Video Understanding as Machine Translation

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Abstract

With the advent of large-scale multimodal video datasets, especially sequences with audio or transcribed speech, there has been a growing interest in self-supervised learning of video representations. Most prior work formulates the objective as a contrastive metric learning problem between the modalities. To enable effective learning, however, these strategies require a careful selection of positive and negative samples often combined with hand-designed curriculum policies. In this work we remove the need for negative sampling by taking a generative modeling approach that poses the objective as a translation problem between modalities. Such a formulation allows us to tackle a wide variety of downstream video understanding tasks by means of a single unified framework, without the need for large batches of negative samples common in contrastive metric learning. We experiment with the large-scale HowTo100M dataset for training, and report performance gains over the state-of-the-art on several downstream tasks including video classification (EPIC-Kitchens), question answering (TVQA), captioning (TVC, YouCook2, and MSR-VTT), and text-based clip retrieval (YouCook2 and MSR-VTT).

1 Introduction

Labeling and curating video understanding datasets is a laborious and expensive process. Most recent video datasets are collected according to one of two possible paradigms: 1) download large amounts of Web videos, and manually label them according to a set of predefined action classes [45, 21, 19, 13]; or 2) draft a set of textual descriptions of actions of interest, and use human actors to act them out [42, 44, 12]. Besides being time-consuming and costly, these approaches are limited to a closed-world understanding of videos. For example, a model trained on an ontology of professional sports classes is unlikely to be useful to recognize everyday kitchen activities. This raises a crucial research question: how can we learn generic video representations that are useful for multiple downstream tasks, without having to label or enact videos with every possible observable action?

Recent work in self-supervised video representation learning attempts to provide a solution. Such approaches typically define pretext tasks that transform the video in a certain way, and train the model to predict that transformation [33, 57, 4]. While these transformations could be defined purely in the video pixel space, several approaches exploit the multimodal nature of videos and propose learning transformations from one modality to the other [2, 37, 20, 34, 31]. These modalities include optical flow/motion, audio, and more recently, speech transcribed to text using automatic speech recognition (ASR). Recently introduced datasets such as Cooking312K [47] and HowTo100M [31] leverage YouTube videos with associated ASR text to train joint video-and-text embeddings that have significantly improved performance on multiple downstream video and video + language tasks [31, 30, 46].

The typical approach followed in such joint embedding models is that of metric learning. Specifically, models are trained to map different modalities into a common embedding space such that distances between modalities in this space preserve instance information. The embedding is typically optimized using a ranking [6] or contrastive [36] objective on the pairwise distances between modalities. While
Figure 1: Overview of the proposed architecture. A multi-modal encoder-decoder transformer is trained on HowTo100M to reconstruct perturbed text, and finetuned on several downstream tasks (i.e., classification, question answering, captioning and retrieval). During finetuning, we combine the trained multi-modal encoder with either the trained decoder (for open-ended text generation and ranking) or a simple linear layer (if candidates outputs are provided—e.g., labels for classification).
text input. Moreover, our encoder-decoder architecture can be transferred and finetuned on several downstream tasks, even novel ones, instead of producing features for a separately-trained model.

Our experiments demonstrate that VideoTranslate can be transferred effectively to a variety of video understanding tasks without the need to alter the model or to append discriminative heads (e.g., classifiers). We merely cast each of these tasks as text prediction and use generative finetuning to further adapt the model to each downstream task. While some of the tasks are naturally defined in the language domain (such as question answering or captioning), we show that our system can obtain excellent performance even on classic discriminative-learning problems such as video retrieval or classification. In fact, our method achieves good accuracy on classification and retrieval even without any form of finetuning on the target dataset, demonstrating strong performance in open-world video understanding. In terms of absolute performance, our model with finetuning achieves the best reported accuracy on the captioning benchmarks of YouCook2 and TVC, as well as on the visual question answering task in TVQA.

2 Related Work

Self-supervised video representations. Inspired by the recent success of self-supervised representation learning in language [40, 41, 38, 28] and images [15, 32, 7], there has been a growing interest in applying similar techniques to learn video representations. Typical approaches use a pretext task defined by predicting transformations of the video data, such as temporal ordering [33, 57, 60, 22, 10], color or geometric transformations [51, 17], multiple views, motion/speed, and optical flow [48, 54, 16, 4]. Although promising, such approaches have still lagged far behind fully supervised video representations [5, 49]. Our work, instead, leverages free supervision in the form of synchronized modalities available with videos, specifically speech transcribed using ASR, which we discuss next.

Multi-modal self-supervision. Videos are generally accompanied by a number of auxiliary data sources which can serve as potent sources of free supervision. The most informative such source is associated metadata, such as tags or titles from social media, which have shown strong transfer performance [11, 27]. In the case of video, there has been a larger focus on using accompanying modalities such as audio [20, 37, 2, 3, 1] and speech, transcribed to text using ASR [31, 46, 47, 30]. Our work is most closely related to the latter thread, with the key difference being our generative translation-based formulation [41] compared to the contrastive metric learning used in most prior work [30, 46].

General-purpose language models. Prior work in general-purpose encoder-based language models [9, 28], pre-trained with self-supervision on large textual corpora, led to strong improvements after finetuning on various downstream classification [53, 52] and ranking [58, 18] tasks. More recently, pre-trained encoder-decoder models, such as BART [26] and T5 [41], achieve further improvements on both discriminative and generative tasks. Our work exploits an encoder-decoder architecture, initialized with T5 weights, in order to learn to generate text from multi-modal representations.

3 Technical Approach

We argue that many video-understanding tasks can be reformulated as text-generation problems. For example classifying an action in a video is nothing more than naming it with words. We use an encoder-decoder architecture as a general solution that enables training with varied supervision (i.e., captions and free-form labels in HowTo100M) and transfer learning to new tasks (e.g., VQA). Our encoder is multi-modal and can be combined during fine-tuning and inference with either (i) the trained decoder for open-ended text generation (e.g., for captioning) or (ii) a simple linear layer if the output space is constrained (e.g., for classification, or multiple-choice VQA). An overview of our model and the overall approach can be seen in Figure 1.

3.1 A Unified Framework for Video-To-Text Translation

Given a task \( a \in \{\text{CLASSIFY, CAPTION, ANSWER,} \cdots \} \), a video \( v_i \), and a target text \( t^a_i \) corresponding to the ground-truth answer, we train our model \( f \) to generate this desired text from the video and a
We note that our model design is surprisingly straightforward. Indeed, the primary contributions of words, of dimensions $V \times C$, where $|V|$ is the vocabulary size (30K in all our experiments). We encode the task, the noise-perturbed text, and a special [CLS] token using this embedding model, i.e., $f_e(a) \rightarrow z^a$, $f_e(n(t^a_i)) \rightarrow z^{a_i^e}$ and $f_e([CLS]) \rightarrow z^{[CLS]}$, generating embedding tensors of dimensions $N_a \times C$, $N_i \times C$ and $1 \times C$ respectively. Here $N_a$ and $N_i$ are the maximum number of tokens used to represent the task and text respectively. Next, the multimodal encoder is implemented as an encoder part of a T5 model [41], implemented using the Transformer architecture [50] and pre-trained on the “Colossal Clean Crawler Corpus” (C4) [41]. We concatenate video features with the task and [CLS] embeddings from the encoder above and pass them through the multimodal encoder, i.e. $f_m(\text{cat} (z^{[CLS]}, z^a, z^{a_i^e}, z^{a_i^e})) \rightarrow z_i$, $z_i$ is a tensor of dimensions $(1 + N_a + N_i) \times C'$, that incorporates the transformation of task, video features using self-attention, and generates $C'$-dimensional features for each. Finally, we pass this resulting feature tensor to the text decoder. The text decoder is implemented using the T5 model decoder, also pretrained on C4. It takes as input the encoded features, and outputs a tensor $f_d(z_i) \rightarrow \hat{t}_i$ of size $N_i \times |V|$. The tensor $\hat{t}_i$ defines $N_i$ probability distributions over the words in the dictionary, which can be used to either sample or evaluate candidate text answers. Note that our model is not limited to operate only on fixed-length strings: while $N_i$ is the maximum number of tokens supported, we pad smaller strings with dummy tokens and both our text encoder and decoder ignore the padded tokens when encoding or generating the output. The noise function $n$ used above is implemented by shuffling the input tokens and masking out $N^m_i$ of them, where $N^m_i$ is a number randomly sampled from a uniform distribution between 1 and $N_i$.

We note that our model design is surprisingly straightforward. Indeed, the primary contributions of this work is to show that video can be treated just as another “language” by directly feeding CNN features extracted from it into an unmodified encoder-decoder architecture originally designed to address a variety of NLP tasks. Despite its simplicity, our experiments demonstrate that this unified vision/NLP framework can outperform specialized designs on a variety of downstream video tasks.

**Training:** We optimize all the parameters of the model $f$ to minimize the loss $l(t^a_i, \hat{t}_i)$. This loss is defined as the mean cross-entropy of word distributions predicted by the model. Our framework of video-to-text translation is flexible enough to allow us to train the model with multiple tasks concurrently without having to add a specialized network head for each of the tasks. Our strategy makes it possible to devote the entire capacity of the encoder-decoder to all tasks, without having to face the typical multi-task dilemma of where to split the shared trunk into task-specific heads. Inference for all tasks is done through the same exact encoder-decoder model but with different actions $a_j$ triggering different executions through the network for the same video input $v_i$.

The primary training of our model is done on the weakly-labelled HowTo100M dataset [31], which includes 136M clips with accompanying textual narrations automatically extracted from the audio channel using ASR. Each clip comes also with a textual description of the activity performed in the video. The textual description correspond to one of 23K total categories, labeled automatically using the clip metadata and is about 8 tokens long on average. We represent narration and description using $N_i = 20$ and $N_i = 12$ tokens, respectively. We clip any longer texts to these lengths. We leverage both types of annotations by performing joint multi-task training, by forcing the network to predict both the activity (using CLASSIFY as task to trigger a classification inference) as well as the narration (using CAPTION as task to trigger a captioning inference) associated to each clip in the mini-batch. For added efficiency of training, we re-use each mini-batch of examples twice in a row by performing
back-to-back training with respect to first narration and then description. This is done by simply updating the task $a_j$ and the corresponding target text $t_j^{(i)}$ in between the two updates.

Note that our formulation of “video understanding as machine translation” makes it possible to use directly the model resulting from this training on different downstream tasks without any further finetuning, as the text generated from the model is a flexible output representation, e.g., it can be used to perform classification with “unseen” class labels without modification or retraining. As shown in our experiments, our model used in this zero-shot setting achieves already good accuracy on many of our downstream tasks. This is a challenging feat considering the domain gap that separates HowTo100M from the downstream datasets (e.g., EpicKitchens contains only first-person view videos recorded in kitchens, which look substantially different from the varied instructional videos of HowTo100M).

Finetuning: Finetuning on the downstream tasks further elevates the accuracy of our model. We experiment with two types of finetuning schemes. We can apply a generative finetuning scheme which consists of minimizing the cross entropy loss on the generated text using as ground truth the labels of the downstream task in textual form. As discussed in the experiments, this also makes it possible to use multiple sources of supervision when different types of annotations are available on the downstream dataset. For example, EpicKitchens includes verb and noun class-labels, as well as action descriptions, which we can leverage simultaneously in our unified multi-task generative setting. For classification tasks, we also experiment with appending and training a linear layer as a classification “head” on top of the multimodal encoder embedding $z_i$ computed for the [CLS] token. We refer to this strategy as discriminative finetuning.

Inference: In case of discriminative finetuning, at test time we use the output of the linear layer as the output. This is typically done for the CLASSIFY tasks. In case of generative finetuning we consider two alternatives. When no candidate outputs are provided (e.g., for captioning) we decode open-ended text [29]. When candidates are provided (e.g., multiple-choice VQA, retrieval) we follow Nogueira et al. [35] and rank the possible choices in textual form (i.e., candidate answers for multiple-choice VQA, candidate class labels for classification) according to the decoder logits for these candidate outputs.

4 Experiments

In this section, we experimentally evaluate our model. We start with an overview of the implementation used in our experiments, followed by a discussion of the downstream tasks and results.

4.1 Implementation details

Model configuration. In the appendix, we present a comprehensive evaluation reporting the effect of different design choices in our model on downstream performance. Here we summarize the best configuration evinced from that empirical study. The input to our video feature extractor is a sequence of 32 frames uniformly spaced-out in the video clip. We apply both masking as well as shuffling to the input text during training; the amount of masking is randomly chosen from a uniform distribution between 0% and 100% for each mini-batch. We generatively train our model to perform both captioning and classification on HowTo100M, as this results in better performance on all downstream tasks compared to single-task training. The video feature extractor (R(2+1)D) and the T5 encoder-decoder are jointly trained on HowTo100M, starting from their pretrained versions on IG65M and C4, respectively, in order to reduce the cost of training. While we envision that it may be possible to learn both our video network and the T5 model from scratch using HowTo100M data, we reserve this for future investigation. For our encoder-decoder, we use the t5-large model with 770M parameters.

Training hyper-parameters. Our model is trained on HowTo100M dataset using Adam [1] with two distinct parameter groups - one for our video feature extractor and one for the multi-modal transformer. We use a base learning rate of $10^{-3}$ for the transformer parameters and $10^{-4}$ for the parameters of the video model. The model is trained for 250K iterations using the inverse square-root schedule following the procedure from [41] with $n = 5 \cdot 10^4$ warm-up iterations. We set a constant
Table 1: Video classification: comparison to the state-of-the-art on EPIC-Kitchens.

| Method                  | Finetuning | Verb | Validation Set (S1) | Noun | Action | Verb | Noun | Action | Test Set (S2) |
|-------------------------|------------|------|---------------------|------|--------|------|------|--------|--------------|
| R(2+1)D-34             | yes        | 56.0 | 34.8                | 24.9 |        |      |      |        | 58.4         |
| R(2+1)D-152 [11]       | yes        | 57.3 | 35.7                | 25.6 | 65.2   | 45.1 | 34.5 | 58.4   | 36.9         |
| GBBlend [55]           | yes        | 59.2 | 36.1                | 25.6 | 66.7   | 48.5 | 37.1 | 58.3   | 36.7         |
| BAIDU [56]             | yes        | 63.2 | 39.1                | 29.0 | 69.8   | 53.3 | 41.4 | 59.7   | 34.2         |
| VIDEOTRANSLATE (ours)  | yes: gen   | 56.3 | 35.6                | 25.7 | 63.8   | 44.0 | 34.0 | 57.2   | 36.2         |
| VIDEOTRANSLATE+gen (ours)| yes: gen-MT| 58.0 | 36.5                | 26.0 | 65.4   | 46.0 | 37.0 | 58.5   | 36.9         |
| VIDEOTRANSLATE (ours)  | yes: discr | 59.4 | 37.8                | 27.8 | 66.1   | 48.4 | 37.2 | 58.6   | 37.0         |

4.2 Experimental results on downstream tasks

4.2.1 Video Classification

We evaluate classification performance of our model on EPIC-Kitchens [8], which is an egocentric video classification dataset with about 28K training video clips, each labeled with one of 352 noun and one of 125 verbs. We report accuracy on the separate noun and verb classification tasks, as well as on the combined (noun,verb) classification (known as action classification). We measure performance on the validation set as well as both splits of the test set (using the online evaluation server), corresponding to seen (S1) and unseen (S2) kitchens. We chose EPIC-Kitchens as classification test bed for our method since it requires recognizing human-object interactions akin to those found in HowTo100M, unlike other video classification datasets which focus on humans exclusively. At the same time, the ego-centric aspect and the restriction to kitchen settings make this a good benchmark to assess the generalization ability of our model. We present top-1 results obtained with several variants of VIDEOTRANSLATE in Table 1 (see appendix for top-5 numbers). It can be noted that VIDEOTRANSLATE provides already decent accuracy without any form of training on EPIC-Kitchens. Generative finetuning effectively finetunes our model to generate the EPIC-Kitchens labels as captions. This yields a significant boost in accuracy over the results without finetuning: +3.0%, +1.6%, +1.1% on verb, noun, and action, respectively, on the validation set. We also note that the performance of VIDEOTRANSLATE with generative finetuning is already superior to that achieved by R(2+1)D-34 (i.e., our video feature extractor) pretrained on IG-65M and discriminatively finetuned on EPIC-Kitchens. Thus, this already shows the added value of our modeling approach. Since EPIC-Kitchens videos come with longer action descriptions in a form of grammatically correct sentence, we also experiment with a multi-task version of generative finetuning (gen-MT), where we finetune VIDEOTRANSLATE to generate both captions and class labels (using two different prompts). At test time, we first generate a caption from video, and then feed the predicted caption as additional text-input to VIDEOTRANSLATE when generating class labels. This yields substantial additional gain. Finally, we also present accuracies obtained by finetuning VIDEOTRANSLATE discriminatively. This produces the best results overall for our model: compared to R(2+1)D-34, the gain on the validation set is +3.4%, +3.0%, +2.9% on verb, noun, and action, respectively. It can be noted that this variant of our model achieves the best reported numbers for noun and action on the unseen kitchens test split (S2). This is indicative of the generalization ability of VIDEOTRANSLATE.

4.2.2 Captioning

We measure the captioning performance of our system on YouCook2 [64], TVC [25], and MSR-VTT [61]. YouCook2 is a cooking video dataset from YouTube with 14K video clips and associated textual descriptions. MSR-VTT contains 200K generic videos clips and associated captions. TVC consists of 4198 TV-show videos, with a caption and a subtitle in English for each clip. For TVC, we present results both with and without using subtitles as auxiliary input to the encoder-decoder. For all of these benchmarks we measure performance in terms of BLEU4 score on the standard dataset splits defined by the authors. The captions for YouCook2 and MSR-VTT are generated using a top-k generation strategy with k = 5. The captions for TVC are generated using greedy decoding strategy as outlined in [25].
Table 2: Captioning results on YouCook2 and MSR-VTT.

| Method          | Finetuning | YouCook2 BLEU4 | METEOR | MSR-VTT BLEU4 | METEOR |
|-----------------|------------|----------------|--------|---------------|--------|
| VideoBERT [47]  | yes        | 4.3            | 11.9   | -             | -      |
| CBT [46]        | yes        | 5.1            | 13.0   | -             | -      |
| ORG [63]        | yes        | -              | -      | -             | -      |
| VIDEOTRANSLATE (ours) | no     | 3.0            | 7.4    | 43.6          | 28.8   |
| VIDEOTRANSLATE (ours) | yes: gen | 5.3            | 13.4   | 41.7          | 28.5   |

Table 3: Captioning results on TVC. All models are finetuned.

| Method          | Subtitles | TVC BLEU4 | METEOR |
|-----------------|-----------|-----------|--------|
| MMT [25]        | yes       | 10.53     | 16.61  |
| VIDEOTRANSLATE (ours) | no     | 9.70      | 15.31  |
| VIDEOTRANSLATE (ours) | yes   | **11.26** | **16.97** |

The results are summarized in Tables 2 and 3. Without any form of finetuning on the downstream dataset, VIDEOTRANSLATE achieves already good accuracy. With generative finetuning, VIDEOTRANSLATE outperforms all previous models on both YouCook2 and TVC, and it achieves performance approaching the best reported results on MSR-VTT.

Table 4 provides a few qualitative captioning examples.

4.2.3 Text-based Retrieval

To assess the ability of our system to retrieve clips given text queries, we use again YouCook2 as well as MSR-VTT. We use the dataset splits and the same exact evaluation protocol as defined in [31], where performance is measured as recall@K (R@K). We reformulate retrieval as a generative task suitable for our model by evaluating the text queries under the probability distribution generated for each candidate video clip. This allows us to evaluate our model directly without any form of finetuning. Table 5 provides a comparison of our model against the methods presented in [31] and [30]. We observe that VIDEOTRANSLATE without any form of finetuning is already competitive despite not being trained on these datasets or even these task. Conversely, we note that the training proposed in [31, 30] directly optimizes the models to discriminate between matching vs non-matching text-

Table 4: Examples of captions generated by VIDEOTRANSLATE for EPIC-Kitchens videos.

| Video Input | Decoder out | Gold          |
|------------|-------------|---------------|
| washing the the vegetables | still stirring vegetables |
| cut t ing with the the knife | take knife |
| put t ing the the kettle down | put down counter |
| put away the the sponge | place sponge away |
Table 5: Text-based video retrieval on YouCook2 and MSR-VTT.

| Method          | Finetuning | YouCook2 R@1↑ | MSR-VTT R@1↑ | YouCook2 R@10↑ | MSR-VTT R@10↑ |
|-----------------|------------|---------------|--------------|----------------|---------------|
| Miech et al. 2019a [31] | no         | 6.1           | 7.5          | 24.8           | 29.6          |
| Miech et al. 2019a [31] | yes        | 8.2           | 14.9         | 35.3           | 52.8          |
| Miech et al. 2019b [30] | no         | 15.1          | 9.9          | 51.2           | 32.4          |
| VIDEOTranslate (ours) | no         | 8.4           | 12.2         | 37.0           | 38.8          |
| VIDEOTranslate (ours) | yes: gen   | 11.6          | 14.7         | 43.9           | 52.8          |

Table 6: Visual Question Answering results on the TVQA dataset.

| Method          | Finetuning | Subtitle as input | Val   | Test* |
|-----------------|------------|-------------------|-------|-------|
| TVQA [23]       | yes        | no                | 45.03 | -     |
| BERT QA [62]    | yes        | no                | 48.95 | 49.23 |
| VIDEOTranslate (ours) | yes: gen    | no                | 58.72 | 58.39 |
| VIDEOTranslate (ours) | yes: discr | no                | 61.09 | 60.55 |
| VIDEOTranslate (ours) gen+discr | yes: gen+discr | no                | 63.01 | 62.84 |
| TVQA [23]       | yes        | yes               | 67.70 | -     |
| BERT QA [62]    | yes        | yes               | 72.41 | 72.23 |
| STAGE [24]      | yes        | yes               | 70.50 | -     |
| VIDEOTranslate (ours) | yes: gen    | yes               | 73.51 | 73.45 |
| VIDEOTranslate (ours) | yes: discr | yes               | 75.19 | 75.01 |
| VIDEOTranslate (ours) gen+discr | yes: gen+discr | yes               | 76.38 | 76.22 |

video pairs, which is effectively the task considered here. Generative finetuning of VIDEOTranslate (in the form of captioning) on these downstream datasets, elevates further the performance of our approach, despite not directly optimizing our model for the metric considered on these benchmarks.

4.2.4 Video Question Answering

We use the TVQA [23] benchmark to assess question answering performance. TVQA is defined over the same set of videos as TVC, and contains several multiple-choice question-answer pairs per video. We use the validation sets defined by the authors to report performance. Note that, since VQA annotations are not available in HowTo100M, we introduce a new prompt denoting this task during finetuning on TVQA, passing the question as textual input to our model. In order to provide additional context to the model we additionally experiment with concatenating the question with subtitles [39]. Table 6 compares the results achieved by our approach against those of the state-of-the-art on this benchmark. Generative finetuning of VIDEOTranslate yields already better results than those reported in prior work. Note that we use beam-search with beam size 5 for generation at test time.

Since each question involves a fixed set of answers, we also consider discriminative finetuning of our model by feeding both question and each candidate answer as text input and training a linear layer on top the resulting embedding obtained for the [CLS] token. As expected, this improves the results of VIDEOTranslate over those obtained with generative finetuning. Finally, we also consider fusing the predictions of the generative and the discriminative versions of our model. This is done by adding a softmax nonlinearity over the fixed set of answers for the scores obtained with the generative model. This yields a probability distribution over answers that can be averaged with that of the discriminative version of our model. As noted in the rows gen + discr of the table, this fusion further elevates the accuracy, producing a large gain of 13.62% in top-1 accuracy on the test set compared to the best reported number in the literature for the setting involving no subtitles.

5 Conclusions

In this work we present an approach that formulates video understanding as machine translation. We argue that this provides several advantages. First, our fully-generative approach bypasses the problem of easy/hard negative sampling that mars constrastive learning methods. Second, it allows us to devote our entire encoder-decoder architecture to address multiple tasks simultaneously without the need to design task-specific heads. Finally, the casting of video understanding as open-ended text generation enables strong transfer performance even without finetuning. Software and models described in this work will be made available upon publication.
**Broader Impact**

The broader impact of this work falls predominantly in the application areas of video understanding systems, such as action recognition, multimedia search, as well as human-computer interaction. The authors do not foresee major ethical issues associated to this work. As with most machine learning systems, our approach is susceptible to biases present in the distribution of the data. This is particularly true for self-supervised approaches such as ours. Since most videos used in our work have origins in English-speaking, Western regions of the world, we anticipate our learned representations to be most effective for applications in these geographic areas. However, as future work we plan to use an internationalized version of the training set [43], which should help assuage such biases.

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Appendix

A Input pre-processing

In this section, we discuss the pre-processing details for video and text.
A.1 Video pre-processing

Our video network takes as input 32 RGB frames of size $112 \times 112$. We apply standard data augmentation transformation (multi-scale random crop, random horizontal flip, and Z normalization) to all input videos at training time. At inference time, we do not flip the videos and use centre crop as opposed to multi-scale random crop.

Since the datasets considered in our experiments are encoded at different frames-per-second (FPS) and have varying lengths, we adopt dataset-specific strategies to form the video input.

**HowTo100M, YouCook2, MSR-VTT:** We do not apply any normalization of the videos themselves. Before loading the annotated segment into memory, we only check if it is longer than 6 seconds and if so, if the sequence is longer than 6 seconds, we randomly select a 6-second segment within the sequence to prevent out-of-memory errors during decoding.

**TVQA/TVC:** This dataset is provided as a series of frames extracted at 3 frames per second. In order to form the video input, we load the frames of a sequence into memory, repeating each frame twice (making the frame rate effectively 6 FPS).

**EPIC-Kitchens:** This dataset is given as a series of high-resolution (up to 1440 pixels on the shorter side), high frame-rate (up to 90 FPS) GoPro videos. In order to reduce the decoding cost, we re-sample each video to 24 FPS at the lowest common resolution of $1280 \times 720$ pixels.

A.2 Text pre-processing

We tokenize the text prior to the input, completely following the procedure from [41]. We append the <CLS> token to the beginning of the input, and the <SEP> token to the end of the masked text input, before additional context if one is used. Note that we do not remove stop words from the HowTo100M annotations.

B Study of design choices

Here we report the results of an empirical study aimed at determining the effects of different design choices on downstream performance. In order to reduce the computational cost of this broad evaluation, we perform training using the smaller t5-small transformer on a subset of HowTo100M consisting of 200k randomly sampled videos. All models are trained for 240k iterations. We measure effects on the downstream tasks of EPIC Kitchens [8] (EK) classification (top-1 accuracy %) and YouCook2 [64] retrieval (R@10 %), without any fine-tuning on these benchmarks (i.e., in a zero-shot setting). Table 7 provides the quantitative results of this study which we summarize next.

**Video input.** We experimented with 32-frame inputs obtained by either (a) sampling the frames with uniform spacing to span the entire clip or (b) sampling 32 consecutive frames at 16 fps from a random starting time of the clip. The former option yields better results (a gain of 1.1% in accuracy on EK and of 3.4% in R10 on YouCook2).

**Video feature pooling.** We found that applying temporal pooling to the video features degrades downstream performance by 2.5% on EK and 1.4% on YouCook2.

**Input text perturbations.** As mentioned, training a model to generate text from video alone is a very hard task. However simply providing the associated narration as input only requires an identity to correctly generate the target. Thus, during training we present the model with perturbed text. Following [41], we evaluate masking and shuffling as viable text perturbations. Training with video features only yields low performance (0.9% and 2.3% on EK and YouCook2 respectively), and adding unmodified text significantly eases the task but does not improve the performance on the downstream tasks (1.3% and 8.9%). Training with perturbed text gives a boost in performance on the downstream tasks compared to training with full text or no text at all. When input text is shuffled, we obtain 8.6% and 11.4% on EK and YouCook2, and when it is masked it further boosts the results to 11.9% and 17.2%. Finally, we found that training with both form of text perturbation yields the best downstream performance (14.3% and 19.3%).
Table 7: Effects of design choices on downstream tasks.

(a) Video input.

| Video input          | YouCook2 R@10 | EK-Action acc@1 |
|----------------------|---------------|-----------------|
| a) 32 frames uniformly spaced | 19.3          | 14.3            |
| b) 32 consecutive frames     | 15.9          | 13.2            |

(b) Video feature pooling.

| Temporal pooling | YouCook2 R@10 | EK-Action acc@1 |
|------------------|---------------|-----------------|
| Yes              | 17.9          | 11.8            |
| No               | 19.3          | 14.3            |

(c) Text perturbation ablation.

| Text input          | YouCook2 R@10 | EK-Action acc@1 |
|---------------------|---------------|-----------------|
| None                | 2.3           | 0.9             |
| Unmodified          | 8.9           | 1.3             |
| Shuffled            | 11.4          | 8.6             |
| Masked              | 17.2          | 11.9            |
| Shuffled & Masked   | 19.3          | 14.3            |

(d) Training task.

| Training task       | YouCook2 R@10 | EK-Action acc@1 |
|---------------------|---------------|-----------------|
| Captioning          | 9.4           | 9.8             |
| Classification      | 11.2          | 12.1            |
| Multi-task          | 19.3          | 14.3            |

(e) Video embedding.

| Video embedding     | YouCook2 R@10 | EK-Action acc@1 |
|---------------------|---------------|-----------------|
| Fixed               | 3.2           | 0.5             |
| Finetune last layer only | 18.2       | 11.9            |
| Finetune all        | 19.3          | 14.3            |

(f) Transformer size.

| Transformer size (params) | YouCook2 R@10 | EK-Action acc@1 |
|---------------------------|---------------|-----------------|
| Small (60M)               | 19.3          | 14.3            |
| Base (220M)               | 19.5          | 15.1            |
| Large (770M)              | 19.9          | 16.7            |

Multi-task training. We found that training our model to perform both captioning and classification on HowTo100M [31] results in better downstream accuracy compared to single-task training (+2.2% on EK and +8.1% on YouCook2).

Training with frozen video embeddings. Due to the computational costs of end-to-end training of video models, most approaches use fixed video or image features as an input. We found that training the video encoder jointly with the transformer is crucial in our model. Training the transformer with a frozen R(2+1)D [49] model fails to converge and produces consistently worse performance on all tasks (0.5% on EK and 3.2% on YouCook2).

Transformer size. We found that the performance on the downstream tasks improves as we increase the number of transformer parameters. Due to memory constraint, the largest transformer we use is a t5-large model with 770M parameters, which outperforms on every task the identical setup with the t5-base model (220M parameters).

C Additional experimental details

Here we present task-specific hyper-parameters, details about dataset splits, and additional training information. In general, all learning rates (LR) are scaled according to the total number of GPUs in a distributed training run.
### Table 8: Action classification: comparison to the state-of-the-art on EPIC-Kitchens.

| Method         | Finetuning | Verb T1 | Verb T5 | Noun T1 | Noun T5 | Action T1 | Action T5 | Verb T1 | Verb T5 | Noun T1 | Noun T5 | Action T1 | Action T5 |
|----------------|------------|---------|---------|---------|---------|-----------|-----------|---------|---------|---------|---------|-----------|-----------|
| R(2+1)D-34    | yes        | 56.0    | 80.2    | 34.8    | 58.0    | 24.9      | 41.9      | 63.2    | 87.4    | 46.0    | 69.6    | 34.1      | 54.0      |
| R(2+1)D-152   | yes        | 57.3    | 81.1    | 35.7    | 58.7    | 25.6      | 42.7      | 65.2    | 87.4    | 45.1    | 67.8    | 34.6      | 53.8      |
| GBNet [45]    | yes        | 59.2    | 84.5    | 36.1    | 58.5    | 25.6      | 43.5      | 66.7    | 88.9    | 48.5    | 71.7    | 37.1      | 56.2      |
| BAEU [50]     | yes        | 63.2    | 84.6    | 39.1    | 65.0    | 29.0      | 49.8      | 69.8    | 91.0    | 53.3    | 76.7    | 41.4      | 63.6      |
| Ours - short  | no         | 53.3    | 75.5    | 34.0    | 58.0    | 24.6      | 41.8      | 57.8    | 78.5    | 35.1    | 59.8    | 24.9      | 42.6      |
| Ours - gen    | yes        | 56.3    | 79.6    | 35.6    | 58.5    | 25.7      | 42.8      | 63.8    | 86.9    | 44.0    | 67.1    | 34.0      | 53.0      |
| Ours - gen-MT | yes        | 58.0    | 82.6    | 36.5    | 60.1    | 26.0      | 43.7      | 65.4    | 87.9    | 46.0    | 69.5    | 37.0      | 54.0      |
| Ours - disc   | yes        | 59.4    | 83.9    | 37.8    | 59.0    | 27.8      | 45.1      | 66.1    | 88.5    | 48.4    | 69.9    | 37.2      | 55.8      |

C.1 General hyper-parameters

For our **discriminative** finetuning, we use LR decay of 0.1 at given intervals. We use an equivalent of 1 epoch of iterations as a linear warm-up wherever we use multiple nodes for finetuning.

For **generative** finetuning we largely follow the procedure in [41], i.e., we finetune the entire encoder-decoder model for $2^{18} = 262,144$ steps with a constant learning rate. The only deviations from the procedure described in [41] are: 1) using 20,000 iterations as a linear warm-up and 2) setting the finetuning learning rate to 0.0001.

C.2 Action classification - EPIC-Kitchens

**Dataset splits.** We optimize our hyper parameters on the same validation set of unseen kitchens used in [11]: videos by person 01 to 25 (28,561 segments) are used for training, and the remaining ones are used for validation (5,886).

**Finetuning parameters - baseline model.** For the finetuning of the baseline R(2+1)D-34 [49] model we use the same hyper-parameters as in [11]: the total training amounts to 27 epochs with a batch size of 6 clips per GPU. The base learning rate of 0.0025 is decayed every 9 epochs. We found that using 1 epoch for a linear warm-up helps with the consistency of the experiments.

**Finetuning parameters - VIDEOTRANSLATE.** For discriminative finetuning, we use a LR of 0.00001 for the video feature extractor and the transformer encoder, and a LR of 0.001 for the linear layers trained on top of the representations. All layers are trained for 40,000 iterations, and the learning rates are scaled down every 15,000 iterations.

**Top-5 Accuracy Results** In Table 8 we present the EK recognition results in terms of top-5 accuracy. All results are computed as an average of predictions on 10 uniformly sampled clips from every video.

C.3 Captioning - TVC/YouCook2/MSR-VTT

We finetune our model for each dataset separately. We use the same general hyper-parameters for each of the datasets (they are all fine-tuned in a generative fashion).

C.4 Retrieval - YouCook2/MSR-VTT:

we fine-tune these models for captioning following the general procedure above, but on the dataset splits provided by [31].