UniViLM: A Unified Video and Language Pre-Training Model for Multimodal Understanding and Generation

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Abstract

We propose UniViLM: a Unified Video and Language pre-training Model for multimodal understanding and generation. Motivated by the recent success of BERT based pre-training technique for NLP and image-language tasks, VideoBERT and CBT are proposed to exploit BERT model for video and language pre-training using narrated instructional videos. Different from their works which only pre-train understanding task, we propose a unified video-language pre-training model for both understanding and generation tasks. Our model comprises of 4 components including two single-modal encoders, a cross encoder and a decoder with the Transformer backbone. We first pre-train our model to learn the universal representation for both video and language on a large instructional video dataset. Then we fine-tune the model on two multimodal tasks including understanding task (text-based video retrieval) and generation task (multimodal video captioning). Our extensive experiments show that our method can improve the performance of both understanding and generation tasks and achieves the state-of-the art results.

1 Introduction

With the recent advances of self-supervised learning, pre-training techniques play a vital role in learning good representation for visual and language. The paradigm is to pre-train the model on a large scale unlabeled data, and then fine-tune the downstream tasks using task specific labeled data. Inspired by the success of BERT (Devlin et al., 2019) model for NLP tasks, numerous multimodal image-language pre-training models (Lu et al., 2019; Li et al., 2019a,b) have been proposed and demonstrated the effectiveness on various visual and language tasks such as VQA (visual question answering) and image-text match etc. Nevertheless, there are still few works on video-linguistic pre-training.

Videos contain rich visual, acoustic and language information for people to acquire knowledge or learn how to perform a task. This motivates researchers to investigate whether AI agents can learn task completion from videos like human with both low-level visual and high-level semantic language signal. Therefore, multimodal video-language tasks are of great importance to investigate for both research and applications. In this work, we first propose to pre-train a unified video-language model using video and acoustic speech recognition (ASR) transcript in instructional videos to learn a joint representation of both video and language. Then, we fine-tune this model on two typical multimodal tasks including text-based video retrieval for understanding and multimodal video captioning for generation. Figure 1 presents a showcase of our pre-training and fine-tuning flow and both tasks take video and language as input. Take multimodal video captioning as an example, the model input video and ASR transcript and predict a captioning sentence.

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{A showcase of video and language pre-train based model for multimodal understanding (retrieval) and generation (captioning).}
\end{figure}
VideoBERT and CBT (Sun et al., 2019b, a) are the first pioneers to investigate video-language pre-training with regard to video representation on instructional videos. They have demonstrated the effectiveness of the BERT based model for capturing video temporal and language sequential features. Our work differs from VideoBERT and CBT on two aspects: 1) previous work only pre-trains the model on understanding task, while we explore to pre-train on both understanding and generation tasks; 2) they fine-tune the downstream tasks for a better video representation with only video as input, while our goal is to learn video and language joint representation by downstream multimodal tasks.

In this paper, we propose UniViLM: a Unified Video and Language pre-training Model for multimodal understanding and generation. Our UniViLM model adopts Transformer (Vaswani et al., 2017) as backbone and has 4 components including two single-modal encoders, a cross encoder and a decoder. In detail, we first encode the text and visual separately by two single-modal encoders. Then we adopt the Transformer based encoder-decoder model to perform the understanding and generation pre-training by 4 tasks: 1) masked language model (MLM for language corruption); 2) masked frame model (MFM for video corruption); 3) video-text alignment and 4) language reconstruction.

As shown in Figure 1, we fine-tune our pre-trained model on two typical video-language tasks: text-based video retrieval and multimodal video captioning. For the first task, we remove the decoder and fine-tune the alignment task. For the second task, we directly fine-tune the pre-trained encoder-decoder model.

We list our contributions below:

1) We propose a multimodal video-language pre-training model trained on a large scale instructional video dataset, which is a unified model for both video-language understanding and generation tasks.

2) The pre-training stage consists of 4 tasks including MLM (masked language model), MFM (masked video frame model), video-text alignment, and language reconstruction.

3) We fine-tune our pre-trained model on two typical multimodal video-language tasks: text-based video retrieval and multimodal video captioning. The extensive experiments demonstrate the effectiveness of our unified pre-trained model on both understanding and generation tasks and achieves state-of-the-art results.

2 Related Works

Single Modal Pre-Training Self supervised representation learning has been shown to be effective for sequential data including language and video. Language pre-training models including BERT (Devlin et al., 2019), GPT (Radford et al., 2018), RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019), MASS (Song et al., 2019), UniLM (Dong et al., 2019), BART (Lewis et al., 2019) have achieved great success on NLP tasks. BERT (Devlin et al., 2019) is a denoising auto-encoder network using Transformer with MLM (masked language model) and NSP (next sentence prediction) as pre-training tasks and has strong performance for understanding task. MASS (Song et al., 2019) focus on pre-training for generation tasks. UniLM (Dong et al., 2019) and BART (Lewis et al., 2019) continuously study a unified pre-training model for both understanding and generation tasks.

Video representation learning mostly focuses on the video sequence reconstruction or future frames prediction as pre-training (pretext) tasks. Early works like (Mathieu et al., 2015; Srivastava et al., 2015; Han et al., 2019) aim to synthetic video frames through the image patches. Similarly, Wang and Gupta (2015) adopt Siamese-triplet network to rank continuous patches more similar than patches of different videos. Other works predict the feature vectors in latent space using auto-regressive models with the noise contrastive estimation (NCE) (Lotter et al., 2016; Oord et al., 2018). Sun et al. (2019a) adopt NCE to make prediction on corrupted (masked) latent space using auto-encoder model.

Multimodal Pre-Training Recently, numerous visual-linguistic pre-training models (Lu et al., 2019; Li et al., 2019b; Tan and Bansal, 2019; Li et al., 2019a; Zhou et al., 2019; Lu et al., 2019; Sun et al., 2019b; Li et al., 2019b) are proposed for multimodal tasks. For image and text pre-training, ViLBERT (Lu et al., 2019), LXMERT (Tan and Bansal, 2019) adopt two separate Transformers for image and text encoding independently. Other models like Unicoder-VL (Li et al., 2019a), VL-BERT (Lu et al., 2019), UNITER (Zhou et al., 2019) use one shared BERT model. These models employ MLM and image-text matching as pre-training tasks which are effective for downstream multi-
modal tasks. VLP (Zhou et al., 2019) proposes a unified image-language model for understanding and generation task. Different from these works, we focus on video and text pre-training for universal representation.

VideoBERT (Sun et al., 2019b) and CBT (Sun et al., 2019a) are the first works of video and language pre-training models which are the most similar works to ours. Although VideoBERT and CBT pre-train the model on multimodal data, the downstream tasks only take video representation for further prediction. We believe that video-language pre-training can learn a universal representation of video and text. Besides, previous works only pre-train the encoder and suffer from uninitialized decoder for generation tasks. We further pre-train the decoder for generation task and experimental results show that the pre-trained decoder is effective for generation.

Multimodal Retrieval and Captioning Multimodal video and language learning is a nascent research area. In this work, we fine-tune and evaluate our pre-trained model on two multimodal tasks including text-based video retrieval and multimodal video captioning. Text-based video retrieval task is to predict whether the video and text query match each other. Yu et al. (2018) densely align each token with each frame. Miech et al. (2019) embed text and video into the same latent space through a joint embedding network on 1.2 million videos. Multimodel video captioning task is to generate captions given an input video together with ASR transcript. Different from existing works (Sun et al., 2019b,a; Krishna et al., 2017; Zhou et al., 2018a,b; Shi et al., 2019; Palaskar et al., 2019; Hessel et al., 2019) which only use video signal, recent works (Shi et al., 2019; Palaskar et al., 2019; Hessel et al., 2019) study the multimodal captioning by taking both video and transcript as input, and show that incorporating transcript can largely improve the performance. Our model achieves state-of-the-art results in both tasks.

3 Method

The problem is defined as: given the input video and the corresponding ASR transcript pairs, pre-train a model to learn a joint video and text representation and fine-tune downstream tasks. In this section, we describe the details of the architecture, and the pre-training tasks.

3.1 Model Architecture

Figure 2 presents the model structure as an encoder-decoder architecture. First, the model extracts representations of the input text tokens and the video frame sequences using various feature extractors. Then a text encoder adopts the BERT model to embed the text and a video encoder utilizes the Transformer model to embed the video frames. Next, we employ a Transformer based cross encoder for interacting between the text and the video. Finally, another Transformer based decoder learns to reconstruct the input text.

Pre-processing First we pre-process video and language before feeding to this model. For the input text, we tokenize all words by WordPieces (Wu et al., 2016) following the pre-processing method in BERT to obtain the token sequence \( t = \{t_i| i \in [1, n]\} \), where \( t_i \) is the \( i \)-th token and \( n \) is the length of token sequence. For each video clip, we sample a frame sequence \( v = \{v_j| j \in [1, m]\} \) to represent the video clip, where \( v_j \) is the \( j \)-th video frame and \( m \) is the length of the frame sequence.

Single Modal Encoder We encode the text and video separately. First we adopt the BERT-base model to encode the token sequence \( t \). The text encoding is \( T_{BERT} \in \mathbb{R}^{n \times d} \),

\[
T_{BERT} = \text{BERT}(t), \tag{1}
\]

where \( d \) is hidden size of text encoding.

Next, we adopt the off-the-shelf image feature extractors to generate input feature matrix for the video frame sequence \( v \) before feeding to the video encoder. While image representation only considers spatial feature, video representation encodes both spatial and temporal feature. We extract video feature using 2D and 3D CNNs for spatial and spatial-temporal representation. Then, we concatenate two features to one unified video feature \( F_v \in \mathbb{R}^{m \times d'_v} \). The \( d'_v \) represents hidden size of video feature. Finally, the \( F_v \) is fed to the video encoder to embed the contextual information,

\[
V_{\text{Transformer}} = \text{Transformer}(F_v). \tag{2}
\]

The dimension of \( V_{\text{Transformer}} \) is \( \mathbb{R}^{m \times d} \).

Cross Encoder To make the text and video fully interact with each other, we design a cross encoder to fuse these features. We first combine the text encoding \( T_{BERT} \) and the video encoding \( V_{\text{Transformer}} \) to get the encoding \( M \in \mathbb{R}^{(n+m) \times d} \). Then, the
Figure 2: The main structure of our pre-training model, which comprises of 4 components including two single-modality encoders, a cross encoder and a decoder with the Transformer backbone. $P$ represents position embedding, and $T$ is segment embedding to represent text and video types. $E$ denotes the embedding of each token.

Transformer based cross encoder takes the encoding $M$ as input to generate the attended encoding $M_{attended} \in \mathbb{R}^{(n+m) \times d}$,

$$M = [T_{BERT}; V_{Transformer}], \quad (3)$$

$$M_{attended} = \text{Transformer}(M), \quad (4)$$

where $[;]$ denotes the combination operation.

**Decoder** The decoder learns to reconstruct the input text during pre-training, as well as generating captions during fine-tuning and inference. The input is the attended encoding $M_{attended}$ of text and video. We unexceptionally exploit Transformer to get the decoded feature $D \in \mathbb{R}^{l \times d}$ from $M_{attended}$,

$$D = \text{Transformer}(M_{attended}), \quad (5)$$

where $l$ is the decoder length.

### 3.2 Pre-training Objectives

We have four pre-training objectives: 1) masked language model (for text corruption); 2) masked frame model (for video corruption); 3) video-text alignment and 4) language reconstruction.

**MLM: Masked Language Model** Following BERT, we randomly mask 15% tokens with the special token [MASK] in the sentence and the objective is to re-produce the masked tokens. Since the ASR transcript is automatically extracted from speech, which is noisy and in low quality, we further conditionally mask key concepts. Specifically, we conditionally mask 15% verbs or nouns in the sentences to compel the encoder to learn these key concepts. This loss function is defined as:

$$L_{MLM}(\theta) = -E_{m \sim t} \log P_{\theta}(t_m | t_{\neg m}, v), \quad (6)$$

where $t_{\neg m}$ means the contextual tokens surrounding the masked token $t_m$, $\theta$ is the trainable parameters.

**MFM: Masked Frame Model** Similarly, we also propose a masked frame model to predict the correct frames given contextual frames. This loss function is NCE (Sun et al., 2019a). We randomly mask 15% vectors (also 15% frames) with zeros. The objective is to identify the correct frame compared to negative distractors. The loss is defined

$$\mathcal{L}_{MFM}(\theta) = -E_{m \sim t} \log P_{\theta}(t_m | t_{\neg m}, v),$$

1. We use package scapy (https://scapy.net) to extract verbs and nouns automatically.
where $s$ means the surrounding frames except $v_m$, $f_v \in \mathbb{R}^{1 \times d}$ is a linear output of $f_v \in F_v$, $F_v$ is the real-valued vectors of video feature, $m_m \in M_{\text{attended}}^{(v)}$ and $M_{\text{attended}}^{(v)}$ is the feature matrix of the video part in $M_{\text{attended}}$. We take other frames in the same batch as negative cases defined as $\mathcal{N}(v_m)$.

**Video-Text Alignment** We use the fused representation that corresponds to the special token [CLS] to predict scores for the Video-Text Alignment task. Specifically, a BertPooler layer and a linear layer are designed to project the first hidden state of $M_{\text{attended}}$ to scores which is similar to the BERT sentence pair classification task. We also adopt the NCE loss to learn to discriminate the positive from negative video-text pairs. To enhance this capability, we not only randomly sample negative cases but also re-sample video clips from the same video (Han et al., 2019). The reason is that the frames inside the same video are more similar than frames of different videos. This loss function is defined as follows,

$$
\mathcal{L}_{\text{Align}}(\theta) = -E_{(t,v) \sim \mathcal{B}} \log \frac{\exp(s(t,v))}{\mathcal{Z}},
$$

$$
\mathcal{Z} = \exp(s(t,v)) + \sum_{u \in \mathcal{N}(v)} \exp(s(t,u)),
$$

where $s(\cdot)$ means the BertPooler layer and linear layer operations. We take other video clips in the same batch $\mathcal{B}$ as negative cases $\mathcal{N}(v)$.

**Language Reconstruction** An auto-regressive decoder is also involved in our pre-training objective, and the loss function is,

$$
\mathcal{L}_{\text{Decoder}}(\theta) = -E_{i \sim \hat{t}} \log P_{\theta}(\hat{i} \mid i, t, v).
$$

It is note that $t$ is the mask of ground-truth text $\hat{t}$ when pre-training. As shown in BART (Lewis et al., 2019), pre-training decoder benefits generation tasks.

**Loss Function** We jointly optimize our model by a weighted loss:

$$
\mathcal{L}_{\text{UniViLM}} = w_{\text{MLM}} \mathcal{L}_{\text{MLM}} + w_{\text{MFM}} \mathcal{L}_{\text{MFM}} + w_{\text{Align}} \mathcal{L}_{\text{Align}} + w_{\text{Decoder}} \mathcal{L}_{\text{Decoder}},
$$

where $w_{\text{MLM}}$, $w_{\text{MFM}}$, $w_{\text{Align}}$, and $w_{\text{Decoder}}$ are set to 1 in this paper.

### 4 Downstream tasks

Figure 3 presents the two downstream tasks: text based video retrieval (left) and multimodal video captioning (right).

#### 4.1 Text based Video Retrieval

Text based video retrieval is defined to retrieve a relevant video/clip given an input text query. During inference, the model takes the input text query and each candidate video to calculate the similarity score, and then rank to select the best matched video clip. The model encodes query and video through text encoder and video encoder respectively, then feed the embeddings to the cross encoder, and make final prediction through the fused representation corresponding to [CLS] by $s(\cdot)$ in Eq. (10). We use $\mathcal{L}_{\text{Align}}$ as the loss during the fine-tuning stage.

#### 4.2 Multimodal Video Captioning

Given a video, multimodal video captioning aims to generate a sequence of descriptive sentences. In this work, we focus on generating better captions and use the ground-truth segments in the experiment. Similarly, the model encodes the input video frames as well as transcripts inside the clips through video encoder and text encoder respectively, then feeds the embeddings to the cross encoder to get a unified representation, and finally generates token sequence by the decoder. We use $\mathcal{L}_{\text{Decoder}}$ as the loss during the fine-tuning stage.

### 5 Experiment

We first pre-train our model on the large scale dataset HowTo100M (Miech et al., 2019), then fine-tune our pre-trained model on two downstream multimodal tasks including text-based video retrieval and multimodal video captioning. Finally, we evaluate our model on both In-domain Youcook2 (Zhou et al., 2018a) dataset and Out-domain MSR-VTT (Xu et al., 2016) dataset.

#### 5.1 Dataset

**HowTo100M (Miech et al., 2019)** is the pre-training dataset. We download videos in the Food
and Entertaining domain with ASR transcript from Howto100M dataset. After filtering the unavailable ones, we finally get 380K videos for pre-training our model. On average, the duration of each video is 6.5 minutes with 110 clip-text pairs.

Youcook2 (Zhou et al., 2018a) is the In-domain dataset for both downstream tasks. It contains 2,000 cooking videos on 89 recipes with 14K video clips. The overall duration is 176 hours (5.26 minutes on average). Each video clip is annotated with one captioning sentence. We evaluate both text-based video retrieval and multimodal video captioning task on this dataset. For the first task, we follow the same experimental setting in (Miech et al., 2019), and use the captions as the input text queries to find the corresponding video clips. For the second task, we use the same setting as in (Shi et al., 2019). We filter the data and make sure there is no overlap between pre-training and evaluation data. In all, we have 1,261 training videos and 439 test videos, that is, 9,776 training clip-text pairs and 3,369 test clip-text pairs.

MSR-VTT (Xu et al., 2016) is the Out-domain dataset for downstream task. It has open domain video clips, and each clip has 20 captioning sentences labeled by human. In all, there are 200K clip-text pairs from 10K videos in 20 categories including sports, music, etc. Following JSFusion (Yu et al., 2018), we randomly sampled 1,000 clip-text pairs as test data to evaluate the performance of our model on text-based video retrieval task.

5.2 Experimental Details

Text encoding for text encoding, we apply WordPiece embeddings (Wu et al., 2016) with a 30,000 token vocabulary to input to BERT model. We exploit the BERT-base model (Devlin et al., 2019) with 12 layers of Transformer blocks. Each block has 12 attention heads and the hidden size is 768.

Video encoding Similar to Miech’s work (Miech et al., 2019), we extract both 2D and 3D features from video clips. We use an off-the-shelf ResNet-152 (He et al., 2016) that pre-trained on the ImageNet dataset to extract 2D feature. For 3D feature extraction, we employ ResNeXt-101 (Hara et al., 2018) that pre-trained on Kinetics to extract 3D features. The fps of 2D and 3D feature extractor are 1 and 1.5 respectively. Then we directly concatenate both 2D and 3D features to one unified 4,096 dimensional vector. For video encoding, we employ Transformer (Vaswani et al., 2017) with 1 layer. Each block has 12 attention heads and the hidden size is 768.

Model setting The model consumes the clip-text pairs. The maximal input tokens of text is 32 and the maximal frames of video is 48. For short sentence and clip, we concatenate contextual tokens and frames. For cross encoder and decoder, we use a 2 layers Transformer as the encoder and a 1 layer Transformer as the decoder with 12 heads. For generation task during the inference stage, we use the beam search with the size of 5.

Training time We pre-train our model on 4 NVIDIA Tesla V100 GPUs. The batch size is set to 96 and the model is trained 12 epochs for 5 days. We use the Adam optimizer (Kingma and Ba, 2015) with an initial learning rate of 1e-4, and employ a linear decay learning rate schedule with warm up strategy. To fasten the pre-training speed, we adopt two-stage training fashion. For the first stage, we only preserve the text BERT and video Transformer to learn the weights using alignment similarity like the work in (Miech et al., 2019). Next we freeze the single modal encoders with the learned weights and continue to further pre-train the subsequent

Figure 3: Two downstream tasks.
| Method                                      | PT data | FT data | R@1  | R@5  | R@10 | Median R |
|---------------------------------------------|---------|---------|------|------|------|----------|
| Random                                      | 0       | 0       | 0.03 | 0.15 | 0.3  | 1675     |
| HGLMM FV CCA (Klein et al., 2015)           | 0       | Youcook2| 4.6  | 14.3 | 21.6 | 75       |
| HowTo100M (Miech et al., 2019)              | 1.2M    | 0       | 6.1  | 17.3 | 24.8 | 46       |
| HowTo100M (Miech et al., 2019)              | 0       | Youcook2| 4.2  | 13.7 | 21.5 | 65       |
| HowTo100M (Miech et al., 2019)              | 1.2M    | Youcook2| 8.2  | 24.5 | 35.3 | 24       |
| HowTo100M†                                  | 380K    | 0       | 6.50 | 19.73| 27.77| 35       |
| HowTo100M†                                  | 380K    | Youcook2| 7.45 | 22.60| 33.34| 25       |
| Our model.1†                                | 380K    | 0       | 5.52 | 17.47| 27.41| 42       |
| Our model.2†                                | 0       | Youcook2| 3.35 | 10.79| 17.76| 76       |
| Our model.3†                                | 200K    | Youcook2| 7.53 | 22.00| 32.77| 28       |
| Our model.4†                                | 380K    | Youcook2| 9.97 | 27.53| 38.77| 20       |
| Table 1: Results of text-based video retrieval on Youcook2 dataset. PT stands for pre-training and FT for fine-tuning. † means the re-running the code of HowTo100M model on our dataset. |

| Method                                      | PT data | FT data | R@1  | R@5  | R@10 | Median R |
|---------------------------------------------|---------|---------|------|------|------|----------|
| Random                                      | 0       | 0       | 0.1  | 0.5  | 1.0  | 500      |
| C+LSTM+SA (Klein et al., 2015)              | 0       | MSR-VTT| 4.2  | 12.9 | 19.9 | 35       |
| VSE (Klein et al., 2015)                    | 0       | MSR-VTT| 3.8  | 12.7 | 17.1 | 66       |
| SNUVL (Klein et al., 2015)                  | 0       | MSR-VTT| 3.5  | 15.9 | 23.8 | 44       |
| Kaufman (Klein et al., 2015)                | 0       | MSR-VTT| 4.7  | 16.6 | 24.1 | 41       |
| CT-SAN (Klein et al., 2015)                 | 0       | MSR-VTT| 4.4  | 16.6 | 22.3 | 35       |
| JSFusion (Klein et al., 2015)               | 0       | MSR-VTT| 10.2 | 31.2 | 43.2 | 13       |
| HowTo100M (Miech et al., 2019)              | 1.2M    | 0       | 7.5  | 21.2 | 29.6 | 38       |
| HowTo100M (Miech et al., 2019)              | 0       | MSR-VTT| 12.1 | 35.0 | 48.0 | 12       |
| HowTo100M (Miech et al., 2019)              | 1.2M    | MSR-VTT| 14.9 | ۴۰.2 | ۵۲.۸ | ۹       |
| HowTo100M†                                  | 380K    | 0       | 5.40 | 13.40| 19.70| 66       |
| HowTo100M†                                  | 380K    | MSR-VTT| ۱۳.۸۰| ۳۲.۳۰| ۴۳.۰۰| ۱۶       |
| Our model.1†                                | 380K    | 0       | 2.90 | 8.30 | 12.40| 173      |
| Our model.2†                                | 0       | MSR-VTT| ۱۴.۶۰| ۳۹.۰۰| ۵۲.۶۰| ۱۰       |
| Our model.3†                                | 380K    | MSR-VTT| ۱۵.۴۰| ۳۹.۵۰| ۵۲.۳۰| ۹       |
| Table 2: Results of text-based video retrieval on MSR-VTT dataset. PT stands for pre-training and FT for fine-tuning. † means the re-running the code of HowTo100M model on our dataset. |

5.3 Task I: Text-based Video Retrieval

We fine-tune our pre-trained model for text-based video retrieval task on both Youcook2 and MSR-VTT datasets. The evaluation metrics are Recall@n (R@n) and Median R.

Youcook2 provides the ground-truth video clip and caption pairs. We use the caption to retrieve the relevant video clip. Miech (Miech et al., 2019) reports baseline methods including Random and KGLMM FV CCA (Klein et al., 2015) and their model results, which we directly apply as our baseline methods. Table 1 lists the results of all baselines and our models. We can see that our model can improve the performance over all baseline methods and achieve state-of-the-art result. Since our 380K data are all food domain related videos, we investigate whether this domain specific data biases the model performance. So we re-run the HowTo100M model on our 380K dataset and fine-tune on Youcook2 dataset. The performance drops a lot which demonstrates that the data does not bias the model. Through the comparison of our model pre-trained on various data sizes, the performance increases with increment of data.

MSR-VTT Besides the Food domain videos, we also evaluate text-based video retrieval on open domain MSR-VTT dataset. We present several baseline methods with/without pre-training. For Out-domain dataset, our pre-trained method (Our model.2nd vs. 3rd) has generalization capability on other domain but not as significant as in-domain data. We also notice that without fine-tuning, our pre-trained model performs worse than the HowTo100M model, which shows that the fine-tuning is a very important stage for our model. Our full model (3rd) achieves the state-of-the-art results on R@1 and Median R metrics. The best results on R@5 and R@10 are achieved by the HowTo100M
model pre-trained on 1.2M dataset which contains more open domain videos that could benefit the results on MSR-VTT. This motivates us to further examine the HowTo100M model pre-trained on our 380K dataset. The experimental results demonstrate our model.3rd outperforms the HowTo100M model pre-trained on the same dataset (380K) on all metrics.

According to our extensive experiments on text based video retrieval, we find that: 1) our model can largely increase the performance of video and language understanding task; 2) with the increase of the training data, our model performs consistently better; 3) Our model outperforms baselines on both In-domain and Out-domain data and achieves the state-of-the-art results. The performance boost is more remarkable for In-domain data.

5.4 Task II: Multimodal Video Captioning

We adopt the corpus-level generation evaluation metric using open-source tool\(^4\) including BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), ROUGE-L (Lin and Och, 2004) and CIDEr (Vedantam et al., 2015).

First we compare our pre-trained model with several baseline methods. We classify the methods with two settings: 1) with/without pre-training; 2) the input is video-only or video+transcript. Zhou et al. (2018a) propose an end-to-end model for both procedural segmentation and captioning. Sun et al. (2019b,a) adopt the pre-training strategy and evaluate the captioning with only video as input. Shi et al. (2019) and Hessel et al. (2019) discuss the multimodal input with both video and transcript. Table 3 presents the results of baseline models and the performance of our model in various settings. We study the video-only captioning models and find that our model (our model.1st) can get comparable results with CBT. Furthermore, we compare our model with various data sizes (our model.2nd, 3rd, 5th), the performance of our models improves with the increasing of the pre-training data size. Moreover, according to the comparison of our models with or without pre-trained decoder (our model.4th vs. 5th), pre-training the decoder improves the performance of generation task, and our full model (our model.5th) on the largest pre-training dataset achieves the best results.

According to our extensive experiments on multimodal video captioning, our key findings are: 1) our pre-trained model can improve the performance of generation task with the help of pre-trained decoder; 2) our model outperforms baseline models for multimodal video captioning task and achieves the state-of-the-art results.

Table 3: The multimodal video captioning results on Youcook2 dataset.

| Methods                  | Input                           | Pre-training Data | B-3 | B-4 | M    | R-L | CIDEr |
|--------------------------|---------------------------------|-------------------|-----|-----|------|-----|-------|
| Bi-LSTM (Zhou et al., 2018a) | Video                           | 0                 |     |     | 0.87 | 8.15|       |
| EM1 (Zhou et al., 2018b)   | Video                           | 0                 |     |     | 4.38 | 11.55| 27.44  |
| VideoBERT (Sun et al., 2019b) | Video                          | 312K              | 6.80| 3.04| 11.01| 27.30| 0.49   |
| VideoBERT (+S3D) (Sun et al., 2019b) | Video                      | 312K              | 7.59| 4.33| 11.94| 28.80| 0.55   |
| CBT (Sun et al., 2019a)    | Video                           | 1.2M              | 5.12| 12.97| 30.44|   |       |
| DPC (Shi et al., 2019)     | Video + Transcript              | 0                 | 7.60| 2.76| 11.08|     |       |
| AT+Video (Hessel et al., 2019) | Video + Transcript          | 0                 | 9.01| 17.77| 36.65| 1.12  |       |
| Our model.1st             | Video                           | 380K              | 10.16| 6.06| 12.47| 31.48| 0.6430 |
| Our model.2nd             | Video + Transcript              | 0                 | 13.57| 8.67| 15.38| 35.18| 1.0015 |
| Our model.3rd             | Video + Transcript              | 200K              | 14.97| 9.92| 16.24| 37.07| 1.1554 |
| Our model.4th (no decoder)| Video + Transcript              | 380K              | 14.43| 9.78| 15.81| 36.84| 1.1043 |
| Our model.5th             | Video + Transcript              | 380K              | 15.52| 10.42| 16.93| 38.02| 1.1998 |

\(^4\)https://github.com/Maluuba/nlg-eval

6 Conclusion and Discussion

In this paper, we study the self-supervised learning for video and language representation on large scale videos and pre-train a multimodal model using video and corresponding ASR transcript. We propose a unified pre-training model for both understanding and generation tasks. Then, we conduct extensive experiments on evaluating our models for two downstream tasks including text-based video retrieval and multimodal video captioning. From the experiments, we find that 1) our pre-trained model can improve the performance to a large extent over the baseline models and achieve the state-of-the-art results on two typical multimodal tasks; 2) The pre-trained decoder can benefit the generation tasks such as captioning. For the future work, we will investigate the performance of our model on a larger dataset and more downstream tasks.
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7 Supplementary Material

Figure 4 presents two randomly selected case studies comparing our results with groundtruth captioning, from which we noticed that most of the results are semantically aligned with the groundtruth sentences.

![Figure 4: Case studies for multimodal video dense captioning](image)

**Clips** | **Groundtruth** | **Our results**
---|---|---
Rinse cabbage and chop some green onions. | Slice the cabbage green onions and add to the pot. | 
Add chopped green onions and ground pork to a bowl and mix together. | Mix the pork with soy sauce sesame oil and salt. | 
Add soy sauce sesame oil and salt and mix together. | Mix the soy sauce sesame oil and salt. | 
Add chopped carrots and shiitake mushrooms and mix. | Add the vegetables to a bowl. | 
Place 1 tbsp of the filling in the center of a pot sticker wrapper and seal the edge. | Add the vegetables to the bowl and mix. | 
Place the pot sticker wrapper on the dumpling and seal the edges. | Marinate the skewers into the hot dogs. | 
Heat a pan and spread vegetable oil on the surface. | Cook the potstickers in the pan. | 
Put the potstickers and cook both the sides until they are browned. | Add the potstickers to the pot. | 
Pour some water and cover with a lid. | Pour water into the pan and cook them for 5 minutes. | 
Combine salt butter milk and hot sauce in a bowl. | Add salt and milk to a saucepan. | 
Place chicken in a small bowl and pour brine over chicken and freeze it for 1 hour. | Mix salt butter milk and hot sauce together and pour the marinade over the chicken. | 
Pour off the brine and rinse chicken off thoroughly and let it dry. | Place the chicken on a plate or tray and season generously. | 
Season the flour with salt pepper and celery salt. | Mix flour salt black pepper and cayenne. | 
Coat the chicken pieces in the flour. | Coat the chicken with the flour. | 
Place chicken in hot oil and fry until golden brown. | Fry the chicken in oil. |