can be read into a `data.frame` object using the `rhdf5` library. The following example function reads the corresponding column names and data values from the values and assembles them into a `data.frame`:

```

# Load values and column names for all datasets from corresponding nodes and
# insert them into one data.frame object.

```

```
library(rhdf5)

loadhdf5data <- function(h5File) {

  listing <- h5ls(h5File)
  # Find all data nodes, values are stored in *_values and corresponding column
  # titles in *_items
  data_nodes <- grep("_values", listing$name)
  name_nodes <- grep("_items", listing$name)
  data_paths = paste(listing$group[data_nodes], listing$name[data_nodes], sep = "/")
  name_paths = paste(listing$group[name_nodes], listing$name[name_nodes], sep = "/")
  columns = list()
  for (idx in seq(data_paths)) {
    # NOTE: matrices returned by h5read have to be transposed to to obtain
    # required Fortran order!
    data <- data.frame(t(h5read(h5File, data_paths[idx])))
    names <- t(h5read(h5File, name_paths[idx]))
    entry <- data.frame(data)
    colnames(entry) <- names
    columns <- append(columns, entry)
  }

  data <- data.frame(columns)

  return(data)
}
```

Now you can import the DataFrame into R:

```
> data = loadhdf5data("transfer.hdf5")
> head(data)
      first      second class
1 0.4170220047 0.3266449    0
2 0.7203244934 0.5270581    0
3 0.0001143748 0.8859421    1
4 0.3023325726 0.3572698    1
5 0.1467558908 0.9085352    1
6 0.0923385948 0.6233601    1
```

Note: The R function lists the entire HDF5 file's contents and assembles the `data.frame` object from all matching nodes, so use this only as a starting point if you have stored multiple DataFrame objects to a single HDF5 file.

24.8.20 Backwards Compatibility

0.10.1 of HDFStore can read tables created in a prior version of pandas, however query terms using the prior (un-documented) methodology are unsupported. HDFStore will issue a warning if you try to use a legacy-format file. You must read in the entire file and write it out using the new format, using the method `copy` to take advantage of the updates. The group attribute `pandas_version` contains the version information. `copy` takes a number of options, please see the docstring.

```
# a legacy store
In [397]: legacy_store = HDFStore(legacy_file_path, 'r')

In [398]: legacy_store
Out[398]:
<class 'pandas.io.pytables.HDFStore'>
```

```

File path: /home/joris/scipy/pandas/doc/source/_static/legacy_0.10.h5
/a          series          (shape->[30])
/b          frame          (shape->[30,4])
/df1_mixed  frame_table    [0.10.0] (typ->appendable,nrows->30,ncols->11,indexers->[index])
/foo/bar    wide           (shape->[3,30,4])
/p1_mixed   wide_table     [0.10.0] (typ->appendable,nrows->120,ncols->9,indexers->[major_axis,minor_axis])
/p4d_mixed  ndim_table     [0.10.0] (typ->appendable,nrows->360,ncols->9,indexers->[items,major_axis,minor_axis])

# copy (and return the new handle)
In [399]: new_store = legacy_store.copy('store_new.h5')

In [400]: new_store
Out[400]:
<class 'pandas.io.pytables.HDFStore'>
File path: store_new.h5
/a          series          (shape->[30])
/b          frame          (shape->[30,4])
/df1_mixed  frame_table    (typ->appendable,nrows->30,ncols->11,indexers->[index])
/foo/bar    wide           (shape->[3,30,4])
/p1_mixed   wide_table     (typ->appendable,nrows->120,ncols->9,indexers->[major_axis,minor_axis])
/p4d_mixed  wide_table     (typ->appendable,nrows->360,ncols->9,indexers->[items,major_axis,minor_axis])

In [401]: new_store.close()

```

24.8.21 Performance

- tables format come with a writing performance penalty as compared to fixed stores. The benefit is the ability to append/delete and query (potentially very large amounts of data). Write times are generally longer as compared with regular stores. Query times can be quite fast, especially on an indexed axis.
- You can pass `chunksize=<int>` to `append`, specifying the write chunksize (default is 50000). This will significantly lower your memory usage on writing.
- You can pass `expectedrows=<int>` to the first `append`, to set the TOTAL number of expected rows that PyTables will expect. This will optimize read/write performance.
- Duplicate rows can be written to tables, but are filtered out in selection (with the last items being selected; thus a table is unique on major, minor pairs)
- A `PerformanceWarning` will be raised if you are attempting to store types that will be pickled by PyTables (rather than stored as endemic types). See [Here](#) for more information and some solutions.

24.8.22 Experimental

HDFStore supports Panel4D storage.

```

In [402]: p4d = Panel4D({ 'l1' : wp })

In [403]: p4d
Out[403]:
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 1 (labels) x 2 (items) x 5 (major_axis) x 4 (minor_axis)
Labels axis: l1 to l1
Items axis: Item1 to Item2
Major_axis axis: 2000-01-01 00:00:00 to 2000-01-05 00:00:00
Minor_axis axis: A to D

```

```
In [404]: store.append('p4d', p4d)
```

```
In [405]: store
```

```
Out [405]:
```

```
<class 'pandas.io.pytables.HDFStore'>
```

```
File path: store.h5
```

```
/df                frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt           frame_table  (typ->appendable,nrows->7,ncols->2,indexers->[index],dc->[A,B])
/df2_mt           frame_table  (typ->appendable,nrows->7,ncols->5,indexers->[index])
/df_coord         frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc            frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,sta
/df_mask          frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi            frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[A,B,C])
/df_mixed         frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfeq             frame_table  (typ->appendable,nrows->10,ncols->1,indexers->[index],dc->[numbe
/dfq              frame_table  (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C])
/dfs              frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index])
/dfs2             frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfss             frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dfss2            frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dftd             frame_table  (typ->appendable,nrows->10,ncols->3,indexers->[index],dc->[A,B,C])
/foo/bar/bah      frame       (shape->[8,3])
/p4d              wide_table   (typ->appendable,nrows->40,ncols->1,indexers->[items,major_axis,minor_axis])
/wp              wide_table   (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,minor_axis])
```

These, by default, index the three axes items, `major_axis`, `minor_axis`. On an `AppendableTable` it is possible to setup with the first append a different indexing scheme, depending on how you want to store your data. Pass the `axes` keyword with a list of dimensions (currently must by exactly 1 less than the total dimensions of the object). This cannot be changed after table creation.

```
In [406]: store.append('p4d2', p4d, axes=['labels', 'major_axis', 'minor_axis'])
```

```
In [407]: store
```

```
Out [407]:
```

```
<class 'pandas.io.pytables.HDFStore'>
```

```
File path: store.h5
```

```
/df                frame_table  (typ->appendable,nrows->8,ncols->3,indexers->[index])
/df1_mt           frame_table  (typ->appendable,nrows->7,ncols->2,indexers->[index],dc->[A,B])
/df2_mt           frame_table  (typ->appendable,nrows->7,ncols->5,indexers->[index])
/df_coord         frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_dc            frame_table  (typ->appendable,nrows->8,ncols->5,indexers->[index],dc->[B,C,sta
/df_mask          frame_table  (typ->appendable,nrows->1000,ncols->2,indexers->[index])
/df_mi            frame_table  (typ->appendable_multi,nrows->10,ncols->5,indexers->[index],dc->[A,B,C])
/df_mixed         frame_table  (typ->appendable,nrows->8,ncols->7,indexers->[index])
/dfeq             frame_table  (typ->appendable,nrows->10,ncols->1,indexers->[index],dc->[numbe
/dfq              frame_table  (typ->appendable,nrows->10,ncols->4,indexers->[index],dc->[A,B,C])
/dfs              frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index])
/dfs2             frame_table  (typ->appendable,nrows->5,ncols->2,indexers->[index],dc->[A])
/dfss             frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dfss2            frame_table  (typ->appendable,nrows->3,ncols->1,indexers->[index])
/dftd             frame_table  (typ->appendable,nrows->10,ncols->3,indexers->[index],dc->[A,B,C])
/foo/bar/bah      frame       (shape->[8,3])
/p4d              wide_table   (typ->appendable,nrows->40,ncols->1,indexers->[items,major_axis,minor_axis])
/p4d2             wide_table   (typ->appendable,nrows->20,ncols->2,indexers->[labels,major_axis,minor_axis])
/wp              wide_table   (typ->appendable,nrows->8,ncols->2,indexers->[major_axis,minor_axis])
```

```
In [408]: store.select('p4d2', [ Term('labels=11'), Term('items=Item1'), Term('minor_axis=A_big_string')])
```

```
Out [408]:
```

```
<class 'pandas.core.panelnd.Panel4D'>
Dimensions: 0 (labels) x 1 (items) x 0 (major_axis) x 0 (minor_axis)
Labels axis: None
Items axis: Item1 to Item1
Major_axis axis: None
Minor_axis axis: None
```

24.9 SQL Queries

The `pandas.io.sql` module provides a collection of query wrappers to both facilitate data retrieval and to reduce dependency on DB-specific API. Database abstraction is provided by SQLAlchemy if installed, in addition you will need a driver library for your database.

New in version 0.14.0.

If SQLAlchemy is not installed, a fallback is only provided for sqlite (and for mysql for backwards compatibility, but this is deprecated and will be removed in a future version). This mode requires a Python database adapter which respect the [Python DB-API](#).

See also some [cookbook examples](#) for some advanced strategies.

The key functions are:

<code>read_sql_table(table_name, con[, schema, ...])</code>	Read SQL database table into a DataFrame.
<code>read_sql_query(sql, con[, index_col, ...])</code>	Read SQL query into a DataFrame.
<code>read_sql(sql, con[, index_col, ...])</code>	Read SQL query or database table into a DataFrame.
<code>DataFrame.to_sql(name, con[, flavor, ...])</code>	Write records stored in a DataFrame to a SQL database.

24.9.1 pandas.read_sql_table

```
pandas.read_sql_table(table_name, con, schema=None, index_col=None, coerce_float=True,
                      parse_dates=None, columns=None, chunksize=None)
```

Read SQL database table into a DataFrame.

Given a table name and an SQLAlchemy engine, returns a DataFrame. This function does not support DBAPI connections.

Parameters `table_name` : string

Name of SQL table in database

con : SQLAlchemy engine

Sqlite DBAPI connection mode not supported

schema : string, default None

Name of SQL schema in database to query (if database flavor supports this). If None, use default schema (default).

index_col : string, optional

Column to set as index

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point. Can result in loss of Precision.

parse_dates : list or dict

- List of column names to parse as dates
- Dict of {column_name: format string} where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps
- Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite

columns : list

List of column names to select from sql table

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

read_sql_query Read SQL query into a DataFrame.

`read_sql`

Notes

Any datetime values with time zone information will be converted to UTC

24.9.2 pandas.read_sql_query

`pandas.read_sql_query(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, chunksize=None)`

Read SQL query into a DataFrame.

Returns a DataFrame corresponding to the result set of the query string. Optionally provide an *index_col* parameter to use one of the columns as the index, otherwise default integer index will be used.

Parameters *sql* : string

SQL query to be executed

con : SQLAlchemy engine or sqlite3 DBAPI2 connection

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

Column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses `%(name)s` so use `params={'name': 'value'}`

parse_dates : list or dict

- List of column names to parse as dates
- Dict of {`column_name`: `format string`} where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps
- Dict of {`column_name`: `arg dict`}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

read_sql_table Read SQL database table into a DataFrame

read_sql

Notes

Any datetime values with time zone information parsed via the *parse_dates* parameter will be converted to UTC

24.9.3 pandas.read_sql

`pandas.read_sql(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, columns=None, chunksize=None)`
Read SQL query or database table into a DataFrame.

Parameters **sql** : string

SQL query to be executed or database table name.

con : SQLAlchemy engine or DBAPI2 connection (fallback mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses `%(name)s` so use `params={'name': 'value'}`

parse_dates : list or dict

- List of column names to parse as dates
- Dict of {`column_name`: `format string`} where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps
- Dict of {`column_name`: `arg dict`}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite

columns : list

List of column names to select from sql table (only used when reading a table).

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

read_sql_table Read SQL database table into a DataFrame

read_sql_query Read SQL query into a DataFrame

Notes

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (and for backward compatibility) and will delegate to the specific function depending on the provided input (database table name or sql query). The delegated function might have more specific notes about their functionality not listed here.

24.9.4 pandas.DataFrame.to_sql

`DataFrame.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : { 'fail', 'replace', 'append' }, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

Note: The function `read_sql()` is a convenience wrapper around `read_sql_table()` and `read_sql_query()` (and for backward compatibility) and will delegate to specific function depending on the provided input (database table name or sql query). Table names do not need to be quoted if they have special characters.

In the following example, we use the [SQLite](#) SQL database engine. You can use a temporary SQLite database where data are stored in “memory”.

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to. For more information on `create_engine()` and the URI formatting, see the examples below and the SQLAlchemy [documentation](#)

```
In [409]: from sqlalchemy import create_engine

# Create your connection.
In [410]: engine = create_engine('sqlite:///memory:')
```

24.9.5 Writing DataFrames

Assuming the following data is in a DataFrame `data`, we can insert it into the database using `to_sql()`.

id	Date	Col_1	Col_2	Col_3
26	2012-10-18	X	25.7	True
42	2012-10-19	Y	-12.4	False
63	2012-10-20	Z	5.73	True

```
In [411]: data.to_sql('data', engine)
```

With some databases, writing large DataFrames can result in errors due to packet size limitations being exceeded. This can be avoided by setting the `chunksize` parameter when calling `to_sql`. For example, the following writes data to the database in batches of 1000 rows at a time:

```
In [412]: data.to_sql('data_chunked', engine, chunksize=1000)
```

SQL data types

`to_sql()` will try to map your data to an appropriate SQL data type based on the dtype of the data. When you have columns of dtype object, pandas will try to infer the data type.

You can always override the default type by specifying the desired SQL type of any of the columns by using the `dtype` argument. This argument needs a dictionary mapping column names to SQLAlchemy types (or strings for the sqlite3 fallback mode). For example, specifying to use the sqlalchemy `String` type instead of the default `Text` type for string columns:

```
In [413]: from sqlalchemy.types import String
```

```
In [414]: data.to_sql('data_dtype', engine, dtype={'Col_1': String})
```

Note: Due to the limited support for `timedelta`'s in the different database flavors, columns with type `timedelta64` will be written as integer values as nanoseconds to the database and a warning will be raised.

Note: Columns of `category` dtype will be converted to the dense representation as you would get with `np.asarray(categorical)` (e.g. for string categories this gives an array of strings). Because of this, reading the database table back in does **not** generate a categorical.

24.9.6 Reading Tables

`read_sql_table()` will read a database table given the table name and optionally a subset of columns to read.

Note: In order to use `read_sql_table()`, you **must** have the SQLAlchemy optional dependency installed.

```
In [415]: pd.read_sql_table('data', engine)
```

```
Out[415]:
```

	index	id	Date	Col_1	Col_2	Col_3
0	0	26	2010-10-18	X	27.50	True
1	1	42	2010-10-19	Y	-12.50	False
2	2	63	2010-10-20	Z	5.73	True

You can also specify the name of the column as the DataFrame index, and specify a subset of columns to be read.

```
In [416]: pd.read_sql_table('data', engine, index_col='id')
```

```
Out[416]:
```

	index	Date	Col_1	Col_2	Col_3
id					
26	0	2010-10-18	X	27.50	True
42	1	2010-10-19	Y	-12.50	False
63	2	2010-10-20	Z	5.73	True

```
In [417]: pd.read_sql_table('data', engine, columns=['Col_1', 'Col_2'])
```

```
Out[417]:
```

	Col_1	Col_2
0	X	27.50

```
1      Y -12.50
2      Z   5.73
```

And you can explicitly force columns to be parsed as dates:

```
In [418]: pd.read_sql_table('data', engine, parse_dates=['Date'])
```

```
Out[418]:
```

	index	id	Date	Col_1	Col_2	Col_3
0	0	26	2010-10-18	X	27.50	True
1	1	42	2010-10-19	Y	-12.50	False
2	2	63	2010-10-20	Z	5.73	True

If needed you can explicitly specify a format string, or a dict of arguments to pass to `pandas.to_datetime()`:

```
pd.read_sql_table('data', engine, parse_dates={'Date': '%Y-%m-%d'})
pd.read_sql_table('data', engine, parse_dates={'Date': {'format': '%Y-%m-%d %H:%M:%S'}})
```

You can check if a table exists using `has_table()`

24.9.7 Schema support

New in version 0.15.0.

Reading from and writing to different schema's is supported through the `schema` keyword in the `read_sql_table()` and `to_sql()` functions. Note however that this depends on the database flavor (sqlite does not have schema's). For example:

```
df.to_sql('table', engine, schema='other_schema')
pd.read_sql_table('table', engine, schema='other_schema')
```

24.9.8 Querying

You can query using raw SQL in the `read_sql_query()` function. In this case you must use the SQL variant appropriate for your database. When using SQLAlchemy, you can also pass SQLAlchemy Expression language constructs, which are database-agnostic.

```
In [419]: pd.read_sql_query('SELECT * FROM data', engine)
```

```
Out[419]:
```

	index	id	Date	Col_1	Col_2	Col_3
0	0	26	2010-10-18 00:00:00.000000	X	27.50	1
1	1	42	2010-10-19 00:00:00.000000	Y	-12.50	0
2	2	63	2010-10-20 00:00:00.000000	Z	5.73	1

Of course, you can specify a more “complex” query.

```
In [420]: pd.read_sql_query("SELECT id, Col_1, Col_2 FROM data WHERE id = 42;", engine)
```

```
Out[420]:
```

	id	Col_1	Col_2
0	42	Y	-12.5

The `read_sql_query()` function supports a `chunksize` argument. Specifying this will return an iterator through chunks of the query result:

```
In [421]: df = pd.DataFrame(np.random.randn(20, 3), columns=list('abc'))
```

```
In [422]: df.to_sql('data_chunks', engine, index=False)
```

```
In [423]: for chunk in pd.read_sql_query("SELECT * FROM data_chunks", engine, chunksize=5):
.....:     print(chunk)
.....:
```

	a	b	c
0	0.280665	-0.073113	1.160339
1	0.369493	1.904659	1.111057
2	0.659050	-1.627438	0.602319
3	0.420282	0.810952	1.044442
4	-0.400878	0.824006	-0.562305

	a	b	c
0	1.954878	-1.331952	-1.760689
1	-1.650721	-0.890556	-1.119115
2	1.956079	-0.326499	-1.342676
3	1.114383	-0.586524	-1.236853
4	0.875839	0.623362	-0.434957

	a	b	c
0	1.407540	0.129102	1.616950
1	0.502741	1.558806	0.109403
2	-1.219744	2.449369	-0.545774
3	-0.198838	-0.700399	-0.203394
4	0.242669	0.201830	0.661020

	a	b	c
0	1.792158	-0.120465	-1.233121
1	-1.182318	-0.665755	-1.674196
2	0.825030	-0.498214	-0.310985
3	-0.001891	-1.396620	-0.861316
4	0.674712	0.618539	-0.443172

You can also run a plain query without creating a dataframe with `execute()`. This is useful for queries that don't return values, such as `INSERT`. This is functionally equivalent to calling `execute` on the SQLAlchemy engine or db connection object. Again, you must use the SQL syntax variant appropriate for your database.

```
from pandas.io import sql
sql.execute('SELECT * FROM table_name', engine)
sql.execute('INSERT INTO table_name VALUES(?, ?, ?)', engine, params=[('id', 1, 12.2, True)])
```

24.9.9 Engine connection examples

To connect with SQLAlchemy you use the `create_engine()` function to create an engine object from database URI. You only need to create the engine once per database you are connecting to.

```
from sqlalchemy import create_engine

engine = create_engine('postgres://scott:tiger@localhost:5432/mydatabase')

engine = create_engine('mysql+mysqldb://scott:tiger@localhost/foo')

engine = create_engine('oracle://scott:tiger@127.0.0.1:1521/sidname')

engine = create_engine('mssql+pyodbc://mydsn')

# sqlite://<nohostname>/<path>
# where <path> is relative:
engine = create_engine('sqlite:///foo.db')

# or absolute, starting with a slash:
engine = create_engine('sqlite:///absolute/path/to/foo.db')
```

For more information see the examples the SQLAlchemy [documentation](#)

24.9.10 Sqlite fallback

The use of sqlite is supported without using SQLAlchemy. This mode requires a Python database adapter which respect the [Python DB-API](#).

You can create connections like so:

```
import sqlite3
con = sqlite3.connect(':memory:')
```

And then issue the following queries:

```
data.to_sql('data', cnx)
pd.read_sql_query("SELECT * FROM data", con)
```

24.10 Google BigQuery (Experimental)

New in version 0.13.0.

The `pandas.io.gbq` module provides a wrapper for Google's BigQuery analytics web service to simplify retrieving results from BigQuery tables using SQL-like queries. Result sets are parsed into a pandas DataFrame with a shape and data types derived from the source table. Additionally, DataFrames can be appended to existing BigQuery tables if the destination table is the same shape as the DataFrame.

For specifics on the service itself, see [here](#)

As an example, suppose you want to load all data from an existing BigQuery table : `test_dataset.test_table` into a DataFrame using the `read_gbq()` function.

```
# Insert your BigQuery Project ID Here
# Can be found in the Google web console
projectid = "xxxxxxx"

data_frame = pd.read_gbq('SELECT * FROM test_dataset.test_table', project_id = projectid)
```

You will then be authenticated to the specified BigQuery account via Google's OAuth2 mechanism. In general, this is as simple as following the prompts in a browser window which will be opened for you. Should the browser not be available, or fail to launch, a code will be provided to complete the process manually. Additional information on the authentication mechanism can be found [here](#)

You can define which column from BigQuery to use as an index in the destination DataFrame as well as a preferred column order as follows:

```
data_frame = pd.read_gbq('SELECT * FROM test_dataset.test_table',
                        index_col='index_column_name',
                        col_order=['col1', 'col2', 'col3'], project_id = projectid)
```

Finally, you can append data to a BigQuery table from a pandas DataFrame using the `to_gbq()` function. This function uses the Google streaming API which requires that your destination table exists in BigQuery. Given the BigQuery table already exists, your DataFrame should match the destination table in column order, structure, and data types. DataFrame indexes are not supported. By default, rows are streamed to BigQuery in chunks of 10,000 rows, but you can pass other chunk values via the `chunksize` argument. You can also see the progress of your post via the `verbose` flag which defaults to `True`. The http response code of Google BigQuery can be successful (200) even if the append failed. For this reason, if there is a failure to append to the table, the complete error response

from BigQuery is returned which can be quite long given it provides a status for each row. You may want to start with smaller chunks to test that the size and types of your dataframe match your destination table to make debugging simpler.

```
df = pandas.DataFrame({'string_col_name' : ['hello'],
                      'integer_col_name' : [1],
                      'boolean_col_name' : [True]})
df.to_gbq('my_dataset.my_table', project_id = projectid)
```

The BigQuery SQL query language has some oddities, see [here](#)

While BigQuery uses SQL-like syntax, it has some important differences from traditional databases both in functionality, API limitations (size and quantity of queries or uploads), and how Google charges for use of the service. You should refer to Google documentation often as the service seems to be changing and evolving. BigQuery is best for analyzing large sets of data quickly, but it is not a direct replacement for a transactional database.

You can access the management console to determine project id's by:
<<https://code.google.com/apis/console/b/0/?noredirect>>

As of 0.15.2, the gbq module has a function `generate_bq_schema` which will produce the dictionary representation of the schema.

```
df = pandas.DataFrame({'A': [1.0]})
gbq.generate_bq_schema(df, default_type='STRING')
```

Warning: To use this module, you will need a valid BigQuery account. See
<<https://cloud.google.com/products/big-query>> for details on the service.

24.11 Stata Format

New in version 0.12.0.

24.11.1 Writing to Stata format

The method `to_stata()` will write a DataFrame into a .dta file. The format version of this file is always 115 (Stata 12).

```
In [424]: df = DataFrame(randn(10, 2), columns=list('AB'))
```

```
In [425]: df.to_stata('stata.dta')
```

Stata data files have limited data type support; only strings with 244 or fewer characters, `int8`, `int16`, `int32`, `float32` and `float64` can be stored in .dta files. Additionally, *Stata* reserves certain values to represent missing data. Exporting a non-missing value that is outside of the permitted range in *Stata* for a particular data type will retype the variable to the next larger size. For example, `int8` values are restricted to lie between -127 and 100 in *Stata*, and so variables with values above 100 will trigger a conversion to `int16`. `nan` values in floating points data types are stored as the basic missing data type (`.` in *Stata*).

Note: It is not possible to export missing data values for integer data types.

The *Stata* writer gracefully handles other data types including `int64`, `bool`, `uint8`, `uint16`, `uint32` by casting to the smallest supported type that can represent the data. For example, data with a type of `uint8` will be cast to `int8` if all values are less than 100 (the upper bound for non-missing `int8` data in *Stata*), or, if values are outside of this range, the variable is cast to `int16`.

Warning: Conversion from `int64` to `float64` may result in a loss of precision if `int64` values are larger than `2**53`.

Warning: `StataWriter` and `to_stata()` only support fixed width strings containing up to 244 characters, a limitation imposed by the version 115 dta file format. Attempting to write *Stata* dta files with strings longer than 244 characters raises a `ValueError`.

24.11.2 Reading from Stata format

The top-level function `read_stata` will read a dta file and return either a `DataFrame` or a `StataReader` that can be used to read the file incrementally.

```
In [426]: pd.read_stata('stata.dta')
```

```
Out[426]:
```

	index	A	B
0	0	1.810535	-1.305727
1	1	-0.344987	-0.230840
2	2	-2.793085	1.937529
3	3	0.366332	-1.044589
4	4	2.051173	0.585662
5	5	0.429526	-0.606998
6	6	0.106223	-1.525680
7	7	0.795026	-0.374438
8	8	0.134048	1.202055
9	9	0.284748	0.262467

New in version 0.16.0.

Specifying a `chunksize` yields a `StataReader` instance that can be used to read `chunksize` lines from the file at a time. The `StataReader` object can be used as an iterator.

```
In [427]: reader = pd.read_stata('stata.dta', chunksize=3)
```

```
In [428]: for df in reader:
.....:     print(df.shape)
.....:
```

```
(3, 3)
(3, 3)
(3, 3)
(1, 3)
```

For more fine-grained control, use `iterator=True` and specify `chunksize` with each call to `read()`.

```
In [429]: reader = pd.read_stata('stata.dta', iterator=True)
```

```
In [430]: chunk1 = reader.read(5)
```

```
In [431]: chunk2 = reader.read(5)
```

Currently the `index` is retrieved as a column.

The parameter `convert_categoricals` indicates whether value labels should be read and used to create a `Categorical` variable from them. Value labels can also be retrieved by the function `value_labels`, which requires `read()` to be called before use.

The parameter `convert_missing` indicates whether missing value representations in Stata should be preserved. If `False` (the default), missing values are represented as `np.nan`. If `True`, missing values are represented using

`StataMissingValue` objects, and columns containing missing values will have `object` data type.

`read_stata()` and `StataReader` supports `.dta` formats 104, 105, 108, 113-115 (Stata 10-12) and 117 (Stata 13+).

Note: Setting `preserve_dtypes=False` will upcast to the standard pandas data types: `int64` for all integer types and `float64` for floating point data. By default, the Stata data types are preserved when importing.

24.11.3 Categorical Data

New in version 0.15.2.

Categorical data can be exported to *Stata* data files as value labeled data. The exported data consists of the underlying category codes as integer data values and the categories as value labels. *Stata* does not have an explicit equivalent to a `Categorical` and information about *whether* the variable is ordered is lost when exporting.

Warning: *Stata* only supports string value labels, and so `str` is called on the categories when exporting data. Exporting `Categorical` variables with non-string categories produces a warning, and can result a loss of information if the `str` representations of the categories are not unique.

Labeled data can similarly be imported from *Stata* data files as `Categorical` variables using the keyword argument `convert_categoricals` (True by default). The keyword argument `order_categoricals` (True by default) determines whether imported `Categorical` variables are ordered.

Note: When importing categorical data, the values of the variables in the *Stata* data file are not preserved since `Categorical` variables always use integer data types between `-1` and `n-1` where `n` is the number of categories. If the original values in the *Stata* data file are required, these can be imported by setting `convert_categoricals=False`, which will import original data (but not the variable labels). The original values can be matched to the imported categorical data since there is a simple mapping between the original *Stata* data values and the category codes of imported `Categorical` variables: missing values are assigned code `-1`, and the smallest original value is assigned `0`, the second smallest is assigned `1` and so on until the largest original value is assigned the code `n-1`.

Note: *Stata* supports partially labeled series. These series have value labels for some but not all data values. Importing a partially labeled series will produce a `Categorical` with string categories for the values that are labeled and numeric categories for values with no label.

24.12 Other file formats

pandas itself only supports IO with a limited set of file formats that map cleanly to its tabular data model. For reading and writing other file formats into and from pandas, we recommend these packages from the broader community.

24.12.1 netCDF

`xray` provides data structures inspired by the pandas `DataFrame` for working with multi-dimensional datasets, with a focus on the netCDF file format and easy conversion to and from pandas.

24.13 Performance Considerations

This is an informal comparison of various IO methods, using pandas 0.13.1.

```
In [3]: df = DataFrame(randn(1000000,2),columns=list('AB'))
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1000000 entries, 0 to 999999
Data columns (total 2 columns):
A      1000000 non-null values
B      1000000 non-null values
dtypes: float64(2)
```

Writing

```
In [14]: %timeit test_sql_write(df)
1 loops, best of 3: 6.24 s per loop

In [15]: %timeit test_hdf_fixed_write(df)
1 loops, best of 3: 237 ms per loop

In [26]: %timeit test_hdf_fixed_write_compress(df)
1 loops, best of 3: 245 ms per loop

In [16]: %timeit test_hdf_table_write(df)
1 loops, best of 3: 901 ms per loop

In [27]: %timeit test_hdf_table_write_compress(df)
1 loops, best of 3: 952 ms per loop

In [17]: %timeit test_csv_write(df)
1 loops, best of 3: 3.44 s per loop
```

Reading

```
In [18]: %timeit test_sql_read()
1 loops, best of 3: 766 ms per loop

In [19]: %timeit test_hdf_fixed_read()
10 loops, best of 3: 19.1 ms per loop

In [28]: %timeit test_hdf_fixed_read_compress()
10 loops, best of 3: 36.3 ms per loop

In [20]: %timeit test_hdf_table_read()
10 loops, best of 3: 39 ms per loop

In [29]: %timeit test_hdf_table_read_compress()
10 loops, best of 3: 60.6 ms per loop

In [22]: %timeit test_csv_read()
1 loops, best of 3: 620 ms per loop
```

Space on disk (in bytes)

```
25843712 Apr  8 14:11 test.sql
24007368 Apr  8 14:11 test_fixed.hdf
15580682 Apr  8 14:11 test_fixed_compress.hdf
24458444 Apr  8 14:11 test_table.hdf
```

```
16797283 Apr  8 14:11 test_table_compress.hdf
46152810 Apr  8 14:11 test.csv
```

And here's the code

```
import sqlite3
import os
from pandas.io import sql

df = DataFrame(randn(1000000,2),columns=list('AB'))

def test_sql_write(df):
    if os.path.exists('test.sql'):
        os.remove('test.sql')
    sql_db = sqlite3.connect('test.sql')
    df.to_sql(name='test_table', con=sql_db)
    sql_db.close()

def test_sql_read():
    sql_db = sqlite3.connect('test.sql')
    pd.read_sql_query("select * from test_table", sql_db)
    sql_db.close()

def test_hdf_fixed_write(df):
    df.to_hdf('test_fixed.hdf', 'test', mode='w')

def test_hdf_fixed_read():
    pd.read_hdf('test_fixed.hdf', 'test')

def test_hdf_fixed_write_compress(df):
    df.to_hdf('test_fixed_compress.hdf', 'test', mode='w', complib='blosc')

def test_hdf_fixed_read_compress():
    pd.read_hdf('test_fixed_compress.hdf', 'test')

def test_hdf_table_write(df):
    df.to_hdf('test_table.hdf', 'test', mode='w', format='table')

def test_hdf_table_read():
    pd.read_hdf('test_table.hdf', 'test')

def test_hdf_table_write_compress(df):
    df.to_hdf('test_table_compress.hdf', 'test', mode='w', complib='blosc', format='table')

def test_hdf_table_read_compress():
    pd.read_hdf('test_table_compress.hdf', 'test')

def test_csv_write(df):
    df.to_csv('test.csv', mode='w')

def test_csv_read():
    pd.read_csv('test.csv', index_col=0)
```

REMOTE DATA ACCESS

Warning: In pandas 0.17.0, the sub-package `pandas.io.data` will be removed in favor of a separately installable `pandas-datareader` package. This will allow the data modules to be independently updated to your pandas installation. The API for `pandas-datareader v0.1.1` is the same as in `pandas v0.16.1`. (GH8961)
You should replace the imports of the following:

```
from pandas.io import data, wb
```

With:

```
from pandas_datareader import data, wb
```

Functions from `pandas.io.data` and `pandas.io.ga` extract data from various Internet sources into a `DataFrame`. Currently the following sources are supported:

- *Yahoo! Finance*
- *Google Finance*
- *St.Louis FED (FRED)*
- *Kenneth French's data library*
- *World Bank*
- *Google Analytics*

It should be noted, that various sources support different kinds of data, so not all sources implement the same methods and the data elements returned might also differ.

25.1 Yahoo! Finance

```
In [1]: import pandas.io.data as web

In [2]: import datetime

In [3]: start = datetime.datetime(2010, 1, 1)

In [4]: end = datetime.datetime(2013, 1, 27)

In [5]: f = web.DataReader("F", 'yahoo', start, end)

In [6]: f.ix['2010-01-04']
Out[6]:
Open                10.17000
```

```
High          10.28000
Low           10.05000
Close         10.28000
Volume        60855800.00000
Adj Close      9.33868
Name: 2010-01-04 00:00:00, dtype: float64
```

25.2 Yahoo! Finance Options

Experimental

The `Options` class allows the download of options data from Yahoo! Finance.

The `get_all_data` method downloads and caches option data for all expiry months and provides a formatted `DataFrame` with a hierarchical index, so it is easy to get to the specific option you want.

```
In [7]: from pandas.io.data import Options
```

```
In [8]: aapl = Options('aapl', 'yahoo')
```

```
In [9]: data = aapl.get_all_data()
```

```
In [10]: data.iloc[0:5, 0:5]
```

```
Out[10]:
```

					Last	Bid	Ask	Chg	PctChg
Strike	Expiry	Type	Symbol						
34.29	2016-01-15	call	AAPL160115C00034290		90.95	0	0	0	0.00%
		put	AAPL160115P00034290		0.03	0	0	0	0.00%
35.71	2016-01-15	call	AAPL160115C00035710		88.30	0	0	0	0.00%
		put	AAPL160115P00035710		0.04	0	0	0	0.00%
37.14	2016-01-15	call	AAPL160115C00037140		90.10	0	0	0	0.00%

```
# Show the $100 strike puts at all expiry dates:
```

```
In [11]: data.loc[(100, slice(None), 'put'),:].iloc[0:5, 0:5]
```

```
Out[11]:
```

					Last	Bid	Ask	Chg	PctChg
Strike	Expiry	Type	Symbol						
100	2015-05-15	put	AAPL150515P00100000		0.03	0	0	0	0.00%
	2015-05-22	put	AAPL150522P00100000		0.04	0	0	0	0.00%
	2015-05-29	put	AAPL150529P00100000		0.05	0	0	0	0.00%
	2015-06-05	put	AAPL150605P00100000		0.06	0	0	0	0.00%
	2015-06-12	put	AAPL150612P00100000		0.11	0	0	0	0.00%

```
# Show the volume traded of $100 strike puts at all expiry dates:
```

```
In [12]: data.loc[(100, slice(None), 'put'), 'Vol'].head()
```

```
Out[12]:
```

Strike	Expiry	Type	Symbol	Vol
100	2015-05-15	put	AAPL150515P00100000	1311
	2015-05-22	put	AAPL150522P00100000	49
	2015-05-29	put	AAPL150529P00100000	29
	2015-06-05	put	AAPL150605P00100000	1000
	2015-06-12	put	AAPL150612P00100000	2

```
Name: Vol, dtype: int64
```

If you don't want to download all the data, more specific requests can be made.

```
In [13]: import datetime
```

```
In [14]: expiry = datetime.date(2016, 1, 1)
```

```
In [15]: data = aapl.get_call_data(expiry=expiry)
```

```
In [16]: data.iloc[0:5:, 0:5]
```

```
Out[16]:
```

					Last	Bid	Ask	Chg	PctChg
Strike	Expiry	Type	Symbol						
34.29	2016-01-15	call	AAPL160115C00034290		90.95	0	0	0	0.00%
35.71	2016-01-15	call	AAPL160115C00035710		88.30	0	0	0	0.00%
37.14	2016-01-15	call	AAPL160115C00037140		90.10	0	0	0	0.00%
38.57	2016-01-15	call	AAPL160115C00038570		86.45	0	0	0	0.00%
40.00	2016-01-15	call	AAPL160115C00040000		87.52	0	0	0	0.00%

Note that if you call `get_all_data` first, this second call will happen much faster, as the data is cached.

If a given expiry date is not available, data for the next available expiry will be returned (January 15, 2015 in the above example).

Available expiry dates can be accessed from the `expiry_dates` property.

```
In [17]: aapl.expiry_dates
```

```
Out[17]:
```

```
[datetime.date(2015, 5, 15),
 datetime.date(2015, 5, 22),
 datetime.date(2015, 5, 29),
 datetime.date(2015, 6, 5),
 datetime.date(2015, 6, 12),
 datetime.date(2015, 6, 19),
 datetime.date(2015, 6, 26),
 datetime.date(2015, 7, 17),
 datetime.date(2015, 8, 21),
 datetime.date(2015, 10, 16),
 datetime.date(2016, 1, 15),
 datetime.date(2017, 1, 20)]
```

```
In [18]: data = aapl.get_call_data(expiry=aapl.expiry_dates[0])
```

```
In [19]: data.iloc[0:5:, 0:5]
```

```
Out[19]:
```

					Last	Bid	Ask	Chg	PctChg
Strike	Expiry	Type	Symbol						
70	2015-05-15	call	AAPL150515C00070000		53.88	0	0	0	0.00%
75	2015-05-15	call	AAPL150515C00075000		52.42	0	0	0	0.00%
80	2015-05-15	call	AAPL150515C00080000		45.60	0	0	0	0.00%
85	2015-05-15	call	AAPL150515C00085000		39.80	0	0	0	0.00%
90	2015-05-15	call	AAPL150515C00090000		37.45	0	0	0	0.00%

A list-like object containing dates can also be passed to the `expiry` parameter, returning options data for all expiry dates in the list.

```
In [20]: data = aapl.get_near_stock_price(expiry=aapl.expiry_dates[0:3])
```

```
In [21]: data.iloc[0:5:, 0:5]
```

```
Out[21]:
```

					Last	Bid	Ask	Chg	PctChg
Strike	Expiry	Type	Symbol						
127	2015-05-22	call	AAPL150522C00127000		2.45	0	0	0	0.00%

```
2015-05-29 call AAPL150529C00127000 2.93 0 0 0 0.00%
128 2015-05-15 call AAPL150515C00128000 1.21 0 0 0 0.00%
2015-05-22 call AAPL150522C00128000 1.90 0 0 0 0.00%
2015-05-29 call AAPL150529C00128000 2.38 0 0 0 0.00%
```

The month and year parameters can be used to get all options data for a given month.

25.3 Google Finance

```
In [22]: import pandas.io.data as web

In [23]: import datetime

In [24]: start = datetime.datetime(2010, 1, 1)

In [25]: end = datetime.datetime(2013, 1, 27)

In [26]: f = web.DataReader("F", 'google', start, end)

In [27]: f.ix['2010-01-04']
Out[27]:
Open          10.17
High          10.28
Low           10.05
Close         10.28
Volume      60855796.00
Name: 2010-01-04 00:00:00, dtype: float64
```

25.4 FRED

```
In [28]: import pandas.io.data as web

In [29]: import datetime

In [30]: start = datetime.datetime(2010, 1, 1)

In [31]: end = datetime.datetime(2013, 1, 27)

In [32]: gdp=web.DataReader("GDP", "fred", start, end)

In [33]: gdp.ix['2013-01-01']
Out[33]:
GDP      16502.4
Name: 2013-01-01 00:00:00, dtype: float64

# Multiple series:
In [34]: inflation = web.DataReader(["CPIAUCSL", "CPILFESL"], "fred", start, end)

In [35]: inflation.head()
Out[35]:
          CPIAUCSL  CPILFESL
DATE
2010-01-01    217.488    220.633
2010-02-01    217.281    220.731
```

```
2010-03-01    217.353    220.783
2010-04-01    217.403    220.822
2010-05-01    217.290    220.962
```

25.5 Fama/French

Dataset names are listed at [Fama/French Data Library](#).

```
In [36]: import pandas.io.data as web
```

```
In [37]: ip = web.DataReader("5_Industry_Portfolios", "famafrch")
```

```
In [38]: ip[4].ix[192607]
```

```
Out[38]:
```

```
1 Cnsmr      5.43
2 Manuf      2.73
3 HiTec      1.83
4 Hlth       1.77
5 Other      2.16
Name: 192607, dtype: float64
```

25.6 World Bank

pandas users can easily access thousands of panel data series from the [World Bank's World Development Indicators](#) by using the `wb` I/O functions.

25.6.1 Indicators

Either from exploring the World Bank site, or using the search function included, every world bank indicator is accessible.

For example, if you wanted to compare the Gross Domestic Products per capita in constant dollars in North America, you would use the `search` function:

```
In [1]: from pandas.io import wb
```

```
In [2]: wb.search('gdp.*capita.*const').iloc[:, :2]
```

```
Out[2]:
```

	id	name
3242	GDPPCKD	GDP per Capita, constant US\$, millions
5143	NY.GDP.PCAP.KD	GDP per capita (constant 2005 US\$)
5145	NY.GDP.PCAP.KN	GDP per capita (constant LCU)
5147	NY.GDP.PCAP.PP.KD	GDP per capita, PPP (constant 2005 internation...

Then you would use the download function to acquire the data from the World Bank's servers:

```
In [3]: dat = wb.download(indicator='NY.GDP.PCAP.KD', country=['US', 'CA', 'MX'], start=2005, end=2007)
```

```
In [4]: print(dat)
```

		NY.GDP.PCAP.KD
country	year	
Canada	2008	36005.5004978584
	2007	36182.9138439757

```
                2006  35785.9698172849
                2005  35087.8925933298
Mexico          2008  8113.10219480083
                2007  8119.21298908649
                2006  7961.96818458178
                2005  7666.69796097264
United States   2008  43069.5819857208
                2007  43635.5852068142
                2006  43228.111147107
                2005  42516.3934699993
```

The resulting dataset is a properly formatted DataFrame with a hierarchical index, so it is easy to apply `.groupby` transformations to it:

```
In [6]: dat['NY.GDP.PCAP.KD'].groupby(level=0).mean()
Out[6]:
country
Canada          35765.569188
Mexico           7965.245332
United States    43112.417952
dtype: float64
```

Now imagine you want to compare GDP to the share of people with cellphone contracts around the world.

```
In [7]: wb.search('cell.*%').iloc[:, :2]
Out[7]:
              id                                     name
3990  IT.CEL.SETS.FE.ZS  Mobile cellular telephone users, female (% of ...
3991  IT.CEL.SETS.MA.ZS  Mobile cellular telephone users, male (% of po...
4027      IT.MOB.COV.ZS  Population coverage of mobile cellular telepho...
```

Notice that this second search was much faster than the first one because pandas now has a cached list of available data series.

```
In [13]: ind = ['NY.GDP.PCAP.KD', 'IT.MOB.COV.ZS']
In [14]: dat = wb.download(indicator=ind, country='all', start=2011, end=2011).dropna()
In [15]: dat.columns = ['gdp', 'cellphone']
In [16]: print(dat.tail())
              gdp  cellphone
country  year
Swaziland  2011  2413.952853      94.9
Tunisia    2011  3687.340170     100.0
Uganda     2011   405.332501     100.0
Zambia     2011   767.911290      62.0
Zimbabwe   2011   419.236086      72.4
```

Finally, we use the `statsmodels` package to assess the relationship between our two variables using ordinary least squares regression. Unsurprisingly, populations in rich countries tend to use cellphones at a higher rate:

```
In [17]: import numpy as np
In [18]: import statsmodels.formula.api as smf
In [19]: mod = smf.ols("cellphone ~ np.log(gdp)", dat).fit()
In [20]: print(mod.summary())

OLS Regression Results
=====
Dep. Variable:      cellphone    R-squared:      0.297
Model:              OLS         Adj. R-squared:  0.274
Method:             Least Squares    F-statistic:  13.08
Date:               Thu, 25 Jul 2013    Prob (F-statistic): 0.00105
```

```

Time: 15:24:42 Log-Likelihood: -139.16
No. Observations: 33 AIC: 282.3
Df Residuals: 31 BIC: 285.3
Df Model: 1
=====
              coef      std err          t      P>|t|      [95.0% Conf. Int.]
-----
Intercept    16.5110     19.071      0.866     0.393     -22.384     55.406
np.log(gdp)   9.9333      2.747      3.616     0.001      4.331     15.535
=====
Omnibus: 36.054 Durbin-Watson: 2.071
Prob(Omnibus): 0.000 Jarque-Bera (JB): 119.133
Skew: -2.314 Prob(JB): 1.35e-26
Kurtosis: 11.077 Cond. No. 45.8
=====

```

25.6.2 Country Codes

New in version 0.15.1.

The `country` argument accepts a string or list of mixed two or three character ISO country codes, as well as dynamic World Bank exceptions to the ISO standards.

For a list of the the hard-coded country codes (used solely for error handling logic) see `pandas.io.wb.country_codes`.

25.6.3 Problematic Country Codes & Indicators

Note: The World Bank's country list and indicators are dynamic. As of 0.15.1, `wb.download()` is more flexible. To achieve this, the warning and exception logic changed.

The world bank converts some country codes in their response, which makes error checking by pandas difficult. Retired indicators still persist in the search.

Given the new flexibility of 0.15.1, improved error handling by the user may be necessary for fringe cases.

To help identify issues:

There are at least 4 kinds of country codes:

1. Standard (2/3 digit ISO) - returns data, will warn and error properly.
2. Non-standard (WB Exceptions) - returns data, but will falsely warn.
3. Blank - silently missing from the response.
4. Bad - causes the entire response from WB to fail, always exception inducing.

There are at least 3 kinds of indicators:

1. Current - Returns data.
2. Retired - Appears in search results, yet won't return data.
3. Bad - Will not return data.

Use the `errors` argument to control warnings and exceptions. Setting errors to ignore or warn, won't stop failed responses. (ie, 100% bad indicators, or a single "bad" (#4 above) country code).

See docstrings for more info.

25.7 Google Analytics

The `ga` module provides a wrapper for [Google Analytics API](#) to simplify retrieving traffic data. Result sets are parsed into a pandas DataFrame with a shape and data types derived from the source table.

25.7.1 Configuring Access to Google Analytics

The first thing you need to do is to setup accesses to Google Analytics API. Follow the steps below:

1. **In the Google Developers Console**

- (a) enable the Analytics API
- (b) create a new project
- (c) create a new Client ID for an “Installed Application” (in the “APIs & auth / Credentials section” of the newly created project)
- (d) download it (JSON file)

2. **On your machine**

- (a) rename it to `client_secrets.json`
- (b) move it to the `pandas/io` module directory

The first time you use the `read_ga()` function, a browser window will open to ask you to authenticate to the Google API. Do proceed.

25.7.2 Using the Google Analytics API

The following will fetch users and pageviews (metrics) data per day of the week, for the first semester of 2014, from a particular property.

```
import pandas.io.ga as ga
ga.read_ga(
    account_id = "2360420",
    profile_id = "19462946",
    property_id = "UA-2360420-5",
    metrics = ['users', 'pageviews'],
    dimensions = ['dayOfWeek'],
    start_date = "2014-01-01",
    end_date = "2014-08-01",
    index_col = 0,
    filters = "pagePath=~aboutus;ga:country==France",
)
```

The only mandatory arguments are `metrics`, `dimensions` and `start_date`. We strongly recommend that you always specify the `account_id`, `profile_id` and `property_id` to avoid accessing the wrong data bucket in Google Analytics.

The `index_col` argument indicates which dimension(s) has to be taken as index.

The `filters` argument indicates the filtering to apply to the query. In the above example, the page URL has to contain `aboutus` AND the visitors country has to be France.

Detailed information in the following:

- [pandas & google analytics](#), by yhat

- [Google Analytics integration in pandas](#), by Chang She
- [Google Analytics Dimensions and Metrics Reference](#)

ENHANCING PERFORMANCE

26.1 Cython (Writing C extensions for pandas)

For many use cases writing pandas in pure python and numpy is sufficient. In some computationally heavy applications however, it can be possible to achieve sizeable speed-ups by offloading work to [cython](#).

This tutorial assumes you have refactored as much as possible in python, for example trying to remove for loops and making use of numpy vectorization, it's always worth optimising in python first.

This tutorial walks through a “typical” process of cythonizing a slow computation. We use an [example from the cython documentation](#) but in the context of pandas. Our final cythonized solution is around 100 times faster than the pure python.

26.1.1 Pure python

We have a DataFrame to which we want to apply a function row-wise.

```
In [1]: df = DataFrame({'a': randn(1000), 'b': randn(1000), 'N': randint(100, 1000, (1000)), 'x': 'x'}
```

```
In [2]: df
```

```
Out[2]:
```

	N	a	b	x
0	585	0.469112	-0.218470	x
1	841	-0.282863	-0.061645	x
2	251	-1.509059	-0.723780	x
3	972	-1.135632	0.551225	x
4	181	1.212112	-0.497767	x
5	458	-0.173215	0.837519	x
6	159	0.119209	1.103245	x
..	...	...	...	..
993	190	0.131892	0.290162	x
994	931	0.342097	0.215341	x
995	374	-1.512743	0.874737	x
996	246	0.933753	1.120790	x
997	157	-0.308013	0.198768	x
998	977	-0.079915	1.757555	x
999	770	-1.010589	-1.115680	x

```
[1000 rows x 4 columns]
```

Here's the function in pure python:

```
In [3]: def f(x):  
...:     return x * (x - 1)
```

```
...:
In [4]: def integrate_f(a, b, N):
...:     s = 0
...:     dx = (b - a) / N
...:     for i in range(N):
...:         s += f(a + i * dx)
...:     return s * dx
...:
```

We achieve our result by using `apply` (row-wise):

```
In [5]: %timeit df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1)
1 loops, best of 3: 291 ms per loop
```

But clearly this isn't fast enough for us. Let's take a look and see where the time is spent during this operation (limited to the most time consuming four calls) using the `prun` [ipython magic function](#):

```
In [6]: %prun -l 4 df.apply(lambda x: integrate_f(x['a'], x['b'], x['N']), axis=1)
610748 function calls (608735 primitive calls) in 0.564 seconds
```

Ordered by: internal time

List reduced from 101 to 4 due to restriction <4>

ncalls	totttime	percall	cumtime	percall	filename:lineno(function)
1000	0.312	0.000	0.491	0.000	<ipython-input-4-91e33489f136>:1(integrate_f)
552423	0.179	0.000	0.179	0.000	<ipython-input-3-bc41a25943f6>:1(f)
3000	0.007	0.000	0.049	0.000	series.py:517(__getitem__)
3000	0.007	0.000	0.016	0.000	internals.py:3481(get_values)

By far the majority of time is spend inside either `integrate_f` or `f`, hence we'll concentrate our efforts cythonizing these two functions.

Note: In python 2 replacing the `range` with its generator counterpart (`xrange`) would mean the `range` line would vanish. In python 3 `range` is already a generator.

26.1.2 Plain cython

First we're going to need to import the cython magic function to `ipython`:

```
In [7]: %load_ext cythonmagic
```

Now, let's simply copy our functions over to cython as is (the suffix is here to distinguish between function versions):

```
In [8]: %%cython
...: def f_plain(x):
...:     return x * (x - 1)
...: def integrate_f_plain(a, b, N):
...:     s = 0
...:     dx = (b - a) / N
...:     for i in range(N):
...:         s += f_plain(a + i * dx)
...:     return s * dx
...:
```

Note: If you're having trouble pasting the above into your `ipython`, you may need to be using bleeding edge `ipython` for paste to play well with cell magics.

```
In [9]: %timeit df.apply(lambda x: integrate_f_plain(x['a'], x['b'], x['N']), axis=1)
10 loops, best of 3: 184 ms per loop
```

Already this has shaved a third off, not too bad for a simple copy and paste.

26.1.3 Adding type

We get another huge improvement simply by providing type information:

```
In [10]: %%cython
.....: cdef double f_typed(double x) except? -2:
.....:     return x * (x - 1)
.....: cpdef double integrate_f_typed(double a, double b, int N):
.....:     cdef int i
.....:     cdef double s, dx
.....:     s = 0
.....:     dx = (b - a) / N
.....:     for i in range(N):
.....:         s += f_typed(a + i * dx)
.....:     return s * dx
.....:
```

```
In [11]: %timeit df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
10 loops, best of 3: 36.9 ms per loop
```

Now, we're talking! It's now over ten times faster than the original python implementation, and we haven't *really* modified the code. Let's have another look at what's eating up time:

```
In [12]: %prun -l 4 df.apply(lambda x: integrate_f_typed(x['a'], x['b'], x['N']), axis=1)
58325 function calls (56312 primitive calls) in 0.079 seconds
```

Ordered by: internal time

List reduced from 100 to 4 due to restriction <4>

ncalls	tottime	percall	cumtime	percall	filename:lineno(function)
3000	0.008	0.000	0.052	0.000	series.py:517(__getitem__)
3000	0.007	0.000	0.017	0.000	internals.py:3481(get_values)
3000	0.007	0.000	0.039	0.000	index.py:1588(get_value)
6000	0.007	0.000	0.026	0.000	{pandas.lib.values_from_object}

26.1.4 Using ndarray

It's calling series... a lot! It's creating a Series from each row, and get-ting from both the index and the series (three times for each row). Function calls are expensive in python, so maybe we could minimise these by cythonizing the apply part.

Note: We are now passing ndarrays into the cython function, fortunately cython plays very nicely with numpy.

```
In [13]: %%cython
.....: cimport numpy as np
.....: import numpy as np
.....: cdef double f_typed(double x) except? -2:
.....:     return x * (x - 1)
.....: cpdef double integrate_f_typed(double a, double b, int N):
```

```

.....:     cdef int i
.....:     cdef double s, dx
.....:     s = 0
.....:     dx = (b - a) / N
.....:     for i in range(N):
.....:         s += f_typed(a + i * dx)
.....:     return s * dx
.....: cpdef np.ndarray[double] apply_integrate_f(np.ndarray col_a, np.ndarray col_b, np.ndarray col_N):
.....:     assert (col_a.dtype == np.float and col_b.dtype == np.float and col_N.dtype == np.int)
.....:     cdef Py_ssize_t i, n = len(col_N)
.....:     assert (len(col_a) == len(col_b) == n)
.....:     cdef np.ndarray[double] res = np.empty(n)
.....:     for i in range(len(col_a)):
.....:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
.....:     return res
.....:

```

The implementation is simple, it creates an array of zeros and loops over the rows, applying our `integrate_f_typed`, and putting this in the zeros array.

Warning: In 0.13.0 since Series has internally been refactored to no longer sub-class ndarray but instead subclass NDFrame, you can **not pass** a Series directly as a ndarray typed parameter to a cython function. Instead pass the actual ndarray using the `.values` attribute of the Series.
Prior to 0.13.0

```
apply_integrate_f(df['a'], df['b'], df['N'])
```

Use `.values` to get the underlying ndarray

```
apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
```

Note: Loops like this would be *extremely* slow in python, but in Cython looping over numpy arrays is *fast*.

```
In [14]: %timeit apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
1000 loops, best of 3: 1.93 ms per loop
```

We've gotten another big improvement. Let's check again where the time is spent:

```
In [15]: %prun -l 4 apply_integrate_f(df['a'].values, df['b'].values, df['N'].values)
39 function calls in 0.002 seconds
```

Ordered by: internal time

List reduced from 15 to 4 due to restriction <4>

ncalls	tottime	percall	cumtime	percall	filename:lineno(function)
1	0.002	0.002	0.002	0.002	{_cython_magic_23eb111f3aa77c1d91c8922c61af3ed1.apply_...
3	0.000	0.000	0.000	0.000	frame.py:1768(__getitem__)
1	0.000	0.000	0.002	0.002	<string>:1(<module>)
3	0.000	0.000	0.000	0.000	generic.py:1079(_get_item_cache)

As one might expect, the majority of the time is now spent in `apply_integrate_f`, so if we wanted to make anymore efficiencies we must continue to concentrate our efforts here.

26.1.5 More advanced techniques

There is still hope for improvement. Here's an example of using some more advanced cython techniques:

```
In [16]: %%cython
...: cimport cython
...: cimport numpy as np
...: import numpy as np
...: cdef double f_typed(double x) except? -2:
...:     return x * (x - 1)
...: cpdef double integrate_f_typed(double a, double b, int N):
...:     cdef int i
...:     cdef double s, dx
...:     s = 0
...:     dx = (b - a) / N
...:     for i in range(N):
...:         s += f_typed(a + i * dx)
...:     return s * dx
...: @cython.boundscheck(False)
...: @cython.wraparound(False)
...: cpdef np.ndarray[double] apply_integrate_f_wrap(np.ndarray[double] col_a, np.ndarray[double] col_b, np.ndarray[double] col_N):
...:     cdef Py_ssize_t i, n = len(col_N)
...:     assert len(col_a) == len(col_b) == n
...:     cdef np.ndarray[double] res = np.empty(n)
...:     for i in range(n):
...:         res[i] = integrate_f_typed(col_a[i], col_b[i], col_N[i])
...:     return res
...:
```

```
In [17]: %timeit apply_integrate_f_wrap(df['a'].values, df['b'].values, df['N'].values)
1000 loops, best of 3: 1.64 ms per loop
```

Even faster, with the caveat that a bug in our cython code (an off-by-one error, for example) might cause a segfault because memory access isn't checked.

26.1.6 Further topics

- Loading C modules into cython.

Read more in the [cython docs](#).

26.2 Expression Evaluation via `eval()` (Experimental)

New in version 0.13.

The top-level function `pandas.eval()` implements expression evaluation of `Series` and `DataFrame` objects.

Note: To benefit from using `eval()` you need to install `numexpr`. See the *recommended dependencies section* for more details.

The point of using `eval()` for expression evaluation rather than plain Python is two-fold: 1) large `DataFrame` objects are evaluated more efficiently and 2) large arithmetic and boolean expressions are evaluated all at once by the underlying engine (by default `numexpr` is used for evaluation).

Note: You should not use `eval()` for simple expressions or for expressions involving small `DataFrames`. In fact,

`eval()` is many orders of magnitude slower for smaller expressions/objects than plain ol' Python. A good rule of thumb is to only use `eval()` when you have a `DataFrame` with more than 10,000 rows.

`eval()` supports all arithmetic expressions supported by the engine in addition to some extensions available only in pandas.

Note: The larger the frame and the larger the expression the more speedup you will see from using `eval()`.

26.2.1 Supported Syntax

These operations are supported by `pandas.eval()`:

- Arithmetic operations except for the left shift (`<<`) and right shift (`>>`) operators, e.g., `df + 2 * pi / s ** 4 % 42 - the_golden_ratio`
- Comparison operations, including chained comparisons, e.g., `2 < df < df2`
- Boolean operations, e.g., `df < df2 and df3 < df4 or not df_bool`
- list and tuple literals, e.g., `[1, 2]` or `(1, 2)`
- Attribute access, e.g., `df.a`
- Subscript expressions, e.g., `df[0]`
- Simple variable evaluation, e.g., `pd.eval('df')` (this is not very useful)

This Python syntax is **not** allowed:

- Expressions
 - Function calls
 - `is/is not` operations
 - `if` expressions
 - `lambda` expressions
 - `list/set/dict` comprehensions
 - Literal `dict` and `set` expressions
 - `yield` expressions
 - Generator expressions
 - Boolean expressions consisting of only scalar values
- Statements
 - Neither `simple` nor `compound` statements are allowed. This includes things like `for`, `while`, and `if`.

26.2.2 `eval()` Examples

`pandas.eval()` works well with expressions containing large arrays.

First let's create a few decent-sized arrays to play with:

```
In [18]: import pandas as pd
In [19]: from pandas import DataFrame, Series
In [20]: from numpy.random import randn
In [21]: import numpy as np
In [22]: nrows, ncols = 20000, 100
In [23]: df1, df2, df3, df4 = [DataFrame(randn(nrows, ncols)) for _ in range(4)]
```

Now let's compare adding them together using plain ol' Python versus `eval()`:

```
In [24]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 22.3 ms per loop

In [25]: %timeit pd.eval('df1 + df2 + df3 + df4')
100 loops, best of 3: 13.4 ms per loop
```

Now let's do the same thing but with comparisons:

```
In [26]: %timeit (df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)
10 loops, best of 3: 67.3 ms per loop

In [27]: %timeit pd.eval('(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0)')
10 loops, best of 3: 30.7 ms per loop
```

`eval()` also works with unaligned pandas objects:

```
In [28]: s = Series(randn(50))

In [29]: %timeit df1 + df2 + df3 + df4 + s
10 loops, best of 3: 94.7 ms per loop

In [30]: %timeit pd.eval('df1 + df2 + df3 + df4 + s')
10 loops, best of 3: 76.1 ms per loop
```

Note: Operations such as

```
1 and 2 # would parse to 1 & 2, but should evaluate to 2
3 or 4  # would parse to 3 | 4, but should evaluate to 3
~1      # this is okay, but slower when using eval
```

should be performed in Python. An exception will be raised if you try to perform any boolean/bitwise operations with scalar operands that are not of type `bool` or `np.bool_`. Again, you should perform these kinds of operations in plain Python.

26.2.3 The `DataFrame.eval` method (Experimental)

New in version 0.13.

In addition to the top level `pandas.eval()` function you can also evaluate an expression in the “context” of a `DataFrame`.

```
In [31]: df = DataFrame(randn(5, 2), columns=['a', 'b'])
```

```
In [32]: df.eval('a + b')
Out[32]:
0    -0.246747
1     0.867786
2    -1.626063
3    -1.134978
4    -1.027798
dtype: float64
```

Any expression that is a valid `pandas.eval()` expression is also a valid `DataFrame.eval()` expression, with the added benefit that you don't have to prefix the name of the `DataFrame` to the column(s) you're interested in evaluating.

In addition, you can perform assignment of columns within an expression. This allows for *formulaic evaluation*. Only a single assignment is permitted. The assignment target can be a new column name or an existing column name, and it must be a valid Python identifier.

```
In [33]: df = DataFrame(dict(a=range(5), b=range(5, 10)))

In [34]: df.eval('c = a + b')

In [35]: df.eval('d = a + b + c')

In [36]: df.eval('a = 1')
```

```
In [37]: df
Out[37]:
   a  b  c  d
0  1  5  5 10
1  1  6  7 14
2  1  7  9 18
3  1  8 11 22
4  1  9 13 26
```

The equivalent in standard Python would be

```
In [38]: df = DataFrame(dict(a=range(5), b=range(5, 10)))

In [39]: df['c'] = df.a + df.b

In [40]: df['d'] = df.a + df.b + df.c

In [41]: df['a'] = 1
```

```
In [42]: df
Out[42]:
   a  b  c  d
0  1  5  5 10
1  1  6  7 14
2  1  7  9 18
3  1  8 11 22
4  1  9 13 26
```

26.2.4 Local Variables

In pandas version 0.14 the local variable API has changed. In pandas 0.13.x, you could refer to local variables the same way you would in standard Python. For example,

```
df = DataFrame(randn(5, 2), columns=['a', 'b'])
newcol = randn(len(df))
df.eval('b + newcol')
```

```
UndefinedVariableError: name 'newcol' is not defined
```

As you can see from the exception generated, this syntax is no longer allowed. You must *explicitly reference* any local variable that you want to use in an expression by placing the @ character in front of the name. For example,

```
In [43]: df = DataFrame(randn(5, 2), columns=list('ab'))
```

```
In [44]: newcol = randn(len(df))
```

```
In [45]: df.eval('b + @newcol')
```

```
Out[45]:
0    -0.173926
1     2.493083
2    -0.881831
3    -0.691045
4     1.334703
dtype: float64
```

```
In [46]: df.query('b < @newcol')
```

```
Out[46]:
      a      b
0  0.863987 -0.115998
2 -2.621419 -1.297879
```

If you don't prefix the local variable with @, pandas will raise an exception telling you the variable is undefined.

When using `DataFrame.eval()` and `DataFrame.query()`, this allows you to have a local variable and a `DataFrame` column with the same name in an expression.

```
In [47]: a = randn()
```

```
In [48]: df.query('@a < a')
```

```
Out[48]:
      a      b
0  0.863987 -0.115998
```

```
In [49]: df.loc[a < df.a] # same as the previous expression
```

```
Out[49]:
      a      b
0  0.863987 -0.115998
```

With `pandas.eval()` you cannot use the @ prefix *at all*, because it isn't defined in that context. pandas will let you know this if you try to use @ in a top-level call to `pandas.eval()`. For example,

```
In [50]: a, b = 1, 2
```

```
In [51]: pd.eval('@a + b')
```

```
File "<string>", line unknown
SyntaxError: The '@' prefix is not allowed in top-level eval calls,
please refer to your variables by name without the '@' prefix
```

In this case, you should simply refer to the variables like you would in standard Python.

```
In [52]: pd.eval('a + b')
```

```
Out[52]: 3
```

26.2.5 pandas.eval() Parsers

There are two different parsers and two different engines you can use as the backend.

The default 'pandas' parser allows a more intuitive syntax for expressing query-like operations (comparisons, conjunctions and disjunctions). In particular, the precedence of the & and | operators is made equal to the precedence of the corresponding boolean operations and and or.

For example, the above conjunction can be written without parentheses. Alternatively, you can use the 'python' parser to enforce strict Python semantics.

```
In [53]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0) '
In [54]: x = pd.eval(expr, parser='python')
In [55]: expr_no_parens = 'df1 > 0 & df2 > 0 & df3 > 0 & df4 > 0'
In [56]: y = pd.eval(expr_no_parens, parser='pandas')
In [57]: np.all(x == y)
Out[57]: True
```

The same expression can be “anded” together with the word and as well:

```
In [58]: expr = '(df1 > 0) & (df2 > 0) & (df3 > 0) & (df4 > 0) '
In [59]: x = pd.eval(expr, parser='python')
In [60]: expr_with_and = 'df1 > 0 and df2 > 0 and df3 > 0 and df4 > 0'
In [61]: y = pd.eval(expr_with_and, parser='pandas')
In [62]: np.all(x == y)
Out[62]: True
```

The and and or operators here have the same precedence that they would in vanilla Python.

26.2.6 pandas.eval() Backends

There's also the option to make eval() operate identical to plain ol' Python.

Note: Using the 'python' engine is generally *not* useful, except for testing other evaluation engines against it. You will achieve **no** performance benefits using eval() with engine='python' and in fact may incur a performance hit.

You can see this by using pandas.eval() with the 'python' engine. It is a bit slower (not by much) than evaluating the same expression in Python

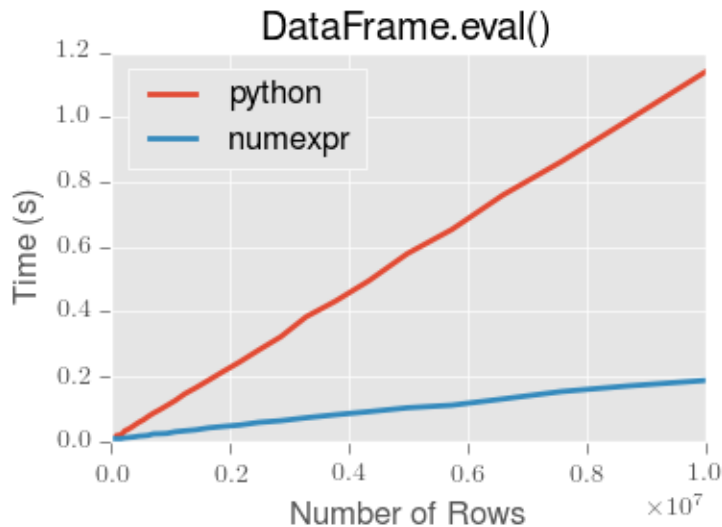
```
In [63]: %timeit df1 + df2 + df3 + df4
10 loops, best of 3: 23.1 ms per loop

In [64]: %timeit pd.eval('df1 + df2 + df3 + df4', engine='python')
10 loops, best of 3: 23.6 ms per loop
```

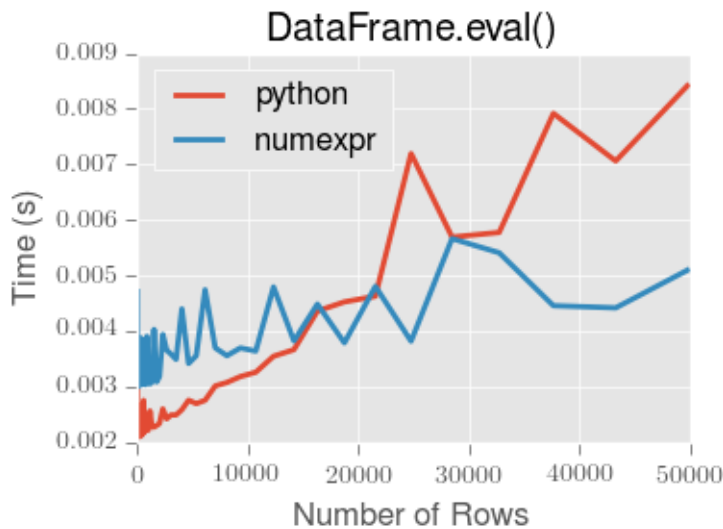
26.2.7 pandas.eval() Performance

eval() is intended to speed up certain kinds of operations. In particular, those operations involving complex expres-

sions with large `DataFrame`/`Series` objects should see a significant performance benefit. Here is a plot showing the running time of `pandas.eval()` as function of the size of the frame involved in the computation. The two lines are two different engines.



Note: Operations with smallish objects (around 15k-20k rows) are faster using plain Python:



This plot was created using a `DataFrame` with 3 columns each containing floating point values generated using `numpy.random.randn()`.

26.2.8 Technical Minutia Regarding Expression Evaluation

Expressions that would result in an object dtype or involve datetime operations (because of `NaT`) must be evaluated in Python space. The main reason for this behavior is to maintain backwards compatibility with versions of `numpy` < 1.7. In those versions of `numpy` a call to `ndarray.astype(str)` will truncate any strings that are more than 60 characters in length. Second, we can't pass object arrays to `numexpr` thus string comparisons must be evaluated

in Python space.

The upshot is that this *only* applies to object-dtype'd expressions. So, if you have an expression—for example

```
In [65]: df = DataFrame({'strings': np.repeat(list('cba'), 3),
.....:                  'nums': np.repeat(range(3), 3)})
.....:
```

```
In [66]: df
```

```
Out[66]:
```

	nums	strings
0	0	c
1	0	c
2	0	c
3	1	b
4	1	b
5	1	b
6	2	a
7	2	a
8	2	a

```
In [67]: df.query('strings == "a" and nums == 1')
```

```
Out[67]:
```

Empty DataFrame
Columns: [nums, strings]
Index: []

the numeric part of the comparison (`nums == 1`) will be evaluated by `numexpr`.

In general, `DataFrame.query()`/`pandas.eval()` will evaluate the subexpressions that *can* be evaluated by `numexpr` and those that must be evaluated in Python space transparently to the user. This is done by inferring the result type of an expression from its arguments and operators.

SPARSE DATA STRUCTURES

We have implemented “sparse” versions of Series, DataFrame, and Panel. These are not sparse in the typical “mostly 0”. You can view these objects as being “compressed” where any data matching a specific value (NaN/missing by default, though any value can be chosen) is omitted. A special `SparseIndex` object tracks where data has been “sparsified”. This will make much more sense in an example. All of the standard pandas data structures have a `to_sparse` method:

```
In [1]: ts = Series(randn(10))
```

```
In [2]: ts[2:-2] = np.nan
```

```
In [3]: sts = ts.to_sparse()
```

```
In [4]: sts
```

```
Out[4]:
0    0.469112
1   -0.282863
2         NaN
3         NaN
4         NaN
5         NaN
6         NaN
7         NaN
8   -0.861849
9   -2.104569
dtype: float64
BlockIndex
Block locations: array([0, 8])
Block lengths: array([2, 2])
```

The `to_sparse` method takes a `kind` argument (for the sparse index, see below) and a `fill_value`. So if we had a mostly zero Series, we could convert it to sparse with `fill_value=0`:

```
In [5]: ts.fillna(0).to_sparse(fill_value=0)
```

```
Out[5]:
0    0.469112
1   -0.282863
2    0.000000
3    0.000000
4    0.000000
5    0.000000
6    0.000000
7    0.000000
8   -0.861849
9   -2.104569
dtype: float64
```

```
BlockIndex
Block locations: array([0, 8])
Block lengths: array([2, 2])
```

The sparse objects exist for memory efficiency reasons. Suppose you had a large, mostly NA DataFrame:

```
In [6]: df = DataFrame(randn(10000, 4))

In [7]: df.ix[:9998] = np.nan

In [8]: sdf = df.to_sparse()

In [9]: sdf
Out[9]:
```

	0	1	2	3
0	NaN	NaN	NaN	NaN
1	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN
6	NaN	NaN	NaN	NaN
...	...	...	...	...
9993	NaN	NaN	NaN	NaN
9994	NaN	NaN	NaN	NaN
9995	NaN	NaN	NaN	NaN
9996	NaN	NaN	NaN	NaN
9997	NaN	NaN	NaN	NaN
9998	NaN	NaN	NaN	NaN
9999	0.280249	-1.648493	1.490865	-0.890819

```
[10000 rows x 4 columns]
```

```
In [10]: sdf.density
Out[10]: 0.0001
```

As you can see, the density (% of values that have not been “compressed”) is extremely low. This sparse object takes up much less memory on disk (pickled) and in the Python interpreter. Functionally, their behavior should be nearly identical to their dense counterparts.

Any sparse object can be converted back to the standard dense form by calling `to_dense`:

```
In [11]: sts.to_dense()
Out[11]:
```

0	0.469112
1	-0.282863
2	NaN
3	NaN
4	NaN
5	NaN
6	NaN
7	NaN
8	-0.861849
9	-2.104569

```
dtype: float64
```

27.1 SparseArray

`SparseArray` is the base layer for all of the sparse indexed data structures. It is a 1-dimensional ndarray-like object storing only values distinct from the `fill_value`:

```
In [12]: arr = np.random.randn(10)
```

```
In [13]: arr[2:5] = np.nan; arr[7:8] = np.nan
```

```
In [14]: sparr = SparseArray(arr)
```

```
In [15]: sparr
```

```
Out [15]:
[-1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297113733, nan, 0.606027190513, 1.3342]
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9])
```

Like the indexed objects (`SparseSeries`, `SparseDataFrame`, `SparsePanel`), a `SparseArray` can be converted back to a regular ndarray by calling `to_dense`:

```
In [16]: sparr.to_dense()
```

```
Out [16]:
array([-1.9557, -1.6589,      nan,      nan,      nan,  1.1589,  0.1453,
        nan,  0.606 ,  1.3342])
```

27.2 SparseList

`SparseList` is a list-like data structure for managing a dynamic collection of `SparseArrays`. To create one, simply call the `SparseList` constructor with a `fill_value` (defaulting to `NaN`):

```
In [17]: spl = SparseList()
```

```
In [18]: spl
```

```
Out [18]: <pandas.sparse.list.SparseList object at 0x9e83dcac>
```

The two important methods are `append` and `to_array`. `append` can accept scalar values or any 1-dimensional sequence:

```
In [19]: from numpy import nan
```

```
In [20]: spl.append(np.array([1., nan, nan, 2., 3.]))
```

```
In [21]: spl.append(5)
```

```
In [22]: spl.append(sparr)
```

```
In [23]: spl
```

```
Out [23]:
<pandas.sparse.list.SparseList object at 0x9e83dcac>
[1.0, nan, nan, 2.0, 3.0]
Fill: nan
IntIndex
Indices: array([0, 3, 4])
```

```
[5.0]
```

```
Fill: nan
IntIndex
Indices: array([0])
```

```
[-1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297113733, nan, 0.606027190513, 1]
Fill: nan
IntIndex
Indices: array([0, 1, 5, 6, 8, 9])
```

As you can see, all of the contents are stored internally as a list of memory-efficient `SparseArray` objects. Once you've accumulated all of the data, you can call `to_array` to get a single `SparseArray` with all the data:

```
In [24]: spl.to_array()
Out[24]:
[1.0, nan, nan, 2.0, 3.0, 5.0, -1.95566352972, -1.6588664276, nan, nan, nan, 1.15893288864, 0.145297]
Fill: nan
IntIndex
Indices: array([ 0,  3,  4,  5,  6,  7, 11, 12, 14, 15])
```

27.3 SparseIndex objects

Two kinds of `SparseIndex` are implemented, `block` and `integer`. We recommend using `block` as it's more memory efficient. The `integer` format keeps an arrays of all of the locations where the data are not equal to the fill value. The `block` format tracks only the locations and sizes of blocks of data.

27.4 Interaction with scipy.sparse

Experimental api to transform between sparse pandas and scipy.sparse structures.

A `SparseSeries.to_coo()` method is implemented for transforming a `SparseSeries` indexed by a `MultiIndex` to a `scipy.sparse.coo_matrix`.

The method requires a `MultiIndex` with two or more levels.

```
In [25]: from numpy import nan
```

```
In [26]: s = Series([3.0, nan, 1.0, 3.0, nan, nan])
```

[illegible]

In [28]: s

Out [28]:

A	B	C	D	
1	2	a	0	3
			1	NaN
	1	b	0	1
			1	3

```
2  1  b  0   NaN
      1   NaN
dtype: float64
```

```
# SparseSeries
```

```
In [29]: ss = s.to_sparse()
```

```
In [30]: ss
```

```
Out[30]:
```

```
A B C D
1 2 a 0   3
      1   NaN
      1  b  0   1
      1   3
2 1 b 0   NaN
      1   NaN
dtype: float64
BlockIndex
Block locations: array([0, 2])
Block lengths: array([1, 2])
```

In the example below, we transform the `SparseSeries` to a sparse representation of a 2-d array by specifying that the first and second `MultiIndex` levels define labels for the rows and the third and fourth levels define labels for the columns. We also specify that the column and row labels should be sorted in the final sparse representation.

```
In [31]: A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
.....:                                column_levels=['C', 'D'],
.....:                                sort_labels=True)
.....:
```

```
In [32]: A
```

```
Out[32]:
<3x4 sparse matrix of type '<type 'numpy.float64'>'
with 3 stored elements in COOrdinate format>
```

```
In [33]: A.todense()
```

```
Out[33]:
matrix([[ 0.,  0.,  1.,  3.],
        [ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  0.,  0.]])
```

```
In [34]: rows
```

```
Out[34]: [(1L, 1L), (1L, 2L), (2L, 1L)]
```

```
In [35]: columns
```

```
Out[35]: [('a', 0L), ('a', 1L), ('b', 0L), ('b', 1L)]
```

Specifying different row and column labels (and not sorting them) yields a different sparse matrix:

```
In [36]: A, rows, columns = ss.to_coo(row_levels=['A', 'B', 'C'],
.....:                                column_levels=['D'],
.....:                                sort_labels=False)
.....:
```

```
In [37]: A
```

```
Out[37]:
<3x2 sparse matrix of type '<type 'numpy.float64'>'
with 3 stored elements in COOrdinate format>
```

```
In [38]: A.todense()
```

```
Out[38]:  
matrix([[ 3.,  0.],  
        [ 1.,  3.],  
        [ 0.,  0.]])
```

```
In [39]: rows
```

```
Out[39]: [(1L, 2L, 'a'), (1L, 1L, 'b'), (2L, 1L, 'b')]
```

```
In [40]: columns
```

```
Out[40]: [0, 1]
```

A convenience method `SparseSeries.from_coo()` is implemented for creating a `SparseSeries` from a `scipy.sparse.coo_matrix`.

```
In [41]: from scipy import sparse
```

```
In [42]: A = sparse.coo_matrix([(3.0, 1.0, 2.0), ([1, 0, 0], [0, 2, 3])],  
.....:                        shape=(3, 4))  
.....:
```

```
In [43]: A
```

```
Out[43]:  
<3x4 sparse matrix of type '<type 'numpy.float64'>'  
with 3 stored elements in COOrdinate format>
```

```
In [44]: A.todense()
```

```
Out[44]:  
matrix([[ 0.,  0.,  1.,  2.],  
        [ 3.,  0.,  0.,  0.],  
        [ 0.,  0.,  0.,  0.]])
```

The default behaviour (with `dense_index=False`) simply returns a `SparseSeries` containing only the non-null entries.

```
In [45]: ss = SparseSeries.from_coo(A)
```

```
In [46]: ss
```

```
Out[46]:  
0 2 1  
3 2  
1 0 3  
dtype: float64  
BlockIndex  
Block locations: array([0])  
Block lengths: array([3])
```

Specifying `dense_index=True` will result in an index that is the Cartesian product of the row and columns coordinates of the matrix. Note that this will consume a significant amount of memory (relative to `dense_index=False`) if the sparse matrix is large (and sparse) enough.

```
In [47]: ss_dense = SparseSeries.from_coo(A, dense_index=True)
```

```
In [48]: ss_dense
```

```
Out[48]:  
0 0 NaN  
1 NaN  
2 1  
3 2
```

```
1  0      3
   1   NaN
   2   NaN
   3   NaN
2  0   NaN
   1   NaN
   2   NaN
   3   NaN
dtype: float64
BlockIndex
Block locations: array([2])
Block lengths: array([3])
```


CAVEATS AND GOTCHAS

28.1 Using If/Truth Statements with pandas

pandas follows the numpy convention of raising an error when you try to convert something to a `bool`. This happens in a `if` or when using the boolean operations, `and`, `or`, or `not`. It is not clear what the result of

```
>>> if Series([False, True, False]):  
    ...
```

should be. Should it be `True` because it's not zero-length? `False` because there are `False` values? It is unclear, so instead, pandas raises a `ValueError`:

```
>>> if pd.Series([False, True, False]):  
    print("I was true")  
Traceback  
...  
ValueError: The truth value of an array is ambiguous. Use a.empty, a.any() or a.all().
```

If you see that, you need to explicitly choose what you want to do with it (e.g., use `any()`, `all()` or `empty`). or, you might want to compare if the pandas object is `None`

```
>>> if pd.Series([False, True, False]) is not None:  
    print("I was not None")  
>>> I was not None
```

or return if any value is `True`.

```
>>> if pd.Series([False, True, False]).any():  
    print("I am any")  
>>> I am any
```

To evaluate single-element pandas objects in a boolean context, use the method `.bool()`:

```
In [1]: Series([True]).bool()  
Out[1]: True  
  
In [2]: Series([False]).bool()  
Out[2]: False  
  
In [3]: DataFrame([[True]]).bool()  
Out[3]: True  
  
In [4]: DataFrame([[False]]).bool()  
Out[4]: False
```

28.1.1 Bitwise boolean

Bitwise boolean operators like `==` and `!=` will return a boolean `Series`, which is almost always what you want anyways.

```
>>> s = pd.Series(range(5))
>>> s == 4
0    False
1    False
2    False
3    False
4     True
dtype: bool
```

See [boolean comparisons](#) for more examples.

28.1.2 Using the `in` operator

Using the Python `in` operator on a `Series` tests for membership in the index, not membership among the values.

If this behavior is surprising, keep in mind that using `in` on a Python dictionary tests keys, not values, and `Series` are dict-like. To test for membership in the values, use the method `isin()`:

For `DataFrames`, likewise, `in` applies to the column axis, testing for membership in the list of column names.

28.2 NaN, Integer NA values and NA type promotions

28.2.1 Choice of NA representation

For lack of NA (missing) support from the ground up in NumPy and Python in general, we were given the difficult choice between either

- A *masked array* solution: an array of data and an array of boolean values indicating whether a value
- Using a special sentinel value, bit pattern, or set of sentinel values to denote NA across the dtypes

For many reasons we chose the latter. After years of production use it has proven, at least in my opinion, to be the best decision given the state of affairs in NumPy and Python in general. The special value NaN (Not-A-Number) is used everywhere as the NA value, and there are API functions `isnull` and `notnull` which can be used across the dtypes to detect NA values.

However, it comes with it a couple of trade-offs which I most certainly have not ignored.

28.2.2 Support for integer NA

In the absence of high performance NA support being built into NumPy from the ground up, the primary casualty is the ability to represent NAs in integer arrays. For example:

```
In [5]: s = Series([1, 2, 3, 4, 5], index=list('abcde'))

In [6]: s
Out[6]:
a      1
b      2
c      3
```

```
d    4
e    5
dtype: int64
```

```
In [7]: s.dtype
Out[7]: dtype('int64')
```

```
In [8]: s2 = s.reindex(['a', 'b', 'c', 'f', 'u'])
```

```
In [9]: s2
Out[9]:
a    1
b    2
c    3
f   NaN
u   NaN
dtype: float64
```

```
In [10]: s2.dtype
Out[10]: dtype('float64')
```

This trade-off is made largely for memory and performance reasons, and also so that the resulting Series continues to be “numeric”. One possibility is to use `dtype=object` arrays instead.

28.2.3 NA type promotions

When introducing NAs into an existing Series or DataFrame via `reindex` or some other means, boolean and integer types will be promoted to a different dtype in order to store the NAs. These are summarized by this table:

Typeclass	Promotion dtype for storing NAs
floating	no change
object	no change
integer	cast to float64
boolean	cast to object

While this may seem like a heavy trade-off, in practice I have found very few cases where this is an issue in practice. Some explanation for the motivation here in the next section.

28.2.4 Why not make NumPy like R?

Many people have suggested that NumPy should simply emulate the NA support present in the more domain-specific statistical programming language R. Part of the reason is the NumPy type hierarchy:

Typeclass	Dtypes
<code>numpy.floating</code>	<code>float16</code> , <code>float32</code> , <code>float64</code> , <code>float128</code>
<code>numpy.integer</code>	<code>int8</code> , <code>int16</code> , <code>int32</code> , <code>int64</code>
<code>numpy.unsignedinteger</code>	<code>uint8</code> , <code>uint16</code> , <code>uint32</code> , <code>uint64</code>
<code>numpy.object_</code>	<code>object_</code>
<code>numpy.bool_</code>	<code>bool_</code>
<code>numpy.character</code>	<code>string_</code> , <code>unicode_</code>

The R language, by contrast, only has a handful of built-in data types: `integer`, `numeric` (floating-point), `character`, and `boolean`. NA types are implemented by reserving special bit patterns for each type to be used as the missing value. While doing this with the full NumPy type hierarchy would be possible, it would be a more substantial trade-off (especially for the 8- and 16-bit data types) and implementation undertaking.

An alternate approach is that of using masked arrays. A masked array is an array of data with an associated boolean *mask* denoting whether each value should be considered NA or not. I am personally not in love with this approach as I feel that overall it places a fairly heavy burden on the user and the library implementer. Additionally, it exacts a fairly high performance cost when working with numerical data compared with the simple approach of using NaN. Thus, I have chosen the Pythonic “practicality beats purity” approach and traded integer NA capability for a much simpler approach of using a special value in float and object arrays to denote NA, and promoting integer arrays to floating when NAs must be introduced.

28.3 Integer indexing

Label-based indexing with integer axis labels is a thorny topic. It has been discussed heavily on mailing lists and among various members of the scientific Python community. In pandas, our general viewpoint is that labels matter more than integer locations. Therefore, with an integer axis index *only* label-based indexing is possible with the standard tools like `.ix`. The following code will generate exceptions:

```
s = Series(range(5))
s[-1]
df = DataFrame(np.random.randn(5, 4))
df
df.ix[-2:]
```

This deliberate decision was made to prevent ambiguities and subtle bugs (many users reported finding bugs when the API change was made to stop “falling back” on position-based indexing).

28.4 Label-based slicing conventions

28.4.1 Non-monotonic indexes require exact matches

28.4.2 Endpoints are inclusive

Compared with standard Python sequence slicing in which the slice endpoint is not inclusive, label-based slicing in pandas **is inclusive**. The primary reason for this is that it is often not possible to easily determine the “successor” or next element after a particular label in an index. For example, consider the following Series:

```
In [11]: s = Series(randn(6), index=list('abcdef'))
```

```
In [12]: s
Out[12]:
a    -0.345411
b     1.721799
c     0.171342
d     1.222367
e     1.228721
f     0.549175
dtype: float64
```

Suppose we wished to slice from c to e, using integers this would be

```
In [13]: s[2:5]
Out[13]:
c     0.171342
d     1.222367
```

```
e    1.228721
dtype: float64
```

However, if you only had `c` and `e`, determining the next element in the index can be somewhat complicated. For example, the following does not work:

```
s.ix['c':'e'+1]
```

A very common use case is to limit a time series to start and end at two specific dates. To enable this, we made the design design to make label-based slicing include both endpoints:

```
In [14]: s.ix['c':'e']
Out[14]:
c    0.171342
d    1.222367
e    1.228721
dtype: float64
```

This is most definitely a “practicality beats purity” sort of thing, but it is something to watch out for if you expect label-based slicing to behave exactly in the way that standard Python integer slicing works.

28.5 Miscellaneous indexing gotchas

28.5.1 Reindex versus ix gotchas

Many users will find themselves using the `ix` indexing capabilities as a concise means of selecting data from a pandas object:

```
In [15]: df = DataFrame(randn(6, 4), columns=['one', 'two', 'three', 'four'],
.....:                  index=list('abcdef'))
.....:
```

```
In [16]: df
Out[16]:
   one    two    three    four
a -1.982099 -0.366112 -0.228622 -1.663680
b  0.527377 -1.428764 -0.177802  0.382121
c -0.049456  0.556557  0.993878 -0.433240
d -0.077343  1.052958  1.528472  0.644673
e -1.261108  1.265039  0.424791  0.385124
f -1.176251 -0.074802 -0.384239  1.075475
```

```
In [17]: df.ix[['b', 'c', 'e']]
Out[17]:
   one    two    three    four
b  0.527377 -1.428764 -0.177802  0.382121
c -0.049456  0.556557  0.993878 -0.433240
e -1.261108  1.265039  0.424791  0.385124
```

This is, of course, completely equivalent *in this case* to using the `reindex` method:

```
In [18]: df.reindex(['b', 'c', 'e'])
Out[18]:
   one    two    three    four
b  0.527377 -1.428764 -0.177802  0.382121
c -0.049456  0.556557  0.993878 -0.433240
e -1.261108  1.265039  0.424791  0.385124
```

Some might conclude that `ix` and `reindex` are 100% equivalent based on this. This is indeed true **except in the case of integer indexing**. For example, the above operation could alternately have been expressed as:

```
In [19]: df.ix[[1, 2, 4]]
Out[19]:
```

	one	two	three	four
b	0.527377	-1.428764	-0.177802	0.382121
c	-0.049456	0.556557	0.993878	-0.433240
e	-1.261108	1.265039	0.424791	0.385124

If you pass `[1, 2, 4]` to `reindex` you will get another thing entirely:

```
In [20]: df.reindex([1, 2, 4])
Out[20]:
```

	one	two	three	four
1	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN

So it's important to remember that `reindex` is **strict label indexing only**. This can lead to some potentially surprising results in pathological cases where an index contains, say, both integers and strings:

```
In [21]: s = Series([1, 2, 3], index=['a', 0, 1])
```

```
In [22]: s
Out[22]:
```

a	1
0	2
1	3

dtype: int64

```
In [23]: s.ix[[0, 1]]
Out[23]:
```

0	2
1	3

dtype: int64

```
In [24]: s.reindex([0, 1])
Out[24]:
```

0	2
1	3

dtype: int64

Because the index in this case does not contain solely integers, `ix` falls back on integer indexing. By contrast, `reindex` only looks for the values passed in the index, thus finding the integers 0 and 1. While it would be possible to insert some logic to check whether a passed sequence is all contained in the index, that logic would exact a very high cost in large data sets.

28.5.2 Reindex potentially changes underlying Series dtype

The use of `reindex_like` can potentially change the dtype of a `Series`.

```
In [25]: series = Series([1, 2, 3])
```

```
In [26]: x = Series([True])
```

```
In [27]: x.dtype
Out[27]: dtype('bool')
```

```
In [28]: x = Series([True]).reindex_like(series)
```

```
In [29]: x.dtype
Out[29]: dtype('O')
```

This is because `reindex_like` silently inserts NaNs and the `dtype` changes accordingly. This can cause some issues when using numpy ufuncs such as `numpy.logical_and`.

See the [this old issue](#) for a more detailed discussion.

28.6 Timestamp limitations

28.6.1 Minimum and maximum timestamps

Since pandas represents timestamps in nanosecond resolution, the timespan that can be represented using a 64-bit integer is limited to approximately 584 years:

```
In [30]: begin = Timestamp.min

In [31]: begin
Out[31]: Timestamp('1677-09-22 00:12:43.145225')

In [32]: end = Timestamp.max

In [33]: end
Out[33]: Timestamp('2262-04-11 23:47:16.854775807')
```

See [here](#) for ways to represent data outside these bound.

28.7 Parsing Dates from Text Files

When parsing multiple text file columns into a single date column, the new date column is prepended to the data and then `index_col` specification is indexed off of the new set of columns rather than the original ones:

```
In [34]: print(open('tmp.csv').read())
KORD,19990127, 19:00:00, 18:56:00, 0.8100
KORD,19990127, 20:00:00, 19:56:00, 0.0100
KORD,19990127, 21:00:00, 20:56:00, -0.5900
KORD,19990127, 21:00:00, 21:18:00, -0.9900
KORD,19990127, 22:00:00, 21:56:00, -0.5900
KORD,19990127, 23:00:00, 22:56:00, -0.5900

In [35]: date_spec = {'nominal': [1, 2], 'actual': [1, 3]}

In [36]: df = read_csv('tmp.csv', header=None,
.....:                 parse_dates=date_spec,
.....:                 keep_date_col=True,
.....:                 index_col=0)
.....:

# index_col=0 refers to the combined column "nominal" and not the original
# first column of 'KORD' strings
In [37]: df
```

Out[37]:

```
          actual    0    1    2    3  \
nominal
1999-01-27 19:00:00 1999-01-27 18:56:00 KORD 19990127 19:00:00 18:56:00
1999-01-27 20:00:00 1999-01-27 19:56:00 KORD 19990127 20:00:00 19:56:00
1999-01-27 21:00:00 1999-01-27 20:56:00 KORD 19990127 21:00:00 20:56:00
1999-01-27 21:00:00 1999-01-27 21:18:00 KORD 19990127 21:00:00 21:18:00
1999-01-27 22:00:00 1999-01-27 21:56:00 KORD 19990127 22:00:00 21:56:00
1999-01-27 23:00:00 1999-01-27 22:56:00 KORD 19990127 23:00:00 22:56:00

          4
nominal
1999-01-27 19:00:00 0.81
1999-01-27 20:00:00 0.01
1999-01-27 21:00:00 -0.59
1999-01-27 21:00:00 -0.99
1999-01-27 22:00:00 -0.59
1999-01-27 23:00:00 -0.59
```

28.8 Differences with NumPy

For Series and DataFrame objects, `var` normalizes by $N-1$ to produce unbiased estimates of the sample variance, while NumPy's `var` normalizes by N , which measures the variance of the sample. Note that `cov` normalizes by $N-1$ in both pandas and NumPy.

28.9 Thread-safety

As of pandas 0.11, pandas is not 100% thread safe. The known issues relate to the `DataFrame.copy` method. If you are doing a lot of copying of DataFrame objects shared among threads, we recommend holding locks inside the threads where the data copying occurs.

See [this link](#) for more information.

28.10 HTML Table Parsing

There are some versioning issues surrounding the libraries that are used to parse HTML tables in the top-level pandas `io` function `read_html`.

Issues with `lxml`

- Benefits
 - `lxml` is very fast
 - `lxml` requires Cython to install correctly.
- Drawbacks
 - `lxml` does *not* make any guarantees about the results of its parse *unless* it is given **strictly valid markup**.
 - In light of the above, we have chosen to allow you, the user, to use the `lxml` backend, but **this backend will use `html5lib` if `lxml` fails to parse**

- It is therefore *highly recommended* that you install both **BeautifulSoup4** and **html5lib**, so that you will still get a valid result (provided everything else is valid) even if **lxml** fails.

Issues with **BeautifulSoup4** using **lxml** as a backend

- The above issues hold here as well since **BeautifulSoup4** is essentially just a wrapper around a parser backend.

Issues with **BeautifulSoup4** using **html5lib** as a backend

- Benefits
 - **html5lib** is far more lenient than **lxml** and consequently deals with *real-life markup* in a much saner way rather than just, e.g., dropping an element without notifying you.
 - **html5lib** *generates valid HTML5 markup from invalid markup automatically*. This is extremely important for parsing HTML tables, since it guarantees a valid document. However, that does NOT mean that it is “correct”, since the process of fixing markup does not have a single definition.
 - **html5lib** is pure Python and requires no additional build steps beyond its own installation.
- Drawbacks
 - The biggest drawback to using **html5lib** is that it is slow as molasses. However consider the fact that many tables on the web are not big enough for the parsing algorithm runtime to matter. It is more likely that the bottleneck will be in the process of reading the raw text from the URL over the web, i.e., IO (input-output). For very large tables, this might not be true.

Issues with using **Anaconda**

- **Anaconda** ships with **lxml** version 3.2.0; the following workaround for **Anaconda** was successfully used to deal with the versioning issues surrounding **lxml** and **BeautifulSoup4**.

Note: Unless you have *both*:

- A strong restriction on the upper bound of the runtime of some code that incorporates `read_html()`
- Complete knowledge that the HTML you will be parsing will be 100% valid at all times

then you should install **html5lib** and things will work swimmingly without you having to muck around with *conda*. If you want the best of both worlds then install both **html5lib** and **lxml**. If you do install **lxml** then you need to perform the following commands to ensure that **lxml** will work correctly:

```
# remove the included version
conda remove lxml

# install the latest version of lxml
pip install 'git+git://github.com/lxml/lxml.git'

# install the latest version of beautifulsoup4
pip install 'bzip2+lp:beautifulsoup4'
```

Note that you need **bzip2** and **git** installed to perform the last two operations.

28.11 Byte-Ordering Issues

Occasionally you may have to deal with data that were created on a machine with a different byte order than the one on which you are running Python. A common symptom of this issue is an error like

Traceback

```
...  
ValueError: Big-endian buffer not supported on little-endian compiler
```

To deal with this issue you should convert the underlying NumPy array to the native system byte order *before* passing it to Series/DataFrame/Panel constructors using something similar to the following:

```
In [38]: x = np.array(list(range(10)), '>i4') # big endian  
  
In [39]: newx = x.byteswap().newbyteorder() # force native byteorder  
  
In [40]: s = Series(newx)
```

See [the NumPy documentation on byte order](#) for more details.

RPY2 / R INTERFACE

Warning: In v0.16.0, the `pandas.rpy` interface has been **deprecated and will be removed in a future version**. Similar functionality can be accessed through the [rpy2](#) project. See the [updating](#) section for a guide to port your code from the `pandas.rpy` to `rpy2` functions.

29.1 Updating your code to use rpy2 functions

In v0.16.0, the `pandas.rpy` module has been **deprecated** and users are pointed to the similar functionality in `rpy2` itself (`rpy2 >= 2.4`).

Instead of importing `import pandas.rpy.common as com`, the following imports should be done to activate the pandas conversion support in `rpy2`:

```
from rpy2.robjects import pandas2ri
pandas2ri.activate()
```

Converting data frames back and forth between `rpy2` and `pandas` should be largely automated (no need to convert explicitly, it will be done on the fly in most `rpy2` functions).

To convert explicitly, the functions are `pandas2ri.py2ri()` and `pandas2ri.ri2py()`. So these functions can be used to replace the existing functions in `pandas`:

- `com.convert_to_r_dataframe(df)` should be replaced with `pandas2ri.py2ri(df)`
- `com.convert_obj(rdf)` should be replaced with `pandas2ri.ri2py(rdf)`

Note: these functions are for the latest version (`rpy2 2.5.x`) and were called `pandas2ri.pandas2ri()` and `pandas2ri.ri2pandas()` previously.

Some of the other functionality in *pandas.rpy* can be replaced easily as well. For example to load R data as done with the `load_data` function, the current method:

```
df_iris = com.load_data('iris')
```

can be replaced with:

```
from rpy2.robjects import r
r.data('iris')
df_iris = pandas2ri.ri2py(r[name])
```

The `convert_to_r_matrix` function can be replaced by the normal `pandas2ri.py2ri` to convert dataframes, with a subsequent call to `R as.matrix` function.

Warning: Not all conversion functions in rpy2 are working exactly the same as the current methods in pandas. If you experience problems or limitations in comparison to the ones in pandas, please report this at the [issue tracker](#).

See also the documentation of the [rpy2](#) project.

29.2 R interface with rpy2

If your computer has R and rpy2 (> 2.2) installed (which will be left to the reader), you will be able to leverage the below functionality. On Windows, doing this is quite an ordeal at the moment, but users on Unix-like systems should find it quite easy. rpy2 evolves in time, and is currently reaching its release 2.3, while the current interface is designed for the 2.2.x series. We recommend to use 2.2.x over other series unless you are prepared to fix parts of the code, yet the rpy2-2.3.0 introduces improvements such as a better R-Python bridge memory management layer so it might be a good idea to bite the bullet and submit patches for the few minor differences that need to be fixed.

```
# if installing for the first time
hg clone http://bitbucket.org/lgautier/rpy2

cd rpy2
hg pull
hg update version_2.2.x
sudo python setup.py install
```

Note: To use R packages with this interface, you will need to install them inside R yourself. At the moment it cannot install them for you.

Once you have done installed R and rpy2, you should be able to import `pandas.rpy.common` without a hitch.

29.3 Transferring R data sets into Python

The `load_data` function retrieves an R data set and converts it to the appropriate pandas object (most likely a DataFrame):

```
In [1]: import pandas.rpy.common as com
```

```
In [2]: infert = com.load_data('infert')
```

```
In [3]: infert.head()
```

```
Out[3]:
```

	education	age	parity	induced	case	spontaneous	stratum	pooled.stratum
1	0-5yrs	26	6	1	1	2	1	3
2	0-5yrs	42	1	1	1	0	2	1
3	0-5yrs	39	6	2	1	0	3	4
4	0-5yrs	34	4	2	1	0	4	2
5	6-11yrs	35	3	1	1	1	5	32

29.4 Converting DataFrames into R objects

New in version 0.8.

Starting from pandas 0.8, there is **experimental** support to convert DataFrames into the equivalent R object (that is, **data.frame**):

```
In [4]: from pandas import DataFrame

In [5]: df = DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]},
...:                  index=["one", "two", "three"])
...:

In [6]: r_dataframe = com.convert_to_r_dataframe(df)

In [7]: print(type(r_dataframe))
<class 'rpy2.robjects.vectors.DataFrame'>

In [8]: print(r_dataframe)
   A B C
one  1 4 7
two  2 5 8
three 3 6 9
```

The DataFrame's index is stored as the `rownames` attribute of the `data.frame` instance.

You can also use **convert_to_r_matrix** to obtain a `Matrix` instance, but bear in mind that it will only work with homogeneously-typed DataFrames (as R matrices bear no information on the data type):

```
In [9]: r_matrix = com.convert_to_r_matrix(df)

In [10]: print(type(r_matrix))
<class 'rpy2.robjects.vectors.Matrix'>

In [11]: print(r_matrix)
   A B C
one  1 4 7
two  2 5 8
three 3 6 9
```

29.5 Calling R functions with pandas objects

29.6 High-level interface to R estimators

PANDAS ECOSYSTEM

Increasingly, packages are being built on top of pandas to address specific needs in data preparation, analysis and visualization. This is encouraging because it means pandas is not only helping users to handle their data tasks but also that it provides a better starting point for developers to build powerful and more focused data tools. The creation of libraries that complement pandas' functionality also allows pandas development to remain focused around its original requirements.

This is an in-exhaustive list of projects that build on pandas in order to provide tools in the PyData space.

We'd like to make it easier for users to find these project, if you know of other substantial projects that you feel should be on this list, please let us know.

30.1 Statistics and Machine Learning

30.1.1 Statsmodels

Statsmodels is the prominent python "statistics and econometrics library" and it has a long-standing special relationship with pandas. Statsmodels provides powerful statistics, econometrics, analysis and modeling functionality that is out of pandas' scope. Statsmodels leverages pandas objects as the underlying data container for computation.

30.1.2 sklearn-pandas

Use pandas DataFrames in your [scikit-learn](#) ML pipeline.

30.2 Visualization

30.2.1 Bokeh

Bokeh is a Python interactive visualization library for large datasets that natively uses the latest web technologies. Its goal is to provide elegant, concise construction of novel graphics in the style of Protovis/D3, while delivering high-performance interactivity over large data to thin clients.

30.2.2 yhat/ggplot

Hadley Wickham's [ggplot2](#) is a foundational exploratory visualization package for the R language. Based on "The Grammar of Graphics" it provides a powerful, declarative and extremely general way to generate bespoke plots of any kind of data. It's really quite incredible. Various implementations to other languages are available, but a faithful

implementation for python users has long been missing. Although still young (as of Jan-2014), the [yhat/ggplot](#) project has been progressing quickly in that direction.

30.2.3 Seaborn

Although pandas has quite a bit of “just plot it” functionality built-in, visualization and in particular statistical graphics is a vast field with a long tradition and lots of ground to cover. The [Seaborn](#) project builds on top of pandas and [matplotlib](#) to provide easy plotting of data which extends to more advanced types of plots than those offered by pandas.

30.2.4 Vincent

The [Vincent](#) project leverages [Vega](#) (that in turn, leverages [d3](#)) to create plots. It has great support for pandas data objects.

30.3 IDE

30.3.1 IPython

IPython is an interactive command shell and distributed computing environment. IPython Notebook is a web application for creating IPython notebooks. An IPython notebook is a JSON document containing an ordered list of input/output cells which can contain code, text, mathematics, plots and rich media. IPython notebooks can be converted to a number of open standard output formats (HTML, HTML presentation slides, LaTeX, PDF, ReStructuredText, Markdown, Python) through ‘Download As’ in the web interface and `ipython nbconvert` in a shell.

Pandas DataFrames implement `_repr_html_` methods which are utilized by IPython Notebook for displaying (abbreviated) HTML tables. (Note: HTML tables may or may not be compatible with non-HTML IPython output formats.)

30.3.2 quantopian/qgrid

qgrid is “an interactive grid for sorting and filtering DataFrames in IPython Notebook” built with SlickGrid.

30.3.3 Spyder

Spyder is a cross-platform Qt-based open-source Python IDE with editing, testing, debugging, and introspection features. Spyder can now introspect and display Pandas DataFrames and show both “column wise min/max and global min/max coloring.”

30.4 API

30.4.1 quandl/Python

Quandl API for Python wraps the Quandl REST API to return Pandas DataFrames with timeseries indexes.

30.4.2 pydatastream

PyDatastream is a Python interface to the [Thomson Dataworks Enterprise \(DWE/Datastream\)](#) SOAP API to return indexed Pandas DataFrames or Panels with financial data. This package requires valid credentials for this API (non free).

30.4.3 pandaSDMX

pandaSDMX is an extensible library to retrieve and acquire statistical data and metadata disseminated in [SDMX 2.1](#). This standard is currently supported by the European statistics office (Eurostat) and the European Central Bank (ECB). Datasets may be returned as pandas Series or multi-indexed DataFrames.

30.4.4 fredapi

fredapi is a Python interface to the [Federal Reserve Economic Data \(FRED\)](#) provided by the Federal Reserve Bank of St. Louis. It works with both the FRED database and ALFRED database that contains point-in-time data (i.e. historic data revisions). fredapi provides a wrapper in python to the FRED HTTP API, and also provides several convenient methods for parsing and analyzing point-in-time data from ALFRED. fredapi makes use of pandas and returns data in a Series or DataFrame. This module requires a FRED API key that you can obtain for free on the FRED website.

30.5 Domain Specific

30.5.1 Geopandas

Geopandas extends pandas data objects to include geographic information which support geometric operations. If your work entails maps and geographical coordinates, and you love pandas, you should take a close look at Geopandas.

30.5.2 xray

xray brings the labeled data power of pandas to the physical sciences by providing N-dimensional variants of the core pandas data structures. It aims to provide a pandas-like and pandas-compatible toolkit for analytics on multi-dimensional arrays, rather than the tabular data for which pandas excels.

30.6 Out-of-core

30.6.1 Blaze

Blaze provides a standard API for doing computations with various in-memory and on-disk backends: NumPy, Pandas, SQLAlchemy, MongoDB, PyTables, PySpark.

COMPARISON WITH R / R LIBRARIES

Since `pandas` aims to provide a lot of the data manipulation and analysis functionality that people use `R` for, this page was started to provide a more detailed look at the `R` language and its many third party libraries as they relate to `pandas`. In comparisons with `R` and CRAN libraries, we care about the following things:

- **Functionality / flexibility:** what can/cannot be done with each tool
- **Performance:** how fast are operations. Hard numbers/benchmarks are preferable
- **Ease-of-use:** Is one tool easier/harder to use (you may have to be the judge of this, given side-by-side code comparisons)

This page is also here to offer a bit of a translation guide for users of these `R` packages.

For transfer of `DataFrame` objects from `pandas` to `R`, one option is to use `HDF5` files, see [External Compatibility](#) for an example.

31.1 Base R

31.1.1 Slicing with R's `c`

`R` makes it easy to access `data.frame` columns by name

```
df <- data.frame(a=rnorm(5), b=rnorm(5), c=rnorm(5), d=rnorm(5), e=rnorm(5))
df[, c("a", "c", "e")]
```

or by integer location

```
df <- data.frame(matrix(rnorm(1000), ncol=100))
df[, c(1:10, 25:30, 40, 50:100)]
```

Selecting multiple columns by name in `pandas` is straightforward

```
In [1]: df = pd.DataFrame(np.random.randn(10, 3), columns=list('abc'))
```

```
In [2]: df[['a', 'c']]
```

```
Out[2]:
```

	a	c
0	-1.039575	-0.424972
1	0.567020	-1.087401
2	-0.673690	-1.478427
3	0.524988	0.577046
4	-1.715002	-0.370647
5	-1.157892	0.844885
6	1.075770	1.643563

```
7 -1.469388 -0.674600
8 -1.776904 -1.294524
9  0.413738 -0.472035
```

```
In [3]: df.loc[:, ['a', 'c']]
```

```
Out[3]:
```

```
      a      c
0 -1.039575 -0.424972
1  0.567020 -1.087401
2 -0.673690 -1.478427
3  0.524988  0.577046
4 -1.715002 -0.370647
5 -1.157892  0.844885
6  1.075770  1.643563
7 -1.469388 -0.674600
8 -1.776904 -1.294524
9  0.413738 -0.472035
```

Selecting multiple noncontiguous columns by integer location can be achieved with a combination of the `iloc` indexer attribute and `numpy.r_`.

```
In [4]: named = list('abcdefg')
```

```
In [5]: n = 30
```

```
In [6]: columns = named + np.arange(len(named), n).tolist()
```

```
In [7]: df = pd.DataFrame(np.random.randn(n, n), columns=columns)
```

```
In [8]: df.iloc[:, np.r_[:10, 24:30]]
```

```
Out[8]:
```

```
      a      b      c      d      e      f      g  \
0 -0.013960 -0.362543 -0.006154 -0.923061  0.895717  0.805244 -1.206412
1  0.545952 -1.219217 -1.226825  0.769804 -1.281247 -0.727707 -0.121306
2  2.396780  0.014871  3.357427 -0.317441 -1.236269  0.896171 -0.487602
3 -0.988387  0.094055  1.262731  1.289997  0.082423 -0.055758  0.536580
4 -1.340896  1.846883 -1.328865  1.682706 -1.717693  0.888782  0.228440
5  0.464000  0.227371 -0.496922  0.306389 -2.290613 -1.134623 -1.561819
6 -0.507516 -0.230096  0.394500 -1.934370 -1.652499  1.488753 -0.896484
..      ...      ...      ...      ...      ...      ...      ...
23 -0.083272 -0.273955 -0.772369 -1.242807 -0.386336 -0.182486  0.164816
24  2.071413 -1.364763  1.122066  0.066847  1.751987  0.419071 -1.118283
25  0.036609  0.359986  1.211905  0.850427  1.554957 -0.888463 -1.508808
26 -1.179240  0.238923  1.756671 -0.747571  0.543625 -0.159609 -0.051458
27  0.025645  0.932436 -1.694531 -0.182236 -1.072710  0.466764 -0.072673
28  0.439086  0.812684 -0.128932 -0.142506 -1.137207  0.462001 -0.159466
29 -0.909806 -0.312006  0.383630 -0.631606  1.321415 -0.004799 -2.008210

      7      8      9      24      25      26      27  \
0  2.565646  1.431256  1.340309  0.875906 -2.211372  0.974466 -2.006747
1 -0.097883  0.695775  0.341734 -1.743161 -0.826591 -0.345352  1.314232
2 -0.082240 -2.182937  0.380396  1.266143  0.299368 -0.863838  0.408204
3 -0.489682  0.369374 -0.034571  0.221471 -0.744471  0.758527  1.729689
4  0.901805  1.171216  0.520260  0.650776 -1.461665 -1.137707 -0.891060
5 -0.260838  0.281957  1.523962 -0.008434  1.952541 -1.056652  0.533946
6  0.576897  1.146000  1.487349  2.015523 -1.833722  1.771740 -0.670027
..      ...      ...      ...      ...      ...      ...      ...
23  0.065624  0.307665 -1.898358  1.389045 -0.873585 -0.699862  0.812477
```

```

24  1.010694  0.877138 -0.611561 -1.040389 -0.796211  0.241596  0.385922
25 -0.617855  0.536164  2.175585  1.872601 -2.513465 -0.139184  0.810491
26  0.937882  0.617547  0.287918 -1.584814  0.307941  1.809049  0.296237
27 -0.026233 -0.051744  0.001402  0.150664 -3.060395  0.040268  0.066091
28 -1.788308  0.753604  0.918071  0.922729  0.869610  0.364726 -0.226101
29 -0.481634 -2.056211 -2.106095  0.039227  0.211283  1.440190 -0.989193

```

```

      28      29
0 -0.410001 -0.078638
1  0.690579  0.995761
2 -1.048089 -0.025747
3 -0.964980 -0.845696
4 -0.693921  1.613616
5 -1.226970  0.040403
6  0.049307 -0.521493
..      ...      ...
23 -0.469503  1.142702
24 -0.486078  0.433042
25  0.571599 -0.000676
26 -0.143550  0.289401
27 -0.192862  1.979055
28 -0.657647 -0.952699
29  0.313335 -0.399709

```

```
[30 rows x 16 columns]
```

31.1.2 aggregate

In R you may want to split data into subsets and compute the mean for each. Using a data.frame called `df` and splitting it into groups `by1` and `by2`:

```

df <- data.frame(
  v1 = c(1,3,5,7,8,3,5,NA,4,5,7,9),
  v2 = c(11,33,55,77,88,33,55,NA,44,55,77,99),
  by1 = c("red", "blue", 1, 2, NA, "big", 1, 2, "red", 1, NA, 12),
  by2 = c("wet", "dry", 99, 95, NA, "damp", 95, 99, "red", 99, NA, NA))
aggregate(x=df[, c("v1", "v2")], by=list(mydf2$by1, mydf2$by2), FUN = mean)

```

The `groupby()` method is similar to base R aggregate function.

```

In [9]: df = pd.DataFrame({
...:     'v1': [1,3,5,7,8,3,5,np.nan,4,5,7,9],
...:     'v2': [11,33,55,77,88,33,55,np.nan,44,55,77,99],
...:     'by1': ["red", "blue", 1, 2, np.nan, "big", 1, 2, "red", 1, np.nan, 12],
...:     'by2': ["wet", "dry", 99, 95, np.nan, "damp", 95, 99, "red", 99, np.nan,
...:             np.nan]
...: })
...:

```

```
In [10]: g = df.groupby(['by1','by2'])
```

```
In [11]: g[['v1','v2']].mean()
```

```

Out[11]:
      v1  v2
by1 by2
1    95    5  55
    99    5  55

```

```
2      95      7  77
      99   NaN NaN
big  damp    3  33
blue dry     3  33
red  red     4  44
      wet     1  11
```

For more details and examples see [the groupby documentation](#).

31.1.3 match / %in%

A common way to select data in R is using `%in%` which is defined using the function `match`. The operator `%in%` is used to return a logical vector indicating if there is a match or not:

```
s <- 0:4
s %in% c(2, 4)
```

The `isin()` method is similar to R `%in%` operator:

```
In [12]: s = pd.Series(np.arange(5), dtype=np.float32)
```

```
In [13]: s.isin([2, 4])
```

```
Out[13]:
0    False
1    False
2     True
3    False
4     True
dtype: bool
```

The `match` function returns a vector of the positions of matches of its first argument in its second:

```
s <- 0:4
match(s, c(2, 4))
```

The `apply()` method can be used to replicate this:

```
In [14]: s = pd.Series(np.arange(5), dtype=np.float32)
```

```
In [15]: pd.Series(pd.match(s, [2, 4], np.nan))
```

```
Out[15]:
0    NaN
1    NaN
2     0
3    NaN
4     1
dtype: float64
```

For more details and examples see [the reshaping documentation](#).

31.1.4 tapply

`tapply` is similar to `aggregate`, but data can be in a ragged array, since the subclass sizes are possibly irregular. Using a `data.frame` called `baseball`, and retrieving information based on the array `team`:

```
baseball <-
  data.frame(team = gl(5, 5,
    labels = paste("Team", LETTERS[1:5])),
    player = sample(letters, 25),
    batting.average = runif(25, .200, .400))

tapply(baseball$batting.average, baseball$team,
  max)
```

In pandas we may use `pivot_table()` method to handle this:

```
In [16]: import random
```

```
In [17]: import string
```

```
In [18]: baseball = pd.DataFrame({
  ....:   'team': ["team %d" % (x+1) for x in range(5)]*5,
  ....:   'player': random.sample(list(string.ascii_lowercase), 25),
  ....:   'batting avg': np.random.uniform(.200, .400, 25)
  ....:   })
  ....:
```

```
In [19]: baseball.pivot_table(values='batting avg', columns='team', aggfunc=np.max)
```

```
Out[19]:
team
team 1    0.394457
team 2    0.395730
team 3    0.343015
team 4    0.388863
team 5    0.377379
Name: batting avg, dtype: float64
```

For more details and examples see [the reshaping documentation](#).

31.1.5 subset

New in version 0.13.

The `query()` method is similar to the base R `subset` function. In R you might want to get the rows of a `data.frame` where one column's values are less than another column's values:

```
df <- data.frame(a=rnorm(10), b=rnorm(10))
subset(df, a <= b)
df[df$a <= df$b,] # note the comma
```

In pandas, there are a few ways to perform subsetting. You can use `query()` or pass an expression as if it were an index/slice as well as standard boolean indexing:

```
In [20]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
```

```
In [21]: df.query('a <= b')
```

```
Out[21]:
   a         b
0 -1.003455 -0.990738
1  0.083515  0.548796
3 -0.524392  0.904400
4 -0.837804  0.746374
8 -0.507219  0.245479
```

```
In [22]: df[df.a <= df.b]
```

```
Out[22]:
```

	a	b
0	-1.003455	-0.990738
1	0.083515	0.548796
3	-0.524392	0.904400
4	-0.837804	0.746374
8	-0.507219	0.245479

```
In [23]: df.loc[df.a <= df.b]
```

```
Out[23]:
```

	a	b
0	-1.003455	-0.990738
1	0.083515	0.548796
3	-0.524392	0.904400
4	-0.837804	0.746374
8	-0.507219	0.245479

For more details and examples see *the query documentation*.

31.1.6 with

New in version 0.13.

An expression using a data.frame called `df` in R with the columns `a` and `b` would be evaluated using `with` like so:

```
df <- data.frame(a=rnorm(10), b=rnorm(10))
with(df, a + b)
df$a + df$b # same as the previous expression
```

In pandas the equivalent expression, using the `eval()` method, would be:

```
In [24]: df = pd.DataFrame({'a': np.random.randn(10), 'b': np.random.randn(10)})
```

```
In [25]: df.eval('a + b')
```

```
Out[25]:
```

0	-0.920205
1	-0.860236
2	1.154370
3	0.188140
4	-1.163718
5	0.001397
6	-0.825694
7	-1.138198
8	-1.708034
9	1.148616

dtype: float64

```
In [26]: df.a + df.b # same as the previous expression
```

```
Out[26]:
```

0	-0.920205
1	-0.860236
2	1.154370
3	0.188140
4	-1.163718
5	0.001397
6	-0.825694

```

7    -1.138198
8    -1.708034
9     1.148616
dtype: float64

```

In certain cases `eval()` will be much faster than evaluation in pure Python. For more details and examples see [the eval documentation](#).

31.2 zoo

31.3 xts

31.4 plyr

`plyr` is an R library for the split-apply-combine strategy for data analysis. The functions revolve around three data structures in R, `a` for arrays, `l` for lists, and `d` for `data.frame`. The table below shows how these data structures could be mapped in Python.

R	Python
array	list
lists	dictionary or list of objects
data.frame	dataframe

31.4.1 ddply

An expression using a `data.frame` called `df` in R where you want to summarize `x` by month:

```

require(plyr)
df <- data.frame(
  x = runif(120, 1, 168),
  y = runif(120, 7, 334),
  z = runif(120, 1.7, 20.7),
  month = rep(c(5,6,7,8),30),
  week = sample(1:4, 120, TRUE)
)

ddply(df, .(month, week), summarize,
      mean = round(mean(x), 2),
      sd = round(sd(x), 2))

```

In pandas the equivalent expression, using the `groupby()` method, would be:

```

In [27]: df = pd.DataFrame({
.....:     'x': np.random.uniform(1., 168., 120),
.....:     'y': np.random.uniform(7., 334., 120),
.....:     'z': np.random.uniform(1.7, 20.7, 120),
.....:     'month': [5,6,7,8]*30,
.....:     'week': np.random.randint(1,4, 120)
.....: })
.....:

In [28]: grouped = df.groupby(['month','week'])

```

```
In [29]: print grouped['x'].agg([np.mean, np.std])
          mean      std
month week
5      1      71.840596  52.886392
        2      71.904794  55.786805
        3      89.845632  49.892367
6      1      97.730877  52.442172
        2      93.369836  47.178389
        3      96.592088  58.773744
7      1      59.255715  43.442336
        2      69.634012  28.607369
        3      84.510992  59.761096
8      1     104.787666  31.745437
        2      69.717872  53.747188
        3      79.892221  52.950459
```

For more details and examples see [the groupby documentation](#).

31.5 reshape / reshape2

31.5.1 melt.array

An expression using a 3 dimensional array called `a` in R where you want to melt it into a data.frame:

```
a <- array(c(1:23, NA), c(2,3,4))
data.frame(melt(a))
```

In Python, since `a` is a list, you can simply use list comprehension.

```
In [30]: a = np.array(list(range(1,24))+[np.NaN]).reshape(2,3,4)
```

```
In [31]: pd.DataFrame([tuple(list(x)+[val]) for x, val in np.ndenumerate(a)])
```

```
Out[31]:
   0  1  2  3
0  0  0  0  1
1  0  0  1  2
2  0  0  2  3
3  0  0  3  4
4  0  1  0  5
5  0  1  1  6
6  0  1  2  7
..  ..  ..  ..
17 1  1  1 18
18 1  1  2 19
19 1  1  3 20
20 1  2  0 21
21 1  2  1 22
22 1  2  2 23
23 1  2  3 NaN
```

```
[24 rows x 4 columns]
```

31.5.2 melt.list

An expression using a list called `a` in R where you want to melt it into a data.frame:

```
a <- as.list(c(1:4, NA))
data.frame(melt(a))
```

In Python, this list would be a list of tuples, so `DataFrame()` method would convert it to a dataframe as required.

```
In [32]: a = list(enumerate(list(range(1,5))+[np.NaN]))
```

```
In [33]: pd.DataFrame(a)
```

```
Out[33]:
   0  1
0  0  1
1  1  2
2  2  3
3  3  4
4  4 NaN
```

For more details and examples see *the Into to Data Structures documentation*.

31.5.3 melt.data.frame

An expression using a data.frame called `cheese` in R where you want to reshape the data.frame:

```
cheese <- data.frame(
  first = c('John', 'Mary'),
  last = c('Doe', 'Bo'),
  height = c(5.5, 6.0),
  weight = c(130, 150)
)
melt(cheese, id=c("first", "last"))
```

In Python, the `melt()` method is the R equivalent:

```
In [34]: cheese = pd.DataFrame({'first' : ['John', 'Mary'],
.....:                        'last' : ['Doe', 'Bo'],
.....:                        'height' : [5.5, 6.0],
.....:                        'weight' : [130, 150]})
.....:
```

```
In [35]: pd.melt(cheese, id_vars=['first', 'last'])
```

```
Out[35]:
   first last variable  value
0  John  Doe   height    5.5
1  Mary  Bo   height    6.0
2  John  Doe  weight   130.0
3  Mary  Bo  weight   150.0
```

```
In [36]: cheese.set_index(['first', 'last']).stack() # alternative way
```

```
Out[36]:
first last
John  Doe   height    5.5
       weight   130.0
Mary  Bo   height    6.0
       weight   150.0
dtype: float64
```

For more details and examples see *the reshaping documentation*.

31.5.4 cast

In R `acast` is an expression using a data.frame called `df` in R to cast into a higher dimensional array:

```
df <- data.frame(
  x = runif(12, 1, 168),
  y = runif(12, 7, 334),
  z = runif(12, 1.7, 20.7),
  month = rep(c(5,6,7),4),
  week = rep(c(1,2), 6)
)

mdf <- melt(df, id=c("month", "week"))
acast(mdf, week ~ month ~ variable, mean)
```

In Python the best way is to make use of `pivot_table()`:

```
In [37]: df = pd.DataFrame({
.....:     'x': np.random.uniform(1., 168., 12),
.....:     'y': np.random.uniform(7., 334., 12),
.....:     'z': np.random.uniform(1.7, 20.7, 12),
.....:     'month': [5,6,7]*4,
.....:     'week': [1,2]*6
.....: })

In [38]: mdf = pd.melt(df, id_vars=['month', 'week'])

In [39]: pd.pivot_table(mdf, values='value', index=['variable', 'week'],
.....:                   columns=['month'], aggfunc=np.mean)
.....:
Out[39]:
variable week      5      6      7
x          1  114.001700  132.227290  65.808204
          2  124.669553  147.495706  82.882820
y          1  225.636630  301.864228  91.706834
          2   57.692665  215.851669  218.004383
z          1  17.793871   7.124644  17.679823
          2  15.068355  13.873974   9.394966
```

Similarly for `dcast` which uses a data.frame called `df` in R to aggregate information based on `Animal` and `FeedType`:

```
df <- data.frame(
  Animal = c('Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
            'Animal2', 'Animal3'),
  FeedType = c('A', 'B', 'A', 'A', 'B', 'B', 'A'),
  Amount = c(10, 7, 4, 2, 5, 6, 2)
)

dcast(df, Animal ~ FeedType, sum, fill=NaN)
# Alternative method using base R
with(df, tapply(Amount, list(Animal, FeedType), sum))
```

Python can approach this in two different ways. Firstly, similar to above using `pivot_table()`:

```
In [40]: df = pd.DataFrame({
.....:     'Animal': ['Animal1', 'Animal2', 'Animal3', 'Animal2', 'Animal1',
.....:               'Animal2', 'Animal3'],
```

```

.....:     'FeedType': ['A', 'B', 'A', 'A', 'B', 'B', 'A'],
.....:     'Amount': [10, 7, 4, 2, 5, 6, 2],
.....: })
.....:

```

```
In [41]: df.pivot_table(values='Amount', index='Animal', columns='FeedType', aggfunc='sum')
```

```

Out[41]:
FeedType  A    B
Animal
Animal1   10   5
Animal2    2  13
Animal3    6 NaN

```

The second approach is to use the `groupby()` method:

```
In [42]: df.groupby(['Animal', 'FeedType'])['Amount'].sum()
```

```

Out[42]:
Animal  FeedType
Animal1  A          10
         B           5
Animal2  A           2
         B          13
Animal3  A           6
Name: Amount, dtype: int64

```

For more details and examples see [the reshaping documentation](#) or [the groupby documentation](#).

31.5.5 factor

New in version 0.15.

pandas has a data type for categorical data.

```

cut(c(1,2,3,4,5,6), 3)
factor(c(1,2,3,2,2,3))

```

In pandas this is accomplished with `pd.cut` and `astype("category")`:

```
In [43]: pd.cut(pd.Series([1,2,3,4,5,6]), 3)
```

```

Out[43]:
0    (0.995, 2.667]
1    (0.995, 2.667]
2    (2.667, 4.333]
3    (2.667, 4.333]
4    (4.333, 6]
5    (4.333, 6]
dtype: category
Categories (3, object): [(0.995, 2.667] < (2.667, 4.333] < (4.333, 6]]

```

```
In [44]: pd.Series([1,2,3,2,2,3]).astype("category")
```

```

Out[44]:
0    1
1    2
2    3
3    2
4    2
5    3

```

```
dtype: category
Categories (3, int64): [1, 2, 3]
```

For more details and examples see *categorical introduction* and the *API documentation*. There is also a documentation regarding the *differences to R's factor*.

COMPARISON WITH SQL

Since many potential pandas users have some familiarity with [SQL](#), this page is meant to provide some examples of how various SQL operations would be performed using pandas.

If you're new to pandas, you might want to first read through *10 Minutes to pandas* to familiarize yourself with the library.

As is customary, we import pandas and numpy as follows:

```
In [1]: import pandas as pd
```

```
In [2]: import numpy as np
```

Most of the examples will utilize the `tips` dataset found within pandas tests. We'll read the data into a `DataFrame` called `tips` and assume we have a database table of the same name and structure.

```
In [3]: url = 'https://raw.githubusercontent.com/pydata/pandas/master/pandas/tests/data/tips.csv'
```

```
In [4]: tips = pd.read_csv(url)
```

```
In [5]: tips.head()
```

```
Out[5]:
```

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

32.1 SELECT

In SQL, selection is done using a comma-separated list of columns you'd like to select (or a `*` to select all columns):

```
SELECT total_bill, tip, smoker, time
FROM tips
LIMIT 5;
```

With pandas, column selection is done by passing a list of column names to your `DataFrame`:

```
In [6]: tips[['total_bill', 'tip', 'smoker', 'time']].head(5)
```

```
Out[6]:
```

	total_bill	tip	smoker	time
0	16.99	1.01	No	Dinner
1	10.34	1.66	No	Dinner
2	21.01	3.50	No	Dinner

```
3      23.68  3.31      No  Dinner
4      24.59  3.61      No  Dinner
```

Calling the DataFrame without the list of column names would display all columns (akin to SQL's *).

32.2 WHERE

Filtering in SQL is done via a WHERE clause.

```
SELECT *
FROM tips
WHERE time = 'Dinner'
LIMIT 5;
```

DataFrames can be filtered in multiple ways; the most intuitive of which is using [boolean indexing](#).

```
In [7]: tips[tips['time'] == 'Dinner'].head(5)
Out[7]:
```

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

The above statement is simply passing a Series of True/False objects to the DataFrame, returning all rows with True.

```
In [8]: is_dinner = tips['time'] == 'Dinner'
```

```
In [9]: is_dinner.value_counts()
Out[9]:
```

True	176
False	68

dtype: int64

```
In [10]: tips[is_dinner].head(5)
Out[10]:
```

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4

Just like SQL's OR and AND, multiple conditions can be passed to a DataFrame using | (OR) and & (AND).

```
-- tips of more than $5.00 at Dinner meals
SELECT *
FROM tips
WHERE time = 'Dinner' AND tip > 5.00;

# tips of more than $5.00 at Dinner meals
In [11]: tips[(tips['time'] == 'Dinner') & (tips['tip'] > 5.00)]
Out[11]:
```

	total_bill	tip	sex	smoker	day	time	size
23	39.42	7.58	Male	No	Sat	Dinner	4

44	30.40	5.60	Male	No	Sun	Dinner	4
47	32.40	6.00	Male	No	Sun	Dinner	4
52	34.81	5.20	Female	No	Sun	Dinner	4
59	48.27	6.73	Male	No	Sat	Dinner	4
116	29.93	5.07	Male	No	Sun	Dinner	4
155	29.85	5.14	Female	No	Sun	Dinner	5
170	50.81	10.00	Male	Yes	Sat	Dinner	3
172	7.25	5.15	Male	Yes	Sun	Dinner	2
181	23.33	5.65	Male	Yes	Sun	Dinner	2
183	23.17	6.50	Male	Yes	Sun	Dinner	4
211	25.89	5.16	Male	Yes	Sat	Dinner	4
212	48.33	9.00	Male	No	Sat	Dinner	4
214	28.17	6.50	Female	Yes	Sat	Dinner	3
239	29.03	5.92	Male	No	Sat	Dinner	3

```
-- tips by parties of at least 5 diners OR bill total was more than $45
SELECT *
FROM tips
WHERE size >= 5 OR total_bill > 45;
```

```
# tips by parties of at least 5 diners OR bill total was more than $45
```

```
In [12]: tips[(tips['size'] >= 5) | (tips['total_bill'] > 45)]
```

```
Out[12]:
```

	total_bill	tip	sex	smoker	day	time	size
59	48.27	6.73	Male	No	Sat	Dinner	4
125	29.80	4.20	Female	No	Thur	Lunch	6
141	34.30	6.70	Male	No	Thur	Lunch	6
142	41.19	5.00	Male	No	Thur	Lunch	5
143	27.05	5.00	Female	No	Thur	Lunch	6
155	29.85	5.14	Female	No	Sun	Dinner	5
156	48.17	5.00	Male	No	Sun	Dinner	6
170	50.81	10.00	Male	Yes	Sat	Dinner	3
182	45.35	3.50	Male	Yes	Sun	Dinner	3
185	20.69	5.00	Male	No	Sun	Dinner	5
187	30.46	2.00	Male	Yes	Sun	Dinner	5
212	48.33	9.00	Male	No	Sat	Dinner	4
216	28.15	3.00	Male	Yes	Sat	Dinner	5

NULL checking is done using the `notnull()` and `isnull()` methods.

```
In [13]: frame = pd.DataFrame({'col1': ['A', 'B', np.NaN, 'C', 'D'],
.....:                        'col2': ['F', np.NaN, 'G', 'H', 'I']})
.....:
```

```
In [14]: frame
```

```
Out[14]:
```

	col1	col2
0	A	F
1	B	NaN
2	NaN	G
3	C	H
4	D	I

Assume we have a table of the same structure as our DataFrame above. We can see only the records where `col2` IS NULL with the following query:

```
SELECT *
FROM frame
WHERE col2 IS NULL;
```

```
In [15]: frame[frame['col2'].isnull()]
Out[15]:
   col1 col2
1     B  NaN
```

Getting items where `col1` IS NOT NULL can be done with `notnull()`.

```
SELECT *
FROM frame
WHERE col1 IS NOT NULL;
```

```
In [16]: frame[frame['col1'].notnull()]
Out[16]:
   col1 col2
0     A     F
1     B  NaN
3     C     H
4     D     I
```

32.3 GROUP BY

In pandas, SQL's GROUP BY operations performed using the similarly named `groupby()` method. `groupby()` typically refers to a process where we'd like to split a dataset into groups, apply some function (typically aggregation), and then combine the groups together.

A common SQL operation would be getting the count of records in each group throughout a dataset. For instance, a query getting us the number of tips left by sex:

```
SELECT sex, count(*)
FROM tips
GROUP BY sex;
/*
Female      87
Male       157
*/
```

The pandas equivalent would be:

```
In [17]: tips.groupby('sex').size()
Out[17]:
sex
Female      87
Male       157
dtype: int64
```

Notice that in the pandas code we used `size()` and not `count()`. This is because `count()` applies the function to each column, returning the number of not null records within each.

```
In [18]: tips.groupby('sex').count()
Out[18]:
   total_bill  tip  smoker  day  time  size
sex
Female         87   87      87   87   87   87
Male         157  157     157  157  157  157
```

Alternatively, we could have applied the `count()` method to an individual column:

```
In [19]: tips.groupby('sex')['total_bill'].count()
```

```
Out[19]:
```

```
sex
Female      87
Male       157
Name: total_bill, dtype: int64
```

Multiple functions can also be applied at once. For instance, say we'd like to see how tip amount differs by day of the week - `agg()` allows you to pass a dictionary to your grouped DataFrame, indicating which functions to apply to specific columns.

```
SELECT day, AVG(tip), COUNT(*)
```

```
FROM tips
```

```
GROUP BY day;
```

```
/*
Fri    2.734737    19
Sat    2.993103    87
Sun    3.255132    76
Thur   2.771452    62
*/
```

```
In [20]: tips.groupby('day').agg({'tip': np.mean, 'day': np.size})
```

```
Out[20]:
```

```
      tip    day
day
Fri    2.734737    19
Sat    2.993103    87
Sun    3.255132    76
Thur   2.771452    62
```

Grouping by more than one column is done by passing a list of columns to the `groupby()` method.

```
SELECT smoker, day, COUNT(*), AVG(tip)
```

```
FROM tips
```

```
GROUP BY smoker, day;
```

```
/*
smoker day
No    Fri      4  2.812500
      Sat     45  3.102889
      Sun     57  3.167895
      Thur    45  2.673778
Yes   Fri     15  2.714000
      Sat     42  2.875476
      Sun     19  3.516842
      Thur    17  3.030000
*/
```

```
In [21]: tips.groupby(['smoker', 'day']).agg({'tip': [np.size, np.mean]})
```

```
Out[21]:
```

```
      tip      size      mean
smoker day
No    Fri      4  2.812500
      Sat     45  3.102889
      Sun     57  3.167895
      Thur    45  2.673778
Yes   Fri     15  2.714000
      Sat     42  2.875476
      Sun     19  3.516842
```

Thur 17 3.030000

32.4 JOIN

JOINS can be performed with `join()` or `merge()`. By default, `join()` will join the DataFrames on their indices. Each method has parameters allowing you to specify the type of join to perform (LEFT, RIGHT, INNER, FULL) or the columns to join on (column names or indices).

```
In [22]: df1 = pd.DataFrame({'key': ['A', 'B', 'C', 'D'],
.....:                      'value': np.random.randn(4)})
.....:
```

```
In [23]: df2 = pd.DataFrame({'key': ['B', 'D', 'D', 'E'],
.....:                      'value': np.random.randn(4)})
.....:
```

Assume we have two database tables of the same name and structure as our DataFrames.

Now let's go over the various types of JOINS.

32.4.1 INNER JOIN

```
SELECT *
FROM df1
INNER JOIN df2
  ON df1.key = df2.key;
```

merge performs an INNER JOIN by default

```
In [24]: pd.merge(df1, df2, on='key')
```

```
Out[24]:
   key  value_x  value_y
0    B  1.075416 -0.227314
1    D  1.065735  2.102726
2    D  1.065735 -0.092796
```

`merge()` also offers parameters for cases when you'd like to join one DataFrame's column with another DataFrame's index.

```
In [25]: indexed_df2 = df2.set_index('key')
```

```
In [26]: pd.merge(df1, indexed_df2, left_on='key', right_index=True)
```

```
Out[26]:
   key  value_x  value_y
1    B  1.075416 -0.227314
3    D  1.065735  2.102726
3    D  1.065735 -0.092796
```

32.4.2 LEFT OUTER JOIN

-- show all records from df1

```
SELECT *
FROM df1
LEFT OUTER JOIN df2
  ON df1.key = df2.key;
```

```
# show all records from df1
In [27]: pd.merge(df1, df2, on='key', how='left')
Out[27]:
```

	key	value_x	value_y
0	A	-0.857326	NaN
1	B	1.075416	-0.227314
2	C	0.371727	NaN
3	D	1.065735	2.102726
4	D	1.065735	-0.092796

32.4.3 RIGHT JOIN

```
-- show all records from df2
SELECT *
FROM df1
RIGHT OUTER JOIN df2
  ON df1.key = df2.key;

# show all records from df2
In [28]: pd.merge(df1, df2, on='key', how='right')
Out[28]:
```

	key	value_x	value_y
0	B	1.075416	-0.227314
1	D	1.065735	2.102726
2	D	1.065735	-0.092796
3	E	NaN	0.094694

32.4.4 FULL JOIN

pandas also allows for FULL JOINS, which display both sides of the dataset, whether or not the joined columns find a match. As of writing, FULL JOINS are not supported in all RDBMS (MySQL).

```
-- show all records from both tables
SELECT *
FROM df1
FULL OUTER JOIN df2
  ON df1.key = df2.key;

# show all records from both frames
In [29]: pd.merge(df1, df2, on='key', how='outer')
Out[29]:
```

	key	value_x	value_y
0	A	-0.857326	NaN
1	B	1.075416	-0.227314
2	C	0.371727	NaN
3	D	1.065735	2.102726
4	D	1.065735	-0.092796
5	E	NaN	0.094694

32.5 UNION

UNION ALL can be performed using `concat()`.

```
In [30]: df1 = pd.DataFrame({'city': ['Chicago', 'San Francisco', 'New York City'],
.....:                      'rank': range(1, 4)})
.....:
```

```
In [31]: df2 = pd.DataFrame({'city': ['Chicago', 'Boston', 'Los Angeles'],
.....:                      'rank': [1, 4, 5]})
.....:
```

```
SELECT city, rank
FROM df1
UNION ALL
SELECT city, rank
FROM df2;
/*
      city  rank
    Chicago    1
San Francisco  2
New York City  3
      Chicago    1
        Boston  4
    Los Angeles  5
*/
```

```
In [32]: pd.concat([df1, df2])
Out[32]:
```

	city	rank
0	Chicago	1
1	San Francisco	2
2	New York City	3
0	Chicago	1
1	Boston	4
2	Los Angeles	5

SQL's UNION is similar to UNION ALL, however UNION will remove duplicate rows.

```
SELECT city, rank
FROM df1
UNION
SELECT city, rank
FROM df2;
-- notice that there is only one Chicago record this time
/*
      city  rank
    Chicago    1
San Francisco  2
New York City  3
        Boston  4
    Los Angeles  5
*/
```

In pandas, you can use `concat()` in conjunction with `drop_duplicates()`.

```
In [33]: pd.concat([df1, df2]).drop_duplicates()
Out[33]:
```

	city	rank
0	Chicago	1
1	San Francisco	2
2	New York City	3
1	Boston	4

2 Los Angeles 5

32.6 UPDATE

32.7 DELETE

API REFERENCE

33.1 Input/Output

33.1.1 Pickling

<code>read_pickle(path)</code>	Load pickled pandas object (or any other pickled object) from the specified
--------------------------------	---

pandas.read_pickle

`pandas.read_pickle(path)`

Load pickled pandas object (or any other pickled object) from the specified file path

Warning: Loading pickled data received from untrusted sources can be unsafe. See:
<http://docs.python.org/2.7/library/pickle.html>

Parameters `path` : string

File path

Returns `unpickled` : type of object stored in file

33.1.2 Flat File

<code>read_table(filepath_or_buffer[, sep, ...])</code>	Read general delimited file into DataFrame
<code>read_csv(filepath_or_buffer[, sep, dialect, ...])</code>	Read CSV (comma-separated) file into DataFrame
<code>read_fwf(filepath_or_buffer[, colspecs, widths])</code>	Read a table of fixed-width formatted lines into DataFrame

pandas.read_table

```
pandas.read_table(filepath_or_buffer, sep='\t', dialect=None, compression='infer', doublequote=True, escapechar=None, quotechar='"', quoting=0, skipinitialspace=False, lineterminator=None, header='infer', index_col=None, names=None, prefix=None, skiprows=None, skipfooter=None, skip_footer=0, na_values=None, na_fvalues=None, true_values=None, false_values=None, delimiter=None, converters=None, dtype=None, usecols=None, engine=None, delim_whitespace=False, as_recarray=False, na_filter=True, compact_ints=False, use_unsigned=False, low_memory=True, buffer_lines=None, warn_bad_lines=True, error_bad_lines=True, keep_default_na=True, thousands=None, comment=None, decimal='.', parse_dates=False, keep_date_col=False, dayfirst=False, date_parser=None, memory_map=False, float_precision=None, nrows=None, iterator=False, chunksize=None, verbose=False, encoding=None, squeeze=False, mangle_dupe_cols=True, tupleize_cols=False, infer_datetime_format=False, skip_blank_lines=True)
```

Read general delimited file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Parameters **filepath_or_buffer** : string or file handle / StringIO

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file ://localhost/path/to/table.csv

sep : string, default t (tab-stop)

Delimiter to use. Regular expressions are accepted.

engine : {'c', 'python'}

Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (length 1)

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default None

Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.

skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

dtype : Type name or dict of column -> type

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} (Unsupported with engine='python')

compression : {'gzip', 'bz2', 'infer', None}, default 'infer'

For on-the-fly decompression of on-disk data. If ‘infer’, then use gzip or bz2 if `filepath_or_buffer` is a string ending in ‘.gz’ or ‘.bz2’, respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or `csv.Dialect` instance, default None

If None defaults to Excel dialect. Ignored if `sep` longer than 1 char See `csv.Dialect` documentation for more details

header : int, list of ints

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise None. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

skiprows : list-like or integer

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider `index_col=False` to force pandas to `_not_` use the first column as the index (row names)

names : array-like

List of column names to use. If file contains no header row, then you should explicitly pass `header=None`

prefix : string, default None

Prefix to add to column numbers when no header, e.g ‘X’ for X0, X1, ...

na_values : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list

Values to consider as True

false_values : list

Values to consider as False

keep_default_na : bool, default True

If `na_values` are specified and `keep_default_na` is False the default NaN values are overridden, otherwise they’re appended to

parse_dates : boolean, list of ints or names, list of lists, or dict

If True -> try parsing the index. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column. {‘foo’ : [1, 3]} -> parse columns 1, 3 as date and call result ‘foo’ A fast-path exists for iso8601-formatted dates.

keep_date_col : boolean, default False

If True and `parse_dates` specifies combining multiple columns then keep the original columns.

date_parser : function

Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by `parse_dates`) as arguments.

dayfirst : boolean, default False

DD/MM format dates, international and European format

thousands : str, default None

Thousands separator

comment : str, default None

Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if `comment='#'`, parsing `#emptyna,b,cn1,2,3` with `header=0` will result in `'a,b,c'` being treated as the header.

decimal : str, default '.'

Character to recognize as decimal point. E.g. use `','` for European data

nrows : int, default None

Number of rows of file to read. Useful for reading pieces of large files

iterator : boolean, default False

Return `TextFileReader` object

chunksize : int, default None

Return `TextFileReader` object for iteration

skipfooter : int, default 0

Number of lines at bottom of file to skip (Unsupported with `engine='c'`)

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

delimiter : string, default None

Alternative argument name for `sep`. Regular expressions are accepted.

encoding : string, default None

Encoding to use for UTF when reading/writing (ex. `'utf-8'`). [List of Python standard encodings](#)

squeeze : boolean, default False

If the parsed data only contains one column then return a Series

na_filter : boolean, default True

Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file

usecols : array-like

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as 'X.0'...'X.N', rather than 'X'...'X'

tupleize_cols : boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

error_bad_lines : boolean, default True

Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these "bad lines" will be dropped from the DataFrame that is returned. (Only valid with C parser)

warn_bad_lines : boolean, default True

If error_bad_lines is False, and warn_bad_lines is True, a warning for each "bad line" will be output. (Only valid with C parser).

infer_datetime_format : boolean, default False

If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing

skip_blank_lines : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

Returns result : DataFrame or TextParser

pandas.read_csv

```
pandas.read_csv(filepath_or_buffer, sep=',', dialect=None, compression='infer', double-
quote=True, escapechar=None, quotechar='"', quoting=0, skipinitialspace=False,
lineterminator=None, header='infer', index_col=None, names=None, pre-
fix=None, skiprows=None, skipfooter=None, skip_footer=0, na_values=None,
na_fvalues=None, true_values=None, false_values=None, delimiter=None, con-
verters=None, dtype=None, usecols=None, engine=None, delim_whitespace=False,
as_reccarray=False, na_filter=True, compact_ints=False, use_unsigned=False,
low_memory=True, buffer_lines=None, warn_bad_lines=True, error_bad_lines=True,
keep_default_na=True, thousands=None, comment=None, decimal='.',
parse_dates=False, keep_date_col=False, dayfirst=False, date_parser=None,
memory_map=False, float_precision=None, nrows=None, iterator=False, chunk-
size=None, verbose=False, encoding=None, squeeze=False, mangle_dupe_cols=True,
tupleize_cols=False, infer_datetime_format=False, skip_blank_lines=True)
```

Read CSV (comma-separated) file into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Parameters `filepath_or_buffer` : string or file handle / StringIO

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file `://local-host/path/to/table.csv`

sep : string, default `'`

Delimiter to use. If sep is None, will try to automatically determine this. Regular expressions are accepted.

engine : {`'c'`, `'python'`}

Parser engine to use. The C engine is faster while the python engine is currently more feature-complete.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (length 1)

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default None

Control field quoting behavior per `csv.QUOTE_*` constants. Use one of `QUOTE_MINIMAL` (0), `QUOTE_ALL` (1), `QUOTE_NONNUMERIC` (2) or `QUOTE_NONE` (3). Default (None) results in `QUOTE_MINIMAL` behavior.

skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is `QUOTE_NONE`.

dtype : Type name or dict of column -> type

Data type for data or columns. E.g. `{ 'a': np.float64, 'b': np.int32 }` (Unsupported with `engine='python'`)

compression : {`'gzip'`, `'bz2'`, `'infer'`, None}, default `'infer'`

For on-the-fly decompression of on-disk data. If `'infer'`, then use `gzip` or `bz2` if `filepath_or_buffer` is a string ending in `'.gz'` or `'.bz2'`, respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See `csv.Dialect` documentation for more details

header : int, list of ints

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise None. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. `[0,1,3]`. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

skiprows : list-like or integer

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider `index_col=False` to force pandas to `_not_` use the first column as the index (row names)

names : array-like

List of column names to use. If file contains no header row, then you should explicitly pass `header=None`

prefix : string, default None

Prefix to add to column numbers when no header, e.g 'X' for X0, X1, ...

na_values : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list

Values to consider as True

false_values : list

Values to consider as False

keep_default_na : bool, default True

If `na_values` are specified and `keep_default_na` is False the default NaN values are overridden, otherwise they're appended to

parse_dates : boolean, list of ints or names, list of lists, or dict

If True -> try parsing the index. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo' A fast-path exists for iso8601-formatted dates.

keep_date_col : boolean, default False

If True and `parse_dates` specifies combining multiple columns then keep the original columns.

date_parser : function

Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by `parse_dates`) as arguments.

dayfirst : boolean, default False

DD/MM format dates, international and European format

thousands : str, default None

Thousands separator

comment : str, default None

Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter *header* but not by *skiprows*. For example, if `comment='#'`, parsing `#emptyna,b,cn1,2,3` with `header=0` will result in `'a,b,c'` being treated as the header.

decimal : str, default '.'

Character to recognize as decimal point. E.g. use `','` for European data

nrows : int, default None

Number of rows of file to read. Useful for reading pieces of large files

iterator : boolean, default False

Return `TextFileReader` object

chunksize : int, default None

Return `TextFileReader` object for iteration

skipfooter : int, default 0

Number of lines at bottom of file to skip (Unsupported with `engine='c'`)

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

delimiter : string, default None

Alternative argument name for `sep`. Regular expressions are accepted.

encoding : string, default None

Encoding to use for UTF when reading/writing (ex. `'utf-8'`). [List of Python standard encodings](#)

squeeze : boolean, default False

If the parsed data only contains one column then return a `Series`

na_filter : boolean, default True

Detect missing value markers (empty strings and the value of `na_values`). In data without any NAs, passing `na_filter=False` can improve the performance of reading a large file

usecols : array-like

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as `'X.0'...'X.N'`, rather than `'X'...'X'`

tupleize_cols : boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

error_bad_lines : boolean, default True

Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these “bad lines” will be dropped from the DataFrame that is returned. (Only valid with C parser)

warn_bad_lines : boolean, default True

If error_bad_lines is False, and warn_bad_lines is True, a warning for each “bad line” will be output. (Only valid with C parser).

infer_datetime_format : boolean, default False

If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing

skip_blank_lines : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

Returns result : DataFrame or TextParser

pandas.read_fwf

`pandas.read_fwf(filepath_or_buffer, colspecs='infer', widths=None, **kws)`

Read a table of fixed-width formatted lines into DataFrame

Also supports optionally iterating or breaking of the file into chunks.

Parameters filepath_or_buffer : string or file handle / StringIO

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file ://local-host/path/to/table.csv

colspecs : list of pairs (int, int) or ‘infer’. optional

A list of pairs (tuples) giving the extents of the fixed-width fields of each line as half-open intervals (i.e., [from, to[). String value ‘infer’ can be used to instruct the parser to try detecting the column specifications from the first 100 rows of the data (default=‘infer’).

widths : list of ints. optional

A list of field widths which can be used instead of ‘colspecs’ if the intervals are contiguous.

lineterminator : string (length 1), default None

Character to break file into lines. Only valid with C parser

quotechar : string (length 1)

The character used to denote the start and end of a quoted item. Quoted items can include the delimiter and it will be ignored.

quoting : int or csv.QUOTE_* instance, default None

Control field quoting behavior per csv.QUOTE_* constants. Use one of QUOTE_MINIMAL (0), QUOTE_ALL (1), QUOTE_NONNUMERIC (2) or QUOTE_NONE (3). Default (None) results in QUOTE_MINIMAL behavior.

skipinitialspace : boolean, default False

Skip spaces after delimiter

escapechar : string (length 1), default None

One-character string used to escape delimiter when quoting is QUOTE_NONE.

dtype : Type name or dict of column -> type

Data type for data or columns. E.g. {'a': np.float64, 'b': np.int32} (Unsupported with engine='python')

compression : {'gzip', 'bz2', 'infer', None}, default 'infer'

For on-the-fly decompression of on-disk data. If 'infer', then use gzip or bz2 if filepath_or_buffer is a string ending in '.gz' or '.bz2', respectively, and no decompression otherwise. Set to None for no decompression.

dialect : string or csv.Dialect instance, default None

If None defaults to Excel dialect. Ignored if sep longer than 1 char See csv.Dialect documentation for more details

header : int, list of ints

Row number(s) to use as the column names, and the start of the data. Defaults to 0 if no names passed, otherwise None. Explicitly pass header=0 to be able to replace existing names. The header can be a list of integers that specify row locations for a multi-index on the columns E.g. [0,1,3]. Intervening rows that are not specified will be skipped (e.g. 2 in this example are skipped). Note that this parameter ignores commented lines and empty lines if skip_blank_lines=True, so header=0 denotes the first line of data rather than the first line of the file.

skiprows : list-like or integer

Line numbers to skip (0-indexed) or number of lines to skip (int) at the start of the file

index_col : int or sequence or False, default None

Column to use as the row labels of the DataFrame. If a sequence is given, a MultiIndex is used. If you have a malformed file with delimiters at the end of each line, you might consider index_col=False to force pandas to _not_ use the first column as the index (row names)

names : array-like

List of column names to use. If file contains no header row, then you should explicitly pass header=None

prefix : string, default None

Prefix to add to column numbers when no header, e.g 'X' for X0, X1, ...

na_values : list-like or dict, default None

Additional strings to recognize as NA/NaN. If dict passed, specific per-column NA values

true_values : list

Values to consider as True

false_values : list

Values to consider as False

keep_default_na : bool, default True

If `na_values` are specified and `keep_default_na` is False the default NaN values are overridden, otherwise they're appended to

parse_dates : boolean, list of ints or names, list of lists, or dict

If True -> try parsing the index. If [1, 2, 3] -> try parsing columns 1, 2, 3 each as a separate date column. If [[1, 3]] -> combine columns 1 and 3 and parse as a single date column. {'foo' : [1, 3]} -> parse columns 1, 3 as date and call result 'foo' A fast-path exists for iso8601-formatted dates.

keep_date_col : boolean, default False

If True and `parse_dates` specifies combining multiple columns then keep the original columns.

date_parser : function

Function to use for converting a sequence of string columns to an array of datetime instances. The default uses `dateutil.parser.parser` to do the conversion. Pandas will try to call `date_parser` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by `parse_dates`) as arguments; 2) concatenate (row-wise) the string values from the columns defined by `parse_dates` into a single array and pass that; and 3) call `date_parser` once for each row using one or more strings (corresponding to the columns defined by `parse_dates`) as arguments.

dayfirst : boolean, default False

DD/MM format dates, international and European format

thousands : str, default None

Thousands separator

comment : str, default None

Indicates remainder of line should not be parsed. If found at the beginning of a line, the line will be ignored altogether. This parameter must be a single character. Like empty lines (as long as `skip_blank_lines=True`), fully commented lines are ignored by the parameter `header` but not by `skiprows`. For example, if `comment='#'`, parsing `#emptyna,b,cn1,2,3` with `header=0` will result in 'a,b,c' being treated as the header.

decimal : str, default '.'

Character to recognize as decimal point. E.g. use ',' for European data

nrows : int, default None

Number of rows of file to read. Useful for reading pieces of large files

iterator : boolean, default False

Return `TextFileReader` object

chunksize : int, default None

Return `TextFileReader` object for iteration

skipfooter : int, default 0

Number of lines at bottom of file to skip (Unsupported with `engine='c'`)

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

delimiter : string, default None

Alternative argument name for sep. Regular expressions are accepted.

encoding : string, default None

Encoding to use for UTF when reading/writing (ex. 'utf-8'). [List of Python standard encodings](#)

squeeze : boolean, default False

If the parsed data only contains one column then return a Series

na_filter : boolean, default True

Detect missing value markers (empty strings and the value of na_values). In data without any NAs, passing na_filter=False can improve the performance of reading a large file

usecols : array-like

Return a subset of the columns. Results in much faster parsing time and lower memory usage.

mangle_dupe_cols : boolean, default True

Duplicate columns will be specified as 'X.0'...'X.N', rather than 'X'...'X'

tupleize_cols : boolean, default False

Leave a list of tuples on columns as is (default is to convert to a Multi Index on the columns)

error_bad_lines : boolean, default True

Lines with too many fields (e.g. a csv line with too many commas) will by default cause an exception to be raised, and no DataFrame will be returned. If False, then these "bad lines" will be dropped from the DataFrame that is returned. (Only valid with C parser)

warn_bad_lines : boolean, default True

If error_bad_lines is False, and warn_bad_lines is True, a warning for each "bad line" will be output. (Only valid with C parser).

infer_datetime_format : boolean, default False

If True and parse_dates is enabled for a column, attempt to infer the datetime format to speed up the processing

skip_blank_lines : boolean, default True

If True, skip over blank lines rather than interpreting as NaN values

Returns result : DataFrame or TextParser

Also, 'delimiter' is used to specify the filler character of the fields if it is not spaces (e.g., '~').

33.1.3 Clipboard

<code>read_clipboard(**kwargs)</code>	Read text from clipboard and pass to read_table.
---------------------------------------	--

pandas.read_clipboard

`pandas.read_clipboard(**kwargs)`

Read text from clipboard and pass to read_table. See read_table for the full argument list

If unspecified, *sep* defaults to 's+'

Returns `parsed` : DataFrame

33.1.4 Excel

<code>read_excel(io[, sheetname])</code>	Read an Excel table into a pandas DataFrame
<code>ExcelFile.parse([sheetname, header, ...])</code>	Read an Excel table into DataFrame

pandas.read_excel

`pandas.read_excel(io, sheetname=0, **kwds)`

Read an Excel table into a pandas DataFrame

Parameters `io` : string, file-like object, or xlrd workbook.

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be file://localhost/path/to/workbook.xlsx

sheetname : string, int, mixed list of strings/int, or None, default 0

Strings are used for sheet names, Integers are used in zero-indexed sheet positions.

Lists of strings/integers are used to request multiple sheets.

Specify None to get all sheets.

str/int -> DataFrame is returned. list/None -> Dict of DataFrames is returned, with keys representing sheets.

Available Cases

- Defaults to 0 -> 1st sheet as a DataFrame
- 1 -> 2nd sheet as a DataFrame
- "Sheet1" -> 1st sheet as a DataFrame
- [0,1,"Sheet5"] -> 1st, 2nd & 5th sheet as a dictionary of DataFrames
- None -> All sheets as a dictionary of DataFrames

header : int, default 0

Row to use for the column labels of the parsed DataFrame

skiprows : list-like

Rows to skip at the beginning (0-indexed)

skip_footer : int, default 0

Rows at the end to skip (0-indexed)

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels, values are functions that take one input argument, the Excel cell content, and return the transformed content.

index_col : int, default None

Column to use as the row labels of the DataFrame. Pass None if there is no such column

parse_cols : int or list, default None

- If None then parse all columns,
- If int then indicates last column to be parsed
- If list of ints then indicates list of column numbers to be parsed
- If string then indicates comma separated list of column names and column ranges (e.g. "A:E" or "A,C,E:F")

na_values : list-like, default None

List of additional strings to recognize as NA/NaN

keep_default_na : bool, default True

If na_values are specified and keep_default_na is False the default NaN values are overridden, otherwise they're appended to

verbose : boolean, default False

Indicate number of NA values placed in non-numeric columns

engine: string, default None

If io is not a buffer or path, this must be set to identify io. Acceptable values are None or xlrd

convert_float : boolean, default True

convert integral floats to int (i.e., 1.0 -> 1). If False, all numeric data will be read in as floats: Excel stores all numbers as floats internally

has_index_names : boolean, default False

True if the cols defined in index_col have an index name and are not in the header. Index name will be placed on a separate line below the header.

Returns **parsed** : DataFrame or Dict of DataFrames

DataFrame from the passed in Excel file. See notes in sheetname argument for more information on when a Dict of Dataframes is returned.

pandas.ExcelFile.parse

```
ExcelFile.parse(sheetname=0, header=0, skiprows=None, skip_footer=0, index_col=None,
                parse_cols=None, parse_dates=False, date_parser=None, na_values=None,
                thousands=None, chunksize=None, convert_float=True, has_index_names=False,
                converters=None, **kws)
```

Read an Excel table into DataFrame

Parameters **sheetname** : string, int, mixed list of strings/ints, or None, default 0

Strings are used for sheet names, Integers are used in zero-indexed sheet positions.

Lists of strings/integers are used to request multiple sheets.

Specify None to get all sheets.

str|int -> DataFrame is returned. list|None -> Dict of DataFrames is returned, with keys representing sheets.

Available Cases

- Defaults to 0 -> 1st sheet as a DataFrame
- 1 -> 2nd sheet as a DataFrame
- "Sheet1" -> 1st sheet as a DataFrame
- [0,1,"Sheet5"] -> 1st, 2nd & 5th sheet as a dictionary of DataFrames
- None -> All sheets as a dictionary of DataFrames

header : int, default 0

Row to use for the column labels of the parsed DataFrame

skiprows : list-like

Rows to skip at the beginning (0-indexed)

skip_footer : int, default 0

Rows at the end to skip (0-indexed)

converters : dict, default None

Dict of functions for converting values in certain columns. Keys can either be integers or column labels

index_col : int, default None

Column to use as the row labels of the DataFrame. Pass None if there is no such column

parse_cols : int or list, default None

- If None then parse all columns
- If int then indicates last column to be parsed
- If list of ints then indicates list of column numbers to be parsed
- If string then indicates comma separated list of column names and column ranges (e.g. "A:E" or "A,C,E:F")

parse_dates : boolean, default False

Parse date Excel values,

date_parser : function default None

Date parsing function

na_values : list-like, default None

List of additional strings to recognize as NA/NaN

thousands : str, default None

Thousands separator

chunksize : int, default None

Size of file chunk to read for lazy evaluation.

convert_float : boolean, default True

convert integral floats to int (i.e., 1.0 -> 1). If False, all numeric data will be read in as floats: Excel stores all numbers as floats internally.

has_index_names : boolean, default False

True if the cols defined in index_col have an index name and are not in the header

verbose : boolean, default False

Set to True to print a single statement when reading each excel sheet.

Returns **parsed** : DataFrame or Dict of DataFrames

DataFrame from the passed in Excel file. See notes in sheetname argument for more information on when a Dict of Dataframes is returned.

33.1.5 JSON

`read_json([path_or_buf, orient, typ, dtype, ...])` Convert a JSON string to pandas object

pandas.read_json

`pandas.read_json` (*path_or_buf=None, orient=None, typ='frame', dtype=True, convert_axes=True, convert_dates=True, keep_default_dates=True, numpy=False, precise_float=False, date_unit=None*)

Convert a JSON string to pandas object

Parameters **filepath_or_buffer** : a valid JSON string or file-like

The string could be a URL. Valid URL schemes include http, ftp, s3, and file. For file URLs, a host is expected. For instance, a local file could be `file://localhost/path/to/table.json`

orient

- *Series*
 - default is 'index'
 - allowed values are: {'split', 'records', 'index'}
 - The Series index must be unique for orient 'index'.
- *DataFrame*
 - default is 'columns'
 - allowed values are: {'split', 'records', 'index', 'columns', 'values'}
 - The DataFrame index must be unique for orients 'index' and 'columns'.
 - The DataFrame columns must be unique for orients 'index', 'columns', and 'records'.
- The format of the JSON string
 - split : dict like {index -> [index], columns -> [columns], data -> [values]}

- records : list like [{column -> value}, ... , {column -> value}]
- index : dict like {index -> {column -> value}}
- columns : dict like {column -> {index -> value}}
- values : just the values array

typ : type of object to recover (series or frame), default 'frame'

dtype : boolean or dict, default True

If True, infer dtypes, if a dict of column to dtype, then use those, if False, then don't infer dtypes at all, applies only to the data.

convert_axes : boolean, default True

Try to convert the axes to the proper dtypes.

convert_dates : boolean, default True

List of columns to parse for dates; If True, then try to parse datelike columns default is True

keep_default_dates : boolean, default True.

If parsing dates, then parse the default datelike columns

numpy : boolean, default False

Direct decoding to numpy arrays. Supports numeric data only, but non-numeric column and index labels are supported. Note also that the JSON ordering MUST be the same for each term if numpy=True.

precise_float : boolean, default False.

Set to enable usage of higher precision (strtod) function when decoding string to double values. Default (False) is to use fast but less precise builtin functionality

date_unit : string, default None

The timestamp unit to detect if converting dates. The default behaviour is to try and detect the correct precision, but if this is not desired then pass one of 's', 'ms', 'us' or 'ns' to force parsing only seconds, milliseconds, microseconds or nanoseconds respectively.

Returns result : Series or DataFrame

33.1.6 HTML

`read_html(io[, match, flavor, header, ...])` Read HTML tables into a list of DataFrame objects.

pandas.read_html

`pandas.read_html(io, match='.', flavor=None, header=None, index_col=None, skiprows=None, infer_types=None, attrs=None, parse_dates=False, tupleize_cols=False, thousands=',', encoding=None)`

Read HTML tables into a list of DataFrame objects.

Parameters io : str or file-like

A URL, a file-like object, or a raw string containing HTML. Note that lxml only accepts the http, ftp and file url protocols. If you have a URL that starts with 'https' you

might try removing the ' s'.

match : str or compiled regular expression, optional

The set of tables containing text matching this regex or string will be returned. Unless the HTML is extremely simple you will probably need to pass a non-empty string here. Defaults to `‘.+’` (match any non-empty string). The default value will return all tables contained on a page. This value is converted to a regular expression so that there is consistent behavior between BeautifulSoup and lxml.

flavor : str or None, container of strings

The parsing engine to use. `‘bs4’` and `‘html5lib’` are synonymous with each other, they are both there for backwards compatibility. The default of `None` tries to use `lxml` to parse and if that fails it falls back on `bs4 + html5lib`.

header : int or list-like or None, optional

The row (or list of rows for a `MultiIndex`) to use to make the columns headers.

index_col : int or list-like or None, optional

The column (or list of columns) to use to create the index.

skiprows : int or list-like or slice or None, optional

0-based. Number of rows to skip after parsing the column integer. If a sequence of integers or a slice is given, will skip the rows indexed by that sequence. Note that a single element sequence means ‘skip the nth row’ whereas an integer means ‘skip n rows’.

infer_types : None, optional

This has no effect since 0.15.0. It is here for backwards compatibility.

attrs : dict or None, optional

This is a dictionary of attributes that you can pass to use to identify the table in the HTML. These are not checked for validity before being passed to lxml or BeautifulSoup. However, these attributes must be valid HTML table attributes to work correctly. For example,

```
attrs = {'id': 'table'}
```

is a valid attribute dictionary because the `‘id’` HTML tag attribute is a valid HTML attribute for *any* HTML tag as per [this document](#).

```
attrs = {'asdf': 'table'}
```

is *not* a valid attribute dictionary because `‘asdf’` is not a valid HTML attribute even if it is a valid XML attribute. Valid HTML 4.01 table attributes can be found [here](#). A working draft of the HTML 5 spec can be found [here](#). It contains the latest information on table attributes for the modern web.

parse_dates : bool, optional

See `read_csv()` for more details.

tupleize_cols : bool, optional

If `False` try to parse multiple header rows into a `MultiIndex`, otherwise return raw tuples. Defaults to `False`.

thousands : str, optional

Separator to use to parse thousands. Defaults to `' , '`.

encoding : str or None, optional

The encoding used to decode the web page. Defaults to `None`. “None” preserves the previous encoding behavior, which depends on the underlying parser library (e.g., the parser library will try to use the encoding provided by the document).

Returns `dfs` : list of DataFrames

See also:

`pandas.read_csv`

Notes

Before using this function you should read the *[gotchas about the HTML parsing libraries](#)*.

Expect to do some cleanup after you call this function. For example, you might need to manually assign column names if the column names are converted to NaN when you pass the `header=0` argument. We try to assume as little as possible about the structure of the table and push the idiosyncrasies of the HTML contained in the table to the user.

This function searches for `<table>` elements and only for `<tr>` and `<th>` rows and `<td>` elements within each `<tr>` or `<th>` element in the table. `<td>` stands for “table data”.

Similar to `read_csv()` the `header` argument is applied **after** `skiprows` is applied.

This function will *always* return a list of `DataFrame` or it will fail, e.g., it will *not* return an empty list.

Examples

See the *[read_html documentation in the IO section of the docs](#)* for some examples of reading in HTML tables.

33.1.7 HDFStore: PyTables (HDF5)

<code>read_hdf(path_or_buf, key, **kwargs)</code>	read from the store, close it if we opened it
<code>HDFStore.put(key, value[, format, append])</code>	Store object in HDFStore
<code>HDFStore.append(key, value[, format, ...])</code>	Append to Table in file.
<code>HDFStore.get(key)</code>	Retrieve pandas object stored in file
<code>HDFStore.select(key[, where, start, stop, ...])</code>	Retrieve pandas object stored in file, optionally based on where

pandas.read_hdf

`pandas.read_hdf(path_or_buf, key, **kwargs)`

read from the store, close it if we opened it

Retrieve pandas object stored in file, optionally based on where criteria

Parameters `path_or_buf` : path (string), or buffer to read from

`key` : group identifier in the store

`where` : list of Term (or convertible) objects, optional

`start` : optional, integer (defaults to None), row number to start

selection

stop : optional, integer (defaults to None), row number to stop

selection

columns : optional, a list of columns that if not None, will limit the

return columns

iterator : optional, boolean, return an iterator, default False

chunksize : optional, n rows to include in iteration, return an iterator

auto_close : optional, boolean, should automatically close the store

when finished, default is False

Returns The selected object

pandas.HDFStore.put

`HDFStore.put` (*key, value, format=None, append=False, **kwargs*)

Store object in HDFStore

Parameters **key** : object

value : {Series, DataFrame, Panel}

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

This will force Table format, append the input data to the existing.

encoding : default None, provide an encoding for strings

dropna : boolean, default True, do not write an ALL nan row to

the store settable by the option 'io.hdf.dropna_table'

pandas.HDFStore.append

`HDFStore.append` (*key, value, format=None, append=True, columns=None, dropna=None, **kwargs*)

Append to Table in file. Node must already exist and be Table format.

Parameters **key** : object

value : {Series, DataFrame, Panel, Panel4D}

format: 'table' is the default

table(t) [table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default True, append the input data to the

existing

data_columns : list of columns to create as data columns, or True to

use all columns

min_itemsize : dict of columns that specify minimum string sizes

nan_rep : string to use as string nan representation

chunksize : size to chunk the writing

expectedrows : expected TOTAL row size of this table

encoding : default None, provide an encoding for strings

dropna : boolean, default True, do not write an ALL nan row to
the store settable by the option 'io.hdf.dropna_table'

Notes

—

Does **not check if data being appended overlaps with existing
data in the table, so be careful**

pandas.HDFStore.get

`HDFStore.get(key)`

Retrieve pandas object stored in file

Parameters **key** : object

Returns **obj** : type of object stored in file

pandas.HDFStore.select

`HDFStore.select(key, where=None, start=None, stop=None, columns=None, iterator=False, chunk-
size=None, auto_close=False, **kwargs)`

Retrieve pandas object stored in file, optionally based on where criteria

Parameters **key** : object

where : list of Term (or convertible) objects, optional

start : integer (defaults to None), row number to start selection

stop : integer (defaults to None), row number to stop selection

columns : a list of columns that if not None, will limit the return
columns

iterator : boolean, return an iterator, default False

chunksize : n rows to include in iteration, return an iterator

auto_close : boolean, should automatically close the store when
finished, default is False

Returns The selected object

33.1.8 SQL

<code>read_sql_table(table_name, con[, schema, ...])</code>	Read SQL database table into a DataFrame.
<code>read_sql_query(sql, con[, index_col, ...])</code>	Read SQL query into a DataFrame.
<code>read_sql(sql, con[, index_col, ...])</code>	Read SQL query or database table into a DataFrame.

pandas.read_sql_table

`pandas.read_sql_table(table_name, con, schema=None, index_col=None, coerce_float=True, parse_dates=None, columns=None, chunksize=None)`
Read SQL database table into a DataFrame.

Given a table name and an SQLAlchemy engine, returns a DataFrame. This function does not support DBAPI connections.

Parameters `table_name` : string

Name of SQL table in database

`con` : SQLAlchemy engine

Sqlite DBAPI connection mode not supported

`schema` : string, default None

Name of SQL schema in database to query (if database flavor supports this). If None, use default schema (default).

`index_col` : string, optional

Column to set as index

`coerce_float` : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point. Can result in loss of Precision.

`parse_dates` : list or dict

- List of column names to parse as dates
- Dict of {`column_name`: `format string`} where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps
- Dict of {`column_name`: `arg dict`}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite

`columns` : list

List of column names to select from sql table

`chunksize` : int, default None

If specified, return an iterator where `chunksize` is the number of rows to include in each chunk.

Returns DataFrame

See also:

`read_sql_query` Read SQL query into a DataFrame.

`read_sql`

Notes

Any datetime values with time zone information will be converted to UTC

pandas.read_sql_query

```
pandas.read_sql_query(sql, con, index_col=None, coerce_float=True, params=None,
                      parse_dates=None, chunksize=None)
```

Read SQL query into a DataFrame.

Returns a DataFrame corresponding to the result set of the query string. Optionally provide an *index_col* parameter to use one of the columns as the index, otherwise default integer index will be used.

Parameters *sql* : string

SQL query to be executed

con : SQLAlchemy engine or sqlite3 DBAPI2 connection

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

Column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name' : 'value'}

parse_dates : list or dict

- List of column names to parse as dates
- Dict of {column_name: format string} where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps
- Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

[read_sql_table](#) Read SQL database table into a DataFrame

[read_sql](#)

Notes

Any datetime values with time zone information parsed via the *parse_dates* parameter will be converted to UTC

pandas.read_sql

`pandas.read_sql(sql, con, index_col=None, coerce_float=True, params=None, parse_dates=None, columns=None, chunksize=None)`

Read SQL query or database table into a DataFrame.

Parameters `sql` : string

SQL query to be executed or database table name.

con : SQLAlchemy engine or DBAPI2 connection (fallback mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

index_col : string, optional

column name to use as index for the returned DataFrame object.

coerce_float : boolean, default True

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

params : list, tuple or dict, optional

List of parameters to pass to execute method. The syntax used to pass parameters is database driver dependent. Check your database driver documentation for which of the five syntax styles, described in PEP 249's paramstyle, is supported. Eg. for psycopg2, uses %(name)s so use params={'name' : 'value'}

parse_dates : list or dict

- List of column names to parse as dates
- Dict of {column_name: format string} where format string is strftime compatible in case of parsing string times or is one of (D, s, ns, ms, us) in case of parsing integer timestamps
- Dict of {column_name: arg dict}, where the arg dict corresponds to the keyword arguments of `pandas.to_datetime()` Especially useful with databases without native Datetime support, such as SQLite

columns : list

List of column names to select from sql table (only used when reading a table).

chunksize : int, default None

If specified, return an iterator where *chunksize* is the number of rows to include in each chunk.

Returns DataFrame

See also:

[`read\_sql\_table`](#) Read SQL database table into a DataFrame

[`read\_sql\_query`](#) Read SQL query into a DataFrame

Notes

This function is a convenience wrapper around `read_sql_table` and `read_sql_query` (and for backward compatibility) and will delegate to the specific function depending on the provided input (database table name or sql query). The delegated function might have more specific notes about their functionality not listed here.

33.1.9 Google BigQuery

<code>read_gbq(query[, project_id, index_col, ...])</code>	Load data from Google BigQuery.
<code>to_gbq(dataframe, destination_table[, ...])</code>	Write a DataFrame to a Google BigQuery table.

`pandas.io.gbq.read_gbq`

`pandas.io.gbq.read_gbq(query, project_id=None, index_col=None, col_order=None, reauth=False)`
Load data from Google BigQuery.

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The main method a user calls to execute a Query in Google BigQuery and read results into a pandas DataFrame using the v2 Google API client for Python. Documentation for the API is available at <https://developers.google.com/api-client-library/python/>. Authentication to the Google BigQuery service is via OAuth 2.0 using the product name 'pandas GBQ'.

Parameters `query` : str

SQL-Like Query to return data values

project_id : str

Google BigQuery Account project ID.

index_col : str (optional)

Name of result column to use for index in results DataFrame

col_order : list(str) (optional)

List of BigQuery column names in the desired order for results DataFrame

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

Returns df: DataFrame

DataFrame representing results of query

`pandas.io.gbq.to_gbq`

`pandas.io.gbq.to_gbq(dataframe, destination_table, project_id=None, chunksize=10000, verbose=True, reauth=False)`
Write a DataFrame to a Google BigQuery table.

THIS IS AN EXPERIMENTAL LIBRARY

If the table exists, the dataframe will be written to the table using the defined table schema and column types. For simplicity, this method uses the Google BigQuery streaming API. The `to_gbq` method chunks data into a

default chunk size of 10,000. Failures return the complete error response which can be quite long depending on the size of the insert. There are several important limitations of the Google streaming API which are detailed at: <https://developers.google.com/bigquery/streaming-data-into-bigquery>.

Parameters **dataframe** : DataFrame

DataFrame to be written

destination_table : string

Name of table to be written, in the form 'dataset.tablename'

project_id : str

Google BigQuery Account project ID.

chunksize : int (default 10000)

Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)

Show percentage complete

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

33.1.10 STATA

`read_stata(filepath_or_buffer[, ...])` Read Stata file into DataFrame

pandas.read_stata

`pandas.read_stata(filepath_or_buffer, convert_dates=True, convert_categoricals=True, encoding=None, index=None, convert_missing=False, preserve_dtypes=True, columns=None, order_categoricals=True, chunksize=None, iterator=False)`

Read Stata file into DataFrame

Parameters **filepath_or_buffer** : string or file-like object

Path to .dta file or object implementing a binary read() functions

convert_dates : boolean, defaults to True

Convert date variables to DataFrame time values

convert_categoricals : boolean, defaults to True

Read value labels and convert columns to Categorical/Factor variables

encoding : string, None or encoding

Encoding used to parse the files. Note that Stata doesn't support unicode. None defaults to iso-8859-1.

index : identifier of index column

identifier of column that should be used as index of the DataFrame

convert_missing : boolean, defaults to False

Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nans. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissing-Value objects.

preserve_dtypes : boolean, defaults to True

Preserve Stata datatypes. If False, numeric data are upcast to pandas default types for foreign data (float64 or int64)

columns : list or None

Columns to retain. Columns will be returned in the given order. None returns all columns

order_categoricals : boolean, defaults to True

Flag indicating whether converted categorical data are ordered.

chunksize : int, default None

Return StataReader object for iterations, returns chunks with given number of lines

iterator : boolean, default False

Return StataReader object

Returns DataFrame or StataReader

Examples

Read a Stata dta file: `>> df = pandas.read_stata('filename.dta')`

Read a Stata dta file in 10,000 line chunks: `>> itr = pandas.read_stata('filename.dta', chunksize=10000) >> for chunk in itr: >> do_something(chunk)`

<code>StataReader.data(**kwargs)</code>	DEPRECATED: Reads observations from Stata file, converting them into a dataframe
<code>StataReader.data_label()</code>	Returns data label of Stata file
<code>StataReader.value_labels()</code>	Returns a dict, associating each variable name a dict, associating
<code>StataReader.variable_labels()</code>	Returns variable labels as a dict, associating each variable name
<code>StataWriter.write_file()</code>	

pandas.io.stata.StataReader.data

`StataReader.data (**kwargs)`

DEPRECATED: Reads observations from Stata file, converting them into a dataframe

This is a legacy method. Use *read* in new code.

Parameters **convert_dates** : boolean, defaults to True

Convert date variables to DataFrame time values

convert_categoricals : boolean, defaults to True

Read value labels and convert columns to Categorical/Factor variables

index : identifier of index column

identifier of column that should be used as index of the DataFrame

convert_missing : boolean, defaults to False

Flag indicating whether to convert missing values to their Stata representations. If False, missing values are replaced with nans. If True, columns containing missing values are returned with object data types and missing values are represented by StataMissing-Value objects.

preserve_dtypes : boolean, defaults to True

Preserve Stata datatypes. If False, numeric data are upcast to pandas default types for foreign data (float64 or int64)

columns : list or None

Columns to retain. Columns will be returned in the given order. None returns all columns

order_categoricals : boolean, defaults to True

Flag indicating whether converted categorical data are ordered.

Returns DataFrame

pandas.io.stata.StataReader.data_label

`StataReader.data_label()`
Returns data label of Stata file

pandas.io.stata.StataReader.value_labels

`StataReader.value_labels()`
Returns a dict, associating each variable name a dict, associating each value its corresponding label

pandas.io.stata.StataReader.variable_labels

`StataReader.variable_labels()`
Returns variable labels as a dict, associating each variable name with corresponding label

pandas.io.stata.StataWriter.write_file

`StataWriter.write_file()`

33.2 General functions

33.2.1 Data manipulations

<code>melt(frame[, id_vars, value_vars, var_name, ...])</code>	“Unpivots” a DataFrame from wide format to long format, optionally leaving
<code>pivot(index, columns, values)</code>	Produce ‘pivot’ table based on 3 columns of this DataFrame.
<code>pivot_table(data[, values, index, columns, ...])</code>	Create a spreadsheet-style pivot table as a DataFrame.
<code>crosstab(index, columns[, values, rownames, ...])</code>	Compute a simple cross-tabulation of two (or more) factors.
<code>cut(x, bins[, right, labels, retbins, ...])</code>	Return indices of half-open bins to which each value of <i>x</i> belongs.
<code>qcut(x, q[, labels, retbins, precision])</code>	Quantile-based discretization function.
<code>merge(left, right[, how, on, left_on, ...])</code>	Merge DataFrame objects by performing a database-style join operation by co

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<code>concat(objs[, axis, join, join_axes, ...])</code>	Concatenate pandas objects along a particular axis with optional set logic along
<code>get_dummies(data[, prefix, prefix_sep, ...])</code>	Convert categorical variable into dummy/indicator variables
<code>factorize(values[, sort, order, ...])</code>	Encode input values as an enumerated type or categorical variable

pandas.melt

`pandas.melt(frame, id_vars=None, value_vars=None, var_name=None, value_name='value', col_level=None)`

“Unpivots” a DataFrame from wide format to long format, optionally leaving identifier variables set.

This function is useful to massage a DataFrame into a format where one or more columns are identifier variables (*id_vars*), while all other columns, considered measured variables (*value_vars*), are “unpivoted” to the row axis, leaving just two non-identifier columns, ‘variable’ and ‘value’.

Parameters `frame` : DataFrame

`id_vars` : tuple, list, or ndarray, optional

Column(s) to use as identifier variables.

`value_vars` : tuple, list, or ndarray, optional

Column(s) to unpivot. If not specified, uses all columns that are not set as *id_vars*.

`var_name` : scalar

Name to use for the ‘variable’ column. If None it uses `frame.columns.name` or ‘variable’.

`value_name` : scalar, default ‘value’

Name to use for the ‘value’ column.

`col_level` : int or string, optional

If columns are a MultiIndex then use this level to melt.

See also:

`pivot_table`, `DataFrame.pivot`

Examples

```
>>> import pandas as pd
>>> df = pd.DataFrame({'A': {0: 'a', 1: 'b', 2: 'c'},
...                   'B': {0: 1, 1: 3, 2: 5},
...                   'C': {0: 2, 1: 4, 2: 6}})
>>> df
   A  B  C
0  a  1  2
1  b  3  4
2  c  5  6

>>> pd.melt(df, id_vars=['A'], value_vars=['B'])
   A variable  value
0  a         B       1
1  b         B       3
2  c         B       5
```

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B', 'C'])
  A variable  value
0  a         B      1
1  b         B      3
2  c         B      5
3  a         C      2
4  b         C      4
5  c         C      6
```

The names of ‘variable’ and ‘value’ columns can be customized:

```
>>> pd.melt(df, id_vars=['A'], value_vars=['B'],
...         var_name='myVarname', value_name='myValname')
  A myVarname myValname
0  a         B          1
1  b         B          3
2  c         B          5
```

If you have multi-index columns:

```
>>> df.columns = [list('ABC'), list('DEF')]
>>> df
   A  B  C
   D  E  F
0  a  1  2
1  b  3  4
2  c  5  6

>>> pd.melt(df, col_level=0, id_vars=['A'], value_vars=['B'])
  A variable  value
0  a         B      1
1  b         B      3
2  c         B      5

>>> pd.melt(df, id_vars=[('A', 'D')], value_vars=[('B', 'E')])
(A, D) variable_0 variable_1  value
0      a         B          E      1
1      b         B          E      3
2      c         B          E      5
```

pandas.pivot

pandas.**pivot** (*index*, *columns*, *values*)

Produce ‘pivot’ table based on 3 columns of this DataFrame. Uses unique values from index / columns and fills with values.

Parameters **index** : ndarray

Labels to use to make new frame’s index

columns : ndarray

Labels to use to make new frame’s columns

values : ndarray

Values to use for populating new frame’s values

Returns DataFrame

Notes

Obviously, all 3 of the input arguments must have the same length

pandas.pivot_table

```
pandas.pivot_table(data, values=None, index=None, columns=None, aggfunc='mean',
                    fill_value=None, margins=False, dropna=True)
```

Create a spreadsheet-style pivot table as a DataFrame. The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame

Parameters **data** : DataFrame

values : column to aggregate, optional

index : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc : function, default numpy.mean, or list of functions

If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves)

fill_value : scalar, default None

Value to replace missing values with

margins : boolean, default False

Add all row / columns (e.g. for subtotal / grand totals)

dropna : boolean, default True

Do not include columns whose entries are all NaN

Returns **table** : DataFrame

Examples

```
>>> df
   A  B  C  D
0  foo one small 1
1  foo one large 2
2  foo one large 2
3  foo two small 3
4  foo two small 3
5  bar one large 4
6  bar one small 5
7  bar two small 6
8  bar two large 7
```

```
>>> table = pivot_table(df, values='D', index=['A', 'B'],
...                      columns=['C'], aggfunc=np.sum)
>>> table
```

		small	large
foo	one	1	4
	two	6	NaN
bar	one	5	4
	two	6	7

pandas.crosstab

`pandas.crosstab` (*index*, *columns*, *values=None*, *rownames=None*, *colnames=None*, *aggfunc=None*, *margins=False*, *dropna=True*)

Compute a simple cross-tabulation of two (or more) factors. By default computes a frequency table of the factors unless an array of values and an aggregation function are passed

Parameters **index** : array-like, Series, or list of arrays/Series

Values to group by in the rows

columns : array-like, Series, or list of arrays/Series

Values to group by in the columns

values : array-like, optional

Array of values to aggregate according to the factors

aggfunc : function, optional

If no values array is passed, computes a frequency table

rownames : sequence, default None

If passed, must match number of row arrays passed

colnames : sequence, default None

If passed, must match number of column arrays passed

margins : boolean, default False

Add row/column margins (subtotals)

dropna : boolean, default True

Do not include columns whose entries are all NaN

Returns **crosstab** : DataFrame

Notes

Any Series passed will have their name attributes used unless row or column names for the cross-tabulation are specified

Examples

```

>>> a
array([foo, foo, foo, foo, bar, bar,
       bar, bar, foo, foo, foo], dtype=object)
>>> b
array([one, one, one, two, one, one,
       one, two, two, two, one], dtype=object)
>>> c
array([dull, dull, shiny, dull, dull, shiny,
       shiny, dull, shiny, shiny, shiny], dtype=object)

>>> crosstab(a, [b, c], rownames=['a'], colnames=['b', 'c'])
b      one      two
c      dull  shiny  dull  shiny
a
bar    1       2       1       0
foo    2       2       1       2

```

pandas.cut

`pandas.cut` (*x*, *bins*, *right=True*, *labels=None*, *retbins=False*, *precision=3*, *include_lowest=False*)

Return indices of half-open bins to which each value of *x* belongs.

Parameters *x* : array-like

Input array to be binned. It has to be 1-dimensional.

bins : int or sequence of scalars

If *bins* is an int, it defines the number of equal-width bins in the range of *x*. However, in this case, the range of *x* is extended by .1% on each side to include the min or max values of *x*. If *bins* is a sequence it defines the bin edges allowing for non-uniform bin width. No extension of the range of *x* is done in this case.

right : bool, optional

Indicates whether the bins include the rightmost edge or not. If *right* == True (the default), then the bins [1,2,3,4] indicate (1,2], (2,3], (3,4].

labels : array or boolean, default None

Used as labels for the resulting bins. Must be of the same length as the resulting bins. If False, return only integer indicators of the bins.

retbins : bool, optional

Whether to return the bins or not. Can be useful if bins is given as a scalar.

precision : int

The precision at which to store and display the bins labels

include_lowest : bool

Whether the first interval should be left-inclusive or not.

Returns *out* : Categorical or Series or array of integers if labels is False

The return type (Categorical or Series) depends on the input: a Series of type category if input is a Series else Categorical. Bins are represented as categories when categorical data is returned.

bins : ndarray of floats

Returned only if *retbins* is True.

Notes

The *cut* function can be useful for going from a continuous variable to a categorical variable. For example, *cut* could convert ages to groups of age ranges.

Any NA values will be NA in the result. Out of bounds values will be NA in the resulting Categorical object

Examples

```
>>> pd.cut(np.array([.2, 1.4, 2.5, 6.2, 9.7, 2.1]), 3, retbins=True)
[(0.191, 3.367], (0.191, 3.367], (0.191, 3.367], (3.367, 6.533], (6.533, 9.7], (0.191, 3.367]]
Categories (3, object): [(0.191, 3.367] < (3.367, 6.533] < (6.533, 9.7]],
array([ 0.1905      ,  3.36666667,  6.53333333,  9.7         ]))
>>> pd.cut(np.array([.2, 1.4, 2.5, 6.2, 9.7, 2.1]), 3, labels=["good", "medium", "bad"])
[good, good, good, medium, bad, good]
Categories (3, object): [good < medium < bad]
>>> pd.cut(np.ones(5), 4, labels=False)
array([1, 1, 1, 1, 1], dtype=int64)
```

pandas.qcut

pandas.**qcut** (*x*, *q*, *labels=None*, *retbins=False*, *precision=3*)

Quantile-based discretization function. Discretize variable into equal-sized buckets based on rank or based on sample quantiles. For example 1000 values for 10 quantiles would produce a Categorical object indicating quantile membership for each data point.

Parameters *x* : ndarray or Series

q : integer or array of quantiles

Number of quantiles. 10 for deciles, 4 for quartiles, etc. Alternately array of quantiles, e.g. [0, .25, .5, .75, 1.] for quartiles

labels : array or boolean, default None

Used as labels for the resulting bins. Must be of the same length as the resulting bins. If False, return only integer indicators of the bins.

retbins : bool, optional

Whether to return the bins or not. Can be useful if bins is given as a scalar.

precision : int

The precision at which to store and display the bins labels

Returns *out* : Categorical or Series or array of integers if labels is False

The return type (Categorical or Series) depends on the input: a Series of type category if input is a Series else Categorical. Bins are represented as categories when categorical data is returned.

bins : ndarray of floats

Returned only if *retbins* is True.

Notes

Out of bounds values will be NA in the resulting Categorical object

Examples

```
>>> pd.qcut(range(5), 4)
[[0, 1], [0, 1], (1, 2], (2, 3], (3, 4]]
Categories (4, object): [[0, 1] < (1, 2] < (2, 3] < (3, 4]]
>>> pd.qcut(range(5), 3, labels=["good", "medium", "bad"])
[good, good, medium, bad, bad]
Categories (3, object): [good < medium < bad]
>>> pd.qcut(range(5), 4, labels=False)
array([0, 0, 1, 2, 3], dtype=int64)
```

pandas.merge

`pandas.merge(left, right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes=('_x', '_y'), copy=True)`

Merge DataFrame objects by performing a database-style join operation by columns or indexes.

If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters `left` : DataFrame

`right` : DataFrame

`how` : {'left', 'right', 'outer', 'inner'}, default 'inner'

- left: use only keys from left frame (SQL: left outer join)
- right: use only keys from right frame (SQL: right outer join)
- outer: use union of keys from both frames (SQL: full outer join)
- inner: use intersection of keys from both frames (SQL: inner join)

`on` : label or list

Field names to join on. Must be found in both DataFrames. If `on` is None and not merging on indexes, then it merges on the intersection of the columns by default.

`left_on` : label or list, or array-like

Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns

`right_on` : label or list, or array-like

Field names to join on in right DataFrame or vector/list of vectors per `left_on` docs

`left_index` : boolean, default False

Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels

`right_index` : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as `left_index`

sort : boolean, default False

Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

copy : boolean, default True

If False, do not copy data unnecessarily

Returns **merged** : DataFrame

The output type will be the same as 'left', if it is a subclass of DataFrame.

Examples

```
>>> A          >>> B
   lkey value    rkey value
0   foo    1      0   foo    5
1   bar    2      1   bar    6
2   baz    3      2   qux    7
3   foo    4      3   bar    8

>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0   foo      1    foo      5
1   foo      4    foo      5
2   bar      2    bar      6
3   bar      2    bar      8
4   baz      3   NaN     NaN
5  NaN     NaN   qux      7
```

pandas.concat

`pandas.concat(objs, axis=0, join='outer', join_axes=None, ignore_index=False, keys=None, levels=None, names=None, verify_integrity=False, copy=True)`

Concatenate pandas objects along a particular axis with optional set logic along the other axes. Can also add a layer of hierarchical indexing on the concatenation axis, which may be useful if the labels are the same (or overlapping) on the passed axis number

Parameters **objs** : a sequence or mapping of Series, DataFrame, or Panel objects

If a dict is passed, the sorted keys will be used as the *keys* argument, unless it is passed, in which case the values will be selected (see below). Any None objects will be dropped silently unless they are all None in which case a `ValueError` will be raised

axis : {0, 1, ...}, default 0

The axis to concatenate along

join : {'inner', 'outer'}, default 'outer'

How to handle indexes on other axis(es)

join_axes : list of Index objects

Specific indexes to use for the other n - 1 axes instead of performing inner/outer set logic

verify_integrity : boolean, default False

Check whether the new concatenated axis contains duplicates. This can be very expensive relative to the actual data concatenation

keys : sequence, default None

If multiple levels passed, should contain tuples. Construct hierarchical index using the passed keys as the outermost level

levels : list of sequences, default None

Specific levels (unique values) to use for constructing a MultiIndex. Otherwise they will be inferred from the keys

names : list, default None

Names for the levels in the resulting hierarchical index

ignore_index : boolean, default False

If True, do not use the index values along the concatenation axis. The resulting axis will be labeled 0, ..., n - 1. This is useful if you are concatenating objects where the concatenation axis does not have meaningful indexing information. Note the the index values on the other axes are still respected in the join.

copy : boolean, default True

If False, do not copy data unnecessarily

Returns concatenated : type of objects

Notes

The keys, levels, and names arguments are all optional

pandas.get_dummies

`pandas.get_dummies(data, prefix=None, prefix_sep='_', dummy_na=False, columns=None, sparse=False)`

Convert categorical variable into dummy/indicator variables

Parameters data : array-like, Series, or DataFrame

prefix : string, list of strings, or dict of strings, default None

String to append DataFrame column names Pass a list with length equal to the number of columns when calling `get_dummies` on a DataFrame. Alternatively, *prefix* can be a dictionary mapping column names to prefixes.

prefix_sep : string, default '_'

If appending prefix, separator/delimiter to use. Or pass a list or dictionary as with *prefix*.

dummy_na : bool, default False

Add a column to indicate NaNs, if False NaNs are ignored.

columns : list-like, default None

Column names in the DataFrame to be encoded. If *columns* is None then all the columns with *object* or *category* dtype will be converted.

sparse : bool, default False

Whether the returned DataFrame should be sparse or not.

Returns dummies : DataFrame

Examples

```
>>> import pandas as pd
>>> s = pd.Series(list('abca'))

>>> get_dummies(s)
   a  b  c
0  1  0  0
1  0  1  0
2  0  0  1
3  1  0  0

>>> s1 = ['a', 'b', np.nan]

>>> get_dummies(s1)
   a  b
0  1  0
1  0  1
2  0  0

>>> get_dummies(s1, dummy_na=True)
   a  b  NaN
0  1  0    0
1  0  1    0
2  0  0    1

>>> df = DataFrame({'A': ['a', 'b', 'a'], 'B': ['b', 'a', 'c'],
                    'C': [1, 2, 3]})

>>> get_dummies(df, prefix=['col1', 'col2']):
   C  col1_a  col1_b  col2_a  col2_b  col2_c
0  1         1         0         0         1         0
1  2         0         1         1         0         0
2  3         1         0         0         0         1
```

See also `Series.str.get_dummies`.

pandas.factorize

`pandas.factorize` (*values*, *sort=False*, *order=None*, *na_sentinel=-1*, *size_hint=None*)

Encode input values as an enumerated type or categorical variable

Parameters values : ndarray (1-d)

Sequence

sort : boolean, default False

Sort by values

order : deprecated

na_sentinel : int, default -1

Value to mark “not found”

size_hint : hint to the hashtable sizer

Returns labels : the indexer to the original array

uniques : ndarray (1-d) or Index

the unique values. Index is returned when passed values is Index or Series

note: an array of Periods will ignore sort as it returns an always sorted PeriodIndex

33.2.2 Top-level missing data

<code>isnull(obj)</code>	Detect missing values (NaN in numeric arrays, None/NaN in object arrays)
<code>notnull(obj)</code>	Replacement for <code>numpy.isfinite</code> / <code>-numpy.isnan</code> which is suitable for use on object arrays.

pandas.isnull

`pandas.isnull(obj)`

Detect missing values (NaN in numeric arrays, None/NaN in object arrays)

Parameters arr : ndarray or object value

Object to check for null-ness

Returns isnulled : array-like of bool or bool

Array or bool indicating whether an object is null or if an array is given which of the element is null.

See also:

`pandas.notnull` boolean inverse of `pandas.isnull`

pandas.notnull

`pandas.notnull(obj)`

Replacement for `numpy.isfinite` / `-numpy.isnan` which is suitable for use on object arrays.

Parameters arr : ndarray or object value

Object to check for *not*-null-ness

Returns isnulled : array-like of bool or bool

Array or bool indicating whether an object is *not* null or if an array is given which of the element is *not* null.

See also:

`pandas.isnull` boolean inverse of `pandas.notnull`

33.2.3 Top-level dealing with datetimelike

<code>to_datetime(arg[, errors, dayfirst, utc, ...])</code>	Convert argument to datetime.
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<code>to_timedelta(arg[, unit, box, coerce])</code>	Convert argument to timedelta
<code>date_range([start, end, periods, freq, tz, ...])</code>	Return a fixed frequency datetime index, with day (calendar) as the default
<code>bdate_range([start, end, periods, freq, tz, ...])</code>	Return a fixed frequency datetime index, with business day as the default
<code>period_range([start, end, periods, freq, name])</code>	Return a fixed frequency datetime index, with day (calendar) as the default
<code>timedelta_range([start, end, periods, freq, ...])</code>	Return a fixed frequency timedelta index, with day as the default
<code>infer_freq(index[, warn])</code>	Infer the most likely frequency given the input index.

pandas.to_datetime

`pandas.to_datetime` (*arg*, *errors*='ignore', *dayfirst*=False, *utc*=None, *box*=True, *format*=None, *exact*=True, *coerce*=False, *unit*='ns', *infer_datetime_format*=False)

Convert argument to datetime.

Parameters *arg* : string, datetime, array of strings (with possible NAs)

errors : {'ignore', 'raise'}, default 'ignore'

Errors are ignored by default (values left untouched)

dayfirst : boolean, default False

If True parses dates with the day first, eg 20/01/2005 Warning: dayfirst=True is not strict, but will prefer to parse with day first (this is a known bug).

utc : boolean, default None

Return UTC DatetimeIndex if True (converting any tz-aware datetime.datetime objects as well)

box : boolean, default True

If True returns a DatetimeIndex, if False returns ndarray of values

format : string, default None

strftime to parse time, eg “%d/%m/%Y”, note that “%f” will parse all the way up to nanoseconds

exact : boolean, True by default

If True, require an exact format match. If False, allow the format to match anywhere in the target string.

coerce : force errors to NaT (False by default)

Timestamps outside the interval between Timestamp.min and Timestamp.max (approximately 1677-09-22 to 2262-04-11) will be also forced to NaT.

unit : unit of the arg (D,s,ms,us,ns) denote the unit in epoch

(e.g. a unix timestamp), which is an integer/float number

infer_datetime_format : boolean, default False

If no *format* is given, try to infer the format based on the first datetime string. Provides a large speed-up in many cases.

Returns *ret* : datetime if parsing succeeded.

Return type depends on input:

- list-like: DatetimeIndex
- Series: Series of datetime64 dtype

- scalar: Timestamp

In case when it is not possible to return designated types (e.g. when any element of input is before Timestamp.min or after Timestamp.max) return will have datetime.datetime type (or corresponding array/Series).

Examples

Take separate series and convert to datetime

```
>>> import pandas as pd
>>> i = pd.date_range('20000101', periods=100)
>>> df = pd.DataFrame(dict(year = i.year, month = i.month, day = i.day))
>>> pd.to_datetime(df.year*10000 + df.month*100 + df.day, format='%Y%m%d')
0      2000-01-01
1      2000-01-02
...
98     2000-04-08
99     2000-04-09
Length: 100, dtype: datetime64[ns]
```

Or from strings

```
>>> df = df.astype(str)
>>> pd.to_datetime(df.day + df.month + df.year, format="%d%m%Y")
0      2000-01-01
1      2000-01-02
...
98     2000-04-08
99     2000-04-09
Length: 100, dtype: datetime64[ns]
```

Date that does not meet timestamp limitations:

```
>>> pd.to_datetime('13000101', format='%Y%m%d')
datetime.datetime(1300, 1, 1, 0, 0)
>>> pd.to_datetime('13000101', format='%Y%m%d', coerce=True)
NaT
```

pandas.to_timedelta

`pandas.to_timedelta` (*arg*, *unit*='ns', *box*=True, *coerce*=False)

Convert argument to timedelta

Parameters *arg* : string, timedelta, array of strings (with possible NAs)

unit : unit of the arg (D,h,m,s,ms,us,ns) denote the unit, which is an integer/float number

box : boolean, default True

If True returns a Timedelta/TimedeltaIndex of the results if False returns a np.timedelta64 or ndarray of values of dtype timedelta64[ns]

coerce : force errors to NaT (False by default)

Returns *ret* : timedelta64/arrays of timedelta64 if parsing succeeded

pandas.date_range

`pandas.date_range` (*start=None, end=None, periods=None, freq='D', tz=None, normalize=False, name=None, closed=None*)

Return a fixed frequency datetime index, with day (calendar) as the default frequency

Parameters **start** : string or datetime-like, default None

Left bound for generating dates

end : string or datetime-like, default None

Right bound for generating dates

periods : integer or None, default None

If None, must specify start and end

freq : string or DateOffset, default 'D' (calendar daily)

Frequency strings can have multiples, e.g. '5H'

tz : string or None

Time zone name for returning localized DatetimeIndex, for example

Asia/Hong_Kong

normalize : bool, default False

Normalize start/end dates to midnight before generating date range

name : str, default None

Name of the resulting index

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

Returns **rng** : DatetimeIndex

Notes

2 of start, end, or periods must be specified

pandas.bdate_range

`pandas.bdate_range` (*start=None, end=None, periods=None, freq='B', tz=None, normalize=True, name=None, closed=None*)

Return a fixed frequency datetime index, with business day as the default frequency

Parameters **start** : string or datetime-like, default None

Left bound for generating dates

end : string or datetime-like, default None

Right bound for generating dates

periods : integer or None, default None

If None, must specify start and end

freq : string or DateOffset, default 'B' (business daily)

Frequency strings can have multiples, e.g. '5H'

tz : string or None

Time zone name for returning localized DatetimeIndex, for example Asia/Beijing

normalize : bool, default False

Normalize start/end dates to midnight before generating date range

name : str, default None

Name for the resulting index

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

Returns rng : DatetimeIndex

Notes

2 of start, end, or periods must be specified

pandas.period_range

pandas.**period_range** (*start=None, end=None, periods=None, freq='D', name=None*)

Return a fixed frequency datetime index, with day (calendar) as the default frequency

Parameters start :

end :

periods : int, default None

Number of periods in the index

freq : str/DateOffset, default 'D'

Frequency alias

name : str, default None

Name for the resulting PeriodIndex

Returns prng : PeriodIndex

pandas.timedelta_range

pandas.**timedelta_range** (*start=None, end=None, periods=None, freq='D', name=None, closed=None*)

Return a fixed frequency timedelta index, with day as the default frequency

Parameters start : string or timedelta-like, default None

Left bound for generating dates

end : string or datetime-like, default None

Right bound for generating dates

periods : integer or None, default None

If None, must specify start and end

freq : string or DateOffset, default 'D' (calendar daily)

Frequency strings can have multiples, e.g. '5H'

name : str, default None

Name of the resulting index

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

Returns **rng** : TimedeltaIndex

Notes

2 of start, end, or periods must be specified

pandas.infer_freq

`pandas.infer_freq(index, warn=True)`

Infer the most likely frequency given the input index. If the frequency is uncertain, a warning will be printed.

Parameters **index** : DatetimeIndex or TimedeltaIndex

if passed a Series will use the values of the series (NOT THE INDEX)

warn : boolean, default True

Returns **freq** : string or None

None if no discernible frequency TypeError if the index is not datetime-like ValueError if there are less than three values.

33.2.4 Top-level evaluation

<code>eval(expr[, parser, engine, truediv, ...])</code>	Evaluate a Python expression as a string using various backends.
---	--

pandas.eval

`pandas.eval(expr, parser='pandas', engine='numexpr', truediv=True, local_dict=None, global_dict=None, resolvers=(), level=0, target=None)`

Evaluate a Python expression as a string using various backends.

The following arithmetic operations are supported: +, -, *, /, **, %, // (python engine only) along with the following boolean operations: | (or), & (and), and ~ (not). Additionally, the 'pandas' parser allows the use of `and`, `or`, and `not` with the same semantics as the corresponding bitwise operators. `Series` and `DataFrame` objects are supported and behave as they would with plain ol' Python evaluation.

Parameters **expr** : str or unicode

The expression to evaluate. This string cannot contain any Python `statements`, only Python `expressions`.

parser : string, default 'pandas', {'pandas', 'python'}

The parser to use to construct the syntax tree from the expression. The default of 'pandas' parses code slightly different than standard Python. Alternatively, you can parse an expression using the 'python' parser to retain strict Python semantics. See the [enhancing performance](#) documentation for more details.

engine : string, default 'numexpr', {'python', 'numexpr'}

The engine used to evaluate the expression. Supported engines are

- **'numexpr'** : This default engine evaluates pandas objects using numexpr for large speed ups in complex expressions with large frames.
- **'python'** : Performs operations as if you had eval'd in top level python. This engine is generally not that useful.

More backends may be available in the future.

truediv : bool, optional

Whether to use true division, like in Python >= 3

local_dict : dict or None, optional

A dictionary of local variables, taken from locals() by default.

global_dict : dict or None, optional

A dictionary of global variables, taken from globals() by default.

resolvers : list of dict-like or None, optional

A list of objects implementing the `__getitem__` special method that you can use to inject an additional collection of namespaces to use for variable lookup. For example, this is used in the `query()` method to inject the `index` and `columns` variables that refer to their respective `DataFrame` instance attributes.

level : int, optional

The number of prior stack frames to traverse and add to the current scope. Most users will **not** need to change this parameter.

target : a target object for assignment, optional, default is None

essentially this is a passed in resolver

Returns ndarray, numeric scalar, DataFrame, Series

See also:

`pandas.DataFrame.query`, `pandas.DataFrame.eval`

Notes

The dtype of any objects involved in an arithmetic % operation are recursively cast to float64.

See the [enhancing performance](#) documentation for more details.

Continued on next

Table 33.16 – continued from previous page

33.2.5 Standard moving window functions

<code>rolling_count(arg, window[, freq, center, how])</code>	Rolling count of number of non-NaN observations inside provided window.
<code>rolling_sum(arg, window[, min_periods, ...])</code>	Moving sum.
<code>rolling_mean(arg, window[, min_periods, ...])</code>	Moving mean.
<code>rolling_median(arg, window[, min_periods, ...])</code>	O(N log(window)) implementation using skip list
<code>rolling_var(arg, window[, min_periods, ...])</code>	Numerically stable implementation using Welford's method.
<code>rolling_std(arg, window[, min_periods, ...])</code>	Moving standard deviation.
<code>rolling_min(arg, window[, min_periods, ...])</code>	Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs.
<code>rolling_max(arg, window[, min_periods, ...])</code>	Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs.
<code>rolling_corr(arg1[, arg2, window, ...])</code>	Moving sample correlation.
<code>rolling_corr_pairwise(df1[, df2, window, ...])</code>	Deprecated.
<code>rolling_cov(arg1[, arg2, window, ...])</code>	Unbiased moving covariance.
<code>rolling_skew(arg, window[, min_periods, ...])</code>	Unbiased moving skewness.
<code>rolling_kurt(arg, window[, min_periods, ...])</code>	Unbiased moving kurtosis.
<code>rolling_apply(arg, window, func[, ...])</code>	Generic moving function application.
<code>rolling_quantile(arg, window, quantile[, ...])</code>	Moving quantile.
<code>rolling_window(arg[, window, win_type, ...])</code>	Applies a moving window of type <code>window_type</code> and size <code>window</code> on the

pandas.rolling_count

`pandas.rolling_count` (*arg, window, freq=None, center=False, how=None*)

Rolling count of number of non-NaN observations inside provided window.

Parameters `arg` : DataFrame or numpy ndarray-like

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

how : string, default 'mean'

Method for down- or re-sampling

Returns `rolling_count` : type of caller

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_sum

```
pandas.rolling_sum(arg, window, min_periods=None, freq=None, center=False, how=None,
                  **kwargs)
```

Moving sum.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_mean

```
pandas.rolling_mean(arg, window, min_periods=None, freq=None, center=False, how=None,
                   **kwargs)
```

Moving mean.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns *y* : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_median

`pandas.rolling_median` (*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how='median'*, ***kwargs*)

$O(N \log(\text{window}))$ implementation using skip list

Moving median.

Parameters *arg* : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'median'

Method for down- or re-sampling

Returns *y* : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_var

`pandas.rolling_var`(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how=None*,
***kwargs*)

Numerically stable implementation using Welford's method.

Moving variance.

Parameters *arg* : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is $N - \text{ddof}$, where N represents the number of elements.

Returns *y* : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_std

`pandas.rolling_std`(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how=None*,
***kwargs*)

Moving standard deviation.

Parameters *arg* : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is $N - \text{ddof}$, where N represents the number of elements.

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_min

`pandas.rolling_min(arg, window, min_periods=None, freq=None, center=False, how='min', **kwargs)`

Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs. Moving minimum.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'min'

Method for down- or re-sampling

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_max

`pandas.rolling_max`(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how='max'*,
***kwargs*)

Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs. Moving maximum.

Parameters *arg* : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'max'

Method for down- or re-sampling

Returns *y* : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_corr

`pandas.rolling_corr`(*arg1*, *arg2=None*, *window=None*, *min_periods=None*, *freq=None*, *center=False*,
pairwise=None, *how=None*)

Moving sample correlation.

Parameters *arg1* : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to *arg1* and produce pairwise output

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns **y** : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise)
DataFrame / Series -> Computes result for each column Series / Series -> Series

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_corr_pairwise

`pandas.rolling_corr_pairwise(df1, df2=None, window=None, min_periods=None, freq=None, center=False)`

Deprecated. Use `rolling_corr(..., pairwise=True)` instead.

Pairwise moving sample correlation

Parameters **df1** : DataFrame

df2 : DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns **y** : Panel whose items are df1.index values

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_cov

`pandas.rolling_cov` (*arg1*, *arg2=None*, *window=None*, *min_periods=None*, *freq=None*, *center=False*, *pairwise=None*, *how=None*, *ddof=1*)
Unbiased moving covariance.

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to arg1 and produce pairwise output

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

pairwise : bool, default False

If False then only matching columns between `arg1` and `arg2` will be used and the output will be a `DataFrame`. If True then all pairwise combinations will be calculated and the output will be a `Panel` in the case of `DataFrame` inputs. In the case of missing elements, only complete pairwise observations will be used.

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is $N - \text{ddof}$, where N represents the number of elements.

Returns `y` : type depends on inputs

`DataFrame / DataFrame` -> `DataFrame` (matches on columns) or `Panel` (pairwise)
`DataFrame / Series` -> Computes result for each column
`Series / Series` -> `Series`

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_skew

`pandas.rolling_skew`(*arg*, *window*, *min_periods=None*, *freq=None*, *center=False*, *how=None*,
 ***kwargs*)

Unbiased moving skewness.

Parameters `arg` : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Set the labels at the center of the window.

how : string, default 'None'

Method for down- or re-sampling

Returns `y` : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

args : tuple

Passed on to func

kwargs : dict

Passed on to func

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_quantile

`pandas.rolling_quantile(arg, window, quantile, min_periods=None, freq=None, center=False)`

Moving quantile.

Parameters **arg** : Series, DataFrame

window : int

Size of the moving window. This is the number of observations used for calculating the statistic.

quantile : float

$0 \leq \text{quantile} \leq 1$

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

Returns **y** : type of input argument

Notes

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The `freq` keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.rolling_window

`pandas.rolling_window` (*arg*, *window=None*, *win_type=None*, *min_periods=None*, *freq=None*, *center=False*, *mean=True*, *axis=0*, *how=None*, ***kwargs*)

Applies a moving window of type `window_type` and size `window` on the data.

Parameters *arg* : Series, DataFrame

window : int or ndarray

Weighting window specification. If the window is an integer, then it is treated as the window length and `win_type` is required

win_type : str, default None

Window type (see Notes)

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

center : boolean, default False

Whether the label should correspond with center of window

mean : boolean, default True

If True computes weighted mean, else weighted sum

axis : {0, 1}, default 0

how : string, default 'mean'

Method for down- or re-sampling

Returns *y* : type of input argument

Notes

The recognized window types are:

- boxcar
- triang
- blackman
- hamming
- bartlett

- parzen
- bohman
- blackmanharris
- nutall
- barthann
- kaiser (needs beta)
- gaussian (needs std)
- general_gaussian (needs power, width)
- slepian (needs width).

By default, the result is set to the right edge of the window. This can be changed to the center of the window by setting `center=True`.

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

33.2.6 Standard expanding window functions

<code>expanding_count(arg[, freq])</code>	Expanding count of number of non-NaN observations.
<code>expanding_sum(arg[, min_periods, freq])</code>	Expanding sum.
<code>expanding_mean(arg[, min_periods, freq])</code>	Expanding mean.
<code>expanding_median(arg[, min_periods, freq])</code>	O(N log(window)) implementation using skip list
<code>expanding_var(arg[, min_periods, freq])</code>	Numerically stable implementation using Welford's method.
<code>expanding_std(arg[, min_periods, freq])</code>	Expanding standard deviation.
<code>expanding_min(arg[, min_periods, freq])</code>	Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs.
<code>expanding_max(arg[, min_periods, freq])</code>	Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs.
<code>expanding_corr(arg1[, arg2, min_periods, ...])</code>	Expanding sample correlation.
<code>expanding_corr_pairwise(df1[, df2, ...])</code>	Deprecated.
<code>expanding_cov(arg1[, arg2, min_periods, ...])</code>	Unbiased expanding covariance.
<code>expanding_skew(arg[, min_periods, freq])</code>	Unbiased expanding skewness.
<code>expanding_kurt(arg[, min_periods, freq])</code>	Unbiased expanding kurtosis.
<code>expanding_apply(arg, func[, min_periods, ...])</code>	Generic expanding function application.
<code>expanding_quantile(arg, quantile[, ...])</code>	Expanding quantile.

pandas.expanding_count

`pandas.expanding_count` (*arg, freq=None*)

Expanding count of number of non-NaN observations.

Parameters *arg* : DataFrame or numpy ndarray-like

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns `expanding_count` : type of caller

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.expanding_sum

`pandas.expanding_sum(arg, min_periods=1, freq=None, **kwargs)`

Expanding sum.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

pandas.expanding_mean

`pandas.expanding_mean(arg, min_periods=1, freq=None, **kwargs)`

Expanding mean.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

pandas.expanding_median

`pandas.expanding_median(arg, min_periods=1, freq=None, **kwargs)`

O(N log(window)) implementation using skip list

Expanding median.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

pandas.expanding_var

`pandas.expanding_var` (*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Numerically stable implementation using Welford's method.

Expanding variance.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is $N - \text{ddof}$, where N represents the number of elements.

Returns *y* : type of input argument

pandas.expanding_std

`pandas.expanding_std` (*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Expanding standard deviation.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

ddof : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is $N - \text{ddof}$, where N represents the number of elements.

Returns *y* : type of input argument

pandas.expanding_min

`pandas.expanding_min` (*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Moving min of 1d array of dtype=float64 along axis=0 ignoring NaNs. Expanding minimum.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

pandas.expanding_max

`pandas.expanding_max(arg, min_periods=1, freq=None, **kwargs)`

Moving max of 1d array of dtype=float64 along axis=0 ignoring NaNs. Expanding maximum.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

pandas.expanding_corr

`pandas.expanding_corr(arg1, arg2=None, min_periods=1, freq=None, pairwise=None)`

Expanding sample correlation.

Parameters *arg1* : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to *arg1* and produce pairwise output

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

pairwise : bool, default False

If False then only matching columns between *arg1* and *arg2* will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns *y* : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise)
DataFrame / Series -> Computes result for each column Series / Series -> Series

pandas.expanding_corr_pairwise

`pandas.expanding_corr_pairwise(df1, df2=None, min_periods=1, freq=None)`

Deprecated. Use `expanding_corr(..., pairwise=True)` instead.

Pairwise expanding sample correlation

Parameters `df1` : DataFrame

`df2` : DataFrame

`min_periods` : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

`freq` : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns `y` : Panel whose items are `df1.index` values

pandas.expanding_cov

`pandas.expanding_cov(arg1, arg2=None, min_periods=1, freq=None, pairwise=None, ddof=1)`

Unbiased expanding covariance.

Parameters `arg1` : Series, DataFrame, or ndarray

`arg2` : Series, DataFrame, or ndarray, optional

if not supplied then will default to `arg1` and produce pairwise output

`min_periods` : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

`freq` : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

`pairwise` : bool, default False

If False then only matching columns between `arg1` and `arg2` will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

`ddof` : int, default 1

Delta Degrees of Freedom. The divisor used in calculations is $N - \text{ddof}$, where N represents the number of elements.

Returns `y` : type depends on inputs

DataFrame / DataFrame -> DataFrame (matches on columns) or Panel (pairwise)
DataFrame / Series -> Computes result for each column Series / Series -> Series

pandas.expanding_skew

pandas.**expanding_skew** (*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Unbiased expanding skewness.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

pandas.expanding_kurt

pandas.**expanding_kurt** (*arg*, *min_periods=1*, *freq=None*, ***kwargs*)

Unbiased expanding kurtosis.

Parameters *arg* : Series, DataFrame

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

pandas.expanding_apply

pandas.**expanding_apply** (*arg*, *func*, *min_periods=1*, *freq=None*, *args=()*, *kwargs={}*)

Generic expanding function application.

Parameters *arg* : Series, DataFrame

func : function

Must produce a single value from an ndarray input

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

args : tuple

Passed on to func

kwargs : dict

Passed on to func

Returns *y* : type of input argument

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

pandas.expanding_quantile

`pandas.expanding_quantile(arg, quantile, min_periods=1, freq=None)`

Expanding quantile.

Parameters *arg* : Series, DataFrame

quantile : float

$0 \leq \text{quantile} \leq 1$

min_periods : int, default None

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : string or DateOffset object, optional (default None)

Frequency to conform the data to before computing the statistic. Specified as a frequency string or DateOffset object.

Returns *y* : type of input argument

Notes

The *freq* keyword is used to conform time series data to a specified frequency by resampling the data. This is done with the default parameters of `resample()` (i.e. using the *mean*).

33.2.7 Exponentially-weighted moving window functions

<code>ewma(arg[, com, span, halflife, ...])</code>	Exponentially-weighted moving average
<code>ewmstd(arg[, com, span, halflife, ...])</code>	Exponentially-weighted moving std
<code>ewmvar(arg[, com, span, halflife, ...])</code>	Exponentially-weighted moving variance
<code>ewmcorr(arg1[, arg2, com, span, halflife, ...])</code>	Exponentially-weighted moving correlation
<code>ewmcov(arg1[, arg2, com, span, halflife, ...])</code>	Exponentially-weighted moving covariance

pandas.ewma

`pandas.ewma(arg, com=None, span=None, halflife=None, min_periods=0, freq=None, adjust=True, how=None, ignore_na=False)`

Exponentially-weighted moving average

Parameters *arg* : Series, DataFrame

com : float, optional

Center of mass: $\alpha = 1/(1 + com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - \exp(\log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

Returns **y** : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a “span” parameter s , we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights $(1-\alpha)^{(n-1)}$, $(1-\alpha)^{(n-2)}$, ..., $1-\alpha$, 1 .

When adjust is False, weighted averages are calculated recursively as: $weighted_average[0] = arg[0]$;
 $weighted_average[i] = (1-\alpha)*weighted_average[i-1] + \alpha*arg[i]$.

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of $[x, None, y]$ are $(1-\alpha)^2$ and 1 (if adjust is True), and $(1-\alpha)^2$ and α (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of $[x, None, y]$ are $1-\alpha$ and 1 (if adjust is True), and $1-\alpha$ and α (if adjust is False).

pandas.ewmstd

`pandas.ewmstd(arg, com=None, span=None, halflife=None, min_periods=0, bias=False, ignore_na=False, adjust=True)`

Exponentially-weighted moving std

Parameters `arg` : Series, DataFrame

`com` : float, optional

Center of mass: $\alpha = 1/(1 + com)$,

`span` : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

`halflife` : float, optional

Specify decay in terms of halflife, $\alpha = 1 - \exp(\log(0.5)/halflife)$

`min_periods` : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

`freq` : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

`adjust` : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

`how` : string, default 'mean'

Method for down- or re-sampling

`ignore_na` : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

`bias` : boolean, default False

Use a standard estimation bias correction

Returns `y` : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a “span” parameter s , we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

When `adjust` is True (default), weighted averages are calculated using weights $(1-\alpha)^{(n-1)}$, $(1-\alpha)^{(n-2)}$, ..., $1-\alpha$, 1.

When `adjust` is False, weighted averages are calculated recursively as: `weighted_average[0] = arg[0];`
`weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i].`

When `ignore_na` is `False` (default), weights are based on absolute positions. For example, the weights of `x` and `y` used in calculating the final weighted average of `[x, None, y]` are $(1-\alpha)^2$ and 1 (if `adjust` is `True`), and $(1-\alpha)^2$ and α (if `adjust` is `False`).

When `ignore_na` is `True` (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of `x` and `y` used in calculating the final weighted average of `[x, None, y]` are $1-\alpha$ and 1 (if `adjust` is `True`), and $1-\alpha$ and α (if `adjust` is `False`).

pandas.ewmvar

`pandas.ewmvar` (*arg, com=None, span=None, halflife=None, min_periods=0, bias=False, freq=None, how=None, ignore_na=False, adjust=True*)
Exponentially-weighted moving variance

Parameters `arg` : Series, DataFrame

com : float, optional

Center of mass: $\alpha = 1/(1 + com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - \exp(\log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

bias : boolean, default False

Use a standard estimation bias correction

Returns `y` : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a “span” parameter s , we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

When `adjust` is True (default), weighted averages are calculated using weights $(1-\alpha)^{(n-1)}, (1-\alpha)^{(n-2)}, \dots, 1-\alpha, 1$.

When `adjust` is False, weighted averages are calculated recursively as: `weighted_average[0] = arg[0]; weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i]`.

When `ignore_na` is False (default), weights are based on absolute positions. For example, the weights of `x` and `y` used in calculating the final weighted average of `[x, None, y]` are $(1-\alpha)^2$ and 1 (if `adjust` is True), and $(1-\alpha)^2$ and α (if `adjust` is False).

When `ignore_na` is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of `x` and `y` used in calculating the final weighted average of `[x, None, y]` are $1-\alpha$ and 1 (if `adjust` is True), and $1-\alpha$ and α (if `adjust` is False).

pandas.ewmcorr

`pandas.ewmcorr` (*arg1*, *arg2=None*, *com=None*, *span=None*, *halflife=None*, *min_periods=0*, *freq=None*, *pairwise=None*, *how=None*, *ignore_na=False*, *adjust=True*)
Exponentially-weighted moving correlation

Parameters **arg1** : Series, DataFrame, or ndarray

arg2 : Series, DataFrame, or ndarray, optional

if not supplied then will default to `arg1` and produce pairwise output

com : float. optional

Center of mass: $\alpha = 1/(1 + com)$,

span : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

halflife : float, optional

Specify decay in terms of halflife, $\alpha = 1 - \exp(\log(0.5)/halflife)$

min_periods : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

freq : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default ‘mean’

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

pairwise : bool, default False

If False then only matching columns between `arg1` and `arg2` will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns `y` : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a “span” parameter s , we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

When `adjust` is True (default), weighted averages are calculated using weights $(1-\alpha)^{(n-1)}, (1-\alpha)^{(n-2)}, \dots, 1-\alpha, 1$.

When `adjust` is False, weighted averages are calculated recursively as: `weighted_average[0] = arg[0]; weighted_average[i] = (1-alpha)*weighted_average[i-1] + alpha*arg[i]`.

When `ignore_na` is False (default), weights are based on absolute positions. For example, the weights of `x` and `y` used in calculating the final weighted average of `[x, None, y]` are $(1-\alpha)^2$ and 1 (if `adjust` is True), and $(1-\alpha)^2$ and α (if `adjust` is False).

When `ignore_na` is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of `x` and `y` used in calculating the final weighted average of `[x, None, y]` are $1-\alpha$ and 1 (if `adjust` is True), and $1-\alpha$ and α (if `adjust` is False).

pandas.ewmcov

`pandas.ewmcov` (*arg1*, *arg2=None*, *com=None*, *span=None*, *halflife=None*, *min_periods=0*, *bias=False*, *freq=None*, *pairwise=None*, *how=None*, *ignore_na=False*, *adjust=True*)
Exponentially-weighted moving covariance

Parameters `arg1` : Series, DataFrame, or ndarray

`arg2` : Series, DataFrame, or ndarray, optional

if not supplied then will default to `arg1` and produce pairwise output

`com` : float, optional

Center of mass: $\alpha = 1/(1 + com)$,

`span` : float, optional

Specify decay in terms of span, $\alpha = 2/(span + 1)$

`halflife` : float, optional

Specify decay in terms of halflife, $\alpha = 1 - \exp(\log(0.5)/halflife)$

`min_periods` : int, default 0

Minimum number of observations in window required to have a value (otherwise result is NA).

`freq` : None or string alias / date offset object, default=None

Frequency to conform to before computing statistic

adjust : boolean, default True

Divide by decaying adjustment factor in beginning periods to account for imbalance in relative weightings (viewing EWMA as a moving average)

how : string, default 'mean'

Method for down- or re-sampling

ignore_na : boolean, default False

Ignore missing values when calculating weights; specify True to reproduce pre-0.15.0 behavior

pairwise : bool, default False

If False then only matching columns between arg1 and arg2 will be used and the output will be a DataFrame. If True then all pairwise combinations will be calculated and the output will be a Panel in the case of DataFrame inputs. In the case of missing elements, only complete pairwise observations will be used.

Returns **y** : type of input argument

Notes

Either center of mass or span must be specified

EWMA is sometimes specified using a “span” parameter s , we have that the decay parameter α is related to the span as $\alpha = 2/(s + 1) = 1/(1 + c)$

where c is the center of mass. Given a span, the associated center of mass is $c = (s - 1)/2$

So a “20-day EWMA” would have center 9.5.

When adjust is True (default), weighted averages are calculated using weights $(1-\alpha)^{(n-1)}$, $(1-\alpha)^{(n-2)}$, ..., $1-\alpha$, 1 .

When adjust is False, weighted averages are calculated recursively as: $\text{weighted_average}[0] = \text{arg}[0]$;
 $\text{weighted_average}[i] = (1-\alpha)*\text{weighted_average}[i-1] + \alpha*\text{arg}[i]$.

When ignore_na is False (default), weights are based on absolute positions. For example, the weights of x and y used in calculating the final weighted average of $[x, \text{None}, y]$ are $(1-\alpha)^{**2}$ and 1 (if adjust is True), and $(1-\alpha)^{**2}$ and α (if adjust is False).

When ignore_na is True (reproducing pre-0.15.0 behavior), weights are based on relative positions. For example, the weights of x and y used in calculating the final weighted average of $[x, \text{None}, y]$ are $1-\alpha$ and 1 (if adjust is True), and $1-\alpha$ and α (if adjust is False).

33.3 Series

33.3.1 Constructor

`Series([data, index, dtype, name, copy, ...])` One-dimensional ndarray with axis labels (including time series).

pandas.Series

class `pandas.Series` (*data=None, index=None, dtype=None, name=None, copy=False, fastpath=False*)

One-dimensional ndarray with axis labels (including time series).

Labels need not be unique but must be any hashable type. The object supports both integer- and label-based indexing and provides a host of methods for performing operations involving the index. Statistical methods from ndarray have been overridden to automatically exclude missing data (currently represented as NaN)

Operations between Series (+, -, /, *, **) align values based on their associated index values— they need not be the same length. The result index will be the sorted union of the two indexes.

Parameters **data** : array-like, dict, or scalar value

Contains data stored in Series

index : array-like or Index (1d)

Values must be unique and hashable, same length as data. Index object (or other iterable of same length as data) Will default to `np.arange(len(data))` if not provided. If both a dict and index sequence are used, the index will override the keys found in the dict.

dtype : `numpy.dtype` or `None`

If `None`, dtype will be inferred

copy : boolean, default `False`

Copy input data

Attributes

<code>T</code>	return the transpose, which is by definition self
<code>at</code>	Fast label-based scalar accessor
<code>axes</code>	
<code>base</code>	return the base object if the memory of the underlying data is shared
<code>blocks</code>	Internal property, property synonym for <code>as_blocks()</code>
<code>data</code>	return the data pointer of the underlying data
<code>dtype</code>	return the dtype object of the underlying data
<code>dtypes</code>	return the dtype object of the underlying data
<code>empty</code>	True if NDFrame is entirely empty [no items]
<code>flags</code>	
<code>ftype</code>	return if the data is sparsedense
<code>ftypes</code>	return if the data is sparsedense
<code>iat</code>	Fast integer location scalar accessor.
<code>iloc</code>	Purely integer-location based indexing for selection by position.
<code>imag</code>	
<code>is_time_series</code>	
<code>itemsizes</code>	return the size of the dtype of the item of the underlying data
<code>ix</code>	A primarily label-location based indexer, with integer position fallback.
<code>loc</code>	Purely label-location based indexer for selection by label.
<code>nbytes</code>	return the number of bytes in the underlying data
<code>ndim</code>	return the number of dimensions of the underlying data, by definition 1
<code>real</code>	
<code>shape</code>	return a tuple of the shape of the underlying data
<code>size</code>	return the number of elements in the underlying data

Continued on next page

Table 33.20 – continued from previous page

<code>strides</code>	return the strides of the underlying data
<code>values</code>	Return Series as ndarray

pandas.Series.T`Series.T`

return the transpose, which is by definition self

pandas.Series.at`Series.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.**pandas.Series.axes**`Series.axes`**pandas.Series.base**`Series.base`

return the base object if the memory of the underlying data is shared

pandas.Series.blocks`Series.blocks`Internal property, property synonym for `as_blocks()`**pandas.Series.data**`Series.data`

return the data pointer of the underlying data

pandas.Series.dtype`Series.dtype`

return the dtype object of the underlying data

pandas.Series.dtypes`Series.dtypes`

return the dtype object of the underlying data

pandas.Series.empty

`Series.empty`

True if NDFrame is entirely empty [no items]

pandas.Series.flags

`Series.flags`

pandas.Series.ftype

`Series.ftype`

return if the data is sparseldense

pandas.Series.ftypes

`Series.ftypes`

return if the data is sparseldense

pandas.Series.iat

`Series.iat`

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Series.iloc

`Series.iloc`

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at [Selection by Position](#)

pandas.Series.imag

`Series.imag`

`pandas.Series.is_time_series`

`Series.is_time_series`

`pandas.Series.itemsize`

`Series.itemsize`

return the size of the dtype of the item of the underlying data

`pandas.Series.ix`

`Series.ix`

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#).

`pandas.Series.loc`

`Series.loc`

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a' : 'f' (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at [Selection by Label](#)

`pandas.Series.nbytes`

`Series.nbytes`

return the number of bytes in the underlying data

pandas.Series.ndim**Series.ndim**

return the number of dimensions of the underlying data, by definition 1

pandas.Series.real**Series.real****pandas.Series.shape****Series.shape**

return a tuple of the shape of the underlying data

pandas.Series.size**Series.size**

return the number of elements in the underlying data

pandas.Series.strides**Series.strides**

return the strides of the underlying data

pandas.Series.values**Series.values**

Return Series as ndarray

Returns **arr** : numpy.ndarray

is_copy	
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Methods

<code>abs()</code>	Return an object with absolute value taken.
<code>add(other[, level, fill_value, axis])</code>	Binary operator add with support to substitute a fill_value for missing data
<code>add_prefix(prefix)</code>	Concatenate prefix string with panel items names.
<code>add_suffix(suffix)</code>	Concatenate suffix string with panel items names
<code>align(other[, join, axis, level, copy, ...])</code>	Align two object on their axes with the
<code>all([axis, bool_only, skipna, level])</code>	Return whether all elements are True over requested axis
<code>any([axis, bool_only, skipna, level])</code>	Return whether any element is True over requested axis
<code>append(to_append[, verify_integrity])</code>	Concatenate two or more Series.
<code>apply(func[, convert_dtype, args])</code>	Invoke function on values of Series.
<code>argmax([axis, out, skipna])</code>	Index of first occurrence of maximum of values.
<code>argmin([axis, out, skipna])</code>	Index of first occurrence of minimum of values.
<code>argsort([axis, kind, order])</code>	Overrides ndarray.argsort.
<code>as_blocks()</code>	Convert the frame to a dict of dtype -> Constructor Types that each has a homog

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<code>as_matrix([columns])</code>	Convert the frame to its Numpy-array representation.
<code>asfreq(freq[, method, how, normalize])</code>	Convert all TimeSeries inside to specified frequency using DateOffset objects.
<code>asof(where)</code>	Return last good (non-NaN) value in TimeSeries if value is NaN for requested data
<code>astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>at_time(time[, asof])</code>	Select values at particular time of day (e.g.
<code>autocorr([lag])</code>	Lag-N autocorrelation
<code>between(left, right[, inclusive])</code>	Return boolean Series equivalent to <code>left <= series <= right</code> .
<code>between_time(start_time, end_time[, ...])</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM)
<code>bfill([axis, inplace, limit, downcast])</code>	Synonym for <code>NDFrame.fillna(method='bfill')</code>
<code>bool()</code>	Return the bool of a single element PandasObject
<code>cat</code>	alias of <code>CategoricalAccessor</code>
<code>clip([lower, upper, out, axis])</code>	Trim values at input threshold(s)
<code>clip_lower(threshold[, axis])</code>	Return copy of the input with values below given value(s) truncated
<code>clip_upper(threshold[, axis])</code>	Return copy of input with values above given value(s) truncated
<code>combine(other, func[, fill_value])</code>	Perform elementwise binary operation on two Series using given function
<code>combine_first(other)</code>	Combine Series values, choosing the calling Series's values first.
<code>compound([axis, skipna, level])</code>	Return the compound percentage of the values for the requested axis
<code>compress(condition[, axis, out])</code>	Return selected slices of an array along given axis as a Series
<code>consolidate([inplace])</code>	Compute NDFrame with "consolidated" internals (data of each dtype grouped together)
<code>convert_objects([convert_dates, ...])</code>	Attempt to infer better dtype for object columns
<code>copy([deep])</code>	Make a copy of this object
<code>corr(other[, method, min_periods])</code>	Compute correlation with <i>other</i> Series, excluding missing values
<code>count([level])</code>	Return number of non-NA/null observations in the Series
<code>cov(other[, min_periods])</code>	Compute covariance with Series, excluding missing values
<code>cummax([axis, dtype, out, skipna])</code>	Return cumulative max over requested axis.
<code>cummin([axis, dtype, out, skipna])</code>	Return cumulative min over requested axis.
<code>cumprod([axis, dtype, out, skipna])</code>	Return cumulative prod over requested axis.
<code>cumsum([axis, dtype, out, skipna])</code>	Return cumulative sum over requested axis.
<code>describe([percentile_width, percentiles, ...])</code>	Generate various summary statistics, excluding NaN values.
<code>diff([periods])</code>	1st discrete difference of object
<code>div(other[, level, fill_value, axis])</code>	Binary operator <code>truediv</code> with support to substitute a <code>fill_value</code> for missing data
<code>divide(other[, level, fill_value, axis])</code>	Binary operator <code>truediv</code> with support to substitute a <code>fill_value</code> for missing data
<code>dot(other)</code>	Matrix multiplication with DataFrame or inner-product with Series
<code>drop(labels[, axis, level, inplace, errors])</code>	Return new object with labels in requested axis removed
<code>drop_duplicates([take_last, inplace])</code>	Return Series with duplicate values removed
<code>dropna([axis, inplace])</code>	Return Series without null values
<code>dt</code>	alias of <code>CombinedDatetimelikeProperties</code>
<code>duplicated([take_last])</code>	Return boolean Series denoting duplicate values
<code>eq(other[, axis])</code>	
<code>equals(other)</code>	Determines if two NDFrame objects contain the same elements.
<code>factorize([sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable
<code>ffill([axis, inplace, limit, downcast])</code>	Synonym for <code>NDFrame.fillna(method='ffill')</code>
<code>fillna([value, method, axis, inplace, ...])</code>	Fill NA/NaN values using the specified method
<code>filter([items, like, regex, axis])</code>	Restrict the info axis to set of items or wildcard
<code>first(offset)</code>	Convenience method for subsetting initial periods of time series data
<code>first_valid_index()</code>	Return label for first non-NA/null value
<code>floordiv(other[, level, fill_value, axis])</code>	Binary operator <code>floordiv</code> with support to substitute a <code>fill_value</code> for missing data
<code>from_array(arr[, index, name, dtype, copy, ...])</code>	
<code>from_csv(path[, sep, parse_dates, header, ...])</code>	Read delimited file into Series
<code>ge(other[, axis])</code>	
<code>get(key[, default])</code>	Get item from object for given key (DataFrame column, Panel slice, etc.).
<code>get_dtype_counts()</code>	Return the counts of dtypes in this object

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<code>get_ftype_counts()</code>	Return the counts of ftypes in this object
<code>get_value(label[, takeable])</code>	Quickly retrieve single value at passed index label
<code>get_values()</code>	same as values (but handles sparseness conversions); is a view
<code>groupby([by, axis, level, as_index, sort, ...])</code>	Group series using mapper (dict or key function, apply given function
<code>gt(other[, axis])</code>	
<code>hasnans()</code>	return if I have any nans; enables various perf speedups
<code>head([n])</code>	Returns first n rows
<code>hist([by, ax, grid, xlabelsize, xrot, ...])</code>	Draw histogram of the input series using matplotlib
<code>idxmax([axis, out, skipna])</code>	Index of first occurrence of maximum of values.
<code>idxmin([axis, out, skipna])</code>	Index of first occurrence of minimum of values.
<code>iget(i[, axis])</code>	Return the i-th value or values in the Series by location
<code>iget_value(i[, axis])</code>	Return the i-th value or values in the Series by location
<code>interpolate([method, axis, limit, inplace, ...])</code>	Interpolate values according to different methods.
<code>irow(i[, axis])</code>	Return the i-th value or values in the Series by location
<code>isin(values)</code>	Return a boolean <i>Series</i> showing whether each element in the <i>Series</i> is exa
<code>isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>item()</code>	return the first element of the underlying data as a python scalar
<code>iteritems()</code>	Lazily iterate over (index, value) tuples
<code>iterkv(*args, **kwargs)</code>	iteritems alias used to get around 2to3. Deprecated
<code>keys()</code>	Alias for index
<code>kurt([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>kurtosis([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>last(offset)</code>	Convenience method for subsetting final periods of time series data
<code>last_valid_index()</code>	Return label for last non-NA/null value
<code>le(other[, axis])</code>	
<code>load(path)</code>	Deprecated.
<code>lt(other[, axis])</code>	
<code>mad([axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis
<code>map(arg[, na_action])</code>	Map values of Series using input correspondence (which can be
<code>mask(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from
<code>max([axis, skipna, level, numeric_only])</code>	This method returns the maximum of the values in the object.
<code>mean([axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis
<code>median([axis, skipna, level, numeric_only])</code>	Return the median of the values for the requested axis
<code>min([axis, skipna, level, numeric_only])</code>	This method returns the minimum of the values in the object.
<code>mod(other[, level, fill_value, axis])</code>	Binary operator mod with support to substitute a fill_value for missing data
<code>mode()</code>	Returns the mode(s) of the dataset.
<code>mul(other[, level, fill_value, axis])</code>	Binary operator mul with support to substitute a fill_value for missing data
<code>multiply(other[, level, fill_value, axis])</code>	Binary operator mul with support to substitute a fill_value for missing data
<code>ne(other[, axis])</code>	
<code>nlargest([n, take_last])</code>	Return the largest <i>n</i> elements.
<code>nonzero()</code>	Return the indices of the elements that are non-zero
<code>notnull()</code>	Return a boolean same-sized object indicating if the values are
<code>nsmallest([n, take_last])</code>	Return the smallest <i>n</i> elements.
<code>nunique([dropna])</code>	Return number of unique elements in the object.
<code>order([na_last, ascending, kind, ...])</code>	Sorts Series object, by value, maintaining index-value link.
<code>pct_change([periods, fill_method, limit, freq])</code>	Percent change over given number of periods.
<code>plot(data[, kind, ax, figsize, use_index, ...])</code>	Make plots of Series using matplotlib / pylab.
<code>pop(item)</code>	Return item and drop from frame.
<code>pow(other[, level, fill_value, axis])</code>	Binary operator pow with support to substitute a fill_value for missing data
<code>prod([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>product([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>ptp([axis, out])</code>	

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<code>put(*args, **kwargs)</code>	return a ndarray with the values put
<code>quantile([q])</code>	Return value at the given quantile, a la numpy.percentile.
<code>radd(other[, level, fill_value, axis])</code>	Binary operator radd with support to substitute a fill_value for missing data
<code>rank([method, na_option, ascending, pct])</code>	Compute data ranks (1 through n).
<code>ravel([order])</code>	Return the flattened underlying data as an ndarray
<code>rdiv(other[, level, fill_value, axis])</code>	Binary operator rtruediv with support to substitute a fill_value for missing data
<code>reindex([index])</code>	Conform Series to new index with optional filling logic, placing NA/NaN in local for compatibility with higher dims
<code>reindex_axis(labels[, axis])</code>	return an object with matching indicies to myself
<code>reindex_like(other[, method, copy, limit])</code>	Alter axes input function or functions.
<code>rename([index])</code>	Alter index and / or columns using input function or functions.
<code>rename_axis(mapper[, axis, copy, inplace])</code>	Rearrange index levels using input order.
<code>reorder_levels(order)</code>	return a new Series with the values repeated reps times
<code>repeat(reps)</code>	Replace values given in 'to_replace' with 'value'.
<code>replace([to_replace, value, inplace, limit, ...])</code>	Convenience method for frequency conversion and resampling of regular time-series
<code>resample(rule[, how, axis, fill_method, ...])</code>	Analogous to the <code>pandas.DataFrame.reset_index()</code> function, see doc
<code>reset_index([level, drop, name, inplace])</code>	return an ndarray with the values shape
<code>reshape(*args, **kwargs)</code>	Binary operator rfloordiv with support to substitute a fill_value for missing data
<code>rfloordiv(other[, level, fill_value, axis])</code>	Binary operator rmod with support to substitute a fill_value for missing data
<code>rmod(other[, level, fill_value, axis])</code>	Binary operator rmul with support to substitute a fill_value for missing data
<code>rmul(other[, level, fill_value, axis])</code>	Return <i>a</i> with each element rounded to the given number of decimals.
<code>round([decimals, out])</code>	Binary operator rpow with support to substitute a fill_value for missing data
<code>rpow(other[, level, fill_value, axis])</code>	Binary operator rsub with support to substitute a fill_value for missing data
<code>rsub(other[, level, fill_value, axis])</code>	Binary operator rtruediv with support to substitute a fill_value for missing data
<code>rtruediv(other[, level, fill_value, axis])</code>	Returns a random sample of items from an axis of object.
<code>sample([n, frac, replace, weights, ...])</code>	Deprecated.
<code>save(path)</code>	Find indices where elements should be inserted to maintain order.
<code>searchsorted(v[, side, sorter])</code>	Return data corresponding to axis labels matching criteria
<code>select(crit[, axis])</code>	Return unbiased standard error of the mean over requested axis.
<code>sem([axis, skipna, level, ddof, numeric_only])</code>	public version of axis assignment
<code>set_axis(axis, labels)</code>	Quickly set single value at passed label.
<code>set_value(label, value[, takeable])</code>	Shift index by desired number of periods with an optional time freq
<code>shift([periods, freq, axis])</code>	Return unbiased skew over requested axis
<code>skew([axis, skipna, level, numeric_only])</code>	Equivalent to <i>shift</i> without copying data.
<code>slice_shift([periods, axis])</code>	Sort values and index labels by value.
<code>sort([axis, ascending, kind, na_position, ...])</code>	Sort object by labels (along an axis)
<code>sort_index([ascending])</code>	Sort Series with MultiIndex by chosen level.
<code>sortlevel([level, ascending, sort_remaining])</code>	squeeze length 1 dimensions
<code>squeeze()</code>	Return unbiased standard deviation over requested axis.
<code>std([axis, skipna, level, ddof, numeric_only])</code>	alias of <code>StringMethods</code>
<code>str</code>	Binary operator sub with support to substitute a fill_value for missing data
<code>sub(other[, level, fill_value, axis])</code>	Binary operator sub with support to substitute a fill_value for missing data
<code>subtract(other[, level, fill_value, axis])</code>	Return the sum of the values for the requested axis
<code>sum([axis, skipna, level, numeric_only])</code>	Interchange axes and swap values axes appropriately
<code>swapaxes(axis1, axis2[, copy])</code>	Swap levels <i>i</i> and <i>j</i> in a MultiIndex
<code>swaplevel(i, j[, copy])</code>	Returns last <i>n</i> rows
<code>tail([n])</code>	return Series corresponding to requested indices
<code>take(indices[, axis, convert, is_copy])</code>	Attempt to write text representation of object to the system clipboard This can be
<code>to_clipboard([excel, sep])</code>	Write Series to a comma-separated values (csv) file
<code>to_csv(path[, index, sep, na_rep, ...])</code>	Return dense representation of NDFrame (as opposed to sparse)
<code>to_dense()</code>	Convert Series to {label -> value} dict
<code>to_dict()</code>	Convert Series to DataFrame
<code>to_frame([name])</code>	

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<code>to_hdf(path_or_buf, key, **kwargs)</code>	activate the HDFStore
<code>to_json([path_or_buf, orient, date_format, ...])</code>	Convert the object to a JSON string.
<code>to_msgpack([path_or_buf])</code>	msgpack (serialize) object to input file path
<code>to_period([freq, copy])</code>	Convert TimeSeries from DatetimeIndex to PeriodIndex with desired
<code>to_pickle(path)</code>	Pickle (serialize) object to input file path
<code>to_sparse([kind, fill_value])</code>	Convert Series to SparseSeries
<code>to_sql(name, con[, flavor, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>to_string([buf, na_rep, float_format, ...])</code>	Render a string representation of the Series
<code>to_timestamp([freq, how, copy])</code>	Cast to datetimeindex of timestamps, at <i>beginning</i> of period
<code>tolist()</code>	Convert Series to a nested list
<code>transpose()</code>	return the transpose, which is by definition self
<code>truediv(other[, level, fill_value, axis])</code>	Binary operator truediv with support to substitute a fill_value for missing data
<code>truncate([before, after, axis, copy])</code>	Truncates a sorted NDFrame before and/or after some particular dates.
<code>tshift([periods, freq, axis])</code>	Shift the time index, using the index's frequency if available
<code>tz_convert(tz[, axis, level, copy])</code>	Convert tz-aware axis to target time zone.
<code>tz_localize(*args, **kwargs)</code>	Localize tz-naive TimeSeries to target time zone
<code>unique()</code>	Return array of unique values in the object.
<code>unstack([level])</code>	Unstack, a.k.a.
<code>update(other)</code>	Modify Series in place using non-NA values from passed Series.
<code>valid([inplace])</code>	
<code>value_counts([normalize, sort, ascending, ...])</code>	Returns object containing counts of unique values.
<code>var([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased variance over requested axis.
<code>view([dtype])</code>	
<code>where(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from
<code>xs(key[, axis, level, copy, drop_level])</code>	Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

pandas.Series.abs`Series.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller**pandas.Series.add**`Series.add(other, level=None, fill_value=None, axis=0)`

Binary operator add with support to substitute a fill_value for missing data in one of the inputs

Parameters **other**: Series or scalar value**fill_value** : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.add_prefix

Series.add_prefix (*prefix*)

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.Series.add_suffix

Series.add_suffix (*suffix*)

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.Series.align

Series.align (*other*, *join*='outer', *axis*=None, *level*=None, *copy*=True, *fill_value*=None, *method*=None, *limit*=None, *fill_axis*=0)

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : { 'outer', 'inner', 'left', 'right' }, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns (**left**, **right**) : (type of input, type of other)

Aligned objects

pandas.Series.all

`Series.all` (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether all elements are True over requested axis

Parameters *axis* : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns *all* : scalar or Series (if level specified)

pandas.Series.any

`Series.any` (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether any element is True over requested axis

Parameters *axis* : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns *any* : scalar or Series (if level specified)

pandas.Series.append

`Series.append` (*to_append, verify_integrity=False*)

Concatenate two or more Series. The indexes must not overlap

Parameters *to_append* : Series or list/tuple of Series

verify_integrity : boolean, default False

If True, raise Exception on creating index with duplicates

Returns *appended* : Series

pandas.Series.apply

`Series.apply` (*func*, *convert_dtype=True*, *args=()*, ***kwargs*)

Invoke function on values of Series. Can be *ufunc* (a NumPy function that applies to the entire Series) or a Python function that only works on single values

Parameters *func* : function

convert_dtype : boolean, default True

Try to find better dtype for elementwise function results. If False, leave as dtype=object

args : tuple

Positional arguments to pass to function in addition to the value

Additional keyword arguments will be passed as keywords to the function

Returns *y* : Series or DataFrame if func returns a Series

See also:

[`Series.map`](#) For element-wise operations

pandas.Series.argmax

`Series.argmax` (*axis=None*, *out=None*, *skipna=True*)

Index of first occurrence of maximum of values.

Parameters *skipna* : boolean, default True

Exclude NA/null values

Returns *idxmax* : Index of maximum of values

See also:

`DataFrame.idxmax`, `numpy.ndarray.argmax`

Notes

This method is the Series version of `ndarray.argmax`.

pandas.Series.argmin

`Series.argmin` (*axis=None*, *out=None*, *skipna=True*)

Index of first occurrence of minimum of values.

Parameters *skipna* : boolean, default True

Exclude NA/null values

Returns *idxmin* : Index of minimum of values

See also:

`DataFrame.idxmin`, `numpy.ndarray.argmin`

Notes

This method is the Series version of `ndarray.argmax`.

pandas.Series.argsort

`Series.argsort` (*axis=0, kind='quicksort', order=None*)

Overrides `ndarray.argsort`. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values

Parameters `axis` : int (can only be zero)

kind : { 'mergesort', 'quicksort', 'heapsort' }, default 'quicksort'

Choice of sorting algorithm. See `np.sort` for more information. 'mergesort' is the only stable algorithm

order : ignored

Returns `argsorted` : Series, with -1 indicated where nan values are present

See also:

`numpy.ndarray.argsort`

pandas.Series.as_blocks

`Series.as_blocks` ()

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in `as_matrix`)

Returns `values` : a dict of dtype -> Constructor Types

pandas.Series.as_matrix

`Series.as_matrix` (*columns=None*)

Convert the frame to its Numpy-array representation.

Parameters `columns`: list, optional, default:None

If None, return all columns, otherwise, returns specified columns.

Returns `values` : ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

See also:

`pandas.DataFrame.values`

Notes

Return is NOT a Numpy-matrix, rather, a Numpy-array.

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use `‘.values’`.

pandas.Series.asfreq

`Series.asfreq(freq, method=None, how=None, normalize=False)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters `freq` : DateOffset object, or string

method : { ‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None }

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : { ‘start’, ‘end’ }, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns `converted` : type of caller

pandas.Series.asof

`Series.asof(where)`

Return last good (non-NaN) value in TimeSeries if value is NaN for requested date.

If there is no good value, NaN is returned.

Parameters `where` : date or array of dates

Returns value or NaN

Notes

Dates are assumed to be sorted

pandas.Series.astype

`Series.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters `dtype` : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns `casted` : type of caller

pandas.Series.at_time

`Series.at_time` (*time, asof=False*)

Select values at particular time of day (e.g. 9:30AM)

Parameters `time` : datetime.time or string

Returns `values_at_time` : type of caller

pandas.Series.autocorr

`Series.autocorr` (*lag=1*)

Lag-N autocorrelation

Parameters `lag` : int, default 1

Number of lags to apply before performing autocorrelation.

Returns `autocorr` : float

pandas.Series.between

`Series.between` (*left, right, inclusive=True*)

Return boolean Series equivalent to `left <= series <= right`. NA values will be treated as False

Parameters `left` : scalar

Left boundary

right : scalar

Right boundary

Returns `is_between` : Series

pandas.Series.between_time

`Series.between_time` (*start_time, end_time, include_start=True, include_end=True*)

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters `start_time` : datetime.time or string

`end_time` : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns `values_between_time` : type of caller

pandas.Series.bfill

`Series.bfill` (*axis=None, inplace=False, limit=None, downcast=None*)

Synonym for `NDFrame.fillna(method='bfill')`

pandas.Series.bool

`Series.bool()`

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

pandas.Series.cat

`Series.cat()`

Accessor object for categorical properties of the Series values.

Be aware that assigning to *categories* is an inplace operation, while all methods return new categorical data per default (but can be called with *inplace=True*).

Examples

```
>>> s.cat.categories
>>> s.cat.categories = list('abc')
>>> s.cat.rename_categories(list('cab'))
>>> s.cat.reorder_categories(list('cab'))
>>> s.cat.add_categories(['d', 'e'])
>>> s.cat.remove_categories(['d'])
>>> s.cat.remove_unused_categories()
>>> s.cat.set_categories(list('abcde'))
>>> s.cat.as_ordered()
>>> s.cat.as_unordered()
```

pandas.Series.clip

`Series.clip(lower=None, upper=None, out=None, axis=None)`

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
   0      1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
   0      1
0  0.335232 -1.256177
1 -1.000000  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
```

```

0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
      0      1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967

```

pandas.Series.clip_lower**Series.clip_lower** (*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters threshold : float or array_like**axis** : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input**See also:**`clip`**pandas.Series.clip_upper****Series.clip_upper** (*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters threshold : float or array_like**axis** : int or string axis name, optional

Align object with threshold along the given axis.

Returns clipped : same type as input**See also:**`clip`**pandas.Series.combine****Series.combine** (*other*, *func*, *fill_value=nan*)

Perform elementwise binary operation on two Series using given function with optional fill value when an

index is missing from one Series or the other

Parameters **other** : Series or scalar value

func : function

fill_value : scalar value

Returns **result** : Series

pandas.Series.combine_first

`Series.combine_first(other)`

Combine Series values, choosing the calling Series's values first. Result index will be the union of the two indexes

Parameters **other** : Series

Returns **y** : Series

pandas.Series.compound

`Series.compound(axis=None, skipna=None, level=None)`

Return the compound percentage of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **compounded** : scalar or Series (if level specified)

pandas.Series.compress

`Series.compress(condition, axis=0, out=None, **kwargs)`

Return selected slices of an array along given axis as a Series

See also:

`numpy.ndarray.compress`

pandas.Series consolidate

`Series consolidate(inplace=False)`

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters **inplace** : boolean, default False

If False return new object, otherwise modify existing object

Returns **consolidated** : type of caller

pandas.Series.convert_objects

`Series.convert_objects(convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True)`

Attempt to infer better dtype for object columns

Parameters **convert_dates** : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns **converted** : same as input object

pandas.Series.copy

`Series.copy(deep=True)`

Make a copy of this object

Parameters **deep** : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns **copy** : type of caller

pandas.Series.corr

`Series.corr(other, method='pearson', min_periods=None)`

Compute correlation with *other* Series, excluding missing values

Parameters **other** : Series

method : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations needed to have a valid result

Returns **correlation** : float

pandas.Series.count

`Series.count (level=None)`

Return number of non-NA/null observations in the Series

Parameters **level** : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

Returns **nobs** : int or Series (if level specified)

pandas.Series.cov

`Series.cov (other, min_periods=None)`

Compute covariance with Series, excluding missing values

Parameters **other** : Series

min_periods : int, optional

Minimum number of observations needed to have a valid result

Returns **covariance** : float

Normalized by N-1 (unbiased estimator).

pandas.Series.cummax

`Series.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **max** : scalar

pandas.Series.cummin

`Series.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative min over requested axis.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **min** : scalar

pandas.Series.cumprod

`Series.cumprod` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative prod over requested axis.

Parameters `axis` : {index (0)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `prod` : scalar

pandas.Series.cumsum

`Series.cumsum` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative sum over requested axis.

Parameters `axis` : {index (0)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `sum` : scalar

pandas.Series.describe

`Series.describe` (*percentile_width=None, percentiles=None, include=None, exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters `percentile_width` : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default `percentiles` is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy.number`. To select categorical objects use type object. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.Series.diff

`Series.diff (periods=1)`

1st discrete difference of object

Parameters `periods` : int, default 1

Periods to shift for forming difference

Returns `diffed` : Series

pandas.Series.div

`Series.div (other, level=None, fill_value=None, axis=0)`

Binary operator `truediv` with support to substitute a `fill_value` for missing data in one of the inputs

Parameters `other`: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result` : Series

pandas.Series.divide

`Series.divide (other, level=None, fill_value=None, axis=0)`

Binary operator `truediv` with support to substitute a `fill_value` for missing data in one of the inputs

Parameters `other`: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.dot

Series.dot (*other*)

Matrix multiplication with DataFrame or inner-product with Series objects

Parameters **other** : Series or DataFrame

Returns **dot_product** : scalar or Series

pandas.Series.drop

Series.drop (*labels, axis=0, level=None, inplace=False, errors='raise'*)

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : { 'ignore', 'raise' }, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : type of caller

pandas.Series.drop_duplicates

Series.drop_duplicates (*take_last=False, inplace=False*)

Return Series with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

inplace : boolean, default False

If True, performs operation inplace and returns None.

Returns **deduplicated** : Series

pandas.Series.dropna

Series.dropna (*axis=0, inplace=False, **kwargs*)

Return Series without null values

Returns **valid** : Series

inplace : boolean, default False

Do operation in place.

pandas.Series.dt

`Series.dt()`

Accessor object for datetimelike properties of the Series values.

Examples

```
>>> s.dt.hour
>>> s.dt.second
>>> s.dt.quarter
```

Returns a Series indexed like the original Series. Raises `TypeError` if the Series does not contain datetime-like values.

pandas.Series.duplicated

`Series.duplicated (take_last=False)`

Return boolean Series denoting duplicate values

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `duplicated` : Series

pandas.Series.eq

`Series.eq (other, axis=None)`

pandas.Series.equals

`Series.equals (other)`

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Series.factorize

`Series.factorize (sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable

Parameters `sort` : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark “not found”

Returns `labels` : the indexer to the original array

`uniques` : the unique Index

pandas.Series.ffill

`Series.ffi11` (*axis=None, inplace=False, limit=None, downcast=None*)
 Synonym for `NDFrame.fillna(method='ffill')`

pandas.Series.fillna

`Series.fillna` (*value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs*)

Fill NA/NaN values using the specified method

Parameters `method` : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series `pad` / `ffill`: propagate last valid observation forward to next valid `backfill` / `bfill`: use NEXT valid observation to fill gap

value : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 'index'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns `filled` : Series

See also:

`reindex`, `asfreq`

pandas.Series.filter

`Series.filter` (*items=None, like=None, regex=None, axis=None*)

Restrict the info axis to set of items or wildcard

Parameters `items` : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where "arg in col == True"

regex : string (regular expression)

Keep info axis with `re.search(regex, col) == True`

axis : int or None

The axis to filter on. By default this is the info axis. The “info axis” is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a': [1, 2, 3, 4]})`; `df['a']`. So, the `DataFrame` columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.Series.first

`Series.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters `offset` : string, `DateOffset`, `dateutil.relativedelta`

Returns `subset` : type of caller

Examples

`ts.last('10D')` -> First 10 days

pandas.Series.first_valid_index

`Series.first_valid_index()`

Return label for first non-NA/null value

pandas.Series.floordiv

`Series.floordiv(other, level=None, fill_value=None, axis=0)`

Binary operator `floordiv` with support to substitute a `fill_value` for missing data in one of the inputs

Parameters `other`: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed `MultiIndex` level

Returns `result` : Series

pandas.Series.from_array

`classmethod Series.from_array(arr, index=None, name=None, dtype=None, copy=False, fastpath=False)`

pandas.Series.from_csv

classmethod `Series.from_csv` (*path*, *sep*=' ', *parse_dates*=True, *header*=None, *index_col*=0, *encoding*=None, *infer_datetime_format*=False)

Read delimited file into Series

Parameters **path** : string file path or file handle / StringIO

sep : string, default ' '

Field delimiter

parse_dates : boolean, default True

Parse dates. Different default from `read_table`

header : int, default 0

Row to use at header (skip prior rows)

index_col : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from `read_table`

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

infer_datetime_format: boolean, default False

If True and *parse_dates* is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

Returns **y** : Series

pandas.Series.ge

`Series.ge` (*other*, *axis*=None)

pandas.Series.get

`Series.get` (*key*, *default*=None)

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters **key** : object

Returns **value** : type of items contained in object

pandas.Series.get_dtype_counts

`Series.get_dtype_counts` ()

Return the counts of dtypes in this object

pandas.Series.get_ftype_counts

Series.get_ftype_counts()
Return the counts of ftypes in this object

pandas.Series.get_value

Series.get_value (*label, takeable=False*)
Quickly retrieve single value at passed index label

Parameters **index** : label

takeable : interpret the index as indexers, default False

Returns **value** : scalar value

pandas.Series.get_values

Series.get_values()
same as values (but handles sparseness conversions); is a view

pandas.Series.groupby

Series.groupby (*by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False*)
Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters **by** : mapping function / list of functions, dict, Series, or tuple /
list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None
If the axis is a MultiIndex (hierarchical), group by a particular level or levels

as_index : boolean, default True
For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively “SQL-style” grouped output

sort : boolean, default True
Sort group keys. Get better performance by turning this off

group_keys : boolean, default True
When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False
reduce the dimensionality of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

pandas.Series.gt

`Series.gt(other, axis=None)`

pandas.Series.hasnans

`Series.hasnans()`
return if I have any nans; enables various perf speedups

pandas.Series.head

`Series.head(n=5)`
Returns first n rows

pandas.Series.hist

`Series.hist(by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, figsize=None, bins=10, **kwds)`
Draw histogram of the input series using matplotlib

Parameters **by** : object, optional

If passed, then used to form histograms for separate groups

ax : matplotlib axis object

If not passed, uses `gca()`

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

figsize : tuple, default None

figure size in inches by default

bins: integer, default 10

Number of histogram bins to be used

kwds : keywords

To be passed to the actual plotting function

Notes

See matplotlib documentation online for more on this

pandas.Series.idxmax

`Series.idxmax` (*axis=None, out=None, skipna=True*)

Index of first occurrence of maximum of values.

Parameters **skipna** : boolean, default True

Exclude NA/null values

Returns **idxmax** : Index of maximum of values

See also:

`DataFrame.idxmax`, `numpy.ndarray.argmax`

Notes

This method is the Series version of `ndarray.argmax`.

pandas.Series.idxmin

`Series.idxmin` (*axis=None, out=None, skipna=True*)

Index of first occurrence of minimum of values.

Parameters **skipna** : boolean, default True

Exclude NA/null values

Returns **idxmin** : Index of minimum of values

See also:

`DataFrame.idxmin`, `numpy.ndarray.argmin`

Notes

This method is the Series version of `ndarray.argmin`.

pandas.Series.iget**Series.iget** (*i*, *axis=0*)Return the *i*-th value or values in the Series by location**Parameters** *i* : int, slice, or sequence of integers**Returns** **value** : scalar (int) or Series (slice, sequence)**pandas.Series.iget_value****Series.iget_value** (*i*, *axis=0*)Return the *i*-th value or values in the Series by location**Parameters** *i* : int, slice, or sequence of integers**Returns** **value** : scalar (int) or Series (slice, sequence)**pandas.Series.interpolate****Series.interpolate** (*method='linear'*, *axis=0*, *limit=None*, *inplace=False*, *downcast=None*,
***kwargs*)

Interpolate values according to different methods.

Parameters **method** : { 'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline' 'piecewise_polynomial', 'pchip' }

- 'linear': ignore the index and treat the values as equally spaced. default
- 'time': interpolation works on daily and higher resolution data to interpolate given length of interval
- 'index', 'values': use the actual numerical values of the index
- 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'polynomial' is passed to `scipy.interpolate.interp1d` with the order given both 'polynomial' and 'spline' require that you also specify an order (int) e.g. `df.interpolate(method='polynomial', order=4)`
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior:
<http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation>
<http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html>

axis : {0, 1}, default 0

- 0: fill column-by-column
- 1: fill row-by-row

limit : int, default None.

Maximum number of consecutive NaNs to fill.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

`pandas.Series.irow`

`Series.irow(i, axis=0)`

Return the i-th value or values in the Series by location

Parameters `i` : int, slice, or sequence of integers

Returns `value` : scalar (int) or Series (slice, sequence)

`pandas.Series.isin`

`Series.isin(values)`

Return a boolean `Series` showing whether each element in the `Series` is exactly contained in the passed sequence of values.

Parameters `values` : list-like

The sequence of values to test. Passing in a single string will raise a `TypeError`. Instead, turn a single string into a list of one element.

Returns `isin` : Series (bool dtype)

Raises `TypeError`

- If `values` is a string

See also:

`pandas.DataFrame.isin`

Examples

```
>>> s = pd.Series(list('abc'))
>>> s.isin(['a', 'c', 'e'])
0      True
1     False
2      True
dtype: bool
```

Passing a single string as `s.isin('a')` will raise an error. Use a list of one element instead:

```
>>> s.isin(['a'])
0      True
1     False
2     False
dtype: bool
```

pandas.Series.isnull

`Series.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of `isnull`

pandas.Series.item

`Series.item()`

return the first element of the underlying data as a python scalar

pandas.Series.iteritems

`Series.iteritems()`

Lazily iterate over (index, value) tuples

pandas.Series.iterkv

`Series.iterkv(*args, **kwargs)`

`iteritems` alias used to get around 2to3. Deprecated

pandas.Series.keys

`Series.keys()`

Alias for `index`

pandas.Series.kurt

`Series.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : scalar or Series (if level specified)

pandas.Series.kurtosis

Series.kurtosis (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : scalar or Series (if level specified)

pandas.Series.last

Series.last (*offset*)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Series.last_valid_index

Series.last_valid_index ()

Return label for last non-NA/null value

pandas.Series.le

`Series.le` (*other*, *axis=None*)

pandas.Series.load

`Series.load` (*path*)
Deprecated. Use `read_pickle` instead.

pandas.Series.lt

`Series.lt` (*other*, *axis=None*)

pandas.Series.mad

`Series.mad` (*axis=None*, *skipna=None*, *level=None*)
Return the mean absolute deviation of the values for the requested axis

Parameters *axis* : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *mad* : scalar or Series (if level specified)

pandas.Series.map

`Series.map` (*arg*, *na_action=None*)
Map values of Series using input correspondence (which can be a dict, Series, or function)

Parameters *arg* : function, dict, or Series

na_action : {None, 'ignore'}

If 'ignore', propagate NA values

Returns *y* : Series

same index as caller

Examples

```
>>> x
one    1
two    2
three  3

>>> y
1    foo
2    bar
3    baz

>>> x.map(y)
one    foo
two    bar
three  baz
```

pandas.Series.mask

`Series.mask(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Series.max

`Series.max(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : scalar or Series (if level specified)

pandas.Series.mean

`Series.mean` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the mean of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : scalar or Series (if level specified)

pandas.Series.median

`Series.median` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the median of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : scalar or Series (if level specified)

pandas.Series.min

`Series.min` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns min : scalar or Series (if level specified)

pandas.Series.mod

`Series.mod(other, level=None, fill_value=None, axis=0)`

Binary operator mod with support to substitute a fill_value for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.mode

`Series.mode()`

Returns the mode(s) of the dataset.

Empty if nothing occurs at least 2 times. Always returns Series even if only one value.

Parameters sort : bool, default True

If True, will lexicographically sort values, if False skips sorting. Result ordering when sort=False is not defined.

Returns modes : Series (sorted)

pandas.Series.mul

`Series.mul(other, level=None, fill_value=None, axis=0)`

Binary operator mul with support to substitute a fill_value for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.multiply

`Series.multiply` (*other, level=None, fill_value=None, axis=0*)

Binary operator mul with support to substitute a fill_value for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.ne

`Series.ne` (*other, axis=None*)

pandas.Series.nlargest

`Series.nlargest` (*n=5, take_last=False*)

Return the largest *n* elements.

Parameters n : int

Return this many descending sorted values

take_last : bool

Where there are duplicate values, take the last duplicate

Returns top_n : Series

The *n* largest values in the Series, in sorted order

See also:

`Series.nsmallest`

Notes

Faster than `.order(ascending=False).head(n)` for small *n* relative to the size of the Series object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10) # only sorts up to the N requested
```

pandas.Series.nonzero

`Series.nonzero()`

Return the indices of the elements that are non-zero

This method is equivalent to calling `numpy.nonzero` on the series data. For compatability with NumPy, the return value is the same (a tuple with an array of indices for each dimension), but it will always be a one-item tuple because series only have one dimension.

See also:

`numpy.nonzero`

Examples

```
>>> s = pd.Series([0, 3, 0, 4])
>>> s.nonzero()
(array([1, 3]),)
>>> s.iloc[s.nonzero()[0]]
1      3
3      4
dtype: int64
```

pandas.Series.notnull

`Series.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

pandas.Series.nsmallest

`Series.nsmallest (n=5, take_last=False)`

Return the smallest *n* elements.

Parameters *n* : int

Return this many ascending sorted values

take_last : bool

Where there are duplicate values, take the last duplicate

Returns *bottom_n* : Series

The *n* smallest values in the Series, in sorted order

See also:

`Series.nlargest`

Notes

Faster than `.order().head(n)` for small *n* relative to the size of the Series object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10) # only sorts up to the N requested
```

pandas.Series.nunique

`Series.nunique` (*dropna=True*)

Return number of unique elements in the object.

Excludes NA values by default.

Parameters `dropna` : boolean, default True

Don't include NaN in the count.

Returns `nunique` : int

pandas.Series.order

`Series.order` (*na_last=None*, *ascending=True*, *kind='quicksort'*, *na_position='last'*, *inplace=False*)

Sorts Series object, by value, maintaining index-value link. This will return a new Series by default. `Series.sort` is the equivalent but as an inplace method.

Parameters `na_last` : boolean (optional, default=True) (DEPRECATED; use `na_position`)

Put NaN's at beginning or end

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See `np.sort` for more information. 'mergesort' is the only stable algorithm

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default False

Do operation in place.

Returns `y` : Series

See also:

`Series.sort`

pandas.Series.pct_change

`Series.pct_change` (*periods=1*, *fill_method='pad'*, *limit=None*, *freq=None*, ***kwargs*)

Percent change over given number of periods.

Parameters `periods` : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the `axis` keyword argument.

pandas.Series.plot

`Series.plot` (*data*, *kind*='line', *ax*=None, *figsize*=None, *use_index*=True, *title*=None, *grid*=None, *legend*=False, *style*=None, *logx*=False, *logy*=False, *loglog*=False, *xticks*=None, *yticks*=None, *xlim*=None, *ylim*=None, *rot*=None, *fontsize*=None, *colormap*=None, *table*=False, *yerr*=None, *xerr*=None, *label*=None, *secondary_y*=False, ***kwds*)

Make plots of Series using matplotlib / pylab.

Parameters **data** : Series

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot

ax : matplotlib axes object

If not passed, uses `gca()`

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)
Axis grid lines

legend : False/True/'reverse'
Place legend on axis subplots

style : list or dict
matplotlib line style per column

logx : boolean, default False
Use log scaling on x axis

logy : boolean, default False
Use log scaling on y axis

loglog : boolean, default False
Use log scaling on both x and y axes

xticks : sequence
Values to use for the xticks

yticks : sequence
Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None
Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None
Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None
Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional
If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float
Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)
(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False
If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str
See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

label : label argument to provide to plot

secondary_y : boolean or sequence of ints, default False

If True then y-axis will be on the right

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns axes : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = ‘bar’ or ‘barh’, you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

pandas.Series.pop

`Series.pop(item)`

Return item and drop from frame. Raise KeyError if not found.

pandas.Series.pow

`Series.pow(other, level=None, fill_value=None, axis=0)`

Binary operator pow with support to substitute a fill_value for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.prod

`Series.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the product of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns prod : scalar or Series (if level specified)

pandas.Series.product

`Series.product (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the product of the values for the requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns prod : scalar or Series (if level specified)

pandas.Series.ptp

`Series.ptp (axis=None, out=None)`

pandas.Series.put

`Series.put (*args, **kwargs)`

return a ndarray with the values put

See also:

`numpy.ndarray.put`

pandas.Series.quantile

`Series.quantile (q=0.5)`

Return value at the given quantile, a la numpy.percentile.

Parameters q : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

Returns quantile : float or Series

if `q` is an array, a Series will be returned where the index is `q` and the values are the quantiles.

Examples

```
>>> s = Series([1, 2, 3, 4])
>>> s.quantile(.5)
2.5
>>> s.quantile([.25, .5, .75])
0.25    1.75
0.50    2.50
0.75    3.25
dtype: float64
```

pandas.Series.radd

`Series.radd(other, level=None, fill_value=None, axis=0)`

Binary operator radd with support to substitute a `fill_value` for missing data in one of the inputs

Parameters `other`: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result` : Series

pandas.Series.rank

`Series.rank(method='average', na_option='keep', ascending=True, pct=False)`

Compute data ranks (1 through n). Equal values are assigned a rank that is the average of the ranks of those values

Parameters `method` : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep'}

keep: leave NA values where they are

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns `ranks` : Series

`pandas.Series.ravel`

`Series.ravel` (*order='C'*)

Return the flattened underlying data as an ndarray

See also:

`numpy.ndarray.ravel`

`pandas.Series.rdiv`

`Series.rdiv` (*other, level=None, fill_value=None, axis=0*)

Binary operator rtruediv with support to substitute a `fill_value` for missing data in one of the inputs

Parameters `other`: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result` : Series

`pandas.Series.reindex`

`Series.reindex` (*index=None, **kwargs*)

Conform Series to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters `index` : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Series

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Series.reindex_axis

`Series.reindex_axis` (*labels, axis=0, **kwargs*)
for compatibility with higher dims

pandas.Series.reindex_like

`Series.reindex_like` (*other, method=None, copy=True, limit=None*)
return an object with matching indicies to myself

Parameters **other** : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

pandas.Series.rename

`Series.rename` (*index=None, **kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **index** : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Series. If True then value of copy is ignored.

Returns `renamed` : Series (new object)

`pandas.Series.rename_axis`

`Series.rename_axis` (*mapper, axis=0, copy=True, inplace=False*)

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters `mapper` : dict-like or function, optional

`axis` : int or string, default 0

`copy` : boolean, default True

Also copy underlying data

`inplace` : boolean, default False

Returns `renamed` : type of caller

`pandas.Series.reorder_levels`

`Series.reorder_levels` (*order*)

Rearrange index levels using input order. May not drop or duplicate levels

Parameters `order`: list of int representing new level order.

(reference level by number or key)

axis: where to reorder levels

Returns type of caller (new object)

`pandas.Series.repeat`

`Series.repeat` (*reps*)

return a new Series with the values repeated *reps* times

See also:

`numpy.ndarray.repeat`

`pandas.Series.replace`

`Series.replace` (*to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters `to_replace` : str, regex, list, dict, Series, numeric, or None

- str or regex:
 - str: string exactly matching *to_replace* will be replaced with *value*
 - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
 - First, if *to_replace* and *value* are both lists, they **must** be the same length.

- Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
- str and regex rules apply as above.
- dict:
 - Nested dictionaries, e.g., `{ 'a': { 'b': nan } }`, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
 - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
 - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also None then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is True then *to_replace* *must* be a string. Otherwise, *to_replace* must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, { 'pad', 'ffill', 'bfill' }

The method to use when for replacement, when *to_replace* is a list.

Returns filled : NDFrame

Raises AssertionError

- If *regex* is not a bool and *to_replace* is not None.

TypeError

- If *to_replace* is a dict and *value* is not a list, dict, ndarray, or Series
- If *to_replace* is None and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are lists or ndarrays, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Series.resample

`Series.resample` (*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters *rule* : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

`pandas.Series.reset_index`

`Series.reset_index` (*level=None, drop=False, name=None, inplace=False*)

Analogous to the `pandas.DataFrame.reset_index()` function, see docstring there.

Parameters **level** : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns

name : object, default None

The name of the column corresponding to the Series values

inplace : boolean, default False

Modify the Series in place (do not create a new object)

Returns **resetted** : DataFrame, or Series if `drop == True`

`pandas.Series.reshape`

`Series.reshape` (**args, **kwargs*)

return an ndarray with the values shape if the specified shape matches exactly the current shape, then return self (for compat)

See also:

`numpy.ndarray.take`

`pandas.Series.rfloordiv`

`Series.rfloordiv` (*other, level=None, fill_value=None, axis=0*)

Binary operator rfloordiv with support to substitute a `fill_value` for missing data in one of the inputs

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

`pandas.Series.rmod`

`Series.rmod` (*other, level=None, fill_value=None, axis=0*)

Binary operator rmod with support to substitute a `fill_value` for missing data in one of the inputs

Parameters **other: Series or scalar value**

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.rmul

`Series.rmul` (*other, level=None, fill_value=None, axis=0*)

Binary operator rmul with support to substitute a fill_value for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.round

`Series.round` (*decimals=0, out=None*)

Return *a* with each element rounded to the given number of decimals.

Refer to *numpy.around* for full documentation.

See also:

`numpy.around` equivalent function

pandas.Series.rpow

`Series.rpow` (*other, level=None, fill_value=None, axis=0*)

Binary operator rpow with support to substitute a fill_value for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.rsub

`Series.rsub` (*other, level=None, fill_value=None, axis=0*)

Binary operator rsub with support to substitute a `fill_value` for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.rtruediv

`Series.rtruediv` (*other, level=None, fill_value=None, axis=0*)

Binary operator rtruediv with support to substitute a `fill_value` for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.sample

`Series.sample` (*n=None, frac=None, replace=False, weights=None, random_state=None, axis=None*)

Returns a random sample of items from an axis of object.

Parameters n : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when *axis* = 0. Weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. inf and -inf values not allowed.

random_state : int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

Returns Same type as caller.

pandas.Series.save

`Series.save(path)`

Deprecated. Use `to_pickle` instead

pandas.Series.searchsorted

`Series.searchsorted(v, side='left', sorter=None)`

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series *self* such that, if the corresponding elements in *v* were inserted before the indices, the order of *self* would be preserved.

Parameters *v* : array_like

Values to insert into *a*.

side : {'left', 'right'}, optional

If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *a*).

sorter : 1-D array_like, optional

Optional array of integer indices that sort *self* into ascending order. They are typically the result of `np.argsort`.

Returns *indices* : array of ints

Array of insertion points with the same shape as *v*.

See also:

`Series.sort`, `Series.order`, `numpy.searchsorted`

Notes

Binary search is used to find the required insertion points.

Examples

```
>>> x = pd.Series([1, 2, 3])
>>> x
0    1
1    2
2    3
```

```
dtype: int64
>>> x.searchsorted(4)
array([3])
>>> x.searchsorted([0, 4])
array([0, 3])
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
>>> x.searchsorted([1, 2], side='right', sorter=[0, 2, 1])
array([1, 3])
```

pandas.Series.select

`Series.select` (*crit*, *axis=0*)

Return data corresponding to axis labels matching criteria

Parameters *crit* : function

To be called on each index (label). Should return True or False

axis : int

Returns *selection* : type of caller

pandas.Series.sem

`Series.sem` (*axis=None*, *skipna=None*, *level=None*, *ddof=1*, *numeric_only=None*, ***kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the *ddof* argument

Parameters *axis* : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *sem* : scalar or Series (if level specified)

pandas.Series.set_axis

`Series.set_axis` (*axis*, *labels*)

public version of axis assignment

pandas.Series.set_value**Series.set_value** (*label, value, takeable=False*)

Quickly set single value at passed label. If label is not contained, a new object is created with the label placed at the end of the result index

Parameters label : object

Partial indexing with MultiIndex not allowed

value : object

Scalar value

takeable : interpret the index as indexers, default False**Returns series** : Series

If label is contained, will be reference to calling Series, otherwise a new object

pandas.Series.shift**Series.shift** (*periods=1, freq=None, axis=0, **kwargs*)

Shift index by desired number of periods with an optional time freq

Parameters periods : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 'index'}**Returns shifted** : Series**Notes**

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.Series.skew**Series.skew** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters axis : {index (0)}**skipna** : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : scalar or Series (if level specified)

pandas.Series.slice_shift

Series.slice_shift (*periods=1, axis=0*)

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters **periods** : int

Number of periods to move, can be positive or negative

Returns **shifted** : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.Series.sort

Series.sort (*axis=0, ascending=True, kind='quicksort', na_position='last', inplace=True*)

Sort values and index labels by value. This is an inplace sort by default. *Series.order* is the equivalent but returns a new Series.

Parameters **axis** : int (can only be zero)

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : { 'mergesort', 'quicksort', 'heapsort' }, default 'quicksort'

Choice of sorting algorithm. See *np.sort* for more information. 'mergesort' is the only stable algorithm

na_position : { 'first', 'last' } (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default True

Do operation in place.

See also:

`Series.order`

pandas.Series.sort_index

Series.sort_index (*ascending=True*)

Sort object by labels (along an axis)

Parameters **ascending** : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

Returns `sorted_obj` : Series

Examples

```
>>> result1 = s.sort_index(ascending=False)
>>> result2 = s.sort_index(ascending=[1, 0])
```

pandas.Series.sortlevel

`Series.sortlevel` (*level=0, ascending=True, sort_remaining=True*)

Sort Series with MultiIndex by chosen level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters `level` : int or level name, default None

`ascending` : bool, default True

Returns `sorted` : Series

pandas.Series.squeeze

`Series.squeeze` ()
squeeze length 1 dimensions

pandas.Series.std

`Series.std` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters `axis` : {index (0)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

`level` : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

`numeric_only` : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `std` : scalar or Series (if level specified)

pandas.Series.str

`Series.str` ()
Vectorized string functions for Series and Index. NAs stay NA unless handled otherwise by a particular method. Patterned after Python's string methods, with some inspiration from R's stringr package.

Examples

```
>>> s.str.split('_')
>>> s.str.replace('_', '')
```

pandas.Series.sub

`Series.sub` (*other*, *level=None*, *fill_value=None*, *axis=0*)

Binary operator sub with support to substitute a *fill_value* for missing data in one of the inputs

Parameters *other*: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : Series

pandas.Series.subtract

`Series.subtract` (*other*, *level=None*, *fill_value=None*, *axis=0*)

Binary operator sub with support to substitute a *fill_value* for missing data in one of the inputs

Parameters *other*: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : Series

pandas.Series.sum

`Series.sum` (*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the sum of the values for the requested axis

Parameters *axis* : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : scalar or Series (if level specified)

pandas.Series.swapaxes

`Series.swapaxes` (*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately

Returns **y** : same as input

pandas.Series.swaplevel

`Series.swaplevel` (*i*, *j*, *copy=True*)

Swap levels *i* and *j* in a MultiIndex

Parameters **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns **swapped** : Series

pandas.Series.tail

`Series.tail` (*n=5*)

Returns last *n* rows

pandas.Series.take

`Series.take` (*indices*, *axis=0*, *convert=True*, *is_copy=False*)

return Series corresponding to requested indices

Parameters **indices** : list / array of ints

convert : translate negative to positive indices (default)

Returns **taken** : Series

See also:

`numpy.ndarray.take`

pandas.Series.to_clipboard

`Series.to_clipboard` (*excel=None*, *sep=None*, ***kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters **excel** : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

pandas.Series.to_csv

`Series.to_csv(path, index=True, sep=',', na_rep='', float_format=None, header=False, index_label=None, mode='w', nanRep=None, encoding=None, date_format=None, decimal='.')`

Write Series to a comma-separated values (csv) file

Parameters path : string file path or file handle / StringIO. If None is provided

the result is returned as a string.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

header : boolean, default False

Write out series name

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

mode : Python write mode, default 'w'

sep : character, default ','

Field delimiter for the output file.

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

date_format: string, default None

Format string for datetime objects.

decimal: string, default '.'

Character recognized as decimal separator. E.g. use ',' for European data

pandas.Series.to_dense`Series.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.Series.to_dict`Series.to_dict()`

Convert Series to {label -> value} dict

Returns `value_dict` : dict**pandas.Series.to_frame**`Series.to_frame(name=None)`

Convert Series to DataFrame

Parameters `name` : object, default None

The passed name should substitute for the series name (if it has one).

Returns `data_frame` : DataFrame**pandas.Series.to_hdf**`Series.to_hdf(path_or_buf, key, **kwargs)`

activate the HDFStore

Parameters `path_or_buf` : the path (string) or buffer to put the store**key** : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to 'a', but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'**fixed(f)** [Fixed format] Fast writing/reading. Not-appendable, nor searchable**table(t)** [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data**append** : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a `complib` is specified compression will be applied where possible

complib : { 'zlib', 'bzip2', 'lzo', 'blosc', None }, default None

If `complevel` is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Series.to_json

`Series.to_json` (*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters `path_or_buf` : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
 - default is 'index'
 - allowed values are: { 'split', 'records', 'index' }
- DataFrame
 - default is 'columns'
 - allowed values are: { 'split', 'records', 'index', 'columns', 'values' }
- The format of the JSON string
 - split : dict like { index -> [index], columns -> [columns], data -> [values] }
 - records : list like [{ column -> value }, ... , { column -> value }]
 - index : dict like { index -> { column -> value } }
 - columns : dict like { column -> { index -> value } }
 - values : just the values array

date_format : { 'epoch', 'iso' }

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding

floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Series.to_msgpack

`Series.to_msgpack` (*path_or_buf=None, **kwargs*)

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters **path** : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no

compression)

pandas.Series.to_period

`Series.to_period` (*freq=None, copy=True*)

Convert TimeSeries from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters **freq** : string, default

Returns **ts** : TimeSeries with PeriodIndex

pandas.Series.to_pickle

`Series.to_pickle` (*path*)

Pickle (serialize) object to input file path

Parameters **path** : string

File path

pandas.Series.to_sparse

`Series.to_sparse` (*kind='block', fill_value=None*)

Convert Series to SparseSeries

Parameters **kind** : { 'block', 'integer' }

fill_value : float, defaults to NaN (missing)

Returns **sp** : SparseSeries

pandas.Series.to_sql

`Series.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : { 'sqlite', 'mysql' }, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : { 'fail', 'replace', 'append' }, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Series.to_string

`Series.to_string(buf=None, na_rep='NaN', float_format=None, header=True, length=False, dtype=False, name=False, max_rows=None)`

Render a string representation of the Series

Parameters **buf** : StringIO-like, optional

buffer to write to

na_rep : string, optional

string representation of NAN to use, default 'NaN'

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats default None

header: boolean, default True

Add the Series header (index name)

length : boolean, default False

Add the Series length

dtype : boolean, default False

Add the Series dtype

name : boolean, default False

Add the Series name if not None

max_rows : int, optional

Maximum number of rows to show before truncating. If None, show all.

Returns formatted : string (if not buffer passed)

pandas.Series.to_timestamp

`Series.to_timestamp(freq=None, how='start', copy=True)`

Cast to datetimeindex of timestamps, at *beginning* of period

Parameters freq : string, default frequency of PeriodIndex

Desired frequency

how : {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

Returns ts : TimeSeries with DatetimeIndex

pandas.Series.tolist

`Series.tolist()`

Convert Series to a nested list

pandas.Series.transpose

`Series.transpose()`

return the transpose, which is by definition self

pandas.Series.truediv

`Series.truediv(other, level=None, fill_value=None, axis=0)`

Binary operator truediv with support to substitute a fill_value for missing data in one of the inputs

Parameters other: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.truncate

Series.truncate (*before=None, after=None, axis=None, copy=True*)

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters before : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns truncated : type of caller

pandas.Series.tshift

Series.tshift (*periods=1, freq=None, axis=0, **kwargs*)

Shift the time index, using the index's frequency if available

Parameters periods : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, default None

Increment to use from datetools module or time rule (e.g. 'EOM')

axis : int or basestring

Corresponds to the axis that contains the Index

Returns shifted : NDFrame

Notes

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

pandas.Series.tz_convert

`Series.tz_convert` (*tz*, *axis=0*, *level=None*, *copy=True*)

Convert tz-aware axis to target time zone.

Parameters *tz* : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis is a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises **TypeError**

If the axis is tz-naive.

pandas.Series.tz_localize

`Series.tz_localize` (**args*, ***kwargs*)

Localize tz-naive TimeSeries to target time zone

Parameters *tz* : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis is a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises **TypeError**

If the TimeSeries is tz-aware and tz is not None.

pandas.Series.unique

`Series.unique` ()

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns **uniques** : ndarray

pandas.Series.unstack

`Series.unstack (level=-1)`

Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame. The level involved will automatically get sorted.

Parameters `level` : int, string, or list of these, default last level

Level(s) to unstack, can pass level name

Returns `unstacked` : DataFrame

Examples

```
>>> s
one  a    1.
one  b    2.
two  a    3.
two  b    4.

>>> s.unstack(level=-1)
      a    b
one  1.  2.
two  3.  4.

>>> s.unstack(level=0)
      one  two
a    1.   2.
b    3.   4.
```

pandas.Series.update

`Series.update (other)`

Modify Series in place using non-NA values from passed Series. Aligns on index

Parameters `other` : Series

pandas.Series.valid

`Series.valid (inplace=False, **kwargs)`

pandas.Series.value_counts

`Series.value_counts (normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters `normalize` : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns **counts** : Series

pandas.Series.var

`Series.var` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : scalar or Series (if level specified)

pandas.Series.view

`Series.view` (*dtype=None*)

pandas.Series.where

`Series.where` (*cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where `cond` is True and otherwise are from `other`.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Series.xs

`Series.xs(key, axis=0, level=None, copy=None, drop_level=True)`

Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).

Parameters **key** : object

Some label contained in the index, or partially in a MultiIndex

axis : int, default 0

Axis to retrieve cross-section on

level : object, defaults to first n levels (n=1 or len(key))

In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

copy : boolean [deprecated]

Whether to make a copy of the data

drop_level : boolean, default True

If False, returns object with same levels as self.

Returns **xs** : Series or DataFrame

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see [MultiIndex Slicers](#)

Examples

```
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
   A  B
a  4  5
C  2
```

```

Name: a
>>> df.xs('C', axis=1)
a      2
b      9
c      3
Name: C

>>> df
      first second third  A  B  C  D
bar  one     1      4  1  8  9
      two     1      7  5  5  0
baz   one     1      6  6  8  0
      three    2      5  3  5  3
>>> df.xs(('baz', 'three'))
      A  B  C  D
third
2      5  3  5  3
>>> df.xs('one', level=1)
      A  B  C  D
first third
bar  1      4  1  8  9
baz   1      6  6  8  0
>>> df.xs(('baz', 2), level=[0, 'third'])
      A  B  C  D
second
three  5  3  5  3

```

33.3.2 Attributes

Axes

- **index:** axis labels

<code>Series.values</code>	Return Series as ndarray
<code>Series.dtype</code>	return the dtype object of the underlying data
<code>Series.ftype</code>	return if the data is sparsedense
<code>Series.shape</code>	return a tuple of the shape of the underlying data
<code>Series.nbytes</code>	return the number of bytes in the underlying data
<code>Series.ndim</code>	return the number of dimensions of the underlying data, by definition 1
<code>Series.size</code>	return the number of elements in the underlying data
<code>Series.strides</code>	return the strides of the underlying data
<code>Series.itemsize</code>	return the size of the dtype of the item of the underlying data
<code>Series.base</code>	return the base object if the memory of the underlying data is shared
<code>Series.T</code>	return the transpose, which is by definition self

pandas.Series.values

Series.values

Return Series as ndarray

Returns `arr` : numpy.ndarray

pandas.Series.dtype

`Series.dtype`
return the dtype object of the underlying data

pandas.Series.ftype

`Series.ftype`
return if the data is sparsedense

pandas.Series.shape

`Series.shape`
return a tuple of the shape of the underlying data

pandas.Series.nbytes

`Series.nbytes`
return the number of bytes in the underlying data

pandas.Series.ndim

`Series.ndim`
return the number of dimensions of the underlying data, by definition 1

pandas.Series.size

`Series.size`
return the number of elements in the underlying data

pandas.Series.strides

`Series.strides`
return the strides of the underlying data

pandas.Series.itemsize

`Series.itemsize`
return the size of the dtype of the item of the underlying data

pandas.Series.base

`Series.base`
return the base object if the memory of the underlying data is shared

pandas.Series.T`Series.T`

return the transpose, which is by definition self

33.3.3 Conversion

<code>Series.astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>Series.copy([deep])</code>	Make a copy of this object
<code>Series.isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>Series.notnull()</code>	Return a boolean same-sized object indicating if the values are

pandas.Series.astype`Series.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters `dtype` : numpy.dtype or Python type`raise_on_error` : raise on invalid input`kwargs` : keyword arguments to pass on to the constructor**Returns** `casted` : type of caller**pandas.Series.copy**`Series.copy(deep=True)`

Make a copy of this object

Parameters `deep` : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns `copy` : type of caller**pandas.Series.isnull**`Series.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:`notnull` boolean inverse of isnull**pandas.Series.notnull**`Series.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:`isnull` boolean inverse of notnull

33.3.4 Indexing, iteration

<code>Series.get(key[, default])</code>	Get item from object for given key (DataFrame column, Panel slice, etc.).
<code>Series.at</code>	Fast label-based scalar accessor
<code>Series.iat</code>	Fast integer location scalar accessor.
<code>Series.ix</code>	A primarily label-location based indexer, with integer position fallback.
<code>Series.loc</code>	Purely label-location based indexer for selection by label.
<code>Series.iloc</code>	Purely integer-location based indexing for selection by position.
<code>Series.__iter__()</code>	
<code>Series.iteritems()</code>	Lazily iterate over (index, value) tuples

pandas.Series.get

`Series.get(key, default=None)`

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters `key` : object

Returns `value` : type of items contained in object

pandas.Series.at

`Series.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Series.iat

`Series.iat`

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Series.ix

`Series.ix`

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#).

pandas.Series.loc

Series.loc

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a' : 'f' (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at [Selection by Label](#)

pandas.Series.iloc

Series.iloc

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at [Selection by Position](#)

pandas.Series.__iter__

`Series.__iter__()`

pandas.Series.iteritems

`Series.iteritems()`

Lazily iterate over (index, value) tuples

For more information on `.at`, `.iat`, `.ix`, `.loc`, and `.iloc`, see the [indexing documentation](#).

33.3.5 Binary operator functions

<code>Series.add(other[, level, fill_value, axis])</code>	Binary operator add with support to substitute a fill_value for missing data
<code>Series.sub(other[, level, fill_value, axis])</code>	Binary operator sub with support to substitute a fill_value for missing data
<code>Series.mul(other[, level, fill_value, axis])</code>	Binary operator mul with support to substitute a fill_value for missing data
<code>Series.div(other[, level, fill_value, axis])</code>	Binary operator truediv with support to substitute a fill_value for missing data
<code>Series.truediv(other[, level, fill_value, axis])</code>	Binary operator truediv with support to substitute a fill_value for missing data
<code>Series.floordiv(other[, level, fill_value, axis])</code>	Binary operator floordiv with support to substitute a fill_value for missing data
<code>Series.mod(other[, level, fill_value, axis])</code>	Binary operator mod with support to substitute a fill_value for missing data
<code>Series.pow(other[, level, fill_value, axis])</code>	Binary operator pow with support to substitute a fill_value for missing data
<code>Series.radd(other[, level, fill_value, axis])</code>	Binary operator radd with support to substitute a fill_value for missing data
<code>Series.rsub(other[, level, fill_value, axis])</code>	Binary operator rsub with support to substitute a fill_value for missing data
<code>Series.rmul(other[, level, fill_value, axis])</code>	Binary operator rmul with support to substitute a fill_value for missing data
<code>Series.rdiv(other[, level, fill_value, axis])</code>	Binary operator rtruediv with support to substitute a fill_value for missing data
<code>Series.rtruediv(other[, level, fill_value, axis])</code>	Binary operator rtruediv with support to substitute a fill_value for missing data
<code>Series.rfloordiv(other[, level, fill_value, ...])</code>	Binary operator rfloordiv with support to substitute a fill_value for missing data
<code>Series.rmod(other[, level, fill_value, axis])</code>	Binary operator rmod with support to substitute a fill_value for missing data
<code>Series.rpow(other[, level, fill_value, axis])</code>	Binary operator rpow with support to substitute a fill_value for missing data
<code>Series.combine(other, func[, fill_value])</code>	Perform elementwise binary operation on two Series using given function
<code>Series.combine_first(other)</code>	Combine Series values, choosing the calling Series's values first.
<code>Series.round([decimals, out])</code>	Return a with each element rounded to the given number of decimals.
<code>Series.lt(other[, axis])</code>	
<code>Series.gt(other[, axis])</code>	
<code>Series.le(other[, axis])</code>	
<code>Series.ge(other[, axis])</code>	
<code>Series.ne(other[, axis])</code>	
<code>Series.eq(other[, axis])</code>	

pandas.Series.add

`Series.add(other, level=None, fill_value=None, axis=0)`

Binary operator add with support to substitute a fill_value for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.sub

`Series.sub(other, level=None, fill_value=None, axis=0)`

Binary operator sub with support to substitute a fill_value for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.mul

`Series.mul (other, level=None, fill_value=None, axis=0)`

Binary operator mul with support to substitute a fill_value for missing data in one of the inputs

Parameters **other**: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.div

`Series.div (other, level=None, fill_value=None, axis=0)`

Binary operator truediv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other**: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.truediv

`Series.truediv (other, level=None, fill_value=None, axis=0)`

Binary operator truediv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other**: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.floordiv

`Series.floordiv` (*other, level=None, fill_value=None, axis=0*)

Binary operator floordiv with support to substitute a `fill_value` for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.mod

`Series.mod` (*other, level=None, fill_value=None, axis=0*)

Binary operator mod with support to substitute a `fill_value` for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.pow

`Series.pow` (*other, level=None, fill_value=None, axis=0*)

Binary operator pow with support to substitute a `fill_value` for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.radd

`Series.radd` (*other, level=None, fill_value=None, axis=0*)

Binary operator radd with support to substitute a `fill_value` for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.rsub

`Series.rsub` (*other, level=None, fill_value=None, axis=0*)

Binary operator rsub with support to substitute a fill_value for missing data in one of the inputs

Parameters **other**: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.rmul

`Series.rmul` (*other, level=None, fill_value=None, axis=0*)

Binary operator rmul with support to substitute a fill_value for missing data in one of the inputs

Parameters **other**: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.rdiv

`Series.rdiv` (*other, level=None, fill_value=None, axis=0*)

Binary operator rtruediv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other**: Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.rtruediv

Series.**rtruediv** (*other*, *level=None*, *fill_value=None*, *axis=0*)

Binary operator rtruediv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.rfloordiv

Series.**rfloordiv** (*other*, *level=None*, *fill_value=None*, *axis=0*)

Binary operator rfloordiv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.rmod

Series.**rmod** (*other*, *level=None*, *fill_value=None*, *axis=0*)

Binary operator rmod with support to substitute a fill_value for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : Series

pandas.Series.rpow

Series.**rpow** (*other*, *level=None*, *fill_value=None*, *axis=0*)

Binary operator rpow with support to substitute a fill_value for missing data in one of the inputs

Parameters **other:** Series or scalar value

fill_value : None or float value, default None (NaN)

Fill missing (NaN) values with this value. If both Series are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : Series

pandas.Series.combine

`Series.combine` (*other, func, fill_value=nan*)

Perform elementwise binary operation on two Series using given function with optional fill value when an index is missing from one Series or the other

Parameters other : Series or scalar value

func : function

fill_value : scalar value

Returns result : Series

pandas.Series.combine_first

`Series.combine_first` (*other*)

Combine Series values, choosing the calling Series's values first. Result index will be the union of the two indexes

Parameters other : Series

Returns y : Series

pandas.Series.round

`Series.round` (*decimals=0, out=None*)

Return *a* with each element rounded to the given number of decimals.

Refer to *numpy.around* for full documentation.

See also:

`numpy.around` equivalent function

pandas.Series.lt

`Series.lt` (*other, axis=None*)

pandas.Series.gt

`Series.gt` (*other, axis=None*)

pandas.Series.le

`Series.le` (*other, axis=None*)

pandas.Series.ge

`Series.ge` (*other*, *axis=None*)

pandas.Series.ne

`Series.ne` (*other*, *axis=None*)

pandas.Series.eq

`Series.eq` (*other*, *axis=None*)

33.3.6 Function application, GroupBy

<code>Series.apply</code> (<i>func</i> [, <i>convert_dtype</i> , <i>args</i>])	Invoke function on values of Series.
<code>Series.map</code> (<i>arg</i> [, <i>na_action</i>])	Map values of Series using input correspondence (which can be
<code>Series.groupby</code> ([<i>by</i> , <i>axis</i> , <i>level</i> , <i>as_index</i> , ...])	Group series using mapper (dict or key function, apply given function

pandas.Series.apply

`Series.apply` (*func*, *convert_dtype=True*, *args=()*, ***kws*)

Invoke function on values of Series. Can be `ufunc` (a NumPy function that applies to the entire Series) or a Python function that only works on single values

Parameters `func` : function

`convert_dtype` : boolean, default True

Try to find better dtype for elementwise function results. If False, leave as `dtype=object`

`args` : tuple

Positional arguments to pass to function in addition to the value

Additional keyword arguments will be passed as keywords to the function

Returns `y` : Series or DataFrame if `func` returns a Series

See also:

`Series.map` For element-wise operations

pandas.Series.map

`Series.map` (*arg*, *na_action=None*)

Map values of Series using input correspondence (which can be a dict, Series, or function)

Parameters `arg` : function, dict, or Series

`na_action` : {None, 'ignore'}

If 'ignore', propagate NA values

Returns `y` : Series

same index as caller

Examples

```
>>> x
one    1
two    2
three  3

>>> y
1    foo
2    bar
3    baz

>>> x.map(y)
one    foo
two    bar
three  baz
```

pandas.Series.groupby

`Series.groupby` (*by=None*, *axis=0*, *level=None*, *as_index=True*, *sort=True*, *group_keys=True*, *squeeze=False*)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters **by** : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None

If the axis is a MultiIndex (hierarchical), group by a particular level or levels

as_index : boolean, default True

For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. `as_index=False` is effectively “SQL-style” grouped output

sort : boolean, default True

Sort group keys. Get better performance by turning this off

group_keys : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionality of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

33.3.7 Computations / Descriptive Stats

<code>Series.abs()</code>	Return an object with absolute value taken.
<code>Series.all([axis, bool_only, skipna, level])</code>	Return whether all elements are True over requested axis
<code>Series.any([axis, bool_only, skipna, level])</code>	Return whether any element is True over requested axis
<code>Series.autocorr([lag])</code>	Lag-N autocorrelation
<code>Series.between(left, right[, inclusive])</code>	Return boolean Series equivalent to <code>left <= series <= right</code> .
<code>Series.clip([lower, upper, out, axis])</code>	Trim values at input threshold(s)
<code>Series.clip_lower(threshold[, axis])</code>	Return copy of the input with values below given value(s) truncated
<code>Series.clip_upper(threshold[, axis])</code>	Return copy of input with values above given value(s) truncated
<code>Series.corr(other[, method, min_periods])</code>	Compute correlation with <i>other</i> Series, excluding missing values
<code>Series.count([level])</code>	Return number of non-NA/null observations in the Series
<code>Series.cov(other[, min_periods])</code>	Compute covariance with Series, excluding missing values
<code>Series.cummax([axis, dtype, out, skipna])</code>	Return cumulative max over requested axis.
<code>Series.cummin([axis, dtype, out, skipna])</code>	Return cumulative min over requested axis.
<code>Series.cumprod([axis, dtype, out, skipna])</code>	Return cumulative prod over requested axis.
<code>Series.cumsum([axis, dtype, out, skipna])</code>	Return cumulative sum over requested axis.
<code>Series.describe([percentile_width, ...])</code>	Generate various summary statistics, excluding NaN values.
<code>Series.diff([periods])</code>	1st discrete difference of object
<code>Series.factorize([sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable
<code>Series.kurt([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>Series.mad([axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis
<code>Series.max([axis, skipna, level, numeric_only])</code>	This method returns the maximum of the values in the object.
<code>Series.mean([axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis
<code>Series.median([axis, skipna, level, ...])</code>	Return the median of the values for the requested axis
<code>Series.min([axis, skipna, level, numeric_only])</code>	This method returns the minimum of the values in the object.
<code>Series.mode()</code>	Returns the mode(s) of the dataset.
<code>Series.pct_change([periods, fill_method, ...])</code>	Percent change over given number of periods.
<code>Series.prod([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>Series.quantile([q])</code>	Return value at the given quantile, a la <code>numpy.percentile</code> .
<code>Series.rank([method, na_option, ascending, pct])</code>	Compute data ranks (1 through n).
<code>Series.sem([axis, skipna, level, ddof, ...])</code>	Return unbiased standard error of the mean over requested axis.
<code>Series.skew([axis, skipna, level, numeric_only])</code>	Return unbiased skew over requested axis
<code>Series.std([axis, skipna, level, ddof, ...])</code>	Return unbiased standard deviation over requested axis.
<code>Series.sum([axis, skipna, level, numeric_only])</code>	Return the sum of the values for the requested axis
<code>Series.var([axis, skipna, level, ddof, ...])</code>	Return unbiased variance over requested axis.
<code>Series.unique()</code>	Return array of unique values in the object.
<code>Series.nunique([dropna])</code>	Return number of unique elements in the object.
<code>Series.value_counts([normalize, sort, ...])</code>	Returns object containing counts of unique values.

pandas.Series.abs

`Series.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.Series.all

`Series.all(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether all elements are True over requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns all : scalar or Series (if level specified)

pandas.Series.any

`Series.any(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether any element is True over requested axis

Parameters axis : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns any : scalar or Series (if level specified)

pandas.Series.autocorr

`Series.autocorr(lag=1)`

Lag-N autocorrelation

Parameters lag : int, default 1

Number of lags to apply before performing autocorrelation.

Returns autocorr : float

pandas.Series.between

Series.**between** (*left, right, inclusive=True*)

Return boolean Series equivalent to $\text{left} \leq \text{series} \leq \text{right}$. NA values will be treated as False

Parameters left : scalar

Left boundary

right : scalar

Right boundary

Returns is_between : Series

pandas.Series.clip

Series.**clip** (*lower=None, upper=None, out=None, axis=None*)

Trim values at input threshold(s)

Parameters lower : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns clipped : Series

Examples

```
>>> df
   0      1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
   0      1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
   0      1
0  0.335232 -0.300000
```

```
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

pandas.Series.clip_lower

`Series.clip_lower` (*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters `threshold` : float or array_like

`axis` : int or string axis name, optional

Align object with threshold along the given axis.

Returns `clipped` : same type as input

See also:

`clip`

pandas.Series.clip_upper

`Series.clip_upper` (*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters `threshold` : float or array_like

`axis` : int or string axis name, optional

Align object with threshold along the given axis.

Returns `clipped` : same type as input

See also:

`clip`

pandas.Series.corr

`Series.corr` (*other*, *method='pearson'*, *min_periods=None*)

Compute correlation with *other* Series, excluding missing values

Parameters `other` : Series

`method` : {'pearson', 'kendall', 'spearman'}

- `pearson` : standard correlation coefficient
- `kendall` : Kendall Tau correlation coefficient
- `spearman` : Spearman rank correlation

`min_periods` : int, optional

Minimum number of observations needed to have a valid result

Returns `correlation` : float

pandas.Series.count

`Series.count (level=None)`

Return number of non-NA/null observations in the Series

Parameters `level` : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a smaller Series

Returns `nobs` : int or Series (if level specified)

pandas.Series.cov

`Series.cov (other, min_periods=None)`

Compute covariance with Series, excluding missing values

Parameters `other` : Series

`min_periods` : int, optional

Minimum number of observations needed to have a valid result

Returns `covariance` : float

Normalized by N-1 (unbiased estimator).

pandas.Series.cummax

`Series.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

Parameters `axis` : {index (0)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `max` : scalar

pandas.Series.cummin

`Series.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative min over requested axis.

Parameters `axis` : {index (0)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `min` : scalar

pandas.Series.cumprod

`Series.cumprod (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative prod over requested axis.

Parameters `axis` : {index (0)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `prod` : scalar

pandas.Series.cumsum

`Series.cumsum` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative sum over requested axis.

Parameters `axis` : {index (0)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `sum` : scalar

pandas.Series.describe

`Series.describe` (*percentile_width=None, percentiles=None, include=None, exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters `percentile_width` : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default `percentiles` is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy.number`. To select categorical objects use `type object`. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`
- If `include` is the string 'all', the output column-set will match the input one.

Returns `summary`: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output `DataFrame` index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.Series.diff

`Series.diff` (*periods=1*)

1st discrete difference of object

Parameters `periods` : int, default 1

Periods to shift for forming difference

Returns `diffed` : Series

pandas.Series.factorize

`Series.factorize` (*sort=False, na_sentinel=-1*)

Encode the object as an enumerated type or categorical variable

Parameters `sort` : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark “not found”

Returns `labels` : the indexer to the original array

`uniques` : the unique Index

pandas.Series.kurt

`Series.kurt` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters `axis` : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : scalar or Series (if level specified)

pandas.Series.mad

Series.**mad** (*axis=None, skipna=None, level=None*)

Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : scalar or Series (if level specified)

pandas.Series.max

Series.**max** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : scalar or Series (if level specified)

pandas.Series.mean

Series.**mean** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the mean of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : scalar or Series (if level specified)

pandas.Series.median

`Series.median` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the median of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : scalar or Series (if level specified)

pandas.Series.min

`Series.min` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : scalar or Series (if level specified)

pandas.Series.mode

`Series.mode()`

Returns the mode(s) of the dataset.

Empty if nothing occurs at least 2 times. Always returns Series even if only one value.

Parameters `sort` : bool, default True

If True, will lexicographically sort values, if False skips sorting. Result ordering when `sort=False` is not defined.

Returns `modes` : Series (sorted)

pandas.Series.pct_change

`Series.pct_change(periods=1, fill_method='pad', limit=None, freq=None, **kwargs)`

Percent change over given number of periods.

Parameters `periods` : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns `chg` : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the `axis` keyword argument.

pandas.Series.prod

`Series.prod(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the product of the values for the requested axis

Parameters `axis` : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : scalar or Series (if level specified)

pandas.Series.quantile

`Series.quantile (q=0.5)`

Return value at the given quantile, a la numpy.percentile.

Parameters **q** : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

Returns **quantile** : float or Series

if q is an array, a Series will be returned where the index is q and the values are the quantiles.

Examples

```
>>> s = Series([1, 2, 3, 4])
>>> s.quantile(.5)
2.5
>>> s.quantile([.25, .5, .75])
0.25    1.75
0.50    2.50
0.75    3.25
dtype: float64
```

pandas.Series.rank

`Series.rank (method='average', na_option='keep', ascending=True, pct=False)`

Compute data ranks (1 through n). Equal values are assigned a rank that is the average of the ranks of those values

Parameters **method** : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep'}

keep: leave NA values where they are

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns **ranks** : Series

pandas.Series.sem

`Series.sem` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters `axis` : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `sem` : scalar or Series (if level specified)

pandas.Series.skew

`Series.skew` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters `axis` : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `skew` : scalar or Series (if level specified)

pandas.Series.std

`Series.std` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters `axis` : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : scalar or Series (if level specified)

pandas.Series.sum

`Series.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the sum of the values for the requested axis

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : scalar or Series (if level specified)

pandas.Series.var

`Series.var(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a scalar

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : scalar or Series (if level specified)

pandas.Series.unique`Series.unique()`Return array of unique values in the object. Significantly faster than `numpy.unique`. Includes NA values.**Returns** `uniques` : ndarray**pandas.Series.nunique**`Series.nunique(dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters `dropna` : boolean, default True

Don't include NaN in the count.

Returns `nunique` : int**pandas.Series.value_counts**`Series.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element.

Excludes NA values by default.

Parameters `normalize` : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optionalRather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data**dropna** : boolean, default True

Don't include counts of NaN.

Returns `counts` : Series**33.3.8 Reindexing / Selection / Label manipulation**`Series.align(other[, join, axis, level, ...])`

Align two object on their axes with the

`Series.drop(labels[, axis, level, inplace, ...])`

Return new object with labels in requested axis removed

`Series.drop_duplicates([take_last, inplace])`

Return Series with duplicate values removed

`Series.duplicated([take_last])`

Return boolean Series denoting duplicate values

Table 33.28 – continued from previous page

<code>Series.equals(other)</code>	Determines if two NDFrame objects contain the same elements.
<code>Series.first(offset)</code>	Convenience method for subsetting initial periods of time series data
<code>Series.head([n])</code>	Returns first n rows
<code>Series.idxmax([axis, out, skipna])</code>	Index of first occurrence of maximum of values.
<code>Series.idxmin([axis, out, skipna])</code>	Index of first occurrence of minimum of values.
<code>Series.isin(values)</code>	Return a boolean <code>Series</code> showing whether each element in the <code>Series</code>
<code>Series.last(offset)</code>	Convenience method for subsetting final periods of time series data
<code>Series.reindex([index])</code>	Conform Series to new index with optional filling logic, placing NA/NaN
<code>Series.reindex_like(other[, method, copy, limit])</code>	return an object with matching indicies to myself
<code>Series.rename([index])</code>	Alter axes input function or functions.
<code>Series.reset_index([level, drop, name, inplace])</code>	Analogous to the <code>pandas.DataFrame.reset_index()</code> function, s
<code>Series.sample([n, frac, replace, weights, ...])</code>	Returns a random sample of items from an axis of object.
<code>Series.select(crit[, axis])</code>	Return data corresponding to axis labels matching criteria
<code>Series.take(indices[, axis, convert, is_copy])</code>	return Series corresponding to requested indices
<code>Series.tail([n])</code>	Returns last n rows
<code>Series.truncate([before, after, axis, copy])</code>	Truncates a sorted NDFrame before and/or after some particular dates.
<code>Series.where(cond[, other, inplace, axis, ...])</code>	Return an object of same shape as self and whose corresponding entries a
<code>Series.mask(cond[, other, inplace, axis, ...])</code>	Return an object of same shape as self and whose corresponding entries a

pandas.Series.align

`Series.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0)`

Align two object on their axes with the specified join method for each axis Index

Parameters `other` : DataFrame or Series

join : { 'outer', 'inner', 'left', 'right' }, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns (`left`, `right`) : (type of input, type of other)

Aligned objects

pandas.Series.drop

`Series.drop` (*labels, axis=0, level=None, inplace=False, errors='raise'*)

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : type of caller

pandas.Series.drop_duplicates

`Series.drop_duplicates` (*take_last=False, inplace=False*)

Return Series with duplicate values removed

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

inplace : boolean, default False

If True, performs operation inplace and returns None.

Returns **deduplicated** : Series

pandas.Series.duplicated

`Series.duplicated` (*take_last=False*)

Return boolean Series denoting duplicate values

Parameters **take_last** : boolean, default False

Take the last observed index in a group. Default first

Returns **duplicated** : Series

pandas.Series.equals

`Series.equals` (*other*)

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Series.first

`Series.first` (*offset*)

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns `subset` : type of caller

Examples

`ts.last('10D')` -> First 10 days

pandas.Series.head

`Series.head(n=5)`
Returns first n rows

pandas.Series.idxmax

`Series.idxmax(axis=None, out=None, skipna=True)`
Index of first occurrence of maximum of values.

Parameters `skipna` : boolean, default True

Exclude NA/null values

Returns `idxmax` : Index of maximum of values

See also:

`DataFrame.idxmax`, `numpy.ndarray.argmax`

Notes

This method is the Series version of `ndarray.argmax`.

pandas.Series.idxmin

`Series.idxmin(axis=None, out=None, skipna=True)`
Index of first occurrence of minimum of values.

Parameters `skipna` : boolean, default True

Exclude NA/null values

Returns `idxmin` : Index of minimum of values

See also:

`DataFrame.idxmin`, `numpy.ndarray.argmin`

Notes

This method is the Series version of `ndarray.argmin`.

pandas.Series.isin

`Series.isin(values)`

Return a boolean `Series` showing whether each element in the `Series` is exactly contained in the passed sequence of values.

Parameters `values` : list-like

The sequence of values to test. Passing in a single string will raise a `TypeError`. Instead, turn a single string into a `list` of one element.

Returns `isin` : `Series` (bool dtype)

Raises `TypeError`

- If `values` is a string

See also:

`pandas.DataFrame.isin`

Examples

```
>>> s = pd.Series(list('abc'))
>>> s.isin(['a', 'c', 'e'])
0      True
1     False
2      True
dtype: bool
```

Passing a single string as `s.isin('a')` will raise an error. Use a list of one element instead:

```
>>> s.isin(['a'])
0      True
1     False
2     False
dtype: bool
```

pandas.Series.last

`Series.last(offset)`

Convenience method for subsetting final periods of time series data based on a date offset

Parameters `offset` : string, `DateOffset`, `dateutil.relativedelta`

Returns `subset` : type of caller

Examples

`ts.last('5M')` -> Last 5 months

pandas.Series.reindex

`Series.reindex(index=None, **kwargs)`

Conform `Series` to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters **index** : array-like, optional (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Series

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Series.reindex_like

`Series.reindex_like` (*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters **other** : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

pandas.Series.rename

`Series.rename(index=None, **kwargs)`

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters `index` : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Series. If True then value of copy is ignored.

Returns `renamed` : Series (new object)

pandas.Series.reset_index

`Series.reset_index(level=None, drop=False, name=None, inplace=False)`

Analogous to the `pandas.DataFrame.reset_index()` function, see docstring there.

Parameters `level` : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns

name : object, default None

The name of the column corresponding to the Series values

inplace : boolean, default False

Modify the Series in place (do not create a new object)

Returns `resetted` : DataFrame, or Series if `drop == True`

pandas.Series.sample

`Series.sample(n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`

Returns a random sample of items from an axis of object.

Parameters `n` : int, optional

Number of items from axis to return. Cannot be used with `frac`. Default = 1 if `frac = None`.

frac : float, optional

Fraction of axis items to return. Cannot be used with `n`.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. Weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. inf and -inf values not allowed.

random_state : int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

Returns Same type as caller.

pandas.Series.select

`Series.select (crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.Series.take

`Series.take (indices, axis=0, convert=True, is_copy=False)`

return Series corresponding to requested indices

Parameters **indices** : list / array of ints

convert : translate negative to positive indices (default)

Returns **taken** : Series

See also:

`numpy.ndarray.take`

pandas.Series.tail

`Series.tail (n=5)`

Returns last n rows

pandas.Series.truncate

`Series.truncate (before=None, after=None, axis=None, copy=True)`

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns truncated : type of caller

pandas.Series.where

`Series.where(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns wh : same type as caller

pandas.Series.mask

`Series.mask(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters cond : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

33.3.9 Missing data handling

<code>Series.dropna([axis, inplace])</code>	Return Series without null values
<code>Series.fillna([value, method, axis, ...])</code>	Fill NA/NaN values using the specified method
<code>Series.interpolate([method, axis, limit, ...])</code>	Interpolate values according to different methods.

pandas.Series.dropna

`Series.dropna` (*axis=0, inplace=False, **kwargs*)
Return Series without null values

Returns **valid** : Series

inplace : boolean, default False

Do operation in place.

pandas.Series.fillna

`Series.fillna` (*value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs*)
Fill NA/NaN values using the specified method

Parameters **method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

value : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 'index'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : Series

See also:

`reindex`, `asfreq`

pandas.Series.interpolate

`Series.interpolate` (*method='linear', axis=0, limit=None, inplace=False, downcast=None, **kwargs*)

Interpolate values according to different methods.

Parameters **method** : { 'linear', 'time', 'index', 'values', 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline', 'piecewise_polynomial', 'pchip' }

- 'linear': ignore the index and treat the values as equally spaced. default
- 'time': interpolation works on daily and higher resolution data to interpolate given length of interval
- 'index', 'values': use the actual numerical values of the index
- 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'polynomial' is passed to `scipy.interpolate.interp1d` with the order given both 'polynomial' and 'spline' require that you also specify an order (int) e.g. `df.interpolate(method='polynomial', order=4)`
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: <http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation> <http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html>

axis : {0, 1}, default 0

- 0: fill column-by-column
- 1: fill row-by-row

limit : int, default None.

Maximum number of consecutive NaNs to fill.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

33.3.10 Reshaping, sorting

<code>Series.argsort([axis, kind, order])</code>	Overrides ndarray.argsort.
<code>Series.order([na_last, ascending, kind, ...])</code>	Sorts Series object, by value, maintaining index-value link.
<code>Series.reorder_levels(order)</code>	Rearrange index levels using input order.
<code>Series.sort([axis, ascending, kind, ...])</code>	Sort values and index labels by value.
<code>Series.sort_index([ascending])</code>	Sort object by labels (along an axis)
<code>Series.sortlevel([level, ascending, ...])</code>	Sort Series with MultiIndex by chosen level.
<code>Series.swaplevel(i, j[, copy])</code>	Swap levels i and j in a MultiIndex
<code>Series.unstack([level])</code>	Unstack, a.k.a.
<code>Series.searchsorted(v[, side, sorter])</code>	Find indices where elements should be inserted to maintain order.

pandas.Series.argsort

`Series.argsort` (*axis=0, kind='quicksort', order=None*)

Overrides ndarray.argsort. Argsorts the value, omitting NA/null values, and places the result in the same locations as the non-NA values

Parameters **axis** : int (can only be zero)

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See np.sort for more information. 'mergesort' is the only stable algorithm

order : ignored

Returns **argsorted** : Series, with -1 indicated where nan values are present

See also:

`numpy.ndarray.argsort`

pandas.Series.order

`Series.order` (*na_last=None, ascending=True, kind='quicksort', na_position='last', inplace=False*)

Sorts Series object, by value, maintaining index-value link. This will return a new Series by default. Series.sort is the equivalent but as an inplace method.

Parameters **na_last** : boolean (optional, default=True) (DEPRECATED; use na_position)

Put NaN's at beginning or end

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : {'mergesort', 'quicksort', 'heapsort'}, default 'quicksort'

Choice of sorting algorithm. See `np.sort` for more information. 'mergesort' is the only stable algorithm

na_position : { 'first', 'last' } (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default False

Do operation in place.

Returns `y` : Series

See also:

`Series.sort`

pandas.Series.reorder_levels

`Series.reorder_levels` (*order*)

Rearrange index levels using input order. May not drop or duplicate levels

Parameters **order**: list of int representing new level order.

(reference level by number or key)

axis: where to reorder levels

Returns type of caller (new object)

pandas.Series.sort

`Series.sort` (*axis=0, ascending=True, kind='quicksort', na_position='last', inplace=True*)

Sort values and index labels by value. This is an inplace sort by default. `Series.order` is the equivalent but returns a new Series.

Parameters **axis** : int (can only be zero)

ascending : boolean, default True

Sort ascending. Passing False sorts descending

kind : { 'mergesort', 'quicksort', 'heapsort' }, default 'quicksort'

Choice of sorting algorithm. See `np.sort` for more information. 'mergesort' is the only stable algorithm

na_position : { 'first', 'last' } (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

inplace : boolean, default True

Do operation in place.

See also:

`Series.order`

pandas.Series.sort_index

`Series.sort_index(ascending=True)`

Sort object by labels (along an axis)

Parameters `ascending` : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

Returns `sorted_obj` : Series

Examples

```
>>> result1 = s.sort_index(ascending=False)
>>> result2 = s.sort_index(ascending=[1, 0])
```

pandas.Series.sortlevel

`Series.sortlevel(level=0, ascending=True, sort_remaining=True)`

Sort Series with MultiIndex by chosen level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters `level` : int or level name, default None

`ascending` : bool, default True

Returns `sorted` : Series

pandas.Series.swaplevel

`Series.swaplevel(i, j, copy=True)`

Swap levels i and j in a MultiIndex

Parameters `i, j` : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns `swapped` : Series

pandas.Series.unstack

`Series.unstack(level=-1)`

Unstack, a.k.a. pivot, Series with MultiIndex to produce DataFrame. The level involved will automatically get sorted.

Parameters `level` : int, string, or list of these, default last level

Level(s) to unstack, can pass level name

Returns `unstacked` : DataFrame

Examples

```

>>> s
one  a    1.
one  b    2.
two  a    3.
two  b    4.

>>> s.unstack(level=-1)
      a    b
one  1.    2.
two  3.    4.

>>> s.unstack(level=0)
      one  two
a    1.    2.
b    3.    4.

```

pandas.Series.searchsorted

`Series.searchsorted(v, side='left', sorter=None)`

Find indices where elements should be inserted to maintain order.

Find the indices into a sorted Series *self* such that, if the corresponding elements in *v* were inserted before the indices, the order of *self* would be preserved.

Parameters *v* : array_like

Values to insert into *a*.

side : {'left', 'right'}, optional

If 'left', the index of the first suitable location found is given. If 'right', return the last such index. If there is no suitable index, return either 0 or N (where N is the length of *a*).

sorter : 1-D array_like, optional

Optional array of integer indices that sort *self* into ascending order. They are typically the result of `np.argsort`.

Returns **indices** : array of ints

Array of insertion points with the same shape as *v*.

See also:

`Series.sort`, `Series.order`, `numpy.searchsorted`

Notes

Binary search is used to find the required insertion points.

Examples

```

>>> x = pd.Series([1, 2, 3])
>>> x
0    1
1    2
2    3

```

```
dtype: int64
>>> x.searchsorted(4)
array([3])
>>> x.searchsorted([0, 4])
array([0, 3])
>>> x.searchsorted([1, 3], side='left')
array([0, 2])
>>> x.searchsorted([1, 3], side='right')
array([1, 3])
>>> x.searchsorted([1, 2], side='right', sorter=[0, 2, 1])
array([1, 3])
```

33.3.11 Combining / joining / merging

<code>Series.append(to_append[, verify_integrity])</code>	Concatenate two or more Series.
<code>Series.replace([to_replace, value, inplace, ...])</code>	Replace values given in 'to_replace' with 'value'.
<code>Series.update(other)</code>	Modify Series in place using non-NA values from passed Series.

pandas.Series.append

`Series.append(to_append, verify_integrity=False)`

Concatenate two or more Series. The indexes must not overlap

Parameters `to_append` : Series or list/tuple of Series

verify_integrity : boolean, default False

If True, raise Exception on creating index with duplicates

Returns `appended` : Series

pandas.Series.replace

`Series.replace(to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None)`

Replace values given in 'to_replace' with 'value'.

Parameters `to_replace` : str, regex, list, dict, Series, numeric, or None

- str or regex:
 - str: string exactly matching *to_replace* will be replaced with *value*
 - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
 - First, if *to_replace* and *value* are both lists, they **must** be the same length.
 - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
 - str and regex rules apply as above.
- dict:

- Nested dictionaries, e.g., `{‘a’: {‘b’: nan}}`, are read as follows: look in column ‘a’ for the value ‘b’ and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
- Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
 - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also None then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is True then *to_replace* must be a string. Otherwise, *to_replace* must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {‘pad’, ‘ffill’, ‘bfill’}

The method to use when for replacement, when *to_replace* is a list.

Returns **filled** : NDFrame

Raises **AssertionError**

- If *regex* is not a bool and *to_replace* is not None.

TypeError

- If *to_replace* is a dict and *value* is not a list, dict, ndarray, or Series
- If *to_replace* is None and *regex* is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If *to_replace* and *value* are lists or ndarrays, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Series.update

`Series.update(other)`

Modify Series in place using non-NA values from passed Series. Aligns on index

Parameters `other` : Series

33.3.12 Time series-related

<code>Series.asfreq(freq[, method, how, normalize])</code>	Convert all TimeSeries inside to specified frequency using DateOffset objects.
<code>Series.asof(when)</code>	Return last good (non-NaN) value in TimeSeries if value is NaN for requested
<code>Series.shift([periods, freq, axis])</code>	Shift index by desired number of periods with an optional time freq
<code>Series.first_valid_index()</code>	Return label for first non-NA/null value
<code>Series.last_valid_index()</code>	Return label for last non-NA/null value
<code>Series.resample(rule[, how, axis, ...])</code>	Convenience method for frequency conversion and resampling of regular time-
<code>Series.tz_convert(tz[, axis, level, copy])</code>	Convert tz-aware axis to target time zone.
<code>Series.tz_localize(*args, **kwargs)</code>	Localize tz-naive TimeSeries to target time zone

pandas.Series.asfreq

`Series.asfreq(freq, method=None, how=None, normalize=False)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters `freq` : DateOffset object, or string

method : { 'backfill', 'bfill', 'pad', 'ffill', None }

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : { 'start', 'end' }, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns `converted` : type of caller

pandas.Series.asof

`Series.asof (where)`

Return last good (non-NaN) value in TimeSeries if value is NaN for requested date.

If there is no good value, NaN is returned.

Parameters `where` : date or array of dates

Returns value or NaN

Notes

Dates are assumed to be sorted

pandas.Series.shift

`Series.shift (periods=1, freq=None, axis=0, **kwargs)`

Shift index by desired number of periods with an optional time freq

Parameters `periods` : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 'index'}

Returns `shifted` : Series

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.Series.first_valid_index

`Series.first_valid_index()`

Return label for first non-NA/null value

pandas.Series.last_valid_index

`Series.last_valid_index()`

Return label for last non-NA/null value

pandas.Series.resample

`Series.resample (rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters `rule` : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : { 'right', 'left' }

Which side of bin interval is closed

label : { 'right', 'left' }

Which bin edge label to label bucket with

convention : { 'start', 'end', 's', 'e' }

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals.
For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.Series.tz_convert

`Series.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters **tz** : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis is a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises **TypeError**

If the axis is tz-naive.

pandas.Series.tz_localize

`Series.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters `tz` : string or `pytz.timezone` object

axis : the axis to localize

level : int, str, default None

If axis is a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an `AmbiguousTimeError` if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises `TypeError`

If the `TimeSeries` is tz-aware and `tz` is not None.

33.3.13 Datetimelike Properties

`Series.dt` can be used to access the values of the series as datetimelike and return several properties. These can be accessed like `Series.dt.<property>`.

Datetime Properties

<code>Series.dt.date</code>	Returns numpy array of <code>datetime.date</code> .
<code>Series.dt.time</code>	Returns numpy array of <code>datetime.time</code> .
<code>Series.dt.year</code>	The year of the datetime
<code>Series.dt.month</code>	The month as January=1, December=12
<code>Series.dt.day</code>	The days of the datetime
<code>Series.dt.hour</code>	The hours of the datetime
<code>Series.dt.minute</code>	The minutes of the datetime
<code>Series.dt.second</code>	The seconds of the datetime
<code>Series.dt.microsecond</code>	The microseconds of the datetime
<code>Series.dt.nanosecond</code>	The nanoseconds of the datetime
<code>Series.dt.second</code>	The seconds of the datetime
<code>Series.dt.week</code>	The week ordinal of the year
<code>Series.dt.weekofyear</code>	The week ordinal of the year
<code>Series.dt.dayofweek</code>	The day of the week with Monday=0, Sunday=6
<code>Series.dt.weekday</code>	The day of the week with Monday=0, Sunday=6
<code>Series.dt.dayofyear</code>	The ordinal day of the year
<code>Series.dt.quarter</code>	The quarter of the date
<code>Series.dt.is_month_start</code>	Logical indicating if first day of month (defined by frequency)
<code>Series.dt.is_month_end</code>	Logical indicating if last day of month (defined by frequency)
<code>Series.dt.is_quarter_start</code>	Logical indicating if first day of quarter (defined by frequency)
<code>Series.dt.is_quarter_end</code>	Logical indicating if last day of quarter (defined by frequency)
<code>Series.dt.is_year_start</code>	Logical indicating if first day of year (defined by frequency)

Continued on next page

Table 33.33 – continued from previous page

<code>Series.dt.is_year_end</code>	Logical indicating if last day of year (defined by frequency)
<code>Series.dt.daysinmonth</code>	The number of days in the month
<code>Series.dt.days_in_month</code>	The number of days in the month
<code>Series.dt.tz</code>	
<code>Series.dt.freq</code>	get/set the frequency of the Index

pandas.Series.dt.date

`Series.dt.date`

Returns numpy array of datetime.date. The date part of the Timestamps.

pandas.Series.dt.time

`Series.dt.time`

Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.Series.dt.year

`Series.dt.year`

The year of the datetime

pandas.Series.dt.month

`Series.dt.month`

The month as January=1, December=12

pandas.Series.dt.day

`Series.dt.day`

The days of the datetime

pandas.Series.dt.hour

`Series.dt.hour`

The hours of the datetime

pandas.Series.dt.minute

`Series.dt.minute`

The minutes of the datetime

pandas.Series.dt.second

`Series.dt.second`

The seconds of the datetime

pandas.Series.dt.microsecond

`Series.dt.microsecond`
The microseconds of the datetime

pandas.Series.dt.nanosecond

`Series.dt.nanosecond`
The nanoseconds of the datetime

pandas.Series.dt.second

`Series.dt.second`
The seconds of the datetime

pandas.Series.dt.week

`Series.dt.week`
The week ordinal of the year

pandas.Series.dt.weekofyear

`Series.dt.weekofyear`
The week ordinal of the year

pandas.Series.dt.dayofweek

`Series.dt.dayofweek`
The day of the week with Monday=0, Sunday=6

pandas.Series.dt.weekday

`Series.dt.weekday`
The day of the week with Monday=0, Sunday=6

pandas.Series.dt.dayofyear

`Series.dt.dayofyear`
The ordinal day of the year

pandas.Series.dt.quarter

`Series.dt.quarter`
The quarter of the date

pandas.Series.dt.is_month_start

`Series.dt.is_month_start`

Logical indicating if first day of month (defined by frequency)

pandas.Series.dt.is_month_end

`Series.dt.is_month_end`

Logical indicating if last day of month (defined by frequency)

pandas.Series.dt.is_quarter_start

`Series.dt.is_quarter_start`

Logical indicating if first day of quarter (defined by frequency)

pandas.Series.dt.is_quarter_end

`Series.dt.is_quarter_end`

Logical indicating if last day of quarter (defined by frequency)

pandas.Series.dt.is_year_start

`Series.dt.is_year_start`

Logical indicating if first day of year (defined by frequency)

pandas.Series.dt.is_year_end

`Series.dt.is_year_end`

Logical indicating if last day of year (defined by frequency)

pandas.Series.dt.daysinmonth

`Series.dt.daysinmonth`

The number of days in the month

pandas.Series.dt.days_in_month

`Series.dt.days_in_month`

The number of days in the month

pandas.Series.dt.tz

`Series.dt.tz`

pandas.Series.dt.freq

`Series.dt.freq`
get/set the frequency of the Index

Datetime Methods

<code>Series.dt.to_period(*args, **kwargs)</code>	Cast to PeriodIndex at a particular frequency
<code>Series.dt.to_pydatetime()</code>	
<code>Series.dt.tz_localize(*args, **kwargs)</code>	Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil),
<code>Series.dt.tz_convert(*args, **kwargs)</code>	Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)
<code>Series.dt.normalize(*args, **kwargs)</code>	Return DatetimeIndex with times to midnight.

pandas.Series.dt.to_period

`Series.dt.to_period(*args, **kwargs)`
Cast to PeriodIndex at a particular frequency

pandas.Series.dt.to_pydatetime

`Series.dt.to_pydatetime()`

pandas.Series.dt.tz_localize

`Series.dt.tz_localize(*args, **kwargs)`
Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters `tz` : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Returns `localized` : DatetimeIndex

Raises `TypeError`

If the DatetimeIndex is tz-aware and tz is not None.

pandas.Series.dt.tz_convert

`Series.dt.tz_convert(*args, **kwargs)`

Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters `tz` : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

Returns `normalized` : DatetimeIndex

Raises `TypeError`

If DatetimeIndex is tz-naive.

pandas.Series.dt.normalize

`Series.dt.normalize(*args, **kwargs)`

Return DatetimeIndex with times to midnight. Length is unaltered

Returns `normalized` : DatetimeIndex

Timedelta Properties

<code>Series.dt.days</code>	Number of days for each element.
<code>Series.dt.seconds</code>	Number of seconds (≥ 0 and less than 1 day) for each element.
<code>Series.dt.microseconds</code>	Number of microseconds (≥ 0 and less than 1 second) for each element.
<code>Series.dt.nanoseconds</code>	Number of nanoseconds (≥ 0 and less than 1 microsecond) for each element.
<code>Series.dt.components</code>	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds)

pandas.Series.dt.days

`Series.dt.days`

Number of days for each element.

pandas.Series.dt.seconds

`Series.dt.seconds`

Number of seconds (≥ 0 and less than 1 day) for each element.

pandas.Series.dt.microseconds

`Series.dt.microseconds`

Number of microseconds (≥ 0 and less than 1 second) for each element.

pandas.Series.dt.nanoseconds

`Series.dt.nanoseconds`

Number of nanoseconds (≥ 0 and less than 1 microsecond) for each element.

pandas.Series.dt.components

Series.dt.components

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns a DataFrame

Timedelta Methods

`Series.dt.to_pytimedelta()`

pandas.Series.dt.to_pytimedelta

`Series.dt.to_pytimedelta()`

33.3.14 String handling

`Series.str` can be used to access the values of the series as strings and apply several methods to it. These can be accessed like `Series.str.<function/property>`.

<code>Series.str.capitalize()</code>	Convert strings in the Series/Index to be capitalized.
<code>Series.str.cat([others, sep, na_rep])</code>	Concatenate strings in the Series/Index with given separator.
<code>Series.str.center(width[, fillchar])</code>	Filling left and right side of strings in the Series/Index with an additional character.
<code>Series.str.contains(pat[, case, flags, na, ...])</code>	Return boolean Series/array whether given pattern/regex is contained in each string.
<code>Series.str.count(pat[, flags])</code>	Count occurrences of pattern in each string of the Series/Index.
<code>Series.str.decode(encoding[, errors])</code>	Decode character string in the Series/Index to unicode using indicated encoding.
<code>Series.str.encode(encoding[, errors])</code>	Encode character string in the Series/Index to some other encoding using indicated encoding.
<code>Series.str.endswith(pat[, na])</code>	Return boolean Series indicating whether each string in the Series/Index ends with given pattern.
<code>Series.str.extract(pat[, flags])</code>	Find groups in each string in the Series using passed regular expression.
<code>Series.str.find(sub[, start, end])</code>	Return lowest indexes in each strings in the Series/Index where the substring is fully contained between [start, end] (inclusive of start, exclusive of end).
<code>Series.str.findall(pat[, flags])</code>	Find all occurrences of pattern or regular expression in the Series/Index.
<code>Series.str.get(i)</code>	Extract element from lists, tuples, or strings in each element in the Series/Index.
<code>Series.str.index(sub[, start, end])</code>	Return lowest indexes in each strings where the substring is fully contained between [start, end] (inclusive of start, exclusive of end).
<code>Series.str.join(sep)</code>	Join lists contained as elements in the Series/Index with passed delimiter.
<code>Series.str.len()</code>	Compute length of each string in the Series/Index.
<code>Series.str.ljust(width[, fillchar])</code>	Filling right side of strings in the Series/Index with an additional character.
<code>Series.str.lower()</code>	Convert strings in the Series/Index to lowercase.
<code>Series.str.lstrip([to_strip])</code>	Strip whitespace (including newlines) from each string in the Series/Index from the left, excluding the right.
<code>Series.str.match(pat[, case, flags, na, ...])</code>	Deprecated: Find groups in each string in the Series/Index using passed regular expression.
<code>Series.str.normalize(form)</code>	Return the Unicode normal form for the strings in the Series/Index.
<code>Series.str.pad(width[, side, fillchar])</code>	Pad strings in the Series/Index with an additional character to specified side.
<code>Series.str.partition([pat, expand])</code>	Split the string at the first occurrence of <i>sep</i> , and return 3 elements containing the three parts.
<code>Series.str.repeat(repeats)</code>	Duplicate each string in the Series/Index by indicated number of times.
<code>Series.str.replace(pat, repl[, n, case, flags])</code>	Replace occurrences of pattern/regex in the Series/Index with some other string.
<code>Series.str.rfind(sub[, start, end])</code>	Return highest indexes in each strings in the Series/Index where the substring is fully contained between [start, end] (inclusive of start, exclusive of end).
<code>Series.str.rindex(sub[, start, end])</code>	Return highest indexes in each strings where the substring is fully contained between [start, end] (inclusive of start, exclusive of end).
<code>Series.str.rjust(width[, fillchar])</code>	Filling left side of strings in the Series/Index with an additional character.
<code>Series.str.rpartition([pat, expand])</code>	Split the string at the last occurrence of <i>sep</i> , and return 3 elements containing the three parts.
<code>Series.str.rstrip([to_strip])</code>	Strip whitespace (including newlines) from each string in the Series/Index from the right, excluding the left.
<code>Series.str.slice([start, stop, step])</code>	Slice substrings from each element in the Series/Index.
<code>Series.str.slice_replace([start, stop, repl])</code>	Replace a slice of each string in the Series/Index with another string.

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<code>Series.str.split(*args, **kwargs)</code>	Split each string (a la <code>re.split</code>) in the Series/Index by given pattern, propagating <code>NaN</code> .
<code>Series.str.startswith(pat[, na])</code>	Return boolean Series/array indicating whether each string in the Series/Index starts with <code>pat</code> .
<code>Series.str.strip([to_strip])</code>	Strip whitespace (including newlines) from each string in the Series/Index.
<code>Series.str.swapcase()</code>	Convert strings in the Series/Index to be swaped.
<code>Series.str.title()</code>	Convert strings in the Series/Index to titlecase.
<code>Series.str.translate(table[, deletechars])</code>	Map all characters in the string through the given mapping table.
<code>Series.str.upper()</code>	Convert strings in the Series/Index to uppercase.
<code>Series.str.wrap(width, **kwargs)</code>	Wrap long strings in the Series/Index to be formatted in paragraphs with length <code>width</code> .
<code>Series.str.zfill(width)</code>	Fill strings with zeros to the left to reach length <code>width</code> .
<code>Series.str.isalnum()</code>	Check whether all characters in each string in the Series/Index are alphanumeric.
<code>Series.str.isalpha()</code>	Check whether all characters in each string in the Series/Index are alphabetic.
<code>Series.str.isdigit()</code>	Check whether all characters in each string in the Series/Index are digits.
<code>Series.str.isspace()</code>	Check whether all characters in each string in the Series/Index are whitespace.
<code>Series.str.islower()</code>	Check whether all characters in each string in the Series/Index are lowercase.
<code>Series.str.isupper()</code>	Check whether all characters in each string in the Series/Index are uppercase.
<code>Series.str.istitle()</code>	Check whether all characters in each string in the Series/Index are titlecase.
<code>Series.str.isnumeric()</code>	Check whether all characters in each string in the Series/Index are numeric.
<code>Series.str.isdecimal()</code>	Check whether all characters in each string in the Series/Index are decimal.
<code>Series.str.get_dummies([sep])</code>	Split each string in the Series by <code>sep</code> and return a frame of dummy/indicator variables.

pandas.Series.str.capitalize

`Series.str.capitalize()`

Convert strings in the Series/Index to be capitalized. Equivalent to `str.capitalize()`.

Returns `converted` : Series/Index of objects

pandas.Series.str.cat

`Series.str.cat (others=None, sep=None, na_rep=None)`

Concatenate strings in the Series/Index with given separator.

Parameters `others` : list-like, or list of list-likes

If `None`, returns str concatenating strings of the Series

`sep` : string or `None`, default `None`

`na_rep` : string or `None`, default `None`

If `None`, an NA in any array will propagate

Returns `concat` : Series/Index of objects or str

Examples

If `others` is specified, corresponding values are concatenated with the separator. Result will be a Series of strings.

```
>>> Series(['a', 'b', 'c']).str.cat(['A', 'B', 'C'], sep=',')
0    a,A
1    b,B
2    c,C
dtype: object
```

Otherwise, strings in the Series are concatenated. Result will be a string.

```
>>> Series(['a', 'b', 'c']).str.cat(sep=',')
'a,b,c'
```

Also, you can pass a list of list-likes.

```
>>> Series(['a', 'b']).str.cat([[ 'x', 'y'], [ '1', '2']], sep=',')
0    a,x,1
1    b,y,2
dtype: object
```

pandas.Series.str.center

`Series.str.center` (*width*, *fillchar*=`' '`)

Filling left and right side of strings in the Series/Index with an additional character. Equivalent to `str.center()`.

Parameters *width* : int

Minimum width of resulting string; additional characters will be filled with *fillchar*

fillchar : str

Additional character for filling, default is whitespace

Returns *filled* : Series/Index of objects

pandas.Series.str.contains

`Series.str.contains` (*pat*, *case*=`True`, *flags*=0, *na*=`nan`, *regex*=`True`)

Return boolean Series/array whether given pattern/regex is contained in each string in the Series/Index.

Parameters *pat* : string

Character sequence or regular expression

case : boolean, default `True`

If `True`, case sensitive

flags : int, default 0 (no flags)

re module flags, e.g. `re.IGNORECASE`

na : default `NaN`, fill value for missing values.

regex : bool, default `True`

If `True` use `re.search`, otherwise use Python in operator

Returns *contained* : Series/array of boolean values

See also:

`match` analogous, but stricter, relying on `re.match` instead of `re.search`

pandas.Series.str.count

`Series.str.count` (*pat*, *flags=0*, ***kwargs*)

Count occurrences of pattern in each string of the Series/Index.

Parameters *pat* : string, valid regular expression

flags : int, default 0 (no flags)

re module flags, e.g. `re.IGNORECASE`

Returns *counts* : Series/Index of integer values

pandas.Series.str.decode

`Series.str.decode` (*encoding*, *errors='strict'*)

Decode character string in the Series/Index to unicode using indicated encoding. Equivalent to `str.decode()`.

Parameters *encoding* : string

errors : string

Returns *decoded* : Series/Index of objects

pandas.Series.str.encode

`Series.str.encode` (*encoding*, *errors='strict'*)

Encode character string in the Series/Index to some other encoding using indicated encoding. Equivalent to `str.encode()`.

Parameters *encoding* : string

errors : string

Returns *encoded* : Series/Index of objects

pandas.Series.str.endswith

`Series.str.endswith` (*pat*, *na=nan*)

Return boolean Series indicating whether each string in the Series/Index ends with passed pattern. Equivalent to `str.endswith()`.

Parameters *pat* : string

Character sequence

na : bool, default NaN

Returns *endswith* : Series/array of boolean values

pandas.Series.str.extract

`Series.str.extract` (*pat*, *flags=0*)

Find groups in each string in the Series using passed regular expression.

Parameters *pat* : string

Pattern or regular expression

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

Returns extracted groups : Series (one group) or DataFrame (multiple groups)

Note that dtype of the result is always object, even when no match is found and the result is a Series or DataFrame containing only NaN values.

Examples

A pattern with one group will return a Series. Non-matches will be NaN.

```
>>> Series(['a1', 'b2', 'c3']).str.extract('[ab](\d)')
0      1
1      2
2     NaN
dtype: object
```

A pattern with more than one group will return a DataFrame.

```
>>> Series(['a1', 'b2', 'c3']).str.extract('([ab])(\d)')
   0  1
0  a  1
1  b  2
2 NaN NaN
```

A pattern may contain optional groups.

```
>>> Series(['a1', 'b2', 'c3']).str.extract('([ab])?(\d)')
   0  1
0  a  1
1  b  2
2 NaN 3
```

Named groups will become column names in the result.

```
>>> Series(['a1', 'b2', 'c3']).str.extract('(P<letter>[ab])(P<digit>\d)')
   letter digit
0      a      1
1      b      2
2     NaN     NaN
```

pandas.Series.str.find

Series.str.find (*sub*, *start*=0, *end*=None)

Return lowest indexes in each strings in the Series/Index where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.find()`.

Parameters **sub** : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns found : Series/Index of integer values

See also:

rfind Return highest indexes in each strings

pandas.Series.str.findall

`Series.str.findall(pat, flags=0, **kwargs)`

Find all occurrences of pattern or regular expression in the Series/Index. Equivalent to `re.findall()`.

Parameters pat : string

Pattern or regular expression

flags : int, default 0 (no flags)

re module flags, e.g. `re.IGNORECASE`

Returns matches : Series/Index of lists

pandas.Series.str.get

`Series.str.get(i)`

Extract element from lists, tuples, or strings in each element in the Series/Index.

Parameters i : int

Integer index (location)

Returns items : Series/Index of objects

pandas.Series.str.index

`Series.str.index(sub, start=0, end=None)`

Return lowest indexes in each strings where the substring is fully contained between [start:end]. This is the same as `str.find` except instead of returning -1, it raises a `ValueError` when the substring is not found. Equivalent to standard `str.index`.

Parameters sub : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns found : Series/Index of objects

See also:

rindex Return highest indexes in each strings

pandas.Series.str.join

`Series.str.join(sep)`

Join lists contained as elements in the Series/Index with passed delimiter. Equivalent to `str.join()`.

Parameters `sep` : string

Delimiter

Returns `joined` : Series/Index of objects

pandas.Series.str.len

`Series.str.len()`

Compute length of each string in the Series/Index.

Returns `lengths` : Series/Index of integer values

pandas.Series.str.ljust

`Series.str.ljust(width, fillchar=' ')`

Filling right side of strings in the Series/Index with an additional character. Equivalent to `str.right()`.

Parameters `width` : int

Minimum width of resulting string; additional characters will be filled with
`fillchar`

fillchar : str

Additional character for filling, default is whitespace

Returns `filled` : Series/Index of objects

pandas.Series.str.lower

`Series.str.lower()`

Convert strings in the Series/Index to lowercase. Equivalent to `str.lower()`.

Returns `converted` : Series/Index of objects

pandas.Series.str.lstrip

`Series.str.lstrip(to_strip=None)`

Strip whitespace (including newlines) from each string in the Series/Index from left side. Equivalent to `str.lstrip()`.

Returns `stripped` : Series/Index of objects

pandas.Series.str.match

`Series.str.match(pat, case=True, flags=0, na=nan, as_indexer=False)`

Deprecated: Find groups in each string in the Series/Index using passed regular expression. If `as_indexer=True`, determine if each string matches a regular expression.

Parameters `pat` : string

Character sequence or regular expression

case : boolean, default True

If True, case sensitive

flags : int, default 0 (no flags)

re module flags, e.g. re.IGNORECASE

na : default NaN, fill value for missing values.

as_indexer : False, by default, gives deprecated behavior better achieved
using str_extract. True return boolean indexer.

Returns Series/array of boolean values

if as_indexer=True

Series/Index of tuples

if as_indexer=False, default but deprecated

See also:

contains analogous, but less strict, relying on re.search instead of re.match

extract now preferred to the deprecated usage of match (as_indexer=False)

Notes

To extract matched groups, which is the deprecated behavior of match, use str.extract.

pandas.Series.str.normalize

`Series.str.normalize(form)`

Return the Unicode normal form for the strings in the Series/Index. For more information on the forms, see the `unicodedata.normalize()`.

Parameters form : {'NFC', 'NFKC', 'NFD', 'NFKD'}

Unicode form

Returns normalized : Series/Index of objects

pandas.Series.str.pad

`Series.str.pad(width, side='left', fillchar=' ')`

Pad strings in the Series/Index with an additional character to specified side.

Parameters width : int

Minimum width of resulting string; additional characters will be filled with spaces

side : {'left', 'right', 'both'}, default 'left'

fillchar : str

Additional character for filling, default is whitespace

Returns padded : Series/Index of objects

pandas.Series.str.partition`Series.str.partition` (*pat*=' ', *expand*=True)

Split the string at the first occurrence of *sep*, and return 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing the string itself, followed by two empty strings.

Parameters *pat* : string, default whitespace

String to split on.

expand : bool, default True

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

Returns *split* : DataFrame/MultiIndex or Series/Index of objects

See also:

`rpartition` Split the string at the last occurrence of *sep*

Examples

```
>>> s = Series(['A_B_C', 'D_E_F', 'X'])
0    A_B_C
1    D_E_F
2         X
dtype: object

>>> s.str.partition('_')
   0  1  2
0  A  _  B_C
1  D  _  E_F
2  X

>>> s.str.rpartition('_')
   0  1  2
0  A_B  _  C
1  D_E  _  F
2         X
```

pandas.Series.str.repeat`Series.str.repeat` (*repeats*)

Duplicate each string in the Series/Index by indicated number of times.

Parameters *repeats* : int or array

Same value for all (int) or different value per (array)

Returns *repeated* : Series/Index of objects

pandas.Series.str.replace

`Series.str.replace(pat, repl, n=-1, case=True, flags=0)`

Replace occurrences of pattern/regex in the Series/Index with some other string. Equivalent to `str.replace()` or `re.sub()`.

Parameters `pat` : string

Character sequence or regular expression

repl : string

Replacement sequence

n : int, default -1 (all)

Number of replacements to make from start

case : boolean, default True

If True, case sensitive

flags : int, default 0 (no flags)

re module flags, e.g. `re.IGNORECASE`

Returns `replaced` : Series/Index of objects

pandas.Series.str.rfind

`Series.str.rfind(sub, start=0, end=None)`

Return highest indexes in each strings in the Series/Index where the substring is fully contained between [start:end]. Return -1 on failure. Equivalent to standard `str.rfind()`.

Parameters `sub` : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns `found` : Series/Index of integer values

See also:

[find](#) Return lowest indexes in each strings

pandas.Series.str.rindex

`Series.str.rindex(sub, start=0, end=None)`

Return highest indexes in each strings where the substring is fully contained between [start:end]. This is the same as `str.rfind` except instead of returning -1, it raises a `ValueError` when the substring is not found. Equivalent to standard `str.rindex`.

Parameters `sub` : str

Substring being searched

start : int

Left edge index

end : int

Right edge index

Returns found : Series/Index of objects**See also:****index** Return lowest indexes in each strings

pandas.Series.str.rjust

`Series.str.rjust` (*width*, *fillchar*= ' ') Filling left side of strings in the Series/Index with an additional character. Equivalent to `str.left()`.**Parameters width** : intMinimum width of resulting string; additional characters will be filled with *fillchar***fillchar** : str

Additional character for filling, default is whitespace

Returns filled : Series/Index of objects

pandas.Series.str.rpartition

`Series.str.rpartition` (*pat*= ' ', *expand*=True) Split the string at the last occurrence of *sep*, and return 3 elements containing the part before the separator, the separator itself, and the part after the separator. If the separator is not found, return 3 elements containing two empty strings, followed by the string itself.**Parameters pat** : string, default whitespace

String to split on.

expand : bool, default True

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

Returns split : DataFrame/MultiIndex or Series/Index of objects**See also:****partition** Split the string at the first occurrence of *sep*

Examples

```
>>> s = Series(['A_B_C', 'D_E_F', 'X'])
0    A_B_C
1    D_E_F
2         X
dtype: object
```

```
>>> s.str.partition('_')
   0  1  2
0  A  _  B_C
1  D  _  E_F
2  X

>>> s.str.rpartition('_')
   0  1  2
0  A_B  _  C
1  D_E  _  F
2           X
```

pandas.Series.str.rstrip

Series.str.**rstrip** (*to_strip=None*)

Strip whitespace (including newlines) from each string in the Series/Index from right side. Equivalent to `str.rstrip()`.

Returns **stripped** : Series/Index of objects

pandas.Series.str.slice

Series.str.**slice** (*start=None, stop=None, step=None*)

Slice substrings from each element in the Series/Index

Parameters **start** : int or None

stop : int or None

step : int or None

Returns **sliced** : Series/Index of objects

pandas.Series.str.slice_replace

Series.str.**slice_replace** (*start=None, stop=None, repl=None*)

Replace a slice of each string in the Series/Index with another string.

Parameters **start** : int or None

stop : int or None

repl : str or None

String for replacement

Returns **replaced** : Series/Index of objects

pandas.Series.str.split

Series.str.**split** (**args, **kwargs*)

Split each string (a la `re.split`) in the Series/Index by given pattern, propagating NA values. Equivalent to `str.split()`.

Parameters **pat** : string, default None

String or regular expression to split on. If None, splits on whitespace

n : int, default -1 (all)

None, 0 and -1 will be interpreted as return all splits

expand : bool, default False

- If True, return DataFrame/MultiIndex expanding dimensionality.
- If False, return Series/Index.

return_type : deprecated, use *expand*

Returns **split** : Series/Index or DataFrame/MultiIndex of objects

pandas.Series.str.startswith

`Series.str.startswith(pat, na=nan)`

Return boolean Series/array indicating whether each string in the Series/Index starts with passed pattern. Equivalent to `str.startswith()`.

Parameters **pat** : string

Character sequence

na : bool, default NaN

Returns **startswith** : Series/array of boolean values

pandas.Series.str.strip

`Series.str.strip(to_strip=None)`

Strip whitespace (including newlines) from each string in the Series/Index from left and right sides. Equivalent to `str.strip()`.

Returns **stripped** : Series/Index of objects

pandas.Series.str.swapcase

`Series.str.swapcase()`

Convert strings in the Series/Index to be swapcased. Equivalent to `str.swapcase()`.

Returns **converted** : Series/Index of objects

pandas.Series.str.title

`Series.str.title()`

Convert strings in the Series/Index to titlecase. Equivalent to `str.title()`.

Returns **converted** : Series/Index of objects

pandas.Series.str.translate

`Series.str.translate(table, deletechars=None)`

Map all characters in the string through the given mapping table. Equivalent to standard `str.translate()`. Note that the optional argument `deletechars` is only valid if you are using python 2. For python 3, character deletion should be specified via the `table` argument.

Parameters `table` : dict (python 3), str or None (python 2)

In python 3, `table` is a mapping of Unicode ordinals to Unicode ordinals, strings, or None. Unmapped characters are left untouched. Characters mapped to None are deleted. `str.maketrans()` is a helper function for making translation tables. In python 2, `table` is either a string of length 256 or None. If the `table` argument is None, no translation is applied and the operation simply removes the characters in `deletechars`. `string.maketrans()` is a helper function for making translation tables.

deletechars : str, optional (python 2)

A string of characters to delete. This argument is only valid in python 2.

Returns `translated` : Series/Index of objects

pandas.Series.str.upper

`Series.str.upper()`

Convert strings in the Series/Index to uppercase. Equivalent to `str.upper()`.

Returns `converted` : Series/Index of objects

pandas.Series.str.wrap

`Series.str.wrap(width, **kwargs)`

Wrap long strings in the Series/Index to be formatted in paragraphs with length less than a given width.

This method has the same keyword parameters and defaults as `textwrap.TextWrapper`.

Parameters `width` : int

Maximum line-width

expand_tabs : bool, optional

If true, tab characters will be expanded to spaces (default: True)

replace_whitespace : bool, optional

If true, each whitespace character (as defined by `string.whitespace`) remaining after tab expansion will be replaced by a single space (default: True)

drop_whitespace : bool, optional

If true, whitespace that, after wrapping, happens to end up at the beginning or end of a line is dropped (default: True)

break_long_words : bool, optional

If true, then words longer than width will be broken in order to ensure that no lines are longer than width. If it is false, long words will not be broken, and some lines may be longer than width. (default: True)

break_on_hyphens : bool, optional

If true, wrapping will occur preferably on whitespace and right after hyphens in compound words, as it is customary in English. If false, only whitespaces will be considered as potentially good places for line breaks, but you need to set `break_long_words` to false if you want truly insecable words. (default: True)

Returns `wrapped` : Series/Index of objects

Notes

Internally, this method uses a `textwrap.TextWrapper` instance with default settings. To achieve behavior matching R's stringr library `str_wrap` function, use the arguments:

- `expand_tabs = False`
- `replace_whitespace = True`
- `drop_whitespace = True`
- `break_long_words = False`
- `break_on_hyphens = False`

Examples

```
>>> s = pd.Series(['line to be wrapped', 'another line to be wrapped'])
>>> s.str.wrap(12)
0          line to be\nwrapped
1  another line\nto be\nwrapped
```

pandas.Series.str.zfill

`Series.str.zfill (width)`

” Filling left side of strings in the Series/Index with 0. Equivalent to `str.zfill()`.

Parameters `width` : int

Minimum width of resulting string; additional characters will be filled with 0

Returns `filled` : Series/Index of objects

pandas.Series.str.isalnum

`Series.str.isalnum()`

Check whether all characters in each string in the Series/Index are alphanumeric. Equivalent to `str.isalnum()`.

Returns `is` : Series/array of boolean values

pandas.Series.str.isalpha

`Series.str.isalpha()`

Check whether all characters in each string in the Series/Index are alphabetic. Equivalent to `str.isalpha()`.

Returns `is` : Series/array of boolean values

pandas.Series.str.isdigit

`Series.str.isdigit()`

Check whether all characters in each string in the Series/Index are digits. Equivalent to `str.isdigit()`.

Returns `is` : Series/array of boolean values

pandas.Series.str.isspace

`Series.str.isspace()`

Check whether all characters in each string in the Series/Index are whitespace. Equivalent to `str.isspace()`.

Returns is : Series/array of boolean values

pandas.Series.str.islower

`Series.str.islower()`

Check whether all characters in each string in the Series/Index are lowercase. Equivalent to `str.islower()`.

Returns is : Series/array of boolean values

pandas.Series.str.isupper

`Series.str.isupper()`

Check whether all characters in each string in the Series/Index are uppercase. Equivalent to `str.isupper()`.

Returns is : Series/array of boolean values

pandas.Series.str.istitle

`Series.str.istitle()`

Check whether all characters in each string in the Series/Index are titlecase. Equivalent to `str.istitle()`.

Returns is : Series/array of boolean values

pandas.Series.str.isnumeric

`Series.str.isnumeric()`

Check whether all characters in each string in the Series/Index are numeric. Equivalent to `str.isnumeric()`.

Returns is : Series/array of boolean values

pandas.Series.str.isdecimal

`Series.str.isdecimal()`

Check whether all characters in each string in the Series/Index are decimal. Equivalent to `str.isdecimal()`.

Returns is : Series/array of boolean values

pandas.Series.str.get_dummies

`Series.str.get_dummies(sep='|')`

Split each string in the Series by sep and return a frame of dummy/indicator variables.

Parameters sep : string, default “|”

String to split on.

Returns dummies : DataFrame

See also:`pandas.get_dummies`**Examples**

```
>>> Series(['a|b', 'a', 'a|c']).str.get_dummies()
   a  b  c
0  1  1  0
1  1  0  0
2  1  0  1

>>> Series(['a|b', np.nan, 'a|c']).str.get_dummies()
   a  b  c
0  1  1  0
1  0  0  0
2  1  0  1
```

33.3.15 Categorical

If the Series is of dtype category, `Series.cat` can be used to change the the categorical data. This accessor is similar to the `Series.dt` or `Series.str` and has the following usable methods and properties:

<code>Series.cat.categories</code>	The categories of this categorical.
<code>Series.cat.ordered</code>	Gets the ordered attribute
<code>Series.cat.codes</code>	

pandas.Series.cat.categories

Series.cat.categories

The categories of this categorical.

`Setting` assigns new values to each category (effectively a rename of each individual category).

The assigned value has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Assigning to *categories* is a inplace operation!

Raises ValueError

If the new categories do not validate as categories or if the number of new categories is unequal the number of old categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`, `set_categories`

pandas.Series.cat.ordered

Series.cat.ordered

Gets the ordered attribute

pandas.Series.cat.codes

Series.cat.codes

<code>Series.cat.rename_categories(*args, **kwargs)</code>	Renames categories.
<code>Series.cat.reorder_categories(*args, **kwargs)</code>	Reorders categories as specified in <code>new_categories</code> .
<code>Series.cat.add_categories(*args, **kwargs)</code>	Add new categories.
<code>Series.cat.remove_categories(*args, **kwargs)</code>	Removes the specified categories.
<code>Series.cat.remove_unused_categories(*args, ...)</code>	Removes categories which are not used.
<code>Series.cat.set_categories(*args, **kwargs)</code>	Sets the categories to the specified <code>new_categories</code> .
<code>Series.cat.as_ordered(*args, **kwargs)</code>	Sets the Categorical to be ordered
<code>Series.cat.as_unordered(*args, **kwargs)</code>	Sets the Categorical to be unordered

pandas.Series.cat.rename_categories

`Series.cat.rename_categories(*args, **kwargs)`

Renames categories.

The new categories has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Parameters `new_categories` : Index-like

The renamed categories.

inplace : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns `cat` : Categorical with renamed categories added or None if inplace.

Raises `ValueError`

If the new categories do not have the same number of items than the current categories or do not validate as categories

See also:

`reorder_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.Series.cat.reorder_categories

`Series.cat.reorder_categories(*args, **kwargs)`

Reorders categories as specified in `new_categories`.

`new_categories` need to include all old categories and no new category items.

Parameters `new_categories` : Index-like

The categories in new order.

ordered : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns `cat` : Categorical with reordered categories or None if inplace.

Raises `ValueError`

If the new categories do not contain all old category items or any new ones

See also:

`rename_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.Series.cat.add_categories

`Series.cat.add_categories(*args, **kwargs)`

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

Parameters `new_categories` : category or list-like of category

The new categories to be included.

inplace : boolean (default: False)

Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns `cat` : Categorical with new categories added or None if inplace.

Raises `ValueError`

If the new categories include old categories or do not validate as categories

See also:

`rename_categories`, `reorder_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.Series.cat.remove_categories

`Series.cat.remove_categories(*args, **kwargs)`

Removes the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters `removals` : category or list of categories

The categories which should be removed.

inplace : boolean (default: False)

Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns `cat` : Categorical with removed categories or None if inplace.

Raises `ValueError`

If the removals are not contained in the categories

See also:

`rename_categories,` `reorder_categories,` `add_categories,`
`remove_unused_categories,` `set_categories`

pandas.Series.cat.remove_unused_categories

`Series.cat.remove_unused_categories(*args, **kwargs)`

Removes categories which are not used.

Parameters `inplace` : boolean (default: False)

Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns `cat` : Categorical with unused categories dropped or None if inplace.

See also:

`rename_categories,` `reorder_categories,` `add_categories,` `remove_categories,`
`set_categories`

pandas.Series.cat.set_categories

`Series.cat.set_categories(*args, **kwargs)`

Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes on python3, which does not considers a S1 string equal to a single char python string.

Parameters `new_categories` : Index-like

The categories in new order.

ordered : boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename : boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns `cat` : Categorical with reordered categories or None if inplace.

Raises `ValueError`

If new_categories does not validate as categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`

pandas.Series.cat.as_ordered

`Series.cat.as_ordered(*args, **kwargs)`

Sets the Categorical to be ordered

Parameters inplace : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.Series.cat.as_unordered

`Series.cat.as_unordered(*args, **kwargs)`

Sets the Categorical to be unordered

Parameters inplace : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

To create a Series of dtype `category`, use `cat = s.astype("category")`.

The following two `Categorical` constructors are considered API but should only be used when adding ordering information or special categories is need at creation time of the categorical data:

<code>Categorical(values[, categories, ordered, ...])</code>	Represents a categorical variable in classic R / S-plus fashion
--	---

pandas.Categorical

class `pandas.Categorical` (*values*, *categories=None*, *ordered=False*, *name=None*, *fastpath=False*, *levels=None*)

Represents a categorical variable in classic R / S-plus fashion

Categoricals can only take on only a limited, and usually fixed, number of possible values (*categories*). In contrast to statistical categorical variables, a *Categorical* might have an order, but numerical operations (additions, divisions, ...) are not possible.

All values of the *Categorical* are either in *categories* or *np.nan*. Assigning values outside of *categories* will raise a *ValueError*. Order is defined by the order of the *categories*, not lexical order of the values.

Parameters values : list-like

The values of the categorical. If categories are given, values not in categories will be replaced with NaN.

categories : Index-like (unique), optional

The unique categories for this categorical. If not given, the categories are assumed to be the unique values of values.

ordered : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will not be ordered.

name : str, optional

Name for the Categorical variable. If name is None, will attempt to infer from values.

Raises ValueError

If the categories do not validate.

TypeError

If an explicit `ordered=True` is given but no *categories* and the *values* are not sortable.

Examples

```
>>> from pandas import Categorical
>>> Categorical([1, 2, 3, 1, 2, 3])
[1, 2, 3, 1, 2, 3]
Categories (3, int64): [1 < 2 < 3]

>>> Categorical(['a', 'b', 'c', 'a', 'b', 'c'])
[a, b, c, a, b, c]
Categories (3, object): [a < b < c]

>>> a = Categorical(['a', 'b', 'c', 'a', 'b', 'c'], ['c', 'b', 'a'])
>>> a.min()
'c'
```

Attributes

<code>categories</code>	The categories of this categorical.
<code>codes</code>	The category codes of this categorical.
<code>ordered</code>	Gets the ordered attribute

<code>name</code>	(string) The name of this Categorical.
-------------------	--

Methods

<code>add_categories(new_categories[, inplace])</code>	Add new categories.
<code>argsort([ascending])</code>	Implements ndarray.argsort.
<code>as_ordered([inplace])</code>	Sets the Categorical to be ordered
<code>as_unordered([inplace])</code>	Sets the Categorical to be unordered
<code>astype(dtype)</code>	coerce this type to another dtype
<code>check_for_ordered(op)</code>	assert that we are ordered
<code>copy()</code>	Copy constructor.
<code>describe()</code>	Describes this Categorical
<code>dropna()</code>	Return the Categorical without null values.
<code>equals(other)</code>	Returns True if categorical arrays are equal.
<code>fillna(*args, **kwargs)</code>	Fill NA/NaN values using the specified method.
<code>from_array(data, **kwargs)</code>	Make a Categorical type from a single array-like object.
<code>from_codes(codes, categories[, ordered, name])</code>	Make a Categorical type from codes and categories arrays.

Continued on next page

Table 33.42 – continued from previous page

<code>get_values()</code>	Return the values.
<code>is_dtype_equal(other)</code>	Returns True if categoricals are the same dtype
<code>isnull()</code>	Detect missing values
<code>max([numeric_only])</code>	The maximum value of the object.
<code>min([numeric_only])</code>	The minimum value of the object.
<code>mode()</code>	Returns the mode(s) of the Categorical.
<code>notnull()</code>	Reverse of <code>isnull</code>
<code>order([inplace, ascending, na_position])</code>	Sorts the Category by category value returning a new Categorical by default.
<code>ravel([order])</code>	Return a flattened (numpy) array.
<code>remove_categories(removals[, inplace])</code>	Removes the specified categories.
<code>remove_unused_categories([inplace])</code>	Removes categories which are not used.
<code>rename_categories(new_categories[, inplace])</code>	Renames categories.
<code>reorder_categories(new_categories[, ...])</code>	Reorders categories as specified in <code>new_categories</code> .
<code>reshape(new_shape, **kwargs)</code>	compat with <code>.reshape</code>
<code>searchsorted(v[, side, sorter])</code>	Find indices where elements should be inserted to maintain order.
<code>set_categories(new_categories[, ordered, ...])</code>	Sets the categories to the specified <code>new_categories</code> .
<code>set_ordered(value[, inplace])</code>	Sets the ordered attribute to the boolean value
<code>sort([inplace, ascending, na_position])</code>	Sorts the Category inplace by category value.
<code>take(indexer[, allow_fill, fill_value])</code>	Take the codes by the indexer, fill with the <code>fill_value</code> .
<code>take_nd(indexer[, allow_fill, fill_value])</code>	Take the codes by the indexer, fill with the <code>fill_value</code> .
<code>to_dense()</code>	Return my ‘dense’ representation
<code>unique()</code>	Return the unique values.
<code>value_counts([dropna])</code>	Returns a Series containing counts of each category.
<code>view()</code>	Return a view of myself.

pandas.Categorical.from_codes

classmethod `Categorical.from_codes` (*codes, categories, ordered=False, name=None*)

Make a Categorical type from codes and categories arrays.

This constructor is useful if you already have codes and categories and so do not need the (computation intensive) factorization step, which is usually done on the constructor.

If your data does not follow this convention, please use the normal constructor.

Parameters **codes** : array-like, integers

An integer array, where each integer points to a category in `categories` or -1 for NaN

categories : index-like

The categories for the categorical. Items need to be unique.

ordered : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will be unordered.

name : str, optional

Name for the Categorical variable.

`Categorical.from_codes(codes, categories[, ...])` Make a Categorical type from codes and categories arrays.

pandas.Categorical.from_codes

classmethod `Categorical.from_codes` (*codes, categories, ordered=False, name=None*)

Make a Categorical type from codes and categories arrays.

This constructor is useful if you already have codes and categories and so do not need the (computation intensive) factorization step, which is usually done on the constructor.

If your data does not follow this convention, please use the normal constructor.

Parameters `codes` : array-like, integers

An integer array, where each integer points to a category in categories or -1 for NaN

categories : index-like

The categories for the categorical. Items need to be unique.

ordered : boolean, (default False)

Whether or not this categorical is treated as a ordered categorical. If not given, the resulting categorical will be unordered.

name : str, optional

Name for the Categorical variable.

`np.asarray(categorical)` works by implementing the array interface. Be aware, that this converts the Categorical back to a numpy array, so levels and order information is not preserved!

`Categorical.__array__([dtype])` The numpy array interface.

pandas.Categorical.__array__

`Categorical.__array__` (*dtype=None*)

The numpy array interface.

Returns `values` : numpy array

A numpy array of either the specified dtype or, if dtype==None (default), the same dtype as `categorical.categories.dtype`

33.3.16 Plotting

<code>Series.hist</code> ([by, ax, grid, xlabelsize, ...])	Draw histogram of the input series using matplotlib
<code>Series.plot</code> (data[, kind, ax, figsize, ...])	Make plots of Series using matplotlib / pylab.

pandas.Series.hist

`Series.hist` (*by=None, ax=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, figsize=None, bins=10, **kwargs*)

Draw histogram of the input series using matplotlib

Parameters `by` : object, optional

If passed, then used to form histograms for separate groups

ax : matplotlib axis object

If not passed, uses `gca()`

grid : boolean, default True
Whether to show axis grid lines

xlabelsize : int, default None
If specified changes the x-axis label size

xrot : float, default None
rotation of x axis labels

ylabelsize : int, default None
If specified changes the y-axis label size

yrot : float, default None
rotation of y axis labels

figsize : tuple, default None
figure size in inches by default

bins: integer, default 10
Number of histogram bins to be used

kwds : keywords
To be passed to the actual plotting function

Notes

See matplotlib documentation online for more on this

pandas.Series.plot

`Series.plot` (*data*, *kind*='line', *ax*=None, *figsize*=None, *use_index*=True, *title*=None, *grid*=None, *legend*=False, *style*=None, *logx*=False, *logy*=False, *loglog*=False, *xticks*=None, *yticks*=None, *xlim*=None, *ylim*=None, *rot*=None, *fontsize*=None, *colormap*=None, *table*=False, *yerr*=None, *xerr*=None, *label*=None, *secondary_y*=False, ***kwds*)
Make plots of Series using matplotlib / pylab.

Parameters *data* : Series

- kind** : str
- 'line' : line plot (default)
 - 'bar' : vertical bar plot
 - 'barh' : horizontal bar plot
 - 'hist' : histogram
 - 'box' : boxplot
 - 'kde' : Kernel Density Estimation plot
 - 'density' : same as 'kde'
 - 'area' : area plot

- ‘pie’ : pie plot

ax : matplotlib axes object

If not passed, uses gca()

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/‘reverse’

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for ‘scatter’ and ‘hexbin’ plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

label : label argument to provide to plot

secondary_y : boolean or sequence of ints, default False

If True then y-axis will be on the right

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend

kws : keywords

Options to pass to matplotlib plotting method

Returns **axes** : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

33.3.17 Serialization / IO / Conversion

<code>Series.from_csv(path[, sep, parse_dates, ...])</code>	Read delimited file into Series
<code>Series.to_pickle(path)</code>	Pickle (serialize) object to input file path
<code>Series.to_csv(path[, index, sep, na_rep, ...])</code>	Write Series to a comma-separated values (csv) file
<code>Series.to_dict()</code>	Convert Series to {label -> value} dict
<code>Series.to_frame([name])</code>	Convert Series to DataFrame
<code>Series.to_hdf(path_or_buf, key, **kwargs)</code>	activate the HDFStore
<code>Series.to_sql(name, con[, flavor, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>Series.to_msgpack([path_or_buf])</code>	msgpack (serialize) object to input file path
<code>Series.to_json([path_or_buf, orient, ...])</code>	Convert the object to a JSON string.
<code>Series.to_sparse([kind, fill_value])</code>	Convert Series to SparseSeries
<code>Series.to_dense()</code>	Return dense representation of NDFrame (as opposed to sparse)
<code>Series.to_string([buf, na_rep, ...])</code>	Render a string representation of the Series
<code>Series.to_clipboard([excel, sep])</code>	Attempt to write text representation of object to the system clipboard This can l

pandas.Series.from_csv

classmethod `Series.from_csv` (*path*, *sep*=', ', *parse_dates*=True, *header*=None, *index_col*=0, *encoding*=None, *infer_datetime_format*=False)

Read delimited file into Series

Parameters **path** : string file path or file handle / StringIO

sep : string, default ','

Field delimiter

parse_dates : boolean, default True

Parse dates. Different default from `read_table`

header : int, default 0

Row to use at header (skip prior rows)

index_col : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from `read_table`

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

infer_datetime_format: boolean, default False

If True and *parse_dates* is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

Returns **y** : Series

pandas.Series.to_pickle

Series.to_pickle (*path*)

Pickle (serialize) object to input file path

Parameters **path** : string

File path

pandas.Series.to_csv

Series.to_csv (*path*, *index*=True, *sep*=', ', *na_rep*='', *float_format*=None, *header*=False, *index_label*=None, *mode*='w', *nanRep*=None, *encoding*=None, *date_format*=None, *decimal*='.')

Write Series to a comma-separated values (csv) file

Parameters **path** : string file path or file handle / StringIO. If None is provided

the result is returned as a string.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

header : boolean, default False

Write out series name

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

mode : Python write mode, default 'w'

sep : character, default ','

Field delimiter for the output file.

encoding : string, optional

a string representing the encoding to use if the contents are non-ascii, for python versions prior to 3

date_format: string, default None

Format string for datetime objects.

decimal: string, default '.'

Character recognized as decimal separator. E.g. use ',' for European data

pandas.Series.to_dict

`Series.to_dict()`

Convert Series to {label -> value} dict

Returns `value_dict` : dict

pandas.Series.to_frame

`Series.to_frame(name=None)`

Convert Series to DataFrame

Parameters `name` : object, default None

The passed name should substitute for the series name (if it has one).

Returns `data_frame` : DataFrame

pandas.Series.to_hdf

`Series.to_hdf(path_or_buf, key, **kwargs)`

activate the HDFStore

Parameters `path_or_buf` : the path (string) or buffer to put the store

`key` : string

identifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to 'a', but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Series.to_sql

`Series.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.

- **replace**: If table exists, drop it, recreate it, and insert data.
- **append**: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Series.to_msgpack

`Series.to_msgpack(path_or_buf=None, **kwargs)`

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no compression)

pandas.Series.to_json

`Series.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=None)`

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters path_or_buf : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
 - default is 'index'
 - allowed values are: {'split', 'records', 'index'}
- DataFrame

- default is ‘columns’
- allowed values are: { ‘split’, ‘records’, ‘index’, ‘columns’, ‘values’ }
- The format of the JSON string
 - split : dict like {index -> [index], columns -> [columns], data -> [values]}
 - records : list like [{column -> value}, ... , {column -> value}]
 - index : dict like {index -> {column -> value}}
 - columns : dict like {column -> {index -> value}}
 - values : just the values array

date_format : { ‘epoch’, ‘iso’ }

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default ‘ms’ (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of ‘s’, ‘ms’, ‘us’, ‘ns’ for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Series.to_sparse

`Series.to_sparse(kind='block', fill_value=None)`

Convert Series to SparseSeries

Parameters **kind** : { ‘block’, ‘integer’ }

fill_value : float, defaults to NaN (missing)

Returns **sp** : SparseSeries

pandas.Series.to_dense

`Series.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.Series.to_string

`Series.to_string(buf=None, na_rep='NaN', float_format=None, header=True, length=False, dtype=False, name=False, max_rows=None)`

Render a string representation of the Series

Parameters **buf** : StringIO-like, optional

buffer to write to

na_rep : string, optional

string representation of NAN to use, default 'NaN'

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats default None

header: boolean, default True

Add the Series header (index name)

length : boolean, default False

Add the Series length

dtype : boolean, default False

Add the Series dtype

name : boolean, default False

Add the Series name if not None

max_rows : int, optional

Maximum number of rows to show before truncating. If None, show all.

Returns **formatted** : string (if not buffer passed)

pandas.Series.to_clipboard

`Series.to_clipboard(excel=None, sep=None, **kwargs)`

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters **excel** : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

33.3.18 Sparse methods

<code>SparseSeries.to_coo([row_levels, ...])</code>	Create a <code>scipy.sparse.coo_matrix</code> from a <code>SparseSeries</code> with <code>MultiIndex</code> .
<code>SparseSeries.from_coo(A[, dense_index])</code>	Create a <code>SparseSeries</code> from a <code>scipy.sparse.coo_matrix</code> .

pandas.SparseSeries.to_coo

`SparseSeries.to_coo(row_levels=(0, ), column_levels=(1, ), sort_labels=False)`

Create a `scipy.sparse.coo_matrix` from a `SparseSeries` with `MultiIndex`.

Use `row_levels` and `column_levels` to determine the row and column coordinates respectively. `row_levels` and `column_levels` are the names (labels) or numbers of the levels. `{row_levels, column_levels}` must be a partition of the `MultiIndex` level names (or numbers).

Parameters `row_levels` : tuple/list

`column_levels` : tuple/list

`sort_labels` : bool, default False

Sort the row and column labels before forming the sparse matrix.

Returns `y` : `scipy.sparse.coo_matrix`

`rows` : list (row labels)

`columns` : list (column labels)

Examples

```
>>> from numpy import nan
>>> s = Series([3.0, nan, 1.0, 3.0, nan, nan])
>>> s.index = MultiIndex.from_tuples([(1, 2, 'a', 0),
                                     (1, 2, 'a', 1),
                                     (1, 1, 'b', 0),
                                     (1, 1, 'b', 1),
                                     (2, 1, 'b', 0),
                                     (2, 1, 'b', 1)],
                                     names=['A', 'B', 'C', 'D'])

>>> ss = s.to_sparse()
>>> A, rows, columns = ss.to_coo(row_levels=['A', 'B'],
                                column_levels=['C', 'D'],
                                sort_labels=True)

>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'
  with 3 stored elements in COOrdinate format>
>>> A.todense()
matrix([[ 0.,  0.,  1.,  3.],
        [ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  0.,  0.]])
>>> rows
[(1, 1), (1, 2), (2, 1)]
>>> columns
[('a', 0), ('a', 1), ('b', 0), ('b', 1)]
```

pandas.SparseSeries.from_coo

`classmethod SparseSeries.from_coo(A, dense_index=False)`

Create a `SparseSeries` from a `scipy.sparse.coo_matrix`.

Parameters `A` : `scipy.sparse.coo_matrix`

`dense_index` : bool, default False

If False (default), the SparseSeries index consists of only the coords of the non-null entries of the original coo_matrix. If True, the SparseSeries index consists of the full sorted (row, col) coordinates of the coo_matrix.

Returns s : SparseSeries

Examples

```
>>> from scipy import sparse
>>> A = sparse.coo_matrix(([3.0, 1.0, 2.0], ([1, 0, 0], [0, 2, 3])),
                          shape=(3, 4))
>>> A
<3x4 sparse matrix of type '<class 'numpy.float64'>'
  with 3 stored elements in COOrdinate format>
>>> A.todense()
matrix([[ 0.,  0.,  1.,  2.],
        [ 3.,  0.,  0.,  0.],
        [ 0.,  0.,  0.,  0.]])
>>> ss = SparseSeries.from_coo(A)
>>> ss
0 2 1
 3 2
1 0 3
dtype: float64
BlockIndex
Block locations: array([0], dtype=int32)
Block lengths: array([3], dtype=int32)
```

33.4 DataFrame

33.4.1 Constructor

`DataFrame([data, index, columns, dtype, copy])` Two-dimensional size-mutable, potentially heterogeneous tabular data structure

pandas.DataFrame

class pandas.**DataFrame** (*data=None, index=None, columns=None, dtype=None, copy=False*)

Two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns). Arithmetic operations align on both row and column labels. Can be thought of as a dict-like container for Series objects. The primary pandas data structure

Parameters **data** : numpy ndarray (structured or homogeneous), dict, or DataFrame

Dict can contain Series, arrays, constants, or list-like objects

index : Index or array-like

Index to use for resulting frame. Will default to np.arange(n) if no indexing information part of input data and no index provided

columns : Index or array-like

Column labels to use for resulting frame. Will default to np.arange(n) if no column labels are provided

dtype : dtype, default None

Data type to force, otherwise infer

copy : boolean, default False

Copy data from inputs. Only affects DataFrame / 2d ndarray input

See also:

DataFrame.from_records constructor from tuples, also record arrays

DataFrame.from_dict from dicts of Series, arrays, or dicts

DataFrame.from_csv from CSV files

DataFrame.from_items from sequence of (key, value) pairs

`pandas.read_csv`, `pandas.read_table`, `pandas.read_clipboard`

Examples

```
>>> d = {'col1': ts1, 'col2': ts2}
>>> df = DataFrame(data=d, index=index)
>>> df2 = DataFrame(np.random.randn(10, 5))
>>> df3 = DataFrame(np.random.randn(10, 5),
...                 columns=['a', 'b', 'c', 'd', 'e'])
```

Attributes

<code>T</code>	Transpose index and columns
<code>at</code>	Fast label-based scalar accessor
<code>axes</code>	
<code>blocks</code>	Internal property, property synonym for <code>as_blocks()</code>
<code>dtypes</code>	Return the dtypes in this object
<code>empty</code>	True if NDFrame is entirely empty [no items]
<code>ftypes</code>	Return the ftypes (indication of sparse/dense and dtype) in this object.
<code>iat</code>	Fast integer location scalar accessor.
<code>iloc</code>	Purely integer-location based indexing for selection by position.
<code>ix</code>	A primarily label-location based indexer, with integer position fallback.
<code>loc</code>	Purely label-location based indexer for selection by label.
<code>ndim</code>	Number of axes / array dimensions
<code>shape</code>	
<code>size</code>	number of elements in the NDFrame
<code>values</code>	Numpy representation of NDFrame

pandas.DataFrame.T

`DataFrame.T`

Transpose index and columns

pandas.DataFrame.at

`DataFrame.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.DataFrame.axes

`DataFrame.axes`

pandas.DataFrame.blocks

`DataFrame.blocks`

Internal property, property synonym for `as_blocks()`

pandas.DataFrame.dtypes

`DataFrame.dtypes`

Return the dtypes in this object

pandas.DataFrame.empty

`DataFrame.empty`

True if NDFrame is entirely empty [no items]

pandas.DataFrame.ftypes

`DataFrame.ftypes`

Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.DataFrame.iat

`DataFrame.iat`

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.DataFrame.iloc

`DataFrame.iloc`

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.

- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at [Selection by Position](#)

pandas.DataFrame.ix

DataFrame.ix

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#).

pandas.DataFrame.loc

DataFrame.loc

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. `5` or `'a'`, (note that `5` is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. `['a', 'b', 'c']`.
- A slice object with labels, e.g. `'a':'f'` (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at [Selection by Label](#)

pandas.DataFrame.ndim

DataFrame.ndim

Number of axes / array dimensions

pandas.DataFrame.shape`DataFrame.shape`**pandas.DataFrame.size**`DataFrame.size`

number of elements in the NDFrame

pandas.DataFrame.values`DataFrame.values`

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

is_copy	
---------	--

Methods

<code>abs()</code>	Return an object with absolute value taken.
<code>add(other[, axis, level, fill_value])</code>	Binary operator add with support to substitute a fill_value for missing data in
<code>add_prefix(prefix)</code>	Concatenate prefix string with panel items names.
<code>add_suffix(suffix)</code>	Concatenate suffix string with panel items names
<code>align(other[, join, axis, level, copy, ...])</code>	Align two object on their axes with the
<code>all([axis, bool_only, skipna, level])</code>	Return whether all elements are True over requested axis
<code>any([axis, bool_only, skipna, level])</code>	Return whether any element is True over requested axis
<code>append(other[, ignore_index, verify_integrity])</code>	Append rows of <i>other</i> to the end of this frame, returning a new object.
<code>apply(func[, axis, broadcast, raw, reduce, args])</code>	Applies function along input axis of DataFrame.
<code>applymap(func)</code>	Apply a function to a DataFrame that is intended to operate elementwise, i.e.
<code>as_blocks()</code>	Convert the frame to a dict of dtype -> Constructor Types that each has a homo
<code>as_matrix([columns])</code>	Convert the frame to its Numpy-array representation.
<code>asfreq(freq[, method, how, normalize])</code>	Convert all TimeSeries inside to specified frequency using DateOffset objects.
<code>assign(**kwargs)</code>	Assign new columns to a DataFrame, returning a new object (a copy) with all t
<code>astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>at_time(time[, asof])</code>	Select values at particular time of day (e.g.
<code>between_time(start_time, end_time[, ...])</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM)
<code>bfill([axis, inplace, limit, downcast])</code>	Synonym for NDFrame.fillna(method='bfill')
<code>bool()</code>	Return the bool of a single element PandasObject
<code>boxplot([column, by, ax, fontsize, rot, ...])</code>	Make a box plot from DataFrame column optionally grouped by some columns
<code>clip([lower, upper, out, axis])</code>	Trim values at input threshold(s)
<code>clip_lower(threshold[, axis])</code>	Return copy of the input with values below given value(s) truncated

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<code>clip_upper(threshold[, axis])</code>	Return copy of input with values above given value(s) truncated
<code>combine(other, func[, fill_value, overwrite])</code>	Add two DataFrame objects and do not propagate NaN values, so if for a
<code>combineAdd(other)</code>	Add two DataFrame objects and do not propagate
<code>combineMult(other)</code>	Multiply two DataFrame objects and do not propagate NaN values, so if
<code>combine_first(other)</code>	Combine two DataFrame objects and default to non-null values in frame calling
<code>compound([axis, skipna, level])</code>	Return the compound percentage of the values for the requested axis
<code>consolidate([inplace])</code>	Compute NDFrame with “consolidated” internals (data of each dtype grouped)
<code>convert_objects([convert_dates, ...])</code>	Attempt to infer better dtype for object columns
<code>copy([deep])</code>	Make a copy of this object
<code>corr([method, min_periods])</code>	Compute pairwise correlation of columns, excluding NA/null values
<code>corrwith(other[, axis, drop])</code>	Compute pairwise correlation between rows or columns of two DataFrame obj
<code>count([axis, level, numeric_only])</code>	Return Series with number of non-NA/null observations over requested axis.
<code>cov([min_periods])</code>	Compute pairwise covariance of columns, excluding NA/null values
<code>cummax([axis, dtype, out, skipna])</code>	Return cumulative max over requested axis.
<code>cummin([axis, dtype, out, skipna])</code>	Return cumulative min over requested axis.
<code>cumprod([axis, dtype, out, skipna])</code>	Return cumulative prod over requested axis.
<code>cumsum([axis, dtype, out, skipna])</code>	Return cumulative sum over requested axis.
<code>describe([percentile_width, percentiles, ...])</code>	Generate various summary statistics, excluding NaN values.
<code>diff([periods, axis])</code>	1st discrete difference of object
<code>div(other[, axis, level, fill_value])</code>	Binary operator truediv with support to substitute a fill_value for missing data i
<code>divide(other[, axis, level, fill_value])</code>	Binary operator truediv with support to substitute a fill_value for missing data i
<code>dot(other)</code>	Matrix multiplication with DataFrame or Series objects
<code>drop(labels[, axis, level, inplace, errors])</code>	Return new object with labels in requested axis removed
<code>drop_duplicates(*args, **kwargs)</code>	Return DataFrame with duplicate rows removed, optionally only
<code>dropna([axis, how, thresh, subset, inplace])</code>	Return object with labels on given axis omitted where alternately any
<code>duplicated(*args, **kwargs)</code>	Return boolean Series denoting duplicate rows, optionally only
<code>eq(other[, axis, level])</code>	Wrapper for flexible comparison methods eq
<code>equals(other)</code>	Determines if two NDFrame objects contain the same elements.
<code>eval(expr, **kwargs)</code>	Evaluate an expression in the context of the calling DataFrame instance.
<code>ffill([axis, inplace, limit, downcast])</code>	Synonym for NDFrame.fillna(method='ffill')
<code>fillna([value, method, axis, inplace, ...])</code>	Fill NA/NaN values using the specified method
<code>filter([items, like, regex, axis])</code>	Restrict the info axis to set of items or wildcard
<code>first(offset)</code>	Convenience method for subsetting initial periods of time series data
<code>first_valid_index()</code>	Return label for first non-NA/null value
<code>floordiv(other[, axis, level, fill_value])</code>	Binary operator floordiv with support to substitute a fill_value for missing data
<code>from_csv(path[, header, sep, index_col, ...])</code>	Read delimited file into DataFrame
<code>from_dict(data[, orient, dtype])</code>	Construct DataFrame from dict of array-like or dicts
<code>from_items(items[, columns, orient])</code>	Convert (key, value) pairs to DataFrame.
<code>from_records(data[, index, exclude, ...])</code>	Convert structured or record ndarray to DataFrame
<code>ge(other[, axis, level])</code>	Wrapper for flexible comparison methods ge
<code>get(key[, default])</code>	Get item from object for given key (DataFrame column, Panel slice, etc.).
<code>get_dtype_counts()</code>	Return the counts of dtypes in this object
<code>get_ftype_counts()</code>	Return the counts of ftypes in this object
<code>get_value(index, col[, takeable])</code>	Quickly retrieve single value at passed column and index
<code>get_values()</code>	same as values (but handles sparseness conversions)
<code>groupby([by, axis, level, as_index, sort, ...])</code>	Group series using mapper (dict or key function, apply given function
<code>gt(other[, axis, level])</code>	Wrapper for flexible comparison methods gt
<code>head([n])</code>	Returns first n rows
<code>hist(data[, column, by, grid, xlabelsize, ...])</code>	Draw histogram of the DataFrame’s series using matplotlib / pylab.
<code>icol(i)</code>	
<code>idxmax([axis, skipna])</code>	Return index of first occurrence of maximum over requested axis.
<code>idxmin([axis, skipna])</code>	Return index of first occurrence of minimum over requested axis.

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<code>iget_value(i, j)</code>	
<code>info([verbose, buf, max_cols, memory_usage, ...])</code>	Concise summary of a DataFrame.
<code>insert(loc, column, value[, allow_duplicates])</code>	Insert column into DataFrame at specified location.
<code>interpolate([method, axis, limit, inplace, ...])</code>	Interpolate values according to different methods.
<code>irow(i[, copy])</code>	
<code>isin(values)</code>	Return boolean DataFrame showing whether each element in the DataFrame is
<code>isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>iteritems()</code>	Iterator over (column, series) pairs
<code>iterkv(*args, **kwargs)</code>	iteritems alias used to get around 2to3. Deprecated
<code>iterrows()</code>	Iterate over rows of DataFrame as (index, Series) pairs.
<code>itertuples([index])</code>	Iterate over rows of DataFrame as tuples, with index value
<code>join(other[, on, how, lsuffix, rsuffix, sort])</code>	Join columns with other DataFrame either on index or on a key column.
<code>keys()</code>	Get the ‘info axis’ (see Indexing for more)
<code>kurt([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>kurtosis([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>last(offset)</code>	Convenience method for subsetting final periods of time series data
<code>last_valid_index()</code>	Return label for last non-NA/null value
<code>le(other[, axis, level])</code>	Wrapper for flexible comparison methods le
<code>load(path)</code>	Deprecated.
<code>lookup(row_labels, col_labels)</code>	Label-based “fancy indexing” function for DataFrame.
<code>lt(other[, axis, level])</code>	Wrapper for flexible comparison methods lt
<code>mad([axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis
<code>mask(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from
<code>max([axis, skipna, level, numeric_only])</code>	This method returns the maximum of the values in the object.
<code>mean([axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis
<code>median([axis, skipna, level, numeric_only])</code>	Return the median of the values for the requested axis
<code>memory_usage([index])</code>	Memory usage of DataFrame columns.
<code>merge(right[, how, on, left_on, right_on, ...])</code>	Merge DataFrame objects by performing a database-style join operation by col
<code>min([axis, skipna, level, numeric_only])</code>	This method returns the minimum of the values in the object.
<code>mod(other[, axis, level, fill_value])</code>	Binary operator mod with support to substitute a fill_value for missing data in
<code>mode([axis, numeric_only])</code>	Gets the mode(s) of each element along the axis selected.
<code>mul(other[, axis, level, fill_value])</code>	Binary operator mul with support to substitute a fill_value for missing data in
<code>multiply(other[, axis, level, fill_value])</code>	Binary operator mul with support to substitute a fill_value for missing data in
<code>ne(other[, axis, level])</code>	Wrapper for flexible comparison methods ne
<code>notnull()</code>	Return a boolean same-sized object indicating if the values are
<code>pct_change([periods, fill_method, limit, freq])</code>	Percent change over given number of periods.
<code>pivot([index, columns, values])</code>	Reshape data (produce a “pivot” table) based on column values.
<code>pivot_table(data[, values, index, columns, ...])</code>	Create a spreadsheet-style pivot table as a DataFrame.
<code>plot(data[, x, y, kind, ax, subplots, ...])</code>	Make plots of DataFrame using matplotlib / pylab.
<code>pop(item)</code>	Return item and drop from frame.
<code>pow(other[, axis, level, fill_value])</code>	Binary operator pow with support to substitute a fill_value for missing data in
<code>prod([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>product([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>quantile([q, axis, numeric_only])</code>	Return values at the given quantile over requested axis, a la numpy.percentile.
<code>query(expr, **kwargs)</code>	Query the columns of a frame with a boolean expression.
<code>radd(other[, axis, level, fill_value])</code>	Binary operator radd with support to substitute a fill_value for missing data in
<code>rank([axis, numeric_only, method, ...])</code>	Compute numerical data ranks (1 through n) along axis.
<code>rdiv(other[, axis, level, fill_value])</code>	Binary operator rtruediv with support to substitute a fill_value for missing data
<code>reindex([index, columns])</code>	Conform DataFrame to new index with optional filling logic, placing NA/NaN
<code>reindex_axis(labels[, axis, method, level, ...])</code>	Conform input object to new index with optional filling logic, placing NA/NaN
<code>reindex_like(other[, method, copy, limit])</code>	return an object with matching indicies to myself
<code>rename([index, columns])</code>	Alter axes input function or functions.

<code>rename_axis(mapper[, axis, copy, inplace])</code>	Alter index and / or columns using input function or functions.
<code>reorder_levels(order[, axis])</code>	Rearrange index levels using input order.
<code>replace([to_replace, value, inplace, limit, ...])</code>	Replace values given in ‘to_replace’ with ‘value’.
<code>resample(rule[, how, axis, fill_method, ...])</code>	Convenience method for frequency conversion and resampling of regular time-
<code>reset_index([level, drop, inplace, ...])</code>	For DataFrame with multi-level index, return new DataFrame with labeling info
<code>rfloordiv(other[, axis, level, fill_value])</code>	Binary operator rfloordiv with support to substitute a fill_value for missing data
<code>rmod(other[, axis, level, fill_value])</code>	Binary operator rmod with support to substitute a fill_value for missing data in
<code>rmul(other[, axis, level, fill_value])</code>	Binary operator rmul with support to substitute a fill_value for missing data in
<code>rpow(other[, axis, level, fill_value])</code>	Binary operator rpow with support to substitute a fill_value for missing data in
<code>rsub(other[, axis, level, fill_value])</code>	Binary operator rsub with support to substitute a fill_value for missing data in
<code>rtruediv(other[, axis, level, fill_value])</code>	Binary operator rtruediv with support to substitute a fill_value for missing data
<code>sample([n, frac, replace, weights, ...])</code>	Returns a random sample of items from an axis of object.
<code>save(path)</code>	Deprecated.
<code>select(crit[, axis])</code>	Return data corresponding to axis labels matching criteria
<code>select_dtypes([include, exclude])</code>	Return a subset of a DataFrame including/excluding columns based on their dt
<code>sem([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased standard error of the mean over requested axis.
<code>set_axis(axis, labels)</code>	public version of axis assignment
<code>set_index(keys[, drop, append, inplace, ...])</code>	Set the DataFrame index (row labels) using one or more existing columns.
<code>set_value(index, col, value[, takeable])</code>	Put single value at passed column and index
<code>shift([periods, freq, axis])</code>	Shift index by desired number of periods with an optional time freq
<code>skew([axis, skipna, level, numeric_only])</code>	Return unbiased skew over requested axis
<code>slice_shift([periods, axis])</code>	Equivalent to <i>shift</i> without copying data.
<code>sort([columns, axis, ascending, inplace, ...])</code>	Sort DataFrame either by labels (along either axis) or by the values in
<code>sort_index([axis, by, ascending, inplace, ...])</code>	Sort DataFrame either by labels (along either axis) or by the values in
<code>sortlevel([level, axis, ascending, inplace, ...])</code>	Sort multilevel index by chosen axis and primary level.
<code>squeeze()</code>	squeeze length 1 dimensions
<code>stack([level, dropna])</code>	Pivot a level of the (possibly hierarchical) column labels, returning a DataFram
<code>std([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased standard deviation over requested axis.
<code>sub(other[, axis, level, fill_value])</code>	Binary operator sub with support to substitute a fill_value for missing data in
<code>subtract(other[, axis, level, fill_value])</code>	Binary operator sub with support to substitute a fill_value for missing data in
<code>sum([axis, skipna, level, numeric_only])</code>	Return the sum of the values for the requested axis
<code>swapaxes(axis1, axis2[, copy])</code>	Interchange axes and swap values axes appropriately
<code>swaplevel(i, j[, axis])</code>	Swap levels i and j in a MultiIndex on a particular axis
<code>tail([n])</code>	Returns last n rows
<code>take(indices[, axis, convert, is_copy])</code>	Analogous to ndarray.take
<code>to_clipboard([excel, sep])</code>	Attempt to write text representation of object to the system clipboard This can
<code>to_csv([path_or_buf, sep, na_rep, ...])</code>	Write DataFrame to a comma-separated values (csv) file
<code>to_dense()</code>	Return dense representation of NDFrame (as opposed to sparse)
<code>to_dict(*args, **kwargs)</code>	Convert DataFrame to dictionary.
<code>to_excel(excel_writer[, sheet_name, na_rep, ...])</code>	Write DataFrame to a excel sheet
<code>to_gbq(destination_table[, project_id, ...])</code>	Write a DataFrame to a Google BigQuery table.
<code>to_hdf(path_or_buf, key, **kwargs)</code>	activate the HDFStore
<code>to_html([buf, columns, col_space, colSpace, ...])</code>	Render a DataFrame as an HTML table.
<code>to_json([path_or_buf, orient, date_format, ...])</code>	Convert the object to a JSON string.
<code>to_latex([buf, columns, col_space, ...])</code>	Render a DataFrame to a tabular environment table.
<code>to_msgpack([path_or_buf])</code>	msgpack (serialize) object to input file path
<code>to_panel()</code>	Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.
<code>to_period([freq, axis, copy])</code>	Convert DataFrame from DatetimeIndex to PeriodIndex with desired
<code>to_pickle(path)</code>	Pickle (serialize) object to input file path
<code>to_records([index, convert_datetime64])</code>	Convert DataFrame to record array.
<code>to_sparse([fill_value, kind])</code>	Convert to SparseDataFrame
<code>to_sql(name, con[, flavor, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.

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<code>to_stata(fname[, convert_dates, ...])</code>	A class for writing Stata binary dta files from array-like objects
<code>to_string([buf, columns, col_space, ...])</code>	Render a DataFrame to a console-friendly tabular output.
<code>to_timestamp([freq, how, axis, copy])</code>	Cast to DatetimeIndex of timestamps, at <i>beginning</i> of period
<code>to_wide(*args, **kwargs)</code>	
<code>transpose()</code>	Transpose index and columns
<code>truediv(other[, axis, level, fill_value])</code>	Binary operator truediv with support to substitute a fill_value for missing data
<code>truncate([before, after, axis, copy])</code>	Truncates a sorted NDFrame before and/or after some particular dates.
<code>tshift([periods, freq, axis])</code>	Shift the time index, using the index's frequency if available
<code>tz_convert(tz[, axis, level, copy])</code>	Convert tz-aware axis to target time zone.
<code>tz_localize(*args, **kwargs)</code>	Localize tz-naive TimeSeries to target time zone
<code>unstack([level])</code>	Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame
<code>update(other[, join, overwrite, ...])</code>	Modify DataFrame in place using non-NA values from passed DataFrame.
<code>var([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased variance over requested axis.
<code>where(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from other
<code>xs(key[, axis, level, copy, drop_level])</code>	Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.

pandas.DataFrame.abs`DataFrame.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller**pandas.DataFrame.add**`DataFrame.add(other, axis='columns', level=None, fill_value=None)`

Binary operator add with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant**axis** : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame**Notes**

Mismatched indices will be unioned together

pandas.DataFrame.add_prefix`DataFrame.add_prefix(prefix)`

Concatenate prefix string with panel items names.

Parameters `prefix` : string

Returns `with_prefix` : type of caller

pandas.DataFrame.add_suffix

`DataFrame.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters `suffix` : string

Returns `with_suffix` : type of caller

pandas.DataFrame.align

`DataFrame.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0)`

Align two object on their axes with the specified join method for each axis Index

Parameters `other` : DataFrame or Series

join : { 'outer', 'inner', 'left', 'right' }, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns (`left`, `right`) : (type of input, type of other)

Aligned objects

pandas.DataFrame.all

`DataFrame.all(axis=None, bool_only=None, skipna=None, level=None, **kwargs)`

Return whether all elements are True over requested axis

Parameters `axis` : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns all : Series or DataFrame (if level specified)

pandas.DataFrame.any

`DataFrame.any` (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether any element is True over requested axis

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns any : Series or DataFrame (if level specified)

pandas.DataFrame.append

`DataFrame.append` (*other, ignore_index=False, verify_integrity=False*)

Append rows of *other* to the end of this frame, returning a new object. Columns not in this frame are added as new columns.

Parameters other : DataFrame or Series/dict-like object, or list of these

The data to append.

ignore_index : boolean, default False

If True, do not use the index labels.

verify_integrity : boolean, default False

If True, raise ValueError on creating index with duplicates.

Returns appended : DataFrame

See also:

[`pandas.concat`](#) General function to concatenate DataFrame, Series or Panel objects

Notes

If a list of dict/series is passed and the keys are all contained in the DataFrame's index, the order of the columns in the resulting DataFrame will be unchanged.

Examples

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=list('AB'))
>>> df
   A  B
0  1  2
1  3  4
>>> df2 = pd.DataFrame([[5, 6], [7, 8]], columns=list('AB'))
>>> df.append(df2)
   A  B
0  1  2
1  3  4
0  5  6
1  7  8
```

With *ignore_index* set to True:

```
>>> df.append(df2, ignore_index=True)
   A  B
0  1  2
1  3  4
2  5  6
3  7  8
```

pandas.DataFrame.apply

`DataFrame.apply(func, axis=0, broadcast=False, raw=False, reduce=None, args=(), **kwargs)`

Applies function along input axis of DataFrame.

Objects passed to functions are Series objects having index either the DataFrame's index (*axis=0*) or the columns (*axis=1*). Return type depends on whether passed function aggregates, or the *reduce* argument if the DataFrame is empty.

Parameters *func* : function

Function to apply to each column/row

axis : {0, 1}

- 0 : apply function to each column
- 1 : apply function to each row

broadcast : boolean, default False

For aggregation functions, return object of same size with values propagated

reduce : boolean or None, default None

Try to apply reduction procedures. If the DataFrame is empty, *apply* will use *reduce* to determine whether the result should be a Series or a DataFrame. If *reduce* is None (the default), *apply*'s return value will be guessed by calling *func* an empty Series (note: while guessing, exceptions raised by *func* will be ignored).

If `reduce` is `True` a `Series` will always be returned, and if `False` a `DataFrame` will always be returned.

raw : boolean, default `False`

If `False`, convert each row or column into a `Series`. If `raw=True` the passed function will receive `ndarray` objects instead. If you are just applying a NumPy reduction function this will achieve much better performance

args : tuple

Positional arguments to pass to function in addition to the array/series

Additional keyword arguments will be passed as keywords to the function

Returns **applied** : `Series` or `DataFrame`

See also:

`DataFrame.applymap` For elementwise operations

Notes

In the current implementation `apply` calls `func` twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if `func` has side-effects, as they will take effect twice for the first column/row.

Examples

```
>>> df.apply(numpy.sqrt) # returns DataFrame
>>> df.apply(numpy.sum, axis=0) # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1) # equiv to df.sum(1)
```

pandas.DataFrame.applymap

`DataFrame.applymap(func)`

Apply a function to a `DataFrame` that is intended to operate elementwise, i.e. like doing `map(func, series)` for each series in the `DataFrame`

Parameters **func** : function

Python function, returns a single value from a single value

Returns **applied** : `DataFrame`

See also:

`DataFrame.apply` For operations on rows/columns

pandas.DataFrame.as_blocks

`DataFrame.as_blocks()`

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in `as_matrix`)

Returns values : a dict of dtype -> Constructor Types

`pandas.DataFrame.as_matrix`

`DataFrame.as_matrix (columns=None)`

Convert the frame to its Numpy-array representation.

Parameters columns: list, optional, default:None

If None, return all columns, otherwise, returns specified columns.

Returns values : ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

See also:

`pandas.DataFrame.values`

Notes

Return is NOT a Numpy-matrix, rather, a Numpy-array.

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use `‘.values’`.

`pandas.DataFrame.asfreq`

`DataFrame.asfreq (freq, method=None, how=None, normalize=False)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters freq : DateOffset object, or string

method : {‘backfill’, ‘bfill’, ‘pad’, ‘ffill’, None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {‘start’, ‘end’}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns converted : type of caller

pandas.DataFrame.assign`DataFrame.assign(**kwargs)`

Assign new columns to a DataFrame, returning a new object (a copy) with all the original columns in addition to the new ones.

New in version 0.16.0.

Parameters `kwargs` : keyword, value pairs

keywords are the column names. If the values are callable, they are computed on the DataFrame and assigned to the new columns. If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

Returns `df` : DataFrame

A new DataFrame with the new columns in addition to all the existing columns.

Notes

Since `kwargs` is a dictionary, the order of your arguments may not be preserved. The make things predicatable, the columns are inserted in alphabetical order, at the end of your DataFrame. Assigning multiple columns within the same `assign` is possible, but you cannot reference other columns created within the same `assign` call.

Examples

```
>>> df = DataFrame({'A': range(1, 11), 'B': np.random.randn(10)})
```

Where the value is a callable, evaluated on `df`:

```
>>> df.assign(ln_A = lambda x: np.log(x.A))
   A      B      ln_A
0  1  0.426905  0.000000
1  2 -0.780949  0.693147
2  3 -0.418711  1.098612
3  4 -0.269708  1.386294
4  5 -0.274002  1.609438
5  6 -0.500792  1.791759
6  7  1.649697  1.945910
7  8 -1.495604  2.079442
8  9  0.549296  2.197225
9 10 -0.758542  2.302585
```

Where the value already exists and is inserted:

```
>>> newcol = np.log(df['A'])
>>> df.assign(ln_A=newcol)
   A      B      ln_A
0  1  0.426905  0.000000
1  2 -0.780949  0.693147
2  3 -0.418711  1.098612
3  4 -0.269708  1.386294
4  5 -0.274002  1.609438
5  6 -0.500792  1.791759
6  7  1.649697  1.945910
7  8 -1.495604  2.079442
```

```
8    9    0.549296    2.197225
9   10   -0.758542    2.302585
```

pandas.DataFrame.astype

`DataFrame.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters dtype : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns casted : type of caller

pandas.DataFrame.at_time

`DataFrame.at_time(time, asof=False)`

Select values at particular time of day (e.g. 9:30AM)

Parameters time : datetime.time or string

Returns values_at_time : type of caller

pandas.DataFrame.between_time

`DataFrame.between_time(start_time, end_time, include_start=True, include_end=True)`

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters start_time : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns values_between_time : type of caller

pandas.DataFrame.bfill

`DataFrame.bfill(axis=None, inplace=False, limit=None, downcast=None)`

Synonym for `NDFrame.fillna(method='bfill')`

pandas.DataFrame.bool

`DataFrame.bool()`

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a `ValueError` if the PandasObject does not have exactly 1 element, or that element is not boolean

pandas.DataFrame.boxplot

`DataFrame.boxplot` (*column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, **kwargs*)

Make a box plot from DataFrame column optionally grouped by some columns or other inputs

Parameters **data** : the pandas object holding the data

column : column name or list of names, or vector

Can be any valid input to groupby

by : string or sequence

Column in the DataFrame to group by

ax : Matplotlib axes object, optional

fontsize : int or string

rot : label rotation angle

figsize : A tuple (width, height) in inches

grid : Setting this to True will show the grid

layout : tuple (optional)

(rows, columns) for the layout of the plot

return_type : { 'axes', 'dict', 'both' }, default 'dict'

The kind of object to return. 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot; 'axes' returns the matplotlib axes the boxplot is drawn on; 'both' returns a namedtuple with the axes and dict.

When grouping with `by`, a dict mapping columns to `return_type` is returned.

kwargs : other plotting keyword arguments to be passed to matplotlib boxplot function

Returns **lines** : dict

ax : matplotlib Axes

(ax, lines): namedtuple

Notes

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

pandas.DataFrame.clip

`DataFrame.clip` (*lower=None, upper=None, out=None, axis=None*)

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns `clipped` : Series

Examples

```
>>> df
   0      1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
   0      1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
   0      1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

`pandas.DataFrame.clip_lower`

`DataFrame.clip_lower` (*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters `threshold` : float or array_like

`axis` : int or string axis name, optional

Align object with threshold along the given axis.

Returns `clipped` : same type as input

See also:

`clip`

`pandas.DataFrame.clip_upper`

`DataFrame.clip_upper` (*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters **threshold** : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

`clip`

pandas.DataFrame.combine

`DataFrame.combine` (*other*, *func*, *fill_value=None*, *overwrite=True*)

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters **other** : DataFrame

func : function

fill_value : scalar value

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

Returns **result** : DataFrame

pandas.DataFrame.combineAdd

`DataFrame.combineAdd` (*other*)

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters **other** : DataFrame

Returns DataFrame

pandas.DataFrame.combineMult

`DataFrame.combineMult` (*other*)

Multiply two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters **other** : DataFrame

Returns DataFrame

pandas.DataFrame.combine_first

`DataFrame.combine_first` (*other*)

Combine two DataFrame objects and default to non-null values in frame calling the method. Result index columns will be the union of the respective indexes and columns

Parameters **other** : DataFrame

Returns **combined** : DataFrame

Examples

a's values prioritized, use values from b to fill holes:

```
>>> a.combine_first(b)
```

pandas.DataFrame.compound

`DataFrame.compound` (*axis=None, skipna=None, level=None*)

Return the compound percentage of the values for the requested axis

Parameters `axis` : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `compounded` : Series or DataFrame (if level specified)

pandas.DataFrame consolidate

`DataFrame consolidate` (*inplace=False*)

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters `inplace` : boolean, default False

If False return new object, otherwise modify existing object

Returns `consolidated` : type of caller

pandas.DataFrame.convert_objects

`DataFrame.convert_objects` (*convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True*)

Attempt to infer better dtype for object columns

Parameters `convert_dates` : boolean, default True

If True, convert to date where possible. If ‘coerce’, force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done).
Note: This is meant for internal use, and should not be confused with inplace.

Returns converted : same as input object

pandas.DataFrame.copy

`DataFrame.copy (deep=True)`
Make a copy of this object

Parameters deep : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns copy : type of caller

pandas.DataFrame.corr

`DataFrame.corr (method='pearson', min_periods=1)`
Compute pairwise correlation of columns, excluding NA/null values

Parameters method : {'pearson', 'kendall', 'spearman'}

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations required per pair of columns to have a valid result. Currently only available for pearson and spearman correlation

Returns y : DataFrame

pandas.DataFrame.corrwith

`DataFrame.corrwith (other, axis=0, drop=False)`
Compute pairwise correlation between rows or columns of two DataFrame objects.

Parameters other : DataFrame

axis : {0, 1}

0 to compute column-wise, 1 for row-wise

drop : boolean, default False

Drop missing indices from result, default returns union of all

Returns correls : Series

pandas.DataFrame.count

`DataFrame.count` (*axis=0, level=None, numeric_only=False*)

Return Series with number of non-NA/null observations over requested axis. Works with non-floating point data as well (detects NaN and None)

Parameters `axis` : {0, 1}

0 for row-wise, 1 for column-wise

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default False

Include only float, int, boolean data

Returns `count` : Series (or DataFrame if level specified)

pandas.DataFrame.cov

`DataFrame.cov` (*min_periods=None*)

Compute pairwise covariance of columns, excluding NA/null values

Parameters `min_periods` : int, optional

Minimum number of observations required per pair of columns to have a valid result.

Returns `y` : DataFrame

Notes

`y` contains the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1 (unbiased estimator).

pandas.DataFrame.cummax

`DataFrame.cummax` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative max over requested axis.

Parameters `axis` : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `max` : Series

pandas.DataFrame.cummin

`DataFrame.cummin` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative min over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **min** : Series

pandas.DataFrame.cumprod

`DataFrame.cumprod` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative prod over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **prod** : Series

pandas.DataFrame.cumsum

`DataFrame.cumsum` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative sum over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : Series

pandas.DataFrame.describe

`DataFrame.describe` (*percentile_width=None, percentiles=None, include=None, exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default `percentiles` is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy.number`. To select categorical objects use `type object`. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`

- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

`pandas.DataFrame.diff`

`DataFrame.diff` (*periods=1, axis=0*)

1st discrete difference of object

Parameters *periods* : int, default 1

Periods to shift for forming difference

axis : {0 or 'index', 1 or 'columns'}, default 0

Returns *diffed* : DataFrame

`pandas.DataFrame.div`

`DataFrame.div` (*other, axis='columns', level=None, fill_value=None*)

Binary operator `truediv` with support to substitute a *fill_value* for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.divide

`DataFrame.divide` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator `truediv` with support to substitute a *fill_value* for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.dot

`DataFrame.dot` (*other*)

Matrix multiplication with DataFrame or Series objects

Parameters *other* : DataFrame or Series

Returns *dot_product* : DataFrame or Series

pandas.DataFrame.drop

`DataFrame.drop` (*labels*, *axis*=0, *level*=None, *inplace*=False, *errors*='raise')

Return new object with labels in requested axis removed

Parameters *labels* : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : type of caller

pandas.DataFrame.drop_duplicates

`DataFrame.drop_duplicates(*args, **kwargs)`

Return DataFrame with duplicate rows removed, optionally only considering certain columns

Parameters **subset** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

Take the last observed row in a row. Defaults to the first row

inplace : boolean, default False

Whether to drop duplicates in place or to return a copy

cols : kwargs only argument of subset [deprecated]

Returns **deduplicated** : DataFrame

pandas.DataFrame.dropna

`DataFrame.dropna(axis=0, how='any', thresh=None, subset=None, inplace=False)`

Return object with labels on given axis omitted where alternately any or all of the data are missing

Parameters **axis** : {0, 1}, or tuple/list thereof

Pass tuple or list to drop on multiple axes

how : { 'any', 'all' }

- any : if any NA values are present, drop that label
- all : if all values are NA, drop that label

thresh : int, default None

int value : require that many non-NA values

subset : array-like

Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include

inplace : boolean, default False

If True, do operation inplace and return None.

Returns **dropped** : DataFrame

pandas.DataFrame.duplicated

`DataFrame.duplicated(*args, **kwargs)`

Return boolean Series denoting duplicate rows, optionally only considering certain columns

Parameters **subset** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

For a set of distinct duplicate rows, flag all but the last row as duplicated. Default is for all but the first row to be flagged

cols : kwargs only argument of subset [deprecated]

Returns **duplicated** : Series

pandas.DataFrame.eq

`DataFrame.eq(other, axis='columns', level=None)`

Wrapper for flexible comparison methods eq

pandas.DataFrame.equals

`DataFrame.equals(other)`

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.DataFrame.eval

`DataFrame.eval(expr, **kwargs)`

Evaluate an expression in the context of the calling DataFrame instance.

Parameters **expr** : string

The expression string to evaluate.

kwargs : dict

See the documentation for `eval()` for complete details on the keyword arguments accepted by `query()`.

Returns **ret** : ndarray, scalar, or pandas object

See also:

`pandas.DataFrame.query`, `pandas.eval`

Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.eval('a + b')
>>> df.eval('c = a + b')
```

pandas.DataFrame.ffmpeg

`DataFrame.ffmpeg` (*axis=None, inplace=False, limit=None, downcast=None*)
Synonym for `NDFrame.fillna(method='ffmpeg')`

pandas.DataFrame.fillna

`DataFrame.fillna` (*value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs*)

Fill NA/NaN values using the specified method

Parameters **method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series `pad` / `ffill`: propagate last valid observation forward to next valid `backfill` / `bfill`: use NEXT valid observation to fill gap

value : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 1, 'index', 'columns'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : DataFrame

See also:

`reindex`, `asfreq`

pandas.DataFrame.filter

`DataFrame.filter` (*items=None, like=None, regex=None, axis=None*)

Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where “arg in col == True”

regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The “info axis” is the axis that is used when indexing with []. For example, `df = DataFrame({'a' : [1, 2, 3, 4]})`; `df['a']`. So, the DataFrame columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.DataFrame.first

`DataFrame.first(offset)`

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

`ts.last('10D')` -> First 10 days

pandas.DataFrame.first_valid_index

`DataFrame.first_valid_index()`

Return label for first non-NA/null value

pandas.DataFrame.floordiv

`DataFrame.floordiv(other, axis='columns', level=None, fill_value=None)`

Binary operator floordiv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.from_csv

```
classmethod DataFrame.from_csv(path, header=0, sep=',', index_col=0,
                               parse_dates=True, encoding=None, tupleize_cols=False,
                               infer_datetime_format=False)
```

Read delimited file into DataFrame

Parameters **path** : string file path or file handle / StringIO

header : int, default 0

Row to use at header (skip prior rows)

sep : string, default ','

Field delimiter

index_col : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from read_table

parse_dates : boolean, default True

Parse dates. Different default from read_table

tupleize_cols : boolean, default False

write multi_index columns as a list of tuples (if True) or new (expanded format) if False)

infer_datetime_format: boolean, default False

If True and *parse_dates* is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

Returns **y** : DataFrame

Notes

Preferable to use read_table for most general purposes but from_csv makes for an easy roundtrip to and from file, especially with a DataFrame of time series data

pandas.DataFrame.from_dict

```
classmethod DataFrame.from_dict(data, orient='columns', dtype=None)
Construct DataFrame from dict of array-like or dicts
```

Parameters **data** : dict

{field : array-like} or {field : dict}

orient : {'columns', 'index'}, default 'columns'

The “orientation” of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass ‘columns’ (default). Otherwise if the keys should be rows, pass ‘index’.

Returns DataFrame

pandas.DataFrame.from_items

classmethod DataFrame.**from_items** (*items*, *columns=None*, *orient='columns'*)

Convert (key, value) pairs to DataFrame. The keys will be the axis index (usually the columns, but depends on the specified orientation). The values should be arrays or Series.

Parameters **items** : sequence of (key, value) pairs

Values should be arrays or Series.

columns : sequence of column labels, optional

Must be passed if orient=‘index’.

orient : {‘columns’, ‘index’}, default ‘columns’

The “orientation” of the data. If the keys of the input correspond to column labels, pass ‘columns’ (default). Otherwise if the keys correspond to the index, pass ‘index’.

Returns **frame** : DataFrame

pandas.DataFrame.from_records

classmethod DataFrame.**from_records** (*data*, *index=None*, *exclude=None*, *columns=None*, *coerce_float=False*, *nrows=None*)

Convert structured or record ndarray to DataFrame

Parameters **data** : ndarray (structured dtype), list of tuples, dict, or DataFrame

index : string, list of fields, array-like

Field of array to use as the index, alternately a specific set of input labels to use

exclude : sequence, default None

Columns or fields to exclude

columns : sequence, default None

Column names to use. If the passed data do not have names associated with them, this argument provides names for the columns. Otherwise this argument indicates the order of the columns in the result (any names not found in the data will become all-NA columns)

coerce_float : boolean, default False

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

Returns **df** : DataFrame

pandas.DataFrame.ge

`DataFrame.ge` (*other*, *axis='columns'*, *level=None*)

Wrapper for flexible comparison methods `ge`

pandas.DataFrame.get

`DataFrame.get` (*key*, *default=None*)

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters `key` : object

Returns `value` : type of items contained in object

pandas.DataFrame.get_dtype_counts

`DataFrame.get_dtype_counts` ()

Return the counts of dtypes in this object

pandas.DataFrame.get_ftype_counts

`DataFrame.get_ftype_counts` ()

Return the counts of ftypes in this object

pandas.DataFrame.get_value

`DataFrame.get_value` (*index*, *col*, *takeable=False*)

Quickly retrieve single value at passed column and index

Parameters `index` : row label

`col` : column label

`takeable` : interpret the index/col as indexers, default False

Returns `value` : scalar value

pandas.DataFrame.get_values

`DataFrame.get_values` ()

same as `values` (but handles sparseness conversions)

pandas.DataFrame.groupby

`DataFrame.groupby` (*by=None*, *axis=0*, *level=None*, *as_index=True*, *sort=True*, *group_keys=True*, *squeeze=False*)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters `by` : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None

If the axis is a MultiIndex (hierarchical), group by a particular level or levels

as_index : boolean, default True

For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. as_index=False is effectively “SQL-style” grouped output

sort : boolean, default True

Sort group keys. Get better performance by turning this off

group_keys : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionality of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

pandas.DataFrame.gt

DataFrame.**gt** (*other*, axis='columns', level=None)
Wrapper for flexible comparison methods gt

pandas.DataFrame.head

DataFrame.**head** (n=5)
Returns first n rows

pandas.DataFrame.hist

DataFrame.**hist** (data, column=None, by=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, ax=None, sharex=False, sharey=False, figsize=None, layout=None, bins=10, **kws)
Draw histogram of the DataFrame's series using matplotlib / pylab.

Parameters **data** : DataFrame

column : string or sequence

If passed, will be used to limit data to a subset of columns

by : object, optional

If passed, then used to form histograms for separate groups

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

ax : matplotlib axes object, default None

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

figsize : tuple

The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10

Number of histogram bins to be used

kwds : other plotting keyword arguments

To be passed to hist function

pandas.DataFrame.icol

DataFrame.**icol** (i)

pandas.DataFrame.idxmax`DataFrame.idxmax` (*axis=0, skipna=True*)

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

Parameters *axis* : {0, 1}

0 for row-wise, 1 for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

Returns *idxmax* : Series**See also:**`Series.idxmax`**Notes**This method is the DataFrame version of `ndarray.argmax`.**pandas.DataFrame.idxmin**`DataFrame.idxmin` (*axis=0, skipna=True*)

Return index of first occurrence of minimum over requested axis. NA/null values are excluded.

Parameters *axis* : {0, 1}

0 for row-wise, 1 for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *idxmin* : Series**See also:**`Series.idxmin`**Notes**This method is the DataFrame version of `ndarray.argmin`.**pandas.DataFrame.iget_value**`DataFrame.iget_value` (*i, j*)**pandas.DataFrame.info**`DataFrame.info` (*verbose=None, buf=None, max_cols=None, memory_usage=None, null_counts=None*)

Concise summary of a DataFrame.

Parameters **verbose** : {None, True, False}, optional

Whether to print the full summary. None follows the *display.max_info_columns* setting. True or False overrides the *display.max_info_columns* setting.

buf : writable buffer, defaults to sys.stdout

max_cols : int, default None

Determines whether full summary or short summary is printed. None follows the *display.max_info_columns* setting.

memory_usage : boolean, default None

Specifies whether total memory usage of the DataFrame elements (including index) should be displayed. None follows the *display.memory_usage* setting. True or False overrides the *display.memory_usage* setting. Memory usage is shown in human-readable units (base-2 representation).

null_counts : boolean, default None

Whether to show the non-null counts. If None, then only show if the frame is smaller than *max_info_rows* and *max_info_columns*. If True, always show counts. If False, never show counts.

pandas.DataFrame.insert

`DataFrame.insert(loc, column, value, allow_duplicates=False)`

Insert column into DataFrame at specified location.

If *allow_duplicates* is False, raises Exception if column is already contained in the DataFrame.

Parameters **loc** : int

Must have $0 \leq \text{loc} \leq \text{len}(\text{columns})$

column : object

value : int, Series, or array-like

pandas.DataFrame.interpolate

`DataFrame.interpolate(method='linear', axis=0, limit=None, inplace=False, downcast=None, **kwargs)`

Interpolate values according to different methods.

Parameters **method** : { 'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline',
'piecewise_polynomial', 'pchip' }

- 'linear': ignore the index and treat the values as equally spaced. default
- 'time': interpolation works on daily and higher resolution data to interpolate given length of interval
- 'index', 'values': use the actual numerical values of the index

- ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘barycentric’, ‘polynomial’ is passed to `scipy.interpolate.interpld` with the order given both ‘polynomial’ and ‘spline’ require that you also specify an order (int) e.g. `df.interpolate(method='polynomial', order=4)`
- ‘krogh’, ‘piecewise_polynomial’, ‘spline’, and ‘pchip’ are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: <http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation> <http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html>

axis : {0, 1}, default 0

- 0: fill column-by-column
- 1: fill row-by-row

limit : int, default None.

Maximum number of consecutive NaNs to fill.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, ‘infer’ or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

pandas.DataFrame.irow

`DataFrame.irow(i, copy=False)`

pandas.DataFrame.isin

`DataFrame.isin(values)`

Return boolean DataFrame showing whether each element in the DataFrame is contained in values.

Parameters **values** : iterable, Series, DataFrame or dictionary

The result will only be true at a location if all the labels match. If *values* is a Series, that's the index. If *values* is a dictionary, the keys must be the column names, which must match. If *values* is a DataFrame, then both the index and column labels must match.

Returns DataFrame of booleans

Examples

When *values* is a list:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> df.isin([1, 3, 12, 'a'])
      A      B
0  True   True
1 False  False
2  True  False
```

When *values* is a dict:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': [1, 4, 7]})
>>> df.isin({'A': [1, 3], 'B': [4, 7, 12]})
      A      B
0  True  False # Note that B didn't match the 1 here.
1 False   True
2  True   True
```

When *values* is a Series or DataFrame:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> other = DataFrame({'A': [1, 3, 3, 2], 'B': ['e', 'f', 'f', 'e']})
>>> df.isin(other)
      A      B
0  True  False
1 False  False # Column A in `other` has a 3, but not at index 1.
2  True   True
```

pandas.DataFrame.isnull

`DataFrame.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of isnull

pandas.DataFrame.iteritems

`DataFrame.iteritems()`

Iterator over (column, series) pairs

pandas.DataFrame.iterkv

`DataFrame.iterkv(*args, **kwargs)`

iteritems alias used to get around 2to3. Deprecated

pandas.DataFrame.iterrows`DataFrame.iterrows()`

Iterate over rows of DataFrame as (index, Series) pairs.

Returns it : generator

A generator that iterates over the rows of the frame.

Notes

- `iterrows` does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
>>> df = DataFrame([[1, 1.0]], columns=['x', 'y'])
>>> row = next(df.iterrows())[1]
>>> print(row['x'].dtype)
float64
>>> print(df['x'].dtype)
int64
```

pandas.DataFrame.itertuples`DataFrame.itertuples(index=True)`

Iterate over rows of DataFrame as tuples, with index value as first element of the tuple

pandas.DataFrame.join`DataFrame.join(other, on=None, how='left', lsuffix='', rsuffix='', sort=False)`

Join columns with other DataFrame either on index or on a key column. Efficiently Join multiple DataFrame objects by index at once by passing a list.

Parameters other : DataFrame, Series with name field set, or list of DataFrame

Index should be similar to one of the columns in this one. If a Series is passed, its name attribute must be set, and that will be used as the column name in the resulting joined DataFrame

on : column name, tuple/list of column names, or array-like

Column(s) to use for joining, otherwise join on index. If multiples columns given, the passed DataFrame must have a MultiIndex. Can pass an array as the join key if not already contained in the calling DataFrame. Like an Excel VLOOKUP operation

how : { 'left', 'right', 'outer', 'inner' }

How to handle indexes of the two objects. Default: 'left' for joining on index, None otherwise

- left: use calling frame's index
- right: use input frame's index
- outer: form union of indexes
- inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

sort : boolean, default False

Order result DataFrame lexicographically by the join key. If False, preserves the index order of the calling (left) DataFrame

Returns **joined** : DataFrame

Notes

on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

pandas.DataFrame.keys

DataFrame.**keys** ()

Get the 'info axis' (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.

pandas.DataFrame.kurt

DataFrame.**kurt** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Series or DataFrame (if level specified)

pandas.DataFrame.kurtosis

DataFrame.**kurtosis** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : Series or DataFrame (if level specified)

pandas.DataFrame.last

`DataFrame.last (offset)`

Convenience method for subsetting final periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

`ts.last('5M')` -> Last 5 months

pandas.DataFrame.last_valid_index

`DataFrame.last_valid_index()`

Return label for last non-NA/null value

pandas.DataFrame.le

`DataFrame.le (other, axis='columns', level=None)`

Wrapper for flexible comparison methods `le`

pandas.DataFrame.load

`DataFrame.load (path)`

Deprecated. Use `read_pickle` instead.

pandas.DataFrame.lookup

`DataFrame.lookup (row_labels, col_labels)`

Label-based “fancy indexing” function for DataFrame. Given equal-length arrays of row and column labels, return an array of the values corresponding to each (row, col) pair.

Parameters row_labels : sequence

The row labels to use for lookup

col_labels : sequence

The column labels to use for lookup

Notes

Akin to:

```
result = []
for row, col in zip(row_labels, col_labels):
    result.append(df.get_value(row, col))
```

Examples

values [ndarray] The found values

pandas.DataFrame.lt

DataFrame.**lt** (*other*, *axis*='columns', *level*=None)

Wrapper for flexible comparison methods lt

pandas.DataFrame.mad

DataFrame.**mad** (*axis*=None, *skipna*=None, *level*=None)

Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : Series or DataFrame (if level specified)

pandas.DataFrame.mask

DataFrame.**mask** (*cond*, *other*=nan, *inplace*=False, *axis*=None, *level*=None, *try_cast*=False, *raise_on_error*=True)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.DataFrame.max

`DataFrame.max` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : Series or DataFrame (if level specified)

pandas.DataFrame.mean

`DataFrame.mean` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the mean of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : Series or DataFrame (if level specified)

pandas.DataFrame.median

DataFrame.**median** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the median of the values for the requested axis

Parameters axis : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns median : Series or DataFrame (if level specified)

pandas.DataFrame.memory_usage

DataFrame.**memory_usage** (*index=False*)

Memory usage of DataFrame columns.

Parameters index : bool

Specifies whether to include memory usage of DataFrame's index in returned Series. If *index=True* (default is False) the first index of the Series is *Index*.

Returns sizes : Series

A series with column names as index and memory usage of columns with units of bytes.

See also:

`numpy.ndarray.nbytes`

Notes

Memory usage does not include memory consumed by elements that are not components of the array.

pandas.DataFrame.merge

DataFrame.**merge** (*right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes=('_x', '_y'), copy=True*)

Merge DataFrame objects by performing a database-style join operation by columns or indexes.

If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters right : DataFrame

how : { 'left', 'right', 'outer', 'inner' }, default 'inner'

- left: use only keys from left frame (SQL: left outer join)

- **right**: use only keys from right frame (SQL: right outer join)
- **outer**: use union of keys from both frames (SQL: full outer join)
- **inner**: use intersection of keys from both frames (SQL: inner join)

on : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

left_on : label or list, or array-like

Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns

right_on : label or list, or array-like

Field names to join on in right DataFrame or vector/list of vectors per left_on docs

left_index : boolean, default False

Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels

right_index : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

sort : boolean, default False

Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

copy : boolean, default True

If False, do not copy data unnecessarily

Returns merged : DataFrame

The output type will be the same as 'left', if it is a subclass of DataFrame.

Examples

```
>>> A          >>> B
   lkey value   rkey value
0  foo    1     0  foo    5
1  bar    2     1  bar    6
2  baz    3     2  qux    7
3  foo    4     3  bar    8

>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0  foo      1    foo      5
1  foo      4    foo      5
2  bar      2    bar      6
3  bar      2    bar      8
```

```
4  baz    3      NaN    NaN
5  NaN    NaN    qux     7
```

pandas.DataFrame.min

`DataFrame.min` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : Series or DataFrame (if level specified)

pandas.DataFrame.mod

`DataFrame.mod` (*other, axis='columns', level=None, fill_value=None*)

Binary operator mod with support to substitute a `fill_value` for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.mode

`DataFrame.mode` (*axis=0, numeric_only=False*)

Gets the mode(s) of each element along the axis selected. Empty if nothing has 2+ occurrences. Adds a row for each mode per label, fills in gaps with nan.

Note that there could be multiple values returned for the selected axis (when more than one item share the maximum frequency), which is the reason why a dataframe is returned. If you want to impute missing values with the mode in a dataframe `df`, you can just do this: `df.fillna(df.mode().iloc[0])`

Parameters `axis`: {0, 1, 'index', 'columns'} (default 0)

- 0/'index': get mode of each column
- 1/'columns': get mode of each row

numeric_only: boolean, default False
if True, only apply to numeric columns

Returns `modes`: DataFrame (sorted)

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 1, 2, 1, 2, 3]})
>>> df.mode()
   A
0  1
1  2
```

pandas.DataFrame.mul

`DataFrame.mul` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator mul with support to substitute a *fill_value* for missing data in one of the inputs

Parameters `other`: Series, DataFrame, or constant

axis: {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value: None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level: int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result`: DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.multiply

`DataFrame.multiply` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator mul with support to substitute a *fill_value* for missing data in one of the inputs

Parameters `other`: Series, DataFrame, or constant

axis: {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.ne

DataFrame.**ne** (*other*, *axis*='columns', *level*=None)

Wrapper for flexible comparison methods ne

pandas.DataFrame.notnull

DataFrame.**notnull** ()

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

pandas.DataFrame.pct_change

DataFrame.**pct_change** (*periods*=1, *fill_method*='pad', *limit*=None, *freq*=None, ***kwargs*)

Percent change over given number of periods.

Parameters periods : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns chg : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

pandas.DataFrame.pivot

`DataFrame.pivot` (*index=None, columns=None, values=None*)

Reshape data (produce a “pivot” table) based on column values. Uses unique values from index / columns to form axes and return either `DataFrame` or `Panel`, depending on whether you request a single value column (`DataFrame`) or all columns (`Panel`)

Parameters `index` : string or object

Column name to use to make new frame’s index

columns : string or object

Column name to use to make new frame’s columns

values : string or object, optional

Column name to use for populating new frame’s values

Returns `pivoted` : `DataFrame`

If no values column specified, will have hierarchically indexed columns

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related `stack/unstack` methods

Examples

```
>>> df
   foo  bar  baz
0  one  A   1.
1  one  B   2.
2  one  C   3.
3  two  A   4.
4  two  B   5.
5  two  C   6.

>>> df.pivot('foo', 'bar', 'baz')
   A  B  C
one 1  2  3
two 4  5  6

>>> df.pivot('foo', 'bar')['baz']
   A  B  C
one 1  2  3
two 4  5  6
```

pandas.DataFrame.pivot_table

`DataFrame.pivot_table`(*data*, *values=None*, *index=None*, *columns=None*, *aggfunc='mean'*,
fill_value=None, *margins=False*, *dropna=True*)

Create a spreadsheet-style pivot table as a DataFrame. The levels in the pivot table will be stored in MultiIndex objects (hierarchical indexes) on the index and columns of the result DataFrame

Parameters *data* : DataFrame

values : column to aggregate, optional

index : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table index. If an array is passed, it is being used as the same manner as column values.

columns : a column, Grouper, array which has the same length as data, or list of them.

Keys to group by on the pivot table column. If an array is passed, it is being used as the same manner as column values.

aggfunc : function, default `numpy.mean`, or list of functions

If list of functions passed, the resulting pivot table will have hierarchical columns whose top level are the function names (inferred from the function objects themselves)

fill_value : scalar, default `None`

Value to replace missing values with

margins : boolean, default `False`

Add all row / columns (e.g. for subtotal / grand totals)

dropna : boolean, default `True`

Do not include columns whose entries are all `NaN`

Returns *table* : DataFrame

Examples

```
>>> df
   A  B  C  D
0  foo one small 1
1  foo one large 2
2  foo one large 2
3  foo two small 3
4  foo two small 3
5  bar one large 4
6  bar one small 5
7  bar two small 6
8  bar two large 7

>>> table = pivot_table(df, values='D', index=['A', 'B'],
...                      columns=['C'], aggfunc=np.sum)
>>> table
      small large
foo one    1    4
   two    6   NaN
```

```

bar  one  5      4
     two  6      7

```

pandas.DataFrame.plot

`DataFrame.plot` (*data*, *x=None*, *y=None*, *kind='line'*, *ax=None*, *subplots=False*, *sharex=None*, *sharey=False*, *layout=None*, *figsize=None*, *use_index=True*, *title=None*, *grid=None*, *legend=True*, *style=None*, *logx=False*, *logy=False*, *loglog=False*, *xticks=None*, *yticks=None*, *xlim=None*, *ylim=None*, *rot=None*, *fontsize=None*, *colormap=None*, *table=False*, *yerr=None*, *xerr=None*, *secondary_y=False*, *sort_columns=False*, ***kwds*)

Make plots of DataFrame using matplotlib / pylab.

Parameters *data* : DataFrame

x : label or position, default None

y : label or position, default None

Allows plotting of one column versus another

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot

ax : matplotlib axes object, default None

subplots : boolean, default False

Make separate subplots for each column

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

layout : tuple (optional)

(rows, columns) for the layout of subplots

figsize : a tuple (width, height) in inches

use_index : boolean, default True
Use index as ticks for x axis

title : string
Title to use for the plot

grid : boolean, default None (matlab style default)
Axis grid lines

legend : False/True/'reverse'
Place legend on axis subplots

style : list or dict
matplotlib line style per column

logx : boolean, default False
Use log scaling on x axis

logy : boolean, default False
Use log scaling on y axis

loglog : boolean, default False
Use log scaling on both x and y axes

xticks : sequence
Values to use for the xticks

yticks : sequence
Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None
Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None
Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None
Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional
If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float
Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)
(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

stacked : boolean, default False in line and

bar plots, and True in area plot. If True, create stacked plot.

sort_columns : boolean, default False

Sort column names to determine plot ordering

secondary_y : boolean or sequence, default False

Whether to plot on the secondary y-axis If a list/tuple, which columns to plot on secondary y-axis

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns axes : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)
- If *kind* = 'scatter' and the argument *c* is the name of a dataframe column, the values of that column are used to color each point.
- If *kind* = 'hexbin', you can control the size of the bins with the *gridsize* argument. By default, a histogram of the counts around each (*x*, *y*) point is computed. You can specify alternative aggregations by passing values to the *C* and *reduce_C_function* arguments. *C* specifies the value at each (*x*, *y*) point and *reduce_C_function* is a function of one argument that reduces all the values in a bin to a single number (e.g. *mean*, *max*, *sum*, *std*).

pandas.DataFrame.pop

DataFrame.**pop**(*item*)

Return item and drop from frame. Raise KeyError if not found.

pandas.DataFrame.pow

DataFrame.**pow** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator pow with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.prod

DataFrame.**prod** (*axis*=None, *skipna*=None, *level*=None, *numeric_only*=None, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Series or DataFrame (if level specified)

pandas.DataFrame.product

DataFrame.**product** (*axis*=None, *skipna*=None, *level*=None, *numeric_only*=None, ***kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Series or DataFrame (if level specified)

pandas.DataFrame.quantile

`DataFrame.quantile (q=0.5, axis=0, numeric_only=True)`

Return values at the given quantile over requested axis, a la numpy.percentile.

Parameters **q** : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

axis : {0, 1}

0 for row-wise, 1 for column-wise

Returns **quantiles** : Series or DataFrame

If q is an array, a DataFrame will be returned where the index is q, the columns are the columns of self, and the values are the quantiles. If q is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

Examples

```
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                    columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
dtype: float64
>>> df.quantile([.1, .5])
      a    b
0.1  1.3  3.7
0.5  2.5 55.0
```

pandas.DataFrame.query

`DataFrame.query (expr, **kwargs)`

Query the columns of a frame with a boolean expression.

New in version 0.13.

Parameters **expr** : string

The query string to evaluate. You can refer to variables in the environment by prefixing them with an '@' character like @a + b.

kwargs : dict

See the documentation for `pandas.eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

Returns `q` : DataFrame

See also:

`pandas.eval`, `DataFrame.eval`

Notes

The result of the evaluation of this expression is first passed to `DataFrame.loc` and if that fails because of a multidimensional key (e.g., a DataFrame) then the result will be passed to `DataFrame.__getitem__()`.

This method uses the top-level `pandas.eval()` function to evaluate the passed query.

The `query()` method uses a slightly modified Python syntax by default. For example, the `&` and `|` (bitwise) operators have the precedence of their boolean cousins, `and` and `or`. This *is* syntactically valid Python, however the semantics are different.

You can change the semantics of the expression by passing the keyword argument `parser='python'`. This enforces the same semantics as evaluation in Python space. Likewise, you can pass `engine='python'` to evaluate an expression using Python itself as a backend. This is not recommended as it is inefficient compared to using `numexpr` as the engine.

The `DataFrame.index` and `DataFrame.columns` attributes of the `DataFrame` instance are placed in the query namespace by default, which allows you to treat both the index and columns of the frame as a column in the frame. The identifier `index` is used for the frame index; you can also use the name of the index to identify it in a query.

For further details and examples see the `query` documentation in [indexing](#).

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.query('a > b')
>>> df[df.a > df.b]  # same result as the previous expression
```

`pandas.DataFrame.radd`

`DataFrame.radd(other, axis='columns', level=None, fill_value=None)`

Binary operator `radd` with support to substitute a `fill_value` for missing data in one of the inputs

Parameters `other` : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result` : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rank

`DataFrame.rank` (*axis=0, numeric_only=None, method='average', na_option='keep', ascending=True, pct=False*)

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values

Parameters **axis** : {0, 1}, default 0

Ranks over columns (0) or rows (1)

numeric_only : boolean, default None

Include only float, int, boolean data

method : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep', 'top', 'bottom'}

- keep: leave NA values where they are
- top: smallest rank if ascending
- bottom: smallest rank if descending

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns **ranks** : DataFrame

pandas.DataFrame.rdiv

`DataFrame.rdiv` (*other, axis='columns', level=None, fill_value=None*)

Binary operator rtruediv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.reindex

DataFrame.**reindex** (*index=None, columns=None, **kwargs*)

Conform DataFrame to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and *copy=False*

Parameters index, columns : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : DataFrame

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.DataFrame.reindex_axis

`DataFrame.reindex_axis` (*labels*, *axis=0*, *method=None*, *level=None*, *copy=True*, *limit=None*, *fill_value=nan*)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters *labels* : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 'index', 'columns'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns *reindexed* : DataFrame

See also:

`reindex`, `reindex_like`

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.DataFrame.reindex_like

`DataFrame.reindex_like` (*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters *other* : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns `reindexed` : same as input

Notes

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

`pandas.DataFrame.rename`

`DataFrame.rename` (*index=None, columns=None, **kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters `index, columns` : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new DataFrame. If True then value of copy is ignored.

Returns `renamed` : DataFrame (new object)

`pandas.DataFrame.rename_axis`

`DataFrame.rename_axis` (*mapper, axis=0, copy=True, inplace=False*)

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters `mapper` : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Returns `renamed` : type of caller

`pandas.DataFrame.reorder_levels`

`DataFrame.reorder_levels` (*order, axis=0*)

Rearrange index levels using input order. May not drop or duplicate levels

Parameters `order` : list of int or list of str

List representing new level order. Reference level by number (position) or by key (label).

axis : int

Where to reorder levels.

Returns type of caller (new object)

pandas.DataFrame.replace

`DataFrame.replace` (*to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters *to_replace* : str, regex, list, dict, Series, numeric, or None

- str or regex:
 - str: string exactly matching *to_replace* will be replaced with *value*
 - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
 - First, if *to_replace* and *value* are both lists, they **must** be the same length.
 - Second, if *regex=True* then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
 - str and regex rules apply as above.
- dict:
 - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
 - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
 - This means that the *regex* argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also None then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is True then *to_replace* must be a string. Otherwise, *to_replace* must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a list.

Returns `filled` : NDFrame

Raises `AssertionError`

- If `regex` is not a `bool` and `to_replace` is not `None`.

TypeError

- If `to_replace` is a `dict` and `value` is not a `list`, `dict`, `ndarray`, or `Series`
- If `to_replace` is `None` and `regex` is not compilable into a regular expression or is a `list`, `dict`, `ndarray`, or `Series`.

ValueError

- If `to_replace` and `value` are `list`s or `ndarray`s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.DataFrame.resample

`DataFrame.resample` (*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters `rule` : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : { 'start', 'end', 's', 'e' }

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.DataFrame.reset_index

`DataFrame.reset_index` (*level=None, drop=False, inplace=False, col_level=0, col_fill=''*)

For DataFrame with multi-level index, return new DataFrame with labeling information in the columns under the index names, defaulting to 'level_0', 'level_1', etc. if any are None. For a standard index, the index name will be used (if set), otherwise a default 'index' or 'level_0' (if 'index' is already taken) will be used.

Parameters level : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns. This resets the index to the default integer index.

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

col_level : int or str, default 0

If the columns have multiple levels, determines which level the labels are inserted into. By default it is inserted into the first level.

col_fill : object, default ''

If the columns have multiple levels, determines how the other levels are named. If None then the index name is repeated.

Returns resetted : DataFrame

pandas.DataFrame.rfloordiv

`DataFrame.rfloordiv` (*other, axis='columns', level=None, fill_value=None*)

Binary operator rfloordiv with support to substitute a fill_value for missing data in one of the inputs

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmod

DataFrame.**rmod** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rmod with support to substitute a fill_value for missing data in one of the inputs

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmul

DataFrame.**rmul** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rmul with support to substitute a fill_value for missing data in one of the inputs

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rpow

DataFrame.**rpow** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rpow with support to substitute a fill_value for missing data in one of the inputs

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rsub

DataFrame.**rsub** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rsub with support to substitute a fill_value for missing data in one of the inputs

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

`pandas.DataFrame.rtruediv`

`DataFrame.rtruediv` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator `rtruediv` with support to substitute a `fill_value` for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

`pandas.DataFrame.sample`

`DataFrame.sample` (*n*=None, *frac*=None, *replace*=False, *weights*=None, *random_state*=None, *axis*=None)

Returns a random sample of items from an axis of object.

Parameters *n* : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when *axis* = 0. Weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. inf and -inf values not allowed.

random_state : int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

Returns Same type as caller.

pandas.DataFrame.save`DataFrame.save(path)`Deprecated. Use `to_pickle` instead**pandas.DataFrame.select**`DataFrame.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters `crit` : function

To be called on each index (label). Should return True or False

`axis` : int**Returns** `selection` : type of caller**pandas.DataFrame.select_dtypes**`DataFrame.select_dtypes(include=None, exclude=None)`Return a subset of a DataFrame including/excluding columns based on their `dtype`.**Parameters** `include, exclude` : list-like

A list of dtypes or strings to be included/excluded. You must pass in a non-empty sequence for at least one of these.

Returns `subset` : DataFrameThe subset of the frame including the dtypes in `include` and excluding the dtypes in `exclude`.**Raises** `ValueError`

- If both of `include` and `exclude` are empty
- If `include` and `exclude` have overlapping elements
- If any kind of string dtype is passed in.

TypeError

- If either of `include` or `exclude` is not a sequence

Notes

- To select all *numeric* types use the numpy dtype `numpy.number`
- To select strings you must use the `object` dtype, but note that this will return *all* object dtype columns
- See the [numpy dtype hierarchy](#)
- To select Pandas categorical dtypes, use 'category'

Examples

```
>>> df = pd.DataFrame({'a': np.random.randn(6).astype('f4'),
...                    'b': [True, False] * 3,
...                    'c': [1.0, 2.0] * 3})
>>> df
   a      b  c
0  0.3962  True  1
1  0.1459 False  2
2  0.2623  True  1
3  0.0764 False  2
4 -0.9703  True  1
5 -1.2094 False  2
>>> df.select_dtypes(include=['float64'])
   c
0  1
1  2
2  1
3  2
4  1
5  2
>>> df.select_dtypes(exclude=['floating'])
   b
0  True
1 False
2  True
3 False
4  True
5 False
```

pandas.DataFrame.sem

`DataFrame.sem` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)
Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters `axis` : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `sem` : Series or DataFrame (if level specified)

pandas.DataFrame.set_axis

`DataFrame.set_axis` (*axis, labels*)
 public version of axis assignment

pandas.DataFrame.set_index

`DataFrame.set_index` (*keys, drop=True, append=False, inplace=False, verify_integrity=False*)
 Set the DataFrame index (row labels) using one or more existing columns. By default yields a new object.

Parameters **keys** : column label or list of column labels / arrays

drop : boolean, default True

Delete columns to be used as the new index

append : boolean, default False

Whether to append columns to existing index

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

verify_integrity : boolean, default False

Check the new index for duplicates. Otherwise defer the check until necessary.
 Setting to False will improve the performance of this method

Returns **dataframe** : DataFrame

Examples

```
>>> indexed_df = df.set_index(['A', 'B'])
>>> indexed_df2 = df.set_index(['A', [0, 1, 2, 0, 1, 2]])
>>> indexed_df3 = df.set_index([[0, 1, 2, 0, 1, 2]])
```

pandas.DataFrame.set_value

`DataFrame.set_value` (*index, col, value, takeable=False*)
 Put single value at passed column and index

Parameters **index** : row label

col : column label

value : scalar value

takeable : interpret the index/col as indexers, default False

Returns **frame** : DataFrame

If label pair is contained, will be reference to calling DataFrame, otherwise a new object

pandas.DataFrame.shift

`DataFrame.shift` (*periods=1, freq=None, axis=0, **kwargs*)

Shift index by desired number of periods with an optional time freq

Parameters `periods` : int

Number of periods to move, can be positive or negative

freq : `DateOffset`, `timedelta`, or time rule string, optional

Increment to use from `datetools` module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 1, 'index', 'columns'}

Returns `shifted` : `DataFrame`

Notes

If `freq` is specified then the index values are shifted but the data is not realigned. That is, use `freq` if you would like to extend the index when shifting and preserve the original data.

pandas.DataFrame.skew

`DataFrame.skew` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters `axis` : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a `MultiIndex` (hierarchical), count along a particular level, collapsing into a `Series`

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `skew` : `Series` or `DataFrame` (if level specified)

pandas.DataFrame.slice_shift

`DataFrame.slice_shift` (*periods=1, axis=0*)

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters `periods` : int

Number of periods to move, can be positive or negative

Returns `shifted` : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.DataFrame.sort

`DataFrame.sort` (*columns=None*, *axis=0*, *ascending=True*, *inplace=False*, *kind='quicksort'*,
na_position='last')

Sort DataFrame either by labels (along either axis) or by the values in column(s)

Parameters **columns** : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

axis : {0, 1}

Sort index/rows versus columns

inplace : boolean, default False

Sort the DataFrame without creating a new instance

kind : {'quicksort', 'mergesort', 'heapsort'}, optional

This option is only applied when sorting on a single column or label.

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

Returns **sorted** : DataFrame

Examples

```
>>> result = df.sort(['A', 'B'], ascending=[1, 0])
```

pandas.DataFrame.sort_index

`DataFrame.sort_index` (*axis=0*, *by=None*, *ascending=True*, *inplace=False*, *kind='quicksort'*,
na_position='last')

Sort DataFrame either by labels (along either axis) or by the values in a column

Parameters **axis** : {0, 1}

Sort index/rows versus columns

by : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

inplace : boolean, default False

Sort the DataFrame without creating a new instance

na_position : { 'first', 'last' } (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

kind : { 'quicksort', 'mergesort', 'heapsort' }, optional

This option is only applied when sorting on a single column or label.

Returns sorted : DataFrame

Examples

```
>>> result = df.sort_index(by=['A', 'B'], ascending=[True, False])
```

pandas.DataFrame.sortlevel

DataFrame.**sortlevel** (*level=0, axis=0, ascending=True, inplace=False, sort_remaining=True*)

Sort multilevel index by chosen axis and primary level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters level : int

axis : {0, 1}

ascending : boolean, default True

inplace : boolean, default False

Sort the DataFrame without creating a new instance

sort_remaining : boolean, default True

Sort by the other levels too.

Returns sorted : DataFrame

pandas.DataFrame.squeeze

DataFrame.**squeeze** ()

squeeze length 1 dimensions

pandas.DataFrame.stack

DataFrame.**stack** (*level=-1, dropna=True*)

Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame (or Series in the case of an object with a single level of column labels) having a hierarchical index with a new inner-most level of row labels. The level involved will automatically get sorted.

Parameters level : int, string, or list of these, default last level

Level(s) to stack, can pass level name

dropna : boolean, default True

Whether to drop rows in the resulting Frame/Series with no valid values

Returns stacked : DataFrame or Series

Examples

```
>>> s
      a    b
one  1.  2.
two  3.  4.

>>> s.stack()
one a    1
   b    2
two a    3
   b    4
```

pandas.DataFrame.std

`DataFrame.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters `axis` : {index (0), columns (1)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

`level` : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

`numeric_only` : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `std` : Series or DataFrame (if level specified)

pandas.DataFrame.sub

`DataFrame.sub(other, axis='columns', level=None, fill_value=None)`

Binary operator sub with support to substitute a `fill_value` for missing data in one of the inputs

Parameters `other` : Series, DataFrame, or constant

`axis` : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

`fill_value` : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

`level` : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns `result` : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.subtract

`DataFrame.subtract` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator sub with support to substitute a *fill_value* for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.sum

`DataFrame.sum` (*axis*=None, *skipna*=None, *level*=None, *numeric_only*=None, ***kwargs*)

Return the sum of the values for the requested axis

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *sum* : Series or DataFrame (if level specified)

pandas.DataFrame.swapaxes

`DataFrame.swapaxes` (*axis1*, *axis2*, *copy*=True)

Interchange axes and swap values axes appropriately

Returns `y` : same as input

pandas.DataFrame.swaplevel

`DataFrame.swaplevel(i, j, axis=0)`

Swap levels `i` and `j` in a MultiIndex on a particular axis

Parameters `i, j` : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns `swapped` : type of caller (new object)

pandas.DataFrame.tail

`DataFrame.tail(n=5)`

Returns last `n` rows

pandas.DataFrame.take

`DataFrame.take(indices, axis=0, convert=True, is_copy=True)`

Analogous to `ndarray.take`

Parameters `indices` : list / array of ints

`axis` : int, default 0

`convert` : translate neg to pos indices (default)

`is_copy` : mark the returned frame as a copy

Returns `taken` : type of caller

pandas.DataFrame.to_clipboard

`DataFrame.to_clipboard(excel=None, sep=None, **kwargs)`

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters `excel` : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

`sep` : optional, defaults to tab

other keywords are passed to `to_csv`

Notes

Requirements for your platform

- Linux: `xclip`, or `xsel` (with `gtk` or `PyQt4` modules)
- Windows: none
- OS X: none

pandas.DataFrame.to_csv

`DataFrame.to_csv` (*path_or_buf=None, sep=',', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, mode='w', encoding=None, quoting=None, quotechar='"', line_terminator='\n', chunksize=None, tupleize_cols=False, date_format=None, doublequote=True, escapechar=None, decimal='.', **kwargs*)

Write DataFrame to a comma-separated values (csv) file

Parameters `path_or_buf` : string or file handle, default None

File path or object, if None is provided the result is returned as a string.

sep : character, default ','

Field delimiter for the output file.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, or False, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex. If False do not print fields for index names. Use *index_label=False* for easier importing in R

nanRep : None

deprecated, use *na_rep*

mode : str

Python write mode, default 'w'

encoding : string, optional

A string representing the encoding to use in the output file, defaults to 'ascii' on Python 2 and 'utf-8' on Python 3.

line_terminator : string, default '\n'

The newline character or character sequence to use in the output file

quoting : optional constant from csv module

defaults to `csv.QUOTE_MINIMAL`

quotechar : string (length 1), default '"'

character used to quote fields

doublequote : boolean, default True

Control quoting of *quotechar* inside a field

escapechar : string (length 1), default None

character used to escape *sep* and *quotechar* when appropriate

chunksize : int or None

rows to write at a time

tupleize_cols : boolean, default False

write multi_index columns as a list of tuples (if True) or new (expanded format) if False)

date_format : string, default None

Format string for datetime objects

decimal: string, default ‘.’

Character recognized as decimal separator. E.g. use ‘,’ for European data

pandas.DataFrame.to_dense

`DataFrame.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.DataFrame.to_dict

`DataFrame.to_dict(*args, **kwargs)`

Convert DataFrame to dictionary.

Parameters **orient** : str { ‘dict’, ‘list’, ‘series’, ‘split’, ‘records’ }

Determines the type of the values of the dictionary.

- dict (default) : dict like {column -> {index -> value}}
- list : dict like {column -> [values]}
- series : dict like {column -> Series(values)}
- split : dict like {index -> [index], columns -> [columns], data -> [values]}
- records : list like [{column -> value}, ... , {column -> value}]

Abbreviations are allowed. *s* indicates *series* and *sp* indicates *split*.

Returns **result** : dict like {column -> {index -> value}}

pandas.DataFrame.to_excel

`DataFrame.to_excel(excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf')`

Write DataFrame to a excel sheet

Parameters **excel_writer** : string or ExcelWriter object

File path or existing ExcelWriter

sheet_name : string, default 'Sheet1'

Name of sheet which will contain DataFrame

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow :

upper left cell row to dump data frame

startcol :

upper left cell column to dump data frame

engine : string, default None

write engine to use - you can also set this via the options
`io.excel.xlsx.writer`, `io.excel.xls.writer`, and
`io.excel.xlsm.writer`.

merge_cells : boolean, default True

Write MultiIndex and Hierarchical Rows as merged cells.

encoding: string, default None

encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep : string, default 'inf'

Representation for infinity (there is no native representation for infinity in Excel)

Notes

If passing an existing ExcelWriter object, then the sheet will be added to the existing workbook. This can be used to save different DataFrames to one workbook:

```
>>> writer = ExcelWriter('output.xlsx')
>>> df1.to_excel(writer, 'Sheet1')
>>> df2.to_excel(writer, 'Sheet2')
>>> writer.save()
```

pandas.DataFrame.to_gbq

```
DataFrame.to_gbq(destination_table, project_id=None, chunksize=10000, verbose=True,
                  reauth=False)
```

Write a DataFrame to a Google BigQuery table.

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If the table exists, the dataframe will be written to the table using the defined table schema and column types. For simplicity, this method uses the Google BigQuery streaming API. The `to_gbq` method chunks data into a default chunk size of 10,000. Failures return the complete error response which can be quite long depending on the size of the insert. There are several important limitations of the Google streaming API which are detailed at: <https://developers.google.com/bigquery/streaming-data-into-bigquery>.

Parameters `dataframe` : DataFrame

DataFrame to be written

destination_table : string

Name of table to be written, in the form 'dataset.tablename'

project_id : str

Google BigQuery Account project ID.

chunksize : int (default 10000)

Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)

Show percentage complete

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

pandas.DataFrame.to_hdf

```
DataFrame.to_hdf(path_or_buf, key, **kwargs)
activate the HDFStore
```

Parameters `path_or_buf` : the path (string) or buffer to put the store

key : string

identifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to **'a'**, but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.DataFrame.to_html

`DataFrame.to_html` (*buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, bold_rows=True, classes=None, escape=True, max_rows=None, max_cols=None, show_dimensions=False*)

Render a DataFrame as an HTML table.

to_html-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

classes [str or list or tuple, default None] CSS class(es) to apply to the resulting html table

escape [boolean, default True] Convert the characters <, >, and & to HTML-safe sequences.=

max_rows [int, optional] Maximum number of rows to show before truncating. If None, show all.

max_cols [int, optional] Maximum number of columns to show before truncating. If None, show all.

Parameters **frame** : DataFrame

object to render

buf : StringIO-like, optional

buffer to write to

columns : sequence, optional

the subset of columns to write; default None writes all columns

col_space : int, optional

the minimum width of each column

header : bool, optional

whether to print column labels, default True

index : bool, optional

whether to print index (row) labels, default True

na_rep : string, optional

string representation of NAN to use, default 'NaN'

formatters : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats, default None. The result of this function must be a unicode string.

sparsify : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_json

`DataFrame.to_json` (*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters path_or_buf : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
 - default is 'index'
 - allowed values are: {'split', 'records', 'index'}

- **DataFrame**
 - default is 'columns'
 - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
 - split : dict like {index -> [index], columns -> [columns], data -> [values]}
 - records : list like [{column -> value}, ... , {column -> value}]
 - index : dict like {index -> {column -> value}}
 - columns : dict like {column -> {index -> value}}
 - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.DataFrame.to_latex

`DataFrame.to_latex` (*buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=True, longtable=False, escape=True*)

Render a DataFrame to a tabular environment table. You can splice this into a LaTeX document. Requires `usepackage{booktabs}`.

to_latex-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

longtable [boolean, default False] Use a longtable environment instead of tabular. Requires adding a `usepackage{longtable}` to your LaTeX preamble.

escape [boolean, default True] When set to False prevents from escaping latex special characters in column names.

Parameters **frame** : DataFrame

object to render

buf : StringIO-like, optional

buffer to write to

columns : sequence, optional

the subset of columns to write; default None writes all columns

col_space : int, optional

the minimum width of each column

header : bool, optional

whether to print column labels, default True

index : bool, optional

whether to print index (row) labels, default True

na_rep : string, optional

string representation of NAN to use, default 'NaN'

formatters : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats, default None. The result of this function must be a unicode string.

sparsify : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

justify : { 'left', 'right' }, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_msgpack

`DataFrame.to_msgpack` (*path_or_buf=None, **kwargs*)

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack
(default is False)

compress : type of compressor (zlib or blosc), default to None (no
compression)

pandas.DataFrame.to_panel

`DataFrame.to_panel()`

Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.

Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

Returns panel : Panel

pandas.DataFrame.to_period

`DataFrame.to_period(freq=None, axis=0, copy=True)`

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters freq : string, default

axis : {0, 1}, default 0

The axis to convert (the index by default)

copy : boolean, default True

If False then underlying input data is not copied

Returns ts : TimeSeries with PeriodIndex

pandas.DataFrame.to_pickle

`DataFrame.to_pickle(path)`

Pickle (serialize) object to input file path

Parameters path : string

File path

pandas.DataFrame.to_records

`DataFrame.to_records(index=True, convert_datetime64=True)`

Convert DataFrame to record array. Index will be put in the 'index' field of the record array if requested

Parameters index : boolean, default True

Include index in resulting record array, stored in 'index' field

convert_datetime64 : boolean, default True

Whether to convert the index to datetime.datetime if it is a DatetimeIndex

Returns y : recarray

pandas.DataFrame.to_sparse`DataFrame.to_sparse` (*fill_value=None, kind='block'*)

Convert to SparseDataFrame

Parameters `fill_value` : float, default NaN`kind` : { 'block', 'integer' }**Returns** `y` : SparseDataFrame**pandas.DataFrame.to_sql**`DataFrame.to_sql` (*name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None*)

Write records stored in a DataFrame to a SQL database.

Parameters `name` : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : { 'sqlite', 'mysql' }, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : { 'fail', 'replace', 'append' }, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default NoneColumn label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.**chunksize** : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.DataFrame.to_stata

`DataFrame.to_stata` (*fname*, *convert_dates=None*, *write_index=True*, *encoding='latin-1'*, *byteorder=None*, *time_stamp=None*, *data_label=None*)

A class for writing Stata binary dta files from array-like objects

Parameters **fname** : file path or buffer

Where to save the dta file.

convert_dates : dict

Dictionary mapping column of datetime types to the stata internal format that you want to use for the dates. Options are 'tc', 'td', 'tm', 'tw', 'th', 'tq', 'ty'. Column can be either a number or a name.

encoding : str

Default is latin-1. Note that Stata does not support unicode.

byteorder : str

Can be ">", "<", "little", or "big". The default is None which uses `sys.byteorder`

Examples

```
>>> writer = StataWriter('./data_file.dta', data)
>>> writer.write_file()
```

Or with dates

```
>>> writer = StataWriter('./date_data_file.dta', data, {2 : 'tw'})
>>> writer.write_file()
```

pandas.DataFrame.to_string

`DataFrame.to_string` (*buf=None*, *columns=None*, *col_space=None*, *colSpace=None*, *header=True*, *index=True*, *na_rep='NaN'*, *formatters=None*, *float_format=None*, *sparsify=None*, *index_names=True*, *justify=None*, *line_width=None*, *max_rows=None*, *max_cols=None*, *show_dimensions=False*)

Render a DataFrame to a console-friendly tabular output.

Parameters **frame** : DataFrame

object to render

buf : StringIO-like, optional

buffer to write to

columns : sequence, optional

the subset of columns to write; default None writes all columns

col_space : int, optional

the minimum width of each column

header : bool, optional

whether to print column labels, default True

index : bool, optional

whether to print index (row) labels, default True

na_rep : string, optional

string representation of NAN to use, default 'NaN'

formatters : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats, default None. The result of this function must be a unicode string.

sparsify : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_timestamp

`DataFrame.to_timestamp(freq=None, how='start', axis=0, copy=True)`

Cast to DatetimeIndex of timestamps, at *beginning* of period

Parameters freq : string, default frequency of PeriodIndex

Desired frequency

how : {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

axis : {0, 1} default 0

The axis to convert (the index by default)

copy : boolean, default True

If false then underlying input data is not copied

Returns df : DataFrame with DatetimeIndex

pandas.DataFrame.to_wide

`DataFrame.to_wide(*args, **kwargs)`

pandas.DataFrame.transpose

`DataFrame.transpose()`
Transpose index and columns

pandas.DataFrame.truediv

`DataFrame.truediv(other, axis='columns', level=None, fill_value=None)`
Binary operator truediv with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.truncate

`DataFrame.truncate(before=None, after=None, axis=None, copy=True)`
Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

pandas.DataFrame.tshift`DataFrame.tshift` (*periods=1, freq=None, axis=0, **kwargs*)

Shift the time index, using the index's frequency if available

Parameters `periods` : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, default None

Increment to use from datetools module or time rule (e.g. 'EOM')

axis : int or basestring

Corresponds to the axis that contains the Index

Returns `shifted` : NDFrame**Notes**

If freq is not specified then tries to use the freq or inferred_freq attributes of the index. If neither of those attributes exist, a ValueError is thrown

pandas.DataFrame.tz_convert`DataFrame.tz_convert` (*tz, axis=0, level=None, copy=True*)

Convert tz-aware axis to target time zone.

Parameters `tz` : string or pytz.timezone object**axis** : the axis to convert**level** : int, str, default None

If axis is a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises `TypeError`

If the axis is tz-naive.

pandas.DataFrame.tz_localize`DataFrame.tz_localize` (**args, **kwargs*)

Localize tz-naive TimeSeries to target time zone

Parameters `tz` : string or pytz.timezone object**axis** : the axis to localize**level** : int, str, default None

If axis is a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises TypeError

If the TimeSeries is tz-aware and tz is not None.

pandas.DataFrame.unstack

DataFrame.**unstack** (*level=-1*)

Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels. If the index is not a MultiIndex, the output will be a Series (the analogue of stack when the columns are not a MultiIndex). The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default -1 (last level)

Level(s) of index to unstack, can pass level name

Returns **unstacked** : DataFrame or Series

See also:

DataFrame.pivot Pivot a table based on column values.

DataFrame.stack Pivot a level of the column labels (inverse operation from *unstack*).

Examples

```
>>> index = pd.MultiIndex.from_tuples([('one', 'a'), ('one', 'b'),
...                                   ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one  a    1
     b    2
two  a    3
     b    4
dtype: float64

>>> s.unstack(level=-1)
     a  b
one  1  2
two  3  4

>>> s.unstack(level=0)
     one  two
a    1    3
b    2    4
```

```
>>> df = s.unstack(level=0)
>>> df.unstack()
one  a  1.
     b  3.
two  a  2.
     b  4.
```

pandas.DataFrame.update

`DataFrame.update` (*other*, *join*='left', *overwrite*=True, *filter_func*=None, *raise_conflict*=False)
 Modify DataFrame in place using non-NA values from passed DataFrame. Aligns on indices

Parameters **other** : DataFrame, or object coercible into a DataFrame

join : { 'left' }, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : boolean

If True, will raise an error if the DataFrame and other both contain data in the same place.

pandas.DataFrame.var

`DataFrame.var` (*axis*=None, *skipna*=None, *level*=None, *ddof*=1, *numeric_only*=None, ***kwargs*)
 Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the *ddof* argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : Series or DataFrame (if level specified)

pandas.DataFrame.where

DataFrame.**where** (*cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.DataFrame.xs

DataFrame.**xs** (*key, axis=0, level=None, copy=None, drop_level=True*)

Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (axis=0).

Parameters **key** : object

Some label contained in the index, or partially in a MultiIndex

axis : int, default 0

Axis to retrieve cross-section on

level : object, defaults to first n levels (n=1 or len(key))

In case of a key partially contained in a MultiIndex, indicate which levels are used. Levels can be referred by label or position.

copy : boolean [deprecated]

Whether to make a copy of the data

drop_level : boolean, default True

If False, returns object with same levels as self.

Returns **xs** : Series or DataFrame

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see [MultiIndex Slicers](#)

Examples

```
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
A    4
B    5
C    2
Name: a
>>> df.xs('C', axis=1)
a    2
b    9
c    3
Name: C

>>> df
      first second third      A  B  C  D
bar   one     1      4  1  8  9
      two     1      7  5  5  0
baz   one     1      6  6  8  0
      three  2      5  3  5  3
>>> df.xs(('baz', 'three'))
      A  B  C  D
third
2      5  3  5  3
>>> df.xs('one', level=1)
      A  B  C  D
first third
bar   1      4  1  8  9
baz   1      6  6  8  0
>>> df.xs(('baz', 2), level=[0, 'third'])
      A  B  C  D
second
three  5  3  5  3
```

33.4.2 Attributes and underlying data

Axes

- **index**: row labels
- **columns**: column labels

DataFrame.as_matrix([columns])	Convert the frame to its Numpy-array representation.
DataFrame.dtypes	Return the dtypes in this object
DataFrame.ftypes	Return the ftypes (indication of sparse/dense and dtype) in this object.
DataFrame.get_dtype_counts()	Return the counts of dtypes in this object
DataFrame.get_ftype_counts()	Return the counts of ftypes in this object
DataFrame.select_dtypes([include, exclude])	Return a subset of a DataFrame including/excluding columns based on their
DataFrame.values	Numpy representation of NDFrame
DataFrame.axes	
DataFrame.ndim	Number of axes / array dimensions

Continued on next page

Table 33.51 – continued from previous page

<code>DataFrame.size</code>	number of elements in the NDFrame
<code>DataFrame.shape</code>	

pandas.DataFrame.as_matrix

`DataFrame.as_matrix` (*columns=None*)

Convert the frame to its Numpy-array representation.

Parameters **columns:** list, optional, default:None

If None, return all columns, otherwise, returns specified columns.

Returns **values** : ndarray

If the caller is heterogeneous and contains booleans or objects, the result will be of dtype=object. See Notes.

See also:

`pandas.DataFrame.values`

Notes

Return is NOT a Numpy-matrix, rather, a Numpy-array.

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

This method is provided for backwards compatibility. Generally, it is recommended to use ‘.values’.

pandas.DataFrame.dtypes

`DataFrame.dtypes`

Return the dtypes in this object

pandas.DataFrame.ftypes

`DataFrame.ftypes`

Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.DataFrame.get_dtype_counts

`DataFrame.get_dtype_counts` ()

Return the counts of dtypes in this object

pandas.DataFrame.get_ftype_counts

`DataFrame.get_ftype_counts` ()

Return the counts of ftypes in this object

pandas.DataFrame.select_dtypes`DataFrame.select_dtypes` (*include=None, exclude=None*)

Return a subset of a DataFrame including/excluding columns based on their dtype.

Parameters `include, exclude` : list-like

A list of dtypes or strings to be included/excluded. You must pass in a non-empty sequence for at least one of these.

Returns `subset` : DataFrameThe subset of the frame including the dtypes in `include` and excluding the dtypes in `exclude`.**Raises** `ValueError`

- If both of `include` and `exclude` are empty
- If `include` and `exclude` have overlapping elements
- If any kind of string dtype is passed in.

TypeError

- If either of `include` or `exclude` is not a sequence

Notes

- To select all *numeric* types use the numpy dtype `numpy.number`
- To select strings you must use the `object` dtype, but note that this will return *all* object dtype columns
- See the [numpy dtype hierarchy](#)
- To select Pandas categorical dtypes, use 'category'

Examples

```
>>> df = pd.DataFrame({'a': np.random.randn(6).astype('f4'),
...                    'b': [True, False] * 3,
...                    'c': [1.0, 2.0] * 3})
>>> df
   a      b  c
0  0.3962  True  1
1  0.1459 False  2
2  0.2623  True  1
3  0.0764 False  2
4 -0.9703  True  1
5 -1.2094 False  2
>>> df.select_dtypes(include=['float64'])
   c
0  1
1  2
2  1
3  2
4  1
5  2
>>> df.select_dtypes(exclude=['floating'])
   b
```

```
0    True
1   False
2     True
3   False
4     True
5   False
```

pandas.DataFrame.values

DataFrame.**values**

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

pandas.DataFrame.axes

DataFrame.**axes**

pandas.DataFrame.ndim

DataFrame.**ndim**

Number of axes / array dimensions

pandas.DataFrame.size

DataFrame.**size**

number of elements in the NDFrame

pandas.DataFrame.shape

DataFrame.**shape**

33.4.3 Conversion

<code>DataFrame.astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>DataFrame.convert_objects([convert_dates, ...])</code>	Attempt to infer better dtype for object columns
<code>DataFrame.copy([deep])</code>	Make a copy of this object
<code>DataFrame.isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>DataFrame.notnull()</code>	Return a boolean same-sized object indicating if the values are

pandas.DataFrame.astype

`DataFrame.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters `dtype` : numpy.dtype or Python type

`raise_on_error` : raise on invalid input

`kwargs` : keyword arguments to pass on to the constructor

Returns `casted` : type of caller

pandas.DataFrame.convert_objects

`DataFrame.convert_objects(convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True)`

Attempt to infer better dtype for object columns

Parameters `convert_dates` : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

`convert_numeric` : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

`convert_timedeltas` : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

`copy` : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with inplace.

Returns `converted` : same as input object

pandas.DataFrame.copy

`DataFrame.copy(deep=True)`

Make a copy of this object

Parameters `deep` : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns `copy` : type of caller

pandas.DataFrame.isnull

`DataFrame.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of isnull

pandas.DataFrame.notnull

`DataFrame.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

33.4.4 Indexing, iteration

<code>DataFrame.head([n])</code>	Returns first n rows
<code>DataFrame.at</code>	Fast label-based scalar accessor
<code>DataFrame.iat</code>	Fast integer location scalar accessor.
<code>DataFrame.ix</code>	A primarily label-location based indexer, with integer position fallback.
<code>DataFrame.loc</code>	Purely label-location based indexer for selection by label.
<code>DataFrame.iloc</code>	Purely integer-location based indexing for selection by position.
<code>DataFrame.insert(loc, column, value[, ...])</code>	Insert column into DataFrame at specified location.
<code>DataFrame.__iter__()</code>	Iterate over infor axis
<code>DataFrame.iteritems()</code>	Iterator over (column, series) pairs
<code>DataFrame.iterrows()</code>	Iterate over rows of DataFrame as (index, Series) pairs.
<code>DataFrame.itertuples([index])</code>	Iterate over rows of DataFrame as tuples, with index value
<code>DataFrame.lookup(row_labels, col_labels)</code>	Label-based “fancy indexing” function for DataFrame.
<code>DataFrame.pop(item)</code>	Return item and drop from frame.
<code>DataFrame.tail([n])</code>	Returns last n rows
<code>DataFrame.xs(key[, axis, level, copy, ...])</code>	Returns a cross-section (row(s) or column(s)) from the Series/DataFrame.
<code>DataFrame.isin(values)</code>	Return boolean DataFrame showing whether each element in the DataFrame is
<code>DataFrame.where(cond[, other, inplace, ...])</code>	Return an object of same shape as self and whose corresponding entries are fro
<code>DataFrame.mask(cond[, other, inplace, axis, ...])</code>	Return an object of same shape as self and whose corresponding entries are fro
<code>DataFrame.query(expr, **kwargs)</code>	Query the columns of a frame with a boolean expression.

pandas.DataFrame.head

`DataFrame.head(n=5)`

Returns first n rows

pandas.DataFrame.at

`DataFrame.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.DataFrame.iat

`DataFrame.iat`

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.DataFrame.ix

DataFrame.ix

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#).

pandas.DataFrame.loc

DataFrame.loc

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a' : 'f' (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at [Selection by Label](#)

pandas.DataFrame.iloc

DataFrame.iloc

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at [Selection by Position](#)

pandas.DataFrame.insert

`DataFrame.insert(loc, column, value, allow_duplicates=False)`

Insert column into DataFrame at specified location.

If `allow_duplicates` is False, raises Exception if column is already contained in the DataFrame.

Parameters `loc` : int

Must have $0 \leq \text{loc} \leq \text{len}(\text{columns})$

column : object

value : int, Series, or array-like

pandas.DataFrame.__iter__

`DataFrame.__iter__()`

Iterate over infor axis

pandas.DataFrame.iteritems

`DataFrame.iteritems()`

Iterator over (column, series) pairs

pandas.DataFrame.iterrows

`DataFrame.iterrows()`

Iterate over rows of DataFrame as (index, Series) pairs.

Returns `it` : generator

A generator that iterates over the rows of the frame.

Notes

- `iterrows` does **not** preserve dtypes across the rows (dtypes are preserved across columns for DataFrames). For example,

```
>>> df = DataFrame([[1, 1.0]], columns=['x', 'y'])
>>> row = next(df.iterrows())[1]
>>> print(row['x'].dtype)
float64
>>> print(df['x'].dtype)
int64
```

pandas.DataFrame.itertuples

`DataFrame.itertuples(index=True)`

Iterate over rows of DataFrame as tuples, with index value as first element of the tuple

pandas.DataFrame.lookup

`DataFrame.lookup` (*row_labels*, *col_labels*)

Label-based “fancy indexing” function for DataFrame. Given equal-length arrays of row and column labels, return an array of the values corresponding to each (row, col) pair.

Parameters `row_labels` : sequence

The row labels to use for lookup

`col_labels` : sequence

The column labels to use for lookup

Notes

Akin to:

```
result = []
for row, col in zip(row_labels, col_labels):
    result.append(df.get_value(row, col))
```

Examples

values [ndarray] The found values

pandas.DataFrame.pop

`DataFrame.pop` (*item*)

Return item and drop from frame. Raise `KeyError` if not found.

pandas.DataFrame.tail

`DataFrame.tail` (*n=5*)

Returns last *n* rows

pandas.DataFrame.xs

`DataFrame.xs` (*key*, *axis=0*, *level=None*, *copy=None*, *drop_level=True*)

Returns a cross-section (row(s) or column(s)) from the Series/DataFrame. Defaults to cross-section on the rows (*axis=0*).

Parameters `key` : object

Some label contained in the index, or partially in a MultiIndex

`axis` : int, default 0

Axis to retrieve cross-section on

`level` : object, defaults to first *n* levels (*n=1* or *len(key)*)

In case of a key partially contained in a MultiIndex, indicate which levels are used.
Levels can be referred by label or position.

`copy` : boolean [deprecated]

Whether to make a copy of the data

drop_level : boolean, default True

If False, returns object with same levels as self.

Returns **xs** : Series or DataFrame

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see [MultiIndex Slicers](#)

Examples

```
>>> df
   A  B  C
a  4  5  2
b  4  0  9
c  9  7  3
>>> df.xs('a')
A    4
B    5
C    2
Name: a
>>> df.xs('C', axis=1)
a    2
b    9
c    3
Name: C

>>> df
      first second third   A  B  C  D
bar   one     1      4  1  8  9
      two     1      7  5  5  0
baz   one     1      6  6  8  0
      three  2      5  3  5  3
>>> df.xs(('baz', 'three'))
      A  B  C  D
third
2      5  3  5  3
>>> df.xs('one', level=1)
      A  B  C  D
first third
bar   1      4  1  8  9
baz   1      6  6  8  0
>>> df.xs(('baz', 2), level=[0, 'third'])
      A  B  C  D
second
three  5  3  5  3
```

pandas.DataFrame.isin

`DataFrame.isin(values)`

Return boolean DataFrame showing whether each element in the DataFrame is contained in values.

Parameters `values` : iterable, Series, DataFrame or dictionary

The result will only be true at a location if all the labels match. If *values* is a Series, that's the index. If *values* is a dictionary, the keys must be the column names, which must match. If *values* is a DataFrame, then both the index and column labels must match.

Returns DataFrame of booleans

Examples

When *values* is a list:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> df.isin([1, 3, 12, 'a'])
```

	A	B
0	True	True
1	False	False
2	True	False

When *values* is a dict:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': [1, 4, 7]})
>>> df.isin({'A': [1, 3], 'B': [4, 7, 12]})
```

	A	B
0	True	False
1	False	True
2	True	True

Note that B didn't match the 1 here.

When *values* is a Series or DataFrame:

```
>>> df = DataFrame({'A': [1, 2, 3], 'B': ['a', 'b', 'f']})
>>> other = DataFrame({'A': [1, 3, 3, 2], 'B': ['e', 'f', 'f', 'e']})
>>> df.isin(other)
```

	A	B
0	True	False
1	False	False
2	True	True

Column A in `other` has a 3, but not at index 1.

pandas.DataFrame.where

`DataFrame.where(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where *cond* is True and otherwise are from *other*.

Parameters `cond` : boolean NDFrame or array

`other` : scalar or NDFrame

`inplace` : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.DataFrame.mask

`DataFrame.mask(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.DataFrame.query

`DataFrame.query(expr, **kwargs)`

Query the columns of a frame with a boolean expression.

New in version 0.13.

Parameters **expr** : string

The query string to evaluate. You can refer to variables in the environment by prefixing them with an '@' character like @a + b.

kwargs : dict

See the documentation for `pandas.eval()` for complete details on the keyword arguments accepted by `DataFrame.query()`.

Returns **q** : DataFrame

See also:

`pandas.eval`, `DataFrame.eval`

Notes

The result of the evaluation of this expression is first passed to `DataFrame.loc` and if that fails because of a multidimensional key (e.g., a `DataFrame`) then the result will be passed to `DataFrame.__getitem__()`.

This method uses the top-level `pandas.eval()` function to evaluate the passed query.

The `query()` method uses a slightly modified Python syntax by default. For example, the `&` and `|` (bitwise) operators have the precedence of their boolean cousins, `and` and `or`. This *is* syntactically valid Python, however the semantics are different.

You can change the semantics of the expression by passing the keyword argument `parser='python'`. This enforces the same semantics as evaluation in Python space. Likewise, you can pass `engine='python'` to evaluate an expression using Python itself as a backend. This is not recommended as it is inefficient compared to using `numexpr` as the engine.

The `DataFrame.index` and `DataFrame.columns` attributes of the `DataFrame` instance are placed in the query namespace by default, which allows you to treat both the index and columns of the frame as a column in the frame. The identifier `index` is used for the frame index; you can also use the name of the index to identify it in a query.

For further details and examples see the `query` documentation in [indexing](#).

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.query('a > b')
>>> df[df.a > df.b] # same result as the previous expression
```

For more information on `.at`, `.iat`, `.ix`, `.loc`, and `.iloc`, see the [indexing documentation](#).

33.4.5 Binary operator functions

```
DataFrame.add(other[, axis, level, fill_value])
DataFrame.sub(other[, axis, level, fill_value])
DataFrame.mul(other[, axis, level, fill_value])
DataFrame.div(other[, axis, level, fill_value])
DataFrame.truediv(other[, axis, level, ...])
DataFrame.floordiv(other[, axis, level, ...])
DataFrame.mod(other[, axis, level, fill_value])
DataFrame.pow(other[, axis, level, fill_value])
DataFrame.radd(other[, axis, level, fill_value])
DataFrame.rsub(other[, axis, level, fill_value])
DataFrame.rmul(other[, axis, level, fill_value])
DataFrame.rdiv(other[, axis, level, fill_value])
DataFrame.rtruediv(other[, axis, level, ...])
DataFrame.rfloordiv(other[, axis, level, ...])
DataFrame.rmod(other[, axis, level, fill_value])
DataFrame.rpow(other[, axis, level, fill_value])
DataFrame.lt(other[, axis, level])
DataFrame.gt(other[, axis, level])
```

```
Binary operator add with support to substitute a fill_value for missing data in
Binary operator sub with support to substitute a fill_value for missing data in
Binary operator mul with support to substitute a fill_value for missing data in
Binary operator truediv with support to substitute a fill_value for missing data in
Binary operator truediv with support to substitute a fill_value for missing data in
Binary operator floordiv with support to substitute a fill_value for missing data in
Binary operator mod with support to substitute a fill_value for missing data in
Binary operator pow with support to substitute a fill_value for missing data in
Binary operator radd with support to substitute a fill_value for missing data in
Binary operator rsub with support to substitute a fill_value for missing data in
Binary operator rmul with support to substitute a fill_value for missing data in
Binary operator rtruediv with support to substitute a fill_value for missing data in
Binary operator rtruediv with support to substitute a fill_value for missing data in
Binary operator rfloordiv with support to substitute a fill_value for missing data in
Binary operator rmod with support to substitute a fill_value for missing data in
Binary operator rpow with support to substitute a fill_value for missing data in
Wrapper for flexible comparison methods lt
Wrapper for flexible comparison methods gt
```

Continued

Table 33.54 – continued from previous page

<code>DataFrame.le(other[, axis, level])</code>	Wrapper for flexible comparison methods le
<code>DataFrame.ge(other[, axis, level])</code>	Wrapper for flexible comparison methods ge
<code>DataFrame.ne(other[, axis, level])</code>	Wrapper for flexible comparison methods ne
<code>DataFrame.eq(other[, axis, level])</code>	Wrapper for flexible comparison methods eq
<code>DataFrame.combine(other, func[, fill_value, ...])</code>	Add two DataFrame objects and do not propagate NaN values, so if for a
<code>DataFrame.combineAdd(other)</code>	Add two DataFrame objects and do not propagate
<code>DataFrame.combine_first(other)</code>	Combine two DataFrame objects and default to non-null values in frame callin
<code>DataFrame.combineMult(other)</code>	Multiply two DataFrame objects and do not propagate NaN values, so if

pandas.DataFrame.add

`DataFrame.add(other, axis='columns', level=None, fill_value=None)`

Binary operator add with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.sub

`DataFrame.sub(other, axis='columns', level=None, fill_value=None)`

Binary operator sub with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.mul

`DataFrame.mul` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator mul with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.div

`DataFrame.div` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator truediv with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.truediv

DataFrame.**truediv** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator truediv with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.floordiv

DataFrame.**floordiv** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator floordiv with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.mod

DataFrame.**mod** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator mod with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.pow

DataFrame.**pow**(*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator pow with support to substitute a fill_value for missing data in one of the inputs

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.radd

DataFrame.**radd**(*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator radd with support to substitute a fill_value for missing data in one of the inputs

Parameters other : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rsub

`DataFrame.rsub (other, axis='columns', level=None, fill_value=None)`

Binary operator rsub with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmul

`DataFrame.rmul (other, axis='columns', level=None, fill_value=None)`

Binary operator rmul with support to substitute a fill_value for missing data in one of the inputs

Parameters **other** : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns **result** : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rdiv

`DataFrame.rdiv` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rtruediv with support to substitute a *fill_value* for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rtruediv

`DataFrame.rtruediv` (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rtruediv with support to substitute a *fill_value* for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rfloordiv

DataFrame.**rfloordiv** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rfloordiv with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rmod

DataFrame.**rmod** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rmod with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns *result* : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.rpow

DataFrame.**rpow** (*other*, *axis*='columns', *level*=None, *fill_value*=None)

Binary operator rpow with support to substitute a fill_value for missing data in one of the inputs

Parameters *other* : Series, DataFrame, or constant

axis : {0, 1, 'index', 'columns'}

For Series input, axis to match Series index on

fill_value : None or float value, default None

Fill missing (NaN) values with this value. If both DataFrame locations are missing, the result will be missing

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

Returns result : DataFrame

Notes

Mismatched indices will be unioned together

pandas.DataFrame.lt

DataFrame.**lt** (*other*, axis='columns', level=None)
Wrapper for flexible comparison methods lt

pandas.DataFrame.gt

DataFrame.**gt** (*other*, axis='columns', level=None)
Wrapper for flexible comparison methods gt

pandas.DataFrame.le

DataFrame.**le** (*other*, axis='columns', level=None)
Wrapper for flexible comparison methods le

pandas.DataFrame.ge

DataFrame.**ge** (*other*, axis='columns', level=None)
Wrapper for flexible comparison methods ge

pandas.DataFrame.ne

DataFrame.**ne** (*other*, axis='columns', level=None)
Wrapper for flexible comparison methods ne

pandas.DataFrame.eq

DataFrame.**eq** (*other*, axis='columns', level=None)
Wrapper for flexible comparison methods eq

pandas.DataFrame.combine

`DataFrame.combine` (*other*, *func*, *fill_value=None*, *overwrite=True*)

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters *other* : DataFrame

func : function

fill_value : scalar value

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

Returns *result* : DataFrame

pandas.DataFrame.combineAdd

`DataFrame.combineAdd` (*other*)

Add two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters *other* : DataFrame

Returns DataFrame

pandas.DataFrame.combine_first

`DataFrame.combine_first` (*other*)

Combine two DataFrame objects and default to non-null values in frame calling the method. Result index columns will be the union of the respective indexes and columns

Parameters *other* : DataFrame

Returns *combined* : DataFrame

Examples

a's values prioritized, use values from b to fill holes:

```
>>> a.combine_first(b)
```

pandas.DataFrame.combineMult

`DataFrame.combineMult` (*other*)

Multiply two DataFrame objects and do not propagate NaN values, so if for a (column, time) one frame is missing a value, it will default to the other frame's value (which might be NaN as well)

Parameters *other* : DataFrame

Returns DataFrame

33.4.6 Function application, GroupBy

<code>DataFrame.apply(func[, axis, broadcast, ...])</code>	Applies function along input axis of DataFrame.
<code>DataFrame.applymap(func)</code>	Apply a function to a DataFrame that is intended to operate elementwise, i.e.
<code>DataFrame.groupby([by, axis, level, ...])</code>	Group series using mapper (dict or key function, apply given function

pandas.DataFrame.apply

`DataFrame.apply` (*func*, *axis=0*, *broadcast=False*, *raw=False*, *reduce=None*, *args=()*, ***kwargs*)

Applies function along input axis of DataFrame.

Objects passed to functions are Series objects having index either the DataFrame's index (*axis=0*) or the columns (*axis=1*). Return type depends on whether passed function aggregates, or the *reduce* argument if the DataFrame is empty.

Parameters *func* : function

Function to apply to each column/row

axis : {0, 1}

- 0 : apply function to each column
- 1 : apply function to each row

broadcast : boolean, default False

For aggregation functions, return object of same size with values propagated

reduce : boolean or None, default None

Try to apply reduction procedures. If the DataFrame is empty, *apply* will use *reduce* to determine whether the result should be a Series or a DataFrame. If *reduce* is None (the default), *apply*'s return value will be guessed by calling *func* an empty Series (note: while guessing, exceptions raised by *func* will be ignored). If *reduce* is True a Series will always be returned, and if False a DataFrame will always be returned.

raw : boolean, default False

If False, convert each row or column into a Series. If *raw=True* the passed function will receive ndarray objects instead. If you are just applying a NumPy reduction function this will achieve much better performance

args : tuple

Positional arguments to pass to function in addition to the array/series

Additional keyword arguments will be passed as keywords to the function

Returns *applied* : Series or DataFrame

See also:

`DataFrame.applymap` For elementwise operations

Notes

In the current implementation *apply* calls *func* twice on the first column/row to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if *func* has side-effects, as they will take effect twice for the first column/row.

Examples

```
>>> df.apply(numpy.sqrt) # returns DataFrame
>>> df.apply(numpy.sum, axis=0) # equiv to df.sum(0)
>>> df.apply(numpy.sum, axis=1) # equiv to df.sum(1)
```

pandas.DataFrame.applymap

`DataFrame.applymap` (*func*)

Apply a function to a DataFrame that is intended to operate elementwise, i.e. like doing `map(func, series)` for each series in the DataFrame

Parameters `func` : function

Python function, returns a single value from a single value

Returns `applied` : DataFrame

See also:

`DataFrame.apply` For operations on rows/columns

pandas.DataFrame.groupby

`DataFrame.groupby` (*by=None, axis=0, level=None, as_index=True, sort=True, group_keys=True, squeeze=False*)

Group series using mapper (dict or key function, apply given function to group, return result as series) or by a series of columns

Parameters `by` : mapping function / list of functions, dict, Series, or tuple /

list of column names. Called on each element of the object index to determine the groups. If a dict or Series is passed, the Series or dict VALUES will be used to determine the groups

axis : int, default 0

level : int, level name, or sequence of such, default None

If the axis is a MultiIndex (hierarchical), group by a particular level or levels

as_index : boolean, default True

For aggregated output, return object with group labels as the index. Only relevant for DataFrame input. `as_index=False` is effectively “SQL-style” grouped output

sort : boolean, default True

Sort group keys. Get better performance by turning this off

group_keys : boolean, default True

When calling apply, add group keys to index to identify pieces

squeeze : boolean, default False

reduce the dimensionality of the return type if possible, otherwise return a consistent type

Returns GroupBy object

Examples

DataFrame results

```
>>> data.groupby(func, axis=0).mean()
>>> data.groupby(['col1', 'col2'])['col3'].mean()
```

DataFrame with hierarchical index

```
>>> data.groupby(['col1', 'col2']).mean()
```

33.4.7 Computations / Descriptive Stats

<code>DataFrame.abs()</code>	Return an object with absolute value taken.
<code>DataFrame.all([axis, bool_only, skipna, level])</code>	Return whether all elements are True over requested axis
<code>DataFrame.any([axis, bool_only, skipna, level])</code>	Return whether any element is True over requested axis
<code>DataFrame.clip([lower, upper, out, axis])</code>	Trim values at input threshold(s)
<code>DataFrame.clip_lower(threshold[, axis])</code>	Return copy of the input with values below given value(s) truncated
<code>DataFrame.clip_upper(threshold[, axis])</code>	Return copy of input with values above given value(s) truncated
<code>DataFrame.corr([method, min_periods])</code>	Compute pairwise correlation of columns, excluding NA/null values
<code>DataFrame.corrwith(other[, axis, drop])</code>	Compute pairwise correlation between rows or columns of two DataFrame
<code>DataFrame.count([axis, level, numeric_only])</code>	Return Series with number of non-NA/null observations over requested axis
<code>DataFrame.cov([min_periods])</code>	Compute pairwise covariance of columns, excluding NA/null values
<code>DataFrame.cummax([axis, dtype, out, skipna])</code>	Return cumulative max over requested axis.
<code>DataFrame.cummin([axis, dtype, out, skipna])</code>	Return cumulative min over requested axis.
<code>DataFrame.cumprod([axis, dtype, out, skipna])</code>	Return cumulative prod over requested axis.
<code>DataFrame.cumsum([axis, dtype, out, skipna])</code>	Return cumulative sum over requested axis.
<code>DataFrame.describe([percentile_width, ...])</code>	Generate various summary statistics, excluding NaN values.
<code>DataFrame.diff([periods, axis])</code>	1st discrete difference of object
<code>DataFrame.eval(expr, **kwargs)</code>	Evaluate an expression in the context of the calling DataFrame instance.
<code>DataFrame.kurt([axis, skipna, level, ...])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>DataFrame.mad([axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis
<code>DataFrame.max([axis, skipna, level, ...])</code>	This method returns the maximum of the values in the object.
<code>DataFrame.mean([axis, skipna, level, ...])</code>	Return the mean of the values for the requested axis
<code>DataFrame.median([axis, skipna, level, ...])</code>	Return the median of the values for the requested axis
<code>DataFrame.min([axis, skipna, level, ...])</code>	This method returns the minimum of the values in the object.
<code>DataFrame.mode([axis, numeric_only])</code>	Gets the mode(s) of each element along the axis selected.
<code>DataFrame.pct_change([periods, fill_method, ...])</code>	Percent change over given number of periods.
<code>DataFrame.prod([axis, skipna, level, ...])</code>	Return the product of the values for the requested axis
<code>DataFrame.quantile([q, axis, numeric_only])</code>	Return values at the given quantile over requested axis, a la numpy.percentile
<code>DataFrame.rank([axis, numeric_only, method, ...])</code>	Compute numerical data ranks (1 through n) along axis.
<code>DataFrame.sem([axis, skipna, level, ddof, ...])</code>	Return unbiased standard error of the mean over requested axis.
<code>DataFrame.skew([axis, skipna, level, ...])</code>	Return unbiased skew over requested axis
<code>DataFrame.sum([axis, skipna, level, ...])</code>	Return the sum of the values for the requested axis
<code>DataFrame.std([axis, skipna, level, ddof, ...])</code>	Return unbiased standard deviation over requested axis.
<code>DataFrame.var([axis, skipna, level, ddof, ...])</code>	Return unbiased variance over requested axis.

pandas.DataFrame.abs

`DataFrame.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller

pandas.DataFrame.all

`DataFrame.all` (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether all elements are True over requested axis

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns *all* : Series or DataFrame (if level specified)

pandas.DataFrame.any

`DataFrame.any` (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether any element is True over requested axis

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns *any* : Series or DataFrame (if level specified)

pandas.DataFrame.clip

`DataFrame.clip` (*lower=None, upper=None, out=None, axis=None*)

Trim values at input threshold(s)

Parameters *lower* : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns *clipped* : Series

Examples

```

>>> df
   0      1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
   0      1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
   0      1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967

```

pandas.DataFrame.clip_lower

`DataFrame.clip_lower` (*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters *threshold* : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns *clipped* : same type as input

See also:

`clip`

pandas.DataFrame.clip_upper

`DataFrame.clip_upper` (*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters *threshold* : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns `clipped` : same type as input

See also:

`clip`

pandas.DataFrame.corr

`DataFrame.corr` (*method='pearson', min_periods=1*)

Compute pairwise correlation of columns, excluding NA/null values

Parameters `method` : {'pearson', 'kendall', 'spearman'}

- `pearson` : standard correlation coefficient
- `kendall` : Kendall Tau correlation coefficient
- `spearman` : Spearman rank correlation

min_periods : int, optional

Minimum number of observations required per pair of columns to have a valid result.
Currently only available for pearson and spearman correlation

Returns `y` : DataFrame

pandas.DataFrame.corrwith

`DataFrame.corrwith` (*other, axis=0, drop=False*)

Compute pairwise correlation between rows or columns of two DataFrame objects.

Parameters `other` : DataFrame

axis : {0, 1}

0 to compute column-wise, 1 for row-wise

drop : boolean, default False

Drop missing indices from result, default returns union of all

Returns `correls` : Series

pandas.DataFrame.count

`DataFrame.count` (*axis=0, level=None, numeric_only=False*)

Return Series with number of non-NA/null observations over requested axis. Works with non-floating point data as well (detects NaN and None)

Parameters `axis` : {0, 1}

0 for row-wise, 1 for column-wise

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default False

Include only float, int, boolean data

Returns `count` : Series (or DataFrame if level specified)

pandas.DataFrame.cov

`DataFrame.cov` (*min_periods=None*)

Compute pairwise covariance of columns, excluding NA/null values

Parameters `min_periods` : int, optional

Minimum number of observations required per pair of columns to have a valid result.

Returns `y` : DataFrame

Notes

`y` contains the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1 (unbiased estimator).

pandas.DataFrame.cummax

`DataFrame.cummax` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative max over requested axis.

Parameters `axis` : {index (0), columns (1)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `max` : Series

pandas.DataFrame.cummin

`DataFrame.cummin` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative min over requested axis.

Parameters `axis` : {index (0), columns (1)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `min` : Series

pandas.DataFrame.cumprod

`DataFrame.cumprod` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative prod over requested axis.

Parameters `axis` : {index (0), columns (1)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `prod` : Series

pandas.DataFrame.cumsum

DataFrame.**cumsum** (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative sum over requested axis.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **sum** : Series

pandas.DataFrame.describe

DataFrame.**describe** (*percentile_width=None, percentiles=None, include=None, exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters **percentile_width** : float, deprecated

The `percentile_width` argument will be removed in a future version. Use `percentiles` instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default `percentiles` is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy.number`. To select categorical objects use `type object`. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`
- If include is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.DataFrame.diff

`DataFrame.diff` (*periods=1, axis=0*)

1st discrete difference of object

Parameters `periods` : int, default 1

Periods to shift for forming difference

`axis` : {0 or 'index', 1 or 'columns'}, default 0

Returns `diffed` : DataFrame

pandas.DataFrame.eval

`DataFrame.eval` (*expr, **kwargs*)

Evaluate an expression in the context of the calling DataFrame instance.

Parameters `expr` : string

The expression string to evaluate.

`kwargs` : dict

See the documentation for `eval()` for complete details on the keyword arguments accepted by `query()`.

Returns `ret` : ndarray, scalar, or pandas object

See also:

`pandas.DataFrame.query`, `pandas.eval`

Notes

For more details see the API documentation for `eval()`. For detailed examples see *enhancing performance with eval*.

Examples

```
>>> from numpy.random import randn
>>> from pandas import DataFrame
>>> df = DataFrame(randn(10, 2), columns=list('ab'))
>>> df.eval('a + b')
>>> df.eval('c = a + b')
```

pandas.DataFrame.kurt

`DataFrame.kurt` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Series or DataFrame (if level specified)

pandas.DataFrame.mad

DataFrame.**mad** (*axis=None, skipna=None, level=None*)

Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : Series or DataFrame (if level specified)

pandas.DataFrame.max

DataFrame.**max** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : Series or DataFrame (if level specified)

pandas.DataFrame.mean

`DataFrame.mean` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the mean of the values for the requested axis

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *mean* : Series or DataFrame (if level specified)

pandas.DataFrame.median

`DataFrame.median` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the median of the values for the requested axis

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *median* : Series or DataFrame (if level specified)

pandas.DataFrame.min

`DataFrame.min` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : Series or DataFrame (if level specified)

pandas.DataFrame.mode

DataFrame.**mode** (*axis=0, numeric_only=False*)

Gets the mode(s) of each element along the axis selected. Empty if nothing has 2+ occurrences. Adds a row for each mode per label, fills in gaps with nan.

Note that there could be multiple values returned for the selected axis (when more than one item share the maximum frequency), which is the reason why a dataframe is returned. If you want to impute missing values with the mode in a dataframe `df`, you can just do this: `df.fillna(df.mode().iloc[0])`

Parameters **axis** : {0, 1, 'index', 'columns'} (default 0)

- 0/'index' : get mode of each column
- 1/'columns' : get mode of each row

numeric_only : boolean, default False

if True, only apply to numeric columns

Returns **modes** : DataFrame (sorted)

Examples

```
>>> df = pd.DataFrame({'A': [1, 2, 1, 2, 1, 2, 3]})
>>> df.mode()
   A
0  1
1  2
```

pandas.DataFrame.pct_change

DataFrame.**pct_change** (*periods=1, fill_method='pad', limit=None, freq=None, **kwargs*)

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the `axis` keyword argument.

pandas.DataFrame.prod

`DataFrame.prod` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

Parameters `axis` : {index (0), columns (1)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

`level` : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

`numeric_only` : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `prod` : Series or DataFrame (if level specified)

pandas.DataFrame.quantile

`DataFrame.quantile` (*q=0.5, axis=0, numeric_only=True*)

Return values at the given quantile over requested axis, a la numpy.percentile.

Parameters `q` : float or array-like, default 0.5 (50% quantile)

0 <= q <= 1, the quantile(s) to compute

`axis` : {0, 1}

0 for row-wise, 1 for column-wise

Returns `quantiles` : Series or DataFrame

If `q` is an array, a DataFrame will be returned where the index is `q`, the columns are the columns of self, and the values are the quantiles. If `q` is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

Examples

```
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                    columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
dtype: float64
>>> df.quantile([.1, .5])
      a    b
0.1  1.3  3.7
0.5  2.5 55.0
```

pandas.DataFrame.rank

`DataFrame.rank` (*axis=0, numeric_only=None, method='average', na_option='keep', ascending=True, pct=False*)

Compute numerical data ranks (1 through n) along axis. Equal values are assigned a rank that is the average of the ranks of those values

Parameters **axis** : {0, 1}, default 0

Ranks over columns (0) or rows (1)

numeric_only : boolean, default None

Include only float, int, boolean data

method : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array
- dense: like 'min', but rank always increases by 1 between groups

na_option : {'keep', 'top', 'bottom'}

- keep: leave NA values where they are
- top: smallest rank if ascending
- bottom: smallest rank if descending

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns **ranks** : DataFrame

pandas.DataFrame.sem

`DataFrame.sem` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sem** : Series or DataFrame (if level specified)

pandas.DataFrame.skew

`DataFrame.skew` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : Series or DataFrame (if level specified)

pandas.DataFrame.sum

`DataFrame.sum` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the sum of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : Series or DataFrame (if level specified)

pandas.DataFrame.std

`DataFrame.std` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : Series or DataFrame (if level specified)

pandas.DataFrame.var

DataFrame.**var** (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : Series or DataFrame (if level specified)

33.4.8 Reindexing / Selection / Label manipulation

DataFrame.add_prefix(prefix)	Concatenate prefix string with panel items names.
DataFrame.add_suffix(suffix)	Concatenate suffix string with panel items names
DataFrame.align(other[, join, axis, level, ...])	Align two object on their axes with the
DataFrame.drop(labels[, axis, level, ...])	Return new object with labels in requested axis removed
DataFrame.drop_duplicates(*args, **kwargs)	Return DataFrame with duplicate rows removed, optionally only
DataFrame.duplicated(*args, **kwargs)	Return boolean Series denoting duplicate rows, optionally only
DataFrame.equals(other)	Determines if two NDFrame objects contain the same elements.
DataFrame.filter([items, like, regex, axis])	Restrict the info axis to set of items or wildcard
DataFrame.first(offset)	Convenience method for subsetting initial periods of time series data
DataFrame.head([n])	Returns first n rows
DataFrame.idxmax([axis, skipna])	Return index of first occurrence of maximum over requested axis.
DataFrame.idxmin([axis, skipna])	Return index of first occurrence of minimum over requested axis.
DataFrame.last(offset)	Convenience method for subsetting final periods of time series data
DataFrame.reindex([index, columns])	Conform DataFrame to new index with optional filling logic, placing NA/N
DataFrame.reindex_axis(labels[, axis, ...])	Conform input object to new index with optional filling logic, placing NA/N
DataFrame.reindex_like(other[, method, ...])	return an object with matching indicies to myself
DataFrame.rename([index, columns])	Alter axes input function or functions.
DataFrame.reset_index([level, drop, ...])	For DataFrame with multi-level index, return new DataFrame with labeling
DataFrame.sample([n, frac, replace, ...])	Returns a random sample of items from an axis of object.
DataFrame.select(crit[, axis])	Return data corresponding to axis labels matching criteria

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<code>DataFrame.set_index(keys[, drop, append, ...])</code>	Set the DataFrame index (row labels) using one or more existing columns.
<code>DataFrame.tail([n])</code>	Returns last n rows
<code>DataFrame.take(indices[, axis, convert, is_copy])</code>	Analogous to ndarray.take
<code>DataFrame.truncate([before, after, axis, copy])</code>	Truncates a sorted NDFrame before and/or after some particular dates.

pandas.DataFrame.add_prefix`DataFrame.add_prefix(prefix)`

Concatenate prefix string with panel items names.

Parameters `prefix` : string**Returns** `with_prefix` : type of caller**pandas.DataFrame.add_suffix**`DataFrame.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters `suffix` : string**Returns** `with_suffix` : type of caller**pandas.DataFrame.align**`DataFrame.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0)`

Align two object on their axes with the specified join method for each axis Index

Parameters `other` : DataFrame or Series**join** : { 'outer', 'inner', 'left', 'right' }, default 'outer'**axis** : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

method : str, default None**limit** : int, default None**fill_axis** : {0, 1}, default 0

Filling axis, method and limit

Returns (`left`, `right`) : (type of input, type of other)

Aligned objects

pandas.DataFrame.drop

`DataFrame.drop(labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : type of caller

pandas.DataFrame.drop_duplicates

`DataFrame.drop_duplicates(*args, **kwargs)`

Return DataFrame with duplicate rows removed, optionally only considering certain columns

Parameters **subset** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

Take the last observed row in a row. Defaults to the first row

inplace : boolean, default False

Whether to drop duplicates in place or to return a copy

cols : kwargs only argument of subset [deprecated]

Returns **deduplicated** : DataFrame

pandas.DataFrame.duplicated

`DataFrame.duplicated(*args, **kwargs)`

Return boolean Series denoting duplicate rows, optionally only considering certain columns

Parameters **subset** : column label or sequence of labels, optional

Only consider certain columns for identifying duplicates, by default use all of the columns

take_last : boolean, default False

For a set of distinct duplicate rows, flag all but the last row as duplicated. Default is for all but the first row to be flagged

cols : kwargs only argument of subset [deprecated]

Returns **duplicated** : Series

pandas.DataFrame.equals

DataFrame.**equals** (*other*)

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.DataFrame.filter

DataFrame.**filter** (*items=None, like=None, regex=None, axis=None*)

Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where “arg in col == True”

regex : string (regular expression)

Keep info axis with re.search(regex, col) == True

axis : int or None

The axis to filter on. By default this is the info axis. The “info axis” is the axis that is used when indexing with []. For example, df = DataFrame({'a': [1, 2, 3, 4]}); df['a']. So, the DataFrame columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.DataFrame.first

DataFrame.**first** (*offset*)

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('10D') -> First 10 days

pandas.DataFrame.head

DataFrame.**head** (*n=5*)

Returns first n rows

pandas.DataFrame.idxmax

`DataFrame.idxmax` (*axis=0, skipna=True*)

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

Parameters *axis* : {0, 1}

0 for row-wise, 1 for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

Returns *idxmax* : Series

See also:

`Series.idxmax`

Notes

This method is the DataFrame version of `ndarray.argmax`.

pandas.DataFrame.idxmin

`DataFrame.idxmin` (*axis=0, skipna=True*)

Return index of first occurrence of minimum over requested axis. NA/null values are excluded.

Parameters *axis* : {0, 1}

0 for row-wise, 1 for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *idxmin* : Series

See also:

`Series.idxmin`

Notes

This method is the DataFrame version of `ndarray.argmin`.

pandas.DataFrame.last

`DataFrame.last` (*offset*)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters *offset* : string, DateOffset, dateutil.relativedelta

Returns *subset* : type of caller

Examples

`ts.last('5M')` -> Last 5 months

pandas.DataFrame.reindex

`DataFrame.reindex` (*index=None, columns=None, **kwargs*)

Conform DataFrame to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters `index, columns` : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns `reindexed` : DataFrame

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.DataFrame.reindex_axis

`DataFrame.reindex_axis` (*labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=nan*)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters `labels` : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 'index', 'columns'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : DataFrame

See also:

`reindex`, `reindex_like`

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.DataFrame.reindex_like

`DataFrame.reindex_like` (*other*, *method=None*, *copy=True*, *limit=None*)
return an object with matching indicies to myself

Parameters **other** : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

pandas.DataFrame.rename

`DataFrame.rename` (*index=None*, *columns=None*, ***kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **index**, **columns** : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new DataFrame. If True then value of copy is ignored.

Returns renamed : DataFrame (new object)

pandas.DataFrame.reset_index

DataFrame.**reset_index** (*level=None, drop=False, inplace=False, col_level=0, col_fill=''*)

For DataFrame with multi-level index, return new DataFrame with labeling information in the columns under the index names, defaulting to 'level_0', 'level_1', etc. if any are None. For a standard index, the index name will be used (if set), otherwise a default 'index' or 'level_0' (if 'index' is already taken) will be used.

Parameters level : int, str, tuple, or list, default None

Only remove the given levels from the index. Removes all levels by default

drop : boolean, default False

Do not try to insert index into dataframe columns. This resets the index to the default integer index.

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

col_level : int or str, default 0

If the columns have multiple levels, determines which level the labels are inserted into. By default it is inserted into the first level.

col_fill : object, default ''

If the columns have multiple levels, determines how the other levels are named. If None then the index name is repeated.

Returns resetted : DataFrame

pandas.DataFrame.sample

DataFrame.**sample** (*n=None, frac=None, replace=False, weights=None, random_state=None, axis=None*)

Returns a random sample of items from an axis of object.

Parameters n : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. Weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. inf and -inf values not allowed.

random_state : int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

Returns Same type as caller.

pandas.DataFrame.select

DataFrame.**select** (*crit*, *axis=0*)

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.DataFrame.set_index

DataFrame.**set_index** (*keys*, *drop=True*, *append=False*, *inplace=False*, *verify_integrity=False*)

Set the DataFrame index (row labels) using one or more existing columns. By default yields a new object.

Parameters **keys** : column label or list of column labels / arrays

drop : boolean, default True

Delete columns to be used as the new index

append : boolean, default False

Whether to append columns to existing index

inplace : boolean, default False

Modify the DataFrame in place (do not create a new object)

verify_integrity : boolean, default False

Check the new index for duplicates. Otherwise defer the check until necessary. Setting to False will improve the performance of this method

Returns **dataframe** : DataFrame

Examples

```
>>> indexed_df = df.set_index(['A', 'B'])
>>> indexed_df2 = df.set_index(['A', [0, 1, 2, 0, 1, 2]])
>>> indexed_df3 = df.set_index([[0, 1, 2, 0, 1, 2]])
```

pandas.DataFrame.tail

`DataFrame.tail` (*n=5*)
Returns last *n* rows

pandas.DataFrame.take

`DataFrame.take` (*indices, axis=0, convert=True, is_copy=True*)
Analogous to `ndarray.take`

Parameters *indices* : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns *taken* : type of caller

pandas.DataFrame.truncate

`DataFrame.truncate` (*before=None, after=None, axis=None, copy=True*)
Truncates a sorted NDFrame before and/or after some particular dates.

Parameters *before* : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns *truncated* : type of caller

33.4.9 Missing data handling

<code>DataFrame.dropna</code> (<i>[axis, how, thresh, ...]</i>)	Return object with labels on given axis omitted where alternately any
<code>DataFrame.fillna</code> (<i>[value, method, axis, ...]</i>)	Fill NA/NaN values using the specified method
<code>DataFrame.replace</code> (<i>[to_replace, value, ...]</i>)	Replace values given in 'to_replace' with 'value'.

pandas.DataFrame.dropna

`DataFrame.dropna` (*axis=0, how='any', thresh=None, subset=None, inplace=False*)
Return object with labels on given axis omitted where alternately any or all of the data are missing

Parameters *axis* : {0, 1}, or tuple/list thereof

Pass tuple or list to drop on multiple axes

how : {'any', 'all'}

- *any* : if any NA values are present, drop that label

- **all** : if all values are NA, drop that label

thresh : int, default None

int value : require that many non-NA values

subset : array-like

Labels along other axis to consider, e.g. if you are dropping rows these would be a list of columns to include

inplace : boolean, default False

If True, do operation inplace and return None.

Returns **dropped** : DataFrame

pandas.DataFrame.fillna

DataFrame.**fillna** (*value=None, method=None, axis=None, inplace=False, limit=None, down-*
*cast=None, **kwargs*)

Fill NA/NaN values using the specified method

Parameters **method** : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

value : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 1, 'index', 'columns'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns **filled** : DataFrame

See also:

[reindex](#), [asfreq](#)

pandas.DataFrame.replace

`DataFrame.replace` (*to_replace=None*, *value=None*, *inplace=False*, *limit=None*, *regex=False*,
method='pad', *axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters *to_replace* : str, regex, list, dict, Series, numeric, or None

- str or regex:
 - str: string exactly matching *to_replace* will be replaced with *value*
 - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
 - First, if *to_replace* and *value* are both lists, they **must** be the same length.
 - Second, if *regex=True* then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
 - str and regex rules apply as above.
- dict:
 - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
 - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
 - This means that the *regex* argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also None then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is True then *to_replace* *must* be a string. Otherwise, *to_replace* must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a list.

Returns `filled` : NDFrame

Raises `AssertionError`

- If `regex` is not a bool and `to_replace` is not None.

TypeError

- If `to_replace` is a dict and `value` is not a list, dict, ndarray, or Series
- If `to_replace` is None and `regex` is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If `to_replace` and `value` are lists or ndarrays, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

33.4.10 Reshaping, sorting, transposing

<code>DataFrame.pivot([index, columns, values])</code>	Reshape data (produce a “pivot” table) based on column values.
<code>DataFrame.reorder_levels(order[, axis])</code>	Rearrange index levels using input order.
<code>DataFrame.sort([columns, axis, ascending, ...])</code>	Sort DataFrame either by labels (along either axis) or by the values in
<code>DataFrame.sort_index([axis, by, ascending, ...])</code>	Sort DataFrame either by labels (along either axis) or by the values in
<code>DataFrame.sortlevel([level, axis, ...])</code>	Sort multilevel index by chosen axis and primary level.
<code>DataFrame.swaplevel(i, j[, axis])</code>	Swap levels i and j in a MultiIndex on a particular axis
<code>DataFrame.stack([level, dropna])</code>	Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame
<code>DataFrame.unstack([level])</code>	Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame
<code>DataFrame.T</code>	Transpose index and columns
<code>DataFrame.to_panel()</code>	Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.
<code>DataFrame.transpose()</code>	Transpose index and columns

pandas.DataFrame.pivot

`DataFrame.pivot` (*index=None, columns=None, values=None*)

Reshape data (produce a “pivot” table) based on column values. Uses unique values from index / columns to form axes and return either DataFrame or Panel, depending on whether you request a single value column (DataFrame) or all columns (Panel)

Parameters `index` : string or object

Column name to use to make new frame's index

columns : string or object

Column name to use to make new frame's columns

values : string or object, optional

Column name to use for populating new frame's values

Returns **pivoted** : DataFrame

If no values column specified, will have hierarchically indexed columns

Notes

For finer-tuned control, see hierarchical indexing documentation along with the related stack/unstack methods

Examples

```
>>> df
   foo  bar  baz
0  one   A   1.
1  one   B   2.
2  one   C   3.
3  two   A   4.
4  two   B   5.
5  two   C   6.

>>> df.pivot('foo', 'bar', 'baz')
   A  B  C
one 1  2  3
two 4  5  6

>>> df.pivot('foo', 'bar')['baz']
   A  B  C
one 1  2  3
two 4  5  6
```

pandas.DataFrame.reorder_levels

DataFrame.**reorder_levels** (*order*, *axis=0*)

Rearrange index levels using input order. May not drop or duplicate levels

Parameters **order** : list of int or list of str

List representing new level order. Reference level by number (position) or by key (label).

axis : int

Where to reorder levels.

Returns type of caller (new object)

pandas.DataFrame.sort

`DataFrame.sort` (*columns=None*, *axis=0*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*)

Sort DataFrame either by labels (along either axis) or by the values in column(s)

Parameters **columns** : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

axis : {0, 1}

Sort index/rows versus columns

inplace : boolean, default False

Sort the DataFrame without creating a new instance

kind : {'quicksort', 'mergesort', 'heapsort'}, optional

This option is only applied when sorting on a single column or label.

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

Returns **sorted** : DataFrame

Examples

```
>>> result = df.sort(['A', 'B'], ascending=[1, 0])
```

pandas.DataFrame.sort_index

`DataFrame.sort_index` (*axis=0*, *by=None*, *ascending=True*, *inplace=False*, *kind='quicksort'*, *na_position='last'*)

Sort DataFrame either by labels (along either axis) or by the values in a column

Parameters **axis** : {0, 1}

Sort index/rows versus columns

by : object

Column name(s) in frame. Accepts a column name or a list for a nested sort. A tuple will be interpreted as the levels of a multi-index.

ascending : boolean or list, default True

Sort ascending vs. descending. Specify list for multiple sort orders

inplace : boolean, default False

Sort the DataFrame without creating a new instance

na_position : {'first', 'last'} (optional, default='last')

'first' puts NaNs at the beginning 'last' puts NaNs at the end

kind : { 'quicksort', 'mergesort', 'heapsort' }, optional

This option is only applied when sorting on a single column or label.

Returns **sorted** : DataFrame

Examples

```
>>> result = df.sort_index(by=['A', 'B'], ascending=[True, False])
```

pandas.DataFrame.sortlevel

DataFrame.**sortlevel** (*level=0, axis=0, ascending=True, inplace=False, sort_remaining=True*)

Sort multilevel index by chosen axis and primary level. Data will be lexicographically sorted by the chosen level followed by the other levels (in order)

Parameters **level** : int

axis : {0, 1}

ascending : boolean, default True

inplace : boolean, default False

Sort the DataFrame without creating a new instance

sort_remaining : boolean, default True

Sort by the other levels too.

Returns **sorted** : DataFrame

pandas.DataFrame.swaplevel

DataFrame.**swaplevel** (*i, j, axis=0*)

Swap levels i and j in a MultiIndex on a particular axis

Parameters **i, j** : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns **swapped** : type of caller (new object)

pandas.DataFrame.stack

DataFrame.**stack** (*level=-1, dropna=True*)

Pivot a level of the (possibly hierarchical) column labels, returning a DataFrame (or Series in the case of an object with a single level of column labels) having a hierarchical index with a new inner-most level of row labels. The level involved will automatically get sorted.

Parameters **level** : int, string, or list of these, default last level

Level(s) to stack, can pass level name

dropna : boolean, default True

Whether to drop rows in the resulting Frame/Series with no valid values

Returns **stacked** : DataFrame or Series

Examples

```
>>> s
      a  b
one  1.  2.
two  3.  4.

>>> s.stack()
one a    1
   b    2
two a    3
   b    4
```

pandas.DataFrame.unstack

`DataFrame.unstack` (*level=-1*)

Pivot a level of the (necessarily hierarchical) index labels, returning a DataFrame having a new level of column labels whose inner-most level consists of the pivoted index labels. If the index is not a MultiIndex, the output will be a Series (the analogue of stack when the columns are not a MultiIndex). The level involved will automatically get sorted.

Parameters `level` : int, string, or list of these, default -1 (last level)

Level(s) of index to unstack, can pass level name

Returns `unstacked` : DataFrame or Series

See also:

`DataFrame.pivot` Pivot a table based on column values.

`DataFrame.stack` Pivot a level of the column labels (inverse operation from *unstack*).

Examples

```
>>> index = pd.MultiIndex.from_tuples([('one', 'a'), ('one', 'b'),
...                                  ('two', 'a'), ('two', 'b')])
>>> s = pd.Series(np.arange(1.0, 5.0), index=index)
>>> s
one a    1
   b    2
two a    3
   b    4
dtype: float64

>>> s.unstack(level=-1)
      a  b
one  1  2
two  3  4

>>> s.unstack(level=0)
      one two
a    1    3
b    2    4
```

```
>>> df = s.unstack(level=0)
>>> df.unstack()
one  a  1.
     b  3.
two  a  2.
     b  4.
```

pandas.DataFrame.T

`DataFrame.T`

Transpose index and columns

pandas.DataFrame.to_panel

`DataFrame.to_panel()`

Transform long (stacked) format (DataFrame) into wide (3D, Panel) format.

Currently the index of the DataFrame must be a 2-level MultiIndex. This may be generalized later

Returns `panel` : Panel

pandas.DataFrame.transpose

`DataFrame.transpose()`

Transpose index and columns

33.4.11 Combining / joining / merging

<code>DataFrame.append(other[, ignore_index, ...])</code>	Append rows of <i>other</i> to the end of this frame, returning a new object.
<code>DataFrame.assign(**kwargs)</code>	Assign new columns to a DataFrame, returning a new object (a copy) with all the columns of the original DataFrame plus the new ones.
<code>DataFrame.join(other[, on, how, lsuffix, ...])</code>	Join columns with other DataFrame either on index or on a key column.
<code>DataFrame.merge(right[, how, on, left_on, ...])</code>	Merge DataFrame objects by performing a database-style join operation by columns.
<code>DataFrame.update(other[, join, overwrite, ...])</code>	Modify DataFrame in place using non-NA values from passed DataFrame.

pandas.DataFrame.append

`DataFrame.append(other, ignore_index=False, verify_integrity=False)`

Append rows of *other* to the end of this frame, returning a new object. Columns not in this frame are added as new columns.

Parameters `other` : DataFrame or Series/dict-like object, or list of these

The data to append.

`ignore_index` : boolean, default False

If True, do not use the index labels.

`verify_integrity` : boolean, default False

If True, raise ValueError on creating index with duplicates.

Returns `appended` : DataFrame

See also:

`pandas.concat` General function to concatenate DataFrame, Series or Panel objects

Notes

If a list of dict/series is passed and the keys are all contained in the DataFrame's index, the order of the columns in the resulting DataFrame will be unchanged.

Examples

```
>>> df = pd.DataFrame([[1, 2], [3, 4]], columns=list('AB'))
>>> df
   A  B
0  1  2
1  3  4
>>> df2 = pd.DataFrame([[5, 6], [7, 8]], columns=list('AB'))
>>> df.append(df2)
   A  B
0  1  2
1  3  4
0  5  6
1  7  8
```

With `ignore_index` set to True:

```
>>> df.append(df2, ignore_index=True)
   A  B
0  1  2
1  3  4
2  5  6
3  7  8
```

pandas.DataFrame.assign

`DataFrame.assign(**kwargs)`

Assign new columns to a DataFrame, returning a new object (a copy) with all the original columns in addition to the new ones.

New in version 0.16.0.

Parameters `kwargs` : keyword, value pairs

keywords are the column names. If the values are callable, they are computed on the DataFrame and assigned to the new columns. If the values are not callable, (e.g. a Series, scalar, or array), they are simply assigned.

Returns `df` : DataFrame

A new DataFrame with the new columns in addition to all the existing columns.

Notes

Since `kwargs` is a dictionary, the order of your arguments may not be preserved. To make things predictable, the columns are inserted in alphabetical order, at the end of your DataFrame. Assigning multiple columns within

the same `assign` is possible, but you cannot reference other columns created within the same `assign` call.

Examples

```
>>> df = DataFrame({'A': range(1, 11), 'B': np.random.randn(10)})
```

Where the value is a callable, evaluated on *df*:

```
>>> df.assign(ln_A = lambda x: np.log(x.A))
```

	A	B	ln_A
0	1	0.426905	0.000000
1	2	-0.780949	0.693147
2	3	-0.418711	1.098612
3	4	-0.269708	1.386294
4	5	-0.274002	1.609438
5	6	-0.500792	1.791759
6	7	1.649697	1.945910
7	8	-1.495604	2.079442
8	9	0.549296	2.197225
9	10	-0.758542	2.302585

Where the value already exists and is inserted:

```
>>> newcol = np.log(df['A'])
>>> df.assign(ln_A=newcol)
```

	A	B	ln_A
0	1	0.426905	0.000000
1	2	-0.780949	0.693147
2	3	-0.418711	1.098612
3	4	-0.269708	1.386294
4	5	-0.274002	1.609438
5	6	-0.500792	1.791759
6	7	1.649697	1.945910
7	8	-1.495604	2.079442
8	9	0.549296	2.197225
9	10	-0.758542	2.302585

pandas.DataFrame.join

`DataFrame.join(other, on=None, how='left', lsuffix='', rsuffix='', sort=False)`

Join columns with other `DataFrame` either on index or on a key column. Efficiently Join multiple `DataFrame` objects by index at once by passing a list.

Parameters *other* : `DataFrame`, `Series` with name field set, or list of `DataFrame`

Index should be similar to one of the columns in this one. If a `Series` is passed, its name attribute must be set, and that will be used as the column name in the resulting joined `DataFrame`

on : column name, tuple/list of column names, or array-like

Column(s) to use for joining, otherwise join on index. If multiples columns given, the passed `DataFrame` must have a `MultiIndex`. Can pass an array as the join key if not already contained in the calling `DataFrame`. Like an Excel `VLOOKUP` operation

how : {'left', 'right', 'outer', 'inner'}

How to handle indexes of the two objects. Default: 'left' for joining on index, None otherwise

- left: use calling frame's index
- right: use input frame's index
- outer: form union of indexes
- inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

sort : boolean, default False

Order result DataFrame lexicographically by the join key. If False, preserves the index order of the calling (left) DataFrame

Returns **joined** : DataFrame

Notes

on, lsuffix, and rsuffix options are not supported when passing a list of DataFrame objects

pandas.DataFrame.merge

`DataFrame.merge(right, how='inner', on=None, left_on=None, right_on=None, left_index=False, right_index=False, sort=False, suffixes=('_x', '_y'), copy=True)`

Merge DataFrame objects by performing a database-style join operation by columns or indexes.

If joining columns on columns, the DataFrame indexes *will be ignored*. Otherwise if joining indexes on indexes or indexes on a column or columns, the index will be passed on.

Parameters **right** : DataFrame

how : {'left', 'right', 'outer', 'inner'}, default 'inner'

- left: use only keys from left frame (SQL: left outer join)
- right: use only keys from right frame (SQL: right outer join)
- outer: use union of keys from both frames (SQL: full outer join)
- inner: use intersection of keys from both frames (SQL: inner join)

on : label or list

Field names to join on. Must be found in both DataFrames. If on is None and not merging on indexes, then it merges on the intersection of the columns by default.

left_on : label or list, or array-like

Field names to join on in left DataFrame. Can be a vector or list of vectors of the length of the DataFrame to use a particular vector as the join key instead of columns

right_on : label or list, or array-like

Field names to join on in right DataFrame or vector/list of vectors per left_on docs

left_index : boolean, default False

Use the index from the left DataFrame as the join key(s). If it is a MultiIndex, the number of keys in the other DataFrame (either the index or a number of columns) must match the number of levels

right_index : boolean, default False

Use the index from the right DataFrame as the join key. Same caveats as left_index

sort : boolean, default False

Sort the join keys lexicographically in the result DataFrame

suffixes : 2-length sequence (tuple, list, ...)

Suffix to apply to overlapping column names in the left and right side, respectively

copy : boolean, default True

If False, do not copy data unnecessarily

Returns **merged** : DataFrame

The output type will be the same as 'left', if it is a subclass of DataFrame.

Examples

```
>>> A          >>> B
   lkey value      rkey value
0   foo    1      0   foo    5
1   bar    2      1   bar    6
2   baz    3      2   qux    7
3   foo    4      3   bar    8

>>> merge(A, B, left_on='lkey', right_on='rkey', how='outer')
   lkey  value_x  rkey  value_y
0   foo      1   foo      5
1   foo      4   foo      5
2   bar      2   bar      6
3   bar      2   bar      8
4   baz      3   NaN     NaN
5   NaN     NaN   qux      7
```

pandas.DataFrame.update

DataFrame.**update** (*other*, *join*='left', *overwrite*=True, *filter_func*=None, *raise_conflict*=False)

Modify DataFrame in place using non-NA values from passed DataFrame. Aligns on indices

Parameters **other** : DataFrame, or object coercible into a DataFrame

join : {'left'}, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling frame

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : boolean

If True, will raise an error if the DataFrame and other both contain data in the same place.

33.4.12 Time series-related

<code>DataFrame.asfreq(freq[, method, how, normalize])</code>	Convert all TimeSeries inside to specified frequency using DateOffset objects
<code>DataFrame.shift([periods, freq, axis])</code>	Shift index by desired number of periods with an optional time frequency
<code>DataFrame.first_valid_index()</code>	Return label for first non-NA/null value
<code>DataFrame.last_valid_index()</code>	Return label for last non-NA/null value
<code>DataFrame.resample(rule[, how, axis, ...])</code>	Convenience method for frequency conversion and resampling of regular time series
<code>DataFrame.to_period([freq, axis, copy])</code>	Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency
<code>DataFrame.to_timestamp([freq, how, axis, copy])</code>	Cast to DatetimeIndex of timestamps, at <i>beginning</i> of period
<code>DataFrame.tz_convert(tz[, axis, level, copy])</code>	Convert tz-aware axis to target time zone.
<code>DataFrame.tz_localize(*args, **kwargs)</code>	Localize tz-naive TimeSeries to target time zone

pandas.DataFrame.asfreq

`DataFrame.asfreq(freq, method=None, how=None, normalize=False)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters **freq** : DateOffset object, or string

method : { 'backfill', 'bfill', 'pad', 'ffill', None }

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : { 'start', 'end' }, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns **converted** : type of caller

pandas.DataFrame.shift

`DataFrame.shift(periods=1, freq=None, axis=0, **kwargs)`

Shift index by desired number of periods with an optional time frequency

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 1, 'index', 'columns'}

Returns **shifted** : DataFrame

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.DataFrame.first_valid_index

`DataFrame.first_valid_index()`
Return label for first non-NA/null value

pandas.DataFrame.last_valid_index

`DataFrame.last_valid_index()`
Return label for last non-NA/null value

pandas.DataFrame.resample

`DataFrame.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`
Convenience method for frequency conversion and resampling of regular time-series data.

Parameters `rule` : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : { 'right', 'left' }

Which side of bin interval is closed

label : { 'right', 'left' }

Which bin edge label to label bucket with

convention : { 'start', 'end', 's', 'e' }

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.DataFrame.to_period

`DataFrame.to_period` (*freq=None, axis=0, copy=True*)

Convert DataFrame from DatetimeIndex to PeriodIndex with desired frequency (inferred from index if not passed)

Parameters `freq` : string, default

`axis` : {0, 1}, default 0

The axis to convert (the index by default)

`copy` : boolean, default True

If False then underlying input data is not copied

Returns `ts` : TimeSeries with PeriodIndex

pandas.DataFrame.to_timestamp

`DataFrame.to_timestamp` (*freq=None, how='start', axis=0, copy=True*)

Cast to DatetimeIndex of timestamps, at *beginning* of period

Parameters `freq` : string, default frequency of PeriodIndex

Desired frequency

`how` : {'s', 'e', 'start', 'end'}

Convention for converting period to timestamp; start of period vs. end

`axis` : {0, 1} default 0

The axis to convert (the index by default)

`copy` : boolean, default True

If false then underlying input data is not copied

Returns `df` : DataFrame with DatetimeIndex

pandas.DataFrame.tz_convert

`DataFrame.tz_convert` (*tz, axis=0, level=None, copy=True*)

Convert tz-aware axis to target time zone.

Parameters `tz` : string or pytz.timezone object

`axis` : the axis to convert

`level` : int, str, default None

If axis is a MultiIndex, convert a specific level. Otherwise must be None

`copy` : boolean, default True

Also make a copy of the underlying data

Raises `TypeError`

If the axis is tz-naive.

pandas.DataFrame.tz_localize`DataFrame.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters `tz` : string or `pytz.timezone` object`axis` : the axis to localize`level` : int, str, default None

If axis is a MultiIndex, localize a specific level. Otherwise must be None

`copy` : boolean, default True

Also make a copy of the underlying data

`ambiguous` : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an `AmbiguousTimeError` if there are ambiguous times

`infer_dst` : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises `TypeError`

If the TimeSeries is tz-aware and tz is not None.

33.4.13 Plotting

<code>DataFrame.boxplot([column, by, ax, ...])</code>	Make a box plot from DataFrame column optionally grouped by some columns or
<code>DataFrame.hist(data[, column, by, grid, ...])</code>	Draw histogram of the DataFrame's series using matplotlib / pylab.
<code>DataFrame.plot(data[, x, y, kind, ax, ...])</code>	Make plots of DataFrame using matplotlib / pylab.

pandas.DataFrame.boxplot`DataFrame.boxplot(column=None, by=None, ax=None, fontsize=None, rot=0, grid=True, figsize=None, layout=None, return_type=None, **kws)`

Make a box plot from DataFrame column optionally grouped by some columns or other inputs

Parameters `data` : the pandas object holding the data`column` : column name or list of names, or vectorCan be any valid input to `groupby``by` : string or sequence

Column in the DataFrame to group by

`ax` : Matplotlib axes object, optional`fontsize` : int or string`rot` : label rotation angle

figsize : A tuple (width, height) in inches

grid : Setting this to True will show the grid

layout : tuple (optional)

(rows, columns) for the layout of the plot

return_type : { 'axes', 'dict', 'both' }, default 'dict'

The kind of object to return. 'dict' returns a dictionary whose values are the matplotlib Lines of the boxplot; 'axes' returns the matplotlib axes the boxplot is drawn on; 'both' returns a namedtuple with the axes and dict.

When grouping with `by`, a dict mapping columns to `return_type` is returned.

kwargs : other plotting keyword arguments to be passed to matplotlib boxplot

function

Returns **lines** : dict

ax : matplotlib Axes

(ax, lines): namedtuple

Notes

Use `return_type='dict'` when you want to tweak the appearance of the lines after plotting. In this case a dict containing the Lines making up the boxes, caps, fliers, medians, and whiskers is returned.

pandas.DataFrame.hist

`DataFrame.hist` (*data*, *column=None*, *by=None*, *grid=True*, *xlabelsize=None*, *xrot=None*, *ylabelsize=None*, *yrot=None*, *ax=None*, *sharex=False*, *sharey=False*, *figsize=None*, *layout=None*, *bins=10*, ***kwargs*)

Draw histogram of the DataFrame's series using matplotlib / pylab.

Parameters **data** : DataFrame

column : string or sequence

If passed, will be used to limit data to a subset of columns

by : object, optional

If passed, then used to form histograms for separate groups

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

ax : matplotlib axes object, default None

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

figsize : tuple

The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10

Number of histogram bins to be used

kwds : other plotting keyword arguments

To be passed to hist function

pandas.DataFrame.plot

`DataFrame.plot` (*data*, *x=None*, *y=None*, *kind='line'*, *ax=None*, *subplots=False*, *sharex=None*, *sharey=False*, *layout=None*, *figsize=None*, *use_index=True*, *title=None*, *grid=None*, *legend=True*, *style=None*, *logx=False*, *logy=False*, *loglog=False*, *xticks=None*, *yticks=None*, *xlim=None*, *ylim=None*, *rot=None*, *fontsize=None*, *colormap=None*, *table=False*, *yerr=None*, *xerr=None*, *secondary_y=False*, *sort_columns=False*, ***kwds*)

Make plots of DataFrame using matplotlib / pylab.

Parameters **data** : DataFrame

x : label or position, default None

y : label or position, default None

Allows plotting of one column versus another

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot

- ‘hexbin’ : hexbin plot

ax : matplotlib axes object, default None

subplots : boolean, default False

Make separate subplots for each column

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

layout : tuple (optional)

(rows, columns) for the layout of subplots

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/‘reverse’

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for 'scatter' and 'hexbin' plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib's default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

stacked : boolean, default False in line and

bar plots, and True in area plot. If True, create stacked plot.

sort_columns : boolean, default False

Sort column names to determine plot ordering

secondary_y : boolean or sequence, default False

Whether to plot on the secondary y-axis If a list/tuple, which columns to plot on secondary y-axis

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with "(right)" in the legend

kws : keywords

Options to pass to matplotlib plotting method

Returns **axes** : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = 'bar' or 'barh', you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

- If *kind* = 'scatter' and the argument *c* is the name of a dataframe column, the values of that column are used to color each point.
- If *kind* = 'hexbin', you can control the size of the bins with the *gridsize* argument. By default, a histogram of the counts around each (*x*, *y*) point is computed. You can specify alternative aggregations by passing values to the *C* and *reduce_C_function* arguments. *C* specifies the value at each (*x*, *y*) point and *reduce_C_function* is a function of one argument that reduces all the values in a bin to a single number (e.g. *mean*, *max*, *sum*, *std*).

33.4.14 Serialization / IO / Conversion

<code>DataFrame.from_csv(path[, header, sep, ...])</code>	Read delimited file into DataFrame
<code>DataFrame.from_dict(data[, orient, dtype])</code>	Construct DataFrame from dict of array-like or dicts
<code>DataFrame.from_items(items[, columns, orient])</code>	Convert (key, value) pairs to DataFrame.
<code>DataFrame.from_records(data[, index, ...])</code>	Convert structured or record ndarray to DataFrame
<code>DataFrame.info([verbose, buf, max_cols, ...])</code>	Concise summary of a DataFrame.
<code>DataFrame.to_pickle(path)</code>	Pickle (serialize) object to input file path
<code>DataFrame.to_csv([path_or_buf, sep, na_rep, ...])</code>	Write DataFrame to a comma-separated values (csv) file
<code>DataFrame.to_hdf(path_or_buf, key, **kwargs)</code>	activate the HDFStore
<code>DataFrame.to_sql(name, con[, flavor, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>DataFrame.to_dict(*args, **kwargs)</code>	Convert DataFrame to dictionary.
<code>DataFrame.to_excel(excel_writer[, ...])</code>	Write DataFrame to a excel sheet
<code>DataFrame.to_json([path_or_buf, orient, ...])</code>	Convert the object to a JSON string.
<code>DataFrame.to_html([buf, columns, col_space, ...])</code>	Render a DataFrame as an HTML table.
<code>DataFrame.to_latex([buf, columns, ...])</code>	Render a DataFrame to a tabular environment table.
<code>DataFrame.to_stata(fname[, convert_dates, ...])</code>	A class for writing Stata binary dta files from array-like objects
<code>DataFrame.to_msgpack([path_or_buf])</code>	msgpack (serialize) object to input file path
<code>DataFrame.to_gbq(destination_table[, ...])</code>	Write a DataFrame to a Google BigQuery table.
<code>DataFrame.to_records([index, convert_datetime64])</code>	Convert DataFrame to record array.
<code>DataFrame.to_sparse([fill_value, kind])</code>	Convert to SparseDataFrame
<code>DataFrame.to_dense()</code>	Return dense representation of NDFrame (as opposed to sparse)
<code>DataFrame.to_string([buf, columns, ...])</code>	Render a DataFrame to a console-friendly tabular output.
<code>DataFrame.to_clipboard([excel, sep])</code>	Attempt to write text representation of object to the system clipboard T

pandas.DataFrame.from_csv

classmethod `DataFrame.from_csv` (*path*, *header*=0, *sep*=' ', *index_col*=0, *parse_dates*=True, *encoding*=None, *tupleize_cols*=False, *infer_datetime_format*=False)

Read delimited file into DataFrame

Parameters *path* : string file path or file handle / StringIO

header : int, default 0

Row to use at header (skip prior rows)

sep : string, default ' '

Field delimiter

index_col : int or sequence, default 0

Column to use for index. If a sequence is given, a MultiIndex is used. Different default from `read_table`

parse_dates : boolean, default True

Parse dates. Different default from `read_table`

tupleize_cols : boolean, default False

write `multi_index` columns as a list of tuples (if True) or new (expanded format) if False)

infer_datetime_format: boolean, default False

If True and `parse_dates` is True for a column, try to infer the datetime format based on the first datetime string. If the format can be inferred, there often will be a large parsing speed-up.

Returns `y` : DataFrame

Notes

Preferable to use `read_table` for most general purposes but `from_csv` makes for an easy roundtrip to and from file, especially with a DataFrame of time series data

pandas.DataFrame.from_dict

classmethod `DataFrame.from_dict` (*data*, *orient*='columns', *dtype*=None)

Construct DataFrame from dict of array-like or dicts

Parameters `data` : dict

{field : array-like} or {field : dict}

orient : {'columns', 'index'}, default 'columns'

The “orientation” of the data. If the keys of the passed dict should be the columns of the resulting DataFrame, pass 'columns' (default). Otherwise if the keys should be rows, pass 'index'.

Returns DataFrame

pandas.DataFrame.from_items

classmethod `DataFrame.from_items` (*items*, *columns*=None, *orient*='columns')

Convert (key, value) pairs to DataFrame. The keys will be the axis index (usually the columns, but depends on the specified orientation). The values should be arrays or Series.

Parameters `items` : sequence of (key, value) pairs

Values should be arrays or Series.

columns : sequence of column labels, optional

Must be passed if `orient`='index'.

orient : {'columns', 'index'}, default 'columns'

The “orientation” of the data. If the keys of the input correspond to column labels, pass 'columns' (default). Otherwise if the keys correspond to the index, pass 'index'.

Returns `frame` : DataFrame

pandas.DataFrame.from_records

classmethod DataFrame.**from_records**(data, index=None, exclude=None, columns=None, coerce_float=False, nrows=None)

Convert structured or record ndarray to DataFrame

Parameters data : ndarray (structured dtype), list of tuples, dict, or DataFrame

index : string, list of fields, array-like

Field of array to use as the index, alternately a specific set of input labels to use

exclude : sequence, default None

Columns or fields to exclude

columns : sequence, default None

Column names to use. If the passed data do not have names associated with them, this argument provides names for the columns. Otherwise this argument indicates the order of the columns in the result (any names not found in the data will become all-NA columns)

coerce_float : boolean, default False

Attempt to convert values to non-string, non-numeric objects (like decimal.Decimal) to floating point, useful for SQL result sets

Returns df : DataFrame

pandas.DataFrame.info

DataFrame.**info**(verbose=None, buf=None, max_cols=None, memory_usage=None, null_counts=None)

Concise summary of a DataFrame.

Parameters verbose : {None, True, False}, optional

Whether to print the full summary. None follows the *display.max_info_columns* setting. True or False overrides the *display.max_info_columns* setting.

buf : writable buffer, defaults to sys.stdout

max_cols : int, default None

Determines whether full summary or short summary is printed. None follows the *display.max_info_columns* setting.

memory_usage : boolean, default None

Specifies whether total memory usage of the DataFrame elements (including index) should be displayed. None follows the *display.memory_usage* setting. True or False overrides the *display.memory_usage* setting. Memory usage is shown in human-readable units (base-2 representation).

null_counts : boolean, default None

Whether to show the non-null counts. If None, then only show if the frame is smaller than max_info_rows and max_info_columns. If True, always show counts. If False, never show counts.

pandas.DataFrame.to_pickle`DataFrame.to_pickle` (*path*)

Pickle (serialize) object to input file path

Parameters `path` : string

File path

pandas.DataFrame.to_csv

`DataFrame.to_csv` (*path_or_buf=None, sep=',', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, mode='w', encoding=None, quoting=None, quotechar='"', line_terminator='\n', chunksize=None, tupleize_cols=False, date_format=None, doublequote=True, escapechar=None, decimal='.', **kwargs*)

Write DataFrame to a comma-separated values (csv) file

Parameters `path_or_buf` : string or file handle, default None

File path or object, if None is provided the result is returned as a string.

sep : character, default ','

Field delimiter for the output file.

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, or False, default NoneColumn label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex. If False do not print fields for index names. Use *index_label=False* for easier importing in R**nanRep** : Nonedeprecated, use *na_rep***mode** : str

Python write mode, default 'w'

encoding : string, optional

A string representing the encoding to use in the output file, defaults to 'ascii' on Python 2 and 'utf-8' on Python 3.

line_terminator : string, default '\n'

The newline character or character sequence to use in the output file

quoting : optional constant from csv module

defaults to csv.QUOTE_MINIMAL

quotechar : string (length 1), default '"'

character used to quote fields

doublequote : boolean, default True

Control quoting of *quotechar* inside a field

escapechar : string (length 1), default None

character used to escape *sep* and *quotechar* when appropriate

chunksize : int or None

rows to write at a time

tupleize_cols : boolean, default False

write multi_index columns as a list of tuples (if True) or new (expanded format) if False)

date_format : string, default None

Format string for datetime objects

decimal: string, default '.'

Character recognized as decimal separator. E.g. use ',' for European data

pandas.DataFrame.to_hdf

`DataFrame.to_hdf` (*path_or_buf*, *key*, ***kwargs*)
activate the HDFStore

Parameters *path_or_buf* : the path (string) or buffer to put the store

key : string

identifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to 'a', but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.DataFrame.to_sql

`DataFrame.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.DataFrame.to_dict

DataFrame.**to_dict** (*args, **kwargs)

Convert DataFrame to dictionary.

Parameters **orient** : str {'dict', 'list', 'series', 'split', 'records'}

Determines the type of the values of the dictionary.

- dict (default) : dict like {column -> {index -> value}}
- list : dict like {column -> [values]}
- series : dict like {column -> Series(values)}
- split : dict like {index -> [index], columns -> [columns], data -> [values]}
- records : list like [{column -> value}, ... , {column -> value}]

Abbreviations are allowed. *s* indicates *series* and *sp* indicates *split*.

Returns **result** : dict like {column -> {index -> value}}

pandas.DataFrame.to_excel

DataFrame.**to_excel** (excel_writer, sheet_name='Sheet1', na_rep='', float_format=None, columns=None, header=True, index=True, index_label=None, startrow=0, startcol=0, engine=None, merge_cells=True, encoding=None, inf_rep='inf')

Write DataFrame to a excel sheet

Parameters **excel_writer** : string or ExcelWriter object

File path or existing ExcelWriter

sheet_name : string, default 'Sheet1'

Name of sheet which will contain DataFrame

na_rep : string, default ''

Missing data representation

float_format : string, default None

Format string for floating point numbers

columns : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow :

upper left cell row to dump data frame

startcol :

upper left cell column to dump data frame

engine : string, default None

write engine to use - you can also set this via the options
`io.excel.xlsx.writer`, `io.excel.xls.writer`, and
`io.excel.xlsm.writer`.

merge_cells : boolean, default True

Write MultiIndex and Hierarchical Rows as merged cells.

encoding: string, default None

encoding of the resulting excel file. Only necessary for xlwt, other writers support unicode natively.

inf_rep : string, default 'inf'

Representation for infinity (there is no native representation for infinity in Excel)

Notes

If passing an existing ExcelWriter object, then the sheet will be added to the existing workbook. This can be used to save different DataFrames to one workbook:

```
>>> writer = ExcelWriter('output.xlsx')
>>> df1.to_excel(writer, 'Sheet1')
>>> df2.to_excel(writer, 'Sheet2')
>>> writer.save()
```

pandas.DataFrame.to_json

`DataFrame.to_json` (*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*,
force_ascii=True, *date_unit='ms'*, *default_handler=None*)

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters *path_or_buf* : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
 - default is 'index'

- allowed values are: { 'split', 'records', 'index' }
- DataFrame
 - default is 'columns'
 - allowed values are: { 'split', 'records', 'index', 'columns', 'values' }
- The format of the JSON string
 - split : dict like {index -> [index], columns -> [columns], data -> [values]}
 - records : list like [{column -> value}, ... , {column -> value}]
 - index : dict like {index -> {column -> value}}
 - columns : dict like {column -> {index -> value}}
 - values : just the values array

date_format : { 'epoch', 'iso' }

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.DataFrame.to_html

`DataFrame.to_html` (*buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, bold_rows=True, classes=None, escape=True, max_rows=None, max_cols=None, show_dimensions=False*)

Render a DataFrame as an HTML table.

to_html-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

classes [str or list or tuple, default None] CSS class(es) to apply to the resulting html table

escape [boolean, default True] Convert the characters <, >, and & to HTML-safe sequences.=

max_rows [int, optional] Maximum number of rows to show before truncating. If None, show all.

max_cols [int, optional] Maximum number of columns to show before truncating. If None, show all.

Parameters frame : DataFrame

object to render

buf : StringIO-like, optional

buffer to write to

columns : sequence, optional

the subset of columns to write; default None writes all columns

col_space : int, optional

the minimum width of each column

header : bool, optional

whether to print column labels, default True

index : bool, optional

whether to print index (row) labels, default True

na_rep : string, optional

string representation of NAN to use, default 'NaN'

formatters : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats, default None. The result of this function must be a unicode string.

sparsify : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by set_option), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns **formatted** : string (or unicode, depending on data and options)

pandas.DataFrame.to_latex

`DataFrame.to_latex` (*buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, bold_rows=True, longtable=False, escape=True*)

Render a DataFrame to a tabular environment table. You can splice this into a LaTeX document. Requires `usepackage{booktabs}`.

to_latex-specific options:

bold_rows [boolean, default True] Make the row labels bold in the output

longtable [boolean, default False] Use a longtable environment instead of tabular. Requires adding a `usepackage{longtable}` to your LaTeX preamble.

escape [boolean, default True] When set to False prevents from escaping latex special characters in column names.

Parameters **frame** : DataFrame

object to render

buf : StringIO-like, optional

buffer to write to

columns : sequence, optional

the subset of columns to write; default None writes all columns

col_space : int, optional

the minimum width of each column

header : bool, optional

whether to print column labels, default True

index : bool, optional

whether to print index (row) labels, default True

na_rep : string, optional

string representation of NAN to use, default 'NaN'

formatters : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats, default None. The result of this function must be a unicode string.

sparsify : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by `set_option`), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_stata

`DataFrame.to_stata` (*fname*, *convert_dates=None*, *write_index=True*, *encoding='latin-1'*, *byteorder=None*, *time_stamp=None*, *data_label=None*)

A class for writing Stata binary dta files from array-like objects

Parameters fname : file path or buffer

Where to save the dta file.

convert_dates : dict

Dictionary mapping column of datetime types to the stata internal format that you want to use for the dates. Options are 'tc', 'td', 'tm', 'tw', 'th', 'tq', 'ty'. Column can be either a number or a name.

encoding : str

Default is latin-1. Note that Stata does not support unicode.

byteorder : str

Can be ">", "<", "little", or "big". The default is None which uses *sys.byteorder*

Examples

```
>>> writer = StataWriter('./data_file.dta', data)
>>> writer.write_file()
```

Or with dates

```
>>> writer = StataWriter('./date_data_file.dta', data, {2 : 'tw'})
>>> writer.write_file()
```

pandas.DataFrame.to_msgpack

`DataFrame.to_msgpack` (*path_or_buf=None*, ***kwargs*)

msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no compression)

pandas.DataFrame.to_gbq

`DataFrame.to_gbq(destination_table, project_id=None, chunksize=10000, verbose=True, reauth=False)`

Write a DataFrame to a Google BigQuery table.

THIS IS AN EXPERIMENTAL LIBRARY

If the table exists, the dataframe will be written to the table using the defined table schema and column types. For simplicity, this method uses the Google BigQuery streaming API. The `to_gbq` method chunks data into a default chunk size of 10,000. Failures return the complete error response which can be quite long depending on the size of the insert. There are several important limitations of the Google streaming API which are detailed at: <https://developers.google.com/bigquery/streaming-data-into-bigquery>.

Parameters `dataframe` : DataFrame

DataFrame to be written

destination_table : string

Name of table to be written, in the form 'dataset.tablename'

project_id : str

Google BigQuery Account project ID.

chunksize : int (default 10000)

Number of rows to be inserted in each chunk from the dataframe.

verbose : boolean (default True)

Show percentage complete

reauth : boolean (default False)

Force Google BigQuery to reauthenticate the user. This is useful if multiple accounts are used.

pandas.DataFrame.to_records

`DataFrame.to_records(index=True, convert_datetime64=True)`

Convert DataFrame to record array. Index will be put in the 'index' field of the record array if requested

Parameters `index` : boolean, default True

Include index in resulting record array, stored in 'index' field

convert_datetime64 : boolean, default True

Whether to convert the index to `datetime.datetime` if it is a `DatetimeIndex`

Returns `y` : recarray

pandas.DataFrame.to_sparse

`DataFrame.to_sparse(fill_value=None, kind='block')`

Convert to SparseDataFrame

Parameters `fill_value` : float, default NaN

kind : {'block', 'integer'}

Returns `y` : SparseDataFrame

pandas.DataFrame.to_dense

`DataFrame.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.DataFrame.to_string

`DataFrame.to_string(buf=None, columns=None, col_space=None, colSpace=None, header=True, index=True, na_rep='NaN', formatters=None, float_format=None, sparsify=None, index_names=True, justify=None, line_width=None, max_rows=None, max_cols=None, show_dimensions=False)`

Render a DataFrame to a console-friendly tabular output.

Parameters **frame** : DataFrame

object to render

buf : StringIO-like, optional

buffer to write to

columns : sequence, optional

the subset of columns to write; default None writes all columns

col_space : int, optional

the minimum width of each column

header : bool, optional

whether to print column labels, default True

index : bool, optional

whether to print index (row) labels, default True

na_rep : string, optional

string representation of NAN to use, default 'NaN'

formatters : list or dict of one-parameter functions, optional

formatter functions to apply to columns' elements by position or name, default None. The result of each function must be a unicode string. List must be of length equal to the number of columns.

float_format : one-parameter function, optional

formatter function to apply to columns' elements if they are floats, default None. The result of this function must be a unicode string.

sparsify : bool, optional

Set to False for a DataFrame with a hierarchical index to print every multiindex key at each row, default True

justify : {'left', 'right'}, default None

Left or right-justify the column labels. If None uses the option from the print configuration (controlled by `set_option`), 'right' out of the box.

index_names : bool, optional

Prints the names of the indexes, default True

force_unicode : bool, default False

Always return a unicode result. Deprecated in v0.10.0 as string formatting is now rendered to unicode by default.

Returns formatted : string (or unicode, depending on data and options)

pandas.DataFrame.to_clipboard

DataFrame.**to_clipboard** (*excel=None, sep=None, **kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters excel : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

33.5 Panel

33.5.1 Constructor

`Panel([data, items, major_axis, minor_axis, ...])` Represents wide format panel data, stored as 3-dimensional array

pandas.Panel

class pandas.**Panel** (*data=None, items=None, major_axis=None, minor_axis=None, copy=False, dtype=None*)

Represents wide format panel data, stored as 3-dimensional array

Parameters data : ndarray (items x major x minor), or dict of DataFrames

items : Index or array-like

axis=0

major_axis : Index or array-like

axis=1

minor_axis : Index or array-like

axis=2

dtype : dtype, default None

Data type to force, otherwise infer

copy : boolean, default False

Copy data from inputs. Only affects DataFrame / 2d ndarray input

Attributes

<code>at</code>	Fast label-based scalar accessor
<code>axes</code>	index(es) of the NDFrame
<code>blocks</code>	Internal property, property synonym for <code>as_blocks()</code>
<code>dtypes</code>	Return the dtypes in this object
<code>empty</code>	True if NDFrame is entirely empty [no items]
<code>ftypes</code>	Return the ftypes (indication of sparse/dense and dtype) in this object.
<code>iat</code>	Fast integer location scalar accessor.
<code>iloc</code>	Purely integer-location based indexing for selection by position.
<code>ix</code>	A primarily label-location based indexer, with integer position fallback.
<code>loc</code>	Purely label-location based indexer for selection by label.
<code>ndim</code>	Number of axes / array dimensions
<code>shape</code>	tuple of axis dimensions
<code>size</code>	number of elements in the NDFrame
<code>values</code>	Numpy representation of NDFrame

pandas.Panel.at

`Panel.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Panel.axes

`Panel.axes`

index(es) of the NDFrame

pandas.Panel.blocks

`Panel.blocks`

Internal property, property synonym for `as_blocks()`

pandas.Panel.dtypes

`Panel.dtypes`

Return the dtypes in this object

pandas.Panel.empty

`Panel.empty`

True if NDFrame is entirely empty [no items]

pandas.Panel.ftypes

Panel.ftypes

Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel.iat

Panel.iat

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Panel.iloc

Panel.iloc

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. `[4, 3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at [Selection by Position](#)

pandas.Panel.ix

Panel.ix

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#).

pandas.Panel.loc

Panel.loc

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a':'f' (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at [Selection by Label](#)

pandas.Panel.ndim

`Panel.ndim`

Number of axes / array dimensions

pandas.Panel.shape

`Panel.shape`

tuple of axis dimensions

pandas.Panel.size

`Panel.size`

number of elements in the NDFrame

pandas.Panel.values

`Panel.values`

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

is_copy	
---------	--

Methods

<code>abs()</code>	Return an object with absolute value taken.
<code>add(other[, axis])</code>	Wrapper method for add
<code>add_prefix(prefix)</code>	Concatenate prefix string with panel items names.
<code>add_suffix(suffix)</code>	Concatenate suffix string with panel items names
<code>align(other[, join, axis, level, copy, ...])</code>	Align two object on their axes with the
<code>all([axis, bool_only, skipna, level])</code>	Return whether all elements are True over requested axis
<code>any([axis, bool_only, skipna, level])</code>	Return whether any element is True over requested axis
<code>apply(func[, axis])</code>	Applies function along input axis of the Panel
<code>as_blocks()</code>	Convert the frame to a dict of dtype -> Constructor Types that each has a homog
<code>as_matrix()</code>	
<code>asfreq(freq[, method, how, normalize])</code>	Convert all TimeSeries inside to specified frequency using DateOffset objects.
<code>astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>at_time(time[, asof])</code>	Select values at particular time of day (e.g.
<code>between_time(start_time, end_time[, ...])</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM)
<code>bfill([axis, inplace, limit, downcast])</code>	Synonym for NDFrame.fillna(method='bfill')
<code>bool()</code>	Return the bool of a single element PandasObject
<code>clip([lower, upper, out, axis])</code>	Trim values at input threshold(s)
<code>clip_lower(threshold[, axis])</code>	Return copy of the input with values below given value(s) truncated
<code>clip_upper(threshold[, axis])</code>	Return copy of input with values above given value(s) truncated
<code>compound([axis, skipna, level])</code>	Return the compound percentage of the values for the requested axis
<code>conform(frame[, axis])</code>	Conform input DataFrame to align with chosen axis pair.
<code>consolidate([inplace])</code>	Compute NDFrame with “consolidated” internals (data of each dtype grouped to
<code>convert_objects([convert_dates, ...])</code>	Attempt to infer better dtype for object columns
<code>copy([deep])</code>	Make a copy of this object
<code>count([axis])</code>	Return number of observations over requested axis.
<code>cummax([axis, dtype, out, skipna])</code>	Return cumulative max over requested axis.
<code>cummin([axis, dtype, out, skipna])</code>	Return cumulative min over requested axis.
<code>cumprod([axis, dtype, out, skipna])</code>	Return cumulative prod over requested axis.
<code>cumsum([axis, dtype, out, skipna])</code>	Return cumulative sum over requested axis.
<code>describe([percentile_width, percentiles, ...])</code>	Generate various summary statistics, excluding NaN values.
<code>div(other[, axis])</code>	Wrapper method for truediv
<code>divide(other[, axis])</code>	Wrapper method for truediv
<code>drop(labels[, axis, level, inplace, errors])</code>	Return new object with labels in requested axis removed
<code>dropna([axis, how, inplace])</code>	Drop 2D from panel, holding passed axis constant
<code>eq(other)</code>	Wrapper for comparison method eq
<code>equals(other)</code>	Determines if two NDFrame objects contain the same elements.
<code>ffill([axis, inplace, limit, downcast])</code>	Synonym for NDFrame.fillna(method='ffill')
<code>fillna([value, method, axis, inplace, ...])</code>	Fill NA/NaN values using the specified method
<code>filter([items, like, regex, axis])</code>	Restrict the info axis to set of items or wildcard
<code>first(offset)</code>	Convenience method for subsetting initial periods of time series data
<code>floordiv(other[, axis])</code>	Wrapper method for floordiv
<code>fromDict(data[, intersect, orient, dtype])</code>	Construct Panel from dict of DataFrame objects
<code>from_dict(data[, intersect, orient, dtype])</code>	Construct Panel from dict of DataFrame objects
<code>ge(other)</code>	Wrapper for comparison method ge
<code>get(key[, default])</code>	Get item from object for given key (DataFrame column, Panel slice, etc.).
<code>get_dtype_counts()</code>	Return the counts of dtypes in this object
<code>get_ftype_counts()</code>	Return the counts of ftypes in this object
<code>get_value(*args, **kwargs)</code>	Quickly retrieve single value at (item, major, minor) location

Table 33.66 – continued from previous

<code>get_values()</code>	same as values (but handles sparseness conversions)
<code>groupby(function[, axis])</code>	Group data on given axis, returning GroupBy object
<code>gt(other)</code>	Wrapper for comparison method gt
<code>head([n])</code>	
<code>interpolate([method, axis, limit, inplace, ...])</code>	Interpolate values according to different methods.
<code>isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>iteritems()</code>	Iterate over (label, values) on info axis
<code>iterkv(*args, **kwargs)</code>	iteritems alias used to get around 2to3. Deprecated
<code>join(other[, how, lsuffix, rsuffix])</code>	Join items with other Panel either on major and minor axes column
<code>keys()</code>	Get the ‘info axis’ (see Indexing for more)
<code>kurt([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>kurtosis([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>last(offset)</code>	Convenience method for subsetting final periods of time series data
<code>le(other)</code>	Wrapper for comparison method le
<code>load(path)</code>	Deprecated.
<code>lt(other)</code>	Wrapper for comparison method lt
<code>mad([axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis
<code>major_xs(key[, copy])</code>	Return slice of panel along major axis
<code>mask(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from
<code>max([axis, skipna, level, numeric_only])</code>	This method returns the maximum of the values in the object.
<code>mean([axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis
<code>median([axis, skipna, level, numeric_only])</code>	Return the median of the values for the requested axis
<code>min([axis, skipna, level, numeric_only])</code>	This method returns the minimum of the values in the object.
<code>minor_xs(key[, copy])</code>	Return slice of panel along minor axis
<code>mod(other[, axis])</code>	Wrapper method for mod
<code>mul(other[, axis])</code>	Wrapper method for mul
<code>multiply(other[, axis])</code>	Wrapper method for mul
<code>ne(other)</code>	Wrapper for comparison method ne
<code>notnull()</code>	Return a boolean same-sized object indicating if the values are
<code>pct_change([periods, fill_method, limit, freq])</code>	Percent change over given number of periods.
<code>pop(item)</code>	Return item and drop from frame.
<code>pow(other[, axis])</code>	Wrapper method for pow
<code>prod([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>product([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>radd(other[, axis])</code>	Wrapper method for radd
<code>rdiv(other[, axis])</code>	Wrapper method for rtruediv
<code>reindex([items, major_axis, minor_axis])</code>	Conform Panel to new index with optional filling logic, placing NA/NaN in locat
<code>reindex_axis(labels[, axis, method, level, ...])</code>	Conform input object to new index with optional filling logic, placing NA/NaN i
<code>reindex_like(other[, method, copy, limit])</code>	return an object with matching indicies to myself
<code>rename([items, major_axis, minor_axis])</code>	Alter axes input function or functions.
<code>rename_axis(mapper[, axis, copy, inplace])</code>	Alter index and / or columns using input function or functions.
<code>replace([to_replace, value, inplace, limit, ...])</code>	Replace values given in ‘to_replace’ with ‘value’.
<code>resample(rule[, how, axis, fill_method, ...])</code>	Convenience method for frequency conversion and resampling of regular time-se
<code>rfloordiv(other[, axis])</code>	Wrapper method for rfloordiv
<code>rmod(other[, axis])</code>	Wrapper method for rmod
<code>rmul(other[, axis])</code>	Wrapper method for rmul
<code>rpow(other[, axis])</code>	Wrapper method for rpow
<code>rsub(other[, axis])</code>	Wrapper method for rsub
<code>rtruediv(other[, axis])</code>	Wrapper method for rtruediv
<code>sample([n, frac, replace, weights, ...])</code>	Returns a random sample of items from an axis of object.
<code>save(path)</code>	Deprecated.
<code>select(crit[, axis])</code>	Return data corresponding to axis labels matching criteria

Table 33.66 – continued from previous

<code>sem([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased standard error of the mean over requested axis.
<code>set_axis(axis, labels)</code>	public version of axis assignment
<code>set_value(*args, **kwargs)</code>	Quickly set single value at (item, major, minor) location
<code>shift(*args, **kwargs)</code>	Shift index by desired number of periods with an optional time freq.
<code>skew([axis, skipna, level, numeric_only])</code>	Return unbiased skew over requested axis
<code>slice_shift([periods, axis])</code>	Equivalent to <i>shift</i> without copying data.
<code>sort_index([axis, ascending])</code>	Sort object by labels (along an axis)
<code>squeeze()</code>	squeeze length 1 dimensions
<code>std([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased standard deviation over requested axis.
<code>sub(other[, axis])</code>	Wrapper method for sub
<code>subtract(other[, axis])</code>	Wrapper method for sub
<code>sum([axis, skipna, level, numeric_only])</code>	Return the sum of the values for the requested axis
<code>swapaxes(axis1, axis2[, copy])</code>	Interchange axes and swap values axes appropriately
<code>swaplevel(i, j[, axis])</code>	Swap levels i and j in a MultiIndex on a particular axis
<code>tail([n])</code>	
<code>take(indices[, axis, convert, is_copy])</code>	Analogous to ndarray.take
<code>toLong(*args, **kwargs)</code>	
<code>to_clipboard([excel, sep])</code>	Attempt to write text representation of object to the system clipboard This can be
<code>to_dense()</code>	Return dense representation of NDFrame (as opposed to sparse)
<code>to_excel(path[, na_rep, engine])</code>	Write each DataFrame in Panel to a separate excel sheet
<code>to_frame([filter_observations])</code>	Transform wide format into long (stacked) format as DataFrame whose columns
<code>to_hdf(path_or_buf, key, **kwargs)</code>	activate the HDFStore
<code>to_json([path_or_buf, orient, date_format, ...])</code>	Convert the object to a JSON string.
<code>to_long(*args, **kwargs)</code>	
<code>to_msgpack([path_or_buf])</code>	msgpack (serialize) object to input file path
<code>to_pickle(path)</code>	Pickle (serialize) object to input file path
<code>to_sparse([fill_value, kind])</code>	Convert to SparsePanel
<code>to_sql(name, con[, flavor, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>transpose(*args, **kwargs)</code>	Permute the dimensions of the Panel
<code>truediv(other[, axis])</code>	Wrapper method for truediv
<code>truncate([before, after, axis, copy])</code>	Truncates a sorted NDFrame before and/or after some particular dates.
<code>tshift([periods, freq, axis])</code>	
<code>tz_convert(tz[, axis, level, copy])</code>	Convert tz-aware axis to target time zone.
<code>tz_localize(*args, **kwargs)</code>	Localize tz-naive TimeSeries to target time zone
<code>update(other[, join, overwrite, ...])</code>	Modify Panel in place using non-NA values from passed Panel, or object coercib
<code>var([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased variance over requested axis.
<code>where(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from
<code>xs(key[, axis, copy])</code>	Return slice of panel along selected axis

pandas.Panel.abs**Panel.abs()**

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller**pandas.Panel.add****Panel.add**(other, axis=0)

Wrapper method for add

Parameters other : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.add_prefix

Panel.add_prefix (*prefix*)

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.Panel.add_suffix

Panel.add_suffix (*suffix*)

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.Panel.align

Panel.align (*other*, *join*='outer', *axis*=None, *level*=None, *copy*=True, *fill_value*=None, *method*=None, *limit*=None, *fill_axis*=0)

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : { 'outer', 'inner', 'left', 'right' }, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns (**left**, **right**) : (type of input, type of other)

Aligned objects

pandas.Panel.all

`Panel.all` (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether all elements are True over requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **all** : DataFrame or Panel (if level specified)

pandas.Panel.any

`Panel.any` (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether any element is True over requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **any** : DataFrame or Panel (if level specified)

pandas.Panel.apply

`Panel.apply` (*func, axis='major', **kwargs*)

Applies function along input axis of the Panel

Parameters **func** : function

Function to apply to each combination of 'other' axes e.g. if axis = 'items', then the combination of major_axis/minor_axis will be passed a Series

axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns result : Pandas Object

Examples

```
>>> p.apply(numpy.sqrt) # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0) # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1) # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2) # equiv to p.sum(2)
```

pandas.Panel.as_blocks

`Panel.as_blocks()`

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in `as_matrix`)

Returns values : a dict of dtype -> Constructor Types

pandas.Panel.as_matrix

`Panel.as_matrix()`

pandas.Panel.asfreq

`Panel.asfreq(freq, method=None, how=None, normalize=False)`

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters freq : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns converted : type of caller

pandas.Panel.astype

`Panel.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type
raise_on_error : raise on invalid input
kwargs : keyword arguments to pass on to the constructor
Returns **casted** : type of caller

pandas.Panel.at_time

Panel.at_time (*time, asof=False*)
Select values at particular time of day (e.g. 9:30AM)
Parameters **time** : datetime.time or string
Returns **values_at_time** : type of caller

pandas.Panel.between_time

Panel.between_time (*start_time, end_time, include_start=True, include_end=True*)
Select values between particular times of the day (e.g., 9:00-9:30 AM)
Parameters **start_time** : datetime.time or string
end_time : datetime.time or string
include_start : boolean, default True
include_end : boolean, default True
Returns **values_between_time** : type of caller

pandas.Panel.bfill

Panel.bfill (*axis=None, inplace=False, limit=None, downcast=None*)
Synonym for `NDFrame.fillna(method='bfill')`

pandas.Panel.bool

Panel.bool ()
Return the bool of a single element `PandasObject` This must be a boolean scalar value, either True or False
Raise a `ValueError` if the `PandasObject` does not have exactly 1 element, or that element is not boolean

pandas.Panel.clip

Panel.clip (*lower=None, upper=None, out=None, axis=None*)
Trim values at input threshold(s)
Parameters **lower** : float or array_like, default None
upper : float or array_like, default None
axis : int or string axis name, optional
Align object with lower and upper along the given axis.

Returns `clipped` : Series

Examples

```
>>> df
   0         1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
   0         1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
   0         1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967
```

`pandas.Panel.clip_lower`

`Panel.clip_lower` (*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters `threshold` : float or array_like

`axis` : int or string axis name, optional

Align object with threshold along the given axis.

Returns `clipped` : same type as input

See also:

[clip](#)

`pandas.Panel.clip_upper`

`Panel.clip_upper` (*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters `threshold` : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns **clipped** : same type as input

See also:

`clip`

pandas.Panel.compound

`Panel.compound` (*axis=None, skipna=None, level=None*)

Return the compound percentage of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **compounded** : DataFrame or Panel (if level specified)

pandas.Panel.conform

`Panel.conform` (*frame, axis='items'*)

Conform input DataFrame to align with chosen axis pair.

Parameters **frame** : DataFrame

axis : {'items', 'major', 'minor'}

Axis the input corresponds to. E.g., if axis='major', then the frame's columns would be items, and the index would be values of the minor axis

Returns DataFrame

pandas.Panel consolidate

`Panel consolidate` (*inplace=False*)

Compute NDFrame with “consolidated” internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters **inplace** : boolean, default False

If False return new object, otherwise modify existing object

Returns **consolidated** : type of caller

pandas.Panel.convert_objects

`Panel.convert_objects` (*convert_dates=True, convert_numeric=False, convert_timedeltas=True, copy=True*)

Attempt to infer better dtype for object columns

Parameters `convert_dates` : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

`convert_numeric` : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

`convert_timedeltas` : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

`copy` : boolean, default True

If True, return a copy even if no copy is necessary (e.g. no conversion was done).
Note: This is meant for internal use, and should not be confused with inplace.

Returns `converted` : same as input object

pandas.Panel.copy

`Panel.copy` (*deep=True*)

Make a copy of this object

Parameters `deep` : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns `copy` : type of caller

pandas.Panel.count

`Panel.count` (*axis='major'*)

Return number of observations over requested axis.

Parameters `axis` : {'items', 'major', 'minor'} or {0, 1, 2}

Returns `count` : DataFrame

pandas.Panel.cummax

`Panel.cummax` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative max over requested axis.

Parameters `axis` : {items (0), major_axis (1), minor_axis (2)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `max` : DataFrame

pandas.Panel.cummin

`Panel.cummin` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative min over requested axis.

Parameters *axis* : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *min* : DataFrame

pandas.Panel.cumprod

`Panel.cumprod` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative prod over requested axis.

Parameters *axis* : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *prod* : DataFrame

pandas.Panel.cumsum

`Panel.cumsum` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative sum over requested axis.

Parameters *axis* : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *sum* : DataFrame

pandas.Panel.describe

`Panel.describe` (*percentile_width=None, percentiles=None, include=None, exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters *percentile_width* : float, deprecated

The *percentile_width* argument will be removed in a future version. Use *percentiles* instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy.number`. To select categorical objects use `type object`. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`
- If `include` is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.Panel.div

`Panel.div (other, axis=0)`

Wrapper method for `truediv`

Parameters `other` : DataFrame or Panel

`axis` : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.divide

`Panel.divide (other, axis=0)`

Wrapper method for `truediv`

Parameters `other` : DataFrame or Panel

`axis` : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.drop

`Panel.drop (labels, axis=0, level=None, inplace=False, errors='raise')`

Return new object with labels in requested axis removed

Parameters labels : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns dropped : type of caller

pandas.Panel.dropna

`Panel.dropna (axis=0, how='any', inplace=False)`

Drop 2D from panel, holding passed axis constant

Parameters axis : int, default 0

Axis to hold constant. E.g. axis=1 will drop major_axis entries having a certain amount of NA data

how : {'all', 'any'}, default 'any'

'any': one or more values are NA in the DataFrame along the axis. For 'all' they all must be.

inplace : bool, default False

If True, do operation inplace and return None.

Returns dropped : Panel

pandas.Panel.eq

`Panel.eq (other)`

Wrapper for comparison method eq

pandas.Panel.equals

`Panel.equals (other)`

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel.fill

`Panel.fill` (*axis=None, inplace=False, limit=None, downcast=None*)
 Synonym for `NDFrame.fillna(method='ffill')`

pandas.Panel.fillna

`Panel.fillna` (*value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs*)

Fill NA/NaN values using the specified method

Parameters `method` : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series `pad` / `ffill`: propagate last valid observation forward to next valid `backfill` / `bfill`: use NEXT valid observation to fill gap

value : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns `filled` : Panel

See also:

`reindex`, `asfreq`

pandas.Panel.filter

`Panel.filter` (*items=None, like=None, regex=None, axis=None*)

Restrict the info axis to set of items or wildcard

Parameters `items` : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where “arg in col == True”

regex : string (regular expression)

Keep info axis with `re.search(regex, col) == True`

axis : int or None

The axis to filter on. By default this is the info axis. The “info axis” is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a' : [1, 2, 3, 4]})`; `df['a']`. So, the `DataFrame` columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

`pandas.Panel.first`

`Panel.first` (*offset*)

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters **offset** : string, `DateOffset`, `dateutil.relativedelta`

Returns **subset** : type of caller

Examples

`ts.last('10D')` -> First 10 days

`pandas.Panel.floordiv`

`Panel.floordiv` (*other, axis=0*)

Wrapper method for `floordiv`

Parameters **other** : `DataFrame` or `Panel`

axis : {`items`, `major_axis`, `minor_axis`}

Axis to broadcast over

Returns `Panel`

`pandas.Panel.fromDict`

classmethod `Panel.fromDict` (*data, intersect=False, orient='items', dtype=None*)

Construct `Panel` from dict of `DataFrame` objects

Parameters **data** : dict

{field : `DataFrame`}

intersect : boolean

Intersect indexes of input `DataFrames`

orient : {`'items'`, `'minor'`}, default `'items'`

The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass ‘items’ (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass ‘minor’

Returns Panel

pandas.Panel.from_dict

classmethod `Panel.from_dict` (*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters *data* : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : {‘items’, ‘minor’}, default ‘items’

The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass ‘items’ (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass ‘minor’

Returns Panel

pandas.Panel.ge

`Panel.ge` (*other*)

Wrapper for comparison method ge

pandas.Panel.get

`Panel.get` (*key*, *default=None*)

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters *key* : object

Returns *value* : type of items contained in object

pandas.Panel.get_dtype_counts

`Panel.get_dtype_counts` ()

Return the counts of dtypes in this object

pandas.Panel.get_ftype_counts

`Panel.get_ftype_counts` ()

Return the counts of ftypes in this object

`pandas.Panel.get_value`

`Panel.get_value(*args, **kwargs)`

Quickly retrieve single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

takeable : interpret the passed labels as indexers, default False

Returns **value** : scalar value

`pandas.Panel.get_values`

`Panel.get_values()`

same as values (but handles sparseness conversions)

`pandas.Panel.groupby`

`Panel.groupby(function, axis='major')`

Group data on given axis, returning GroupBy object

Parameters **function** : callable

Mapping function for chosen access

axis : {'major', 'minor', 'items'}, default 'major'

Returns **grouped** : PanelGroupBy

`pandas.Panel.gt`

`Panel.gt(other)`

Wrapper for comparison method gt

`pandas.Panel.head`

`Panel.head(n=5)`

`pandas.Panel.interpolate`

`Panel.interpolate(method='linear', axis=0, limit=None, inplace=False, downcast=None, **kwargs)`

Interpolate values according to different methods.

Parameters **method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero',

'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline',
'piecewise_polynomial', 'pchip'}

- 'linear': ignore the index and treat the values as equally spaced. default

- ‘time’: interpolation works on daily and higher resolution data to interpolate given length of interval
- ‘index’, ‘values’: use the actual numerical values of the index
- ‘nearest’, ‘zero’, ‘slinear’, ‘quadratic’, ‘cubic’, ‘barycentric’, ‘polynomial’ is passed to `scipy.interpolate.interpld` with the order given both ‘polynomial’ and ‘spline’ require that you also specify an order (int) e.g. `df.interpolate(method='polynomial', order=4)`
- ‘krogh’, ‘piecewise_polynomial’, ‘spline’, and ‘pchip’ are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior: <http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation> <http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html>

axis : {0, 1}, default 0

- 0: fill column-by-column
- 1: fill row-by-row

limit : int, default None.

Maximum number of consecutive NaNs to fill.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, ‘infer’ or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

pandas.Panel.isnull

`Panel.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of `isnull`

pandas.Panel.iteritems

`Panel.iteritems()`

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

pandas.Panel.iterkv

`Panel.iterkv(*args, **kwargs)`

iteritems alias used to get around 2to3. Deprecated

pandas.Panel.join

`Panel.join(other, how='left', lsuffix='', rsuffix='')`

Join items with other Panel either on major and minor axes column

Parameters other : Panel or list of Panels

Index should be similar to one of the columns in this one

how : { 'left', 'right', 'outer', 'inner' }

How to handle indexes of the two objects. Default: 'left' for joining on index,
None otherwise * left: use calling frame's index * right: use input frame's index
* outer: form union of indexes * inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

Returns joined : Panel

pandas.Panel.keys

`Panel.keys()`

Get the 'info axis' (see Indexing for more)

This is index for Series, columns for DataFrame and major_axis for Panel.

pandas.Panel.kurt

`Panel.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : DataFrame or Panel (if level specified)

pandas.Panel.kurtosis

Panel.kurtosis (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : DataFrame or Panel (if level specified)

pandas.Panel.last

Panel.last (*offset*)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters offset : string, DateOffset, dateutil.relativedelta

Returns subset : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Panel.le

Panel.le (*other*)

Wrapper for comparison method le

pandas.Panel.load

Panel.load (*path*)

Deprecated. Use read_pickle instead.

pandas.Panel.lt

Panel.**lt** (*other*)

Wrapper for comparison method lt

pandas.Panel.mad

Panel.**mad** (*axis=None, skipna=None, level=None*)

Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : DataFrame or Panel (if level specified)

pandas.Panel.major_xs

Panel.**major_xs** (*key, copy=None*)

Return slice of panel along major axis

Parameters **key** : object

Major axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see [MultiIndex Slicers](#)

pandas.Panel.mask

Panel.**mask** (*cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Panel.max

`Panel.max` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : DataFrame or Panel (if level specified)

pandas.Panel.mean

`Panel.mean` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the mean of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : DataFrame or Panel (if level specified)

pandas.Panel.median

`Panel.median` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the median of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **median** : DataFrame or Panel (if level specified)

pandas.Panel.min

`Panel.min` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **min** : DataFrame or Panel (if level specified)

pandas.Panel.minor_xs

`Panel.minor_xs` (*key, copy=None*)

Return slice of panel along minor axis

Parameters **key** : object

Minor axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns *y* : DataFrame

index -> major axis, columns -> items

Notes

minor_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see [MultiIndex Slicers](#)

pandas.Panel.mod

`Panel.mod (other, axis=0)`

Wrapper method for mod

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.mul

`Panel.mul (other, axis=0)`

Wrapper method for mul

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.multiply

`Panel.multiply (other, axis=0)`

Wrapper method for mul

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

`pandas.Panel.ne`

`Panel.ne` (*other*)
Wrapper for comparison method `ne`

`pandas.Panel.notnull`

`Panel.notnull` ()
Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of `notnull`

`pandas.Panel.pct_change`

`Panel.pct_change` (*periods=1, fill_method='pad', limit=None, freq=None, **kwargs*)
Percent change over given number of periods.

Parameters `periods` : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or `BDay()`)

Returns `chg` : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or `Index`, for `DataFrame` and 1, or `minor` for `Panel`. You can change this with the `axis` keyword argument.

`pandas.Panel.pop`

`Panel.pop` (*item*)
Return item and drop from frame. Raise `KeyError` if not found.

`pandas.Panel.pow`

`Panel.pow` (*other, axis=0*)
Wrapper method for `pow`

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.prod

Panel.**prod** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : DataFrame or Panel (if level specified)

pandas.Panel.product

Panel.**product** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : DataFrame or Panel (if level specified)

pandas.Panel.radd

Panel.**radd** (*other, axis=0*)

Wrapper method for radd

Parameters **other** : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rdiv

`Panel.rdiv` (*other*, *axis=0*)
Wrapper method for `rtruediv`

Parameters **other** : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.reindex

`Panel.reindex` (*items=None*, *major_axis=None*, *minor_axis=None*, ***kwargs*)

Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters **items**, **major_axis**, **minor_axis** : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Panel

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Panel.reindex_axis

`Panel.reindex_axis` (*labels*, *axis=0*, *method=None*, *level=None*, *copy=True*, *limit=None*, *fill_value=nan*)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and *copy=False*

Parameters *labels* : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns *reindexed* : Panel

See also:

`reindex`, `reindex_like`

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.Panel.reindex_like

`Panel.reindex_like` (*other*, *method=None*, *copy=True*, *limit=None*)

return an object with matching indicies to myself

Parameters **other** : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

pandas.Panel.rename

`Panel.rename` (*items=None, major_axis=None, minor_axis=None, **kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **items, major_axis, minor_axis** : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Panel. If True then value of copy is ignored.

Returns **renamed** : Panel (new object)

pandas.Panel.rename_axis

`Panel.rename_axis` (*mapper, axis=0, copy=True, inplace=False*)

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters **mapper** : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Returns **renamed** : type of caller

pandas.Panel.replace

`Panel.replace` (*to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters `to_replace` : str, regex, list, dict, Series, numeric, or None

- str or regex:
 - str: string exactly matching *to_replace* will be replaced with *value*
 - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
 - First, if *to_replace* and *value* are both lists, they **must** be the same length.
 - Second, if `regex=True` then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
 - str and regex rules apply as above.
- dict:
 - Nested dictionaries, e.g., `{ 'a': { 'b': nan } }`, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
 - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- None:
 - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If *value* is also None then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as *to_replace*, default False

Whether to interpret *to_replace* and/or *value* as regular expressions. If this is True then *to_replace* *must* be a string. Otherwise, *to_replace* must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, { 'pad', 'ffill', 'bfill' }

The method to use when for replacement, when *to_replace* is a list.

Returns **filled** : NDFrame

Raises AssertionError

- If *regex* is not a `bool` and *to_replace* is not `None`.

TypeError

- If *to_replace* is a `dict` and *value* is not a `list`, `dict`, `ndarray`, or `Series`
- If *to_replace* is `None` and *regex* is not compilable into a regular expression or is a `list`, `dict`, `ndarray`, or `Series`.

ValueError

- If *to_replace* and *value* are `list`s or `ndarray`s, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Panel.resample

`Panel.resample` (*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters *rule* : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the “origin” of the aggregated intervals. For example, for ‘5min’ frequency, base could range from 0 through 4. Defaults to 0

pandas.Panel.rfloordiv

`Panel.rfloordiv(other, axis=0)`

Wrapper method for rfloordiv

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.rmod

`Panel.rmod(other, axis=0)`

Wrapper method for rmod

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.rmul

`Panel.rmul(other, axis=0)`

Wrapper method for rmul

Parameters **other** : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.rpow

`Panel.rpow(other, axis=0)`

Wrapper method for rpow

Parameters **other** : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rsub

`Panel.rsub (other, axis=0)`
Wrapper method for rsub
Parameters **other** : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rtruediv

`Panel.rtruediv (other, axis=0)`
Wrapper method for rtruediv
Parameters **other** : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.sample

`Panel.sample (n=None, frac=None, replace=False, weights=None, random_state=None, axis=None)`
Returns a random sample of items from an axis of object.
Parameters **n** : int, optional
Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.
frac : float, optional
Fraction of axis items to return. Cannot be used with *n*.
replace : boolean, optional
Sample with or without replacement. Default = False.
weights : str or ndarray-like, optional
Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when *axis* = 0. Weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. inf and -inf values not allowed.

random_state : int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

Returns Same type as caller.

pandas.Panel.save

`Panel.save(path)`

Deprecated. Use `to_pickle` instead

pandas.Panel.select

`Panel.select(crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.Panel.sem

`Panel.sem(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sem** : DataFrame or Panel (if level specified)

pandas.Panel.set_axis

`Panel.set_axis(axis, labels)`

public version of axis assignment

`pandas.Panel.set_value`

`Panel.set_value(*args, **kwargs)`

Quickly set single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

value : scalar

takeable : interpret the passed labels as indexers, default False

Returns **panel** : Panel

If label combo is contained, will be reference to calling Panel, otherwise a new object

`pandas.Panel.shift`

`Panel.shift(*args, **kwargs)`

Shift index by desired number of periods with an optional time freq. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original. This is different from the behavior of `DataFrame.shift()`

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : `DateOffset`, `timedelta`, or time rule string, optional

axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns **shifted** : Panel

`pandas.Panel.skew`

`Panel.skew(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a `MultiIndex` (hierarchical), count along a particular level, collapsing into a `DataFrame`

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : `DataFrame` or `Panel` (if level specified)

pandas.Panel.slice_shift**Panel.slice_shift** (*periods=1, axis=0*)

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters **periods** : int

Number of periods to move, can be positive or negative

Returns **shifted** : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.Panel.sort_index**Panel.sort_index** (*axis=0, ascending=True*)

Sort object by labels (along an axis)

Parameters **axis** : {0, 1}

Sort index/rows versus columns

ascending : boolean, default True

Sort ascending vs. descending

Returns **sorted_obj** : type of caller

pandas.Panel.squeeze**Panel.squeeze** ()

squeeze length 1 dimensions

pandas.Panel.std**Panel.std** (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `std` : DataFrame or Panel (if level specified)

pandas.Panel.sub

`Panel.sub` (*other*, *axis=0*)

Wrapper method for sub

Parameters `other` : DataFrame or Panel

`axis` : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.subtract

`Panel.subtract` (*other*, *axis=0*)

Wrapper method for sub

Parameters `other` : DataFrame or Panel

`axis` : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.sum

`Panel.sum` (*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the sum of the values for the requested axis

Parameters `axis` : {items (0), major_axis (1), minor_axis (2)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

`level` : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

`numeric_only` : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `sum` : DataFrame or Panel (if level specified)

pandas.Panel.swapaxes

`Panel.swapaxes` (*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately

Returns `y` : same as input

pandas.Panel.swaplevel

`Panel.swaplevel(i, j, axis=0)`

Swap levels i and j in a MultiIndex on a particular axis

Parameters *i, j* : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns *swapped* : type of caller (new object)

pandas.Panel.tail

`Panel.tail(n=5)`

pandas.Panel.take

`Panel.take(indices, axis=0, convert=True, is_copy=True)`

Analogous to ndarray.take

Parameters *indices* : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns *taken* : type of caller

pandas.Panel.toLong

`Panel.toLong(*args, **kwargs)`

pandas.Panel.to_clipboard

`Panel.to_clipboard(excel=None, sep=None, **kwargs)`

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters *excel* : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

sep : optional, defaults to tab

other keywords are passed to to_csv

Notes**Requirements for your platform**

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none

- OS X: none

pandas.Panel.to_dense

`Panel.to_dense()`

Return dense representation of NDFrame (as opposed to sparse)

pandas.Panel.to_excel

`Panel.to_excel(path, na_rep='', engine=None, **kwargs)`

Write each DataFrame in Panel to a separate excel sheet

Parameters **path** : string or ExcelWriter object

File path or existing ExcelWriter

na_rep : string, default ''

Missing data representation

engine : string, default None

write engine to use - you can also set this via the options
`io.excel.xlsx.writer`, `io.excel.xls.writer`, and
`io.excel.xlsm.writer`.

Other Parameters **float_format** : string, default None

Format string for floating point numbers

cols : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow : upper left cell row to dump data frame

startcol : upper left cell column to dump data frame

Notes

Keyword arguments (and *na_rep*) are passed to the `to_excel` method for each DataFrame written.

pandas.Panel.to_frame**Panel.to_frame** (*filter_observations=True*)

Transform wide format into long (stacked) format as DataFrame whose columns are the Panel's items and whose index is a MultiIndex formed of the Panel's major and minor axes.

Parameters **filter_observations** : boolean, default True

Drop (major, minor) pairs without a complete set of observations across all the items

Returns **y** : DataFrame

pandas.Panel.to_hdf**Panel.to_hdf** (*path_or_buf, key, **kwargs*)

activate the HDFStore

Parameters **path_or_buf** : the path (string) or buffer to put the store

key : string

indentifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to 'a', but the file must already exist.

format : 'fixed(f)ltable(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a complib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Panel.to_json

`Panel.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=None)`

Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters `path_or_buf` : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
 - default is 'index'
 - allowed values are: {'split','records','index'}
- DataFrame
 - default is 'columns'
 - allowed values are: {'split','records','index','columns','values'}
- The format of the JSON string
 - split : dict like {index -> [index], columns -> [columns], data -> [values]}
 - records : list like [{column -> value}, ... , {column -> value}]
 - index : dict like {index -> {column -> value}}
 - columns : dict like {column -> {index -> value}}
 - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Panel.to_long

`Panel.to_long(*args, **kwargs)`

pandas.Panel.to_msgpack

`Panel.to_msgpack(path_or_buf=None, **kwargs)`
msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters **path** : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack

(default is False)

compress : type of compressor (zlib or blosc), default to None (no compression)

pandas.Panel.to_pickle

`Panel.to_pickle(path)`
Pickle (serialize) object to input file path

Parameters **path** : string

File path

pandas.Panel.to_sparse

`Panel.to_sparse(fill_value=None, kind='block')`
Convert to SparsePanel

Parameters **fill_value** : float, default NaN

kind : { 'block', 'integer' }

Returns **y** : SparseDataFrame

pandas.Panel.to_sql

`Panel.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`
Write records stored in a DataFrame to a SQL database.

Parameters **name** : string

Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : { 'sqlite', 'mysql' }, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : { 'fail', 'replace', 'append' }, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Panel.transpose

`Panel.transpose(*args, **kwargs)`

Permute the dimensions of the Panel

Parameters *args* : three positional arguments: each one of

{0, 1, 2, 'items', 'major_axis', 'minor_axis'}

copy : boolean, default False

Make a copy of the underlying data. Mixed-dtype data will always result in a copy

Returns *y* : same as input

Examples

```
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

pandas.Panel.truediv

`Panel.truediv` (*other*, *axis=0*)

Wrapper method for `truediv`

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.truncate

`Panel.truncate` (*before=None*, *after=None*, *axis=None*, *copy=True*)

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters *before* : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns *truncated* : type of caller

pandas.Panel.tshift

`Panel.tshift` (*periods=1*, *freq=None*, *axis='major'*, ***kws*)

pandas.Panel.tz_convert

`Panel.tz_convert` (*tz*, *axis=0*, *level=None*, *copy=True*)

Convert tz-aware axis to target time zone.

Parameters *tz* : string or `pytz.timezone` object

axis : the axis to convert

level : int, str, default None

If *axis* is a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises `TypeError`

If the axis is tz-naive.

pandas.Panel.tz_localize

`Panel.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters **tz** : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis is a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises **TypeError**

If the TimeSeries is tz-aware and tz is not None.

pandas.Panel.update

`Panel.update(other, join='left', overwrite=True, filter_func=None, raise_conflict=False)`

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

Parameters **other** : Panel, or object coercible to Panel

join : How to join individual DataFrames

{ 'left', 'right', 'outer', 'inner' }, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling panel

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : bool

If True, will raise an error if a DataFrame and other both contain data in the same place.

pandas.Panel.var

`Panel.var` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters `axis` : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `var` : DataFrame or Panel (if level specified)

pandas.Panel.where

`Panel.where` (*cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where `cond` is True and otherwise are from `other`.

Parameters `cond` : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns `wh` : same type as caller

pandas.Panel.xs

`Panel.xs` (*key, axis=1, copy=None*)

Return slice of panel along selected axis

Parameters `key` : object

Label

axis : { 'items', 'major', 'minor', default 1/'major' }

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : ndim(self)-1

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see [MultiIndex Slicers](#)

33.5.2 Attributes and underlying data

Axes

- **items**: axis 0; each item corresponds to a DataFrame contained inside
- **major_axis**: axis 1; the index (rows) of each of the DataFrames
- **minor_axis**: axis 2; the columns of each of the DataFrames

<code>Panel.values</code>	Numpy representation of NDFrame
<code>Panel.axes</code>	index(es) of the NDFrame
<code>Panel.ndim</code>	Number of axes / array dimensions
<code>Panel.size</code>	number of elements in the NDFrame
<code>Panel.shape</code>	tuple of axis dimensions
<code>Panel.dtypes</code>	Return the dtypes in this object
<code>Panel.ftypes</code>	Return the ftypes (indication of sparse/dense and dtype) in this object.
<code>Panel.get_dtype_counts()</code>	Return the counts of dtypes in this object
<code>Panel.get_ftype_counts()</code>	Return the counts of ftypes in this object

pandas.Panel.values

`Panel.values`

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

pandas.Panel.axes

`Panel.axes`

index(es) of the NDFrame

pandas.Panel.ndim**Panel.ndim**

Number of axes / array dimensions

pandas.Panel.size**Panel.size**

number of elements in the NDFrame

pandas.Panel.shape**Panel.shape**

tuple of axis dimensions

pandas.Panel.dtypes**Panel.dtypes**

Return the dtypes in this object

pandas.Panel.ftypes**Panel.ftypes**

Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel.get_dtype_counts**Panel.get_dtype_counts()**

Return the counts of dtypes in this object

pandas.Panel.get_ftype_counts**Panel.get_ftype_counts()**

Return the counts of ftypes in this object

33.5.3 Conversion

<code>Panel.astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>Panel.copy([deep])</code>	Make a copy of this object
<code>Panel.isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>Panel.notnull()</code>	Return a boolean same-sized object indicating if the values are

pandas.Panel.astype**Panel.astype** (*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.Panel.copy

`Panel.copy (deep=True)`

Make a copy of this object

Parameters **deep** : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns **copy** : type of caller

pandas.Panel.isnull

`Panel.isnull ()`

Return a boolean same-sized object indicating if the values are null

See also:

notnull boolean inverse of isnull

pandas.Panel.notnull

`Panel.notnull ()`

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

33.5.4 Getting and setting

<code>Panel.get_value(*args, **kwargs)</code>	Quickly retrieve single value at (item, major, minor) location
<code>Panel.set_value(*args, **kwargs)</code>	Quickly set single value at (item, major, minor) location

pandas.Panel.get_value

`Panel.get_value (*args, **kwargs)`

Quickly retrieve single value at (item, major, minor) location

Parameters **item** : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

takeable : interpret the passed labels as indexers, default False

Returns **value** : scalar value

pandas.Panel.set_value

`Panel.set_value(*args, **kwargs)`

Quickly set single value at (item, major, minor) location

Parameters `item` : item label (panel item)

major : major axis label (panel item row)

minor : minor axis label (panel item column)

value : scalar

takeable : interpret the passed labels as indexers, default False

Returns `panel` : Panel

If label combo is contained, will be reference to calling Panel, otherwise a new object

33.5.5 Indexing, iteration, slicing

<code>Panel.at</code>	Fast label-based scalar accessor
<code>Panel.iat</code>	Fast integer location scalar accessor.
<code>Panel.ix</code>	A primarily label-location based indexer, with integer position fallback.
<code>Panel.loc</code>	Purely label-location based indexer for selection by label.
<code>Panel.iloc</code>	Purely integer-location based indexing for selection by position.
<code>Panel.__iter__()</code>	Iterate over infor axis
<code>Panel.iteritems()</code>	Iterate over (label, values) on info axis
<code>Panel.pop(item)</code>	Return item and drop from frame.
<code>Panel.xs(key[, axis, copy])</code>	Return slice of panel along selected axis
<code>Panel.major_xs(key[, copy])</code>	Return slice of panel along major axis
<code>Panel.minor_xs(key[, copy])</code>	Return slice of panel along minor axis

pandas.Panel.at

`Panel.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Panel.iat

`Panel.iat`

Fast integer location scalar accessor.

Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Panel.ix

`Panel.ix`

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#).

pandas.Panel.loc

Panel.loc

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a' : 'f' (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at [Selection by Label](#)

pandas.Panel.iloc

Panel.iloc

Purely integer-location based indexing for selection by position.

`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.

Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. [4, 3, 0].
- A slice object with ints, e.g. 1:7.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at [Selection by Position](#)

pandas.Panel.__iter__

Panel.__iter__()

Iterate over infor axis

pandas.Panel.iteritems

`Panel.iteritems()`

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, major_axis for Panel, and so on.

pandas.Panel.pop

`Panel.pop(item)`

Return item and drop from frame. Raise KeyError if not found.

pandas.Panel.xs

`Panel.xs(key, axis=1, copy=None)`

Return slice of panel along selected axis

Parameters `key` : object

Label

axis : {'items', 'major', 'minor'}, default 1/'major'

copy : boolean [deprecated]

Whether to make a copy of the data

Returns `y` : `ndim(self)-1`

Notes

`xs` is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of `xs` functionality, see [*MultiIndex Slicers*](#)

pandas.Panel.major_xs

`Panel.major_xs(key, copy=None)`

Return slice of panel along major axis

Parameters `key` : object

Major axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns `y` : DataFrame

index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see [MultiIndex Slicers](#)

pandas.Panel.minor_xs

Panel.**minor_xs** (*key*, *copy=None*)

Return slice of panel along minor axis

Parameters *key* : object

Minor axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns *y* : DataFrame

index -> major axis, columns -> items

Notes

minor_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of minor_xs functionality, see [MultiIndex Slicers](#)

For more information on `.at`, `.iat`, `.ix`, `.loc`, and `.iloc`, see the [indexing documentation](#).

33.5.6 Binary operator functions

<code>Panel.add(other[, axis])</code>	Wrapper method for add
<code>Panel.sub(other[, axis])</code>	Wrapper method for sub
<code>Panel.mul(other[, axis])</code>	Wrapper method for mul
<code>Panel.div(other[, axis])</code>	Wrapper method for truediv
<code>Panel.truediv(other[, axis])</code>	Wrapper method for truediv
<code>Panel.floordiv(other[, axis])</code>	Wrapper method for floordiv
<code>Panel.mod(other[, axis])</code>	Wrapper method for mod
<code>Panel.pow(other[, axis])</code>	Wrapper method for pow
<code>Panel.radd(other[, axis])</code>	Wrapper method for radd
<code>Panel.rsub(other[, axis])</code>	Wrapper method for rsub
<code>Panel.rmula(other[, axis])</code>	Wrapper method for rmul
<code>Panel.rdiv(other[, axis])</code>	Wrapper method for rtruediv
<code>Panel.rtruediv(other[, axis])</code>	Wrapper method for rtruediv
<code>Panel.rfloordiv(other[, axis])</code>	Wrapper method for rfloordiv
<code>Panel.rmod(other[, axis])</code>	Wrapper method for rmod
<code>Panel.rpow(other[, axis])</code>	Wrapper method for rpow
<code>Panel.lt(other)</code>	Wrapper for comparison method lt
<code>Panel.gt(other)</code>	Wrapper for comparison method gt
<code>Panel.le(other)</code>	Wrapper for comparison method le

Continued on next page

Table 33.71 – continued from previous page

<code>Panel.ge(other)</code>	Wrapper for comparison method ge
<code>Panel.ne(other)</code>	Wrapper for comparison method ne
<code>Panel.eq(other)</code>	Wrapper for comparison method eq

pandas.Panel.add`Panel.add(other, axis=0)`

Wrapper method for add

Parameters `other` : DataFrame or Panel**axis** : {items, major_axis, minor_axis}**Axis to broadcast over****Returns** Panel**pandas.Panel.sub**`Panel.sub(other, axis=0)`

Wrapper method for sub

Parameters `other` : DataFrame or Panel**axis** : {items, major_axis, minor_axis}**Axis to broadcast over****Returns** Panel**pandas.Panel.mul**`Panel.mul(other, axis=0)`

Wrapper method for mul

Parameters `other` : DataFrame or Panel**axis** : {items, major_axis, minor_axis}**Axis to broadcast over****Returns** Panel**pandas.Panel.div**`Panel.div(other, axis=0)`

Wrapper method for truediv

Parameters `other` : DataFrame or Panel**axis** : {items, major_axis, minor_axis}**Axis to broadcast over****Returns** Panel

pandas.Panel.truediv

Panel.**truediv** (*other*, *axis=0*)

Wrapper method for truediv

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.floordiv

Panel.**floordiv** (*other*, *axis=0*)

Wrapper method for floordiv

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.mod

Panel.**mod** (*other*, *axis=0*)

Wrapper method for mod

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.pow

Panel.**pow** (*other*, *axis=0*)

Wrapper method for pow

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.radd

Panel.**radd** (*other*, *axis=0*)

Wrapper method for radd

Parameters *other* : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rsub

`Panel.rsub(other, axis=0)`
Wrapper method for rsub

Parameters *other* : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rmul

`Panel.rmul(other, axis=0)`
Wrapper method for rmul

Parameters *other* : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rdiv

`Panel.rdiv(other, axis=0)`
Wrapper method for rtruediv

Parameters *other* : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rtruediv

`Panel.rtruediv(other, axis=0)`
Wrapper method for rtruediv

Parameters *other* : DataFrame or Panel
axis : {items, major_axis, minor_axis}
Axis to broadcast over
Returns Panel

pandas.Panel.rfloordiv

Panel.**rfloordiv** (*other*, *axis=0*)

Wrapper method for rfloordiv

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.rmod

Panel.**rmod** (*other*, *axis=0*)

Wrapper method for rmod

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.rpow

Panel.**rpow** (*other*, *axis=0*)

Wrapper method for rpow

Parameters *other* : DataFrame or Panel

axis : {items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel

pandas.Panel.lt

Panel.**lt** (*other*)

Wrapper for comparison method lt

pandas.Panel.gt

Panel.**gt** (*other*)

Wrapper for comparison method gt

pandas.Panel.le

Panel.**le** (*other*)

Wrapper for comparison method le

pandas.Panel.ge

`Panel.ge (other)`
 Wrapper for comparison method ge

pandas.Panel.ne

`Panel.ne (other)`
 Wrapper for comparison method ne

pandas.Panel.eq

`Panel.eq (other)`
 Wrapper for comparison method eq

33.5.7 Function application, GroupBy

<code>Panel.apply(func[, axis])</code>	Applies function along input axis of the Panel
<code>Panel.groupby(function[, axis])</code>	Group data on given axis, returning GroupBy object

pandas.Panel.apply

`Panel.apply (func, axis='major', **kwargs)`
 Applies function along input axis of the Panel

Parameters `func` : function

Function to apply to each combination of 'other' axes e.g. if axis = 'items', then the combination of major_axis/minor_axis will be passed a Series

axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns `result` : Pandas Object

Examples

```
>>> p.apply(numpy.sqrt) # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0) # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1) # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2) # equiv to p.sum(2)
```

pandas.Panel.groupby

`Panel.groupby (function, axis='major')`
 Group data on given axis, returning GroupBy object

Parameters `function` : callable

Mapping function for chosen access

axis : { 'major', 'minor', 'items' }, default 'major'

Returns **grouped** : PanelGroupBy

33.5.8 Computations / Descriptive Stats

<code>Panel.abs()</code>	Return an object with absolute value taken.
<code>Panel.clip([lower, upper, out, axis])</code>	Trim values at input threshold(s)
<code>Panel.clip_lower(threshold[, axis])</code>	Return copy of the input with values below given value(s) truncated
<code>Panel.clip_upper(threshold[, axis])</code>	Return copy of input with values above given value(s) truncated
<code>Panel.count([axis])</code>	Return number of observations over requested axis.
<code>Panel.cummax([axis, dtype, out, skipna])</code>	Return cumulative max over requested axis.
<code>Panel.cummin([axis, dtype, out, skipna])</code>	Return cumulative min over requested axis.
<code>Panel.cumprod([axis, dtype, out, skipna])</code>	Return cumulative prod over requested axis.
<code>Panel.cumsum([axis, dtype, out, skipna])</code>	Return cumulative sum over requested axis.
<code>Panel.max([axis, skipna, level, numeric_only])</code>	This method returns the maximum of the values in the object.
<code>Panel.mean([axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis
<code>Panel.median([axis, skipna, level, numeric_only])</code>	Return the median of the values for the requested axis
<code>Panel.min([axis, skipna, level, numeric_only])</code>	This method returns the minimum of the values in the object.
<code>Panel.pct_change([periods, fill_method, ...])</code>	Percent change over given number of periods.
<code>Panel.prod([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>Panel.sem([axis, skipna, level, ddof, ...])</code>	Return unbiased standard error of the mean over requested axis.
<code>Panel.skew([axis, skipna, level, numeric_only])</code>	Return unbiased skew over requested axis
<code>Panel.sum([axis, skipna, level, numeric_only])</code>	Return the sum of the values for the requested axis
<code>Panel.std([axis, skipna, level, ddof, ...])</code>	Return unbiased standard deviation over requested axis.
<code>Panel.var([axis, skipna, level, ddof, ...])</code>	Return unbiased variance over requested axis.

pandas.Panel.abs

`Panel.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns **abs**: type of caller

pandas.Panel.clip

`Panel.clip(lower=None, upper=None, out=None, axis=None)`

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None

upper : float or array_like, default None

axis : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series

Examples

```
>>> df
0      1
```

```

0    0.335232 -1.256177
1   -1.367855  0.746646
2    0.027753 -1.176076
3    0.230930 -0.679613
4    1.261967  0.570967
>>> df.clip(-1.0, 0.5)
      0      1
0    0.335232 -1.000000
1   -1.000000  0.500000
2    0.027753 -1.000000
3    0.230930 -0.679613
4    0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
      0      1
0    0.335232 -0.300000
1   -0.200000  0.746646
2    0.027753 -0.100000
3    0.230930  0.000000
4    1.100000  0.570967

```

pandas.Panel.clip_lower

`Panel.clip_lower` (*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters `threshold` : float or array_like

`axis` : int or string axis name, optional

Align object with threshold along the given axis.

Returns `clipped` : same type as input

See also:

`clip`

pandas.Panel.clip_upper

`Panel.clip_upper` (*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters `threshold` : float or array_like

`axis` : int or string axis name, optional

Align object with threshold along the given axis.

Returns `clipped` : same type as input

See also:

`clip`

pandas.Panel.count

`Panel.count (axis='major')`

Return number of observations over requested axis.

Parameters `axis` : { 'items', 'major', 'minor' } or { 0, 1, 2 }

Returns `count` : DataFrame

pandas.Panel.cummax

`Panel.cummax (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative max over requested axis.

Parameters `axis` : { items (0), major_axis (1), minor_axis (2) }

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `max` : DataFrame

pandas.Panel.cummin

`Panel.cummin (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative min over requested axis.

Parameters `axis` : { items (0), major_axis (1), minor_axis (2) }

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `min` : DataFrame

pandas.Panel.cumprod

`Panel.cumprod (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative prod over requested axis.

Parameters `axis` : { items (0), major_axis (1), minor_axis (2) }

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `prod` : DataFrame

pandas.Panel.cumsum

`Panel.cumsum (axis=None, dtype=None, out=None, skipna=True, **kwargs)`

Return cumulative sum over requested axis.

Parameters `axis` : { items (0), major_axis (1), minor_axis (2) }

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `sum` : DataFrame

pandas.Panel.max

`Panel.max` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters `axis` : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `max` : DataFrame or Panel (if level specified)

pandas.Panel.mean

`Panel.mean` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the mean of the values for the requested axis

Parameters `axis` : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `mean` : DataFrame or Panel (if level specified)

pandas.Panel.median

`Panel.median` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the median of the values for the requested axis

Parameters `axis` : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns median : DataFrame or Panel (if level specified)

pandas.Panel.min

Panel.**min** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters axis : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns min : DataFrame or Panel (if level specified)

pandas.Panel.pct_change

Panel.**pct_change** (*periods=1, fill_method='pad', limit=None, freq=None, **kwargs*)

Percent change over given number of periods.

Parameters periods : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns chg : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the `axis` keyword argument.

pandas.Panel.prod

`Panel.prod` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

Parameters *axis* : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *prod* : DataFrame or Panel (if level specified)

pandas.Panel.sem

`Panel.sem` (*axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs*)

Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters *axis* : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *sem* : DataFrame or Panel (if level specified)

pandas.Panel.skew

`Panel.skew` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters *axis* : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : DataFrame or Panel (if level specified)

pandas.Panel.sum

`Panel.sum(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`

Return the sum of the values for the requested axis

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **sum** : DataFrame or Panel (if level specified)

pandas.Panel.std

`Panel.std(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **std** : DataFrame or Panel (if level specified)

pandas.Panel.var

`Panel.var(axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {items (0), major_axis (1), minor_axis (2)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a DataFrame

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : DataFrame or Panel (if level specified)

33.5.9 Reindexing / Selection / Label manipulation

<code>Panel.add_prefix(prefix)</code>	Concatenate prefix string with panel items names.
<code>Panel.add_suffix(suffix)</code>	Concatenate suffix string with panel items names
<code>Panel.drop(labels[, axis, level, inplace, ...])</code>	Return new object with labels in requested axis removed
<code>Panel.equals(other)</code>	Determines if two NDFrame objects contain the same elements.
<code>Panel.filter([items, like, regex, axis])</code>	Restrict the info axis to set of items or wildcard
<code>Panel.first(offset)</code>	Convenience method for subsetting initial periods of time series data
<code>Panel.last(offset)</code>	Convenience method for subsetting final periods of time series data
<code>Panel.reindex([items, major_axis, minor_axis])</code>	Conform Panel to new index with optional filling logic, placing NA/NaN in
<code>Panel.reindex_axis(labels[, axis, method, ...])</code>	Conform input object to new index with optional filling logic, placing NA/
<code>Panel.reindex_like(other[, method, copy, limit])</code>	return an object with matching indices to myself
<code>Panel.rename([items, major_axis, minor_axis])</code>	Alter axes input function or functions.
<code>Panel.sample([n, frac, replace, weights, ...])</code>	Returns a random sample of items from an axis of object.
<code>Panel.select(crit[, axis])</code>	Return data corresponding to axis labels matching criteria
<code>Panel.take(indices[, axis, convert, is_copy])</code>	Analogous to ndarray.take
<code>Panel.truncate([before, after, axis, copy])</code>	Truncates a sorted NDFrame before and/or after some particular dates.

pandas.Panel.add_prefix

`Panel.add_prefix` (*prefix*)

Concatenate prefix string with panel items names.

Parameters **prefix** : string

Returns **with_prefix** : type of caller

pandas.Panel.add_suffix

`Panel.add_suffix` (*suffix*)

Concatenate suffix string with panel items names

Parameters **suffix** : string

Returns **with_suffix** : type of caller

pandas.Panel.drop

`Panel.drop` (*labels*, *axis=0*, *level=None*, *inplace=False*, *errors='raise'*)

Return new object with labels in requested axis removed

Parameters **labels** : single label or list-like

axis : int or axis name

level : int or level name, default None

For MultiIndex

inplace : bool, default False

If True, do operation inplace and return None.

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns **dropped** : type of caller

pandas.Panel.equals

`Panel.equals` (*other*)

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel.filter

`Panel.filter` (*items=None*, *like=None*, *regex=None*, *axis=None*)

Restrict the info axis to set of items or wildcard

Parameters **items** : list-like

List of info axis to restrict to (must not all be present)

like : string

Keep info axis where "arg in col == True"

regex : string (regular expression)

Keep info axis with `re.search(regex, col) == True`

axis : int or None

The axis to filter on. By default this is the info axis. The "info axis" is the axis that is used when indexing with `[]`. For example, `df = DataFrame({'a': [1, 2, 3, 4]})`; `df['a']`. So, the DataFrame columns are the info axis.

Notes

Arguments are mutually exclusive, but this is not checked for

pandas.Panel.first**Panel.first** (*offset*)

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters *offset* : string, DateOffset, dateutil.relativedelta**Returns** *subset* : type of caller**Examples**

ts.last('10D') -> First 10 days

pandas.Panel.last**Panel.last** (*offset*)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters *offset* : string, DateOffset, dateutil.relativedelta**Returns** *subset* : type of caller**Examples**

ts.last('5M') -> Last 5 months

pandas.Panel.reindex**Panel.reindex** (*items=None, major_axis=None, minor_axis=None, **kwargs*)

Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and copy=False

Parameters *items, major_axis, minor_axis* : array-like, optional (can be specified in order, or as keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data**method** : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional**Method to use for filling holes in reindexed DataFrame:**

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Panel

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Panel.reindex_axis

Panel.reindex_axis (*labels*, *axis*=0, *method*=None, *level*=None, *copy*=True, *limit*=None, *fill_value*=nan)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and *copy*=False

Parameters **labels** : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Panel

See also:

[reindex](#), [reindex_like](#)

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.Panel.reindex_like

`Panel.reindex_like` (*other, method=None, copy=True, limit=None*)
 return an object with matching indices to myself

Parameters *other* : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : same as input

Notes

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

pandas.Panel.rename

`Panel.rename` (*items=None, major_axis=None, minor_axis=None, **kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters *items, major_axis, minor_axis* : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Panel. If True then value of copy is ignored.

Returns **renamed** : Panel (new object)

pandas.Panel.sample

`Panel.sample` (*n=None, frac=None, replace=False, weights=None, random_state=None, axis=None*)

Returns a random sample of items from an axis of object.

Parameters *n* : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when axis = 0. Weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. inf and -inf values not allowed.

random_state : int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

Returns Same type as caller.

pandas.Panel.select

`Panel.select (crit, axis=0)`

Return data corresponding to axis labels matching criteria

Parameters **crit** : function

To be called on each index (label). Should return True or False

axis : int

Returns **selection** : type of caller

pandas.Panel.take

`Panel.take (indices, axis=0, convert=True, is_copy=True)`

Analogous to ndarray.take

Parameters **indices** : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns **taken** : type of caller

pandas.Panel.truncate

`Panel.truncate (before=None, after=None, axis=None, copy=True)`

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

33.5.10 Missing data handling

<code>Panel.dropna([axis, how, inplace])</code>	Drop 2D from panel, holding passed axis constant
<code>Panel.fillna([value, method, axis, inplace, ...])</code>	Fill NA/NaN values using the specified method

pandas.Panel.dropna

`Panel.dropna` (*axis=0, how='any', inplace=False*)
Drop 2D from panel, holding passed axis constant

Parameters **axis** : int, default 0

Axis to hold constant. E.g. `axis=1` will drop `major_axis` entries having a certain amount of NA data

how : { 'all', 'any' }, default 'any'

'any': one or more values are NA in the DataFrame along the axis. For 'all' they all must be.

inplace : bool, default False

If True, do operation inplace and return None.

Returns **dropped** : Panel

pandas.Panel.fillna

`Panel.fillna` (*value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs*)
Fill NA/NaN values using the specified method

Parameters **method** : { 'backfill', 'bfill', 'pad', 'ffill', None }, default None

Method to use for filling holes in reindexed Series `pad` / `ffill`: propagate last valid observation forward to next valid `backfill` / `bfill`: use NEXT valid observation to fill gap

value : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns filled : Panel

See also:

`reindex, asfreq`

33.5.11 Reshaping, sorting, transposing

<code>Panel.sort_index([axis, ascending])</code>	Sort object by labels (along an axis)
<code>Panel.swaplevel(i, j[, axis])</code>	Swap levels i and j in a MultiIndex on a particular axis
<code>Panel.transpose(*args, **kwargs)</code>	Permute the dimensions of the Panel
<code>Panel.swapaxes(axis1, axis2[, copy])</code>	Interchange axes and swap values axes appropriately
<code>Panel.conform(frame[, axis])</code>	Conform input DataFrame to align with chosen axis pair.

pandas.Panel.sort_index

`Panel.sort_index (axis=0, ascending=True)`
Sort object by labels (along an axis)

Parameters axis : {0, 1}

Sort index/rows versus columns

ascending : boolean, default True

Sort ascending vs. descending

Returns sorted_obj : type of caller

pandas.Panel.swaplevel

`Panel.swaplevel (i, j, axis=0)`
Swap levels i and j in a MultiIndex on a particular axis

Parameters i, j : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns swapped : type of caller (new object)

pandas.Panel.transpose

`Panel.transpose (*args, **kwargs)`
Permute the dimensions of the Panel

Parameters args : three positional arguments: each one of

{0, 1, 2, 'items', 'major_axis', 'minor_axis'}

copy : boolean, default False

Make a copy of the underlying data. Mixed-dtype data will always result in a copy

Returns **y** : same as input

Examples

```
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

pandas.Panel.swapaxes

Panel.swapaxes (*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately

Returns **y** : same as input

pandas.Panel.conform

Panel.conform (*frame*, *axis='items'*)

Conform input DataFrame to align with chosen axis pair.

Parameters **frame** : DataFrame

axis : { 'items', 'major', 'minor' }

Axis the input corresponds to. E.g., if axis='major', then the frame's columns would be items, and the index would be values of the minor axis

Returns DataFrame

33.5.12 Combining / joining / merging

Panel.join(*other*[, *how*, *lsuffix*, *rsuffix*]) Join items with other Panel either on major and minor axes column

Panel.update(*other*[, *join*, *overwrite*, ...]) Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel

pandas.Panel.join

Panel.join (*other*, *how='left'*, *lsuffix=''*, *rsuffix=''*)

Join items with other Panel either on major and minor axes column

Parameters **other** : Panel or list of Panels

Index should be similar to one of the columns in this one

how : { 'left', 'right', 'outer', 'inner' }

How to handle indexes of the two objects. Default: 'left' for joining on index, None otherwise * left: use calling frame's index * right: use input frame's index * outer: form union of indexes * inner: use intersection of indexes

lsuffix : string

Suffix to use from left frame's overlapping columns

rsuffix : string

Suffix to use from right frame's overlapping columns

Returns **joined** : Panel

pandas.Panel.update

Panel.update (*other*, *join*='left', *overwrite*=True, *filter_func*=None, *raise_conflict*=False)

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

Parameters **other** : Panel, or object coercible to Panel

join : How to join individual DataFrames

{ 'left', 'right', 'outer', 'inner' }, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling panel

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : bool

If True, will raise an error if a DataFrame and other both contain data in the same place.

33.5.13 Time series-related

<code>Panel.asfreq(freq[, method, how, normalize])</code>	Convert all TimeSeries inside to specified frequency using DateOffset objects.
<code>Panel.shift(*args, **kwargs)</code>	Shift index by desired number of periods with an optional time freq.
<code>Panel.resample(rule[, how, axis, ...])</code>	Convenience method for frequency conversion and resampling of regular time-series
<code>Panel.tz_convert(tz[, axis, level, copy])</code>	Convert tz-aware axis to target time zone.
<code>Panel.tz_localize(*args, **kwargs)</code>	Localize tz-naive TimeSeries to target time zone

pandas.Panel.asfreq

Panel.asfreq (*freq*, *method*=None, *how*=None, *normalize*=False)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters **freq** : DateOffset object, or string

method : { 'backfill', 'bfill', 'pad', 'ffill', None }

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : { 'start', 'end' }, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns **converted** : type of caller

pandas.Panel.shift

`Panel.shift(*args, **kwargs)`

Shift index by desired number of periods with an optional time freq. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original. This is different from the behavior of `DataFrame.shift()`

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

axis : {'items', 'major', 'minor'} or {0, 1, 2}

Returns **shifted** : Panel

pandas.Panel.resample

`Panel.resample(rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0)`

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters **rule** : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.Panel.tz_convert

`Panel.tz_convert(tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters `tz` : string or `pytz.timezone` object

`axis` : the axis to convert

`level` : int, str, default None

If axis is a `MultiIndex`, convert a specific level. Otherwise must be None

`copy` : boolean, default True

Also make a copy of the underlying data

Raises `TypeError`

If the axis is tz-naive.

pandas.Panel.tz_localize

`Panel.tz_localize(*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters `tz` : string or `pytz.timezone` object

`axis` : the axis to localize

`level` : int, str, default None

If axis is a `MultiIndex`, localize a specific level. Otherwise must be None

`copy` : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an `AmbiguousTimeError` if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises `TypeError`

If the TimeSeries is tz-aware and tz is not None.

33.5.14 Serialization / IO / Conversion

<code>Panel.from_dict(data[, intersect, orient, dtype])</code>	Construct Panel from dict of DataFrame objects
<code>Panel.to_pickle(path)</code>	Pickle (serialize) object to input file path
<code>Panel.to_excel(path[, na_rep, engine])</code>	Write each DataFrame in Panel to a separate excel sheet

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<code>Panel.to_hdf(path_or_buf, key, **kwargs)</code>	activate the HDFStore
<code>Panel.to_json([path_or_buf, orient, ...])</code>	Convert the object to a JSON string.
<code>Panel.to_sparse([fill_value, kind])</code>	Convert to SparsePanel
<code>Panel.to_frame([filter_observations])</code>	Transform wide format into long (stacked) format as DataFrame whose columns are the original columns
<code>Panel.to_clipboard([excel, sep])</code>	Attempt to write text representation of object to the system clipboard This can be useful for debugging

pandas.Panel.from_dict

classmethod `Panel.from_dict` (*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters *data* : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : { 'items', 'minor' }, default 'items'

The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass 'items' (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-dtype data you should do), instead pass 'minor'

Returns Panel

pandas.Panel.to_pickle

`Panel.to_pickle` (*path*)

Pickle (serialize) object to input file path

Parameters *path* : string

File path

pandas.Panel.to_excel

`Panel.to_excel` (*path*, *na_rep=''*, *engine=None*, ***kwargs*)

Write each DataFrame in Panel to a separate excel sheet

Parameters *path* : string or ExcelWriter object

File path or existing ExcelWriter

na_rep : string, default ''

Missing data representation

engine : string, default None

write engine to use - you can also set this via the options
`io.excel.xlsx.writer`, `io.excel.xls.writer`, and
`io.excel.xlsm.writer`.

Other Parameters *float_format* : string, default None

Format string for floating point numbers

cols : sequence, optional

Columns to write

header : boolean or list of string, default True

Write out column names. If a list of string is given it is assumed to be aliases for the column names

index : boolean, default True

Write row names (index)

index_label : string or sequence, default None

Column label for index column(s) if desired. If None is given, and *header* and *index* are True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

startrow : upper left cell row to dump data frame

startcol : upper left cell column to dump data frame

Notes

Keyword arguments (and `na_rep`) are passed to the `to_excel` method for each DataFrame written.

pandas.Panel.to_hdf

`Panel.to_hdf` (*path_or_buf*, *key*, ***kwargs*)
activate the HDFStore

Parameters *path_or_buf* : the path (string) or buffer to put the store

key : string

identifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

'r' Read-only; no data can be modified.

'w' Write; a new file is created (an existing file with the same name would be deleted).

'a' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

'r+' It is similar to 'a', but the file must already exist.

format : 'fixed(f)|table(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

If a `complib` is specified compression will be applied where possible

complib : { 'zlib', 'bzip2', 'lzo', 'blosc', None }, default None

If `complevel` is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

If applying compression use the fletcher32 checksum

pandas.Panel.to_json

`Panel.to_json` (*path_or_buf=None*, *orient=None*, *date_format='epoch'*, *double_precision=10*, *force_ascii=True*, *date_unit='ms'*, *default_handler=None*)
Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters `path_or_buf` : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
 - default is 'index'
 - allowed values are: { 'split', 'records', 'index' }
- DataFrame
 - default is 'columns'
 - allowed values are: { 'split', 'records', 'index', 'columns', 'values' }
- The format of the JSON string
 - split : dict like {index -> [index], columns -> [columns], data -> [values]}
 - records : list like [{column -> value}, ... , {column -> value}]
 - index : dict like {index -> {column -> value}}
 - columns : dict like {column -> {index -> value}}
 - values : just the values array

date_format : { 'epoch', 'iso' }

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Panel.to_sparse

`Panel.to_sparse` (*fill_value=None, kind='block'*)
Convert to SparsePanel

Parameters `fill_value` : float, default NaN

`kind` : { 'block', 'integer' }

Returns `y` : SparseDataFrame

pandas.Panel.to_frame

`Panel.to_frame` (*filter_observations=True*)

Transform wide format into long (stacked) format as DataFrame whose columns are the Panel's items and whose index is a MultiIndex formed of the Panel's major and minor axes.

Parameters `filter_observations` : boolean, default True

Drop (major, minor) pairs without a complete set of observations across all the items

Returns `y` : DataFrame

pandas.Panel.to_clipboard

`Panel.to_clipboard` (*excel=None, sep=None, **kwargs*)

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters `excel` : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

`sep` : optional, defaults to tab

other keywords are passed to `to_csv`

Notes

Requirements for your platform

- Linux: xclip, or xsel (with gtk or PyQt4 modules)
- Windows: none
- OS X: none

33.6 Panel4D

33.6.1 Constructor

`Panel4D([data, labels, items, major_axis, ...])` Represents a 4 dimensional structured

pandas.Panel4D

class `pandas.Panel4D` (*data=None, labels=None, items=None, major_axis=None, minor_axis=None, copy=False, dtype=None*)

Represents a 4 dimensional structured

Parameters `data` : ndarray (labels x items x major x minor), or dict of Panels

`labels` : Index or array-like

`items` : Index or array-like

`major_axis` : Index or array-like: axis=2

`minor_axis` : Index or array-like: axis=3

`dtype` : dtype, default None

Data type to force, otherwise infer

`copy` : boolean, default False

Copy data from inputs. Only affects DataFrame / 2d ndarray input

Attributes

<code>at</code>	Fast label-based scalar accessor
<code>axes</code>	index(es) of the NDFrame
<code>blocks</code>	Internal property, property synonym for <code>as_blocks()</code>
<code>dtypes</code>	Return the dtypes in this object
<code>empty</code>	True if NDFrame is entirely empty [no items]
<code>ftypes</code>	Return the ftypes (indication of sparse/dense and dtype) in this object.
<code>iat</code>	Fast integer location scalar accessor.
<code>iloc</code>	Purely integer-location based indexing for selection by position.
<code>ix</code>	A primarily label-location based indexer, with integer position fallback.
<code>loc</code>	Purely label-location based indexer for selection by label.
<code>ndim</code>	Number of axes / array dimensions
<code>shape</code>	tuple of axis dimensions
<code>size</code>	number of elements in the NDFrame
<code>values</code>	Numpy representation of NDFrame

pandas.Panel4D.at

`Panel4D.at`

Fast label-based scalar accessor

Similarly to `loc`, `at` provides **label** based scalar lookups. You can also set using these indexers.

pandas.Panel4D.axes

`Panel4D.axes`
index(es) of the NDFrame

pandas.Panel4D.blocks

`Panel4D.blocks`
Internal property, property synonym for `as_blocks()`

pandas.Panel4D.dtypes

`Panel4D.dtypes`
Return the dtypes in this object

pandas.Panel4D.empty

`Panel4D.empty`
True if NDFrame is entirely empty [no items]

pandas.Panel4D.ftypes

`Panel4D.ftypes`
Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel4D.iat

`Panel4D.iat`
Fast integer location scalar accessor.
Similarly to `iloc`, `iat` provides **integer** based lookups. You can also set using these indexers.

pandas.Panel4D.iloc

`Panel4D.iloc`
Purely integer-location based indexing for selection by position.
`.iloc[]` is primarily integer position based (from 0 to `length-1` of the axis), but may also be used with a boolean array.
Allowed inputs are:

- An integer, e.g. 5.
- A list or array of integers, e.g. `[4, -3, 0]`.
- A slice object with ints, e.g. `1:7`.
- A boolean array.

`.iloc` will raise `IndexError` if a requested indexer is out-of-bounds, except *slice* indexers which allow out-of-bounds indexing (this conforms with python/numpy *slice* semantics).

See more at [Selection by Position](#)

pandas.Panel4D.ix

Panel4D.ix

A primarily label-location based indexer, with integer position fallback.

`.ix[]` supports mixed integer and label based access. It is primarily label based, but will fall back to integer positional access unless the corresponding axis is of integer type.

`.ix` is the most general indexer and will support any of the inputs in `.loc` and `.iloc`. `.ix` also supports floating point label schemes. `.ix` is exceptionally useful when dealing with mixed positional and label based hierarchical indexes.

However, when an axis is integer based, **ONLY** label based access and not positional access is supported. Thus, in such cases, it's usually better to be explicit and use `.iloc` or `.loc`.

See more at [Advanced Indexing](#).

pandas.Panel4D.loc

Panel4D.loc

Purely label-location based indexer for selection by label.

`.loc[]` is primarily label based, but may also be used with a boolean array.

Allowed inputs are:

- A single label, e.g. 5 or 'a', (note that 5 is interpreted as a *label* of the index, and **never** as an integer position along the index).
- A list or array of labels, e.g. ['a', 'b', 'c'].
- A slice object with labels, e.g. 'a' : 'f' (note that contrary to usual python slices, **both** the start and the stop are included!).
- A boolean array.

`.loc` will raise a `KeyError` when the items are not found.

See more at [Selection by Label](#)

pandas.Panel4D.ndim

Panel4D.ndim

Number of axes / array dimensions

pandas.Panel4D.shape

Panel4D.shape

tuple of axis dimensions

pandas.Panel4D.size**Panel4D.size**

number of elements in the NDFrame

pandas.Panel4D.values**Panel4D.values**

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

is_copy	
---------	--

Methods

<code>abs()</code>	Return an object with absolute value taken.
<code>add(other[, axis])</code>	Wrapper method for add
<code>add_prefix(prefix)</code>	Concatenate prefix string with panel items names.
<code>add_suffix(suffix)</code>	Concatenate suffix string with panel items names
<code>align(other[, join, axis, level, copy, ...])</code>	Align two object on their axes with the
<code>all([axis, bool_only, skipna, level])</code>	Return whether all elements are True over requested axis
<code>any([axis, bool_only, skipna, level])</code>	Return whether any element is True over requested axis
<code>apply(func[, axis])</code>	Applies function along input axis of the Panel
<code>as_blocks()</code>	Convert the frame to a dict of dtype -> Constructor Types that each has a homog
<code>as_matrix()</code>	
<code>asfreq(freq[, method, how, normalize])</code>	Convert all TimeSeries inside to specified frequency using DateOffset objects.
<code>astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>at_time(time[, asof])</code>	Select values at particular time of day (e.g.
<code>between_time(start_time, end_time[, ...])</code>	Select values between particular times of the day (e.g., 9:00-9:30 AM)
<code>bfill([axis, inplace, limit, downcast])</code>	Synonym for NDFrame.fillna(method='bfill')
<code>bool()</code>	Return the bool of a single element PandasObject
<code>clip([lower, upper, out, axis])</code>	Trim values at input threshold(s)
<code>clip_lower(threshold[, axis])</code>	Return copy of the input with values below given value(s) truncated
<code>clip_upper(threshold[, axis])</code>	Return copy of input with values above given value(s) truncated
<code>compound([axis, skipna, level])</code>	Return the compound percentage of the values for the requested axis
<code>conform(frame[, axis])</code>	Conform input DataFrame to align with chosen axis pair.
<code>consolidate([inplace])</code>	Compute NDFrame with "consolidated" internals (data of each dtype grouped to
<code>convert_objects([convert_dates, ...])</code>	Attempt to infer better dtype for object columns
<code>copy([deep])</code>	Make a copy of this object
<code>count([axis])</code>	Return number of observations over requested axis.
<code>cummax([axis, dtype, out, skipna])</code>	Return cumulative max over requested axis.
<code>cummin([axis, dtype, out, skipna])</code>	Return cumulative min over requested axis.

Table 33.82 – continued from previous page

<code>cumprod([axis, dtype, out, skipna])</code>	Return cumulative prod over requested axis.
<code>cumsum([axis, dtype, out, skipna])</code>	Return cumulative sum over requested axis.
<code>describe([percentile_width, percentiles, ...])</code>	Generate various summary statistics, excluding NaN values.
<code>div(other[, axis])</code>	Wrapper method for <code>truediv</code>
<code>divide(other[, axis])</code>	Wrapper method for <code>truediv</code>
<code>drop(labels[, axis, level, inplace, errors])</code>	Return new object with labels in requested axis removed
<code>dropna(*args, **kwargs)</code>	
<code>eq(other)</code>	Wrapper for comparison method <code>eq</code>
<code>equals(other)</code>	Determines if two NDFrame objects contain the same elements.
<code>ffill([axis, inplace, limit, downcast])</code>	Synonym for <code>NDFrame.fillna(method='ffill')</code>
<code>fillna([value, method, axis, inplace, ...])</code>	Fill NA/NaN values using the specified method
<code>filter(*args, **kwargs)</code>	
<code>first(offset)</code>	Convenience method for subsetting initial periods of time series data
<code>floordiv(other[, axis])</code>	Wrapper method for <code>floordiv</code>
<code>fromDict(data[, intersect, orient, dtype])</code>	Construct Panel from dict of DataFrame objects
<code>from_dict(data[, intersect, orient, dtype])</code>	Construct Panel from dict of DataFrame objects
<code>ge(other)</code>	Wrapper for comparison method <code>ge</code>
<code>get(key[, default])</code>	Get item from object for given key (DataFrame column, Panel slice, etc.).
<code>get_dtype_counts()</code>	Return the counts of dtypes in this object
<code>get_ftype_counts()</code>	Return the counts of ftypes in this object
<code>get_value(*args, **kwargs)</code>	Quickly retrieve single value at (item, major, minor) location
<code>get_values()</code>	same as <code>values</code> (but handles sparseness conversions)
<code>groupby(*args, **kwargs)</code>	
<code>gt(other)</code>	Wrapper for comparison method <code>gt</code>
<code>head([n])</code>	
<code>interpolate([method, axis, limit, inplace, ...])</code>	Interpolate values according to different methods.
<code>isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>iteritems()</code>	Iterate over (label, values) on info axis
<code>iterkv(*args, **kwargs)</code>	<code>iteritems</code> alias used to get around 2to3. Deprecated
<code>join(*args, **kwargs)</code>	
<code>keys()</code>	Get the 'info axis' (see Indexing for more)
<code>kurt([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>kurtosis([axis, skipna, level, numeric_only])</code>	Return unbiased kurtosis over requested axis using Fishers definition of kurtosis
<code>last(offset)</code>	Convenience method for subsetting final periods of time series data
<code>le(other)</code>	Wrapper for comparison method <code>le</code>
<code>load(path)</code>	Deprecated.
<code>lt(other)</code>	Wrapper for comparison method <code>lt</code>
<code>mad([axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis
<code>major_xs(key[, copy])</code>	Return slice of panel along major axis
<code>mask(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from
<code>max([axis, skipna, level, numeric_only])</code>	This method returns the maximum of the values in the object.
<code>mean([axis, skipna, level, numeric_only])</code>	Return the mean of the values for the requested axis
<code>median([axis, skipna, level, numeric_only])</code>	Return the median of the values for the requested axis
<code>min([axis, skipna, level, numeric_only])</code>	This method returns the minimum of the values in the object.
<code>minor_xs(key[, copy])</code>	Return slice of panel along minor axis
<code>mod(other[, axis])</code>	Wrapper method for <code>mod</code>
<code>mul(other[, axis])</code>	Wrapper method for <code>mul</code>
<code>multiply(other[, axis])</code>	Wrapper method for <code>mul</code>
<code>ne(other)</code>	Wrapper for comparison method <code>ne</code>
<code>notnull()</code>	Return a boolean same-sized object indicating if the values are
<code>pct_change([periods, fill_method, limit, freq])</code>	Percent change over given number of periods.
<code>pop(item)</code>	Return item and drop from frame.

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<code>pow(other[, axis])</code>	Wrapper method for <code>pow</code>
<code>prod([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>product([axis, skipna, level, numeric_only])</code>	Return the product of the values for the requested axis
<code>radd(other[, axis])</code>	Wrapper method for <code>radd</code>
<code>rdiv(other[, axis])</code>	Wrapper method for <code>rtruediv</code>
<code>reindex([items, major_axis, minor_axis])</code>	Conform Panel to new index with optional filling logic, placing NA/NaN in location
<code>reindex_axis(labels[, axis, method, level, ...])</code>	Conform input object to new index with optional filling logic, placing NA/NaN in location
<code>reindex_like(other[, method, copy, limit])</code>	return an object with matching indicies to myself
<code>rename([items, major_axis, minor_axis])</code>	Alter axes input function or functions.
<code>rename_axis(mapper[, axis, copy, inplace])</code>	Alter index and / or columns using input function or functions.
<code>replace([to_replace, value, inplace, limit, ...])</code>	Replace values given in ‘to_replace’ with ‘value’.
<code>resample(rule[, how, axis, fill_method, ...])</code>	Convenience method for frequency conversion and resampling of regular time-series
<code>rfloordiv(other[, axis])</code>	Wrapper method for <code>rfloordiv</code>
<code>rmod(other[, axis])</code>	Wrapper method for <code>rmod</code>
<code>rmul(other[, axis])</code>	Wrapper method for <code>rmul</code>
<code>rpow(other[, axis])</code>	Wrapper method for <code>rpow</code>
<code>rsub(other[, axis])</code>	Wrapper method for <code>rsub</code>
<code>rtruediv(other[, axis])</code>	Wrapper method for <code>rtruediv</code>
<code>sample([n, frac, replace, weights, ...])</code>	Returns a random sample of items from an axis of object.
<code>save(path)</code>	Deprecated.
<code>select(crit[, axis])</code>	Return data corresponding to axis labels matching criteria
<code>sem([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased standard error of the mean over requested axis.
<code>set_axis(axis, labels)</code>	public version of axis assignment
<code>set_value(*args, **kwargs)</code>	Quickly set single value at (item, major, minor) location
<code>shift(*args, **kwargs)</code>	
<code>skew([axis, skipna, level, numeric_only])</code>	Return unbiased skew over requested axis
<code>slice_shift([periods, axis])</code>	Equivalent to <i>shift</i> without copying data.
<code>sort_index([axis, ascending])</code>	Sort object by labels (along an axis)
<code>squeeze()</code>	squeeze length 1 dimensions
<code>std([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased standard deviation over requested axis.
<code>sub(other[, axis])</code>	Wrapper method for <code>sub</code>
<code>subtract(other[, axis])</code>	Wrapper method for <code>sub</code>
<code>sum([axis, skipna, level, numeric_only])</code>	Return the sum of the values for the requested axis
<code>swapaxes(axis1, axis2[, copy])</code>	Interchange axes and swap values axes appropriately
<code>swaplevel(i, j[, axis])</code>	Swap levels i and j in a MultiIndex on a particular axis
<code>tail([n])</code>	
<code>take(indices[, axis, convert, is_copy])</code>	Analogous to <code>ndarray.take</code>
<code>toLong(*args, **kwargs)</code>	
<code>to_clipboard([excel, sep])</code>	Attempt to write text representation of object to the system clipboard This can be used to write to a file
<code>to_dense()</code>	Return dense representation of NDFrame (as opposed to sparse)
<code>to_excel(*args, **kwargs)</code>	
<code>to_frame(*args, **kwargs)</code>	
<code>to_hdf(path_or_buf, key, **kwargs)</code>	activate the HDFStore
<code>to_json([path_or_buf, orient, date_format, ...])</code>	Convert the object to a JSON string.
<code>to_long(*args, **kwargs)</code>	
<code>to_msgpack([path_or_buf])</code>	msgpack (serialize) object to input file path
<code>to_pickle(path)</code>	Pickle (serialize) object to input file path
<code>to_sparse(*args, **kwargs)</code>	
<code>to_sql(name, con[, flavor, schema, ...])</code>	Write records stored in a DataFrame to a SQL database.
<code>transpose(*args, **kwargs)</code>	Permute the dimensions of the Panel
<code>truediv(other[, axis])</code>	Wrapper method for <code>truediv</code>
<code>truncate([before, after, axis, copy])</code>	Truncates a sorted NDFrame before and/or after some particular dates.

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<code>tshift([periods, freq, axis])</code>	
<code>tz_convert(tz[, axis, level, copy])</code>	Convert tz-aware axis to target time zone.
<code>tz_localize(*args, **kwargs)</code>	Localize tz-naive TimeSeries to target time zone
<code>update(other[, join, overwrite, ...])</code>	Modify Panel in place using non-NA values from passed Panel, or object coercib
<code>var([axis, skipna, level, ddof, numeric_only])</code>	Return unbiased variance over requested axis.
<code>where(cond[, other, inplace, axis, level, ...])</code>	Return an object of same shape as self and whose corresponding entries are from
<code>xs(key[, axis, copy])</code>	Return slice of panel along selected axis

pandas.Panel4D.abs`Panel4D.abs()`

Return an object with absolute value taken. Only applicable to objects that are all numeric

Returns abs: type of caller**pandas.Panel4D.add**`Panel4D.add(other, axis=0)`

Wrapper method for add

Parameters `other` : Panel or Panel4D**axis** : {labels, items, major_axis, minor_axis}**Axis to broadcast over****Returns** Panel4D**pandas.Panel4D.add_prefix**`Panel4D.add_prefix(prefix)`

Concatenate prefix string with panel items names.

Parameters `prefix` : string**Returns** `with_prefix` : type of caller**pandas.Panel4D.add_suffix**`Panel4D.add_suffix(suffix)`

Concatenate suffix string with panel items names

Parameters `suffix` : string**Returns** `with_suffix` : type of caller**pandas.Panel4D.align**`Panel4D.align(other, join='outer', axis=None, level=None, copy=True, fill_value=None, method=None, limit=None, fill_axis=0)`

Align two object on their axes with the specified join method for each axis Index

Parameters **other** : DataFrame or Series

join : { 'outer', 'inner', 'left', 'right' }, default 'outer'

axis : allowed axis of the other object, default None

Align on index (0), columns (1), or both (None)

level : int or level name, default None

Broadcast across a level, matching Index values on the passed MultiIndex level

copy : boolean, default True

Always returns new objects. If copy=False and no reindexing is required then original objects are returned.

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any “compatible” value

method : str, default None

limit : int, default None

fill_axis : {0, 1}, default 0

Filling axis, method and limit

Returns (**left**, **right**) : (type of input, type of other)

Aligned objects

pandas.Panel4D.all

`Panel4D.all` (*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*)

Return whether all elements are True over requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **all** : Panel or Panel4D (if level specified)

pandas.Panel4D.any

`Panel4D.any` (*axis=None*, *bool_only=None*, *skipna=None*, *level=None*, ***kwargs*)

Return whether any element is True over requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns **any** : Panel or Panel4D (if level specified)

pandas.Panel4D.apply

Panel4D.**apply** (*func*, *axis*=*'major'*, ***kwargs*)

Applies function along input axis of the Panel

Parameters **func** : function

Function to apply to each combination of 'other' axes e.g. if axis = 'items', then the combination of major_axis/minor_axis will be passed a Series

axis : {'major', 'minor', 'items'}

Additional keyword arguments will be passed as keywords to the function

Returns **result** : Pandas Object

Examples

```
>>> p.apply(numpy.sqrt) # returns a Panel
>>> p.apply(lambda x: x.sum(), axis=0) # equiv to p.sum(0)
>>> p.apply(lambda x: x.sum(), axis=1) # equiv to p.sum(1)
>>> p.apply(lambda x: x.sum(), axis=2) # equiv to p.sum(2)
```

pandas.Panel4D.as_blocks

Panel4D.**as_blocks** ()

Convert the frame to a dict of dtype -> Constructor Types that each has a homogeneous dtype.

NOTE: the dtypes of the blocks WILL BE PRESERVED HERE (unlike in as_matrix)

Returns **values** : a dict of dtype -> Constructor Types

pandas.Panel4D.as_matrix

Panel4D.**as_matrix** ()

pandas.Panel4D.asfreq

Panel4D.**asfreq** (*freq*, *method*=None, *how*=None, *normalize*=False)

Convert all TimeSeries inside to specified frequency using DateOffset objects. Optionally provide fill method to pad/backfill missing values.

Parameters **freq** : DateOffset object, or string

method : {'backfill', 'bfill', 'pad', 'ffill', None}

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill method

how : {'start', 'end'}, default end

For PeriodIndex only, see PeriodIndex.asfreq

normalize : bool, default False

Whether to reset output index to midnight

Returns **converted** : type of caller

pandas.Panel4D.astype

Panel4D.astype (*dtype*, *copy=True*, *raise_on_error=True*, ***kwargs*)

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters **dtype** : numpy.dtype or Python type

raise_on_error : raise on invalid input

kwargs : keyword arguments to pass on to the constructor

Returns **casted** : type of caller

pandas.Panel4D.at_time

Panel4D.at_time (*time*, *asof=False*)

Select values at particular time of day (e.g. 9:30AM)

Parameters **time** : datetime.time or string

Returns **values_at_time** : type of caller

pandas.Panel4D.between_time

Panel4D.between_time (*start_time*, *end_time*, *include_start=True*, *include_end=True*)

Select values between particular times of the day (e.g., 9:00-9:30 AM)

Parameters **start_time** : datetime.time or string

end_time : datetime.time or string

include_start : boolean, default True

include_end : boolean, default True

Returns **values_between_time** : type of caller

pandas.Panel4D.bfill

Panel4D.bfill (*axis=None*, *inplace=False*, *limit=None*, *downcast=None*)

Synonym for NDFrame.fillna(method='bfill')

pandas.Panel4D.bool**Panel4D.bool()**

Return the bool of a single element PandasObject This must be a boolean scalar value, either True or False

Raise a ValueError if the PandasObject does not have exactly 1 element, or that element is not boolean

pandas.Panel4D.clip**Panel4D.clip** (*lower=None, upper=None, out=None, axis=None*)

Trim values at input threshold(s)

Parameters **lower** : float or array_like, default None**upper** : float or array_like, default None**axis** : int or string axis name, optional

Align object with lower and upper along the given axis.

Returns **clipped** : Series**Examples**

```

>>> df
   0      1
0  0.335232 -1.256177
1 -1.367855  0.746646
2  0.027753 -1.176076
3  0.230930 -0.679613
4  1.261967  0.570967
>>> df.clip(-1.0, 0.5)
   0      1
0  0.335232 -1.000000
1 -1.000000  0.500000
2  0.027753 -1.000000
3  0.230930 -0.679613
4  0.500000  0.500000
>>> t
0   -0.3
1   -0.2
2   -0.1
3    0.0
4    0.1
dtype: float64
>>> df.clip(t, t + 1, axis=0)
   0      1
0  0.335232 -0.300000
1 -0.200000  0.746646
2  0.027753 -0.100000
3  0.230930  0.000000
4  1.100000  0.570967

```

`pandas.Panel4D.clip_lower`

`Panel4D.clip_lower` (*threshold*, *axis=None*)

Return copy of the input with values below given value(s) truncated

Parameters *threshold* : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns *clipped* : same type as input

See also:

`clip`

`pandas.Panel4D.clip_upper`

`Panel4D.clip_upper` (*threshold*, *axis=None*)

Return copy of input with values above given value(s) truncated

Parameters *threshold* : float or array_like

axis : int or string axis name, optional

Align object with threshold along the given axis.

Returns *clipped* : same type as input

See also:

`clip`

`pandas.Panel4D.compound`

`Panel4D.compound` (*axis=None*, *skipna=None*, *level=None*)

Return the compound percentage of the values for the requested axis

Parameters *axis* : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *compounded* : Panel or Panel4D (if level specified)

pandas.Panel4D.conform`Panel4D.conform` (*frame*, *axis*='items')

Conform input DataFrame to align with chosen axis pair.

Parameters *frame* : DataFrame**axis** : {'items', 'major', 'minor'}Axis the input corresponds to. E.g., if *axis*='major', then the frame's columns would be items, and the index would be values of the minor axis**Returns** DataFrame**pandas.Panel4D.consolidate**`Panel4D.consolidate` (*inplace*=False)

Compute NDFrame with "consolidated" internals (data of each dtype grouped together in a single ndarray). Mainly an internal API function, but available here to the savvy user

Parameters *inplace* : boolean, default False

If False return new object, otherwise modify existing object

Returns *consolidated* : type of caller**pandas.Panel4D.convert_objects**`Panel4D.convert_objects` (*convert_dates*=True, *convert_numeric*=False, *convert_timedeltas*=True, *copy*=True)

Attempt to infer better dtype for object columns

Parameters *convert_dates* : boolean, default True

If True, convert to date where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

convert_numeric : boolean, default False

If True, attempt to coerce to numbers (including strings), with unconvertible values becoming NaN.

convert_timedeltas : boolean, default True

If True, convert to timedelta where possible. If 'coerce', force conversion, with unconvertible values becoming NaT.

copy : boolean, default TrueIf True, return a copy even if no copy is necessary (e.g. no conversion was done). Note: This is meant for internal use, and should not be confused with *inplace*.**Returns** *converted* : same as input object**pandas.Panel4D.copy**`Panel4D.copy` (*deep*=True)

Make a copy of this object

Parameters *deep* : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns `copy` : type of caller

pandas.Panel4D.count

`Panel4D.count` (*axis='major'*)

Return number of observations over requested axis.

Parameters `axis` : {'items', 'major', 'minor'} or {0, 1, 2}

Returns `count` : DataFrame

pandas.Panel4D.cummax

`Panel4D.cummax` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative max over requested axis.

Parameters `axis` : {labels (0), items (1), major_axis (2), minor_axis (3)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `max` : Panel

pandas.Panel4D.cummin

`Panel4D.cummin` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative min over requested axis.

Parameters `axis` : {labels (0), items (1), major_axis (2), minor_axis (3)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `min` : Panel

pandas.Panel4D.cumprod

`Panel4D.cumprod` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative prod over requested axis.

Parameters `axis` : {labels (0), items (1), major_axis (2), minor_axis (3)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns `prod` : Panel

pandas.Panel4D.cumsum

`Panel4D.cumsum` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative sum over requested axis.

Parameters *axis* : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *sum* : Panel

pandas.Panel4D.describe

`Panel4D.describe` (*percentile_width=None, percentiles=None, include=None, exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters *percentile_width* : float, deprecated

The *percentile_width* argument will be removed in a future version. Use *percentiles* instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy.number`. To select categorical objects use `type` object. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`
- If *include* is the string 'all', the output column-set will match the input one.

Returns *summary*: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.Panel4D.div

`Panel4D.div (other, axis=0)`
Wrapper method for `truediv`

Parameters `other` : Panel or Panel4D

`axis` : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.divide

`Panel4D.divide (other, axis=0)`
Wrapper method for `truediv`

Parameters `other` : Panel or Panel4D

`axis` : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.drop

`Panel4D.drop (labels, axis=0, level=None, inplace=False, errors='raise')`
Return new object with labels in requested axis removed

Parameters `labels` : single label or list-like

`axis` : int or axis name

`level` : int or level name, default None

For MultiIndex

`inplace` : bool, default False

If True, do operation inplace and return None.

`errors` : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns `dropped` : type of caller

pandas.Panel4D.dropna

`Panel4D.dropna (*args, **kwargs)`

pandas.Panel4D.eq`Panel4D.eq` (*other*)Wrapper for comparison method `eq`**pandas.Panel4D.equals**`Panel4D.equals` (*other*)

Determines if two NDFrame objects contain the same elements. NaNs in the same location are considered equal.

pandas.Panel4D.ffill`Panel4D.ffill` (*axis=None, inplace=False, limit=None, downcast=None*)Synonym for `NDFrame.fillna(method='ffill')`**pandas.Panel4D.fillna**`Panel4D.fillna` (*value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs*)

Fill NA/NaN values using the specified method

Parameters method : {'backfill', 'bfill', 'pad', 'ffill', None}, default NoneMethod to use for filling holes in reindexed Series `pad` / `ffill`: propagate last valid observation forward to next valid `backfill` / `bfill`: use NEXT valid observation to fill gap**value** : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}**inplace** : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns filled : Panel

See also:

`reindex`, `asfreq`

pandas.Panel4D.filter

`Panel4D.filter` (**args*, ***kwargs*)

pandas.Panel4D.first

`Panel4D.first` (*offset*)

Convenience method for subsetting initial periods of time series data based on a date offset

Parameters `offset` : string, `DateOffset`, `dateutil.relativedelta`

Returns `subset` : type of caller

Examples

`ts.last('10D')` -> First 10 days

pandas.Panel4D.floordiv

`Panel4D.floordiv` (*other*, *axis=0*)

Wrapper method for `floordiv`

Parameters `other` : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.fromDict

classmethod `Panel4D.fromDict` (*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters `data` : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : { 'items', 'minor' }, default 'items'

The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass 'items' (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-type data you should do), instead pass 'minor'

Returns Panel

pandas.Panel4D.from_dict**classmethod** `Panel4D.from_dict` (*data*, *intersect=False*, *orient='items'*, *dtype=None*)

Construct Panel from dict of DataFrame objects

Parameters *data* : dict

{field : DataFrame}

intersect : boolean

Intersect indexes of input DataFrames

orient : { 'items', 'minor' }, default 'items'

The “orientation” of the data. If the keys of the passed dict should be the items of the result panel, pass 'items' (default). Otherwise if the columns of the values of the passed DataFrame objects should be the items (which in the case of mixed-type data you should do), instead pass 'minor'

Returns Panel**pandas.Panel4D.ge**`Panel4D.ge` (*other*)

Wrapper for comparison method ge

pandas.Panel4D.get`Panel4D.get` (*key*, *default=None*)

Get item from object for given key (DataFrame column, Panel slice, etc.). Returns default value if not found

Parameters *key* : object**Returns** *value* : type of items contained in object**pandas.Panel4D.get_dtype_counts**`Panel4D.get_dtype_counts` ()

Return the counts of dtypes in this object

pandas.Panel4D.get_ftype_counts`Panel4D.get_ftype_counts` ()

Return the counts of ftypes in this object

pandas.Panel4D.get_value`Panel4D.get_value` (**args*, ***kwargs*)

Quickly retrieve single value at (item, major, minor) location

Parameters **item** : item label (panel item)
major : major axis label (panel item row)
minor : minor axis label (panel item column)
takeable : interpret the passed labels as indexers, default False
Returns **value** : scalar value

pandas.Panel4D.get_values

`Panel4D.get_values()`
same as `values` (but handles sparseness conversions)

pandas.Panel4D.groupby

`Panel4D.groupby(*args, **kwargs)`

pandas.Panel4D.gt

`Panel4D.gt(other)`
Wrapper for comparison method `gt`

pandas.Panel4D.head

`Panel4D.head(n=5)`

pandas.Panel4D.interpolate

`Panel4D.interpolate(method='linear', axis=0, limit=None, inplace=False, downcast=None, **kwargs)`
Interpolate values according to different methods.

Parameters **method** : {'linear', 'time', 'index', 'values', 'nearest', 'zero',
'slinear', 'quadratic', 'cubic', 'barycentric', 'krogh', 'polynomial', 'spline',
'piecewise_polynomial', 'pchip'}

- 'linear': ignore the index and treat the values as equally spaced. default
- 'time': interpolation works on daily and higher resolution data to interpolate given length of interval
- 'index', 'values': use the actual numerical values of the index
- 'nearest', 'zero', 'slinear', 'quadratic', 'cubic', 'barycentric', 'polynomial' is passed to `scipy.interpolate.interpld` with the order given both 'polynomial' and 'spline' require that you also specify an order (int) e.g. `df.interpolate(method='polynomial', order=4)`
- 'krogh', 'piecewise_polynomial', 'spline', and 'pchip' are all wrappers around the scipy interpolation methods of similar names. See the scipy documentation for more on their behavior:

<http://docs.scipy.org/doc/scipy/reference/interpolate.html#univariate-interpolation> <http://docs.scipy.org/doc/scipy/reference/tutorial/interpolate.html>

axis : {0, 1}, default 0

- 0: fill column-by-column
- 1: fill row-by-row

limit : int, default None.

Maximum number of consecutive NaNs to fill.

inplace : bool, default False

Update the NDFrame in place if possible.

downcast : optional, 'infer' or None, defaults to None

Downcast dtypes if possible.

Returns Series or DataFrame of same shape interpolated at the NaNs

See also:

`reindex`, `replace`, `fillna`

Examples

Filling in NaNs

```
>>> s = pd.Series([0, 1, np.nan, 3])
>>> s.interpolate()
0    0
1    1
2    2
3    3
dtype: float64
```

`pandas.Panel4D.isnull`

`Panel4D.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of `isnull`

`pandas.Panel4D.iteritems`

`Panel4D.iteritems()`

Iterate over (label, values) on info axis

This is index for Series, columns for DataFrame, `major_axis` for Panel, and so on.

pandas.Panel4D.iterkv

`Panel4D.iterkv(*args, **kwargs)`
iteritems alias used to get around 2to3. Deprecated

pandas.Panel4D.join

`Panel4D.join(*args, **kwargs)`

pandas.Panel4D.keys

`Panel4D.keys()`
Get the 'info axis' (see Indexing for more)
This is index for Series, columns for DataFrame and major_axis for Panel.

pandas.Panel4D.kurt

`Panel4D.kurt(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns kurt : Panel or Panel4D (if level specified)

pandas.Panel4D.kurtosis

`Panel4D.kurtosis(axis=None, skipna=None, level=None, numeric_only=None, **kwargs)`
Return unbiased kurtosis over requested axis using Fishers definition of kurtosis (kurtosis of normal == 0.0). Normalized by N-1

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **kurt** : Panel or Panel4D (if level specified)

pandas.Panel4D.last

Panel4D.**last** (*offset*)

Convenience method for subsetting final periods of time series data based on a date offset

Parameters **offset** : string, DateOffset, dateutil.relativedelta

Returns **subset** : type of caller

Examples

ts.last('5M') -> Last 5 months

pandas.Panel4D.le

Panel4D.**le** (*other*)

Wrapper for comparison method le

pandas.Panel4D.load

Panel4D.**load** (*path*)

Deprecated. Use read_pickle instead.

pandas.Panel4D.lt

Panel4D.**lt** (*other*)

Wrapper for comparison method lt

pandas.Panel4D.mad

Panel4D.**mad** (*axis=None, skipna=None, level=None*)

Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : Panel or Panel4D (if level specified)

pandas.Panel4D.major_xs

`Panel4D.major_xs` (*key*, *copy=None*)

Return slice of panel along major axis

Parameters **key** : object

Major axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : DataFrame

index -> minor axis, columns -> items

Notes

major_xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of major_xs functionality, see [MultiIndex Slicers](#)

pandas.Panel4D.mask

`Panel4D.mask` (*cond*, *other=nan*, *inplace=False*, *axis=None*, *level=None*, *try_cast=False*, *raise_on_error=True*)

Return an object of same shape as self and whose corresponding entries are from self where cond is False and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Panel4D.max

`Panel4D.max` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the maximum of the values in the object. If you want the *index* of the maximum, use `idxmax`. This is the equivalent of the `numpy.ndarray` method `argmax`.

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **max** : Panel or Panel4D (if level specified)

pandas.Panel4D.mean

`Panel4D.mean` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the mean of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mean** : Panel or Panel4D (if level specified)

pandas.Panel4D.median

`Panel4D.median` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the median of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns median : Panel or Panel4D (if level specified)

pandas.Panel4D.min

`Panel4D.min` (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

This method returns the minimum of the values in the object. If you want the *index* of the minimum, use `idxmin`. This is the equivalent of the `numpy.ndarray` method `argmin`.

Parameters axis : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns min : Panel or Panel4D (if level specified)

pandas.Panel4D.minor_xs

`Panel4D.minor_xs` (*key, copy=None*)

Return slice of panel along minor axis

Parameters key : object

Minor axis label

copy : boolean [deprecated]

Whether to make a copy of the data

Returns y : DataFrame

index -> major axis, columns -> items

Notes

`minor_xs` is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of `minor_xs` functionality, see [MultiIndex Slicers](#)

pandas.Panel4D.mod

Panel4D.**mod** (*other*, *axis=0*)

Wrapper method for mod

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.mul

Panel4D.**mul** (*other*, *axis=0*)

Wrapper method for mul

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.multiply

Panel4D.**multiply** (*other*, *axis=0*)

Wrapper method for mul

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.ne

Panel4D.**ne** (*other*)

Wrapper for comparison method ne

pandas.Panel4D.notnull

Panel4D.**notnull** ()

Return a boolean same-sized object indicating if the values are not null

See also:

isnull boolean inverse of notnull

pandas.Panel4D.pct_change

Panel4D.**pct_change** (*periods=1, fill_method='pad', limit=None, freq=None, **kwargs*)

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the `axis` keyword argument.

pandas.Panel4D.pop

Panel4D.**pop** (*item*)

Return item and drop from frame. Raise KeyError if not found.

pandas.Panel4D.pow

Panel4D.**pow** (*other, axis=0*)

Wrapper method for pow

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.prod

Panel4D.**prod** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Panel or Panel4D (if level specified)

pandas.Panel4D.product

Panel4D.**product** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return the product of the values for the requested axis

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **prod** : Panel or Panel4D (if level specified)

pandas.Panel4D.radd

Panel4D.**radd** (*other, axis=0*)

Wrapper method for radd

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.rdiv

Panel4D.**rdiv** (*other, axis=0*)

Wrapper method for rtruediv

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.reindex

`Panel4D.reindex` (*items=None, major_axis=None, minor_axis=None, **kwargs*)

Conform Panel to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters *items, major_axis, minor_axis* : array-like, optional (can be specified in order, or as

keywords) New labels / index to conform to. Preferably an Index object to avoid duplicating data

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

fill_value : scalar, default np.NaN

Value to use for missing values. Defaults to NaN, but can be any "compatible" value

limit : int, default None

Maximum size gap to forward or backward fill

Returns **reindexed** : Panel

Examples

```
>>> df.reindex(index=[date1, date2, date3], columns=['A', 'B', 'C'])
```

pandas.Panel4D.reindex_axis

`Panel4D.reindex_axis` (*labels, axis=0, method=None, level=None, copy=True, limit=None, fill_value=nan*)

Conform input object to new index with optional filling logic, placing NA/NaN in locations having no value in the previous index. A new object is produced unless the new index is equivalent to the current one and `copy=False`

Parameters *labels* : array-like

New labels / index to conform to. Preferably an Index object to avoid duplicating data

axis : {0, 1, 2, 'items', 'major_axis', 'minor_axis'}

method : {None, 'backfill'/'bfill', 'pad'/'ffill', 'nearest'}, optional

Method to use for filling holes in reindexed DataFrame:

- default: don't fill gaps
- pad / ffill: propagate last valid observation forward to next valid
- backfill / bfill: use next valid observation to fill gap
- nearest: use nearest valid observations to fill gap

copy : boolean, default True

Return a new object, even if the passed indexes are the same

level : int or name

Broadcast across a level, matching Index values on the passed MultiIndex level

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : Panel

See also:

`reindex`, `reindex_like`

Examples

```
>>> df.reindex_axis(['A', 'B', 'C'], axis=1)
```

pandas.Panel4D.reindex_like

`Panel4D.reindex_like` (*other*, *method=None*, *copy=True*, *limit=None*)
return an object with matching indicies to myself

Parameters other : Object

method : string or None

copy : boolean, default True

limit : int, default None

Maximum size gap to forward or backward fill

Returns reindexed : same as input

Notes

Like calling `s.reindex(index=other.index, columns=other.columns, method=...)`

`pandas.Panel4D.rename`

`Panel4D.rename` (*items=None, major_axis=None, minor_axis=None, **kwargs*)

Alter axes input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters *items, major_axis, minor_axis* : dict-like or function, optional

Transformation to apply to that axis values

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Whether to return a new Panel. If True then value of copy is ignored.

Returns *renamed* : Panel (new object)

`pandas.Panel4D.rename_axis`

`Panel4D.rename_axis` (*mapper, axis=0, copy=True, inplace=False*)

Alter index and / or columns using input function or functions. Function / dict values must be unique (1-to-1). Labels not contained in a dict / Series will be left as-is.

Parameters *mapper* : dict-like or function, optional

axis : int or string, default 0

copy : boolean, default True

Also copy underlying data

inplace : boolean, default False

Returns *renamed* : type of caller

`pandas.Panel4D.replace`

`Panel4D.replace` (*to_replace=None, value=None, inplace=False, limit=None, regex=False, method='pad', axis=None*)

Replace values given in 'to_replace' with 'value'.

Parameters *to_replace* : str, regex, list, dict, Series, numeric, or None

- str or regex:
 - str: string exactly matching *to_replace* will be replaced with *value*
 - regex: regexs matching *to_replace* will be replaced with *value*
- list of str, regex, or numeric:
 - First, if *to_replace* and *value* are both lists, they **must** be the same length.
 - Second, if *regex=True* then all of the strings in **both** lists will be interpreted as regexs otherwise they will match directly. This doesn't matter much for *value* since there are only a few possible substitution regexes you can use.
 - str and regex rules apply as above.

- **dict:**
 - Nested dictionaries, e.g., {'a': {'b': nan}}, are read as follows: look in column 'a' for the value 'b' and replace it with nan. You can nest regular expressions as well. Note that column names (the top-level dictionary keys in a nested dictionary) **cannot** be regular expressions.
 - Keys map to column names and values map to substitution values. You can treat this as a special case of passing two lists except that you are specifying the column to search in.
- **None:**
 - This means that the `regex` argument must be a string, compiled regular expression, or list, dict, ndarray or Series of such elements. If `value` is also `None` then this **must** be a nested dictionary or Series.

See the examples section for examples of each of these.

value : scalar, dict, list, str, regex, default None

Value to use to fill holes (e.g. 0), alternately a dict of values specifying which value to use for each column (columns not in the dict will not be filled). Regular expressions, strings and lists or dicts of such objects are also allowed.

inplace : boolean, default False

If True, in place. Note: this will modify any other views on this object (e.g. a column from a DataFrame). Returns the caller if this is True.

limit : int, default None

Maximum size gap to forward or backward fill

regex : bool or same types as `to_replace`, default False

Whether to interpret `to_replace` and/or `value` as regular expressions. If this is True then `to_replace` must be a string. Otherwise, `to_replace` must be None because this parameter will be interpreted as a regular expression or a list, dict, or array of regular expressions.

method : string, optional, {'pad', 'ffill', 'bfill'}

The method to use when for replacement, when `to_replace` is a list.

Returns **filled** : NDFrame

Raises **AssertionError**

- If `regex` is not a bool and `to_replace` is not None.

TypeError

- If `to_replace` is a dict and `value` is not a list, dict, ndarray, or Series
- If `to_replace` is None and `regex` is not compilable into a regular expression or is a list, dict, ndarray, or Series.

ValueError

- If `to_replace` and `value` are lists or ndarrays, but they are not the same length.

See also:

`NDFrame.reindex`, `NDFrame.asfreq`, `NDFrame.fillna`

Notes

- Regex substitution is performed under the hood with `re.sub`. The rules for substitution for `re.sub` are the same.
- Regular expressions will only substitute on strings, meaning you cannot provide, for example, a regular expression matching floating point numbers and expect the columns in your frame that have a numeric dtype to be matched. However, if those floating point numbers *are* strings, then you can do this.
- This method has *a lot* of options. You are encouraged to experiment and play with this method to gain intuition about how it works.

pandas.Panel4D.resample

`Panel4D.resample` (*rule*, *how=None*, *axis=0*, *fill_method=None*, *closed=None*, *label=None*, *convention='start'*, *kind=None*, *loffset=None*, *limit=None*, *base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters **rule** : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to 'mean' for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : {'right', 'left'}

Which side of bin interval is closed

label : {'right', 'left'}

Which bin edge label to label bucket with

convention : {'start', 'end', 's', 'e'}

kind : "period"/"timestamp"

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the "origin" of the aggregated intervals. For example, for '5min' frequency, base could range from 0 through 4. Defaults to 0

pandas.Panel4D.rfloordiv

`Panel4D.rfloordiv` (*other*, *axis=0*)

Wrapper method for rfloordiv

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.rmod

`Panel4D.rmod` (*other*, *axis=0*)

Wrapper method for rmod

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.rmul

`Panel4D.rmul` (*other*, *axis=0*)

Wrapper method for rmul

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.rpow

`Panel4D.rpow` (*other*, *axis=0*)

Wrapper method for rpow

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.rsub

`Panel4D.rsub` (*other*, *axis=0*)

Wrapper method for rsub

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.rtruediv

Panel4D.**rtruediv** (*other*, *axis=0*)

Wrapper method for rtruediv

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.sample

Panel4D.**sample** (*n=None*, *frac=None*, *replace=False*, *weights=None*, *random_state=None*,
axis=None)

Returns a random sample of items from an axis of object.

Parameters *n* : int, optional

Number of items from axis to return. Cannot be used with *frac*. Default = 1 if *frac* = None.

frac : float, optional

Fraction of axis items to return. Cannot be used with *n*.

replace : boolean, optional

Sample with or without replacement. Default = False.

weights : str or ndarray-like, optional

Default 'None' results in equal probability weighting. If called on a DataFrame, will accept the name of a column when *axis* = 0. Weights must be same length as axis being sampled. If weights do not sum to 1, they will be normalized to sum to 1. Missing values in the weights column will be treated as zero. inf and -inf values not allowed.

random_state : int or numpy.random.RandomState, optional

Seed for the random number generator (if int), or numpy RandomState object.

axis : int or string, optional

Axis to sample. Accepts axis number or name. Default is stat axis for given data type (0 for Series and DataFrames, 1 for Panels).

Returns Same type as caller.

pandas.Panel4D.save

`Panel4D.save (path)`
 Deprecated. Use `to_pickle` instead

pandas.Panel4D.select

`Panel4D.select (crit, axis=0)`
 Return data corresponding to axis labels matching criteria

Parameters `crit` : function

To be called on each index (label). Should return True or False

`axis` : int

Returns `selection` : type of caller

pandas.Panel4D.sem

`Panel4D.sem (axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`
 Return unbiased standard error of the mean over requested axis.

Normalized by N-1 by default. This can be changed using the `ddof` argument

Parameters `axis` : {labels (0), items (1), major_axis (2), minor_axis (3)}

`skipna` : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

`level` : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

`numeric_only` : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `sem` : Panel or Panel4D (if level specified)

pandas.Panel4D.set_axis

`Panel4D.set_axis (axis, labels)`
 public version of axis assignment

pandas.Panel4D.set_value

`Panel4D.set_value (*args, **kwargs)`
 Quickly set single value at (item, major, minor) location

Parameters `item` : item label (panel item)

`major` : major axis label (panel item row)

`minor` : minor axis label (panel item column)

value : scalar

takeable : interpret the passed labels as indexers, default False

Returns **panel** : Panel

If label combo is contained, will be reference to calling Panel, otherwise a new object

pandas.Panel4D.shift

Panel4D.**shift** (*args, **kwargs)

pandas.Panel4D.skew

Panel4D.**skew** (axis=None, skipna=None, level=None, numeric_only=None, **kwargs)

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : Panel or Panel4D (if level specified)

pandas.Panel4D.slice_shift

Panel4D.**slice_shift** (periods=1, axis=0)

Equivalent to *shift* without copying data. The shifted data will not include the dropped periods and the shifted axis will be smaller than the original.

Parameters **periods** : int

Number of periods to move, can be positive or negative

Returns **shifted** : same type as caller

Notes

While the *slice_shift* is faster than *shift*, you may pay for it later during alignment.

pandas.Panel4D.sort_index

`Panel4D.sort_index (axis=0, ascending=True)`

Sort object by labels (along an axis)

Parameters `axis` : {0, 1}

Sort index/rows versus columns

ascending : boolean, default True

Sort ascending vs. descending

Returns `sorted_obj` : type of caller

pandas.Panel4D.squeeze

`Panel4D.squeeze ()`

squeeze length 1 dimensions

pandas.Panel4D.std

`Panel4D.std (axis=None, skipna=None, level=None, ddof=1, numeric_only=None, **kwargs)`

Return unbiased standard deviation over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters `axis` : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns `std` : Panel or Panel4D (if level specified)

pandas.Panel4D.sub

`Panel4D.sub (other, axis=0)`

Wrapper method for sub

Parameters `other` : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.subtract

`Panel4D.subtract` (*other*, *axis=0*)

Wrapper method for sub

Parameters *other* : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.sum

`Panel4D.sum` (*axis=None*, *skipna=None*, *level=None*, *numeric_only=None*, ***kwargs*)

Return the sum of the values for the requested axis

Parameters *axis* : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns *sum* : Panel or Panel4D (if level specified)

pandas.Panel4D.swapaxes

`Panel4D.swapaxes` (*axis1*, *axis2*, *copy=True*)

Interchange axes and swap values axes appropriately

Returns *y* : same as input

pandas.Panel4D.swaplevel

`Panel4D.swaplevel` (*i*, *j*, *axis=0*)

Swap levels *i* and *j* in a MultiIndex on a particular axis

Parameters *i*, *j* : int, string (can be mixed)

Level of index to be swapped. Can pass level name as string.

Returns *swapped* : type of caller (new object)

pandas.Panel4D.tail

`Panel4D.tail` (*n=5*)

pandas.Panel4D.take

`Panel4D.take (indices, axis=0, convert=True, is_copy=True)`

Analogous to `ndarray.take`

Parameters `indices` : list / array of ints

`axis` : int, default 0

`convert` : translate neg to pos indices (default)

`is_copy` : mark the returned frame as a copy

Returns `taken` : type of caller

pandas.Panel4D.toLong

`Panel4D.toLong (*args, **kwargs)`

pandas.Panel4D.to_clipboard

`Panel4D.to_clipboard (excel=None, sep=None, **kwargs)`

Attempt to write text representation of object to the system clipboard This can be pasted into Excel, for example.

Parameters `excel` : boolean, defaults to True

if True, use the provided separator, writing in a csv format for allowing easy pasting into excel. if False, write a string representation of the object to the clipboard

`sep` : optional, defaults to tab

other keywords are passed to `to_csv`

Notes**Requirements for your platform**

- Linux: `xclip`, or `xsel` (with `gtk` or `PyQt4` modules)
- Windows: none
- OS X: none

pandas.Panel4D.to_dense

`Panel4D.to_dense ()`

Return dense representation of `NDFrame` (as opposed to sparse)

pandas.Panel4D.to_excel

`Panel4D.to_excel (*args, **kwargs)`

pandas.Panel4D.to_frame

`Panel4D.to_frame(*args, **kwargs)`

pandas.Panel4D.to_hdf

`Panel4D.to_hdf(path_or_buf, key, **kwargs)`
activate the HDFStore

Parameters `path_or_buf` : the path (string) or buffer to put the store

key : string

 identifier for the group in the store

mode : optional, {'a', 'w', 'r', 'r+'}, default 'a'

 '**r**' Read-only; no data can be modified.

 '**w**' Write; a new file is created (an existing file with the same name would be deleted).

 '**a**' Append; an existing file is opened for reading and writing, and if the file does not exist it is created.

 '**r+'**' It is similar to '**a**', but the file must already exist.

format : 'fixed(f)ltable(t)', default is 'fixed'

fixed(f) [Fixed format] Fast writing/reading. Not-appendable, nor searchable

table(t) [Table format] Write as a PyTables Table structure which may perform worse but allow more flexible operations like searching / selecting subsets of the data

append : boolean, default False

 For Table formats, append the input data to the existing

complevel : int, 1-9, default 0

 If a compilib is specified compression will be applied where possible

complib : {'zlib', 'bzip2', 'lzo', 'blosc', None}, default None

 If complevel is > 0 apply compression to objects written in the store wherever possible

fletcher32 : bool, default False

 If applying compression use the fletcher32 checksum

pandas.Panel4D.to_json

`Panel4D.to_json(path_or_buf=None, orient=None, date_format='epoch', double_precision=10, force_ascii=True, date_unit='ms', default_handler=None)`
Convert the object to a JSON string.

Note NaN's and None will be converted to null and datetime objects will be converted to UNIX timestamps.

Parameters `path_or_buf` : the path or buffer to write the result string

if this is None, return a StringIO of the converted string

orient : string

- Series
 - default is 'index'
 - allowed values are: {'split', 'records', 'index'}
- DataFrame
 - default is 'columns'
 - allowed values are: {'split', 'records', 'index', 'columns', 'values'}
- The format of the JSON string
 - split : dict like {index -> [index], columns -> [columns], data -> [values]}
 - records : list like [{column -> value}, ... , {column -> value}]
 - index : dict like {index -> {column -> value}}
 - columns : dict like {column -> {index -> value}}
 - values : just the values array

date_format : {'epoch', 'iso'}

Type of date conversion. *epoch* = epoch milliseconds, *iso* = ISO8601, default is epoch.

double_precision : The number of decimal places to use when encoding floating point values, default 10.

force_ascii : force encoded string to be ASCII, default True.

date_unit : string, default 'ms' (milliseconds)

The time unit to encode to, governs timestamp and ISO8601 precision. One of 's', 'ms', 'us', 'ns' for second, millisecond, microsecond, and nanosecond respectively.

default_handler : callable, default None

Handler to call if object cannot otherwise be converted to a suitable format for JSON. Should receive a single argument which is the object to convert and return a serialisable object.

Returns same type as input object with filtered info axis

pandas.Panel4D.to_long

Panel4D.to_long(*args, **kwargs)

pandas.Panel4D.to_msgpack

Panel4D.to_msgpack(path_or_buf=None, **kwargs)
msgpack (serialize) object to input file path

THIS IS AN EXPERIMENTAL LIBRARY and the storage format may not be stable until a future release.

Parameters path : string File path, buffer-like, or None

if None, return generated string

append : boolean whether to append to an existing msgpack
(default is False)

compress : type of compressor (zlib or blosc), default to None (no
compression)

pandas.Panel4D.to_pickle

`Panel4D.to_pickle(path)`

Pickle (serialize) object to input file path

Parameters path : string
File path

pandas.Panel4D.to_sparse

`Panel4D.to_sparse(*args, **kwargs)`

pandas.Panel4D.to_sql

`Panel4D.to_sql(name, con, flavor='sqlite', schema=None, if_exists='fail', index=True, index_label=None, chunksize=None, dtype=None)`

Write records stored in a DataFrame to a SQL database.

Parameters name : string
Name of SQL table

con : SQLAlchemy engine or DBAPI2 connection (legacy mode)

Using SQLAlchemy makes it possible to use any DB supported by that library. If a DBAPI2 object, only sqlite3 is supported.

flavor : {'sqlite', 'mysql'}, default 'sqlite'

The flavor of SQL to use. Ignored when using SQLAlchemy engine. 'mysql' is deprecated and will be removed in future versions, but it will be further supported through SQLAlchemy engines.

schema : string, default None

Specify the schema (if database flavor supports this). If None, use default schema.

if_exists : {'fail', 'replace', 'append'}, default 'fail'

- fail: If table exists, do nothing.
- replace: If table exists, drop it, recreate it, and insert data.
- append: If table exists, insert data. Create if does not exist.

index : boolean, default True

Write DataFrame index as a column.

index_label : string or sequence, default None

Column label for index column(s). If None is given (default) and *index* is True, then the index names are used. A sequence should be given if the DataFrame uses MultiIndex.

chunksize : int, default None

If not None, then rows will be written in batches of this size at a time. If None, all rows will be written at once.

dtype : dict of column name to SQL type, default None

Optional specifying the datatype for columns. The SQL type should be a SQLAlchemy type, or a string for sqlite3 fallback connection.

pandas.Panel4D.transpose

Panel4D.**transpose** (*args, **kwargs)

Permute the dimensions of the Panel

Parameters **args** : three positional arguments: each one of

{0, 1, 2, 'items', 'major_axis', 'minor_axis'}

copy : boolean, default False

Make a copy of the underlying data. Mixed-dtype data will always result in a copy

Returns **y** : same as input

Examples

```
>>> p.transpose(2, 0, 1)
>>> p.transpose(2, 0, 1, copy=True)
```

pandas.Panel4D.truediv

Panel4D.**truediv** (other, axis=0)

Wrapper method for truediv

Parameters **other** : Panel or Panel4D

axis : {labels, items, major_axis, minor_axis}

Axis to broadcast over

Returns Panel4D

pandas.Panel4D.truncate

Panel4D.**truncate** (before=None, after=None, axis=None, copy=True)

Truncates a sorted NDFrame before and/or after some particular dates.

Parameters **before** : date

Truncate before date

after : date

Truncate after date

axis : the truncation axis, defaults to the stat axis

copy : boolean, default is True,

return a copy of the truncated section

Returns **truncated** : type of caller

pandas.Panel4D.tshift

`Panel4D.tshift (periods=1, freq=None, axis='major', **kws)`

pandas.Panel4D.tz_convert

`Panel4D.tz_convert (tz, axis=0, level=None, copy=True)`

Convert tz-aware axis to target time zone.

Parameters **tz** : string or pytz.timezone object

axis : the axis to convert

level : int, str, default None

If axis is a MultiIndex, convert a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

Raises **TypeError**

If the axis is tz-naive.

pandas.Panel4D.tz_localize

`Panel4D.tz_localize (*args, **kwargs)`

Localize tz-naive TimeSeries to target time zone

Parameters **tz** : string or pytz.timezone object

axis : the axis to localize

level : int, str, default None

If axis is a MultiIndex, localize a specific level. Otherwise must be None

copy : boolean, default True

Also make a copy of the underlying data

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False designates a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Raises **TypeError**

If the TimeSeries is tz-aware and tz is not None.

pandas.Panel4D.update

Panel4D.update (*other*, *join*='left', *overwrite*=True, *filter_func*=None, *raise_conflict*=False)

Modify Panel in place using non-NA values from passed Panel, or object coercible to Panel. Aligns on items

Parameters **other** : Panel, or object coercible to Panel

join : How to join individual DataFrames

{ 'left', 'right', 'outer', 'inner' }, default 'left'

overwrite : boolean, default True

If True then overwrite values for common keys in the calling panel

filter_func : callable(1d-array) -> 1d-array<boolean>, default None

Can choose to replace values other than NA. Return True for values that should be updated

raise_conflict : bool

If True, will raise an error if a DataFrame and other both contain data in the same place.

pandas.Panel4D.var

Panel4D.var (*axis*=None, *skipna*=None, *level*=None, *ddof*=1, *numeric_only*=None, ***kwargs*)

Return unbiased variance over requested axis.

Normalized by N-1 by default. This can be changed using the ddof argument

Parameters **axis** : {labels (0), items (1), major_axis (2), minor_axis (3)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Panel

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **var** : Panel or Panel4D (if level specified)

pandas.Panel4D.where

`Panel4D.where(cond, other=nan, inplace=False, axis=None, level=None, try_cast=False, raise_on_error=True)`

Return an object of same shape as self and whose corresponding entries are from self where cond is True and otherwise are from other.

Parameters **cond** : boolean NDFrame or array

other : scalar or NDFrame

inplace : boolean, default False

Whether to perform the operation in place on the data

axis : alignment axis if needed, default None

level : alignment level if needed, default None

try_cast : boolean, default False

try to cast the result back to the input type (if possible),

raise_on_error : boolean, default True

Whether to raise on invalid data types (e.g. trying to where on strings)

Returns **wh** : same type as caller

pandas.Panel4D.xs

`Panel4D.xs(key, axis=1, copy=None)`

Return slice of panel along selected axis

Parameters **key** : object

Label

axis : {'items', 'major', 'minor'}, default 1/'major'

copy : boolean [deprecated]

Whether to make a copy of the data

Returns **y** : `ndim(self)-1`

Notes

xs is only for getting, not setting values.

MultiIndex Slicers is a generic way to get/set values on any level or levels it is a superset of xs functionality, see [MultiIndex Slicers](#)

33.6.2 Attributes and underlying data

Axes

- **labels**: axis 1; each label corresponds to a Panel contained inside
- **items**: axis 2; each item corresponds to a DataFrame contained inside
- **major_axis**: axis 3; the index (rows) of each of the DataFrames

- **minor_axis**: axis 4; the columns of each of the DataFrames

<code>Panel4D.values</code>	Numpy representation of NDFrame
<code>Panel4D.axes</code>	index(es) of the NDFrame
<code>Panel4D.ndim</code>	Number of axes / array dimensions
<code>Panel4D.size</code>	number of elements in the NDFrame
<code>Panel4D.shape</code>	tuple of axis dimensions
<code>Panel4D.dtypes</code>	Return the dtypes in this object
<code>Panel4D.ftypes</code>	Return the ftypes (indication of sparse/dense and dtype) in this object.
<code>Panel4D.get_dtype_counts()</code>	Return the counts of dtypes in this object
<code>Panel4D.get_ftype_counts()</code>	Return the counts of ftypes in this object

pandas.Panel4D.values

`Panel4D.values`

Numpy representation of NDFrame

Notes

The dtype will be a lower-common-denominator dtype (implicit upcasting); that is to say if the dtypes (even of numeric types) are mixed, the one that accommodates all will be chosen. Use this with care if you are not dealing with the blocks.

e.g. If the dtypes are float16 and float32, dtype will be upcast to float32. If dtypes are int32 and uint8, dtype will be upcase to int32.

pandas.Panel4D.axes

`Panel4D.axes`

index(es) of the NDFrame

pandas.Panel4D.ndim

`Panel4D.ndim`

Number of axes / array dimensions

pandas.Panel4D.size

`Panel4D.size`

number of elements in the NDFrame

pandas.Panel4D.shape

`Panel4D.shape`

tuple of axis dimensions

pandas.Panel4D.dtypes

`Panel4D.dtypes`

Return the dtypes in this object

pandas.Panel4D.ftypes

`Panel4D.ftypes`

Return the ftypes (indication of sparse/dense and dtype) in this object.

pandas.Panel4D.get_dtype_counts

`Panel4D.get_dtype_counts()`

Return the counts of dtypes in this object

pandas.Panel4D.get_ftype_counts

`Panel4D.get_ftype_counts()`

Return the counts of ftypes in this object

33.6.3 Conversion

<code>Panel4D.astype(dtype[, copy, raise_on_error])</code>	Cast object to input numpy.dtype
<code>Panel4D.copy([deep])</code>	Make a copy of this object
<code>Panel4D.isnull()</code>	Return a boolean same-sized object indicating if the values are null
<code>Panel4D.notnull()</code>	Return a boolean same-sized object indicating if the values are

pandas.Panel4D.astype

`Panel4D.astype(dtype, copy=True, raise_on_error=True, **kwargs)`

Cast object to input numpy.dtype Return a copy when copy = True (be really careful with this!)

Parameters `dtype` : numpy.dtype or Python type

`raise_on_error` : raise on invalid input

`kwargs` : keyword arguments to pass on to the constructor

Returns `casted` : type of caller

pandas.Panel4D.copy

`Panel4D.copy(deep=True)`

Make a copy of this object

Parameters `deep` : boolean or string, default True

Make a deep copy, i.e. also copy data

Returns `copy` : type of caller

pandas.Panel4D.isnull

`Panel4D.isnull()`

Return a boolean same-sized object indicating if the values are null

See also:

`notnull` boolean inverse of isnull

pandas.Panel4D.notnull

`Panel4D.notnull()`

Return a boolean same-sized object indicating if the values are not null

See also:

`isnull` boolean inverse of notnull

33.7 Index

Many of these methods or variants thereof are available on the objects that contain an index (Series/Dataframe) and those should most likely be used before calling these methods directly.

`Index` Immutable ndarray implementing an ordered, sliceable set.

33.7.1 pandas.Index

class `pandas.Index`

Immutable ndarray implementing an ordered, sliceable set. The basic object storing axis labels for all pandas objects

Parameters `data` : array-like (1-dimensional)

`dtype` : NumPy dtype (default: object)

`copy` : bool

Make a copy of input ndarray

`name` : object

Name to be stored in the index

`tupleize_cols` : bool (default: True)

When True, attempt to create a MultiIndex if possible

Notes

An Index instance can **only** contain hashable objects

Attributes

<code>T</code>	return the transpose, which is by definition self
<code>base</code>	return the base object if the memory of the underlying data is shared
<code>data</code>	return the data pointer of the underlying data
<code>flags</code>	
<code>has_duplicates</code>	
<code>is_monotonic</code>	alias for <code>is_monotonic_increasing</code> (deprecated)
<code>is_monotonic_decreasing</code>	return if the index is monotonic decreasing (only equal or
<code>is_monotonic_increasing</code>	return if the index is monotonic increasing (only equal or
<code>itemsize</code>	return the size of the dtype of the item of the underlying data
<code>names</code>	
<code>nbytes</code>	return the number of bytes in the underlying data
<code>ndim</code>	return the number of dimensions of the underlying data, by definition 1
<code>nlevels</code>	
<code>shape</code>	return a tuple of the shape of the underlying data
<code>size</code>	return the number of elements in the underlying data
<code>strides</code>	return the strides of the underlying data
<code>values</code>	return the underlying data as an ndarray

pandas.Index.T

`Index.T`
return the transpose, which is by definition self

pandas.Index.base

`Index.base`
return the base object if the memory of the underlying data is shared

pandas.Index.data

`Index.data`
return the data pointer of the underlying data

pandas.Index.flags

`Index.flags`

pandas.Index.has_duplicates

`Index.has_duplicates`

pandas.Index.is_monotonic

`Index.is_monotonic`
alias for `is_monotonic_increasing` (deprecated)

pandas.Index.is_monotonic_decreasing

`Index.is_monotonic_decreasing`

return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.Index.is_monotonic_increasing

`Index.is_monotonic_increasing`

return if the index is monotonic increasing (only equal or increasing) values.

pandas.Index.itemsize

`Index.itemsize`

return the size of the dtype of the item of the underlying data

pandas.Index.names

`Index.names`

pandas.Index.nbytes

`Index.nbytes`

return the number of bytes in the underlying data

pandas.Index.ndim

`Index.ndim`

return the number of dimensions of the underlying data, by definition 1

pandas.Index.nlevels

`Index.nlevels`

pandas.Index.shape

`Index.shape`

return a tuple of the shape of the underlying data

pandas.Index.size

`Index.size`

return the number of elements in the underlying data

pandas.Index.strides

`Index.strides`

return the strides of the underlying data

pandas.Index.values**Index.values**

return the underlying data as an ndarray

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Methods

<code>all(*args, **kwargs)</code>	Return whether all elements are True
<code>any(*args, **kwargs)</code>	Return whether any element is True
<code>append(other)</code>	Append a collection of Index options together
<code>argmax([axis])</code>	return a ndarray of the maximum argument indexer
<code>argmin([axis])</code>	return a ndarray of the minimum argument indexer
<code>argsort(*args, **kwargs)</code>	return an ndarray indexer of the underlying data
<code>asof(label)</code>	For a sorted index, return the most recent label up to and including the passed label
<code>asof_locs(where, mask)</code>	where : array of timestamps
<code>astype(dtype)</code>	
<code>copy([names, name, dtype, deep])</code>	Make a copy of this object.
<code>delete(loc)</code>	Make new Index with passed location(-s) deleted
<code>diff(*args, **kwargs)</code>	
<code>difference(other)</code>	Compute sorted set difference of two Index objects
<code>drop(labels[, errors])</code>	Make new Index with passed list of labels deleted
<code>drop_duplicates([take_last])</code>	Return Index with duplicate values removed
<code>duplicated([take_last])</code>	Return boolean np.array denoting duplicate values
<code>equals(other)</code>	Determines if two Index objects contain the same elements.
<code>factorize([sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable
<code>format([name, formatter])</code>	Render a string representation of the Index
<code>get_duplicates()</code>	
<code>get_indexer(target[, method, limit])</code>	Compute indexer and mask for new index given the current index.
<code>get_indexer_for(target, **kwargs)</code>	guaranteed return of an indexer even when non-unique
<code>get_indexer_non_unique(target)</code>	return an indexer suitable for taking from a non unique index
<code>get_level_values(level)</code>	Return vector of label values for requested level, equal to the length
<code>get_loc(key[, method])</code>	Get integer location for requested label
<code>get_slice_bound(label, side, kind)</code>	Calculate slice bound that corresponds to given label.
<code>get_value(series, key)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>get_values()</code>	return the underlying data as an ndarray
<code>groupby(to_groupby)</code>	Group the index labels by a given array of values.
<code>hasnans()</code>	return if I have any nans; enables various perf speedups
<code>holds_integer()</code>	
<code>identical(other)</code>	Similar to equals, but check that other comparable attributes are
<code>insert(loc, item)</code>	Make new Index inserting new item at location.
<code>intersection(other)</code>	Form the intersection of two Index objects.
<code>is_(other)</code>	More flexible, faster check like <code>is</code> but that works through views
<code>is_boolean()</code>	
<code>is_categorical()</code>	
<code>is_floating()</code>	

Continued on next page

Table 33.87 – continued from previous page

<code>is_integer()</code>	
<code>is_lexsorted_for_tuple(tup)</code>	
<code>is_mixed()</code>	
<code>is_numeric()</code>	
<code>is_object()</code>	
<code>is_type_compatible(kind)</code>	
<code>isin(values[, level])</code>	Compute boolean array of whether each index value is found in the passed set of values
<code>item()</code>	return the first element of the underlying data as a python scalar
<code>join(other[, how, level, return_indexers])</code>	<i>this is an internal non-public method</i>
<code>map(mapper)</code>	
<code>max()</code>	The maximum value of the object
<code>min()</code>	The minimum value of the object
<code>nunique([dropna])</code>	Return number of unique elements in the object.
<code>order([return_indexer, ascending])</code>	Return sorted copy of Index
<code>putmask(mask, value)</code>	return a new Index of the values set with the mask
<code>ravel([order])</code>	return an ndarray of the flattened values of the underlying data
<code>reindex(target[, method, level, limit])</code>	Create index with target's values (move/add/delete values as necessary)
<code>rename(name[, inplace])</code>	Set new names on index.
<code>repeat(n)</code>	return a new Index of the values repeated n times
<code>searchsorted(key[, side])</code>	np.ndarray searchsorted compat
<code>set_names(names[, level, inplace])</code>	Set new names on index.
<code>set_value(arr, key, value)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>shift([periods, freq])</code>	Shift Index containing datetime objects by input number of periods and freq
<code>slice_indexer([start, end, step, kind])</code>	For an ordered Index, compute the slice indexer for input labels and freq
<code>slice_locs([start, end, step, kind])</code>	Compute slice locations for input labels.
<code>sort(*args, **kwargs)</code>	
<code>str</code>	alias of StringMethods
<code>summary([name])</code>	
<code>sym_diff(other[, result_name])</code>	Compute the sorted symmetric difference of two Index objects.
<code>take(indexer[, axis])</code>	return a new Index of the values selected by the indexer
<code>to_datetime([dayfirst])</code>	For an Index containing strings or datetime.datetime objects, attempt to parse as datetime
<code>to_native_types([slicer])</code>	slice and dice then format
<code>to_series(**kwargs)</code>	Create a Series with both index and values equal to the index keys
<code>tolist()</code>	return a list of the Index values
<code>transpose()</code>	return the transpose, which is by definition self
<code>union(other)</code>	Form the union of two Index objects and sorts if possible
<code>unique()</code>	Return array of unique values in the object.
<code>value_counts([normalize, sort, ascending, ...])</code>	Returns object containing counts of unique values.
<code>view([cls])</code>	

pandas.Index.all

`Index.all(*args, **kwargs)`

Return whether all elements are True

Parameters All arguments to `numpy.all` are accepted.

Returns `all` : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.any

`Index.any(*args, **kwargs)`

Return whether any element is True

Parameters All arguments to `numpy.any` are accepted.

Returns `any` : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.append

`Index.append(other)`

Append a collection of Index options together

Parameters `other` : Index or list/tuple of indices

Returns `appended` : Index

pandas.Index.argmax

`Index.argmax(axis=None)`

return a ndarray of the maximum argument indexer

See also:

`numpy.ndarray.argmax`

pandas.Index.argmin

`Index.argmin(axis=None)`

return a ndarray of the minimum argument indexer

See also:

`numpy.ndarray.argmin`

pandas.Index.argsort

`Index.argsort(*args, **kwargs)`

return an ndarray indexer of the underlying data

See also:

`numpy.ndarray.argsort`

pandas.Index.asof

`Index.asof(label)`

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

`get_loc` `asof` is a thin wrapper around `get_loc` with `method='pad'`

pandas.Index.asof_locs

`Index.asof_locs` (*where, mask*)

where : array of timestamps *mask* : array of booleans where data is not NA

pandas.Index.astype

`Index.astype` (*dtype*)

pandas.Index.copy

`Index.copy` (*names=None, name=None, dtype=None, deep=False*)

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters *name* : string, optional

dtype : numpy dtype or pandas type

Returns *copy* : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.Index.delete

`Index.delete` (*loc*)

Make new Index with passed location(-s) deleted

Returns *new_index* : Index

pandas.Index.diff

`Index.diff` (**args, **kwargs*)

pandas.Index.difference

`Index.difference` (*other*)

Compute sorted set difference of two Index objects

Parameters *other* : Index or array-like

Returns *diff* : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.Index.drop

`Index.drop(labels, errors='raise')`

Make new Index with passed list of labels deleted

Parameters `labels` : array-like

`errors` : { 'ignore', 'raise' }, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns `dropped` : Index

pandas.Index.drop_duplicates

`Index.drop_duplicates(take_last=False)`

Return Index with duplicate values removed

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `deduplicated` : Index

pandas.Index.duplicated

`Index.duplicated(take_last=False)`

Return boolean np.array denoting duplicate values

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `duplicated` : np.array

pandas.Index.equals

`Index.equals(other)`

Determines if two Index objects contain the same elements.

pandas.Index.factorize

`Index.factorize(sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable

Parameters `sort` : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns `labels` : the indexer to the original array

`uniques` : the unique Index

pandas.Index.format

`Index.format` (*name=False, formatter=None, **kwargs*)
 Render a string representation of the Index

pandas.Index.get_duplicates

`Index.get_duplicates()`

pandas.Index.get_indexer

`Index.get_indexer` (*target, method=None, limit=None*)
 Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index.

Parameters `target` : Index

method : {None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit : int

Maximum number of consecutive labels in `target` to match for inexact matches.

Returns `indexer` : ndarray of int

Integers from 0 to `n - 1` indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.Index.get_indexer_for

`Index.get_indexer_for` (*target, **kwargs*)
 guaranteed return of an indexer even when non-unique

pandas.Index.get_indexer_non_unique

`Index.get_indexer_non_unique` (*target*)
 return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.Index.get_level_values

`Index.get_level_values (level)`

Return vector of label values for requested level, equal to the length of the index

Parameters `level` : int

Returns `values` : ndarray

pandas.Index.get_loc

`Index.get_loc (key, method=None)`

Get integer location for requested label

Parameters `key` : label

method : {None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

Returns `loc` : int if unique index, possibly slice or mask if not

pandas.Index.get_slice_bound

`Index.get_slice_bound (label, side, kind)`

Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters `label` : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.Index.get_value

`Index.get_value (series, key)`

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.Index.get_values

`Index.get_values ()`

return the underlying data as an ndarray

pandas.Index.groupby

`Index.groupby (to_groupby)`

Group the index labels by a given array of values.

Parameters `to_groupby` : array

Values used to determine the groups.

Returns `groups` : dict

{group name -> group labels}

pandas.Index.hasnans

`Index.hasnans ()`

return if I have any nans; enables various perf speedups

pandas.Index.holds_integer

`Index.holds_integer ()`

pandas.Index.identical

`Index.identical (other)`

Similar to equals, but check that other comparable attributes are also equal

pandas.Index.insert

`Index.insert (loc, item)`

Make new Index inserting new item at location. Follows Python list.append semantics for negative values

Parameters `loc` : int

`item` : object

Returns `new_index` : Index

pandas.Index.intersection

`Index.intersection (other)`

Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters `other` : Index or array-like

Returns `intersection` : Index

pandas.Index.is

`Index.is_ (other)`

More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical ()`, which checks that metadata is also the same.

Parameters `other` : object

other object to compare against.

Returns True if both have same underlying data, False otherwise : bool

pandas.Index.is_boolean

`Index.is_boolean()`

pandas.Index.is_categorical

`Index.is_categorical()`

pandas.Index.is_floating

`Index.is_floating()`

pandas.Index.is_integer

`Index.is_integer()`

pandas.Index.is_lexsorted_for_tuple

`Index.is_lexsorted_for_tuple(tup)`

pandas.Index.is_mixed

`Index.is_mixed()`

pandas.Index.is_numeric

`Index.is_numeric()`

pandas.Index.is_object

`Index.is_object()`

pandas.Index.is_type_compatible

`Index.is_type_compatible(kind)`

pandas.Index.isin

`Index.isin (values, level=None)`

Compute boolean array of whether each index value is found in the passed set of values.

Parameters **values** : set or sequence of values

Sought values.

level : str or int, optional

Name or position of the index level to use (if the index is a MultiIndex).

Returns **is_contained** : ndarray (boolean dtype)

Notes

If *level* is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

pandas.Index.item

`Index.item()`

return the first element of the underlying data as a python scalar

pandas.Index.join

`Index.join (other, how='left', level=None, return_indexers=False)`

this is an internal non-public method

Compute join_index and indexers to conform data structures to the new index.

Parameters **other** : Index

how : { 'left', 'right', 'inner', 'outer' }

level : int or level name, default None

return_indexers : boolean, default False

Returns join_index, (left_indexer, right_indexer)

pandas.Index.map

`Index.map (mapper)`

pandas.Index.max

`Index.max()`

The maximum value of the object

pandas.Index.min

`Index.min()`
The minimum value of the object

pandas.Index.nunique

`Index.nunique(dropna=True)`
Return number of unique elements in the object.
Excludes NA values by default.
Parameters `dropna` : boolean, default True
Don't include NaN in the count.
Returns `nunique` : int

pandas.Index.order

`Index.order(return_indexer=False, ascending=True)`
Return sorted copy of Index

pandas.Index.putmask

`Index.putmask(mask, value)`
return a new Index of the values set with the mask
See also:
`numpy.ndarray.putmask`

pandas.Index.ravel

`Index.ravel(order='C')`
return an ndarray of the flattened values of the underlying data
See also:
`numpy.ndarray.ravel`

pandas.Index.reindex

`Index.reindex(target, method=None, level=None, limit=None)`
Create index with target's values (move/add/delete values as necessary)
Parameters `target` : an iterable
Returns `new_index` : pd.Index
Resulting index
`indexer` : np.ndarray or None
Indices of output values in original index

pandas.Index.rename`Index.rename (name, inplace=False)`

Set new names on index. Defaults to returning new index.

Parameters `name` : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]**pandas.Index.repeat**`Index.repeat (n)`

return a new Index of the values repeated n times

See also:`numpy.ndarray.repeat`**pandas.Index.searchsorted**`Index.searchsorted (key, side='left')`

np.ndarray searchsorted compat

pandas.Index.set_names`Index.set_names (names, level=None, inplace=False)`

Set new names on index. Defaults to returning new index.

Parameters `names` : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)

Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]**Examples**

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')],
                                names=['foo', 'bar'])
```

```
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'bar'])
```

pandas.Index.set_value

`Index.set_value` (*arr, key, value*)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.Index.shift

`Index.shift` (*periods=1, freq=None*)

Shift Index containing datetime objects by input number of periods and DateOffset

Returns `shifted` : Index

pandas.Index.slice_indexer

`Index.slice_indexer` (*start=None, end=None, step=None, kind=None*)

For an ordered Index, compute the slice indexer for input labels and step

Parameters `start` : label, default None

If None, defaults to the beginning

`end` : label, default None

If None, defaults to the end

`step` : int, default None

`kind` : string, default None

Returns `indexer` : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.Index.slice_locs

`Index.slice_locs` (*start=None, end=None, step=None, kind=None*)

Compute slice locations for input labels.

Parameters `start` : label, default None

If None, defaults to the beginning

`end` : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns start, end : int

pandas.Index.sort

`Index.sort(*args, **kwargs)`

pandas.Index.summary

`Index.summary(name=None)`

pandas.Index.sym_diff

`Index.sym_diff(other, result_name=None)`

Compute the sorted symmetric difference of two Index objects.

Parameters other : array-like

result_name : str

Returns sym_diff : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by $(idx1 - idx2) + (idx2 - idx1)$ with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.Index.take

`Index.take(indexer, axis=0)`

return a new Index of the values selected by the indexer

See also:

`numpy.ndarray.take`

pandas.Index.to_datetime

`Index.to_datetime (dayfirst=False)`

For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

pandas.Index.to_native_types

`Index.to_native_types (slicer=None, **kwargs)`

slice and dice then format

pandas.Index.to_series

`Index.to_series (**kwargs)`

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

pandas.Index.tolist

`Index.tolist ()`

return a list of the Index values

pandas.Index.transpose

`Index.transpose ()`

return the transpose, which is by definition self

pandas.Index.union

`Index.union (other)`

Form the union of two Index objects and sorts if possible

Parameters other : Index or array-like

Returns union : Index

pandas.Index.unique

`Index.unique ()`

Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.Index.value_counts

`Index.value_counts (normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters **normalize** : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns **counts** : Series

pandas.Index.view

`Index.view(cls=None)`

33.7.2 Attributes

<code>Index.values</code>	return the underlying data as an ndarray
<code>Index.is_monotonic</code>	alias for <code>is_monotonic_increasing</code> (deprecated)
<code>Index.is_monotonic_increasing</code>	return if the index is monotonic increasing (only equal or
<code>Index.is_monotonic_decreasing</code>	return if the index is monotonic decreasing (only equal or
<code>Index.is_unique</code>	
<code>Index.has_duplicates</code>	
<code>Index.dtype</code>	
<code>Index.inferred_type</code>	
<code>Index.is_all_dates</code>	
<code>Index.shape</code>	return a tuple of the shape of the underlying data
<code>Index.nbytes</code>	return the number of bytes in the underlying data
<code>Index.ndim</code>	return the number of dimensions of the underlying data, by definition 1
<code>Index.size</code>	return the number of elements in the underlying data
<code>Index.strides</code>	return the strides of the underlying data
<code>Index.itemsize</code>	return the size of the dtype of the item of the underlying data
<code>Index.base</code>	return the base object if the memory of the underlying data is shared
<code>Index.T</code>	return the transpose, which is by definition self

pandas.Index.values

`Index.values`

return the underlying data as an ndarray

pandas.Index.is_monotonic

Index.is_monotonic
alias for `is_monotonic_increasing` (deprecated)

pandas.Index.is_monotonic_increasing

Index.is_monotonic_increasing
return if the index is monotonic increasing (only equal or increasing) values.

pandas.Index.is_monotonic_decreasing

Index.is_monotonic_decreasing
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.Index.is_unique

Index.is_unique = None

pandas.Index.has_duplicates

Index.has_duplicates

pandas.Index.dtype

Index.dtype = None

pandas.Index.inferred_type

Index.inferred_type = None

pandas.Index.is_all_dates

Index.is_all_dates = None

pandas.Index.shape

Index.shape
return a tuple of the shape of the underlying data

pandas.Index.nbytes

Index.nbytes
return the number of bytes in the underlying data

pandas.Index.ndim**Index.ndim**

return the number of dimensions of the underlying data, by definition 1

pandas.Index.size**Index.size**

return the number of elements in the underlying data

pandas.Index.strides**Index.strides**

return the strides of the underlying data

pandas.Index.itemsize**Index.itemsize**

return the size of the dtype of the item of the underlying data

pandas.Index.base**Index.base**

return the base object if the memory of the underlying data is shared

pandas.Index.T**Index.T**

return the transpose, which is by definition self

33.7.3 Modifying and Computations

<code>Index.all(*args, **kwargs)</code>	Return whether all elements are True
<code>Index.any(*args, **kwargs)</code>	Return whether any element is True
<code>Index.argmax([axis])</code>	return a ndarray of the minimum argument indexer
<code>Index.argmax([axis])</code>	return a ndarray of the maximum argument indexer
<code>Index.copy([names, name, dtype, deep])</code>	Make a copy of this object.
<code>Index.delete(loc)</code>	Make new Index with passed location(-s) deleted
<code>Index.diff(*args, **kwargs)</code>	
<code>Index.sym_diff(other[, result_name])</code>	Compute the sorted symmetric difference of two Index objects.
<code>Index.drop(labels[, errors])</code>	Make new Index with passed list of labels deleted
<code>Index.drop_duplicates([take_last])</code>	Return Index with duplicate values removed
<code>Index.duplicated([take_last])</code>	Return boolean np.array denoting duplicate values
<code>Index.equals(other)</code>	Determines if two Index objects contain the same elements.
<code>Index.factorize([sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable
<code>Index.identical(other)</code>	Similar to equals, but check that other comparable attributes are
<code>Index.insert(loc, item)</code>	Make new Index inserting new item at location.
<code>Index.min()</code>	The minimum value of the object

Continued on next page

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<code>Index.max()</code>	The maximum value of the object
<code>Index.order([return_indexer, ascending])</code>	Return sorted copy of Index
<code>Index.reindex(target[, method, level, limit])</code>	Create index with target's values (move/add/delete values as necessary)
<code>Index.repeat(n)</code>	return a new Index of the values repeated n times
<code>Index.take(indexer[, axis])</code>	return a new Index of the values selected by the indexer
<code>Index.putmask(mask, value)</code>	return a new Index of the values set with the mask
<code>Index.set_names(names[, level, inplace])</code>	Set new names on index.
<code>Index.unique()</code>	Return array of unique values in the object.
<code>Index.nunique([dropna])</code>	Return number of unique elements in the object.
<code>Index.value_counts([normalize, sort, ...])</code>	Returns object containing counts of unique values.

pandas.Index.all

`Index.all (*args, **kwargs)`

Return whether all elements are True

Parameters All arguments to `numpy.all` are accepted.

Returns `all` : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.any

`Index.any (*args, **kwargs)`

Return whether any element is True

Parameters All arguments to `numpy.any` are accepted.

Returns `any` : bool or array_like (if axis is specified)

A single element array_like may be converted to bool.

pandas.Index.argmin

`Index.argmin (axis=None)`

return a ndarray of the minimum argument indexer

See also:

`numpy.ndarray.argmin`

pandas.Index.argmax

`Index.argmax (axis=None)`

return a ndarray of the maximum argument indexer

See also:

`numpy.ndarray.argmax`

pandas.Index.copy

`Index.copy` (*names=None, name=None, dtype=None, deep=False*)

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters `name` : string, optional

`dtype` : numpy dtype or pandas type

Returns `copy` : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.Index.delete

`Index.delete` (*loc*)

Make new Index with passed location(-s) deleted

Returns `new_index` : Index

pandas.Index.diff

`Index.diff` (**args, **kwargs*)

pandas.Index.sym_diff

`Index.sym_diff` (*other, result_name=None*)

Compute the sorted symmetric difference of two Index objects.

Parameters `other` : array-like

`result_name` : str

Returns `sym_diff` : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by `(idx1 - idx2) + (idx2 - idx1)` with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.Index.drop

`Index.drop(labels, errors='raise')`

Make new Index with passed list of labels deleted

Parameters `labels` : array-like

`errors` : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns `dropped` : Index

pandas.Index.drop_duplicates

`Index.drop_duplicates(take_last=False)`

Return Index with duplicate values removed

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `deduplicated` : Index

pandas.Index.duplicated

`Index.duplicated(take_last=False)`

Return boolean np.array denoting duplicate values

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `duplicated` : np.array

pandas.Index.equals

`Index.equals(other)`

Determines if two Index objects contain the same elements.

pandas.Index.factorize

`Index.factorize(sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable

Parameters `sort` : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark "not found"

Returns labels : the indexer to the original array

uniques : the unique Index

pandas.Index.identical

`Index.identical (other)`

Similar to equals, but check that other comparable attributes are also equal

pandas.Index.insert

`Index.insert (loc, item)`

Make new Index inserting new item at location. Follows Python list.append semantics for negative values

Parameters loc : int

item : object

Returns new_index : Index

pandas.Index.min

`Index.min ()`

The minimum value of the object

pandas.Index.max

`Index.max ()`

The maximum value of the object

pandas.Index.order

`Index.order (return_indexer=False, ascending=True)`

Return sorted copy of Index

pandas.Index.reindex

`Index.reindex (target, method=None, level=None, limit=None)`

Create index with target's values (move/add/delete values as necessary)

Parameters target : an iterable

Returns new_index : pd.Index

Resulting index

indexer : np.ndarray or None

Indices of output values in original index

pandas.Index.repeat

`Index.repeat (n)`
return a new Index of the values repeated n times

See also:

`numpy.ndarray.repeat`

pandas.Index.take

`Index.take (indexer, axis=0)`
return a new Index of the values selected by the indexer

See also:

`numpy.ndarray.take`

pandas.Index.putmask

`Index.putmask (mask, value)`
return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.Index.set_names

`Index.set_names (names, level=None, inplace=False)`
Set new names on index. Defaults to returning new index.

Parameters `names` : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels) Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')],
                                names=['foo', 'bar'])
>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
```

```

        labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
        names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'bar'])

```

pandas.Index.unique

`Index.unique()`

Return array of unique values in the object. Significantly faster than `numpy.unique`. Includes NA values.

Returns `uniques` : ndarray

pandas.Index.nunique

`Index.nunique(dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters `dropna` : boolean, default True

Don't include NaN in the count.

Returns `nunique` : int

pandas.Index.value_counts

`Index.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element.

Excludes NA values by default.

Parameters `normalize` : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns `counts` : Series

33.7.4 Conversion

<code>Index.astype(dtype)</code>	
<code>Index.tolist()</code>	return a list of the Index values
<code>Index.to_datetime([dayfirst])</code>	For an Index containing strings or datetime.datetime objects, attempt
<code>Index.to_series(**kwargs)</code>	Create a Series with both index and values equal to the index keys

pandas.Index.astype

`Index.astype(dtype)`

pandas.Index.tolist

`Index.tolist()`
return a list of the Index values

pandas.Index.to_datetime

`Index.to_datetime(dayfirst=False)`
For an Index containing strings or datetime.datetime objects, attempt conversion to DatetimeIndex

pandas.Index.to_series

`Index.to_series(**kwargs)`
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

33.7.5 Sorting

<code>Index.argsort(*args, **kwargs)</code>	return an ndarray indexer of the underlying data
<code>Index.order([return_indexer, ascending])</code>	Return sorted copy of Index
<code>Index.sort(*args, **kwargs)</code>	

pandas.Index.argsort

`Index.argsort(*args, **kwargs)`
return an ndarray indexer of the underlying data

See also:

`numpy.ndarray.argsort`

pandas.Index.order

`Index.order(return_indexer=False, ascending=True)`
Return sorted copy of Index

pandas.Index.sort

`Index.sort (*args, **kwargs)`

33.7.6 Time-specific operations

<code>Index.shift([periods, freq])</code>	Shift Index containing datetime objects by input number of periods and
---	--

pandas.Index.shift

`Index.shift (periods=1, freq=None)`

Shift Index containing datetime objects by input number of periods and DateOffset

Returns `shifted` : Index

33.7.7 Combining / joining / merging

<code>Index.append(other)</code>	Append a collection of Index options together
<code>Index.intersection(other)</code>	Form the intersection of two Index objects.
<code>Index.join(other[, how, level, return_indexers])</code>	<i>this is an internal non-public method</i>
<code>Index.union(other)</code>	Form the union of two Index objects and sorts if possible

pandas.Index.append

`Index.append (other)`

Append a collection of Index options together

Parameters `other` : Index or list/tuple of indices

Returns `appended` : Index

pandas.Index.intersection

`Index.intersection (other)`

Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters `other` : Index or array-like

Returns `intersection` : Index

pandas.Index.join

`Index.join (other, how='left', level=None, return_indexers=False)`

this is an internal non-public method

Compute `join_index` and `indexers` to conform data structures to the new index.

Parameters `other` : Index

how : { 'left', 'right', 'inner', 'outer' }

level : int or level name, default None

return_indexers : boolean, default False

Returns join_index, (left_indexer, right_indexer)

pandas.Index.union

`Index.union` (*other*)

Form the union of two Index objects and sorts if possible

Parameters **other** : Index or array-like

Returns **union** : Index

33.7.8 Selecting

<code>Index.get_indexer(target[, method, limit])</code>	Compute indexer and mask for new index given the current index.
<code>Index.get_indexer_non_unique(target)</code>	return an indexer suitable for taking from a non unique index
<code>Index.get_level_values(level)</code>	Return vector of label values for requested level, equal to the length
<code>Index.get_loc(key[, method])</code>	Get integer location for requested label
<code>Index.get_value(series, key)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>Index.isin(values[, level])</code>	Compute boolean array of whether each index value is found in the passed set of values
<code>Index.slice_indexer([start, end, step, kind])</code>	For an ordered Index, compute the slice indexer for input labels and
<code>Index.slice_locs([start, end, step, kind])</code>	Compute slice locations for input labels.

pandas.Index.get_indexer

`Index.get_indexer` (*target, method=None, limit=None*)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index.

Parameters **target** : Index

method : {None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit : int

Maximum number of consecutive labels in `target` to match for inexact matches.

Returns **indexer** : ndarray of int

Integers from 0 to `n - 1` indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.Index.get_indexer_non_unique

Index.**get_indexer_non_unique** (*target*)

return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.Index.get_level_values

Index.**get_level_values** (*level*)

Return vector of label values for requested level, equal to the length of the index

Parameters *level* : int

Returns *values* : ndarray

pandas.Index.get_loc

Index.**get_loc** (*key*, *method=None*)

Get integer location for requested label

Parameters *key* : label

method : {None, 'pad'/'ffill', 'backfill'/'bfill', 'nearest'}

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

Returns *loc* : int if unique index, possibly slice or mask if not

pandas.Index.get_value

Index.**get_value** (*series*, *key*)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.Index.isin

Index.**isin** (*values*, *level=None*)

Compute boolean array of whether each index value is found in the passed set of values.

Parameters *values* : set or sequence of values

Sought values.

level : str or int, optional

Name or position of the index level to use (if the index is a MultiIndex).

Returns *is_contained* : ndarray (boolean dtype)

Notes

If *level* is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

pandas.Index.slice_indexer

Index.**slice_indexer** (*start=None, end=None, step=None, kind=None*)

For an ordered Index, compute the slice indexer for input labels and step

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, default None

kind : string, default None

Returns **indexer** : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.Index.slice_locs

Index.**slice_locs** (*start=None, end=None, step=None, kind=None*)

Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns **start, end** : int

33.8 CategoricalIndex

`CategoricalIndex` Immutable Index implementing an ordered, sliceable set.

33.8.1 pandas.CategoricalIndex

class pandas.CategoricalIndex

Immutable Index implementing an ordered, sliceable set. CategoricalIndex represents a sparsely populated Index with an underlying Categorical.

Parameters **data** : array-like or Categorical, (1-dimensional)

categories : optional, array-like

categories for the CategoricalIndex

ordered : boolean,

designating if the categories are ordered

copy : bool

Make a copy of input ndarray

name : object

Name to be stored in the index

Attributes

<code>T</code>	return the transpose, which is by definition self
<code>base</code>	return the base object if the memory of the underlying data is shared
<code>categories</code>	
<code>codes</code>	
<code>data</code>	return the data pointer of the underlying data
<code>flags</code>	
<code>has_duplicates</code>	
<code>inferred_type</code>	
<code>is_monotonic</code>	alias for <code>is_monotonic_increasing</code> (deprecated)
<code>is_monotonic_decreasing</code>	return if the index is monotonic decreasing (only equal or
<code>is_monotonic_increasing</code>	return if the index is monotonic increasing (only equal or
<code>itemsize</code>	return the size of the dtype of the item of the underlying data
<code>names</code>	
<code>nbytes</code>	return the number of bytes in the underlying data
<code>ndim</code>	return the number of dimensions of the underlying data, by definition 1
<code>nlevels</code>	
<code>ordered</code>	
<code>shape</code>	return a tuple of the shape of the underlying data
<code>size</code>	return the number of elements in the underlying data
<code>strides</code>	return the strides of the underlying data
<code>values</code>	return the underlying data, which is a Categorical

pandas.CategoricalIndex.T

CategoricalIndex.**T**

return the transpose, which is by definition self

pandas.CategoricalIndex.base

`CategoricalIndex.base`

return the base object if the memory of the underlying data is shared

pandas.CategoricalIndex.categories

`CategoricalIndex.categories`

pandas.CategoricalIndex.codes

`CategoricalIndex.codes`

pandas.CategoricalIndex.data

`CategoricalIndex.data`

return the data pointer of the underlying data

pandas.CategoricalIndex.flags

`CategoricalIndex.flags`

pandas.CategoricalIndex.has_duplicates

`CategoricalIndex.has_duplicates`

pandas.CategoricalIndex.inferred_type

`CategoricalIndex.inferred_type`

pandas.CategoricalIndex.is_monotonic

`CategoricalIndex.is_monotonic`

alias for `is_monotonic_increasing` (deprecated)

pandas.CategoricalIndex.is_monotonic_decreasing

`CategoricalIndex.is_monotonic_decreasing`

return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.CategoricalIndex.is_monotonic_increasing

`CategoricalIndex.is_monotonic_increasing`

return if the index is monotonic increasing (only equal or increasing) values.

pandas.CategoricalIndex.itemsize

`CategoricalIndex.itemsize`

return the size of the dtype of the item of the underlying data

pandas.CategoricalIndex.names

`CategoricalIndex.names`

pandas.CategoricalIndex.nbytes

`CategoricalIndex.nbytes`

return the number of bytes in the underlying data

pandas.CategoricalIndex.ndim

`CategoricalIndex.ndim`

return the number of dimensions of the underlying data, by definition 1

pandas.CategoricalIndex.nlevels

`CategoricalIndex.nlevels`

pandas.CategoricalIndex.ordered

`CategoricalIndex.ordered`

pandas.CategoricalIndex.shape

`CategoricalIndex.shape`

return a tuple of the shape of the underlying data

pandas.CategoricalIndex.size

`CategoricalIndex.size`

return the number of elements in the underlying data

pandas.CategoricalIndex.strides

`CategoricalIndex.strides`

return the strides of the underlying data

pandas.CategoricalIndex.values**CategoricalIndex.values**

return the underlying data, which is a Categorical

asi8	
dtype	
is_all_dates	
is_unique	
name	

Methods

<code>add_categories(*args, **kwargs)</code>	Add new categories.
<code>all([other])</code>	
<code>any([other])</code>	
<code>append(other)</code>	Append a collection of CategoricalIndex options together
<code>argmax([axis])</code>	return a ndarray of the maximum argument indexer
<code>argmin([axis])</code>	return a ndarray of the minimum argument indexer
<code>argsort(*args, **kwargs)</code>	
<code>as_ordered(*args, **kwargs)</code>	Sets the Categorical to be ordered
<code>as_unordered(*args, **kwargs)</code>	Sets the Categorical to be unordered
<code>asof(label)</code>	For a sorted index, return the most recent label up to and including the passed
<code>asof_locs(where, mask)</code>	where : array of timestamps
<code>astype(dtype)</code>	
<code>copy([names, name, dtype, deep])</code>	Make a copy of this object.
<code>delete(loc)</code>	Make new Index with passed location(-s) deleted
<code>diff(*args, **kwargs)</code>	
<code>difference(other)</code>	Compute sorted set difference of two Index objects
<code>drop(labels[, errors])</code>	Make new Index with passed list of labels deleted
<code>drop_duplicates([take_last])</code>	Return Index with duplicate values removed
<code>duplicated([take_last])</code>	Return boolean np.array denoting duplicate values
<code>equals(other)</code>	Determines if two CategoricalIndex objects contain the same elements.
<code>factorize([sort, na_sentinel])</code>	Encode the object as an enumerated type or categorical variable
<code>format([name, formatter])</code>	Render a string representation of the Index
<code>get_duplicates()</code>	
<code>get_indexer(target[, method, limit])</code>	Compute indexer and mask for new index given the current index.
<code>get_indexer_for(target, **kwargs)</code>	guaranteed return of an indexer even when non-unique
<code>get_indexer_non_unique(target)</code>	this is the same for a CategoricalIndex for get_indexer; the API returns the m
<code>get_level_values(level)</code>	Return vector of label values for requested level, equal to the length
<code>get_loc(key[, method])</code>	Get integer location for requested label
<code>get_slice_bound(label, side, kind)</code>	Calculate slice bound that corresponds to given label.
<code>get_value(series, key)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>get_values()</code>	return the underlying data as an ndarray
<code>groupby(to_groupby)</code>	Group the index labels by a given array of values.
<code>hasnans()</code>	return if I have any nans; enables various perf speedups
<code>holds_integer()</code>	
<code>identical(other)</code>	Similar to equals, but check that other comparable attributes are
<code>insert(loc, item)</code>	Make new Index inserting new item at location.
<code>intersection(other)</code>	Form the intersection of two Index objects.
<code>is_(other)</code>	More flexible, faster check like <code>is</code> but that works through views
<code>is_boolean()</code>	

Contin

Table 33.97 – continued from previous page

<code>is_categorical()</code>	
<code>is_floating()</code>	
<code>is_integer()</code>	
<code>is_lexsorted_for_tuple(tup)</code>	
<code>is_mixed()</code>	
<code>is_numeric()</code>	
<code>is_object()</code>	
<code>is_type_compatible(kind)</code>	
<code>isin(values[, level])</code>	Compute boolean array of whether each index value is found in the passed series
<code>item()</code>	return the first element of the underlying data as a python scalar
<code>join(other[, how, level, return_indexers])</code>	<i>this is an internal non-public method</i>
<code>map mapper)</code>	
<code>max(*args, **kwargs)</code>	The maximum value of the object.
<code>min(*args, **kwargs)</code>	The minimum value of the object.
<code>nunique([dropna])</code>	Return number of unique elements in the object.
<code>order([return_indexer, ascending])</code>	Return sorted copy of Index
<code>putmask(mask, value)</code>	return a new Index of the values set with the mask
<code>ravel([order])</code>	return an ndarray of the flattened values of the underlying data
<code>reindex(target[, method, level, limit])</code>	Create index with target's values (move/add/delete values as necessary)
<code>remove_categories(*args, **kwargs)</code>	Removes the specified categories.
<code>remove_unused_categories(*args, **kwargs)</code>	Removes categories which are not used.
<code>rename(name[, inplace])</code>	Set new names on index.
<code>rename_categories(*args, **kwargs)</code>	Renames categories.
<code>reorder_categories(*args, **kwargs)</code>	Reorders categories as specified in new_categories.
<code>repeat(n)</code>	return a new Index of the values repeated n times
<code>searchsorted(key[, side])</code>	np.ndarray searchsorted compat
<code>set_categories(*args, **kwargs)</code>	Sets the categories to the specified new_categories.
<code>set_names(names[, level, inplace])</code>	Set new names on index.
<code>set_value(arr, key, value)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>shift([periods, freq])</code>	Shift Index containing datetime objects by input number of periods and
<code>slice_indexer([start, end, step, kind])</code>	For an ordered Index, compute the slice indexer for input labels and
<code>slice_locs([start, end, step, kind])</code>	Compute slice locations for input labels.
<code>sort(*args, **kwargs)</code>	
<code>str</code>	alias of StringMethods
<code>summary([name])</code>	
<code>sym_diff(other[, result_name])</code>	Compute the sorted symmetric difference of two Index objects.
<code>take(indexer[, axis])</code>	return a new CategoricalIndex of the values selected by the indexer
<code>to_datetime([dayfirst])</code>	For an Index containing strings or datetime.datetime objects, attempt
<code>to_native_types([slicer])</code>	slice and dice then format
<code>to_series(**kwargs)</code>	Create a Series with both index and values equal to the index keys
<code>tolist()</code>	return a list of the Index values
<code>transpose()</code>	return the transpose, which is by definition self
<code>union(other)</code>	Form the union of two Index objects and sorts if possible
<code>unique()</code>	Return array of unique values in the object.
<code>value_counts([normalize, sort, ascending, ...])</code>	Returns object containing counts of unique values.
<code>view([cls])</code>	

pandas.CategoricalIndex.add_categories

`CategoricalIndex.add_categories(*args, **kwargs)`

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after

this call.

Parameters `new_categories` : category or list-like of category

The new categories to be included.

inplace : boolean (default: False)

Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns `cat` : Categorical with new categories added or None if inplace.

Raises `ValueError`

If the new categories include old categories or do not validate as categories

See also:

`rename_categories`, `reorder_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.all

`CategoricalIndex.all` (*other=None*)

pandas.CategoricalIndex.any

`CategoricalIndex.any` (*other=None*)

pandas.CategoricalIndex.append

`CategoricalIndex.append` (*other*)

Append a collection of `CategoricalIndex` options together

Parameters `other` : Index or list/tuple of indices

Returns `appended` : Index

Raises `ValueError` if `other` is not in the categories

pandas.CategoricalIndex.argmax

`CategoricalIndex.argmax` (*axis=None*)

return a ndarray of the maximum argument indexer

See also:

`numpy.ndarray.argmax`

pandas.CategoricalIndex.argmin

`CategoricalIndex.argmin` (*axis=None*)

return a ndarray of the minimum argument indexer

See also:

`numpy.ndarray.argmin`

pandas.CategoricalIndex.argsort

`CategoricalIndex.argsort(*args, **kwargs)`

pandas.CategoricalIndex.as_ordered

`CategoricalIndex.as_ordered(*args, **kwargs)`

Sets the Categorical to be ordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.CategoricalIndex.as_unordered

`CategoricalIndex.as_unordered(*args, **kwargs)`

Sets the Categorical to be unordered

Parameters **inplace** : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

pandas.CategoricalIndex.asof

`CategoricalIndex.asof(label)`

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

`get_loc` `asof` is a thin wrapper around `get_loc` with `method='pad'`

pandas.CategoricalIndex.asof_locs

`CategoricalIndex.asof_locs(where, mask)`

`where` : array of timestamps `mask` : array of booleans where data is not NA

pandas.CategoricalIndex.astype

`CategoricalIndex.astype(dtype)`

pandas.CategoricalIndex.copy

`CategoricalIndex.copy(names=None, name=None, dtype=None, deep=False)`

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters **name** : string, optional

dtype : numpy dtype or pandas type

Returns **copy** : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.CategoricalIndex.delete

`CategoricalIndex.delete` (*loc*)

Make new Index with passed location(-s) deleted

Returns `new_index` : Index

pandas.CategoricalIndex.diff

`CategoricalIndex.diff` (**args, **kwargs*)

pandas.CategoricalIndex.difference

`CategoricalIndex.difference` (*other*)

Compute sorted set difference of two Index objects

Parameters `other` : Index or array-like

Returns `diff` : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.CategoricalIndex.drop

`CategoricalIndex.drop` (*labels, errors='raise'*)

Make new Index with passed list of labels deleted

Parameters `labels` : array-like

errors : {'ignore', 'raise'}, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns `dropped` : Index

pandas.CategoricalIndex.drop_duplicates

`CategoricalIndex.drop_duplicates` (*take_last=False*)

Return Index with duplicate values removed

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `deduplicated` : Index

pandas.CategoricalIndex.duplicated

`CategoricalIndex.duplicated` (*take_last=False*)

Return boolean np.array denoting duplicate values

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `duplicated` : np.array

pandas.CategoricalIndex.equals

`CategoricalIndex.equals` (*other*)

Determines if two CategoricalIndex objects contain the same elements.

pandas.CategoricalIndex.factorize

`CategoricalIndex.factorize` (*sort=False, na_sentinel=-1*)

Encode the object as an enumerated type or categorical variable

Parameters `sort` : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark “not found”

Returns `labels` : the indexer to the original array

`uniques` : the unique Index

pandas.CategoricalIndex.format

`CategoricalIndex.format` (*name=False, formatter=None, **kwargs*)

Render a string representation of the Index

pandas.CategoricalIndex.get_duplicates

`CategoricalIndex.get_duplicates` ()

pandas.CategoricalIndex.get_indexer

`CategoricalIndex.get_indexer` (*target, method=None, limit=None*)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index. The mask determines whether labels are found or not in the current index

Parameters `target` : MultiIndex or Index (of tuples)

method : {‘pad’, ‘ffill’, ‘backfill’, ‘bfill’}

pad / ffill: propagate LAST valid observation forward to next valid backfill / bfill:
use NEXT valid observation to fill gap

Returns (`indexer, mask`) : (ndarray, ndarray)

Notes

This is a low-level method and probably should be used at your own risk

Examples

```
>>> indexer, mask = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
>>> new_values[-mask] = np.nan
```

pandas.CategoricalIndex.get_indexer_for

`CategoricalIndex.get_indexer_for(target, **kwargs)`
guaranteed return of an indexer even when non-unique

pandas.CategoricalIndex.get_indexer_non_unique

`CategoricalIndex.get_indexer_non_unique(target)`
this is the same for a `CategoricalIndex` for `get_indexer`; the API returns the missing values as well

pandas.CategoricalIndex.get_level_values

`CategoricalIndex.get_level_values(level)`
Return vector of label values for requested level, equal to the length of the index

Parameters `level` : int

Returns `values` : ndarray

pandas.CategoricalIndex.get_loc

`CategoricalIndex.get_loc(key, method=None)`
Get integer location for requested label

Parameters `key` : label

method : {None}

- default: exact matches only.

Returns `loc` : int if unique index, possibly slice or mask if not

pandas.CategoricalIndex.get_slice_bound

`CategoricalIndex.get_slice_bound(label, side, kind)`
Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters `label` : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.CategoricalIndex.get_value

`CategoricalIndex.get_value (series, key)`

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.CategoricalIndex.get_values

`CategoricalIndex.get_values ()`

return the underlying data as an ndarray

pandas.CategoricalIndex.groupby

`CategoricalIndex.groupby (to_groupby)`

Group the index labels by a given array of values.

Parameters `to_groupby` : array

Values used to determine the groups.

Returns `groups` : dict

{group name -> group labels}

pandas.CategoricalIndex.hasnans

`CategoricalIndex.hasnans ()`

return if I have any nans; enables various perf speedups

pandas.CategoricalIndex.holds_integer

`CategoricalIndex.holds_integer ()`

pandas.CategoricalIndex.identical

`CategoricalIndex.identical (other)`

Similar to equals, but check that other comparable attributes are also equal

pandas.CategoricalIndex.insert

`CategoricalIndex.insert (loc, item)`

Make new Index inserting new item at location. Follows Python list.append semantics for negative values

Parameters `loc` : int

`item` : object

Returns `new_index` : Index

Raises `ValueError` if the item is not in the categories

pandas.CategoricalIndex.intersection

`CategoricalIndex.intersection(other)`

Form the intersection of two Index objects. Sortedness of the result is not guaranteed

Parameters *other* : Index or array-like

Returns *intersection* : Index

pandas.CategoricalIndex.is

`CategoricalIndex.is_(other)`

More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters *other* : object

other object to compare against.

Returns `True` if both have same underlying data, `False` otherwise : bool

pandas.CategoricalIndex.is_boolean

`CategoricalIndex.is_boolean()`

pandas.CategoricalIndex.is_categorical

`CategoricalIndex.is_categorical()`

pandas.CategoricalIndex.is_floating

`CategoricalIndex.is_floating()`

pandas.CategoricalIndex.is_integer

`CategoricalIndex.is_integer()`

pandas.CategoricalIndex.is_lexsorted_for_tuple

`CategoricalIndex.is_lexsorted_for_tuple(tup)`

pandas.CategoricalIndex.is_mixed

`CategoricalIndex.is_mixed()`

pandas.CategoricalIndex.is_numeric

`CategoricalIndex.is_numeric()`

pandas.CategoricalIndex.is_object

`CategoricalIndex.is_object()`

pandas.CategoricalIndex.is_type_compatible

`CategoricalIndex.is_type_compatible(kind)`

pandas.CategoricalIndex.isin

`CategoricalIndex.isin(values, level=None)`

Compute boolean array of whether each index value is found in the passed set of values.

Parameters `values` : set or sequence of values

Sought values.

level : str or int, optional

Name or position of the index level to use (if the index is a MultiIndex).

Returns `is_contained` : ndarray (boolean dtype)

Notes

If *level* is specified:

- if it is the name of one *and only one* index level, use that level;
- otherwise it should be a number indicating level position.

pandas.CategoricalIndex.item

`CategoricalIndex.item()`

return the first element of the underlying data as a python scalar

pandas.CategoricalIndex.join

`CategoricalIndex.join(other, how='left', level=None, return_indexers=False)`

this is an internal non-public method

Compute `join_index` and `indexers` to conform data structures to the new index.

Parameters `other` : Index

how : { 'left', 'right', 'inner', 'outer' }

level : int or level name, default None

return_indexers : boolean, default False

Returns `join_index`, (`left_indexer`, `right_indexer`)

pandas.CategoricalIndex.map

`CategoricalIndex.map mapper)`

pandas.CategoricalIndex.max

`CategoricalIndex.max(*args, **kwargs)`

The maximum value of the object.

Only ordered *Categoricals* have a maximum!

Returns `max` : the maximum of this *Categorical*

Raises `TypeError`

If the *Categorical* is not *ordered*.

pandas.CategoricalIndex.min

`CategoricalIndex.min(*args, **kwargs)`

The minimum value of the object.

Only ordered *Categoricals* have a minimum!

Returns `min` : the minimum of this *Categorical*

Raises `TypeError`

If the *Categorical* is not *ordered*.

pandas.CategoricalIndex.nunique

`CategoricalIndex.nunique(dropna=True)`

Return number of unique elements in the object.

Excludes NA values by default.

Parameters `dropna` : boolean, default True

Don't include NaN in the count.

Returns `nunique` : int

pandas.CategoricalIndex.order

`CategoricalIndex.order(return_indexer=False, ascending=True)`

Return sorted copy of Index

pandas.CategoricalIndex.putmask

`CategoricalIndex.putmask(mask, value)`

return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.CategoricalIndex.ravel

`CategoricalIndex.ravel` (*order='C'*)
 return an ndarray of the flattened values of the underlying data

See also:

`numpy.ndarray.ravel`

pandas.CategoricalIndex.reindex

`CategoricalIndex.reindex` (*target, method=None, level=None, limit=None*)
 Create index with target's values (move/add/delete values as necessary)

Returns `new_index` : `pd.Index`

Resulting index

indexer : `np.ndarray` or `None`

Indices of output values in original index

pandas.CategoricalIndex.remove_categories

`CategoricalIndex.remove_categories` (**args, **kwargs*)
 Removes the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters `removals` : category or list of categories

The categories which should be removed.

inplace : boolean (default: False)

Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns `cat` : Categorical with removed categories or None if inplace.

Raises `ValueError`

If the removals are not contained in the categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.remove_unused_categories

`CategoricalIndex.remove_unused_categories` (**args, **kwargs*)
 Removes categories which are not used.

Parameters `inplace` : boolean (default: False)

Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns `cat` : Categorical with unused categories dropped or None if inplace.

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`,
`set_categories`

pandas.CategoricalIndex.rename

`CategoricalIndex.rename` (*name*, *inplace=False*)

Set new names on index. Defaults to returning new index.

Parameters *name* : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

pandas.CategoricalIndex.rename_categories

`CategoricalIndex.rename_categories` (**args*, ***kwargs*)

Renames categories.

The new categories has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Parameters *new_categories* : Index-like

The renamed categories.

inplace : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns *cat* : Categorical with renamed categories added or None if inplace.

Raises `ValueError`

If the new categories do not have the same number of items than the current categories or do not validate as categories

See also:

`reorder_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.reorder_categories

`CategoricalIndex.reorder_categories` (**args*, ***kwargs*)

Reorders categories as specified in *new_categories*.

new_categories need to include all old categories and no new category items.

Parameters *new_categories* : Index-like

The categories in new order.

ordered : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns **cat** : Categorical with reordered categories or None if inplace.

Raises **ValueError**

If the new categories do not contain all old category items or any new ones

See also:

`rename_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.repeat

`CategoricalIndex.repeat(n)`
return a new Index of the values repeated n times

See also:

`numpy.ndarray.repeat`

pandas.CategoricalIndex.searchsorted

`CategoricalIndex.searchsorted(key, side='left')`
`np.ndarray.searchsorted` compat

pandas.CategoricalIndex.set_categories

`CategoricalIndex.set_categories(*args, **kwargs)`
Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes on python3, which does not considers a S1 string equal to a single char python string.

Parameters **new_categories** : Index-like

The categories in new order.

ordered : boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename : boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns cat : Categorical with reordered categories or None if inplace.

Raises ValueError

If new_categories does not validate as categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`, `remove_unused_categories`

pandas.CategoricalIndex.set_names

`CategoricalIndex.set_names` (*names*, *level=None*, *inplace=False*)

Set new names on index. Defaults to returning new index.

Parameters names : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)
Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')],
                                names=['foo', 'bar'])

>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'bar'])
```

pandas.CategoricalIndex.set_value

`CategoricalIndex.set_value` (*arr, key, value*)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.CategoricalIndex.shift

`CategoricalIndex.shift` (*periods=1, freq=None*)

Shift Index containing datetime objects by input number of periods and DateOffset

Returns `shifted` : Index

pandas.CategoricalIndex.slice_indexer

`CategoricalIndex.slice_indexer` (*start=None, end=None, step=None, kind=None*)

For an ordered Index, compute the slice indexer for input labels and step

Parameters `start` : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, default None

kind : string, default None

Returns `indexer` : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.CategoricalIndex.slice_locs

`CategoricalIndex.slice_locs` (*start=None, end=None, step=None, kind=None*)

Compute slice locations for input labels.

Parameters `start` : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns `start, end` : int

pandas.CategoricalIndex.sort

`CategoricalIndex.sort(*args, **kwargs)`

pandas.CategoricalIndex.summary

`CategoricalIndex.summary(name=None)`

pandas.CategoricalIndex.sym_diff

`CategoricalIndex.sym_diff(other, result_name=None)`
Compute the sorted symmetric difference of two Index objects.

Parameters `other` : array-like

`result_name` : str

Returns `sym_diff` : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by $(idx1 - idx2) + (idx2 - idx1)$ with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.CategoricalIndex.take

`CategoricalIndex.take(indexer, axis=0)`
return a new CategoricalIndex of the values selected by the indexer

See also:

`numpy.ndarray.take`

pandas.CategoricalIndex.to_datetime

`CategoricalIndex.to_datetime(dayfirst=False)`
For an Index containing strings or `datetime.datetime` objects, attempt conversion to `DatetimeIndex`

pandas.CategoricalIndex.to_native_types

`CategoricalIndex.to_native_types` (*slicer=None, **kwargs*)
slice and dice then format

pandas.CategoricalIndex.to_series

`CategoricalIndex.to_series` (***kwargs*)
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

pandas.CategoricalIndex.tolist

`CategoricalIndex.tolist` ()
return a list of the Index values

pandas.CategoricalIndex.transpose

`CategoricalIndex.transpose` ()
return the transpose, which is by definition self

pandas.CategoricalIndex.union

`CategoricalIndex.union` (*other*)
Form the union of two Index objects and sorts if possible

Parameters other : Index or array-like

Returns union : Index

pandas.CategoricalIndex.unique

`CategoricalIndex.unique` ()
Return array of unique values in the object. Significantly faster than numpy.unique. Includes NA values.

Returns uniques : ndarray

pandas.CategoricalIndex.value_counts

`CategoricalIndex.value_counts` (*normalize=False, sort=True, ascending=False, bins=None, dropna=True*)

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters normalize : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns **counts** : Series

pandas.CategoricalIndex.view

`CategoricalIndex.view(cls=None)`

33.8.2 Categorical Components

<code>CategoricalIndex.codes</code>	
<code>CategoricalIndex.categories</code>	
<code>CategoricalIndex.ordered</code>	
<code>CategoricalIndex.rename_categories(*args, ...)</code>	Renames categories.
<code>CategoricalIndex.reorder_categories(*args, ...)</code>	Reorders categories as specified in <code>new_categories</code> .
<code>CategoricalIndex.add_categories(*args, **kwargs)</code>	Add new categories.
<code>CategoricalIndex.remove_categories(*args, ...)</code>	Removes the specified categories.
<code>CategoricalIndex.remove_unused_categories(...)</code>	Removes categories which are not used.
<code>CategoricalIndex.set_categories(*args, **kwargs)</code>	Sets the categories to the specified <code>new_categories</code> .
<code>CategoricalIndex.as_ordered(*args, **kwargs)</code>	Sets the Categorical to be ordered
<code>CategoricalIndex.as_unordered(*args, **kwargs)</code>	Sets the Categorical to be unordered

pandas.CategoricalIndex.codes

`CategoricalIndex.codes`

pandas.CategoricalIndex.categories

`CategoricalIndex.categories`

pandas.CategoricalIndex.ordered

`CategoricalIndex.ordered`

pandas.CategoricalIndex.rename_categories

`CategoricalIndex.rename_categories(*args, **kwargs)`
Renames categories.

The new categories has to be a list-like object. All items must be unique and the number of items in the new categories must be the same as the number of items in the old categories.

Parameters `new_categories` : Index-like

The renamed categories.

inplace : boolean (default: False)

Whether or not to rename the categories inplace or return a copy of this categorical with renamed categories.

Returns `cat` : Categorical with renamed categories added or None if inplace.

Raises `ValueError`

If the new categories do not have the same number of items than the current categories or do not validate as categories

See also:

`reorder_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.reorder_categories

`CategoricalIndex.reorder_categories(*args, **kwargs)`

Reorders categories as specified in `new_categories`.

new_categories need to include all old categories and no new category items.

Parameters `new_categories` : Index-like

The categories in new order.

ordered : boolean, optional

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns `cat` : Categorical with reordered categories or None if inplace.

Raises `ValueError`

If the new categories do not contain all old category items or any new ones

See also:

`rename_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.add_categories

`CategoricalIndex.add_categories(*args, **kwargs)`

Add new categories.

new_categories will be included at the last/highest place in the categories and will be unused directly after this call.

Parameters `new_categories` : category or list-like of category

The new categories to be included.

inplace : boolean (default: False)

Whether or not to add the categories inplace or return a copy of this categorical with added categories.

Returns `cat` : Categorical with new categories added or None if inplace.

Raises `ValueError`

If the new categories include old categories or do not validate as categories

See also:

`rename_categories`, `reorder_categories`, `remove_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.remove_categories

`CategoricalIndex.remove_categories(*args, **kwargs)`

Removes the specified categories.

removals must be included in the old categories. Values which were in the removed categories will be set to NaN

Parameters `removals` : category or list of categories

The categories which should be removed.

inplace : boolean (default: False)

Whether or not to remove the categories inplace or return a copy of this categorical with removed categories.

Returns `cat` : Categorical with removed categories or None if inplace.

Raises `ValueError`

If the removals are not contained in the categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`,
`remove_unused_categories`, `set_categories`

pandas.CategoricalIndex.remove_unused_categories

`CategoricalIndex.remove_unused_categories(*args, **kwargs)`

Removes categories which are not used.

Parameters `inplace` : boolean (default: False)

Whether or not to drop unused categories inplace or return a copy of this categorical with unused categories dropped.

Returns `cat` : Categorical with unused categories dropped or None if inplace.

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`,
`set_categories`

pandas.CategoricalIndex.set_categories`CategoricalIndex.set_categories(*args, **kwargs)`

Sets the categories to the specified new_categories.

new_categories can include new categories (which will result in unused categories) or or remove old categories (which results in values set to NaN). If *rename==True*, the categories will simple be renamed (less or more items than in old categories will result in values set to NaN or in unused categories respectively).

This method can be used to perform more than one action of adding, removing, and reordering simultaneously and is therefore faster than performing the individual steps via the more specialised methods.

On the other hand this methods does not do checks (e.g., whether the old categories are included in the new categories on a reorder), which can result in surprising changes, for example when using special string dtypes on python3, which does not considers a S1 string equal to a single char python string.

Parameters *new_categories* : Index-like

The categories in new order.

ordered : boolean, (default: False)

Whether or not the categorical is treated as a ordered categorical. If not given, do not change the ordered information.

rename : boolean (default: False)

Whether or not the new_categories should be considered as a rename of the old categories or as reordered categories.

inplace : boolean (default: False)

Whether or not to reorder the categories inplace or return a copy of this categorical with reordered categories.

Returns *cat* : Categorical with reordered categories or None if inplace.**Raises** `ValueError`

If new_categories does not validate as categories

See also:

`rename_categories`, `reorder_categories`, `add_categories`, `remove_categories`,
`remove_unused_categories`

pandas.CategoricalIndex.as_ordered`CategoricalIndex.as_ordered(*args, **kwargs)`

Sets the Categorical to be ordered

Parameters *inplace* : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to True

pandas.CategoricalIndex.as_unordered`CategoricalIndex.as_unordered(*args, **kwargs)`

Sets the Categorical to be unordered

Parameters *inplace* : boolean (default: False)

Whether or not to set the ordered attribute inplace or return a copy of this categorical with ordered set to False

33.9 DatetimeIndex

`DatetimeIndex` Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp o

33.9.1 pandas.DatetimeIndex

class `pandas.DatetimeIndex`

Immutable ndarray of datetime64 data, represented internally as int64, and which can be boxed to Timestamp objects that are subclasses of datetime and carry metadata such as frequency information.

Parameters **data** : array-like (1-dimensional), optional

Optional datetime-like data to construct index with

copy : bool

Make a copy of input ndarray

freq : string or pandas offset object, optional

One of pandas date offset strings or corresponding objects

start : starting value, datetime-like, optional

If data is None, start is used as the start point in generating regular timestamp data.

periods : int, optional, > 0

Number of periods to generate, if generating index. Takes precedence over end argument

end : end time, datetime-like, optional

If periods is none, generated index will extend to first conforming time on or just past end argument

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

tz : pytz.timezone or dateutil.tz.tzfile

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

name : object

Name to be stored in the index

Attributes

T	return the transpose, which is by definition self
asi8	
asobject	
base	return the base object if the memory of the underlying data is shared
data	return the data pointer of the underlying data
date	Returns numpy array of datetime.date.
day	The days of the datetime
dayofweek	The day of the week with Monday=0, Sunday=6
dayofyear	The ordinal day of the year
days_in_month	The number of days in the month
daysinmonth	The number of days in the month
dtype	
flags	
freq	get/set the frequency of the Index
freqstr	return the frequency object as a string if its set, otherwise None
has_duplicates	
hour	The hours of the datetime
inferred_type	
is_all_dates	
is_monotonic	alias for is_monotonic_increasing (deprecated)
is_monotonic_decreasing	return if the index is monotonic decreasing (only equal or
is_monotonic_increasing	return if the index is monotonic increasing (only equal or
is_month_end	Logical indicating if last day of month (defined by frequency)
is_month_start	Logical indicating if first day of month (defined by frequency)
is_quarter_end	Logical indicating if last day of quarter (defined by frequency)
is_quarter_start	Logical indicating if first day of quarter (defined by frequency)
is_year_end	Logical indicating if last day of year (defined by frequency)
is_year_start	Logical indicating if first day of year (defined by frequency)
itemsize	return the size of the dtype of the item of the underlying data
microsecond	The microseconds of the datetime
millisecond	The milliseconds of the datetime
minute	The minutes of the datetime
month	The month as January=1, December=12
names	
nanosecond	The nanoseconds of the datetime
nbytes	return the number of bytes in the underlying data
ndim	return the number of dimensions of the underlying data, by definition 1
nlevels	
quarter	The quarter of the date
second	The seconds of the datetime
shape	return a tuple of the shape of the underlying data
size	return the number of elements in the underlying data
strides	return the strides of the underlying data
time	Returns numpy array of datetime.time.
tzinfo	Alias for tz attribute
values	return the underlying data as an ndarray
week	The week ordinal of the year
weekday	The day of the week with Monday=0, Sunday=6

Continued on next page

Table 33.100 – continued from previous page

<code>weekofyear</code>	The week ordinal of the year
<code>year</code>	The year of the datetime

pandas.DatetimeIndex.T`DatetimeIndex.T`

return the transpose, which is by definition self

pandas.DatetimeIndex.asi8`DatetimeIndex.asi8`**pandas.DatetimeIndex.asobject**`DatetimeIndex.asobject`**pandas.DatetimeIndex.base**`DatetimeIndex.base`

return the base object if the memory of the underlying data is shared

pandas.DatetimeIndex.data`DatetimeIndex.data`

return the data pointer of the underlying data

pandas.DatetimeIndex.date`DatetimeIndex.date`

Returns numpy array of datetime.date. The date part of the Timestamps.

pandas.DatetimeIndex.day`DatetimeIndex.day`

The days of the datetime

pandas.DatetimeIndex.dayofweek`DatetimeIndex.dayofweek`

The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.dayofyear`DatetimeIndex.dayofyear`

The ordinal day of the year

pandas.DatetimeIndex.days_in_month

`DatetimeIndex.days_in_month`
The number of days in the month

pandas.DatetimeIndex.daysinmonth

`DatetimeIndex.daysinmonth`
The number of days in the month

pandas.DatetimeIndex.dtype

`DatetimeIndex.dtype`

pandas.DatetimeIndex.flags

`DatetimeIndex.flags`

pandas.DatetimeIndex.freq

`DatetimeIndex.freq`
get/set the frequency of the Index

pandas.DatetimeIndex.freqstr

`DatetimeIndex.freqstr`
return the frequency object as a string if its set, otherwise None

pandas.DatetimeIndex.has_duplicates

`DatetimeIndex.has_duplicates`

pandas.DatetimeIndex.hour

`DatetimeIndex.hour`
The hours of the datetime

pandas.DatetimeIndex.inferred_type

`DatetimeIndex.inferred_type`

pandas.DatetimeIndex.is_all_dates

`DatetimeIndex.is_all_dates`

pandas.DatetimeIndex.is_monotonic

`DatetimeIndex.is_monotonic`
alias for `is_monotonic_increasing` (deprecated)

pandas.DatetimeIndex.is_monotonic_decreasing

`DatetimeIndex.is_monotonic_decreasing`
return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.DatetimeIndex.is_monotonic_increasing

`DatetimeIndex.is_monotonic_increasing`
return if the index is monotonic increasing (only equal or increasing) values.

pandas.DatetimeIndex.is_month_end

`DatetimeIndex.is_month_end`
Logical indicating if last day of month (defined by frequency)

pandas.DatetimeIndex.is_month_start

`DatetimeIndex.is_month_start`
Logical indicating if first day of month (defined by frequency)

pandas.DatetimeIndex.is_quarter_end

`DatetimeIndex.is_quarter_end`
Logical indicating if last day of quarter (defined by frequency)

pandas.DatetimeIndex.is_quarter_start

`DatetimeIndex.is_quarter_start`
Logical indicating if first day of quarter (defined by frequency)

pandas.DatetimeIndex.is_year_end

`DatetimeIndex.is_year_end`
Logical indicating if last day of year (defined by frequency)

pandas.DatetimeIndex.is_year_start

`DatetimeIndex.is_year_start`
Logical indicating if first day of year (defined by frequency)

pandas.DatetimeIndex.itemsize

`DatetimeIndex.itemsize`

return the size of the dtype of the item of the underlying data

pandas.DatetimeIndex.microsecond

`DatetimeIndex.microsecond`

The microseconds of the datetime

pandas.DatetimeIndex.millisecond

`DatetimeIndex.millisecond`

The milliseconds of the datetime

pandas.DatetimeIndex.minute

`DatetimeIndex.minute`

The minutes of the datetime

pandas.DatetimeIndex.month

`DatetimeIndex.month`

The month as January=1, December=12

pandas.DatetimeIndex.names

`DatetimeIndex.names`

pandas.DatetimeIndex.nanosecond

`DatetimeIndex.nanosecond`

The nanoseconds of the datetime

pandas.DatetimeIndex.nbytes

`DatetimeIndex.nbytes`

return the number of bytes in the underlying data

pandas.DatetimeIndex.ndim

`DatetimeIndex.ndim`

return the number of dimensions of the underlying data, by definition 1

pandas.DatetimeIndex.nlevels

`DatetimeIndex.nlevels`

pandas.DatetimeIndex.quarter

`DatetimeIndex.quarter`
The quarter of the date

pandas.DatetimeIndex.second

`DatetimeIndex.second`
The seconds of the datetime

pandas.DatetimeIndex.shape

`DatetimeIndex.shape`
return a tuple of the shape of the underlying data

pandas.DatetimeIndex.size

`DatetimeIndex.size`
return the number of elements in the underlying data

pandas.DatetimeIndex.strides

`DatetimeIndex.strides`
return the strides of the underlying data

pandas.DatetimeIndex.time

`DatetimeIndex.time`
Returns numpy array of datetime.time. The time part of the Timestamps.

pandas.DatetimeIndex.tzinfo

`DatetimeIndex.tzinfo`
Alias for tz attribute

pandas.DatetimeIndex.values

`DatetimeIndex.values`
return the underlying data as an ndarray

pandas.DatetimeIndex.week

`DatetimeIndex.week`
The week ordinal of the year

pandas.DatetimeIndex.weekday`DatetimeIndex.weekday`

The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.weekofyear`DatetimeIndex.weekofyear`

The week ordinal of the year

pandas.DatetimeIndex.year`DatetimeIndex.year`

The year of the datetime

hasnans	
inferred_freq	
is_normalized	
is_unique	
name	
offset	
resolution	
tz	

Methods

```

all([other])
any([other])
append(other)
argmax([axis])
argmin([axis])
argsort(*args, **kwargs)
asof(label)
asof_locs(where, mask)
astype(dtype)
copy([names, name, dtype, deep])
delete(loc)
diff(*args, **kwargs)
difference(other)
drop(labels[, errors])
drop_duplicates([take_last])
duplicated([take_last])
equals(other)
factorize([sort, na_sentinel])
format([name, formatter])
get_duplicates()
get_indexer(target[, method, limit])
get_indexer_for(target, **kwargs)
get_indexer_non_unique(target)
get_level_values(level)

```

Append a collection of Index options together
 return a ndarray of the maximum argument indexer
 return a ndarray of the minimum argument indexer
 return an ndarray indexer of the underlying data
 For a sorted index, return the most recent label up to and including the passed location(s)
 where : array of timestamps

Make a copy of this object.
 Make a new DatetimeIndex with passed location(s) deleted.

Compute sorted set difference of two Index objects
 Make new Index with passed list of labels deleted
 Return Index with duplicate values removed
 Return boolean np.array denoting duplicate values
 Determines if two Index objects contain the same elements.
 Encode the object as an enumerated type or categorical variable
 Render a string representation of the Index

Compute indexer and mask for new index given the current index.
 guaranteed return of an indexer even when non-unique
 return an indexer suitable for taking from a non unique index
 Return vector of label values for requested level, equal to the length of the index

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Table 33.101 – continued from previous page

<code>get_loc(key[, method])</code>	Get integer location for requested label
<code>get_slice_bound(label, side, kind)</code>	Calculate slice bound that corresponds to given label.
<code>get_value(series, key)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>get_value_maybe_box(series, key)</code>	
<code>get_values()</code>	return the underlying data as an ndarray
<code>groupby(f)</code>	
<code>holds_integer()</code>	
<code>identical(other)</code>	Similar to equals, but check that other comparable attributes are
<code>indexer_at_time(time[, asof])</code>	Select values at particular time of day (e.g.
<code>indexer_between_time(start_time, end_time[, ...])</code>	Select values between particular times of day (e.g., 9:00-9:30AM)
<code>insert(loc, item)</code>	Make new Index inserting new item at location
<code>intersection(other)</code>	Specialized intersection for DatetimeIndex objects.
<code>is_(other)</code>	More flexible, faster check like <code>is</code> but that works through views
<code>is_boolean()</code>	
<code>is_categorical()</code>	
<code>is_floating()</code>	
<code>is_integer()</code>	
<code>is_lexsorted_for_tuple(tup)</code>	
<code>is_mixed()</code>	
<code>is_numeric()</code>	
<code>is_object()</code>	
<code>is_type_compatible(typ)</code>	
<code>isin(values)</code>	Compute boolean array of whether each index value is found in the
<code>item()</code>	return the first element of the underlying data as a python scalar
<code>join(other[, how, level, return_indexers])</code>	See Index.join
<code>map(f)</code>	
<code>max([axis])</code>	return the maximum value of the Index
<code>min([axis])</code>	return the minimum value of the Index
<code>normalize()</code>	Return DatetimeIndex with times to midnight.
<code>nunique([dropna])</code>	Return number of unique elements in the object.
<code>order([return_indexer, ascending])</code>	Return sorted copy of Index
<code>putmask(mask, value)</code>	return a new Index of the values set with the mask
<code>ravel([order])</code>	return an ndarray of the flattened values of the underlying data
<code>reindex(target[, method, level, limit])</code>	Create index with target's values (move/add/delete values as necessary)
<code>rename(name[, inplace])</code>	Set new names on index.
<code>repeat(repeats[, axis])</code>	Analogous to ndarray.repeat
<code>searchsorted(key[, side])</code>	
<code>set_names(names[, level, inplace])</code>	Set new names on index.
<code>set_value(arr, key, value)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>shift(n[, freq])</code>	Specialized shift which produces a DatetimeIndex
<code>slice_indexer([start, end, step, kind])</code>	Return indexer for specified label slice.
<code>slice_locs([start, end, step, kind])</code>	Compute slice locations for input labels.
<code>snap([freq])</code>	Snap time stamps to nearest occurring frequency
<code>sort(*args, **kwargs)</code>	
<code>str</code>	alias of StringMethods
<code>summary([name])</code>	return a summarized representation
<code>sym_diff(other[, result_name])</code>	Compute the sorted symmetric difference of two Index objects.
<code>take(indices[, axis])</code>	Analogous to ndarray.take
<code>to_datetime([dayfirst])</code>	
<code>to_julian_date()</code>	Convert DatetimeIndex to Float64Index of Julian Dates.
<code>to_native_types([slicer])</code>	slice and dice then format
<code>to_period([freq])</code>	Cast to PeriodIndex at a particular frequency

Continued on r

Table 33.101 – continued from previous page

<code>to_pydatetime()</code>	Return DatetimeIndex as object ndarray of datetime.datetime objects
<code>to_series([keep_tz])</code>	Create a Series with both index and values equal to the index keys
<code>tolist()</code>	return a list of the underlying data
<code>transpose()</code>	return the transpose, which is by definition self
<code>tz_convert(tz)</code>	Convert tz-aware DatetimeIndex from one time zone to another (using pytz)
<code>tz_localize(*args, **kwargs)</code>	Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil),
<code>union(other)</code>	Specialized union for DatetimeIndex objects.
<code>union_many(others)</code>	A bit of a hack to accelerate unioning a collection of indexes
<code>unique()</code>	Index.unique with handling for DatetimeIndex/PeriodIndex metadata
<code>value_counts([normalize, sort, ascending, ...])</code>	Returns object containing counts of unique values.
<code>view([cls])</code>	

pandas.DatetimeIndex.all

DatetimeIndex.**all** (*other=None*)

pandas.DatetimeIndex.any

DatetimeIndex.**any** (*other=None*)

pandas.DatetimeIndex.append

DatetimeIndex.**append** (*other*)

Append a collection of Index options together

Parameters *other* : Index or list/tuple of indices

Returns *appended* : Index

pandas.DatetimeIndex.argmax

DatetimeIndex.**argmax** (*axis=None*)

return a ndarray of the maximum argument indexer

See also:

`numpy.ndarray.argmax`

pandas.DatetimeIndex.argmin

DatetimeIndex.**argmin** (*axis=None*)

return a ndarray of the minimum argument indexer

See also:

`numpy.ndarray.argmin`

pandas.DatetimeIndex.argsort

`DatetimeIndex.argsort` (*args, **kwargs)
return an ndarray indexer of the underlying data

See also:

`numpy.ndarray.argsort`

pandas.DatetimeIndex.asof

`DatetimeIndex.asof` (label)

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

`get_loc` asof is a thin wrapper around `get_loc` with `method='pad'`

pandas.DatetimeIndex.asof_locs

`DatetimeIndex.asof_locs` (where, mask)

where : array of timestamps mask : array of booleans where data is not NA

pandas.DatetimeIndex.astype

`DatetimeIndex.astype` (dtype)

pandas.DatetimeIndex.copy

`DatetimeIndex.copy` (names=None, name=None, dtype=None, deep=False)

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters name : string, optional

dtype : numpy dtype or pandas type

Returns copy : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to `deepcopy`.

pandas.DatetimeIndex.delete

`DatetimeIndex.delete` (loc)

Make a new `DatetimeIndex` with passed location(s) deleted.

Parameters loc: int, slice or array of ints

Indicate which sub-arrays to remove.

Returns new_index : `DatetimeIndex`

pandas.DatetimeIndex.diff

`DatetimeIndex.diff(*args, **kwargs)`

pandas.DatetimeIndex.difference

`DatetimeIndex.difference(other)`

Compute sorted set difference of two Index objects

Parameters `other` : Index or array-like

Returns `diff` : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.DatetimeIndex.drop

`DatetimeIndex.drop(labels, errors='raise')`

Make new Index with passed list of labels deleted

Parameters `labels` : array-like

`errors` : { 'ignore', 'raise' }, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns `dropped` : Index

pandas.DatetimeIndex.drop_duplicates

`DatetimeIndex.drop_duplicates(take_last=False)`

Return Index with duplicate values removed

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `deduplicated` : Index

pandas.DatetimeIndex.duplicated

`DatetimeIndex.duplicated(take_last=False)`

Return boolean np.array denoting duplicate values

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `duplicated` : np.array

pandas.DatetimeIndex.equals

`DatetimeIndex.equals` (*other*)

Determines if two Index objects contain the same elements.

pandas.DatetimeIndex.factorize

`DatetimeIndex.factorize` (*sort=False, na_sentinel=-1*)

Encode the object as an enumerated type or categorical variable

Parameters *sort* : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark “not found”

Returns *labels* : the indexer to the original array

uniques : the unique Index

pandas.DatetimeIndex.format

`DatetimeIndex.format` (*name=False, formatter=None, **kwargs*)

Render a string representation of the Index

pandas.DatetimeIndex.get_duplicates

`DatetimeIndex.get_duplicates` ()

pandas.DatetimeIndex.get_indexer

`DatetimeIndex.get_indexer` (*target, method=None, limit=None*)

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index.

Parameters *target* : Index

method : {None, ‘pad’/’ffill’, ‘backfill’/’bfill’, ‘nearest’}

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit : int

Maximum number of consecutive labels in *target* to match for inexact matches.

Returns *indexer* : ndarray of int

Integers from 0 to *n* - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.DatetimeIndex.get_indexer_for

`DatetimeIndex.get_indexer_for(target, **kwargs)`
 guaranteed return of an indexer even when non-unique

pandas.DatetimeIndex.get_indexer_non_unique

`DatetimeIndex.get_indexer_non_unique(target)`
 return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.DatetimeIndex.get_level_values

`DatetimeIndex.get_level_values(level)`
 Return vector of label values for requested level, equal to the length of the index

Parameters `level` : int

Returns `values` : ndarray

pandas.DatetimeIndex.get_loc

`DatetimeIndex.get_loc(key, method=None)`
 Get integer location for requested label

Returns `loc` : int

pandas.DatetimeIndex.get_slice_bound

`DatetimeIndex.get_slice_bound(label, side, kind)`
 Calculate slice bound that corresponds to given label.

Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters `label` : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.DatetimeIndex.get_value

`DatetimeIndex.get_value(series, key)`
 Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.DatetimeIndex.get_value_maybe_box

`DatetimeIndex.get_value_maybe_box(series, key)`

pandas.DatetimeIndex.get_values

`DatetimeIndex.get_values()`
return the underlying data as an ndarray

pandas.DatetimeIndex.groupby

`DatetimeIndex.groupby(f)`

pandas.DatetimeIndex.holds_integer

`DatetimeIndex.holds_integer()`

pandas.DatetimeIndex.identical

`DatetimeIndex.identical(other)`
Similar to equals, but check that other comparable attributes are also equal

pandas.DatetimeIndex.indexer_at_time

`DatetimeIndex.indexer_at_time(time, asof=False)`
Select values at particular time of day (e.g. 9:30AM)

Parameters `time` : datetime.time or string

Returns `values_at_time` : TimeSeries

pandas.DatetimeIndex.indexer_between_time

`DatetimeIndex.indexer_between_time(start_time, end_time, include_start=True, include_end=True)`
Select values between particular times of day (e.g., 9:00-9:30AM)

Parameters `start_time` : datetime.time or string

`end_time` : datetime.time or string

`include_start` : boolean, default True

`include_end` : boolean, default True

`tz` : string or pytz.timezone or dateutil.tz.tzfile, default None

Returns `values_between_time` : TimeSeries

pandas.DatetimeIndex.insert

`DatetimeIndex.insert(loc, item)`

Make new Index inserting new item at location

Parameters `loc` : int

`item` : object

if not either a Python datetime or a numpy integer-like, returned Index dtype will be object rather than datetime.

Returns `new_index` : Index

pandas.DatetimeIndex.intersection

`DatetimeIndex.intersection(other)`

Specialized intersection for DatetimeIndex objects. May be much faster than `Index.intersection`

Parameters `other` : DatetimeIndex or array-like

Returns `y` : Index or DatetimeIndex

pandas.DatetimeIndex.is

`DatetimeIndex.is_(other)`

More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters `other` : object

other object to compare against.

Returns True if both have same underlying data, False otherwise : bool

pandas.DatetimeIndex.is_boolean

`DatetimeIndex.is_boolean()`

pandas.DatetimeIndex.is_categorical

`DatetimeIndex.is_categorical()`

pandas.DatetimeIndex.is_floating

`DatetimeIndex.is_floating()`

pandas.DatetimeIndex.is_integer

`DatetimeIndex.is_integer()`

pandas.DatetimeIndex.is_lexsorted_for_tuple

`DatetimeIndex.is_lexsorted_for_tuple(tup)`

pandas.DatetimeIndex.is_mixed

`DatetimeIndex.is_mixed()`

pandas.DatetimeIndex.is_numeric

`DatetimeIndex.is_numeric()`

pandas.DatetimeIndex.is_object

`DatetimeIndex.is_object()`

pandas.DatetimeIndex.is_type_compatible

`DatetimeIndex.is_type_compatible(typ)`

pandas.DatetimeIndex.isin

`DatetimeIndex.isin(values)`

Compute boolean array of whether each index value is found in the passed set of values

Parameters *values* : set or sequence of values

Returns *is_contained* : ndarray (boolean dtype)

pandas.DatetimeIndex.item

`DatetimeIndex.item()`

return the first element of the underlying data as a python scalar

pandas.DatetimeIndex.join

`DatetimeIndex.join(other, how='left', level=None, return_indexers=False)`

See `Index.join`

pandas.DatetimeIndex.map

`DatetimeIndex.map(f)`

pandas.DatetimeIndex.max

`DatetimeIndex.max` (*axis=None*)
return the maximum value of the Index

See also:

`numpy.ndarray.max`

pandas.DatetimeIndex.min

`DatetimeIndex.min` (*axis=None*)
return the minimum value of the Index

See also:

`numpy.ndarray.min`

pandas.DatetimeIndex.normalize

`DatetimeIndex.normalize` ()
Return DatetimeIndex with times to midnight. Length is unaltered
Returns `normalized` : DatetimeIndex

pandas.DatetimeIndex.nunique

`DatetimeIndex.nunique` (*dropna=True*)
Return number of unique elements in the object.
Excludes NA values by default.
Parameters `dropna` : boolean, default True
Don't include NaN in the count.
Returns `nunique` : int

pandas.DatetimeIndex.order

`DatetimeIndex.order` (*return_indexer=False, ascending=True*)
Return sorted copy of Index

pandas.DatetimeIndex.putmask

`DatetimeIndex.putmask` (*mask, value*)
return a new Index of the values set with the mask
See also:
`numpy.ndarray.putmask`

pandas.DatetimeIndex.ravel

`DatetimeIndex.ravel` (*order='C'*)
return an ndarray of the flattened values of the underlying data

See also:

`numpy.ndarray.ravel`

pandas.DatetimeIndex.reindex

`DatetimeIndex.reindex` (*target, method=None, level=None, limit=None*)
Create index with target's values (move/add/delete values as necessary)

Parameters *target* : an iterable

Returns *new_index* : `pd.Index`

Resulting index

indexer : `np.ndarray` or `None`

Indices of output values in original index

pandas.DatetimeIndex.rename

`DatetimeIndex.rename` (*name, inplace=False*)
Set new names on index. Defaults to returning new index.

Parameters *name* : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

pandas.DatetimeIndex.repeat

`DatetimeIndex.repeat` (*repeats, axis=None*)
Analogous to `ndarray.repeat`

pandas.DatetimeIndex.searchsorted

`DatetimeIndex.searchsorted` (*key, side='left'*)

pandas.DatetimeIndex.set_names

`DatetimeIndex.set_names` (*names, level=None, inplace=False*)
Set new names on index. Defaults to returning new index.

Parameters *names* : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)

If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)
Otherwise level must be None

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

Examples

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')],
                                names=['foo', 'bar'])

>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'bar'])
```

pandas.DatetimeIndex.set_value

DatetimeIndex.**set_value** (arr, key, value)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.DatetimeIndex.shift

DatetimeIndex.**shift** (n, freq=None)

Specialized shift which produces a DatetimeIndex

Parameters n : int

Periods to shift by

freq : DateOffset or timedelta-like, optional

Returns shifted : DatetimeIndex

pandas.DatetimeIndex.slice_indexer

DatetimeIndex.**slice_indexer** (start=None, end=None, step=None, kind=None)

Return indexer for specified label slice. Index.slice_indexer, customized to handle time slicing.

In addition to functionality provided by Index.slice_indexer, does the following:

- if both *start* and *end* are instances of *datetime.time*, it invokes *indexer_between_time*
- if *start* and *end* are both either string or None perform value-based selection in non-monotonic cases.

pandas.DatetimeIndex.slice_locs

`DatetimeIndex.slice_locs` (*start=None, end=None, step=None, kind=None*)
Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns **start, end** : int

pandas.DatetimeIndex.snap

`DatetimeIndex.snap` (*freq='S'*)
Snap time stamps to nearest occurring frequency

pandas.DatetimeIndex.sort

`DatetimeIndex.sort` (**args, **kwargs*)

pandas.DatetimeIndex.summary

`DatetimeIndex.summary` (*name=None*)
return a summarized representation

pandas.DatetimeIndex.sym_diff

`DatetimeIndex.sym_diff` (*other, result_name=None*)
Compute the sorted symmetric difference of two Index objects.

Parameters **other** : array-like

result_name : str

Returns **sym_diff** : Index

Notes

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by $(idx1 - idx2) + (idx2 - idx1)$ with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the ^ operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.DatetimeIndex.take

`DatetimeIndex.take` (*indices, axis=0*)
Analogous to `ndarray.take`

pandas.DatetimeIndex.to_datetime

`DatetimeIndex.to_datetime` (*dayfirst=False*)

pandas.DatetimeIndex.to_julian_date

`DatetimeIndex.to_julian_date` ()
Convert `DatetimeIndex` to `Float64Index` of Julian Dates. 0 Julian date is noon January 1, 4713 BC.
http://en.wikipedia.org/wiki/Julian_day

pandas.DatetimeIndex.to_native_types

`DatetimeIndex.to_native_types` (*licer=None, **kwargs*)
slice and dice then format

pandas.DatetimeIndex.to_period

`DatetimeIndex.to_period` (*freq=None*)
Cast to `PeriodIndex` at a particular frequency

pandas.DatetimeIndex.to_pydatetime

`DatetimeIndex.to_pydatetime` ()
Return `DatetimeIndex` as object `ndarray` of `datetime.datetime` objects
Returns `datetimes` : `ndarray`

pandas.DatetimeIndex.to_series

`DatetimeIndex.to_series` (*keep_tz=False*)
Create a `Series` with both index and values equal to the index keys useful with `map` for returning an indexer based on an index

Parameters `keep_tz` : optional, defaults False.

return the data keeping the timezone.

If `keep_tz` is True:

If the timezone is not set, the resulting Series will have a `datetime64[ns]` dtype. Otherwise the Series will have an object dtype; the tz will be preserved.

If `keep_tz` is False:

Series will have a `datetime64[ns]` dtype. TZ aware objects will have the tz removed.

Returns Series

pandas.DatetimeIndex.tolist

`DatetimeIndex.tolist()`

return a list of the underlying data

pandas.DatetimeIndex.transpose

`DatetimeIndex.transpose()`

return the transpose, which is by definition self

pandas.DatetimeIndex.tz_convert

`DatetimeIndex.tz_convert(tz)`

Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters `tz` : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

Returns `normalized` : DatetimeIndex

Raises `TypeError`

If DatetimeIndex is tz-naive.

pandas.DatetimeIndex.tz_localize

`DatetimeIndex.tz_localize(*args, **kwargs)`

Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters `tz` : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order

- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Returns localized : DatetimeIndex

Raises TypeError

If the DatetimeIndex is tz-aware and tz is not None.

pandas.DatetimeIndex.union

DatetimeIndex.**union** (*other*)

Specialized union for DatetimeIndex objects. If combine overlapping ranges with the same DateOffset, will be much faster than Index.union

Parameters other : DatetimeIndex or array-like

Returns y : Index or DatetimeIndex

pandas.DatetimeIndex.union_many

DatetimeIndex.**union_many** (*others*)

A bit of a hack to accelerate unioning a collection of indexes

pandas.DatetimeIndex.unique

DatetimeIndex.**unique** ()

Index.unique with handling for DatetimeIndex/PeriodIndex metadata

Returns result : DatetimeIndex or PeriodIndex

pandas.DatetimeIndex.value_counts

DatetimeIndex.**value_counts** (*normalize=False, sort=True, ascending=False, bins=None, dropna=True*)

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters normalize : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns **counts** : Series

pandas.DatetimeIndex.view

`DatetimeIndex.view` (*cls=None*)

33.9.2 Time/Date Components

<code>DatetimeIndex.year</code>	The year of the datetime
<code>DatetimeIndex.month</code>	The month as January=1, December=12
<code>DatetimeIndex.day</code>	The days of the datetime
<code>DatetimeIndex.hour</code>	The hours of the datetime
<code>DatetimeIndex.minute</code>	The minutes of the datetime
<code>DatetimeIndex.second</code>	The seconds of the datetime
<code>DatetimeIndex.microsecond</code>	The microseconds of the datetime
<code>DatetimeIndex.nanosecond</code>	The nanoseconds of the datetime
<code>DatetimeIndex.date</code>	Returns numpy array of datetime.date.
<code>DatetimeIndex.time</code>	Returns numpy array of datetime.time.
<code>DatetimeIndex.dayofyear</code>	The ordinal day of the year
<code>DatetimeIndex.weekofyear</code>	The week ordinal of the year
<code>DatetimeIndex.week</code>	The week ordinal of the year
<code>DatetimeIndex.dayofweek</code>	The day of the week with Monday=0, Sunday=6
<code>DatetimeIndex.weekday</code>	The day of the week with Monday=0, Sunday=6
<code>DatetimeIndex.quarter</code>	The quarter of the date
<code>DatetimeIndex.tz</code>	
<code>DatetimeIndex.freq</code>	get/set the frequency of the Index
<code>DatetimeIndex.freqstr</code>	return the frequency object as a string if its set, otherwise None
<code>DatetimeIndex.is_month_start</code>	Logical indicating if first day of month (defined by frequency)
<code>DatetimeIndex.is_month_end</code>	Logical indicating if last day of month (defined by frequency)
<code>DatetimeIndex.is_quarter_start</code>	Logical indicating if first day of quarter (defined by frequency)
<code>DatetimeIndex.is_quarter_end</code>	Logical indicating if last day of quarter (defined by frequency)
<code>DatetimeIndex.is_year_start</code>	Logical indicating if first day of year (defined by frequency)
<code>DatetimeIndex.is_year_end</code>	Logical indicating if last day of year (defined by frequency)
<code>DatetimeIndex.inferred_freq</code>	

pandas.DatetimeIndex.year

`DatetimeIndex.year`

The year of the datetime

pandas.DatetimeIndex.month

`DatetimeIndex.month`

The month as January=1, December=12

pandas.DatetimeIndex.day

`DatetimeIndex.day`

The days of the datetime

pandas.DatetimeIndex.hour

`DatetimeIndex.hour`

The hours of the datetime

pandas.DatetimeIndex.minute

`DatetimeIndex.minute`

The minutes of the datetime

pandas.DatetimeIndex.second

`DatetimeIndex.second`

The seconds of the datetime

pandas.DatetimeIndex.microsecond

`DatetimeIndex.microsecond`

The microseconds of the datetime

pandas.DatetimeIndex.nanosecond

`DatetimeIndex.nanosecond`

The nanoseconds of the datetime

pandas.DatetimeIndex.date

`DatetimeIndex.date`

Returns numpy array of `datetime.date`. The date part of the Timestamps.

pandas.DatetimeIndex.time

`DatetimeIndex.time`

Returns numpy array of `datetime.time`. The time part of the Timestamps.

pandas.DatetimeIndex.dayofyear

`DatetimeIndex.dayofyear`
The ordinal day of the year

pandas.DatetimeIndex.weekofyear

`DatetimeIndex.weekofyear`
The week ordinal of the year

pandas.DatetimeIndex.week

`DatetimeIndex.week`
The week ordinal of the year

pandas.DatetimeIndex.dayofweek

`DatetimeIndex.dayofweek`
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.weekday

`DatetimeIndex.weekday`
The day of the week with Monday=0, Sunday=6

pandas.DatetimeIndex.quarter

`DatetimeIndex.quarter`
The quarter of the date

pandas.DatetimeIndex.tz

`DatetimeIndex.tz = None`

pandas.DatetimeIndex.freq

`DatetimeIndex.freq`
get/set the frequency of the Index

pandas.DatetimeIndex.freqstr

`DatetimeIndex.freqstr`
return the frequency object as a string if its set, otherwise None

pandas.DatetimeIndex.is_month_start

`DatetimeIndex.is_month_start`
Logical indicating if first day of month (defined by frequency)

pandas.DatetimeIndex.is_month_end`DatetimeIndex.is_month_end`

Logical indicating if last day of month (defined by frequency)

pandas.DatetimeIndex.is_quarter_start`DatetimeIndex.is_quarter_start`

Logical indicating if first day of quarter (defined by frequency)

pandas.DatetimeIndex.is_quarter_end`DatetimeIndex.is_quarter_end`

Logical indicating if last day of quarter (defined by frequency)

pandas.DatetimeIndex.is_year_start`DatetimeIndex.is_year_start`

Logical indicating if first day of year (defined by frequency)

pandas.DatetimeIndex.is_year_end`DatetimeIndex.is_year_end`

Logical indicating if last day of year (defined by frequency)

pandas.DatetimeIndex.inferred_freq`DatetimeIndex.inferred_freq = None`

33.9.3 Selecting

<code>DatetimeIndex.indexer_at_time(time[, asof])</code>	Select values at particular time of day (e.g.
<code>DatetimeIndex.indexer_between_time(...[, ...])</code>	Select values between particular times of day (e.g., 9:00-9:30AM)

pandas.DatetimeIndex.indexer_at_time`DatetimeIndex.indexer_at_time` (*time*, *asof=False*)

Select values at particular time of day (e.g. 9:30AM)

Parameters *time* : datetime.time or string**Returns** *values_at_time* : TimeSeries**pandas.DatetimeIndex.indexer_between_time**`DatetimeIndex.indexer_between_time` (*start_time*, *end_time*, *include_start=True*, *include_end=True*)

Select values between particular times of day (e.g., 9:00-9:30AM)

Parameters `start_time` : datetime.time or string
`end_time` : datetime.time or string
`include_start` : boolean, default True
`include_end` : boolean, default True
`tz` : string or pytz.timezone or dateutil.tz.tzfile, default None
Returns `values_between_time` : TimeSeries

33.9.4 Time-specific operations

<code>DatetimeIndex.normalize()</code>	Return DatetimeIndex with times to midnight.
<code>DatetimeIndex.snap([freq])</code>	Snap time stamps to nearest occurring frequency
<code>DatetimeIndex.tz_convert(tz)</code>	Convert tz-aware DatetimeIndex from one time zone to another (using pytz/
<code>DatetimeIndex.tz_localize(*args, **kwargs)</code>	Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil),

pandas.DatetimeIndex.normalize

`DatetimeIndex.normalize()`
 Return DatetimeIndex with times to midnight. Length is unaltered
Returns `normalized` : DatetimeIndex

pandas.DatetimeIndex.snap

`DatetimeIndex.snap(freq='S')`
 Snap time stamps to nearest occurring frequency

pandas.DatetimeIndex.tz_convert

`DatetimeIndex.tz_convert(tz)`
 Convert tz-aware DatetimeIndex from one time zone to another (using pytz/dateutil)

Parameters `tz` : string, pytz.timezone, dateutil.tz.tzfile or None
 Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding UTC time.

Returns `normalized` : DatetimeIndex

Raises `TypeError`
 If DatetimeIndex is tz-naive.

pandas.DatetimeIndex.tz_localize

`DatetimeIndex.tz_localize(*args, **kwargs)`
 Localize tz-naive DatetimeIndex to given time zone (using pytz/dateutil), or remove timezone from tz-aware DatetimeIndex

Parameters `tz` : string, pytz.timezone, dateutil.tz.tzfile or None

Time zone for time. Corresponding timestamps would be converted to time zone of the TimeSeries. None will remove timezone holding local time.

ambiguous : 'infer', bool-ndarray, 'NaT', default 'raise'

- 'infer' will attempt to infer fall dst-transition hours based on order
- bool-ndarray where True signifies a DST time, False signifies a non-DST time (note that this flag is only applicable for ambiguous times)
- 'NaT' will return NaT where there are ambiguous times
- 'raise' will raise an AmbiguousTimeError if there are ambiguous times

infer_dst : boolean, default False (DEPRECATED)

Attempt to infer fall dst-transition hours based on order

Returns localized : DatetimeIndex

Raises TypeError

If the DatetimeIndex is tz-aware and tz is not None.

33.9.5 Conversion

<code>DatetimeIndex.to_datetime([dayfirst])</code>	
<code>DatetimeIndex.to_period([freq])</code>	Cast to PeriodIndex at a particular frequency
<code>DatetimeIndex.to_pydatetime()</code>	Return DatetimeIndex as object ndarray of datetime.datetime objects
<code>DatetimeIndex.to_series([keep_tz])</code>	Create a Series with both index and values equal to the index keys

pandas.DatetimeIndex.to_datetime

`DatetimeIndex.to_datetime (dayfirst=False)`

pandas.DatetimeIndex.to_period

`DatetimeIndex.to_period (freq=None)`
Cast to PeriodIndex at a particular frequency

pandas.DatetimeIndex.to_pydatetime

`DatetimeIndex.to_pydatetime ()`
Return DatetimeIndex as object ndarray of datetime.datetime objects

Returns datetimes : ndarray

pandas.DatetimeIndex.to_series

`DatetimeIndex.to_series (keep_tz=False)`
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Parameters keep_tz : optional, defaults False.

return the data keeping the timezone.

If keep_tz is True:

If the timezone is not set, the resulting Series will have a datetime64[ns] dtype. Otherwise the Series will have an object dtype; the tz will be preserved.

If keep_tz is False:

Series will have a datetime64[ns] dtype. TZ aware objects will have the tz removed.

Returns Series

33.10 TimedeltaIndex

`TimedeltaIndex` Immutable ndarray of timedelta64 data, represented internally as int64, and

33.10.1 pandas.TimedeltaIndex

class `pandas.TimedeltaIndex`

Immutable ndarray of timedelta64 data, represented internally as int64, and which can be boxed to timedelta objects

Parameters **data** : array-like (1-dimensional), optional

Optional timedelta-like data to construct index with

unit: **unit of the arg (D,h,m,s,ms,us,ns) denote the unit, optional**

which is an integer/float number

freq: **a frequency for the index, optional**

copy : bool

Make a copy of input ndarray

start : starting value, timedelta-like, optional

If data is None, start is used as the start point in generating regular timedelta data.

periods : int, optional, > 0

Number of periods to generate, if generating index. Takes precedence over end argument

end : end time, timedelta-like, optional

If periods is none, generated index will extend to first conforming time on or just past end argument

closed : string or None, default None

Make the interval closed with respect to the given frequency to the 'left', 'right', or both sides (None)

name : object

Name to be stored in the index

Attributes

<code>T</code>	return the transpose, which is by definition self
<code>asi8</code>	
<code>asobject</code>	
<code>base</code>	return the base object if the memory of the underlying data is shared
<code>components</code>	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds)
<code>data</code>	return the data pointer of the underlying data
<code>days</code>	Number of days for each element.
<code>dtype</code>	
<code>flags</code>	
<code>freqstr</code>	return the frequency object as a string if its set, otherwise None
<code>has_duplicates</code>	
<code>inferred_type</code>	
<code>is_all_dates</code>	
<code>is_monotonic</code>	alias for <code>is_monotonic_increasing</code> (deprecated)
<code>is_monotonic_decreasing</code>	return if the index is monotonic decreasing (only equal or
<code>is_monotonic_increasing</code>	return if the index is monotonic increasing (only equal or
<code>itemsize</code>	return the size of the dtype of the item of the underlying data
<code>microseconds</code>	Number of microseconds (≥ 0 and less than 1 second) for each element.
<code>names</code>	
<code>nanoseconds</code>	Number of nanoseconds (≥ 0 and less than 1 microsecond) for each element.
<code>nbytes</code>	return the number of bytes in the underlying data
<code>ndim</code>	return the number of dimensions of the underlying data, by definition 1
<code>nlevels</code>	
<code>seconds</code>	Number of seconds (≥ 0 and less than 1 day) for each element.
<code>shape</code>	return a tuple of the shape of the underlying data
<code>size</code>	return the number of elements in the underlying data
<code>strides</code>	return the strides of the underlying data
<code>values</code>	return the underlying data as an ndarray

pandas.TimedeltaIndex.T`TimedeltaIndex.T`

return the transpose, which is by definition self

pandas.TimedeltaIndex.asi8`TimedeltaIndex.asi8`**pandas.TimedeltaIndex.asobject**`TimedeltaIndex.asobject`**pandas.TimedeltaIndex.base**`TimedeltaIndex.base`

return the base object if the memory of the underlying data is shared

pandas.TimedeltaIndex.components

`TimedeltaIndex.components`

Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns a DataFrame

pandas.TimedeltaIndex.data

`TimedeltaIndex.data`

return the data pointer of the underlying data

pandas.TimedeltaIndex.days

`TimedeltaIndex.days`

Number of days for each element.

pandas.TimedeltaIndex.dtype

`TimedeltaIndex.dtype`

pandas.TimedeltaIndex.flags

`TimedeltaIndex.flags`

pandas.TimedeltaIndex.freqstr

`TimedeltaIndex.freqstr`

return the frequency object as a string if its set, otherwise None

pandas.TimedeltaIndex.has_duplicates

`TimedeltaIndex.has_duplicates`

pandas.TimedeltaIndex.inferred_type

`TimedeltaIndex.inferred_type`

pandas.TimedeltaIndex.is_all_dates

`TimedeltaIndex.is_all_dates`

pandas.TimedeltaIndex.is_monotonic

`TimedeltaIndex.is_monotonic`

alias for `is_monotonic_increasing` (deprecated)

pandas.TimedeltaIndex.is_monotonic_decreasing

`TimedeltaIndex.is_monotonic_decreasing`

return if the index is monotonic decreasing (only equal or decreasing) values.

pandas.TimedeltaIndex.is_monotonic_increasing

`TimedeltaIndex.is_monotonic_increasing`

return if the index is monotonic increasing (only equal or increasing) values.

pandas.TimedeltaIndex.itemsize

`TimedeltaIndex.itemsize`

return the size of the dtype of the item of the underlying data

pandas.TimedeltaIndex.microseconds

`TimedeltaIndex.microseconds`

Number of microseconds (≥ 0 and less than 1 second) for each element.

pandas.TimedeltaIndex.names

`TimedeltaIndex.names`

pandas.TimedeltaIndex.nanoseconds

`TimedeltaIndex.nanoseconds`

Number of nanoseconds (≥ 0 and less than 1 microsecond) for each element.

pandas.TimedeltaIndex.nbytes

`TimedeltaIndex.nbytes`

return the number of bytes in the underlying data

pandas.TimedeltaIndex.ndim

`TimedeltaIndex.ndim`

return the number of dimensions of the underlying data, by definition 1

pandas.TimedeltaIndex.nlevels

`TimedeltaIndex.nlevels`

pandas.TimedeltaIndex.seconds

`TimedeltaIndex.seconds`

Number of seconds (≥ 0 and less than 1 day) for each element.

pandas.TimedeltaIndex.shape

`TimedeltaIndex.shape`

return a tuple of the shape of the underlying data

pandas.TimedeltaIndex.size

`TimedeltaIndex.size`

return the number of elements in the underlying data

pandas.TimedeltaIndex.strides

`TimedeltaIndex.strides`

return the strides of the underlying data

pandas.TimedeltaIndex.values

`TimedeltaIndex.values`

return the underlying data as an ndarray

freq	
hasnans	
inferred_freq	
is_unique	
name	
resolution	

Methods

`all([other])`
`any([other])`
`append(other)`
`argmax([axis])`
`argmin([axis])`
`argsort(*args, **kwargs)`
`asof(label)`
`asof_locs(where, mask)`
`astype(dtype)`
`copy([names, name, dtype, deep])`
`delete(loc)`
`diff(*args, **kwargs)`
`difference(other)`
`drop(labels[, errors])`
`drop_duplicates([take_last])`
`duplicated([take_last])`
`equals(other)`
`factorize([sort, na_sentinel])`
`format([name, formatter])`
`get_duplicates()`
`get_indexer(target[, method, limit])`

Append a collection of Index options together
 return a ndarray of the maximum argument indexer
 return a ndarray of the minimum argument indexer
 return an ndarray indexer of the underlying data
 For a sorted index, return the most recent label up to and including the passed label
 where : array of timestamps

Make a copy of this object.
 Make a new DatetimeIndex with passed location(s) deleted.

Compute sorted set difference of two Index objects
 Make new Index with passed list of labels deleted
 Return Index with duplicate values removed
 Return boolean np.array denoting duplicate values
 Determines if two Index objects contain the same elements.
 Encode the object as an enumerated type or categorical variable
 Render a string representation of the Index

Compute indexer and mask for new index given the current index.

Continued on next page

Table 33.108 – continued from previous page

<code>get_indexer_for(target, **kwargs)</code>	guaranteed return of an indexer even when non-unique
<code>get_indexer_non_unique(target)</code>	return an indexer suitable for taking from a non unique index
<code>get_level_values(level)</code>	Return vector of label values for requested level, equal to the length
<code>get_loc(key[, method])</code>	Get integer location for requested label
<code>get_slice_bound(label, side, kind)</code>	Calculate slice bound that corresponds to given label.
<code>get_value(series, key)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>get_value_maybe_box(series, key)</code>	
<code>get_values()</code>	return the underlying data as an ndarray
<code>groupby(f)</code>	
<code>holds_integer()</code>	
<code>identical(other)</code>	Similar to equals, but check that other comparable attributes are
<code>insert(loc, item)</code>	Make new Index inserting new item at location
<code>intersection(other)</code>	Specialized intersection for TimedeltaIndex objects.
<code>is_(other)</code>	More flexible, faster check like <code>is</code> but that works through views
<code>is_boolean()</code>	
<code>is_categorical()</code>	
<code>is_floating()</code>	
<code>is_integer()</code>	
<code>is_lexsorted_for_tuple(tup)</code>	
<code>is_mixed()</code>	
<code>is_numeric()</code>	
<code>is_object()</code>	
<code>is_type_compatible(typ)</code>	
<code>isin(values)</code>	Compute boolean array of whether each index value is found in the
<code>item()</code>	return the first element of the underlying data as a python scalar
<code>join(other[, how, level, return_indexers])</code>	See <code>Index.join</code>
<code>map(f)</code>	
<code>max([axis])</code>	return the maximum value of the Index
<code>min([axis])</code>	return the minimum value of the Index
<code>nunique([dropna])</code>	Return number of unique elements in the object.
<code>order([return_indexer, ascending])</code>	Return sorted copy of Index
<code>putmask(mask, value)</code>	return a new Index of the values set with the mask
<code>ravel([order])</code>	return an ndarray of the flattened values of the underlying data
<code>reindex(target[, method, level, limit])</code>	Create index with target's values (move/add/delete values as necessary)
<code>rename(name[, inplace])</code>	Set new names on index.
<code>repeat(repeats[, axis])</code>	Analogous to <code>ndarray.repeat</code>
<code>searchsorted(key[, side])</code>	
<code>set_names(names[, level, inplace])</code>	Set new names on index.
<code>set_value(arr, key, value)</code>	Fast lookup of value from 1-dimensional ndarray.
<code>shift(n[, freq])</code>	Specialized shift which produces a <code>DatetimeIndex</code>
<code>slice_indexer([start, end, step, kind])</code>	For an ordered Index, compute the slice indexer for input labels and
<code>slice_locs([start, end, step, kind])</code>	Compute slice locations for input labels.
<code>sort(*args, **kwargs)</code>	
<code>str</code>	alias of <code>StringMethods</code>
<code>summary([name])</code>	return a summarized representation
<code>sym_diff(other[, result_name])</code>	Compute the sorted symmetric difference of two Index objects.
<code>take(indices[, axis])</code>	Analogous to <code>ndarray.take</code>
<code>to_datetime([dayfirst])</code>	For an Index containing strings or <code>datetime.datetime</code> objects, attempt
<code>to_native_types([slicer])</code>	slice and dice then format
<code>to_pytimedelta()</code>	Return <code>TimedeltaIndex</code> as object ndarray of <code>datetime.timedelta</code> objects
<code>to_series(**kwargs)</code>	Create a Series with both index and values equal to the index keys
<code>tolist()</code>	return a list of the underlying data

Continued on next page

Table 33.108 – continued from previous page

<code>transpose()</code>	return the transpose, which is by definition self
<code>union(other)</code>	Specialized union for TimedeltaIndex objects.
<code>unique()</code>	Index.unique with handling for DatetimeIndex/PeriodIndex metadata
<code>value_counts([normalize, sort, ascending, ...])</code>	Returns object containing counts of unique values.
<code>view([cls])</code>	

pandas.TimedeltaIndex.all

`TimedeltaIndex.all` (*other=None*)

pandas.TimedeltaIndex.any

`TimedeltaIndex.any` (*other=None*)

pandas.TimedeltaIndex.append

`TimedeltaIndex.append` (*other*)

Append a collection of Index options together

Parameters *other* : Index or list/tuple of indices

Returns *appended* : Index

pandas.TimedeltaIndex.argmax

`TimedeltaIndex.argmax` (*axis=None*)

return a ndarray of the maximum argument indexer

See also:

`numpy.ndarray.argmax`

pandas.TimedeltaIndex.argmin

`TimedeltaIndex.argmin` (*axis=None*)

return a ndarray of the minimum argument indexer

See also:

`numpy.ndarray.argmin`

pandas.TimedeltaIndex.argsort

`TimedeltaIndex.argsort` (**args, **kwargs*)

return an ndarray indexer of the underlying data

See also:

`numpy.ndarray.argsort`

pandas.TimedeltaIndex.asof

`TimedeltaIndex.asof` (*label*)

For a sorted index, return the most recent label up to and including the passed label. Return NaN if not found.

See also:

`get_loc` `asof` is a thin wrapper around `get_loc` with `method='pad'`

pandas.TimedeltaIndex.asof_locs

`TimedeltaIndex.asof_locs` (*where, mask*)

where : array of timestamps *mask* : array of booleans where data is not NA

pandas.TimedeltaIndex.astype

`TimedeltaIndex.astype` (*dtype*)

pandas.TimedeltaIndex.copy

`TimedeltaIndex.copy` (*names=None, name=None, dtype=None, deep=False*)

Make a copy of this object. Name and dtype sets those attributes on the new object.

Parameters *name* : string, optional

dtype : numpy dtype or pandas type

Returns *copy* : Index

Notes

In most cases, there should be no functional difference from using `deep`, but if `deep` is passed it will attempt to deepcopy.

pandas.TimedeltaIndex.delete

`TimedeltaIndex.delete` (*loc*)

Make a new DatetimeIndex with passed location(s) deleted.

Parameters *loc*: int, slice or array of ints

Indicate which sub-arrays to remove.

Returns *new_index* : TimedeltaIndex

pandas.TimedeltaIndex.diff

`TimedeltaIndex.diff` (**args, **kwargs*)

pandas.TimedeltaIndex.difference

`TimedeltaIndex.difference` (*other*)

Compute sorted set difference of two Index objects

Parameters `other` : Index or array-like

Returns `diff` : Index

Notes

One can do either of these and achieve the same result

```
>>> index.difference(index2)
```

pandas.TimedeltaIndex.drop

`TimedeltaIndex.drop` (*labels*, *errors='raise'*)

Make new Index with passed list of labels deleted

Parameters `labels` : array-like

`errors` : { 'ignore', 'raise' }, default 'raise'

If 'ignore', suppress error and existing labels are dropped.

Returns `dropped` : Index

pandas.TimedeltaIndex.drop_duplicates

`TimedeltaIndex.drop_duplicates` (*take_last=False*)

Return Index with duplicate values removed

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `deduplicated` : Index

pandas.TimedeltaIndex.duplicated

`TimedeltaIndex.duplicated` (*take_last=False*)

Return boolean np.array denoting duplicate values

Parameters `take_last` : boolean, default False

Take the last observed index in a group. Default first

Returns `duplicated` : np.array

pandas.TimedeltaIndex.equals

`TimedeltaIndex.equals` (*other*)

Determines if two Index objects contain the same elements.

pandas.TimedeltaIndex.factorize

`TimedeltaIndex.factorize (sort=False, na_sentinel=-1)`

Encode the object as an enumerated type or categorical variable

Parameters `sort` : boolean, default False

Sort by values

na_sentinel: int, default -1

Value to mark “not found”

Returns `labels` : the indexer to the original array

`uniques` : the unique Index

pandas.TimedeltaIndex.format

`TimedeltaIndex.format (name=False, formatter=None, **kwargs)`

Render a string representation of the Index

pandas.TimedeltaIndex.get_duplicates

`TimedeltaIndex.get_duplicates ()`

pandas.TimedeltaIndex.get_indexer

`TimedeltaIndex.get_indexer (target, method=None, limit=None)`

Compute indexer and mask for new index given the current index. The indexer should be then used as an input to `ndarray.take` to align the current data to the new index.

Parameters `target` : Index

method : {None, ‘pad’/‘ffill’, ‘backfill’/‘bfill’, ‘nearest’}

- default: exact matches only.
- pad / ffill: find the PREVIOUS index value if no exact match.
- backfill / bfill: use NEXT index value if no exact match
- nearest: use the NEAREST index value if no exact match. Tied distances are broken by preferring the larger index value.

limit : int

Maximum number of consecutive labels in `target` to match for inexact matches.

Returns `indexer` : ndarray of int

Integers from 0 to n - 1 indicating that the index at these positions matches the corresponding target values. Missing values in the target are marked by -1.

Examples

```
>>> indexer = index.get_indexer(new_index)
>>> new_values = cur_values.take(indexer)
```

pandas.TimedeltaIndex.get_indexer_for

`TimedeltaIndex.get_indexer_for(target, **kwargs)`
guaranteed return of an indexer even when non-unique

pandas.TimedeltaIndex.get_indexer_non_unique

`TimedeltaIndex.get_indexer_non_unique(target)`
return an indexer suitable for taking from a non unique index return the labels in the same order as the target, and return a missing indexer into the target (missing are marked as -1 in the indexer); target must be an iterable

pandas.TimedeltaIndex.get_level_values

`TimedeltaIndex.get_level_values(level)`
Return vector of label values for requested level, equal to the length of the index

Parameters `level` : int

Returns `values` : ndarray

pandas.TimedeltaIndex.get_loc

`TimedeltaIndex.get_loc(key, method=None)`
Get integer location for requested label

Returns `loc` : int

pandas.TimedeltaIndex.get_slice_bound

`TimedeltaIndex.get_slice_bound(label, side, kind)`
Calculate slice bound that corresponds to given label.
Returns leftmost (one-past-the-rightmost if `side=='right'`) position of given label.

Parameters `label` : object

side : {'left', 'right'}

kind : string / None, the type of indexer

pandas.TimedeltaIndex.get_value

`TimedeltaIndex.get_value(series, key)`
Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.TimedeltaIndex.get_value_maybe_box

`TimedeltaIndex.get_value_maybe_box(series, key)`

pandas.TimedeltaIndex.get_values

`TimedeltaIndex.get_values()`
return the underlying data as an ndarray

pandas.TimedeltaIndex.groupby

`TimedeltaIndex.groupby(f)`

pandas.TimedeltaIndex.holds_integer

`TimedeltaIndex.holds_integer()`

pandas.TimedeltaIndex.identical

`TimedeltaIndex.identical(other)`
Similar to `equals`, but check that other comparable attributes are also equal

pandas.TimedeltaIndex.insert

`TimedeltaIndex.insert(loc, item)`
Make new Index inserting new item at location

Parameters `loc` : int

`item` : object

if not either a Python datetime or a numpy integer-like, returned Index dtype will be object rather than datetime.

Returns `new_index` : Index

pandas.TimedeltaIndex.intersection

`TimedeltaIndex.intersection(other)`
Specialized intersection for `TimedeltaIndex` objects. May be much faster than `Index.intersection`

Parameters `other` : `TimedeltaIndex` or array-like

Returns `y` : Index or `TimedeltaIndex`

pandas.TimedeltaIndex.is

`TimedeltaIndex.is_(other)`
More flexible, faster check like `is` but that works through views

Note: this is *not* the same as `Index.identical()`, which checks that metadata is also the same.

Parameters `other` : object

other object to compare against.

Returns True if both have same underlying data, False otherwise : bool

pandas.TimedeltaIndex.is_boolean

`TimedeltaIndex.is_boolean()`

pandas.TimedeltaIndex.is_categorical

`TimedeltaIndex.is_categorical()`

pandas.TimedeltaIndex.is_floating

`TimedeltaIndex.is_floating()`

pandas.TimedeltaIndex.is_integer

`TimedeltaIndex.is_integer()`

pandas.TimedeltaIndex.is_lexsorted_for_tuple

`TimedeltaIndex.is_lexsorted_for_tuple(tup)`

pandas.TimedeltaIndex.is_mixed

`TimedeltaIndex.is_mixed()`

pandas.TimedeltaIndex.is_numeric

`TimedeltaIndex.is_numeric()`

pandas.TimedeltaIndex.is_object

`TimedeltaIndex.is_object()`

pandas.TimedeltaIndex.is_type_compatible

`TimedeltaIndex.is_type_compatible(typ)`

pandas.TimedeltaIndex.isin

`TimedeltaIndex.isin(values)`

Compute boolean array of whether each index value is found in the passed set of values

Parameters *values* : set or sequence of values

Returns *is_contained* : ndarray (boolean dtype)

pandas.TimedeltaIndex.item

`TimedeltaIndex.item()`
return the first element of the underlying data as a python scalar

pandas.TimedeltaIndex.join

`TimedeltaIndex.join(other, how='left', level=None, return_indexers=False)`
See `Index.join`

pandas.TimedeltaIndex.map

`TimedeltaIndex.map(f)`

pandas.TimedeltaIndex.max

`TimedeltaIndex.max(axis=None)`
return the maximum value of the Index

See also:

`numpy.ndarray.max`

pandas.TimedeltaIndex.min

`TimedeltaIndex.min(axis=None)`
return the minimum value of the Index

See also:

`numpy.ndarray.min`

pandas.TimedeltaIndex.nunique

`TimedeltaIndex.nunique(dropna=True)`
Return number of unique elements in the object.

Excludes NA values by default.

Parameters `dropna` : boolean, default True

Don't include NaN in the count.

Returns `nunique` : int

pandas.TimedeltaIndex.order

`TimedeltaIndex.order(return_indexer=False, ascending=True)`
Return sorted copy of Index

pandas.TimedeltaIndex.putmask

`TimedeltaIndex.putmask(mask, value)`
return a new Index of the values set with the mask

See also:

`numpy.ndarray.putmask`

pandas.TimedeltaIndex.ravel

`TimedeltaIndex.ravel(order='C')`
return an ndarray of the flattened values of the underlying data

See also:

`numpy.ndarray.ravel`

pandas.TimedeltaIndex.reindex

`TimedeltaIndex.reindex(target, method=None, level=None, limit=None)`
Create index with target's values (move/add/delete values as necessary)

Parameters `target` : an iterable

Returns `new_index` : `pd.Index`

Resulting index

indexer : `np.ndarray` or `None`

Indices of output values in original index

pandas.TimedeltaIndex.rename

`TimedeltaIndex.rename(name, inplace=False)`
Set new names on index. Defaults to returning new index.

Parameters `name` : str or list

name to set

inplace : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]

pandas.TimedeltaIndex.repeat

`TimedeltaIndex.repeat(repeats, axis=None)`
Analogous to `ndarray.repeat`

pandas.TimedeltaIndex.searchsorted

`TimedeltaIndex.searchsorted(key, side='left')`

pandas.TimedeltaIndex.set_names`TimedeltaIndex.set_names` (*names*, *level=None*, *inplace=False*)

Set new names on index. Defaults to returning new index.

Parameters *names* : str or sequence

name(s) to set

level : int or level name, or sequence of int / level names (default None)If the index is a MultiIndex (hierarchical), level(s) to set (None for all levels)
Otherwise level must be None**inplace** : bool

if True, mutates in place

Returns new index (of same type and class...etc) [if inplace, returns None]**Examples**

```
>>> Index([1, 2, 3, 4]).set_names('foo')
Int64Index([1, 2, 3, 4], dtype='int64')
>>> Index([1, 2, 3, 4]).set_names(['foo'])
Int64Index([1, 2, 3, 4], dtype='int64')
>>> idx = MultiIndex.from_tuples([(1, u'one'), (1, u'two'),
                                (2, u'one'), (2, u'two')],
                                names=['foo', 'bar'])

>>> idx.set_names(['baz', 'quz'])
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'quz'])
>>> idx.set_names('baz', level=0)
MultiIndex(levels=[[1, 2], [u'one', u'two']],
            labels=[[0, 0, 1, 1], [0, 1, 0, 1]],
            names=[u'baz', u'bar'])
```

pandas.TimedeltaIndex.set_value`TimedeltaIndex.set_value` (*arr*, *key*, *value*)

Fast lookup of value from 1-dimensional ndarray. Only use this if you know what you're doing

pandas.TimedeltaIndex.shift`TimedeltaIndex.shift` (*n*, *freq=None*)

Specialized shift which produces a DatetimeIndex

Parameters *n* : int

Periods to shift by

freq : DateOffset or timedelta-like, optional**Returns** *shifted* : DatetimeIndex

pandas.TimedeltaIndex.slice_indexer

`TimedeltaIndex.slice_indexer` (*start=None, end=None, step=None, kind=None*)

For an ordered Index, compute the slice indexer for input labels and step

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, default None

kind : string, default None

Returns **indexer** : ndarray or slice

Notes

This function assumes that the data is sorted, so use at your own peril

pandas.TimedeltaIndex.slice_locs

`TimedeltaIndex.slice_locs` (*start=None, end=None, step=None, kind=None*)

Compute slice locations for input labels.

Parameters **start** : label, default None

If None, defaults to the beginning

end : label, default None

If None, defaults to the end

step : int, defaults None

If None, defaults to 1

kind : string, defaults None

Returns **start, end** : int

pandas.TimedeltaIndex.sort

`TimedeltaIndex.sort` (**args, **kwargs*)

pandas.TimedeltaIndex.summary

`TimedeltaIndex.summary` (*name=None*)

return a summarized representation

pandas.TimedeltaIndex.sym_diff`TimedeltaIndex.sym_diff` (*other*, *result_name=None*)

Compute the sorted symmetric difference of two Index objects.

Parameters *other* : array-like**result_name** : str**Returns** *sym_diff* : Index**Notes**

`sym_diff` contains elements that appear in either `idx1` or `idx2` but not both. Equivalent to the Index created by $(idx1 - idx2) + (idx2 - idx1)$ with duplicates dropped.

The sorting of a result containing NaN values is not guaranteed across Python versions. See GitHub issue #6444.

Examples

```
>>> idx1 = Index([1, 2, 3, 4])
>>> idx2 = Index([2, 3, 4, 5])
>>> idx1.sym_diff(idx2)
Int64Index([1, 5], dtype='int64')
```

You can also use the `^` operator:

```
>>> idx1 ^ idx2
Int64Index([1, 5], dtype='int64')
```

pandas.TimedeltaIndex.take`TimedeltaIndex.take` (*indices*, *axis=0*)Analogous to `ndarray.take`**pandas.TimedeltaIndex.to_datetime**`TimedeltaIndex.to_datetime` (*dayfirst=False*)For an Index containing strings or `datetime.datetime` objects, attempt conversion to `DatetimeIndex`**pandas.TimedeltaIndex.to_native_types**`TimedeltaIndex.to_native_types` (*slicer=None, **kwargs*)

slice and dice then format

pandas.TimedeltaIndex.to_pytimedelta`TimedeltaIndex.to_pytimedelta` ()Return `TimedeltaIndex` as object ndarray of `datetime.timedelta` objects**Returns** *datetimes* : ndarray

pandas.TimedeltaIndex.to_series

`TimedeltaIndex.to_series(**kwargs)`

Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

pandas.TimedeltaIndex.tolist

`TimedeltaIndex.tolist()`

return a list of the underlying data

pandas.TimedeltaIndex.transpose

`TimedeltaIndex.transpose()`

return the transpose, which is by definition self

pandas.TimedeltaIndex.union

`TimedeltaIndex.union(other)`

Specialized union for TimedeltaIndex objects. If combine overlapping ranges with the same DateOffset, will be much faster than Index.union

Parameters other : TimedeltaIndex or array-like

Returns y : Index or TimedeltaIndex

pandas.TimedeltaIndex.unique

`TimedeltaIndex.unique()`

Index.unique with handling for DatetimeIndex/PeriodIndex metadata

Returns result : DatetimeIndex or PeriodIndex

pandas.TimedeltaIndex.value_counts

`TimedeltaIndex.value_counts(normalize=False, sort=True, ascending=False, bins=None, dropna=True)`

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters normalize : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns **counts** : Series

pandas.TimedeltaIndex.view

`TimedeltaIndex.view(cls=None)`

33.10.2 Components

<code>TimedeltaIndex.days</code>	Number of days for each element.
<code>TimedeltaIndex.seconds</code>	Number of seconds (≥ 0 and less than 1 day) for each element.
<code>TimedeltaIndex.microseconds</code>	Number of microseconds (≥ 0 and less than 1 second) for each element.
<code>TimedeltaIndex.nanoseconds</code>	Number of nanoseconds (≥ 0 and less than 1 microsecond) for each element.
<code>TimedeltaIndex.components</code>	Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.
<code>TimedeltaIndex.inferred_freq</code>	

pandas.TimedeltaIndex.days

`TimedeltaIndex.days`
Number of days for each element.

pandas.TimedeltaIndex.seconds

`TimedeltaIndex.seconds`
Number of seconds (≥ 0 and less than 1 day) for each element.

pandas.TimedeltaIndex.microseconds

`TimedeltaIndex.microseconds`
Number of microseconds (≥ 0 and less than 1 second) for each element.

pandas.TimedeltaIndex.nanoseconds

`TimedeltaIndex.nanoseconds`
Number of nanoseconds (≥ 0 and less than 1 microsecond) for each element.

pandas.TimedeltaIndex.components

`TimedeltaIndex.components`
Return a dataframe of the components (days, hours, minutes, seconds, milliseconds, microseconds, nanoseconds) of the Timedeltas.

Returns a DataFrame

pandas.TimedeltaIndex.inferred_freq

TimedeltaIndex.inferred_freq = None

33.10.3 Conversion

<code>TimedeltaIndex.to_pytimedelta()</code>	Return TimedeltaIndex as object ndarray of datetime.timedelta objects
<code>TimedeltaIndex.to_series(**kwargs)</code>	Create a Series with both index and values equal to the index keys

pandas.TimedeltaIndex.to_pytimedelta

TimedeltaIndex.to_pytimedelta()
Return TimedeltaIndex as object ndarray of datetime.timedelta objects

Returns datetimes : ndarray

pandas.TimedeltaIndex.to_series

TimedeltaIndex.to_series(**kwargs)
Create a Series with both index and values equal to the index keys useful with map for returning an indexer based on an index

Returns Series : dtype will be based on the type of the Index values.

33.11 GroupBy

GroupBy objects are returned by groupby calls: `pandas.DataFrame.groupby()`, `pandas.Series.groupby()`, etc.

33.11.1 Indexing, iteration

<code>GroupBy.__iter__()</code>	Groupby iterator
<code>GroupBy.groups</code>	dict {group name -> group labels}
<code>GroupBy.indices</code>	dict {group name -> group indices}
<code>GroupBy.get_group(name[, obj])</code>	Constructs NDFrame from group with provided name

pandas.core.groupby.GroupBy.__iter__

GroupBy.__iter__()
Groupby iterator

Returns Generator yielding sequence of (name, subsetted object)
for each group

pandas.core.groupby.GroupBy.groups

GroupBy.**groups**
dict {group name -> group labels}

pandas.core.groupby.GroupBy.indices

GroupBy.**indices**
dict {group name -> group indices}

pandas.core.groupby.GroupBy.get_group

GroupBy.**get_group** (*name*, *obj=None*)
Constructs NDFrame from group with provided name

Parameters **name** : object

the name of the group to get as a DataFrame

obj : NDFrame, default None

the NDFrame to take the DataFrame out of. If it is None, the object groupby was called on will be used

Returns **group** : type of obj

`Grouper`([key, level, freq, axis, sort]) A Grouper allows the user to specify a groupby instruction for a target object

pandas.Grouper

class pandas.**Grouper** (*key=None*, *level=None*, *freq=None*, *axis=0*, *sort=False*)

A Grouper allows the user to specify a groupby instruction for a target object

This specification will select a column via the key parameter, or if the level and/or axis parameters are given, a level of the index of the target object.

These are local specifications and will override 'global' settings, that is the parameters axis and level which are passed to the groupby itself.

Parameters **key** : string, defaults to None

groupby key, which selects the grouping column of the target

level : name/number, defaults to None

the level for the target index

freq : string / frequency object, defaults to None

This will groupby the specified frequency if the target selection (via key or level) is a datetime-like object

axis : number/name of the axis, defaults to 0

sort : boolean, default to False

whether to sort the resulting labels

additional kwargs to control time-like groupers (when freq is passed)

closed : closed end of interval; left or right

label : interval boundary to use for labeling; left or right

convention : { 'start', 'end', 'e', 's' }

If grouper is PeriodIndex

Returns A specification for a groupby instruction

Examples

```
>>> df.groupby(Grouper(key='A')) : syntatic sugar for df.groupby('A')
>>> df.groupby(Grouper(key='date',freq='60s')) : specify a resample on the column 'date'
>>> df.groupby(Grouper(level='date',freq='60s',axis=1)) :
    specify a resample on the level 'date' on the columns axis with a frequency of 60s
```

Attributes

`ax`
`groups`

pandas.Grouper.ax

Grouper.**ax**

pandas.Grouper.groups

Grouper.**groups**

33.11.2 Function application

<code>GroupBy.apply(func, *args, **kwargs)</code>	Apply function and combine results together in an intelligent way.
<code>GroupBy.aggregate(func, *args, **kwargs)</code>	
<code>GroupBy.transform(func, *args, **kwargs)</code>	

pandas.core.groupby.GroupBy.apply

GroupBy.**apply** (*func*, *args, **kwargs)

Apply function and combine results together in an intelligent way. The split-apply-combine combination rules attempt to be as common sense based as possible. For example:

case 1: group DataFrame apply aggregation function (f(chunk) -> Series) yield DataFrame, with group axis having group labels

case 2: group DataFrame apply transform function ((f(chunk) -> DataFrame with same indexes) yield DataFrame with resulting chunks glued together

case 3: group Series apply function with f(chunk) -> DataFrame yield DataFrame with result of chunks glued together

Parameters `func` : function

Returns `applied` : type depending on grouped object and function

See also:

`aggregate`, `transform`

Notes

See online documentation for full exposition on how to use `apply`.

In the current implementation `apply` calls `func` twice on the first group to decide whether it can take a fast or slow code path. This can lead to unexpected behavior if `func` has side-effects, as they will take effect twice for the first group.

`pandas.core.groupby.GroupBy.aggregate`

`GroupBy.aggregate` (*func*, *args, **kwargs)

`pandas.core.groupby.GroupBy.transform`

`GroupBy.transform` (*func*, *args, **kwargs)

33.11.3 Computations / Descriptive Stats

<code>GroupBy.count([axis])</code>	
<code>GroupBy.cumcount([ascending])</code>	Number each item in each group from 0 to the length of that group - 1.
<code>GroupBy.first()</code>	Compute first of group values
<code>GroupBy.head([n])</code>	Returns first n rows of each group.
<code>GroupBy.last()</code>	Compute last of group values
<code>GroupBy.max()</code>	Compute max of group values
<code>GroupBy.mean()</code>	Compute mean of groups, excluding missing values
<code>GroupBy.median()</code>	Compute median of groups, excluding missing values
<code>GroupBy.min()</code>	Compute min of group values
<code>GroupBy.nth(n[, dropna])</code>	Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.
<code>GroupBy.ohlc()</code>	Compute sum of values, excluding missing values
<code>GroupBy.prod()</code>	Compute prod of group values
<code>GroupBy.size()</code>	Compute group sizes
<code>GroupBy.sem([ddof])</code>	Compute standard error of the mean of groups, excluding missing values
<code>GroupBy.std([ddof])</code>	Compute standard deviation of groups, excluding missing values
<code>GroupBy.sum()</code>	Compute sum of group values
<code>GroupBy.var([ddof])</code>	Compute variance of groups, excluding missing values
<code>GroupBy.tail([n])</code>	Returns last n rows of each group

`pandas.core.groupby.GroupBy.count`

`GroupBy.count` (*axis=0*)

pandas.core.groupby.GroupBy.cumcount

GroupBy.**cumcount** (*ascending=True*)

Number each item in each group from 0 to the length of that group - 1.

Essentially this is equivalent to

```
>>> self.apply(lambda x: Series(np.arange(len(x)), x.index))
```

Parameters **ascending**: bool, default True

If False, number in reverse, from length of group - 1 to 0.

Examples

```
>>> df = pd.DataFrame(['a'], ['a'], ['a'], ['b'], ['b'], ['a']],
...                    columns=['A'])
>>> df
   A
0  a
1  a
2  a
3  b
4  b
5  a
>>> df.groupby('A').cumcount()
0    0
1    1
2    2
3    0
4    1
5    3
dtype: int64
>>> df.groupby('A').cumcount(ascending=False)
0    3
1    2
2    1
3    1
4    0
5    0
dtype: int64
```

pandas.core.groupby.GroupBy.first

GroupBy.**first**()

Compute first of group values

pandas.core.groupby.GroupBy.head

GroupBy.**head** (*n=5*)

Returns first n rows of each group.

Essentially equivalent to `.apply(lambda x: x.head(n))`, except ignores `as_index` flag.

Examples

```
>>> df = DataFrame([[1, 2], [1, 4], [5, 6]],
                    columns=['A', 'B'])
>>> df.groupby('A', as_index=False).head(1)
   A  B
0  1  2
2  5  6
>>> df.groupby('A').head(1)
   A  B
0  1  2
2  5  6
```

pandas.core.groupby.GroupBy.last

GroupBy.**last**()
 Compute last of group values

pandas.core.groupby.GroupBy.max

GroupBy.**max**()
 Compute max of group values

pandas.core.groupby.GroupBy.mean

GroupBy.**mean**()
 Compute mean of groups, excluding missing values
 For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.median

GroupBy.**median**()
 Compute median of groups, excluding missing values
 For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.min

GroupBy.**min**()
 Compute min of group values

pandas.core.groupby.GroupBy.nth

GroupBy.**nth**(n, dropna=None)
 Take the nth row from each group if n is an int, or a subset of rows if n is a list of ints.
 If dropna, will take the nth non-null row, dropna is either Truthy (if a Series) or 'all', 'any' (if a DataFrame); this is equivalent to calling dropna(how=dropna) before the groupby.

Parameters n : int or list of ints

a single nth value for the row or a list of nth values

dropna : None or str, optional

apply the specified dropna operation before counting which row is the nth row. Needs to be None, 'any' or 'all'

Examples

```
>>> df = DataFrame([[1, np.nan], [1, 4], [5, 6]], columns=['A', 'B'])
>>> g = df.groupby('A')
>>> g.nth(0)
   A  B
0  1 NaN
2  5  6
>>> g.nth(1)
   A  B
1  1  4
>>> g.nth(-1)
   A  B
1  1  4
2  5  6
>>> g.nth(0, dropna='any')
   B
A
1  4
5  6
>>> g.nth(1, dropna='any') # NaNs denote group exhausted when using dropna
   B
A
1 NaN
5 NaN
```

pandas.core.groupby.GroupBy.ohlc

GroupBy.**ohlc**()

Compute sum of values, excluding missing values For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.prod

GroupBy.**prod**()

Compute prod of group values

pandas.core.groupby.GroupBy.size

GroupBy.**size**()

Compute group sizes

pandas.core.groupby.GroupBy.sem

GroupBy.**sem**(ddof=1)

Compute standard error of the mean of groups, excluding missing values

For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.std

`GroupBy.std(ddof=1)`
 Compute standard deviation of groups, excluding missing values
 For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.sum

`GroupBy.sum()`
 Compute sum of group values

pandas.core.groupby.GroupBy.var

`GroupBy.var(ddof=1)`
 Compute variance of groups, excluding missing values
 For multiple groupings, the result index will be a MultiIndex

pandas.core.groupby.GroupBy.tail

`GroupBy.tail(n=5)`
 Returns last n rows of each group
 Essentially equivalent to `.apply(lambda x: x.tail(n))`, except ignores `as_index` flag.

Examples

```
>>> df = DataFrame([[ 'a', 1], [ 'a', 2], [ 'b', 1], [ 'b', 2]],
                    columns=[ 'A', 'B'])
>>> df.groupby('A').tail(1)
   A  B
1  a  2
3  b  2
>>> df.groupby('A').head(1)
   A  B
0  a  1
2  b  1
```

The following methods are available in both `SeriesGroupBy` and `DataFrameGroupBy` objects, but may differ slightly, usually in that the `DataFrameGroupBy` version usually permits the specification of an axis argument, and often an argument indicating whether to restrict application to columns of a specific data type.

<code>DataFrameGroupBy.bfill([axis, inplace, ...])</code>	Synonym for <code>NDFrame.fillna(method='bfill')</code>
<code>DataFrameGroupBy.cummax([axis, dtype, out, ...])</code>	Return cumulative max over requested axis.
<code>DataFrameGroupBy.cummin([axis, dtype, out, ...])</code>	Return cumulative min over requested axis.
<code>DataFrameGroupBy.cumprod([axis, dtype, out, ...])</code>	Return cumulative prod over requested axis.
<code>DataFrameGroupBy.cumsum([axis, dtype, out, ...])</code>	Return cumulative sum over requested axis.
<code>DataFrameGroupBy.describe(...)</code>	Generate various summary statistics, excluding NaN values.
<code>DataFrameGroupBy.all([axis, bool_only, ...])</code>	Return whether all elements are True over requested axis
<code>DataFrameGroupBy.any([axis, bool_only, ...])</code>	Return whether any element is True over requested axis
<code>DataFrameGroupBy.corr([method, min_periods])</code>	Compute pairwise correlation of columns, excluding NA/null values

Continued

Table 33.116 – continued from previous page

<code>DataFrameGroupBy.cov([min_periods])</code>	Compute pairwise covariance of columns, excluding NA/null values
<code>DataFrameGroupBy.diff([periods, axis])</code>	1st discrete difference of object
<code>DataFrameGroupBy.ffill([axis, inplace, ...])</code>	Synonym for <code>NDFrame.fillna(method='ffill')</code>
<code>DataFrameGroupBy.fillna([value, method, ...])</code>	Fill NA/NaN values using the specified method
<code>DataFrameGroupBy.hist(data[, column, by, ...])</code>	Draw histogram of the DataFrame's series using matplotlib / pylab.
<code>DataFrameGroupBy.idxmax([axis, skipna])</code>	Return index of first occurrence of maximum over requested axis.
<code>DataFrameGroupBy.idxmin([axis, skipna])</code>	Return index of first occurrence of minimum over requested axis.
<code>DataFrameGroupBy.irow(i[, copy])</code>	
<code>DataFrameGroupBy.mad([axis, skipna, level])</code>	Return the mean absolute deviation of the values for the requested axis
<code>DataFrameGroupBy.pct_change([periods, ...])</code>	Percent change over given number of periods.
<code>DataFrameGroupBy.plot(data[, x, y, kind, ...])</code>	Make plots of DataFrame using matplotlib / pylab.
<code>DataFrameGroupBy.quantile([q, axis, ...])</code>	Return values at the given quantile over requested axis, a la numpy.percentile
<code>DataFrameGroupBy.rank([axis, numeric_only, ...])</code>	Compute numerical data ranks (1 through n) along axis.
<code>DataFrameGroupBy.resample(rule[, how, axis, ...])</code>	Convenience method for frequency conversion and resampling of regular time series
<code>DataFrameGroupBy.shift([periods, freq, axis])</code>	Shift index by desired number of periods with an optional time frequency
<code>DataFrameGroupBy.skew([axis, skipna, level, ...])</code>	Return unbiased skew over requested axis
<code>DataFrameGroupBy.take(indices[, axis, ...])</code>	Analogous to <code>ndarray.take</code>
<code>DataFrameGroupBy.tshift([periods, freq, axis])</code>	Shift the time index, using the index's frequency if available

pandas.core.groupby.DataFrameGroupBy.bfill

`DataFrameGroupBy.bfill` (*axis=None, inplace=False, limit=None, downcast=None*)
 Synonym for `NDFrame.fillna(method='bfill')`

pandas.core.groupby.DataFrameGroupBy.cummax

`DataFrameGroupBy.cummax` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative max over requested axis.

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *max* : Series

pandas.core.groupby.DataFrameGroupBy.cummin

`DataFrameGroupBy.cummin` (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative min over requested axis.

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *min* : Series

pandas.core.groupby.DataFrameGroupBy.cumprod

DataFrameGroupBy.**cumprod** (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative prod over requested axis.

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *prod* : Series

pandas.core.groupby.DataFrameGroupBy.cumsum

DataFrameGroupBy.**cumsum** (*axis=None, dtype=None, out=None, skipna=True, **kwargs*)

Return cumulative sum over requested axis.

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns *sum* : Series

pandas.core.groupby.DataFrameGroupBy.describe

DataFrameGroupBy.**describe** (*percentile_width=None, percentiles=None, include=None, exclude=None*)

Generate various summary statistics, excluding NaN values.

Parameters *percentile_width* : float, deprecated

The *percentile_width* argument will be removed in a future version. Use *percentiles* instead. width of the desired uncertainty interval, default is 50, which corresponds to lower=25, upper=75

percentiles : array-like, optional

The percentiles to include in the output. Should all be in the interval [0, 1]. By default *percentiles* is [.25, .5, .75], returning the 25th, 50th, and 75th percentiles.

include, exclude : list-like, 'all', or None (default)

Specify the form of the returned result. Either:

- None to both (default). The result will include only numeric-typed columns or, if none are, only categorical columns.
- A list of dtypes or strings to be included/excluded. To select all numeric types use `numpy.number`. To select categorical objects use type object. See also the `select_dtypes` documentation. eg. `df.describe(include=['O'])`
- If *include* is the string 'all', the output column-set will match the input one.

Returns summary: NDFrame of summary statistics

See also:

`DataFrame.select_dtypes`

Notes

The output DataFrame index depends on the requested dtypes:

For numeric dtypes, it will include: count, mean, std, min, max, and lower, 50, and upper percentiles.

For object dtypes (e.g. timestamps or strings), the index will include the count, unique, most common, and frequency of the most common. Timestamps also include the first and last items.

For mixed dtypes, the index will be the union of the corresponding output types. Non-applicable entries will be filled with NaN. Note that mixed-dtype outputs can only be returned from mixed-dtype inputs and appropriate use of the include/exclude arguments.

If multiple values have the highest count, then the *count* and *most common* pair will be arbitrarily chosen from among those with the highest count.

The include, exclude arguments are ignored for Series.

pandas.core.groupby.DataFrameGroupBy.all

DataFrameGroupBy.**all** (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether all elements are True over requested axis

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns *all* : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.any

DataFrameGroupBy.**any** (*axis=None, bool_only=None, skipna=None, level=None, **kwargs*)

Return whether any element is True over requested axis

Parameters *axis* : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

bool_only : boolean, default None

Include only boolean data. If None, will attempt to use everything, then use only boolean data

Returns *any* : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.corr

DataFrameGroupBy.**corr** (*method='pearson', min_periods=1*)

Compute pairwise correlation of columns, excluding NA/null values

Parameters **method** : { 'pearson', 'kendall', 'spearman' }

- pearson : standard correlation coefficient
- kendall : Kendall Tau correlation coefficient
- spearman : Spearman rank correlation

min_periods : int, optional

Minimum number of observations required per pair of columns to have a valid result.
Currently only available for pearson and spearman correlation

Returns **y** : DataFrame

pandas.core.groupby.DataFrameGroupBy.cov

DataFrameGroupBy.**cov** (*min_periods=None*)

Compute pairwise covariance of columns, excluding NA/null values

Parameters **min_periods** : int, optional

Minimum number of observations required per pair of columns to have a valid result.

Returns **y** : DataFrame

Notes

y contains the covariance matrix of the DataFrame's time series. The covariance is normalized by N-1 (unbiased estimator).

pandas.core.groupby.DataFrameGroupBy.diff

DataFrameGroupBy.**diff** (*periods=1, axis=0*)

1st discrete difference of object

Parameters **periods** : int, default 1

Periods to shift for forming difference

axis : {0 or 'index', 1 or 'columns'}, default 0

Returns **differed** : DataFrame

pandas.core.groupby.DataFrameGroupBy.ffill

DataFrameGroupBy.**ffill** (*axis=None, inplace=False, limit=None, downcast=None*)

Synonym for NDFrame.fillna(method='ffill')

pandas.core.groupby.DataFrameGroupBy.fillna

DataFrameGroupBy.**fillna** (*value=None, method=None, axis=None, inplace=False, limit=None, downcast=None, **kwargs*)

Fill NA/NaN values using the specified method

Parameters method : {'backfill', 'bfill', 'pad', 'ffill', None}, default None

Method to use for filling holes in reindexed Series pad / ffill: propagate last valid observation forward to next valid backfill / bfill: use NEXT valid observation to fill gap

value : scalar, dict, Series, or DataFrame

Value to use to fill holes (e.g. 0), alternately a dict/Series/DataFrame of values specifying which value to use for each index (for a Series) or column (for a DataFrame). (values not in the dict/Series/DataFrame will not be filled). This value cannot be a list.

axis : {0, 1, 'index', 'columns'}

inplace : boolean, default False

If True, fill in place. Note: this will modify any other views on this object, (e.g. a no-copy slice for a column in a DataFrame).

limit : int, default None

If method is specified, this is the maximum number of consecutive NaN values to forward/backward fill. In other words, if there is a gap with more than this number of consecutive NaNs, it will only be partially filled. If method is not specified, this is the maximum number of entries along the entire axis where NaNs will be filled.

downcast : dict, default is None

a dict of item->dtype of what to downcast if possible, or the string 'infer' which will try to downcast to an appropriate equal type (e.g. float64 to int64 if possible)

Returns filled : DataFrame

See also:

reindex, asfreq

pandas.core.groupby.DataFrameGroupBy.hist

DataFrameGroupBy.**hist** (*data, column=None, by=None, grid=True, xlabelsize=None, xrot=None, ylabelsize=None, yrot=None, ax=None, sharex=False, sharey=False, figsize=None, layout=None, bins=10, **kws*)

Draw histogram of the DataFrame's series using matplotlib / pylab.

Parameters data : DataFrame

column : string or sequence

If passed, will be used to limit data to a subset of columns

by : object, optional

If passed, then used to form histograms for separate groups

grid : boolean, default True

Whether to show axis grid lines

xlabelsize : int, default None

If specified changes the x-axis label size

xrot : float, default None

rotation of x axis labels

ylabelsize : int, default None

If specified changes the y-axis label size

yrot : float, default None

rotation of y axis labels

ax : matplotlib axes object, default None

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all subplots in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

figsize : tuple

The size of the figure to create in inches by default

layout: (optional) a tuple (rows, columns) for the layout of the histograms

bins: integer, default 10

Number of histogram bins to be used

kwds : other plotting keyword arguments

To be passed to hist function

pandas.core.groupby.DataFrameGroupBy.idxmax

DataFrameGroupBy.**idxmax** (*axis=0, skipna=True*)

Return index of first occurrence of maximum over requested axis. NA/null values are excluded.

Parameters **axis** : {0, 1}

0 for row-wise, 1 for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be first index.

Returns **idxmax** : Series

See also:

`Series.idxmax`

Notes

This method is the DataFrame version of `ndarray.argmax`.

pandas.core.groupby.DataFrameGroupBy.idxmin

DataFrameGroupBy.**idxmin** (*axis=0, skipna=True*)

Return index of first occurrence of minimum over requested axis. NA/null values are excluded.

Parameters **axis** : {0, 1}

0 for row-wise, 1 for column-wise

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

Returns **idxmin** : Series

See also:

`Series.idxmin`

Notes

This method is the DataFrame version of `ndarray.argmin`.

pandas.core.groupby.DataFrameGroupBy.irow

DataFrameGroupBy.**irow** (*i, copy=False*)

pandas.core.groupby.DataFrameGroupBy.mad

DataFrameGroupBy.**mad** (*axis=None, skipna=None, level=None*)

Return the mean absolute deviation of the values for the requested axis

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **mad** : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.pct_change

DataFrameGroupBy.**pct_change** (*periods=1, fill_method='pad', limit=None, freq=None, **kwargs*)

Percent change over given number of periods.

Parameters **periods** : int, default 1

Periods to shift for forming percent change

fill_method : str, default 'pad'

How to handle NAs before computing percent changes

limit : int, default None

The number of consecutive NAs to fill before stopping

freq : DateOffset, timedelta, or offset alias string, optional

Increment to use from time series API (e.g. 'M' or BDay())

Returns **chg** : NDFrame

Notes

By default, the percentage change is calculated along the stat axis: 0, or Index, for DataFrame and 1, or minor for Panel. You can change this with the `axis` keyword argument.

pandas.core.groupby.DataFrameGroupBy.plot

DataFrameGroupBy.**plot** (*data*, *x=None*, *y=None*, *kind='line'*, *ax=None*, *subplots=False*, *sharex=None*, *sharey=False*, *layout=None*, *figsize=None*, *use_index=True*, *title=None*, *grid=None*, *legend=True*, *style=None*, *logx=False*, *logy=False*, *loglog=False*, *xticks=None*, *yticks=None*, *xlim=None*, *ylim=None*, *rot=None*, *font-size=None*, *colormap=None*, *table=False*, *yerr=None*, *xerr=None*, *secondary_y=False*, *sort_columns=False*, ***kwds*)

Make plots of DataFrame using matplotlib / pylab.

Parameters **data** : DataFrame

x : label or position, default None

y : label or position, default None

Allows plotting of one column versus another

kind : str

- 'line' : line plot (default)
- 'bar' : vertical bar plot
- 'barh' : horizontal bar plot
- 'hist' : histogram
- 'box' : boxplot
- 'kde' : Kernel Density Estimation plot
- 'density' : same as 'kde'
- 'area' : area plot
- 'pie' : pie plot
- 'scatter' : scatter plot
- 'hexbin' : hexbin plot

ax : matplotlib axes object, default None

subplots : boolean, default False

Make separate subplots for each column

sharex : boolean, default True if ax is None else False

In case subplots=True, share x axis and set some x axis labels to invisible; defaults to True if ax is None otherwise False if an ax is passed in; Be aware, that passing in both an ax and sharex=True will alter all x axis labels for all axis in a figure!

sharey : boolean, default False

In case subplots=True, share y axis and set some y axis labels to invisible

layout : tuple (optional)

(rows, columns) for the layout of subplots

figsize : a tuple (width, height) in inches

use_index : boolean, default True

Use index as ticks for x axis

title : string

Title to use for the plot

grid : boolean, default None (matlab style default)

Axis grid lines

legend : False/True/'reverse'

Place legend on axis subplots

style : list or dict

matplotlib line style per column

logx : boolean, default False

Use log scaling on x axis

logy : boolean, default False

Use log scaling on y axis

loglog : boolean, default False

Use log scaling on both x and y axes

xticks : sequence

Values to use for the xticks

yticks : sequence

Values to use for the yticks

xlim : 2-tuple/list

ylim : 2-tuple/list

rot : int, default None

Rotation for ticks (xticks for vertical, yticks for horizontal plots)

fontsize : int, default None

Font size for xticks and yticks

colormap : str or matplotlib colormap object, default None

Colormap to select colors from. If string, load colormap with that name from matplotlib.

colorbar : boolean, optional

If True, plot colorbar (only relevant for ‘scatter’ and ‘hexbin’ plots)

position : float

Specify relative alignments for bar plot layout. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)

layout : tuple (optional)

(rows, columns) for the layout of the plot

table : boolean, Series or DataFrame, default False

If True, draw a table using the data in the DataFrame and the data will be transposed to meet matplotlib’s default layout. If a Series or DataFrame is passed, use passed data to draw a table.

yerr : DataFrame, Series, array-like, dict and str

See *Plotting with Error Bars* for detail.

xerr : same types as yerr.

stacked : boolean, default False in line and

bar plots, and True in area plot. If True, create stacked plot.

sort_columns : boolean, default False

Sort column names to determine plot ordering

secondary_y : boolean or sequence, default False

Whether to plot on the secondary y-axis If a list/tuple, which columns to plot on secondary y-axis

mark_right : boolean, default True

When using a secondary_y axis, automatically mark the column labels with “(right)” in the legend

kwds : keywords

Options to pass to matplotlib plotting method

Returns **axes** : matplotlib.AxesSubplot or np.array of them

Notes

- See matplotlib documentation online for more on this subject
- If *kind* = ‘bar’ or ‘barh’, you can specify relative alignments for bar plot layout by *position* keyword. From 0 (left/bottom-end) to 1 (right/top-end). Default is 0.5 (center)
- If *kind* = ‘scatter’ and the argument *c* is the name of a dataframe column, the values of that column are used to color each point.
- If *kind* = ‘hexbin’, you can control the size of the bins with the *gridsize* argument. By default, a histogram of the counts around each (*x*, *y*) point is computed. You can specify alternative aggregations by passing values to the *C* and *reduce_C_function* arguments. *C* specifies the value at each (*x*, *y*) point and

reduce_C_function is a function of one argument that reduces all the values in a bin to a single number (e.g. *mean*, *max*, *sum*, *std*).

pandas.core.groupby.DataFrameGroupBy.quantile

DataFrameGroupBy.**quantile** (*q=0.5, axis=0, numeric_only=True*)

Return values at the given quantile over requested axis, a la *numpy.percentile*.

Parameters *q* : float or array-like, default 0.5 (50% quantile)

0 <= *q* <= 1, the quantile(s) to compute

axis : {0, 1}

0 for row-wise, 1 for column-wise

Returns *quantiles* : Series or DataFrame

If *q* is an array, a DataFrame will be returned where the index is *q*, the columns are the columns of self, and the values are the quantiles. If *q* is a float, a Series will be returned where the index is the columns of self and the values are the quantiles.

Examples

```
>>> df = DataFrame(np.array([[1, 1], [2, 10], [3, 100], [4, 100]]),
                    columns=['a', 'b'])
>>> df.quantile(.1)
a    1.3
b    3.7
dtype: float64
>>> df.quantile([.1, .5])
      a    b
0.1  1.3  3.7
0.5  2.5 55.0
```

pandas.core.groupby.DataFrameGroupBy.rank

DataFrameGroupBy.**rank** (*axis=0, numeric_only=None, method='average', na_option='keep', ascending=True, pct=False*)

Compute numerical data ranks (1 through *n*) along axis. Equal values are assigned a rank that is the average of the ranks of those values

Parameters *axis* : {0, 1}, default 0

Ranks over columns (0) or rows (1)

numeric_only : boolean, default None

Include only float, int, boolean data

method : {'average', 'min', 'max', 'first', 'dense'}

- average: average rank of group
- min: lowest rank in group
- max: highest rank in group
- first: ranks assigned in order they appear in the array

- **dense**: like ‘min’, but rank always increases by 1 between groups

na_option : { ‘keep’, ‘top’, ‘bottom’ }

- **keep**: leave NA values where they are
- **top**: smallest rank if ascending
- **bottom**: smallest rank if descending

ascending : boolean, default True

False for ranks by high (1) to low (N)

pct : boolean, default False

Computes percentage rank of data

Returns **ranks** : DataFrame

pandas.core.groupby.DataFrameGroupBy.resample

DataFrameGroupBy.**resample** (*rule, how=None, axis=0, fill_method=None, closed=None, label=None, convention='start', kind=None, loffset=None, limit=None, base=0*)

Convenience method for frequency conversion and resampling of regular time-series data.

Parameters **rule** : string

the offset string or object representing target conversion

how : string

method for down- or re-sampling, default to ‘mean’ for downsampling

axis : int, optional, default 0

fill_method : string, default None

fill_method for upsampling

closed : { ‘right’, ‘left’ }

Which side of bin interval is closed

label : { ‘right’, ‘left’ }

Which bin edge label to label bucket with

convention : { ‘start’, ‘end’, ‘s’, ‘e’ }

kind : “period”/“timestamp”

loffset : timedelta

Adjust the resampled time labels

limit : int, default None

Maximum size gap to when reindexing with fill_method

base : int, default 0

For frequencies that evenly subdivide 1 day, the “origin” of the aggregated intervals. For example, for ‘5min’ frequency, base could range from 0 through 4. Defaults to 0

pandas.core.groupby.DataFrameGroupBy.shift

DataFrameGroupBy.**shift** (*periods=1, freq=None, axis=0, **kwargs*)

Shift index by desired number of periods with an optional time freq

Parameters **periods** : int

Number of periods to move, can be positive or negative

freq : DateOffset, timedelta, or time rule string, optional

Increment to use from datetools module or time rule (e.g. 'EOM'). See Notes.

axis : {0, 1, 'index', 'columns'}

Returns **shifted** : DataFrame

Notes

If freq is specified then the index values are shifted but the data is not realigned. That is, use freq if you would like to extend the index when shifting and preserve the original data.

pandas.core.groupby.DataFrameGroupBy.skew

DataFrameGroupBy.**skew** (*axis=None, skipna=None, level=None, numeric_only=None, **kwargs*)

Return unbiased skew over requested axis Normalized by N-1

Parameters **axis** : {index (0), columns (1)}

skipna : boolean, default True

Exclude NA/null values. If an entire row/column is NA, the result will be NA

level : int or level name, default None

If the axis is a MultiIndex (hierarchical), count along a particular level, collapsing into a Series

numeric_only : boolean, default None

Include only float, int, boolean data. If None, will attempt to use everything, then use only numeric data

Returns **skew** : Series or DataFrame (if level specified)

pandas.core.groupby.DataFrameGroupBy.take

DataFrameGroupBy.**take** (*indices, axis=0, convert=True, is_copy=True*)

Analogous to ndarray.take

Parameters **indices** : list / array of ints

axis : int, default 0

convert : translate neg to pos indices (default)

is_copy : mark the returned frame as a copy

Returns **taken** : type of caller

pandas.core.groupby.DataFrameGroupBy.tshift

`DataFrameGroupBy.tshift` (*periods=1, freq=None, axis=0, **kwargs*)

Shift the time index, using the index's frequency if available

Parameters `periods` : int

Number of periods to move, can be positive or negative

freq : `DateOffset`, `timedelta`, or time rule string, default `None`

Increment to use from `datetools` module or time rule (e.g. 'EOM')

axis : int or basestring

Corresponds to the axis that contains the Index

Returns `shifted` : `NDFrame`

Notes

If `freq` is not specified then tries to use the `freq` or `inferred_freq` attributes of the index. If neither of those attributes exist, a `ValueError` is thrown

The following methods are available only for `SeriesGroupBy` objects.

<code>SeriesGroupBy.nlargest([n, take_last])</code>	Return the largest <i>n</i> elements.
<code>SeriesGroupBy.nsmallest([n, take_last])</code>	Return the smallest <i>n</i> elements.
<code>SeriesGroupBy.nunique([dropna])</code>	Return number of unique elements in the object.
<code>SeriesGroupBy.unique()</code>	Return array of unique values in the object.
<code>SeriesGroupBy.value_counts([normalize, ...])</code>	Returns object containing counts of unique values.

pandas.core.groupby.SeriesGroupBy.nlargest

`SeriesGroupBy.nlargest` (*n=5, take_last=False*)

Return the largest *n* elements.

Parameters `n` : int

Return this many descending sorted values

take_last [bool] Where there are duplicate values, take the last duplicate

Returns `top_n` : `Series`

The *n* largest values in the `Series`, in sorted order

Notes

Faster than `.order(ascending=False).head(n)` for small *n* relative to the size of the `Series` object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
```

```
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nlargest(10)  # only sorts up to the N requested
```

pandas.core.groupby.SeriesGroupBy.nsmallest

SeriesGroupBy.**nsmallest** (*n=5, take_last=False*)

Return the smallest *n* elements.

Parameters *n* : int

Return this many ascending sorted values

take_last [bool] Where there are duplicate values, take the last duplicate

Returns *bottom_n* : Series

The *n* smallest values in the Series, in sorted order

Notes

Faster than `.order().head(n)` for small *n* relative to the size of the Series object.

Examples

```
>>> import pandas as pd
>>> import numpy as np
>>> s = pd.Series(np.random.randn(1e6))
>>> s.nsmallest(10)  # only sorts up to the N requested
```

pandas.core.groupby.SeriesGroupBy.nunique

SeriesGroupBy.**nunique** (*dropna=True*)

Return number of unique elements in the object.

Excludes NA values by default.

Parameters *dropna* : boolean, default True

Don't include NaN in the count.

Returns *nunique* : int

pandas.core.groupby.SeriesGroupBy.unique

SeriesGroupBy.**unique** ()

Return array of unique values in the object. Significantly faster than `numpy.unique`. Includes NA values.

Returns *uniques* : ndarray

pandas.core.groupby.SeriesGroupBy.value_counts

`SeriesGroupBy.value_counts` (*normalize=False, sort=True, ascending=False, bins=None, dropna=True*)

Returns object containing counts of unique values.

The resulting object will be in descending order so that the first element is the most frequently-occurring element. Excludes NA values by default.

Parameters `normalize` : boolean, default False

If True then the object returned will contain the relative frequencies of the unique values.

sort : boolean, default True

Sort by values

ascending : boolean, default False

Sort in ascending order

bins : integer, optional

Rather than count values, group them into half-open bins, a convenience for `pd.cut`, only works with numeric data

dropna : boolean, default True

Don't include counts of NaN.

Returns `counts` : Series

The following methods are available only for `DataFrameGroupBy` objects.

<code>DataFrameGroupBy.corrwith</code> (<i>other[, axis, drop]</i>)	Compute pairwise correlation between rows or columns of two DataFrames
<code>DataFrameGroupBy.boxplot</code> (<i>grouped[, ...]</i>)	Make box plots from DataFrameGroupBy data.

pandas.core.groupby.DataFrameGroupBy.corrwith

`DataFrameGroupBy.corrwith` (*other, axis=0, drop=False*)

Compute pairwise correlation between rows or columns of two DataFrame objects.

Parameters `other` : DataFrame

axis : {0, 1}

0 to compute column-wise, 1 for row-wise

drop : boolean, default False

Drop missing indices from result, default returns union of all

Returns `correls` : Series

pandas.core.groupby.DataFrameGroupBy.boxplot

`DataFrameGroupBy.boxplot` (*grouped, subplots=True, column=None, fontsize=None, rot=0, grid=True, ax=None, figsize=None, layout=None, **kwargs*)

Make box plots from DataFrameGroupBy data.

Parameters `grouped` : Grouped DataFrame

subplots :

- `False` - no subplots will be used
- `True` - create a subplot for each group

column : column name or list of names, or vectorCan be any valid input to `groupby`**fontsize :** int or string**rot :** label rotation angle**grid :** Setting this to `True` will show the grid**ax :** Matplotlib axis object, default `None`**figsize :** A tuple (width, height) in inches**layout :** tuple (optional)

(rows, columns) for the layout of the plot

kwargs : other plotting keyword arguments to be passed to matplotlib boxplot function**Returns** dict of key/value = group key/DataFrame.boxplot return value
or DataFrame.boxplot return value in case `subplots=figures=False`**Examples**

```
>>> import pandas
>>> import numpy as np
>>> import itertools
>>>
>>> tuples = [t for t in itertools.product(range(1000), range(4))]
>>> index = pandas.MultiIndex.from_tuples(tuples, names=['lv10', 'lv11'])
>>> data = np.random.randn(len(index), 4)
>>> df = pandas.DataFrame(data, columns=list('ABCD'), index=index)
>>>
>>> grouped = df.groupby(level='lv11')
>>> boxplot_frame_groupby(grouped)
>>>
>>> grouped = df.unstack(level='lv11').groupby(level=0, axis=1)
>>> boxplot_frame_groupby(grouped, subplots=False)
```

33.12 General utility functions

33.12.1 Working with options

<code>describe_option(pat[, _print_desc])</code>	Prints the description for one or more registered options.
<code>reset_option(pat)</code>	Reset one or more options to their default value.
<code>get_option(pat)</code>	Retrieves the value of the specified option.
<code>set_option(pat, value)</code>	Sets the value of the specified option.
<code>option_context(*args)</code>	Context manager to temporarily set options in the <i>with</i> statement context.

pandas.describe_option

`pandas.describe_option(pat, _print_desc=False)` = <pandas.core.config.CallableDynamicDoc object at 0xb5699b4c>

Prints the description for one or more registered options.

Call with not arguments to get a listing for all registered options.

Available options:

- `display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]`
- `io.excel.xls.[writer]`
- `io.excel.xlsm.[writer]`
- `io.excel.xlsx.[writer]`
- `io.hdf.[default_format, dropna_table]`
- `mode.[chained_assignment, sim_interactive, use_inf_as_null]`

Parameters pat : str

Regexp pattern. All matching keys will have their description displayed.

`_print_desc` : bool, default True

If True (default) the description(s) will be printed to stdout. Otherwise, the description(s) will be returned as a unicode string (for testing).

Returns None by default, the description(s) as a unicode string if `_print_desc` is False

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by `to_string`, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, `max_columns` is still respected, but the output will wrap-around across multiple “pages” if its width exceeds `display.width`. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See core.format.EngFormatter for an example. [default: None] [currently: None]

display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use *display.max_rows* instead.)

display.large_repr ['truncate'/'info'] For DataFrames exceeding max_rows/max_cols, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from df.info() (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use *display.width* instead.)

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype “category”. [default: 8] [currently: 8]

display.max_columns [int] If max_cols is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 20] [currently: 20]

display.max_colwidth [int] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “...” placeholder is embedded in the output. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions then specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of “...” to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

display.mpl_style [bool] Setting this to ‘default’ will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

display.multi_sparse [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

- display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 7] [currently: 7]
- display.show_dimensions** [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]
- display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]
- io.excel.xls.writer** [string] The default Excel writer engine for 'xls' files. Available options: 'xlwt' (the default). [default: xlwt] [currently: xlwt]
- io.excel.xlsm.writer** [string] The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default). [default: openpyxl] [currently: openpyxl]
- io.excel.xlsx.writer** [string] The default Excel writer engine for 'xlsx' files. Available options: 'xlsxwriter' (the default), 'openpyxl'. [default: xlsxwriter] [currently: xlsxwriter]
- io.hdf.default_format** [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]
- io.hdf.dropna_table** [boolean] drop ALL nan rows when appending to a table [default: True] [currently: True]
- mode.chained_assignment** [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]
- mode.sim_interactive** [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]
- mode.use_inf_as_null** [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.reset_option

`pandas.reset_option(pat) = <pandas.core.config.CallableDynamicDoc object at 0xb5699b2c>`

Reset one or more options to their default value.

Pass "all" as argument to reset all options.

Available options:

- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]
- io.excel.xls.[writer]
- io.excel.xlsm.[writer]
- io.excel.xlsx.[writer]
- io.hdf.[default_format, dropna_table]
- mode.[chained_assignment, sim_interactive, use_inf_as_null]

Parameters `pat` : str/regex

If specified only options matching *prefix** will be reset. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. `x.y.z.option_name`), your code may break in future versions if new options with similar names are introduced.

Returns None

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by `to_string`, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

display.expand_frame_repr [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple “pages” if its width exceeds *display.width*. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See `core.format.EngFormatter` for an example. [default: None] [currently: None]

display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use *display.max_rows* instead.)

display.large_repr ['truncate'/'info'] For DataFrames exceeding *max_rows*/*max_cols*, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from `df.info()` (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use *display.width* instead.)

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype “category”. [default: 8] [currently: 8]

display.max_columns [int] If *max_cols* is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 20] [currently: 20]

display.max_colwidth [int] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “...” placeholder is embedded in the output. [default: 50] [currently: 50]

display.max_info_columns [int] *max_info_columns* is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

- display.max_info_rows** [int or None] `df.info()` will usually show null-counts for each column. For large frames this can be quite slow. `max_info_rows` and `max_info_cols` limit this null check only to frames with smaller dimensions then specified. [default: 1690785] [currently: 1690785]
- display.max_rows** [int] If `max_rows` is exceeded, switch to truncate view. Depending on `large_repr`, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.
- In case python/IPython is running in a terminal and `large_repr` equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]
- display.max_seq_items** [int or None] when pretty-printing a long sequence, no more then `max_seq_items` will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.
- If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]
- display.memory_usage** [bool or None] This specifies if the memory usage of a DataFrame should be displayed when `df.info()` is called. [default: True] [currently: True]
- display.mpl_style** [bool] Setting this to 'default' will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]
- display.multi_sparse** [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]
- display.notebook_repr_html** [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]
- display.pprint_nest_depth** [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]
- display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 7] [currently: 7]
- display.show_dimensions** [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]
- display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]
- io.excel.xls.writer** [string] The default Excel writer engine for 'xls' files. Available options: 'xlwt' (the default). [default: xlwt] [currently: xlwt]
- io.excel.xlsm.writer** [string] The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default). [default: openpyxl] [currently: openpyxl]
- io.excel.xlsx.writer** [string] The default Excel writer engine for 'xlsx' files. Available options: 'xlsxwriter' (the default), 'openpyxl'. [default: xlsxwriter] [currently: xlsxwriter]
- io.hdf.default_format** [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]
- io.hdf.dropna_table** [boolean] drop ALL nan rows when appending to a table [default: True] [currently: True]
- mode.chained_assignment** [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_null [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.get_option

`pandas.get_option(pat) = <pandas.core.config.CallableDynamicDoc object at 0xb5699aec>`
Retrieves the value of the specified option.

Available options:

- `display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]`
- `io.excel.xls.[writer]`
- `io.excel.xlsm.[writer]`
- `io.excel.xlsx.[writer]`
- `io.hdf.[default_format, dropna_table]`
- `mode.[chained_assignment, sim_interactive, use_inf_as_null]`

Parameters `pat` : str

Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. `x.y.z.option_name`), your code may break in future versions if new options with similar names are introduced.

Returns `result` : the value of the option

Raises `OptionError` : if no such option exists

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by DataFrameFormatter. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by `to_string`, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

- display.expand_frame_repr** [boolean] Whether to print out the full DataFrame repr for wide DataFrames across multiple lines, *max_columns* is still respected, but the output will wrap-around across multiple “pages” if its width exceeds *display.width*. [default: True] [currently: True]
- display.float_format** [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like SeriesFormatter. See `core.format.EngFormatter` for an example. [default: None] [currently: None]
- display.height** [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use *display.max_rows* instead.)
- display.large_repr** ['truncate'/'info'] For DataFrames exceeding *max_rows*/*max_cols*, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from `df.info()` (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]
- display.line_width** [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use *display.width* instead.)
- display.max_categories** [int] This sets the maximum number of categories pandas should output when printing out a *Categorical* or a Series of dtype “category”. [default: 8] [currently: 8]
- display.max_columns** [int] If *max_cols* is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.
- In case python/IPython is running in a terminal and *large_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 20] [currently: 20]
- display.max_colwidth** [int] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a “...” placeholder is embedded in the output. [default: 50] [currently: 50]
- display.max_info_columns** [int] *max_info_columns* is used in `DataFrame.info` method to decide if per column information will be printed. [default: 100] [currently: 100]
- display.max_info_rows** [int or None] `df.info()` will usually show null-counts for each column. For large frames this can be quite slow. *max_info_rows* and *max_info_cols* limit this null check only to frames with smaller dimensions then specified. [default: 1690785] [currently: 1690785]
- display.max_rows** [int] If *max_rows* is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.
- In case python/IPython is running in a terminal and *large_repr* equals ‘truncate’ this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]
- display.max_seq_items** [int or None] when pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of “...” to the resulting string.
- If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]
- display.memory_usage** [bool or None] This specifies if the memory usage of a DataFrame should be displayed when `df.info()` is called. [default: True] [currently: True]
- display.mpl_style** [bool] Setting this to ‘default’ will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]
- display.multi_sparse** [boolean] “sparsify” MultiIndex display (don’t display repeated elements in outer levels within groups) [default: True] [currently: True]
- display.notebook_repr_html** [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

- display.pprint_nest_depth** [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]
- display.precision** [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 7] [currently: 7]
- display.show_dimensions** [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]
- display.width** [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]
- io.excel.xls.writer** [string] The default Excel writer engine for 'xls' files. Available options: 'xlwt' (the default). [default: xlwt] [currently: xlwt]
- io.excel.xlsm.writer** [string] The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default). [default: openpyxl] [currently: openpyxl]
- io.excel.xlsx.writer** [string] The default Excel writer engine for 'xlsx' files. Available options: 'xlsxwriter' (the default), 'openpyxl'. [default: xlsxwriter] [currently: xlsxwriter]
- io.hdf.default_format** [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]
- io.hdf.dropna_table** [boolean] drop ALL nan rows when appending to a table [default: True] [currently: True]
- mode.chained_assignment** [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]
- mode.sim_interactive** [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]
- mode.use_inf_as_null** [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.set_option

`pandas.set_option(pat, value) = <pandas.core.config.CallableDynamicDoc object at 0xb5699b0c>`
Sets the value of the specified option.

Available options:

- display.[chop_threshold, colheader_justify, column_space, date_dayfirst, date_yearfirst, encoding, expand_frame_repr, float_format, height, large_repr, line_width, max_categories, max_columns, max_colwidth, max_info_columns, max_info_rows, max_rows, max_seq_items, memory_usage, mpl_style, multi_sparse, notebook_repr_html, pprint_nest_depth, precision, show_dimensions, width]
- io.excel.xls.[writer]
- io.excel.xlsm.[writer]
- io.excel.xlsx.[writer]
- io.hdf.[default_format, dropna_table]
- mode.[chained_assignment, sim_interactive, use_inf_as_null]

Parameters pat : str

Regexp which should match a single option. Note: partial matches are supported for convenience, but unless you use the full option name (e.g. `x.y.z.option_name`), your code may break in future versions if new options with similar names are introduced.

value :

new value of option.

Returns None

Raises `OptionError` if no such option exists

Notes

The available options with its descriptions:

display.chop_threshold [float or None] if set to a float value, all float values smaller then the given threshold will be displayed as exactly 0 by repr and friends. [default: None] [currently: None]

display.colheader_justify ['left'/'right'] Controls the justification of column headers. used by `DataFrameFormatter`. [default: right] [currently: right]

display.column_space No description available. [default: 12] [currently: 12]

display.date_dayfirst [boolean] When True, prints and parses dates with the day first, eg 20/01/2005 [default: False] [currently: False]

display.date_yearfirst [boolean] When True, prints and parses dates with the year first, eg 2005/01/20 [default: False] [currently: False]

display.encoding [str/unicode] Defaults to the detected encoding of the console. Specifies the encoding to be used for strings returned by `to_string`, these are generally strings meant to be displayed on the console. [default: UTF-8] [currently: UTF-8]

display.expand_frame_repr [boolean] Whether to print out the full `DataFrame` repr for wide `DataFrames` across multiple lines, `max_columns` is still respected, but the output will wrap-around across multiple “pages” if its width exceeds `display.width`. [default: True] [currently: True]

display.float_format [callable] The callable should accept a floating point number and return a string with the desired format of the number. This is used in some places like `SeriesFormatter`. See `core.format.EngFormatter` for an example. [default: None] [currently: None]

display.height [int] Deprecated. [default: 60] [currently: 15] (Deprecated, use `display.max_rows` instead.)

display.large_repr ['truncate'/'info'] For `DataFrames` exceeding `max_rows/max_cols`, the repr (and HTML repr) can show a truncated table (the default from 0.13), or switch to the view from `df.info()` (the behaviour in earlier versions of pandas). [default: truncate] [currently: truncate]

display.line_width [int] Deprecated. [default: 80] [currently: 80] (Deprecated, use `display.width` instead.)

display.max_categories [int] This sets the maximum number of categories pandas should output when printing out a `Categorical` or a `Series` of dtype “category”. [default: 8] [currently: 8]

display.max_columns [int] If `max_cols` is exceeded, switch to truncate view. Depending on `large_repr`, objects are either centrally truncated or printed as a summary view. ‘None’ value means unlimited.

In case python/IPython is running in a terminal and `large_repr` equals ‘truncate’ this can be set to 0 and pandas will auto-detect the width of the terminal and print a truncated object which fits the screen width. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 20] [currently: 20]

display.max_colwidth [int] The maximum width in characters of a column in the repr of a pandas data structure. When the column overflows, a "..." placeholder is embedded in the output. [default: 50] [currently: 50]

display.max_info_columns [int] max_info_columns is used in DataFrame.info method to decide if per column information will be printed. [default: 100] [currently: 100]

display.max_info_rows [int or None] df.info() will usually show null-counts for each column. For large frames this can be quite slow. max_info_rows and max_info_cols limit this null check only to frames with smaller dimensions then specified. [default: 1690785] [currently: 1690785]

display.max_rows [int] If max_rows is exceeded, switch to truncate view. Depending on *large_repr*, objects are either centrally truncated or printed as a summary view. 'None' value means unlimited.

In case python/IPython is running in a terminal and *large_repr* equals 'truncate' this can be set to 0 and pandas will auto-detect the height of the terminal and print a truncated object which fits the screen height. The IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to do correct auto-detection. [default: 60] [currently: 15]

display.max_seq_items [int or None] when pretty-printing a long sequence, no more then *max_seq_items* will be printed. If items are omitted, they will be denoted by the addition of "..." to the resulting string.

If set to None, the number of items to be printed is unlimited. [default: 100] [currently: 100]

display.memory_usage [bool or None] This specifies if the memory usage of a DataFrame should be displayed when df.info() is called. [default: True] [currently: True]

display.mpl_style [bool] Setting this to 'default' will modify the rcParams used by matplotlib to give plots a more pleasing visual style by default. Setting this to None/False restores the values to their initial value. [default: None] [currently: None]

display.multi_sparse [boolean] "sparsify" MultiIndex display (don't display repeated elements in outer levels within groups) [default: True] [currently: True]

display.notebook_repr_html [boolean] When True, IPython notebook will use html representation for pandas objects (if it is available). [default: True] [currently: True]

display.pprint_nest_depth [int] Controls the number of nested levels to process when pretty-printing [default: 3] [currently: 3]

display.precision [int] Floating point output precision (number of significant digits). This is only a suggestion [default: 7] [currently: 7]

display.show_dimensions [boolean or 'truncate'] Whether to print out dimensions at the end of DataFrame repr. If 'truncate' is specified, only print out the dimensions if the frame is truncated (e.g. not display all rows and/or columns) [default: truncate] [currently: truncate]

display.width [int] Width of the display in characters. In case python/IPython is running in a terminal this can be set to None and pandas will correctly auto-detect the width. Note that the IPython notebook, IPython qtconsole, or IDLE do not run in a terminal and hence it is not possible to correctly detect the width. [default: 80] [currently: 80]

io.excel.xls.writer [string] The default Excel writer engine for 'xls' files. Available options: 'xlwt' (the default). [default: xlwt] [currently: xlwt]

io.excel.xlsm.writer [string] The default Excel writer engine for 'xlsm' files. Available options: 'openpyxl' (the default). [default: openpyxl] [currently: openpyxl]

io.excel.xlsx.writer [string] The default Excel writer engine for 'xlsx' files. Available options: 'xlsxwriter' (the default), 'openpyxl'. [default: xlsxwriter] [currently: xlsxwriter]

io.hdf.default_format [format] default format writing format, if None, then put will default to 'fixed' and append will default to 'table' [default: None] [currently: None]

io.hdf.dropna_table [boolean] drop ALL nan rows when appending to a table [default: True] [currently: True]

mode.chained_assignment [string] Raise an exception, warn, or no action if trying to use chained assignment, The default is warn [default: warn] [currently: warn]

mode.sim_interactive [boolean] Whether to simulate interactive mode for purposes of testing [default: False] [currently: False]

mode.use_inf_as_null [boolean] True means treat None, NaN, INF, -INF as null (old way), False means None and NaN are null, but INF, -INF are not null (new way). [default: False] [currently: False]

pandas.option_context

class pandas.**option_context** (*args)

Context manager to temporarily set options in the *with* statement context.

You need to invoke as `option_context(pat, val, [(pat, val), ...])`.

Examples

```
>>> with option_context('display.max_rows', 10, 'display.max_columns', 5):  
    ...
```


INTERNALS

This section will provide a look into some of pandas internals.

34.1 Indexing

In pandas there are a few objects implemented which can serve as valid containers for the axis labels:

- `Index`: the generic “ordered set” object, an ndarray of object dtype assuming nothing about its contents. The labels must be hashable (and likely immutable) and unique. Populates a dict of label to location in Cython to do $O(1)$ lookups.
- `Int64Index`: a version of `Index` highly optimized for 64-bit integer data, such as time stamps
- `Float64Index`: a version of `Index` highly optimized for 64-bit float data
- `MultiIndex`: the standard hierarchical index object
- `DatetimeIndex`: An `Index` object with `Timestamp` boxed elements (impl are the int64 values)
- `TimedeltaIndex`: An `Index` object with `Timedelta` boxed elements (impl are the in64 values)
- `PeriodIndex`: An `Index` object with `Period` elements

These are range generators to make the creation of a regular index easy:

- `date_range`: fixed frequency date range generated from a time rule or `DateOffset`. An ndarray of Python datetime objects
- `period_range`: fixed frequency date range generated from a time rule or `DateOffset`. An ndarray of `Period` objects, representing Timespans

The motivation for having an `Index` class in the first place was to enable different implementations of indexing. This means that it’s possible for you, the user, to implement a custom `Index` subclass that may be better suited to a particular application than the ones provided in pandas.

From an internal implementation point of view, the relevant methods that an `Index` must define are one or more of the following (depending on how incompatible the new object internals are with the `Index` functions):

- `get_loc`: returns an “indexer” (an integer, or in some cases a slice object) for a label
- `slice_locs`: returns the “range” to slice between two labels
- `get_indexer`: Computes the indexing vector for reindexing / data alignment purposes. See the source / docstrings for more on this
- `get_indexer_non_unique`: Computes the indexing vector for reindexing / data alignment purposes when the index is non-unique. See the source / docstrings for more on this
- `reindex`: Does any pre-conversion of the input index then calls `get_indexer`

- `union, intersection`: computes the union or intersection of two Index objects
- `insert`: Inserts a new label into an Index, yielding a new object
- `delete`: Delete a label, yielding a new object
- `drop`: Deletes a set of labels
- `take`: Analogous to `ndarray.take`

34.1.1 MultiIndex

Internally, the `MultiIndex` consists of a few things: the **levels**, the integer **labels**, and the level **names**:

```
In [1]: index = MultiIndex.from_product([range(3), ['one', 'two']], names=['first', 'second'])
```

```
In [2]: index
```

```
Out[2]: MultiIndex(levels=[[0, 1, 2], [u'one', u'two']],
                    labels=[[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]],
                    names=[u'first', u'second'])
```

```
In [3]: index.levels
```

```
Out[3]: FrozenList([[0, 1, 2], [u'one', u'two']])
```

```
In [4]: index.labels
```

```
Out[4]: FrozenList([[0, 0, 1, 1, 2, 2], [0, 1, 0, 1, 0, 1]])
```

```
In [5]: index.names
```

```
Out[5]: FrozenList([u'first', u'second'])
```

You can probably guess that the labels determine which unique element is identified with that location at each layer of the index. It's important to note that sortedness is determined **solely** from the integer labels and does not check (or care) whether the levels themselves are sorted. Fortunately, the constructors `from_tuples` and `from_arrays` ensure that this is true, but if you compute the levels and labels yourself, please be careful.

34.2 Subclassing pandas Data Structures

Warning: There are some easier alternatives before considering subclassing pandas data structures.

1. Monkey-patching: See [Adding Features to your pandas Installation](#).
2. Use *composition*. See [here](#).

This section describes how to subclass pandas data structures to meet more specific needs. There are 2 points which need attention:

1. Override constructor properties.
2. Define original properties

Note: You can find a nice example in [geopandas](#) project.

34.2.1 Override Constructor Properties

Each data structure has constructor properties to specifying data constructors. By overriding these properties, you can retain defined-classes through pandas data manipulations.

There are 3 constructors to be defined:

- `_constructor`: Used when a manipulation result has the same dimesions as the original.
- `_constructor_sliced`: Used when a manipulation result has one lower dimension(s) as the original, such as `DataFrame` single columns slicing.
- `_constructor_expanddim`: Used when a manipulation result has one higher dimension as the original, such as `Series.to_frame()` and `DataFrame.to_panel()`.

Following table shows how pandas data structures define constructor properties by default.

Property Attributes	Series	DataFrame	Panel
<code>_constructor</code>	Series	DataFrame	Panel
<code>_constructor_sliced</code>	NotImplementedError	Series	DataFrame
<code>_constructor_expanddim</code>	DataFrame	Panel	NotImplementedError

Below example shows how to define `SubclassedSeries` and `SubclassedDataFrame` overriding constructor properties.

```
class SubclassedSeries(Series):

    @property
    def _constructor(self):
        return SubclassedSeries

    @property
    def _constructor_expanddim(self):
        return SubclassedDataFrame

class SubclassedDataFrame(DataFrame):

    @property
    def _constructor(self):
        return SubclassedDataFrame

    @property
    def _constructor_sliced(self):
        return SubclassedSeries

>>> s = SubclassedSeries([1, 2, 3])
>>> type(s)
<class '__main__.SubclassedSeries'>

>>> to_framed = s.to_frame()
>>> type(to_framed)
<class '__main__.SubclassedDataFrame'>

>>> df = SubclassedDataFrame({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9
```

```
>>> type(df)
<class '__main__.SubclassedDataFrame'>

>>> sliced1 = df[['A', 'B']]
>>> sliced1
   A  B
0  1  4
1  2  5
2  3  6
>>> type(sliced1)
<class '__main__.SubclassedDataFrame'>

>>> sliced2 = df['A']
>>> sliced2
0    1
1    2
2    3
Name: A, dtype: int64
>>> type(sliced2)
<class '__main__.SubclassedSeries'>
```

34.2.2 Define Original Properties

To let original data structures have additional properties, you should let pandas know what properties are added. pandas maps unknown properties to data names overriding `__getattr__`. Defining original properties can be done in one of 2 ways:

1. Define `_internal_names` and `_internal_names_set` for temporary properties which WILL NOT be passed to manipulation results.
2. Define `_metadata` for normal properties which will be passed to manipulation results.

Below is an example to define 2 original properties, “`internal_cache`” as a temporary property and “`added_property`” as a normal property

```
class SubclassedDataFrame2(DataFrame):

    # temporary properties
    _internal_names = DataFrame._internal_names + ['internal_cache']
    _internal_names_set = set(_internal_names)

    # normal properties
    _metadata = ['added_property']

    @property
    def _constructor(self):
        return SubclassedDataFrame2

>>> df = SubclassedDataFrame2({'A': [1, 2, 3], 'B': [4, 5, 6], 'C': [7, 8, 9]})
>>> df
   A  B  C
0  1  4  7
1  2  5  8
2  3  6  9
```

```
>>> df.internal_cache = 'cached'
>>> df.added_property = 'property'

>>> df.internal_cache
cached
>>> df.added_property
property

# properties defined in _internal_names is reset after manipulation
>>> df[['A', 'B']].internal_cache
AttributeError: 'SubclassedDataFrame2' object has no attribute 'internal_cache'

# properties defined in _metadata are retained
>>> df[['A', 'B']].added_property
property
```


RELEASE NOTES

This is the list of changes to pandas between each release. For full details, see the commit logs at <http://github.com/pydata/pandas>

What is it

pandas is a Python package providing fast, flexible, and expressive data structures designed to make working with “relational” or “labeled” data both easy and intuitive. It aims to be the fundamental high-level building block for doing practical, real world data analysis in Python. Additionally, it has the broader goal of becoming the most powerful and flexible open source data analysis / manipulation tool available in any language.

Where to get it

- Source code: <http://github.com/pydata/pandas>
- Binary installers on PyPI: <http://pypi.python.org/pypi/pandas>
- Documentation: <http://pandas.pydata.org>

35.1 pandas 0.16.1

Release date: (May 11, 2015)

This is a minor release from 0.16.0 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. A small number of API changes were necessary to fix existing bugs.

See the [v0.16.1 Whatsnew](#) overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.16.1.

35.1.1 Thanks

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- jnmclarty
- jreback
- ksanghai
- lucas
- mschmohl
- ptype
- rockg
- scls19fr
- sinhrks

35.2 pandas 0.16.0

Release date: (March 22, 2015)

This is a major release from 0.15.2 and includes a number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- `DataFrame.assign` method, see [here](#)
- `Series.to_coo/from_coo` methods to interact with `scipy.sparse`, see [here](#)
- Backwards incompatible change to `Timedelta` to conform the `.seconds` attribute with `datetime.timedelta`, see [here](#)
- Changes to the `.loc` slicing API to conform with the behavior of `.ix` see [here](#)
- Changes to the default for ordering in the `Categorical` constructor, see [here](#)
- The `pandas.tools.rplot`, `pandas.sandbox.qtpandas` and `pandas.rpy` modules are deprecated. We refer users to external packages like [seaborn](#), [pandas-qt](#) and [rpy2](#) for similar or equivalent functionality, see [here](#)

See the [v0.16.0 Whatsnew](#) overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.16.0.

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- bjonen
- cel4
- clham
- hsperr
- ischwabacher
- jnmclarty
- josham
- jreback
- omtinez
- roch
- sinhrks
- unutbu

35.3 pandas 0.15.2

Release date: (December 12, 2014)

This is a minor release from 0.15.1 and includes a large number of bug fixes along with several new features, enhancements, and performance improvements. A small number of API changes were necessary to fix existing bugs.

See the [v0.15.2 Whatsnew](#) overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.2.

35.3.1 Thanks

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- Matthew Brett
- Phillip Cloud
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- Tiago Antao
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- Will Holmgren
- behzad nouri
- broessli
- charalampos papaloizou
- immerrr
- jnmclarty
- jreback
- mgilbert
- onesandzeroes
- peadarcoyle
- rockg
- seth-p

- sinhrks
- unutbu
- wavedatalab
- Åsmund Hjulstad

35.4 pandas 0.15.1

Release date: (November 9, 2014)

This is a minor release from 0.15.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

See the [v0.15.1 Whatsnew](#) overview for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.1.

35.4.1 Thanks

- Aaron Staple
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- Nick Stahl
- Sanghee Kim
- Stephan Hoyer
- TomAugspurger
- WANG Aiyong
- behzad nouri
- immerrr
- jnmclarty
- jreback
- pallav-fdsi
- unutbu

35.5 pandas 0.15.0

Release date: (October 18, 2014)

This is a major release from 0.14.1 and includes a number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- Drop support for numpy < 1.7.0 ([GH7711](#))
- The `Categorical` type was integrated as a first-class pandas type, see [here](#)
- New scalar type `Timedelta`, and a new index type `TimedeltaIndex`, see [here](#)
- New `DataFrame` default display for `df.info()` to include memory usage, see [Memory Usage](#)
- New datetimelike properties accessor `.dt` for `Series`, see [Datetimelike Properties](#)
- Split indexing documentation into [Indexing and Selecting Data](#) and [MultiIndex / Advanced Indexing](#)
- Split out string methods documentation into [Working with Text Data](#)
- `read_csv` will now by default ignore blank lines when parsing, see [here](#)
- API change in using `Indexes` in set operations, see [here](#)
- Internal refactoring of the `Index` class to no longer sub-class `ndarray`, see [Internal Refactoring](#)
- dropping support for `PyTables` less than version 3.0.0, and `numexpr` less than version 2.1 ([GH7990](#))

See the [v0.15.0 Whatsnew](#) overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.15.0.

35.5.1 Thanks

- Aaron Schumacher
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- Chris Stoafer
- Dav Clark
- dlovel

- DSM
- dsm054
- FragLegs
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- Hsiaoming Yang
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- ischwabacher
- Jacob Schaer
- Jacob Wasserman
- Jan Schulz
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- jnmclarty
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- Joris Van den Bossche
- jreback
- Kevin Sheppard
- klonuo
- Kyle Meyer
- lexical
- Max Chang
- mcjcode
- Michael Mueller
- Michael W Schatzow
- Mike Kelly
- Mortada Mehyar
- mtrbean
- Nathan Sanders
- Nathan Typanski

- onesandzeroes
- Paul Masurel
- Phillip Cloud
- Pietro Battiston
- RenzoBertocchi
- rockg
- Ross Petchler
- seth-p
- Shahul Hameed
- Shashank Agarwal
- sinhrks
- someben
- stahlous
- stas-sl
- Stephan Hoyer
- thatneat
- tom-alcorn
- TomAugspurger
- Tom Augspurger
- Tony Lorenzo
- unknown
- unutbu
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35.6 pandas 0.14.1

Release date: (July 11, 2014)

This is a minor release from 0.14.0 and includes a small number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- New methods `select_dtypes()` to select columns based on the dtype and `sem()` to calculate the standard error of the mean.
- Support for dateutil timezones (see *docs*).

- Support for ignoring full line comments in the `read_csv()` text parser.
- New documentation section on *Options and Settings*.
- Lots of bug fixes.

See the [v0.14.1 Whatsnew](#) overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.14.1.

35.6.1 Thanks

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- David Stephens
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- dsm054
- helger
- immerrr
- Jacob Schaer
- jaimefrio
- Jan Schulz
- John David Reaver
- John W. O'Brien
- Joris Van den Bossche
- jreback
- Julien Danjou
- Kevin Sheppard
- K.-Michael Aye
- Kyle Meyer
- lexical
- Matthew Brett
- Matt Wittmann

- Michael Mueller
- Mortada Mehیار
- onesandzeroes
- Phillip Cloud
- Rob Levy
- rockg
- sanguineturtle
- Schaer, Jacob C
- seth-p
- sinhrks
- Stephan Hoyer
- Thomas Kluyver
- Todd Jennings
- TomAugspurger
- unknown
- yelite

35.7 pandas 0.14.0

Release date: (May 31, 2014)

This is a major release from 0.13.1 and includes a number of API changes, several new features, enhancements, and performance improvements along with a large number of bug fixes.

Highlights include:

- Officially support Python 3.4
- SQL interfaces updated to use `sqlalchemy`, see [here](#).
- Display interface changes, see [here](#)
- MultiIndexing using Slicers, see [here](#).
- Ability to join a singly-indexed DataFrame with a multi-indexed DataFrame, see [here](#)
- More consistency in groupby results and more flexible groupby specifications, see [here](#)
- Holiday calendars are now supported in `CustomBusinessDay`, see [here](#)
- Several improvements in plotting functions, including: hexbin, area and pie plots, see [here](#).
- Performance doc section on I/O operations, see [here](#)

See the [v0.14.0 Whatsnew](#) overview or the issue tracker on GitHub for an extensive list of all API changes, enhancements and bugs that have been fixed in 0.14.0.

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- benjamin
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- bwignall
- cgohlke
- chebee7i
- Christopher Whelan
- Clark Fitzgerald
- clham
- Dale Jung
- Dan Allan
- Dan Birken
- danielballan
- Daniel Waeber
- David Jung
- David Stephens
- Douglas McNeil
- DSM
- Garrett Drapala
- Gouthaman Balaraman
- Guillaume Poulin

- hshimizu77
- hugo
- immerrr
- ischwabacher
- Jacob Howard
- Jacob Schaer
- jaimefrio
- Jason Sexauer
- Jeff Reback
- Jeffrey Starr
- Jeff Tratner
- John David Reaver
- John McNamara
- John W. O'Brien
- Jonathan Chambers
- Joris Van den Bossche
- jreback
- jsexauer
- Julia Evans
- Júlio
- Katie Atkinson
- kdiether
- Kelsey Jordahl
- Kevin Sheppard
- K.-Michael Aye
- Matthias Kuhn
- Matt Wittmann
- Max Grender-Jones
- Michael E. Gruen
- michaelws
- mikebailey
- Mike Kelly
- Nipun Batra
- Noah Spies
- ojdo
- onesandzeroes

- Patrick O’Keeffe
- phaebz
- Phillip Cloud
- Pietro Battiston
- PKEuS
- Randy Carnevale
- ribonooous
- Robert Gibboni
- rockg
- sinhrks
- Skipper Seabold
- SplashDance
- Stephan Hoyer
- Tim Cera
- Tobias Brandt
- Todd Jennings
- TomAugspurger
- Tom Augspurger
- unutbu
- westurner
- Yaroslav Halchenko
- y-p
- zach powers

35.8 pandas 0.13.1

Release date: (February 3, 2014)

35.8.1 New Features

- Added `date_format` and `datetime_format` attribute to `ExcelWriter`. ([GH4133](#))

35.8.2 API Changes

- `Series.sort` will raise a `ValueError` (rather than a `TypeError`) on sorting an object that is a view of another ([GH5856](#), [GH5853](#))
- Raise/Warn `SettingWithCopyError` (according to the option `chained_assignment` in more cases, when detecting chained assignment, related ([GH5938](#), [GH6025](#)))

- `DataFrame.head(0)` returns self instead of empty frame (GH5846)
- `autocorrelation_plot` now accepts `**kwargs`. (GH5623)
- `convert_objects` now accepts a `convert_timedeltas='coerce'` argument to allow forced dtype conversion of timedeltas (GH5458, issue:5689)
- Add `-NaN` and `-nan` to the default set of NA values (GH5952). See *NA Values*.
- `NDFrame` now has an `equals` method. (GH5283)
- `DataFrame.apply` will use the `reduce` argument to determine whether a `Series` or a `DataFrame` should be returned when the `DataFrame` is empty (GH6007).

35.8.3 Experimental Features

35.8.4 Improvements to existing features

- perf improvements in `Series` datetime/timedelta binary operations (GH5801)
- `option_context` context manager now available as top-level API (GH5752)
- `df.info()` view now display dtype info per column (GH5682)
- `df.info()` now honors option `max_info_rows`, disable null counts for large frames (GH5974)
- perf improvements in `DataFrame.count/dropna` for `axis=1`
- `Series.str.contains` now has a `regex=False` keyword which can be faster for plain (non-regex) string patterns. (GH5879)
- support dtypes property on `Series/Panel/Panel4D`
- extend `Panel.apply` to allow arbitrary functions (rather than only ufuncs) (GH1148) allow multiple axes to be used to operate on slabs of a `Panel`
- The `ArrayFormatter` for datetime and `timedelta64` now intelligently limit precision based on the values in the array (GH3401)
- `pd.show_versions()` is now available for convenience when reporting issues.
- perf improvements to `Series.str.extract` (GH5944)
- perf improvements in `dtypes/ftypes` methods (GH5968)
- perf improvements in indexing with object dtypes (GH5968)
- improved dtype inference for `timedelta` like passed to constructors (GH5458, GH5689)
- escape special characters when writing to latex (issue: 5374)
- perf improvements in `DataFrame.apply` (GH6013)
- `pd.read_csv` and `pd.to_datetime` learned a new `infer_datetime_format` keyword which greatly improves parsing perf in many cases. Thanks to @lexical for suggesting and @danbirken for rapidly implementing. (GH5490, issue:6021)
- add ability to recognize '%p' format code (am/pm) to date parsers when the specific format is supplied (GH5361)
- Fix performance regression in JSON IO (GH5765)
- performance regression in Index construction from `Series` (GH6150)

35.8.5 Bug Fixes

- Bug in `io.wb.get_countries` not including all countries (GH6008)
- Bug in Series replace with timestamp dict (GH5797)
- `read_csv/read_table` now respects the *prefix* kwarg (GH5732).
- Bug in selection with missing values via `.ix` from a duplicate indexed DataFrame failing (GH5835)
- Fix issue of boolean comparison on empty DataFrames (GH5808)
- Bug in `isnull` handling NaT in an object array (GH5443)
- Bug in `to_datetime` when passed a `np.nan` or integer datelike and a format string (GH5863)
- Bug in groupby dtype conversion with datetimelike (GH5869)
- Regression in handling of empty Series as indexers to Series (GH5877)
- Bug in internal caching, related to (GH5727)
- Testing bug in reading JSON/msgpack from a non-filepath on windows under py3 (GH5874)
- Bug when assigning to `.ix[tuple(...)]` (GH5896)
- Bug in fully reindexing a Panel (GH5905)
- Bug in `idxmin/max` with object dtypes (GH5914)
- Bug in `BusinessDay` when adding `n` days to a date not on offset when `n>5` and `n%5==0` (GH5890)
- Bug in assigning to chained series with a series via `ix` (GH5928)
- Bug in creating an empty DataFrame, copying, then assigning (GH5932)
- Bug in `DataFrame.tail` with empty frame (GH5846)
- Bug in propagating metadata on `resample` (GH5862)
- Fixed string-representation of NaT to be “NaT” (GH5708)
- Fixed string-representation for Timestamp to show nanoseconds if present (GH5912)
- `pd.match` not returning passed sentinel
- `Panel.to_frame()` no longer fails when `major_axis` is a `MultiIndex` (GH5402).
- Bug in `pd.read_msgpack` with inferring a `DateTimeIndex` frequency incorrectly (GH5947)
- Fixed `to_datetime` for array with both Tz-aware datetimes and NaT’s (GH5961)
- Bug in rolling skew/kurtosis when passed a Series with bad data (GH5749)
- Bug in `scipy.interpolate` methods with a datetime index (GH5975)
- Bug in NaT comparison if a mixed datetime/`np.datetime64` with NaT were passed (GH5968)
- Fixed bug with `pd.concat` losing dtype information if all inputs are empty (GH5742)
- Recent changes in IPython cause warnings to be emitted when using previous versions of pandas in QTConsole, now fixed. If you’re using an older version and need to suppress the warnings, see (GH5922).
- Bug in merging `timedelta` dtypes (GH5695)
- Bug in `plotting.scatter_matrix` function. Wrong alignment among diagonal and off-diagonal plots, see (GH5497).
- Regression in Series with a multi-index via `ix` (GH6018)

- Bug in `Series.xs` with a multi-index (GH6018)
- Bug in Series construction of mixed type with datelike and an integer (which should result in object type and not automatic conversion) (GH6028)
- Possible segfault when chained indexing with an object array under numpy 1.7.1 (GH6026, GH6056)
- Bug in setting using fancy indexing a single element with a non-scalar (e.g. a list), (GH6043)
- `to_sql` did not respect `if_exists` (GH4110 GH4304)
- Regression in `.get(None)` indexing from 0.12 (GH5652)
- Subtle `iloc` indexing bug, surfaced in (GH6059)
- Bug with insert of strings into `DatetimeIndex` (GH5818)
- Fixed unicode bug in `to_html/HTML repr` (GH6098)
- Fixed missing arg validation in `get_options_data` (GH6105)
- Bug in assignment with duplicate columns in a frame where the locations are a slice (e.g. next to each other) (GH6120)
- Bug in propagating `_ref_locs` during construction of a `DataFrame` with dups index/columns (GH6121)
- Bug in `DataFrame.apply` when using mixed datelike reductions (GH6125)
- Bug in `DataFrame.append` when appending a row with different columns (GH6129)
- Bug in `DataFrame` construction with recarray and non-ns datetime dtype (GH6140)
- Bug in `.loc` setitem indexing with a dataframe on rhs, multiple item setting, and a datetimelike (GH6152)
- Fixed a bug in `query/eval` during lexicographic string comparisons (GH6155).
- Fixed a bug in `query` where the index of a single-element `Series` was being thrown away (GH6148).
- Bug in `HDFStore` on appending a dataframe with multi-indexed columns to an existing table (GH6167)
- Consistency with dtypes in setting an empty `DataFrame` (GH6171)
- Bug in selecting on a multi-index `HDFStore` even in the presence of under specified column spec (GH6169)
- Bug in `nanops.var` with `ddof=1` and 1 elements would sometimes return `inf` rather than `nan` on some platforms (GH6136)
- Bug in Series and DataFrame bar plots ignoring the `use_index` keyword (GH6209)
- Bug in groupby with mixed str/int under python3 fixed; `argsort` was failing (GH6212)

35.9 pandas 0.13.0

Release date: January 3, 2014

35.9.1 New Features

- `plot(kind='kde')` now accepts the optional parameters `bw_method` and `ind`, passed to `scipy.stats.gaussian_kde()` (for `scipy >= 0.11.0`) to set the bandwidth, and to `gkde.evaluate()` to specify the indices at which it is evaluated, respectively. See `scipy` docs. (GH4298)
- Added `isin` method to `DataFrame` (GH4211)

- `df.to_clipboard()` learned a new `excel` keyword that let's you paste df data directly into excel (enabled by default). (GH5070).
- Clipboard functionality now works with PySide (GH4282)
- New `extract` string method returns regex matches more conveniently (GH4685)
- Auto-detect field widths in `read_fwf` when unspecified (GH4488)
- `to_csv()` now outputs datetime objects according to a specified format string via the `date_format` keyword (GH4313)
- Added `LastWeekOfMonth` `DateOffset` (GH4637)
- Added `cumcount` `groupby` method (GH4646)
- Added `FY5253`, and `FY5253Quarter` `DateOffsets` (GH4511)
- Added `mode()` method to `Series` and `DataFrame` to get the statistical mode(s) of a column/series. (GH5367)

35.9.2 Experimental Features

- The new `eval()` function implements expression evaluation using `numexpr` behind the scenes. This results in large speedups for complicated expressions involving large `DataFrames`/`Series`.
- `DataFrame` has a new `eval()` that evaluates an expression in the context of the `DataFrame`; allows inline expression assignment
- A `query()` method has been added that allows you to select elements of a `DataFrame` using a natural query syntax nearly identical to Python syntax.
- `pd.eval` and friends now evaluate operations involving `datetime64` objects in Python space because `numexpr` cannot handle `NaT` values (GH4897).
- Add `msgpack` support via `pd.read_msgpack()` and `pd.to_msgpack()` / `df.to_msgpack()` for serialization of arbitrary pandas (and python objects) in a lightweight portable binary format (GH686, GH5506)
- Added PySide support for the `qtandas DataFrameModel` and `DataFrameWidget`.
- Added `pandas.io.gbq` for reading from (and writing to) Google BigQuery into a `DataFrame`. (GH4140)

35.9.3 Improvements to existing features

- `read_html` now raises a `URLError` instead of catching and raising a `ValueError` (GH4303, GH4305)
- `read_excel` now supports an integer in its `sheetname` argument giving the index of the sheet to read in (GH4301).
- `get_dummies` works with `NaN` (GH4446)
- Added a test for `read_clipboard()` and `to_clipboard()` (GH4282)
- Added `bins` argument to `value_counts` (GH3945), also `sort` and `ascending`, now available in `Series` method as well as top-level function.
- Text parser now treats anything that reads like `inf` ("`inf`", "`Inf`", "`-Inf`", "`iNf`", etc.) to infinity. (GH4220, GH4219), affecting `read_table`, `read_csv`, etc.
- Added a more informative error message when plot arguments contain overlapping color and style arguments (GH4402)
- Significant table writing performance improvements in `HDFStore`

- JSON date serialization now performed in low-level C code.
- JSON support for encoding `datetime.time`
- Expanded JSON docs, more info about orient options and the use of the `numpy` param when decoding.
- Add `drop_level` argument to `xs` ([GH4180](#))
- Can now resample a `DataFrame` with `ohlc` ([GH2320](#))
- `Index.copy()` and `MultiIndex.copy()` now accept keyword arguments to change attributes (i.e., `names`, `levels`, `labels`) ([GH4039](#))
- Add `rename` and `set_names` methods to `Index` as well as `set_names`, `set_levels`, `set_labels` to `MultiIndex`. ([GH4039](#)) with improved validation for all ([GH4039](#), [GH4794](#))
- A `Series` of dtype `timedelta64[ns]` can now be divided/multiplied by an integer series ([GH4521](#))
- A `Series` of dtype `timedelta64[ns]` can now be divided by another `timedelta64[ns]` object to yield a `float64` dtyped `Series`. This is frequency conversion; astyping is also supported.
- `Timedelta64` support `fillna/ffill/bfill` with an integer interpreted as seconds, or a `timedelta` ([GH3371](#))
- Box numeric ops on `timedelta` `Series` ([GH4984](#))
- `Datetime64` support `ffill/bfill`
- Performance improvements with `__getitem__` on `DataFrames` with when the key is a column
- Support for using a `DatetimeIndex/PeriodsIndex` directly in a datelike calculation e.g. `s.s.index` ([GH4629](#))
- Better/cleaned up exceptions in `core/common`, `io/excel` and `core/format` ([GH4721](#), [GH3954](#)), as well as cleaned up test cases in `tests/test_frame`, `tests/test_multilevel` ([GH4732](#)).
- Performance improvement of timeseries plotting with `PeriodIndex` and added test to `vbench` ([GH4705](#) and [GH4722](#))
- Add `axis` and `level` keywords to `where`, so that the `other` argument can now be an alignable pandas object.
- `to_datetime` with a format of `'%Y%m%d'` now parses much faster
- It's now easier to hook new Excel writers into pandas (just subclass `ExcelWriter` and register your engine). You can specify an engine in `to_excel` or in `ExcelWriter`. You can also specify which writers you want to use by default with config options `io.excel.xlsx.writer` and `io.excel.xls.writer`. ([GH4745](#), [GH4750](#))
- `Panel.to_excel()` now accepts keyword arguments that will be passed to its `DataFrame's to_excel()` methods. ([GH4750](#))
- Added `XlsxWriter` as an optional `ExcelWriter` engine. This is about 5x faster than the default `openpyxl` `xlsx` writer and is equivalent in speed to the `xlwt` `xls` writer module. ([GH4542](#))
- allow `DataFrame` constructor to accept more list-like objects, e.g. `list` of `collections.Sequence` and `array.Array` objects ([GH3783](#), [GH4297](#), [GH4851](#)), thanks @lgautier
- `DataFrame` constructor now accepts a `numpy` masked record array ([GH3478](#)), thanks @jnothman
- `__getitem__` with tuple key (e.g., `[:, 2]`) on `Series` without `MultiIndex` raises `ValueError` ([GH4759](#), [GH4837](#))
- `read_json` now raises a (more informative) `ValueError` when the dict contains a bad key and `orient='split'` ([GH4730](#), [GH4838](#))

- `read_stata` now accepts Stata 13 format ([GH4291](#))
- `ExcelWriter` and `ExcelFile` can be used as contextmanagers. ([GH3441](#), [GH4933](#))
- `pandas` is now tested with two different versions of `statsmodels` (0.4.3 and 0.5.0) ([GH4981](#)).
- Better string representations of `MultiIndex` (including ability to roundtrip via `repr`). ([GH3347](#), [GH4935](#))
- Both `ExcelFile` and `read_excel` to accept an `xlrd.Book` for the `io` (formerly `path_or_buf`) argument; this requires engine to be set. ([GH4961](#)).
- `concat` now gives a more informative error message when passed objects that cannot be concatenated ([GH4608](#)).
- Add `halflife` option to exponentially weighted moving functions (PR [GH4998](#))
- `to_dict` now takes `records` as a possible outtype. Returns an array of column-keyed dictionaries. ([GH4936](#))
- `tz_localize` can infer a fall daylight savings transition based on the structure of unlocalized data ([GH4230](#))
- `DatetimeIndex` is now in the API documentation
- Improve support for converting R datasets to pandas objects (more informative index for timeseries and numeric, support for factors, dist, and high-dimensional arrays).
- `read_html()` now supports the `parse_dates`, `tupleize_cols` and `thousands` parameters ([GH4770](#)).
- `json_normalize()` is a new method to allow you to create a flat table from semi-structured JSON data. *See the docs* ([GH1067](#))
- `DataFrame.from_records()` will now accept generators ([GH4910](#))
- `DataFrame.interpolate()` and `Series.interpolate()` have been expanded to include interpolation methods from `scipy`. ([GH4434](#), [GH1892](#))
- `Series` now supports a `to_frame` method to convert it to a single-column `DataFrame` ([GH5164](#))
- `DatetimeIndex` (and `date_range`) can now be constructed in a left- or right-open fashion using the `closed` parameter ([GH4579](#))
- Python csv parser now supports `usecols` ([GH4335](#))
- Added support for Google Analytics v3 API segment IDs that also supports v2 IDs. ([GH5271](#))
- `NDFrame.drop()` now accepts names as well as integers for the `axis` argument. ([GH5354](#))
- Added short docstrings to a few methods that were missing them + fixed the docstrings for Panel flex methods. ([GH5336](#))
- `NDFrame.drop()`, `NDFrame.dropna()`, and `.drop_duplicates()` all accept `inplace` as a keyword argument; however, this only means that the wrapper is updated `inplace`, a copy is still made internally. ([GH1960](#), [GH5247](#), [GH5628](#), and related [GH2325](#) [still not closed])
- Fixed bug in `tools.plotting.andrews_curves` so that lines are drawn grouped by color as expected.
- `read_excel()` now tries to convert integral floats (like `1.0`) to `int` by default. ([GH5394](#))
- Excel writers now have a default option `merge_cells` in `to_excel()` to merge cells in `MultiIndex` and Hierarchical Rows. Note: using this option it is no longer possible to round trip Excel files with merged `MultiIndex` and Hierarchical Rows. Set the `merge_cells` to `False` to restore the previous behaviour. ([GH5254](#))
- The FRED `DataReader` now accepts multiple series (:issue‘3413’)
- `StataWriter` adjusts variable names to Stata’s limitations ([GH5709](#))

35.9.4 API Changes

- `DataFrame.reindex()` and forward/backward filling now raises `ValueError` if either index is not monotonic ([GH4483](#), [GH4484](#)).
- pandas now is Python 2/3 compatible without the need for 2to3 thanks to @jtratrner. As a result, pandas now uses iterators more extensively. This also led to the introduction of substantive parts of the Benjamin Peterson's `six` library into `compat`. ([GH4384](#), [GH4375](#), [GH4372](#))
- `pandas.util.compat` and `pandas.util.py3compat` have been merged into `pandas.compat`. `pandas.compat` now includes many functions allowing 2/3 compatibility. It contains both list and iterator versions of `range`, `filter`, `map` and `zip`, plus other necessary elements for Python 3 compatibility. `lmap`, `lzip`, `lrange` and `lfilter` all produce lists instead of iterators, for compatibility with `numpy`, subscripting and pandas constructors. ([GH4384](#), [GH4375](#), [GH4372](#))
- deprecated `iterkv`, which will be removed in a future release (was just an alias of `iteritems` used to get around 2to3's changes). ([GH4384](#), [GH4375](#), [GH4372](#))
- `Series.get` with negative indexers now returns the same as `[]` ([GH4390](#))
- allow `ix/loc` for `Series/DataFrame/Panel` to set on any axis even when the single-key is not currently contained in the index for that axis ([GH2578](#), [GH5226](#), [GH5632](#), [GH5720](#), [GH5744](#), [GH5756](#))
- Default export for `to_clipboard` is now `csv` with a sep of `t` for `compat` ([GH3368](#))
- `at` now will enlarge the object inplace (and return the same) ([GH2578](#))
- `DataFrame.plot` will scatter plot `x` versus `y` by passing `kind='scatter'` ([GH2215](#))
- `HDFStore`
 - `append_to_multiple` automatically synchronizes writing rows to multiple tables and adds a `dropna` kwarg ([GH4698](#))
 - handle a passed `Series` in table format ([GH4330](#))
 - added an `is_open` property to indicate if the underlying file handle is `open`; a closed store will now report 'CLOSED' when viewing the store (rather than raising an error) ([GH4409](#))
 - a close of a `HDFStore` now will close that instance of the `HDFStore` but will only close the actual file if the ref count (by `PyTables`) w.r.t. all of the open handles are 0. Essentially you have a local instance of `HDFStore` referenced by a variable. Once you close it, it will report closed. Other references (to the same file) will continue to operate until they themselves are closed. Performing an action on a closed file will raise `ClosedFileError`
 - removed the `_quiet` attribute, replace by a `DuplicateWarning` if retrieving duplicate rows from a table ([GH4367](#))
 - removed the `warn` argument from `open`. Instead a `PossibleDataLossError` exception will be raised if you try to use `mode='w'` with an `OPEN` file handle ([GH4367](#))
 - allow a passed locations array or mask as a `where` condition ([GH4467](#))
 - add the keyword `dropna=True` to `append` to change whether ALL nan rows are not written to the store (default is `True`, ALL nan rows are NOT written), also settable via the option `io.hdf.dropna_table` ([GH4625](#))
 - the `format` keyword now replaces the `table` keyword; allowed values are `fixed(f) | table(t)` the `Storer` format has been renamed to `Fixed`
 - a column multi-index will be recreated properly ([GH4710](#)); raise on trying to use a multi-index with `data_columns` on the same axis
 - `select_as_coordinates` will now return an `Int64Index` of the resultant selection set

- support `timedelta64[ns]` as a serialization type (GH3577)
- store `datetime.date` objects as ordinals rather than `timetuples` to avoid timezone issues (GH2852), thanks @tavistmorph and @numband
- `numexpr` 2.2.2 fixes incompatibility in `PyTables` 2.4 (GH4908)
- `flush` now accepts an `fsync` parameter, which defaults to `False` (GH5364)
- `unicode` indices not supported on `table` formats (GH5386)
- pass thru store creation arguments; can be used to support in-memory stores
- JSON
 - added `date_unit` parameter to specify resolution of timestamps. Options are seconds, milliseconds, microseconds and nanoseconds. (GH4362, GH4498).
 - added `default_handler` parameter to allow a callable to be passed which will be responsible for handling otherwise unserializable objects. (GH5138)
- Index and MultiIndex changes (GH4039):
 - Setting `levels` and `labels` directly on `MultiIndex` is now deprecated. Instead, you can use the `set_levels()` and `set_labels()` methods.
 - `levels`, `labels` and `names` properties no longer return lists, but instead return containers that do not allow setting of items ('mostly immutable')
 - `levels`, `labels` and `names` are validated upon setting and are either copied or shallow-copied.
 - inplace setting of `levels` or `labels` now correctly invalidates the cached properties. (GH5238).
 - `__deepcopy__` now returns a shallow copy (currently: a view) of the data - allowing metadata changes.
 - `MultiIndex.astype()` now only allows `np.object_`-like dtypes and now returns a `MultiIndex` rather than an `Index`. (GH4039)
 - Added `is_` method to `Index` that allows fast equality comparison of views (similar to `np.may_share_memory` but no false positives, and changes on `levels` and `labels` setting on `MultiIndex`). (GH4859, GH4909)
 - Aliased `__iadd__` to `__add__`. (GH4996)
 - Added `is_` method to `Index` that allows fast equality comparison of views (similar to `np.may_share_memory` but no false positives, and changes on `levels` and `labels` setting on `MultiIndex`). (GH4859, GH4909)
- Infer and downcast dtype if `downcast='infer'` is passed to `fillna/ffill/bfill` (GH4604)
- `__nonzero__` for all `NDFrame` objects, will now raise a `ValueError`, this reverts back to (GH1073, GH4633) behavior. Add `.bool()` method to `NDFrame` objects to facilitate evaluating of single-element boolean Series
- `DataFrame.update()` no longer raises a `DataConflictError`, it now will raise a `ValueError` instead (if necessary) (GH4732)
- `Series.isin()` and `DataFrame.isin()` now raise a `TypeError` when passed a string (GH4763). Pass a list of one element (containing the string) instead.
- Remove undocumented/unused `kind` keyword argument from `read_excel`, and `ExcelFile`. (GH4713, GH4712)
- The method argument of `NDFrame.replace()` is valid again, so that a a list can be passed to `to_replace` (GH4743).

- provide automatic dtype conversions on `_reduce` operations ([GH3371](#))
- exclude non-numerics if mixed types with datelike in `_reduce` operations ([GH3371](#))
- default for `tupleize_cols` is now `False` for both `to_csv` and `read_csv`. Fair warning in 0.12 ([GH3604](#))
- moved `timedeltas` support to `pandas.tseries.timedeltas.py`; add `timedeltas` string parsing, add top-level `to_timedelta` function
- `NDFrame` now is compatible with Python's `abs()` function ([GH4821](#)).
- raise a `TypeError` on invalid comparison ops on `Series/DataFrame` (e.g. integer/datetime) ([GH4968](#))
- Added a new index type, `Float64Index`. This will be automatically created when passing floating values in index creation. This enables a pure label-based slicing paradigm that makes `[]`, `ix`, `loc` for scalar indexing and slicing work exactly the same. Indexing on other index types are preserved (and positional fallback for `[]`, `ix`), with the exception, that floating point slicing on indexes on non `Float64Index` will raise a `TypeError`, e.g. `Series(range(5))[3.5:4.5]` ([GH263](#),:issue:5375)
- Make Categorical repr nicer ([GH4368](#))
- Remove deprecated `Factor` ([GH3650](#))
- Remove deprecated `set_printoptions/reset_printoptions` (:issue:3046)
- Remove deprecated `_verbose_info` ([GH3215](#))
- Begin removing methods that don't make sense on `GroupBy` objects ([GH4887](#)).
- Remove deprecated `read_clipboard/to_clipboard/ExcelFile/ExcelWriter` from `pandas.io.parsers` ([GH3717](#))
- All non-Index `NDFrames` (`Series`, `DataFrame`, `Panel`, `Panel4D`, `SparsePanel`, etc.), now support the entire set of arithmetic operators and arithmetic flex methods (`add`, `sub`, `mul`, etc.). `SparsePanel` does not support `pow` or `mod` with non-scalars. ([GH3765](#))
- Arithmetic func factories are now passed real names (suitable for using with `super`) ([GH5240](#))
- Provide numpy compatibility with 1.7 for a calling convention like `np.prod(pandas_object)` as numpy call with additional keyword args ([GH4435](#))
- Provide `__dir__` method (and local context) for tab completion / remove `ipython` completers code ([GH4501](#))
- Support non-unique axes in a `Panel` via indexing operations ([GH4960](#))
- `.truncate` will raise a `ValueError` if invalid before and after dates are given ([GH5242](#))
- `Timestamp` now supports `now/today/utcnow` class methods ([GH5339](#))
- default for `display.max_seq_len` is now 100 rather than `None`. This activates truncated display ("...") of long sequences in various places. ([GH3391](#))
- All division with `NDFrame` - likes is now `truedivision`, regardless of the `future` import. You can use `//` and `floordiv` to do integer division.

```
In [3]: arr = np.array([1, 2, 3, 4])
```

```
In [4]: arr2 = np.array([5, 3, 2, 1])
```

```
In [5]: arr / arr2
```

```
Out[5]: array([0, 0, 1, 4])
```

```
In [6]: pd.Series(arr) / pd.Series(arr2) # no future import required
```

```
Out[6]:
```

```

0    0.200000
1    0.666667
2    1.500000
3    4.000000
dtype: float64

```

- raise/warn `SettingWithCopyError/Warning` exception/warning when setting of a copy thru chained assignment is detected, settable via option `mode.chained_assignment`
- test the list of NA values in the csv parser. add N/A, #NA as independent default na values ([GH5521](#))
- The refactoring involving “Series” deriving from `NDFrame` breaks `rpy2<=2.3.8`. an Issue has been opened against `rpy2` and a workaround is detailed in [GH5698](#). Thanks @JanSchulz.
- `Series.argmax` and `Series.argmin` are now aliased to `Series.idxmax` and `Series.idxmin`. These return the *index* of the min or max element respectively. Prior to 0.13.0 these would return the position of the min / max element ([GH6214](#))

35.9.5 Internal Refactoring

In 0.13.0 there is a major refactor primarily to subclass `Series` from `NDFrame`, which is the base class currently for `DataFrame` and `Panel`, to unify methods and behaviors. `Series` formerly subclassed directly from `ndarray`. ([GH4080](#), [GH3862](#), [GH816](#)) See *Internal Refactoring*

- Refactor of `series.py/frame.py/panel.py` to move common code to `generic.py`
- added `__setup_axes` to created generic `NDFrame` structures
- moved methods
 - `from_axes`, `__wrap_array`, `axes`, `ix`, `loc`, `iloc`, `shape`, `empty`, `swapaxes`, `transpose`, `pop`
 - `__iter__`, `keys`, `__contains__`, `__len__`, `__neg__`, `__invert__`
 - `convert_objects`, `as_blocks`, `as_matrix`, `values`
 - `__getstate__`, `__setstate__` (compat remains in `frame/panel`)
 - `__getattr__`, `__setattr__`
 - `_indexed_same`, `reindex_like`, `align`, `where`, `mask`
 - `fillna`, `replace` (`Series replace` is now consistent with `DataFrame`)
 - `filter` (also added `axis` argument to selectively filter on a different axis)
 - `reindex`, `reindex_axis`, `take`
 - `truncate` (moved to become part of `NDFrame`)
 - `isnull/notnull` now available on `NDFrame` objects
- These are API changes which make `Panel` more consistent with `DataFrame`
- `swapaxes` on a `Panel` with the same axes specified now return a copy
- support attribute access for setting
- `filter` supports same API as original `DataFrame filter`
- `fillna` refactored to `core/generic.py`, while `> 3ndim` is Not Implemented

- Series now inherits from `NDFrame` rather than directly from `ndarray`. There are several minor changes that affect the API.
- numpy functions that do not support the array interface will now return `ndarrays` rather than series, e.g. `np.diff`, `np.ones_like`, `np.where`
- `Series(0.5)` would previously return the scalar `0.5`, this is no longer supported
- `TimeSeries` is now an alias for `Series`. the property `is_time_series` can be used to distinguish (if desired)
- Refactor of Sparse objects to use `BlockManager`
- Created a new block type in internals, `SparseBlock`, which can hold multi-dtypes and is non-consolidatable. `SparseSeries` and `SparseDataFrame` now inherit more methods from there hierarchy (`Series/DataFrame`), and no longer inherit from `SparseArray` (which instead is the object of the `SparseBlock`)
- Sparse suite now supports integration with non-sparse data. Non-float sparse data is supportable (partially implemented)
- Operations on sparse structures within `DataFrames` should preserve sparseness, merging type operations will convert to dense (and back to sparse), so might be somewhat inefficient
- enable `setitem` on `SparseSeries` for boolean/integer/slices
- `SparsePanels` implementation is unchanged (e.g. not using `BlockManager`, needs work)
- added `ftypes` method to `Series/DataFrame`, similar to `dtypes`, but indicates if the underlying is sparse/dense (as well as the dtype)
- All `NDFrame` objects now have a `_prop_attributes`, which can be used to indicate various values to propagate to a new object from an existing (e.g. name in `Series` will follow more automatically now)
- Internal type checking is now done via a suite of generated classes, allowing `isinstance(value, klass)` without having to directly import the class, courtesy of @jtratrner
- Bug in `Series` update where the parent frame is not updating its cache based on changes ([GH4080](#), [GH5216](#)) or types ([GH3217](#)), `fillna` ([GH3386](#))
- Indexing with dtype conversions fixed ([GH4463](#), [GH4204](#))
- Refactor `Series.reindex` to `core/generic.py` ([GH4604](#), [GH4618](#)), allow `method=` in reindexing on a `Series` to work
- `Series.copy` no longer accepts the `order` parameter and is now consistent with `NDFrame` copy
- Refactor `rename` methods to `core/generic.py`; fixes `Series.rename` for ([GH4605](#)), and adds `rename` with the same signature for `Panel`
- `Series` (for index) / `Panel` (for items) now as attribute access to its elements ([GH1903](#))
- Refactor `clip` methods to `core/generic.py` ([GH4798](#))
- Refactor of `_get_numeric_data/_get_bool_data` to `core/generic.py`, allowing `Series/Panel` functionality
- Refactor of `Series` arithmetic with time-like objects (`datetime/timedelta/time` etc.) into a separate, cleaned up wrapper class. ([GH4613](#))
- Complex compat for `Series` with `ndarray`. ([GH4819](#))
- Removed unnecessary `rwproperty` from codebase in favor of builtin `property`. ([GH4843](#))
- Refactor object level numeric methods (`mean/sum/min/max...`) from object level modules to `core/generic.py` ([GH4435](#)).

- Refactor cum objects to core/generic.py (GH4435), note that these have a more numpy-like function signature.
- `read_html()` now uses `TextParser` to parse HTML data from bs4/lxml (GH4770).
- Removed the `keep_internal` keyword parameter in `pandas/core/groupby.py` because it wasn't being used (GH5102).
- Base `DateOffsets` are no longer all instantiated on importing pandas, instead they are generated and cached on the fly. The internal representation and handling of `DateOffsets` has also been clarified. (GH5189, related GH5004)
- `MultiIndex` constructor now validates that passed levels and labels are compatible. (GH5213, GH5214)
- Unity `dropna` for `Series/DataFrame` signature (GH5250), tests from GH5234, courtesy of @rockg
- Rewrite `assert_almost_equal()` in cython for performance (GH4398)
- Added an internal `_update_inplace` method to facilitate updating `NDFrame` wrappers on inplace ops (only is for convenience of caller, doesn't actually prevent copies). (GH5247)

35.9.6 Bug Fixes

- `HDFStore`
 - raising an invalid `TypeError` rather than `ValueError` when appending with a different block ordering (GH4096)
 - `read_hdf` was not respecting `as` passed mode (GH4504)
 - appending a 0-len table will work correctly (GH4273)
 - `to_hdf` was raising when passing both arguments `append` and `table` (GH4584)
 - reading from a store with duplicate columns across dtypes would raise (GH4767)
 - Fixed a bug where `ValueError` wasn't correctly raised when column names weren't strings (GH4956)
 - A zero length series written in Fixed format not deserializing properly. (GH4708)
 - Fixed decoding perf issue on py3 (GH5441)
 - Validate levels in a multi-index before storing (GH5527)
 - Correctly handle `data_columns` with a `Panel` (GH5717)
- Fixed bug in `tslib.tz_convert(vals, tz1, tz2)`: it could raise `IndexError` exception while trying to access `trans[pos + 1]` (GH4496)
- The `by` argument now works correctly with the `layout` argument (GH4102, GH4014) in `*.hist` plotting methods
- Fixed bug in `PeriodIndex.map` where using `str` would return the `str` representation of the index (GH4136)
- Fixed test failure `test_time_series_plot_color_with_empty_kwargs` when using custom matplotlib default colors (GH4345)
- Fix running of stata IO tests. Now uses temporary files to write (GH4353)
- Fixed an issue where `DataFrame.sum` was slower than `DataFrame.mean` for integer valued frames (GH4365)
- `read_html` tests now work with Python 2.6 (GH4351)
- Fixed bug where network testing was throwing `NameError` because a local variable was undefined (GH4381)

- In `to_json`, raise if a passed `orient` would cause loss of data because of a duplicate index (GH4359)
- In `to_json`, fix date handling so milliseconds are the default timestamp as the docstring says (GH4362).
- `as_index` is no longer ignored when doing `groupby` apply (GH4648, GH3417)
- JSON NaT handling fixed, NaTs are now serialized to `null` (GH4498)
- Fixed JSON handling of escapable characters in JSON object keys (GH4593)
- Fixed passing `keep_default_na=False` when `na_values=None` (GH4318)
- Fixed bug with `values` raising an error on a DataFrame with duplicate columns and mixed dtypes, surfaced in (GH4377)
- Fixed bug with duplicate columns and type conversion in `read_json` when `orient='split'` (GH4377)
- Fixed JSON bug where locales with decimal separators other than `'.'` threw exceptions when encoding / decoding certain values. (GH4918)
- Fix `.iat` indexing with a `PeriodIndex` (GH4390)
- Fixed an issue where `PeriodIndex` joining with self was returning a new instance rather than the same instance (GH4379); also adds a test for this for the other index types
- Fixed a bug with all the dtypes being converted to object when using the CSV cparser with the `usecols` parameter (GH3192)
- Fix an issue in merging blocks where the resulting DataFrame had partially set `_ref_locs` (GH4403)
- Fixed an issue where hist subplots were being overwritten when they were called using the top level matplotlib API (GH4408)
- Fixed a bug where calling `Series.astype(str)` would truncate the string (GH4405, GH4437)
- Fixed a py3 compat issue where bytes were being repr'd as tuples (GH4455)
- Fixed Panel attribute naming conflict if item is named `'a'` (GH3440)
- Fixed an issue where duplicate indexes were raising when plotting (GH4486)
- Fixed an issue where `cumsum` and `cumprod` didn't work with bool dtypes (GH4170, GH4440)
- Fixed Panel slicing issued in `xs` that was returning an incorrect dimmed object (GH4016)
- Fix resampling bug where custom reduce function not used if only one group (GH3849, GH4494)
- Fixed Panel assignment with a transposed frame (GH3830)
- Raise on set indexing with a Panel and a Panel as a value which needs alignment (GH3777)
- `frozenset` objects now raise in the `Series` constructor (GH4482, GH4480)
- Fixed issue with sorting a duplicate multi-index that has multiple dtypes (GH4516)
- Fixed bug in `DataFrame.set_values` which was causing name attributes to be lost when expanding the index. (GH3742, GH4039)
- Fixed issue where individual names, levels and labels could be set on `MultiIndex` without validation (GH3714, GH4039)
- Fixed (GH3334) in `pivot_table`. Margins did not compute if values is the index.
- Fix bug in having a rhs of `np.timedelta64` or `np.offsets.DateOffset` when operating with date-times (GH4532)
- Fix arithmetic with series/datetimeindex and `np.timedelta64` not working the same (GH4134) and buggy `timedelta` in numpy 1.6 (GH4135)

- Fix bug in `pd.read_clipboard` on windows with PY3 (GH4561); not decoding properly
- `tslib.get_period_field()` and `tslib.get_period_field_arr()` now raise if code argument out of range (GH4519, GH4520)
- Fix boolean indexing on an empty series loses index names (GH4235), `infer_dtype` works with empty arrays.
- Fix reindexing with multiple axes; if an axes match was not replacing the current axes, leading to a possible lazy frequency inference issue (GH3317)
- Fixed issue where `DataFrame.apply` was reraising exceptions incorrectly (causing the original stack trace to be truncated).
- Fix selection with `ix/loc` and `non_unique` selectors (GH4619)
- Fix assignment with `iloc/loc` involving a dtype change in an existing column (GH4312, GH5702) have internal `setitem_with_indexer` in `core/indexing` to use `Block.setitem`
- Fixed bug where thousands operator was not handled correctly for floating point numbers in `csv_import` (GH4322)
- Fix an issue with `CacheableOffset` not properly being used by many `DateOffset`; this prevented the `DateOffset` from being cached (GH4609)
- Fix boolean comparison with a `DataFrame` on the lhs, and a list/tuple on the rhs (GH4576)
- Fix error/dtype conversion with `setitem` of `None` on `Series/DataFrame` (GH4667)
- Fix decoding based on a passed in non-default encoding in `pd.read_stata` (GH4626)
- Fix `DataFrame.from_records` with a plain-vanilla `ndarray`. (GH4727)
- Fix some inconsistencies with `Index.rename` and `MultiIndex.rename`, etc. (GH4718, GH4628)
- Bug in using `iloc/loc` with a cross-sectional and duplicate indices (GH4726)
- Bug with using `QUOTE_NONE` with `to_csv` causing `Exception`. (GH4328)
- Bug with `Series` indexing not raising an error when the right-hand-side has an incorrect length (GH2702)
- Bug in multi-indexing with a partial string selection as one part of a `MultiIndex` (GH4758)
- Bug with reindexing on the index with a non-unique index will now raise `ValueError` (GH4746)
- Bug in setting with `loc/ix` a single indexer with a multi-index axis and a numpy array, related to (GH3777)
- Bug in concatenation with duplicate columns across dtypes not merging with `axis=0` (GH4771, GH4975)
- Bug in `iloc` with a slice index failing (GH4771)
- Incorrect error message with no colspecs or width in `read_fwf`. (GH4774)
- Fix bugs in indexing in a `Series` with a duplicate index (GH4548, GH4550)
- Fixed bug with reading compressed files with `read_fwf` in Python 3. (GH3963)
- Fixed an issue with a duplicate index and assignment with a dtype change (GH4686)
- Fixed bug with reading compressed files in as `bytes` rather than `str` in Python 3. Simplifies bytes-producing file-handling in Python 3 (GH3963, GH4785).
- Fixed an issue related to `ticklocs/ticklabels` with log scale bar plots across different versions of `matplotlib` (GH4789)
- Suppressed `DeprecationWarning` associated with internal calls issued by `repr()` (GH4391)
- Fixed an issue with a duplicate index and duplicate selector with `.loc` (GH4825)

- Fixed an issue with `DataFrame.sort_index` where, when sorting by a single column and passing a list for ascending, the argument for ascending was being interpreted as `True` (GH4839, GH4846)
- Fixed `Panel.tshift` not working. Added *freq* support to `Panel.shift` (GH4853)
- Fix an issue in `TextFileReader` w/ Python engine (i.e. `PythonParser`) with thousands != “,” (GH4596)
- Bug in `getitem` with a duplicate index when using `where` (GH4879)
- Fix Type inference code coerces float column into datetime (GH4601)
- Fixed `_ensure_numeric` does not check for complex numbers (GH4902)
- Fixed a bug in `Series.hist` where two figures were being created when the `by` argument was passed (GH4112, GH4113).
- Fixed a bug in `convert_objects` for > 2 ndims (GH4937)
- Fixed a bug in `DataFrame/Panel` cache insertion and subsequent indexing (GH4939, GH5424)
- Fixed string methods for `FrozenNDArray` and `FrozenList` (GH4929)
- Fixed a bug with setting invalid or out-of-range values in indexing enlargement scenarios (GH4940)
- Tests for `fillna` on empty `Series` (GH4346), thanks @immerrr
- Fixed `copy()` to shallow copy axes/indices as well and thereby keep separate metadata. (GH4202, GH4830)
- Fixed `skiprows` option in Python parser for `read_csv` (GH4382)
- Fixed bug preventing `cut` from working with `np.inf` levels without explicitly passing labels (GH3415)
- Fixed wrong check for overlapping in `DatetimeIndex.union` (GH4564)
- Fixed conflict between thousands separator and date parser in `csv_parser` (GH4678)
- Fix appending when dtypes are not the same (error showing mixing float/np.datetime64) (GH4993)
- Fix repr for `DateOffset`. No longer show duplicate entries in `kwds`. Removed unused offset fields. (GH4638)
- Fixed wrong index name during `read_csv` if using `usecols`. Applies to `c` parser only. (GH4201)
- `Timestamp` objects can now appear in the left hand side of a comparison operation with a `Series` or `DataFrame` object (GH4982).
- Fix a bug when indexing with `np.nan` via `iloc/loc` (GH5016)
- Fixed a bug where low memory `c` parser could create different types in different chunks of the same file. Now coerces to numerical type or raises warning. (GH3866)
- Fix a bug where reshaping a `Series` to its own shape raised `TypeError` (GH4554) and other reshaping issues.
- Bug in setting with `ix/loc` and a mixed int/string index (GH4544)
- Make sure series-series boolean comparisons are label based (GH4947)
- Bug in multi-level indexing with a `Timestamp` partial indexer (GH4294)
- Tests/fix for multi-index construction of an all-nan frame (GH4078)
- Fixed a bug where `read_html()` wasn’t correctly inferring values of tables with commas (GH5029)
- Fixed a bug where `read_html()` wasn’t providing a stable ordering of returned tables (GH4770, GH5029).
- Fixed a bug where `read_html()` was incorrectly parsing when passed `index_col=0` (GH5066).
- Fixed a bug where `read_html()` was incorrectly inferring the type of headers (GH5048).
- Fixed a bug where `DatetimeIndex` joins with `PeriodIndex` caused a stack overflow (GH3899).

- Fixed a bug where `groupby` objects didn't allow plots (GH5102).
- Fixed a bug where `groupby` objects weren't tab-completing column names (GH5102).
- Fixed a bug where `groupby.plot()` and `friends` were duplicating figures multiple times (GH5102).
- Provide automatic conversion of `object` dtypes on `fillna`, related (GH5103)
- Fixed a bug where default options were being overwritten in the option parser cleaning (GH5121).
- Treat a list/ndarray identically for `iloc` indexing with list-like (GH5006)
- Fix `MultiIndex.get_level_values()` with missing values (GH5074)
- Fix bound checking for `Timestamp()` with `datetime64` input (GH4065)
- Fix a bug where `TestReadHtml` wasn't calling the correct `read_html()` function (GH5150).
- Fix a bug with `NDFrame.replace()` which made replacement appear as though it was (incorrectly) using regular expressions (GH5143).
- Fix better error message for `to_datetime` (GH4928)
- Made sure different locales are tested on `travis-ci` (GH4918). Also adds a couple of utilities for getting locales and setting locales with a context manager.
- Fixed segfault on `isnull(MultiIndex)` (now raises an error instead) (GH5123, GH5125)
- Allow duplicate indices when performing operations that align (GH5185, GH5639)
- Compound dtypes in a constructor raise `NotImplementedError` (GH5191)
- Bug in comparing duplicate frames (GH4421) related
- Bug in `describe` on duplicate frames
- Bug in `to_datetime` with a format and `coerce=True` not raising (GH5195)
- Bug in `loc` setting with multiple indexers and a rhs of a Series that needs broadcasting (GH5206)
- Fixed bug where inplace setting of levels or labels on `MultiIndex` would not clear cached values property and therefore return wrong values. (GH5215)
- Fixed bug where filtering a grouped `DataFrame` or `Series` did not maintain the original ordering (GH4621).
- Fixed `Period` with a business date freq to always roll-forward if on a non-business date. (GH5203)
- Fixed bug in Excel writers where frames with duplicate column names weren't written correctly. (GH5235)
- Fixed issue with `drop` and a non-unique index on `Series` (GH5248)
- Fixed seg fault in C parser caused by passing more names than columns in the file. (GH5156)
- Fix `Series.isin` with date/time-like dtypes (GH5021)
- C and Python Parser can now handle the more common multi-index column format which doesn't have a row for index names (GH4702)
- Bug when trying to use an out-of-bounds date as an object dtype (GH5312)
- Bug when trying to display an embedded `PandasObject` (GH5324)
- Allows operating of `Timestamps` to return a `datetime` if the result is out-of-bounds related (GH5312)
- Fix return value/type signature of `initObjToJSON()` to be compatible with `numpy's import_array()` (GH5334, GH5326)
- Bug when renaming then `set_index` on a `DataFrame` (GH5344)

- Test suite no longer leaves around temporary files when testing graphics. (GH5347) (thanks for catching this @yarikoptic!)
- Fixed html tests on win32. (GH4580)
- Make sure that `head/tail` are `iloc` based, (GH5370)
- Fixed bug for `PeriodIndex` string representation if there are 1 or 2 elements. (GH5372)
- The `GroupBy` methods `transform` and `filter` can be used on `Series` and `DataFrames` that have repeated (non-unique) indices. (GH4620)
- Fix empty series not printing name in `repr` (GH4651)
- Make tests create temp files in temp directory by default. (GH5419)
- `pd.to_timedelta` of a scalar returns a scalar (GH5410)
- `pd.to_timedelta` accepts `NaN` and `NaT`, returning `NaT` instead of raising (GH5437)
- performance improvements in `isnull` on larger size pandas objects
- Fixed various setitem with 1d ndarray that does not have a matching length to the indexer (GH5508)
- Bug in `getitem` with a multi-index and `iloc` (GH5528)
- Bug in `delitem` on a `Series` (GH5542)
- Bug fix in `apply` when using custom function and objects are not mutated (GH5545)
- Bug in selecting from a non-unique index with `loc` (GH5553)
- Bug in `groupby` returning non-consistent types when user function returns a `None`, (GH5592)
- Work around regression in numpy 1.7.0 which erroneously raises `IndexError` from `ndarray.item` (GH5666)
- Bug in repeated indexing of object with resultant non-unique index (GH5678)
- Bug in `fillna` with `Series` and a passed series/dict (GH5703)
- Bug in `groupby` transform with a datetime-like grouper (GH5712)
- Bug in multi-index selection in PY3 when using certain keys (GH5725)
- Row-wise concat of differing dtypes failing in certain cases (GH5754)

35.10 pandas 0.12.0

Release date: 2013-07-24

35.10.1 New Features

- `pd.read_html()` can now parse HTML strings, files or urls and returns a list of `DataFrame`s courtesy of @cpcloud. (GH3477, GH3605, GH3606)
- Support for reading Amazon S3 files. (GH3504)
- Added module for reading and writing JSON strings/files: `pandas.io.json` includes `to_json` `DataFrame`/`Series` method, and a `read_json` top-level reader various issues (GH1226, GH3804, GH3876, GH3867, GH1305)
- Added module for reading and writing Stata files: `pandas.io.stata` (GH1512) includes `to_stata` `DataFrame` method, and a `read_stata` top-level reader

- Added support for writing in `to_csv` and reading in `read_csv`, multi-index columns. The `header` option in `read_csv` now accepts a list of the rows from which to read the index. Added the option, `tupleize_cols` to provide compatibility for the pre 0.12 behavior of writing and reading multi-index columns via a list of tuples. The default in 0.12 is to write lists of tuples and *not* interpret list of tuples as a multi-index column. Note: The default value will change in 0.12 to make the default *to* write and read multi-index columns in the new format. (GH3571, GH1651, GH3141)
- Add iterator to `Series.str` (GH3638)
- `pd.set_option()` now allows N option, value pairs (GH3667).
- Added keyword parameters for different types of `scatter_matrix` subplots
- A `filter` method on grouped Series or DataFrames returns a subset of the original (GH3680, GH919)
- Access to historical Google Finance data in `pandas.io.data` (GH3814)
- DataFrame plotting methods can sample column colors from a Matplotlib colormap via the `colormap` keyword. (GH3860)

35.10.2 Improvements to existing features

- Fixed various issues with internal pprinting code, the `repr()` for various objects including `TimeStamp` and `Index` now produces valid python code strings and can be used to recreate the object, (GH3038, GH3379, GH3251, GH3460)
- `convert_objects` now accepts a `copy` parameter (defaults to `True`)
- `HDFStore`
 - will retain index attributes (`freq,tz,name`) on recreation (GH3499, issue:4098)
 - will warn with a `AttributeConflictWarning` if you are attempting to append an index with a different frequency than the existing, or attempting to append an index with a different name than the existing
 - support datelike columns with a `timezone` as `data_columns` (GH2852)
 - table writing performance improvements.
 - support python3 (via `PyTables 3.0.0`) (GH3750)
- Add modulo operator to Series, DataFrame
- Add `date` method to `DatetimeIndex`
- Add `dropna` argument to `pivot_table` (issue: 3820)
- Simplified the API and added a `describe` method to Categorical
- `melt` now accepts the optional parameters `var_name` and `value_name` to specify custom column names of the returned DataFrame (GH3649), thanks @hoechenberger. If `var_name` is not specified and `dataframe.columns.name` is not `None`, then this will be used as the `var_name` (GH4144). Also support for MultiIndex columns.
- clipboard functions use `pyperclip` (no dependencies on Windows, alternative dependencies offered for Linux) (GH3837).
- Plotting functions now raise a `TypeError` before trying to plot anything if the associated objects have a `dtype` of `object` (GH1818, GH3572, GH3911, GH3912), but they will try to convert object arrays to numeric arrays if possible so that you can still plot, for example, an object array with floats. This happens before any drawing takes place which eliminates any spurious plots from showing up.
- Added `Faq` section on `repr` display options, to help users customize their setup.

- where operations that result in block splitting are much faster ([GH3733](#))
- Series and DataFrame hist methods now take a `figsize` argument ([GH3834](#))
- DatetimeIndexes no longer try to convert mixed-integer indexes during join operations ([GH3877](#))
- Add `unit` keyword to `Timestamp` and `to_datetime` to enable passing of integers or floats that are in an epoch unit of `D`, `s`, `ms`, `us`, `ns`, thanks @mtkini ([GH3969](#)) (e.g. unix timestamps or epoch `s`, with fractional seconds allowed) ([GH3540](#))
- DataFrame `corr` method (`spearman`) is now cythonized.
- Improved `network` test decorator to catch `IOError` (and therefore `URLError` as well). Added `with_connectivity_check` decorator to allow explicitly checking a website as a proxy for seeing if there is network connectivity. Plus, new `optional_args` decorator factory for decorators. ([GH3910](#), [GH3914](#))
- `read_csv` will now throw a more informative error message when a file contains no columns, e.g., all newline characters
- Added `layout` keyword to `DataFrame.hist()` for more customizable layout ([GH4050](#))
- `Timestamp.min` and `Timestamp.max` now represent valid `Timestamp` instances instead of the default `datetime.min` and `datetime.max` (respectively), thanks @SleepingPills
- `read_html` now raises when no tables are found and `BeautifulSoup==4.2.0` is detected ([GH4214](#))

35.10.3 API Changes

- `HDFStore`
 - When removing an object, `remove(key)` raises `KeyError` if the key is not a valid store object.
 - raise a `TypeError` on passing `where` or `columns` to select with a `Storer`; these are invalid parameters at this time ([GH4189](#))
 - can now specify an `encoding` option to `append/put` to enable alternate encodings ([GH3750](#))
 - enable support for `iterator/chunksize` with `read_hdf`
- The `repr()` for `(Multi)Index` now obeys `display.max_seq_items` rather than `numpy` threshold print options. ([GH3426](#), [GH3466](#))
- Added `mangle_dupe_cols` option to `read_table/csv`, allowing users to control legacy behaviour re dupe cols (A, A.1, A.2 vs A, A) ([GH3468](#)) Note: The default value will change in 0.12 to the “no mangle” behaviour, If your code relies on this behaviour, explicitly specify `mangle_dupe_cols=True` in your calls.
- Do not allow astypes on `datetime64[ns]` except to `object`, and `timedelta64[ns]` to `object/int` ([GH3425](#))
- The behavior of `datetime64` dtypes has changed with respect to certain so-called reduction operations ([GH3726](#)). The following operations now raise a `TypeError` when performed on a `Series` and return an *empty* `Series` when performed on a `DataFrame` similar to performing these operations on, for example, a `DataFrame` of `slice` objects: - `sum`, `prod`, `mean`, `std`, `var`, `skew`, `kurt`, `corr`, and `cov`
- Do not allow `datetimelike/timedeltalike` creation except with valid types (e.g. cannot pass `datetime64[ms]`) ([GH3423](#))
- Add `squeeze` keyword to `groupby` to allow reduction from `DataFrame` -> `Series` if groups are unique. Regression from 0.10.1, partial revert on ([GH2893](#)) with ([GH3596](#))
- Raise on `iloc` when boolean indexing with a label based indexer mask e.g. a boolean `Series`, even with integer labels, will raise. Since `iloc` is purely positional based, the labels on the `Series` are not alignable ([GH3631](#))

- The `raise_on_error` option to plotting methods is obviated by [GH3572](#), so it is removed. Plots now always raise when data cannot be plotted or the object being plotted has a dtype of `object`.
- `DataFrame.interpolate()` is now deprecated. Please use `DataFrame.fillna()` and `DataFrame.replace()` instead ([GH3582](#), [GH3675](#), [GH3676](#)).
- the method and axis arguments of `DataFrame.replace()` are deprecated
- `DataFrame.replace` 's `infer_types` parameter is removed and now performs conversion by default. ([GH3907](#))
- Deprecated `display.height`, `display.width` is now only a formatting option does not control triggering of summary, similar to < 0.11.0.
- Add the keyword `allow_duplicates` to `DataFrame.insert` to allow a duplicate column to be inserted if `True`, default is `False` (same as prior to 0.12) ([GH3679](#))
- io API changes
 - added `pandas.io.api` for i/o imports
 - removed Excel support to `pandas.io.excel`
 - added top-level `pd.read_sql` and `to_sql` `DataFrame` methods
 - removed clipboard support to `pandas.io.clipboard`
 - replace top-level and instance methods `save` and `load` with top-level `read_pickle` and `to_pickle` instance method, `save` and `load` will give deprecation warning.
- the method and axis arguments of `DataFrame.replace()` are deprecated
- set `FutureWarning` to require `data_source`, and to replace year/month with expiry date in `pandas.io` options. This is in preparation to add options data from Google ([GH3822](#))
- the method and axis arguments of `DataFrame.replace()` are deprecated
- Implement `__nonzero__` for `NDFrame` objects ([GH3691](#), [GH3696](#))
- `as_matrix` with mixed signed and unsigned dtypes will result in 2 x the lcd of the unsigned as an int, maxing with `int64`, to avoid precision issues ([GH3733](#))
- `na_values` in a list provided to `read_csv/read_excel` will match string and numeric versions e.g. `na_values=['99']` will match 99 whether the column ends up being int, float, or string ([GH3611](#))
- `read_html` now defaults to `None` when reading, and falls back on `bs4` + `html5lib` when `lxml` fails to parse. a list of parsers to try until success is also valid
- more consistency in the `to_datetime` return types (give string/array of string inputs) ([GH3888](#))
- The internal pandas class hierarchy has changed (slightly). The previous `PandasObject` now is called `PandasContainer` and a new `PandasObject` has become the baseclass for `PandasContainer` as well as `Index`, `Categorical`, `GroupBy`, `SparseList`, and `SparseArray` (+ their base classes). Currently, `PandasObject` provides string methods (from `StringMixin`). ([GH4090](#), [GH4092](#))
- New `StringMixin` that, given a `__unicode__` method, gets python 2 and python 3 compatible string methods (`__str__`, `__bytes__`, and `__repr__`). Plus string safety throughout. Now employed in many places throughout the pandas library. ([GH4090](#), [GH4092](#))

35.10.4 Experimental Features

- Added experimental `CustomBusinessDay` class to support `DateOffsets` with custom holiday calendars and custom weekmasks. ([GH2301](#))

35.10.5 Bug Fixes

- Fixed an esoteric excel reading bug, xlrd $\geq$ 0.9.0 now required for excel support. Should provide python3 support (for reading) which has been lacking. (GH3164)
- Disallow Series constructor called with MultiIndex which caused segfault (GH4187)
- Allow unioning of date ranges sharing a timezone (GH3491)
- Fix to_csv issue when having a large number of rows and NaT in some columns (GH3437)
- .loc was not raising when passed an integer list (GH3449)
- Unordered time series selection was misbehaving when using label slicing (GH3448)
- Fix sorting in a frame with a list of columns which contains datetime64[ns] dtypes (GH3461)
- DataFrames fetched via FRED now handle '.' as a NaN. (GH3469)
- Fix regression in a DataFrame apply with axis=1, objects were not being converted back to base dtypes correctly (GH3480)
- Fix issue when storing uint dtypes in an HDFStore. (GH3493)
- Non-unique index support clarified (GH3468)
 - Addressed handling of dupe columns in df.to_csv new and old (GH3454, GH3457)
 - Fix assigning a new index to a duplicate index in a DataFrame would fail (GH3468)
 - Fix construction of a DataFrame with a duplicate index
 - ref_locs support to allow duplicative indices across dtypes, allows iget support to always find the index (even across dtypes) (GH2194)
 - applymap on a DataFrame with a non-unique index now works (removed warning) (GH2786), and fix (GH3230)
 - Fix to_csv to handle non-unique columns (GH3495)
 - Duplicate indexes with getitem will return items in the correct order (GH3455, GH3457) and handle missing elements like unique indices (GH3561)
 - Duplicate indexes with and empty DataFrame.from_records will return a correct frame (GH3562)
 - Concat to produce a non-unique columns when duplicates are across dtypes is fixed (GH3602)
 - Non-unique indexing with a slice via loc and friends fixed (GH3659)
 - Allow insert/delete to non-unique columns (GH3679)
 - Extend reindex to correctly deal with non-unique indices (GH3679)
 - DataFrame.itertuples() now works with frames with duplicate column names (GH3873)
 - Bug in non-unique indexing via iloc (GH4017); added takeable argument to reindex for location-based taking
 - Allow non-unique indexing in series via .ix/.loc and __getitem__ (GH4246)
 - Fixed non-unique indexing memory allocation issue with .ix/.loc (GH4280)
- Fixed bug in groupby with empty series referencing a variable before assignment. (GH3510)
- Allow index name to be used in groupby for non MultiIndex (GH4014)
- Fixed bug in mixed-frame assignment with aligned series (GH3492)

- Fixed bug in selecting month/quarter/year from a series would not select the time element on the last day (GH3546)
- Fixed a couple of MultiIndex rendering bugs in `df.to_html()` (GH3547, GH3553)
- Properly convert `np.datetime64` objects in a Series (GH3416)
- Raise a `TypeError` on invalid datetime/timedelta operations e.g. add datetimes, multiple timedelta x datetime
- Fix `.diff` on datelike and timedelta operations (GH3100)
- `combine_first` not returning the same dtype in cases where it can (GH3552)
- Fixed bug with `Panel.transpose` argument aliases (GH3556)
- Fixed platform bug in `PeriodIndex.take` (GH3579)
- Fixed bud in incorrect conversion of `datetime64[ns]` in `combine_first` (GH3593)
- Fixed bug in `reset_index` with `NaN` in a multi-index (GH3586)
- `fillna` methods now raise a `TypeError` when the `value` parameter is a list or tuple.
- Fixed bug where a time-series was being selected in preference to an actual column name in a frame (GH3594)
- Make `secondary_y` work properly for bar plots (GH3598)
- Fix modulo and integer division on Series/DataFrames to act similiary to `float` dtypes to return `np.nan` or `np.inf` as appropriate (GH3590)
- Fix incorrect dtype on `groupby` with `as_index=False` (GH3610)
- Fix `read_csv/read_excel` to correctly encode identical `na_values`, e.g. `na_values=[-999.0, -999]` was failing (GH3611)
- Disable HTML output in `qtconsole` again. (GH3657)
- Reworked the new repr display logic, which users found confusing. (GH3663)
- Fix indexing issue in `ndim >= 3` with `iloc` (GH3617)
- Correctly parse date columns with embedded (nan/NaT) into `datetime64[ns]` dtype in `read_csv` when `parse_dates` is specified (GH3062)
- Fix not consolidating before `to_csv` (GH3624)
- Fix alignment issue when setitem in a DataFrame with a piece of a DataFrame (GH3626) or a mixed DataFrame and a Series (GH3668)
- Fix plotting of unordered `DatetimeIndex` (GH3601)
- `sql.write_frame` failing when writing a single column to `sqlite` (GH3628), thanks to @stonebig
- Fix pivoting with `nan` in the index (GH3558)
- Fix running of `bs4` tests when it is not installed (GH3605)
- Fix parsing of html table (GH3606)
- `read_html()` now only allows a single backend: `html5lib` (GH3616)
- `convert_objects` with `convert_dates='coerce'` was parsing some single-letter strings into today's date
- `DataFrame.from_records` did not accept empty recarrays (GH3682)
- `DataFrame.to_csv` will succeed with the deprecated option `nanRep`, @tdsmith
- `DataFrame.to_html` and `DataFrame.to_latex` now accept a path for their first argument (GH3702)

- Fix file tokenization error with r delimiter and quoted fields ([GH3453](#))
- Groupby transform with item-by-item not upcasting correctly ([GH3740](#))
- Incorrectly read a HDFStore multi-index Frame with a column specification ([GH3748](#))
- `read_html` now correctly skips tests ([GH3741](#))
- PandasObjects raise `TypeError` when trying to hash ([GH3882](#))
- Fix incorrect arguments passed to `concat` that are not list-like (e.g. `concat(df1,df2)`) ([GH3481](#))
- Correctly parse when passed the `dtype=str` (or other variable-len string dtypes) in `read_csv` ([GH3795](#))
- Fix index name not propagating when using `loc/ix` ([GH3880](#))
- Fix groupby when applying a custom function resulting in a returned DataFrame was not converting dtypes ([GH3911](#))
- Fixed a bug where `DataFrame.replace` with a compiled regular expression in the `to_replace` argument wasn't working ([GH3907](#))
- Fixed `__truediv__` in Python 2.7 with `numexpr` installed to actually do true division when dividing two integer arrays with at least 10000 cells total ([GH3764](#))
- Indexing with a string with seconds resolution not selecting from a time index ([GH3925](#))
- csv parsers would loop infinitely if `iterator=True` but no `chunksize` was specified ([GH3967](#)), python parser failing with `chunksize=1`
- Fix index name not propagating when using `shift`
- Fixed `dropna=False` being ignored with multi-index stack ([GH3997](#))
- Fixed flattening of columns when renaming MultiIndex columns DataFrame ([GH4004](#))
- Fix `Series.clip` for datetime series. NA/NaN threshold values will now throw `ValueError` ([GH3996](#))
- Fixed insertion issue into DataFrame, after rename ([GH4032](#))
- Fixed testing issue where too many sockets were open thus leading to a connection reset issue ([GH3982](#), [GH3985](#), [GH4028](#), [GH4054](#))
- Fixed failing tests in `test_yahoo`, `test_google` where symbols were not retrieved but were being accessed ([GH3982](#), [GH3985](#), [GH4028](#), [GH4054](#))
- `Series.hist` will now take the figure from the current environment if one is not passed
- Fixed bug where a 1xN DataFrame would barf on a 1xN mask ([GH4071](#))
- Fixed running of `tox` under python3 where the pickle import was getting rewritten in an incompatible way ([GH4062](#), [GH4063](#))
- Fixed bug where `sharex` and `sharey` were not being passed to `grouped_hist` ([GH4089](#))
- Fix bug where `HDFStore` will fail to append because of a different block ordering on-disk ([GH4096](#))
- Better error messages on inserting incompatible columns to a frame ([GH4107](#))
- Fixed bug in `DataFrame.replace` where a nested dict wasn't being iterated over when `regex=False` ([GH4115](#))
- Fixed bug in `convert_objects(convert_numeric=True)` where a mixed numeric and object Series/Frame was not converting properly ([GH4119](#))
- Fixed bugs in multi-index selection with column multi-index and duplicates ([GH4145](#), [GH4146](#))
- Fixed bug in the parsing of microseconds when using the `format` argument in `to_datetime` ([GH4152](#))

- Fixed bug in `PandasAutoDateLocator` where `invert_xaxis` triggered incorrectly `MilliSecondLocator` (GH3990)
- Fixed bug in `Series.where` where broadcasting a single element input vector to the length of the series resulted in multiplying the value inside the input (GH4192)
- Fixed bug in plotting that wasn't raising on invalid colormap for matplotlib 1.1.1 (GH4215)
- Fixed the legend displaying in `DataFrame.plot(kind='kde')` (GH4216)
- Fixed bug where Index slices weren't carrying the name attribute (GH4226)
- Fixed bug in initializing `DatetimeIndex` with an array of strings in a certain time zone (GH4229)
- Fixed bug where `html5lib` wasn't being properly skipped (GH4265)
- Fixed bug where `get_data_famafrench` wasn't using the correct file edges (GH4281)

35.11 pandas 0.11.0

Release date: 2013-04-22

35.11.1 New Features

- New documentation section, 10 Minutes to Pandas
- New documentation section, Cookbook
- Allow mixed dtypes (e.g `float32/float64/int32/int16/int8`) to coexist in DataFrames and propagate in operations
- Add function to `pandas.io.data` for retrieving stock index components from Yahoo! finance (GH2795)
- Support slicing with time objects (GH2681)
- Added `.iloc` attribute, to support strict integer based indexing, analogous to `.ix` (GH2922)
- Added `.loc` attribute, to support strict label based indexing, analogous to `.ix` (GH3053)
- Added `.iat` attribute, to support fast scalar access via integers (replaces `iget_value/iset_value`)
- Added `.at` attribute, to support fast scalar access via labels (replaces `get_value/set_value`)
- Moved functionality from `irow, icol, iget_value/iset_value` to `.iloc` indexer (via `_ixs` methods in each object)
- Added support for expression evaluation using the `numexpr` library
- Added `convert=boolean` to take routines to translate negative indices to positive, defaults to `True`
- Added `to_series()` method to indices, to facilitate the creation of indexers (GH3275)

35.11.2 Improvements to existing features

- Improved performance of `df.to_csv()` by up to 10x in some cases. (GH3059)
- added `blocks` attribute to DataFrames, to return a dict of dtypes to homogeneously dtyped DataFrames
- added keyword `convert_numeric` to `convert_objects()` to try to convert object dtypes to numeric types (default is `False`)

- `convert_dates` in `convert_objects` can now be `coerce` which will return a `datetime64[ns]` dtype with non-convertibles set as `NaT`; will preserve an all-nan object (e.g. strings), default is `True` (to perform soft-conversion)
- Series print output now includes the dtype by default
- Optimize internal reindexing routines ([GH2819](#), [GH2867](#))
- `describe_option()` now reports the default and current value of options.
- Add `format` option to `pandas.to_datetime` with faster conversion of strings that can be parsed with `datetime.strptime`
- Add `axes` property to `Series` for compatibility
- Add `xs` function to `Series` for compatibility
- Allow `setitem` in a frame where only mixed numerics are present (e.g. `int` and `float`), ([GH3037](#))
- `HDFStore`
 - Provide dotted attribute access to get from stores (e.g. `store.df == store['df']`)
 - New keywords `iterator=boolean`, and `chunksizes=number_in_a_chunk` are provided to support iteration on `select` and `select_as_multiple` ([GH3076](#))
 - support `read_hdf/to_hdf` API similar to `read_csv/to_csv` ([GH3222](#))
- Add `squeeze` method to possibly remove length 1 dimensions from an object.

```
In [1]: p = Panel(randn(3,4,4),items=['ItemA','ItemB','ItemC'],
...:               major_axis=date_range('20010102',periods=4),
...:               minor_axis=['A','B','C','D'])
...:
```

```
In [2]: p
Out[2]:
<class 'pandas.core.panel.Panel'>
Dimensions: 3 (items) x 4 (major_axis) x 4 (minor_axis)
Items axis: ItemA to ItemC
Major_axis axis: 2001-01-02 00:00:00 to 2001-01-05 00:00:00
Minor_axis axis: A to D
```

```
In [3]: p.reindex(items=['ItemA']).squeeze()
Out[3]:
```

	A	B	C	D
2001-01-02	0.469112	-0.282863	-1.509059	-1.135632
2001-01-03	1.212112	-0.173215	0.119209	-1.044236
2001-01-04	-0.861849	-2.104569	-0.494929	1.071804
2001-01-05	0.721555	-0.706771	-1.039575	0.271860

```
In [4]: p.reindex(items=['ItemA'],minor=['B']).squeeze()
Out[4]:
2001-01-02    -0.282863
2001-01-03    -0.173215
2001-01-04    -2.104569
2001-01-05    -0.706771
Freq: D, Name: B, dtype: float64
```

- Improvement to Yahoo API access in `pd.io.data.Options` ([GH2758](#))
- added option `display.max_seq_items` to control the number of elements printed per sequence pprinting it. ([GH2979](#))

- added option `display.chop_threshold` to control display of small numerical values. (GH2739)
- added option `display.max_info_rows` to prevent verbose_info from being calculated for frames above 1M rows (configurable). (GH2807, GH2918)
- `value_counts()` now accepts a “normalize” argument, for normalized histograms. (GH2710).
- `DataFrame.from_records` now accepts not only dicts but any instance of the collections.Mapping ABC.
- Allow selection semantics via a string with a datelike index to work in both Series and DataFrames (GH3070)

```
In [5]: idx = date_range("2001-10-1", periods=5, freq='M')
```

```
In [6]: ts = Series(np.random.rand(len(idx)), index=idx)
```

```
In [7]: ts['2001']
```

```
Out[7]:
2001-10-31    0.838796
2001-11-30    0.897333
2001-12-31    0.732592
Freq: M, dtype: float64
```

```
In [8]: df = DataFrame(dict(A = ts))
```

```
In [9]: df['2001']
```

```
Out[9]:
          A
2001-10-31  0.838796
2001-11-30  0.897333
2001-12-31  0.732592
```

- added option `display.mpl_style` providing a sleeker visual style for plots. Based on <https://gist.github.com/huyng/816622> (GH3075).
- Improved performance across several core functions by taking memory ordering of arrays into account. Courtesy of @stephenwlin (GH3130)
- Improved performance of groupby transform method (GH2121)
- Handle “ragged” CSV files missing trailing delimiters in rows with missing fields when also providing explicit list of column names (so the parser knows how many columns to expect in the result) (GH2981)
- On a mixed DataFrame, allow setting with indexers with ndarray/DataFrame on rhs (GH3216)
- Treat boolean values as integers (values 1 and 0) for numeric operations. (GH2641)
- Add `time` method to DatetimeIndex (GH3180)
- Return NA when using `Series.str[...]` for values that are not long enough (GH3223)
- Display cursor coordinate information in time-series plots (GH1670)
- `to_html()` now accepts an optional “escape” argument to control reserved HTML character escaping (enabled by default) and escapes `&`, in addition to `<` and `>`. (GH2919)

35.11.3 API Changes

- Do not automatically upcast numeric specified dtypes to `int64` or `float64` (GH622 and GH797)
- DataFrame construction of lists and scalars, with no dtype present, will result in casting to `int64` or `float64`, regardless of platform. This is not an apparent change in the API, but noting it.
- Guarantee that `convert_objects()` for Series/DataFrame always returns a copy

- groupby operations will respect dtypes for numeric float operations (float32/float64); other types will be operated on, and will try to cast back to the input dtype (e.g. if an int is passed, as long as the output doesn't have nans, then an int will be returned)
- backfill/pad/take/diff/ohlc will now support float32/int16/int8 operations
- Block types will upcast as needed in where/masking operations ([GH2793](#))
- Series now automatically will try to set the correct dtype based on passed datetimelike objects (datetime/Timestamp)
 - timedelta64 are returned in appropriate cases (e.g. Series - Series, when both are datetime64)
 - mixed datetimes and objects ([GH2751](#)) in a constructor will be cast correctly
 - astype on datetimes to object are now handled (as well as NaT conversions to np.nan)
 - all timedelta like objects will be correctly assigned to timedelta64 with mixed NaN and/or NaT allowed
- arguments to DataFrame.clip were inconsistent to numpy and Series clipping ([GH2747](#))
- util.testing.assert_frame_equal now checks the column and index names ([GH2964](#))
- Constructors will now return a more informative ValueError on failures when invalid shapes are passed
- Don't suppress TypeError in GroupBy.agg ([GH3238](#))
- Methods return None when inplace=True ([GH1893](#))
- HDFStore
 - added the method select_column to select a single column from a table as a Series.
 - deprecated the unique method, can be replicated by select_column(key, column).unique()
 - min_itemsize parameter will now automatically create data_columns for passed keys
- Downcast on pivot if possible ([GH3283](#)), adds argument downcast to fillna
- Introduced options display.height/width for explicitly specifying terminal height/width in characters. Deprecated display.line_width, now replaced by display.width. These defaults are in effect for scripts as well, so unless disabled, previously very wide output will now be output as "expand_repr" style wrapped output.
- Various defaults for options (including display.max_rows) have been revised, after a brief survey concluded they were wrong for everyone. Now at w=80,h=60.
- HTML repr output in IPython qtconsole is once again controlled by the option display.notebook_repr_html, and on by default.

35.11.4 Bug Fixes

- Fix seg fault on empty data frame when fillna with pad or backfill ([GH2778](#))
- Single element ndarrays of datetimelike objects are handled (e.g. np.array(datetime(2001,1,1,0,0))), w/o dtype being passed
- 0-dim ndarrays with a passed dtype are handled correctly (e.g. np.array(0.,dtype='float32'))
- Fix some boolean indexing inconsistencies in Series.__getitem__/_setitem__ ([GH2776](#))
- Fix issues with DataFrame and Series constructor with integers that overflow int64 and some mixed typed type lists ([GH2845](#))
- HDFStore

- Fix weird PyTables error when using too many selectors in a where also correctly filter on any number of values in a Term expression (so not using numexpr filtering, but isin filtering)
- Internally, change all variables to be private-like (now have leading underscore)
- Fixes for query parsing to correctly interpret boolean and != ([GH2849](#), [GH2973](#))
- Fixes for pathological case on SparseSeries with 0-len array and compression ([GH2931](#))
- Fixes bug with writing rows if part of a block was all-nan ([GH3012](#))
- Exceptions are now ValueError or TypeError as needed
- A table will now raise if min_itemsize contains fields which are not queryables
- Bug showing up in applymap where some object type columns are converted ([GH2909](#)) had an incorrect default in convert_objects
- TimeDeltas
 - Series ops with a Timestamp on the rhs was throwing an exception ([GH2898](#)) added tests for Series ops with datetimes, timedeltas, Timestamps, and datelike Series on both lhs and rhs
 - Fixed subtle timedelta64 inference issue on py3 & numpy 1.7.0 ([GH3094](#))
 - Fixed some formatting issues on timedelta when negative
 - Support null checking on timedelta64, representing (and formatting) with NaT
 - Support setitem with np.nan value, converts to NaT
 - Support min/max ops in a Dataframe (abs not working, nor do we error on non-supported ops)
 - Support idxmin/idxmax/abs/max/min in a Series ([GH2989](#), [GH2982](#))
- Bug on in-place putmasking on an integer series that needs to be converted to float ([GH2746](#))
- Bug in argsort of datetime64[ns] Series with NaT ([GH2967](#))
- Bug in value_counts of datetime64[ns] Series ([GH3002](#))
- Fixed printing of NaT in an index
- Bug in idxmin/idxmax of datetime64[ns] Series with NaT ([GH2982](#))
- Bug in iocol, take with negative indicies was producing incorrect return values (see [GH2922](#), [GH2892](#)), also check for out-of-bounds indices ([GH3029](#))
- Bug in DataFrame column insertion when the column creation fails, existing frame is left in an irrecoverable state ([GH3010](#))
- Bug in DataFrame update, combine_first where non-specified values could cause dtype changes ([GH3016](#), [GH3041](#))
- Bug in groupby with first/last where dtypes could change ([GH3041](#), [GH2763](#))
- Formatting of an index that has nan was inconsistent or wrong (would fill from other values), ([GH2850](#))
- Unstack of a frame with no nans would always cause dtype upcasting ([GH2929](#))
- Fix scalar datetime.datetime parsing bug in read_csv ([GH3071](#))
- Fixed slow printing of large Dataframes, due to inefficient dtype reporting ([GH2807](#))
- Fixed a segfault when using a function as grouper in groupby ([GH3035](#))
- Fix pretty-printing of infinite data structures (closes [GH2978](#))
- Fixed exception when plotting timeseries bearing a timezone (closes [GH2877](#))

- `str.contains` ignored `na` argument (GH2806)
- Substitute warning for `segfault` when grouping with categorical grouper of mismatched length (GH3011)
- Fix exception in `SparseSeries.density` (GH2083)
- Fix upsampling bug with `closed='left'` and daily to daily data (GH3020)
- Fixed missing tick bars on `scatter_matrix` plot (GH3063)
- Fixed bug in `Timestamp(d,tz=foo)` when `d` is `date()` rather than `datetime()` (GH2993)
- `series.plot(kind='bar')` now respects `pylab` color schem (GH3115)
- Fixed bug in `reshape` if not passed correct input, now raises `TypeError` (GH2719)
- Fixed a bug where `Series` ctor did not respect ordering if `OrderedDict` passed in (GH3282)
- Fix `NameError` issue on `RESO_US` (GH2787)
- Allow selection in an *unordered* timeseries to work similiary to an *ordered* timeseries (GH2437).
- Fix implemented `.xs` when called with `axes=1` and a level parameter (GH2903)
- `Timestamp` now supports the class method `fromordinal` similar to `datetimes` (GH3042)
- Fix issue with indexing a series with a boolean key and specifying a 1-len list on the rhs (GH2745) or a list on the rhs (GH3235)
- Fixed bug in `groupby` apply when kernel generate list of arrays having unequal len (GH1738)
- fixed handling of `rolling_corr` with `center=True` which could produce `corr>1` (GH3155)
- Fixed issues where indices can be passed as 'index/column' in addition to 0/1 for the axis parameter
- `PeriodIndex.tolist` now boxes to `Period` (GH3178)
- `PeriodIndex.get_loc` `KeyError` now reports `Period` instead of ordinal (GH3179)
- `df.to_records` bug when handling `MultiIndex` (GH3189)
- Fix `Series.__getitem__` `segfault` when index less than -length (GH3168)
- Fix bug when using `Timestamp` as a date parser (GH2932)
- Fix bug creating date range from `Timestamp` with time zone and passing same time zone (GH2926)
- Add comparison operators to `Period` object (GH2781)
- Fix bug when concatenating two `Series` into a `DataFrame` when they have the same name (GH2797)
- Fix automatic color cycling when plotting consecutive timeseries without color arguments (GH2816)
- fixed bug in the pickling of `PeriodIndex` (GH2891)
- Upcast/split blocks when needed in a mixed `DataFrame` when `setitem` with an indexer (GH3216)
- Invoking `df.applymap` on a dataframe with dupe cols now raises a `ValueError` (GH2786)
- Apply with invalid returned indices raise correct Exception (GH2808)
- Fixed a bug in plotting log-scale bar plots (GH3247)
- `df.plot()` grid on/off now obeys the `mpl` default style, just like `series.plot()`. (GH3233)
- Fixed a bug in the legend of `plotting.andrews_curves()` (GH3278)
- Produce a series on apply if we only generate a singular series and have a simple index (GH2893)
- Fix Python ASCII file parsing when integer falls outside of floating point spacing (GH3258)

- fixed pretty printing of sets ([GH3294](#))
- `Panel()` and `Panel.from_dict()` now respects ordering when give `OrderedDict` ([GH3303](#))
- `DataFrame` where with a datetimelike incorrectly selecting ([GH3311](#))
- Ensure index casts work even in `Int64Index`
- Fix `set_index` segfault when passing `MultiIndex` ([GH3308](#))
- Ensure pickles created in py2 can be read in py3
- Insert ellipsis in `MultiIndex` summary repr ([GH3348](#))
- `Groupby` will handle mutation among an input groups columns (and fallback to non-fast apply) ([GH3380](#))
- Eliminated unicode errors on FreeBSD when using MPL GTK backend ([GH3360](#))
- `Period.strftime` should return unicode strings always ([GH3363](#))
- Respect passed `read_*` chunksize in `get_chunk` function ([GH3406](#))

35.12 pandas 0.10.1

Release date: 2013-01-22

35.12.1 New Features

- Add data interface to World Bank WDI `pandas.io.wb` ([GH2592](#))

35.12.2 API Changes

- Restored `inplace=True` behavior returning self (same object) with deprecation warning until 0.11 ([GH1893](#))
- `HDFStore`
 - refactored `HDFStore` to deal with non-table stores as objects, will allow future enhancements
 - removed keyword `compression` from `put` (replaced by keyword `complib` to be consistent across library)
 - warn *PerformanceWarning* if you are attempting to store types that will be pickled by `PyTables`

35.12.3 Improvements to existing features

- `HDFStore`
 - enables storing of multi-index dataframes (closes [GH1277](#))
 - support data column indexing and selection, via `data_columns` keyword in `append`
 - support write chunking to reduce memory footprint, via `chunksize` keyword to `append`
 - support automagic indexing via `index` keyword to `append`
 - support `expectedrows` keyword in `append` to inform `PyTables` about the expected tablesize
 - support `start` and `stop` keywords in `select` to limit the row selection space
 - added `get_store` context manager to automatically import with `pandas`

- added column filtering via `columns` keyword in `select`
- added methods `append_to_multiple/select_as_multiple/select_as_coordinates` to do multiple-table append/selection
- added support for `datetime64` in `columns`
- added method `unique` to select the unique values in an indexable or data column
- added method `copy` to copy an existing store (and possibly upgrade)
- show the shape of the data on disk for non-table stores when printing the store
- added ability to read PyTables flavor tables (allows compatibility to other HDF5 systems)
- Add `logx` option to `DataFrame/Series.plot` ([GH2327](#), [GH2565](#))
- Support reading gzipped data from file-like object
- `pivot_table` `aggfunc` can be anything used in `GroupBy.aggregate` ([GH2643](#))
- Implement `DataFrame` merges in case where set cardinalities might overflow 64-bit integer ([GH2690](#))
- Raise exception in C file parser if integer dtype specified and have NA values. ([GH2631](#))
- Attempt to parse ISO8601 format dates when `parse_dates=True` in `read_csv` for major performance boost in such cases ([GH2698](#))
- Add methods `neg` and `inv` to `Series`
- Implement `kind` option in `ExcelFile` to indicate whether it's an XLS or XLSX file ([GH2613](#))
- Documented a fast-path in `pd.read_csv` when parsing iso8601 datetime strings yielding as much as a 20x speedup. ([GH5993](#))

35.12.4 Bug Fixes

- Fix `read_csv/read_table` multithreading issues ([GH2608](#))
- `HDFStore`
 - correctly handle `nan` elements in string columns; serialize via the `nan_rep` keyword to append
 - raise correctly on non-implemented column types (unicode/date)
 - handle correctly `Term` passed types (e.g. `index<1000`, when `index` is `Int64`), (closes [GH512](#))
 - handle `Timestamp` correctly in `data_columns` (closes [GH2637](#))
 - contains correctly matches on non-natural names
 - correctly store `float32` dtypes in tables (if not other float types in the same table)
- Fix `DataFrame.info` bug with UTF8-encoded columns. ([GH2576](#))
- Fix `DatetimeIndex` handling of `FixedOffset` tz ([GH2604](#))
- More robust detection of being in IPython session for wide `DataFrame` console formatting ([GH2585](#))
- Fix platform issues with `file:///` in unit test ([GH2564](#))
- Fix bug and possible segfault when grouping by hierarchical level that contains NA values ([GH2616](#))
- Ensure that `MultiIndex` tuples can be constructed with NAs ([GH2616](#))
- Fix `int64` overflow issue when unstacking `MultiIndex` with many levels ([GH2616](#))
- Exclude non-numeric data from `DataFrame.quantile` by default ([GH2625](#))

- Fix a Cython C int64 boxing issue causing read_csv to return incorrect results ([GH2599](#))
- Fix groupby summing performance issue on boolean data ([GH2692](#))
- Don't bork Series containing datetime64 values with to_datetime ([GH2699](#))
- Fix DataFrame.from_records corner case when passed columns, index column, but empty record list ([GH2633](#))
- Fix C parser-tokenizer bug with trailing fields. ([GH2668](#))
- Don't exclude non-numeric data from GroupBy.max/min ([GH2700](#))
- Don't lose time zone when calling DatetimeIndex.drop ([GH2621](#))
- Fix setitem on a Series with a boolean key and a non-scalar as value ([GH2686](#))
- Box datetime64 values in Series.apply/map ([GH2627](#), [GH2689](#))
- Upconvert datetime + datetime64 values when concatenating frames ([GH2624](#))
- Raise a more helpful error message in merge operations when one DataFrame has duplicate columns ([GH2649](#))
- Fix partial date parsing issue occurring only when code is run at EOM ([GH2618](#))
- Prevent MemoryError when using counting sort in sortlevel with high-cardinality MultiIndex objects ([GH2684](#))
- Fix Period resampling bug when all values fall into a single bin ([GH2070](#))
- Fix buggy interaction with usecols argument in read_csv when there is an implicit first index column ([GH2654](#))
- Fix bug in Index.summary() where string format methods were being called incorrectly. ([GH3869](#))

35.13 pandas 0.10.0

Release date: 2012-12-17

35.13.1 New Features

- Brand new high-performance delimited file parsing engine written in C and Cython. 50% or better performance in many standard use cases with a fraction as much memory usage. ([GH407](#), [GH821](#))
- Many new file parser (read_csv, read_table) features:
 - Support for on-the-fly gzip or bz2 decompression (*compression* option)
 - Ability to get back numpy.recarray instead of DataFrame (*as_recarray=True*)
 - *dtype* option: explicit column dtypes
 - *usecols* option: specify list of columns to be read from a file. Good for reading very wide files with many irrelevant columns ([GH1216](#) [GH926](#), [GH2465](#))
 - Enhanced unicode decoding support via *encoding* option
 - *skipinitialspace* dialect option
 - Can specify strings to be recognized as True (*true_values*) or False (*false_values*)
 - High-performance *delim_whitespace* option for whitespace-delimited files; a preferred alternative to the 's+' regular expression delimiter
 - Option to skip “bad” lines (wrong number of fields) that would otherwise have caused an error in the past (*error_bad_lines* and *warn_bad_lines* options)

- Substantially improved performance in the parsing of integers with thousands markers and lines with comments
- Easy of European (and other) decimal formats (*decimal* option) (GH584, GH2466)
- Custom line terminators (e.g. `lineterminator='~'`) (GH2457)
- Handling of no trailing commas in CSV files (GH2333)
- Ability to handle fractional seconds in `date_converters` (GH2209)
- `read_csv` allow scalar arg to `na_values` (GH1944)
- Explicit column dtype specification in `read_*` functions (GH1858)
- Easier CSV dialect specification (GH1743)
- Improve parser performance when handling special characters (GH1204)
- Google Analytics API integration with easy oauth2 workflow (GH2283)
- Add error handling to `Series.str.encode/decode` (GH2276)
- Add `where` and `mask` to `Series` (GH2337)
- Grouped histogram via `by` keyword in `Series/DataFrame.hist` (GH2186)
- Support optional `min_periods` keyword in `corr` and `cov` for both `Series` and `DataFrame` (GH2002)
- Add `duplicated` and `drop_duplicates` functions to `Series` (GH1923)
- Add docs for `HDFStore table` format
- 'density' property in `SparseSeries` (GH2384)
- Add `ffill` and `bfill` convenience functions for forward- and backfilling time series data (GH2284)
- New option configuration system and functions `set_option`, `get_option`, `describe_option`, and `reset_option`. Deprecate `set_printoptions` and `reset_printoptions` (GH2393). You can also access options as attributes via `pandas.options.X`
- Wide `DataFrames` can be viewed more easily in the console with new `expand_frame_repr` and `line_width` configuration options. This is on by default now (GH2436)
- Scikits.timeseries-like moving window functions via `rolling_window` (GH1270)

35.13.2 Experimental Features

- Add support for `Panel4D`, a named 4 Dimensional structure
- Add support for `ndpanel` factory functions, to create custom, domain-specific N-Dimensional containers

35.13.3 API Changes

- The default binning/labeling behavior for `resample` has been changed to `closed='left'`, `label='left'` for daily and lower frequencies. This had been a large source of confusion for users. See “what’s new” page for more on this. (GH2410)
- Methods with `inplace` option now return `None` instead of the calling (modified) object (GH1893)
- The special case `DataFrame - TimeSeries` doing column-by-column broadcasting has been deprecated. Users should explicitly do e.g. `df.sub(ts, axis=0)` instead. This is a legacy hack and can lead to subtle bugs.

- `inf/-inf` are no longer considered as NA by `isnull/notnull`. To be clear, this is legacy cruft from early pandas. This behavior can be globally re-enabled using the new option `mode.use_inf_as_null` (GH2050, GH1919)
- `pandas.merge` will now default to `sort=False`. For many use cases sorting the join keys is not necessary, and doing it by default is wasteful
- Specify `header=0` explicitly to replace existing column names in file in `read_*` functions.
- Default column names for header-less parsed files (yielded by `read_csv`, etc.) are now the integers 0, 1, A new argument `prefix` has been added; to get the v0.9.x behavior specify `prefix='X'` (GH2034). This API change was made to make the default column names more consistent with the DataFrame constructor's default column names when none are specified.
- DataFrame selection using a boolean frame now preserves input shape
- If function passed to `Series.apply` yields a Series, result will be a DataFrame (GH2316)
- Values like YES/NO/yes/no will not be considered as boolean by default any longer in the file parsers. This can be customized using the new `true_values` and `false_values` options (GH2360)
- `obj.fillna()` is no longer valid; make `method='pad'` no longer the default option, to be more explicit about what kind of filling to perform. Add `ffill/bfill` convenience functions per above (GH2284)
- `HDFStore.keys()` now returns an absolute path-name for each key
- `to_string()` now always returns a unicode string. (GH2224)
- File parsers will not handle NA sentinel values arising from passed converter functions

35.13.4 Improvements to existing features

- Add `nrows` option to `DataFrame.from_records` for iterators (GH1794)
- Unstack/reshape algorithm rewrite to avoid high memory use in cases where the number of observed key-tuples is much smaller than the total possible number that could occur (GH2278). Also improves performance in most cases.
- Support duplicate columns in `DataFrame.from_records` (GH2179)
- Add `normalize` option to `Series/DataFrame.asfreq` (GH2137)
- `SparseSeries` and `SparseDataFrame` construction from empty and scalar values now no longer create dense ndarrays unnecessarily (GH2322)
- `HDFStore` now supports hierarchical keys (GH2397)
- Support multiple query selection formats for `HDFStore` tables (GH1996)
- Support `del store['df']` syntax to delete `HDFStores`
- Add multi-dtype support for `HDFStore` tables
- `min_itemsize` parameter can be specified in `HDFStore` table creation
- Indexing support in `HDFStore` tables (GH698)
- Add `line_terminator` option to `DataFrame.to_csv` (GH2383)
- added implementation of `str(x)/unicode(x)/bytes(x)` to major pandas data structures, which should do the right thing on both py2.x and py3.x. (GH2224)
- Reduce `groupby.apply` overhead substantially by low-level manipulation of internal NumPy arrays in DataFrames (GH535)
- Implement `value_vars` in `melt` and add `melt` to pandas namespace (GH2412)

- Added boolean comparison operators to Panel
- Enable `Series.str.strip/lstrip/rstrip` methods to take an argument (GH2411)
- The `DataFrame` ctor now respects column ordering when given an `OrderedDict` (GH2455)
- Assigning `DatetimeIndex` to `Series` changes the class to `TimeSeries` (GH2139)
- Improve performance of `.value_counts` method on non-integer data (GH2480)
- `get_level_values` method for `MultiIndex` return `Index` instead of `ndarray` (GH2449)
- `convert_to_r_dataframe` conversion for datetime values (GH2351)
- Allow `DataFrame.to_csv` to represent `inf` and `nan` differently (GH2026)
- Add `min_i` argument to `nancorr` to specify minimum required observations (GH2002)
- Add `inplace` option to `sortlevel / sort` functions on `DataFrame` (GH1873)
- Enable `DataFrame` to accept scalar constructor values like `Series` (GH1856)
- `DataFrame.from_records` now takes optional `size` parameter (GH1794)
- include iris dataset (GH1709)
- No `datetime64` `DataFrame` column conversion of `datetime.datetime` with `tzinfo` (GH1581)
- Micro-optimizations in `DataFrame` for tracking state of internal consolidation (GH217)
- Format parameter in `DataFrame.to_csv` (GH1525)
- Partial string slicing for `DatetimeIndex` for daily and higher frequencies (GH2306)
- Implement `col_space` parameter in `to_html` and `to_string` in `DataFrame` (GH1000)
- Override `Series.tolist` and box `datetime64` types (GH2447)
- Optimize `unstack` memory usage by compressing indices (GH2278)
- Fix HTML repr in IPython qtconsole if opening window is small (GH2275)
- Escape more special characters in console output (GH2492)
- `df.select` now invokes `bool` on the result of `crit(x)` (GH2487)

35.13.5 Bug Fixes

- Fix major performance regression in `DataFrame.iteritems` (GH2273)
- Fixes bug when negative period passed to `Series/DataFrame.diff` (GH2266)
- Escape tabs in console output to avoid alignment issues (GH2038)
- Properly box `datetime64` values when retrieving cross-section from mixed-dtype `DataFrame` (GH2272)
- Fix concatenation bug leading to GH2057, GH2257
- Fix regression in `Index` console formatting (GH2319)
- Box `Period` data when assigning `PeriodIndex` to frame column (GH2243, GH2281)
- Raise exception on calling `reset_index` on `Series` with `inplace=True` (GH2277)
- Enable setting multiple columns in `DataFrame` with hierarchical columns (GH2295)
- Respect `dtype=object` in `DataFrame` constructor (GH2291)
- Fix `DatetimeIndex.join` bug with tz-aware indexes and `how='outer'` (GH2317)

- `pop(...)` and `del` works with DataFrame with duplicate columns (GH2349)
- Treat empty strings as NA in date parsing (rather than let `dateutil` do something weird) (GH2263)
- Prevent `uint64` -> `int64` overflows (GH2355)
- Enable joins between MultiIndex and regular Index (GH2024)
- Fix time zone metadata issue when unioning non-overlapping DatetimeIndex objects (GH2367)
- Raise/handle `int64` overflows in parsers (GH2247)
- Deleting of consecutive rows in `HDFStore` tables is much faster than before
- Appending on a `HDFStore` would fail if the table was not first created via `put`
- Use `col_space` argument as minimum column width in `DataFrame.to_html` (GH2328)
- Fix tz-aware `DatetimeIndex.to_period` (GH2232)
- Fix DataFrame row indexing case with MultiIndex (GH2314)
- Fix `to_excel` exporting issues with Timestamp objects in index (GH2294)
- Fixes assigning scalars and array to hierarchical column chunk (GH1803)
- Fixed a `UnicodeDecodeError` with series `tidy_repr` (GH2225)
- Fixed issued with duplicate keys in an index (GH2347, GH2380)
- Fixed issues re: Hash randomization, default on starting w/ py3.3 (GH2331)
- Fixed issue with missing attributes after loading a pickled dataframe (GH2431)
- Fix Timestamp formatting with `tzoffset` time zone in `dateutil` 2.1 (GH2443)
- Fix `GroupBy.apply` issue when using `BinGrouper` to do ts binning (GH2300)
- Fix issues resulting from `datetime.datetime` columns being converted to `datetime64` when calling `DataFrame.apply`. (GH2374)
- Raise exception when calling `to_panel` on non uniquely-indexed frame (GH2441)
- Improved detection of console encoding on IPython zmq frontends (GH2458)
- Preserve time zone when `.append`-ing two time series (GH2260)
- Box timestamps when calling `reset_index` on time-zone-aware index rather than creating a tz-less `datetime64` column (GH2262)
- Enable searching non-string columns in `DataFrame.filter(like=...)` (GH2467)
- Fixed issue with losing nanosecond precision upon conversion to `DatetimeIndex` (GH2252)
- Handle timezones in `Datetime.normalize` (GH2338)
- Fix test case where dtype specification with endianness causes failures on big endian machines (GH2318)
- Fix plotting bug where upsampling causes data to appear shifted in time (GH2448)
- Fix `read_csv` failure for UTF-16 with BOM and `skiprows` (GH2298)
- `read_csv` with `names` arg not implicitly setting `header=None` (GH2459)
- Unrecognized compression mode causes segfault in `read_csv` (GH2474)
- In `read_csv`, `header=0` and passed `names` should discard first row (GH2269)
- Correctly route to `stdout/stderr` in `read_table` (GH2071)
- Fix exception when `Timestamp.to_datetime` is called on a Timestamp with `tzoffset` (GH2471)

- Fixed unintentional conversion of datetime64 to long in `groupby.first()` (GH2133)
- Union of empty DataFrames now return empty with concatenated index (GH2307)
- `DataFrame.sort_index` raises more helpful exception if sorting by column with duplicates (GH2488)
- `DataFrame.to_string` formatters can be list, too (GH2520)
- `DataFrame.combine_first` will always result in the union of the index and columns, even if one DataFrame is length-zero (GH2525)
- Fix several `DataFrame.icol/irow` with duplicate indices issues (GH2228, GH2259)
- Use Series names for column names when using `concat` with `axis=1` (GH2489)
- Raise Exception if `start`, `end`, `periods` all passed to `date_range` (GH2538)
- Fix Panel resampling issue (GH2537)

35.14 pandas 0.9.1

Release date: 2012-11-14

35.14.1 New Features

- Can specify multiple sort orders in `DataFrame/Series.sort/sort_index` (GH928)
- New *top* and *bottom* options for handling NAs in `rank` (GH1508, GH2159)
- Add *where* and *mask* functions to `DataFrame` (GH2109, GH2151)
- Add *at_time* and *between_time* functions to `DataFrame` (GH2149)
- Add flexible *pow* and *rpow* methods to `DataFrame` (GH2190)

35.14.2 API Changes

- Upsampling period index “spans” intervals. Example: annual periods upsampled to monthly will span all months in each year
- `Period.end_time` will yield timestamp at last nanosecond in the interval (GH2124, GH2125, GH1764)
- File parsers no longer coerce to float or bool for columns that have custom converters specified (GH2184)

35.14.3 Improvements to existing features

- Time rule inference for week-of-month (e.g. WOM-2FRI) rules (GH2140)
- Improve performance of datetime + business day offset with large number of offset periods
- Improve HTML display of `DataFrame` objects with hierarchical columns
- Enable referencing of Excel columns by their column names (GH1936)
- `DataFrame.dot` can accept `ndarrays` (GH2042)
- Support negative periods in `Panel.shift` (GH2164)
- Make `.drop(...)` work with non-unique indexes (GH2101)

- Improve performance of Series/DataFrame.diff (re: [GH2087](#))
- Support unary ~ (`__invert__`) in DataFrame ([GH2110](#))
- Turn off pandas-style tick locators and formatters ([GH2205](#))
- DataFrame[DataFrame] uses DataFrame.where to compute masked frame ([GH2230](#))

35.14.4 Bug Fixes

- Fix some duplicate-column DataFrame constructor issues ([GH2079](#))
- Fix bar plot color cycle issues ([GH2082](#))
- Fix off-center grid for stacked bar plots ([GH2157](#))
- Fix plotting bug if inferred frequency is offset with $N > 1$ ([GH2126](#))
- Implement comparisons on date offsets with fixed delta ([GH2078](#))
- Handle inf/-inf correctly in read_* parser functions ([GH2041](#))
- Fix matplotlib unicode interaction bug
- Make WLS r-squared match statsmodels 0.5.0 fixed value
- Fix zero-trimming DataFrame formatting bug
- Correctly compute/box datetime64 min/max values from Series.min/max ([GH2083](#))
- Fix unstacking edge case with unrepresented groups ([GH2100](#))
- Fix Series.str failures when using pipe pattern 'l' ([GH2119](#))
- Fix pretty-printing of dict entries in Series, DataFrame ([GH2144](#))
- Cast other datetime64 values to nanoseconds in DataFrame ctor ([GH2095](#))
- Alias Timestamp.astimezone to tz_convert, so will yield Timestamp ([GH2060](#))
- Fix timedelta64 formatting from Series ([GH2165](#), [GH2146](#))
- Handle None values gracefully in dict passed to Panel constructor ([GH2075](#))
- Box datetime64 values as Timestamp objects in Series/DataFrame.iget ([GH2148](#))
- Fix Timestamp indexing bug in DatetimeIndex.insert ([GH2155](#))
- Use index name(s) (if any) in DataFrame.to_records ([GH2161](#))
- Don't lose index names in Panel.to_frame/DataFrame.to_panel ([GH2163](#))
- Work around length-0 boolean indexing NumPy bug ([GH2096](#))
- Fix partial integer indexing bug in DataFrame.xs ([GH2107](#))
- Fix variety of cut/qcut string-bin formatting bugs ([GH1978](#), [GH1979](#))
- Raise Exception when xs view not possible of MultiIndex'd DataFrame ([GH2117](#))
- Fix groupby(...).first() issue with datetime64 ([GH2133](#))
- Better floating point error robustness in some rolling_* functions ([GH2114](#), [GH2527](#))
- Fix ewma NA handling in the middle of Series ([GH2128](#))
- Fix numerical precision issues in diff with integer data ([GH2087](#))
- Fix bug in MultiIndex.__getitem__ with NA values ([GH2008](#))

- Fix DataFrame.from_records dict-arg bug when passing columns (GH2179)
- Fix Series and DataFrame.diff for integer dtypes (GH2087, GH2174)
- Fix bug when taking intersection of DatetimeIndex with empty index (GH2129)
- Pass through timezone information when calling DataFrame.align (GH2127)
- Properly sort when joining on datetime64 values (GH2196)
- Fix indexing bug in which False/True were being coerced to 0/1 (GH2199)
- Many unicode formatting fixes (GH2201)
- Fix improper MultiIndex conversion issue when assigning e.g. DataFrame.index (GH2200)
- Fix conversion of mixed-type DataFrame to ndarray with dup columns (GH2236)
- Fix duplicate columns issue (GH2218, GH2219)
- Fix SparseSeries.__pow__ issue with NA input (GH2220)
- Fix icol with integer sequence failure (GH2228)
- Fixed resampling tz-aware time series issue (GH2245)
- SparseDataFrame.icol was not returning SparseSeries (GH2227, GH2229)
- Enable ExcelWriter to handle PeriodIndex (GH2240)
- Fix issue constructing DataFrame from empty Series with name (GH2234)
- Use console-width detection in interactive sessions only (GH1610)
- Fix parallel_coordinates legend bug with mpl 1.2.0 (GH2237)
- Make tz_localize work in corner case of empty Series (GH2248)

35.15 pandas 0.9.0

Release date: 10/7/2012

35.15.1 New Features

- Add `str.encode` and `str.decode` to Series (GH1706)
- Add `to_latex` method to DataFrame (GH1735)
- Add convenient expanding window equivalents of all rolling_* ops (GH1785)
- Add Options class to pandas.io.data for fetching options data from Yahoo! Finance (GH1748, GH1739)
- Recognize and convert more boolean values in file parsing (Yes, No, TRUE, FALSE, variants thereof) (GH1691, GH1295)
- Add Panel.update method, analogous to DataFrame.update (GH1999, GH1988)

35.15.2 Improvements to existing features

- Proper handling of NA values in merge operations ([GH1990](#))
- Add `flags` option for `re.compile` in some `Series.str` methods ([GH1659](#))
- Parsing of UTC date strings in `read_*` functions ([GH1693](#))
- Handle generator input to `Series` ([GH1679](#))
- Add `na_action='ignore'` to `Series.map` to quietly propagate NAs ([GH1661](#))
- Add `args/kwds` options to `Series.apply` ([GH1829](#))
- Add `inplace` option to `Series/DataFrame.reset_index` ([GH1797](#))
- Add `level` parameter to `Series.reset_index`
- Add quoting option for `DataFrame.to_csv` ([GH1902](#))
- Indicate long column value truncation in `DataFrame` output with ... ([GH1854](#))
- `DataFrame.dot` will not do data alignment, and also work with `Series` ([GH1915](#))
- Add `na` option for missing data handling in some vectorized string methods ([GH1689](#))
- If `index_label=False` in `DataFrame.to_csv`, do not print fields/commas in the text output. Results in easier importing into R ([GH1583](#))
- Can pass tuple/list of axes to `DataFrame.dropna` to simplify repeated calls (dropping both columns and rows) ([GH924](#))
- Improve `DataFrame.to_html` output for hierarchically-indexed rows (do not repeat levels) ([GH1929](#))
- `TimeSeries.between_time` can now select times across midnight ([GH1871](#))
- Enable `skip_footer` parameter in `ExcelFile.parse` ([GH1843](#))

35.15.3 API Changes

- Change default header names in `read_*` functions to more Pythonic `X0`, `X1`, etc. instead of `X.1`, `X.2`. ([GH2000](#))
- Deprecated `day_of_year` API removed from `PeriodIndex`, use `dayofyear` ([GH1723](#))
- Don't modify NumPy suppress printoption at import time
- The internal HDF5 data arrangement for `DataFrames` has been transposed. Legacy files will still be readable by `HDFStore` ([GH1834](#), [GH1824](#))
- Legacy cruft removed: `pandas.stats.misc.quantileTS`
- Use ISO8601 format for `Period repr`: monthly, daily, and on down ([GH1776](#))
- Empty `DataFrame` columns are now created as object dtype. This will prevent a class of `TypeError`s that was occurring in code where the dtype of a column would depend on the presence of data or not (e.g. a SQL query having results) ([GH1783](#))
- Setting parts of `DataFrame/Panel` using `ix` now aligns input `Series/DataFrame` ([GH1630](#))
- `first` and `last` methods in `GroupBy` no longer drop non-numeric columns ([GH1809](#))
- Resolved inconsistencies in specifying custom NA values in text parser. `na_values` of type dict no longer override default NAs unless `keep_default_na` is set to false explicitly ([GH1657](#))
- Enable `skipfooter` parameter in text parsers as an alias for `skip_footer`

35.15.4 Bug Fixes

- Perform arithmetic column-by-column in mixed-type DataFrame to avoid type upcasting issues. Caused downstream DataFrame.diff bug ([GH1896](#))
- Fix matplotlib auto-color assignment when no custom spectrum passed. Also respect passed color keyword argument ([GH1711](#))
- Fix resampling logical error with closed='left' ([GH1726](#))
- Fix critical DatetimeIndex.union bugs ([GH1730](#), [GH1719](#), [GH1745](#), [GH1702](#), [GH1753](#))
- Fix critical DatetimeIndex.intersection bug with unanchored offsets ([GH1708](#))
- Fix MM-YYYY time series indexing case ([GH1672](#))
- Fix case where Categorical group key was not being passed into index in GroupBy result ([GH1701](#))
- Handle Ellipsis in Series.__getitem__/_setitem__ ([GH1721](#))
- Fix some bugs with handling datetime64 scalars of other units in NumPy 1.6 and 1.7 ([GH1717](#))
- Fix performance issue in MultiIndex.format ([GH1746](#))
- Fixed GroupBy bugs interacting with DatetimeIndex asof / map methods ([GH1677](#))
- Handle factors with NAs in pandas.rpy ([GH1615](#))
- Fix statsmodels import in pandas.stats.var ([GH1734](#))
- Fix DataFrame repr/info summary with non-unique columns ([GH1700](#))
- Fix Series.iget_value for non-unique indexes ([GH1694](#))
- Don't lose tzinfo when passing DatetimeIndex as DataFrame column ([GH1682](#))
- Fix tz conversion with time zones that haven't had any DST transitions since first date in the array ([GH1673](#))
- Fix field access with UTC->local conversion on unsorted arrays ([GH1756](#))
- Fix isnull handling of array-like (list) inputs ([GH1755](#))
- Fix regression in handling of Series in Series constructor ([GH1671](#))
- Fix comparison of Int64Index with DatetimeIndex ([GH1681](#))
- Fix min_periods handling in new rolling_max/min at array start ([GH1695](#))
- Fix errors with how='median' and generic NumPy resampling in some cases caused by SeriesBinGrouper ([GH1648](#), [GH1688](#))
- When grouping by level, exclude unobserved levels ([GH1697](#))
- Don't lose tzinfo in DatetimeIndex when shifting by different offset ([GH1683](#))
- Hack to support storing data with a zero-length axis in HDFStore ([GH1707](#))
- Fix DatetimeIndex tz-aware range generation issue ([GH1674](#))
- Fix method='time' interpolation with intraday data ([GH1698](#))
- Don't plot all-NA DataFrame columns as zeros ([GH1696](#))
- Fix bug in scatter_plot with by option ([GH1716](#))
- Fix performance problem in infer_freq with lots of non-unique stamps ([GH1686](#))
- Fix handling of PeriodIndex as argument to create MultiIndex ([GH1705](#))
- Fix re: unicode MultiIndex level names in Series/DataFrame repr ([GH1736](#))

- Handle PeriodIndex in to_datetime instance method ([GH1703](#))
- Support StaticTzInfo in DatetimeIndex infrastructure ([GH1692](#))
- Allow MultiIndex setops with length-0 other type indexes ([GH1727](#))
- Fix handling of DatetimeIndex in DataFrame.to_records ([GH1720](#))
- Fix handling of general objects in isnull on which bool(...) fails ([GH1749](#))
- Fix .ix indexing with MultiIndex ambiguity ([GH1678](#))
- Fix .ix setting logic error with non-unique MultiIndex ([GH1750](#))
- Basic indexing now works on MultiIndex with > 1000000 elements, regression from earlier version of pandas ([GH1757](#))
- Handle non-float64 dtypes in fast DataFrame.corr/cov code paths ([GH1761](#))
- Fix DatetimeIndex.isin to function properly ([GH1763](#))
- Fix conversion of array of tz-aware datetime.datetime to DatetimeIndex with right time zone ([GH1777](#))
- Fix DST issues with generating anchored date ranges ([GH1778](#))
- Fix issue calling sort on result of Series.unique ([GH1807](#))
- Fix numerical issue leading to square root of negative number in rolling_std ([GH1840](#))
- Let Series.str.split accept no arguments (like str.split) ([GH1859](#))
- Allow user to have dateutil 2.1 installed on a Python 2 system ([GH1851](#))
- Catch ImportError less aggressively in pandas/__init__.py ([GH1845](#))
- Fix pip source installation bug when installing from GitHub ([GH1805](#))
- Fix error when window size > array size in rolling_apply ([GH1850](#))
- Fix pip source installation issues via SSH from GitHub
- Fix OLS.summary when column is a tuple ([GH1837](#))
- Fix bug in __doc__ patching when -OO passed to interpreter ([GH1792](#) [GH1741](#) [GH1774](#))
- Fix unicode console encoding issue in IPython notebook ([GH1782](#), [GH1768](#))
- Fix unicode formatting issue with Series.name ([GH1782](#))
- Fix bug in DataFrame.duplicated with datetime64 columns ([GH1833](#))
- Fix bug in Panel internals resulting in error when doing fillna after truncate not changing size of panel ([GH1823](#))
- Prevent segfault due to MultiIndex not being supported in HDFStore table format ([GH1848](#))
- Fix UnboundLocalError in Panel.__setitem__ and add better error ([GH1826](#))
- Fix to_csv issues with list of string entries. Isnull works on list of strings now too ([GH1791](#))
- Fix Timestamp comparisons with datetime values outside the nanosecond range (1677-2262)
- Revert to prior behavior of normalize_date with datetime.date objects (return datetime)
- Fix broken interaction between np.nansum and Series.any/all
- Fix bug with multiple column date parsers ([GH1866](#))
- DatetimeIndex.union(Int64Index) was broken
- Make plot x vs y interface consistent with integer indexing ([GH1842](#))

- `set_index` inplace modified data even if unique check fails ([GH1831](#))
- Only use Q-OCT/NOV/DEC in quarterly frequency inference ([GH1789](#))
- Upcast to `dtype=object` when unstacking boolean DataFrame ([GH1820](#))
- Fix float64/float32 merging bug ([GH1849](#))
- Fixes to `Period.start_time` for non-daily frequencies ([GH1857](#))
- Fix failure when converter used on `index_col` in `read_csv` ([GH1835](#))
- Implement `PeriodIndex.append` so that `pandas.concat` works correctly ([GH1815](#))
- Avoid Cython out-of-bounds access causing segfault sometimes in `pad_2d`, `backfill_2d`
- Fix resampling error with intraday times and anchored target time (like AS-DEC) ([GH1772](#))
- Fix `.ix` indexing bugs with mixed-integer indexes ([GH1799](#))
- Respect passed `color` keyword argument in `Series.plot` ([GH1890](#))
- Fix `rolling_min/max` when the window is larger than the size of the input array. Check other malformed inputs ([GH1899](#), [GH1897](#))
- Rolling variance / standard deviation with only a single observation in window ([GH1884](#))
- Fix unicode sheet name failure in `to_excel` ([GH1828](#))
- Override `DatetimeIndex.min/max` to return Timestamp objects ([GH1895](#))
- Fix column name formatting issue in length-truncated column ([GH1906](#))
- Fix broken handling of copying Index metadata to new instances created by `view(...)` calls inside the NumPy infrastructure
- Support `datetime.date` again in `DateOffset.rollback/rollforward`
- Raise Exception if `set` passed to `Series` constructor ([GH1913](#))
- Add `TypeError` when appending `HDFStore` table w/ wrong index type ([GH1881](#))
- Don't raise exception on empty inputs in EW functions (e.g. `ewma`) ([GH1900](#))
- Make `asof` work correctly with `PeriodIndex` ([GH1883](#))
- Fix extlinks in doc build
- Fill boolean DataFrame with NaN when calling `shift` ([GH1814](#))
- Fix `setuptools` bug causing pip not to Cythonize `.pyx` files sometimes
- Fix negative integer indexing regression in `.ix` from 0.7.x ([GH1888](#))
- Fix error while retrieving timezone and utc offset from subclasses of `datetime.tzinfo` without `.zone` and `._utcoffset` attributes ([GH1922](#))
- Fix DataFrame formatting of small, non-zero FP numbers ([GH1911](#))
- Various fixes by upcasting of `date` -> `datetime` ([GH1395](#))
- Raise better exception when passing multiple functions with the same name, such as lambdas, to `GroupBy.aggregate`
- Fix DataFrame `apply` with `axis=1` on a non-unique index ([GH1878](#))
- Proper handling of Index subclasses in `pandas.unique` ([GH1759](#))
- Set index names in `DataFrame.from_records` ([GH1744](#))

- Fix time series indexing error with duplicates, under and over hash table size cutoff ([GH1821](#))
- Handle list keys in addition to tuples in `DataFrame.xs` when partial-indexing a hierarchically-indexed `DataFrame` ([GH1796](#))
- Support multiple column selection in `DataFrame.__getitem__` with duplicate columns ([GH1943](#))
- Fix time zone localization bug causing improper fields (e.g. hours) in time zones that have not had a UTC transition in a long time ([GH1946](#))
- Fix errors when parsing and working with with fixed offset timezones ([GH1922](#), [GH1928](#))
- Fix text parser bug when handling UTC datetime objects generated by `dateutil` ([GH1693](#))
- Fix plotting bug when 'B' is the inferred frequency but index actually contains weekends ([GH1668](#), [GH1669](#))
- Fix plot styling bugs ([GH1666](#), [GH1665](#), [GH1658](#))
- Fix plotting bug with index/columns with unicode ([GH1685](#))
- Fix `DataFrame` constructor bug when passed `Series` with `datetime64` dtype in a dict ([GH1680](#))
- Fixed regression in generating `DatetimeIndex` using timezone aware `datetime.datetime` ([GH1676](#))
- Fix `DataFrame` bug when printing concatenated `DataFrames` with duplicated columns ([GH1675](#))
- Fixed bug when plotting time series with multiple intraday frequencies ([GH1732](#))
- Fix bug in `DataFrame.duplicated` to enable iterables other than list-types as input argument ([GH1773](#))
- Fix resample bug when passed list of lambdas as *how* argument ([GH1808](#))
- Repr fix for `MultiIndex` level with all NAs ([GH1971](#))
- Fix `PeriodIndex` slicing bug when slice start/end are out-of-bounds ([GH1977](#))
- Fix `read_table` bug when parsing unicode ([GH1975](#))
- Fix `BlockManager.iget` bug when dealing with non-unique `MultiIndex` as columns ([GH1970](#))
- Fix `reset_index` bug if both `drop` and `level` are specified ([GH1957](#))
- Work around unsafe NumPy object->int casting with Cython function ([GH1987](#))
- Fix `datetime64` formatting bug in `DataFrame.to_csv` ([GH1993](#))
- Default start date in `pandas.io.data` to 1/1/2000 as the docs say ([GH2011](#))

35.16 pandas 0.8.1

Release date: July 22, 2012

35.16.1 New Features

- Add vectorized, NA-friendly string methods to `Series` ([GH1621](#), [GH620](#))
- Can pass dict of per-column line styles to `DataFrame.plot` ([GH1559](#))
- Selective plotting to secondary y-axis on same subplot ([GH1640](#))
- Add new `bootstrap_plot` plot function
- Add new `parallel_coordinates` plot function ([GH1488](#))
- Add `radviz` plot function ([GH1566](#))

- Add `multi_sparse` option to `set_printoptions` to modify display of hierarchical indexes (GH1538)
- Add `dropna` method to Panel (GH171)

35.16.2 Improvements to existing features

- Use moving min/max algorithms from Bottleneck in `rolling_min/rolling_max` for > 100x speedup. (GH1504, GH50)
- Add Cython group median method for >15x speedup (GH1358)
- Drastically improve `to_datetime` performance on ISO8601 datetime strings (with no time zones) (GH1571)
- Improve single-key groupby performance on large data sets, accelerate use of groupby with a Categorical variable
- Add ability to append hierarchical index levels with `set_index` and to drop single levels with `reset_index` (GH1569, GH1577)
- Always apply passed functions in `resample`, even if upsampling (GH1596)
- Avoid unnecessary copies in DataFrame constructor with explicit dtype (GH1572)
- Cleaner DatetimeIndex string representation with 1 or 2 elements (GH1611)
- Improve performance of array-of-Period to PeriodIndex, convert such arrays to PeriodIndex inside Index (GH1215)
- More informative string representation for weekly Period objects (GH1503)
- Accelerate 3-axis multi data selection from homogeneous Panel (GH979)
- Add `adjust` option to `ewma` to disable adjustment factor (GH1584)
- Add new matplotlib converters for high frequency time series plotting (GH1599)
- Handling of tz-aware datetime.datetime objects in `to_datetime`; raise Exception unless `utc=True` given (GH1581)

35.16.3 Bug Fixes

- Fix NA handling in `DataFrame.to_panel` (GH1582)
- Handle TypeError issues inside `PyObject_RichCompareBool` calls in `khash` (GH1318)
- Fix resampling bug to lower case daily frequency (GH1588)
- Fix kendall/spearman `DataFrame.corr` bug with no overlap (GH1595)
- Fix bug in `DataFrame.set_index` (GH1592)
- Don't ignore axes in boxplot if by specified (GH1565)
- Fix Panel `.ix` indexing with integers bug (GH1603)
- Fix Partial indexing bugs (years, months, ...) with PeriodIndex (GH1601)
- Fix MultiIndex console formatting issue (GH1606)
- Unordered index with duplicates doesn't yield scalar location for single entry (GH1586)
- Fix resampling of tz-aware time series with "anchored" freq (GH1591)
- Fix `DataFrame.rank` error on integer data (GH1589)
- Selection of multiple SparseDataFrame columns by list in `__getitem__` (GH1585)

- Override Index.tolist for compatibility with MultiIndex (GH1576)
- Fix hierarchical summing bug with MultiIndex of length 1 (GH1568)
- Work around numpy.concatenate use/bug in Series.set_value (GH1561)
- Ensure Series/DataFrame are sorted before resampling (GH1580)
- Fix unhandled IndexError when indexing very large time series (GH1562)
- Fix DatetimeIndex intersection logic error with irregular indexes (GH1551)
- Fix unit test errors on Python 3 (GH1550)
- Fix .ix indexing bugs in duplicate DataFrame index (GH1201)
- Better handle errors with non-existing objects in HDFStore (GH1254)
- Don't copy int64 array data in DatetimeIndex when copy=False (GH1624)
- Fix resampling of conforming periods quarterly to annual (GH1622)
- Don't lose index name on resampling (GH1631)
- Support python-dateutil version 2.1 (GH1637)
- Fix broken scatter_matrix axis labeling, esp. with time series (GH1625)
- Fix cases where extra keywords weren't being passed on to matplotlib from Series.plot (GH1636)
- Fix BusinessMonthBegin logic for dates before 1st bday of month (GH1645)
- Ensure string alias converted (valid in DatetimeIndex.get_loc) in DataFrame.xs / __getitem__ (GH1644)
- Fix use of string alias timestamps with tz-aware time series (GH1647)
- Fix Series.max/min and Series.describe on len-0 series (GH1650)
- Handle None values in dict passed to concat (GH1649)
- Fix Series.interpolate with method='values' and DatetimeIndex (GH1646)
- Fix IndexError in left merges on a DataFrame with 0-length (GH1628)
- Fix DataFrame column width display with UTF-8 encoded characters (GH1620)
- Handle case in pandas.io.data.get_data_yahoo where Yahoo! returns duplicate dates for most recent business day
- Avoid downsampling when plotting mixed frequencies on the same subplot (GH1619)
- Fix read_csv bug when reading a single line (GH1553)
- Fix bug in C code causing monthly periods prior to December 1969 to be off (GH1570)

35.17 pandas 0.8.0

Release date: 6/29/2012

35.17.1 New Features

- New unified DatetimeIndex class for nanosecond-level timestamp data
- New Timestamp datetime.datetime subclass with easy time zone conversions, and support for nanoseconds

- New `PeriodIndex` class for timespans, calendar logic, and `Period` scalar object
- High performance resampling of timestamp and period data. New *resample* method of all pandas data structures
- New frequency names plus shortcut string aliases like `'15h'`, `'1h30min'`
- Time series string indexing shorthand ([GH222](#))
- Add `week`, `dayofyear` array and other timestamp array-valued field accessor functions to `DatetimeIndex`
- Add `GroupBy.prod` optimized aggregation function and `'prod'` fast time series conversion method ([GH1018](#))
- Implement robust frequency inference function and *inferred_freq* attribute on `DatetimeIndex` ([GH391](#))
- New `tz_convert` and `tz_localize` methods in `Series / DataFrame`
- Convert `DatetimeIndexes` to UTC if time zones are different in `join/setops` ([GH864](#))
- Add `limit` argument for forward/backward filling to `reindex`, `fillna`, etc. ([GH825](#) and others)
- Add support for indexes (dates or otherwise) with duplicates and common sense indexing/selection functionality
- `Series/DataFrame.update` methods, in-place variant of `combine_first` ([GH961](#))
- Add `match` function to API ([GH502](#))
- Add Cython-optimized `first`, `last`, `min`, `max`, `prod` functions to `GroupBy` ([GH994](#), [GH1043](#))
- Dates can be split across multiple columns ([GH1227](#), [GH1186](#))
- Add experimental support for converting pandas `DataFrame` to R `data.frame` via `rpy2` ([GH350](#), [GH1212](#))
- Can pass list of (name, function) to `GroupBy.aggregate` to get aggregates in a particular order ([GH610](#))
- Can pass dicts with lists of functions or dicts to `GroupBy.aggregate` to do much more flexible multiple function aggregation ([GH642](#), [GH610](#))
- New `ordered_merge` functions for merging `DataFrames` with ordered data. Also supports group-wise merging for panel data ([GH813](#))
- Add `keys()` method to `DataFrame`
- Add flexible `replace` method for replacing potentially values to `Series` and `DataFrame` ([GH929](#), [GH1241](#))
- Add `'kde'` plot kind for `Series/DataFrame.plot` ([GH1059](#))
- More flexible multiple function aggregation with `GroupBy`
- Add `pct_change` function to `Series/DataFrame`
- Add option to interpolate by Index values in `Series.interpolate` ([GH1206](#))
- Add `max_colwidth` option for `DataFrame`, defaulting to 50
- Conversion of `DataFrame` through `rpy2` to R `data.frame` ([GH1282](#),)
- Add `keys()` method on `DataFrame` ([GH1240](#))
- Add new `match` function to API (similar to R) ([GH502](#))
- Add `dayfirst` option to parsers ([GH854](#))
- Add `method` argument to `align` method for forward/backward fillin ([GH216](#))
- Add `Panel.transpose` method for rearranging axes ([GH695](#))
- Add new `cut` function (patterned after R) for discretizing data into equal range-length bins or arbitrary breaks of your choosing ([GH415](#))
- Add new `qcut` for cutting with quantiles ([GH1378](#))

- Add `value_counts` top level array method ([GH1392](#))
- Added Andrews curves plot tupe ([GH1325](#))
- Add lag plot ([GH1440](#))
- Add autocorrelation_plot ([GH1425](#))
- Add support for tox and Travis CI ([GH1382](#))
- Add support for Categorical use in GroupBy ([GH292](#))
- Add `any` and `all` methods to DataFrame ([GH1416](#))
- Add `secondary_y` option to Series.plot
- Add experimental `lreshape` function for reshaping wide to long

35.17.2 Improvements to existing features

- Switch to klib/khash-based hash tables in Index classes for better performance in many cases and lower memory footprint
- Shipping some functions from `scipy.stats` to reduce dependency, e.g. `Series.describe` and `DataFrame.describe` ([GH1092](#))
- Can create MultiIndex by passing list of lists or list of arrays to Series, DataFrame constructor, etc. ([GH831](#))
- Can pass arrays in addition to column names to `DataFrame.set_index` ([GH402](#))
- Improve the speed of “square” reindexing of homogeneous DataFrame objects by significant margin ([GH836](#))
- Handle more dtypes when passed MaskedArrays in DataFrame constructor ([GH406](#))
- Improved performance of join operations on integer keys ([GH682](#))
- Can pass multiple columns to GroupBy object, e.g. `grouped[[col1, col2]]` to only aggregate a subset of the value columns ([GH383](#))
- Add histogram / kde plot options for `scatter_matrix` diagonals ([GH1237](#))
- Add inplace option to `Series/DataFrame.rename` and `sort_index`, `DataFrame.drop_duplicates` ([GH805](#), [GH207](#))
- More helpful error message when nothing passed to `Series.reindex` ([GH1267](#))
- Can mix array and scalars as dict-value inputs to DataFrame ctor ([GH1329](#))
- Use DataFrame columns’ name for legend title in plots
- Preserve frequency in DatetimeIndex when possible in boolean indexing operations
- Promote `datetime.date` values in data alignment operations ([GH867](#))
- Add `order` method to Index classes ([GH1028](#))
- Avoid hash table creation in large monotonic hash table indexes ([GH1160](#))
- Store time zones in HDFStore ([GH1232](#))
- Enable storage of sparse data structures in HDFStore ([GH85](#))
- Enable `Series.asof` to work with arrays of timestamp inputs
- Cython implementation of `DataFrame.corr` speeds up by > 100x ([GH1349](#), [GH1354](#))
- Exclude “nuisance” columns automatically in `GroupBy.transform` ([GH1364](#))
- Support functions-as-strings in `GroupBy.transform` ([GH1362](#))

- Use index name as xlabel/ylabel in plots ([GH1415](#))
- Add `convert_dtype` option to `Series.apply` to be able to leave data as `dtype=object` ([GH1414](#))
- Can specify all index level names in `concat` ([GH1419](#))
- Add `dialect` keyword to parsers for quoting conventions ([GH1363](#))
- Enable `DataFrame[bool_DataFrame] += value` ([GH1366](#))
- Add `retries` argument to `get_data_yahoo` to try to prevent Yahoo! API 404s ([GH826](#))
- Improve performance of reshaping by using $O(N)$ categorical sorting
- Series names will be used for index of `DataFrame` if no index passed ([GH1494](#))
- Header argument in `DataFrame.to_csv` can accept a list of column names to use instead of the object's columns ([GH921](#))
- Add `raise_conflict` argument to `DataFrame.update` ([GH1526](#))
- Support file-like objects in `ExcelFile` ([GH1529](#))

35.17.3 API Changes

- Rename `pandas._tseries` to `pandas.lib`
- Rename `Factor` to `Categorical` and add improvements. Numerous `Categorical` bug fixes
- Frequency name overhaul, `WEEKDAY/EOM` and rules with `@` deprecated. `get_legacy_offset_name` backwards compatibility function added
- Raise `ValueError` in `DataFrame.__nonzero__`, so “if df” no longer works ([GH1073](#))
- Change `BDay` (business day) to not normalize dates by default ([GH506](#))
- Remove deprecated `DataMatrix` name
- Default merge suffixes for overlap now have underscores instead of periods to facilitate tab completion, etc. ([GH1239](#))
- Deprecation of `offset`, `time_rule` `timeRule` parameters throughout codebase
- `Series.append` and `DataFrame.append` no longer check for duplicate indexes by default, add `verify_integrity` parameter ([GH1394](#))
- Refactor `Factor` class, old constructor moved to `Factor.from_array`
- Modified internals of `MultiIndex` to use less memory (no longer represented as array of tuples) internally, speed up construction time and many methods which construct intermediate hierarchical indexes ([GH1467](#))

35.17.4 Bug Fixes

- Fix `OverflowError` from storing pre-1970 dates in `HDFStore` by switching to `datetime64` ([GH179](#))
- Fix logical error with February leap year end in `YearEnd` offset
- `Series([False, nan])` was getting casted to `float64` ([GH1074](#))
- Fix binary operations between boolean `Series` and object `Series` with booleans and NAs ([GH1074](#), [GH1079](#))
- Couldn't assign whole array to column in mixed-type `DataFrame` via `.ix` ([GH1142](#))
- Fix label slicing issues with float index values ([GH1167](#))

- Fix segfault caused by empty groups passed to groupby ([GH1048](#))
- Fix occasionally misbehaved reindexing in the presence of NaN labels ([GH522](#))
- Fix imprecise logic causing weird Series results from .apply ([GH1183](#))
- Unstack multiple levels in one shot, avoiding empty columns in some cases. Fix pivot table bug ([GH1181](#))
- Fix formatting of MultiIndex on Series/DataFrame when index name coincides with label ([GH1217](#))
- Handle Excel 2003 #N/A as NaN from xlrd ([GH1213](#), [GH1225](#))
- Fix timestamp locale-related deserialization issues with HDFStore by moving to datetime64 representation ([GH1081](#), [GH809](#))
- Fix DataFrame.duplicated/drop_duplicates NA value handling ([GH557](#))
- Actually raise exceptions in fast reducer ([GH1243](#))
- Fix various timezone-handling bugs from 0.7.3 ([GH969](#))
- GroupBy on level=0 discarded index name ([GH1313](#))
- Better error message with unmergeable DataFrames ([GH1307](#))
- Series.__repr__ alignment fix with unicode index values ([GH1279](#))
- Better error message if nothing passed to reindex ([GH1267](#))
- More robust NA handling in DataFrame.drop_duplicates ([GH557](#))
- Resolve locale-based and pre-epoch HDF5 timestamp deserialization issues ([GH973](#), [GH1081](#), [GH179](#))
- Implement Series.repeat ([GH1229](#))
- Fix indexing with namedtuple and other tuple subclasses ([GH1026](#))
- Fix float64 slicing bug ([GH1167](#))
- Parsing integers with commas ([GH796](#))
- Fix groupby improper data type when group consists of one value ([GH1065](#))
- Fix negative variance possibility in nanvar resulting from floating point error ([GH1090](#))
- Consistently set name on groupby pieces ([GH184](#))
- Treat dict return values as Series in GroupBy.apply ([GH823](#))
- Respect column selection for DataFrame in in GroupBy.transform ([GH1365](#))
- Fix MultiIndex partial indexing bug ([GH1352](#))
- Enable assignment of rows in mixed-type DataFrame via .ix ([GH1432](#))
- Reset index mapping when grouping Series in Cython ([GH1423](#))
- Fix outer/inner DataFrame.join with non-unique indexes ([GH1421](#))
- Fix MultiIndex groupby bugs with empty lower levels ([GH1401](#))
- Calling fillna with a Series will have same behavior as with dict ([GH1486](#))
- SparseSeries reduction bug ([GH1375](#))
- Fix unicode serialization issue in HDFStore ([GH1361](#))
- Pass keywords to pyplot.boxplot in DataFrame.boxplot ([GH1493](#))
- Bug fixes in MonthBegin ([GH1483](#))

- Preserve MultiIndex names in drop ([GH1513](#))
- Fix Panel DataFrame slice-assignment bug ([GH1533](#))
- Don't use locals() in read_* functions ([GH1547](#))

35.18 pandas 0.7.3

Release date: April 12, 2012

35.18.1 New Features

- Support for non-unique indexes: indexing and selection, many-to-one and many-to-many joins ([GH1306](#))
- Added fixed-width file reader, read_fwf ([GH952](#))
- Add group_keys argument to groupby to not add group names to MultiIndex in result of apply ([GH938](#))
- DataFrame can now accept non-integer label slicing ([GH946](#)). Previously only DataFrame.ix was able to do so.
- DataFrame.apply now retains name attributes on Series objects ([GH983](#))
- Numeric DataFrame comparisons with non-numeric values now raises proper TypeError ([GH943](#)). Previously raise "PandasError: DataFrame constructor not properly called!"
- Add kurt methods to Series and DataFrame ([GH964](#))
- Can pass dict of column -> list/set NA values for text parsers ([GH754](#))
- Allows users specified NA values in text parsers ([GH754](#))
- Parsers checks for openpyxl dependency and raises ImportError if not found ([GH1007](#))
- New factory function to create HDFStore objects that can be used in a with statement so users do not have to explicitly call HDFStore.close ([GH1005](#))
- pivot_table is now more flexible with same parameters as groupby ([GH941](#))
- Added stacked bar plots ([GH987](#))
- scatter_matrix method in pandas/tools/plotting.py ([GH935](#))
- DataFrame.boxplot returns plot results for ex-post styling ([GH985](#))
- Short version number accessible as pandas.version.short_version ([GH930](#))
- Additional documentation in panel.to_frame ([GH942](#))
- More informative Series.apply docstring regarding element-wise apply ([GH977](#))
- Notes on rpy2 installation ([GH1006](#))
- Add rotation and font size options to hist method ([GH1012](#))
- Use exogenous / X variable index in result of OLS.y_predict. Add OLS.predict method ([GH1027](#), [GH1008](#))

35.18.2 API Changes

- Calling apply on grouped Series, e.g. describe(), will no longer yield DataFrame by default. Will have to call unstack() to get prior behavior
- NA handling in non-numeric comparisons has been tightened up ([GH933](#), [GH953](#))

- No longer assign dummy names key_0, key_1, etc. to groupby index (GH1291)

35.18.3 Bug Fixes

- Fix logic error when selecting part of a row in a DataFrame with a MultiIndex index (GH1013)
- Series comparison with Series of differing length causes crash (GH1016).
- Fix bug in indexing when selecting section of hierarchically-indexed row (GH1013)
- DataFrame.plot(logy=True) has no effect (GH1011).
- Broken arithmetic operations between SparsePanel-Panel (GH1015)
- Unicode repr issues in MultiIndex with non-ASCII characters (GH1010)
- DataFrame.lookup() returns inconsistent results if exact match not present (GH1001)
- DataFrame arithmetic operations not treating None as NA (GH992)
- DataFrameGroupBy.apply returns incorrect result (GH991)
- Series.reshape returns incorrect result for multiple dimensions (GH989)
- Series.std and Series.var ignores ddof parameter (GH934)
- DataFrame.append loses index names (GH980)
- DataFrame.plot(kind='bar') ignores color argument (GH958)
- Inconsistent Index comparison results (GH948)
- Improper int dtype DataFrame construction from data with NaN (GH846)
- Removes default 'result' name in groupby results (GH995)
- DataFrame.from_records no longer mutate input columns (GH975)
- Use Index name when grouping by it (GH1313)

35.19 pandas 0.7.2

Release date: March 16, 2012

35.19.1 New Features

- Add additional tie-breaking methods in DataFrame.rank (GH874)
- Add ascending parameter to rank in Series, DataFrame (GH875)
- Add sort_columns parameter to allow unsorted plots (GH918)
- IPython tab completion on GroupBy objects

35.19.2 API Changes

- Series.sum returns 0 instead of NA when called on an empty series. Analogously for a DataFrame whose rows or columns are length 0 (GH844)

35.19.3 Improvements to existing features

- Don't use groups dict in `Grouper.size` (GH860)
- Use `khash` for `Series.value_counts`, add `raw` function to `algorithms.py` (GH861)
- Enable column access via attributes on `GroupBy` (GH882)
- Enable setting existing columns (only) via attributes on `DataFrame`, `Panel` (GH883)
- Intercept `__builtin__.sum` in `groupby` (GH885)
- Can pass dict to `DataFrame.fillna` to use different values per column (GH661)
- Can select multiple hierarchical groups by passing list of values in `.ix` (GH134)
- Add `level` keyword to `drop` for dropping values from a level (GH159)
- Add `coerce_float` option on `DataFrame.from_records` (GH893)
- Raise exception if passed `date_parser` fails in `read_csv`
- Add `axis` option to `DataFrame.fillna` (GH174)
- Fixes to `Panel` to make it easier to subclass (GH888)

35.19.4 Bug Fixes

- Fix overflow-related bugs in `groupby` (GH850, GH851)
- Fix unhelpful error message in parsers (GH856)
- Better err msg for failed boolean slicing of dataframe (GH859)
- `Series.count` cannot accept a string (level name) in the level argument (GH869)
- Group index platform int check (GH870)
- `concat` on `axis=1` and `ignore_index=True` raises `TypeError` (GH871)
- Further unicode handling issues resolved (GH795)
- Fix failure in multiindex-based access in `Panel` (GH880)
- Fix `DataFrame` boolean slice assignment failure (GH881)
- Fix `combineAdd` `NotImplementedError` for `SparseDataFrame` (GH887)
- Fix `DataFrame.to_html` encoding and columns (GH890, GH891, GH909)
- Fix na-filling handling in mixed-type `DataFrame` (GH910)
- Fix to `DataFrame.set_value` with non-existent row/col (GH911)
- Fix malformed block in `groupby` when excluding nuisance columns (GH916)
- Fix inconsistent NA handling in `dtype=object` arrays (GH925)
- Fix missing center-of-mass computation in `ewmcov` (GH862)
- Don't raise exception when opening read-only HDF5 file (GH847)
- Fix possible out-of-bounds memory access in 0-length `Series` (GH917)

35.20 pandas 0.7.1

Release date: February 29, 2012

35.20.1 New Features

- Add `to_clipboard` function to pandas namespace for writing objects to the system clipboard ([GH774](#))
- Add `itertuples` method to DataFrame for iterating through the rows of a dataframe as tuples ([GH818](#))
- Add ability to pass `fill_value` and `method` to DataFrame and Series `align` method ([GH806](#), [GH807](#))
- Add `fill_value` option to `reindex`, `align` methods ([GH784](#))
- Enable `concat` to produce DataFrame from Series ([GH787](#))
- Add `between` method to Series ([GH802](#))
- Add HTML representation hook to DataFrame for the IPython HTML notebook ([GH773](#))
- Support for reading Excel 2007 XML documents using `openpyxl`

35.20.2 Improvements to existing features

- Improve performance and memory usage of `fillna` on DataFrame
- Can concatenate a list of Series along `axis=1` to obtain a DataFrame ([GH787](#))

35.20.3 Bug Fixes

- Fix memory leak when inserting large number of columns into a single DataFrame ([GH790](#))
- Appending length-0 DataFrame with new columns would not result in those new columns being part of the resulting concatenated DataFrame ([GH782](#))
- Fixed groupby corner case when passing dictionary grouper and `as_index` is False ([GH819](#))
- Fixed bug whereby bool array sometimes had object dtype ([GH820](#))
- Fix exception thrown on `np.diff` ([GH816](#))
- Fix `to_records` where columns are non-strings ([GH822](#))
- Fix `Index.intersection` where indices have incomparable types ([GH811](#))
- Fix `ExcelFile` throwing an exception for two-line file ([GH837](#))
- Add clearer error message in csv parser ([GH835](#))
- Fix loss of fractional seconds in `HDFStore` ([GH513](#))
- Fix DataFrame join where columns have datetimes ([GH787](#))
- Work around numpy performance issue in `take` ([GH817](#))
- Improve comparison operations for NA-friendliness ([GH801](#))
- Fix indexing operation for floating point values ([GH780](#), [GH798](#))
- Fix groupby case resulting in malformed dataframe ([GH814](#))
- Fix behavior of `reindex` of Series dropping name ([GH812](#))

- Improve on redundant groupby computation ([GH775](#))
- Catch possible NA assignment to int/bool series with exception ([GH839](#))

35.21 pandas 0.7.0

Release date: 2/9/2012

35.21.1 New Features

- New `merge` function for efficiently performing full gamut of database / relational-algebra operations. Refactored existing join methods to use the new infrastructure, resulting in substantial performance gains ([GH220](#), [GH249](#), [GH267](#))
- New `concat` function for concatenating `DataFrame` or `Panel` objects along an axis. Can form union or intersection of the other axes. Improves performance of `DataFrame.append` ([GH468](#), [GH479](#), [GH273](#))
- Handle differently-indexed output values in `DataFrame.apply` ([GH498](#))
- Can pass list of dicts (e.g., a list of shallow JSON objects) to `DataFrame` constructor ([GH526](#))
- Add `reorder_levels` method to `Series` and `DataFrame` ([GH534](#))
- Add dict-like `get` function to `DataFrame` and `Panel` ([GH521](#))
- `DataFrame.iterrows` method for efficiently iterating through the rows of a `DataFrame`
- Added `DataFrame.to_panel` with code adapted from `LongPanel.to_long`
- `reindex_axis` method added to `DataFrame`
- Add `level` option to binary arithmetic functions on `DataFrame` and `Series`
- Add `level` option to the `reindex` and `align` methods on `Series` and `DataFrame` for broadcasting values across a level ([GH542](#), [GH552](#), others)
- Add attribute-based item access to `Panel` and add IPython completion (PR [GH554](#))
- Add `logy` option to `Series.plot` for log-scaling on the Y axis
- Add `index`, `header`, and `justify` options to `DataFrame.to_string`. Add option to ([GH570](#), [GH571](#))
- Can pass multiple `DataFrames` to `DataFrame.join` to join on index ([GH115](#))
- Can pass multiple `Panels` to `Panel.join` ([GH115](#))
- Can pass multiple `DataFrames` to `DataFrame.append` to concatenate (stack) and multiple `Series` to `Series.append` too
- Added `justify` argument to `DataFrame.to_string` to allow different alignment of column headers
- Add `sort` option to `GroupBy` to allow disabling sorting of the group keys for potential speedups ([GH595](#))
- Can pass `MaskedArray` to `Series` constructor ([GH563](#))
- Add `Panel` item access via attributes and IPython completion ([GH554](#))
- Implement `DataFrame.lookup`, fancy-indexing analogue for retrieving values given a sequence of row and column labels ([GH338](#))
- Add `verbose` option to `read_csv` and `read_table` to show number of NA values inserted in non-numeric columns ([GH614](#))

- Can pass a list of dicts or Series to `DataFrame.append` to concatenate multiple rows ([GH464](#))
- Add `level` argument to `DataFrame.xs` for selecting data from other MultiIndex levels. Can take one or more levels with potentially a tuple of keys for flexible retrieval of data ([GH371](#), [GH629](#))
- New `crosstab` function for easily computing frequency tables ([GH170](#))
- Can pass a list of functions to aggregate with `groupby` on a `DataFrame`, yielding an aggregated result with hierarchical columns ([GH166](#))
- Add integer-indexing functions `iget` in `Series` and `irow / iget` in `DataFrame` ([GH628](#))
- Add new `Series.unique` function, significantly faster than `numpy.unique` ([GH658](#))
- Add new `cummin` and `cummax` instance methods to `Series` and `DataFrame` ([GH647](#))
- Add new `value_range` function to return min/max of a dataframe ([GH288](#))
- Add `drop` parameter to `reset_index` method of `DataFrame` and added method to `Series` as well ([GH699](#))
- Add `isin` method to `Index` objects, works just like `Series.isin` ([GH](#) [GH657](#))
- Implement array interface on `Panel` so that ufuncs work (re: [GH740](#))
- Add `sort` option to `DataFrame.join` ([GH731](#))
- Improved handling of NAs (propagation) in binary operations with `dtype=object` arrays ([GH737](#))
- Add `abs` method to Pandas objects
- Added `algorithms` module to start collecting central algos

35.21.2 API Changes

- Label-indexing with integer indexes now raises `KeyError` if a label is not found instead of falling back on location-based indexing ([GH700](#))
- Label-based slicing via `ix` or `[]` on `Series` will now only work if exact matches for the labels are found or if the index is monotonic (for range selections)
- Label-based slicing and sequences of labels can be passed to `[]` on a `Series` for both getting and setting ([GH86](#))
- `[]` operator (`__getitem__` and `__setitem__`) will raise `KeyError` with integer indexes when an index is not contained in the index. The prior behavior would fall back on position-based indexing if a key was not found in the index which would lead to subtle bugs. This is now consistent with the behavior of `.ix` on `DataFrame` and friends ([GH328](#))
- Rename `DataFrame.delevel` to `DataFrame.reset_index` and add deprecation warning
- `Series.sort` (an in-place operation) called on a `Series` which is a view on a larger array (e.g. a column in a `DataFrame`) will generate an `Exception` to prevent accidentally modifying the data source ([GH316](#))
- Refactor to remove deprecated `LongPanel` class ([GH552](#))
- Deprecated `Panel.to_long`, renamed to `to_frame`
- Deprecated `colSpace` argument in `DataFrame.to_string`, renamed to `col_space`
- Rename `precision` to `accuracy` in engineering float formatter ([GH](#) [GH395](#))
- The default delimiter for `read_csv` is comma rather than letting `csv.Sniffer` infer it
- Rename `col_or_columns` argument in `DataFrame.drop_duplicates` ([GH](#) [GH734](#))

35.21.3 Improvements to existing features

- Better error message in DataFrame constructor when passed column labels don't match data ([GH497](#))
- Substantially improve performance of multi-GroupBy aggregation when a Python function is passed, reuse ndarray object in Cython ([GH496](#))
- Can store objects indexed by tuples and floats in HDFStore ([GH492](#))
- Don't print length by default in Series.to_string, add *length* option ([GH](#) [GH489](#))
- Improve Cython code for multi-groupby to aggregate without having to sort the data ([GH93](#))
- Improve MultiIndex reindexing speed by storing tuples in the MultiIndex, test for backwards unpickling compatibility
- Improve column reindexing performance by using specialized Cython take function
- Further performance tweaking of Series.__getitem__ for standard use cases
- Avoid Index dict creation in some cases (i.e. when getting slices, etc.), regression from prior versions
- Friendlier error message in setup.py if NumPy not installed
- Use common set of NA-handling operations (sum, mean, etc.) in Panel class also ([GH536](#))
- Default name assignment when calling reset_index on DataFrame with a regular (non-hierarchical) index ([GH476](#))
- Use Cythonized groupers when possible in Series/DataFrame stat ops with level parameter passed ([GH545](#))
- Ported skiplist data structure to C to speed up rolling_median by about 5-10x in most typical use cases ([GH374](#))
- Some performance enhancements in constructing a Panel from a dict of DataFrame objects
- Made Index._get_duplicates a public method by removing the underscore
- Prettier printing of floats, and column spacing fix ([GH395](#), [GH571](#))
- Add bold_rows option to DataFrame.to_html ([GH586](#))
- Improve the performance of DataFrame.sort_index by up to 5x or more when sorting by multiple columns
- Substantially improve performance of DataFrame and Series constructors when passed a nested dict or dict, respectively ([GH540](#), [GH621](#))
- Modified setup.py so that pip / setuptools will install dependencies ([GH](#) [GH507](#), various pull requests)
- Unstack called on DataFrame with non-MultiIndex will return Series ([GH](#) [GH477](#))
- Improve DataFrame.to_string and console formatting to be more consistent in the number of displayed digits ([GH395](#))
- Use bottleneck if available for performing NaN-friendly statistical operations that it implemented ([GH91](#))
- Monkey-patch context to traceback in DataFrame.apply to indicate which row/column the function application failed on ([GH614](#))
- Improved ability of read_table and read_clipboard to parse console-formatted DataFrames (can read the row of index names, etc.)
- Can pass list of group labels (without having to convert to an ndarray yourself) to groupby in some cases ([GH659](#))
- Use kind argument to Series.order for selecting different sort kinds ([GH668](#))

- Add option to `Series.to_csv` to omit the index ([GH684](#))
- Add `delimiter` as an alternative to `sep` in `read_csv` and other parsing functions
- Substantially improved performance of `groupby` on DataFrames with many columns by aggregating blocks of columns all at once ([GH745](#))
- Can pass a file handle or `StringIO` to `Series/DataFrame.to_csv` ([GH765](#))
- Can pass sequence of integers to `DataFrame.irow(icol)` and `Series.iget`, ([GH GH654](#))
- Prototypes for some vectorized string functions
- Add float64 hash table to solve the `Series.unique` problem with NAs ([GH714](#))
- Memoize objects when reading from file to reduce memory footprint
- Can get and set a column of a DataFrame with hierarchical columns containing “empty” (“”) lower levels without passing the empty levels ([PR GH768](#))

35.21.4 Bug Fixes

- Raise exception in out-of-bounds indexing of `Series` instead of seg-faulting, regression from earlier releases ([GH495](#))
- Fix error when joining DataFrames of different dtypes within the same typeclass (e.g. `float32` and `float64`) ([GH486](#))
- Fix bug in `Series.min/Series.max` on objects like `datetime.datetime` ([GH GH487](#))
- Preserve index names in `Index.union` ([GH501](#))
- Fix bug in `Index` joining causing subclass information (like `DateRange` type) to be lost in some cases ([GH500](#))
- Accept empty list as input to `DataFrame` constructor, regression from 0.6.0 ([GH491](#))
- Can output `DataFrame` and `Series` with `ndarray` objects in a `dtype=object` array ([GH490](#))
- Return empty string from `Series.to_string` when called on empty `Series` ([GH GH488](#))
- Fix exception passing empty list to `DataFrame.from_records`
- Fix `Index.format` bug (excluding name field) with datetimes with time info
- Fix scalar value access in `Series` to always return NumPy scalars, regression from prior versions ([GH510](#))
- Handle rows skipped at beginning of file in `read_*` functions ([GH505](#))
- Handle improper dtype casting in `set_value` methods
- Unary `'-' / __neg__` operator on `DataFrame` was returning integer values
- Unbox 0-dim `ndarrays` from certain operators like `all`, `any` in `Series`
- Fix handling of missing columns (was `combine_first`-specific) in `DataFrame.combine` for general case ([GH529](#))
- Fix type inference logic with boolean lists and arrays in `DataFrame` indexing
- Use centered sum of squares in R-square computation if `entity_effects=True` in panel regression
- Handle all NA case in `Series.{corr, cov}`, was raising exception ([GH548](#))
- Aggregating by multiple levels with `level` argument to `DataFrame`, `Series` stat method, was broken ([GH545](#))
- Fix Cython buf when converter passed to `read_csv` produced a numeric array (buffer dtype mismatch when passed to Cython type inference function) ([GH GH546](#))
- Fix exception when setting scalar value using `.ix` on a `DataFrame` with a `MultiIndex` ([GH551](#))

- Fix outer join between two DateRanges with different offsets that returned an invalid DateRange
- Cleanup DataFrame.from_records failure where index argument is an integer
- Fix Data.from_records failure when passed a dictionary
- Fix NA handling in {Series, DataFrame}.rank with non-floating point dtypes
- Fix bug related to integer type-checking in .ix-based indexing
- Handle non-string index name passed to DataFrame.from_records
- DataFrame.insert caused the columns name(s) field to be discarded (GH527)
- Fix erroneous in monotonic many-to-one left joins
- Fix DataFrame.to_string to remove extra column white space (GH571)
- Format floats to default to same number of digits (GH395)
- Added decorator to copy docstring from one function to another (GH449)
- Fix error in monotonic many-to-one left joins
- Fix __eq__ comparison between DateOffsets with different relativedelta keywords passed
- Fix exception caused by parser converter returning strings (GH583)
- Fix MultiIndex formatting bug with integer names (GH601)
- Fix bug in handling of non-numeric aggregates in Series.groupby (GH612)
- Fix TypeError with tuple subclasses (e.g. namedtuple) in DataFrame.from_records (GH611)
- Catch misreported console size when running IPython within Emacs
- Fix minor bug in pivot table margins, loss of index names and length-1 'All' tuple in row labels
- Add support for legacy WidePanel objects to be read from HDFStore
- Fix out-of-bounds segfault in pad_object and backfill_object methods when either source or target array are empty
- Could not create a new column in a DataFrame from a list of tuples
- Fix bugs preventing SparseDataFrame and SparseSeries working with groupby (GH666)
- Use sort kind in Series.sort / argsort (GH668)
- Fix DataFrame operations on non-scalar, non-pandas objects (GH672)
- Don't convert DataFrame column to integer type when passing integer to __setitem__ (GH669)
- Fix downstream bug in pivot_table caused by integer level names in MultiIndex (GH678)
- Fix SparseSeries.combine_first when passed a dense Series (GH687)
- Fix performance regression in HDFStore loading when DataFrame or Panel stored in table format with datetimes
- Raise Exception in DateRange when offset with n=0 is passed (GH683)
- Fix get/set inconsistency with .ix property and integer location but non-integer index (GH707)
- Use right dropna function for SparseSeries. Return dense Series for NA fill value (GH730)
- Fix Index.format bug causing incorrectly string-formatted Series with datetime indexes (GH726, GH758)
- Fix errors caused by object dtype arrays passed to ols (GH759)
- Fix error where column names lost when passing list of labels to DataFrame.__getitem__, (GH662)

- Fix error whereby top-level week iterator overwrote week instance
- Fix circular reference causing memory leak in sparse array / series / frame, (GH663)
- Fix integer-slicing from integers-as-floats (GH670)
- Fix zero division errors in nanops from object dtype arrays in all NA case (GH676)
- Fix csv encoding when using unicode (GH705, GH717, GH738)
- Fix assumption that each object contains every unique block type in concat, (GH708)
- Fix sortedness check of multiindex in to_panel (GH719, 720)
- Fix that None was not treated as NA in PyObjectHashtable
- Fix hashing dtype because of endianness confusion (GH747, GH748)
- Fix SparseSeries.dropna to return dense Series in case of NA fill value (GH GH730)
- Use map_infer instead of np.vectorize. handle NA sentinels if converter yields numeric array, (GH753)
- Fixes and improvements to DataFrame.rank (GH742)
- Fix catching AttributeError instead of NameError for bottleneck
- Try to cast non-MultiIndex to better dtype when calling reset_index (GH726 GH440)
- Fix #1.QNAN0' float bug on 2.6/win64
- Allow subclasses of dicts in DataFrame constructor, with tests
- Fix problem whereby set_index destroys column multiindex (GH764)
- Hack around bug in generating DateRange from naive DateOffset (GH770)
- Fix bug in DateRange.intersection causing incorrect results with some overlapping ranges (GH771)

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35.22 pandas 0.6.1

Release date: 12/13/2011

35.22.1 API Changes

- Rename *names* argument in `DataFrame.from_records` to *columns*. Add deprecation warning
- Boolean get/set operations on Series with boolean Series will reindex instead of requiring that the indexes be exactly equal ([GH429](#))

35.22.2 New Features

- Can pass Series to `DataFrame.append` with `ignore_index=True` for appending a single row ([GH430](#))
- Add Spearman and Kendall correlation options to `Series.corr` and `DataFrame.corr` ([GH428](#))
- Add new *get_value* and *set_value* methods to Series, DataFrame, and Panel to very low-overhead access to scalar elements. `df.get_value(row, column)` is about 3x faster than `df[column][row]` by handling fewer cases ([GH437](#), [GH438](#)). Add similar methods to sparse data structures for compatibility
- Add Qt table widget to sandbox ([GH435](#))
- `DataFrame.align` can accept Series arguments, add `axis` keyword ([GH461](#))
- Implement new `SparseList` and `SparseArray` data structures. `SparseSeries` now derives from `SparseArray` ([GH463](#))
- `max_columns` / `max_rows` options in `set_printoptions` ([GH453](#))
- Implement `Series.rank` and `DataFrame.rank`, fast versions of `scipy.stats.rankdata` ([GH428](#))
- Implement `DataFrame.from_items` alternate constructor ([GH444](#))

- `DataFrame.convert_objects` method for inferring better dtypes for object columns (GH302)
- Add `rolling_corr_pairwise` function for computing Panel of correlation matrices (GH189)
- Add `margins` option to `pivot_table` for computing subgroup aggregates (GH GH114)
- Add `Series.from_csv` function (GH482)

35.22.3 Improvements to existing features

- Improve memory usage of `DataFrame.describe` (do not copy data unnecessarily) (GH425)
- Use same formatting function for outputting floating point Series to console as in DataFrame (GH420)
- `DataFrame.delevel` will try to infer better dtype for new columns (GH440)
- Exclude non-numeric types in `DataFrame.{corr, cov}`
- Override `Index.astype` to enable dtype casting (GH412)
- Use same float formatting function for `Series.__repr__` (GH420)
- Use available console width to output DataFrame columns (GH453)
- Accept ndarrays when setting items in Panel (GH452)
- Infer console width when printing `__repr__` of DataFrame to console (PR GH453)
- Optimize scalar value lookups in the general case by 25% or more in Series and DataFrame
- Can pass DataFrame/DataFrame and DataFrame/Series to `rolling_corr/rolling_cov` (GH462)
- Fix performance regression in cross-sectional count in DataFrame, affecting DataFrame.dropna speed
- Column deletion in DataFrame copies no data (computes views on blocks) (GH GH158)
- `MultiIndex.get_level_values` can take the level name
- More helpful error message when `DataFrame.plot` fails on one of the columns (GH478)
- Improve performance of `DataFrame.{index, columns}` attribute lookup

35.22.4 Bug Fixes

- Fix $O(K^2)$ memory leak caused by inserting many columns without consolidating, had been present since 0.4.0 (GH467)
- `DataFrame.count` should return Series with zero instead of NA with length-0 axis (GH423)
- Fix Yahoo! Finance API usage in `pandas.io.data` (GH419, GH427)
- Fix upstream bug causing failure in `Series.align` with empty Series (GH434)
- Function passed to `DataFrame.apply` can return a list, as long as it's the right length. Regression from 0.4 (GH432)
- Don't "accidentally" upcast scalar values when indexing using `.ix` (GH431)
- Fix groupby exception raised with `as_index=False` and single column selected (GH421)
- Implement `DateOffset.__ne__` causing downstream bug (GH456)
- Fix `__doc__`-related issue when converting py -> pyo with py2exe
- Bug fix in left join Cython code with duplicate monotonic labels

- Fix bug when unstacking multiple levels described in [GH451](#)
- Exclude NA values in dtype=object arrays, regression from 0.5.0 ([GH469](#))
- Use Cython map_infer function in DataFrame.applymap to properly infer output type, handle tuple return values and other things that were breaking ([GH465](#))
- Handle floating point index values in HDFStore ([GH454](#))
- Fixed stale column reference bug (cached Series object) caused by type change / item deletion in DataFrame ([GH473](#))
- Index.get_loc should always raise Exception when there are duplicates
- Handle differently-indexed Series input to DataFrame constructor ([GH475](#))
- Omit nuisance columns in multi-groupby with Python function
- Buglet in handling of single grouping in general apply
- Handle type inference properly when passing list of lists or tuples to DataFrame constructor ([GH484](#))
- Preserve Index / MultiIndex names in GroupBy.apply concatenation step (GH [GH481](#))

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35.23 pandas 0.6.0

Release date: 11/25/2011

35.23.1 API Changes

- Arithmetic methods like *sum* will attempt to sum dtype=object values by default instead of excluding them (GH382)

35.23.2 New Features

- Add *melt* function to *pandas.core.reshape*
- Add *level* parameter to group by level in Series and DataFrame descriptive statistics (GH313)
- Add *head* and *tail* methods to Series, analogous to to DataFrame (PR GH296)
- Add *Series.isin* function which checks if each value is contained in a passed sequence (GH289)
- Add *float_format* option to *Series.to_string*
- Add *skip_footer* (GH291) and *converters* (GH343) options to *read_csv* and *read_table*
- Add proper, tested weighted least squares to standard and panel OLS (GH GH303)
- Add *drop_duplicates* and *duplicated* functions for removing duplicate DataFrame rows and checking for duplicate rows, respectively (GH319)
- Implement logical (boolean) operators *&*, *|*, *^* on DataFrame (GH347)
- Add *Series.mad*, mean absolute deviation, matching DataFrame
- Add *QuarterEnd* DateOffset (GH321)
- Add matrix multiplication function *dot* to DataFrame (GH65)
- Add *orient* option to *Panel.from_dict* to ease creation of mixed-type Panels (GH359, GH301)
- Add *DataFrame.from_dict* with similar *orient* option
- Can now pass list of tuples or list of lists to *DataFrame.from_records* for fast conversion to DataFrame (GH357)
- Can pass multiple levels to groupby, e.g. *df.groupby(level=[0, 1])* (GH GH103)
- Can sort by multiple columns in *DataFrame.sort_index* (GH92, GH362)
- Add fast *get_value* and *put_value* methods to DataFrame and micro-performance tweaks (GH360)
- Add *cov* instance methods to Series and DataFrame (GH194, GH362)
- Add bar plot option to *DataFrame.plot* (GH348)
- Add *idxmin* and *idxmax* functions to Series and DataFrame for computing index labels achieving maximum and minimum values (GH286)
- Add *read_clipboard* function for parsing DataFrame from OS clipboard, should work across platforms (GH300)
- Add *nunique* function to Series for counting unique elements (GH297)
- DataFrame constructor will use Series name if no columns passed (GH373)
- Support regular expressions and longer delimiters in *read_table/read_csv*, but does not handle quoted strings yet (GH364)
- Add *DataFrame.to_html* for formatting DataFrame to HTML (GH387)
- MaskedArray can be passed to DataFrame constructor and masked values will be converted to NaN (GH396)
- Add *DataFrame.boxplot* function (GH368, others)
- Can pass extra args, kwds to DataFrame.apply (GH376)

35.23.3 Improvements to existing features

- Raise more helpful exception if date parsing fails in `DateRange` (GH298)
- Vastly improved performance of `GroupBy` on axes with a `MultiIndex` (GH299)
- Print level names in hierarchical index in `Series repr` (GH305)
- Return `DataFrame` when performing `GroupBy` on selected column and `as_index=False` (GH308)
- Can pass vector to `on` argument in `DataFrame.join` (GH312)
- Don't show `Series` name if it's `None` in the repr, also omit length for short `Series` (GH317)
- Show legend by default in `DataFrame.plot`, add `legend` boolean flag (GH GH324)
- Significantly improved performance of `Series.order`, which also makes `np.unique` called on a `Series` faster (GH327)
- Faster cythonized count by level in `Series` and `DataFrame` (GH341)
- Raise exception if `dateutil 2.0` installed on Python 2.x runtime (GH346)
- Significant `GroupBy` performance enhancement with multiple keys with many “empty” combinations
- New Cython vectorized function `map_infer` speeds up `Series.apply` and `Series.map` significantly when passed elementwise Python function, motivated by GH355
- Cythonized `cache_readonly`, resulting in substantial micro-performance enhancements throughout the codebase (GH361)
- Special Cython matrix iterator for applying arbitrary reduction operations with 3-5x better performance than `np.apply_along_axis` (GH309)
- Add `raw` option to `DataFrame.apply` for getting better performance when the passed function only requires an `ndarray` (GH309)
- Improve performance of `MultiIndex.from_tuples`
- Can pass multiple levels to `stack` and `unstack` (GH370)
- Can pass multiple values columns to `pivot_table` (GH381)
- Can call `DataFrame.delevel` with standard `Index` with name set (GH393)
- Use `Series` name in `GroupBy` for result index (GH363)
- Refactor `Series/DataFrame` stat methods to use common set of NaN-friendly function
- Handle NumPy scalar integers at C level in Cython conversion routines

35.23.4 Bug Fixes

- Fix bug in `DataFrame.to_csv` when writing a `DataFrame` with an index name (GH290)
- `DataFrame` should clear its `Series` caches on consolidation, was causing “stale” `Series` to be returned in some corner cases (GH304)
- `DataFrame` constructor failed if a column had a list of tuples (GH293)
- Ensure that `Series.apply` always returns a `Series` and implement `Series.round` (GH314)
- Support boolean columns in Cythonized groupby functions (GH315)
- `DataFrame.describe` should not fail if there are no numeric columns, instead return categorical describe (GH323)

- Fixed bug which could cause columns to be printed in wrong order in *DataFrame.to_string* if specific list of columns passed (GH325)
- Fix legend plotting failure if DataFrame columns are integers (GH326)
- Shift start date back by one month for Yahoo! Finance API in *pandas.io.data* (GH329)
- Fix *DataFrame.join* failure on unconsolidated inputs (GH331)
- *DataFrame.min/max* will no longer fail on mixed-type DataFrame (GH337)
- Fix *read_csv / read_table* failure when passing list to *index_col* that is not in ascending order (GH349)
- Fix failure passing *Int64Index* to *Index.union* when both are monotonic
- Fix error when passing *SparseSeries* to (dense) DataFrame constructor
- Added missing bang at top of *setup.py* (GH352)
- Change *is_monotonic* on *MultiIndex* so it properly compares the tuples
- Fix *MultiIndex* outer join logic (GH351)
- Set index name attribute with single-key groupby (GH358)
- Bug fix in reflexive binary addition in Series and DataFrame for non-commutative operations (like string concatenation) (GH353)
- *setuptools.py* will invoke Cython (GH192)
- Fix block consolidation bug after inserting column into *MultiIndex* (GH366)
- Fix bug in join operations between *Index* and *Int64Index* (GH367)
- Handle *min_periods=0* case in moving window functions (GH365)
- Fixed corner cases in *DataFrame.apply/pivot* with empty DataFrame (GH378)
- Fixed repr exception when Series name is a tuple
- Always return *DateRange* from *asfreq* (GH390)
- Pass level names to *swaplevel* (GH379)
- Don't lose index names in *MultiIndex.droplevel* (GH394)
- Infer more proper return type in *DataFrame.apply* when no columns or rows depending on whether the passed function is a reduction (GH389)
- Always return NA/NaN from *Series.min/max* and *DataFrame.min/max* when all of a row/column/values are NA (GH384)
- Enable partial setting with *.ix / advanced indexing* (GH397)
- Handle mixed-type DataFrames correctly in *unstack*, do not lose type information (GH403)
- Fix integer name formatting bug in *Index.format* and in *Series.__repr__*
- Handle label types other than string passed to groupby (GH405)
- Fix bug in *.ix*-based indexing with partial retrieval when a label is not contained in a level
- Index name was not being pickled (GH408)
- Level name should be passed to result index in *GroupBy.apply* (GH416)

35.23.5 Thanks

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- carljv
- rsamson

35.24 pandas 0.5.0

Release date: 10/24/2011

This release of pandas includes a number of API changes (see below) and cleanup of deprecated APIs from pre-0.4.0 releases. There are also bug fixes, new features, numerous significant performance enhancements, and includes a new ipython completer hook to enable tab completion of DataFrame columns accesses and attributes (a new feature).

In addition to the changes listed here from 0.4.3 to 0.5.0, the minor releases 4.1, 0.4.2, and 0.4.3 brought some significant new functionality and performance improvements that are worth taking a look at.

Thanks to all for bug reports, contributed patches and generally providing feedback on the library.

35.24.1 API Changes

- *read_table*, *read_csv*, and *ExcelFile.parse* default arguments for *index_col* is now None. To use one or more of the columns as the resulting DataFrame's index, these must be explicitly specified now
- Parsing functions like *read_csv* no longer parse dates by default (GH [GH225](#))
- Removed *weights* option in panel regression which was not doing anything principled (GH155)
- Changed *buffer* argument name in *Series.to_string* to *buf*

- *Series.to_string* and *DataFrame.to_string* now return strings by default instead of printing to `sys.stdout`
- Deprecated *nanRep* argument in various *to_string* and *to_csv* functions in favor of *na_rep*. Will be removed in 0.6 ([GH275](#))
- Renamed *delimiter* to *sep* in *DataFrame.from_csv* for consistency
- Changed order of *Series.clip* arguments to match those of *numpy.clip* and added (unimplemented) *out* argument so *numpy.clip* can be called on a Series ([GH272](#))
- Series functions renamed (and thus deprecated) in 0.4 series have been removed:
 - *asOf*, use *asof*
 - *toDict*, use *to_dict*
 - *toString*, use *to_string*
 - *toCSV*, use *to_csv*
 - *merge*, use *map*
 - *applymap*, use *apply*
 - *combineFirst*, use *combine_first*
 - *_firstTimeWithValue* use *first_valid_index*
 - *_lastTimeWithValue* use *last_valid_index*
- DataFrame functions renamed / deprecated in 0.4 series have been removed:
 - *asMatrix* method, use *as_matrix* or *values* attribute
 - *combineFirst*, use *combine_first*
 - *getXS*, use *xs*
 - *merge*, use *join*
 - *fromRecords*, use *from_records*
 - *fromcsv*, use *from_csv*
 - *toRecords*, use *to_records*
 - *toDict*, use *to_dict*
 - *toString*, use *to_string*
 - *toCSV*, use *to_csv*
 - *_firstTimeWithValue* use *first_valid_index*
 - *_lastTimeWithValue* use *last_valid_index*
 - *toDataMatrix* is no longer needed
 - *rows()* method, use *index* attribute
 - *cols()* method, use *columns* attribute
 - *dropEmptyRows()*, use *dropna(how='all')*
 - *dropIncompleteRows()*, use *dropna()*
 - *tapply(f)*, use *apply(f, axis=1)*
 - *tgroupby(keyfunc, aggfunc)*, use *groupby* with *axis=1*

35.24.2 Deprecations Removed

- *indexField* argument in *DataFrame.from_records*
- *missingAtEnd* argument in *Series.order*. Use *na_last* instead
- *Series.fromValue* classmethod, use regular *Series* constructor instead
- Functions *parseCSV*, *parseText*, and *parseExcel* methods in *pandas.io.parsers* have been removed
- *Index.asOfDate* function
- *Panel.getMinorXS* (use *minor_xs*) and *Panel.getMajorXS* (use *major_xs*)
- *Panel.toWide*, use *Panel.to_wide* instead

35.24.3 New Features

- Added *DataFrame.align* method with standard join options
- Added *parse_dates* option to *read_csv* and *read_table* methods to optionally try to parse dates in the index columns
- Add *nrows*, *chunksize*, and *iterator* arguments to *read_csv* and *read_table*. The last two return a new *TextParser* class capable of lazily iterating through chunks of a flat file (GH242)
- Added ability to join on multiple columns in *DataFrame.join* (GH214)
- Added private *_get_duplicates* function to *Index* for identifying duplicate values more easily
- Added column attribute access to *DataFrame*, e.g. *df.A* equivalent to *df['A']* if 'A' is a column in the *DataFrame* (GH213)
- Added IPython tab completion hook for *DataFrame* columns. (GH233, GH230)
- Implement *Series.describe* for *Series* containing objects (GH241)
- Add inner join option to *DataFrame.join* when joining on key(s) (GH248)
- Can select set of *DataFrame* columns by passing a list to *__getitem__* (GH GH253)
- Can use *&* and *|* to intersection / union *Index* objects, respectively (GH GH261)
- Added *pivot_table* convenience function to pandas namespace (GH234)
- Implemented *Panel.rename_axis* function (GH243)
- *DataFrame* will show index level names in console output
- Implemented *Panel.take*
- Add *set_eng_float_format* function for setting alternate *DataFrame* floating point string formatting
- Add convenience *set_index* function for creating a *DataFrame* index from its existing columns

35.24.4 Improvements to existing features

- Major performance improvements in file parsing functions *read_csv* and *read_table*
- Added Cython function for converting tuples to *ndarray* very fast. Speeds up many *MultiIndex*-related operations
- File parsing functions like *read_csv* and *read_table* will explicitly check if a parsed index has duplicates and raise a more helpful exception rather than deferring the check until later

- Refactored merging / joining code into a tidy class and disabled unnecessary computations in the float/object case, thus getting about 10% better performance ([GH211](#))
- Improved speed of *DataFrame.xs* on mixed-type DataFrame objects by about 5x, regression from 0.3.0 ([GH215](#))
- With new *DataFrame.align* method, speeding up binary operations between differently-indexed DataFrame objects by 10-25%.
- Significantly sped up conversion of nested dict into DataFrame ([GH212](#))
- Can pass hierarchical index level name to *groupby* instead of the level number if desired ([GH223](#))
- Add support for different delimiters in *DataFrame.to_csv* ([GH244](#))
- Add more helpful error message when importing pandas post-installation from the source directory ([GH250](#))
- Significantly speed up DataFrame *__repr__* and *count* on large mixed-type DataFrame objects
- Better handling of pyx file dependencies in Cython module build ([GH271](#))

35.24.5 Bug Fixes

- *read_csv* / *read_table* fixes
 - Be less aggressive about converting float->int in cases of floating point representations of integers like 1.0, 2.0, etc.
 - “True”/“False” will not get correctly converted to boolean
 - Index name attribute will get set when specifying an index column
 - Passing column names should force *header=None* ([GH257](#))
 - Don’t modify passed column names when *index_col* is not None ([GH258](#))
 - Can sniff CSV separator in zip file (since seek is not supported, was failing before)
- Worked around matplotlib “bug” in which *series[:, np.newaxis]* fails. Should be reported upstream to matplotlib ([GH224](#))
- *DataFrame.iteritems* was not returning Series with the name attribute set. Also neither was *DataFrame._series*
- Can store *datetime.date* objects in *HDFStore* ([GH231](#))
- Index and Series names are now stored in *HDFStore*
- Fixed problem in which data would get upcasted to object dtype in *GroupBy.apply* operations ([GH237](#))
- Fixed outer join bug with empty DataFrame ([GH238](#))
- Can create empty Panel ([GH239](#))
- Fix join on single key when passing list with 1 entry ([GH246](#))
- Don’t raise Exception on plotting DataFrame with an all-NA column ([GH251](#), [GH254](#))
- Bug min/max errors when called on integer DataFrames ([GH241](#))
- *DataFrame.iteritems* and *DataFrame._series* not assigning name attribute
- *Panel.__repr__* raised exception on length-0 major/minor axes
- *DataFrame.join* on key with empty DataFrame produced incorrect columns
- Implemented *MultiIndex.diff* ([GH260](#))
- *Int64Index.take* and *MultiIndex.take* lost name field, fix downstream issue [GH262](#)

- Can pass list of tuples to *Series* ([GH270](#))
- Can pass level name to *DataFrame.stack*
- Support set operations between MultiIndex and Index
- Fix many corner cases in MultiIndex set operations - Fix MultiIndex-handling bug with GroupBy.apply when returned groups are not indexed the same
- Fix corner case bugs in DataFrame.apply
- Setting DataFrame index did not cause Series cache to get cleared
- Various int32 -> int64 platform-specific issues
- Don't be too aggressive converting to integer when parsing file with MultiIndex ([GH285](#))
- Fix bug when slicing Series with negative indices before beginning

35.24.6 Thanks

- Thomas Kluyver
- Daniel Fortunov
- Aman Thakral
- Luca Beltrame
- Wouter Overmeire

35.25 pandas 0.4.3

Release date: 10/9/2011

is is largely a bugfix release from 0.4.2 but also includes a handful of new d enhanced features. Also, pandas can now be installed and used on Python 3 hanks Thomas Kluyver!).

35.25.1 New Features

- Python 3 support using 2to3 ([GH200](#), Thomas Kluyver)
- Add *name* attribute to *Series* and added relevant logic and tests. Name now prints as part of *Series.__repr__*
- Add *name* attribute to standard Index so that stacking / unstacking does not discard names and so that indexed DataFrame objects can be reliably round-tripped to flat files, pickle, HDF5, etc.
- Add *isnull* and *notnull* as instance methods on Series ([GH209](#), [GH203](#))

35.25.2 Improvements to existing features

- Skip xldr-related unit tests if not installed
- *Index.append* and *MultiIndex.append* can accept a list of Index objects to concatenate together
- Altered binary operations on differently-indexed SparseSeries objects to use the integer-based (dense) alignment logic which is faster with a larger number of blocks ([GH205](#))
- Refactored *Series.__repr__* to be a bit more clean and consistent

35.25.3 API Changes

- *Series.describe* and *DataFrame.describe* now bring the 25% and 75% quartiles instead of the 10% and 90% deciles. The other outputs have not changed
- *Series.toString* will print deprecation warning, has been de-camelCased to *to_string*

35.25.4 Bug Fixes

- Fix broken interaction between *Index* and *Int64Index* when calling *intersection*. Implement *Int64Index.intersection*
- *MultiIndex.sortlevel* discarded the level names (GH202)
- Fix bugs in *groupby*, *join*, and *append* due to improper concatenation of *MultiIndex* objects (GH201)
- Fix regression from 0.4.1, *isnull* and *notnull* ceased to work on other kinds of Python scalar objects like *datetime.datetime*
- Raise more helpful exception when attempting to write empty *DataFrame* or *LongPanel* to *HDFStore* (GH204)
- Use *stdlib csv* module to properly escape strings with commas in *DataFrame.to_csv* (GH206, Thomas Kluyver)
- Fix Python *ndarray* access in Cython code for sparse blocked index integrity check
- Fix bug writing *Series* to CSV in Python 3 (GH209)
- Miscellaneous Python 3 bugfixes

35.25.5 Thanks

- Thomas Kluyver
- rsamson

35.26 pandas 0.4.2

Release date: 10/3/2011

is a performance optimization release with several bug fixes. The new *Int64Index* and new merging / joining Cython code and related Python frastructure are the main new additions

35.26.1 New Features

- Added fast *Int64Index* type with specialized *join*, *union*, *intersection*. Will result in significant performance enhancements for *int64*-based time series (e.g. using NumPy's *datetime64* one day) and also faster operations on *DataFrame* objects storing record array-like data.
- Refactored *Index* classes to have a *join* method and associated data alignment routines throughout the codebase to be able to leverage optimized joining / merging routines.
- Added *Series.align* method for aligning two series with choice of *join* method
- Wrote faster Cython data alignment / merging routines resulting in substantial speed increases
- Added *is_monotonic* property to *Index* classes with associated Cython code to evaluate the monotonicity of the *Index* values

- Add method *get_level_values* to *MultiIndex*
- Implemented shallow copy of *BlockManager* object in *DataFrame* internals

35.26.2 Improvements to existing features

- Improved performance of *isnull* and *notnull*, a regression from v0.3.0 ([GH187](#))
- Wrote templating / code generation script to auto-generate Cython code for various functions which need to be available for the 4 major data types used in pandas (float64, bool, object, int64)
- Refactored code related to *DataFrame.join* so that intermediate aligned copies of the data in each *DataFrame* argument do not need to be created. Substantial performance increases result ([GH176](#))
- Substantially improved performance of generic *Index.intersection* and *Index.union*
- Improved performance of *DateRange.union* with overlapping ranges and non-cacheable offsets (like Minute). Implemented analogous fast *DateRange.intersection* for overlapping ranges.
- Implemented *BlockManager.take* resulting in significantly faster *take* performance on mixed-type *DataFrame* objects ([GH104](#))
- Improved performance of *Series.sort_index*
- Significant groupby performance enhancement: removed unnecessary integrity checks in *DataFrame* internals that were slowing down slicing operations to retrieve groups
- Added informative Exception when passing dict to *DataFrame* groupby aggregation with axis != 0

35.26.3 API Changes

35.26.4 Bug Fixes

- Fixed minor unhandled exception in Cython code implementing fast groupby aggregation operations
- Fixed bug in unstacking code manifesting with more than 3 hierarchical levels
- Throw exception when step specified in label-based slice ([GH185](#))
- Fix *isnull* to correctly work with *np.float32*. Fix upstream bug described in [GH182](#)
- Finish implementation of *as_index=False* in groupby for *DataFrame* aggregation ([GH181](#))
- Raise *SkipTest* for pre-epoch *HDFStore* failure. Real fix will be sorted out via *datetime64* dtype

35.26.5 Thanks

- Uri Laserson
- Scott Sinclair

35.27 pandas 0.4.1

Release date: 9/25/2011

is is primarily a bug fix release but includes some new features and improvements

35.27.1 New Features

- Added new *DataFrame* methods *get_dtype_counts* and property *dtypes*
- Setting of values using *.ix* indexing attribute in mixed-type *DataFrame* objects has been implemented (fixes [GH135](#))
- *read_csv* can read multiple columns into a *MultiIndex*. *DataFrame*'s *to_csv* method will properly write out a *MultiIndex* which can be read back ([GH151](#), thanks to Skipper Seabold)
- Wrote fast time series merging / joining methods in Cython. Will be integrated later into *DataFrame.join* and related functions
- Added *ignore_index* option to *DataFrame.append* for combining unindexed records stored in a *DataFrame*

35.27.2 Improvements to existing features

- Some speed enhancements with internal Index type-checking function
- *DataFrame.rename* has a new *copy* parameter which can rename a *DataFrame* in place
- Enable unstacking by level name ([GH142](#))
- Enable sortlevel to work by level name ([GH141](#))
- *read_csv* can automatically “sniff” other kinds of delimiters using *csv.Sniffer* ([GH146](#))
- Improved speed of unit test suite by about 40%
- Exception will not be raised calling *HDFStore.remove* on non-existent node with where clause
- Optimized *_ensure_index* function resulting in performance savings in type-checking Index objects

35.27.3 API Changes

35.27.4 Bug Fixes

- Fixed *DataFrame* constructor bug causing downstream problems (e.g. *.copy()* failing) when passing a *Series* as the values along with a column name and index
- Fixed single-key groupby on *DataFrame* with *as_index=False* ([GH160](#))
- *Series.shift* was failing on integer *Series* ([GH154](#))
- *unstack* methods were producing incorrect output in the case of duplicate hierarchical labels. An exception will now be raised ([GH147](#))
- Calling *count* with level argument caused reduceat failure or segfault in earlier NumPy ([GH169](#))
- Fixed *DataFrame.corrwith* to automatically exclude non-numeric data (GH [GH144](#))
- Unicode handling bug fixes in *DataFrame.to_string* ([GH138](#))
- Excluding OLS degenerate unit test case that was causing platform specific failure ([GH149](#))
- Skip *blosc*-dependent unit tests for *PyTables* < 2.2 ([GH137](#))
- Calling *copy* on *DateRange* did not copy over attributes to the new object ([GH168](#))
- Fix bug in *HDFStore* in which Panel data could be appended to a Table with different item order, thus resulting in an incorrect result read back

35.27.5 Thanks

- Yaroslav Halchenko
- Jeff Reback
- Skipper Seabold
- Dan Lovell
- Nick Pentreath

35.28 pandas 0.4.0

Release date: 9/12/2011

35.28.1 New Features

- *pandas.core.sparse* module: “Sparse” (mostly-NA, or some other fill value) versions of *Series*, *DataFrame*, and *Panel*. For low-density data, this will result in significant performance boosts, and smaller memory footprint. Added *to_sparse* methods to *Series*, *DataFrame*, and *Panel*. See online documentation for more on these
- Fancy indexing operator on *Series* / *DataFrame*, e.g. via *.ix* operator. Both getting and setting of values is supported; however, setting values will only currently work on homogeneously-typed *DataFrame* objects. Things like:
 - `series.ix[[d1, d2, d3]]`
 - `frame.ix[5:10, ['C', 'B', 'A']], frame.ix[5:10, 'A':'C']`
 - `frame.ix[date1:date2]`
- Significantly enhanced *groupby* functionality
 - Can groupby multiple keys, e.g. `df.groupby(['key1', 'key2'])`. Iteration with multiple groupings products a flattened tuple
 - “Nuisance” columns (non-aggregatable) will automatically be excluded from *DataFrame* aggregation operations
 - Added automatic “dispatching to *Series* / *DataFrame* methods to more easily invoke methods on groups. e.g. `s.groupby(crit).std()` will work even though *std* is not implemented on the *GroupBy* class
- Hierarchical / multi-level indexing
 - New the *MultiIndex* class. Integrated *MultiIndex* into *Series* and *DataFrame* fancy indexing, slicing, `__getitem__` and `__setitem__`, reindexing, etc. Added *level* keyword argument to *groupby* to enable grouping by a level of a *MultiIndex*
- New data reshaping functions: *stack* and *unstack* on *DataFrame* and *Series*
 - Integrate with *MultiIndex* to enable sophisticated reshaping of data
- *Index* objects (labels for axes) are now capable of holding tuples
- *Series.describe*, *DataFrame.describe*: produces an R-like table of summary statistics about each data column
- *DataFrame.quantile*, *Series.quantile* for computing sample quantiles of data across requested axis
- Added general *DataFrame.dropna* method to replace *dropIncompleteRows* and *dropEmptyRows*, deprecated those.

- *Series* arithmetic methods with optional `fill_value` for missing data, e.g. `a.add(b, fill_value=0)`. If a location is missing for both it will still be missing in the result though.
- `fill_value` option has been added to *DataFrame*.{`add`, `mul`, `sub`, `div`} methods similar to *Series*
- Boolean indexing with *DataFrame* objects: `data[data > 0.1] = 0.1` or `data[data > other] = 1`.
- *pytz* / *tzinfo* support in *DateRange*
 - `tz_localize`, `tz_normalize`, and `tz_validate` methods added
- Added *ExcelFile* class to *pandas.io.parsers* for parsing multiple sheets out of a single Excel 2003 document
- *GroupBy* aggregations can now optionally *broadcast*, e.g. produce an object of the same size with the aggregated value propagated
- Added *select* function in all data structures: *reindex* axis based on arbitrary criterion (function returning boolean value), e.g. `frame.select(lambda x: 'foo' in x, axis=1)`
- *DataFrame.consolidate* method, API function relating to redesigned internals
- *DataFrame.insert* method for inserting column at a specified location rather than the default `__setitem__` behavior (which puts it at the end)
- *HDFStore* class in *pandas.io.pytables* has been largely rewritten using patches from Jeff Reback from others. It now supports mixed-type *DataFrame* and *Series* data and can store *Panel* objects. It also has the option to query *DataFrame* and *Panel* data. Loading data from legacy *HDFStore* files is supported explicitly in the code
- Added *set_printoptions* method to modify appearance of *DataFrame* tabular output
- *rolling_quantile* functions; a moving version of *Series.quantile* / *DataFrame.quantile*
- Generic *rolling_apply* moving window function
- New *drop* method added to *Series*, *DataFrame*, etc. which can drop a set of labels from an axis, producing a new object
- *reindex* methods now sport a *copy* option so that data is not forced to be copied then the resulting object is indexed the same
- Added *sort_index* methods to *Series* and *Panel*. Renamed *DataFrame.sort* to *sort_index*. Leaving *DataFrame.sort* for now.
- Added *skipna* option to statistical instance methods on all the data structures
- *pandas.io.data* module providing a consistent interface for reading time series data from several different sources

35.28.2 Improvements to existing features

- The 2-dimensional *DataFrame* and *DataMatrix* classes have been extensively redesigned internally into a single class *DataFrame*, preserving where possible their optimal performance characteristics. This should reduce confusion from users about which class to use.
 - Note that under the hood there is a new essentially “lazy evaluation” scheme within respect to adding columns to *DataFrame*. During some operations, like-typed blocks will be “consolidated” but not before.
- *DataFrame* accessing columns repeatedly is now significantly faster than *DataMatrix* used to be in 0.3.0 due to an internal *Series* caching mechanism (which are all views on the underlying data)
- Column ordering for mixed type data is now completely consistent in *DataFrame*. In prior releases, there was inconsistent column ordering in *DataMatrix*
- Improved console / string formatting of *DataMatrix* with negative numbers
- Improved tabular data parsing functions, *read_table* and *read_csv*:

- Added *skiprows* and *na_values* arguments to *pandas.io.parsers* functions for more flexible IO
- *parseCSV* / *read_csv* functions and others in *pandas.io.parsers* now can take a list of custom NA values, and also a list of rows to skip
- Can slice *DataFrame* and get a view of the data (when homogeneously typed), e.g. `frame.xs(idx, copy=False)` or `frame.ix[idx]`
- Many speed optimizations throughout *Series* and *DataFrame*
- Eager evaluation of groups when calling *groupby* functions, so if there is an exception with the grouping function it will be raised immediately versus sometime later on when the groups are needed
- *datetools.WeekOfMonth* offset can be parameterized with *n* different than 1 or -1.
- Statistical methods on *DataFrame* like *mean*, *std*, *var*, *skew* will now ignore non-numerical data. Before a not very useful error message was generated. A flag *numeric_only* has been added to *DataFrame.sum* and *DataFrame.count* to enable this behavior in those methods if so desired (disabled by default)
- *DataFrame.pivot* generalized to enable pivoting multiple columns into a *DataFrame* with hierarchical columns
- *DataFrame* constructor can accept structured / record arrays
- *Panel* constructor can accept a dict of *DataFrame*-like objects. Do not need to use *from_dict* anymore (*from_dict* is there to stay, though).

35.28.3 API Changes

- The *DataMatrix* variable now refers to *DataFrame*, will be removed within two releases
- *WidePanel* is now known as *Panel*. The *WidePanel* variable in the pandas namespace now refers to the renamed *Panel* class
- *LongPanel* and *Panel* / *WidePanel* now no longer have a common subclass. *LongPanel* is now a subclass of *DataFrame* having a number of additional methods and a hierarchical index instead of the old *LongPanelIndex* object, which has been removed. Legacy *LongPanel* pickles may not load properly
- Cython is now required to build *pandas* from a development branch. This was done to avoid continuing to check in cythonized C files into source control. Builds from released source distributions will not require Cython
- Cython code has been moved up to a top level *pandas/src* directory. Cython extension modules have been renamed and promoted from the *lib* subpackage to the top level, i.e.
 - *pandas.lib.tseries* -> *pandas._tseries*
 - *pandas.lib.sparse* -> *pandas._sparse*
- *DataFrame* pickling format has changed. Backwards compatibility for legacy pickles is provided, but it's recommended to consider PyTables-based *HDFStore* for storing data with a longer expected shelf life
- A *copy* argument has been added to the *DataFrame* constructor to avoid unnecessary copying of data. Data is no longer copied by default when passed into the constructor
- Handling of boolean dtype in *DataFrame* has been improved to support storage of boolean data with NA / NaN values. Before it was being converted to float64 so this should not (in theory) cause API breakage
- To optimize performance, Index objects now only check that their labels are unique when uniqueness matters (i.e. when someone goes to perform a lookup). This is a potentially dangerous tradeoff, but will lead to much better performance in many places (like *groupby*).
- Boolean indexing using *Series* must now have the same indices (labels)
- Backwards compatibility support for *begin/end/nPeriods* keyword arguments in *DateRange* class has been removed

- More intuitive / shorter filling aliases *ffill* (for *pad*) and *bfill* (for *backfill*) have been added to the functions that use them: *reindex*, *asfreq*, *fillna*.
- *pandas.core.mixins* code moved to *pandas.core.generic*
- *buffer* keyword arguments (e.g. *DataFrame.toString*) renamed to *buf* to avoid using Python built-in name
- *DataFrame.rows()* removed (use *DataFrame.index*)
- Added deprecation warning to *DataFrame.cols()*, to be removed in next release
- *DataFrame* deprecations and de-camelCasing: *merge*, *asMatrix*, *toDataMatrix*, *_firstTimeWithValue*, *_lastTimeWithValue*, *toRecords*, *fromRecords*, *tgrouby*, *toString*
- *pandas.io.parsers* method deprecations
 - *parseCSV* is now *read_csv* and keyword arguments have been de-camelCased
 - *parseText* is now *read_table*
 - *parseExcel* is replaced by the *ExcelFile* class and its *parse* method
- *fillMethod* arguments (deprecated in prior release) removed, should be replaced with *method*
- *Series.fill*, *DataFrame.fill*, and *Panel.fill* removed, use *fillna* instead
- *groupby* functions now exclude NA / NaN values from the list of groups. This matches R behavior with NAs in factors e.g. with the *tapply* function
- Removed *parseText*, *parseCSV* and *parseExcel* from pandas namespace
- *Series.combineFunc* renamed to *Series.combine* and made a bit more general with a *fill_value* keyword argument defaulting to NaN
- Removed *pandas.core.pytools* module. Code has been moved to *pandas.core.common*
- Tacked on *groupName* attribute for groups in *GroupBy* renamed to *name*
- *Panel/LongPanel dims* attribute renamed to *shape* to be more conformant
- Slicing a *Series* returns a view now
- More Series deprecations / renaming: *toCSV* to *to_csv*, *asOf* to *asof*, *merge* to *map*, *applymap* to *apply*, *toDict* to *to_dict*, *combineFirst* to *combine_first*. Will print *FutureWarning*.
- *DataFrame.to_csv* does not write an “index” column label by default anymore since the output file can be read back without it. However, there is a new *index_label* argument. So you can do *index_label='index'* to emulate the old behavior
- *datetools.Week* argument renamed from *dayOfWeek* to *weekday*
- *timeRule* argument in *shift* has been deprecated in favor of using the *offset* argument for everything. So you can still pass a time rule string to *offset*
- Added optional *encoding* argument to *read_csv*, *read_table*, *to_csv*, *from_csv* to handle unicode in python 2.x

35.28.4 Bug Fixes

- Column ordering in *pandas.io.parsers.parseCSV* will match CSV in the presence of mixed-type data
- Fixed handling of Excel 2003 dates in *pandas.io.parsers*
- *DateRange* caching was happening with high resolution *DateOffset* objects, e.g. *DateOffset(seconds=1)*. This has been fixed
- Fixed *__truediv__* issue in *DataFrame*

- Fixed *DataFrame.toCSV* bug preventing IO round trips in some cases
- Fixed bug in *Series.plot* causing matplotlib to barf in exceptional cases
- Disabled *Index* objects from being hashable, like ndarrays
- Added `__ne__` implementation to *Index* so that operations like `ts[ts != idx]` will work
- Added `__ne__` implementation to *DataFrame*
- Bug / unintuitive result when calling *fillna* on unordered labels
- Bug calling *sum* on boolean *DataFrame*
- Bug fix when creating a *DataFrame* from a dict with scalar values
- `Series.{sum, mean, std, ...}` now return NA/NaN when the whole Series is NA
- NumPy 1.4 through 1.6 compatibility fixes
- Fixed bug in bias correction in *rolling_cov*, was affecting *rolling_corr* too
- R-square value was incorrect in the presence of fixed and time effects in the *PanelOLS* classes
- *HDFStore* can handle duplicates in table format, will take

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35.29 pandas 0.3.0

Release date: February 20, 2011

35.29.1 New features

- *corrwith* function to compute column- or row-wise correlations between two DataFrame objects
- Can boolean-index DataFrame objects, e.g. `df[df > 2] = 2`, `px[px > last_px] = 0`
- Added comparison magic methods (`__lt__`, `__gt__`, etc.)
- Flexible explicit arithmetic methods (`add`, `mul`, `sub`, `div`, etc.)
- Added *reindex_like* method
- Added *reindex_like* method to WidePanel
- Convenience functions for accessing SQL-like databases in *pandas.io.sql* module
- Added (still experimental) HDFStore class for storing pandas data structures using HDF5 / PyTables in *pandas.io.pytables* module
- Added WeekOfMonth date offset
- *pandas.rpy* (experimental) module created, provide some interfacing / conversion between rpy2 and pandas

35.29.2 Improvements to existing features

- Unit test coverage: 100% line coverage of core data structures
- Speed enhancement to `rolling_{median, max, min}`
- Column ordering between DataFrame and DataMatrix is now consistent: before DataFrame would not respect column order
- Improved `{Series, DataFrame}.plot` methods to be more flexible (can pass matplotlib Axis arguments, plot DataFrame columns in multiple subplots, etc.)

35.29.3 API Changes

- Exponentially-weighted moment functions in *pandas.stats.moments* have a more consistent API and accept a `min_periods` argument like their regular moving counterparts.
- `fillMethod` argument in Series, DataFrame changed to `method`, *FutureWarning* added.
- `fill` method in Series, DataFrame/DataMatrix, WidePanel renamed to `fillna`, *FutureWarning* added to `fill`
- Renamed `DataFrame.getXS` to `xs`, *FutureWarning* added
- Removed `cap` and `floor` functions from DataFrame, renamed to `clip_upper` and `clip_lower` for consistency with NumPy

35.29.4 Bug Fixes

- Fixed bug in `IndexableSkiplist` Cython code that was breaking `rolling_max` function
- Numerous `numpy.int64`-related indexing fixes
- Several NumPy 1.4.0 NaN-handling fixes
- Bug fixes to `pandas.io.parsers.parseCSV`
- Fixed `DateRange` caching issue with unusual date offsets
- Fixed bug in `DateRange.union`
- Fixed corner case in `IndexableSkiplist` implementation

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