EASIER: Relevance-Boosted Captioning and Structural Information Extraction for Zero-Shot Video-Text Retrieval

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Abstract

While recent progress in video-text retrieval (VTR) has been advanced by the exploration of supervised representation learning, in this paper, we present a novel zero-shot VTR framework, EASIER, to retrieve video/text with off-the-shelf captioning methods, large language models (LLMs), and text retrieval methods. Specifically, we first map videos into captions and then retrieve video captions and text using text retrieval methods, without any model training or fine-tuning. However, due to the limited power of captioning methods, the captions often miss important content in the video, resulting in unsatisfactory retrieval performance. To translate more information into video captions, we designed a novel **relevance-boosted caption generation** method, bringing extra relevant details into video captions by LLMs. Moreover, to emphasize key information and reduce the noise brought by imagination, we extract key visual tokens from captions and design different templates for structuring these tokens with the proposed **structural information extraction**, further boosting the retrieval performance. Benefiting from the enriched captions and structuralized information, extensive experiments on several video-text retrieval benchmarks demonstrate the superiority of EASIER over existing fine-tuned and pretraining methods without any data. A comprehensive study with both human and automatic evaluations shows that the enriched captions capture the key details and barely bring noise to the captions. Codes and data will be released.

1 Introduction

Video-text retrieval (VTR) (Luo et al., 2022; Gao et al., 2021; Ma et al., 2022; Liu et al., 2022a; Zhao et al., 2022; Gorti et al., 2022; Fang et al., 2022) aims to retrieve the corresponding video or text given the query in another modality. Recent years have witnessed the rapid development of VTR with the support from powerful pretraining models (Luo et al., 2022; Gao et al., 2021; Ma et al., 2022; Liu et al., 2022a), improved retrieval methods (Bertasius et al., 2021; Dong et al., 2019; Jin et al., 2021), and video-language datasets construction (Xu et al., 2016). However, it remains challenging to precisely match video and language due to the raw data being in heterogeneous spaces and the use of modality-specific encoders.

The most popular paradigm in VTR (Luo et al., 2022; Ma et al., 2022; Liu et al., 2022b) firstly learns a joint feature space across modalities and then compares representations in this space. However, with the discrepancy between different modalities and the design of modality-independent encoders, it is challenging to directly match representations of different modalities generated from different encoders (Liang et al., 2022). On the other side, pioneering works (Wang et al., 2021, 2022e) convert images into captions for better presentation learning on image-language tasks, demonstrating that captioners can mitigate modality discrepancy.

In this work, to take one step forward, we present a zero-shot video-text retrieval framework with our proposed r**E**levance-boosted captioning **A**nd **S**tructural **I**nformation **E**xt**R**action, EASIER. EASIER first captions videos into video captions. However, we notice that the captions always miss important information in the video, thus leading to bad retrieval performance (see Table 1 without paraphrase and visual tokens). To this end, we propose **relevance-boosted captioning**, which augments video captions by encouraging large language models (LLMs) to add relevant details to captions. Later, to emphasize the key information in the captions, *e.g.*, objects, events, and attributes, we design a **structural information extraction** procedure for extracting and formatting "visual tokens". Finally, EASIER utilizes off-the-shelf text retrieval methods for zero-shot text retrieval matching video captions with structured visual tokens and text.

Finally, to evaluate the effectiveness of our proposed zero-shot EASIER, we conducted experiments on three representative video-text benchmarks (Chen and Dolan, 2011; Fabian Caba Heilbron and Niebles, 2015; Xu et al., 2016). Results show that EASIER outperforms previous methods, including fine-tuning methods and few-shot methods benefiting from relevance-boosted captioning and structural information extraction.

In summary, our contributions are as follows:

- We propose a **real zero-shot** video-text retrieval method without requiring any training procedure or human-annotated data, only using the off-the-shelf captioning method, large language models, and text retrieval methods.
- Our proposed EASIER achieves SOTA performance on several metrics across three VTR benchmarks.
- Detailed analysis reveals the importance of relevance-boosted captioning and structural information extraction. We will open-source the code and data to facilitate future research.

2 Related Work

Video-text retrieval, which involves cross-modal alignment and abstract understanding of temporal images (videos), has been a popular and fundamental task of language-grounding problems (Wang et al., 2020a,b, 2021; Yu et al., 2023). Most of the existing video-text retrieval frameworks (Yu et al., 2017; Dong et al., 2019; Zhu and Yang, 2020; Miech et al., 2020; Gabeur et al., 2020; Dzabraev et al., 2021; Croitoru et al., 2021) focus on learning powerful representations for video and text and extracting separated representations. For example, in Dong et al. (2019), videos and texts are encoded using convolutional neural networks and a bi-GRU (Schuster and Paliwal, 1997) while mean pooling is employed to obtain multi-level representations. MMT (Gabeur et al., 2020) uses a cross-modal encoder to aggregate features extracted by temporal images, audio, and speech for encoding videos. Following that, MDMMT (Dzabraev et al., 2021) further utilizes knowledge learned from multi-domain datasets to improve performance empirically. Further, MIL-NCE (Miech et al., 2020) adopts Multiple Instance Learning and Noise Contrastive Estimation, addressing the problem of visually misaligned narrations from uncurated videos.

Recently, with the success of self-supervised pretraining methods (Devlin et al., 2019; Radford et al., 2019; Brown et al., 2020), vision-language pretraining (Li et al., 2020b; Gan et al., 2020; Singh et al., 2022) on large-scale unlabeled cross-modal data has shown promising performance in various tasks, *e.g.*, image retrieval (Radford et al., 2021), image captioning (Chan et al., 2023), and video retrieval (Luo et al., 2022; Wang and Shi, 2023a). Recent works (Lei et al., 2021; Cheng et al., 2021; Gao et al., 2021; Ma et al., 2022; Park et al., 2022a; Wang et al., 2022b,d; Zhao et al., 2022; Gorti et al., 2022) have attempted to pretrain or fine-tune video-text retrieval models in an end-to-end manner. CLIPBERT (Lei et al., 2021; Bain et al., 2021), as a pioneer, proposes to sparsely sample video clips for end-to-end training to obtain clip-level predictions and then summarize them. Frozen in time (Bain et al., 2021) uses end-to-end training on both image-text and video-text pairs data by uniformly sampling video frames. CLIP4Clip (Luo et al., 2022) finetunes models and investigates three similarity calculation approaches for video-sentence contrastive learning on CLIP (Radford et al., 2021). Further, TS2-Net (Liu et al., 2022b) proposes a novel token shift and selection transformer architecture that adjusts the token sequence and selects informative tokens in both temporal and spatial dimensions from input video samples. While the mainstream of VTR models (Xue et al., 2023; Wu et al., 2023) focuses on fine-tuning powerful image-text pre-trained models, on the other side, as a pioneer, (Tiong et al., 2022; Wang et al., 2022e) propose to use large language models (LLMs) for zero-shot video question answering.

Zero-shot cross-modal retrieval. With the huge success of pretrained visual-language model (Radford et al., 2021; Luo et al., 2022), zero-shot cross-modal retrieval has attracted more and more research interest recently. Due to the powerful representation learning ability in image and text domains, CLIP (Radford et al., 2021) achieves satisfying zero-shot retrieval performance on several representative image-text retrieval benchmarks (Huiskes and Lew, 2008; Lin et al., 2014). Inspired by this achievement, Liu et al. (2023a,b); Chen et al. (2023c); Liu et al. (2024); Guo et al. (2024) boost the performance of zero-shot image-text retrieval by better representation learning methods. On the other side, benefiting from large-scale video-text benchmarks (Xu et al., 2016; Chen and

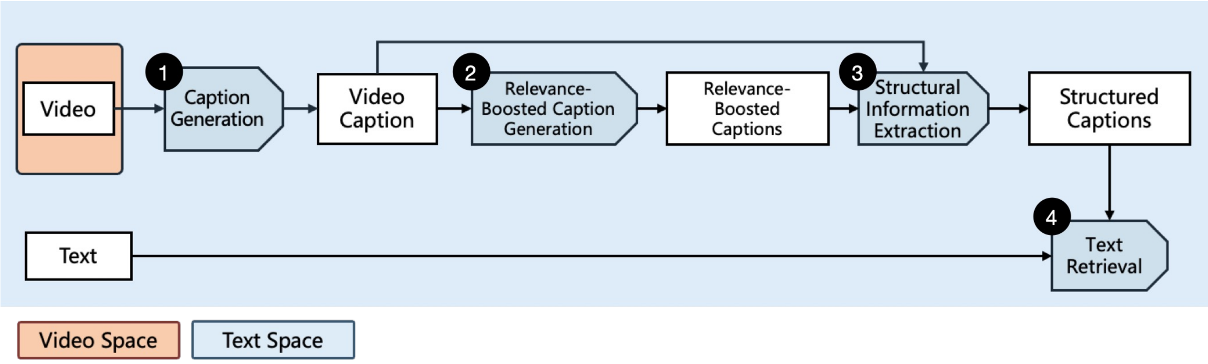

Figure 1: The illustration of our proposed EASIER. EASIER includes four steps. First, we generate video captions for video using off-the-shelf video captioning methods. Second, to enrich the captions, we propose the relevance-boosted caption-generation method using LLMs. Third, to emphasize the important information in the captions, we propose a novel structural information extraction. Finally, after obtaining structured video captions, we employ off-the-shelf text retrieval methods to perform zero-shot video-text retrieval.

Dolan, 2011; Fabian Caba Heilbron and Niebles, 2015), video-language pre-trained models (Wang et al., 2022c; Chen et al., 2023a; Xu et al., 2023; Chen et al., 2023c; Li et al., 2023b; Liu et al., 2023c; Zhu et al., 2024) also achieve satisfying zero-shot video-text retrieval results.

In this paper, inspired by these pioneering works, to explore zero-shot video-text retrieval, we step forward and propose a simple but effective zero-shot video-text retrieval method, EASIER, by utilizing off-the-shelf captioning, large language models, and text retrieval methods.

3 EASIER - Zero-Shot Video Text Retrieval

In this section, we present the details of our proposed method, EASIER. Specifically, we first generate captions for videos using video caption generation methods. Then, to cover most of the details in videos, with our proposed **relevance-boosted caption generation**, we obtain a detailed caption containing almost all the details. Finally, we propose the **structural information extraction** to emphasize important information in the captions for better video-text retrieval performance. The whole procedure is summarized in Figure 1.

3.1 Step 1 - Video Caption Generation

Video captioning with off-the-shelf captioners. Specifically, we employ Tewel et al. (2021, 2022) to generate video captions and then use GPT-2 (Radford et al., 2019) to enrich sentences using the prompts, *i.e.*, “Video presents”.

3.2 Step 2 - Relevance-Boosted Caption Generation

As shown in Figure 3, we notice that the generated captions always miss some important information, leading to unsatisfying retrieval performance. A simple solution to this problem is to fine-tune the captioning models, which will improve their caption-generation abilities. However, this approach needs a huge amount of annotated video-caption data and expensive computation resources, and the fine-tuned models are always not able to be transferred to other benchmarks. To this end, we propose the **relevance-boosted caption generation**, which is training-free and generates detailed captions that contain almost every detail of the video.

Specifically, we use large language models (LLMs) (Brown et al., 2020; Touvron et al., 2023) to conduct the hallucination-based generation using the following prompt template.

```
The following is a caption from a
video: [" + <Video Caption> + "].
Based on this caption, generate two
paraphrased captions capturing the
key information and main themes,
each of which should be in one
sentence with up to twenty words.
Meanwhile, please be creative, you
can have some imagination and add
the necessary details. Generated
sentences should be in the number
list. Also please generate text
without any comment.
```

Our proposed method generates multiple captions (*e.g.*, 1, 2, and 3). However, some of these captions might introduce noise or lack strong relevance to the video's content. To mitigate potential negative impacts, we apply a filtering method to assess the semantic similarity between relevance-boosted captions and the original video caption by leveraging a pre-trained text encoder (Reimers and Gurevych, 2019). Then we concatenate the filtered captions along with the original video caption to obtain the final captions.

3.3 Step 3 - Structural Information Extraction

To understand which kind of information is essential to VTR, we analyze the contextual text of video captions by breaking down the video captions into four different visual tokens using NLTK (Bird et al., 2009), *i.e.*, phrase, object, event, and attribute. Then we structure the information into the following structure,

```
<Caption> <Phrases> <Attributes> <
Events> <Objects>
```

3.4 Step 4 - Video (Video Caption)-Text Retrieval

Finally, after obtaining structured video caption data, we are ready to perform the retrieval step. Specifically, we compute the similarity score at the video level between text and video caption using off-the-shelf retrieval methods, *i.e.*, BM25 (Robertson and Walker, 1994) and Sentence transformers (Reimers and Gurevych, 2019).

4 Experiments

4.1 Benchmarks, Baselines, and Evaluation Metrics

Benchmarks. Following previous work (Luo et al., 2022; Ma et al., 2022), we use three representative benchmarks for evaluating EASIER, *i.e.*, MSR-VTT (Xu et al., 2016), MSVD (Chen and Dolan, 2011), and ActivityNet (Fabian Caba Heilbron and Niebles, 2015). Details of the dataset split are presented in appendix A.1.

Baselines. To show the empirical efficiency of our EASIER, we compare it with fine-tuned models, pre-trained methods, and few-shot methods. Details are presented in Appendix A.2.

Evaluation metric. To evaluate the retrieval performance of our proposed model, we use recall at Rank K (R@K, higher is better), median rank (MdR, lower is better), and mean rank (MnR, lower is better) as retrieval metrics, which are widely used in previous retrieval works (Radford et al., 2021; Luo et al., 2022; Ma et al., 2022).

Implementation details and related model details are defferd to Appendix A.3.

4.2 Quantitative Results

In this part, we present the qualitative results of EASIER on three VTR benchmarks.

MSR-VTT. We found that the contextual video text obtained directly through video captioning methods generally have mediocre performance (R@1: 20.3) compared to other baseline Text-Video Retrieval method. However, after using LLM to do relevance boosting from the video caption, the R@1 of our method nearly doubled (R@1 = 40.9) shown in Table 5 . Therefore, we further boosted each sentence and expanded it into two sentences. From the results presented in Table 1, it can be seen that this approach outperforms the second-best method by 9.9. This indicates the significant impact of relevance boosting and expanding captions on enhancing the performance of Text-Video Retrieval systems. Compared to DiscreteCodebook (Liu et al., 2022a), which aligns modalities in an unsupervised manner, EASIER outperforms DiscreteCodebook on every metric. Meanwhile, EASIER also outperforms VidIL (Wang et al., 2022e), which uses few-shot prompting, demonstrating the usability of integrating zero-shot LLM on text-to-video retrieval. This suggests that leveraging zero-shot on LLMs is a promising approach to enhance text-to-video retrieval performance. Also, we notice that EASIER has bad results on mean rank. To understand why this happens, we visualize the distribution of rank in Figure 2. It is obvious that though most of the videos have very good rank, *e.g.*, lower than 10, there are still some captions ranked in the last. This might be due to the failure of caption generation for some videos, where the generated captions do not contain any information from the video.

MSVD and ActivityNet. The results on MSVD and ActicityNet are shown in Table 3. EASIER achieves the best R@1 on text-to-video retrieval on two datasets compared to the previous methods.

4.3 Ablation Studies

In this part, we present a series of ablation experiments on MSR-VTT to better understand the effectiveness of different components of EASIER, using LLaMA2-7b-chat-hf and BM25. Due to space limitations, we present the ablation study on retrieval

Methods	Venue	Text-to-Video Retrieval					Video-to-Text Retrieval				
		R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓
Training-based											
LiteVL-S	EMNLP'22	46.7	71.8	81.7	2.0	-	-	-	-	-	-
X-Pool	CVPR'22	46.9	72.8	82.2	2.0	14.3	-	-	-	-	-
CenterCLIP	SIGIR'22	44.2	71.6	82.1	2.0	15.1	42.8	71.7	82.2	2.0	10.9
TS2-Net	ECCV'22	47.0	74.5	83.8	2.0	13.0	45.3	74.1	83.7	2.0	9.2
X-CLIP	ACM MM'22	46.1	74.3	83.1	2.0	13.2	46.8	73.3	84.0	2.0	9.1
NCL	EMNLP'22	43.9	71.2	81.5	2.0	15.5	44.9	71.8	80.7	2.0	12.8
TABLE	AAAI'23	47.1	74.3	82.9	2.0	13.4	47.2	74.2	84.2	2.0	11.0
VOP	CVPR'23	44.6	69.9	80.3	2.0	16.3	44.5	70.7	80.6	2.0	11.5
DiscreteCodebook	ACL'22	43.4	72.3	81.2	-	14.8	42.5	71.2	81.1	-	12.0
VCM	AAAI'22	43.8	71.0	-	2.0	14.3	45.1	72.3	82.3	2.0	10.7
CenterCLIP	SIGIR'22	48.4	73.8	82.0	2.0	13.8	47.7	75.0	83.3	2.0	10.2
HiSE	ACM MM'22	45.0	72.7	81.3	2.0	-	46.6	73.3	82.3	2.0	-
TS2-Net	ECCV'22	49.4	75.6	85.3	2.0	13.5	46.6	75.9	84.9	2.0	8.9
S3MA	EMNLP'23	53.1	78.2	86.2	1.0	10.5	52.7	79.2	86.3	1.0	8.2
UCOFIA	ICCV'23	49.4	72.1	-	-	12.9	47.1	74.3	-	-	-
ProST	ICCV'23	49.5	75.0	84.0	2.0	11.7	48.0	75.9	85.2	2.0	8.3
UATVR	ICCV'23	49.8	76.1	85.5	2.0	12.9	51.1	74.8	85.1	1.0	8.3
MV-Adapter	CVPR'24	46.2	73.2	82.7	-	-	47.2	74.8	83.9	-	-
Zero-Shot (Pretrained Models)											
VLM	ACL'21	28.1	55.5	67.4	4.0	-	-	-	-	-	-
HERO	EMNLP'21	16.8	43.3	57.7	-	-	-	-	-	-	-
VideoCLIP	EMNLP'21	30.9	55.4	66.8	-	-	-	-	-	-	-
EvO	CVPR'22	23.7	52.1	63.7	4.0	-	-	-	-	-	-
OA-Trans	CVPR'22	35.8	63.4	76.5	3.0	-	-	-	-	-	-
RaP	EMNLP'22	40.9	67.2	76.9	2.0	-	-	-	-	-	
OmniVL	NeurIPS'22	34.6	58.4	66.6	-	-	-	-	-	-	-
mPLUG-2	ICML'23	48.3	<u>75.0</u>	<u>83.2</u>	-	-	-	-	-	-	-
InternVL	Arxiv'23	42.4	65.9	75.4	-	-	**46.3**	**70.5**	**79.6**	-	-
LanguageBind	ICLR'24	42.6	65.4	75.5	-	-	-	-	-	-	-
Few-Shot											
VidIL	NeurIPS'22	40.8	65.2	-	-	-	<u>39.6</u>	<u>64.5</u>	-	-	-
Zero-Shot											
EASIER w/o paraphrase and visual tokens		20.3	40.9	51.7	9.0	60.3	17.5	36.7	47.3	12.0	<u>82.3</u>
EASIER w/o visual tokens		<u>54.0</u>	73.9	80.2	1.0	<u>24.5</u>	27.9	41.3	47.3	15.0	136.2
EASIER		**58.2**	**75.8**	**83.5**	1.0	**18.9**	36.4	56.5	<u>63.8</u>	3.0	**75.7**

Table 1: Video-Text retrieval results on MSR-VTT. The best results are marked in **bold**. The second best results are <u>underlined</u>. "NC" refers to Neurocomputing.

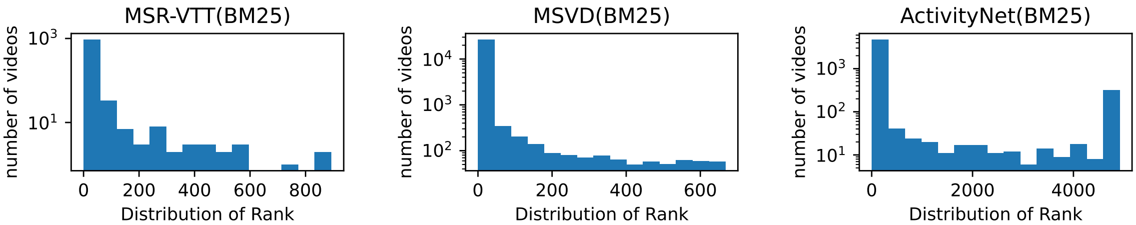

Figure 2: These figures illustrate the distribution of the rank of each (test) gallery video (captions) retrieved by (test) text queries.

methods and the investigation on the need for structural information extraction and relevance-boosted captions in appendix A.4 and appendix A.6.

Impact of combination of structural information (visual tokens). To choose the best combination method for the extracted visual tokens (phrases, attributes, objects, and events), we conduct experiments using different arrangements of these visual tokens, as shown in Table 2. By reducing the inclusion of visual tokens, the retrieval performance of EASIER decreases, thereby proving the superiority of integrating these four visual tokens together.

The order of different structural information. Another important factor to consider is the order of these visual tokens. To this end, we systematically evaluate which specific order of <phrase>, <object>, <attribute>, and <event> maximizes the efficiency and accuracy of the retrieval process. The results are shown in Table 4. We discover that among various arrangements, the model performs best when either phrases or objects are placed at the end of the sequence. This superior performance

Caption	Phrase	Object	Event	Attribute	Text-to-Video Retrieval R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	Video-to-Text Retrieval R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
✓					54.0	73.9	80.2	1.0	24.5	27.9	41.3	47.3	15.0	136.2
✓	✓				57.4	76.2	83.0	1.0	19.3	29.9	45.6	52.3	8.0	115.4
✓		✓			56.9	**77.5**	83.8	1.0	18.6	35.8	56.9	64.8	3.0	73.9
✓			✓		54.2	73.2	79.6	1.0	24.9	28.4	42.7	49.1	12.0	130.3
✓				✓	55.0	74.2	80.2	1.0	24.1	28.6	43.3	48.9	11.0	132.2
✓	✓	✓			57.4	76.2	83.5	1.0	18.7	34.5	54.0	62.5	4.0	79.9
✓	✓		✓		57.3	76.3	82.6	1.0	19.8	31.5	47.3	54.2	7.0	109.0
✓	✓			✓	57.6	76.3	83.5	1.0	19.1	31.0	47.4	54.7	7.0	110.5
✓		✓	✓		56.9	76.6	83.2	1.0	19.3	35.9	57.9	65.6	3.0	71.2
✓		✓		✓	57.6	77.4	83.8	1.0	**18.2**	37.4	58.5	66.3	3.0	71.8
✓			✓	✓	54.0	73.3	79.6	1.0	24.9	30.0	44.3	51.1	10.0	126.1
✓	✓	✓	✓		58.0	75.9	83.7	1.0	19.3	35.1	55.1	63.0	4.0	77.3
✓	✓	✓		✓	57.8	76.3	**84.1**	1.0	18.3	35.7	55.5	63.1	3.0	78.3
✓	✓		✓	✓	57.8	76.0	82.5	1.0	19.5	31.8	48.5	55.2	6.0	106.6
✓		✓	✓	✓	57.3	76.7	83.2	1.0	18.9	**37.5**	**59.4**	**67.0**	3.0	**69.2**
✓	✓	✓	✓	✓	**58.2**	75.8	83.5	1.0	18.9	36.4	56.5	63.8	3.0	75.7

Table 2: Retrieval performance with different combinations of four visual tokens (Phrase, Object, Event, Attribute) on MSR-VTT using EASIER. Best in **Bold**.

Methods	Venue	Text-to-Video Retrieval R@1↑	R@5↑	R@10↑	MnR↓
MSVD					
RaP	EMNLP'22	35.9	64.3	73.7	-
LanguageBind	ICLR'24	52.2	79.4	87.3	-
EASIER		**57.2**	**80.0**	**88.2**	15.6
ActivityNet					
LanguageBind	ICLR'24	35.1	63.4	76.6	-
EASIER		**59.0**	**71.4**	**77.0**	387.4

Table 3: Text-Video retrieval results on MSVD and ActivityNet. The best results are marked in **bold**.

might be due to the detailed and specific information that phrases and objects offer, enhancing the model's ability to accurately match and retrieve relevant video content.

Number of relevance-boosted captions. In this part, we aim to explore how many relevance-boosted captions work the best. More captions have the potential to offer more detailed descriptions, which may enhance the viewer's comprehension of the visual content. Previous studies (Biten et al., 2019; Tang et al., 2023) have demonstrated that longer captions tend to be more descriptive and semantically rich, achieving improved comprehension and retrieval performance. However, more relevance-boosted captions also mean more noises are injected. So balancing the number of relevance-boosted captions would be highly important. From the results shown in Table 5, we notice that paraphrasing into two or three sentences significantly improved R@1, R@5, and R@10. Considering computational constraints and the similar effectiveness of paraphrasing into two and three sentences, we decide to boost into two sentences.

Complexity of prompt templates for structural information extraction. The complexity of the prompt plays a pivotal role in shaping the output generated by the model, influencing the depth of analysis and the richness of information conveyed. An intricate prompt may provide the model with additional context and guidance, enabling it to produce more detailed responses. Specifically, we compare four templates (Basic, Structured, Detailed Description, and Narrative Format) offering different levels of complexity for organizing video content as shown in Appendix A.5. The results are shown in Table 6. We notice that intricate prompts provide the model with additional context and guidance, enabling it to produce more detailed responses. However, it may also lead to a loss of information, which is important for the retrieval performance. The results show that with the narrative format template, R@1, R@5, and R@10 on text-to-video retrieval are improved. This might be because the simplest format template provides insights into storytelling elements such as objects, events, and phrases, which leads to more precise keyword assignments.

5 Analysis on Quality of Relevance-Boosted Captions

As the details brought by relevance-boosted generation might bring irrelevant information, we analyze the quality of relevance-boosted captions.

5.1 Automatic Evaluation

Inspired by Li et al. (2023a), we generate video captions with varying levels of relevant details by using different prompts to control the level of relevance generation. Specifically, we generate cap-

Order List	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
Order List 1	**58.2**	75.8	**83.5**	1.0	18.9	36.4	56.5	63.8	3.0	**75.7**
Order List 2	57.9	**75.9**	83.4	1.0	**18.7**	**36.7**	56.4	**64.4**	3.0	75.3
Order List 3	58.0	75.7	83.2	1.0	19.1	36.3	**56.6**	64.2	3.0	75.0

Table 4: Retrieval performance with different order of four visual tokens (Phrase, Object, Event, Attribute) on MSR-VTT using EASIER. Best in **Bold**. We discovered three unique sequencing methods for visual tokens, each producing distinct outcomes based on their specific arrangements. Order List 1 places objects or phrases to the end, *i.e.*, {Caption}, . . ., {Phrase/Object}, Order List 2 represents {Caption}, . . ., {Event}, and Order List 3 represents {Caption}, . . ., {Attribute}.

# of Hullucinated Captions	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
1	40.9	55.5	60.9	3.0	227.3	34.3	54.2	62.6	4.0	114.0
2	**58.2**	**75.8**	**83.5**	1.0	**18.9**	**36.4**	**56.5**	**63.8**	3.0	**75.7**
3	55.7	73.9	82.2	1.0	21.2	35.1	52.8	62.4	4.0	87.1

Table 5: Retrieval performance with different numbers of relevance-boosted captions on MSR-VTT using EASIER. Best in **Bold**.

Template	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
Basic Template	**58.2**	**75.8**	**83.5**	1.0	**18.9**	**36.4**	**56.5**	**63.8**	3.0	**75.7**
Structured Template	55.7	74.6	81.2	1.0	21.1	31.0	45.4	51.5	9.0	77.2
Template with Detailed Description	55.9	74.6	81.7	1.0	21.2	34.3	53.9	61.7	4.0	84.7
Narrative Format Template	56.5	74.7	81.7	1.0	20.9	26.9	43.4	49.0	11.0	129.7

Table 6: Retrieval performance with different template formats on MSR-VTT using EASIER. Best in **Bold**.

	Automatic Evaluation Metric	Human Evaluation				Text-to-Video Retrieval					Video-to-Text Retrieval				
Relevance	HHEM	Factual Accuracy	Relevance	Coherence	Specificity	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
High-level	16.1%	0.33	0.42	0.24	-0.95	56.9	75.1	82.6	1.0	21.4	23.1	37.0	43.2	22.0	147.6
Medium-level	14.7%	0.52	0.78	1.21	0.07	57.3	75.2	82.4	1.0	**18.1**	25.0	37.7	43.5	19.0	150.1
Low-level	9.6%	0.85	0.81	**1.38**	**0.68**	57.6	74.9	83.3	1.0	19.1	34.7	52.6	**64.2**	3.0	88.6
EASIER	10.9%	**0.87**	**0.86**	1.28	0.52	**58.2**	**75.8**	**83.5**	1.0	18.9	36.4	56.5	63.8	3.0	**75.7**

Table 7: Retrieval performance with different level of Relevance Boosting on MSR-VTT. Best in **Bold**.

tions at three levels: high, medium, and low (see Appendix B). We used the HHEM model (Honovich et al., 2022) to compute the hallucination rate by comparing the relevance-boosted captions and original video captions. As shown in Table 7, lower levels of generation do not significantly change retrieval results. We also observe that captions with a lower boosting rate perform worse than captions with higher levels.

5.2 Human Evaluation

We also conduct a human evaluation to further evaluate the relevance-boosted captions.

Participants: Our human evaluation task involves reading relevance-boosted captions from different levels, video captions without relevance-boosting, and rating those relevance-boosted captions from them. We recruited 10 participants (7M, 3F). We conducted a rigorous qualification process, evaluating their English proficiency, to ensure high-quality annotations. We hired them by sending invited emails to graduate students. We allocated up to 30 minutes for each participant to complete the study, and for their valuable time and input, each participant received a compensation of $15.

Task: We randomly selected 50 pairs of relevance-boosted captions and original video captions from EASIER. Note that each pair has only one relevance-boosted caption and one original video caption. Each participant is assigned 50 pairs. Each pair is evaluated by 10 individuals. In each trial, a participant reads 4 relevance-boosted captions for the original video caption: one by high-level boosting, one by medium-level boosting, one by low-level boosting, and one from EASIER. The order of these four is also randomized, so participants do not know which generated caption is from which method. The participant is asked to rate the 4 captions along four dimensions using a five-point Likert scale from -2 to 2.

- *Factual Accuracy*: The relevance-boosted caption is factually correct to convey the content from the video caption.
- *Relevance*: The relevance-boosted caption is relevant to the video caption.
- *Coherence*: The relevance-boosted caption is coherent to the video caption.
- *Specificity*: The relevance-boosted caption is spe-

LLM	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
LLaMA	58.2	75.8	83.5	1.0	18.9	**36.4**	56.5	63.8	3.0	**75.7**
GPT 3.5	**61.2**	**80.4**	**86.8**	1.0	**15.0**	35.5	**58.3**	**65.5**	3.0	77.6

Table 8: Retrieval performance with different LLM models on MSR-VTT using EASIER. Best in **Bold**.

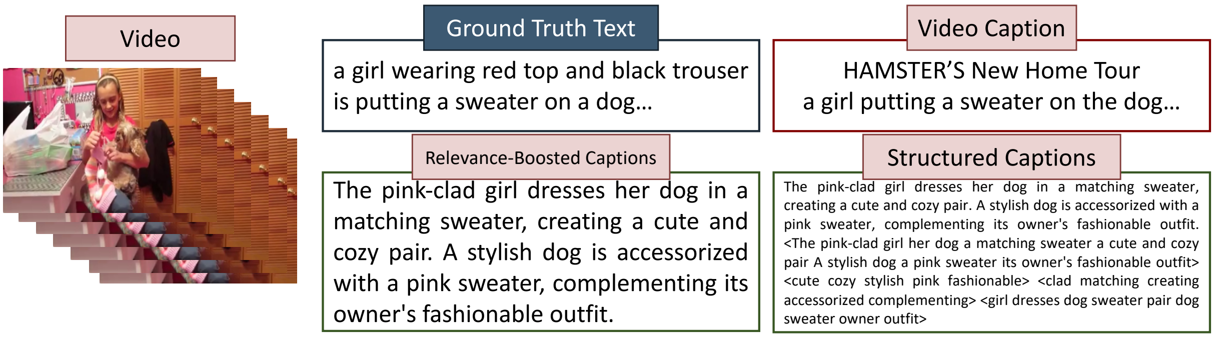

Figure 3: An example. Relevance-boosted captions contain more information compared to vanilla video captions in the video though some noises are also injected.

cific and detailed to the video caption.

Evaluation Results: We conducted *Wilcoxon tests* (Woolson, 2007) with a significance level of 0.05 to compare the performance of high-level, medium-level, low-level boosting, and EASIER in the Factual Accuracy, Relevance, Coherence, and Specificity dimensions. The Wilcoxon test is a non-parametric statistical test used to compare two paired groups of data. The obtained p-values indicate the probability of observing the reported differences if there were no true differences between the models.

The results indicate significant differences in the Factual Accuracy dimension, where EASIER outperforms High-level boosting (V = 4836, p = 1.45e-30), Medium-level boosting (V = 4819, p = 7.22e-31). For the Coherence dimension, we notice that they are almost at the same level, likely because captions refined by the LLM are already sufficiently coherent for users. In the Relevance dimension, EASIER surpasses high-level boosting (V = 3247, p = 1.44e-21), medium-level boosting (V = 3693, p = 1.69e-20), low-level boosting (V = 3188, p = 1.53e-20). For the Specificity dimension which considers whether the relevance-boosted caption is detailed and specified, Low-level boosting outperforms all methods: High-level boosting (V = 4463, p = 1.25e-7), Medium-level boosting (V = 3830, p = 3.48e-14), EASIER (V = 2260, p = 2.63e-7). It is worth noting that while low-level boosting is more detailed than EASIER, it performs slightly worse in VTR, possibly due to the higher importance of factual accuracy in evaluating the effectiveness of relevance-boosted captions. Future work can focus on designing an innovative framework for the relevance-boosted captioning method to integrate useful dimensions.

5.3 Qualitative Results

To qualitatively validate the effectiveness of EASIER, we present an example in fig. 3. The retrieval results show that relevance-boosted captions have more information in the video than vanilla video captions. Besides, our proposed structural information extraction methods clearly emphasize the important visual tokens, *i.e.*, phrase, object, event, and attribute, further boosting the performance.

6 Conclusion

In this paper, we present an innovative zero-shot framework, EASIER, which revolutionizes video-text retrieval by capitalizing on existing captioning methods, large language models (LLMs), and text retrieval techniques. By sidestepping the need for model training or fine-tuning, our framework offers a streamlined approach to retrieval. To overcome the shortcomings of traditional captioning methods, we propose a groundbreaking relevance-boosted caption generation technique that incorporates LLMs' generated information into video captions. Moreover, our introduction of structural information extraction further enhances retrieval performance by highlighting key visual tokens. Through extensive experimentation across diverse benchmarks, we demonstrate the superior efficacy of EASIER compared to conventional fine-tuned and pretraining methods, even in the absence of training data.

Limitations

In the future, it would be interesting to explore more detailed methods for zero-shot video-text retrieval, such as incorporating the audio modality and corresponding off-the-shelf foundation models. Moreover, as a pioneering work, our work mainly focuses on establishing the paradigm. It would be great if we could explore more text retrieval methods, video captioning methods, and LLMs for relevance-boosted caption generation.

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A Experiments

A.1 Details of Benchmarks

- **MSR-VTT** (Xu et al., 2016) contains 10,000 videos with length varying from 10 to 32 seconds, each paired with about 20 human-labeled captions. Following the evaluation protocol from previous works (Yu et al., 2018; Miech et al., 2019), we use the training-9k / test 1k-A splits for training and testing respectively.

- **MSVD** (Chen and Dolan, 2011) contains 1,970 videos with a split of 1200, 100, and 670 as the train, validation, and test set, respectively. The duration of videos varies from 1 to 62 seconds. Each video is paired with 40 English captions.

- **ActivityNet** (Fabian Caba Heilbron and Niebles, 2015) is consisted of 20,000 Youtube videos with 100,000 densely annotated descriptions. For a fair comparison, following the previous setting (Luo et al., 2022; Gabeur et al., 2020), we concatenate all captions together as a paragraph to perform a video-paragraph retrieval task by concatenating all the descriptions of a video. Performances are reported on the "val1" split of the ActivityNet.

A.2 Baselines

To show the empirical efficiency of our EASIER, we compare it with fine-tuned models (LiteVL (Chen et al., 2022), NCL (Park et al., 2022b), TABLE (Chen et al., 2023b), VOP (Huang et al., 2023), X-CLIP (Ma et al., 2022), DiscreteCodebook (Liu et al., 2022a), TS2-Net (Liu et al., 2022b), VCM (Cao et al., 2022), HiSE (Wang et al., 2022b), CenterCLIP (Zhao et al., 2022), X-Pool (Gorti et al., 2022), S3MA (Wang and Shi, 2023b)), and MV-Apapter (Jin et al., 2024), pre-trained methods (VLM (Xu et al., 2021a), HERO (Li et al., 2020a), VideoCLIP (Xu et al., 2021b), EvO (Shvetsova et al., 2022), OA-Trans (Wang et al., 2022a), RaP (Wu et al., 2022), OmniVL (Wang et al., 2022c), mPLUG-2 (Xu et al., 2023), InternVL (Chen et al., 2023c), Langauge-Bind (Zhu et al., 2024), UCOFIA (Wang et al., 2023), ProST (Li et al., 2023c), and UATVR (Fang et al., 2023),), and a few-shot method, *i.e.*, VidIL (Wang et al., 2022e).

A.3 Implementation Details

For video caption generation, we use Tewel et al. (2021, 2022) to generate video captions and GPT-2 (Radford et al., 2019) to enrich sentences. For relevance-boosted caption generation, we employ LLaMA2-7b-chat-hf (Touvron et al., 2023) and get two boosted captions. For structural information extraction, we use NLTK (Bird et al., 2009). For text retrieval, we use BM25 (Robertson and Walker, 1994).

We use **GPT2** (Radford et al., 2019) for sentence enrichment during video caption generation. GPT-2 (Radford et al., 2019), developed by OpenAI, is a large-scale transformer-based language model renowned for its ability to generate coherent and contextually relevant text. With 1.5 billion parameters, GPT-2 can be fine-tuned for a variety of natural language processing tasks, such as text generation, summarization, and captioning. In our task, we enrich image captions with GPT-2 with one NVIDIA A100 GPU using around 20 hours.

We use Llama (Touvron et al., 2023)(version: Llama-2-7b-chat-hf) to conduct the relevance-boosted caption generation task. **Llama** (Touvron et al., 2023) is an advanced language model with approximately 65 billion parameters. Its default backend is designed for efficiency and scalability. The computational budget for LlaMA in our task is approximately 23 hours with one NVIDIA A100 GPU. Its ability to understand context, generate coherent and contextually relevant responses, and perform a wide range of language-related tasks is significantly enhanced. LlaMA is a powerful and accessible tool, widely used in various applications. Therefore, it is included as an advanced baseline.

A.4 Choice of Retrieval Methods

In this part, we investigate the impact of different retrieval methods, *i.e.*, BM25 (Robertson and Walker, 1994) and sentence transformers (Reimers and Gurevych, 2019). The results are shown in section 6. It shows that BM25 outperforms the sentence transformer.

A.5 Prompts for Structural Information Extraction

1. Basic Template: the simplest, providing a straightforward list of video elements, the one shown in Section 3.3.

2. Structured Template: It adds categorized elements, making the information easier to navi-

Retrieval Methods	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
BM25	**58.2**	**75.8**	**83.5**	1.0	**18.9**	**36.4**	56.5	63.8	3.0	75.7
Sentence Transformer	41.2	62.1	70.5	2.0	33.5	34.7	**57.8**	**67.5**	3.0	**36.0**

Table 9: Retrieval performance with different retrieval models on MSR-VTT using EASIER. Best in **Bold**.

Retrieval Methods	Text-to-Video Retrieval					Video-to-Text Retrieval				
	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓	R@1↑	R@5↑	R@10↑	MdR↓	MnR ↓
EASIER	**58.2**	**75.8**	**83.5**	1.0	**18.9**	**36.4**	**56.5**	**63.8**	3.0	**75.7**
EASIER (video caption only repeats to the same length as structured caption)	54.0	73.9	80.2	1.0	24.6	27.9	41.3	47.3	491.5	136.2
EASIER (structured information extraction only repeats to the same length as video caption)	18.6	25.1	27.1	15.0	444.6	25.1	40.2	44.9	21.0	287.6

Table 10: Comparative Analysis of Caption Repetition and Extracted Structural Information Repetition on Retrieval Performance

gate for the retrieval method.

```
Video Caption : <Caption>. Key
Phrases: <{Phrases}>. Main
Objects: <Objects>. Notable
Features: <{Attributes}>. Key
Events: <Events>
```

3. Template with Detailed Description: This further elaborates on each element, offering in-depth insights.

```
Detailed Video Description:
Caption: <{Caption}> Objects and
 Attributes Overview: Each
object, <{Objects}>, is detailed
 with attributes such as <{
Attributes}> to provide a
clearer image. Event Analysis:
The video's narrative is driven
by events like <{Events}>, which
 are elaborated for better
understanding. Phrases Insight:
Phrases like <{Phrases}> are
explained for their significance
 to the content.
```

4. Narrative Format Template: it weaves the elements into a cohesive story, enhancing engagement and providing a thematic understanding.

```
Caption: <Caption> In this video
, we observe <{Objects}> with <{
Attributes}>, a vivid
representation of <{Events}>.
Phrases such as <{Phrases}>
punctuate the narrative,
offering insights into the
unfolding story.
```

A.6 Ablation Study: Are Structural Information Extraction and Relevance-Boosted Caption Generation necessary?

We also conduct another ablation study to investigate the effect of the video caption repeating itself several times to form text that is the same length as the structured caption stage. According to the Table section 6, we find that our EASIER method outperforms the others, indicating that a blend of relevance boosting (imagined or generated content) and structured information significantly improves retrieval results. Specifically, in text-to-video retrieval, EASIER achieves much higher recall rates and lower median and mean ranks than the other methods, which rely solely on caption repetition or structured information extraction. Also, we find that caption repetition outperforms structured information extraction repetition. This suggests that incorporating relevance boosting is crucial for enhancing retrieval effectiveness.

B Prompt to Generate Captions in Different Levels of Relevance Boosting

B.1 Low-level Relevance

```
The following is a caption from a
video: [" + text + "]. Based on this
 caption, generate two paraphrased
captions capturing the key
information and main themes, each of
 which should be in one sentence
with up to twenty words (Do not
include any details not mentioned in
```

```
 the text. Focus on the main points
and key details.). Also Please
generate text without any comment.
```

B.2 Medium-level Relevance

```
The following is a caption from a
video: [" + text + "]. Based on this
 caption, generate two paraphrased
captions capturing the key
information and main themes, each of
 which should be in one sentence
with up to twenty words (Feel free
to elaborate on points that seem
important, even if not explicitly
mentioned.). Also Please generate
text without any comment.
```

B.3 High-level Relevance

```
The following is a caption from a
video: [" + text + "]. Based on this
 caption, generate two paraphrased
captions capturing the key
information and main themes, each of
 which should be in one sentence
with up to twenty words (Feel free
to add any details or
interpretations that you think
enhance the summary, even if they
are not directly mentioned in the
text.). Also Please generate text
without any comment.
```