CLIP2TV: An Empirical Study on Transformer-based Methods for Video-Text Retrieval

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Abstract

Modern video-text retrieval frameworks basically consist of three parts: video encoder, text encoder and the similarity head. With the success on both visual and textual representation learning, transformer based encoders and fusion methods have also been adopted in the field of video-text retrieval. In this report, we present CLIP2TV, aiming at exploring where the critical elements lie in transformer based methods. To achieve this, we first revisit some recent works on multi-modal learning, then introduce some techniques into video-text retrieval, finally evaluate them through extensive experiments in different configurations. Notably, CLIP2TV achieves 52.9@R1 on MSR-VTT dataset, outperforming the previous SOTA result by 4.1%.

1. Introduction

Recent works in video-text retrieval have adopted transformer based methods into both video and text encoders, and the similarity head. In CLIP4Clip [11], CLIP [15] encoders are adopted in both sides. Specifically, ViT [3] is used to encode raw videos and a bert-like transformer is used to encode texts. Various similarity heads are also explored and evaluated in [11], where a sequential transformer has shown the potential to replace the traditional mean-pooling method. Similar in the field of image-text retrieval, ALBEF [8] adopts a heavier similarity head of more layers of transformer to fuse the two modalities at an earlier stage. Besides it, momentum distillation borrowed from self-supervised learning [7] is also utilized. To revise the output similarity matrix of similarity head, very recent work of [2] revise it via a dual-softmax operation. In this report, we present CLIP2TV. We start from basing our framework on CLIP4Clip, then introduce momentum distillation, multi-modal transformer with matching head and revised symmetric dual-softmax at the inference stage. Without bells and whistles, we achieve the result of 52.9@R1 on MSR-VTT dataset.

2. Approach

Given a set of captions and a set of videos, video-text retrieval task aims at seeking a matching function calculating similarities between captions and videos. Recent works like [11] and [5] have showed the benefits of image-text retrieval pre-training and advantages of end-to-end training for video-text retrieval task. Inspired by these, we adopt CLIP model [15] as our multi-modal encoder and follow [11] as our basic framework. Fig.1 shows the structure.

2.1. Framework

Video Encoder $f_v$. Given a video denoted by series of frames, we first randomly extract consecutive frames with a fixed length as a video clip $v = \{v_i\}_{i=1}^{N_v}$, where $N_v$ is number of frames. A transformer-based Video Encoder, i.e., ViT used in CLIP [15], encodes it into frame embeddings $V_{emb} \in \mathbb{R}^{N_v \times D_v}$, where $D_v$ is the dimension of frame embedding. After that, an temporal transformer with frame position embedding and residual connection is applied to frame embeddings to enhance temporal information. Then, a projector will project contextualized frame embeddings into a multi-modal sub space. For simplicity, we re-use $V_{emb} \in \mathbb{R}^{N_v \times D_v}$ as enhanced temporal embeddings, where $D$ is the dimension. The final video representation is calculated as $v = \text{mean-pooling}(V_{emb}) \in \mathbb{R}^D$.

Text Encoder $f_t$. The bert-like transformer used in CLIP is adopted as our text encoder. The caption denoted as $w = \{w_i\}_{i=1}^{N_w}$ is fed into encoder to acquire token embeddings $W_{emb} \in \mathbb{R}^{N_w \times D_w}$, where $N_w$ and $D_w$ are the number and dimension of token embeddings. Same with the procedure of encoding videos, a text projector projects token embeddings into a common sub space with dimension $D$. Finally, the representation of [EOS] token will serve as the representation of the whole caption $w \in \mathbb{R}^D$.

Contrastive learning. As the frame representations $v$ and caption representations $w$ are all projected in multi-modal
space, we try to align videos and captions in a feature level with cosine similarity and contrastive loss. The cosine similarity is calculated between normalized frame representations and normalized caption representations. Given a batch $B$ with $B$ video-text pairs, cross-entropy loss acts as contrastive loss to train two modality encoders:

$$p^{v2t}(v) = \frac{\exp(s(v, w)/\tau)}{\sum_{w \in B} \exp(s(v, w)/\tau)},$$  \hspace{1cm} (1)
$$L_{v2t} = \mathbb{E}_{v \sim B} \left[ H(p^{v2t}(v), y^{v2t}(v)) \right],$$  \hspace{1cm} (2)

where $s(\cdot, \cdot)$ denotes cosine similarity, $\tau$ represents a learnable temperature parameter, $y^{v2t}(v)$ is the ground-truth binary label that positive pairs and negative pairs are 1 and 0 respectively, and $H(\cdot, \cdot)$ is cross-entropy formulation. Meanwhile, $L_{t2v}$ is calculated vice versa. Then, the contrastive loss is formulated as:

$$L_{vta} = \frac{1}{2}(L_{v2t} + L_{t2v}).$$  \hspace{1cm} (3)

### 2.2. Momentum Distillation

Limited by the length of captions and video frame extracting strategy, it is difficult for video-text pairs completely corresponding to each other at the semantic level. Captions may not fully describe video content and video clip may not cover text descriptions. Enlightened by momentum distillation used in ALBEF [8] which tackles weak correlation between image-text pairs, we plant it into video-text retrieval task.

Same as [8], we maintain two queues $Q_v$ and $Q_t$ to store recent video representations $v_m$ and caption representations $w_m$ extracted by teacher model. Teacher model with identical architecture to student is initialized by student model and updated by exponential-moving-average (ema) strategy. Specifically, during training, similarity and contrastive loss are not only computed within batch, but also in queues. We combine pseudo soft label $y^{v2t}_m$ calculated by eq.(1) with ground-truth label as follow:

$$\hat{y} = \alpha * y_m + (1 - \alpha) * y,$$  \hspace{1cm} (4)

where $\alpha$ is coefficient of distillation. Therefore, we reformulate eq.(1)-(2) as follow:

$$p^{v2t}(v) = \frac{\exp(s(v, w)/\tau)}{\sum_{w \in \{B_v, Q_t\}} \exp(s(v, w)/\tau)},$$  \hspace{1cm} (5)
$$L_{v2t} = \mathbb{E}_{v \sim B} \left[ H(p^{v2t}(v), \hat{y}^{v2t}(v)) \right],$$  \hspace{1cm} (6)

### 2.3. Multi-Modal Fusion

To fully exploit the abundant information between two modalities and enhance cross-modal interactions, we utilize a multi-modal encoder $f_{\theta_j}$ to predict whether a video-text pair is positive or negative. Same as TACo [17] and ALBEF [8], our multi-modal encoder consists of self-attention layers. It takes video frame embedding $V_{emb} \in \mathbb{R}^{N_v \times D}$ and caption token embedding $W_{emb} \in \mathbb{R}^{N_w \times D}$ as input and output fusion embedding $F_{emb} \in \mathbb{R}^{(N_v+N_w) \times D}$. We take representation of [EOS] token as fusion feature of video-text pairs, which is $f \in \mathbb{R}^D$. Then, a matching head
We further revise it to make it symmetric:

\[ L_{vtm} = -\sum_{p} \log \left( \frac{\exp(g(f_p))}{\exp(g(f_p)) + \sum \exp(g(f_n))} \right), \]

where \( \mathcal{P} \) denotes the set of video-text pairs and \( f_p \) and \( f_n \) are fusion features of positive pairs and negative pairs in the pair set, respectively.

In order to improve efficiency and reduce computational cost, we only select in-batch hard negative samples for multi-modal fusion. Concretely, for each video, we choose top-K negative text samples during real-time training according to eq. (1) and vice versa. Finally, \( B \times (2K + 1) \) pairs are fed into multi-modal fusion. Through this fine-grained interaction method, model learns to capture and distinguish the subtle differences between videos and captions with similar features but different semantics.

### 2.4. Dual Softmax at Inference

The latest work called CAMoE [2] proposed a novel similarity computing method which achieves significant improvement. Specifically, a prior probability calculated in similarity computing method which achieves significant improvement.

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### 3. Experiments

#### 3.1. Dataset and Evaluation Metric

MSR-VTT[16]. This dataset is the most popular benchmark for video-text retrieval task which consists of 10000 videos with 20 captions for each. We report the standard full split [4] and 1K-A split [18]. The former contains 6513 videos for training, 497 videos for validating and 2990 videos for testing. And the latter uses 9000 videos for training and 1000 video-text pairs for test. In this paper, we only present the experiment results on MSR-VTT dataset.

**Evaluation Metric.** We report experiments under the standard retrieval metrics which contains recall at K (R@K, K=1,5,10), median rank (MdR) and mean rank (MnR).

#### 3.2. Implementation Details

The basic video encoder and text encoder are both initialized by CLIP(ViT-B-16) [15]. Besides basic encoders, frame position embedding is initialized with position embedding used in CLIP’s text encoder. Both temporal transformer and multi-modal transformer are initialized by part of layers from text encoder in CLIP. Concretely, the width, heads, and layers are 512, 8 and 4, respectively. The distillation coefficient \( \alpha \) is set to 0.4 and momentum update rate is 0.995 for teacher model. The fixed video length is 12 and caption length is 32. Following [11], we finetune our model with Adam optimizer in 10 epochs with 192 batch size and 8 for \( K \). The learning rate is \( 1e - 7 \) for the basic video encoder and text encoder, and \( 1e - 4 \) for new layers such as frame position embedding, temporal transformer and multi-modal transformer.

#### 3.3. Comparison with SOTA

The experiment results on MSR-VTT 1k split are reported in Table[1]. For fair comparison, we categorize video-text retrieval methods into CLIP-based and others. Methods in type of others are usually trained at feature-level that they take cached video frame features extracted by off-the-shelf pre-trained visual models as inputs. Comparing with them, even the CLIP under zero-shot setting [14] surpass the most of the feature-level methods, indicating the benefits and necessity of large scale image-text pre-training for video-text retrieval. Furthermore, CLIP-based method trained at pixel-level with end-to-end manners shows great advantage and capacity of transformer-based method.

As showed in Table[1] with the addition of dual-softmax operation in inference, we achieve the state-of-the-art performance by a large margin of 4.1% in text-to-video retrieval and 3.8% in video-to-video retrieval at R@1. Even without it, we acquire a comparable performance to CAMoE [2] in text-to-video retrieval. We also achieve the state-of-the-art results on MSR-VTT full split which is showed in Table[2].

#### 3.4. Ablation Studies

We conduct extensive experiments to study the effect of each module and method we used. ‘Base’, ‘Temp’, ‘M&D’, ‘Fusion’ and ‘Dual’ represent CLIP(ViT-B-16) with mean-pooling, temporal transformer with frame positional embedding, momentum distillation, multi-modal transformer and dual softmax, respectively. It should be noted that even if only imposing dual softmax on similarity matrix in the test phase, the retrieval results can be greatly promoted. And we observe instability of temporal transformer when it meets momentum distillation. And we find an interesting results that despite of the inferior retrieval prediction output by multi-modal transformer and matching head, the fusion method really prompts model to learn and capture fine-grained difference between video-text pair.
| Method       | Text-to-Video Retrieval | Video-to-Text Retrieval |
|--------------|-------------------------|-------------------------|
|              | R@1 | R@5 | R@10 | MdR | MnR | R@1  | R@5 | R@10 | MdR | MnR |
| CLIP         | 31.2 | 53.7 | 64.2 | 4.0 | -   | 27.2 | 51.7 | 62.6 | 3.0 | -   |
| MDMMT        | 38.9 | 69.0 | 79.7 | 2.0 | 16.5| -    | -    | -    | -   | -   |
| CLIP4Clip-meanP | 43.1 | 70.4 | 80.8 | 2.0 | 16.2| -    | -    | -    | -   | -   |
| CLIP4Clip-seqTransf | 44.5 | 71.4 | 81.6 | 2.0 | 15.3| -    | -    | -    | -   | -   |
| CLIP2Video   | 45.6 | 72.6 | 81.7 | 2.0 | 14.3| -    | -    | -    | -   | -   |
| CAMoE        | 44.6 | 72.6 | 81.8 | 2.0 | 13.3| -    | -    | -    | -   | -   |
| CAMoE+DS     | 47.3 | 74.2 | 84.5 | 2.0 | 11.9| -    | -    | -    | -   | -   |
| CLIP2TV      | 52.9 | 78.5 | 86.5 | 1.0 | 12.8| 54.1 | 77.4 | 85.7 | 1.0 | 9.0 |

**Table 1.** Retrieval result on MSR-VTT 1k split. CAMoE* means we copy the results from paperswithcode website and DS means dual-softmax operation.

| Method         | Text-to-Video Retrieval | Video-to-Text Retrieval |
|----------------|-------------------------|-------------------------|
|                | R@1 | R@5 | R@10 | MdR | MnR | R@1  | R@5 | R@10 | MdR | MnR |
| CLIP           | 21.4 | 41.1 | 50.4 | 10.0 | -   | -    | -    | -    | -   | -   |
| UNiVL          | 21.2 | 49.6 | 63.1 | 6.0  | -   | -    | -    | -    | -   | -   |
| MDMMT          | 23.1 | 49.8 | 61.8 | 6.0  | 52.8| -    | -    | -    | -   | -   |
| TACo           | 24.8 | 52.1 | 64.0 | 5.0  | -   | -    | -    | -    | -   | -   |
| CLIP2Video     | 29.8 | 55.5 | 66.2 | 4.0  | 45.5| -    | -    | -    | -   | -   |
| CAMoE*         | 32.9 | 58.3 | 68.4 | 3.0  | 42.6| -    | -    | -    | -   | -   |
| CLIP2TV w/o DS | 32.1 | 58.1 | 68.2 | 4.0  | 43.9| -    | -    | -    | -   | -   |
| CLIP2TV       | 33.1 | 58.9 | 68.9 | 3.0  | 44.7| -    | -    | -    | -   | -   |

**Table 2.** Results on MSR-VTT full split.

| Base Temp M&D Fusion Dual | Text-to-Video Retrieval | Video-to-Video Retrieval |
|--------------------------|-------------------------|-------------------------|
|                         | R@1 | R@5 | R@10 | MdR | MnR | R@1  | R@5 | R@10 | MdR | MnR |
| ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | 44.6 | 73.2 | 82.0 | 2.0 | 13.6| 46.5 | 72.7 | 81.3 | 2.0 | 15.5|
| ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | 46.1 | 72.2 | 81.3 | 2.0 | 13.9| 46.3 | 72.0 | 81.0 | 2.0 | 14.4|
| ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | 48.3 | 74.6 | 82.8 | 2.0 | 14.9| 49.3 | 77.3 | 84.3 | 2.0 | 12.6|
| ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ | 55.7 | 75.6 | 82.6 | 2.0 | 14.2| 52.9 | 78.5 | 86.5 | 1.0 | 12.8|

**Table 3.** Ablation results on MSR-VTT 1k.

### 4. Conclusion

In this paper, we revisit some recent works on multimodal learning and try to transfer knowledge and plant approaches into video-text retrieval. Eventually, we achieve the state-of-the-art and exceed other methods by a large margin on MSR-VTT dataset. The experiment results reveal that large scale image-text transformer-based model, like CLIP, provides a powerful tool for video-text retrieval task. In the future, we will further study the capacity of transformer-based models with other multi-modal learning techniques on the other video-text retrieval datasets.

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