Learning Video Representations from Large Language Models

Yue Zhao[1,2*] Ishan Misra[1] Philipp Krähenbühl[2] Rohit Girdhar[1]
[1]FAIR, Meta AI [2]University of Texas, Austin
facebookresearch.github.io/LaViLa

Abstract

We introduce **LaViLa**, *a new approach to learning video-language representations by leveraging Large Language Models (LLMs). We repurpose pre-trained LLMs to be conditioned on visual input, and finetune them to create automatic video narrators. Our auto-generated narrations offer a number of advantages, including dense coverage of long videos, better temporal synchronization of the visual information and text, and much higher diversity of text. The video-language embedding learned contrastively with these narrations outperforms the previous state-of-the-art on multiple first-person and third-person video tasks, both in zero-shot and finetuned setups. Most notably,* LaViLa *obtains an absolute gain of* **10.1%** *on EGTEA classification and* **5.9%** *Epic-Kitchens-100 multi-instance retrieval benchmarks. Furthermore,* LaViLa *trained with only half the narrations from the Ego4D dataset outperforms models trained on the full set, and shows positive scaling behavior on increasing pre-training data and model size.*

1. Introduction

Learning visual representation using web-scale image-text data is a powerful tool for computer vision. Vision-language approaches [31, 49, 80] have pushed the state-of-the-art across a variety of tasks, including zero-shot classification [49], novel object detection [87], and even image generation [52]. Similar approaches for videos [4, 39, 46], however, have been limited by the small size of paired video-text corpora compared to the billion-scale image-text datasets [31, 49, 84]—even though access to raw video data has exploded in the past decade. In this work, we show it is possible to *automatically* generate text pairing for such videos by leveraging Large Language Models (LLMs), thus taking full advantage of the massive video data. Learning video-language models with these automatically generated annotations leads to stronger representations, and as Figure 1 shows, sets a new state-of-the-art on six popular first and third-person video benchmarks.

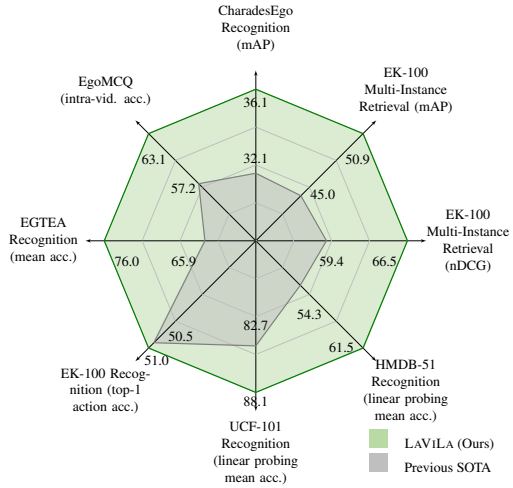


Figure 1. **LaViLa sets a new state-of-the-art** across a number of first and third-person video understanding tasks (*cf*. Table 1 for details), by learning a video-language representation using supervision from large language models as narrators.

Our method, called **LaViLa**: **La**nguage-model **a**ugmented **Vi**deo-**La**nguage pre-training, leverages pre-trained LLMs, *e.g.* GPT-2 [50], which encode within their weights a treasure trove of factual knowledge and conversational ability. As shown in Figure 2, we repurpose these LLMs to be "visually-conditioned narrators", and finetune on all accessible paired video-text clips. Once trained, we use the model to densely annotate thousands of hours of videos by generating rich textual descriptions. This pseudo-supervision can thus pervade the entire video, in between and beyond the annotated snippets. Paired with another LLM trained to rephrase existing narrations, LaViLa is able to create a much larger and more diverse set of text targets for video-text contrastive learning. In addition to setting a new state-of-the-art as noted earlier, the stronger representation learned by LaViLa even outperforms prior work using only half the groundtruth annotations (Figure 5).

LaViLa's strong performance can be attributed to a number of factors. First, LaViLa can provide temporally dense supervision for long-form videos, where the associ-

*Work done during an internship at Meta.

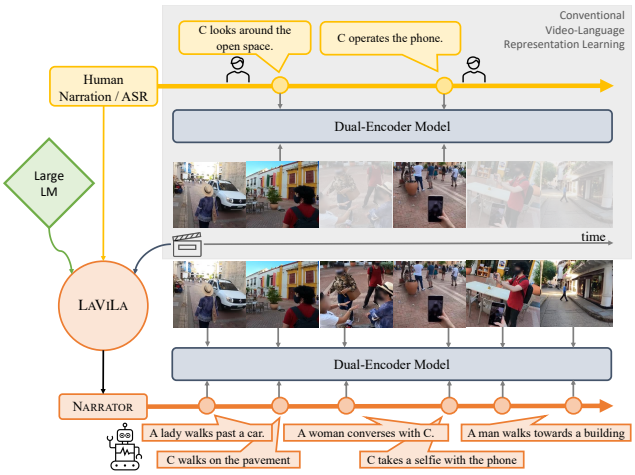


Figure 2. **LAVILA** leverages Large Language Models (LLMs) to densely narrate long videos, and uses those narrations to train strong dual-encoder models. While prior work uses sparsely labeled text by humans, or weakly aligned text transcribed from speech, LAVILA is able to leverage dense, diverse, and well-aligned text generated by a LLM.

ated captions are either too sparse, or the video-level "Alt-Text" (in the case of web videos) does not describe all the nuanced activities happening in it. Second, the generated text is well-aligned with the visual input. Although prior work has leveraged automatic speech transcription on How-To videos [45] to automatically extract clips paired with text from the speech, such datasets have relatively poor alignment between the visual and textual content ($\leq 50\%$, *cf*. [25, 45]), limiting the quality of the learned representations. Third, LAVILA can significantly expand annotations when only a little is available. For instance, videos of mundane day-to-day activities, especially from an egocentric viewpoint, could be very useful for assistive and augmented reality applications. Such videos, however, are rare on the internet, and hence do not readily exist with associated web text. Recent work [24] instead opted to manually capture and narrate such video data. These narrations however required significant manual effort: 250K hours of annotator time spent in narrating 3.6K hours of video. In contrast, LAVILA is able to automatically narrate each video multiple times and far more densely, and hence learns much stronger representations.

We extensively evaluate LAVILA across multiple video-text pre-training datasets and downstream tasks to validate its effectiveness. Specifically, after being pre-trained on Ego4D, the largest egocentric video datasets with narrations, LAVILA can re-narrate the whole dataset $10\times$ over. The resulting model learned on these expanded narrations sets a new state-of-the-art on a wide range of downstream tasks across challenging datasets, including multi-instance video retrieval on Epic-Kitchens-100 (**5.9%** absolute gain on mAP), multiple-choice question answering on Ego4D (**5.9%** absolute gain on intra-video accuracy), and action recognition on EGTEA (**10.1%** absolute gain on mean accuracy). It obtains gains both when evaluated for zero-shot transfer to the new dataset, as well as after fine-tuning on that dataset. Similar gains are shown in third-person video data. When training LAVILA after densely re-narrating HowTo100M, we outperform prior work on downstream action classification on UCF-101 and HMDB-51. In a case study of semi-supervised learning, we show that our model, which only ever sees 50% of the human-labeled data, is capable of outperforming the baseline model trained with all the narrations. Moreover, the gains progressively increase as we go to larger data regimes and larger backbones, suggesting the scalability of our method.

2. Related Work

Vision-language representation learning maps visual and textual embeddings into a common space using metric-learning techniques [21, 73]. Recently, different pretext tasks are proposed to learn a finer-grained association between visual and textual modality, *e.g*. masked language modeling (MLM) [10, 41, 62] and captioning [16, 80]. Another line of research focuses on scaling up both models and pre-training data. For instance, CLIP [49] is pre-trained on 400M image-text pairs with a contrastive loss (InfoNCE [48, 59]) while CoCa [80] unifies contrastive and generative approaches with a single foundation model. Similar trends are also witnessed in the video-text domain [36, 64, 88]. However, collecting high-quality video-text data is more difficult than image-text. Therefore, efforts are made to learn from uncurated videos with machine-generated audio transcripts via contrastive learning [44, 77, 82] or unsupervised alignment [25] while other works focus on either adapting well-performing image-text models to videos [32, 40, 47, 78], or curriculum learning from a single frame to multiple frames [4]. In contrast, our approach leverages language models to generate temporally dense textual supervision on long-form videos.

Generative Visual Language Models (VLM) were first used for image/video captioning using recurrent networks [17, 68] and Transformer-based architectures [42, 56]. More recently, generative VLMs have unified multiple vision tasks [11, 89] by training multi-modal Transformers on visual-text pairs [30, 81]. Meanwhile, generative VLMs also excel at multimodal tasks via zero-shot or few-shot prompting [1, 65, 83] by leveraging multi-billion-parameter LLMs pre-trained on massive text corpus [7, 28, 50]. In our work, we demonstrate that generative VLMs can narrate long videos and the resulting video-text data benefits video-language representation learning.

Large-scale multimodal video datasets are crucial for

video understanding tasks but are hard to collect. Conventional video-text datasets [8, 53, 86] either have limited scenarios, *e.g.* cooking, or are not large enough to learn generic video representation. Miech *et al.* [45] scrape over 100 million video-text pairs via automatic audio transcription from long-form How-To videos. However, ASR introduces textual noise and visual-text unalignment [25]. WebVid [4] contains 10 million short videos with textual descriptions. But it is still several orders of magnitude smaller than the image counterparts [49, 54] and is harder to scale up since it is sourced from stock footage sites. The recently released Ego4D [24] dataset offers 3,600 hours of egocentric videos in which written sentence narrations are manually annotated every few seconds but requires significant manual effort. In contrast, our method shows a promising alternative by automatically narrating videos using supervision from LLM.

Data augmentation techniques in NLP, including word-level replacement based on synonyms [72, 85] or nearest-neighbor retrieval [19, 70], improve text classification accuracy. We refer readers to [20] for a comprehensive survey. In this paper, we show that sentence-level paraphrasing based on text-to-text models [51] is helpful for video-language pre-training.

3. Preliminaries

A video V is a stream of moving images I. The number of frames $|V|$ can be arbitrarily long while video models typically operate on shorter clips, which are often in the range of a few seconds. Therefore, we skim through a long-form video and represent it by a set of N short clips, *i.e.* $\mathcal{X}$. Each clip x_i is defined by a specific start and end frame $x_i = \{I_{t_i}, \cdots, I_{e_i}\}$, where $0 < t_i < e_i \leq |V|$, and is typically associated with some annotation y_i. This annotation could be a class label or free-form textual description of the clip. We denote a video by the set of annotated clips with their corresponding annotations, *i.e.* $(\mathcal{X}, \mathcal{Y}) = \{(x_1, y_1), \cdots, (x_N, y_N)\}$. Note that the annotated clips often cannot densely cover the entire video due to the annotation cost and visual redundancy, *i.e.* $\bigcup_i [t_i, e_i] \subsetneq [0, |V|]$.

A typical video model $\mathcal{F}(\mathcal{X}, \mathcal{Y})$ learns from these clip-level annotations using a standard training objective such as a cross-entropy loss when the annotations are class labels with a fixed vocabulary. However, more recently, dual-encoder-based contrastive approaches like CLIP [49, 77] have gained popularity. They work with free-form textual annotations which are tokenized [55] into sequences of discrete symbols, *i.e.* $y = (s_1, s_2, \cdots, s_L) \in \{1, 0\}^{|\mathbb{S}| \times L}$. The model consists of a visual encoder $f_{\text{v}} : \mathbb{R}^{T \times 3 \times H \times W} \mapsto \mathbb{R}^{D_{\text{v}}}$ plus a projection head $h_{\text{v}} : \mathbb{R}^{D_{\text{v}}} \mapsto \mathbb{R}^d$ and a textual encoder $f_{\text{t}} : \{1, 0\}^{|\mathbb{S}| \times L} \mapsto \mathbb{R}^{D_{\text{t}}}$ plus a projection head $h_{\text{t}} : \mathbb{R}^{D_{\text{t}}} \mapsto \mathbb{R}^d$ in parallel to obtain the global visual and textual embedding respectively:

$$\mathbf{v} = h_{\text{v}}(f_{\text{v}}(x)), \quad \mathbf{u} = h_{\text{t}}(f_{\text{t}}(y)).$$

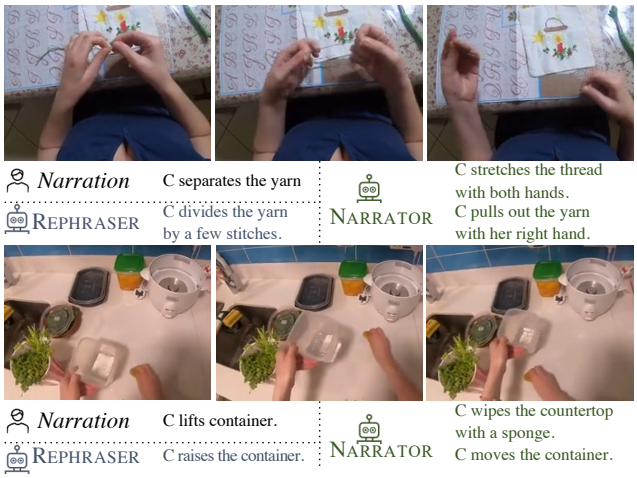


Figure 3. **Generated samples by NARRATOR and REPHRASER.** NARRATOR generates new descriptions of the action taking place, potentially focusing on other objects being interacted with. REPHRASER not only changes the word order of the human narration but also diversifies it by using related verbs or nouns.

A contrastive loss, such as InfoNCE [48], learns global embeddings that associate corresponding video and text embeddings within a batch of samples $\mathcal{B}$,

$$\frac{1}{|\mathcal{B}|} \sum_{(x,y) \in \mathcal{B}} \left(\text{InfoNCE}(\mathbf{v}, \mathbf{u}) + \text{InfoNCE}(\mathbf{u}, \mathbf{v}) \right). \quad (1)$$

4. LAVILA

In LAVILA, we leverage large language models (LLMs) as supervision to train the dual-encoder model, where the LLMs serve as vision-conditioned narrators and automatically generate textual descriptions from video clips. In particular, we exploit supervision from two LLMs: (1) **NARRATOR** (§ 4.1) is a *visually-conditioned* LLM that pseudo-labels existing and new clips with narrations, generating new annotations $(\mathcal{X}', \mathcal{Y}')$. (2) **REPHRASER** (§ 4.2) is a standard LLM that paraphrases narrations in existing clips, augmenting those annotations to $(\mathcal{X}, \mathcal{Y}'')$. As illustrated in Figure 3, NARRATOR generates new descriptions of the action taking place, potentially focusing on other objects being interacted with. REPHRASER serves to augment the text input, *e.g.*, changes word order of the human narration and additionally replaces common verbs or nouns, making annotations more diverse. Finally, we train the **dual-encoders** (§ 4.3) on all these annotations combined, *i.e.* $(\mathcal{X}, \mathcal{Y}) \cup (\mathcal{X}', \mathcal{Y}') \cup (\mathcal{X}, \mathcal{Y}'')$.

4.1. NARRATOR

Traditional LLMs, such as GPT-2 [50], are trained to generate a sequence of text tokens $(s_1 \cdots s_L)$ from scratch

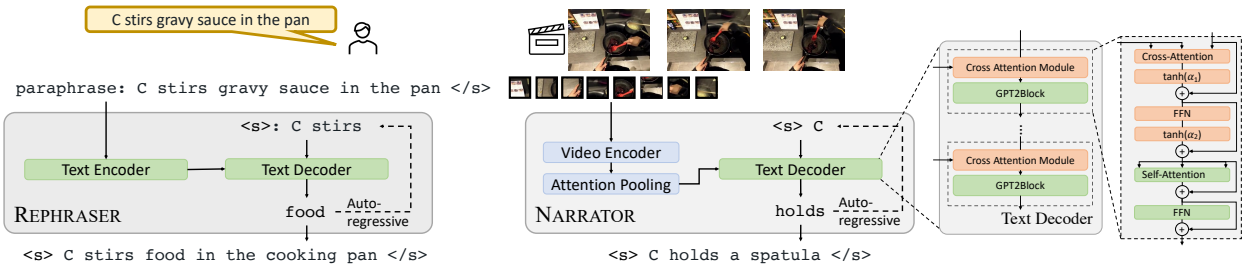


Figure 4. **Language supervision from REPHRASER and NARRATOR**. REPHRASER*(left)* takes the narration as input, passes it through a text encoder and uses a text decoder to autoregressively generate the rephrased output. NARRATOR*(right)* takes video frames as input and obtains the visual embeddings through a video encoder followed by attentional pooling. Equipped with a few additional cross-attention modules, the text decoder autoregressively generates new narrations for those new frames.

by modeling the probability of the next token given all tokens seen so far: $p(s_l|s_{<l})$. NARRATOR repurposes existing LLMs to be conditioned on the visual input and is trained on the original annotations $(\mathcal{X}, \mathcal{Y})$. The resulting model produces dense new annotations $(\mathcal{X}', \mathcal{Y}')$ on the full video. Following the formulation of factorized probabilities in language models [5], we model the visually conditioned text likelihood as follows:

$$p_{\text{NARRATOR}}(y'|x') = \prod_{\ell=1}^{L} p(s'_\ell|s'_{<\ell}, x'). \tag{2}$$

Architecture. We design NARRATOR to closely follow the architecture of standard LLMs, with only a few additional cross-attention modules added to provide visual conditioning, as illustrated in Figure 4 (*right*). This enables NARRATOR to be initialized from pre-trained weights, which is crucial for our task as the data we use to train NARRATOR (narrations associated with video clips) are far smaller in scale compared to the large text corpus typically used to train LLMs. Moreover, video narrations are less diverse and noisier because they are either collected by only a few annotators or automatically transcribed from speech. Similar "frozen-LM" approaches have shown effectiveness in multimodal few-shot adaptation in recent work [1, 65].

Specifically, we take a frozen pre-trained LLM and add a cross-attention module before each Transformer decoder layer so that the text input can attend to visual information. The cross-attended output then sums with the input text feature via residual connection [26] and goes to the Transformer decoder layer. Each cross-attention module comprises a cross-attention layer, which takes textual tokens as queries and visual embedding as keys and values, followed by a feed-forward network (FFN). Layer Normalization [3] is applied at the beginning of both cross-attention and FFN. We add `tanh`-gating [27], with an initial value of zero, such that the output of the new model is the same as that from the original language model at the beginning.

While features from any video model are applicable for conditioning, for convenience we adopt the video encoder from $\mathcal{F}$ in § 3, trained contrastively on the ground-truth data $(\mathcal{X}, \mathcal{Y})$. We use features before global pooling to allow the LLM to leverage fine-grained spatial-temporal information.

Training. We train NARRATOR on all of, or a subset of, the ground-truth annotations $(\mathcal{X}, \mathcal{Y})$. For each pair (x, y), the captioning loss is the sum of the negative log-likelihood of the correct word at each step,

$$\mathcal{L}_{\text{NARRATOR}}(x, y) = -\sum_{\ell=1}^{L} \log p(s_\ell|s_{<\ell}, x). \tag{3}$$

Inference. At inference time, we query NARRATOR by feeding visual input x plus a special start-of-sentence token `<s>`. We sample from the distribution recursively, *i.e.* $\tilde{s}_\ell \sim p(s|[\texttt{<s>}, \cdots, \tilde{s}_{\ell-1}], x)$ until an end-of-sentence token `</s>` is reached. Following [29], at each step we sample from a subset of tokens that contain the vast majority of the probability mass, which is known as nucleus sampling.

The effect of nucleus sampling is two-fold. On the one hand, it generates more diverse, open-ended, and human-like text than maximum-likelihood-based methods such as beam search and its variants [67]. On the other hand, the generated text may contain irrelevant or noisy information due to sampling without post-processing based on sentence-level likelihood. To address this, we repeat the sampling process for K times on the same visual input. We later demonstrate that the contrastive pre-training objective is robust to the noise caused by sampling, and the final performance benefits from a more diverse set of narrations.

To sample video clips for captioning, we start by simply re-captioning the existing clips labeled in the dataset $\mathcal{X}$, resulting in expanded annotations. Furthermore, long-form videos are typically sparsely narrated, meaning that the temporal union of all labeled clips cannot cover the entire video. Hence, we use NARRATOR to annotate the remainder of the video to obtain additional annotations by pseudo-captioning. With a simple assumption that video is a stationary process, we uniformly sample clips from the unlabeled intervals. The clip duration is equal to the average of all ground-truth clips, *i.e.* $\Delta = \frac{1}{N}\sum_{i=1}^{N}(e_i - t_i)$ while the sampling stride is computed likewise. Finally, by

combining both re-captioned and pseudo-captioned narrations, we refer to the final set of annotations generated by NARRATOR as $(\mathcal{X}', \mathcal{Y}')$.

Post-processing. Exhaustive pseudo-captioning may contain some uninformative visual clips and generate text that is not useful. Thus, we add a filtering process to eliminate low-quality clips and their associated descriptions. We use the baseline dual-encoder model $\mathcal{F}$, which is trained on the ground-truth paired clips, to compute the visual and textual embedding of pseudo-labeled pairs and filter based on the similarity score, *i.e.* $\text{Filter}(f_{\text{v}}(x'_j)^\top \cdot f_{\text{t}}(y'_j))$, where $\text{Filter}(\cdot)$ can be either top-k of all generated text or a threshold filtering. In the experiments, we use a threshold of 0.5.

4.2. REPHRASER

The data generated by NARRATOR is several times larger than the ground-truth pairs. To ensure that we do not overfit the pseudo-labeled data, we increase the number of ground-truth narrations by paraphrasing. In particular, we use a text-to-text LLM which models conditional text likelihood:

$$p_{\text{REPHRASER}}(y''|y) = \prod_{\ell=1}^{L} p(s''_\ell | s''_{<\ell}, y).$$

The text-to-text model is implemented by an encoder-decoder architecture, *e.g.* T5 [51], to auto-regressively generate a new sentence given the original one. We observe that REPHRASER is able to do basic manipulations such as replacing synonyms or changing word order, which serves as an efficient way of automatic data augmentation. The resulting annotations are referred to as $(\mathcal{X}, \mathcal{Y}'')$.

4.3. Training the Dual-Encoders

We train the dual-encoders as described in Algorithm 1 in Appendix E. In each iteration, we first sample a batch $\mathcal{B}$ of video clips. It comprises a subset of clips $\mathcal{B}_l$ with labeled timestamps as well as narrations, and a subset $\mathcal{B}_u$ whose clips are randomly sampled from videos without narrations. For clip $x_i \in \mathcal{B}_u$, we obtain the pseudo-caption y'_i by querying the NARRATOR $y'_i \sim p_{\text{NARRATOR}}(y'|x)$, resulting in a set of clips with LLM-generated narrations $\widetilde{\mathcal{B}}_u$. For clip $(x_i, y_i) \in \mathcal{B}_l$, the text supervision is obtained from either the REPHRASER or the NARRATOR, with a probability of 0.5. Hence, the effective number of iterations per epoch for LAVILA is the same as that for the baseline Dual-Encoder. We denote the resulting set of pairs to be $\widetilde{\mathcal{B}}_l$ similarly. Following CLIP [49], we use the symmetric cross-entropy loss over the similarity scores of samples in the batch $\widetilde{\mathcal{B}}_l \cup \widetilde{\mathcal{B}}_u$.

In practice, we run REPHRASER and NARRATOR in advance and cache the resulting video-narration pairs so that there is no computational overhead during pre-training. Therefore, training a dual-encoder in LAVILA is as fast as training a standard dual-encoder contrastive model.

Datasets	Task	Ego?	Metrics	Eval. Prot.
EK-100 [14]	MIR	✓	mAP, nDCG	ZS, FT
EK-100 [14]	CLS	✓	top-1 action acc.	FT
Ego4D [24]	MCQ	✓	inter-/intra-video acc.	ZS
Ego4D [24]	NLQ	✓	Recall@N	FT
EGTEA [37]	CLS	✓	top-1, mean acc.	ZS, FT
CharadesEgo [58]	CLS	✓	video-level mAP	ZS, FT
UCF-101 [60]	CLS	✗	mean acc.	LP
HMDB-51 [35]	CLS	✗	mean acc.	LP

Table 1. **Downstream datasets** and metrics used for evaluation. We evaluate LAVILA on a wide range of tasks including Multi-Instance Retrieval (MIR), Multiple-Choice Question (MCQ), Natural Language Query (NLQ), and Action Recognition (CLS). The evaluation protocols include zero-shot (ZS), fine-tuning (FT), and linear-probing (LP). Please refer to Appendix C for more details.

5. Experiments

Dual-Encoder Architecture. The video-language model follows a dual-encoder architecture as CLIP [49]. The Visual encoder is a TimeSformer (TSF) [6], whose spatial attention modules are initialized from a ViT [18] which is contrastively pre-trained on large-scale paired image-text data as in CLIP [49]. We sample 4 frames per clip during pre-training and 16 when finetuning on downstream tasks. The text encoder is a 12-layer Transformer [50, 66]. We use BPE tokenizer [55] to pre-process the full sentence corresponding to the video clip and keep at most 77 tokens.

NARRATOR's architecture is a visually conditioned auto-regressive Language Model. The visual encoder is by default TimeSformer-L while the text decoder is a GPT-2 XL. During inference, we use nucleus sampling [29] with $p = 0.95$ and return $K = 10$ candidate outputs.

REPHRASER. We use an open-source paraphraser [23] based on T5-large [51]. It is pre-trained on C4 [51] and then finetuned on a cleaned subset of ParaNMT [74]. During inference, we use Diverse Beam Search [67] with group number the same as beam number ($G = B = 20$) and set the diversity penalty to be 0.7. We keep 3 candidates per sentence, remove punctuations, and do basic de-duplication.

Pre-training dataset. We train on the video-narration pairs from Ego4D [13, 24], the largest egocentric video dataset to date. We exclude videos that appear in the validation and test sets of the Ego4D benchmark and determine each clip's interval using the same pairing strategy in [39]. This results in around 4M video-text pairs with an average clip length of 1 second. We also experiment with third-person videos by pre-training on HowTo100M [45] in § 5.2.

Evaluation protocols. We evaluate the learned video-text encoders using three evaluation protocols. (1) *Zero-Shot (ZS)*, meaning that we apply the pre-trained video-text encoders directly on the downstream validation dataset to perform video↔text retrieval tasks, without any tuning on the downstream dataset. Zero-shot classification is performed

Method	Backbone	mAP			nDCG		
		V→T	T→V	Avg.	V→T	T→V	Avg.
(ZERO-SHOT)							
EgoVLP [39]	TSF-B	19.4	13.9	16.6	24.1	22.0	23.1
EgoVLP* [39]	TSF-B	26.0	20.6	23.3	28.8	27.0	27.9
LAVILA	TSF-B	**35.1**	**26.6**	**30.9**	**33.7**	**30.4**	**32.0**
LAVILA	TSF-L	**40.0**	**32.2**	**36.1**	**36.1**	**33.2**	**34.6**
(FINETUNED)							
MME [75]	TBN	43.0	34.0	38.5	50.1	46.9	48.5
JPoSE [75]	TBN	49.9	38.1	44.0	55.5	51.6	53.5
EgoVLP [39]	TSF-B	49.9	40.5	45.0	60.9	57.9	59.4
LAVILA	TSF-B	**55.2**	**45.7**	**50.5**	**66.5**	**63.4**	**65.0**
LAVILA	TSF-L	**54.7**	**47.1**	**50.9**	**68.1**	**64.9**	**66.5**

Table 2. **EK-100 MIR**. LAVILA outperforms prior work across all settings, metrics and directions of retrieval, with larger gains when switching to a larger model. Specifically, our best model achieves over 10% absolute gain in the zero-shot setting and 5.9 $\sim$ 7.1% gain in the finetuned setting. EgoVLP* refers to our improved version of [39], details of which are given in Appendix F.

similarly, where we compute the similarity score between the video clip and the textual description of all possible categories. (2) *Finetuned (FT)*, where we take the pre-trained video-text model and perform end-to-end fine-tuning on the training split of the target downstream dataset. (3) *Linear-Probe (LP)*, where we compute the video features from a frozen encoder and train a linear SVM on top of the training split of the downstream dataset.

Downstream benchmarks. We use multiple benchmarks across four first-person (egocentric) and two third-person datasets, as enumerated in Table 1. We summarize them here and refer the reader to Appendix C for details on datasets and metrics. (1) Two tasks on Epic-Kitchens-100: Multi-Instance Retrieval (**EK-100 MIR**) and Action Recognition (**EK-100 CLS**) [14]. EK-100 is a very popular and challenging egocentric video recognition benchmark. The MIR task requires retrieving the text given videos (V→T) and videos given text (T→V). The CLS task requires classifying each video into one of 97 verbs and 300 nouns each, resulting in a combination of 3,806 action categories. (2) Two downstream tasks of Ego4D: Multiple-Choice Questions (**EgoMCQ**) and Natural Language Query (**EgoNLQ**). EgoMCQ requires selecting the correct textual description from five choices given a query video clip while EgoNLQ asks the model to output the relevant temporal intervals of video given a text query. We select these two benchmarks because they require reasoning about both visual and textual information. (3) Action Recognition on **EGTEA** [37]. It requires classifying into 106 classes of fine-grained cooking activities. (4) Action Recognition on **CharadesEgo** [58]. It requires classification into 157 classes of daily indoor activities. Note that CharadesEgo is very different from EK-100, Ego4D and EGTEA since its videos are captured by head-mounted phone cameras in a crowd-sourcing way.

Method	EgoMCQ		EgoNLQ			
	Accuracy (%)		mIOU@0.3		mIOU@0.5	
	Inter-video	Intra-video	R@1	R@5	R@1	R@5
SlowFast [24]	-	-	5.45	10.74	3.12	6.63
EgoVLP [39]	90.6	57.2	**10.84**	18.84	**6.81**	13.45
LAVILA (B)	**93.8**	**59.9**	10.53	**19.13**	6.69	**13.68**
LAVILA (L)	**94.5**	**63.1**	**12.05**	**22.38**	**7.43**	**15.44**

Table 3. **Ego4D EgoMCQ and EgoNLQ.** LAVILA outperforms prior work on both Multiple-Choice Questions and Natural Language Questions on Ego4D, with nearly 6% absolute gain on the challenging intra-video MCQ task that requires reasoning over multiple clips from the same video to answer a question.

In all tables, we bold and underline the best and second-best performing methods with comparable backbones architectures. We highlight the overall best performing method, which typically uses a larger backbone, if applicable.

5.1. Main Results

EK-100. We compare LAVILA with prior works on EK-100 MIR in Table 2. In the zero-shot setup, LAVILA remarkably surpasses an improved version of EgoVLP [39] under similar model complexity: we use TSF-Base+GPT-2 as the dual-encoder architecture while EgoVLP uses TSF-Base+Distil-BERT. With a stronger video encoder, *i.e.* TSF-Large, the performance improves further. In the fine-tuned setting, LAVILA significantly outperforms all previous supervised approaches including MME, JPOSE [75] and EgoVLP [39]. We also compare LAVILA on EK-100 CLS in Appendix E, and establish a new state-of-the-art.

Ego4D. We evaluate the pre-trained LAVILA model on EgoMCQ and EgoNLQ tasks and compare the results in Table 3. On EgoMCQ, our method achieves 93.8% inter-video accuracy and 59.9% intra-video accuracy, outperforming EgoVLP by a noticeable margin. Note that EgoVLP's performance reported in Table 3 is obtained by using EgoNCE loss [39], a variant of InfoNCE specialized for Ego4D while ours uses a standard InfoNCE loss. EgoVLP with InfoNCE has lower performance (89.4% inter-video and 51.5% intra-video accuracy). On EgoNLQ, LAVILA achieves comparable results with EgoVLP with similar model complexity.

EGTEA. We evaluate the learned video representation by finetuning the video encoder for action classification in Table 4 on another popular egocentric dataset, EGTEA [37]. Our method surpasses the previous state-of-the-art which takes multiple modalities including visual, auditory and textual inputs [33] by a more than 10% absolute margin on the mean accuracy metric. Since previous methods are based on different backbones, we experiment with a TSF-Base ("Visual only") model pre-trained on Kinetics [9] as a fair baseline for LAVILA. We observe that its accuracy is comparable to previous methods but much lower than LAVILA, implying the effectiveness of learning visual representation

Method	Backbone	Pretrain	Top-1 Acc.	Mean Acc.
Li *et al.* [37]	I3D	K400	-	53.30
LSTA [63]	ConvLSTM	IN-1k	61.86	53.00
IPL [71]	I3D	K400	-	60.15
MTCN [33]	SlowFast (V+A+T)	K400+VGG-Sound	73.59	65.87
Visual only	TSF-B	IN-21k+K400	65.58	59.32
LAVILA	TSF-B	WIT+Ego4D	**77.45**	**70.12**
LAVILA	TSF-L	WIT+Ego4D	**81.75**	**76.00**

Table 4. **EGTEA Classification**. LAVILA obtains significant gains on this task, outperforming prior work with over 10% mean accuracy. Since the backbones used are not all comparable, we also report a comparable baseline with TSF-B ("Visual only").

Method	Backbone	mAP (ZS)	mAP (FT)
ActorObserverNet [57]	ResNet-152	-	20.0
SSDA [12]	I3D	-	25.8
Ego-Exo [38]	SlowFast-R101	-	30.1
EgoVLP [39]	TSF-B	25.0	32.1
LAVILA	TSF-B	**26.8**	**33.7**
LAVILA	TSF-L	**28.9**	**36.1**

Table 5. **CharadesEgo Action Recognition**. LAVILA sets new state-of-the-art in both zero-shot (ZS) and finetuned (FT) settings. Note that CharadesEgo videos are visually different compared to Ego4D videos, on which LAVILA is pretrained.

on large-scale egocentric videos and using LLM as textual supervision during pre-training.

CharadesEgo. Next, we compare LAVILA's representation on the CharadesEgo action classification task. As shown in Table 5, LAVILA's representation excels on this task as well, which is notable as CharadesEgo videos are significantly different compared to Ego4D, being captured by crowdsourced workers using mobile cameras.

5.2. Application to Third-Person Video Pre-training

We apply LAVILA to third-person videos by experimenting with the HowTo100M [45] dataset. Specifically, we use the temporally aligned subset provided by [25], which contains 3.3M sentences from 247k videos. We evaluate the video representation on two third-person video datasets, *i.e.*

Method	Vis. Enc.	UCF-101	HMDB-51
MIL-NCE [44]	S3D	82.7	54.3
TAN [25]	S3D	83.2	56.7
Baseline (w/o LLM)	TSF-B	86.5	**59.4**
LAVILA	TSF-B	**87.4**	57.2
LAVILA	TSF-L	**88.1**	**61.5**

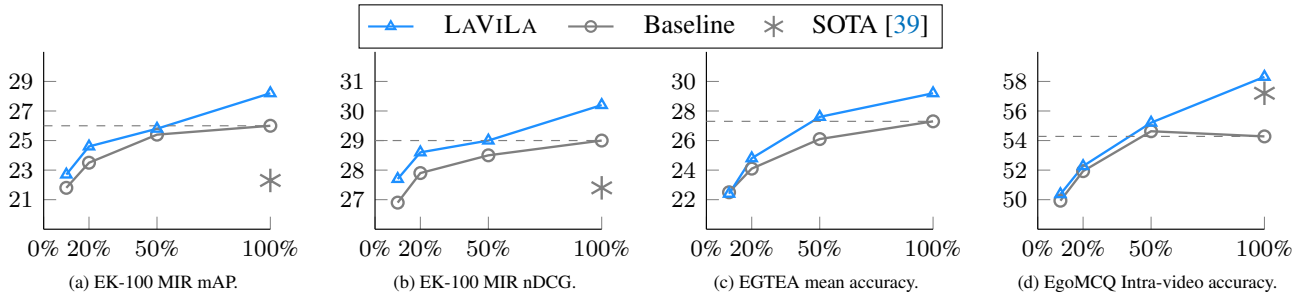
Table 6. **LAVILA on third-person videos**. We measure the linear-probing action classification performance of the video model after pre-training on HowTo100M [45].

UCF-101 [60] and HMDB-51 [35] for action classification using the linear probing protocol. For more details, please refer to Appendix D. From Table 6, we see that LAVILA outperforms previous methods such as MIL-NCE [44] and TAN [25] by a large margin. Since we use a different backbone, we report a baseline without LLM and show that LAVILA indeed benefits from the language supervision.

5.3. Application to Semi-supervised Learning

While LAVILA is very effective at leveraging existing narrations to augment them, we now show that it is also applicable when only a limited number of narrations are available to begin with. We first divide each long video from Ego4D into 15-second chunks and assume only the annotated clips within every N chunks is available during pre-training, leading to approximately $\frac{100}{N}\%$ of the full set, where $N \in \{2, 5, 10\}$. This can be considered a practical scenario when we want to annotate as many videos as possible for diversity when the annotation budget is limited. In the remainder $(1 - \frac{100}{N}\%)$ part that is skipped, we uniformly sample the same number of the clips per chunk with the same clip length as that in the seen chunks. Both the dual-encoder model and NARRATOR are trained on the $\frac{100}{N}\%$ available annotations.

We plot the zero-shot performance curve of pre-training with different proportions in Figure 5. We can see that LAVILA consistently outperforms the ground-truth-only baseline at all points (10, 20, 50, and 100%). The improvement



(a) EK-100 MIR mAP. (b) EK-100 MIR nDCG. (c) EGTEA mean accuracy. (d) EgoMCQ Intra-video accuracy.

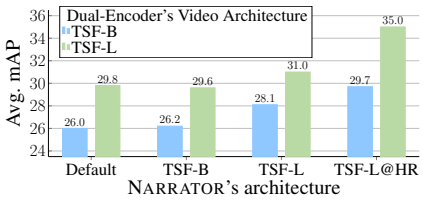
Figure 5. **LAVILA is effective in a semi-supervised setting where only a limited amout of narrations are given**. Comparing zero-shot performance of pre-training, LAVILA consistently outperforms the groundtruth-only baseline when 10, 20, 50, 100% data is used. We also achieve comparable result with state-of-the-art with only 50% of the annotated data.

Text Dec. arch.	Text Dec. init.	Freeze LM	METEOR	ROUGE-L	CIDEr	Avg. mAP
(baseline)			-	-	-	26.0
GPT-2	random	✗	0.284	0.524	0.882	24.3
GPT-2	WebText	✓	0.270	0.505	0.804	24.0
GPT-2 XL	WebText	✓	**0.289**	**0.530**	**0.940**	**26.2**

(a) **Generation Quality**. Using a sufficiently large language model as the text decoder is crucial for good text generation quality and downstream performance.

Sampling method	# of sentences	Avg. mAP
N/A (baseline)	-	26.0
Beam search	1	27.9
Nucleus	1	29.6
Nucleus	10	**29.7**

(b) **Sampling**. LAVILA benefits more from narrations produced by nucleus sampling than beam search.



(c) **Scaling effect of LAVILA.** Gains increase on scaling the video encoder in NARRATOR. Default refers to only using the original narrations.

Table 7. **Ablations of NARRATOR**. We report zero-shot average mAP on EK-100 MIR for comparing downstream performance. We study NARRATOR from the perspective of generation quality (*left*), sampling techniques (*middle*), and scaling effect (*right*).

Rephr.	Recap.	Pseudo cap.	EK-100 MIR Avg. mAP	EK-100 MIR Avg. nDCG	EgoMCQ inter-video	EgoMCQ Intra-video	EGTEA Mean	EGTEA Top-1
			26.0	28.8	**93.6**	54.3	27.3	30.1
✓			28.0	30.1	93.5	56.9	29.8	30.8
	✓		27.1	29.9	93.2	**59.2**	26.8	31.2
✓	✓		29.7	**31.5**	**93.6**	58.3	29.4	**36.6**
✓	✓	✓	**29.9**	31.4	**93.6**	59.1	**31.1**	36.0

Table 8. **Contributions of different Language Supervision.** We can see that (1) using REPHRASER ("Rephr.") and NARRATOR ("Recap.") improve downstream zero-shot performance complementarily, (2) dense pseudo-captioning further improves performance on 3 out of 6 metrics.

tends to be larger when more data is available, indicating the method's scalability as more videos are narrated in the future. Furthermore, we observe our method can achieve a similar level of performance with the baseline often using less than 50% data. We also achieve a comparable result with the state-of-the-art using much fewer data.

5.4. Ablation Studies

Contributions of Different Language Supervisions. We ablate different language supervisions in Table 8 on EK-100 MIR (zero-shot), EgoMCQ and EGTEA. Using the text-only REPHRASER ("rephr.") or visually conditioned NARRATOR ("recap.") separately improves the ground-truth baseline noticeably. Combining both REPHRASER and NARRATOR gives an improvement of 3.5% average mAP on EK-100 MIR. We see that dense captioning on the entire video ("pseudo-cap.") is also helpful. Though the gain on EK-100 MIR is not as significant, it shows nontrivial improvements on EgoMCQ intra-video accuracy and EGTEA mean accuracy. Our conjecture for this marginal gain is that informative clips are mostly covered in Ego4D because all videos are inspected by two annotators.

Generation Quality of NARRATOR. We study how the NARRATOR's configurations affect the quality of generated text and the downstream performance. The generation quality is measured by standard unsupervised automatic metrics including METEOR, ROUGE, and CIDEr [43]. We use a NARRATOR with a smaller GPT-2 as the text decoder and consider two scenarios in Table 7a: (1) LM is randomly initialized but jointly trained with the gated cross-attention modules, and (2) LM is initialized from the original GPT-2. The generation quality decreases compared to GPT-2 XL in both cases and the zero-shot retrieval result on EK-100 MIR is worse. This indicates that the language model should be sufficiently large and pre-trained on web text data.

Sampling. In Table 7b, we investigate different sampling methods for text generation from NARRATOR. We see that nucleus sampling works much better than beam search while repetitive sampling shows marginal improvement.

Scaling effect. In Table 7c, we compare the zero-shot retrieval result by progressively increasing the size of NARRATOR's video encoder from TSF-B to TSF-L and TSF-L@HR, which increases the input resolution to be narrated from 224 to 336 while fixing the dual-encoder architecture. The retrieval performance steadily increases while NARRATOR becomes stronger. We conduct this experiment by varying the dual-encoder architecture, namely TSF-Base and TSF-Large, and show similar trends. Both phenomena suggest that LAVILA can scale to larger models.

6. Conclusion and Future Work

In this paper, we proposed LAVILA, a new approach to video-language representation learning by automatically narrating long videos with LLMs. We achieve strong improvements over baselines trained with the same amount of human-narrated videos and set new state-of-the-art on six popular benchmark tasks across first- and third-person video understanding benchmarks. LAVILA also shows positive scaling behavior when adding more training narrations, using larger visual backbones, and using stronger LLMs, all of which are promising areas for future work.

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