

Cap4Video: What Can Auxiliary Captions Do for Text-Video Retrieval?

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Abstract

Most existing text-video retrieval methods focus on cross-modal matching between the visual content of videos and textual query sentences. However, in real-world scenarios, online videos are often accompanied by relevant text information such as titles, tags, and even subtitles, which can be utilized to match textual queries. This insight has motivated us to propose a novel approach to text-video retrieval, where we directly generate associated captions from videos using zero-shot video captioning with knowledge from web-scale pre-trained models (e.g., CLIP and GPT-2). Given the generated captions, a natural question arises: what benefits do they bring to text-video retrieval? To answer this, we introduce Cap4Video, a new framework that leverages captions in three ways: i) Input data: video-caption pairs can augment the training data. ii) Intermediate feature interaction: we perform cross-modal feature interaction between the video and caption to produce enhanced video representations. iii) Output score: the Query-Caption matching branch can complement the original Query-Video matching branch for text-video retrieval. We conduct comprehensive ablation studies to demonstrate the effectiveness of our approach. Without any post-processing, Cap4Video achieves state-of-the-art performance on four standard text-video retrieval benchmarks:

MSR-VTT (51.4%), VATEX (66.6%), MSVD (51.8%), and DiDeMo (52.0%). The code is available <https://github.com/whwu95/Cap4Video>.

1. Introduction

Text-video retrieval is a fundamental task in video-language learning. With the rapid advancements in image-language pre-training [15, 30, 46, 47], researchers have focused on expanding pre-trained image-language models, especially CLIP [30], to tackle the text-video retrieval task. The research path has evolved from the most direct global

Figure 1. (a) An existing end-to-end learning paradigm for text-video retrieval. (b) Zero-shot video captioning achieved by guiding a large language model (LLM) such as GPT-2 [31] with CLIP [30]. (c) Our Cap4Video framework leverages the generated captions in three aspects: input data augmentation, intermediate feature interaction, and output score fusion.

matching (e.g., video-sentence alignment [11, 24]) to fine-grained matching (e.g., frame-word alignment [36], video-word alignment [13], multi-hierarchical alignment [9, 28], etc). These studies have demonstrated remarkable performance and significantly outperformed previous models. Two key factors contribute to this improvement. Firstly, CLIP offers powerful visual and textual representations that are pre-aligned in the semantic embedding space, thereby reducing the challenge of cross-modal learning in video-text matching. Secondly, these methods can fine-tune the pre-trained vision and text encoders using sparsely sampled frames in an end-to-end manner. All of these methods aim to learn cross-modal alignment between the visual represen-

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tation of videos and the textual representation of the corresponding query, as depicted in Figure 1(a).

However, in real-life scenarios, online videos usually come with related content such as the video's title or tag on the video website. In addition to the visual signal in the video, the associated textual information can also be used to some extent to describe the video content and match the query (i.e., the common text-to-text retrieval). This raises a pertinent question: How can we generate associated text descriptions for videos? One possible solution is to crawl the video title from the video website. However, this method relies on annotations, and there is a risk that the video URL may have become invalid. Another automated solution is to generate captions using zero-shot video caption models. Therefore, we turn our attention to knowledge-rich pre-trained models to handle such challenging open-set scenarios. We find that the recent study ZeroCap [34] provides a good practice to use frozen CLIP [30] and GPT-2 [31] for zero-shot image captioning. Thus, we leverage a video extension [33] of ZeroCap for generating captions in the video domain without any further training.

When provided with auxiliary captions, a natural question naturally arises: How can we leverage these captions to enhance the text-video retrieval task? In this paper, we propose the Cap4Video learning framework, as illustrated in Figure 1(c), which utilizes captions in three key ways: (i) **Input Data** One simple approach is to augment the training data with the generated captions. Specifically, the given video and its generated caption can be treated as a matched pair, which serves as an additional positive sample pair for training beyond the query-video pairs. (ii) **Intermediate Feature Interaction** Cross-modal interaction between the video and captions can be leveraged to improve the video representation. Specifically, we can exploit the complementary information between videos and captions to reduce redundant features from videos and learn more discriminative video representations. (iii) **Output score** The generated caption can also represent the video's content, allowing us to employ query-caption matching to complement standard query-video matching for the text-video retrieval task. Moreover, a two-stream architecture can be utilized to reduce model bias and produce more robust results.

We hope that our novel paradigm will encourage further investigation into the video-language learning. In summary, our contributions are as follows:

- We explore a novel problem: leveraging auxiliary captions to further enhance existing text-video retrieval. Besides labor-intensive manual crawling of video website titles, we investigate the potential of rich captions automatically generated by large language models (LLMs) to benefit text-video retrieval.
- We propose the Cap4Video learning framework,

which maximizes the utility of the auxiliary captions through three aspects: input data, feature interaction, and output score. Our framework improves the performance of existing query-video matching mechanisms, including global matching and fine-grained matching.

- Extensive experiments conducted on four video benchmarks demonstrate the effectiveness of our method. Our Cap4Video achieves state-of-the-art performance on MSR-VTT [44] (51.4%), VATEX [38] (66.6%), MSVD [43] (51.8%), and DiDeMo [1] (52.0%).

2. Methodology

2.1. Background: Text-Video Matching

Text-video matching aims to evaluate the similarity between a given sentence Q_i and a given video V_j , typically using a similarity function $f(Q_i; V_j)$. In text-to-video retrieval, the goal is to rank all videos based on their similarity scores to a given query sentence. To improve text-video retrieval, recent works [9, 11, 24] have applied CLIP [30] for initialization, leveraging pre-trained knowledge from image-text learning. Our baselines for text-video matching include two typical mechanisms: global matching and fine-grained matching, as illustrated in Figure 2(b).

Global Matching is a commonly used technique in cross-modal contrastive learning [16, 24, 30]. In global matching, each modality is encoded independently to obtain global features, which are then used to calculate similarity. We train the visual encoder to output frame embeddings for a given video that samples F frames. Similarly, the query encoder returns word embeddings and the [CLS] embedding as the global representation for a given query sentence that contains N words. The frame embeddings are integrated using average pooling to obtain the global video embedding, which is then compared with the global query embedding to calculate similarity.

Fine-grained Matching focuses on modeling the token-level alignment between two modalities, such as frame-word alignment. In order to achieve token-level patch-word alignment for image-text learning, FILIP [45] and CoBERT [17] employ a Max-Mean pipeline. This pipeline finds the token-wise maximum similarity between patch and word tokens, and then averages the maximum similarity of tokens in the image or text to obtain the similarity between an image and a text or vice versa. Moreover, DRL [36] extends the token-wise alignment to text-video retrieval and introduces an attention mechanism to learn weighted pooling instead of mean pooling. We have adopted this mechanism as our enhanced baseline.

2.2. Preprocessing: Caption Generation

To obtain auxiliary captions for a given video, we consider the following two approaches.

Figure 2. An overview of ouCap4Video for text-video retrieval. We first generate captions using a zero-shot video captioner that combines CLIP [30] with GPT-2 [31], leveraging knowledge from both frozen web-scale models. We then utilize the pre-extracted caption information from three different perspectives. Input data: We use the video and captions to create new positive pairs for data augmentation during training. ii) Feature interaction: We perform feature interaction between video and caption to capture intra- and inter-modality context, yielding enhanced video representations. Output score: The Query-Caption matching branch can complement the original Query-Video matching branch for text-video retrieval.

Manual Crawling of Video Titles. We extract the video website title by crawling the original links (such as YouTube ID) of each video and utilize it as the caption. However, we skip this step for videos with expired links.

Automatic Video Captioning. In contrast to the manual approach that relies on annotations, we leverage knowledge from the LLM to generate rich and diverse captions. Given the scalability of our framework, we aim to generate captions directly from downstream videos without any additional training, a process known as zero-shot video captioning. To achieve this, we follow [33, 34] and use GPT-2 [31] to predict the next word from an initial prompt, e.g., “Video shows”. A calibrated CLIP [30] loss is then used to drive the model to generate sentences that describe the video, incorporating video-related knowledge into the auto-regressive process. See Supplementary for more details.

2.3. Data Augmentation with Auxiliary Captions

Auxiliary captions can be used to augment training data. For example, for a dataset consisting of N videos and their corresponding query sentences, each video and its generated caption can be considered as a positive sample pair for training, in addition to the original query-video pairs. By selecting one caption per video, we can add at least N pairs

as additional data augmentation during training. The automatic video captioner can generate multiple captions (e.g., 20) for each video. However, some of these captions may contain noise and may not be entirely relevant to the video content. To avoid negative effects on training, we use a filtering mechanism that evaluates the semantic similarity between each caption and the ground-truth query of the video using a pre-trained text encoder. The caption with the highest similarity is then chosen for data augmentation. Note that we only use the ground-truth query for caption filtering during the training phase.

2.4. Video-Caption Cross-Modal Interaction

We further consider taking advantage of the complementarity between videos and captions to reduce redundant features and learn more discriminative video representations. To preserve the pre-trained CLIP encoder architecture for efficient transfer learning, we limit the interaction to the video caption and frame embeddings. Specifically, we pass the frame embeddings $\mathbf{v} = [v_1; v_2; \dots; v_F]$ and caption embeddings $\mathbf{c} = [c_1; c_2; \dots; c_C]$ to the interaction module, where F and C represent the number of frames and captions, respectively. Figure 2(b) depicts several ways of interaction between the two modalities.

Sum. To obtain an enhanced frame embedding, an intuitive approach is to compute the sum of the global caption embedding c_g and each frame embedding:

$$\text{Sum}(v_i; c_g) = v_i + c_g; \quad i = 1; \dots; F; \quad (1)$$

where $v_i \in \mathbb{R}^D$ is the i -th frame embedding, and $c_g \in \mathbb{R}^D$ is computed by averaging the [CLS] embeddings of generated captions $c_g = \frac{1}{C} \sum_{i=1}^C c_i$.

MLP. To model weighted combinations of each frame embedding and the global caption embedding, we concatenate them together and pass the result through a learnable Multi-layer Perceptron (MLP):

$$\text{MLP}(v_i; c_g) = f([v_i; c_g]); \quad \text{for } i = 1; \dots; F; \quad (2)$$

where $[\]$ denotes the concatenation operation, is the MLP with parameter θ .

Cross Transformer. We also investigate the use of self-attention [35] for interactions. The Cross Transformer operates on a sequence $e_v; e_c = f(v_1; \dots; v_F; c_1; \dots; c_C)$ and processes them through an encoder-style transformer blocks to generate global representations:

$$\text{Cross}(e_v; e_c) = f(f(e_v; e_c)); \quad (3)$$

where f denotes the transformer encoders with parameter θ , and e_v and e_c form a sequence, and f represents the transformer encoders with parameter θ .

Co-attention Transformer. Co-attention [23] is another common method for exchanging information between modalities, allowing for mutual attention between video and caption. After this co-attentional transformer layer, we include L transformer layers to model temporal information:

$$\text{CoAttn}(e_v; e_c) = f_2(f_1(f(e_v; e_c))); \quad (4)$$

where f_1 is the co-attentional transformer with parameter θ_1 and f_2 is the transformer encoders with parameter θ_2 .

The video-caption interaction module generates frame embeddings that can be further processed based on the type of matching needed. For global matching, the frame embeddings can be averaged to obtain a single video representation. Alternatively, for fine-grained matching, the individual frame embeddings can be retained.

2.5. Complementary Query-Caption Matching

Besides using the caption for data augmentation and video feature enhancement, it can also directly represent the video content, allowing for text-text retrieval. Specifically, each of the C captions generated by the video is then passed through the caption encoder to obtain its [CLS] text embedding. These caption embeddings are then aggregated to form a global representation, as illustrated in Figure 2(c).

The cosine similarity between this global caption embedding and the global query embedding is then calculated to complement the query-video matching.

Figure 3. Illustration of four Video-Caption interaction strategies. The enhanced frame embeddings will be followed by a mean pooling for global matching or will remain for fine-grained matching.

Notation. Let $\{e_{v_i}; e_{t_i}; e_{c_i}\}_{i=1}^B$ be a batch of B triples, where e_{v_i} , e_{t_i} , and e_{c_i} denote the i -th video, query, and caption embedding, respectively. Note that the term “embedding” used here is more general for convenience and can vary in meaning depending on the situation. For instance, in query-video global matching, e_{v_i} and e_{t_i} represent the averaged video feature and global [CLS] text feature, respectively. In query-video fine-grained matching, e_{v_i} and e_{t_i} represent a sequence of frame embeddings and a sequence of word embeddings, respectively. In query-caption matching, e_{c_i} represents a sequence of caption embeddings, and e_{t_i} represents a global [CLS] text feature.

Learning Objectives. For the Query-Caption branch, we want the caption embedding e_c and the query embedding e_t to be close while they are related and far apart when they are not during training phase. We follow the common practice [24, 36] to consider the bidirectional learning objective. We employ symmetric cross-entropy loss to maximize the similarity between matched Query-Caption pairs and minimize the similarity for other pairs:

$$\begin{aligned} L_{Q2C} &= \frac{1}{B} \sum_i \log P_j^B \frac{\exp(s_{qc}(e_{t_i}; e_{c_i}))}{\sum_j \exp(s_{qc}(e_{t_i}; e_{c_j}))}; \\ L_{C2Q} &= \frac{1}{B} \sum_i \log P_j^B \frac{\exp(s_{qc}(e_{t_i}; e_{c_i}))}{\sum_j \exp(s_{qc}(e_{t_j}; e_{c_i}))}; \\ L_{QC} &= \frac{1}{2}(L_{Q2C} + L_{C2Q}); \end{aligned} \quad (5)$$

where $s_{qc}(\cdot; \cdot)$ represents the query-caption matching similarity function shown in Figure 2(c), and refers to the temperature hyper-parameter for scaling. Similarly, the con-

trastive loss for Query-Video branch is formulated as:

$$\begin{aligned} L_{Q2V} &= \frac{1}{B} \sum_i \log P \frac{\exp(s_{qv}(e_{ti}; e_{vi}))}{\sum_j \exp(s_{qv}(e_{ti}; e_{vj}))}; \\ L_{V2Q} &= \frac{1}{B} \sum_i \log P \frac{\exp(s_{qv}(e_{ti}; e_{vi}))}{\sum_j \exp(s_{qv}(e_{tj}; e_{vi}))}; \\ L_{QV} &= \frac{1}{2}(L_{Q2V} + L_{V2Q}); \end{aligned} \quad (6)$$

where $s_{qv}(\cdot; \cdot)$ represents the query-video matching (global matching, fine-grained matching) similarity function shown in Figure 2(b). The total loss is the sum of Query-Video loss L_{QV} and Query-Caption loss L_{QC} :

$$L = L_{QV} + L_{QC} : \quad (7)$$

3. Experiments: Text-Video Retrieval

3.1. Setups

Datasets. We conduct experiment on four popular benchmarks for video-to-text retrieval and text-to-video retrieval tasks. MSR-VTT [44] contains a total of 10K video clips, each having 20 captions. Following the data splits from [10, 24, 27], we train models with associated captions on the Training-9K set and report results on the test 1K-A set. DiDeMo [1] has 10K videos paired with 40K descriptions. Following previous works [2, 19, 24], we concatenate all descriptions of one video to a single query, acting as a video-paragraph retrieval task. VATEX [38] collects 35K videos, each with multiple annotations. There are 26K videos for training, 1,500 videos for validation and 1,500 videos for testing. MSVD [43] contains 1,970 videos with 80K captions, with 40 captions on average per video. There are 1,200, 100, and 670 videos in the train, validation, and test sets, respectively.

Evaluation Metrics. For brevity, we abbreviate Recall at K to R@K ($K = 1; 5; 10$) upon all datasets, which computes the percentage of correct videos among the K top-retrieved videos given textual queries (Text-Video, and vice versa). MdR, Median Rank, computes the median of the ground-truth in the retrieval ranking list. MnR, Mean Rank, computes the mean rank of the correct results in the retrieval ranking list. Note that for MdR and MnR, the lower score means the better (indicated by \downarrow).

Implementation Details. All experiments use the visual encoder in CLIP [30] as the video encoder, and the textual encoder in CLIP as both the caption encoder and query encoder. The caption encoder and query encoder share parameters. To reduce conflict between the two branches, the query-video branch is trained first, followed by the query-caption branch. The text length is fixed to 32, and the video length is fixed to 12 for all datasets except DiDeMo (64 max words and 64 frames). The initial learning rate is set to $1e-7$

for the clip parameters and $1e-4$ for the non-clip parameters. The model is trained with a batch size of 128 for 5 epochs, except for DiDeMo (15 epochs), using the Adam [18] optimizer. All learning rates follow the cosine schedule with a linear warmup [14] strategy. For the number of generated captions per video, we set to 30. The interaction module employs L transformer layers, where L is set to 4 for VATEX and MSR-VTT, and 1 for DiDeMo and MSVD. In the caption branch, the number of transformer layers is set to 2. For caption generation, we directly use the original pre-trained CLIP and GPT-2, without any additional tuning.

3.2. Comparison with State-of-the-Art

In this section, we compare our Cap4Video with recent state-of-the-art methods on four benchmarks: MSR-VTT [44], MSVD [43], VATEX [38], and DiDeMo [1].

Table 1 shows the comparisons on DiDeMo, where our Cap4Video outperforms CLIP4Clip [24] by a significant margin of 9.2% in R@1 and exceeds DRL [36] by 0%, demonstrating the effectiveness of our method.

Table 2 provides a comparison of our approach with recent state-of-the-art models on MSR-VTT. Our method achieves new state-of-the-art performance on text-to-video retrieval for both ViT-B/32 and ViT-B/16 backbones, significantly surpassing previous works. For instance, we achieve a +4.8% higher R@1 than CLIP4Clip with the same ViT-B/32 on text-to-video retrieval. Additionally, our Cap4Video outperforms the recent TS2-Net [22] by 2.9% and 2.0% with ViT-B/32 and ViT-B/16, respectively.

Table 3 and Table 4 show the results for the MSVD and VATEX datasets, respectively, where we use ViT-B/16 as our backbone. For MSVD, our Cap4Video achieves a remarkable performance of 51.8% R@1 and outperforms CLIP-based models CLIP4Clip [24] and X-Pool [25] by 6.6% and 4.6% on text-to-video retrieval, respectively. For VATEX, our approach also outperforms the recent state-of-the-art methods and achieves a 7.5% R@1 improvement over TS2-Net [22] for text-to-video retrieval.

In recent studies, several methods have been proposed

Method	R@1	R@5	R@10	MdR	MnR
CE [21]	15.6	40.9	-	8.2	-
ClipBERT [19]	21.1	47.3	61.1	6.3	-
Frozen [2]	31.0	59.8	72.4	3.0	-
TMVM [20]	36.5	64.9	75.4	3.0	-
CLIP4Clip [24]	42.8	68.5	79.2	2.0	18.9
TS2-Net [22]	41.8	71.6	82.0	2.0	14.8
HunYuan [28]	45.0	75.6	83.4	2.0	12.0
DRL [36]	49.0	76.5	84.5	2.0	-
Cap4Video	52.0	79.4	87.5	1	10.5

Table 1. Results of text-to-video retrieval on the DiDeMo [1].

Method	Venue	Text ! Video					Video ! Text				
		R@1	R@5	R@10	MdR#	MnR#	R@1	R@5	R@10	MdR#	MnR#
ClipBERT [19]	CVPR'20	22.0	46.8	59.9	6.0	-	-	-	-	-	-
MMT [10]	ECCV'20	26.6	57.1	69.6	4.0	-	27.0	57.5	69.7	3.7	21.3
T2VLAD [39]	CVPR'21	29.5	59.0	70.1	4.0	-	31.8	60.0	71.1	3.0	-
SupportSet [29]	ICLR'21	30.1	58.5	69.3	3.0	-	28.5	58.6	71.6	3.0	-
Frozen [2]	ICCV'21	32.5	61.5	71.2	3.0	-	-	-	-	-	-
BridgeFormer [12]	CVPR'22	37.6	64.8	75.1	-	-	-	-	-	-	-
TMVM [20]	NeurIPS'22	36.2	64.2	75.7	3.0	-	34.8	63.8	73.7	3.0	-
CLIP-ViT-B/32											
CLIP4Clip [24]	arXiv'21	44.5	71.4	81.6	2.0	15.3	42.7	70.9	80.6	2.0	11.6
CenterCLIP [48]	SIGIR'22	44.2	71.6	82.1	2.0	15.1	42.8	71.7	82.2	2.0	10.9
CAMoE [7]	arXiv'21	44.6	72.6	81.8	2.0	13.3	45.1	72.4	83.1	2.0	10.0
CLIP2Video [9]	arXiv'21	45.6	72.6	81.7	2.0	14.6	43.5	72.3	82.1	2.0	10.2
X-Pool [13]	CVPR'22	46.9	72.8	82.2	2.0	14.3	-	-	-	-	-
QB-Norm [4]	CVPR'22	47.2	73.0	83.0	2.0	-	-	-	-	-	-
TS2-Net [22]	ECCV'22	47.0	74.5	83.8	2.0	13.0	45.3	74.1	83.7	2.0	9.2
DRL [36]	arXiv'22	47.4	74.6	83.8	2.0	-	45.3	73.9	83.3	2.0	-
Cap4Video		49.3	74.3	83.8	2.0	12.0	47.1	73.7	84.3	2.0	8.7
CLIP-ViT-B/16											
CLIP2TV [11]	arXiv'21	48.3	74.6	82.8	2.0	14.9	46.5	75.4	84.9	2.0	10.2
CenterCLIP [48]	SIGIR'22	48.4	73.8	82.0	2.0	13.8	47.7	75.0	83.3	2.0	10.2
TS2-Net [22]	ECCV'22	49.4	75.6	85.3	2.0	13.5	46.6	75.9	84.9	2.0	8.9
DRL [36]	arXiv'22	50.2	76.5	84.7	1.0	-	48.9	76.3	85.4	2.0	-
Cap4Video		51.4	75.7	83.9	1.0	12.4	49.0	75.2	85.0	2.0	8

Table 2. Retrieval results on the validation set of MSR-VTT 1K [44]. Here we report results without any post-processing operations, e.g., DSL [7] or QB-Norm [4] during inference.

Method	R@1	R@5	R@10	MdR	MnR
CE [21]	19.8	49.0	63.8	6.0	-
SUPPORT [29]	28.4	60.0	72.9	4.0	-
CLIP [30]	37.0	64.1	73.8	3.0	-
Frozen [2]	33.7	64.7	76.3	3.0	-
TMVM [20]	36.7	67.4	81.3	2.5	-
CLIP4Clip [24]	45.2	75.5	84.3	2.0	10.3
X-Pool [13]	47.2	77.4	86.0	2.0	9.3
Cap4Video	51.8	80.8	88.3	1	8.3

Table 3. Results of text-to-video retrieval on the MSVD [43].

Method	R@1	R@5	R@10	MdR	MnR
HGR [6]	35.1	73.5	83.5	2.0	-
CLIP [30]	39.7	72.3	82.2	2.0	12.8
SUPPORT [29]	44.9	82.1	89.7	1.0	-
CLIP4Clip [24]	55.9	89.2	95.0	1.0	3.9
Clip2Video [9]	57.3	90.0	95.5	1.0	3.6
QB-Norm [4]	58.8	88.3	93.8	1.0	-
TS2-Net [22]	59.1	90.0	95.2	1.0	3.5
Cap4Video	66.6	93.1	97.0	1	2.7

Table 4. Results of text-to-video retrieval on the VATEX [38].

3.3. Ablation Study

to improve text-video retrieval performance by adjusting similarity during inference using other query information. In this section, we provide detailed ablation studies to Notably, our results adheres to the standard retrieval logic, clarify the effects of each part of our design. where the most relevant video is retrieved for each query Auxiliary Caption as Data Augmentation. We begin by from a set of videos, without any knowledge of the relation- investigating the impact of captions on data augmentation ship between other queries and videos. Therefore, all results for training. In a real-world scenario, the original video reported in our tables do not involve any post-processing title would naturally serve as an additional auxiliary cap- procedures such as DSL [7] and QB-Norm [4]. Overall, the tion. Therefore, we manually extracted the title from the consistent state-of-the-art performance across four bench- video's original webpage and compared it to the caption marks demonstrates the effectiveness of our Cap4Video. generated by the GPT-2 model. Table 5 presents the re-

Method	Global Matching					Fine-grained Matching				
	R@1	R@5	R@10	MdR#	MnR#	R@1	R@5	R@10	MdR#	MnR#
Baseline	42.8	70.4	79.0	2	16.6	45.7	73.7	82.6	2	13.1
+Different Sources of Caption as Data Augmentation										
Video Title from Source URL	43.8	71.1	80.9	2	15.1	44.3	72.7	83.5	2	13.1
Zero-shot Video Captioning	44.2	70.7	81.5	2	16.2	46.3	72.5	81.7	2	12.9
+Different Number of Captions for Data Augmentation										
Top-1	44.2	70.7	81.5	2	16.2	46.3	72.5	81.7	2	12.9
Top-3	43.3	71.7	81.6	2	15.0	45.5	73.8	82.4	2	12.7
Top-5	43.4	70.6	80.4	2	16.2	45.6	72.7	82.7	2	12.9
+Video-Caption Feature Interaction										
Video Only	44.2	70.7	81.5	2	16.2	46.3	72.5	81.7	2	12.9
Sum	43.8	71.5	80.3	2	16.1	47.2	73.3	82.8	2	13.1
Concat-MLP	37.5	66.1	78.4	3	15.7	40.0	68.7	79.9	2	12.7
Cross Transformer	44.6	71.6	80.3	2	14.6	47.9	75.4	83.0	2	11.5
Co-attention Transformer	45.3	71.2	80.9	2	15.0	48.5	74.0	82.5	2	12.7
+Query-Caption Matching Score										
Query-Video Only	45.3	71.2	80.9	2	15.0	48.5	74.0	82.5	2	12.7
Query-Caption Only	30.3	55.2	67.5	4	26.4	30.3	55.2	67.5	4	26.4
Query-Video + Query-Caption	45.6	71.7	81.2	2	14.8	49.3	74.2	83.4	2	12.1

Table 5. Component-wise evaluation of our framework on the MSR-VTT 1K validation set. With the ViT-B/32 backbone, we report the text-to-video retrieval results for two representative Query-Video matching mechanisms: global matching and fine-grained matching. The consistent improvement on two typical matching mechanisms demonstrates the generalization ability and effectiveness of our method.

sults of using different sources of the caption, from which we observe that using captions generated by the web-scale model as data augmentation for training can lead to direct improvements in R@1 (+1.4%, +0.6%) under both matching mechanisms. Using video titles can also bring a 1% improvement for global matching.

We also explore the impact of the number of generated captions used for augmentation. We used the caption iteration mechanism mentioned in Sec. 2.3 to rank the relevance of captions and the ground-truth query, and selected different numbers of captions for training. The results demonstrated that using only one caption is sufficient.

Benefit on Both Online and Offline Videos Scenarios. Our method is applicable for both online and offline videos. Offline videos are local videos with no title, while online videos have a title on the video website. Therefore, for online videos, the step of generating a caption with CLIP+GPT-2 is skipped, and the website title is used directly as a caption. In Table 6, the results show that our method has significantly improved over the global matching baseline for both offline and online videos.

Video-Caption Feature Interaction. As mentioned in Sec. 2.4, we have designed four approaches for Video-Caption feature interaction. Based on the results presented in Table 5, we can conclude the following: 1) The basic approach of Sum has been shown to enhance fine-grained matching by 0.9% R@1, but there is no noticeable improvement in global matching. 2) The MLP approach is difficult

	Caption Source	R@1
Baseline	N/A	42.8
Cap4Video	Original Website Title	45.8
	Captioner (CLIP+GPT-2)	45.6

Table 6. Exploring the effectiveness of captions from different sources on MSR-VTT 1k-A. Setting: ViT-B/32, global matching.

to optimize and performs poorly in both matching scenarios. We speculate that the MLP’s operation in a black-box environment, despite creating a nonlinear metric space, may lead to degradation. 3) The Cross Transformer approach has demonstrated improvements of +0.4% and +1.6% in two matching settings, respectively. These enhancements may be attributed to the self-attention mechanism’s ability to capture the inter-modal relationship between the video and caption. 4) Moreover, the Co-attention Transformer approach has significantly boosted performance, with gains of +1.1% and +2.2% for these two matching mechanisms. In summary, the results indicate that proper interaction between the video and generated caption can lead to better

video representation and improved Query-Video matching. **Query-Caption matching.** We also investigate the Query-Caption matching branch for text-video retrieval. We aggregate caption embeddings using mean pooling to yield a global embedding. As shown in Table 5, the single Query-Caption matching branch achieves 30.3% R@1 on text-to-

Figure 4. The text-video results on the MSR-VTT 1K-A test set. Left: The ranking results of the query-video matching model. Right: The ranking results of Cap4Video, which incorporates generated captions to enhance retrieval. Please zoom in for best view

video retrieval, outperforming previous query-video matching methods such as ClipBERT [19] (22.0%) and MMT [10] (26.6%). This suggests that the Query-Caption matching branch can complement the regular Query-Video matching branch for improved text-video retrieval. Combining the score of Query-Caption matching branch with Query-Video matching branch further improves performance (+0.8%).

Overall, Cap4Video utilizes generated captions in three ways: input data augmentation, intermediate feature interaction, and output score fusion, leading to consistent improvements (+2.8% / +3.6%) in both matching mechanisms.

3.4. Visualization

We provide two examples of videos retrieved by our Cap4Video method and a model without auxiliary captions. As illustrated in Figure 4, our approach successfully retrieves the ground-truth video with the assistance of the caption, while the video-only model returns multiple videos that are somewhat relevant to the query but not precise. See more qualitative results in Supplementary

4. Related Works

Zero-shot Image Captioning. In the field of natural language processing, transformer-based GPT models [5, 31] have been successful in generating text from prompts by training on large-scale text corpora. Similarly, CLIP [30], a vision-language alignment model trained on 400 million




image-text pairs, has demonstrated impressive zero-shot performance on vision tasks. However, research on transferring web-scale models to zero-shot video captioning remains limited. Recently, ZeroCap [34] proposed a method of using CLIP and the GPT-2 language model to generate textual descriptions of input images, leveraging knowledge from both models in a truly zero-shot manner without re-training or re-tuning model parameters. MAGIC [32] has also used CLIP scores to align GPT-2 logits with corresponding images but requires re-tuning on the MS-COCO caption text corpus. More recently, a study [33] extended the zero-shot capability of ZeroCap to the video domain. In this paper, we employ this video extension to generate auxiliary captions without any additional training.

Text-Video Retrieval aims to retrieve relevant video content based on natural language descriptions. Early studies [6, 10, 21, 37, 39] focused on knowledge transfer from “expert” models and captured intra-modal and cross-modal interactions based on pre-extracted features. However, the performance of these methods is limited since they cannot perform end-to-end optimization. Recently, more methods have involved end-to-end training for text-video retrieval. One typical approach [2, 26, 27] is to first perform large-scale text-video pre-training, then transfer the model to downstream text-video retrieval tasks. With the emergence of pre-trained Vision-Language Models (VLMs), there have been increased efforts to leverage them for improving video understanding [41, 42]. Thus, another training-efficient line is to directly expand the pre-trained VLM to the text-video retrieval task. CLIPBERT [19] enables affordable pioneering end-to-end training with a sparse sampling strategy. After that, recent works [3, 4, 8, 9, 11, 13, 22, 24, 40, 48] focus on transferring knowledge from CLIP models that have been pre-trained on 400M image-text pairs. The research path has evolved from the most direct global matching, (video-sentence alignment [11, 24]) to fine-grained matching (e.g., frame-word alignment [36], video-word alignment [13], multi-hierarchical alignment [9, 28]). Unlike above CLIP-Based efforts on query-video matching, we propose to generate auxiliary captions from videos to improve text-video retrieval. Thus our method is compatible with both global and fine-grained matching.

5. Conclusion

We introduce Cap4Video, a novel framework that leverages captions generated by web-scale language models to enhance text-video matching in three key ways: 1) Input data augmentation for training, 2) Intermediate video-caption feature interaction for compact video representations, and 3) Output score fusion for improved text-video retrieval. Our approach demonstrates consistent performance gains on four standard text-video retrieval benchmarks, outperforming state-of-the-art methods by a clear margin.

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