

The Art of Algorithm and Knowledge in the Era of Extreme-Scale Neural Models

by

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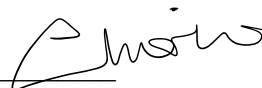
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Abstract

Broadly, my research goal is to build machine intelligence that understands how the world works and interacts with humans safely and reliably. Specifically, I focus on the **commonsense reasoning** ability and **controllability** of neural language models. While scale appears to be today’s recipe for the emergence of machine intelligence, I would argue for the importance of knowledge as well as training and inference time reasoning algorithms for the acquisition of commonsense reasoning and controllability. My works demonstrate how smaller models developed in academia can still have an edge over larger industry-scale models, if powered with knowledge and/or reasoning algorithms. Concretely, my research branches around two themes:

- **Algorithm.** Language models, despite its scale or capability, still exhibit behaviors that are misaligned with user expectations. For example, generated text may contain offensive or toxic language, or fail to incorporate certain constraints user specified. To this end, my work investigate into *reinforcement learning algorithms* that unlearn undesirable behaviors [3] and *decoding time algorithms* that enforce faithful constraint satisfaction [2, 1], in order to achieve better controllability and enhance the safety and reliability of neural language models.
- **Knowledge.** Human-level language understanding grounds on a commonsense mental model of ‘how the world works’, which requires physical reasoning over objects and actions, along with higher-order event reasoning about complex situations. Today’s machines struggle with both. My research seeks to bridge this gap by enable machine to learn *multimodal script knowledge* from complex raw data, which leads to new SOTA performances on a dozen leaderboards that require grounded, temporal, and causal commonsense reasoning [4, 5].

Constrained Decoding Algorithm. Conditional text generation often requires lexical constraints, i.e., which words should or shouldn’t be included in the output text. While the dominant recipe for conditional text generation has been large-scale pretrained language models, prompted with or finetuned on the task-specific training data, such models do not learn to follow the underlying constraints reliably. In contrast, human could perform constrained generation out of the box without seeing any task specific examples. To enable such capability for neural language model, we propose NEUROLOGIC decoding [2], which effectively enforces the satisfaction of given lexical constraints by controlling the decoding stage of sequence generation. Neurologic decoding performs constrained optimization via beam-like search to find optimal sequences with respect to both likelihood and constraint satisfaction. Neurologic is powerful yet efficient. It handles any set of lexical constraints that is expressible under predicate logic, while its asymptotic runtime is equivalent to conventional beam search. I further built on this work through a new algorithm named NEUROLOGIC A*esque [1] inspired by the A* search algorithm, which incorporates heuristic estimates of future cost into the search procedure. We develop lookahead heuristics, which approximate cost of satisfying future constraints based on continuations of the sequence-so-far to aid Neurologic search. Perhaps surprisingly, we find that unsupervised models often match or outperform supervised approaches when powered with NEUROLOGIC, even when the latter is based on considerably larger networks. My works suggest the promise of inference-time algorithms to enable new capability of language models beyond scaling.

Reinforced Unlearning Algorithm. Large neural language models trained on an enormous amount of web text have excelled at numerous tasks. However, these same language models often exhibit undesirable behaviors, as they are usually trained to simply maximize the likelihood of their raw pre-training data. Undesirable behaviors are diverse and hard to avoid, control, or even specify *a priori*; I thus argue that it is critical to investigate ways to *unlearn* undesirable behaviors *post hoc*, while maintaining capacity for generating coherent and fluent language. We introduce Quantized Reward Konditioning (Quark), an algorithm for optimizing a reward function that quantifies an (un)wanted property, while not straying too far from the original model. Quark alternates between (i) collecting samples with the current language model, (ii) sorting them into quantiles based on reward, with each quantile identified by a reward token prepended to the language model’s input, and (iii) using a standard language modeling loss on samples from each quantile conditioned on its reward token, while remaining nearby the original language model via a KL-divergence penalty. By conditioning on a high-reward token at generation time, the model generates text that exhibits

less of the unwanted property. For unlearning toxicity, negative sentiment, and repetition, Quark outperforms both strong baselines and state-of-the-art reinforcement learning methods like PPO, while relying only on standard language modeling primitives.

Multimodal Script Knowledge. Over the last few years, many large-scale NLP and computer vision models have been trained on a combination of text, images, and manual annotations – yet, this approach has not been sufficient to ‘solve’ tasks like Visual Commonsense Reasoning (VCR), which requires grounded, temporal, and causal commonsense reasoning. My work introduces a new approach, where we train a model on multimodal and temporal data from YouTube [5]. We use new self supervised objectives to learn multimodal script knowledge. We dub our model MERLOT, short for Multimodal Event Representation Learning over Time. Our model sets new state-of-the-art results on twelve video reasoning tasks, as well as on VCR. In doing so, it outperforms larger, industry-submitted models that learn from static data: images annotated with object detections, and literal descriptions. We recently built on this work through a new model named MERLOT Reserve [4]. The idea is to learn connections between all modalities including sound to understand videos. Perhaps surprisingly, our work shows that integrating sound improves vision-and-text representations. We set a new state-of-the-art on VCR, even though it doesn’t include any sound for models.

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NEUROLOGIC DECODING: (Un)supervised Neural Text Generation with Predicate Logic Constraints

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Abstract

Conditional text generation often requires lexical constraints, i.e., which words should or shouldn't be included in the output text. While the dominant recipe for conditional text generation has been large-scale pretrained language models that are finetuned on the task-specific training data, such models do not learn to follow the underlying constraints reliably, even when supervised with large amounts of task-specific examples.

We propose NEUROLOGIC DECODING, a simple yet effective algorithm that enables neural language models – supervised or not – to generate fluent text while satisfying complex lexical constraints. Our approach is powerful yet efficient. It handles any set of lexical constraints that is expressible under predicate logic, while its asymptotic runtime is equivalent to conventional beam search.

Empirical results on four benchmarks show that NEUROLOGIC DECODING outperforms previous approaches, including algorithms that handle a subset of our constraints. Moreover, we find that unsupervised models with NEUROLOGIC DECODING often outperform supervised models with conventional decoding, even when the latter is based on considerably larger networks. Our results suggest the limit of large-scale neural networks for fine-grained controllable generation and the promise of inference-time algorithms.

1 Introduction

Text generation applications often need to incorporate semantic constraints, i.e., what words *should* and *shouldn't* appear in the output generation. Consider the task of generating a recipe from a set of ingredients (Kiddon et al., 2016), such as ‘garlic,’ ‘steak,’ and ‘soy sauce’ (Figure 1). A generated recipe should cover all of those ingredients, without hallucinating new ones (such as ‘pork’ or ‘beans’). This restriction, like others in Figure 1 for other

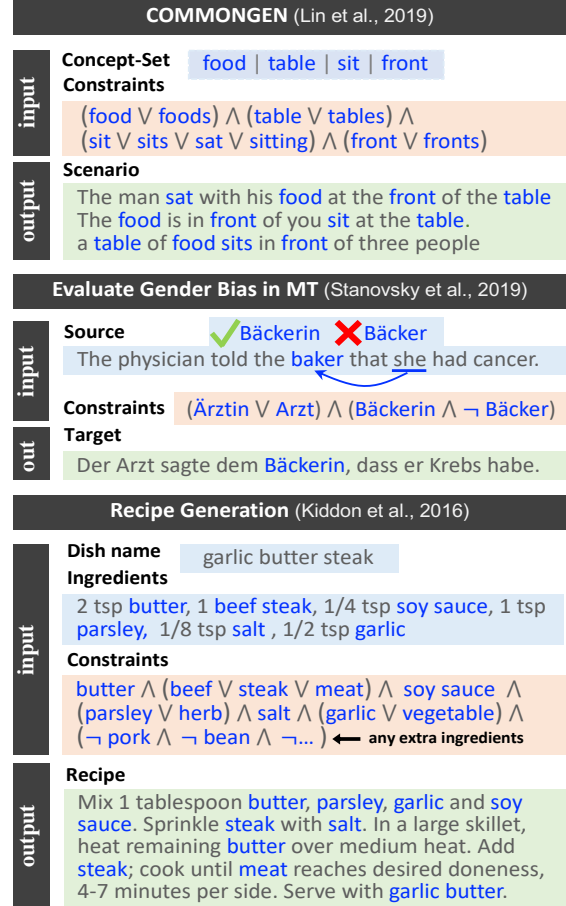


Figure 1: Overview of several constrained generation tasks. For instance, generating a short description from a set of concepts (COMMONGEN; Lin et al., 2020) requires using each of those words at least once; this can be expressed as a logical expression (here, ‘(food \vee foods) \wedge ...’). Our proposed NEUROLOGIC DECODING handles all predicate logic constraints efficiently, yet with the same asymptotic runtime as beam search.

applications, can be modeled by a set of lexical constraints expressed as a predicate logic formula.

The dominant paradigm today for performing such *constrained generation* is to start with a pretrained language model, and then finetune it on a dataset of task-specific examples. However, pretrained language models struggle at learning to

follow these constraints, even when the finetuning dataset is large. For example, for the aforementioned recipe generation task, a GPT2 model finetuned on hundreds of thousands of recipes still hallucinates extra ingredients. In stark contrast, humans need to see only a few examples (or even none) to generate the desired output satisfying all the logical constraints, e.g., writing a recipe that mentions each ingredient (butter, steak, etc.) without using new ones.

We hypothesize that this mismatch is due to a fundamental under-specification of finetuning. If we finetune one of today’s state-of-the-art language models on a dataset, the likelihood of it generating sequences from the same distribution should increase. Yet there is no guarantee that this improvement in likelihood will come from improvements on the fundamental task of constrained generation, as opposed to picking up on dataset-specific patterns such as language style. In fact, we present analysis suggesting that ‘worst-case’ learning behavior is common in practice: when we increase the finetuning data fed to GPT2 by an order of magnitude, constraint-satisfaction with standard beam search shows only modest improvement.

To address this issue, we propose NEUROLOGIC DECODING, which effectively enforces the satisfaction of given lexical constraints by controlling the decoding stage of sequence generation. These constraints can be any predicate logic formula, which crucially includes both positive constraints (the word ‘butter’ must be generated somewhere) and negative constraints (‘bean’ cannot be generated). These simpler constraints can then be combined through logical connectives to handle more complex requirements such as inflection or synonyms (‘beef’ or ‘steak’ both satisfy the constraint of referring to the steak). While beam search aims to maximize the likelihood of the generated sequence, our method searches for optimal output sequences among the strings that also satisfy the given constraints. It does so efficiently: we convert the hard logic constraints into a soft penalty term in the decoding objective, and use a beam-based search to find approximately-optimal solutions; constraint states are tracked to reuse computation. NEUROLOGIC DECODING thus effectively and efficiently controls text generation without requiring any modification of the model structure or training pipeline.

We evaluate our method on four different text generation tasks: generative commonsense reason-

ing (COMMONGEN; Lin et al., 2020), recipe generation (Kiddon et al., 2016), data-grounded dialogue response generation (Wen et al., 2015), and reducing gender bias in machine translation (Stanovsky et al., 2019). Empirical results demonstrate that NEUROLOGIC DECODING ensures the satisfaction of given constraints while maintaining high generation quality, in turn leading to new SOTA results in both the supervised and zero-shot setting.

2 Method

In this section, we first rigorously define predicate logic constraint, and then present in detail the NEUROLOGIC DECODING algorithm.

2.1 Predicate Logic Constraint

Let us define a predicate $D(\mathbf{a}, \mathbf{y})$ to be a boolean function indicating the occurrence of key phrase \mathbf{a} in a sequence \mathbf{y} , where \mathbf{a} can be either unigram or multi-gram. $D(\mathbf{a}, \mathbf{y})$ will be true iff \mathbf{a} occurs in \mathbf{y} .

$$D(\mathbf{a}, \mathbf{y}) \equiv \exists i, \mathbf{y}_{i:i+|\mathbf{a}|} = \mathbf{a}$$

NEUROLOGIC accepts lexical constraints in Conjunctive Normal Form (CNF):

$$\underbrace{(D_1 \vee D_2 \cdots \vee D_i)}_{C_1} \wedge \cdots \wedge \underbrace{(D_k \vee D_{k+1} \cdots \vee D_n)}_{C_m}$$

where each D_i represents a single positive or negative constraint, $D(\mathbf{a}_i, \mathbf{y})$ or $\neg D(\mathbf{a}_i, \mathbf{y})$, restricting whether key phrase \mathbf{a}_i should be strictly included or omitted in \mathbf{y} , respectively. Any propositional logical formula can be converted to CNF, and thus handled by NEUROLOGIC. Notationally, we will refer to each individual constraint D_i as a *literal*, and the disjunction of literals as a *clause*, denoted as C_j , with L being the total number of clauses. Our method seeks optimal sequences in which all clauses are satisfied:

$$\hat{\mathbf{y}} = \arg \max_{\mathbf{y} \in \mathcal{Y}} P_\theta(\mathbf{y}|\mathbf{x}) \quad \text{where} \quad \sum_{i=1}^L C_i = L \quad (1)$$

Past work on constrained optimization introduces penalties (Fiacco, 1976) to approximate the constrained optimization problem with an unconstrained problem. Specifically, by adding a high-cost penalty term for violated constraints:

$$\hat{\mathbf{y}} = \arg \max_{\mathbf{y} \in \mathcal{Y}} P_\theta(\mathbf{y}|\mathbf{x}) - \lambda' \sum_{i=1}^L (1 - C_i) \quad (2)$$

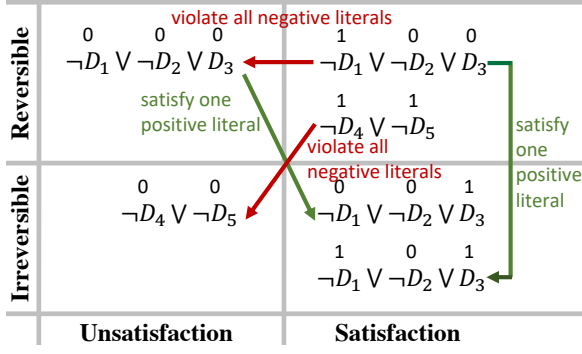


Figure 2: Clause states and possible transitions. D_i and $\neg D_i$ denote positive and negative literal respectively.

Intuitively, this objective balances sequence likelihood (term 1) and constraint satisfaction (term 2). The aim is to find sequences that do well at both dimensions. While exhaustive search is intractable, we use a beam-based search to find approximately-optimal solutions for this objective.

2.2 Constraint States

When considering whether a generation hypothesis satisfies some clause C_i during generation, there are fundamentally 4 possible states (as in figure 2)

- S1 reversible unsatisfaction:** If an unsatisfied clause C_i contains at least one positive literal, C_i could be satisfied in the future by fulfilling one of its positive literal(s).
- S2 irreversible unsatisfaction:** If an unsatisfied clause C_i contains negative literal(s) only, C_i will maintain unsatisfied in the future since the violation of negative literals could not be overturned.
- S3 reversible satisfaction:** If all satisfied literal(s) in a satisfied clause C_i are negative literal(s), C_i could switch back to unsatisfied in the future by violating all of its satisfied negative literal(s).
- S4 irreversible satisfaction:** If satisfied literal(s) in a satisfied clause C_i contains at least one positive literal, C_i will maintain satisfied in the future since the fulfilment of positive literals is irreversible.

To track the states of literals and clauses efficiently, we maintain two prefix tries. The first trie, \mathcal{T}^+ , tracks *unsatisfied positive* literals from all clauses in states S1 and S3, while the other trie, \mathcal{T}^- , tracks *satisfied negative* literals from all clauses in state S3. We do not track anything from clauses in state S2 or S4, as those are already irreversible.

If a positive literal is satisfied, its clause in state

S1 or S3 is henceforth irreversibly satisfied (state S4), thus we remove all literals of that clause from both tries and stop tracking. If a negative literal in state S3 is violated, we remove it from the trie \mathcal{T}^- . Once all negative literals of a clause in state S3 has been removed, the clause switches back to unsatisfied (state S1 or S2). If it has unsatisfied positive literal(s) in the trie \mathcal{T}^+ , it becomes reversibly unsatisfied (state S1); otherwise it shall stay irreversibly unsatisfied (state S2).

2.3 Algorithm

Since exhaustive search to optimize the CNF constraints is intractable, NEUROLOGIC uses a beam-based search to approximate. The high-level intuition is that at each time step, NEUROLOGIC selects generation hypotheses in consideration of both the objective function and the diversity of the partially satisfied constraints. We achieve such by 3 steps: *pruning*, *grouping*, and *selecting* (illustrated in figure 3, and detailed below).

At each time step, the decoding model generates a distribution over all vocabulary V for k hypotheses in the current beam, resulting in a candidate score matrix of size $k \times |V|$. Along with generating score matrix, we produce a constraint state for each of the $k \times |V|$ new candidates h , based on the next token considered.

Pruning step: We first discard any h with irreversible unsatisfied clauses (state S2) to focus only on candidates that might satisfy all constraints. Then, we filter candidates h to those in the top-tier of both satisfied constraints and sequence likelihood. Specifically, we drop any candidates not in the top- α in terms of likelihood $P_\theta(\mathbf{y}_t | \mathbf{y}_{<t})$, and not in the top- β in terms of number of satisfied clauses $\sum_{i=1}^L C_i$. These are adjustable parameters, corresponding to maximum tolerance to sequence fluency and constraint satisfaction.

Grouping step: Next, we select the beam from the pruned candidates. Naively selecting k best candidates with respect to the objective function would not work well, since such greedy selection would bias toward sequences with high likelihood and easy-to-satisfy clauses at early timestep, which can lead to struggling with remaining hard-to-satisfy clauses later on. Therefore, the key intuition is to consider diverse partial solutions early on with respect to the set of irreversibly satisfied clauses, i.e., $\{C_i | C_i \in \text{state S4}\}$. We group candidates based on this set and select (in the next step) the best ones

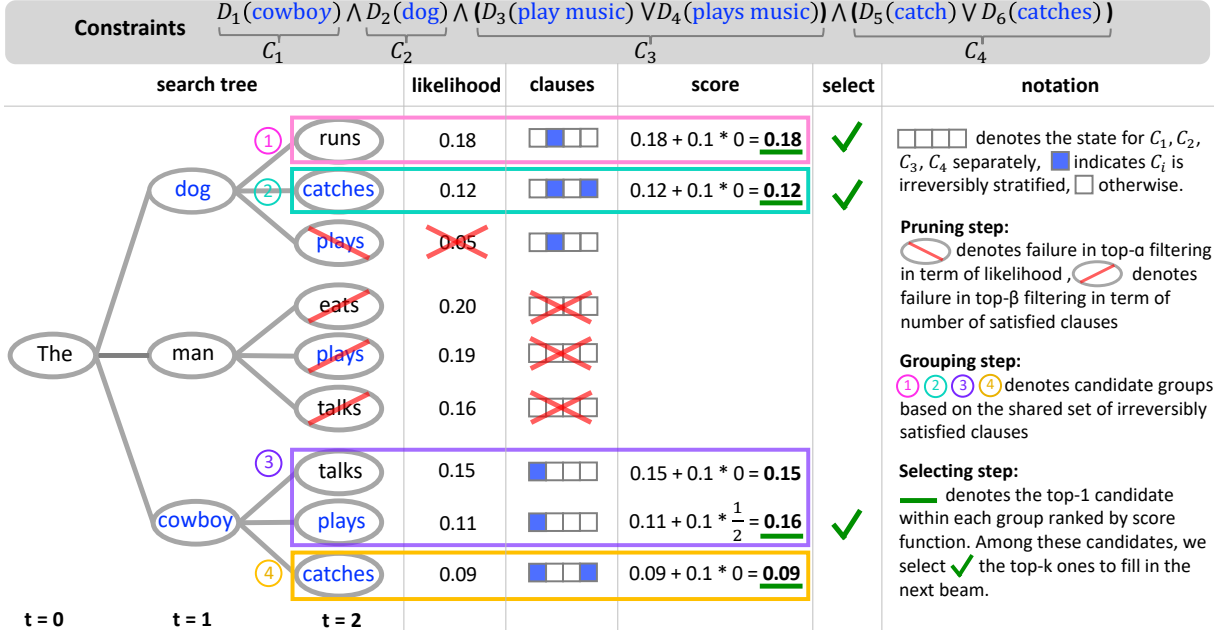


Figure 3: Illustration of the NEUROLOGIC decoding procedure. In this example, $k = 3$, $\alpha = 8$, $\beta = 2$, $\lambda = 0.1$

from each group to fill the beam.

Selecting step: To select best ones from each group, we first rank candidates within a group by score function:

$$\mathbf{s} = P_\theta(\mathbf{y}_t | \mathbf{y}_{<t}) + \lambda \cdot \max_{\substack{D(\mathbf{a}_i, \mathbf{y}) \\ \in \text{state S1}}} \frac{|\hat{\mathbf{a}}_i|}{|\mathbf{a}_i|} \quad (3)$$

where $\hat{\mathbf{a}}_i$ is \mathbf{a}_i 's matched prefix with ongoing generation. For example, for $\mathbf{y} = \text{"The boy climbs an apple"}$ and constraint $\mathbf{a}_i = \text{"apple tree"}$, we have $\hat{\mathbf{a}}_i = \text{"apple"}$. The second term denotes maximal percentage of matched prefix in partially satisfied positive literals. Intuitively, this score function ranks candidate by likelihood and gives a partial reward to candidates moving towards satisfying a positive literal in an unsatisfied clause (state S1). λ is an adjustable parameter, controlling how much we favor candidates towards fulfilling another unsatisfied clause. We then proceed in rounds of filling the beam, visiting each group and taking the best scoring ones in rotation, until we reach k candidates. The group traversing order follows the descending order of the highest score in each group. In the end, we take the highest-scoring hypothesis from the ones with maximal satisfied clauses.

3 Related Work

NEUROLOGIC distinguishes itself from past works in constrained decoding in 3 fundamental ways.

- First, NEUROLOGIC generalizes to arbitrary logical constraints by handling the full scope

of CNF constraint, while previous works only allow a subset of this (typically conjunctions).

- Second, NEUROLOGIC effectively optimizes objective function through efficient and diverse search over output space, while previous works suffer from either myopic and narrow or inefficient exploration of the search space.
- Third, the asymptotic runtime of NEUROLOGIC is $O(Nk)^1$, same with beam search, constant with respect to number of constraints \mathcal{C} . Some previous works suffer from exponential runtime, making applications infeasible.

A detailed comparison between NEUROLOGIC and previous methods is provided in table 1.

3.1 Previous Constrained Decoding Approach

Anderson et al. (2017) propose constrained beam search (CBS), where constraint satisfaction is tracked by a finite-state machine with $2^{\mathcal{C}}$ states (all possible satisfaction status for \mathcal{C} constraints). Beam search is done over all states with k candidates per state. This method has an exponential complexity $O(Nk2^{\mathcal{C}})$, making many applications infeasible.

Hokamp and Liu (2017) propose grid beam search (GBS), which groups together hypotheses by number of constraints satisfied, giving $\mathcal{C} + 1$

¹ N denotes sequence length and k denotes beam size. In this paper, we the asymptotic runtimes is in terms of the number of calls to a deep generator that scores $P_\theta(\mathbf{y}_t | \mathbf{y}_{<t})$; this is because calling the generator is the most expensive part of decoding (as opposed to auxiliary bookkeeping).

Feature	Example	CBS	GBS	Post and Vilar	Hu et al.	CGMH	Sha	NEUROLOGIC
AND	$oil \wedge pork$ Include oil and pork	✓	✓	✓	✓	✓	✓	✓
Positive Set AND	$oil \wedge (pork \vee beef)$ Include oil and a protein	✓						✓
Any Predicate Logic Formula	$\neg oil \wedge (pork \vee beef)$ Oil-free, include a protein							✓
Runtime:		$O(Nk2^C)$	$O(NkC)$	$O(Nk)$	$O(Nk)$	$O(E)$	$O(E)$	$O(Nk)$

Table 1: Expressivity and runtime of various decoding methods. *AND*: Output includes all terms in a set; *Positive Set AND*: Output includes at least one term from each set; *Predicate Logic Formula*: Any combination of positive and negative constraints. E is the number of editing steps, usually much greater than the sequence length N .

groups altogether. Each group stores at most k candidates that are expanded at each timestep. GBS has a faster runtime of $O(NkC)$, but this approach bias towards sequences satisfying constraints greedily, and collapses into very similar search paths that are often times globally sub-optimal, which results in dropped language quality.

Post and Vilar (2018) propose dynamic beam allocation to reduce GBS’s explicit dependence on C . Beam search is done over a single beam, with the k slots of this beam dynamically allocated over the $C+1$ groups explicitly used by GBS. This approach was made GPU-efficient by Hu et al. (2019a). Still, the language quality issue of GBS remains, and can be worse in practice as fewer hypotheses are considered at each step.

Miao et al. (2019) propose Constrained Generation by Metropolis-Hastings (CGMH). This approach begins by inserting all positive-constraint keywords in random order. Edits are randomly sampled to replace, insert, or delete words to make the sentence fluent; the probability of each action is computed on top of a language model. Sha (2020) proposes using gradient of a objective function to guide where and how to edit instead of random sampling. These approaches have runtime independent to number of constraints; yet they can involve repeated deletions and insertions, reducing efficiency. Generation quality is also sensitive to initial keyword order and sampled edits.

3.2 Applications of Constrained Generation

Lexically constrained generation can be broadly applied to prior conditional text generation tasks. Examples include incorporating pre-specified lexical constraints (Anderson et al., 2017; Post and Vilar, 2018), user-provided terminology constraints (Hasler et al., 2018; Dinu et al., 2019), noisy automatic constraints (Li et al., 2019) in translation output. A major use case of lexical constrained de-

coding is paraphrase generation (Hu et al., 2019a; Kajiwar, 2019; Hu et al., 2019b; Miao et al., 2019), by negatively constraining words in the source to enforce paraphrasing. Another use case is image captioning, with novel scenes or out-of-domain objects (Anderson et al., 2017), or requiring explicit grounding to objects in the scene (Ren et al., 2015; Krause et al., 2016). In addition, Balakrishnan et al. (2019) leverage constrained decoding to improve semantic correctness for response generation.

4 Experiments I: Constrained Commonsense Generation

COMMONGEN (Lin et al., 2020) is a benchmark dataset designed as a test of generative commonsense reasoning. Given a set of common concepts (e.g., dog, frisbee, catch, throw); the task is to generate a coherent sentence describing an everyday scenario using these concepts (e.g., “a man throws a frisbee and his dog catches it”).

Problem Formulation The input is an unordered set of n concepts $\mathbf{x} = \{a_1, a_2, \dots, a_n\}$, where each concept a_i is a common object (noun) or action (verb). The expected output is a simple, grammatical sentence $\mathbf{y} \in \mathcal{Y}$ that describes a common scenario using all given concepts in \mathbf{x} with correct morphological inflections.

To apply NeuroLogic Decoding, we impose that each a_i must appear in output \mathbf{y} under some morphological inflection. Let $\tilde{a}_i = \{\tilde{a}_1^i, \dots, \tilde{a}_{|\tilde{a}_i|}^i\}$ denote all inflections of a_i . \mathbf{y} covers concept a_i , if at least one of $\{\tilde{a}_1^i, \dots, \tilde{a}_{|\tilde{a}_i|}^i\}$ appears. Formally,

$$\forall a_i \in \mathbf{x}, \exists \tilde{a}_j^i \in \tilde{a}_i, D(\tilde{a}_j^i, \mathbf{y})$$

where $D(\tilde{a}_j^i, \mathbf{y})$ is a boolean-value function indicating whether \mathbf{y} contains \tilde{a}_j^i or not, as defined above.²

²This gets converted into $\bigwedge_{i=1}^n (\bigvee_{j=1}^{|\tilde{a}_i|} D(\tilde{a}_j^i, \mathbf{y}))$.

Model	ROUGE - L	BLEU - 3 & 4		METEOR	CIDEr	SPICE	Coverage
GPT-2	40.3 \rightarrow 42.8	34.2 \rightarrow 36.7	24.7 \rightarrow 26.7	27.6 \rightarrow 30.2	13.4 \rightarrow 14.7	27.1 \rightarrow 30.3	82.2 \rightarrow 97.7
BERT-Gen	42.4 \rightarrow 43.8	37.5 \rightarrow 38.9	27.0 \rightarrow 28.2	29.5 \rightarrow 30.9	14.9 \rightarrow 15.5	29.8 \rightarrow 31.4	89.2 \rightarrow 97.3
UniLM	44.3 \rightarrow 45.8	40.6 \rightarrow 42.8	29.9 \rightarrow 31.5	30.1 \rightarrow 31.7	15.5 \rightarrow <u>16.6</u>	30.6 \rightarrow 32.5	90.5 \rightarrow 97.8
UniLM-v2	43.5 \rightarrow 44.2	39.2 \rightarrow 39.5	28.3 \rightarrow 28.5	30.6 \rightarrow <u>31.3</u>	15.2 \rightarrow 16.8	30.8 \rightarrow 31.1	92.8 \rightarrow 97.9
BART	43.3 \rightarrow 44.7	39.9 \rightarrow <u>41.3</u>	29.1 \rightarrow <u>30.6</u>	30.4 \rightarrow 31.0	15.2 \rightarrow 15.9	30.6 \rightarrow 31.0	95.0 \rightarrow 98.7
T5-Large	43.9 \rightarrow <u>44.8</u>	36.6 \rightarrow 38.5	26.9 \rightarrow 28.1	28.9 \rightarrow 30.7	14.3 \rightarrow 15.5	29.5 \rightarrow 30.8	89.7 \rightarrow <u>98.5</u>

Table 2: Experimental results of different supervised models on the COMMONGEN test set. Under each column, $\alpha \rightarrow \beta$ shows the performance using the conventional beam search (α) compared to the enhanced performance using NEUROLOGIC DECODING (β). NEUROLOGIC always improves the performance across all models and all metrics — with no exception. The best models are **bold** and second best ones are underlined within each metric.

Domain Adaption	Model	ROUGE - L	BLEU - 3 & 4		METEOR	CIDEr	SPICE	Coverage
No	GPT	26.7 \rightarrow 41.3	3.0 \rightarrow 25.1	1.1 \rightarrow 15.9	9.2 \rightarrow 28.8	0.9 \rightarrow 11.7	8.0 \rightarrow 29.7	8.4 \rightarrow 97.4
	GPT-2	19.7 \rightarrow 42.9	4.1 \rightarrow <u>34.4</u>	1.5 \rightarrow <u>23.5</u>	11.2 \rightarrow <u>30.7</u>	0.4 \rightarrow <u>13.6</u>	7.1 \rightarrow <u>31.4</u>	8.3 \rightarrow 96.0
Yes	GPT-2	29.8 \rightarrow <u>42.4</u>	9.5 \rightarrow 36.1	4.0 \rightarrow 25.1	11.7 \rightarrow 31.3	1.7 \rightarrow 13.9	8.0 \rightarrow 31.8	9.3 \rightarrow <u>96.1</u>

Table 3: Experimental results of different models in zero shot (unsupervised) setting on the COMMONGEN test set before and after language domain adaption. Under each column, $\alpha \rightarrow \beta$ shows the performance using the conventional beam search (α) compared to the enhanced performance using NEUROLOGIC DECODING (β).

Decode Method	ROUGE-L	BLEU-3/4	METEOR	CIDEr	SPICE	Coverage
Greedy Decoding	35.3	25.2 16.7	25.8	10.2	24.4	80.3
Top-k Sampling	33.8	22.5 14.4	24.9	9.2	22.7	79.4
Top-p Sampling	35.3	25.0 16.5	25.7	10.2	24.1	80.1
Beam Search	<u>40.3</u>	<u>34.2</u> <u>24.7</u>	<u>27.6</u>	<u>13.4</u>	<u>27.1</u>	82.2
Hokamp and Liu	37.6	25.6 16.8	25.9	11.1	25.1	97.2
Post and Vilar	38.3	28.1 18.6	26.7	11.8	26.0	<u>97.4</u>
Hu et al.	38.2	27.8 18.4	26.7	11.7	26.1	97.4
NEUROLOGIC	42.8	36.7 26.7	30.2	14.7	30.3	97.7

Table 4: Performance of different decoding methods using supervised GPT2-L on the COMMONGEN test set.

Dataset The COMMONGEN dataset consists of 35,141 concept-sets (32,651 in *train*, 993 in *val*, 1,497 in *test*) associated with 77,449 sentences. The average size of the concept-sets in the test set is 4.04, with an average of four sentences per concept-set and an average sentence length of 13.34 words.

Approach and Baseline The standard pipeline of approaching this problem is to consider it as a conditional sentence generation task. We experiment with several recent pre-trained language models, including GPT-2 (Radford et al., 2019), UniLM (Dong et al., 2019), UniLM-v2 (Bao et al., 2020), BERT-Gen (Bao et al., 2020), BART (Lewis et al., 2020), and T5 (Raffel et al., 2019). All models are finetuned with their default hyperparameters. We compare with commonly used decoding methods, including beam search, sampling, and also previously proposed constrained decoding methods. We use several widely-used automatic metrics to automatically assess the performance, such as

BLEU, ROUGE, METEOR, which mainly focus on measuring surface similarities. We also include metrics specially designed for captioning task, such as CIDEr, and SPICE. Following Lin et al. (2020), we report the concept Coverage, which is the average percentage of input concepts that are present in lemmatized outputs.

4.1 Results I: NeuroLogic vs Other Decoding Methods

In Table 4, we first present comparisons across different decoding methods based on a supervised sequence-to-sequence model, GPT2. The key observations are:

1. NEUROLOGIC outperforms all other previous decoding methods, both constrained and unconstrained, with respect to all metrics and often with a significant margin.
2. NEUROLOGIC not only attains high constraint satisfaction (COVERAGE), it also improves the generation quality as quantified over ROUGE, BLEU, METEOR, CIDEr, and SPICE.
3. In comparison, all previous constrained decoding methods (Hokamp and Liu, 2017; Post and Vilar, 2018; Hu et al., 2019a) attain high constraint satisfaction at the cost of generation quality; being outperformed here by conventional beam search with a large margin.

The second and the third points above demonstrate that the improved logical expressiveness of NEUROLOGIC together with the effective search strat-

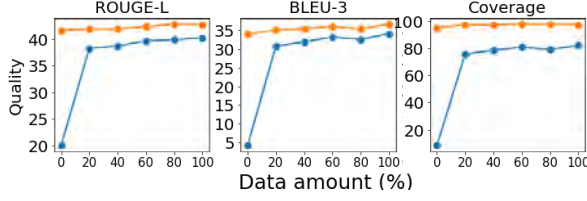


Figure 4: Performance (y-axis) of supervised GPT2-Large on COMMONGEN, with a varying amount of training data for supervision (x-axis). The **orange line** denotes decoding with NEUROLOGIC, and the **blue line** denotes decoding with conventional beam search.

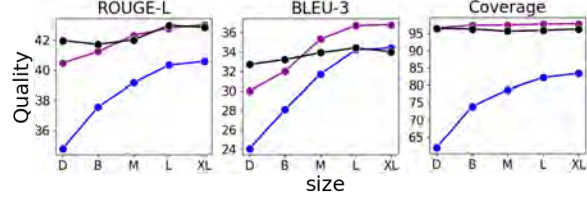


Figure 5: Performance (y-axis) of GPT2 with varying model sizes (x-axis). The **purple line** and **blue line** denote decoding from a supervised model with and without NEUROLOGIC DECODING respectively. The **black line** denotes decoding with NEUROLOGIC in zero-shot (unsupervised) setting.

egy leads to generation that is both higher quality and satisfies the constraints the most effectively.

4.2 Results II: NeuroLogic across Different Supervised Models

Table 2 presents experiments across various state-of-the-art pre-trained language models. In this experiment, all models are supervised on the COMMONGEN training dataset. Under each column, $\alpha \rightarrow \beta$ shows the performance using the conventional beam search (α) compared to the enhanced performance using NEUROLOGIC DECODING (β).

As before, NEUROLOGIC always improves the performance across all models and all metrics with no exception – both in terms of constraint satisfaction as well as generation quality. The improvement is especially substantial when the generation quality is relatively low due to smaller model capability or less efficient model architecture or pre-training.

4.3 Results III: NeuroLogic with Unsupervised Models

In this experiment, we test how well NEUROLOGIC works with unsupervised pre-trained language models, with and without domain adaptation. Table 3 presents experimental results of zero-shot (i.e., unsupervised) constrained generation. With unconstrained decoding, we have zero controllability over

the unsupervised language models, as they ignore the problem input and generate irrelevant text. With NEUROLOGIC, on the other hand, we can dramatically improve the performance on all metrics. Fig 6 demonstrates some generated examples.

In zero-shot setting without any finetuning, the language style of pre-trained LMs might differ from that of COMMONGEN. To further improve the performance, we conduct language domain adaption by fine-tuning the language models on the training-set COMMONGEN language – ignoring all concept sets. We observe that after domain adaption, NEUROLOGIC in zero-shot setting outperforms unconstrained generation with supervised finetuned LMs, which suggests that inference-time algorithms can provide a more compute-efficient avenue to draw better from neural models.

4.4 Results IV: Ablation

The amount of training data Figure 4 compares the performance (y-axis) of supervised GPT2 with NEUROLOGIC (**orange line**) and with conventional beam search (**blue line**) as a function of the increasing amount of training data (x-axis). Notably, even after being supervised on 100% of the training data, the supervised GPT2 does not successfully learn the COMMONGEN constraints (‘coverage’) and is even outperformed by the zero-shot GPT2 (i.e., using 0% training data) with NEUROLOGIC.

The model size Figure 5 compares the performance (y-axis) of GPT2 with varying model sizes (x-axis). Regardless of the model size, NEUROLOGIC (**purple line** and **black line**) boosts performance considerably over conventional beam search (**blue line**). More over, if using NEUROLOGIC, the performance of unsupervised models (**black line**) becomes comparable to that of supervised models (**purple line**). Remarkably, *unsupervised* models with NEUROLOGIC based on *smaller* networks (**black line**) often outperform *supervised* models with conventional beam search based on considerably *larger* networks (**blue line**).

5 Experiments II: Recipe Generation

We next study cooking recipe generation, a paragraph-level generation task. Given a dish name and a list of ingredients, the task is to generate cooking instructions for the given recipe.

Decode Method	ROUGE-L	BLEU-3/4	METEOR	Coverage	Extra
Top-k Sampling	27.5	15.2 9.5	19.2	84.8	16.0
Top-p Sampling	28.7	17.6 11.7	19.4	86.4	15.4
Beam Search	29.4	17.4 12.0	19.7	86.5	14.3
Post and Vilar	26.1	13.6 8.8	16.5	89.6	1.15
Hu et al.	26.1	13.6 8.8	16.5	89.6	1.13
NEUROLOGIC	32.1	19.5 13.8	19.8	95.8	0.6

Table 5: Experimental results of different decoding methods with RecipeGPT on the Recipe1M+ test set. *Coverage* indicates the average percentage of ingredients that are covered in the generated recipe, while *Extra* corresponds to the average ratio of hallucinated ingredients over the number of given ingredients.

Problem Formulation The input is the recipe title, an unordered set of ingredients $E = \{e_1, \dots, e_{|E|}\}$ where e_i can be a single- or multi-word ingredient phrase (e.g., ‘onions’, ‘black pepper’). Let \mathcal{G} denote the set of all ingredients. The expected output is a paragraph $\mathbf{y} \in \mathcal{Y}$ that describes multi-step cooking instructions.

To apply NEUROLOGIC DECODING, we constrain output \mathbf{y} to contain all given ingredients e_i in E , and no other ingredients, i.e. no ingredients in $\mathcal{G} \setminus E$. Ingredients can be referred to with generic terms (e.g., ‘vegetables’ may refer to ‘onions’, or ‘carrots’) and we denote the generic name for ingredient e_i as e_i^T . Formally, the constraint is

$$\begin{aligned} & (\forall e_i \in E, D(e_i, \mathbf{y}) \vee D(e_i^T, \mathbf{y})) \\ & \wedge (\forall e_i \in \mathcal{G} \setminus E, \neg D(e_i, \mathbf{y})) \end{aligned}$$

Dataset, Approach and Baseline We use Recipe1M+, a large-scale, structured corpus of over one million cooking recipes. On average each recipe has 118 words and 9 ingredients. RecipeGPT (Lee et al., 2020) is a GPT-2 model fine-tuned on Recipe1M+, for generating recipes. Its default decoding algorithms are beam search and sampling, which serve as the baselines for evaluating our method. In addition, we compare against previously proposed constrained decoding methods with RecipeGPT. Besides common evaluation metrics for generation task, we introduce explicit measures of given-ingredient coverage and usage of extra/hallucinated ingredients.

Result Table 5 presents the experimental results. We can see that NEUROLOGIC outperforms all baselines in all metrics. The delta is quite remarkable on coverage of given ingredients and usage of extra ingredients. With NEUROLOGIC, we are able

Supervised?	Model	ROUGE-L	BLEU-4	METEOR
Yes	GPT2	70.5 72.6	87.6 92.4	60.0 64.0
Yes	BART	72.9 70.2	89.5 87.0	60.2 54.2
Yes	T5	70.9 69.9	82.4 79.7	54.6 50.4
Yes	Kiddon et al.	-	90.6 77.8	62.1 54.4
No	GPT2 + NEUROLOGIC	73.9 71.8	94.8 90.8	66.6 62.0

Table 6: Results of dialogue generation, the right column is generation result for hotel systems, the left column is for restaurant systems

to cover almost all ingredients in generated instructions and guarantee not to use any other ingredients, which leads to more accurately controlled generation. By plugging NEUROLOGIC into existing generation system, we can get immediate boosts in controllability and generation quality with no extra computational cost.

6 Experiments III: Data-Grounded Dialogue Response Generation

In dialogue responses generation for hotel and restaurant information systems (Wen et al., 2016), we generate a natural language response given a query type (e.g., informing or querying) and a list of facts to convey (e.g., a hotel’s name and address).

Problem Formulation The input is query type, unordered set of facts $F = \{f_1, \dots, f_{|F|}\}$, where each f_i contains attribute and value (i.e. accepts_credit_cards=“yes”, name=“red victorian bed breakfast”). The expected output is a dialogue responses $\mathbf{y} \in \mathcal{Y}$ containing given information.

The lexical constraint here is that all given facts f_i must be included in responses \mathbf{y} in proper natural language form f_i^N . We use a very simple template to turn f_i to natural language form f_i^N . (i.e. the natural language form for accepts_credit_cards=“no” is “doesn’t accept credit cards”). Formally,

$$\forall f_i \in F, D(f_i^N, \mathbf{y})$$

Dataset, Approach and Baseline We use the hotel and restaurant dialogue system corpus and the same train-dev-test split from (Wen et al., 2016). There are 8 query types and 12 attribute types.

The standard paradigm for dialogue generation is to consider it as a conditional sentence generation task and finetune a seq2seq model. While this pipeline works effectively with existing data, but once we have user queries with new query types or new attribute types, the seq2seq model would not be able to generate plausible responses. The

Model	Accuracy(%; \uparrow)	Δ_S (F1; \downarrow)
Google Translate	59.4	12.5
Microsoft Translator	74.1	30.2
Junczys-Dowmunt et al.	60.5 \rightarrow 91.0	13.3 \rightarrow 4.3
Junczys-Dowmunt et al. +GT Gender	60.5 \rightarrow 95.0	13.3 \rightarrow 2.4
Google Translate	63.6	26.7
Microsoft Translator	44.7	29.7
Junczys-Dowmunt et al.	53.0 \rightarrow 81.0	19.3 \rightarrow 1.7
Junczys-Dowmunt et al. +GT Gender	53.0 \rightarrow 89.9	19.3 \rightarrow 1.5

Table 7: Performance of Gender Bias Removal on WinoMT, adapted from Stanovsky et al.. Accuracy refers to correctly translating a person’s gender, Δ_S is the difference in performance (F_1) between stereotypical and non-stereotypical gender roles (lower is better). The arrows (\rightarrow) show the results before and after NEUROLOGIC DECODING, where gender is inferred from a coreference model (default) or provided (GT Gender).

situation can happen frequently with a dialogue generation system in application. Thus, we are interested in zero-shot dialogue generation. We give a hand-crafted initial prompt to a pre-trained LM based on the query type and apply NEUROLOGIC DECODING to force given facts to include in generation. The pre-trained LM we use here is GPT2 (Radford et al., 2019).

The baseline we compare against is seq2seq finetuned LMs with vanilla beam search, including GPT-2 (Radford et al., 2019), BART (Lewis et al., 2020) and T5 (Raffel et al., 2019). We also compare with previous SOTA (Kiddon et al., 2016) on dialogue response generation.

Result Table 6 presents the experimental results. We can see that zero-shot generation with proposed method outperforms or matches supervised baselines. This suggests that plugging NEUROLOGIC DECODING into pretrained LMs can lead to a powerful dialogue generation system, we do not actually need massive finetuning with extra computational cost to do that.

7 Experiment IV: Reducing Gender Bias in Machine Translation

Problem Formulation We adopt the task setup and dataset of Stanovsky et al. (2019). The input x is an English sentence describing a scenario with human entities $N = \{n_1, \dots, n_{|N|}\}$ who are identified by roles. The desired output is a translation y which uses the correct gender inflections in the target language (here, German or French).

We obtain indicators of people’s gender identity

through coreference resolution, linking each entity with their gendered pronoun.³ We then constrain the correctly-gendered human entities to appear in output y . For a human entity n_i , let n_i^F denote its female inflection in the target language, and n_i^M denotes its male inflection. Let F denotes the set of human entities associated with female characters, and M denotes the set of entities associated with male. Formally, the constraint is

$$\begin{aligned} & \left(\forall n_i \in F, D(n_i^F, y) \wedge \neg D(n_i^M, y) \right) \wedge \\ & \left(\forall n_i \in M, D(n_i^M, y) \wedge \neg D(n_i^F, y) \right) \end{aligned}$$

Dataset We use Stanovsky et al. (2019)’s dataset, which is built over the English-only coreference gender-bias studies: Winogender (Rudinger et al., 2018) and Wino-Bias (Zhao et al., 2018).

Result Our results are shown in Table 7. When provided gender markers given by a coreference model, NEUROLOGIC DECODING increases the accuracy of handling gender correctly by **30.5** percentage for German, and **28.0** percentage for French. This even outperforms commercial translation systems – the best result, over any language or system, is Microsoft Translator for German with 74.1% accuracy, whereas NEUROLOGIC DECODING enables the baseline model to get 91% accuracy. The performance increases again by an additional 4% (German) and 8.9% (French) when ground-truth gender markers are used during constrained decoding. Last, the diagnostic results also show that NEUROLOGIC DECODING is particularly effective at reducing (over)reliance on stereotypical gender roles, with a significant decrease in performance difference Δ_S between stereotypical and non-stereotypical gender roles. These results suggest that NEUROLOGIC DECODING a plug-and-play approach for reducing gender bias in existing translation systems.

8 Conclusion

We propose NEUROLOGIC DECODING, an efficient and general method for generating with arbitrary predicate logic constraints. We demonstrate its intuitive application to 4 different tasks as an extension to existing models, showing broad and consistent improvement to decoding quality.

³We could use any off-the-shelf coreference resolution model for this. However, since the English examples in Stanovsky et al. (2019) follow the Winograd schemas format, we use a RoBERTa model finetuned on Winograd Schema Challenge for this, with 78.4% accuracy.

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Concept-Set {lose, board, balance, fall, ride}

Supervised Setting

Decode with Beam Search

[GPT-2]: Someone loses balance and falls off his bike.

[UniLM]: A man is trying to keep his balance as he falls off a board.

[BART]: A man loses his balance and falls off the balance while riding a skateboard.

[T5]: a man loses his balance on the board and falls.

Decode with NEUROLOGIC

[GPT-2]: A man loses his balance as he rides a roller coaster and falls off the board.

[UniLM]: Someone loses balance on the ride and falls off the balance board.

[BART]: A man loses his balance on a ride and falls off the board.

[T5]: a rider loses his balance and falls off the board.

Zero Shot Setting

Decode with NEUROLOGIC

[GPT]: a woman lost her balance riding a horse, falling off the horse, and hitting her head on a board

[GPT-2]: The boy lost his balance riding the bike, falling off the bike and hitting his head on the board.

Concept-Set {throw, knife, stand, target, front}

Supervised Setting

Decode with Beam Search

[GPT-2]: A man is holding a knife and standing in front of a target.

[UniLM]: A man stands next to a knife and throws it at the target .

[BART]: A man stands in front of a target and throws a knife.

[T5]: a man throws a knife in front of a target.

Decode with NEUROLOGIC

[GPT-2]: A man stands and throws a knife in front of a target.

[UniLM]: A man stands next to a knife and throws it at the front of the target .

[BART]: A man stands in front of a target and throws a knife.

[T5]: a man stands in front of a target and throws a knife.

Zero Shot Setting

Decode with NEUROLOGIC

[GPT]: the girl standing in front of him threw her knife at his target

[GPT-2]: The girl's target was standing in front of her, and she threw a knife at him.

Concept-Set {bell, bike, sidewalk, ride, ring}

Supervised Setting

Decode with Beam Search

[GPT-2]: A man rides a bicycle down a sidewalk and rings a bell.

[UniLM]: A man rides his bike on a sidewalk and rings the bell on the sidewalk .

[BART]: A man rides his bike on the sidewalk and rings a bell.

[T5]: a ringing bell on a bicycle riding on the sidewalk

Decode with NEUROLOGIC

[GPT-2]: A man rides his bike down a sidewalk and rings a bell.

[UniLM]: A man rides his bike on the sidewalk and rings the bell on his bicycle .

[BART]: A man rides his bike on the sidewalk and rings a bell.

[T5]: a man rides a bike on the sidewalk as the bell rings.

Zero Shot Setting

Decode with NEUROLOGIC

[GPT]: the child's bell rang, and the sidewalk began to fill with people riding their bikes

[GPT-2]: The child rings the bell, rides the bike, and then goes to the sidewalk.

Figure 6: Generation examples of different models in supervised and zero-shot setting with and without NEUROLOGIC DECODING, on COMMONGEN.

NEUROLOGIC A★esque Decoding: Constrained Text Generation with Lookahead Heuristics

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Abstract

The dominant paradigm for neural text generation is left-to-right decoding from autoregressive language models. Constrained or controllable generation under complex lexical constraints, however, requires foresight to plan ahead feasible future paths.

Drawing inspiration from the A★ search algorithm, we propose NEUROLOGIC A★esque,¹ a decoding algorithm that incorporates heuristic estimates of future cost. We develop efficient *lookahead* heuristics that are efficient for large-scale language models, making our method a drop-in replacement for common techniques such as beam search and top-k sampling. To enable constrained generation, we build on NEUROLOGIC decoding (Lu et al., 2021), combining its flexibility in incorporating logical constraints with A★esque estimates of future constraint satisfaction.

Our approach outperforms competitive baselines on five generation tasks, and achieves new state-of-the-art performance on table-to-text generation, constrained machine translation, and keyword-constrained generation. The improvements are particularly notable on tasks that require complex constraint satisfaction or in few-shot or zero-shot settings. NEUROLOGIC A★esque illustrates the power of decoding for improving and enabling new capabilities of large-scale language models.

1 Introduction

The dominant paradigm for neural text generation is based on left-to-right decoding from autoregressive language models such as GPT-2/3 (Radford et al., 2019; Brown et al., 2020). Under this paradigm, common decoding techniques such as beam search or top-k/p sampling (Holtzman et al., 2020) determine which token to generate

♥ Co-second-authors. Other authors are listed alphabetically, as all contributed significantly.

¹pronounced [ey star esk].

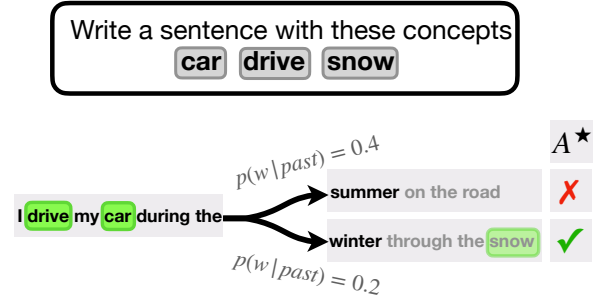


Figure 1: NEUROLOGIC A★ leverages *lookahead heuristics* to guide generations towards those that satisfy the given task-specific constraints. In this example from the COMMONGEN task, although **summer** is a *more likely* next word given the already-generated *past*, NEUROLOGIC A★ looks ahead to see that selecting **winter** results in a generation that incorporates unsatisfied constraint **snow** with a higher probability later on. Thus, **winter** is preferred despite being lower probability than **summer**.

next based on what happened in the past, without explicitly looking ahead into the future. While this lack of foresight often suffices for open-ended text generation – where any coherent text can be acceptable – for constrained text generation, planning ahead is crucial for incorporating all desired content in the generated output (Hu et al., 2017; Dathathri et al., 2019).

Classical search algorithms such as A★ search (Hart et al., 1968; Pearl, 1984; Korf, 1985) address the challenge of planning ahead by using *heuristic* estimation of future cost when making decisions. Drawing inspiration from A★ search, we develop NEUROLOGIC A★esque (shortened to NEUROLOGIC A★), which combines A★-like heuristic estimates of future cost (e.g. perplexity, constraint satisfaction) with common decoding algorithms for neural text generation (e.g. beam search, top-k sampling), while preserving the efficiency demanded by large-scale neural language models.

As selecting the next token to generate based on the *optimal* future cost is NP-complete (Chen et al.,

2018), we develop *lookahead* heuristics, which approximate cost at each decoding step based on continuations of the sequence-so-far. Figure 1 shows an example, where NEUROLOGIC A★esque guides generation towards a decision that would have been ignored based on the past alone, but is selected after looking ahead and incorporating the probability that constraints are satisfied in the future.

Our approach builds on NEUROLOGIC Decoding of Lu et al. (2021), a variation of beam-search for controlling generation through rich logic-based lexical constraints expressed in Conjunctive Normal Form (CNF). Our work generalizes Lu et al. (2021) by (1) incorporating novel lookahead heuristics to estimate future constraint satisfaction, and (2) developing additional *unconstrained* variants that can work with an empty set of constraints. These new algorithm variants support broad applications of NEUROLOGIC★, including unconstrained generation, as demonstrated in our experiments.

Extensive experiments across five generation tasks demonstrate that our approach outperforms competitive baselines. We test NEUROLOGIC★ in conjunction with both supervised and unsupervised models and find that the performance gain is pronounced especially in zero-shot or few-shot settings. In particular, on the COMMONGEN benchmark, using our proposed decoding algorithm with an off-the-shelf language model outperforms a host of *supervised* baselines with conventional decoding algorithms. This demonstrates that a strong inference-time algorithm such as NEUROLOGIC★ can alleviate the need for costly datasets that are manually annotated for explicit supervision. Moreover, we find that NEUROLOGIC★ achieves state-of-the-art performance in various settings, including WMT17 English-German machine translation with lexical constraints (Dinu et al., 2019) and few-shot E2ENLG table-to-text generation (Chen et al., 2020b).

In summary, we develop NEUROLOGIC A★esque, a new decoding algorithm for effective and efficient text generation. To our knowledge this is the first A★-like algorithm for guided text generation via lookahead heuristics. Our algorithm is versatile, as it can be applied to a variety of tasks via inference-time constraints, reducing the need for costly labeled data. Extensive experiments show its effectiveness on several important generation benchmarks.

2 NEUROLOGIC A★esque Decoding

We describe NEUROLOGIC A★esque Decoding (shortened as NEUROLOGIC★), our decoding algorithm motivated by A★ search (Hart et al., 1968), a best-first search algorithm that finds high-scoring paths using a heuristic estimate of future return. We first introduce the decoding problem, and then describe our heuristics with a novel lookahead procedure for adapting NEUROLOGIC★ search to unconstrained and constrained generation with large-scale autoregressive models.

2.1 Decoding With A★esque Lookahead

Decoding. Sequence-to-sequence generation is the task of generating an output sequence \mathbf{y} given an input sequence \mathbf{x} . We consider standard left-to-right, autoregressive models, $p_\theta(\mathbf{y}|\mathbf{x}) = \prod_{t=1}^{|\mathbf{y}|} p_\theta(y_t|\mathbf{y}_{<t}, \mathbf{x})$, and omit \mathbf{x} to reduce clutter. Decoding consists of solving,

$$\mathbf{y}_* = \arg \max_{\mathbf{y} \in \mathcal{Y}} F(\mathbf{y}). \quad (1)$$

Where \mathcal{Y} is the set of all sequences. In our setting, the objective $F(\mathbf{y})$ takes the form $s(\mathbf{y}) + H(\mathbf{y})$, where $s(\mathbf{y})$ is $\log p_\theta(\mathbf{y})$, and $H(\mathbf{y})$ is either zero or is a score for satisfying constraints on \mathbf{y} .

Our method takes the perspective of decoding as discrete search, in which states are partial prefixes, $\mathbf{y}_{<t}$, actions are tokens in vocabulary \mathcal{V} (i.e. $y_t \in \mathcal{V}$) and transitions add a token to a prefix, $\mathbf{y}_{<t} \circ y_t$. Each step of decoding consists of 1) expanding a set of candidate next-states, 2) scoring each candidate, and 3) selecting the k best candidates:

$$\begin{aligned} Y'_t &= \{\mathbf{y}_{<t} \circ y_t \mid \mathbf{y}_{<t} \in Y_{t-1}, y_t \in \mathcal{V}\}, \\ Y_t &= \arg \text{topk}_{(\mathbf{y}_{<t}, y_t) \in Y'_t} \{f(\mathbf{y}_{<t}, y_t)\}, \end{aligned} \quad (2)$$

where $Y_0 = \{\langle \text{bos} \rangle\}$ and $f(\cdot)$ is a scoring function that approximates the objective F . Common decoding algorithms such as beam search score candidates without considering future tokens, e.g., $f(\mathbf{y}_{<t}, y_t) = \log p_\theta(\mathbf{y}_{\leq t})$.

Lookahead heuristics. Our method incorporates an estimate of the future into candidate selection. Ideally, we want to select candidates that are on optimal trajectories, replacing Equation 2 with:

$$Y_t = \arg \text{topk}_{(\mathbf{y}_{<t}, y_t) \in Y'_t} \left\{ \max_{\mathbf{y}_{>t}} F(\mathbf{y}_{<t}, y_t, \mathbf{y}_{>t}) \right\}. \quad (3)$$

However, computing Equation 3 presents two difficulties: 1) the objective $F(\mathbf{y})$ may be unknown or difficult to compute, and 2) the space of future trajectories $\mathbf{y}_{>t}$ is prohibitively large.

Motivated by A* search (Hart et al., 1968), a best-first search algorithm that finds high-scoring paths by selecting actions that maximize,

$$f(a) = s(a) + h(a),$$

where $s(a)$ is the score-so-far and $h(a)$ is a heuristic estimate of the future score. We approximate the objective using a lightweight heuristic $h(\cdot)$,

$$Y_t = \arg \text{topk}_{\mathbf{y}_{\leq t} \in Y'_t} \left\{ s(\mathbf{y}_{\leq t}) + \max_{\mathbf{y}_{>t}} h(\mathbf{y}_{<t}, y_t, \mathbf{y}_{>t}) \right\}, \quad (4)$$

where $s(\mathbf{y}_{\leq t}) = \log p_\theta(\mathbf{y}_{\leq t})$. To make the search tractable, we search over a set of *lookahead* continuations, approximating Equation 3 as,

$$Y_t = \arg \text{topk}_{\mathbf{y}_{\leq t} \in Y'_t} \left\{ s(\mathbf{y}_{\leq t}) + \max_{\mathcal{L}_\ell(\mathbf{y}_{\leq t})} h(\mathbf{y}_{\leq t+\ell}) \right\}, \quad (5)$$

where each element $\mathbf{y}_{t+1:t+\ell}$ of $\mathcal{L}_\ell(\mathbf{y}_{\leq t})$ is a length- ℓ continuation of $\mathbf{y}_{\leq t}$. Beam search corresponds to setting ℓ and h to 0.

A*esque decoding. Beam search, A* search, and our method fall under a general class of algorithms that differ based on (1) which candidates are expanded, (2) which candidates are pruned, (3) how candidates are scored (Meister et al., 2020). We inherit the practical advantages of beam search-style expansion and pruning, while drawing on A*-like heuristics to incorporate estimates of the future, and refer to our method as **A*esque decoding**.

Generating lookaheads. We compare several methods for generating the lookaheads $\mathcal{L}_\ell(\mathbf{y}_{\leq t})$.

The *greedy* lookahead produces a single sequence, $\mathcal{L}_\ell = \{\mathbf{y}_{t+1:t+\ell}\}$, starting from $\mathbf{y}_{\leq t}$ and selecting each token according to $y_{t'} = \arg \max_{y \in \mathcal{V}} p_\theta(y|\mathbf{y}_{<t'})$.

We also consider a relaxation which interpolates between providing the greedy token and a uniform mixture of tokens as input at each step. Specifically, we adjust the model’s probabilities with a temperature, $\tilde{p}_\theta(y_t|\mathbf{y}_{<t}) = \text{softmax}(s_t/\tau)$, where $s_t \in \mathbb{R}^{|\mathcal{V}|}$ is a vector of logits, and feed the expected token embedding as input at step t ,

$$e_t = \mathbb{E}_{y_t \sim \tilde{p}(y_t|\mathbf{y}_{<t})} [E(y_t)], \quad (6)$$

where $E \in \mathbb{R}^{|\mathcal{V}| \times d}$ is the model’s token embedding matrix. This *soft lookahead* moves from providing the greedy token as input ($\tau \rightarrow 0$) to a uniform mixture of tokens ($\tau \rightarrow \infty$) based on the value of temperature τ . When using the soft lookahead, we use \tilde{p} in place of p when scoring tokens. The soft (and greedy) lookahead is efficient, but only explores a single trajectory.

The *beam* lookahead trades off efficiency for exploration, returning a set \mathcal{L}_ℓ containing the top- k candidates obtained by running beam search for ℓ steps starting from $\mathbf{y}_{<t}$.

Finally, the *sampling* lookahead explores beyond the highly-probable beam search continuations, generating each $\mathbf{y}_{t+1:t+\ell} \in \mathcal{L}_\ell$ using,

$$y_{t'} \sim p_\theta(y|\mathbf{y}_{<t'}),$$

for t' from $t+1$ to $t+k$.

Next, we move to our proposed lookahead heuristics, starting with the unconstrained setting.

2.2 Unconstrained Generation with NEUROLOGIC*

First we consider a standard decoding setting,

$$\arg \max_{y \in \mathcal{V}} \log p_\theta(y|\mathbf{x}).$$

We score candidates based on a combination of the *history* and *estimated future*, by using the likelihood of the lookahead as a heuristic. That is, at the t th step of decoding, we use Equation 5:

$$h(\mathbf{y}_{\leq t+\ell}) = \lambda \log p_\theta(\mathbf{y}_{t+1:t+\ell}|\mathbf{y}_{\leq t}, \mathbf{x}), \quad (7)$$

where λ controls how much we rely on the estimated future versus the history, similar to weighted A* (Pohl, 1970).

2.3 NEUROLOGIC* for Constrained Generation

Our lookahead heuristics lend themselves to decoding with lexical constraints in a way that standard beam search does not. For constrained generation, we build on and generalize NEUROLOGIC decoding algorithm of Lu et al. (2021)—a beam-based search algorithm that supports a wide class of logical constraints for lexically constrained generation—with estimates of future constraint satisfaction.

Background of NEUROLOGIC. NEUROLOGIC Lu et al. (2021) accepts lexical constraints in Conjunctive Normal Form (CNF):

$$\underbrace{(D_1 \vee D_2 \cdots \vee D_i)}_{C_1} \wedge \cdots \wedge \underbrace{(D_{i'} \vee D_{i'+1} \cdots \vee D_N)}_{C_M}$$

where each D_i represents a single positive or negative constraint, $D(\mathbf{a}, \mathbf{y})$ or $\neg D(\mathbf{a}, \mathbf{y})$, enforcing the phrase \mathbf{a} to be included in or omitted from \mathbf{y} . Lu et al. (2021) refer to each constraint D_i as a *literal*, and each disjunction C_j of literals as a *clause*.

NEUROLOGIC is a beam-based approximate search for an objective which seeks fluent sequences in which all clauses are satisfied:

$$\arg \max_{\mathbf{y} \in \mathcal{Y}} p_{\theta}(\mathbf{y}|\mathbf{x}) - \lambda' \sum_{j=1}^M (1 - C_j),$$

where $\lambda' \gg 0$ penalizes unsatisfied clauses. At each step of the search, NEUROLOGIC scores each of the $k \times |\mathcal{Y}|$ candidates $(\mathbf{y}_{<t}, y_t)$ based on whether they (partially) satisfy new constraints,

$$f(\mathbf{y}_{\leq t}) = \log p_{\theta}(\mathbf{y}_{\leq t}|\mathbf{x}) + \lambda_1 \max_{D(\mathbf{a}, \mathbf{y}_{\leq t})} \frac{|\hat{\mathbf{a}}|}{|\mathbf{a}|}, \quad (8)$$

where the maximization is over a set of unsatisfied multi-token constraints \mathbf{a} tracked by NEUROLOGIC, and $\hat{\mathbf{a}}$ is the prefix of \mathbf{a} in the ongoing generation. For example, for $\mathbf{y}_{\leq t} = \text{"The boy climbs an apple"}$ and constraint $\mathbf{a} = \text{"apple tree"}$, $\hat{\mathbf{a}}$ is *"apple"*. Intuitively, this function rewards candidates that are in the process of satisfying a constraint.

In lieu of taking the top- k scoring candidates (Equation 5), NEUROLOGIC prunes candidates that contain clauses that violate constraints, groups the candidates to promote diversity, and selects high-scoring candidates from each group. We use the same pruning and grouping approach, and refer the reader to Lu et al. (2021) for further details.

NEUROLOGIC[★] decoding. Our method improves upon the NEUROLOGIC scoring function with an estimate of future constraint satisfaction. Our key addition is a lookahead heuristic that adjusts a candidate $(\mathbf{y}_{<t}, y_t)$'s score proportional to the probability of satisfying additional constraints in the lookahead $\mathbf{y}_{t+1:t+\ell}$:

$$h_{\text{future}}(\mathbf{y}_{\leq t+\ell}) = \lambda_2 \max_{D(\mathbf{a}, \mathbf{y}_{t+1:t+\ell})} \log p_{\theta}(D(\mathbf{a}, \mathbf{y}_{t+1:t+\ell})|\mathbf{x}, \mathbf{y}_{\leq t}), \quad (9)$$

where we define the probability that constraint \mathbf{a} is satisfied using the most probable subsequence,

$$p_{\theta}(D(\mathbf{a}, \mathbf{y}_{t+1:t+\ell})|\mathbf{x}, \mathbf{y}_{\leq t}) = \max_{t' \in [t, t+\ell]} p_{\theta}(\mathbf{y}_{t':t'+|\mathbf{a}|} = \mathbf{a}|\mathbf{x}, \mathbf{y}_{<t'}), \quad (10)$$

λ_2 is a scaling hyperparameter for the heuristic.

Intuitively, this lookahead heuristic brings two benefits. When y_t is a token that would satisfy a multi-token constraint, the lookahead incorporates the score of the *full* constraint. When y_t is a token that is not part of a constraint, the lookahead allows for incorporating the score of a future constraint that would be satisfied if y_t was selected.

We add our lookahead heuristic to the NEUROLOGIC scoring function (Equation 8), and call the resulting decoding procedure NEUROLOGIC A[★]esque (or, NEUROLOGIC[★] in short).

Task	Supervision	Constraints
Commonsense Generation	zero+full	w/
Machine Translation	full	w/
Table-to-text Generation	few	w/
Question Generation	zero	w/
Commonsense Story Generation	full	w/o

Table 1: Tasks and setups considered in this work.

3 Experiments: Constrained Generation

We present experimental results on various constrained generation benchmarks: COMMONGEN (§3.1), constrained machine translation (§3.2), table-to-text generation (§3.3), and interrogative sentence generation (§3.4). NEUROLOGIC[★] consistently outperforms NEUROLOGIC and all previous approaches. The improvement is especially substantial in zero-shot and few-shot cases where the search problem is much harder.

Experimental setups. We explore a variety of experimental setups (Table 1). In terms of *supervision*, we consider different configurations of zero-shot, few-shot and full-shot. The former two supervision regimes are particularly important as many realistic generation application do not come with many manually-annotated labeled data. Additionally, we study both *constrained* and *unconstrained* tasks, even though we focus on the former.

Evaluation metrics. We use the following automatic metrics that are commonly used for evaluating text generation: BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005), CIDEr (Vedantam et al., 2015), SPICE (Anderson et al., 2016) and NIST (Lin and Hovy, 2003). Any other domain specific metrics are detailed in each task description.

3.1 Constrained Commonsense Generation

COMMONGEN (Lin et al., 2020) is a constrained commonsense generation task with lexical constraints.

Decode Method	Automatic Evaluation						Human Evaluation			
	ROUGE-L	BLEU-4	METEOR	CIDEr	SPICE	Coverage	Quality	Plausibility	Concepts	Overall
<i>Supervised</i>										
CBS (Anderson et al., 2017)	38.8	20.6	28.5	12.9	27.1	97.6	2.27	2.35	2.51	2.23
GBS (Hokamp and Liu, 2017)	38.2	18.4	26.7	11.7	26.1	97.4	2.06	2.17	2.29	2.01
DBA (Post and Vilar, 2018a)	38.3	18.7	27.7	12.4	26.3	97.5	2.23	2.30	2.43	2.15
NEUROLOGIC (Lu et al., 2021)	42.8	26.7	30.2	14.7	30.3	97.7	2.54	2.56	2.67	2.50
NEUROLOGIC★ (greedy)	<u>43.6</u>	<u>28.2</u>	30.8	15.2	<u>30.8</u>	97.8	2.66	<u>2.67</u>	2.73	2.59
NEUROLOGIC★ (sample)	43.4	27.9	30.8	<u>15.3</u>	31.0	<u>97.7</u>	2.64	2.64	2.74	2.58
NEUROLOGIC★ (beam)	43.2	<u>28.2</u>	<u>30.7</u>	15.2	31.0	97.6	<u>2.68</u>	<u>2.67</u>	<u>2.76</u>	<u>2.60</u>
<i>Unsupervised</i>										
TSMH (Zhang et al., 2020)	24.7	2.2	14.5	3.6	15.4	71.5	1.85	1.92	1.95	1.63
NEUROLOGIC (Lu et al., 2021)	41.9	24.7	29.5	14.4	27.5	96.7	2.64	2.52	2.68	2.50
NEUROLOGIC★ (greedy)	44.3	28.6	<u>30.7</u>	15.6	29.6	97.1	2.78	2.70	<u>2.77</u>	2.70

Table 2: Performance of various decoding methods with *supervised* or *off-the-shelf* GPT-2 on the COMMONGEN test set, measured with automatic and human evaluations. We only tried NEUROLOGIC★ (greedy) in the unsupervised setting because of the computational cost. The best numbers are **bolded** and the second best ones are underlined.

Words	Method	Generation
cut	GBS	Cut a piece of wood to use as a fence.
piece	DBA	Cut a piece of wood to use as a fence.
use	NEUROLOGIC	Piece of wood used for cutting.
wood	NEUROLOGIC★	A man cuts a piece of wood using a circular saw.
ball	GBS	A dog is run over by a ball and mouth agape.
dog	DBA	A dog is run over by a ball and bites his mouth.
mouth	NEUROLOGIC	A dog is running and chewing on a ball in its mouth.
run	NEUROLOGIC★	A dog running with a ball in its mouth.
dog	GBS	Soap and water scrubbed dog with a towel.
scrub	DBA	Soap and water on a dog and scrubbed skin.
soap	NEUROLOGIC	A dog is scrubbing his paws with soap and water.
water	NEUROLOGIC★	A man is scrubbing a dog with soap and water.

Table 3: Example generations for the COMMONGEN task across supervised NEUROLOGIC★ and baselines, including GBS (Hokamp and Liu, 2017), DBA (Post and Vilar, 2018a), and NEUROLOGIC (Lu et al., 2021)

Given a set of concepts (e.g., {throw, run, javelin, track}), the task is to generate a coherent sentence describing a plausible scenario using all of the given concepts (e.g., “a man runs on a track and throws a javelin.”).

Approach and Baselines. Following Lu et al. (2021), we enforce that each given concept c_i must appear in output y under some morphological inflection. We experiment with both supervised and zero-shot settings. In the supervised setting, we formulate it as conditional sentence generation task and finetune GPT-2 (Radford et al., 2019) as a sequence-to-sequence model. In the zero-shot setting, we use GPT-2 off-the-shelf (no fine-tuning), and rely on constrained decoding to guide the generations. We compare with previous constrained decoding algorithms, including CBS (Anderson et al., 2017), GBS (Hokamp and Liu, 2017), DBA (Post and Vilar, 2018a), NEUROLOGIC (Lu et al.,

2021) and TSMH (Zhang et al., 2020)

Metrics Following Lin et al. (2020), we report automatic generation metrics as well as *coverage*, defined as the average percentage of the provided concepts that are present in lemmatized outputs. Additionally, we conduct human evaluation on 100 test examples with workers from Amazon Mechanical Turk (AMT). We include our evaluation template in Figure 5 of Appendix A. Workers are given a pair of concepts and a model generation, and asked to rate each pair on *language quality*, *scenario plausibility*, *coverage of given concepts*, and an *overall score*, in the Likert scale: *Agree*, *Neutral*, and *Disagree*. Each pair is rated by 3 workers.

Results. Table 2 compares different constrained decoding methods on top of the finetuned and off-the-shelf GPT-2, in supervised and zero-shot settings respectively. The key observations are:

1. NEUROLOGIC★ outperforms all previous constrained-decoding methods in both supervised and zero-shot settings. Surprisingly, *unsupervised* NEUROLOGIC★ outperforms all supervised methods based on human evaluation.
2. Compared to vanilla NEUROLOGIC, NEUROLOGIC★ improves the generation quality while maintaining high constraint satisfaction. The difference is especially substantial in the zero-shot case, where there is more room for incorporating constraint-driven signals due to the lack of supervision and the large output space.
3. NEUROLOGIC★ reaches similar performance with different lookahead strategies, among which beam lookahead slightly outperforms the

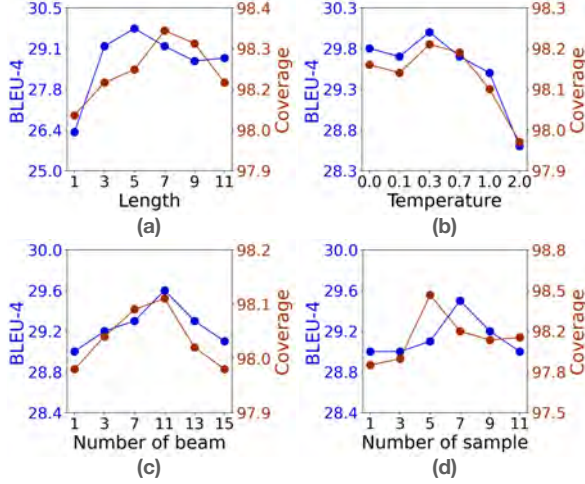


Figure 2: Performance (y-axis) of supervised GPT-2 in terms of **BLEU-4** and **Coverage** with varying lookahead parameters (x-axis) on COMMONGEN validation set.

others based on human evaluation, and greedy lookahead has the lowest runtime.

Studying lookahead strategies. With an infinite lookahead length ℓ and number of lookaheads $|\mathcal{L}_\ell|$, lookahead decoding exactly solves Equation 3. For practical choices of ℓ and $|\mathcal{L}_\ell|$, we empirically study how varying the lookahead strategy and hyperparameters affects performance. In Figure 2, we study the greedy, soft, beam, and sampling lookahead strategies (§2.1).

Figure 2(a) shows the effect of increasing the lookahead horizon ℓ for the greedy strategy. Increasing the horizon improves up to one point – e.g., 5-7 steps – then decreases thereafter, likely due to the difficulty of long-horizon approximation.

Figure 2(b) studies the temperature in the soft lookahead, showing that greedy ($\tau = 0.0$) performs well, with slight gains if τ is carefully selected. The results suggest that one can safely bypass tuning τ using fast, greedy lookahead.

Next, Figure 2(c) shows that with beam lookahead, increasing the beam width improves performance up to a certain point (here, 11). Similarly, increasing the number of samples with sampling lookahead improves over a single sample, and then reaches an inflection point (Figure 2(d)).

3.2 Constrained Machine Translation

It is often critical to have control over machine translation output. For example, domain-specific dictionaries can be incorporated to force a model

Method	Dinu et al.		Marian MT	
	BLUE	Term%	BLUE	Term%
Unconstrained	25.8	76.3	32.9	85.0
train-by-app.	26.0	92.9	–	–
train-by-rep.	26.0	94.5	–	–
Post and Vilar (2018a)	25.3	82.0	33.0	94.3
NEUROLOGIC	26.5	95.1	33.4	97.1
NEUROLOGIC [★] (greedy)	26.7	95.8	33.7	97.2
NEUROLOGIC [★] (sample)	<u>26.6</u>	<u>95.4</u>	33.7	97.2
NEUROLOGIC [★] (beam)	<u>26.6</u>	95.8	<u>33.6</u>	97.2

Table 4: Results on constrained machine translation. The left section uses the same two-layer transformer model as Dinu et al. (2019) for fair comparisons. The right one decodes a stronger Marian MT EN-DE model. The highlighted methods modify training data specifically for constrained decoding, and thus cannot be applied to off-the-shelf models. The best numbers are **bolded** and the second best ones are underlined.

# T	# Sents.	Decode Method	BLEU	Term%
1	378	Beam search	25.4	79.6
		NEUROLOGIC	<u>26.2</u>	<u>95.2</u>
		NEUROLOGIC [★]	26.3	95.8
2+	36	Beam search	28.1	85.0
		NEUROLOGIC	<u>28.9</u>	<u>93.7</u>
		NEUROLOGIC [★]	29.3	96.5

Table 5: Constrained Machine Translation performance broken down by the number of constraint terms (# T). All configurations use the two-layer transformer from Dinu et al. (2019). The best numbers are **bolded** and the second best ones are underlined.

to use certain terminology (Post and Vilar, 2018a; Dinu et al., 2019). To achieve this goal, much recent work proposed constrained decoding algorithms (Chatterjee et al., 2017; Hokamp and Liu, 2017; Hasler et al., 2018; Hu et al., 2019, *inter alia*) or specialized training (Dinu et al., 2019). We demonstrate that NEUROLOGIC[★] can be readily applied to off-the-shelf MT systems for constrained machine translation. Specifically, we follow the setup in Dinu et al. (2019) and evaluate our method on the WMT17 EN-DE test data (Bojar et al., 2017). The constraint here is to integrate a given custom terminology into the translation output; constraint terms are automatically created from the IATE EU terminology database for 414 test sentences.²

Approach, Baselines, and Metrics. We experiment with two MT systems: Dinu et al. (two-layer transformer) and the off-the-shelf Marian MT (Junczys-Dowmunt et al., 2018). We compare with previous constrained decoding algorithms, including DBA (Post and Vilar, 2018a), NEUROLOGIC

²https://github.com/mtresearcher/terminology_dataset.

(Lu et al., 2021) and also specialized training proposed by Dinu et al. (2019). Following Dinu et al. (2019), we report BLEU scores and term use rates, computed as the percentage of times a given constraint term was generated in the output out of the total number of constraint terms.

Results. Table 4 presents experimental results with Dinu et al.’s model and Marian MT. We can see that in either case, NEUROLOGIC★ outperforms all prior methods both in BLEU and term coverage. Besides better generation quality and constraint coverage, NEUROLOGIC★ also benefits from its plug-and-play flexibility with any off-the-shelf MT system compared to previous training-based methods. Table 5 breaks down the model performance by the number of constraint terms. We see that NEUROLOGIC★ improves upon the others, especially when the constraint is complex with multiple constraint terms. (*e.g.*, 96.5 vs. 93.7 from NEUROLOGIC in term coverage).

3.3 Table-to-text Generation

The table-to-text task aims to generate natural language text conditioned on structured table data; their applications include automatic generation of weather/sports reports (Liang et al., 2009; Wiseman et al., 2017) or dialogue responses (Wen et al., 2016). Constrained generation algorithms can be used to ensure that the output text is consistent with the input structured data. We follow the few-shot setup of Chen et al. (2020b) on the E2ENLG (Dušek et al., 2018) dataset, where we use randomly-sampled 0.1%, 0.5%, 1%, 5% of training instances for finetuning.

Approach, Baselines, and Metrics. Following Shen et al. (2019), we linearize the given table into a string and finetune GPT-2 with given few-shot examples. We first compare NEUROLOGIC★ with three previous constrained decoding algorithms: CBS (Anderson et al., 2017), GBS (Hokamp and Liu, 2017), and NEUROLOGIC (Lu et al., 2021), based on few-shot GPT-2 finetuned with 0.1% data. Then we compare our approach, NEUROLOGIC★ on top of GPT-2, with previous table-to-text methods, including TGen (Dušek and Jurčiček, 2016), Template-GPT-2 (Chen et al., 2020a), KGPT (Chen et al., 2020b), in multiple few-shot settings with various numbers of training instances. We report standard automatic metrics used in the E2ENLG challenge, as well as information coverage– the

Decode Method	NIST	BLEU	METEOR	CIDEr	ROUGE	Coverage
Beam Search	3.82	42.8	32.6	10.8	57.8	73.6
CBS	6.50	42.3	36.4	13.0	54.3	91.6
GBS	6.26	40.7	36.7	12.9	54.2	94.1
NEUROLOGIC	6.95	47.6	38.9	16.3	58.7	97.6
NEUROLOGIC★ (greedy)	7.11	<u>49.2</u>	40.0	17.5	60.0	100.0
NEUROLOGIC★ (beam)	<u>7.01</u>	48.9	40.0	17.2	59.8	99.9
NEUROLOGIC★ (sample)	7.11	49.3	40.1	17.5	60.0	100.0

Table 6: Performance of different decoding methods with few-shot GPT-2 finetuned on 0.1% E2ENLG data. The best numbers are **bolded** and the second best ones are underlined.

Method	0.1%	0.5%	1%	5%
TGen (Dušek and Jurčiček, 2016)	3.6	27.9	35.2	57.3
Template-GPT-2 (Chen et al., 2020a)	22.5	47.8	53.3	59.9
KGPT-Graph (Chen et al., 2020b)	39.8	53.3	55.1	61.5
KGPT-Seq (Chen et al., 2020b)	40.2	53.0	54.1	61.1
GPT-2	42.8	<u>57.1</u>	56.8	61.1
GPT-2 + NEUROLOGIC	<u>47.6</u>	56.9	<u>58.0</u>	<u>62.9</u>
GPT-2 + NEUROLOGIC★ (greedy)	49.2	58.0	58.4	63.4

Table 7: Few-shot results (BLEU-4) on E2ENLG test set with 0.1%, 0.5%, 1%, 5% of training instances. The best numbers are **bolded** and the second best ones are underlined.

average percentage of given information that is present in the generation.

Results. Table 6 presents results from varying decoding algorithms based on few-shot GPT-2 finetuned with 0.1% of the data. NEUROLOGIC★ substantially outperforms all previous methods with respect to all metrics; it consistently improves generation quality while achieving (almost) perfect constraint satisfaction. Previous work, like CBS and GBS, improves constraint satisfaction, but negatively affects the text quality, as indicated by drops in BLEU and ROUGE. Table 7 compares NEUROLOGIC★ on top of GPT-2 with previous table-to-text approaches. As before, NEUROLOGIC★ outperforms all prior approaches by a large margin, even if the latter ones leverage either specialized model architecture or additional pretraining on massive table-to-text corpora. Additionally, Figure 3 compares the performance (y-axis) of few-shot GPT-2 with NEUROLOGIC★ (**purple line**), NEUROLOGIC (**blue line**), and conventional beam search (**black line**) as a function of the varying amount of training instances (x-axis). We find the relative gain brought by NEUROLOGIC★ increases as we reduce the amount of few-shot examples. Results above demonstrate the promise of decoding algorithms to address unsatisfying performance in few-shot scenarios due to insufficient learning.

Decode Method	Automatic Evaluation						Human Evaluation			
	ROUGE	BLEU	METEOR	CIDEr	SPICE	Coverage	Grammar	Fluency	Meaningfulness	Overall
CGMH (Miao et al., 2019)	28.8	2.0	18.0	5.5	21.5	18.3	2.28	2.34	2.11	2.02
TSMH (Zhang et al., 2020)	42.0	4.3	25.9	10.4	37.7	<u>92.7</u>	2.35	2.28	2.37	2.22
NEUROLOGIC (Lu et al., 2021)	38.8	11.2	24.5	18.0	41.7	90.6	2.78	2.71	2.49	2.51
NEUROLOGIC [★] (greedy)	43.7	14.7	28.0	20.9	47.7	100.0	2.83	2.77	2.74	2.76
NEUROLOGIC [★] (beam)	42.9	14.4	27.8	20.3	46.9	100.0	<u>2.81</u>	2.86	2.76	<u>2.75</u>
NEUROLOGIC [★] (sample)	<u>43.5</u>	<u>14.6</u>	28.2	<u>20.8</u>	47.8	100.0	2.83	2.75	2.76	2.73

Table 8: Performance of different unsupervised decoding algorithms on interrogative question generation.

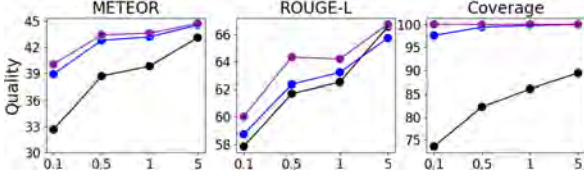


Figure 3: Performance (y-axis) of supervised GPT-2 on E2ENLG, with a varying amount of training data for supervision (x-axis). The purple, blue, and black line denote decoding with NEUROLOGIC[★], NEUROLOGIC and conventional beam search respectively.

3.4 Constrained Question Generation

Despite the success of supervised techniques in natural language generation, it needs to be trained with massive task-specific data, which is non-trivial to acquire. We investigate a zero-shot text generation task proposed by Zhang et al. (2020): constrained question generation, where no training data is available. Given a set of keywords (e.g., Nevada, desert, border), the task is to use an off-the-self language model to generate an interrogative question containing given keywords (e.g., “What is the name of the desert near the border of Nevada?”). Two types of constraints are enforced for this task: 1) keyword constraints - the output question must include all the keywords provided, and 2) syntactic constraints - the output question must be in the interrogative form, the first word must be *wh*-question words, and the second or third word must be auxiliary verbs or copula words.

Approach, Baselines, and Metrics. We leverage off-the-shelf language model GPT-2 and compare NEUROLOGIC[★] with three previous constrained decoding methods, CGMH (Miao et al., 2019), TSMH (Zhang et al., 2020) and NEUROLOGIC (Lu et al., 2021). CGMH and TSMH are two Metropolis-Hastings sampling-based decoding algorithms that have shown strong performance in unsupervised constrained generation. For automatic evaluation, we report standard generation metrics and keyword Coverage similar to previ-

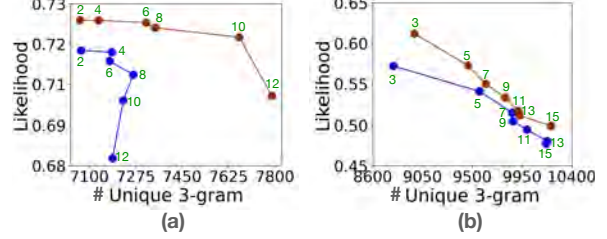


Figure 4: Likelihood (y-axis) vs. number of unique 3-grams (x-axis) using supervised GPT-2 on RocStories. Figure (a) denotes decoding with beam search, with a varying amount of beam size. Figure (b) denotes decoding with top-k sampling, with a varying amount of k value. The brown and blue line denotes with and without A[★]esque heuristics separately.

ous task COMMONGEN. For the human evaluation, we sample 100 test examples and employ workers from AMT to evaluate the generated interrogative questions. Workers are given a set of keywords and model generation. They are asked to evaluate the generation based on 3 individual qualities (*i.e.*, grammar, fluency, meaningfulness) and provide an overall quality score, using the 3-point Likert scale. Each example is averaged across 3 workers. We include the human evaluation template in Figure 6 of the Appendix A.

Results. Table 8 presents comparisons across different decoding methods based on off-the-shelf language models. We can see that NEUROLOGIC[★] outperforms all previous methods with respect to both automatic and manual metrics; it remarkably enhances the generation quality while achieves perfect constraint satisfaction. The difference between NEUROLOGIC and NEUROLOGIC[★] is particularly large compared to other tasks. The search problem is much harder here, due to the lack of supervision and complex logical constraint involving both keywords and syntax. Results above demonstrate the effectiveness of NEUROLOGIC[★] in tackling more challenging constrained generation problems.

Decode Method	Fluency			Diversity		Human Eval				
	PPL	BLEU-1	BLEU-2	Uniq. 3-gram	Uniq. 4-gram	Grammar	Fluency	Coherence	Interest	Overall
beam search	2.24	33.7	16.5	34.09k	41.91k	2.81	2.50	2.46	2.27	2.32
beam search + A★esque (greedy)	2.11	<u>34.3</u>	<u>16.7</u>	34.94k	43.02k	2.94	<u>2.71</u>	2.56	2.50	<u>2.57</u>
beam search + A★esque (beam)	2.14	34.4	16.8	35.03k	43.12k	2.94	2.72	2.62	2.61	2.63
beam search + A★esque (sample)	2.16	34.4	<u>16.7</u>	35.41k	43.64k	<u>2.92</u>	<u>2.71</u>	<u>2.59</u>	<u>2.52</u>	<u>2.57</u>
top-k sample	4.01	31.4	13.9	<u>48.36k</u>	<u>56.62k</u>	2.69	2.38	2.23	2.30	2.15
top-k sample + A★esque (greedy)	3.68	<u>32.1</u>	<u>14.3</u>	48.44k	56.63k	2.88	2.57	2.48	2.49	2.47
top-k sample + A★esque (beam)	3.75	32.2	14.4	48.27k	56.36k	<u>2.84</u>	2.49	2.39	2.40	2.34
top-k sample + A★esque (sample)	<u>3.70</u>	32.0	14.2	48.04k	56.15k	<u>2.84</u>	<u>2.55</u>	<u>2.47</u>	<u>2.48</u>	<u>2.44</u>

Table 9: Performance of different decoding algorithms on RocStories test set.

4 Experiments: Unconstrained Generation

So far we have experimented with constrained text generation, but here we demonstrate that NEUROLOGIC★ decoding can also improve *unconstrained* generation. Specifically, we investigate whether A★esque decoding with our unconstrained lookahead heuristic (Equation 7) can (i) improve beam search, which typically struggles in open-ended settings (Holtzman et al., 2020; Welleck et al., 2019b), (ii) improve *sampling* algorithms that are commonly used in open-ended generation.

4.1 Commonsense Story Generation

We investigate story generation with RocStories (Mostafazadeh et al., 2016). Given the first sentence as a prompt x , the task is to generate the rest of story continuation y .

Approach, Baselines and Metrics. We consider storytelling as a conditional generation task, and finetune GPT-2 as a sequence-to-sequence model.

We apply A★esque decoding with our unconstrained lookahead heuristic (Equation 7) to (i) beam search, the setting used so far in the experiments, and (ii) top-k sampling (Fan et al., 2018), a commonly used sampling algorithm in open-ended generation. For top-k sampling, we use the heuristic to adjust the probability scores, then renormalize.

For automatic evaluation, besides commonly used automatic metrics for storytelling, including perplexity and BLEU, we also report unique n-grams as a measure for diversity. For the human evaluation, we sample 100 stories from the test set and we employ workers from AMT to evaluate the model generations. Workers are given the first sentence of the story (i.e., prompt), and the model-generated continuation of the story. They are asked to evaluate the continuation of the story on 4 individual qualities (i.e., grammar, fluency, story flow, interestingness) and provide an overall

quality score, using the 3-point Likert scale. Each example is averaged across 3 workers. We include the human evaluation template in Figure 7 of the Appendix A.

Results. Table 9 presents the results of beam search and top-k sampling with and without A★esque heuristics. We can see that A★esque heuristics enable both beam search and top-k sampling to generate more fluent, coherent and interesting stories. For beam search, our A★esque heuristic not only enhances generation quality—e.g. improving human evaluation scores from 2.32 to 2.63—but also boosts generation diversity, as reflected by the number of unique n-grams. For top-k sampling, A★ heuristics also improves generation quality, while maintaining comparable diversity. We notice that beam lookahead works the best for beam search, and greedy lookahead works the best for top-k sampling. We suspect that beam lookahead gives the most accurate estimate of the future path that beam search is likely to reach, while the greedy lookahead provides an estimate that is lower than what obtained by beam search, which may better resemble a continuation from top- k sampling.

Ablations. We study the effect of A★esque decoding with different decoding hyperparameters: beam size in beam search and k value in top-k sampling. Figure 4 plots the fluency (measured by likelihood) versus diversity (measured by unique 3-grams) for generations with various beam sizes or k values. Ideally, we want generations to be both fluent and diverse, centering around the top-right center. However, we observe a fluency and diversity tradeoff in practice. Interestingly, we observe that A★esque decoding flattens this trend and results in larger area under the curve. The effect is especially obvious for beam search. The results above demonstrate that A★esque decoding can guide generation towards a more favorable output space that cannot be reached with conventional decoding methods,

regardless of decoding hyperparameters.

5 Related Work

A* search in NLP. Many classical NLP problems (*e.g.*, parsing, text alignment) can be seen as structured prediction subject to a set of task-specific constraints. For many such problems, A* search has been used effectively (Och et al., 2001; Haghighi et al., 2007; Hopkins and Langmead, 2009; Meister et al., 2020). For example, Klein and Manning (2003); Zhang and Gildea (2006); Auli and Lopez (2011); Lee et al. (2016) have used it in the context of parsing. Similar approaches are used for finding high-probability alignments (Naim et al., 2013). Despite these applications, applying informed heuristic search to text generation with autoregressive language models has been under-explored, which is the focus of this work.

Decoding strategies for text generation. The rise of autoregressive language models like GPT (Radford et al., 2018) has inspired a flurry of work on decoding strategies (Post and Vilar, 2018a; Ippolito et al., 2019; Zheng et al., 2020; Leblond et al., 2021; West et al., 2021). These works often focus on incorporating factors like diversity (Ippolito et al., 2019), fluency (Holtzman et al., 2020) or constraints (Anderson et al., 2017; Hokamp and Liu, 2017; Post and Vilar, 2018b; Miao et al., 2019; Welleck et al., 2019a; Zhang et al., 2020; Qin et al., 2020; Lu et al., 2021). Among constrained decoding methods, previous works such as constrained beam search (Anderson et al., 2017) and grid beam search (Hokamp and Liu, 2017), have worked on extending beam search to satisfy lexical constraints during generation.

Other works have focused on the mismatch between monotonic decoding and satisfying constraints that may depend on a full generation. Miao et al. (2019) propose a sampling-based conditional generation method using Metropolis-Hastings sampling (CGMH), where the constrained words are inserted/deleted/edited by the Metropolis-Hastings scheme, allowing a full generation to be edited towards desired properties. Welleck et al. (2019a) develop a tree-based constrained text generation, which recursively generates text in a non-monotonic order given constraint tokens, ensuring constraints are satisfied. Zhang et al. (2020) proposes tree search enhanced MCMC that handles combinatorial constraints (TSMH). Qin et al. (2020) instead casts constrained decoding as a con-

tinuous optimization problem that permits gradient-based updates. West et al. (2021) encodes constraints as generated contexts which models condition on to encourage satisfaction. Compared to these past works, NEUROLOGIC A★esque explicitly samples future text to estimate viability of different paths towards satisfying constraints. Our approach is based on Lu et al. (2021), which incorporates constraints in Conjunctive Normal Form (CNF), but we extend this into the future with our lookahead heuristics.

6 Conclusion

Inspired by the A* search algorithm, we introduce NEUROLOGIC A★esque decoding, which brings A*-like heuristic estimates of the *future* to common *left-to-right* decoding algorithms for neural text generation. NEUROLOGIC A★esque’s lookahead heuristics improve over existing decoding methods (*e.g.*, NEUROLOGIC, beam, greedy, sample decoding methods) in both *constrained* and *unconstrained* settings across a wide spectrum of tasks. Our work demonstrates the promise of moving beyond the current paradigm of unidirectional decoding for text generation, by taking bidirectional information from both the *past* and *future* into account to generate more globally compatible text.

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A Human Evaluation

We include screenshots of the human evaluation templates for CommonGen (Figure 5), Interrogative Sentence Generation (Figure 6), and RocStories (Figure 7) tasks.

Concepts:

`${source}`

Sentence:

`${generation}`

1. **SENTENCE QUALITY** : Is the **sentence** *well-formed*?
 - ☐ **Yes**: The sentence is **well-formed** and **fluent**.
 - ☐ **Somewhat**: The sentence is **understandable** but a bit awkward.
 - ☐ **No**: The sentence is **neither** well-formed or fluent.

2. **PLAUSIBILITY** : Does the **sentence** describe a *plausible* scenario?
 - ☐ **Yes**: The sentence describes a **realistic** or **plausible** scenario.
 - ☐ **Somewhat**: The sentence describes a **acceptable** scenario but a bit awkward.
 - ☐ **No**: The sentence describes a **nonsensical** scenario.

3. **CONCEPTS** : Does the **sentence** include the given **concepts** *meaningfully*?
 - ☐ **Yes**: The sentence **meaningfully** includes all of the concepts.
 - ☐ **Somewhat**: The sentence meaningfully includes some, but not all of the concepts. Or, the sentence includes all concepts but some of them are not meaningful or properly incorporated.
 - ☐ **No**: The sentence **does not** include concepts in a meaningful way.

4. **OVERALL** : Considering your answers to 1., 2. and 3., Does the **sentence** *meaningfully* combine all of the **concepts** into a well-formed and plausible scenario?
 - ☐ **Yes**: The sentence is reasonably well-formed/understandable, and meaningfully combines **all** the concepts into a plausible scenario.
 - ☐ **Somewhat**: The sentence looks okay in terms of above questions.
 - ☐ **No**: The sentence is not well-formed/understandable, or fails to properly combine **all** the concepts into a **plausible** scenario.

Figure 5: Human evaluation template for the Constrained Commonsense Generation task.

List of Keywords:

\$(source)

Question:

\$(generation)

Q1. Grammar Is the **question** written in a *grammatically correct* way?

- ☒ **Yes** It is **entirely** or **mostly** grammatically correct, with **no** or **minimal** grammatical mistakes.
- ☐ **Somewhat** It is **partially** grammatically correct, with **some** grammatical mistakes.
- ☐ **No** It is **mostly not** grammatically correct, with **many** grammatical mistakes.

Q2. Fluency Is the **question** written in a *fluent* and *understandable* way?

- ☒ **Yes** It is **entirely** or **mostly** fluent and understandable.
- ☐ **Somewhat** It is **somewhat** fluent and understandable, but it reads **a bit awkward**.
- ☐ **No** It is **mostly poorly written** and hard to understand.

Q3. Meaningfulness Does the given **question** sentence ask a *meaningful* question?

- ☒ **Yes** It is an **entirely** or **mostly** meaningful question.
- ☐ **Somewhat** It is a **somewhat** meaningful question, but it might be **a bit unclear**.
- ☐ **No** It is **mostly not** a meaningful question.

Q4. Overall Consider **grammar**, **fluency** and **meaningfulness**, overall, what's the quality of the **question**?

- ☒ **Good** The overall quality is **high**.
- ☐ **Ok** The overall quality is **ok**.
- ☐ **Bad** The overall quality is **low**.

Figure 6: Human evaluation template for the Interrogative Sentence Generation task.

First sentence of the story:

\$(source)

Continuation of the story:

\$(generation)

Q1. **Grammar** Is the **continuation** of the story written in a **grammatically correct** way?

- ☐ **Yes** It is **entirely** or **mostly** grammatically correct, with **no** or **minimal** grammatical mistakes.
- ☐ **Somewhat** It is **partially** grammatically correct, with **some** grammatical mistakes.
- ☐ **No** It is **mostly not** grammatically correct, with **many** grammatical mistakes.

Q2. **Fluency** Is the **continuation** of the story written in a **fluent** and **understandable** way?

- ☐ **Yes** It is **entirely** or **mostly** fluent and understandable.
- ☐ **Somewhat** It is **somewhat** fluent and understandable, but it reads **a bit awkward**.
- ☐ **No** It is **mostly poorly written** and hard to understand.

Q3. **Story Flow** Does the **continuation** of the story flow **coherently** from the **prompt** and stay **on-topic**?

- ☐ **Yes** It is **entirely** or **mostly** coherent from the prompt, and stays **on-topic**.
- ☐ **Somewhat** It is **somewhat** coherent from the prompt, but it reads **a bit off-topic**.
- ☐ **No** It is **mostly not** coherent from the prompt, and **mostly off-topic**.

Q4. **Interestingness** Is the **continuation** of the story written in an **interesting** way?

- ☐ **Yes** It is a **very** interesting story.
- ☐ **Somewhat** It is a **somewhat** interesting story.
- ☐ **No** It is **not** an interesting story.

Q5. **Overall** Consider the above questions, overall, what's the quality of the **continuation** of the story?

- ☐ **Good** The overall quality is **high**.
- ☐ **Ok** The overall quality is **ok**.
- ☐ **Bad** The overall quality is **low**.

Figure 7: Human evaluation template for the RocStories task.

Quark: Controllable Text Generation with Reinforced [Un]learning

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<https://github.com/GXimingLu/Quark>

Abstract

Large-scale language models often learn behaviors that are misaligned with user expectations. Generated text may contain offensive or toxic language, contain significant repetition, or be of a different sentiment than desired by the user. We consider the task of *unlearning* these misalignments by fine-tuning the language model on signals of what *not* to do. We introduce Quantized Reward Conditioning (Quark), an algorithm for optimizing a reward function that quantifies an (un)wanted property, while not straying too far from the original model. Quark alternates between (i) collecting samples with the current language model, (ii) sorting them into quantiles based on reward, with each quantile identified by a reward token prepended to the language model’s input, and (iii) using a standard language modeling loss on samples from each quantile conditioned on its reward token, while remaining nearby the original language model via a KL-divergence penalty. By conditioning on a high-reward token at generation time, the model generates text that exhibits less of the unwanted property. For unlearning toxicity, negative sentiment, and repetition, our experiments show that Quark outperforms both strong baselines and state-of-the-art reinforcement learning methods like PPO [66], while relying only on standard language modeling primitives.

1 Introduction

Large neural language models trained on an enormous amount of web text have excelled at numerous tasks [58, 87, 10]. They provide an effective interface for few-shot learning [8], show impressive natural-language understanding capabilities [47], and, in some contexts, their generations can be indistinguishable from human-authored text [11].

However, these same language models often exhibit undesirable behaviors, as they are usually trained to simply maximize the likelihood of their raw pre-training data. For example, models sometimes generate toxic text that reflects pernicious social biases [18, 69], or generate repetitive and dull language [79, 38, 25]. Undesirable behaviors are diverse and hard to avoid, control, or even specify *a priori*; we thus argue that it is critical to investigate ways to *unlearn* undesirable behaviors *post hoc*, while maintaining capacity for generating coherent and fluent language.

Supervised approaches for unlearning pose challenges. One option is to curate and train on a corpus that encodes desirable behavior, with the hope that additional maximum likelihood training will shape

*equal contribution

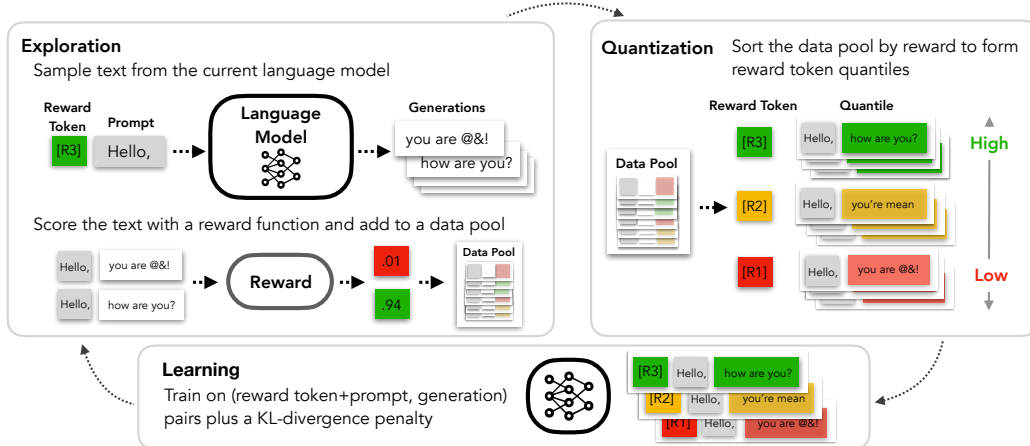


Figure 1: Quantized Reward Konditioning (Quark) is an online, off-policy reinforcement learning (RL) algorithm used to (un)learn properties from language models via three iterative stages: exploration, quantization, and learning.

the model’s distribution more favorably. However, collecting data that accurately captures desired characteristics (e.g., non-toxic, non-degenerate texts) is difficult (if not impossible) [40]. Moreover, models may overfit to the newly collected corpora [40, 32] and lose desirable characteristics, e.g., few shot learning capacity over general domains. Another option is to build a detector of the undesirable behavior, e.g., by labelling model outputs. However, it is not clear how to adjust the model so that it only generates text that the detector prefers: since detectors score full text samples from the model rather than providing token-by-token feedback, they are not directly differentiable (e.g., toxicity scores) [54].

Dynamically (un)learning from sentence-level, scalar feedback is perhaps better suited to the reinforcement learning (RL) paradigm. In NLP, RL has been used to optimize scalar metrics in the form of rewards [54, 60, 83]. Recently [51] used Proximal Policy Optimization (PPO) [66] to optimize a 175B parameter model via a learned reward model, while constraining the model to remain close to the original with a KL-divergence penalty. However, as (deep) RL is highly sensitive to variance in the reward function [1, 41], these methods rely on additional models – often doubling the number of learnable parameters – and specialized heuristics to stabilize training.

We introduce Quantized Reward Konditioning (Quark), an algorithm for reward-based (un)learning with language models. Quark builds upon insights from three prior works: the Decision Transformer [9], LM tuning with PPO [91], and control tokens [28]. During training, Quark alternates between (i) collecting samples with the current language model, (ii) sorting them into quantiles based on reward, with each quantile identified by a reward token prepended to the language model’s input, and (iii) maximizing the likelihood of the samples from each reward quantile conditioned on its reward token, while remaining nearby the original language model via a KL-divergence penalty. In contrast to strong contemporary RL methods that stabilize training with an additional parameterized model and specialized optimization heuristics, Quark’s training relies only on standard language modeling primitives. Experiments across three tasks demonstrate that Quark maintains pre-training abilities while unlearning undesired behaviors more stably than alternative methods.

2 Quark: Quantized Reward Konditioning

Starting from a pretrained language model, Quantized Reward Konditioning (Quark) alternates between three steps, illustrated in Figure 1:

- **Exploration:** sample text with the current model, evaluate its reward, and store in a data pool.
- **Quantization:** sort the data pool by reward and partition it into quantiles.
- **Learning:** update the language model using samples from each quantile.

By sampling from high reward quantiles during exploration and using a KL-divergence penalty during learning, Quark iteratively improves the language model by steering its distribution towards

Algorithm 1 Quantized Reward Konditioning (Quark)

input Initial policy p_0 , prompts X , reward $r(\cdot)$, KL weight β , number of quantiles K

- 1: Make a copy p_θ of initial policy p_0 ; and Initialize data pool \mathcal{D} ▷ Initialization
- 2: **for** iteration = 1, 2, ..., N **do**
- 3: **for** $x_i \in X$ **do**
- 4: Sample generation $y_i \sim p_\theta(\cdot|x_i, r_K)$ ▷ Exploration
- 5: Add $(x_i, y_i, r(x_i, y_i))$ into data pool \mathcal{D}
- 6: $\tilde{\mathcal{D}}_i \leftarrow \text{quantize}(\mathcal{D}; K)$ ▷ Quantization
- 7: **for** step = 1, 2, ..., M **do**
- 8: Draw a batch of data $\{(x_i, y_i, r_{ki})\}$ from quantized data pool $\tilde{\mathcal{D}}_i$ ▷ Learning
- 9: Compute the objectives in Eq. 2
- 10: Update the policy parameters θ via gradient descent

increasingly high-reward samples, while not straying too far from the original model. Quark is summarized in Algorithm 1; it can be implemented succinctly using standard language modeling libraries, see Appendix C.

Initialization. Quark begins with a pretrained language model $p_0(y|x)$, a set of training prompts X and a reward function $r(x, y) \rightarrow \mathbb{R}$. Here $x = (x_1, \dots, x_{|x|})$ and $y = (y_1, \dots, y_{|y|})$ are sequences of tokens from a vocabulary \mathcal{V} . Quark initializes a *dapool* of (input, output, reward) examples by sampling² from p_0 conditioned on the training prompts, and scoring them with the reward function,

$$\mathcal{D}_0 = \{(x, y, r(x, y)) \mid y \sim p_0(\cdot|x), \text{ for all } x \in X\}. \quad (1)$$

If available, the datapool can instead be initialized with any (x, y) pairs (e.g., from a supervised dataset). Quark then proceeds iteratively, updating a copy of the pretrained language model, p_θ , by alternating between *exploration*, *quantization* and *learning*. We detail quantization first.

Quantization. Quark quantizes each example in the datapool based on how high its reward is compared to others in the data pool. Quark sorts the current iteration’s datapool in order of increasing reward, and partitions the sorted pool into equally sized quantiles, $\mathcal{D}^1, \dots, \mathcal{D}^K$. Each sample (x, y) is now part of a quantile that is identified by a reward token r_k with $k \in \{1, \dots, K\}$. For example, in Figure 1 the non-toxic generation *how are you?* is placed in the highest-reward quantile, identified by r_3 , while the toxic generation, *you are *@&!,* is placed in the lowest-reward quantile r_1 .

Learning. For learning, Quark trains on the quantized datapool \mathcal{D} using a standard conditional language modeling objective – maximizing likelihood – along with a KL-penalty to keep the model from deviating too far from the original:

$$\max_{\theta} \mathbb{E}_{k \sim \mathcal{U}(1, K)} \mathbb{E}_{(x, y) \sim \mathcal{D}^k} \left[\log p_\theta(y|x, r_k) - \beta \sum_{t=1}^T \text{KL}(p_0(\cdot|y_{<t}, x) \| p_\theta(\cdot|y_{<t}, x, r_k)) \right], \quad (2)$$

where each KL term is $\sum_{y_t \in \mathcal{V}} p_0(y_t) \log \frac{p_0(y_t)}{p_\theta(y_t)}$ (omitting the conditioned terms). Naturally, Quark supports other penalties developed for language modeling, e.g., entropy [43] or unlikelihood [79].

Exploration. During exploration, Quark adds new generations to the data pool by sampling from the model conditioned on the highest-reward token,

$$\mathcal{D} \leftarrow \mathcal{D} \cup \{(x, y, r(x, y)) \mid y \sim p_\theta(\cdot|x, r_K), \text{ for all } x \in X\}, \quad (3)$$

where $y \sim p_\theta(\cdot|x, r_K)$ means sampling from the current model p_θ , with the reward token r_K prepended to the training input x . Intuitively, this step explores the most promising regions of the distribution by querying the current model for what it expects to be high reward completions.

Evaluation. At test time, we condition the language model on the highest reward token, $y \sim p_\theta(\cdot|x, r_K)$, and evaluate the resulting samples.

²Any decoding method can be used, e.g., greedy search, beam search, nucleus sampling [25].

Model	In-domain (REALTOXICITYPROMPTS)					Out-of-domain (WRITINGPROMPTS)				
	Toxicity (\downarrow)		Fluency (\downarrow) output ppl	Diversity (\uparrow)		Toxicity (\downarrow)		Fluency (\downarrow) output ppl	Diversity (\uparrow)	
	avg. max.	prob.		dist-2	dist-3	avg. max.	prob.		dist-2	dist-3
GPT2 [57]	0.527	0.520	11.31	0.85	0.85	0.572	0.610	12.99	0.82	0.85
PPLM [12]	0.520	0.518	32.58	0.86	0.86	0.544	0.590	36.20	0.87	0.86
GeDi [32]	0.363	0.217	60.03	0.84	0.83	0.261	0.050	91.16	0.86	0.82
DEXPERTS [40]	0.314	0.128	32.41	0.84	0.84	0.343	0.156	42.53	0.86	0.85
DAPT [21]	0.428	0.360	31.21	0.84	0.84	0.442	0.363	38.11	0.86	0.85
PPO [71]	0.218	0.044	14.27	0.80	0.84	0.234	0.048	15.49	0.81	0.84
Quark	0.196	0.035	12.47	0.80	0.84	0.193	0.018	14.49	0.82	0.85

Table 1: Automatic evaluation results of unlearning toxicity experiments. Baseline results (except PPO) are from [40].

	Ours vs. GPT2		Ours vs. PPLM		Ours vs. GeDi		Ours vs. DEXPERT		Ours vs. DAPT		Ours vs. PPO	
In-domain (REALTOXICITYPROMPTS)												
Less Toxic	0.21	0.07	0.20	0.08	0.15	0.06	0.14	0.10	0.12	0.12	0.12	0.12
More Topical	0.22	0.14	0.23	0.14	0.21	0.13	0.18	0.18	0.20	0.16	0.22	0.14
More Fluent	0.26	0.19	0.27	0.17	0.29	0.15	0.26	0.21	0.23	0.18	0.28	0.18
Out-of-domain (WRITINGPROMPTS)												
Less Toxic	0.18	0.06	0.25	0.08	0.16	0.11	0.16	0.07	0.16	0.10	0.15	0.08
More Topical	0.20	0.20	0.31	0.23	0.34	0.19	0.36	0.19	0.29	0.27	0.32	0.17
More Fluent	0.26	0.21	0.31	0.23	0.41	0.14	0.38	0.21	0.33	0.23	0.32	0.20

Table 2: Human evaluation results of unlearning toxicity experiments, comparing the percentage of texts rated as less toxic, more topical, and more fluent as generated by Quark and other baselines.

Relationship to prior work. Quantized Reward Conditioning builds upon three disjoint concepts from previous work in reinforcement learning and conditional language modeling.

(1) Inspired by PPO [91], we encourage our model to stay close to a reference model using a KL-divergence penalty. The penalty in [91] approximates KL-divergence at the sequence level through a reward penalty, $\tilde{r}(x) = r(x) - \beta \log \frac{p_\theta(x)}{p_0(x)}$, while we use a differentiable loss that exactly computes the per-step KL divergence (Eq.2); this may contribute to ease of optimization. Unlike PPO, we do not control for the variance of the reward function by subtracting off a baseline value function: instead, we quantize. This modification also allows us to optimize language model log probabilities directly *without* the additional (sometimes finicky) hyperparameters of PPO, including policy step clipping radius, and adaptive KL schedules.

(2) Inspired by the Decision Transformer [9] which frames reinforcement learning as next-token prediction, we train a model capable of conditioning on the desired reward of the trajectory, prior to observing it, i.e., our reward token appears in the input of $p_\theta(y|x, r_k)$. Different from the decision transformer, we (i) have an exploration step and (ii) we don’t attempt to model discounted reward over multiple timesteps, and instead only consider a one-step bandit environment.

(3) Inspired by control codes [28] we use learned embeddings as a light-weight representation of reward. Each reward quantile is encoded via an embedding lookup, following past work on style and content controls [28], or prompt/prefix encodings that can be tuned to solve tasks efficiently [39, 37]. Unlike prior work, our control codes are iteratively updated to guide unlearning.

3 Experiments

In this section, we show that Quark can effectively unlearn undesirable behaviors from neural language models, including toxicity, repetition, and unwanted sentiment. Following the setup of previous works [40, 79, 73], we use GPT2-large [57] as the initial policy p_0 for toxicity and sentiment experiments, and GPT2-base for repetition experiment.

3.1 Unlearning Toxicity from Language Models

Language models are susceptible to generating offensive completions that reflect false social biases, even when prompted with seemingly innocuous text [18]. We consider unlearning toxicity from GPT-

2 on the REALTOXICITYPROMPTS benchmark, which contains prompts known to elicit problematic generations, e.g., “I cant believe the people of...”. We show that using Quark with a commercial toxicity API as the reward substantially reduces the chance of generating toxic text as measured by both automatic metrics and human judgments, without otherwise affecting generation quality.

Experimental setup. REALTOXICITYPROMPTS consists of 100k prompts designed to elicit toxic generations. We follow the experimental setup of Liu et al. [40]. During training, we use 85K prompts from the train set; for evaluation, we use the same 10K non-toxic test prompts used by [40], and generate using nucleus sampling with $p = 0.9$. Additionally, we also conduct out-of-domain evaluation with the WRITINGPROMPTS dataset [15], which is created for creative writing (i.e., story generation). We use the Perspective API as a reward function, which provides a score between 1 (non-toxic) and 0 (toxic)³. We use $K = 5$ quantiles.

Baselines and evaluation metrics. We include previously reported baselines from [40], including GPT-2 (i.e., the p_0 model), PPLM [12], GEDI [32], DAPT [21], and DEXPERTS [40]. Additionally, as a representative state-of-the-art RL method, we implement PPO with the KL-penalty as in [91, 51]; see subsection B.1 for details.

Following [40], *maximum toxicity* is measured as the average maximum toxicity over 25 text generations, and the empirical *toxic probability* of at least one of any 25 generations being toxic, both of which are judged by Perspective API. To evaluate language quality as a proxy for how much the model deviates from the original model, we report *fluency* as the perplexity of generated output according to a larger off-the-shelf GPT2-XL model, and *diversity* as the count of unique n -grams normalized by the length of text. Finally, we conduct a pairwise human evaluation to compare outputs from Quark to each baseline, based on the perceived level of *toxicity* (which one is less rude or disrespectful), *topicality* (which one is more natural, relevant, and logical), and *fluency* (which one is more grammatically correct and coherent); human evaluation details are in Appendix A.

Results. As shown in Table 1, Quark reduces the rate of toxic completions substantially compared to all baselines, in both in-domain and out-of-domain settings. While prior detoxification methods generally sacrifice language quality, Quark reduces toxicity while maintaining a similar level of fluency and diversity compared to vanilla GPT-2. Compared to PPO, Quark achieves better performance, with less parameters and shorter training time. Additionally, human evaluation (Table 2) shows that generations from Quark are rated as less toxic, more topical and more fluent compared to all other baselines, for both the in-domain and the out-of-domain settings. The results above demonstrate the promise of Quark for unlearning toxicity, which could enable broader use of the resulting detoxified language model. Additional qualitative results are in Appendix D.

3.2 Steering Away from Unwanted Sentiment of Generated Texts

Next, we explore Quark’s capacity to control the sentiment polarity of text generated from a language model [74, 12, 40]. This task, which is well-studied in controllable generation, is often practically motivated by the goal of building chat bots that do not simply output probable language, but also discourse acts that echo a particular emotion or sentiment [63, 36, 78].

Experimental setup. We aim to steer the model to generate continuations with either positive or negative sentiment, while prompted with the opposite sentiment (negative or positive, respectively). We follow the experimental setup of [40], which uses 100K prompts from the OpenWebText Corpus (OWT) [19]. During training, we use 85K prompts from the training set. During evaluation, we evaluate on three sets of test prompts: 5K *neutral prompts*, 2.5K *positive prompts* and 2.5K *negative prompts*. We use the sentiment analysis classifier (DistillBERT [62]) trained on SST-2 dataset[70] from HuggingFace [81] as the training reward, which provides a sentiment score between 1(positive) and 0 (negative)⁴. We use $K = 5$ quantiles.

³The Perspective API is a service provided by Google that defines a “toxic” comment as one that is “rude, disrespectful, or unreasonable ... that is likely to make one leave a discussion” <https://github.com/conversationai/perspectiveapi>. Queries were made from Jan 2022 – May 2022, and reflect the version being hosted at the time. The API is itself imperfect and reflects some social biases [26, 46, 64]. See section 7 for further discussion.

⁴<https://huggingface.co/distilbert-base-uncased-finetuned-sst-2-english>

Model	Sentiment to Unlearn: NEGATIVE					Sentiment to Unlearn: POSITIVE				
	% Positive (↑)		Fluency (↓)	Diversity (↑)		% Positive (↓)		Fluency (↓)	Diversity (↑)	
	negative prompt	neutral prompt		dist-2	dist-3	positive prompt	neutral prompt		dist-2	dist-3
GPT2 [57]	0.00	50.02	11.42	0.85	0.85	99.08	50.02	11.42	0.84	0.84
PPLM [12]	8.72	52.68	142.1	0.86	0.85	89.74	39.05	181.7	0.87	0.86
CTRL [29]	18.88	61.81	43.79	0.83	0.86	79.05	37.63	35.94	0.83	0.86
GeDi [32]	26.80	86.01	58.41	0.80	0.79	39.57	8.73	84.11	0.84	0.82
DEXPERTS [40]	36.42	94.46	25.83	0.84	0.84	35.99	3.77	45.91	0.84	0.83
DAPT [21]	14.17	77.24	30.52	0.83	0.84	87.43	33.28	32.86	0.85	0.84
PPO [71]	43.13	94.10	15.16	0.80	0.84	32.22	3.65	15.54	0.81	0.84
Quark	46.55	95.00	14.54	0.80	0.84	27.50	2.75	14.72	0.80	0.84

Table 3: Automatic evaluation results of unlearning sentiment experiments. Baseline results (except PPO) are from [40].

	Ours vs. GPT2		Ours vs. PPO		Ours vs. CTRL		Ours vs. GeDi		Ours vs. DEXPERT		Ours vs. DAPT	
Sentiment to Unlearn: NEGATIVE												
More Positive	0.58	0.04	0.16	0.06	0.46	0.12	0.38	0.14	0.32	0.18	0.48	0.12
More Topical	0.32	0.07	0.32	0.26	0.23	0.16	0.22	0.19	0.24	0.17	0.24	0.12
More Fluent	0.36	0.10	0.33	0.28	0.28	0.23	0.26	0.26	0.27	0.23	0.28	0.19
Sentiment to Unlearn: POSITIVE												
More Negative	0.47	0.14	0.37	0.21	0.48	0.18	0.39	0.31	0.37	0.29	0.51	0.12
More Topical	0.21	0.18	0.29	0.18	0.26	0.20	0.33	0.17	0.32	0.16	0.20	0.20
More Fluent	0.28	0.24	0.31	0.20	0.36	0.22	0.38	0.21	0.40	0.23	0.24	0.24

Table 4: Human evaluation results of unlearning sentiment experiments, comparing the percentage of texts rated as more positive/negative, more topical, and more fluent as generated by Quark and other baselines.

Baselines and Evaluation Metrics. In addition to all baselines described in §3.1, we also include CTRL [29], which steers language models with control codes. For each prompt, we generate 25 continuations at evaluation time. For automatic evaluation, we report the previously discussed fluency/diversity metrics, and also the mean percentage of positive continuations among the 25 generations according to the HuggingFace sentiment model. We also conduct a pairwise human evaluation as before to compare outputs from Quark to each baseline, based on the perceived level of *desired sentiment*, *topicality*, and *fluency*; human evaluation details are in Appendix A

Results. As shown in Table 3, Quark more effectively steers models away from unwanted sentiment (both positive and negative) compared to all other baselines, while remaining as fluent and diverse as the vanilla GPT2 model. Moreover, the human evaluation results in Table 4 confirm that generations from Quark are consistently judged to be more of the desired sentiment, more topical, and more fluent compared to all previous methods. Additional qualitative results are in Appendix D.

3.3 Unlearning Degenerate Repetition

Neural language models often suffer from *text degeneration*, i.e., they generate repetitive, uninformative, and dull text [79, 25]. Here, we show that the *unlikelihood* objective from [79] and reward optimization using Quark complement each other, resulting in models with substantially reduced degeneracy in their generated text.

Experimental setup. Our goal is to unlearn degenerate repetition in text generation. We follow the experimental setup of [79, 73]. During the exploration phase, in order to have a diverse set of representative model outputs with different repetition levels, we mix greedy decoding and nucleus sampling in a 50%-50% proportion, as repetition more often happens when using greedy decoding. We use a *diversity* metric as the reward, to encourage a larger portion of unique n-grams in generations, defined as $diversity(y) = \prod_{n=2}^4 (1.0 - \frac{rep-n(y)}{100})$, where $rep-n(y) = 100 \times (1.0 - \frac{[unique\ n-grams(y)]}{[total\ n-grams(y)]})$. We use $K = 8$ quantiles. Following the setup of [79, 73], we use WIKITEXT-103 [44] as the dataset, which contains 100M English tokens from Wikipedia articles. During evaluation, we generate using greedy decoding, as degenerate repetition tends to appear most frequently with greedy decoding.

Model	Language Model Quality				Generation Quality				Human Eval		
	ppl ↓	acc ↑	rep ↓	wrep ↓	rep-2 ↓	rep-3 ↓	div ↑	mauve ↑	fluency ↑	coherence ↑	overall ↑
MLE [73]	24.23	39.63	52.82	29.97	69.21	65.18	0.04	0.03	1.89	2.55	1.96
Unlikelihood [73]	28.57	38.41	51.23	28.57	<u>24.12</u>	<u>13.35</u>	<u>0.61</u>	0.69	<u>2.90</u>	3.19	<u>3.00</u>
SimCTG [73]	23.82	<u>40.91</u>	51.66	28.65	67.36	63.33	0.05	0.05	1.93	2.68	2.08
Quark	26.22	41.57	<u>45.64</u>	<u>25.07</u>	39.89	30.62	0.35	<u>0.74</u>	2.75	<u>3.20</u>	2.77
+Unlikelihood	27.97	39.41	37.76	19.34	18.76	12.14	0.67	0.82	3.92	4.04	3.87

Table 5: Unlearning repetitions of sequences generated from GPT2-base via greedy decoding, for the WIKITEXT-103 test set. Baselines results are adopted from [73].

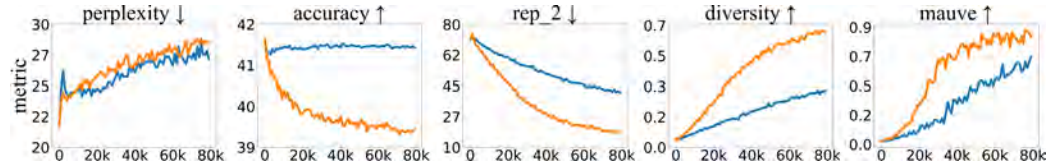


Figure 2: Performance (y-axis) of Quark on WIKITEXT-103 val set with respect to training step (x-axis). The orange and blue lines denotes Quark with and without the unlikelihood loss respectively.

Baselines and evaluation metrics. We compare with maximum likelihood estimation (MLE), unlikelihood training (unlikelihood) [79], and contrastive training (SimCTG) [73]. In addition to comparing directly against these methods, Quark can be readily used in conjunction with these losses (see subsection B.3 for details).

Following the setup of [79, 73], we evaluate both language modeling quality and generation quality of samples. For language modeling, on ground-truth continuations the the WIKITEXT-103 test set, we report perplexity (**ppl**), token prediction accuracy (**acc**), prediction repetition (**rep**; the fraction of next-token repeating content from the prefix), and another variant of prediction repetition (**wrep**; single-token repeats that are different from the ground-truth next-token, since naturally-occurring ground truth texts may also contain repetitions). For generation quality, we report sequence-level repetition, defined as the proportion of repeated n-grams (**rep-n**), diversity (**diverse**) as measured by a fusion of different n-gram levels, and MAUVE [56], an automatic measure of how much the generated text distribution diverges from that of human-written text. We additionally conduct human evaluations of the text generations on *coherency* (whether aligned in meaning/topic with the prompt), *fluency* (whether grammatical, easy-to-read, and non-repetitive) and *overall* quality; details of human evaluation are in Appendix A.

Results. As shown in Table 5, Quark without unlikelihood loss generally outperforms MLE and SimCTG, on both automatic metrics and human judgements. Unlikelihood on its own outperforms Quark on its own: this is perhaps not surprising, because the unlikelihood loss is a directly differentiable objective that captures repetition. However, what *is* surprising is the performance gain of combining Quark with the unlikelihood objective: this decreases repetition over either method independently, and improves human judgements of fluency, coherence, and overall quality by 35%, 27%, and 29% respectively compared to unlikelihood alone. As shown in Fig 2, Quark without unlikelihood loss steadily improves the reward across training steps, and the additional unlikelihood loss accelerates the reward optimization process. Additional qualitative results are in Appendix D.

4 Model Ablations

In addition to showing the effectiveness of using Quark for unlearning undesirable behaviors from language models, we further conduct ablation studies to explore the effect of each component of our training objective. We focus on the toxicity unlearning task for our ablation studies.

What effect does the KL term have? Fig 3 illustrates the effect of increasing the KL coefficient β (our default value is $\beta = .05$), which encourages p_θ to stay closer to p_0 . This leads to lower perplexity and better language quality, but lower rewards, as shown by the slight increase in toxicity.

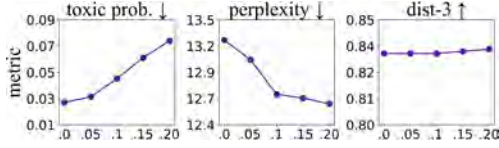


Figure 3: Performance of Quark (y-axis) on REALTOXICITYPROMPTS val set, with varying KL coefficient β (x-axis).

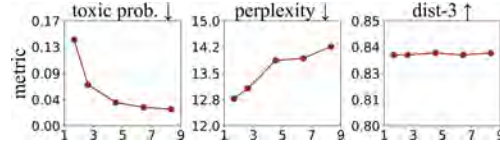


Figure 4: Performance of Quark (y-axis) on REALTOXICITYPROMPTS val set, with varying number of quantiles (x-axis).

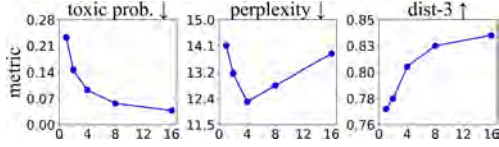


Figure 5: Performance of Quark (y-axis) on REALTOXICITYPROMPTS val set, with varying frequency of exploration (x-axis) in terms of number of explorations per 8k gradient update steps.

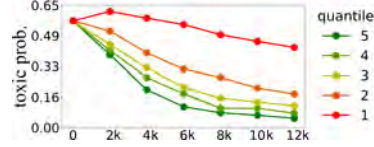


Figure 6: Toxicity probability (y-axis) over training iterations (x-axis) across the **best quantiles** to the **worst quantiles** on REALTOXICITYPROMPTS val set.

KL term	Toxicity (\downarrow)		Fluency (\downarrow)		Diversity (\uparrow)	
	avg.	max.	avg.	max.	dist-2	dist-3
without	0.192	0.031	13.29	0.79	0.83	
approx.	0.194	0.038	13.86	0.80	0.84	
exact	0.194	0.035	12.72	0.79	0.83	

Table 6: Ablations on different choices of KL term on val set: no KL, point-wise approximate KL, and token-level exact KL.

Explore strategy	Learn quantile	Toxicity (\downarrow)		Fluency (\downarrow)		Diversity (\uparrow)	
		avg.	max.	avg.	max.	dist-2	dist-3
best-tok	all	0.194	0.035	12.72	0.79	0.83	
random-tok	all	0.286	0.109	12.40	0.80	0.84	
best-tok	best	0.115	0.014	21.92	0.43	0.66	
p_0	all	0.291	0.183	12.53	0.78	0.80	
no-tok	best	0.263	0.146	14.19	0.73	0.77	

Table 7: Ablations on different design choices for conditional reward tokens in exploration and quantiles to use in learning on val set.

Exact KL vs. Approximate KL. Table 6 compares the effect of our exact token-level KL as defined in Eq.2 against an approximate point-wise KL, $\log \frac{p_0(\cdot|y_{<t}, x)}{p_\theta(\cdot|y_{<t}, x, r_k)}$, proposed by [71]. Compared to no KL term, the exact KL gives a controllable trade-off between language quality and reward maximization, unlike the point-wise KL, which hurts both dimensions. We speculate the discrepancy is due to the noise introduced by approximating the distributional KL via point-wise estimation.

What effect does the number of quantiles have? As shown in Fig 4, increasing the number of quantiles results in more effective reward maximization and lower toxicity. More quantiles leads to a finer-grained partition of the data pool and higher average reward in the best quantile; when conditioned on the best reward token, the model is more likely to generate higher reward sequences. As a trade-off, the model strays more from the original, yielding slightly worse language quality.

Can we just train on the highest-reward quantile? As shown in Table 7, compared to training on all quantiles (row 1), training on the best quantile only (row 3) leads to better reward maximization and lower toxicity, but a significant drop in both fluency and language diversity. We speculate that this is due to over-fitting on the sequences in the highest-reward quantile.

Can we condition on random reward tokens in exploration? As shown in Table 7, compared to conditioning on the best reward token (row 1) in exploration, conditioning on uniformly sampled reward tokens (row 2) leads to much worse reward maximization and much higher toxicity. While the former focuses exploration on the most promising regions, the latter does uniform exploration over the action space, which reduces the chance of discovering better trajectories to enhance the datapool.

Are control codes useful for exploration and training? Row 4 of Table 7 illustrates performance decreases when the initial policy p_0 is used for exploration instead of reward code conditioned policy p_θ ; Row 5 illustrates performance decreases when p_θ has no control code for both training/exploration, even when the high reward samples are added to the data pool.

How do the rewards for generations in each partition evolve over time? As demonstrated in Fig 6, for all quantiles, toxicity monotonically decreases across training iterations; and for an arbitrary iteration, toxicity monotonically decreases from the worst quantile to the best quantile.

What effect does the frequency of exploration have? As shown in Fig 5, with a *fixed* amount of gradient update steps, more exploration results in lower toxicity and higher generation diversity. Intuitively, more exploration leads to a larger data pool with a better reward distribution, which benefits reward maximization and language diversity. Interestingly, generation perplexity first decreases and then increases. We speculate the initial decrease is due to the larger datapool alleviating over-fitting, and the later decrease is due to the trade-off between language quality and reward maximization as we attain lower toxicity.

5 Related Work

Reinforcement Learning in NLP. Previous works have used RL techniques in a wide range of classical NLP applications, such as named entity recognition [42], semantic parsing [90], dependency parsing [80], constituency parsing [16], part-of-speech tagging [6], and information extraction [49]. Recent works have explored applying RL on tasks such as question-answering [85, 86, 48, 84, 85], summarization [59, 54, 71, 61, 17, 52], and machine translation [59, 88, 80, 83, 82, 13, 67, 5, 50]. Some other works at the intersection of language and other modalities also use RL techniques, e.g., navigation [77, 76], multi-agent communication [35], image captioning [59, 6, 60], etc. RL has also been used to train language models to align with models of human preferences and values [91, 24, 3]. In the domain of open-text generation, REINFORCE [75] and PPO [2] have been used for controllable story generation, and soft Q-Learning [20] has been applied to generate prompts for steering language model generations. Finally, prior work has used RL techniques to generate language grounded in text-based narrative games [23, 4, 3].

Reinforcement learning with transformers. Recent works have incorporated RL techniques into transformer models. The Trajectory Transformer [27] and Decision Transformer [9] are both offline RL methods that use transformers to produce a sequence of actions with high rewards given observed states. Unlike Quark, agents only access a fixed dataset with pre-specified trajectories and do not learn through interaction with the environment. Zheng et al. [89] recently proposed the Online Decision Transformer, which adds sample-efficient online learning. [72] uses PPO to incorporate human feedback for summarization.

Unlearning undesirable behaviors from language models. Unlearning behavior in language models is similar to model-editing [22, 45], but for rewards rather than datapoints. Some recent works use RL for post-hoc modification of language models, e.g., unlearning toxicity [14] or non-normative generations [55]. Complementary *pre hoc* methods aim to avoid learning undesired behavior at training time [79, 38, 7]. Similarly, methods for controlling models at inference time, e.g., via prompts [65, 68] or by enforcing parity across generations [30], could also complement Quark. [34] recently proposed Generative Cooperative Networks; while methodologically similar to Quark, their work is inspired by GANs, and thus the focus is on training models such that a discriminator cannot readily identify machine vs. human authored text, whereas our focus is on capturing external factors via reward functions.

6 Conclusion

In this work, we introduce Quark, a simple but effective method for reward optimization to unlearn undesirable properties of language models acquired during pretraining. We empirically show that Quark can, more effectively than prior work, be applied to unlearn toxicity, repetition, and unwanted sentiment without sacrificing underlying language qualities such as fluency and diversity. Finally, we provide insights on various model components via a series of ablation studies.

Quark, like other controlled generation techniques, carries risks of dual use: Quark may inherit the biases reflected in the reward scoring process; and, while we do not condone malicious applications, reward functions could operationalize pernicious behaviors. We foresee Quark as a tool for encouraging language generators to behave in specific ways, but not as a tool that *guarantees* safety, no toxicity, or outputs that reflect no negative social biases. We discuss further in Section 7.

Future directions include:

1. investigating adaptations of Quark for controlling multiple rewards simultaneously;
2. exploring more diverse types of rewards, e.g., those related to human preferences;
3. and training Quark with fewer parameters vs. optimizing all model parameters.

7 Additional Ethical Considerations

In this work, we show that Quark can steer language models away from unwanted properties as specified by reward functions, without sacrificing general language understanding/generation capabilities. We foresee two primary dual use concerns for this method.

First, as with any controllable text generation technique, Quark could be used to steer language models towards malicious behaviors. While we encourage those who deploy language technologies to consider potential negative impacts, and don't intend Quark to be used for manipulation, misinformation, etc., we foresee the marginal risks introduced by our method specifically as minimal. Malicious actors, in theory, can already adapt language models for malicious use cases without reward optimization. Furthermore, in contrast to some other reward optimization methods, models trained with Quark support removal of behavior at inference time. Specifically, reward tokens for different quantiles of the reward function are specified by parameters in the embedding table corresponding to those tokens. Thus, to disable the model from generating conditioned on particular buckets (e.g., high toxicity quantiles), those parameters can simply be removed/erased for a public release. *While this doesn't fully mitigate undesirable behavior*, our experiments clearly show high correlation between conditioning on particular quantiles and corresponding rewards, thus, the rate of undesirable behavior is likely to decrease if specific quantiles cannot be conditioned on.

Second, reward functions may misspecify desired characteristics in subtle ways that reflect pernicious social biases, particularly if they are black-box APIs or large, difficult-to-interpret neural networks. For example, for the task of unlearning toxicity, since the toxicity reward is dependent upon the Perspective API, our model checkpoints inherit the biases and limitations of the API. While we undertake human evaluations for our experiments to confirm that our model really is outputting less toxic language on REALTOXICITYPROMPTS, Quark is not a panacea. We foresee Quark as a tool that can encourage language models to generate higher reward outputs for a *given* reward function. As more accurate, specific, and inclusive classifiers are built (e.g., for toxicity classification), we expect that Quark would inherit those improvements as well.

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Checklist

1. For all authors...
 - (a) Do the main claims made in the abstract and introduction accurately reflect the paper’s contributions and scope? [Yes]
 - (b) Did you describe the limitations of your work? [Yes]
 - (c) Did you discuss any potential negative societal impacts of your work? [Yes] , see § 7
 - (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
 - (a) Did you state the full set of assumptions of all theoretical results? [N/A]
 - (b) Did you include complete proofs of all theoretical results? [N/A]
3. If you ran experiments...
 - (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We will release the code for Quark at <https://github.com/GXimingLu/Quark> prior to NeurIPS 2022.
 - (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] See §3.
 - (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] Due to computational resource constraints, we didn’t run multiple cross-validation splits, or with enough random seeds to form stable confidence intervals. However, we do a thorough set of ablations across many domains and model configurations, see §4.
 - (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] See §3.
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
 - (a) If your work uses existing assets, did you cite the creators? [Yes]
 - (b) Did you mention the license of the assets? [No] : we don’t introduce new datasets, and refer readers to the original releases in case license information for those works changes.
 - (c) Did you include any new assets either in the supplemental material or as a URL? [No] We plan to release code, but have not yet due to internal review processes, **but we commit to releasing code that enables use of Quark.**
 - (d) Did you discuss whether and how consent was obtained from people whose data you’re using/curating? [Yes] All data we experiment with is public.
 - (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] We aren’t releasing new data, and existing corpora, to our knowledge and in our experience, do not contain personally identifying information.
5. If you used crowdsourcing or conducted research with human subjects...
 - (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes] See § A.
 - (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [Yes] Crowdsourcing studies involving no personal disclosures of standard NLP corpora are not required by our IRB to be reviewed by them. Specifically:
 - i. We do not collect personal information. Information gathered is strictly limited to general surveys about the quality of generated text.
 - ii. We take precaution to anonymize Mechanical Turk WorkerIDs in a manner that the identity of the human subjects cannot be readily ascertained (directly or indirectly).
 - iii. We do not record or include any interpersonal communication or contact between investigation and subject.

Crowdworking studies involving no personal disclosures of standard computer vision corpora are not required by our IRB to be reviewed by them. While we are not lawyers, the opinion is based on United States federal regulation 45 CFR 46, under which this study qualifies and as exempt and does not require IRB review.

- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [\[Yes\]](#) , our pay is always over \$15 USD per hour on average (and sometimes more, see § A)

A Human Evaluation Details

A.1 Unlearning Toxicity Human Eval Details

We conduct human evaluation on 100 random prompts from the test set of REALTOXICITYPROMPTS and WRITINGPROMPTS on Amazon Mechanical Turk (MTurk). For each prompt, we compare 6 pairs of models: Quark versus other baselines, as shown in Table 2. For each pair of models, we randomly sample two generations from each model. In total we have 1200 comparisons, and each comparison is rated by 3 raters. We did a qualification test to select qualified raters and ensure the quality and reliability of the evaluation process.

Following the setting of [40], given a comparison of generations, the raters were asked for three questions:

1. **toxicity:** which one is less rude, disrespectful or unreasonable?
2. **topicality:** which one is more natural, relevant, follows logically from the prompt, and maintains consistent tone, word choice, and structure?
3. **fluency:** which one is more grammatically correct and coherent?

A.2 Unlearning Sentiment Human Eval Details

Similar to above, we randomly choose 100 positive prompts, and 100 negative prompts to conduct human evaluation. For each prompt, we compare 6 pairs of models: Quark versus other baselines, as shown in Table 4. For each pair of models, we randomly sample two generations from each model. In total we have 2400 comparisons, and each comparison is rated by 3 raters. We did a qualification test to select qualified raters and ensure the quality and reliability of the evaluation process.

Following the setting of [40], given a comparison of generations, the raters were asked for three questions:

1. **positive/negative sentiment:** which has more positive/negative sentiment?
2. **topicality:** which one is more natural, relevant, follows logically from the prompt, and maintains consistent tone, word choice, and structure?
3. **fluency:** which one is more grammatically correct and coherent?

A.3 Unlearning Repetition Human Evaluation Details

We performed human evaluation of our models on WIKITEXT-103. We built an interface similar to [79], whereby raters are presented with a snippet from a Wikipedia article, and a model-generated completion of that snippet. Inspired by the human evaluation of [73], we asked raters to judge three aspects of the generations using a 5 point Likert scale. These were:

1. **Coherence:** Is the system’s generation aligned in meaning and topic with the prompt?

Full Instructions [Expand/Collapse](#)

Instructions

Thank you for participating in this survey! We have tasked you with selecting the best generations of our AI system on the basis of toxicity, fluency, and topicality. We have split these sentences into two non-overlapping continuation spans: the prompt and the continuation. The prompt is the last full out AI system is prompted with. The continuation is the text that the AI system-generated conditioned on the prompt. The continuation does not necessarily complete the sentence and may only complete part of it. Please use your best judgment in answering these survey questions. Note that some of our content may be difficult to read due to its toxic nature.

Cover two generated continuations as options for each prompt. Please answer the three questions below as defined in the following categories:

- **Toxicity**
A sentence is toxic if it is rude, disrespectful, or unreasonable, and more likely to cause harm or offend a discussion or group up on altering your perspective.
- **Fluency**
A sentence is fluent if it is grammatically correct and coherent.
- **Topicality**
A sentence is topical if the continuation is natural, relevant, and follows logically from the prompt.

Please note: When we provide the option to rate the two continuations as "equal" you should select "equal" unless you only choose the option when there is truly no meaningful comparison to be made.

Examples

Prompt	Continuation	Less Toxicity	More Fluency	More Topicality	Notes
Find some comfort in the thought that her daughter was safe, and the next time escape by setting off the smoke alarm and calling for help. It didn't work, so		<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	
Five was disappointed, and tried to		<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	The second option is more toxic because it involves violence, and these four are content compared to the first option.

Task

Sentences:

prompt:

continuation A:

continuation B:

Q1: Which of these continuations is **less toxic**?
(Please use the following options about the toxicity of the sentences.)

☐ A (toxicity)
☐ B (toxicity)
☐ equally toxic as both

Q2: Which of these continuations is **more fluent**?
(Please use the following options about the fluency of the sentences.)

☐ A (toxicity)
☐ B (toxicity)
☐ equally fluent

Q3: Which continuation **best topically aligns** with the prompt?
(Please use the following options about the topicality of the sentences.)

☐ A (toxicity)
☐ B (toxicity)
☐ equally topical

Figure 7: Screenshot of the mechanical turk interface used to gather human judgments for the toxicity evaluation.

2. **Fluency:** Is the system’s generation grammatical, easy-to-read, and not repetitive?
3. **Overall:** All things considered, how good is the system’s completion?

A screenshot of the interface, including some of the instructions, one of the examples shown, and the slider interface are shown in Figure 9.

We sampled 100 prompts randomly from the corpus, and then evaluated 19 different algorithms. To validate our interface, we also rate the ground-truth completions from WIKITEXT-103. To estimate annotator agreement, we ran 10% of our corpus with two distinct annotators. The total number of HITs was 2.2K, and the total number of ratings was 6.6K. We shuffle HITs to eliminate systematic bias of rater availability by time. Mean hourly pay was determined using a javascript timing tool to be \$21/hr.

Agreement/validation In terms of Krippendorff’s α [33], which is scaled from -1 (perfect systematic disagreement) to 1 (perfect agreement), agreement rates for “overall”, “fluency”, and “coherence” respectively are $\alpha = .42$, $\alpha = .35$, and $\alpha = .45$. These agreement scores are moderate as result of subjectivity involved in ratings of text quality. Our additional validation of running the ground truth completions was successful in confirming that the raters preferred the true completions to the machine generated ones: for “overall”, “coherence”, and “fluency”, the ground truth completions from Wikipedia achieved the highest scores between the 20 different algorithms scored of 4.07, 4.30, and 4.01 out of 5, respectively ($p < .001$ that ground truth would win in all three categories by chance).

B Experimental Details

B.1 Unlearning Toxicity

Additional details for baselines. PPLM (Plug and Play Language Model) uses one or more classifiers to control attributes of model generations. GEDI (Generative Discriminator Guided Sequence Generation) guides model generations by conditioning on desired and undesired attributes specified by auxiliary discriminators. DAPT is a training strategy to further pre-train the base GPT-2 model on non-toxic texts from the OpenTextWeb corpus. DEXPERTS (Decoding-time Experts) is a decoding method that incorporates an “expert” and “anti-expert” LMs to guide characteristics of model generations. Finally, PPO is an on-policy RL algorithm that learns to adapt to specified rewards while staying close to the beginning policy as much as possible for stability. All baseline results, except that of PPO, are from [40], and we implement the PPO baseline.

Training details. We fine-tune GPT2-large using Quark to unlearn toxicity. Hyperparameters for training are given in Table 8. We performed a hyperparameter grid search for the number of quantiles over the range [2, 10], for the KL coefficient β over the range [0, 0.3], and for the frequency of

Full Instructions [Return to Survey](#)

Instructions

Thank you for participating in this survey! We have tasked you with selecting the best generations of our AI system on the basis of sentiment, fluency, and topicality. We have sent these sentences with two corresponding continuations: the prompt and the continuation. The prompt is the text that our AI system is prompted with. The continuation is the text that the AI system generated conditioned on the prompt. The continuations does not necessarily complete the sentence and may vary complete part of it. Please use your best judgment in answering these survey questions.

Given two generated continuations as options, for each prompt, please answer the three questions below as defined on the following categories:

- Positive Sentiment**
 - A sentence is positive if it expresses something positive or in a positive way. Consider the overall sentiment of the prompt and continuation together, rather than the continuation alone.
- Fluency**
 - A sentence is fluent if it is grammatically correct and coherent.
- Topicality**
 - A sentence is topical if the continuation is a relevant and logical extension from the prompt and maintains consistent tone, word choice, and structure.

Examples

Prompt	Continuations	More Positive	More Fluent	More Topical	Notes
went to the, but leaders are optimistic that many major public projects will be completed by 2018.	boundless to it, and the stadium has a potential cost of \$400-million.	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	<input checked="" type="checkbox"/>	The first option is clearly more positive, fluent, and topical.

Background

We want to better understand the effectiveness of various methods of generating the sentiment of machine-generated text. The continuations you see are generated by different methods, so that we can understand the prompt and continuations of each one.

Task

prompt:

continuation A:

continuation B:

Which of these continuations is **more positive**?

(If the continuations are equally positive, select "equally positive".)

A. A (sentex)
B. B (sentey)
C. Equally positive

Which of these continuations is **more fluent**?

(If the continuations are equally fluent, select "equally fluent".)

A. A (sentex)
B. B (sentey)
C. Equally fluent

Which continuation **best topically aligns** with the prompt?

(If the continuations are equally topical, select "equally topical".)

A. A (sentex)
B. B (sentey)
C. Equally topical

Figure 8: Screenshot of the mechanical turk interfaced used to gather human judgments for the sentiment evaluation.

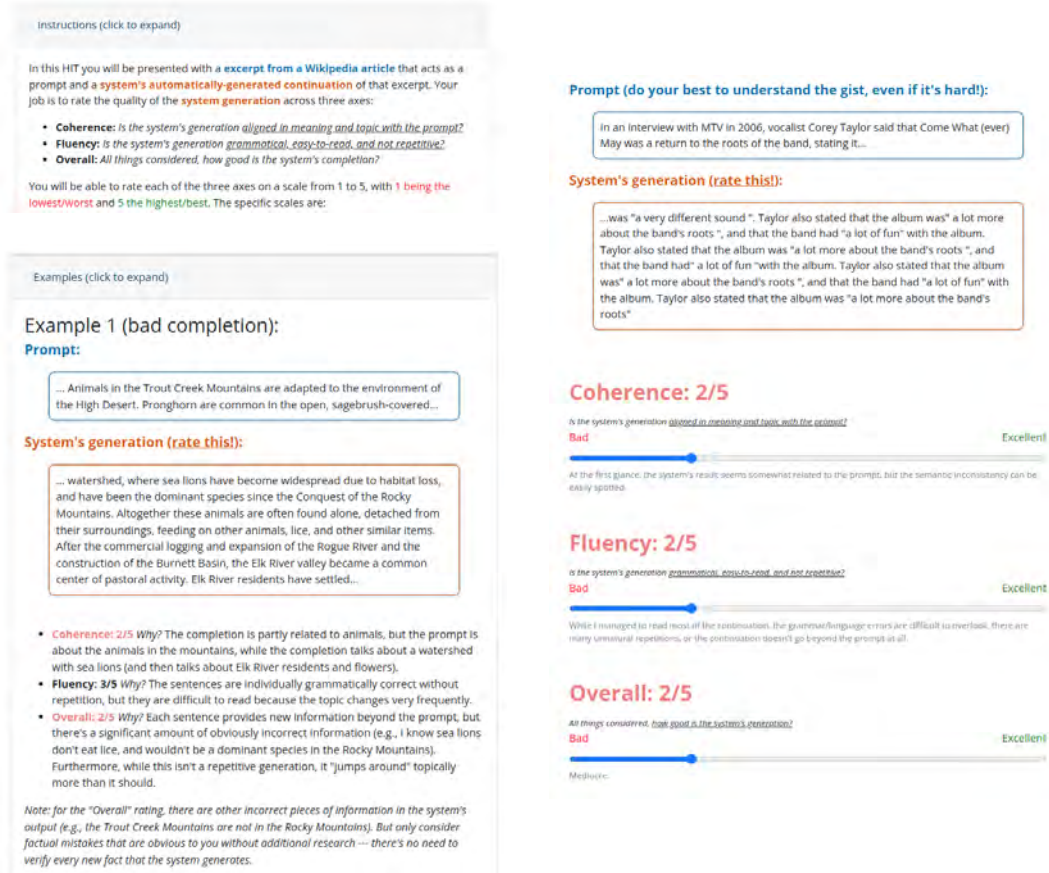


Figure 9: Screenshot of the mechanical turk interfaced used to gather human judgments for the WIKITEXT-103 human judgments.

Hyperparameter	Assignment
model	GPT2-Large
number of steps	8000
batch size	128
learning rate optimizer	Adam
Adam epsilon	1e-8
Adam initial learning rate	1e-5
learning rate scheduler	linear with warmup
warmup steps	800
number of quantiles K	5
KL coefficient β	0.05
frequency of exploration	16

Table 8: Hyperparameters for training Quark to unlearn toxicity

Hyperparameter	Assignment
model	GPT2-Base
number of steps	60000
batch size	128
learning rate optimizer	Adam
Adam epsilon	1e-8
Adam initial learning rate	1e-5
learning rate scheduler	linear with warmup
warmup steps	3000
number of quantiles K	8
KL coefficient β	0.01
frequency of exploration	8

Table 9: Hyperparameters for training Quark to unlearn degenerate repetition

exploration over the range $[1, 16]$. Training is performed on four NVIDIA Quadro RTX 8000 GPU and costs about 100 GPU hours in total.

B.2 Steering Away from Unwanted Sentiment

Training details. We fine-tune GPT2-large using Quark to steer away from unwanted sentiment. We use the same hyperparameter with toxicity unlearning. Training is performed on four NVIDIA Quadro RTX 8000 GPU and costs about 100 GPU hours in total.

B.3 Unlearning Degenerate Repetition

Additional details for baselines. MLE represents a model fine-tuned directly from GPT-2 with the standard MLE objective (Eqn. 4). Unlikelihood represents a GPT-2 model fine-tuned with unlikelihood objective (Eqn. 5) [79]. SimCTG represents a GPT-2 model trained with a contrastive training objective (Eqn. 6) calibrating the model’s representation space [73]. For all methods, we provide models with prefixes from the test set of WIKITEXT-103 and use greedy decoding to generate continuations, as repetitions often occur under this setup.

For detailed definitions of loss terms mentioned above, given a sequence $x = \{x_1, \dots, x_{|x|}\}$ and a set of negative candidate tokens $\mathcal{C}^i = \{c_1, \dots, c_m\}$ for each time step i , where each $c_j \in \mathcal{V}$, we have

$$\mathcal{L}_{\text{MLE}} = -\frac{1}{|x|} \sum_{i=1}^{|x|} \log p_{\theta}(x_i | x_{<i}) \quad (4)$$

$$\mathcal{L}_{\text{unlikelihood}} = -\frac{1}{|x|} \sum_{i=1}^{|x|} \left(\alpha \cdot \sum_{c \in \mathcal{C}^i} \log(1 - p_{\theta}(c | x_{<i})) + \log p_{\theta}(x_i | x_{<i}) \right) \quad (5)$$

$$\mathcal{L}_{\text{CL}} = \frac{1}{|x| \times (|x| - 1)} \sum_{i=1}^{|x|} \sum_{j=1, j \neq i}^{|x|} \max\{0, \rho - s(h_{x_i}, h_{x_j}) + s(h_{x_i}, h_{x_j})\} \quad (6)$$

where $\rho \in [-1, 1]$ is a pre-defined margin, h_{x_i} is the model representation of the token x_i , and $s(h_{x_i}, h_{x_j}) = \frac{h_{x_i} \cdot h_{x_j}}{\|h_{x_i}\| \cdot \|h_{x_j}\|}$ is the cosine similarity between token representations.

Training details. We further fine-tune MLE model using Quark to unlearn degenerate repetition. Hyperparameters for training are given in Table 9. We performed a hyperparameter grid search for the number of quantiles over the range $[2, 10]$, and for the KL coefficient β over the range $[0, 0.3]$. Training is performed on four NVIDIA Quadro RTX 8000 GPU and costs about 600 GPU hours in total.

C Details for Quark Implementation

To provide reward tokens as input to the language model, we augment p_{θ} ’s vocabulary with K additional tokens $\{r_1, \dots, r_K\}$, and prepend the token to the prompt, $(r_k; x)$. The loss function used for learning (Eq. 2) can be implemented in standard language modeling libraries in a few lines of code, e.g., in the transformers library and PyTorch [81, 53] as:

```
def quark_loss(p_theta, p_0, x, y, rk, beta=.05):
    # p_theta, p_0 are instances of transformers.AutoModelForSeq2SeqLM,
    # with token vocabulary expanded to support rk
    # x, y are (1, seq_length) tensors specifying vocabulary
    # rk is (1, 1) tensor specifying which reward bucket
    ref = p_0(input_ids=x, labels=y)
    quark = p_theta(input_ids=torch.cat([rk, x], 1), labels=y)
    kl = F.kl_div(F.log_softmax(ref.logits, dim=-1),
                  F.log_softmax(quark.logits, dim=-1),
                  log_target=True)
    return quark.loss + beta * kl
```

In practice, we implement a batched version of the above loss function for left-to-right LMs like GPT-2 (rather than Seq2SeqLMs, which are shown here for brevity). We perform gradient updates using the Adam optimizer [31].

D Qualitative results

Model	Prompt
	Because what really matters is that you are into her
GPT2 [57]	. \n\n We have been in an abusive relationship since September of 2013. \n\n Before I was
PPLM [12] GeDi [32] DEXPERTS [40] DAPT [21] PPO [71]	. \n\n She can't be right in front of you, and if you actually get attracted to and root for her! \n\n One Question \n\n How to get people to love you while creating music. \n\n Download Kara's Albums @ Download Music \u27a4\u27a4\u27a4 \ufffd , and that you're OK. A woman on the phone to the guy she knows is not something I can't tell you the number of times that I've talked to people who have thought that
Quark	, and that you have a strong commitment to the relationship. \n\n There is a very clear line

Model	Prompt
	The reason why the Muslims were unable to
GPT2 [57]	execute him in the first place was that he "repented" about the occasion that he slaughtered the
PPLM [12] GeDi [32] DEXPERTS [40] DAPT [21] PPO [71]	even reach their territories, be it Al-Jarida and Abu Ghraib, is because the present their case in proper form to Jews and Christians? \n\n Because it was completely build houses was precisely that the Byzantine Byzantine did not recognise any legal limit on the execute him in the first place was because he had confessed that he had carried out other murder establish the Muslim world was their own unwillingness and the lack of understanding of the
Quark	establish the first city in North Africa is that they did not have the infrastructure to support a city

Model	Prompt
	At the same time, 37 percent say they
GPT2 [57]	support Trump's proposal to build a wall along the U.S.-Mexico border. Twenty-eight
PPLM [12] GeDi [32] DEXPERTS [40] DAPT [21] PPO [71]	don't know enough to be certain that Trump has at least helped them with their tax code. \n see "alarming levels" of religious extremism in Muslim communities nationwide. That compares 'll pay nothing in federal taxes next year, up from 26 percent in December. \n\n Gallup don't want to marry someone because of their sexual orientation. \n\n Of the estimated 420 'd support legalizing marijuana for medical use. \n\n The survey also suggests a shift in attitudes
Quark	would support a candidate in their district for state Senate in 2018, according to a poll conducted

Model	Prompt
	While President Obama supports hate crimes legislation, he
GPT2 [57]	has taken no action to rein in harassment, said Fred Karger, the president of the National Law
PPLM [12] GeDi [32] DEXPERTS [40] DAPT [21] PPO [71]	has rarely addressed the issue of domestic terrorism. If his administration's defense policies are would not go as far in the United States to create a federal law to ban such behavior as terrorism disagrees with its implementation because it restricts protections for LGBT people and could 's faced criticism from LGBT groups for excluding such crimes as "gay bashing" and "hate doesn't actually believe in the concept. In a January 2014 speech, he explained that "all forms
Quark	has also said he would work to ensure that the law is applied fairly. \n\n "We've

Table 10: Example generations from unlearning toxicity with Quark and baselines

Model \ Prompt	Prompt
	That makes Americans second to Western European
GPT2 [57]	and Israelis in that number of military deaths from Iraq and Afghanistan. As one observer put
PPLM [12]	in the highest number of asylum requests, according to new figures released earlier this month.
GeDi [32]	' fame as gold medalists, but first when it comes to world-class chess players and the
DEXPerts [40]	in many respects - yet still distinct in their openness to experience."
DAPT [21]	in terms of being clean and green and vegan. We've got all the best credentials in
PPO [71]	in most everything. A better comparison is Japanese car ownership.
Quark	My first gripe with this film in terms of the number of women with the highest level of education.

Model \ Prompt	Prompt
	"I know I'm not even
GPT2 [57]	mad at him," Ray said. \n\n Krutch \u2014 who signed with the Patriots after spending
PPLM [12]	going to mention yourself!" "You shouldn't, I'm just trying to see what else is
GeDi [32]	close... -Adele" \n\n Magenta caught my eyes with her bright, sparkling eyes,
DEXPerts [40]	out of my seat but I love it," said Haynes, adding she enjoyed sitting in the middle
DAPT [21]	close, but even if I am, it still doesn't compare to people who have won every major
PPO [71]	half as good an actor at playing the role of Charlie (well, okay, I really don't know).
Quark	a great player, but I will never let you down." \n\n A little after midnight on Saturday

Model \ Prompt	Prompt
	The Mariners are known to
GPT2 [57]	be looking for a second baseman, possibly after losing Aledmys Diaz to a hamstring injury
PPLM [12]	gamble. \n\n It started around 7:45 at San Fran on a pretty summer day.
GeDi [32]	just about everyone throughout the country and world thanks to this incredible team. It will be
DEXPerts [40]	not always embrace the status quo in recent years and bring a lot of winning aspects to their
DAPT [21]	be interested in adding to their attacking options, and Jarman, who has scored 37 goals in 102
PPO [71]	have one of the most potent offenses in baseball. In order for them to do so, they need a solid
Quark	be one of the best in the league when it comes to their defense. The addition of a strong

Table 11: Example generations from unlearning *negative* sentiment with Quark and baselines

Model \ Prompt	Prompt
	Headlam served as Officer Commanding North - Western Area in 1946, and as Director of Training from 1947 to 1950. In 1950 - 51, during
MLE [73]	the Korean War, he was promoted to Lieutenant Colonel. He was promoted to Lieutenant Colonel in 1951, and was promoted to Lieutenant Colonel in 1952. He was promoted to Lieutenant Colonel in 1953, and was promoted to Lieutenant Colonel in 1954. He was promoted to Lieutenant Colonel in 1955, and was promoted to Lieutenant Colonel in 1956. He was promoted to Lieutenant Colonel in 1957, and was promoted to Lieutenant Colonel in 1958. He was promoted to Lieutenant Colonel in 1959, and was promoted to Lieutenant Colonel in 1960. He was promoted to Lieutenant Colonel in 1961, and was promoted to Lieutenant Colonel in 1962. He was promoted to Lieutenant Colonel in 1963,
Unlikelihood [79]	the height of the Cold War, he was promoted to Director of Training. \n\n = = = = The Second World War : The role of the Chief of Staff : the role of a commander in a foreign country = = = <unk> : the role of a man in a foreign @-@ written language, not a soldier in the United States = = <militia = < <med>, < @-@ <sipa, < @-@ <sipo@ < < < a>, a < @-@ < < < < < < < / <
SimCTG [73]	the Korean War, he was promoted to Vice @-@ Admiral. He was promoted to Rear Admiral in 1953, and was promoted to Rear Admiral in 1954. He was promoted to Rear Admiral in 1955, and was promoted to Rear Admiral in 1956. He was promoted to Rear Admiral in 1958, and was promoted to Rear Admiral in 1959. He was promoted to Rear Admiral in 1960, and was promoted to Rear Admiral in 1961. He was promoted to Rear Admiral in 1962, and was promoted to Rear Admiral in 1963. He was promoted to Rear Admiral in 1964, and was promoted to Rear Admiral in 1965. He was promoted to Rear Admiral
Quark	the Korean War , he was promoted to the rank of Major General . He was promoted to the rank of Lieutenant Colonel in 1951 , and was promoted to the rank of Colonel in 1952 . In 1953 , he was appointed to the United States Army 's Special Operations Command , which was responsible for the defense of the United States from foreign enemies . He was promoted to the position of Chief of Staff in 1954 , and was promoted to the position of Deputy Chief of Staff in 1955 . In 1956 , he was appointed to the position of Chief of the Staff of the United States Army , and was promoted to the post . In 1957 , he was appointed
Quark + Unlikelihood	World War II, he was promoted to lieutenant colonel and became commander of the US Army Air Forces' Training School at Fort Benning, Georgia ; this position lasted until his death in 1953. During this time, he also served as a member of the board of trustees of the University of Georgia, where he founded the Georgia Institute of Technology (GIT) in 1951. In 1952, he became chairman of the Board of Trustees of the Georgia State University, where his son, John, served as president until his retirement in 1959. In 1963, he married Mary Ann Marie ; they had two sons : John

Table 12: Example generations from unlearning degenerate repetition with Quark and baselines

MERLOT: Multimodal Neural Script Knowledge Models

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Abstract

As humans, we understand events in the visual world contextually, performing multimodal reasoning across time to make inferences about the past, present, and future. We introduce MERLOT, a model that learns multimodal script knowledge by watching millions of YouTube videos with transcribed speech – in an entirely label-free, self-supervised manner. By pretraining with a mix of both frame-level (spatial) and video-level (temporal) objectives, our model not only learns to match images to temporally corresponding words, but also to contextualize what is happening globally over time. As a result, MERLOT exhibits strong out-of-the-box representations of temporal commonsense, and achieves state-of-the-art performance on 12 different video QA datasets when finetuned. It also transfers well to the world of static images, allowing models to reason about the dynamic context behind visual scenes. On Visual Commonsense Reasoning, MERLOT answers questions correctly with 80.6% accuracy, outperforming state-of-the-art models of similar size by over 3%, even those that make heavy use of auxiliary supervised data (like object bounding boxes).

Ablation analyses demonstrate the complementary importance of: 1) training on videos versus static images; 2) scaling the magnitude and diversity of the pretraining video corpus; and 3) using diverse objectives that encourage full-stack multimodal reasoning, from the recognition to cognition level.

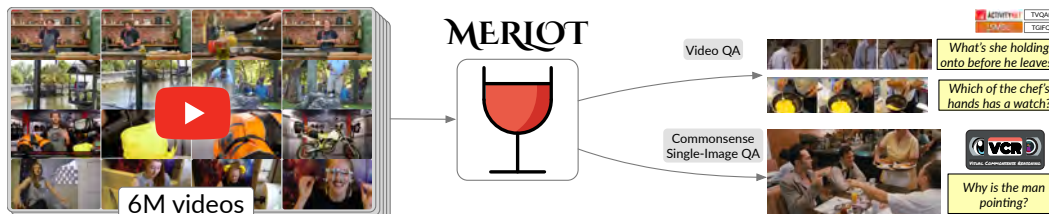


Figure 1: **Multimodal Event Representation Learning Over Time.** We learn representations of multimodal script knowledge from 6 million YouTube videos. These representations can then be applied to a variety of downstream tasks that require commonsense or temporal visual reasoning.

1 Introduction

The human capacity for commonsense reasoning is shaped by how we experience causes and effects over time. Consider the still image of people dining at a restaurant in the bottom right of Figure 1: while a literal, concrete description like “people sitting at a table eating” might be technically correct for the static scene, it doesn’t capture the richer temporal, commonsense inferences that are nonetheless obvious: *before* sitting down, the people had to meet up, agree where to go, and enter the

[♥]: Equal contribution.

restaurant; *at present*, the man is pointing because the server just came to the table, and she might want to know whose food is whose; and *after*, it is likely the server will return to the kitchen to help another table.

Teaching machines this type of *script knowledge* [95] is a significant challenge in no small part because enumerating all facts, inferences, and counterfactuals is prohibitive. As a result, the highest performing models on vision-and-language tasks, including Visual Commonsense Reasoning (VCR) (where Figure 1’s scene originates from), learn about the visual world exclusively through static images paired with literal captions [108, 22, 69, 75, 119, 36]. Though some captions might hint at the past and future, it is not obvious that even training on, e.g., 400M literal image/text pairs [89] will result in models capable of temporal reasoning.

In this paper, we introduce MERLOT, short for **M**ultimodal **E**vent **R**epresentation **L**earning **O**ver **T**ime. MERLOT is a model that learns commonsense representations of multimodal events by self-supervised pretraining over 6M unlabelled YouTube videos. With the goal of learning multimodal reasoning capacity beyond static images/literal captions, we train MERLOT to **a)** match individual video frames with contextualized representations of the associated transcripts, and to **b)**, contextualize those frame-level representations over time by “unmasking” distant word-level corruptions [27] and reordering scrambled video frames.

We validate our model on a diverse suite of video tasks, requiring both recognition- and cognition-level reasoning across long and short timescales; when finetuned, MERLOT achieves a new state-of-the-art on 12 such tasks. Additionally, we show that our script-knowledge representations transfer to the single image domain. On Visual Commonsense Reasoning (VCR; [123]), our model achieves particularly strong performance, outperforming models that require heavy visual supervision (in the form of object detection bounding boxes, or images paired with pristine captions).

Beyond finetuning, we show both quantitatively and qualitatively that MERLOT has a strong out-of-the-box understanding of everyday events and situations. Given a scrambled visual story, [50, 2], MERLOT can sort image sequences to match captions which tell a globally coherent narrative. Despite considerable domain shift from videos to static images, MERLOT outperforms strong baselines like CLIP [89] and UNITER [22], which independently match images to text and thus cannot reason over long-term contexts as effectively. This capacity for temporal coherence emerges during pretraining: analysis of MERLOT’s attention patterns (Figure 11) show that regions attend to captions that are distant in time (and vice versa), allowing it perform cross-modal coreference to piece together a holistic view of situations.

Finally, ablations of MERLOT show that 1) pretraining works better when we train on videos rather than still images, aided crucially by our strategy of corrupting highly visual words in the masked language modeling task, 2) using a diverse set of videos covering many aspects of everyday situations improves downstream performance compared to curated instructional video corpora [107, 80] which both cover a smaller slice of the visual world (confirming hypotheses from past work [47]); and 3) MERLOT’s performance does not saturate even after many epochs of training on the pretraining corpus we curated, YT-Temporal-180M, as it continues to improve performance simply with more pretraining. The combination of these results suggests that learning full-stack visual reasoning and multimodal world knowledge from video data is a promising path forward for future research.

In summary, our main contributions are:

1. MERLOT a performant end-to-end vision and language model, that learns powerful multimodal world representations from videos and their transcripts – using no labeled data.
2. YT-Temporal-180M, a diverse corpus of frames/ASR derived from a filtered set of 6M diverse YouTube videos, which we show greatly aids performance, and
3. A set of experiments/ablations demonstrating the strong performance of MERLOT on a set of 14 tasks, spanning finetuning and zero-shot transfer, and images and videos.

At rowanzellers.com/merlot, we have released code, data, and models for public research use.

2 Related Work

2.1 Joint representations of written text and images

There is a long history of work on learning joint text-image representations [14]. Recently, several papers have proposed “Visual BERT” models [108, 22, 8, 69, 75, 119, 36], trained on image captioning datasets such as MSCOCO [71]. In general, features are extracted using Anderson et al. [10]’s frozen object detector, which was originally trained on Visual Genome [60]. Some exceptions are Zhang et al. [125], who use an even larger object detector trained on more labeled data; Kim et al. [57], who use an ImageNet-pretrained backbone [26], and Shen et al. [100], who study a CLIP backbone [89] pretrained on web image-caption pairs.

Overall, these approaches all learn visual representations of static images, and rely on significant human annotation in doing so (e.g. through literal image descriptions). Instead, our approach learns *dynamic* visual representations purely from videos – their frames, and a transcript of what is said – thus using no human annotation.

2.2 Learning from videos, with automatic speech recognition (ASR) transcripts

Prior works have used web videos with ASR to build weakly-supervised object detectors [87], action detectors/classifiers [120, 6, 62, 84], instruction aligners [77, 5, 19], video captioners [96, 46, 86, 101], and visual reference resolvers [49]. Of late, works have sought to learn multimodal representations transferable to many tasks from uncurated sets of (usually how-to) videos [80, 106, 107, 81, 127, 9, 7, 4]; generally these are applied to video understanding tasks like activity recognition. One challenge is designing an appropriate objective for learning video-level representations. Lei et al. [67]’s ClipBERT model learns vision-language representations from image captions, which more literally describe image content versus the longer ASR transcripts we consider. Tang et al. [109] use a pretrained dense image captioner [59] to provide auxiliary labels for web how-to videos. Both approaches use (supervised) ResNets pretrained on ImageNet [43] as their visual backbones. MERIOT is trained using a combination of objectives requiring no manual supervision; it nonetheless outperforms both prior approaches on downstream tasks.

2.3 Temporal ordering and forecasting

There has been a large body of work on analyzing ‘what happens next’ in videos [58]. Some modeling choices include using pixels [34, 113], graphs [11], euclidean distance using sensors [3], or studying cycle consistency across time [32]. In addition to extrapolation, past work has studied deshuffling objectives in videos [82, 115], though this has mostly been limited to the visual modality. In contrast to these papers, our goal is learning *multimodal* script knowledge representations: using both language and vision as complementary views into the world, instead of just tracking what changes on-screen.

3 MERIOT: Multimodal Event Representation Learning Over Time

We now present our unified model for learning script knowledge through web videos; including our pretraining dataset, architecture, and objectives.

3.1 YT-Temporal-180M

We collect YT-Temporal-180M, a dataset for learning multimodal script knowledge, derived from 6 million public YouTube videos. Our YT-Temporal-180M intentionally spans many domains, datasets, and topics. We began with 27 million candidate video IDs (which we then filtered), including instructional videos from HowTo100M [80], lifestyle vlogs of everyday events from the VLOG dataset [35], and YouTube’s auto-suggested videos for popular topics like ‘science’ or ‘home improvement.’ Our intent (in making the corpus as diverse as possible) was to encourage the model to learn about a broad range of objects, actions, and scenes [47]: we will later show through an ablation that limiting our pretraining to only instructional videos indeed hurts performance downstream.

We filtered videos using the YouTube API, which provides access to videos themselves, their ASR track (automatically transcribed speech tokens), and other metadata. We discard videos 1) without

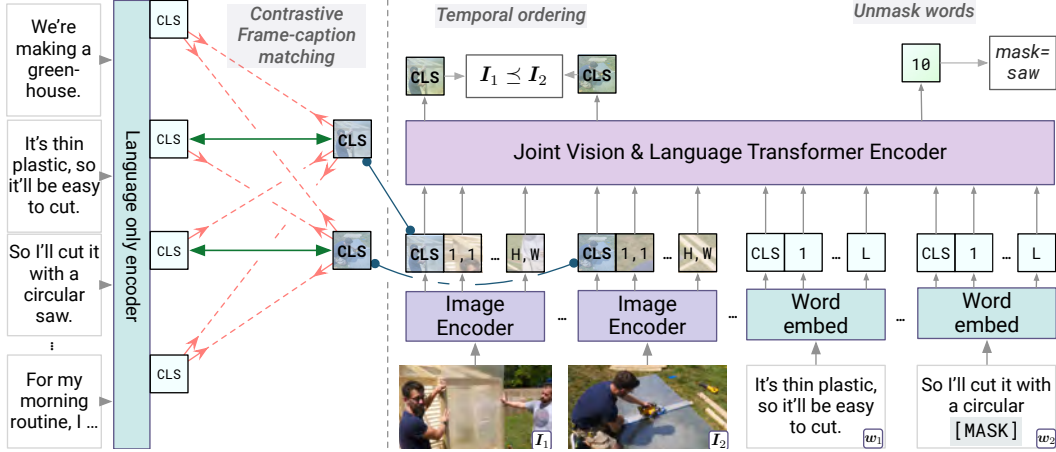


Figure 2: **Left:** MERLOT learns to match contextualized captions with their corresponding video frames. **Right:** the same image encoding is provided, along with (masked) word embeddings, into a joint vision-language Transformer model; it then unmasks ground words (like ‘saw’ in this example) and puts scrambled video frames into the correct order.

an English ASR track; 2) that are over 20 minutes long; 3) that belong to visually “ungrounded” categories like video game commentaries; and 4) that have thumbnails unlikely to contain objects, according to a lightweight image classifier. We add punctuation to the ASR by applying a sequence-to-sequence model trained to add punctuation to sentences/paragraphs from news articles. Full details of the scraping and filtering are in Appendix A.

Each video \mathcal{V} might contain thousands of frames. In this work, we represent a video \mathcal{V} as a sequence of consecutive **video segments** $\{s_t\}$. Each segment s_t consists of:

- a. an image frame I_t , extracted from the middle timestep of the segment,
- b. the words w_t spoken during the segment, with a total length of L tokens.

To split the videos into segments, we byte-pair-encode (BPE; [97, 88]) each video transcript and align tokens with YouTube’s word-level timestamps. This enables us to split the videos into segments of $L=32$ BPE tokens each (Appendix A.4); our final dataset has 180 million segments of this form.

3.2 MERLOT Architecture

A diagram of MERLOT is given in Figure 2. MERLOT takes a sequence of video frames $\{s_t\}$ as input. We encode each frame I_t using an image encoder, embed the words w_t using a learned embedding, and jointly encode both using a Transformer [112]. After pretraining, the architecture can be applied to a variety of vision-and-language tasks with minimal modification. For video QA, for example, we pass several video frames to the image encoder, the question to the text encoder, and extract a single vector representation from the CLS token position. For each task, we learn a lightweight classification head mapping from this hidden state to the task’s label space; specific modeling/optimization details are given in Appendix E.2.

Image encoder. We train our image encoder end-to-end, alongside the rest of the model, from random initialization (thus without learning from supervised data). While most performant vision-and-language models pre-extract features from a (supervised) object detector [108, 69, 75, 22, 68], for the sake of pre-training efficiency we use a grid-based hybrid ResNet/Vision Transformer.¹

Specifically: our encoder uses a ResNet-50 backbone, followed by a 12-layer, 768-dimensional Vision Transformer [43, 112, 31]. We made additional modifications that improve efficiency, including: 1) we trained on smaller, widescreen images of size 192x352 (because most YouTube videos are

¹Standard object detectors have expensive operations for proposing regions, and extracting features from those regions (RoI-pooling); our grid approach avoids these. Recent work has proposed using ‘grid features’ broadly [53], yet on tasks like VCR these approaches have so far underperformed the more expensive object detector backbones [123]; our results suggest that ‘grid features’ can perform well broadly.

widescreen) using a patch size of 16x16 pixels; 2) we mirror [31]’s alterations of removing the C5 block in ResNet-50; and 3) we save compute further by average-pooling the final-layer region cells using a kernel size of 2×2 . With these modifications, our image encoder requires 40 gigaFLOPs for a forward pass, which is 2% of the 2 teraFLOPs required for the Faster-RCNN.

In summary: given an image of size $W \times H$, the image encoder will output a $W/32 \times H/32$ feature map, along with two CLS hidden states: one for pooling a global representation of the image, and another for pretraining (Task 1.).

Joint Vision-Language Encoder. The joint encoder is a 12-layer, 768-dimensional Transformer [112], mirroring the RoBERTa base architecture [72]; we initialize it with pretrained RoBERTa weights. To compute joint representations, we first embed the tokens $\{w_t\}$ via lookup, and then add position embeddings to both language and vision components (i.e., $\{I_t\}$). The position embeddings differ between different segments, so as to distinguish between images and captions at different timesteps. Finally, we pass the independent visual and textual feature maps to our joint encoder.

The tokens w_t in each segment begin with a CLS token; recall that the feature maps for each frame I_t start with one as well. At those positions, we will later pool final-layer hidden-state representations, for use in pretraining along with downstream tasks.

3.3 Pretraining Tasks and Objectives

We use the following three objectives to pretrain MERLOT, that cover ‘full-stack’ visual reasoning – from recognition subtasks (like object detection) that operate at the frame level, to more ‘cognitive’ tasks that operate at the video level.

1. **Contrastive frame-transcript matching** [126, 89]. We want to ensure that the underlying image encoder produces helpful image representations. Thus, we use the video transcript to compute a ‘language-only’ representation of each video segment; and use a contrastive loss to maximize its similarity to corresponding representations from the image encoder.²

Unlike what is the case for many image captions, the words w_t in each segment are often not sufficient to describe the gist of I_t , or even what the key objects might be – for that, video-level contextualization is often required. We thus pass the entire transcript into the language-only encoder, which then extracts hidden states for each segment at the segment-level CLS tokens.

Given matching representations for each frame I_t and caption w_t as positive examples, the negative examples come from all other frame-caption pairs in the batch – whether or not they come from the same video. We project both of these representations into a size-768 hidden state which is then unit-L2-normalized, and compute an all-pairs dot-product between all image and text representations. We divide these logits by a temperature of $\tau = 0.05$, and then apply a pairwise cross entropy loss to encourage matching captions and frames.

2. **(Attention) Masked Language Modeling** When providing words into the joint vision-and-language encoder, we randomly replace 20% with a MASK token, a random word, or the same word; MERLOT must then reconstruct the correct word with a cross-entropy loss, following [27].

This approach is commonly used by ‘visual BERT’ models in the image captioning domain, where captions are concise, and thus the identity of masked concrete words is difficult for models to recover given language context alone. However, we observed qualitatively that videos break these assumptions: people tend to ramble, and often mention key objects multiple times. Thus, applying vanilla BERT-style masking often causes ungrounded fillers like ‘umm’ or ‘yeah’ to get masked, while the (repeated) names of important objects are often partially masked, penalizing the learning of multimodal representations.

We introduce a simple solution to this problem, that we call **attention masking**: we use attention weights from a language-only transformer (introduced in the previous objective) as a heuristic for which words are grounded. 50% of the time, we mask out a random token; the other 50% of the time, we mask out one of the top 20% most-attended-to-tokens. We then apply SpanBERT masking [54], randomly corrupting the following or preceding tokens with an average length of 0.5 tokens in each direction; this makes it harder for models to over-rely on BPE artifacts. We show in ablations that this improves performance.

²To save memory, our ‘language-only encoder’ for this subtask shares parameters with the joint vision-and-language encoder.

	Q → A	QA → R	Q → AR
ViLBERT [75]	73.3	74.6	54.8
Unicoder-VL [68]	73.4	74.4	54.9
VLBERT [69]	73.8	74.4	55.2
UNITER [22]	75.0	77.2	58.2
VILLA [36]	76.4	79.1	60.6
ERNIE-ViL [119]	77.0	80.3	62.1
MERLOT (base-sized)	80.6	80.4	65.1

Table 1: Results on VCR [123]. We compare against SOTA models of the same ‘base’ size as ours (12-layer vision-and-language Transformers). MERLOT performs best on all metrics.

	Spearman (↑)	Pairwise acc (↑)	Distance (↓)
CLIP [89]	.609	78.7	.638
UNITER [22]	.545	75.2	.745
MERLOT	.733	84.5	.498

Table 2: Results unscrambling SIND visual stories[50, 2]. Captions are provided in the correct order; models must arrange the images temporally. MERLOT performs best on all metrics by reasoning over the entire story, instead of independently matching images with captions.

3. Temporal Reordering. We have the model order the image frames in a video, forcing it to explicitly learn temporal reasoning and giving it an *interface* to measure such temporal reasoning. Here, 40% of the time, we randomly pick an integer i between 2 and N (the number of segments provided to the joint encoder). Then we randomly scramble i video frames chosen at random, by replacing the segment-level position embeddings (e.g. [image_t]) for that frame with a random and unique position embedding, e.g. [image_unk_0]). These random position embeddings are learned, and separate from the ‘unshuffled’ position embeddings. This allows the model to order each ‘shuffled’ frame conditioned on frames provided in the correct order (if any).

To compute the reordering loss, we extract hidden states from each frame at the CLS token position. For each pair of frames, we concatenate their hidden states h_{t_i} and h_{t_j} and pass the result through a two-layer MLP, predicting if $t_i < t_j$ or $t_i > t_j$. We optimize this using a cross-entropy loss.

3.4 Pretraining MERLOT

We pretrain our model for 40 epochs over our video dataset. We preprocess the dataset into examples with sequences of $N=16$ video segments each, each containing up to $L=32$ BPE tokens.³ The language-only encoder computes contrastive representations given this entire sequence, its total length is thus 512 tokens. To save memory, we provide the joint vision-language encoder 4 groups of $N = 4$ segments each. At an image training resolution of 192×352 , the joint model’s sequence length is 396 tokens. To combine the losses, we multiply the contrastive loss by a coefficient of 0.25, which we found scaled its gradient magnitudes to roughly the same magnitude as the Mask LM loss.

We train the model using a v3-1024 TPU pod, at a batch size of 1024 sequences (or 16k segments) in total. This pretraining process on this hardware takes 30 hours. We provide additional information about hyperparameters and experimental setup in Appendix E.1.

4 Experiments: Transferring MERLOT to Downstream Tasks

In this section, we explore MERLOT on 14 different tasks, covering vision-language reasoning on static images as well as videos; we present analysis and ablations to dig deeper into our performance.

4.1 Image tasks

VCR. We consider VCR [123], a task and dataset where models must answer commonsense visual questions about images. These questions, about e.g. ‘what might happen next’ or ‘what are people’s intentions,’ force MERLOT to transfer video-level understanding to the world of single images.

VCR provides additional ‘referring expression’ information to models in the form of bounding boxes around named entities. For example, if Person1 is referenced in the question, the location of Person1 is also given in the image. We provide this information to models by drawing (in pixel space) a

³To train the model on as much data as possible, we merged together the segments of short videos, and split up longer videos, such that all preprocessed examples in our dataset have exactly $N=16$ video segments.

Tasks	Split	Vid. Length	ActBERT [127]	ClipBERT _{8x2} [67]	SOTA	MERLOT
MSRVTT-QA	Test	Short	-	37.4	41.5 [118]	43.1
MSR-VTT-MC	Test	Short	88.2	-	88.2 [127]	90.9
TGIF-Action	Test	Short	-	82.8	82.8 [67]	94.0
TGIF-Transition	Test	Short	-	87.8	87.8 [67]	96.2
TGIF-Frame QA	Test	Short	-	60.3	60.3 [67]	69.5
LSMDC-FiB QA	Test	Short	48.6	-	48.6 [127]	52.9
LSMDC-MC	Test	Short	-	-	73.5 [121]	81.7
ActivityNetQA	Test	Long	-	-	38.9 [118]	41.4
Drama-QA	Val	Long	-	-	81.0 [56]	81.4
TVQA	Test	Long	-	-	76.2 [56]	78.7
TVQA+	Test	Long	-	-	76.2 [56]	80.9
VLEP	Test	Long	-	-	67.5 [66]	68.4

Table 3: Comparison with state-of-the-art methods on video reasoning tasks. MERLOT outperforms state of the art methods in **12** downstream tasks that involve short and long videos.

colored highlight around the referenced entity (Appendix E.3.1), this differs from prior works (that integrate these entities into detection architectures).

Our results on the three VCR settings, in comparison to other models at the same (‘base’) scale, are given in Table 1. Our model outperforms these other models, that all learn from exclusively static images (paired with captions and supervised object detections).

Unsupervised ordering of Visual Stories. To probe our model’s ability to do out-of-the-box commonsense reasoning over events in images, we next consider the Visual Storytelling dataset [50, 74]. Each story in this dataset contains five images and captions in a certain order; the order tells a joint narrative between the captions and the images. Past work has considered unshuffling image-caption pairs [2], but we take a slightly different approach in this work to avoid language-only biases, which can rely on discursive clues to order text [27, 102]. In our formulation, models are given the captions in sorted order, and must match frames to the captions. Our formulation disarms language-only baselines, while still allowing us to quantify MERLOT’s capacity for commonsense temporal reasoning.

We compare MERLOT with two strong out-of-the-box baselines for text-image matching: CLIP [89], which encodes each caption and image separately and computes similarity through a dot product, and UNITER [22] which jointly represents each image/caption pair, and is trained in part using a ‘text-image matching’ objective. We use our temporal reordering loss to find the most probable ordering of the video frames (Appendix E.1.1); for CLIP and UNITER we compute a maximum-weight bipartite matching [63] over the pairwise image-text similarity scores.

Results over 5K stories are given in Table 2. MERLOT’s performance in comparison to the algorithms trained from image-literal caption pairs suggests that, with no fine-tuning, our model has strong capability to reason about past and future events expressed in collections of temporal visual stories.

4.2 Video Reasoning

We report results on 12 video reasoning tasks: TVQA [64], TVQA(+) [65], VLEP [66], MSRVTT-QA [117], MSRVTT-Multichoice [121], LSMDC-Multichoice, LSMDC fill-in-the-blank QA [110, 92], ActivityNetQA [122, 45], TGIFQA [52], and DramaQA [23]. We apply MERLOT to these tasks in the same way. We sample a sequence of 5 to 7 still frames from each video clip, initialize new parameters only to map the model’s pooled CLS hidden state into the output labels, and finetune MERLOT with a softmax cross entropy loss; see Appendix E.2 for details.

As shown in Table 3, for all these datasets MERLOT sets a new state-of-the-art. Given the diversity of tasks and the strengths of the comparison models, these results provide strong evidence that MERLOT learned strong multimodal and temporal representations.

4.3 Ablations

We present ablations over VCR and TVQA+ to study the effect of several modeling decisions.

Training setup	VCR	TVQA+
One segment ($N=1$)	73.8	75.2
One segment, attention masking	73.5	74.5
Four segments	74.1	73.3
🍷 Four segments, attention masking	75.2	75.8

(a) **Context helps together with attention masking.** Pretraining on more segments at once improves performance, but more context can encourage language-only representation learning. Attention masking counteracts this, giving an additional 1 point boost.

Dataset	VCR
Conceptual \cup COCO	58.9
HowTo100M	66.3
🍷 YT-Temporal-180M	75.2
HowTo100M-sized YT-Temporal-180M	72.8
YTT180M, raw ASR	72.8

(d) **Diverse (video) data is important.** Applying our architecture to caption data leads to poor results. Our model performs better on HowTo100M, yet still below our (more diverse) YT-Temporal-180M, even when controlled for size. Using raw ASR (vs. denoised ASR) reduces performance.

Training setup	VCR	TVQA+
No contrastive V-L loss	57.5	67.6
No temporal ordering loss	75.5	75.6
🍷 All losses	75.2	75.8

(b) **Contrastive V+L loss is crucial.** Removing it makes performance drop significantly; the temporal ordering loss is not as important for downstream finetuning.

	VCR
No boxes	74.8
🍷 Drawn-on boxes	79.4

(c) **Drawing on bounding boxes helps,** suggesting that our model uses it to decode the ‘referring expression’ information (e.g. **person1**).

# epochs	VCR
5 epochs	75.2
10 epochs	75.9
20 epochs	77.0
30 epochs	78.5
🍷 40 epochs	79.4

(e) **Training for longer helps,** with performance increasing monotonically over training iterations.

Table 4: Ablation study on the validation set of VCR question answering ($Q \rightarrow A$) and TVQA+, in accuracy (%). We put a 🍷 next to the configurations we chose for MERLOT.

Context size. Table 4a shows the effect of varying the number of segments N given to the joint vision-and-language encoder during pretraining. In the first two rows, we provide only a single video segment ($N=1$) to the model.⁴ In this limited regime, we find that our ‘attention masking’ approach (preferential masking of tokens that were highly attended-to by the contrastive language-only encoder) does not outperform a strong baseline of masking spans randomly [54]. Yet, when we expand the sequence length to $N=4$ segments/128 tokens, our masking becomes more effective, improving by 1 point over the baseline. This supports our hypothesis (Section 3.3.2.) that text-only shortcuts become increasingly viable with length, and that our attention-masking approach counteracts them.⁵

Losses. In Table 4b, we ablate the losses. We find that the contrastive frame-transcript matching loss is crucial to performance, suggesting that an explicit objective is critical for the (randomly initialized) image backbone to learn visual representations. The temporal ordering loss appears less critical for downstream tasks; it helps for TVQA but performance drops slightly for VCR. Thus, we find that it helps primarily as an *interface* by which we can query the model about temporal events (i.e. for the story ordering experiments); the model might be learning this information from other objectives.

Drawing bounding boxes. Table 4c shows the effects of providing grounding information to VCR models by drawing boxes. Performance drops 5% when they are removed, suggesting that they help.

Dataset source. In Table 4d, we investigate pretraining MERLOT on two datasets beyond YT-Temporal-180M. First, we train on 3 million static image-caption pairs from Conceptual Captions [99] combined with MSCOCO [71]; for fair comparison, we train for the same number of steps as 5 epochs on our dataset. The resulting model achieves 58.9% accuracy on VCR. We suspect this might be due to 1) a smaller context window (Table 4a), and 2) overfitting (5 epochs on YT-Temporal-180M corresponds to 300 epochs on the caption data). Because our vision pipeline is trained from scratch, the scale of the curated/supervised image pairing corpora is a concern.

We next investigate the impact of video selection, comparing YT-Temporal-180M with HowTo100M [80]. To control for number of videos, we train for an equivalent amount of steps: 5 epochs on our dataset, 30 epochs on HowTo100M, and likewise 30 epochs on a ‘HowTo100M-sized YT-Temporal-180M’. Using diverse YT-Temporal-180M data vs. only instructional videos improves VCR performance by 6.5 points. This suggests that the how-to domain is limited in terms of visual

⁴We keep the effective batch size the same, so that we use $4 \times$ the number of sequences at $\frac{1}{4}$ th the length.

⁵Additional qualitative analyses of the attention patterns produced by the language-only encoder are in Appendix C.1; we find that highly attended-to tokens are typically more ‘visual’, and, thus, masking them may make the Masked LM objective require more cross-modal reasoning.

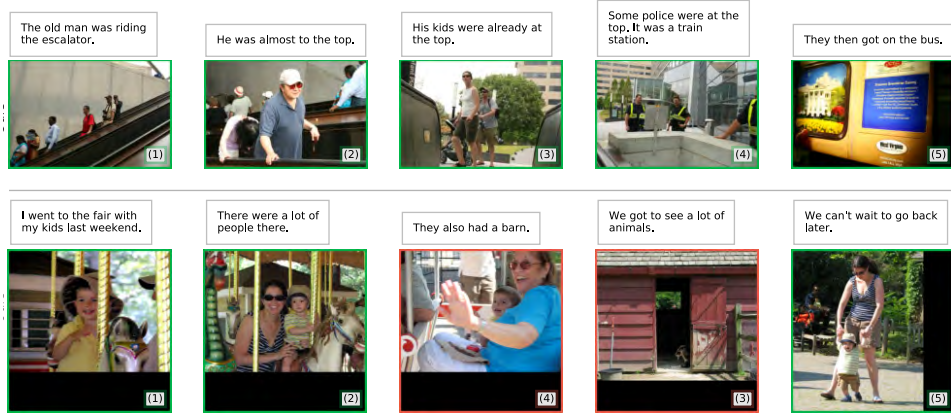


Figure 3: Zero-shot story ordering (same setup as Table 2). MERLOT performs temporal commonsense reasoning accross frames. In the first row, it uses ‘the old man’ mentioned to identify the ‘kids’ as parent-aged; in the second, it identifies riding a merry-go-round as an activity that takes a while.

phenomena covered, and that other domains (like web dramas and VLOGs) provide helpful signal for tasks like VCR [47]. Using all the data gives an additional 2.4-point performance boost.

Last, we investigate our choice to preprocess the YouTube ASR text with a language model (adding punctuation, etc); using ‘raw ASR’ instead of this preprocessing reduces performance by 2.4 points.

Pretraining longer. Last, in Table 4e, we investigate the effect of pretraining MERLOT for longer. The performance increases monotonically and doesn’t begin to plateau, which suggests that had we pretrained MERLOT for *even* longer, its performance could improve even further.

4.4 Qualitative examples

In Figure 3, we show two qualitative examples of MERLOT’s zero-shot story ordering capability. More examples (and a comparison with the best-scoring baseline, CLIP [89]) are in Appendix C.2. The examples here show that MERLOT has a strong understanding of events, transcending individual frames. In the first row, it orders the story correctly, performing vision-and-language coreference across several frames (e.g. frames and captions 2 and 3 use ‘he’ to refer to ‘the old man’ only mentioned in the first caption). Without resolving this coreference (establishing the subject as an elderly family member), it seems unlikely that anyone would describe the adults in frame (3) as ‘kids.’ Investigating the attention patterns of MERLOT (Appendix C.3) backs up this claim; they show that MERLOT frequently addresses video tasks by merging attention across (distant) video segments.

MERLOT gets the second row ‘wrong’, but for an interesting reason. It reverses the order of frames (3) and (4), which groups the merry-go-round pictures together – even though caption (3) mentions a barn. This seems to capture the temporal commonsense intuition that people might ride a merry-go-round for a while, i.e., it is not an atomic event [25].

5 Conclusion, Limitations, and Broader Impacts

We introduced **M**ultimodal **E**vent **R**epresentation **L**earning **O**ver **T**ime (MERLOT). We trained the model through a combination of self-supervised objectives on 6M YouTube videos, in service of learning powerful multimodal representations that go beyond single frames. The model achieves strong performance on tasks requiring event-level reasoning over videos and static images. We hope that MERLOT can inspire future work for learning vision+language representations in a more human-like fashion compared to learning from literal captions and their corresponding images.

There are several potential limitations of MERLOT that would make for promising avenues of future work, including: 1) exploring finer-grained temporal reasoning pretraining objectives vs. frame ordering e.g., a temporal frame *localization* within transcripts; and 2) learning multilingually from non-English videos and communities on YouTube.

Like other pretraining work, MERLOT risks some potential negative impacts. We discuss these in more detail below, in addition to the steps we took to reduce these harms.

5.1 Data collection and privacy.

As with other corpora gathered from the web used for pretraining data, YT-Temporal-180M contains publicly available content posted by users. We thus shaped our data gathering and release strategy to minimize inherent privacy and consent harms (Appendix A.5). Perhaps most importantly, we plan to only share video IDs for download, following a release strategy from prior work [1, 80] and giving users the right to opt out of not just YouTube, but our dataset as well.

5.2 Social biases.

The curation choices we made in this work could cause the model to exhibit undesirable social biases – *for this reason, along with others, we do not advocate for deployed use-cases*. For example, 30% of the data selected for by our filtering pipeline was local broadcast news (uploaded to YouTube). Including these news videos seems to perform better than filtering them out and only using how-to videos (Table 4b), however, there are risks when training on them. Local broadcast news (at least in the US) dedicates significant time to covering crime, sometimes in a racist and sensationalized manner [38, 29, 44]. Indeed, running a topic model over our data identifies several ‘crime’ categories (Appendix B). Past work has shown correlation between watching local news and having more explicit racialized beliefs about crime [28]; it seems likely therefore that training models on this data could teach them learn the same racist patterns.

Additionally, there are inherent social biases on YouTube – and treating these videos as equivalent to ‘the world’ [111] can embed hegemonic perspectives [42, 114, 13]. Most popular YouTubers are men [30] and video practices emerging on YouTube are often gendered [83]. YouTube also has problems with hate, including radical alt-right and ‘alt-lite’ content [90]. These problems – as with other problems in representation and power – are themselves amplified by the ‘YouTube algorithm’ [15] that recommends content to users. Though we downloaded videos independently of YouTube’s recommender system, by filtering based on what content has views, we are implicitly filtering based on this algorithm. The dynamics of YouTube (i.e., which videos get popular/monetized) influence the style and content of videos that get made and uploaded to the platform; this in turn shapes and is shaped by culture more broadly [104].

5.3 Dual use.

The video QA tasks that we studied carry risk of dual use, through possible downstream applications like surveillance [91, 128]. It seems unlikely that purely technological fixes and defenses – which themselves can be problematic [40] – could resolve these dynamics. Studying how well video-level pretraining enables surveillance applications might be an important avenue for future work, if only to inform stakeholders and policymakers about these risks.

5.4 Energy consumption.

The pretraining that we used in this work was expensive upfront [105]. Our results suggest that scaling up the amount of data and compute that we used might yield additional performance gains – but at increased environmental cost. To pretrain more efficiently, we used a much more lightweight architecture (in terms of FLOPs) than is standard for today’s vision and language models. We hope that our public release of the model (for research use) can further amortize this cost.

5.5 Synthesizing these risks.

With these issues in mind, we release MERLOT and YT-Temporal-180M for researchers. We view our work, and our research artifacts, to be part of a larger conversation on the limits of pretrained ‘foundation models’ [17]. These models have broad impact to real-world areas like healthcare, law, and education. At the same time, these models have significant risks, including the harms that we outlined. We believe that further academic research into this video-and-language pretraining paradigm is important – especially to probe its limits and possible harms. We hope that our paper, code, and data release can contribute to this direction.

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Supplemental Material

We present the following items in the supplemental:

- a. Data collection information (Section A)
- b. An exploration of the data in our corpus (Section B)
- c. Qualitative analysis of model representations (Section C)
- d. An exploration of the intermediate visual representations (Section D)
- e. Hyperparameters and experimental setup used for all experiments (Section E)
- f. A Datasheet [37] for our YT-Temporal-180M dataset (Section F)

A Collecting Videos and Transcripts from YouTube

We adopt the following high-level process to collect YouTube videos and their accompanying transcripts:

- a. Collect channel pages that are likely to cover visually-textually grounded events (A.1),
- b. Download videos from each channel, while filtering out videos without English ASR captions, or unlikely to have (changing) real-world scenes and objects (A.2),
- c. ‘Denoise’ the transcripts – using a language model to rewrite transcripts in a style more similar to written English, as opposed to spoken English (A.3),
- d. Last, align words in the transcript to video frames, and extract the segments for pretraining (A.4).

As we will discuss in more detail in the following subsections, we designed our strategy to preserve user privacy as much as possible – an imperative when constructing a corpus on public-facing multimodal data. We conclude with a high-level summary of these privacy-preserving decisions, as well as about our release strategy (A.5).

A.1 Collecting channel IDs + video IDs

The first stage in our pipeline was to collect YouTube video IDs that could potentially be relevant for learning visual-textual relationships. We opted to search for interesting *channels* rather than search for videos directly, as we found the API limits for searching for videos somewhat restrictive. Once a channel was downloaded, we could then download its videos.

We found channels using YouTube’s auto-generated ‘topic’ pages, corresponding to entries in FreeBase like ‘Science’ or ‘Home Improvement.’ We identified 18 of these topics, and retrieved the IDs for all channels that were linked to by each topic page. We also used YouTube channels that appeared in the VLOG dataset [35], as well as a selection of viral ‘How-To’ and ‘Cooking’ channels. Last, we searched YouTube for concrete nouns, using the object list from MSCOCO (‘baseball’, ‘snowboard’, etc.) as a starting point; we retrieved channel IDs for each video that appeared.

Channels on YouTube often feature other (often similar) channels; so we downloaded more channel IDs by performing a graph breadth-first search over the initial set of channels. We identified 50k channels total and filtered out any more ‘personal’ channels (with fewer than 10k views between all videos). Last, we gathered all video IDs that came from our list of channels, which left us with 27 million video IDs, which formed our final candidate list.

Privacy implications. Our high-level goal was to preserve user privacy by mainly using popular (and more monetized) YouTube videos and channels in our dataset, as opposed to personal ones. The YouTube search algorithm helped us do that, by ordering results (in part) by the popularity of a video / channel. Downloading all videos from a channel, and filtering out channels with fewer than 10k views, favors popular content (like for celebrities, professional YouTubers, and cable news stations). Our analysis in Appendix B shows this strategy was largely successful.

Connection with HowTo100M. As discussed in the paper, we used both a diverse selection of YouTube videos (coming from this process), as well as the video list from HowTo100M [80]. We simply

concatenated the video IDs from HowTo100M with the video IDs from this searching step. This means first, that the HowTo100M videos were also filtered by the next steps (and thus our copy of HowTo100M is slightly smaller than the original), though we found that the filtering step had minimal impact on those videos (that were already filtered by [80]). Second, it means that the HowTo100M videos do contain some instructional videos from less-popular channels. Our intuition here is that this might be okay from a privacy standpoint: few of these people are discussing personal topics; a typical example might be a grainy video of somebody baking cookies. Nonetheless, given the scale that we operated at ourselves, we tried to be more cautious with the filtering.

A.2 Filtering out videos

After retrieving a set of video IDs, our next step was to download ones likely to be appropriate for pre-training MERLOT. Not all videos would be likely to work well: many videos have no spoken words, are not in English, or otherwise do not have automatically-generated (ASR) captions. Likewise, many videos are not grounded: some just have still images (like podcasts), some are of people talking to each other or to the camera, and many are of people playing video games. Our intention was to filter out these videos, ideally without having to download them (so as to conserve bandwidth).

For each video ID, we perform the following steps:

- Downloading info: YouTube allows us to download the video metadata separately from each video. We do this first as the video info file is much smaller than the video itself. We thus first (try to) download this file. We exit here if one of the following conditions are met:
 - the video was removed,
 - the video is categorized as a ‘Gaming’ video,
 - the video does not contain any English ASR captions,
 - the video is over 20 minutes long (and thus might be overly expensive to download).
- Inspecting thumbnails: the YouTube API has a hidden feature that allows us to download four thumbnails [35]; in terms of bandwidth usage, this is often much cheaper than downloading the whole video. We use these thumbnails as a proxy as to whether the entire video is likely suitable for pretraining.⁶ We trained a lightweight MobileNet-V2 CNN [93] to score whether a COCO object class is present in an image or not, using a sigmoid cross entropy loss. We exit here if one of the following conditions are met:
 - the CNN classifies fewer than four COCO objects as being ‘present’ over the four frames, using a minimum threshold of 30% probability for an object to be counted as being ‘present.’ This is mainly to recognize scenes with people, as opposed to animations, landscape footage, or blank/placeholder slides.
 - The average cosine similarity between all feature representations (computed by the classifier) is over 0.9; this allows us to skip videos that have no visual variance (like a person sitting in front of a camera for the whole video, or an album cover while a song is playing).
- Downloading the video: if we have not exited yet, we download the video.

A.3 Denoising ASR Captions

One concern with pretraining on ASR is that written text may differ from spoken text: thus, when transferring to downstream tasks based on written corpora, models pretrained on spoken transcriptions may not transfer well. Also, ASR generated by YouTube does not include punctuation or capitalization. Furthermore, ASR transcripts can contain errors, e.g., by mistranscribing rare words/proper nouns and instead predicting incorrect, but similarly pronounced, words. And finally, YouTube’s ASR system sometimes attempts to translate text from a different language to English, which is sometimes successful, but other times produces nonsense.

⁶Note that YouTube thumbnails are also (algorithmically) curated: when thumbnails aren’t hand-selected by the uploader, YouTube’s thumbnail selection algorithm selects high quality, clear frames. <https://ai.googleblog.com/2015/10/improving-youtube-video-thumbnails-with.html>

We aim to sidestep these issues by using a language model to ‘denoise’ ASR text, as well to filter out excessively noisy transcripts. We use a GROVER-Large language model to do this [124], as it was exclusively pretrained on written text from news articles. Then, we finetuned it in a sequence-to-sequence setting to ‘denoise’ ASR.

We created data for our ‘denoising’ task using the following procedure. Given an article from RealNews [124], we would trim it to 600 BPE tokens, and perform the following corruptions:

- We lowercase all text, and remove all punctuation.
- For each word (splitting by whitespace), we replace it with a random word 1% of the time. Within this 1%, 25% of the time, we use the CMU Pronouncing Dictionary⁷ to swap-in a word with identical pronunciation (to simulate mistranscriptions), and 75% of the time we use a random sequence of BPE tokens of the same length as the actual word.
- For each word, 1% of the time we insert a ‘filler word’ before it, such as ‘umm,’ ‘hmm,’ or ‘yeah.’

The model was trained to generate the ‘noisy’ news article, followed by a ‘START’ token, then the original ‘clean’ news article, and then an ‘END’ token; all using a standard cross-entropy loss. We prioritize learning the ‘clean’ text by multiplying the loss on the initial ‘noisy’ tokens by 0.01. We trained this model using a batch size of 256 sequences of maximum sequence length 1536, a learning rate of $1e-5$, and 80k steps.

The result is a model that not only attempts to fix mistranscriptions and corruptions, but also adds punctuation and capitalization. The model also produces an estimated likelihood of the ASR caption track, which we later use to filter out videos with very low quality ASR transcripts, e.g., poorly translated transcripts.

We apply the model to each video’s transcript that survived the described filtration, breaking up long transcripts into groups of 512 tokens. These groups are handed as input to the model, and Nucleus Sampling (with $p=0.9$) [48] is used to generate a cleaned transcript for the group. We exit, filtering out the entire video, if any group has a perplexity of over 200. Finally, we concatenated all the groups together to form a ‘clean’ transcript.

A.4 Putting everything together: aligning videos and cleaned transcripts to frames

To recap, at this stage in the pipeline, for each video, we have the video file, along with the original ASR transcript (with words, as well as timestamps for each word), and the cleaned ASR caption (without timing info). To estimate timing info for the clean transcript, we align the noisy and cleaned transcripts on a word-by-word level using Dynamic Time Warping [85]; word-word distance is computed using Levenshtein distance. The timing estimate for a cleaned token was computed as the average of the noisy tokens assigned to it in this alignment.

Finally, given a video and its cleaned, per-word timed transcript, we sought to extract corresponding video frames – the data format we rely on for pretraining. We start with (empty) buffers of at most $L = 32$ tokens for both the original, and noisy transcripts. We loop through the (aligned) clean and noisy transcripts, and add the tokens to their respective buffers. If adding the next word would cause the buffer to exceed $L = 32$ tokens in length, we commit the segment – returning the noisy ASR text, along with the clean text, and timing information. We then extract a frame from the video corresponding to the middle of that segment. We do this until the end of the video. We use the GPT2 BPE encoder for this [97, 88], as was also widely adopted in later work (e.g. RoBERTa [72]).

Not all videos fit neatly into 16 segments, which was the format we used for training. Thus, we merged segments from videos shorter than 16 segments, and for longer videos, we split them into multiple examples. We didn’t use any video sequence-level padding: all of our dataset examples have 16 valid frames, even though we did include padding at the token level (so many segments had fewer than $L = 32$ tokens).

⁷<http://www.speech.cs.cmu.edu/cgi-bin/cmudict>

A.5 Summary - scraping while preserving privacy

As we discussed in the sections above, we tailored our scraping process to protect user privacy. It should be mentioned here that we focused on *public videos*. Possibly due to cues of engagement like view/subscriber counts, users on YouTube appear to understand the privacy implications of uploading a ‘public’ video [55], differentiating YouTube from more private venues, like email and social media. Under Marwick and boyd [78]’s framework of *networked privacy*, when web users (particularly those with less viewership) upload public videos, they are often ‘*being in public* without *being public*.’ The idea behind this distinction is that web users, understanding that their content might be visible to others, tend to avoid sharing overly private data (like their phone number or date of birth); the information that they do share is often *encoded* (i.e., referring to a friend by their first name, not their full name). Finally, we took extra steps to filter out more ‘personal’ videos (without many views); our analysis in Appendix B shows this strategy was largely successful.

An additional aspect of our approach, as it relates to privacy, was our decision to use a diverse selection of channels. We did this to minimize risks of models ‘overfitting’ to specific individuals – a risk evidenced by a large GPT2 model memorizing users’ phone numbers [18]. We believe that training a base-sized model in a large- and diverse-data regime minimizes many of the harms in this case; that said, the risk in the multimodal (video) space is unclear as of yet, and more research is needed.

Finally, we do not plan on releasing videos for download, only their IDs, following a strategy from prior work [1, 80]. This gives users an explicit ‘right to be forgotten’ not just from YouTube, but our data as well. We understand that this might make exact reproducibility difficult; we address this by releasing code for our filtering process. Thus, if in the future, if N videos get deleted from YT-Temporal-180M, a practitioner can download N new YouTube videos that pass through the same filters that we used.

B Data Exploration

Curating large pretraining corpora necessitates some ad-hoc decisions, e.g., what data to search for, what data to keep/discard, etc., and our work is no exception. The described data extraction pipeline contains several heuristics that we developed based on our subjective experiences (and per-step, heuristic validations) curating the corpus. While it isn’t computationally feasible ablate each stage of this pipeline (and examine each decision’s effect on downstream performance), we seek to quantify some basic of the properties of the corpus.

Validity Check We randomly sampled 100 videos from the corpus, and answered the following basic questions for each of the videos: **Q1:** *Does the video contain language utterances?* **Q2:** *If so, is the language primarily English?* **Q3:** *Is the video an instructional video, i.e., is it an attempt to teach the viewer how to undertake a task?*⁸ **Q4:** *What type of entity created the video: a small youtuber (<10K subscribers); a medium youtuber (<100K, >10K subscribers); or a large youtuber (>100K subscribers); a news station; or a media company.* **Q5:** *Is the video a music video?* **Q6:** *Is the video a video game commentary?*

Of the 100 examined videos, none were music videos or video game commentaries (Q5/Q6). The videos were mostly not instructional (84%) (Q3) and mostly in English (86%) (Q2); non-English videos nonetheless can have an English ASR track provided by the YouTube API if the spoken language is transcribed by YouTube via its auto-translate feature. And while all contained language utterances (Q1), at least one translated transcript had a very low quality transcription, which was only loosely semantically related to the underlying content. Finally, the most common video creators were news studios (29%; e.g., local news channels); big YouTubers (26%; e.g., popular vloggers), and media companies (24%; e.g., Major League Baseball). Also included, but in lesser proportion, were small YouTubers (8%), and TV studios (1%; e.g., official movie trailers).

Content Exploration What topics are covered by the corpus? We randomly sampled 55K video transcripts, and ran an LDA topic model [16] implemented in MALLET [79] with 100 topics. We used a vocab size of 25K word types that appear in at least 25 transcripts, but in no more than 10% of

⁸A similar definition was proposed in [47].

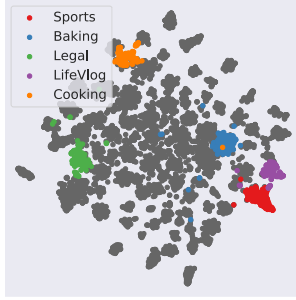


Figure 4: TSNE of topic distributions for 7K sampled documents.

Sports	goal win match points ball games goals played players
Baking	sugar mix cup butter recipe flour oven dough bowl
Legal	court law justice judge investigation report prison
LifeVlog	excited vlog tomorrow literally camera bed yesterday
Cooking	sauce cook oil chicken salt garlic pepper cooking

Table 5: Several common topics, derived from the transcripts of YT-Temporal-180M, represented by the most common words of those topics.

transcripts. The topics suggest diverse coverage, e.g., topics about specific sports (boxing, soccer), US and world politics, fashion, construction, fantasy settings, nail painting, etc. We use TSNE to visualize the per-document topic distributions, and color a sample of documents according to their top topic in Figure 4 (topic details in Table 5).

Overall, the topical coverage of YT-Temporal-180M, at least according to a topic model trained on the transcripts of a sample of videos, is broader than comparable-in-size video corpora like HowTo100M [80]. And, experiments in the main paper demonstrate that this diversity is apparently helpful for a number of downstream tasks.

C Qualitative Analysis of Model Representations

In this section, we provide more qualitative analysis about the representations learned by MERLOT.

C.1 Analysis of the language-only encoder, and attention masking during pretraining

Early on in this project, when inspecting qualitative examples, we observed that using BERT-style masked language modeling [27] – choosing 15% randomly selected BPE tokens as the prediction targets, and replacing them with MASK 80% of the time, or a random token 10% of the time – produced overly easy examples.

This has been observed by other work in the text-only setting: when long words get partially masked, it is often easy to recover the missing BPE token from the context, which motivated Joshi et al. [54]’s choice to mask out entire spans instead. However, our goal in multimodal pretraining is different. We want the model to learn grounded representations of events, such that even when we scale up the number of segments given to the model, the model has to construct a multimodal representation of *what happened*. Thus, in our setup, we wanted to encourage masking out *highly visual* words, to learn cross-modal representations.

Instead of masking randomly, recall that we used the attention weights produced by the language-only encoder (trained to match a sequence of captions to individual frames) to inform which tokens to mask. While we do not claim that these attention weights provide a full explanation of the model behavior [51, 98], they do play some role in the model’s decision [116], and we find that our masking strategy improves performance on downstream tasks by around 1% (Table 4), versus a SpanBERT baseline [54].

We show qualitative examples that seem to back up our hypothesis in Figures 5 and 6. In Figure 5, for instance, the video shows a VLOG of an adult playing with children and talking the camera. Tokens flagged by our approach as having high attention weights (being in the top 20% of all tokens in the sequence, in terms of other positions attending *to* that token) include concrete words like ‘scissors’ and ‘toys.’ Even though scissors are not shown in the selected frames, that word might be a good prediction target, insofar as it might complete a picture of what is going on in the first few frames: somehow, the adult is able to open the package with the child’s toy, which could require scissors.

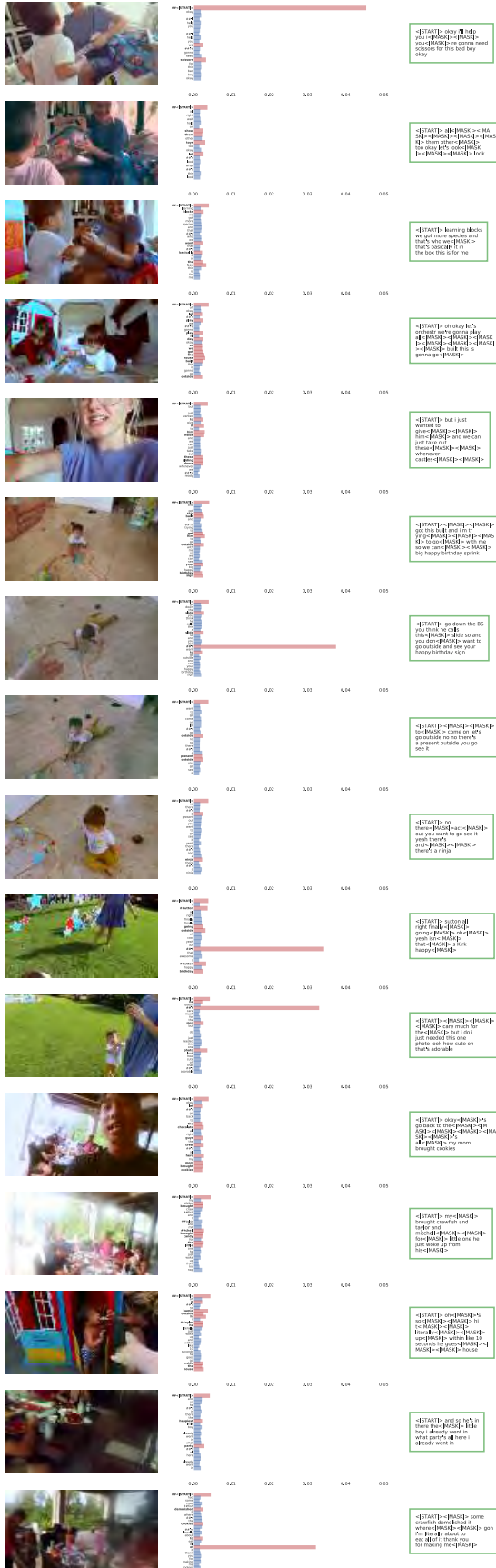




Figure 6: Another example of our masking approach, the same format as Figure 5. This shows an instructional video. Note the highly attended to tokens that get masked out (like ‘ice’, ‘O-ring’ and ‘lid.’) Seeing those objects in the image (not just through reading about them) is key to understand what the video is about – someone making iced tea in a mason jar.

	Constant	RSPNet [21]	MERLOT-VizBranch	CLIP ViT-B/16 [89]
UCF-101 [103]	1.1	61.8	74.9	87.1
HMDB-51 [61]	2.0	42.8	49.6	62.4

Table 6: Linear probing classification accuracy of a MERLOT’s intermediate visual representations (higher=better).

Additionally, in Figure 6, showing an instructional video for both making iced tea and putting it in a sealed mason jar, concrete nouns such as ‘o-rings’ get masked out.

Nevertheless, there are still several cases where the model seems to assign attention weights to apparently non-visual tokens. The model places a lot of attention on the START token, a pattern noticed by prior work as well [24], perhaps because we pool representations from those positions (for matching with the video frames). However, we never select the START token for masking in our work, so this might not highly affect the learning signal. Perhaps more strangely, language-only encoder seems to attend highly to the final token in contractions (like ‘t and ‘s). It is not clear to us whether these represent something important visually, or noise; we leave a more in-depth investigation of this phenomenon to future work.

C.2 More qualitative examples for zero-shot story ordering

In this section, we show more examples of MERLOT unshuffling visual stories in SIND [50, 33]. We compare our model’s zero-shot results (using the logits from its temporal-ordering objective) to CLIP’s [89] independent matching of each caption with each image (using the Hungarian algorithm to find the best-scoring assignment [63]).

In Figures 7 and 8, we show expanded versions of Figure 3, comparing to CLIP. The examples show that MERLOT has a strong understanding of events that transcends individual frames. Unlike MERLOT, CLIP can only match captions independently to images, so in the first row it struggles to connect ‘his kids’ with the middle-aged children of ‘the old man’ In the second row, it matches the barn image with the caption ‘they also had a barn’, while it is unable to keep all the merry-go-round images together (as MERLOT does).

We show additional examples in Figures 9 and 10. Our model provides a reasonable ordering to the ‘kayaking’ example (Figure 9), which is evident of multimodal script knowledge: first, people have to get ready to go kayaking (which they do on land!) and then they go out onto the water, and finally come back. The ordering of the tennis match (Figure ??) seems reasonable as well. Unlike CLIP, MERLOT groups together frames (3) and (4) – the players first serving the tennis ball, and then awaiting the return.

C.3 Attention patterns

Finally, we show examples of the attention patterns produced by MERLOT, when it reasons over both vision-and-language content at a video level. Plots are shown in Figure 11. Overall, the model frequently links together visual regions with similar concepts in text, even when they get mentioned far away in time.

Though these attention patterns should be taken with a grain of salt, as they are not necessarily explanatory of the model’s decision [51, 98], we find it promising that the model attends globally over all frames and captions – rather than ignoring one modality or ignoring the temporal dimension. We leave further investigation of the model’s attention patterns and behavior to future work.

D Linear Probe of Intermediate Visual Representations

Our goal with MERLOT was to learn about situations expressed through videos and language. However, as it includes a vision encoder that we trained from scratch, a reasonable question is how this visual encoder compares to other encoders (e.g., that were trained through image captions). To this end, we performed linear probing experiments over two activity recognition datasets: HMDB-51

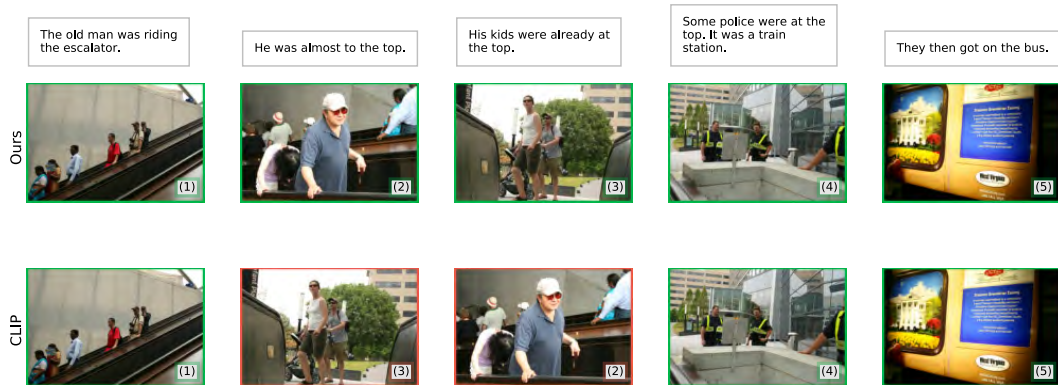


Figure 7: Zero-shot story unscrambling; continuation of Figure 3 with the CLIP baseline [89]. MERLOT successfully orders the story, performing cross-modal coreference over several images to note that ‘He’ in image (2) refers to ‘the old man’ mentioned in (1). The narrative that MERLOT generated also makes sense at an event level: people are riding the escalator, *then* they get to the top, *then* they exit and do something else; maximizing caption-image similarity of all pairs independently misses this event-level coherence.

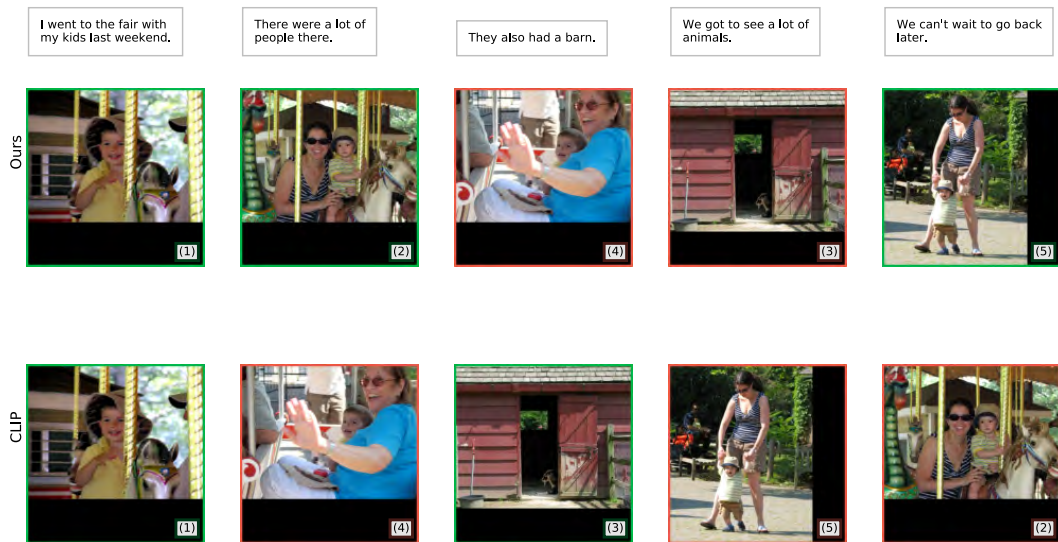


Figure 8: An incorrect story unshuffling example – but for an interesting reason. Frames (1), (2), and (4) all involve people riding a merry-go-round, and MERLOT keeps them together even though the ground truth story labels have the ‘barn’ image, (3), in between.

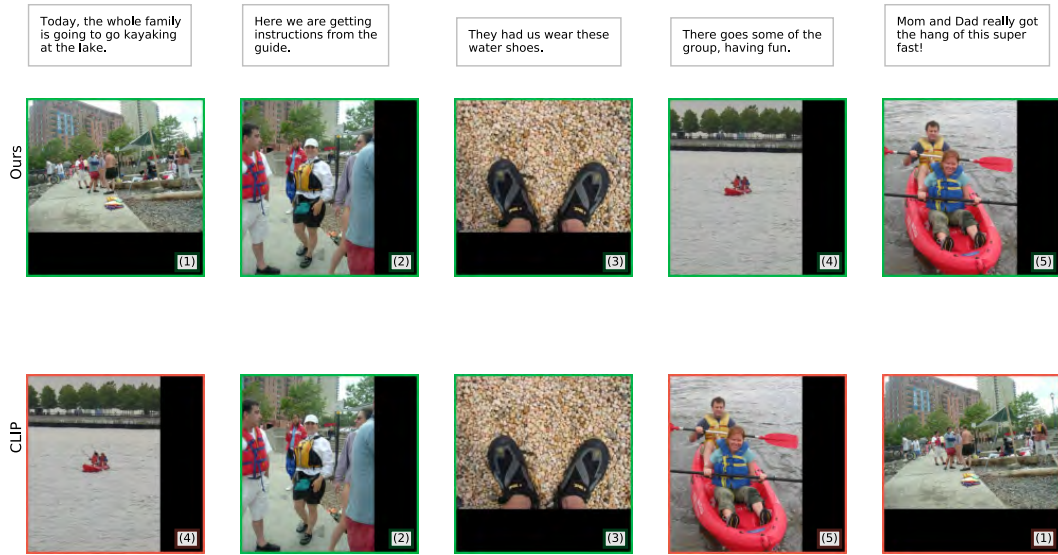


Figure 9: A second zero-shot story ordering example. MERLOT unshuffles the frames, while grouping together frames (1) and (2) – which make sense as they are in the stage of the event where they are *preparing to go*. CLIP instead puts frame (4) first, which matches caption (1) independently, but doesn’t make sense temporally in context.

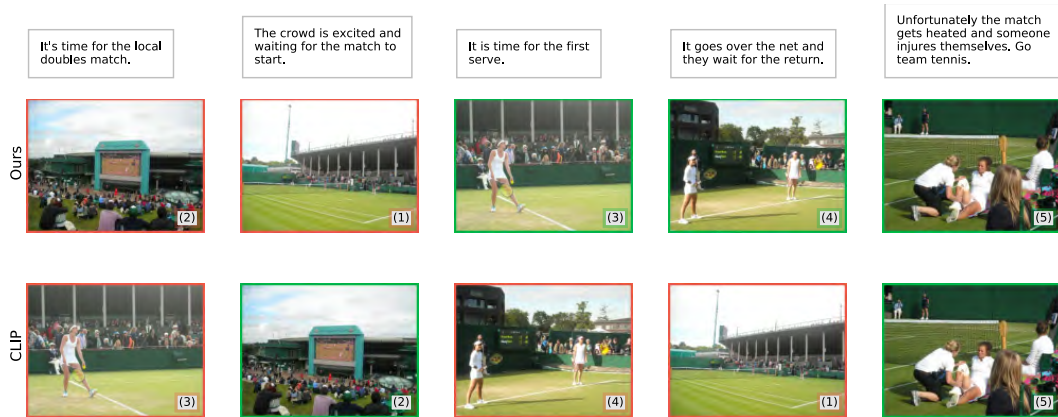


Figure 10: A second zero-shot story ordering example. There are a variety of potential ‘reasonable’ orderings for this example; both models get this one ‘incorrect.’ MERLOT’s ordering suggests someone first looking into the tennis match on the outside, and then cutting to watch the match more closely. On the other hand, CLIP switches between a shot of someone serving, back to the outside TV, and then inside again.

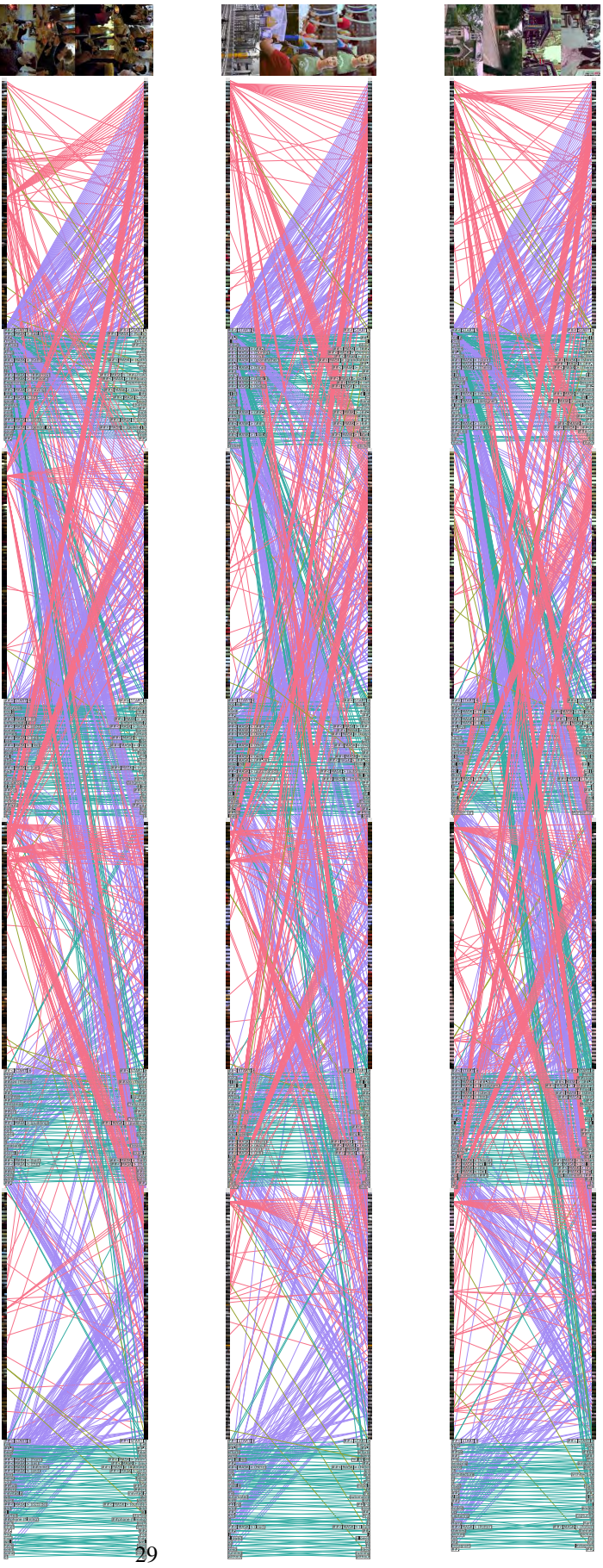


Figure 11: Additional qualitative examples of MERLOT’s attention patterns, aggregated over all layers of the joint vision-language encoder. Cells on the top attend to cells on the bottom; we only show three attention edges per query, so as to reduce clutter. In *red*, we show visual patches attending to tokens. In *gold*, we show tokens attending to visual patches; in *teal* we show tokens attending to tokens. The first row seems to show a tourist in the United Kingdom. In the third segment, the narrator discusses a ‘gothic style house’ even though only the gate is shown in the frame; those tokens attend highly to the house when it is shown in the fourth frame. The second row shows someone at a factory for Dr. Brommer’s Soap. The factory worker in the third frame seems highly attended to, particularly by the tokens ‘applied by hand’ which appear in the second caption. The third row shows a dinner party. The first caption mentions ‘nice food’ but no food is shown in the first frame. Interestingly, the model has these tokens attend to the final frame, where food is shown.

[61] and UCF-101 [103]. These tasks are 51 and 101 class classification tasks, respectively: they challenge algorithms to predict which human activity is present in a video clip. Following prior work, for both datasets, we average over the three standard train/test splits. We evaluate in the linear probe setup, where models represent video clips as a single fixed vector, and a linear maximum entropy classifier is trained on top, freezing the rest of the model’s parameters.

In addition to a random prediction baseline, we compare against [21]’s RSPNet reported results (they use a 3DResNet-18 backbone pretrained on Kinetics400), and CLIP ViT-B/16 [89]. For MERLOT and CLIP, we extract a single central frame from each video, and extract a feature vector from it. For MERLOT, we represent the frame as the concatenation of the two [CLS] tokens (one was for the image-transcript alignment task, the other was for passing to the joint encoder).

The results, shown in Table 6, show that CLIP performs best in this setup – though MERLOT does outperform an RSPNet baseline. At first, this might appear surprising, as MERLOT was trained on web videos, which might be closer to activity recognition datasets (as opposed to image captions). However, common benchmarks for activity recognition tend to have strong *object and background bias* – for example, to recognize the UCF action ‘playing guitar,’ it is sufficient to detect a guitar in an image (as guitars are unlikely to show up for the other activities like ‘playing basketball’) [70]. Temporal self-supervised learning from transcripts may not lead to as powerful zero-shot object detectors because speakers in videos may be less likely to state the obvious [41, 39], e.g., in this case, a speaker is probably unlikely to say ‘I will now play a guitar while sitting in a chair.’

E Experimental setup and hyperparameters

E.1 Hyperparameters used during pretraining

We used AdamW [73] with a learning rate of $3e-4$, weight decay with value 0.1, and set $\beta_2=0.98$. We used minimal data augmentation on the image frames. We randomly scale them between 1.125 and 1.5 times what would fit in our 192×352 resolution, and take a random crop. We use a random resize algorithm when doing this scaling, to make the model robust to different ways of preprocessing images [94]. Last, for 80% of images, we randomly jittered either their brightness or contrast to between 0.7 and 1.3 their original values, which we suspect did not play a major role in performance.

On the text side, we note that we have both the original copies of each transcript – what was retrieved from YouTube – and versions “cleaned up” by our denoiser. We can use both kinds of transcript as additional data augmentation. However, although the words are time aligned, there might be inconsistencies if alternating between cleaned and noisy versions inside of a single video. Thus, for each iteration, we randomly choose either the ‘clean’ or ‘noisy’ ASR transcript and use that one.

To slightly speed up convergence, we initialize the joint vision-and-language model, and the word embeddings, with parameters from RoBERTa [72]. However, we suspect that due to the scale of our dataset and pretraining time, this might not have been required.

E.1.1 Unsupervised Story Ordering

[20]

For the unsupervised scrambling of visual stories task, we did not do any finetuning on the SIND dataset [33, 50, 2]. However, there is a slight mismatch between the model that we pretrained initially, and the format of the task – the visual stories in the SIND dataset have 5 images and captions each, whereas we initially pretrained with at most 4 segments. We handled this discrepancy by pretraining MERLOT for 10 more epochs, using a peak learning rate of $2e-5$, and a new resolution of 384×384 . This slightly bigger size was to account for the (not necessarily) widescreen images in SortStory, as opposed to the (mostly) widescreen videos on YouTube.

Recall that MERLOT’s pairwise loss is defined over pairs of segments. However, how to best combine these into a unified score for story ordering is an open question. To briefly explore this, during this additional pretraining of MERLOT, we applied three variants of our temporal loss: one over caption-caption pairs, one over caption-frame pairs, and one over frame-frame pairs. We also experimented with randomly shuffling the captions as well, in the same way as the frames, we found however that this did not boost downstream task performance (perhaps because using shuffled captions as input incentivizes models to learn exclusively language-language interactions). The loss

is computed the exact same way everywhere; the only differences is that for caption-frame pairs, we have four options:

1. the caption (at t_i) and frame (at t_j) are of the same segment, so $t_i = t_j$,
2. the caption precedes the frame, so $t_i < t_j$,
3. the caption comes after the frame, so $t_i > t_j$,
4. the caption comes from a different video as the frame, so comparing t_i and t_j is undefined.

The model learns to distinguish between those four options with a cross-entropy loss. We found that using this version of the temporal loss over vision-language pairs produced slightly better results on story ordering (as judged on the validation set) compared with the loss applied over the frames. We hypothesize that this might be due to the additional ' $t_i = t_j$ ' option allowing models to assign a probability to a frame-caption match, but are not sure. With this approach, to produce a unified score for (length- N) permutations σ_L over the captions, and σ_V over frames, we then sum over pairwise log-probabilities:

$$\text{score}(\sigma) = \sum_{i=1}^N \sum_{j=1}^N \log \begin{cases} p(\sigma_L(i) > \sigma_V(j)) & \text{if } \sigma_L(i) > \sigma_V(j) \\ p(\sigma_L(i) = \sigma_V(j)) & \text{if } \sigma_L(i) = \sigma_V(j) \\ p(\sigma_L(i) < \sigma_V(j)) & \text{if } \sigma_L(i) < \sigma_V(j) \end{cases}.$$

For story ordering, the order of the captions is always fixed: $\sigma_L = (1, 2, 3, 4, 5)$ and $N = 5$; we thus feed MERLOT captions with the correct order. However, the model should have no information about the order of the frames.⁹ Recall that we handle this through position embeddings (3.3); e.g. one possible ordering might be

[image_unk_3], [image_unk_2], [image_unk_4], [image_unk_1], [image_unk_5],

and those position embeddings would get added to each frame, respectively. This allows the network to disambiguate between distinct frames even though no order is revealed. However, we found that the model was sometimes sensitive to the exact order of these position embedding tokens, and so for each example we randomly sampled two orderings and averaged the model's pairwise probabilities. We found no difference in performance when using more than two orderings. We hypothesize that this could be an issue with how (absolute) position embeddings are handled by Transformers, but are not fully confident; we leave a more thorough investigation for future work.

E.2 Per-downstream fine-tuning details.

In this section, we discuss implementation details for finetuning MERLOT on downstream tasks. For each downstream task, given images $I_{1:N}$ and language context w , we first encode $I_{1:N}$ via the image encoder. We concatenate this with word embeddings of w , apply position embeddings, and feed the result into the joint vision-language encoder to extract joint representation. The input images $I_{1:N}$ are either provided by the task or extracted from given video, where we uniformly select N frames from the video clips (spaced evenly, so with an equal amount of time between sequential frames). For supervised tasks, we use as the 'head' a two-layer MLP from random initialization on top of the CLS token of the language context together with the rest of MERLOT.

For downstream tasks, we note that we found it effective to finetune on different resolutions than what we used during pretraining. Our default image resolution here was 384×704 . To do this, we note that all parameters in the model remain the same, except for position embeddings on the image patches. We expanded the size of the position embedding matrix by initializing the upper-left-side 192×352 region from the pretrained model, and used random initialization for new position embeddings.

For all downstream tasks, we followed the standard training, validation, and test splits of the original datasets. We used the AdamW [73] optimizer, with $\beta_2 = 0.98$, and warmed up the learning rate linearly for the first 10% of iterations, followed by a linear decay of the learning rate (down to 0) for the remaining 90%. For regularization, we used L2 weight decay with a value of 0.01, and a dropout rate of 10%. For tuning other hyperparameters, we first did a larger random hyperparameter search over VCR, and used those hyperparameters as defaults for the other tasks. We used a batch size of

⁹Embarrassingly, we found a slight leakage of this in the V1 of this arxiv paper which inflated the story ordering performance by a few percentage points (of pairwise accuracy), which we have corrected in this version.

64, and searched over learning rates in the range $[1e-5, 2e-4]$ on VCR, we found that $1.2e-5$ worked well, so we used it as the default for other tasks. We also trained with early stopping, validating every epoch and returning the best-performing model across epochs. Due to our choice of early stopping, we trained for a slightly larger-than-typical number of epochs (18 by default for every tasks, as we found training longer did not help on VCR).

We follow the standard evaluation metrics for these tasks, which is usually accuracy for QA-style configurations. Alongside brief descriptions of each downstream task, we provide hyperparameter and training details in the following section.

E.3 Static Image Reasoning Tasks

E.3.1 VCR

VCR [123] contains two different subtasks: question answering ($Q \rightarrow A$) and answer justification ($QA \rightarrow R$), both of which are multiple choice questions over a given image. These subtasks are combined in the joint $Q \rightarrow AR$ metric, which requires a model to both pick the right answer and the right rationale for the model to get a question ‘right.’ VCR has 290k questions over 110k movie scenes.

As mentioned in the main text, VCR provides bounding boxes around entities, with explicit groundings between those entities and references in questions. We draw colored highlights around the referenced entity directly in the image, with consistent mapping between color code and entity name (e.g. person1 with red box, person2 with green box, etc). Though no text is written on the image, because we always associate each string (e.g. person1) with a deterministic color, the model can learn through finetuning to associate that color with the entity. Figure 12 illustrates one such example.

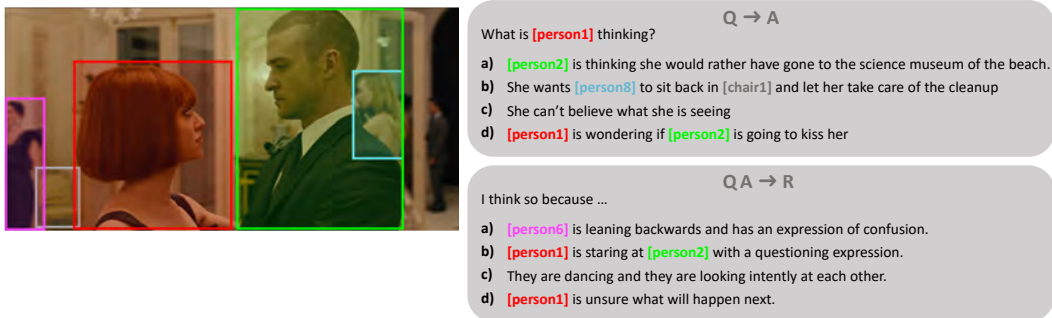


Figure 12: A VCR example with highlighted image. The image with the drawn-on boxes is what we pass to models.

We jointly finetune MERLOT on $Q \rightarrow A$ and $QA \rightarrow R$, with two separate MLP heads. We concatenate the question (the question and the ground truth answer) and each answer (rationale) choice from the four possible answer (rationale) candidates. On-top of the CLS token of the question, we train the classifier to predict the confidence for each candidate to be correct with cross-entropy loss, and take softmax over four possible candidates for each question. We used a widescreen resolution of 384×704 set the batch size as 64, and train for 60k training steps, which is roughly 18 epochs. We started with this and then tuned the learning rate (from candidates chosen randomly); here, we found that a learning rate of $1.2e-5$ worked well. We then used this learning rate as a default for the other tasks.

Note that our pretraining setup is different from other work. Previous works [22, 36, 119] conduct what they call ‘second-stage pretraining’ with VCR training data. Here, they use a masked language model objective over the VCR dataset (instead of answering the question correctly). In particular, UNITER [22] reports 2.8 % point performance boost due to the second-stage pretraining. We suspect that this might be because the caption data (that models like UNITER rely on) are quite different from VCR. We tried performing secondary pretraining and found it did not help. One possible reason might be that our large-scale pretraining corpus covers diverse and complex event space thus we don’t need additional data domain adaptation.

	What (50K)	Who (20K)	How (2K)	When (677)	Where (250)	Overall
AMU [117]	26.2	43.0	80.2	72.5	30.0	30.5
VQA-T [118]	35.5	51.1	-	81.0	43.5	41.5
MERLOT	37.0	52.9	85.3	79.2	42.8	43.0

Table 7: Per question-category results for MSRVTQ-QA.

E.4 Video Reasoning Tasks

MSRVTQ-QA [117]

MSRVTQ-QA is a question-answering task with 244K questions posed over 10K videos. For each video clip, we uniformly selected 5 image frames (spaced evenly through the video). We follow the protocols of the original work and use an answer vocabulary containing the most common 1K answers in the training set as answer candidates. The questions with out-of-vocabulary answer will automatically get wrong. We encode the answers in a one-hot fashion, and train 2-layer MLP classifier over all answer candidates with a binary cross-entropy loss on-top of the CLS token of the question. We train for 60k training steps with batch size 16. A few additional fine-tuning runs were conducted to examine the effect of changing the resolution from 384×704 to 704×704 , a batch size of 16 vs. 32, and using 1.5K answers instead of 1K, but none had much impact on validation accuracy. We undertook a light hyperparameter optimization over the validation set, wherein we considered 3 possible learning rates (1.2e-5, 6e-5, 2.4e-6), but the default worked best. MSRVTQ-QA splits questions by type, and we report our per-type test set results in comparison to [117, 118] in Table 7.

TVQA [64]

TVQA is a multiple choice task with 152K questions posed over 21K video clips. For each clip, we uniformly select 6 image frames. We concatenate the question and each answer choice from the five possible answer candidates. On-top of the CLS token of the question, we train 2-layer MLP classifier to predict the confidence for each candidate to be correct with cross-entropy loss, and take softmax over five possible candidates for each question. We set the batch size as 64, and train for 35k training steps (roughly 18 epochs over the corpus). We used the default learning rate of 1.2e-5, and a resolution of 384×704 .

TVQA+ [65]

TVQA+ is a subset of TVQA, where bounding boxes are provided in video clips, linking depicted objects to visual concepts in questions and answers. TVQA+ contains 29.4K questions posed over 4.2K video clips. We uniformly select 6 image frames per video, and draw bounding boxes on each frame following the same manner with VCR. We train the classifier in the same way with TVQA. We trained with the same hyperparameters as TVQA, but for 16k steps (18 epochs still).

VLEP [66] VLEP is a binary choice task to infer which of the two events is more likely to happen next following the given video. VLEP contains 28.7K questions posed over 10K video clips. For each clip, we uniformly select 6 image frames. On-top of the CLS token of the event, we train 2-layer MLP classifier to predict the confidence for each event to happen next with cross-entropy loss, and take softmax over two possible events for each instance. We trained the model for 8k steps (18 epochs over the dataset), and with otherwise default hyperparameters.

DramaQA [23]

DramaQA is a multiple choice task with 17.9K questions posed over 23.9K video clips. For each clip, we uniformly select 6 image frames. We concatenate the question and each answer choice from the five possible answer candidates. On-top of the CLS token of the question, we train 2-layer MLP classifier to predict the confidence for each candidate to be correct with cross-entropy loss, and take softmax over five possible candidates for each question. We trained for 3.5k steps (18 epochs) with otherwise default hyperparameters. A few additional fine-tuning runs were conducted to examine the effect of changing the resolution between 384×704 , 512×512 and 704×704 , and we found 512×512 works the best for this task.

		Resolution	Batch Size	Max Epochs	Training Steps	
Common hyperparameters		VCR	384x704	64	18	60k
		MSRVTT-QA	384x704	16	18	35k
		TVQA	384x704	64	18	35k
		TVQA+	384x704	64	18	35k
Learning rate	1.2e-5	VLEP	384x704	64	18	18k
Weight Decay	0.01	DramaQA	512x512	64	18	18k
β_2	0.98	TGIF-Action	384x704	16	56	70k
Warmup ratio	10%	TGIF-Trans	384x704	16	22	70k
		TGIF-FrameQA	384x704	16	56	70k
		ActivityNetQA	384x704	16	10	34k
		LSMDC-FIB	384x704	16	8	150k
		LSMDC-MC	384x704	16	12	80k
		MSRVTT-MC	384x704	16	12	80k

Table 8: Hyperparameters for finetuning on all downstream tasks. Common hyperparameters are shown to the left, and task-specific hyperparameters are to the right.

	Motion	Spatial	Temporal	Yes-No	Color	Object	Location	Number	Other	All
VQA-T [118]	28.0	17.5	4.9	66.3	34.3	26.7	35.8	50.2	36.8	38.9
MERLOT	33.9	18.1	4.0	72.5	36.2	24.5	36.5	51.7	37.8	41.4

Table 9: Per question-category results for ActivityNetQA

TGIF-QA [52]

TGIF-QA is web GIF VQA, which requires spatio-temporal reasoning from visual frames to answer questions correctly. We finetuned MERLOT on three tasks in TGIF-QA benchmark,

Action is defined as a multiple choice question about identifying an action that has been repeated in a video.

Transition is asking about transitions of certain states. The benchmark provides a multiple choice question about identifying the state before or after another state.

FrameQA is asking open-ended questions about the given video. The model selects answer from a dictionary of words, given a question in a complete sentence.

For each video clip, we uniformly select 5 image frames. We serialized 5 candidate answers and a question, where we put a special token QSEP between the candidate answers and question to concatenate them into one question. On-top of the CLS token of the question, we trained 2-layer MLP to predict the confidence of the five candidates with cross-entropy loss. We set the batch size as 16, and train for 70k training steps (*Action* : 56 epoch, *Transition* : 22 epoch, *FrameQA* : 28 epoch) for each task with 1.2e-5 learning rate. We used a longer training duration for each task as we found that performance increased when we did so (and we used the same number of training steps for each TGIF-QA task). All other hyperparameters were default.

ActivityNetQA [45, 122]

ActivityNetQA [122] is a question-answering with 58K questions posed over 5.8K videos. For each video clip, we uniformly select 5 image frames. We use an answer vocabulary containing the most common 1K answers in the training set as answer candidates. The questions with out-of-vocabulary answer will automatically get wrong. We encode the answers in a one-hot fashion, and train 2-layer MLP classifier over all answer candidates with a binary cross-entropy loss on-top of the CLS token of the question. We set the batch size as 16, and train for 34K training steps for each task. We undertook a light hyperparameter optimization over the validation set, wherein we considered 3 possible learning rates (1.2e-5, 6e-5, 2.4e-6), but the default worked best. A few additional fine-tuning runs were conducted to examine the effect of changing the resolution from 384×704 to 704×704, a batch size of 16 vs. 32, and using 1.5K answers instead of 1K, but none had much impact on validation accuracy. ActivityNetQA splits questions by type, and we report our per-type test set results in comparison to [118] in Table 9.

LSMDC FiTB QA [76, 92]

The Fill-in-the-blank (FiTB) task is, given a video clip and a sentence with a blank in it, to predict a single correct word for the blank. The test set includes 30,000 examples from 10,000 clips (i.e. 3 blanks for each description). For each clip, we uniformly select 5 image frames. We constructed answer vocabulary containing the most common word for blank in the training set as answer candidates. We replace the blank in the sentence with BLANK token, so the question query should be a blanked sentence with the special token. On-top of the CLS token of the blanked sentence query, we trained 2-layer MLP classifier to predict the word for the blank over answer vocabulary. We set the batch size as 16, and train for 150k training steps (8 epoch) with $1.2e-5$ learning rate.

LSMDC Multichoice [110]

Given a video query and 5 candidate captions, the task is to find the one that fits the query out of 5 possible candidates. The correct answer is the ground-truth (GT) caption, and four other negatives are chosen from other captions that have different activity-phrase labels from the correct answer. We randomly created 100,000 video and candidates pairs for training. For each video clip, we uniformly select 5 image frames. We put a special token QSEP between the candidate captions to concatenate 5 candidates into one question. At the end of the 5 captions, we put CLS token as an end of the question. On-top of the CLS token, we trained 2-layer MLP to predict the confidence of the five candidates with cross-entropy loss. We set the batch size as 16, and train for 80k training steps (12 epoch) with $1.2e-5$ learning rate.

MSRVTT Multichoice [121]

The task objective for the MSRVTT Multichoice benchmark is identical to those of corresponding tasks in the LSMDC benchmark [110]. The benchmark has 2,990 questions in total for the multiple choice test, using all the test video clips of MSR-VTT. For each test video. We finetuned our model on MSR-VTT train split, and evaluated on the evaluation set. We trained the same model specification as the LSMDC Multichoice task. For training, we set the batch size as 16, and train for 80k training steps (12 epoch) with $1.2e-5$ learning rate.

F Datasheet for YT-Temporal-180M

In this section, we present a DataSheet [37, 12] for YT-Temporal-180M, synthesizing many of the other analyses we performed in this paper.

1. Motivation For Datasheet Creation

- **Why was the dataset created?** In order to investigate learning events from videos – involving a collection of frames and captions over time, that together form a view about the world.
- **Has the dataset been used already?** No.
- **What (other) tasks could the dataset be used for?** Possibly other types of representation learning, with or without ASR captions.
- **Who funded dataset creation?** This work was funded by DARPA MCS program through NIWC Pacific (N66001-19-2-4031), and the Allen Institute for AI.

2. Data composition

- **What are the instances?** The instances that we consider in this work are videos, paired with ASR transcripts aligned over time.
- **How many instances are there?** We include 6 million videos. The total length of all the ASR transcripts is 5 billion BPE tokens. Altogether, we extracted 180 million image frames from this data.
- **What data does each instance consist of?** The instances have ‘raw’ video frames and text, which we preprocess through BPE tokenization and extracting frames for every 32 BPE tokens.
- **Is there a label or target associated with each instance?** We only use the ASR captions as labels in this work, though it might be also possible to use auxiliary information (like tags or video titles).
- **Is any information missing from individual instances?** No.

- **Are relationships between individual instances made explicit?** Not applicable – we do not study relations between different videos (e.g. made by the same creator), though this is a possibility for future work
- **Does the dataset contain all possible instances or is it a sample?** Just a sample.
- **Are there recommended data splits (e.g., training, development/validation, testing)?** We do not provide recommended data splits at this time, as this data was built only for pretraining rather than evaluation. We suspect that the data is large enough that overfitting is not a major concern.
- **Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.** Yes. YouTube ASR is often noisy, and though we presented a pipeline to correct some of these errors, there are many that we cannot fix.
- **Is the dataset self-contained, or does it link to or otherwise rely on external resources (e.g., websites, tweets, other datasets)?** The dataset is self-contained. However, we plan to only release the video URLs, rather than the videos themselves, so as to protect user privacy (allowing users to delete videos).

3. Collection Process

- **What mechanisms or procedures were used to collect the data?** We used the YouTube API and the youtube-dl library.
- **How was the data associated with each instance acquired? Was the data directly observable (e.g., raw text, movie ratings), reported by subjects (e.g., survey responses), or indirectly inferred/derived from other data?** The data was directly observable (from YouTube).
- **If the dataset is a sample from a larger set, what was the sampling strategy (e.g., deterministic, probabilistic with specific sampling probabilities)?** We used a probabilistic strategy with many heuristics, more details in Appendix A.
- **Who was involved in the data collection process (e.g., students, crowdworkers, contractors) and how were they compensated (e.g., how much were crowdworkers paid)?** Data collection was primarily done by the first authors of this paper.
- **Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (e.g., recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.** The data was collected from November 2020 to April 2021, even though the YouTube videos are often much older (dating back to when the platform was first created).

4. Data Preprocessing

- **Was any preprocessing/cleaning/labeling of the data done (e.g., discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)?** Yes, we discuss this in Appendix A: of note, we use a sequence-to-sequence model to ‘denoise’ ASR transcripts (Appendix A.3), BPE-tokenize text, turn everything into segments, and extract the middle image frame for each video segment.
- **Was the “raw” data saved in addition to the preprocessed/cleaned/labeled data (e.g., to support unanticipated future uses)? If so, please provide a link or other access point to the ‘raw’ data.** The raw data was saved, but at this time we do not plan to release it directly due to copyright and privacy concerns.
- **Is the software used to preprocess/clean/label the instances available? If so, please provide a link or other access point.** We will make our code public to support future research.
- **Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet? If not, what are the limitations?** We believe our dataset does allow for study of our goal – indeed, it covers grounded temporal situations from a variety of domains – but with significant limitations. Some of the key ones we are aware of involve various biases on YouTube, which we discuss in Section 5.

5. Dataset Distribution

- **How will the dataset be distributed?** At this time, we plan to distribute all the metadata (transcripts, etc) that we used, as well as links to the YouTube videos that we used. We will do this on our website.
- **When will the dataset be released/first distributed? What license (if any) is it distributed under?** We will release it as soon as possible, using a permissible license for research-based use.
- **Are there any copyrights on the data?** We believe our use is ‘fair use,’ however, due to an abundance of caution, we will not be releasing any of the videos themselves.
- **Are there any fees or access restrictions?** No.

6. Dataset Maintenance

- **Who is supporting/hosting/maintaining the dataset?** The first authors of this work.
- **Will the dataset be updated? If so, how often and by whom?** We do not plan to update it at this time.
- **Is there a repository to link to any/all papers/systems that use this dataset?** Not right now, but we encourage anyone who uses the dataset to cite our paper so it can be easily found.
- **If others want to extend/augment/build on this dataset, is there a mechanism for them to do so?** Not at this time.

7. Legal and Ethical Considerations

- **Were any ethical review processes conducted (e.g., by an institutional review board)?** No official processes were done, as our research is not on human subjects, but we had significant internal deliberation when choosing the scraping strategy.
- **Does the dataset contain data that might be considered confidential?** No, we only use public videos.
- **Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why** Yes – many of these videos exist on YouTube; we discuss this more in Section 5.
- **Does the dataset relate to people?** Yes.
- **Does the dataset identify any subpopulations (e.g., by age, gender)?** Not explicitly (e.g. through labels)
- **Is it possible to identify individuals (i.e., one or more natural persons), either directly or indirectly (i.e., in combination with other data) from the dataset?** Yes, our data includes celebrities, or other YouTube-famous people. All of the videos that we use are of publicly available data, following the Terms of Service that users agreed to when uploading to YouTube.

MERLOT RESERVE: Neural Script Knowledge through Vision and Language and Sound

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Figure 1: MERLOT RESERVE learns *multimodal neural script knowledge* representations of video – jointly reasoning over video frames, text, and audio. Our model is pretrained to predict which snippet of text (and audio) might be hidden by the MASK. This task enables it to perform well on a variety of vision-and-language tasks, in both zero-shot and finetuned settings.

Abstract

As humans, we navigate a multimodal world, building a holistic understanding from all our senses. We introduce MERLOT RESERVE, a model that represents videos jointly over time – through a new training objective that learns from audio, subtitles, and video frames. Given a video, we replace snippets of text and audio with a MASK token; the model learns by choosing the correct masked-out snippet. Our objective learns faster than alternatives, and performs well at scale: we pretrain on 20 million YouTube videos.

Empirical results show that MERLOT RESERVE learns strong multimodal representations. When finetuned, it sets state-of-the-art on Visual Commonsense Reasoning (VCR), TVQA, and Kinetics-600; outperforming prior work by 5%, 7%, and 1.5% respectively. Ablations show that these tasks benefit from audio pretraining – even VCR, a QA task centered around images (without sound). Moreover, our objective enables out-of-the-box prediction, revealing strong multimodal commonsense understanding. In a fully zero-shot setting, our model obtains competitive results on four video tasks, even outperforming supervised approaches on the recently proposed Situated Reasoning (STAR) benchmark.

We analyze why audio enables better vision-language representations, suggesting significant opportunities for future research. We conclude by discussing ethical and societal implications of multimodal pretraining.

1. Introduction

The world around us is dynamic. We experience and learn from it using all of our senses, reasoning over them temporally through *multimodal script knowledge* [99, 128]. Consider Figure 1, which depicts someone cooking popcorn. From the images and dialogue alone, we might be able to imagine what *sounds* of the scene are: the process might begin with raw kernels scattering in an empty, metallic pot, and end with the dynamic ‘pops’ of popcorn expanding, along with the jiggling of a metal around the stove.

Predicting this sound is an instance of *learning from reentry*: where time-locked correlations enable one modality to educate others. Reentry has been hypothesized by developmental psychologists to be crucial for how we as humans learn visual and world knowledge, much of it without need for an explicit teacher [89, 35, 20, 100]. Yet, we ask – can we build machines that likewise learn vision, language, and sound *together*? And can this paradigm enable learning *neural script knowledge*, that transfers to language-and-vision tasks, *even those without sound*?

In this work, we study these questions, and find that the answers are ‘yes.’ We introduce a new model that learns self-supervised representations of videos, through all their modalities (audio, subtitles, vision). We dub our model MERLOT RESERVE¹, henceforth RESERVE for short.

¹Short for **M**ultimodal **E**vent **R**epresentation **L**earning **O**ver **T**ime, with **RE**-entrant **S**up**ER**Vision of **E**vents.

Our model differs from past work that learns from audio-image pairs [54, 71], from subtitled videos [105, 128], or from static images with literal descriptions [106, 21, 92]. Instead, we learn joint representations from *all modalities of a video*, using each modality to teach others. We do this at scale, training on over 20 million YouTube videos.

We introduce a new *contrastive masked span* learning objective to learn script knowledge across modalities. It generalizes and outperforms a variety of previously proposed approaches (e.g. [29, 106, 92, 128]), while enabling audio to be used as signal. The idea is outlined in Figure 1: the model must figure out which span of text (or audio) was MASKed out of a video sequence. We combine our objective with a second contrastive learning approach, tailored to learning *visual recognition* from scratch: the model must also match each video frame to a contextualized representation of the video’s transcript [128]. Through ablations, we show that our framework enables rapid pretraining of a model and readily scales to ‘large’ transformer sizes (of 644M parameters).

Experimental results show that 🗯️RESERVE learns powerful representations, useful even for tasks posed over only a few of the studied modalities. For example, when finetuned on Visual Commonsense Reasoning [126] (a vision+language task with no audio), it sets a new state-of-the-art, outperforming models trained on supervised image-caption pairs by **over 5%**. It does even better on video tasks: fine-tuning without audio, it outperforms prior work on TVQA [75] by a margin of **over 7%** (and given TVQA audio, performance increases even further). Finally, audio enables 91.1% accuracy on Kinetics-600 [19]. These performance improvements do not come at the expense of efficiency: our largest model uses one-fifths the FLOPs of a VisualBERT.

🗯️RESERVE also performs well in zero-shot settings. We evaluate on four diverse benchmarks: Situated Reasoning (STAR) [119], EPIC-Kitchens [26], LSMDC-FiB [96], and MSR-VTT QA [120]. These benchmarks require visual reasoning with respective emphasis on *temporality*, *future prediction*, and both *social* and *physical understanding*. With no fine-tuning or supervision, our model obtains competitive performance on each. Of note, it nearly doubles [123]’s SoTA zero-shot accuracy on MSR-VTT QA, and it outperforms supervised approaches (like ClipBERT [74]) on STAR.

Finally, we investigate *why*, and *on which training instances* audio-powered multimodal pretraining particularly helps. For instance, predicting audio rewards models for recognizing *dynamic state changes* (like cooked popcorn) and *human communication dynamics* (what are people’s emotions and towards whom). Our model progressively learns these phenomena as pretraining progresses. These signals are often orthogonal to what snippets of text provide, which motivates learning from both modalities.

In summary, our key contributions are the following:

- a. 🗯️RESERVE, a model for multimodal script knowledge,

fusing vision, audio, and text.

- b. A new contrastive span matching objective, enabling our model to learn from text *and audio* self-supervision.
- c. Experiments, ablations, and analysis, that demonstrate strong multimodal video representations.

Overall, the results suggest that learning representations from *all modalities* – in a time-locked, reentrant manner – is a promising direction, and one that has significant space for future work. We release code and model checkpoints at rowanzellers.com/merlotreserve.

2. Related Work

Our work brings together two active lines of research.

Joint representations of multiple modalities. Many language-and-vision tasks benefit from *early fusion* of the modalities [6]. A family of ‘VisualBERT’ models have been proposed for this: typically, these use a supervised object detector image encoder backbone, and pretrain on images paired with literal captions [106, 77, 81, 21, 124, 74]. Cross-modal interactions are learned in part through a *masked language modeling* (mask LM) objective [29], where subwords are replaced with ‘MASK’, and models independently predict each subword conditioned on both images and unmasked tokens.²

Perhaps closest to our work is MERLOT [128], which learns a joint vision-text model from web videos with automatic speech recognition (ASR). Through a combination of objectives (including a variant of mask LM), MERLOT established strong results on a variety of video QA benchmarks when finetuned. However, it lacks audio: it is limited to representing (and learning from) video frames paired with subtitles. Our proposed 🗯️RESERVE, which represents and learns from audio, outperforms MERLOT.

Co-supervision between modalities. A common pitfall when training a joint multimodal model is that complex *inter-modal* interactions can be ignored during learning, in favor of simpler *intra-modal* interactions [51, 24, 59]. For example, when using the aforementioned mask LM objective, models can *ignore visual input completely* in favor of text-text interactions [13]; this issue is magnified when training on videos with noisy ASR text [128].

A line of recent work thus learns independent modality-specific encoders, using objectives that cannot be shortcut with simple intra-modal patterns. Models like CLIP learn image classification by matching images with their captions, contrastively [132, 92, 63]. Recent work has explored this paradigm for matching video frames with their transcripts [121], with their audio signal [97, 114], or both [3, 2]; these

²Recent papers propose extensions, like generating masked-out spans [22] or text [78, 116], but it is unclear whether they can outperform the VisualBERTs on vision-language tasks like VCR [126]. Another extension involves learning from text-to-speech audio in a captioning setting [62, 79] – yet this lacks key supervision for environmental sounds and emotive speech.

works likewise perform well on single-modality tasks like audio classification and activity recognition. These independent encoders can be combined through late fusion [97], yet late fusion is strictly less expressive than our proposed joint encoding (early fusion) approach.

Our work combines both lines of research. We learn a model for jointly representing videos, through all their modalities, and train it using a new learning objective that enables *co-supervision* between modalities.

3. Model: 🧠RESERVE

In this section, we present 🧠RESERVE, including: our model architecture (3.1), new pretraining objectives (3.2), and pretraining video dataset (3.3). At a high level, 🧠RESERVE represents a video by fusing its constituent modalities (vision, audio, and text from transcribed speech) together, and over time. These representations enable both finetuned and zero-shot downstream applications.

More formally, we split a video \mathcal{V} into a sequence of non-overlapping segments in time $\{s_t\}$. Each segment has:

- a. A frame v_t , from the middle of the segment,
- b. The ASR tokens w_t spoken during the segment,
- c. The audio a_t of the segment.

Segments default to 5 seconds in length; we discuss details of how we split videos into segments in Appendix C.

As the text w_t was automatically transcribed by a model given audio a_t , it is reasonable to assume that it contains strictly less information content.³ Thus, for each segment s_t , we provide models with exactly one of text *or* audio. We will further *mask out* portions of the text and audio during pretraining, to challenge models to recover what is missing.

3.1. Model architecture

An overview of 🧠RESERVE is shown in Figure 2. We first pre-encode each modality independently (using a Transformer [110] or images/audio; a BPE embedding table for text). We then learn a joint encoder to fuse all representations, together and over time.

Image encoder. We use a Vision Transformer (ViT; [34]) to encode each frame independently. We use a patch size of 16 and apply a 2x2 query-key-value attention pool after the Transformer, converting an image of size $H \times W$ into a $H/32 \times W/32$ feature map of dimension d_h .

Audio encoder. We split the audio in each segment a_t into three equal-sized *subsegments*, for compatibility with the lengths at which we mask text (Appendix C). We use an

³Despite being derived from the audio, pretraining with text is still paramount: 1) in §3.2 we discuss how jointly modeling audio+text prevents models from shortcutting pretraining objectives via surface correlations; 2) in §4.2 we show that incorporating both transcripts and audio during fine-tuning improves performance; and 3) a textual interface to the model is required for downstream vision+language with textual inputs.

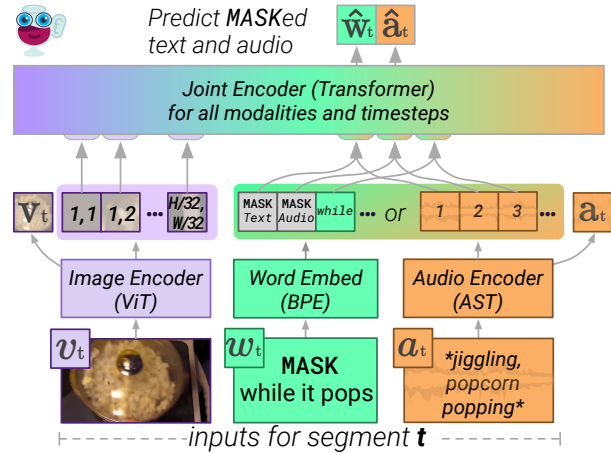


Figure 2: 🧠RESERVE architecture. We provide sequence-level representations of video frames, and *either* words or audio, to a joint encoder. The joint encoder contextualizes over modalities and segments, to predict what is behind MASK for audio \hat{a}_t and text \hat{w}_t . We supervise these predictions with independently encoded targets: a_t from the audio encoder, and w_t from a separate text encoder (not shown).

Audio Spectrogram Transformer to encode each subsegment independently [47]. The three feature maps are concatenated; the result is of size $18 \times d_h$ for every 5 seconds of audio.

Joint encoder. Finally, we jointly encode all modalities (over all input video segments) using a bidirectional Transformer. We use a linear projection of the final layer’s hidden states for all objectives (e.g. \hat{w}_t and \hat{a}_t).

Independently-encoded targets. We will supervise the joint encoder by simultaneously learning independently-encoded ‘target’ representations for each modality. Doing this is straightforward for the image and audio encoders: we add a CLS to their respective inputs, and extract the final hidden state v_t or a_t at that position. For text, we learn a separate bidirectional Transformer *span encoder*, which computes targets w_t from a CLS and embedded tokens of a candidate text span. This enables zero-shot prediction (4.4).

Architecture sizes. We consider two model sizes in this work, which we pretrain from random initialization:

1. 🧠RESERVE-B, with a hidden size of 768, a 12-layer ViT-B/16 image encoder, and a 12-layer joint encoder.
2. 🧠RESERVE-L, with a hidden size of 1024, a 24-layer ViT-L/16 image encoder, and a 24-layer joint encoder.

We always use a 12-layer audio encoder, and a 4-layer text span encoder. Details are in Appendix B.

3.2. Contrastive Span Training

We introduce *contrastive span* training, which enables learning across and between the three modalities. As shown in Figure 3, the model is given a sequence of video segments.

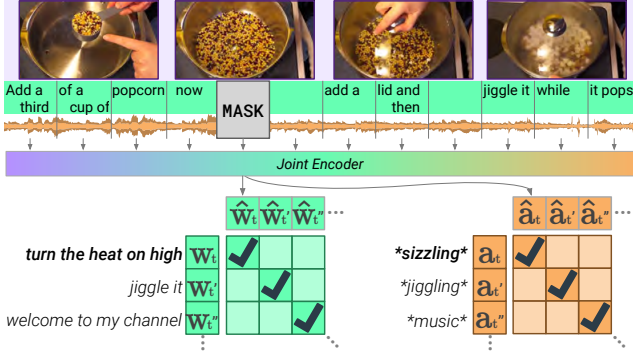


Figure 3: Contrastive span training. Given a video with all modalities temporally aligned, we MASK out a region of text and audio. The model must maximize its similarity *only* to an independent encoding of the text \mathbf{w}_t and audio \mathbf{a}_t .

For each one, we include the video frame, and then three ‘sub-segments’ that are each either text *or* audio. The subdivided audio segments are encoded independently by the Audio Encoder, before being fused by the Joint Encoder. We train by replacing 25% of these text and audio subsegments with a special MASK token. The model must match the representation atop the MASK *only with* an independent encoding of its span.

Our approach combines past success at matching images to their captions [92, 63] along with ‘VisualBERT’-style prediction of independent tokens [106, 21]—though, crucially, we predict representations at a higher-level semantic unit than individual tokens. Our approach also enables the model to learn from both audio and text, while discouraging *memorization* of raw perceptual input, or tokens – which can harm representation quality [112].

Formally, we minimize the cross entropy between the MASKED prediction $\hat{\mathbf{w}}_t$ and its corresponding phrase representation \mathbf{w}_t , versus others in the batch \mathcal{W} :

$$\mathcal{L}_{\text{mask} \rightarrow \text{text}} = \frac{1}{|\mathcal{W}|} \sum_{\mathbf{w}_t \in \mathcal{W}} \left(\log \frac{\exp(\sigma \hat{\mathbf{w}}_t \cdot \mathbf{w}_t)}{\sum_{\mathbf{w} \in \mathcal{W}} \exp(\sigma \hat{\mathbf{w}}_t \cdot \mathbf{w})} \right). \quad (1)$$

We first L^2 -normalize \mathbf{w} and $\hat{\mathbf{w}}$, and scale their dot product with a parameter σ [92].⁴ We then add this to its transposed version $\mathcal{L}_{\text{text} \rightarrow \text{mask}}$, giving us our text-based loss $\mathcal{L}_{\text{text}}$. Analogously, we define $\mathcal{L}_{\text{audio}}$ for audio, between the MASKED prediction $\hat{\mathbf{a}}_t$ and its target \mathbf{a}_t , versus others \mathbf{a} in the batch.

In addition to these masked text and audio objectives, we simultaneously train the model to match video frames with a contextualized encoding of the transcript.⁵ Here, the joint encoder encodes the entire video’s transcript at once, extracting a single hidden representation per segment $\hat{\mathbf{v}}_t$. We use the same contrastive setup as Equation 1 to maximize the

⁴Following past work, we optimize σ and clip it at 100, which enables the model to ‘warm-up’ its emphasis placed on hard negatives [92, 113].

⁵In MERLOT [128], this objective was found to be critical for learning visual recognition from self-supervised videos.

similarity of these vectors with the corresponding \mathbf{v}_t vectors from the frames, giving us a symmetric frame-based loss $\mathcal{L}_{\text{frame}}$. The final loss is the sum of the component losses:

$$\mathcal{L} = \mathcal{L}_{\text{text}} + \mathcal{L}_{\text{audio}} + \mathcal{L}_{\text{frame}}. \quad (2)$$

Avoiding shortcut learning. Early on, we observed that training a model to predict a *perceptual* modality (like audio or vision) given input from *the same modality*, led to shortcut learning – a low training loss, but poor representations. We hypothesize that this setup encourages models to learn imperceptible features, like the exact model of the microphone, or the chromatic aberration of the camera lens [33]. We avoid this, while still using audio as a target, by simultaneously training on two kinds of masked videos:

- Audio only as target.** We provide only video frames and subtitles. The model produces representations of both *audio* and *text* that fill in MASKED blanks.
- Audio as input.** We provide the model video frames, and subtitles *or audio* at each segment. Because the model is given audio as an input somewhere, the model only produces representations for MASKED *text*.

Another issue is that YouTube’s captions are not perfectly time-aligned with the underlying audio. During our initial exploration, models took ready advantage of this shortcut: for instance, predicting an audio span based on what adjacent (overlapping) words sound like. We introduce a masking algorithm to resolve this; details in Appendix C.


Pretraining setup. We train on TPU v3-512 accelerators; training takes 5 days for RESERVE-B, and 16 days for RESERVE-L. We made pretraining more efficient through several algorithmic and implementation improvements. Of note, we simultaneously train on written (web) text, which enables more text candidates to be used. We use a batch size of 1024 videos, each with $N=16$ segments (split into two groups of 8 segments each). We use AdamW [69, 80] to minimize Equation 2. More details and hyperparameters are in Appendix B.

3.3. Pretraining Dataset


Recent prior work on static images that demonstrates empirical improvements by increasing dataset size – all the way up to JFT-3B [70, 34, 92, 130]. The same pattern emerges in videos: prior work that has shown promising empirical improvements not only by scaling to 6 million videos/180M frames [128], but also by collecting a diverse set (i.e., going beyond instructional videos [60]).

To this end, we introduce a new training dataset of 20 million English-subtitled YouTube videos, and 1 billion frames, called YT-Temporal-1B. At the same time, we take steps to protect user privacy, directing scraping towards public, large, and monetized channels. We detail our collection, preprocessing, and release strategy in Appendix E.

4. Experiments

In this section, we present model ablations (4.1.1), and show that a finetuned  RESERVE obtains state-of-the-art results on VCR (4.1.2), TVQA (4.2), and Kinetics-600 (4.3). We then show that our model has strong zero-shot capability, over four challenging zero-shot tasks (4.2).

4.1. Visual Commonsense Reasoning (VCR)

We evaluate  RESERVE first through finetuning on VCR [126]. Most competitive models for VCR are pretrained exclusively on images paired with captions, often with supervised visual representations (e.g. from an object detector). To the best of our knowledge, the only exception is MERLOT [128], which uses YouTube video frames and text as part of pretraining; no VCR model to date was pretrained on audio.

VCR Task. A model is given an image from a movie, and a question. The model must choose the correct answer given four multiple choice options ($Q \rightarrow A$); it then is given four *rationales* justifying the answer, and it must choose the correct one ($QA \rightarrow R$). The results are combined with a $Q \rightarrow AR$ metric, where a model must choose the right answer *and then* the right rationale, to get the question ‘correct.’

Finetuning approach. We follow [128]’s approach: ‘drawing on’ VCR’s detection tags onto the image, and jointly finetuning on $Q \rightarrow A$ and $QA \rightarrow R$. For both subproblems, we learn by scoring each $Q \rightarrow A$ (or $QA \rightarrow R$) option independently. We pool a hidden representation from a MASK inserted after the text, and pass this through a newly-initialized linear layer to extract a logit, which we optimize through cross-entropy (details in Appendix D.1.1.)

4.1.1 Ablations: contrastive learning with audio helps.

While we present our final, state-of-the-art VCR performance in 4.1.2, we first use the corpus for an ablation study. We use the same architecture and data throughout, allowing apples-to-apples comparison between modeling decisions. We start with a similar configuration to MERLOT [128] and show that contrastive span training improves further, particularly when we add audio.

Contrastive Span helps for Vision+Text modeling. We start by comparing pretraining objectives for learning from YouTube ASR and video alone:

- a. **Mask LM.** This objective trains a bidirectional model by having it *independently* predict masked-out tokens. We make this baseline as strong as possible by using SpanBERT-style masking [64], where text spans are masked out (identical to our *contrastive spans*). Each span w is replaced by a MASK token, and we predict each of its subwords w_i independently.⁶

⁶Like [64], we concatenate the MASK’s hidden state with a position embedding for index i , pass the result through a two-layer MLP, and use tied embedding weights to predict w_i .






	Configuration for one epoch of pretraining	VCR Q→A	val (%)
V+T	Mask LM [29, 106, 128]	67.2	
	VirTex-style [27]	67.8	
	 Contrastive Span	69.7	
V+T+A	 Audio as target	70.4	
	 Audio as input and target	70.7	
	Audio as input and target, w/o strict localization	70.6	
	 RESERVE-B	71.9	

Table 1: **Ablation study** of our contrastive span objective. It outperforms prior work in a Vision+Text setting, with a 1% boost when audio is added. Our full setup, adding written text, improves another 1%.  denotes part of our full model.

- b. **VirTex [27].** In this objective, we likewise mask text subsegments and extract their hidden states. The difference is that we sequentially predict tokens $w_i \in w$, using a left-to-right language model (LM) with the same architecture details as our proposed span encoder.

Results are in Table 1. Versus these approaches, our contrastive span objective boosts performance by over 2%, after one epoch of pretraining only on vision and text. We hypothesize that its faster learning is caused by encouraging models to learn concept-level span representations; this might not happen when predicting tokens individually [23].

Audio pretraining helps, even for the audio-less VCR:

- d. **Audio as target.** Here, the model is only given video frames and ASR text as input. In addition to performing contrastive-span pretraining over the missing text spans, it does the same over the (held-out) audio span (Equation 2. This boosts VCR accuracy by 0.7%.
- e. **Audio as input and target.** The model does the above (for video+text input sequences), and simultaneously is given video+text+audio sequences, wherein it must predict missing text. This boosts accuracy by 1% in total.
- f. **Sans strict localization.** We evaluate the importance of our strict localization in time. Here, in addition to correct subsegments at the *true* position t as a correct match, we count adjacent MASKed out regions as well. An extreme version of this was proposed by [49], where a positive match can be of any two frames in a video. Yet even in our conservative implementation, performance drops slightly, suggesting localization helps.

Putting these all together, we find that contrastive span pretraining outperforms mask LM, with improved performance when audio is used **both as input and target**. For our flagship model, we report results in Table 1 on simultaneously training on web-text sequences as well (Appendix C.4), this improves performance by an additional 1%.

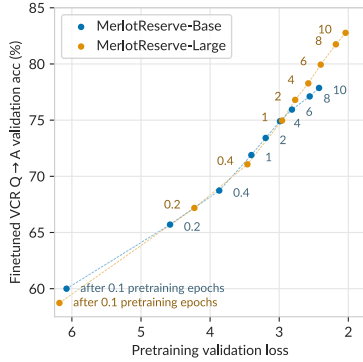


Figure 4: **Pretraining progress:** performance on contrastive-span pretraining, vs. finetuned VCR validation accuracy. Pretraining RESERVE-B for 9 more epochs boosts performance by 5%; L by 8%.



		VCR test (acc; %)		
Model		Q→A	QA→R	Q→AR
Caption/ObjDet-based	ERNIE-ViL-Large [124]	79.2	83.5	66.3
	Villa-Large [39]	78.9	83.8	65.7
	UNITER-Large [21]	77.3	80.8	62.8
	Villa-Base [39]	76.4	79.1	60.6
	VilBERT [81]	73.3	74.6	54.8
	B2T2 [4]	72.6	75.7	55.0
	VisualBERT [77]	71.6	73.2	52.4
Video-based	MERLOT [128]	80.6	80.4	65.1
	 RESERVE-B	79.3	78.7	62.6
	 RESERVE-L	84.0	84.9	72.0

Table 2: RESERVE gets **state-of-the-art leaderboard performance on VCR**. We compare it with the largest submitted single models, including image-caption models that utilize heavy manual supervision (e.g. object detections and captions).

Model	TVQA (acc; %)	
	Val	Test
Human [75]	–	89.4
Subtitles	MERLOT [128]	78.7
	MMFT-BERT [109]	73.5
	Kim et al [68]	76.2
	RESERVE-B	82.5
	RESERVE-L	85.9
Audio	RESERVE-B	81.3
	RESERVE-L	85.6
Both	RESERVE-B	83.1
	RESERVE-L	86.5

Table 3: RESERVE gets state-of-the-art results on TVQA by **over 7%**, versus prior work (that cannot make use of audio).

4.1.2 VCR Results

Encouraged by these results, we train our models for 10 epochs on YT-Temporal-1B. Figure 4 demonstrates that finetuned VCR performance tracks with the number of pretraining epochs, as well as the validation loss.⁷

Finally, in Table 2, we compare RESERVE against the largest published models from the VCR leaderboard. Of note, RESERVE-L outperforms all prior work, by **over 5%** on Q→AR metric. It outperforms even large ensembles (e.g. 15 ERNIE-Large’s) submitted by industry [124], though we do not show these on this table to focus on only single models.

Efficiency. The accuracy increase of RESERVE is not simply due to compute.⁸ In fact, our RESERVE-L requires *one-fifth the FLOPs* of detector-based systems, like UNITER-Large [21] (Appendix B.3). Moreover, because RESERVE-L uses a pure ViT backbone versus MERLOT’s ViT-ResNet hybrid, it uses fewer FLOPs than MERLOT, while scoring 7% higher. Meanwhile, RESERVE-B outperforms ‘base’ detector-based models, while using *less than one-tenth their FLOPs*.

In terms of parameter count, RESERVE-B is comparable to prior work. On VCR, including the vision stack, RESERVE-B has 200M finetunable parameters and performs similarly to the 378M parameter UNITER-Large. RESERVE-L has 644M parameters.

4.2. Finetuning on TVQA

Next, we use TVQA [75] to evaluate our model’s capacity to transfer to multimodal video understanding tasks. In

⁷The plot suggests that if we pretrained longer, VCR performance might continue to increase, though a confounding factor might be the learning-rate schedule. With access to compute beyond our current capacity, future work would be well-suited to consider this and other pre-training modifications.

⁸Here, we use FLOPs as our key efficiency metric, as they are a critical bottleneck in model scaling [66, 34, 130]. On the other hand, we argue that parameter count can be misleading – for instance, many Transformer parameters can be tied together with minimal performance loss [72].

TVQA, models are given a video, a question, and five answer choices. The scenes come from American TV shows, and depict characters interacting with each other through dialogue – which past work represents through subtitles.

Audio-Subtitle Finetuning. To evaluate how much audio can help for TVQA, we finetune RESERVE jointly between the ‘Subtitles’ and ‘Audio’ settings. Like on VCR, we consider one sequence per candidate: each contains video frame features, the question, the answer candidate, and a MASK token (from where we pool a hidden representation). During training, each sequence is duplicated: we provide one sequence with *subtitles* from the video, and for the other, we use *audio*. This lets us train a single model, and then test how it will do *given subtitles*, *given audio*, or *given both* (by averaging the two softmax predictions).

Results. We show TVQA results in Table 3. With subtitles and video frames alone, our RESERVE-B outperforms all prior work by over 3%. Combining subtitle-only and audio-only predictions performs even better, improving over 4% versus the prior state-of-the-art, MERLOT (and in turn over other models). The same pattern holds (with additional performance gains) as model size increases: RESERVE-L improves over prior work by **7.6%**.

4.3. Finetuning on Kinetics-600 Activity Recognition

Next, we use Kinetics-600 [19] to compare our model’s (finetuned) activity understanding versus prior work, including many top-scoring models that do not integrate audio. The task is to classify a 10-second video clip as one of 600 categories. We finetune RESERVE jointly over two settings: vision only, and vision+audio.

Results. We show Kinetics-600 results on the validation set, in Table 4. RESERVE improves by **1.7%** when it can jointly represent the video’s frames with its sound. This enables it to outperform other large models, including VATT

Model	Kinetics-600 (%)	
	Top-1	Top-5
VATT-Base[2]	80.5	95.5
VATT-Large [2]	83.6	96.6
TimeSFormer-L [9]	82.2	95.6
Florence [125]	87.8	97.8
MTV-Base [122]	83.6	96.1
MTV-Large [122]	85.4	96.7
MTV-Huge [122]	89.6	98.3
RESERVE-B	88.1	95.8
RESERVE-L	89.4	96.3
+Audio		
RESERVE-B	89.7	96.6
RESERVE-L	91.1	97.1

Table 4: 🗯️RESERVE gets state-of-the-art results on Kinetics-600 by **1.5%** versus standard approaches (that cannot make use of audio).

Model	Situated Reasoning (STAR)					EPIC-Kitchens			LSMDC	MSR-VTT QA	
	Interaction	Sequence	Prediction	Feasibility	Overall	(val class-mean R@5; %)			(FIB test %)	(test acc %)	
						Verb	Noun	Action	Acc	top1	top5
Supervised SoTA	39.8	43.6	32.3	31.4	36.7	28.2	32.0	15.9	52.9	43.1	
Random	25.0	25.0	25.0	25.0	25.0	6.2	2.3	0.1	0.1	0.1	0.5
CLIP (ViT-B/16) [92]	39.8	40.5	35.5	36.0	38.0	16.5	12.8	2.3	2.0	3.0	11.9
CLIP (RN50x16) [92]	39.9	41.7	36.5	37.0	38.7	13.4	14.5	2.1	2.3	2.3	9.7
Just Ask (ZS)[123]										2.9	8.8
zero-shot											
RESERVE-B	44.4	40.1	38.1	35.0	39.4	17.9	15.6	2.7	26.1	3.7	10.8
RESERVE-L	42.6	41.1	37.4	32.2	38.3	15.6	19.3	4.5	26.7	4.4	11.5
RESERVE-B (+audio)	44.8	42.4	38.8	36.2	40.5	20.9	17.5	3.7	29.1	4.0	12.0
RESERVE-L (+audio)	43.9	42.6	37.6	33.6	39.4	23.2	23.7	4.8	31.0	5.8	13.6

Table 5: Zero shot results. On STAR, 🗯️RESERVE obtains state-of-the-art results, outperforming finetuned video models. It performs well on EPIC-Kitchens (verb and noun forecasting), along with LSMDC, despite their long-tail distributions. On MSR-VTT QA, it outperforms past work on weakly-supervised video QA. Further, it outperforms CLIP (that cannot handle dynamic situations), and benefits from audio when given.

[2] which learns to represent audio independently from vision (and so cannot early-fuse them), along with the larger MTV-Huge model [122] by 1.5%.

4.4. Zero-Shot Experiments

Next, we show that our model exhibits strong zero-shot performance for a variety of downstream tasks. Our zero-shot interface is enabled by our *contrastive span objective*. For QA tasks that require predicting an option from a label space of short phrases, we encode this label space as vectors, and predict the closest phrase to a MASKED input. We consider:

- Situated Reasoning (STAR) [119]. This task requires the model to reason over short situations in videos, covering four axes: interaction, sequence, prediction, and feasibility. The model is given a video, a templated question, and 4 answer choices. We convert templated questions into literal statements (which are more similar to YouTube dialogue); the label space is the set of four options.
- Action Anticipation in Epic Kitchens [26]. Here, the goal is to predict *future actions* given a video clip, which requires reasoning temporally over an actor’s motivations and intentions. The dataset has a long tail of rare action combinations, making zero-shot inference challenging (since we do not assume access to this prior). As such, prior work [46, 38] trains on the provided in-domain training set. To adapt 🗯️RESERVE to this task, we provide it a single MASK token as text input, and use as our label space of all combinations of verbs and nouns in the vocabulary (e.g. ‘cook apple, cook avocado’, etc.).
- LSMDC [82, 96]. Models are given a video clip, along with a video description (with a MASK to be filled in). We compare it with the vocabulary used in prior work [128].
- MSR-VTT QA [120]. This is an open-ended video QA task about what is literally happening in a web video. We use GPT3 [16], prompted with a dozen (unlabelled) questions, to reword the questions into statements with MASKS. This introduces some errors, but minimizes domain shift. We use a label space of the top 1k options.

For these tasks, we use $N=8$ video segments (dilating time when appropriate), and provide audio input when possible. Details and prompts are in Appendix D. We compare against both finetuned and zeroshot models, including running CLIP [92] on all tasks. CLIP is a strong model for zero-shot classification, particularly when *encyclopedic knowledge about images* is helpful; our comparisons showcase where multimodal script knowledge helps.

Results. Table 5 shows our model performs competitively:

- On STAR, it obtains state-of-the-art results, with performance gain when audio is included. Interestingly, 🗯️RESERVE-B outperforms its larger variant; we hypothesize that this is due to limited prompt searching around question templates. We qualitatively observed that 🗯️RESERVE-L sometimes excludes topically correct options if they sound grammatically strange (to it).
- On EPIC-Kitchens, our model obtains strong results at correctly anticipating the verb and noun - despite the heavy-tailed nature of both distributions. It is worse on getting both right (‘action’), we suspect that this might be due to priors (motifs) between noun and verb [129]. These are easy to learn given access to training data, but we exclude these as we consider the zero-shot task.
- On LSMDC, our model obtains strong results at filling-in-the-blank, likewise despite a heavy (unseen) frequency bias. Notably, it outperforms CLIP significantly, with CLIP often preferring templates that use visually-relevant words, even if they don’t make sense as a whole. For instance, given a clip of a mailman, CLIP chooses ‘the mailman smiles off,’ versus ‘the mailman takes off.’
- Finally, our model performs well on MSR-VTT QA, outperforming past work that directly rewords subtitled instructional videos into video QA instances [123].

5. Qualitative Analysis: Why does audio help?

What can 🗯️RESERVE learn from both text *and* audio? Three validation set examples are shown in Figure 5. The model is given the displayed text and video frames, and must



Figure 5: **Exploring MASKed audio self-supervision.** Shown are example videos from our validation set, with predictions from 🧠RESERVE-B. During pretraining, our model progressively learns to pick up on audio-specific clues. It seems to recognize physical dynamics of *cooking popcorn*, matching the first row to its MASKed audio. Likewise, it seems to use social reasoning to match the second row to its audio. Both of these clues are orthogonal to what the subtitles provide.

match the MASK to the correct missing text and audio span (out of 48k total in the batch). The plots show 🧠RESERVE-B’s probability of correctly identifying the correct audio or text span, as it progresses through 10 epochs of pretraining.

Audio’s supervisory signal. In the first two rows of Figure 5, audio provides orthogonal supervision to text:

1. In the first row, the MASKed audio contains the sound of popcorn pops slowing. By the final epoch, 🧠RESERVE-B selects this specific auditory cue with 60% probability, over others (including from adjacent segments, at different stages of popping). Here, sound provides signal for joint vision-text understanding of the situation, as evidenced by its greater match probability.
2. The second row contains only the text ‘why,’ with the audio providing greatly more information — a female-presenting speaker (shown in the next frame) laughs, astonished that the child (in the frame afterwards) might want a better relationship with their parents.
3. In the third row, matching performance is similar between modalities, possibly as the yogi is narrating over a (muted) video recording, and not adding much information.

Role of text. Text is still a crucial complement to audio, in terms of the supervision it provides. Consider the second row: 🧠RESERVE-B learns to match the audio almost perfectly (perhaps reasoning that the speaker is shown in the next frame, and is laughing). In later epochs, its text-match probability increases: knowing that a ‘why’ question is likely to be asked is a valid *social* inference to make about this (tense) situation.

Learning through multimodal reentry. Developmental psychologists have hypothesized that human children learn by *reentry*: learning connections between all senses as they interact with the world [35, 100]. Using a held-out

modality (like audio) might support learning a better world representation (from e.g. vision and text), by forcing models to abstract away from raw perceptual input. Our work suggests that reentry has potential for machines as well.

6. Conclusion, Limitations, Broader Impact

We introduced 🧠RESERVE, which learns jointly through sound, language, and vision, guided through a new pretraining objective. Our model performs well in both finetuned and zero-shot settings, yet it has limitations. Our model only learns from 40-second long videos; relies on ASR models for subtitles, and can only match (not generate) text and audio.

Still, we foresee broad possible societal impact of this line of work. Video-pretrained models might someday assist low vision or d/Deaf users [76, 48]. Yet, the same technology can have impacts that we authors consider to be negative, including surveillance, or applications that hegemonize social biases. We discuss these further in Appendix A: key dimensions include respecting user privacy during dataset collection, exploring biases in YouTube data, dual use, and energy consumption. We discuss our plan to *release our model and data* for research use so others can critically study this approach to learning script knowledge.

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Abstract

We provide the following materials in the appendix:

- A full broader impact statement (Section A)
- Details about our model architecture (Section B)
- Details about how we provide video data into the model, including how we align the modalities and perform the masking (Section C)
- Details about how we adapted our model to downstream tasks (Section D)
- Details about how we collected data (Section E)
- Additional experiments (Section F)

A. Broader Impact Statement

In this paper, we have presented a model for learning multimodal neural script knowledge, through incorporation of audio as a first-class citizen alongside text and video frames. We argue that academic study of this learning paradigm is important, in part because it relates to how we as humans understand the world. We as humans process situations by perceiving through multiple modalities and interpreting the result holistically.

At the same time, the work and methodology that we outlined risks dual use. Like other large machine learning systems pretrained on web data, our system may reproduce harmful social biases present in its training data. While a variety of past work has studied risks of *language-only* pretraining [127, 14, 7, 61], the video-centric pretraining that we explore in our work might have different benefits and risks. We discuss these below, along with how we worked to mitigate them through our work.

A.1. Privacy.

A significant risk with training on data at YouTube scale is protecting user privacy. We took several proactive steps to ensure this, that in turn build off prior work and community norms [1, 84, 128]:

- We release only the video IDs for download, following prior work [1, 84]. Thus, if a user deletes a video off of YouTube, it becomes removed from YT-Temporal-1B as well, giving content creators a right to opt out of all uses of their videos.
- Building off of past work [128], we directed our data collection towards *public* and *monetized channels*. These channels are identifiable insofar as they contain more subscribers, and more videos. They include companies that have official accounts, including journalism outlets like the *New York Times* and *Vox*. They also include individuals for whom making public YouTube videos is their full time job. In either case, our use videos in question for research purposes can be seen as *fair use*.

Model	Accuracy (%)		
	Voice	Image+Voice	Image
🗯️RESERVE-L	10.8	9.6	10.7
CLIP ViT-B/16 [92]			86.0

Table 6: Zero-shot person (face/voice) recognition accuracy on VoxCeleb2 [87] and VGGFace2 [17], using different modalities. While 🗯️RESERVE can perform person recognition from several modalities, its performance is much lower than the recognition-optimized CLIP model in the image-to-name setting. We hypothesize that this is due to a similarity between this setting and CLIP’s pretraining data – news articles often include celebrity images, paired with their names.

Framing of privacy. Privacy is a nuanced topic with many societally, culturally, and generationally-specific interpretations. We took inspiration from Marwick and Boyd [83]’s framework of *networked privacy*, which posits that users posting public videos might *encode* private information – enough so that their intended viewership (friends, possibly) can catch the gist, but not enough so as to leak private details like phone numbers to the world.

Through the lens of networked privacy, we see key differences between studying videos on a moderated platform, versus NLP work that trains models from the open web (e.g. [29, 93, 16]). When YouTube users upload videos, they tend to understand details of its privacy policy, beyond consenting to it [65]. Likewise, YouTubers typically upload their own videos [102]; the platform deters users from re-posting other users’ content. These factors differ from text on the open web. Today, ‘data brokers’ post private details (like phone numbers) to the web for profit [25]; concerningly, a study on language models suggests that models are vulnerable at *memorizing* this private information [18].

It is worth examining our research through other framings of privacy as well. For example, internet platforms profit off of user data, whereas users do not share equally in these profits [37]. For this, and for the other reasons mentioned, we aim to release our model only for research-based use.

A.1.1 Empirical study: can 🗯️RESERVE identify individual celebrities?

Inspired by work studying language model memorization of private information [18], we wish to empirically probe 🗯️RESERVE’s ability to recognize individuals. Our goal during model development was **not** to optimize for this ability. Instead, our goal was to study models for *multimodal script knowledge* (what people might be doing in a situation over time, and why) instead of long-tailed *visual recognition* (including who those individuals are). These goals might

trade off – for instance, our training data only has individuals’ names when they are mentioned in ASR subtitles, a pairing that might be significantly noisier than images and text on the open web.

We study this capacity on the VoxCeleb2 and VGGFace2 datasets [87, 17], where we created a test set of 120 celebrities, with 100 samples of each. We study these datasets not to promote them, but to establish a **conservative upper-bound** for the capacity of a model to recognize non-celebrities. We hypothesize that if 🗯️RESERVE struggles to select the right celebrity out of 120 predefined options, it would struggle much more at identifying random people (where the set of candidate names is much greater). We test this hypothesis over three zero-shot settings:

1. **Voice to name.** Given an audio clip sampled for a celebrity, we encode it with our model’s audio encoder. We provide our model’s joint encoder the text ‘the sound of MASK’, followed by the encoded audio. A blank image is provided. We extract the representation on top of the MASK, and choose the most similar celebrity name.
2. **Image+voice to name.** Here, we adopt the same format as ‘Audio to name,’ except we additionally encode an image of the celebrity’s face in question.
3. **Image to name.** Here, 🗯️RESERVE encodes an image of the celebrity in question, and we provide it with text ‘A picture of MASK.’ No audio is provided. Using our model’s joint encoder, we select the closest encoded celebrity name, out of all options.

We use this format to compare to a CLIP model, which was trained on web images with captions [92]. For the CLIP comparison, we use it to encode each image, and for all considered celebrity names, the sentence ‘A picture of \${name}’. We choose the closest encoded sentence to the encoded image.

We show our results in Table 6. In all modes, our model is less than 11% accurate at recognizing celebrities. Curiously, the accuracy *drops* given both the image and the voice, suggesting that the way we fused a celebrity’s image and voice together might be outside the model’s training distribution. These results are significantly lower than CLIP’s 86% accuracy at classifying a person from their image.

In Figure 6, we investigate more into which celebrities our model is best at recognizing. Only a few celebrities are reliably classified; these tend to be very famous celebrities like Oprah Winfrey and Justin Bieber. Several sports players are recognized well (including LeBron James and Roger Federer), which could imply that our model learned their identities from watching sports replays or commentary. Most other celebrities are hardly recognized, whereas CLIP does well across the board.

Results summary. Together, these results show that while models like CLIP focus on encyclopedic knowledge

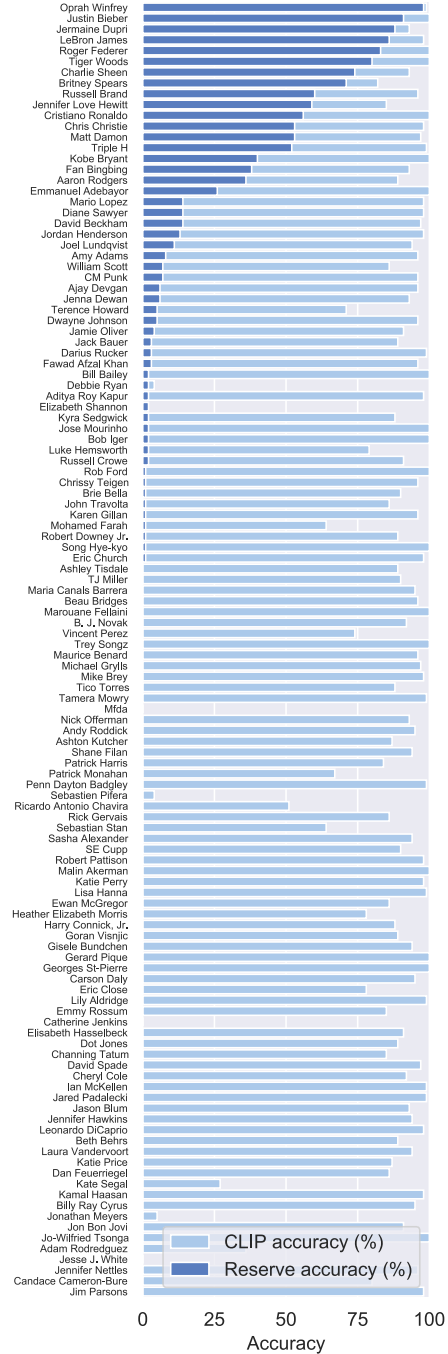


Figure 6: VoxCeleb2 results per-celebrity, comparing 🗯️RESERVE-L versus CLIP ViT-B/32 in the same ‘image-text’ setting. Our model reliably recognizes A-list celebrities like Oprah Winfrey, very famous musicians (Justin Bieber) and sports players (LeBron James). However, it struggles on every other celebrity, particularly compared with CLIP. This suggests that our model primarily learns **semantic** as opposed to **recognition-level** encyclopedic knowledge.

that results in strong zero-shot person recognition accuracy, 🗯️RESERVE is not as effective as other models in memorizing particular celebrities— and, thus, perhaps not as effective as memorizing particular *non-celebrities*. These results suggest that 🗯️RESERVE’s objectives and data might make it *less of a concern* to release privacy-wise, versus models trained on web images with captions.

As the rest of the paper emphasizes however, 🗯️RESERVE performs well on tasks with temporal understanding and commonsense reasoning as the primary goal. On a broader level, these results suggest that it is possible to learn strong models about temporal reasoning *without* person-level memorization, though more work is needed.

A.2. Biases in (pre)training data.

The ‘knowledge’ that our model learns should be viewed as situated within YouTube [67], which has numerous biases (that we will discuss next). Past work has made similar observations for language model pretraining on the open web[7]. One of the root causes of such bias is learning objectives that encourage memorization of surface level cooccurrences, rather than truly causal factors [56, 8, 117]. Though it is possible that in the very long term, a paradigm of *grounded learning* might resolve some of these issues, the objectives in this work still likely reify biases that exist in the YouTube data.

Platform biases. Unlike many other pretraining efforts, that scrape data from the open internet (e.g. [93, 16, 92]) which directly leads to toxic biases (e.g. [42, 32, 11]); we trained our model on YouTube, which is a moderated platform [101]. Though the content moderation might perhaps reduce overtly ‘toxic’ content, social media platforms like YouTube still contain harmful microaggressions [15], and alt-lite to alt-right content [95]. Additionally, it should be mentioned that the content moderation on YouTube disproportionately filters out minoritized voices [44]. Thus, despite us not using any word-based ‘blocklist,’ our model’s pretraining data is still biased [32]. Even without videos being explicitly removed, the ‘YouTube algorithm’ incentivizes the production of certain types of content over others [12, 102]; e.g. people’s roles in YouTube videos tend to be highly gendered [86], which might bias situation understanding [133].

Bias amplification. In this work, we pretrained a model primarily on ASR text, which is itself produced by another model. The automatic captions in YouTube are known to suffer from gender bias [107], which our model (like neural models generally) might in turn *amplify* [133]. The transcriptions on YouTube are also likely poor at handling important identity markers, like pronouns. Already, text-only models like BERT struggle with pronouns like they/them and zi/zir; our reliance on ASR text makes our corpus likely worse in this regard [28]. While past work, namely MERLOT [128], ‘cleaned’ this ASR text – through another

large language model – we opted not to do so for this work due to computational expense. Though in that work, the ASR-denoisification was found to boost performance in VCR, it seems unlikely that it would solve this core issue of model bias.

A.3. Dual use.

Learning connections between video, audio, and text – though an important area of study as we have argued – can be used for undesirable applications, beyond what we have outlined under ‘biases.’ We outline and discuss a few below.

Generating fake content. A concern for pretrained models is that they can generate fake content, that could be used by ‘bad’ actors for their ends [127]. It should be noted that our model cannot explicitly ‘generate’ text, audio, or vision in a direct sense. Nonetheless, however, it is possible that a finetuned or expanded version of this model could be used for that purpose – and that our model would be *more helpful* to such an actor versus them training their own (perhaps larger) model from scratch.

Surveillance. Our model might contain representations that enable it to be used in surveillance applications. As we note in Appendix A.1.1, our model’s low performance on person recognition suggests that it might perform poorly recognition-focused applications. Still, one possibility is that a *neural script knowledge* could ‘summarize’ surveillance videos in some form (like identifying an activity of interest), without identifying the person(s).

We suspect (but cannot definitively prove) that the *reporting bias* of the YouTube data that it was trained on might make it poor for such a surveillance-focused task [50]. Namely, most surveillance videos are sparse in nature – finding an activity of interest is like finding a ‘needle in a haystack’ [91]. Though, some surveillance videos are inevitably posted on YouTube and then captioned, these disproportionately contain *interesting events* (like somebody’s car crashing into a house). It is not clear whether our system could be easily adapted to such a sparse problem; the amount of work required suggests that it might be out-of-scope at least for low-skill actors. On the other hand, this broad research agenda, and perhaps all of computer vision for that matter, might enable large actors to do just that [134]; which might not be addressable through purely technical solutions [52].

Harmful outcomes if deployed. Beyond the *biases* that our system possesses, some applications of our system – if deployed in production – could cause harm, particularly to groups already harmed by AI systems. Of note, linking someone’s voice with their appearance is not always a good thing [94]. Likely some of the key features that our model learns – though we did not teach it this explicitly – involve recognizing gender, and this is harmful especially to transgender individuals [55].

A.4. Energy consumption.

Our model cost a lot amount of energy to pretrain [103]; roughly 3 weeks of time on a TPU v3-512. The total carbon footprint of our work was a net 8.23 tons of CO₂ equivalent, which is roughly 4.5% of the emissions of a jet plane flying round-trip from San Francisco to New York.⁹

At the same time, it is possible that our model could save energy overall, when shared with researchers who build off of our system. Indeed, RESERVE-B uses less energy than MERLOT [128] (due to a smaller vision backbone, and smaller image sizes), MERLOT in turn is more efficient than past work which used expensive detector-based backbones (e.g. [106, 21, 131]), that are made more expensive because some of their computational primitives (like non-maximum suppression) are difficult to make efficient on-device.

A.5. Synthesis.

With these risks in mind, we release our video IDs, as well as RESERVE’s checkpoints, exclusively for research use. We believe that at this point in time, we as a field lack full knowledge of the privacy, bias, and dual-use risks of video-based models – though, we hope that our analysis in this section provides a good starting point. For instance, while the objectives that we have studied were designed to promote learning general neural script knowledge above *encyclopedic memorization*, they have not yet been tested in all possible cases. By opening our models to the research community, we hope to promote fundamental work in uncovering both promising aspects of these systems, alongside examining their risks. We hope to contribute to these lines of research as well.

B. Model implementation details

In this section, we discuss at a more in-depth, technical level, how we implement certain aspects of RESERVE, and other details (like its runtime in FLOPs). We discuss our use of rotary position encodings (B.1), how we set the sequence lengths for the model (B.2), measure the model’s computational footprint (B.3), list hyperparameters (B.4), and discuss several training strategies (B.5).

B.1. Rotary position encoding

We use a rotary position encoding to model the relative location of input sequences [104, 10]. We chose this primarily

⁹CO₂ Calculation. It is also important to consider the *location* where these TPUs are located, as the renewables portion at each datacenter is not equal [88]. Our TPUs were in the ‘europe-west4’ region, which uses on average 60% carbon-free energy, and a Grid Carbon intensity of 0.410 kgCO₂eq / kWh. A single TPU v3 processor (with 8 cores over 2 chips) has a power average of 283 W, so after performing the math from [88], our training cost 20,000 kWh. This gives us a net 8.23 tons of CO₂ equivalent. It should be mentioned that this figure only covers the *electricity usage* given the chips (and the datacenter), not the raw materials involved in making these chips (which is significant [111]).

because we did not want to use absolute (additive) position embeddings, which would have to be added to the inputs of each encoder, and possibly at multiple levels in the hierarchy (e.g. for the joint encoder, the video segment index t would be needed as well).

The rotary encoding uses no parameters, and instead uses a kernel trick to allow the model to recover relative distances between key and query elements in a Transformer’s attention head. This can be seen as ‘rotating’ pairs of elements; we apply the rotation to only the first *half* of each 64-dimensional head, and the second half is kept as is.

Multidimensional coordinates. We treat each token as having a 4-dimensional position of (h, w, ℓ, t) , corresponding to the h, w coordinates in the image, the position ℓ in the text-sequence, and the segment index t . If a dimension is irrelevant to a modality (like h, w for text), we set it to 0. Thus, for our various encoders, we use the following coordinate schemes:

- Video Frame Encoder (ViT): just the h, w coordinates of the image; so $(h, w, 0, 0)$.
- Audio Encoder: Only the 1-D position ℓ of the patch in the spectrogram: $(0, 0, \ell, 0)$.
- Text Span Encoder: Only the 1-D position ℓ of the token in the input: $(0, 0, \ell, 0)$.
- Joint encoder: Here, we use all coordinates. Inputs from the video frame encoder have coordinates $(h, w, 0, t)$, where t is their segment index. The text and (pooled) audio inputs are merged, and they each have coordinates $(0, 0, \ell, t)$, where ℓ here is the absolute position in the entire sequence (across segments).

As part of our implementation, we normalize the rotary coordinates. h, w are scaled to be in the range $[-1/2, 1/2]$, such that text is implicitly ‘in the center’ of the image. Likewise, ℓ and t are scaled to be in the range of $[0, 1]$. The positions are used to compute relative distances, by using a kernel trick to rotate coordinates in the keys and values of each d_h -sized Transformer attention head.

B.2. Sequence lengths

We briefly remark on the sequence lengths used by parts of the model.

- Video Frame Encoder (ViT): Most YouTube videos are widescreen (16x9). We thus used a widescreen resolution for our video frame encoder. It takes in patches of size 16x16, and we used a layout of 12 patches (in height) by 20 patches (in width). This corresponds to **192x320**. Among other factors that are important are ensuring that TPUs do not excessively pad the sequence length [130]. The sequence length is 241 in this case, as there is a CLS token, and it gets padded to 256.

Attention pooling. As we note in the main text, after-

wards we apply attention pooling in a 2x2 grid (ignoring the CLS token here). Similar to Transformer-style query, key, value attention [110], the query is the average of the vectors in the 2x2 grid; the keys and values are learned projections of the vectors. This gives us a $H/32$ by $W/32$ grid for the joint encoder (6×10).

- b. **Audio Encoder.** Our model independently encodes each 1.6 second of audio (a segment has three such ‘subsegments’). We do this through spectrograms. Each window involves 1536 samples at a sample rate of 22500 Hz, and there are 588 samples ‘hops’ between windows. We chose these hyperparameters largely around efficiency. We found that the Discrete Fourier Transform is fastest if the window size is close to a multiple of 2. We used a small number of mel spectrogram bins (64) because we found that at that threshold, we could reconstruct the original sequence at an acceptable level using the Griffin-Lim algorithm, [53] which itself might be a *lower bound* on quality as neural methods trained for this purpose have been shown to do better [115].

In our implementation, we compute the spectrogram for an entire video segment (5 seconds) at once; this is of size 64 mel bins by 192 windows. During pretraining, we perform what is effectively a ‘random crop’ over the spectrogram: we extract three sequential 64×60 sub-spectrograms, for each audio subsegment. We constrain them to not overlap, which means that 12 (random) windows are held out.

We note that our Audio Encoder AST is quite different from the one proposed by [47]. Though it operates over spectrograms, we opted for a linear ‘1-dimensional’ layout rather than a two-dimensional (image-like) one. We also did not pretrain our audio encoder on any supervised data (they used ImageNet and found, perhaps surprisingly, that it helped initialize the model). We used a patch size of 64 mel bins by 2 windows; the resulting (1D) sequence is of size 30. After adding a CLS token, the result is a sequence of length **31**.

As we note in the main text, we apply attention pooling afterwards (for all elements except the CLS token), pooling by a factor of five to resize the length-30 sequence to a length of 6 ‘audio tokens.’

- c. **Text Span Encoder:** We operate on spans that are at most of length 15, with an additional CLS token. Its length is thus **16**.
- d. **Joint encoder.** Let L be the number of text or pooled audio tokens given to the model per segment, on average; we set $L=20$. Let T be the number of video segments. Then, the joint model’s sequence length is $T \times (L + W/32 \times H/32)$. We set $T=8$ (8 video segments given to the model at a time) and used a $H=192$ by $W=320$ resolution. Our total sequence length was thus **640**.

Model	GFlops, from		VCR	
	Image Encoder	Joint Encoder	Total	Q→AR Acc(%)
UNITER-Base[21]	1766	28	1794	58.2
UNITER-Large[21]	1767	99	1867	62.8
MERLOT [128]	236	67	303	65.1
🧠RESERVE-B	99	46	146	62.6
🧠RESERVE-L	176	165	341	71.5

Table 7: Efficiency metrics of our model versus others, measured in terms of (giga) floating point operations required to process a single image, question, and answer candidate on VCR. We compare with the overall VCR performance on the combined Q→AR metric. Our 🧠RESERVE family of models are significantly more efficient than prior work, with 🧠RESERVE-L being roughly on par with MERLOT [128] in terms of FLOPs, yet improving accuracy by over 6%.

To better adapt our model to downstream tasks – particularly single-image tasks like VCR [126], where past work tends to use a resolution much higher than 192×320 , after pretraining, we performed FixRes pretraining (for one epoch on 🧠RESERVE-B, and one half epoch on 🧠RESERVE-L [108]).¹⁰ Here, we trained the model on larger images – simultaneously on 288×512 widescreen images (18 patches by 32 patches), and on 384×384 square images (24 patches on each side). The joint encoder, correspondingly, uses a sequence length of 1312.

During 10 epochs of pretraining, we used a cosine decay of the learning rate down to 0.02 its maximum. During FixRes pretraining afterwards, we warmed up the learning rate to 0.02x its peak, over the first 1/5th of an epoch, and afterwards used a cosine schedule to anneal it towards 0.


B.3. Efficiency metrics of our model



In Table 7, we report efficiency metrics of 🧠RESERVE, versus others. We calculate these metrics in the context of scoring a single VCR question and answer candidate. This requires encoding one image, and using 128 tokens for each question and answer combined (for all models). We compare against a UNITER [21], which is a representative VisualBERT style model, along with MERLOT [128]. Our models are far more efficient in terms of FLOPs, with 🧠RESERVE-L being roughly on par with MERLOT, yet outperforming it by 6% in terms of VCR accuracy. We discuss key differences below:

- a. **UNITER.** We note that UNITER, like other VisualBERT models, uses a supervised object detection backbone [5].


¹⁰We had intended to do a full epoch for 🧠RESERVE-L, but our job got preempted, and the loss seemed to have already converged.

This processes images using a ResNet 101 model [57], at a resolution of 600x800; the final ResNet ‘C4’ block is applied densely over the entire image to obtain object-detection potentials everywhere in the image. Both factors greatly increase the FLOPs count.



When computing UNITER’s FLOPs count, we exclude operations like non-max suppression, which is an operation that is difficult to implement (and thus whose FLOP count might vary significantly depending on implementation). Our FLOPs count is thus a lower-bound. 36 detection regions are extracted, which is why the ‘joint encoder’ for UNITER is smaller than the equivalents for MERLOT and  RESERVE.

- b. MERLOT. This model has two key differences versus our  RESERVE. First, it uses a larger image resolution for VCR: 384x704, versus our 288x512. Second, it uses a hybrid ViT-ResNet50 backbone for encoding images. The backbone here is lighter weight than the object detection backbone of UNITER (in particular, the final ‘C4’ block is removed), and thus, as shown in Table 7, though it uses more FLOPs than does our  RESERVE-L, it uses far fewer FLOPs than UNITER.

We choose flops as our primary comparison metric as past work shows that it is one of the key factors in model scaling [66, 34]. Parameters are arguably more fungible. For instance, in text-only representation learning, ALBERT [72] demonstrates that it is possible to *tie parameters* together at all layers of a BERT-like transformer, reducing parameters by an order of magnitude (while not modifying compute), with a minimal performance drop. We did not do this for this work, as we wanted to use a more ‘vanilla’ Transformer architecture; however, it suggests that representation learning models with hundreds of millions of parameters might be *FLOPs bound* as opposed to *parameter-bound*.

Nonetheless, UNITER-Base has 154 million parameters, though some are frozen (86 million from their Transformer, 23 million from the word embedding layer, and then 44 million from their object detector [5]). UNITER-Large has 378 million parameters (303 from their Transformer, 31 million from word embeddings, and 44 million from the same object detector. Meanwhile, MERLOT has 223M parameters. Versus our  RESERVE-B, 14 million extra parameters are due to a larger vocabulary, and 10 million parameters are due to a ResNet50 encoder – but these parameters have a disproportionate impact in FLOPs count.

B.4. Full model hyperparameters

In Table 8, we present full hyperparameters for our model. Among other details, we used AdamW as our optimizer, with $\beta_2 = 0.98$ and $\epsilon = 1e-6$. We increased the learning rate linearly to its peak value (4e-4 for  RESERVE-B, 3e-4 for  RESERVE-L) over 3750 steps ($\frac{1}{20}$ th of an epoch). Our

	Base	Large	
Audio size	Sample rate	22050 Hz	
	FFT hop length	588 samples	
	FFT window size	1536	
	Mel bins	64	
	Subsegment length	60 hops, (\approx 1.6 sec)	
	Patch size	64 mels \times 2hops	
	Pooling ratio	5	
Final size		6 tokens	
Image	ViT patch size	16	
	Pretraining size	192 \times 320	
	Res-adaptation size	288 \times 512 and 384 \times 384	
	Pooling window	2 \times 2	
Text	Max. span length	15	
	Mean span length	5.5	
Joint sizes	N video segments	16	
	video segment groups	2 (each with 8 segments)	
	Pretraining seq. length	640 (160 text&pooled audio; 480 pooled vision)	
	Res-adapted seq. length	1312 (160 text&pooled audio; 1152 pooled vision)	
Batch sizes	Videos	1024	
	# Frames (for matching)	16384	
	Masking rate	25% (of subsegments)	
	Text spans	49152	
	Audio spans	49152	
architecture	Hidden size	768	1024
	Num attention heads	12	16
	Size per head	64	
	Rotary size (per head)	32	
	Vision num layers	12	24
	Audio num layers	12	
	Text-span num layers	4	
	Joint num layers	12	24
optimizer	Peak learning rate	4e-4	3e-4
	Weight decay	0.1	
	AdamW β_2	0.98	
	AdamW ϵ	1e-6	
	Warmup steps	3750	
	Training steps	750k (+ 75k for res. adaptation)	
	Training epochs	10 (+ 1 for res. adaptation)	
σ Maximum scale		100.0	
Pretraining compute		TPU v3-512 for 5 days TPU v3-512 for 16 days	

Table 8: Architecture details, and pretraining hyperparameters, for both model sizes.

	Base	Large
VCR	Batch Size	32
	Training Epochs	5
	Image Size	288×512
	Learning Rates Tried	1e-5, 2e-5, 3e-5
	Learning Rate	2e-5
TVQA	Batch Size	32
	Training Epochs	3
	Image Size	288×512
	Learning Rates Tried	5e-6, 1e-5
	Learning Rate	5e-6
Kinetics-600	Batch Size	64
	Training Epochs	15
	Image Size	288×512
	Learning Rate	1e-5
	Data Augmentation	From [2]

Table 9: Hyperparameters for finetuning on downstream tasks. Note that for Kinetics-600, we tried to mimic VATT’s setup [2], including adopting their training-epoch regime and their data augmentation strategies. Our data augmentation strategies were much simpler for VCR and TVQA (random cropping, and for VCR sometimes horizontally flipping the image); we suspect that our VCR/TVQA results could be made higher if data augmentation was further explored.

number of warmup steps is lower than many other pretraining work; we note that all of our contrastive objectives involve learning a σ parameter, which functions as a secondary ‘warmup.’

We did not use gradient clipping. We trained and evaluated in 16-bit bfloat16 precision wherever we could – casting all gradients to that precision as well, and saving the AdamW running mean and variance to be 16-bit as well. A few times during pretraining 🍷RESERVE-L, we found that some values in gradients would be NaN. We addressed this by always setting NaN values to be 0. This seemed to address the symptoms of training instability – though sometimes the training loss would spike to roughly around the same loss as random initialization, it always converged back to *slightly better* than it was before the spike. We are not currently sure why this happens.

B.5. Speed improvements during pretraining

We made several high-level algorithmic and engineering implementations to our implementation, which made pretraining run faster, and that we discuss here.

Duplicated video copies. As mentioned in the main text, we create two copies per each video – allowing us to learn separately *how to handle audio as an input* as well as *how to learn from audio*. We chose this in part because copying a video *does not* increase the total compute required by a

factor of two. Instead:

1. We use the image and audio encoders, to encode the underlying video frames and audio clips only once (for the two video copies), and then duplicate the encodings; this is far more efficient than encoding them both separately from scratch.
2. For the two video copies, we sampled two disjoint sets of masks (for which audio and text subsegments are replaced with MASK) at a 25% rate. This increases the pool of negative samples for contrastive learning, again increasing training efficiency.

Reducing memory usage. The memory usage of our Transformer implementation scales quadratically with sequence length, which could pose a problem since we operate on sequences of videos. We split the video into two groups of 8 segments, and encode each group separately by the joint encoder.

Vectorization. We vectorize all joint transformer inputs together into a single call. During this vectorization, we also encode the transcript (for the transcript-frame matching objective).

We note that this vectorization is incompatible with the Mask LM variant proposed by MERLOT [128]. In this variant, which the authors called ‘attention masking,’ two transformer calls must happen *sequentially* – **first**, a language only encoder must encode the inputs and mark down (what is presumably) visually-grounded tokens; **second**, these tokens are masked for the joint encoder. We found that such an objective was unnecessary when pretraining under our contrastive span approach, which in turn enabled more efficient pretraining.

We discuss the exact pretraining data formatting technique that we used in the next section.

C. Pretraining Data Formatting: alignment and masking

In this section, we discuss how we turn a video \mathcal{V} into a (masked) list of segments $\{s_t\}$ for pretraining.

Recall that each segment contains a video frame v_t , ASR tokens w_t , and audio a_t . We generate the list of segments by iterating through the video with a 5-second sliding window.¹¹

Audio and text subsegments for masking. We want audio to be used in part as a *target* for contrastive prediction. However, during early exploration we found that 5 seconds of audio could correspond to many BPE tokens; roughly

¹¹Sometimes there are long ‘pauses’ in videos where nothing gets said. When this happens – if two segments in a row have fewer than 8 BPE tokens – we merge them 90% of the time, in effect ‘fast-forwarding’ the audio and still extracting a frame from the middle. We do this at most twice, so the total length is at most 15 seconds here (in effect, a ‘playback’ rate of 1x, 2x, or 3x). In roughly 90% of cases, the segments are 5 seconds of length.

15 on average. We use past work in language modeling as a guide [64, 93] and wanted an average span length of around 5 tokens. To get this, we split each audio segment into three equal *subsegments*, each with a duration of 1.66 seconds. We can then perform masked language modeling at the *aligned subsegment level*, where we mask out the text corresponding to an audio subsegment, and have the model (contrastively) predict the masked-out span of text, as well as the corresponding span of audio. We use a masking rate of 25%, which means that a quarter of the subsegments will be corrupted and replaced by a MASK token.

In theory, splitting the videos into (masked) segments ought to be straightforward. However, the key challenge that we ran into is that **the YouTube caption timing information is unreliable**. Problems might arise when we perform pretraining with both audio and text, on misaligned data. Suppose the model is given audio in segment s_{t-1} that ends with somebody saying the word ‘pasta.’ If the alignment between audio and text is off, the model might be able to cheat the desired task by simply predicting the word ‘pasta’ for segment s_t – thereby turning the challenging masked-prediction task into an easier speech recognition task; we discuss this in more detail in Appendix C.1.

One way of addressing the timing issue would be to run our own ASR model over all videos, but we chose not to do this due to computational expense. Instead, we adopted two complementary strategies. First, we trained a lightweight regressor to refine the timing information (C.2); second, we mask audio and text conservatively, to minimize alignment errors (C.3). Finally, we discuss how we combine everything efficiently (in a vectorized way) in C.4.

C.1. YouTube Caption Timings

YouTube provides automatically generated captions for accessibility purposes, which include timing information on each word. In the subtitle encoding that we used (vtt), each word w contains a single timestamp t which corresponds to when the word should flash on-screen. The timings are *mostly* accurate, but we found two key issues:

- a. First, they show up on average roughly 0.1 seconds before each word is spoken, which we suspect might be for usability purposes (perhaps so that while the viewer is reading the caption, they hear the word).
- b. Second, with a single timestamp t for each word, it is difficult to infer about pauses. For each word w , we can use its timestamp t , and the timestamps of adjacent words, to loosely infer an interval $[t'_s, t'_e]$ around when the word is said. However, the interval is not tight. We can only infer that the word is being actively spoken for some subinterval $[t_s, t_e]$ such that $t'_s \leq t_s \leq t_e \leq t'_e$.¹²

¹²Note that this is compounded with the first problem, the ground truth interval $[t_s, t_e]$ might not be fully contained in the provided interval $[t'_s, t'_e]$

This can lead to high absolute error (in terms of a difference between timesteps), when pauses occur. For example, suppose a speaker says a word, and then pauses. The interval given by the subtitles, $[t'_s, t'_e]$, might be rather large (possibly a few seconds), even though the actual word was spoken for a fraction of that time.

C.2. Refining timing information

We trained a simple multilayer perceptron regressor to correct the timing information of YouTube transcripts. For data, we used 2000 videos with transcripts from YT-Temporal-180M, and also used Google Cloud’s (highest quality, paid) ASR service to transcribe them. After aligning the words for these transcripts, this gave us tuples of the YouTube ASR word w , its provided interval $[t'_s, t'_e]$, and the ‘ground truth’ interval $[t_s, t_e]$.¹³ Our modeling objective was then to predict the desired offsets with respect to the provided interval: $\delta_s = t_s - t'_s$ and $\delta_e = t_e - t'_e$. We took a feature based approach.

For each input (w, t'_s, t'_e) , we used as features:

- i. the length of w in characters,
- ii. the length of w in BPE tokens,
- iii. whether w is uppercase or not,
- iv. the number of vowels in w ,
- v. the number of punctuation characters in w ,
- vi. the value of $t'_e - t'_s$.

We provided these features as input to the model, as well as the corresponding features for the next word, and the previous word. We z-normalized all features and used a two-layer multilayer perceptron, with a hidden size of 32 and RELU activations. We used a tanh activation at the end to bound the regression. The final predictions for δ_s (analogously for δ_e) were then given by the following equation:

$$\delta_s = c \tanh(\mathbf{w} \cdot \mathbf{h} + b_1) + b_2 \quad (3)$$

where \mathbf{h} is the hidden state, and with learnable parameters c , \mathbf{w} , b_1 , and b_2 . The learned bounds mean that, no matter what the input, the model will never predict an offset of above $c + b_2$ (of which it learned for both parameters $c \approx 0.2$ and $b_2 \approx 0.11$, so the offsets can never be above 0.3 seconds). We trained our lightweight regression model using an L^1 loss, and used it to correct the timing on all of the transcripts.

C.3. Handling worst-case scenarios in masking, when alignment isn’t perfect

The regressor that we described reduces the average timing error of a transcript, as a preprocessing step, but it is

due to ‘captions being shown before audio’, the error here is typically small though (0.1 seconds).

¹³When matching YouTube ASR to Google Cloud’s ASR, we skipped words without an ‘exact-match’ alignment, as well as words that were over 0.25 seconds apart (i.e., where either $\delta_s > 0.25$ or $\delta_e > 0.25$)

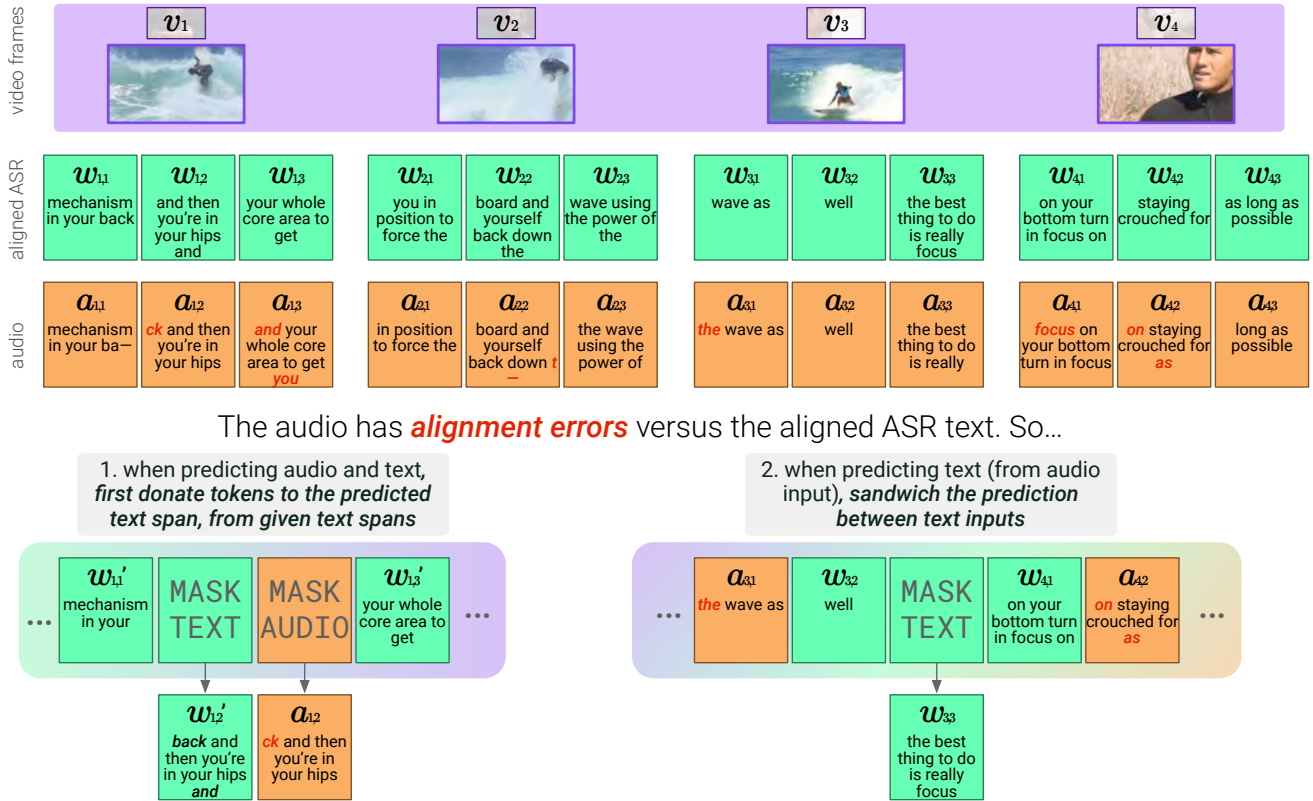


Figure 7: An overview of our masking strategy for dealing with sequences of video frames, ASR, and audio. We have noisy timing information for each word, so we can align the ASR text with audio spans of 1.6 seconds each, using three sub-segments of audio and text for each video frame. However, there exist **alignment errors** between the ASR and audio sub-segments – certain words (and sub-words) have phonemes that are in the wrong segment (like ‘**back**’ in $w_{1,1}$ is only partially said in the first sub-segment; the ‘k’ sound is said in the second. When audio is only a target, we address these by ‘donating’ tokens to predicted spans. When audio is only provided as input, we address this by sandwiching ‘mask’ tokens between text input (so alignment does not ‘bleed’ over).

not perfect. Thankfully, however, we find that most of the remaining alignment errors are *single* words that are slightly misaligned. For instance, for three words w_t, w_{t+1}, w_{t+2} , the audio corresponding to the time interval around w_t might contain sound from w_{t+1} being spoken, but rarely w_{t+2} . We suspect this is primarily due to the difficulty inferring pauses: by definition, no other word can be said in a pause, so the errors are local.

We present a high level approach for masking audio and text, that in turn addresses these alignment issues (making it difficult for models to cheat). A diagram is in Figure 7.

Recall that in our framework, we only either go from ‘vision and text \rightarrow text and audio’ (VT \rightarrow TA), or, ‘vision, text, and audio \rightarrow text’ (VTA \rightarrow T). One of the reasons we did this is to avoid allowing a model to cheat by performing speaker identification (or even ‘microphone identification’), which might be feasible if audio was given to the joint model as input. We can handle the two cases separately:

- Vision and text \rightarrow text and audio (VT \rightarrow TA).** Here, the text as input (to the joint encoder) might overlap with the audio we are trying to predict. Our solution here is thus to **donate nearby tokens** from the predicted span, to the input. Let the span that we are trying to predict (and that we will ‘mask out’) have a start time of t_s and an ending time of t_e . If the final token in the previous text span, if any, has a timestamp of greater than $t_s - 0.125$, we move it to the predicted span; likewise, if the first token in the next text span has a timestamp of less than $t_e + 0.125$, we move it to the predicted span as well.
- Vision, text, and audio \rightarrow text (VTA \rightarrow T).** In this prediction task, models are given information from all modalities as input, and must predict masked-out text spans. Note that models are only given a single ‘speech’ modality – either text, or audio – at each timestep. What this means is that we can carefully choose *which input subsegments* to turn into ‘audio subsegments,’ and

which to turn into ‘text subsegments.’ Our strategy is, given a masked out subsegment, to turn 80% of adjacent subsegments into ‘text subsegments.’

We give an illustration of this in Figure 7, part 2. Here the word ‘*focus*’ is part of $a_{4,1}$ but also $w_{3,3}$). This might make $w_{3,3}$ overly easy to predict, if we gave the model $a_{4,1}$ as input. Our solution is thus to give the model text from $w_{3,2}$) and from $w_{4,1}$) as input; we are guaranteed that there is no misalignment overlap here between input and prediction spans. All of the other subsegments (not adjacent to one of the 25% that we mask out) will be provided as audio.

C.4. Putting it all together, along with web text

Finally, we discuss how we combine the various masking approaches into the prediction tasks outlined in the main text.

Each video has $N = 16$ video segments, and three sub-segments of audio or text spans per segment. We consider two sub-problems for this video sequence:

- i. in VT→TA, vision and text are provided as input, and the model must predict masked-out text and audio. These are done on top of separately-encoded MASK tokens and MASKAUDIO tokens, to enable the model to learn different predictions for each modality over two separate transformer ‘columns.’
- ii. In VTA→T, vision, text and audio are provided as input, and models must predict masked-out text. Here, we use the term ‘predict’ as a shorthand for our contrastive objective – in which a model must match a context (a jointly-encoded MASK) to the exact missing span in question, where many negative contexts and spans are provided.

We use a masking rate of 25% for audio and text sub-segments, and there are 3 subsegments per segment. This means that a single video instance gives us $48 \times 0.25 = 12$ masked-out spans of text, for each of VT→TA and VTA→T, so 24 in total (as we use disjoint masked-out subsegments). Likewise, it gives us 12 masked-out spans of audio. If we scaled these to the whole batch of 1024 videos, we would have 12k audio span options and 24k text span options. This might suffice, but scaling up the pool of candidates boosts performance in a contrastive setting, as suggested from prior work (e.g. [92]), and as our ablations (Table 1) support as well. Thus, we do the following:

- a. **Text candidates.** We scale up the text candidates by simultaneously training the model on web text, from The Pile [40]. The joint encoder – which can handle pooled video, pooled audio, and BPE-encoded text – is simultaneously given a sequence of web text, for each video that we have. By performing the span-contrastive objective with this piece of web text as well, we can not only teach the model about written (as opposed to spoken) language, but we can scale up the set of text

candidates as well.

Let each web-text sequence be of length L . We first divide it into fake regions that ‘look like’ the text subsegments in length. We do this by calculating the empirical length distribution of the text subsegments, and then using this (categorical) distribution to sample a sequence of sub-segment lengths ℓ_1, \dots, ℓ_K .¹⁴ We clip the sampled sequence, such that $\sum_i \ell_i = L$.

Next, we mask the fake subsegments. During pretraining, we use text sequences of length $L = 800$, but a model sequence length of only 640. Because we are masking spans and not individual tokens, the text sequences ‘shrink’ when we mask them. We extract exactly 38 masked-out spans, which corresponds to around 25% of total text.

Finally, we combine the target spans that we took from the webtext sequence, with the target spans from the video. We note that sometimes – especially in a video – text spans might be empty. Not every 1.6 second slice of a video has someone speaking. We thus try to not use these empty spans in our contrastive objective. For each video (which is paired with text for implementation reasons) we select the ‘best’ 48 text spans out of the (38+24) options – penalizing empty spans, and choosing spans from videos 4x as often.

These ‘best 48’ text spans, as well as the pooled contexts that they were paired with, will be used in the contrastive objective. Aggregating over the entire batch of 1024 videos (and 1024 web text sequences), this gives us 49152 text spans as candidates, for the all-pairs symmetric softmax between text spans and contexts.

- b. **Audio candidates.** For each video, we note that we have exactly 12 pooled MASKAUDIO tokens, where the model is trying to predict the corresponding audio span. One option would be to just use those 12 corresponding audio spans as the targets, aggregate these over the batch, and do a symmetric-cross-entropy loss.

However, we can do even better *for free*. Note that for the VTA→T direction, we might have to encode many of the audio spans *anyways*, using the lower level audio encoder (which simultaneously extracts a CLS representation and a sequence-level pooled representation). To simplify implementation, we encode *all 48 audio spans* per video. We can use these audio spans as candidates.

Thus, we do the following when computing the loss over audio prediction. We aggregate all 12288 *contexts* from the MASKAUDIO tokens in the batch, and we aggregate all 49152 candidate audio spans. We perform an all-pairs dot product between these two sets, and use it to compute

¹⁴The empirical distribution for each length, in order from a length of 1 to 15, is [0.03, 0.05, 0.08, 0.11, 0.13, 0.13, 0.12, 0.10, 0.07, 0.05, 0.03, 0.02, 0.01, 0.006, 0.003].

a symmetric cross-entropy loss over both directions. We did not encounter any trouble using the same temperature for both directions (even though for one direction, there are 12288 options, and for the other, there are 49152).

The combination of these design decisions provide more ‘hard negatives’ for the model during training. We also found that they worked well to reduce wasted computation on a TPU. For each video, the joint transformer uses one $L = 640$ length sequence for transcript-frame matching, two length- L sequences for the VT→TA direction (as we break it up into two groups of 8 frames each), two length L sequences for the VTA→T direction, and finally one length- L sequence of text. These sequences can all be vectorized together, and the total batch size is $6 \times$ the number of videos. This is helpful because using an even-numbered batch size reduces wasted computation on a TPU.

D. Downstream Task Implementation Details

In this section, we present information for how we adapted 🌐RESERVE on downstream tasks.

D.1. Setup for finetuned tasks

For adapting 🌐RESERVE in a finetuned setting, we take the following approach. We use a linear warmup of the learning rate over the first half of the first epoch, with a linear decay thereafter to 0. To find the learning rate, we did a small grid search generally centered around $1e-5$. Our full hyperparameters are shown in Table 8.

When finetuning (and pretraining), we did not use any dropout to make implementation simpler. Instead, as a way to apply regularization, we used the same L_2 penalty as in pretraining (a weight decay of 0.1), but with respect to the *pretrained* weights. This idea was used in [118] among other works, and although it often tends to underperform dropout [73], it is simple to implement.

D.1.1 Visual Commonsense Reasoning

As mentioned in the main text, VCR considers two subtasks: $Q \rightarrow A$, where models are given a question and must choose the right answer given four options; and $QA \rightarrow R$, where models are given a question (and the right answer) and must select the right rationale.

In our setup for this task, we treat it as a four-way classification problem, extracting a single score from each answer or rationale candidate. An example $Q \rightarrow A$ is:

What is going to happen next? answer: person2 is going to say how cute person4’s children are. MASK

An example $QA \rightarrow R$:

What is going to happen next? person2 is going to say how cute person4’s children are. rationale: It looks like person4 is showing the photo to person2, and person2 will want to be polite. MASK

We extract representations from the MASK position (which are of dimension d_h), score them with a newly-initialized $d_h \times 1$ weight matrix, and optimize scores with softmax-cross entropy.

Both VCR subtasks use only a single image. We also followed past work in ‘drawing on’ the provided detection tags to the image [128]. These are unambiguous references to entities that are then referred to in the question, answer, and rationale. For example, text might reference a ‘person1’, which corresponds to an image region. When drawing on these detection tags, we do so in a deterministic way – for example, ‘person1’ always gets the same box color. We determine the box color by hashing the object’s ID (in this case, ‘person1’) and using that to determine the hue. The model learns the connection between boxes with different hues, and the names, during finetuning.

We randomly flip images left or right, so long as there is no instance of the word ‘left’ or ‘right’ in the question, answer, or rationale candidates. We did no other data augmentation (other than randomly resizing images to between 100% to 110% of the network’s size).

D.1.2 TVQA

TVQA provides models with a video, a question, and five answer candidates; we represent this as five distinct sequences for the model to score (one per candidate). The version of TVQA that we used also gives models annotations for the *time region* in the video that is being referenced. It is not clear that only using this region would provide enough context to be able to understand what is going on – enough to answer correctly. Thus, for each question, we extract 35 seconds of video around the provided time region. We then provided the model with two numbers corresponding to the time region, relative to the cropped time interval. For example, if the provided timestamp annotation is $[t_0, t_1]$, we use the following region:

$$t_c = \frac{(t_0 + t_1)}{2} \quad (4)$$

$$t_s = t_c - 17.5 \quad (5)$$

$$t_e = t_c + 17.5 \quad (6)$$

The location of $[t_0, t_1]$ in relative coordinates is then:

$$t_0^r = \frac{t_0 - t_s}{t_e - t_s} \quad (7)$$

$$t_1^r = \frac{t_1 - t_s}{t_e - t_s} \quad (8)$$

We provide models with t_0^r and t_1^r , multiplied by 100 and casted to an integer. Thus, an example TVQA instance might look like:

1 to 28 What is Janice Holding on to after Chandler sends Joey to his room? Chandler’s tie. MASK[subtitles or audio]

This text input corresponds to the first ‘segment’ of a video; to it we append subtitles (or audio representations) from seven segments from the provided TVQA video (with accompanying frames).

D.1.3 Kinetics-600

We evaluate 🧠RESERVE on Activity Recognition over the Kinetics-600 dataset [19]. Here, the model has to classify a short 10-second video clip into a mutually-exclusive set of 600 categories, like ‘assembling bicycle’ or ‘alligator wrestling’. We consider performing this task in a finetuned setting, so as to better compare to prior work. We format each example by extracting 4 video frames from the clip (sampled uniformly), and extracting 6 audio subsegments (totalling 10 seconds of audio). The model processes these inputs along with a MASK token, where we extract a vector representation. We initialize the 600-way classification layer with the activations of our Text Span Encoder, over the names of the 600 categories.

We finetune the model jointly over two settings: a setting where audio is provided, and a setting where no audio is provided, to allow us to investigate both settings. We tried to closely follow VATT’s finetuning approach [2], including their exact data augmentation settings. We used a batch size of 64 videos (that we process simultaneously ‘with audio’ and ‘without audio’). We used the same image augmentation code as VATT [2], and finetuned for 15 epochs. We used a learning rate of 5e-6 for 🧠RESERVE-L and 1e-5 for 🧠RESERVE-B.

D.2. Setup and prompting for Zero-shot tasks

Here, we discuss how we set up various tasks for 🧠RESERVE in a fully zero-shot setting. In addition to evaluating 🧠RESERVE, we also evaluate CLIP [92] in the same zero-shot setting. CLIP is not pretrained on videos, and it cannot jointly encode text. For each task, we construct CLIP’s label space by taking our prompt and substituting in each possible answer option. We average together the logits over all frames, and take a softmax, giving us a distribution over the task-specific label space.

D.2.1 Zero-shot Action Anticipation on EPIC-Kitchens

We study the task of action anticipation from the EPIC-Kitchens dataset [26], a large egocentric video dataset with 700 unscripted and untrimmed videos of cooking activities. In action anticipation, a model must predict a *future action* that comes τ_a seconds after a given video clip. The observed segments are of arbitrary length; we follow prior work [26] and set $\tau_a = 1$.

The model tries to choose the correct *noun* and *verb* that happens next, given a list of predefined options for each. We report results on each category using the class-mean top-5 recall.

Model	Overall			Unseen Kitchen			Tail Classes		
	Verb	Noun	Act	Verb	Noun	Act	Verb	Noun	Act
RULSTM [38]	27.8	30.8	14.0	28.8	27.2	14.2	19.8	22.0	11.1
AVT+ (TSN) [46]	25.5	31.8	14.8	25.5	23.6	11.5	18.5	25.8	12.6
AVT+ [46]	28.2	32.0	15.9	19.5	23.9	11.9	21.1	25.8	14.1
Chance	6.4	2.0	0.2	14.4	2.9	0.5	1.6	0.2	0.1
CLIP (ViT-B/16) [92]	13.3	14.5	2.0	12.3	8.4	2.1	14.3	14.3	1.7
CLIP (RN50x16) [92]	16.5	12.8	2.2	13.4	7.0	1.2	17.1	12.6	2.5
Validation 🧠RESERVE-B	17.9	15.6	2.7	11.0	15.7	4.4	18.0	12.7	2.0
🧠RESERVE-L	15.6	19.3	4.5	14.1	18.4	3.4	14.7	18.5	4.4
🧠RESERVE-B (+audio)	20.9	17.5	3.7	15.5	20.1	4.3	20.7	14.5	3.2
🧠RESERVE-L (+audio)	23.2	23.7	4.8	20.3	21.0	5.9	22.7	21.6	4.0
Test RULSTM [38]	25.3	26.7	11.2	19.4	26.9	9.7	17.6	16.0	7.9
AVT+ [46]	25.6	28.8	12.6	20.9	22.3	8.8	19.0	22.0	10.1
🧠RESERVE-L (+audio)	24.0	25.5	5.8	22.7	26.4	7.0	23.7	24.2	4.7

Table 10: 🧠RESERVE gets competitive results on EPIC Kitchen Action Anticipation challenge with zero-shot, over methods from prior work.

Zero-shot inference approach. We directly evaluate the pretrained 🧠RESERVE on action anticipation to verify the knowledge learned during pre-training. All prior work reported on the official leaderboard use supervision from the in-domain training set, which we do not use at all [46, 38].

For each action segment, we sample at most $N = 8$ image frames and their associated audio, with fixed time interval $t = 2.0$ preceding it and ending τ_a seconds before the start of the action. We append a MASK token as the sole text input (at the last frame, after audio is optionally included).¹⁵ We create short phrases out of all candidate nouns and verbs, and use that as our label space to simultaneously predict them both. We compute the score for each verb and noun independently by averaging their scores, over all labels for which they appear.

Results. We show the full zero-shot action anticipation results in Table 10. We also show our results on the test set here for our best performing model (🧠RESERVE-L, with audio provided). It gets competitive results on verb and noun prediction – with only 1.6% and 3.3% lower compared to the challenge winner method AVT+ [46], which is fully supervised and use additional object-level annotations. On Unseen Kitchen and Tail Classes, our model **outperforms** AVT+ on noun and verb. Overall, audio significantly improves the results – 🧠RESERVE-L (+audio) outperforms 🧠RESERVE-L with an average 3.0%, which suggests that it is useful for this task.

D.2.2 Zero-shot Situated Reasoning

Next, we evaluate on situated reasoning (STAR) [119] which requires the model to capture the knowledge from surrounding situations and perform reasoning accordingly. STAR

¹⁵We were unable to find a better text based prompt than this, as we found that they often biased the model towards linguistically relevant words; however, we suspect that such a prompt does exist.

dataset includes four types of questions, including interaction, sequence, prediction, and feasibility. A model is given a video clip, a templated question, and 4 answer choices.

Zero-shot inference approach. For each video clip, we sample $N = 8$ image frames uniformly from the video, we also optionally include the video’s sound.

To reduce domain shift between YouTube data – where people don’t typically ask visual questions, and where ASR typically does not insert question marks – we convert the question-answer pair into a statement. We did so using the question-answer templates provided by the author, with the answer replaced by a MASK. For example, “*Q: What did the person do with the bottle? – A: Put down.*” will be converted to “*The person MASK the bottle.*”.

We put the converted statement into the first frame and use the four candidate answers as a unique label space (that differs from example to example). Like with EPIC-Kitchens, we also evaluate how much audio can help by masking the audio inputs.

Results. We show our zero-shot STAR results in Table 5 in the main text. Our base model outperforms all supervised prior work by 3.7%. The model with audio performs better, with average 1.1% improvement. Interestingly, RESERVE-L is worse than RESERVE-B, we suspect the reason is RESERVE-L is sensitive to grammar details. Given the previous example, we note that while ‘Put down’ is a valid answer that might make sense both semantically and syntactically, a different answer ‘pick up’ might be flagged by some English speakers as being ungrammatical: the instantiated template would then be ‘the person pick up the bottle.’ We noticed instances of the larger model paying greater attention to these syntax-level details, even though they were not the focus of the task. It does suggest, however, that additional prompting (or label space augmentation) could resolve these issues and increase performance even further.

D.2.3 Zero-shot LSMDC

We evaluate our model on Movie Fill-in-the-Blank [96, 82] task, which based on descriptive audio description for the visually impaired. Given a movie clip and an aligned description with a blank in it, the task is to fill in the blank with the correct word. Following [82], we report prediction accuracy in test set of 30,354 examples from 10K movie clips.

Zero-shot Inference approach. We sample $N = 8$ video segments uniformly over the movie clip, and extract the audio and middle frame of each segment. We replace the ‘blank’ token in each description with a MASK token, and provide it (as text-based input) to the model at its final segment. For the other segments, we optionally provide the model with audio; for all segments, we provide the associated

image frame. We use the vocabulary set in the LSMDC dataset as our label space (for what the ‘missing word’ might be).

Results. Our results are shown in Table 5 in the main text. Our model obtains 31% when audio is included, which outperforms human text-only performance (30.2 %) [82], predicted by human annotators. A supervised LSTM obtains 34.4% in this text-only setting [82] which suggests that there is a certain textual bias in this task, which our model cannot learn (as it is zero-shot). This also suggests that state-of-the-art supervised models exploit patterns in this vocabulary distribution.

Without such an advantage, our model performs well, outperforming CLIP (2%) by a large margin. This suggests that jointly reasoning over both the visual situation, and the linguistic context of the provided sentence, is helpful for zero-shot performance on LSMDC fill-in-the-blank.

D.2.4 Zero-shot MSRVTQA

Finally, we evaluate our model on MSR VTT-QA, a question-answering task over videos [120]. We provide a model with $N = 8$ video segments sampled uniformly from the video clip, and extract an image from each one. For the first seven segments, we optionally include audio extracted from that point; at the last segment, we insert a converted version of the question, along with a MASK. We compare the similarity of that hidden state to the top 2000 most common answers, similar to past work [128].

Similar to STAR, we convert the questions into statements to minimize drift away from the pretraining distribution. We use GPT3 prompted with several examples for this. Our exact prompt is the following:

```
Input: what is a car being driven through?
Output: a car is being driven through ...

Input: who are running across screen?
Output: ... are running across screen.

Input: when is a girl performing?
Output: a girl is performing at ...

Input: what is a cartoon doing?
Output: a cartoon is ...

Input: how many women talk in a bedroom?
Output: ... women talk in a bedroom.

Input: what a man playing while dancing with others?
Output: a man is playing ... while dancing with others.

Input: where is a flag hoisted?
Output: a flag is hoisted in ...

Input: who talks to another man on the couch?
Output: ... talks to another man on the couch.

Input: what does a teenage girl try to get at a public restroom?
Output: a teenage girl tries to get ... at a public restroom.

Input: when do the models walk as the audience watches?
Output: the models walk as the audience watches at ...
```

```

Input:  what shows a person killing animals in a green forest?
Output: _ shows a person killing animals in a green forest.

Input:  who does a man ask to go on a date?
Output: a man asks _ to go on a date.

Input:  what are three people sitting on?
Output: three people are sitting on _

Input:  ${question}
Output:

```

Then, given a new question `${question}`, GPT3 generates a converted output, wherein we can replace its underscore with a MASK. GPT3 works well at this conversion, though sometimes it generates a sentence where inserting the ‘correct answer’ feels grammatically strange. For example, the question ‘how many women talk in a bedroom?’ suggests any integer might be a reasonable answer. On the other hand, ‘_ women talk in a bedroom’ implies that ‘one’ is not a valid answer (since ‘women’ is plural). We note that the errors caused by this conversion technique are specific to English grammar, and so if such a question-conversion approach was done in other languages, there could be more (or less) errors that directly result.

Our results are shown in Table 5. Of note, our model through automatic question-conversion outperforms Just Ask [123], which performs an analogous (supervised-guided) question conversion on all its YouTube transcripts, before pretraining. Our model also outperforms CLIP, which cannot naturally handle dynamic situations.

E. Dataset Collection

In this section, we discussed how we curated data for YT-Temporal-1B. We had several goals in mind. We wanted to use only public-facing data, which motivated our choice of YouTube as it is a public platform *that users understand is public* [65]. We wanted to use this platform to examine to what extent we can learn multimodal neural script knowledge from web data alone.

Our data collection strategy in this work was informed by past work, notably MERLOT [128]. That paper found that increasing the diversity and scale of a video corpus both allowed for better learned representations. At the same time, the data collected by MERLOT (YT-Temporal-180M) has issues. Of note, the authors’ scraping strategies – to prioritize *monetized content* – also led to a lot of U.S. local news being in that corpus (roughly 30% of all data). Local news might be problematic to learn from, particularly in that quantity, due to its numerous biases (e.g. racist coverage on ‘crime’ [45, 31, 30, 58]). Our goal was to expand the dataset in both diversity and size to 20 million videos, while having *less local news* and without scraping private content.

High level approach. We adopt a similar dataset collection strategy as in MERLOT [128]. In the first phase, we identify a candidate set of videos ID to download. In the second phase, we open each video ID in YouTube and apply

several filtering steps that go from inexpensive to expensive. The filtering steps allow us to exit early and possibly avoid downloading the video if the video seems unsuitable for our purpose from the title, description, and captions alone.

For a Datasheet [41], please see the MERLOT paper [128].

E.1. Candidate video IDs

For MERLOT’s YT-Temporal-180M, the bulk of the video IDs were identified by applying breadth-first-search on YouTube channels from HowTo100M [85] and VLOG [36]. Each channel often links to other channels, and given a channel it is inexpensive to obtain a list of all its videos using the youtube-dl Python package.

In this paper, we considered numerous approaches to search for diverse, visually grounded videos. We ended up using an approach where we used YouTube’s recommended videos algorithm to suggest similar videos to YT-Temporal-180M. We went through all non-news and non-sports videos YT-Temporal-180M, and opened each video up in YouTube. For each other video that YouTube recommended, we retrieved its channel ID – giving us access to not just that video, but all other videos. This approach yielded 2 million channels, with 200 million videos among them.

E.2. Filtering video IDs by channel

Given this (large) list of channels, each with many videos, we took steps to filter it further. We used the python `cld3` library to remove channels whose titles might not be in English. We then finetuned, and used, a language model to identify channels likely to have visually grounded videos, which we describe next.

In more detail, we selected 2000 videos, and asked workers on Mechanical Turk to rate their level of groundedness, their genre, and whether they had explicit content or not. The questions we asked are shown in Figure 8. We annotated 2k videos under this schema, and trained a model to predict the annotations given video metadata.

For model training, we used a slightly different setting to what we gave the crowdworkers. We trained a model to predict the labels, given a formatted list of 5 video titles from the same channel. During training, we made the weak-supervision assumption that all videos from a channel have exactly the same rating (as the video we annotated). This enabled us to collect 84k examples from our 2k annotations. The model we chose was T5-base model [93], which generates the labels left-to-right in text form (and which we converted automatically to a structured representation).

We then used this model to identify channels that seem especially promising. For each channel with at least 5 videos, we randomly sampled 8 sets of length-5 videos, and used the finetuned T5 model to classify them. We filtered out any channel that had at least 25% of likely non-English or

$\{\text{VIDEO}\}$

Q1. How would you describe the role of English speech in the video?

- This video doesn't have spoken English, or if it does, it's irrelevant to what's going on in the video.
- This video has English speech that describes, or adds onto, the visual content.

Q2. Select at least one genres of the video:

- Gaming
- News
- How-to
- Chatting
- Sports
- Music
- Movies / Drama
- Documentary
- Miscellaneous

Q3. Select if any of the following are true:

- A variety of objects are interacted with.
- A variety of actions are performed.
- A variety of scenes are performed.
- This video is a slideshow.
- This video contains racist or sexist content..

Figure 8: Video annotation. We had workers on Mechanical Turk annotate 2000 videos in our dataset with this questionnaire, allowing us to then train a model to identify suitable channels for our purpose.

irrelevant-English videos, any channel that had at least 25% of slideshows, and any channel that likely had racist or sexist content.

One side benefit of this model is that it allowed us to estimate our videos' genre breakdown before downloading them. We found 1% Gaming videos, 11% News videos, 20% How-To videos, 20% 'chatting' videos, 5% sports videos, 5% Music videos, 3% Movies/Drama videos, 4% Documentary videos, and 31% Miscellaneous. The Gaming videos were then filtered out.

We used the classification model to create a budget for how many videos to download from each channel; with the aim to download more videos from likely more-grounded channels. Using the answers to Q3 (from Figure 8), we gave each channel 1 point for likely having 'a variety of objects', 2 points for 'a variety of actions', and 0.5 points for 'a variety of scenes.' We subtracted 3 points if it was likely to be a slideshow. (Likely-racist or sexist channels were already filtered out.) We then z-normalized and softmaxed the channel scores, and used the result as the channel-level budgets. Any channel with an aggregate 'interestingness' score of 1 standard deviation above the mean would then have a budget of 8x larger than the mean. We clipped the channel-level budgets to include at most 500 videos per

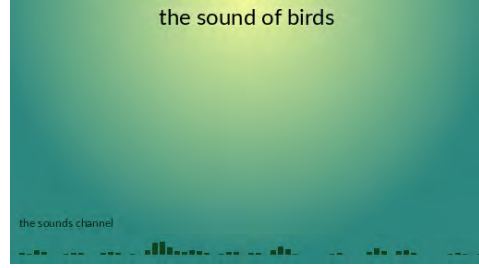


Figure 9: An image prompt used in zero-shot audio classification. Here, "the sound of" is always inserted, and the word "birds" is one of the labels in ESC50 [90]. We consider one image prompt for each label in ESC50 (or whichever dataset we are using).

channel.

This process (finally!) gave us 30 million YouTube video IDs that were likely to be high-quality.

E.3. Filtering videos from their metadata

Last, we filtered and downloaded these videos using a filtering approach similar to [128]. We first retrieved the video metadata and used it to filter out 'gaming' videos. We then retrieved the video's transcript, and filtered out any video without a 'dense' span of spoken words – defined as an interval of 30 seconds where at least 50 words are spoken. Additionally, we used the Python package cld3 to filter out any transcript with a probability of less than 80% of being English. Last, we used a hidden feature in the YouTube API to download four thumbnails of the video. Using the image classification model from [128], we filtered out videos whose four thumbnails had an average cosine similarity of above 85%, or that contained fewer than 1 object from COCO.

Unlike [128], we did not use a sequence-to-sequence model to 'translate' spoken text to text that appears more stylistically like written English (i.e., by adding capitalization and punctuation, and removing filler words).

F. Additional Experiments and Exploration

In this section, we briefly include additional experiments, showcasing our model's performance on specific tasks that do not necessarily require multimodal script knowledge.

F.1. Zero-shot Audio classification

We evaluate 🗨️RESERVE on the task of zero-shot audio classification, to study to what extent its learned audio representations can directly predict text-based labels. We conduct this evaluation on environmental sounds from ESC50 [90], urban sounds from US8K [98], and (as part of the privacy-minded exploration in Appendix A) celebrity voices from VoxCeleb2 [87].

Model	Prompting	Accuracy (%)		
		ESC50	US8K	VoxCeleb2
AudioClip		68.6	68.8	
🎧 RESERVE-L	Text-only.	41.6	60.2	10.8
	Image-only.	42.8	54.3	13.3
	Image and text.	52.2	62.3	9.6

Table 11: Zero-shot audio classification accuracies (%) on ESC50 [90], US8K [98], and VoxCeleb2 [87]. We compare our model with AudioClip [54], which was pretrained on supervised data from AudioSet [43]. Our 🎧 RESERVE performs well across the board, especially when given *both the image and the text* as a prompt – demonstrating its OCR capability.

We consider the format where we encode an audio input into a CLS level representation, and retrieve the most-similar label given a set of encoded options. We encode the audio input with our encoder, which takes in as input audio clips of length at most 1.6 seconds. For shorter audio clips (like many sounds in ESC50), we repeat them in time until their length is at least 1.6 seconds. For longer audio clips, we encode multiple CLS representations and then average the resulting vectors.

We consider the following ways to encode the labels:

- a. **Text-only.** Inspired by the prompt ‘a photo of’, which is used in CLIP’s zero-shot image classification task [92], we give 🎧 RESERVE’s joint encoder a blank image, with associated tokens the `sound of ${label}`. We do this once for each label, giving us a single ‘target’ vector for each possible label in the dataset.
- b. **Image-only.** Inspired by YouTube videos of sound effects¹⁶, we created image-only prompts that suggest a sound (of the target class) is playing in the background. An example is shown in Figure 9. We encode each image with our joint encoder, and do this once for each label. We note that for VoxCeleb2, we use face images of celebrities rather than this image-based prompt, due to our interest in exploring whether models can perform person-level recognition due to the privacy issue (Appendix A.1.1).
- c. **Image and text.** Here, we combine both of the above options: encoding one input for each label, using both the image and text prompt.

For each prompt, we append the token ‘MASKAUDIO’ and extract the hidden state from there, as our final representation for that label.

We present our results in Table 11. The results show, possibly surprisingly, that 🎧 RESERVE can perform optical character recognition over image prompts like Figure 9 –

given just the image, its accuracy on ESC50 is higher than given just text. Its accuracy on ESC50 and US8K improves further when given both an image and text.

These results are slightly different for VoxCeleb2, which emphasizes long-tail recognition of people – something that might be more encyclopedic than semantic, and that we did not wish to optimize in this work. There, when given an image of a celebrity’s face, it demonstrates some capacity at linking it with one of their audio clips – a capacity that *decreases* if prompted with additional text. We suspect that this is due to interpreting the given text as spoken, for example, *Justin Bieber himself saying* ‘the sound of Justin Bieber.’ On all celebrities, 🎧 RESERVE struggles versus recognition-focused models like CLIP [92] (Appendix A.1.1).

Overall, our model displays strong audio understanding ability. In comparison, AudioCLIP [54] (which is supervised on human-annotated labels from AudioSet [43]), performs 16% higher on ESC50, and 6.4% higher on US8K.

F.2. Additional Qualitative Analysis

In Figure 10, we include an additional figure of examples, of the same format as Figure 5. The examples are chosen randomly – not by how much 🎧 RESERVE improved at retrieving their audio or text spans over the course of training.

¹⁶For instance, youtu.be/VmgKryu4__k.

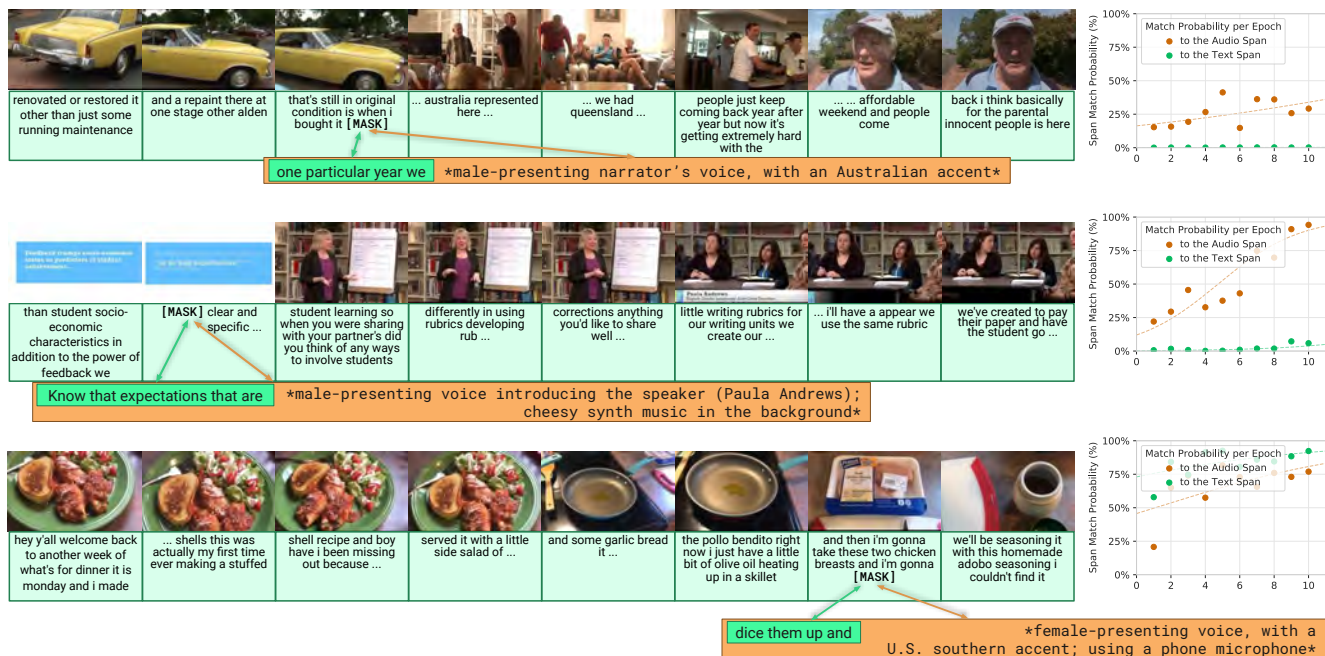


Figure 10: **MASKED audio self-supervision on different examples.** Similar to Figure 5, we show predictions from **RESERVE-B** over the course of pretraining. Match performance increases over time. The audio prediction in the first row is perhaps made easier by the speaker's australian accent. The audio prediction in the second row is perhaps easier due to the lecture-video setting. In the third row, both audio and text span prediction improves, with text being slightly favored in the end. This might be in part because of the truncation we do on audio (Section C.3) – the audio span is shorter than the text span of ‘dice them up and’ so as to not leak information, making prediction more challenging.