WAVER: WRITING-STYLE AGNOSTIC TEXT-VIDEO RETRIEVAL VIA DISTILLING VISION-LANGUAGE MODELS THROUGH OPEN-VOCABULARY KNOWLEDGE

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ABSTRACT

Text-video retrieval, a prominent sub-field within the domain of multimodal information retrieval, has witnessed remarkable growth in recent years. However, existing methods assume video scenes are consistent with unbiased descriptions. These limitations fail to align with real-world scenarios since descriptions can be influenced by annotator biases, diverse writing styles, and varying textual perspectives. To overcome the aforementioned problems, we introduce WAVER, a cross-domain knowledge distillation framework via visionlanguage models through open-vocabulary knowledge designed to tackle the challenge of handling different writing styles in video descriptions. WAVER capitalizes on the openvocabulary properties that lie in pre-trained vision-language models and employs an implicit knowledge distillation approach to transfer text-based knowledge from a teacher model to a vision-based student. Empirical studies conducted across four standard benchmark datasets, encompassing various settings, provide compelling evidence that WAVER can achieve state-of-the-art performance in text-video retrieval task while handling writing-style variations. The code is available at: https://github.com/Fsoft-AIC/WAVER

Index Terms— Text-Video Retrieval, Open-Vocabulary, Writing-style Agnostic, Knowledge Distillation

1. INTRODUCTION

Text-video retrieval (TVR), the task of retrieving videos based on textual queries, has grown significantly in multimedia information retrieval. Current works focus on cross-modal feature matching, assuming consistent video scenes and unbiased descriptions. However, existing TVR datasets [1, 2, 3, 4] are manually annotated by numerous annotators, introducing complexities due to variations in imperfect annotations, writing styles, and diverse perspectives. Consequently, this results in distinct semantic interpretations among descriptions associated with the same video. Moreover, the advent of large-scale pre-trained Vision-Language Models (VLMs) like CLIP [5] has marked significant progress in TVR over recent years. However, existing methods fully fine-tune CLIP for feature extraction and fusion in a brute-force manner, missing out on fully harnessing its pre-trained knowledge.

To address the aforementioned challenges, we propose WAVER with a cross-domain knowledge distillation (KD) mechanism to address a novel task referred to as "writingstyle agnostic". WAVER's primary objective is to alleviate the influence of diverse writing styles on TVR by exploring the open-vocabulary (open-vocab) properties present in VLMs through our cross-domain KD mechanism. Within this method, we first compile a Video Content Dictionary (VCD) that comprises phrases. Each phrase represents a specific activity and is among the top-k relevant activities for a given video. This knowledge source, derived from the VCD and extracted from large-scale datasets (usually training sets, but not limited to) encompasses a multitude of writing styles contributed by numerous annotators. The knowledge from VCD is treated as a teacher, embodying comprehensive information enriched by a wide spectrum of writing styles. Our proposed cross-domain KD aims to distill text-based knowledge from the large-capacity teacher (i.e., comprising various writing styles) into a vision-based student model when presented with a specific video and its associated content. This approach equips WAVER with the flexibility to effectively handle a wide variety of writing styles. To evaluate the effectiveness of our approach, we conducted a series of comprehensive experiments and ablation studies across four prominent benchmarks: MSR-VTT [1], MSVD [2], VA-*TEX* [3], and *DiDeMo* [4].

2. RELATED WORK

Vision-Language Models. VLMs [5, 6, 7] have been applied to various vision tasks with the use of open-vocab knowledge. For example, for image classification, ALIGN [8] and UniCL [9] improve accuracy by matching images with text descriptions; for object detection, X-DETR [10] and OWL-ViT [11] utilize VLMs for localization and recognition; for image segmentation, DenseCLIP [12] and OpenSeg [13] utilizes VLMs for pixel-level classification. TVR methods [14, 15, 16, 17, 18] in the second group have also benefited from VLMs by extending CLIP to train text-video matching models using a contrastive loss. However, most of these approaches fully fine-tune VLMs, under-utilizing pre-trained multi-modal information in videos. In our work, we leverage both fine-tuning and pre-trained VLMs feature

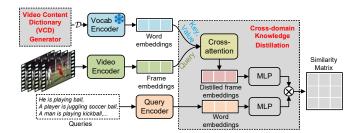


Fig. 1: Overview framework of WAVER. We propose a cross-domain KD, in which open-vocab knowledge from pretrained VLM implicitly acts as the teacher. By distilling text-based knowledge from the large-capacity teacher into a vision-based student model (described in Section 3) to handle writing-style variations.

to enhance TVR performance further.

Knowledge Distillation. The concept of KD [19] is to transfer knowledge from a teacher model with robust knowledge to a student model while maintaining high accuracy. Existing KD methods [20, 21] explicitly maintain teacher and student models to focus mainly on the technique to transfer knowledge between them. In contrast, to the best of our knowledge, our framework is the first study that uses open-vocab knowledge as the teacher to implicitly transfer the large knowledge from the teacher to the student to address the TVR task.

3. METHODOLOGY

In WAVER, we extract features from both the video and the query using the *Video Encoder* and *Query Encoder*, respectively, as described in Section 3.1. To tackle the challenge of writing-style variations, our WAVER creates a VCD, which compiles diverse video descriptions produced by different annotators, capturing a range of writing styles (cf. Section 3.2). The knowledge extracted from the VCD serves as the teacher, while the *Video Encoder* functions as the student. Subsequently, we introduce Cross-domain KD (cf. Section 3.3) to transfer the teacher's text-based knowledge to the student's vision. The overall workflow of WAVER is illustrated in Fig. 1. **Problem Setup.** We have L trimmed videos $\mathcal{V} = \{\mathbf{V}^{(l)}\}_{l=1}^L$ accompanied by a set of corresponding textual descriptions $\mathcal{T} = \{\mathbf{T}^{(l)}\}_{l=1}^L$. The primary goal of this problem is to retrieve video $\mathbf{V}^{(l)}$ based on $\mathbf{T}^{(l)}$.

3.1. Feature Encoders

We use Vision Transformer (ViT) [22] from CLIP [5] as our *Video Encoder*. Given a video $\mathbf{V}^{(i)}$ composed of N frames, we extract visual features $\mathbf{v}^{(i)} = f_v(\mathbf{V}^{(i)}|\theta_v)$. Here, $\mathbf{v}^{(i)} = \langle \mathbf{v}_1^{(i)}, \dots, \mathbf{v}_N^{(i)} \rangle$ is an embedding sequence of N frames and $f_v(\cdot|\theta_v)$ is the *Video Encoder*, which is parameterized by ViT's weights θ_v . As for the *Query Encoder* for textual feature extraction, we employ CLIP's text encoder. Given a textual description $\mathbf{T}^{(i)}$, which consists of S tokens, we obtain textual features $\mathbf{t}^{(i)} = f_t(\mathbf{T}^{(i)}|\theta_t)$. Here, $\mathbf{t}^{(i)} = \langle \mathbf{t}_1^{(i)}, \dots, \mathbf{t}_S^{(i)} \rangle$ is an embedding sequence of S tokens and $f_t(\cdot|\theta_t)$ is the *Query Encoder*, which is parameterized by Transformer's weights θ_t .

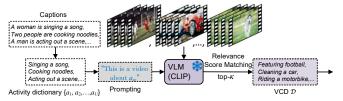


Fig. 2: The details of Video Content Dictionary Generator. As described in Section 3.2, we first form a list of all activities extracted from each caption. Then we propose a matching scheme to form a set of video-related vocabularies and select the top- κ most relevant vocabularies to create a VCD.

3.2. Video Content Dictionary Generator

To explore the open-vocab capability in a pre-trained VLM, we propose to construct a VCD using auxiliary information from the VLM to identify the most relevant knowledge. As depicted in Fig.2, given a TVR dataset, we first use $spaCy^1$ to extract existing activities (i.e., verb phrases) in each caption. As a result, we form a list of all activities $\{a_1, a_2, ..., a_U\}$, where U is the number of activities. We then propose a matching strategy to form a set of video-related vocabularies. For each activity a_u , we add a manually-designed prompt to a prefix to form a full query i.e., $q_u =$ "This is a video about a_u ". These queries q_i are processed through a frozen pre-trained CLIP's text encoder, resulting in embedding vocabularies $(\mathbf{h}_1, \dots, \mathbf{h}_U)$. Additionally, we use a frozen pretrained CLIP's visual encoder to extract frame-level embedding $(\mathbf{q}_1^{(i)}, \dots, \mathbf{q}_N^{(i)})$ for each video $\mathbf{V}^{(i)}$. The global video embedding $(e^{(i)})$ for each video is obtained by Eq. 1.

$$\mathbf{e}^{(i)} = \frac{1}{N} \sum_{t=1}^{N} \mathbf{q}_{t}^{(i)}.$$
 (1)

Next, we use function s to measure the similarity between each video and the entire vocabulary set by calculating the cosine similarity between the video's global embedding $e^{(i)}$ and vocabularies embedding h_u .

$$s(\mathbf{e}^{(i)}, \mathbf{h}_u) = \frac{\mathbf{e}^{(i)} \cdot \mathbf{h}_u}{||\mathbf{e}^{(i)}|| \cdot ||\mathbf{h}_u||},$$
 (2)

where \cdot denotes the dot product operation, and $\|\cdot\|$ denote the ℓ_2 -norm of the feature vectors.

We then select the top- κ most relevant vocabularies $d^{(i)} = \langle d_1^{(i)}, d_2^{(i)}, \dots, d_K^{(i)} \rangle = \text{top-}\kappa(\{s(\mathbf{e}^{(i)}, \mathbf{h}_u)\}_{u=1}^U)$ for each video $\mathbf{V}^{(i)}$. Then, $d^{(i)}$ serves as a vocabulary. As a result, we finally form a VCD denoted as $\mathcal{D} = \{d^{(i)}\}_{i=1}^L$.

3.3. Cross-domain Knowledge Distillation

By utilizing VCD \mathcal{D} , our WAVER framework efficiently highlights the open-vocab property in pre-trained VLM to transfer the foundational knowledge from teacher \mathcal{D} to the video encoder. As illustrated in Fig. 1, we leverage the knowledge extracted from the VCD \mathcal{D} as the teacher, while the *Video Encoder* functions as the student. To facilitate the transfer of knowledge from the teacher to the student, we employ crossattention mechanism [23]. We initiate the process by creating

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prompts $\mathbf{C}^{(i)}$ of the form "This is a video about $d^{(i)}$ " for each vocabulary $d^{(i)}$. These prompts, $\mathbf{C}^{(i)}$, are then inputted into the *Vocab Encoder*, $f_c(\cdot|\theta_c)$, which is a frozen pre-trained CLIP's text encoder. The output $\mathbf{c}^{(i)}$ is computed as $\mathbf{c}^{(i)} = f_c(\mathbf{C}^{(i)}|\theta_c)$, where θ_c is network weights. As a result, we acquire a general knowledge corpus $\mathcal C$ independent of any specific writing style, and it is defined as $\mathcal C = \{\mathbf{c}^{(i)}\}_{i=1}^L$. Given a video $\mathbf{V}^{(i)}$ containing visual features $\mathbf{v}^{(i)} = \mathbf{v}^{(i)}$

Given a video $\mathbf{V}^{(i)}$ containing visual features $\mathbf{v}^{(i)} = \langle \mathbf{v}_1^{(i)}, \dots, \mathbf{v}_N^{(i)} \rangle$, we define the cross-attention between $\mathbf{v}^{(i)}$ and \mathcal{C} as outlined in Eq. 3, where $\mathbf{v}^{(i)}$ takes on the role of the query, and \mathcal{C} serves as the key/value. As a result, we obtain a distilled video embedding $\mathbf{\bar{v}}^{(i)}$ at the student side.

$$\mathbf{\bar{v}}^{(i)} = \operatorname{softmax}(\mathbf{\underline{v}}^{(i)}\mathcal{C}^{\top})\mathcal{C},$$
 (3)

where z is the scaling factor.

3.4. Learning Objective Functions

Inspired by [24], we align the distilled video embedding $\bar{\mathbf{v}}^{(i)}$ and query embedding $\mathbf{t}^{(i)}$ with two Multi-layer Perceptrons (MLPs), respectively. The MLPs project $\bar{\mathbf{v}}^{(i)}$ and $\mathbf{t}^{(i)}$ into a normalized, lower-dimensional representation in the shared latent space. Then, we calculate the similarity $s(\mathbf{t}^{(i)}, \bar{\mathbf{v}}^{(i)})$, where $f_{\phi}(\cdot|\theta_{\phi})$ and $f_{\psi}(\cdot|\theta_{\psi})$ are MLPs parameterized by a stack of three Fully-Connected (FC) layers θ_{ϕ} and θ_{ψ} , respectively. Next, during the training phase, we aim to pull the query embedding $\mathbf{t}^{(i)}$ and the distilled video embedding $\bar{\mathbf{v}}^{(i)}$ when they are related and push them apart when they are not related. To achieve this, we employ the InfoNCE loss [25] to maximize the similarity for matching pairs $\mathbf{t}^{(i)}$, $\bar{\mathbf{v}}^{(i)}$ and minimize it for other pairs. This loss function is used for both the Video-to-Text and Text-to-Video problems.

$$\mathcal{L}_{t \to v} = -\frac{1}{B} \sum_{i}^{B} \log \frac{\exp\left(s\left(\mathbf{t}^{(i)}, \bar{\mathbf{v}}^{(i)}\right)/\tau\right)}{\sum_{j=1}^{B} \exp\left(s\left(\mathbf{t}^{(i)}, \bar{\mathbf{v}}^{(j)}\right)/\tau\right)}, \quad (4)$$

$$\mathcal{L}_{v \to t} = -\frac{1}{B} \sum_{i}^{B} \log \frac{\exp \left(s\left(\bar{\mathbf{v}}^{(i)}, \mathbf{t}^{(i)}\right) / \tau\right)}{\sum_{j=1}^{B} \exp \left(s\left(\bar{\mathbf{v}}^{(i)}, \mathbf{t}^{(j)}\right) / \tau\right)}, \quad (5)$$

where au is a learnable temperature parameter and B is the batch size. The overall InfoNCE loss is computed as:

$$\mathcal{L}_{\text{InfoNCE}} = \frac{1}{2} (\mathcal{L}_{t \to v} + \mathcal{L}_{v \to t}). \tag{6}$$

4. EXPERIMENTS

4.1. Datasets, Metrics & Implementation Details

We benchmark our WAVER on Text-to-Video (T2V) task on MSR-VTT [1], MSVD [2], VATEX [3], and DiDeMo [4]. MSR-VTT contains 10,000 videos, 20 descriptions per video. We train on 9,000 videos and test on 1,000 videos. MSVD contains 1,970 videos with multiple descriptions in various languages. We use 1,200 videos for training and 670 for testing, considering only English descriptions. VATEX contains over 40,000 videos and 825,000 captions in both English and Chinese. We only consider English descriptions in our experiment with 26,000/1,500/1,500 videos for training/validation/testing. DiDeMo contains 10,000 videos with over

Table 1: **T2V** comparison between our WAVER with existing SOTA methods on *MSR-VTT*.

Type	Method	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓
w/o. CLIP	CE [26]	20.9	48.8	62.4	6.0	28.2
w/o. CLIP	ClipBERT [18]	22.0	46.8	59.9	6.0	-
w/o. CLIP	MMT [17]	26.6	57.1	69.6	4.0	-
w/o. CLIP	SupportSet [27]	30.1	58.5	69.3	3.0	-
w/o. CLIP	Frozen [28]	32.5	61.5	71.2	3.0	-
w/o. CLIP	BridgeFormer [16]	37.6	64.8	75.1	-	-
w/o. CLIP	TMVM [29]	36.2	64.2	75.7	3.0	-
w/o. CLIP	Clover [30]	40.5	69.8	79.4	2.0	-
ViT-B/32	CenterCLIP [31]	44.2	71.6	82.1	2.0	15.1
ViT-B/32	CLIP4Clip[14]	44.5	71.4	81.6	2.0	15.3
ViT-B/32	VoP [32]	44.6	69.9	80.3	2.0	16.3
ViT-B/32	CAMoE [33]	44.6	72.6	81.8	2.0	13.3
ViT-B/32	CLIP2Video [15]	45.6	72.6	81.7	2.0	14.6
ViT-B/32	X-Pool [34]	46.9	72.8	82.2	2.0	14.3
ViT-B/32	TS2-Net [35]	47.0	74.5	83.8	2.0	13.0
ViT-B/32	WAVER (ours)	47.8	74.6	83.9	2.0	12.8
ViT-B/16	CLIP2TV [36]	48.3	74.6	82.8	2.0	14.9
ViT-B/16	CenterCLIP [35]	48.4	73.8	82.0	2.0	13.8
ViT-B/16	TS2-Net [35]	49.4	75.6	85.3	2.0	13.5
ViT-B/16	WAVER (ours)	50.4	77.2	86.4	1.0	10.8

Table 2: T2V comparison between our WAVER with existing SOTA methods on *MSVD*.

Type	Method	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓
w/o. CLIP	CE [26]	19.8	49.0	63.8	6.0	-
w/o. CLIP	SupportSet [27]	28.4	60.0	72.9	4.0	-
w/o. CLIP	Frozen [28]	33.7	64.7	76.3	3.0	-
w/o. CLIP	TMVM [29]	36.7	67.4	81.3	2.5	-
ViT-B/16	CLIP4Clip[14]	45.2	75.5	84.3	2.0	10.3
ViT-B/16	X-Pool [34]	47.2	77.4	86.0	2.0	9.3
ViT-B/16	WAVER (ours)	50.2	83.5	88.1	2.0	8.9

40,000 text descriptions. Training on 9,000 videos, we report results on the remaining 1,000 videos.

Following previous works [14], we report the result of the testing set with evaluation on multiple captions per video, except for MSR-VTT, where each video has only one caption. We evaluate the performance on the T2V task with various metrics including R@1, R@5, R@10, MdR, and MnR.

We set the token length to 32, the video sample frame to 12 for MSR-VTT and MSVD and the token length to 64, the video sample frame to 64 for DiDeMo and VATEX. The scaling factor is set z to 64 and the batch size is 126. and the initial learning rate is set to 10^{-4} and 10^{-7} for non-/ CLIP-based methods, respectively. The number of epochs is 5 for both versions. The model is implemented in PyTorch [40] and trained by $2 \times A100$ GPUs.

4.2. Comparison with State-of-the-art Methods

In *Table* 1, our WAVER with both CLIP's video encoder backbones versions (i.e., ViT-B/32, ViT-B/16) achieves SOTA results. With ViT-B/32, we achieve 47.8 R@1 surpassing the runner-up TS2-Net [35] by 0.8 point in T2V. With ViT-B/16, WAVER achieves 50.4 R@1 outperforming the runner-up TS2-Net [35] by 1.0 point in T2V. *Table* 2 shows that we WAVER significantly outperforms the runner-up X-Pool [34] by 3.0 points R@1 achieving SOTA performance of 50.2 R@1. *Table* 3 and *Table* 4 further demonstrate that WAVER achieves SOTA performance on both *VATEX*

Table 3: **T2V** comparison between our WAVER with existing SOTA methods on *VATEX*.

Type	Method	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓
w/o. CLIP	HGR [37]	35.1	73.5	83.5	2.0	
	SupportSet [27]	44.9	82.1	89.7	1.0	-
ViT-B/16	CLIP4Clip[14]	55.9	89.2	95.0	1.0	3.9
ViT-B/16	CLIP2Video [15]	57.3	90.0	95.5	1.0	3.6
ViT-B/16	QB-Norm [38]	58.8	88.3	93.8	1.0	-
ViT-B/16	TS2-Net [35]	59.1	90.0	95.2	1.0	3.5
ViT-B/16	WAVER (ours)	66.5	93.3	97.0	1.0	2.8

Table 4: T2V comparison between our WAVER with existing SOTA on *DiDeMo*.

Type	Method	R@1↑	R@5↑	R@10↑	MdR↓	MnR↓
w/o. CLIP	CE [26]	15.6	40.9	-	8.2	-
w/o. CLIP	ClipBERT [27]	21.1	47.3	61.1	6.3	-
w/o. CLIP	Frozen [28]	31.0	59.8	72.4	3.0	-
w/o. CLIP	TMVM [29]	36.5	64.9	75.4	3.0	-
ViT-B/16	CLIP4Clip[14]	42.8	68.5	79.2	2.0	18.9
ViT-B/16	TS2-Net [35]	41.8	71.6	82.0	2.0	14.8
ViT-B/16	HunYuan [39]	45.0	75.6	83.4	2.0	12.0
ViT-B/16	WAVER (ours)	49.2	77.2	85.6	2.0	11.2

and DiDeMo datasets. For VATEX, our WAVER exhibits outstanding performance with a 66.5% R@1 score, surpassing the runner-up TS2-Net [35] and QB-Norm [38] 7.4 and 7.7 points on R@1. Additionally, for DiDeMo, our approach outperforms the recent SOTA X-Pool [34] with 2.0 points on R@1. In smaller-scale datasets like MSVD, we emphasize the effectiveness of our proposed KD during transferring the knowledge from the general teacher $\mathcal C$ to the student video encoder function, enhancing distilled video feature $\bar{\mathbf v}$.

Table 5: Effectiveness of Cross-domain KD on *MSR-VTT*.

Method	R@1↑	R@5↑	R@10↑	MdR↓
Baseline	45.6	72.8	82.2	2.0
	+ Differe	nt values	of top- κ	
$\kappa = 1$	47.6	73.3	82.4	2.0
$\kappa = 3$	47.7	73.1	82.8	2.0
$\kappa = 5$	47.8	74.6	83.9	2.0
$\kappa = 7$	47.4	73.3	83.8	2.0
$\kappa = 9$	46.9	73.5	84.8	2.0

Table 6: Performance of WAVER on MSR-VTT testing set using various VCD \mathcal{D} (MSR-VTT, MSVD, VATEX, DiDeMo).

Vocab	No. Vocab	R@1↑	R@5↑	R@10↑	MdR↓
MSR-VTT	50,482	47.8	74.6	83.9	2.0
MSVD	21,168	47.1	74.0	83.8	2.0
VATEX	108,596	47.3	73.6	83.7	2.0
DiDeMo	9,132	47.6	72.7	82.1	2.0

Effectiveness of Cross-domain KD. In *Table 5*, we highlight

the impact of cross-domain KD in WAVER by comparing it

4.3. Ablation Study

with the baseline model, Clip4clip [14]. Specifically, we observe that when we disable the Cross-domain KD module, the baseline framework essentially functions as a basic TVR model, resulting in modest performance. This underscores the effectiveness of our KD method in enhancing accuracy and bolstering model robustness. Moreover, we experiment with different values of κ ranging from 1, 3, 5, 7, to 9, to assess their impact on performance. We note that when κ is excessively large, the framework encounters difficulty distilling discriminative features from the captions, likely due to the captions being over-specific. Conversely, when κ is too small, the captions may fail to fully leverage the open-vocab knowledge embedded in the pre-trained VLM, as they lack sufficient semantic context, ultimately leading to sub-optimal results. We attain the most favorable outcomes when $\kappa = 5$. Robustness of WAVER. We investigate the robustness of the WAVER model by employing different vocabulary datasets to construct VCD \mathcal{D} . In Table 6, we present the performance of MSR-VTT, where the VCD \mathcal{D} is generated from various datasets MSR-VTT, MSVD, VATEX, and DiDeMo. Even when the VCD \mathcal{D} is created using different datasets, the framework consistently achieves high accuracy, with negligible differences in the results. This underscores the robustness of the open-vocab knowledge embedded within WAVER framework.

Table 7: Evaluation on *MSR-VTT* testing set with different writing styles randomly selected using various seed values.

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Method	Seed	R@1↑	R@5↑	R@10↑	MdR↓
Baseline	16	45.0	72.4	81.2	2.0
Baseline	171	45.2	72.5	81.5	2.0
Baseline	1710	44.6	71.8	81.0	2.0
Baseline	2804	44.4	71.6	80.8	2.0
Mean	-	44.8	72.1	81.1	2.0
Std	-	0.37	0.44	0.30	0.0
WAVER	16	47.3	74.3	83.5	2.0
WAVER	171	47.5	74.5	83.8	2.0
WAVER	1710	47.2	74.2	83.4	2.0
WAVER	2804	47.1	74.1	83.3	2.0
Mean	-	47.3	74.3	83.5	2.0
Std	-	0.27	0.17	0.22	0.0

Table 8: Performance of WAVER on 100 videos from *MSR-VTT* testing set conducted by four different annotators.

Method	Annotators	R@1↑	R@5↑	R@10↑	MdR↓
Baseline	#1	67.3	91.4	94.1	1.0
Baseline	#2	65.7	90.2	93.3	1.0
Baseline	#3	66.5	90.7	93.8	1.0
Baseline	#4	64.8	89.9	92.2	1.0
WAVER	#1	75.0	95.2	97.4	1.0
WAVER	#2	74.2	94.5	96.9	1.0
WAVER	#3	74.4	94.9	97.2	1.0
WAVER	#4	73.8	94.0	96.5	1.0

WAVER in Writing-style Agnostic Task. In Table 7, in addition to the best-performing as in the default setting, we also introduce writing-style diversity by selecting a random writing style for each video evaluation. This randomness is achieved using a random seed, and a random writing style is represented by a randomly selected caption. Table 7 demonstrates WAVER's capacity to retrieve the target videos consistently and accurately, regardless of writing style. Compared to the baseline, the standard deviation (Std) of WAVER highlights its remarkable consistency in retrieving the target videos, even when the writing style of each video's description is altered. To further illustrate WAVER's effectiveness in handling diverse writing styles, we engaged four annotators to evaluate 100 videos from the MSR-VTT testing set. It's important to note that each video contains 20 captions. Based on their writing style, each annotator selected one caption out of the 20 for each video. Table 8 underscores that despite the biases introduced by different annotators in choosing corresponding captions for each video, our WAVER' results outperform the baseline approach consistently. This study introduces a promising avenue for future research within the TVR task.

5. CONCLUSION & DISCUSSION

In this work, we have presented WAVER, a writing-style agnostic video retrieval via distilling vision-language models through open-vocab knowledge framework. Our WAVER is a novel framework for the TVR task, where we proposed a cross-domain knowledge distillation mechanism through open-vocabulary properties to effectively utilize the powerful representation knowledge from the pre-trained VLM. To further highlight the applicability of the open-vocabulary properties in dealing with different semantic meanings, we denote a new task namely writing-style agnostic task, which evaluates the consistency of the retrieval results from different query descriptions. We hope that our work will inspire future research of writing-style agnostic problem and the potential of TVR task in addressing this problem.

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