

Bidirectional Cross-Modal Knowledge Exploration for Video Recognition with Pre-trained Vision-Language Models

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Abstract

Vision-language models (VLMs) pre-trained on large-scale image-text pairs have demonstrated impressive transferability on various visual tasks. Transferring knowledge from such powerful VLMs is a promising direction for building effective video recognition models. However, current exploration in this field is still limited. We believe that the greatest value of pre-trained VLMs lies in building a bridge between visual and textual domains. In this paper, we propose a novel framework called **BIKE**, which utilizes the cross-modal bridge to explore bidirectional knowledge: i) We introduce the Video Attribute Association mechanism, which leverages the Video-to-Text knowledge to generate textual auxiliary attributes for complementing video recognition. ii) We also present a Temporal Concept Spotting mechanism that uses the Text-to-Video expertise to capture temporal saliency in a parameter-free manner, leading to enhanced video representation. Extensive studies on six popular video datasets, including Kinetics-400 & 600, UCF-101, HMDB-51, ActivityNet and Charades, show that our method achieves state-of-the-art performance in various recognition scenarios, such as general, zero-shot, and few-shot video recognition. Our best model achieves a state-of-the-art accuracy of 88.6% on the challenging Kinetics-400 using the released CLIP model. The code is available at <https://github.com/whwu95/BIKE>.

1. Introduction

In recent years, the remarkable success of large-scale pre-training in NLP (e.g., BERT [9], GPT [4, 38], ERNIE [69] and T5 [39]) has inspired the computer vision community. Vision-language models (VLMs) leverage large-scale noisy image-text pairs with weak correspondence for contrastive learning (e.g., CLIP [37], ALIGN [19], CoCa [65], Florence [66]), and demonstrate impressive transferability across a wide range of visual tasks.

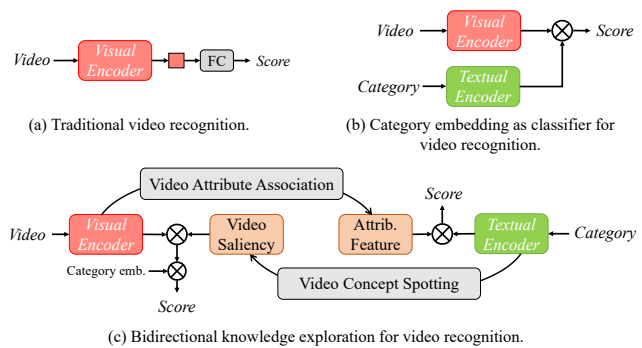


Figure 1. Illustration of the difference between our paradigm (c) with existing unimodality paradigm (a) and cross-modal paradigm (b). Please zoom in for the best view.

Naturally, transferring knowledge from such powerful pre-trained VLMs is emerging as a promising paradigm for building video recognition models. Currently, exploration in this field can be divided into two lines. As depicted in Figure 1(a), one approach [27, 35, 64] follows the traditional unimodal video recognition paradigm, initializing the video encoder with the pre-trained visual encoder of VLM. Conversely, the other approach [21, 34, 48, 58] directly transfers the entire VLM into a video-text learning framework that utilizes natural language (i.e., class names) as supervision, as shown in Figure 1(b). This leads to an question: *have we fully utilized the knowledge of VLMs for video recognition?*

In our opinion, the answer is No. The greatest charm of VLMs is their ability to build a bridge between the visual and textual domains. Despite this, previous research employing pre-aligned vision-text features of VLMs for video recognition has only utilized unidirectional video-to-text matching. In this paper, we aim to facilitate bidirectional knowledge exploration through the cross-modal bridge for enhanced video recognition. With this in mind, we mine Video-to-Text and Text-to-Video knowledge by 1) generating textual information from the input video and

2) utilizing category descriptions to extract valuable video-related signals.

In the first Video-to-Text direction, a common practice for mining VLM knowledge is to embed the input video and category description into a pre-aligned feature space, and then select the category that is closest to the video, as illustrated in Figure 1(b), which serves as our baseline. One further question naturally arises: *Can we incorporate auxiliary textual information for video recognition?* To address this question, we introduce an **Video-Attributes Association** mechanism, which leverages the zero-shot capability of VLMs to retrieve the most relevant phrases from a pre-defined lexicon for the video. These phrases are considered potential “attributes” of the video and can predict the video category directly. For example, a video of someone kicking a soccer ball may be associated with relevant phrases such as “running on the grass”, “juggling soccer ball” and “shooting goal”. Surprisingly, using only the generated attributes, we can achieve 69% top-1 accuracy on the challenging Kinetics-400 dataset. Furthermore, these attributes provide additional information that the video visual signal may not capture, allowing us to build an *Attributes Recognition Branch* for video recognition.

In the second Text-to-Video direction, we believe that temporal saliency in videos can be leveraged to improve video representations. For instance, in a video with the category “kicking soccer ball”, certain frames of kicking the ball should have higher saliency, while other frames that are unrelated to the category or background frames should have lower saliency. This insight motivates us to propose the **Video Concept Spotting** mechanism, which utilizes the cross-model bridge to generate category-dependent temporal saliency. In previous works [34, 48, 58], this intuitive exploration was disregarded. To be more specific, instead of treating each video frame equally, we use the correlation between each frame and the given concept (e.g., category) as a measure of frame-level saliency. This saliency is then used to temporally aggregate the frames, resulting in a compact video representation.

In the light of the above explorations, we propose **BIKE**, a simple yet effective framework via **BI**directional cross-modal **K**nowledge **E**xploration for enhanced video recognition. Our **BIKE** comprises two branches: the *Attributes branch*, which utilizes the **Video-Attributes Association** mechanism to introduce auxiliary attributes for complementary video recognition, and the *Video branch*, which uses the **Video Concept Spotting** mechanism to introduce temporal saliency to enhance video recognition. To demonstrate the effectiveness of our **BIKE**, we conduct comprehensive experiments on popular video datasets, including Kinetics-400 [22] & 600 [6], UCF-101 [43], HMDB-51 [24], ActivityNet [5] and Charades [41]. The results show that our method achieves state-of-the-art performance in most sce-

narios, e.g., general, zero-shot, and few-shot recognition.

Our main contributions can be summarized as follows:

- We propose a novel framework called **BIKE** that explores bidirectional knowledge from pre-trained vision-language models for video recognition.
- In the Video-to-Text direction, we introduce the **Video-Attributes Association** mechanism to generate extra attributes for complementary video recognition.
- In the Text-to-Video direction, we introduce the **Video Concept Spotting** mechanism to generate temporal saliency, which is used to yield the compact video representation for enhanced video recognition.

2. Methodology

An overview of our proposed **BIKE** is shown in Figure 2. We next elaborate on each component in more detail.

2.1. Preliminary: Video Recognition with VLM

In this section, we describe the typical cross-modal video recognition pipeline [21, 34, 48, 58] based on the pre-trained vision-language model (VLM). Given a video, we sample T frames from the video as input v . We also have a collection of categories $C = \{c_1, c_2, \dots, c_K\}$, where K is the number of classes. The goal of the video recognition task is to classify the video v into a category $c \in C$. Under the formulation of video recognition, the video v is encoded with a vision encoder $f(\cdot|\theta_v)$ to obtain the video embedding \mathbf{e}_v , and the category c is encoded with a text encoder $g(\cdot|\phi_c)$ to obtain the category embedding \mathbf{e}_c , where

$$\mathbf{e}_v = f(v|\theta_v), \mathbf{e}_c = g(c|\phi_c). \quad (1)$$

Finally, we obtain the similarity score S_V as follows:

$$S_V = s(\mathbf{e}_v, \mathbf{e}_c), \quad (2)$$

where $s(\cdot, \cdot)$ is the cosine similarity function. The objective during training is to maximize S_V if v and c are matched, and minimize it in all other cases. During inference, we compute the score between the video embedding and each category embedding, and choose the category with the highest S_V as the top-1 prediction. The parameter θ_v and ϕ_c of the video encoder and text encoder are initialized with weights from the pre-trained VLM (e.g., CLIP [37]). Throughout the rest of this work, we use the same notation.

2.2. Video-to-Text: Video-Attributes Association

First we focus on exploring Video-to-Text auxiliary signals. We present an *Attributes branch* as a complement to the regular *Video branch* in Sec. 2.1 for video recognition. **Pre-generated Attributes.** We begin by describing how to generate auxiliary attributes. As depicted in Figure 2(b), we

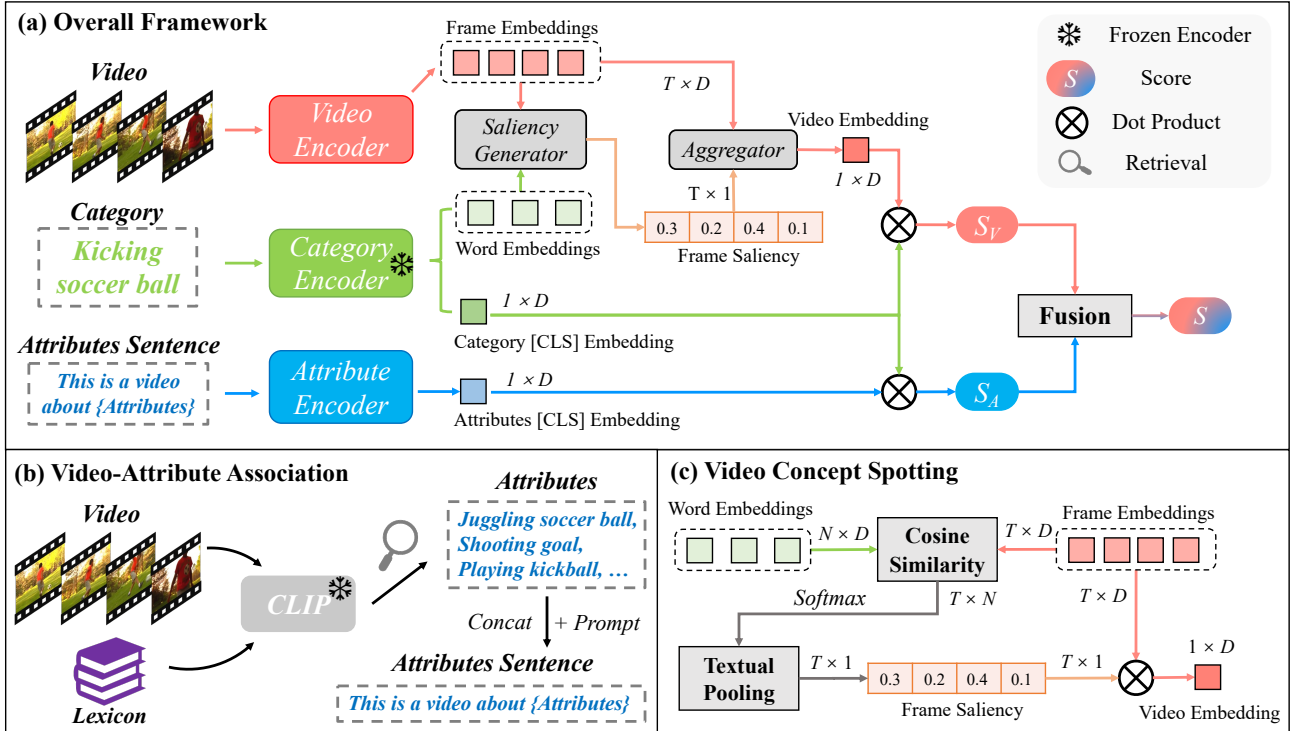


Figure 2. An overview of our **BIKE** for video recognition. (a) **BIKE** explores bidirectional cross-modal knowledge from the pre-trained vision-language model (e.g., CLIP) to introduce auxiliary attributes and category-dependent temporal saliency for improved video recognition. **BIKE** comprises an auxiliary *Attributes branch* and a main *Video branch*. (b) In the *Video-to-Text* direction, we present the **Video-Attribute Association** mechanism, which retrieves semantically relevant phrases from a pre-defined lexicon as video attributes for the input video. These attributes are concatenated and combined with a textual prefix to form an attribute sentence for text recognition. (c) In the *Text-to-Video* direction, we present the **Video Concept Spotting** mechanism, which computes the similarity between video frames and a given category as a measure of temporal saliency to enhance video representation. D is the dimension of embedding, T is the number of frames, and N is the number of words in the category name.

utilize the zero-shot capability of the VLM (e.g., CLIP [37]) to identify the most relevant phases from a pre-defined lexicon as possible “Attributes” of the video. To achieve this, we first apply the CLIP’s image encoder to the input video V to extract frame-level features. These features are then combined using average pooling to yield a video embedding. Next, we feed each phase in the pre-defined lexicon into the CLIP’s text encoder to produce a set of text embeddings. We then calculate the similarity between this video embedding and each text embedding, sort the results, and select the top few phrases as the “Attributes”. Once we have obtained the attributes, we employ a simple fusion method that concatenates them into a single attributes sentence a . We also add a manually-designed prompt as a prefix to the sentence, such as “This is a video about {”.

Attributes Recognition. As shown in Figure 2(a), the attributes sentence a is encoded with a text encoder $g(\cdot|\phi_a)$ to produce the attribute embedding e_a :

$$e_a = g(a|\phi_a). \quad (3)$$

We use this attribute embedding to perform *Attributes Recognition* by calculating the similarity S_A between the attribute embedding and category embeddings. Note that both the attribute sentence and categories are encoded using the same text encoder from CLIP. Interestingly, the *Attributes branch* can achieve a certain level of recognition performance (e.g., $\sim 56\%$) without any extra training, even though it’s a lightweight text recognition pipeline. During inference, we combine the well-trained *Video branch* with the plug-and-play *Attributes branch* using the following fusion equation:

$$S = \lambda S_V + (1 - \lambda) S_A, \quad (4)$$

where λ is the fusion weight. Without any additional training, the *Attributes Recognition* surprisingly improve the video recognition performance, e.g., $78.8\% \xrightarrow{+1.2\%} 80.0\%$ on the challenging Kinetics-400. Naturally, the text encoder $g(\cdot|\phi_a)$ can be further trained in an end-to-end manner to improve the *Attributes branch* and provide a stronger complementary capability, e.g., $78.8\% \xrightarrow{+2.6\%} 81.4\%$.

2.3. Text-to-Video: Video Concept Spotting

In Sec. 2.2, the Video-to-Text knowledge is employed to generate auxiliary attributes, thereby constructing a complementary *Attributes branch*. Naturally, we also conduct an exploration to leverage the Text-to-Video knowledge to enhance the standard *Video branch* for video recognition. Specifically, we propose the use of category-dependent temporal saliency to guide the temporal aggregation process, resulting in a compact video representation that enhances video recognition.

Background. To obtain a video representation based on a pre-trained image model, the typical pipeline involves two stages. First, we employ the image model to extract the spatial embedding of each frame. Next, the embeddings of these frames are temporally aggregated (e.g., mean pooling) to yield a video-level representation.

Parameter-Free Video Concept Spotting. Mean pooling is a widely used technique to aggregate the frame embeddings and obtain the final video representation. Instead of treating each video frame equally as in mean pooling, we propose a parameter-free solution that utilizes the pre-aligned visual and textual semantics offered by the VLM (e.g., CLIP [37]) to capture temporal saliency for video feature aggregation, as illustrated in Figure 2(c). To estimate temporal saliency, we employ word embeddings as the query to obtain finer word-to-frame saliency. Formally, the pre-trained VLM can encode each video or category name separately, and output two sets of embeddings: $\{\mathbf{v}_t \in \mathbb{R}^d | t = 1, 2, \dots, T\}$ is a set of frame embeddings, where T is the number of sampled frames, and $\{\mathbf{t}_n \in \mathbb{R}^d | n = 1, 2, \dots, N\}$ is a set of word embeddings, where N is the number of words in the class name. We calculate the similarity between each word and each frame to measure the fine-grained relevancy. After that, we perform a softmax operation to normalize the similarities for each frame, and then aggregate the similarities between a certain frame and different words to obtain a frame-level saliency.

$$\mathcal{S}_t = \frac{1}{N} \sum_{n=1}^N \frac{\exp(\mathbf{v}_t^\top \mathbf{t}_n / \tau)}{\sum_{t=1}^T \exp(\mathbf{v}_t^\top \mathbf{t}_n / \tau)}, t \in [1, T], n \in [1, N], \quad (5)$$

where τ is the temperature of this softmax function. See Figure 3 for the visualization of temporal saliency. Next, we utilize the temporal saliency to aggregate these frame embeddings as follows:

$$\mathbf{e}_v = \sum_{t=1}^T \mathbf{v}_t \mathcal{S}_t, \quad (6)$$

$\mathbf{e}_v \in \mathbb{R}^d$ is the final enhanced video representation.

2.4. Objectives of BIKE

We present the **BIKE** learning framework for video recognition, as depicted in Figure 2(a). Formally, our **BIKE** extracts feature representations \mathbf{e}_v , \mathbf{e}_a , and \mathbf{e}_c for a given video v , pre-generated attributes a , and category c with the corresponding encoders $f(\cdot | \theta_v)$, $g(\cdot | \phi_a)$, and $g(\cdot | \phi_c)$. Model parameters θ_v , θ_a , and θ_c are initialized with the weights from the pre-trained VLM (e.g., CLIP [37]). In this paper, we freeze the parameters of the pre-trained text encoder for $g(\cdot | \phi_c)$ and design extra manual prompts for the category c and attributes sentence a .

During the training phase, our objective is to ensure that the video representation \mathbf{e}_v and the category representation \mathbf{e}_c are similar when they are related and dissimilar when they are not, and the same applies to the attributes-category pairs. Given a batch of B quadruples $\{\mathbf{e}_{vi}, \mathbf{e}_{ai}, \mathbf{e}_{ci} \equiv C[y_i], y_i\}_{i=1}^B$, where C is the collection of K categories indexed by $y_i \in [0, K - 1]$ and y_i is a label indicating the index of the category in the dataset, and \mathbf{e}_{vi} , \mathbf{e}_{ai} , \mathbf{e}_{ci} denote the i -th video embedding, attributes embedding, and category embedding, respectively. We follow the common practice [21, 48] to consider the bidirectional learning objective and employ symmetric cross-entropy loss to maximize the similarity between matched *Video-Category* pairs and minimize the similarity for other pairs:

$$\begin{aligned} \mathcal{L}_{V2C} &= -\frac{1}{B} \sum_i \frac{1}{|\mathcal{K}(i)|} \sum_{k \in \mathcal{K}(i)} \log \frac{\exp(s(\mathbf{e}_{ci}, \mathbf{e}_{vk}) / \tau)}{\sum_j \exp(s(\mathbf{e}_{ci}, \mathbf{e}_{vj}) / \tau)}, \\ \mathcal{L}_{C2V} &= -\frac{1}{B} \sum_i \frac{1}{|\mathcal{K}(i)|} \sum_{k \in \mathcal{K}(i)} \log \frac{\exp(s(\mathbf{e}_{ck}, \mathbf{e}_{vi}) / \tau)}{\sum_j \exp(s(\mathbf{e}_{cj}, \mathbf{e}_{vi}) / \tau)}, \\ \mathcal{L}_V &= \frac{1}{2} (\mathcal{L}_{V2C} + \mathcal{L}_{C2V}), \end{aligned} \quad (7)$$

where $k \in \mathcal{K}(i) = \{k | k \in [1, B], y_k = y_i\}$, $s(\cdot, \cdot)$ is the cosine similarity, and τ refers to the temperature hyperparameter for scaling. Similarly, the loss for *Attributes branch* is formulated as:

$$\begin{aligned} \mathcal{L}_{A2C} &= -\frac{1}{B} \sum_i \frac{1}{|\mathcal{K}(i)|} \sum_{k \in \mathcal{K}(i)} \log \frac{\exp(s(\mathbf{e}_{ci}, \mathbf{e}_{ak}) / \tau)}{\sum_j \exp(s(\mathbf{e}_{ci}, \mathbf{e}_{aj}) / \tau)}, \\ \mathcal{L}_{C2A} &= -\frac{1}{B} \sum_i \frac{1}{|\mathcal{K}(i)|} \sum_{k \in \mathcal{K}(i)} \log \frac{\exp(s(\mathbf{e}_{ck}, \mathbf{e}_{ai}) / \tau)}{\sum_j \exp(s(\mathbf{e}_{cj}, \mathbf{e}_{ai}) / \tau)}, \\ \mathcal{L}_A &= \frac{1}{2} (\mathcal{L}_{A2C} + \mathcal{L}_{C2A}). \end{aligned} \quad (8)$$

The total loss \mathcal{L} is the sum of \mathcal{L}_V and \mathcal{L}_A :

$$\mathcal{L} = \mathcal{L}_V + \mathcal{L}_A. \quad (9)$$

For inference, we simply combine the similarity score of the two branches as Equation 4.

Method	Venue	Input	Pre-training	Top-1(%)	Top-5(%)	Views	FLOPs	Param
NL I3D-101 [49]	CVPR'18	128×224 ²	ImageNet-1K	77.7	93.3	10×3	359×30	61.8
MVFNet _{En} [54]	AAAI'21	24×224 ²	ImageNet-1K	79.1	93.8	10×3	188×30	-
TimeSformer-L [2]	ICML'21	96×224 ²	ImageNet-21K	80.7	94.7	1×3	2380×3	121.4
ViViT-L/16×2 [1]	ICCV'21	32×320 ²	ImageNet-21K	81.3	94.7	4×3	3992×12	310.8
VideoSwin-L [30]	CVPR'22	32×384 ²	ImageNet-21K	84.9	96.7	10×5	2107×50	200.0
<i>Methods with large-scale image pre-training</i>								
ViViT-L/16×2 [1]	ICCV'21	32×320 ²	JFT-300M	83.5	95.5	4×3	3992×12	310.8
ViViT-H/16×2 [1]	ICCV'21	32×224 ²	JFT-300M	84.8	95.8	4×3	8316×12	647.5
TokenLearner-L/10 [40]	NeurIPS'21	32×224 ²	JFT-300M	85.4	96.3	4×3	4076×12	450
MTV-H [63]	CVPR'22	32×224 ²	JFT-300M	85.8	96.6	4×3	3706×12	-
CoVeR [68]	arXiv'21	16×448 ²	JFT-300M	86.3	-	1×3	-	-
CoVeR [68]	arXiv'21	16×448 ²	JFT-3B	87.2	-	1×3	-	-
<i>Methods with large-scale image-language pre-training</i>								
CoCa ViT-giant [65]	arXiv'22	6×288 ²	JFT-3B+ALIGN-1.8B	88.9	-	-	-	2100
VideoPrompt ViT-B/16 [21]	ECCV'22	16×224 ²	WIT-400M	76.9	93.5	-	-	-
ActionCLIP ViT-B/16 [48]	arXiv'21	32×224 ²	WIT-400M	83.8	96.2	10×3	563×30	141.7
Florence [66]	arXiv'21	32×384 ²	FLD-900M	86.5	97.3	4×3	-	647
ST-Adapter ViT-L/14 [35]	NeurIPS'22	32×224 ²	WIT-400M	87.2	97.6	3×1	8248	-
AIM ViT-L/14 [64]	ICLR'23	32×224 ²	WIT-400M	87.5	97.7	3×1	11208	341
EVL ViT-L/14 [27]	ECCV'22	32×224 ²	WIT-400M	87.3	-	3×1	8088	-
EVL ViT-L/14 [27]	ECCV'22	32×336 ²	WIT-400M	87.7	-	3×1	18196	-
X-CLIP ViT-L/14 [34]	ECCV'22	16×336 ²	WIT-400M	87.7	97.4	4×3	3086×12	-
Text4Vis ViT-L/14 [58]	AAAI'23	32×336 ²	WIT-400M	87.8	97.6	1×3	3829×3	230.7
		16×224 ²		88.1	97.9	4×3	830×12	230
BIKE ViT-L/14	CVPR'23	8×336 ²	WIT-400M	88.3	98.1	4×3	932×12	230
		32×336 ²		88.6	98.3	4×3	3728×12	230

Table 1. Comparisons with state-of-the-art methods on Kinetics-400. We report the FLOPs in inference phase. “Views” indicates # temporal clip × # spatial crop. The magnitudes are Giga (10⁹) and Mega (10⁶) for FLOPs and Param.

3. Experiments

3.1. Setups

We conduct experiments on six widely used video benchmarks, *i.e.*, Kinetics-400 [22] & 600 [6], ActivityNet [5], Charades [41], UCF-101 [43] and HMDB-51 [24]. See Supplementary for statistics of these datasets.

Training & Inference. In our experiments, we adopt the visual encoder of CLIP [37] as the video encoder and use the textual encoder of CLIP for both the category and attributes encoders. To avoid conflict between the two branches, we first train the video encoder and then the attributes encoder. To prepare the video input, we sparsely sample T (*e.g.*, 8, 16, 32) frames. We set the temperature hyperparameter τ to 0.01 for all training phases. See Supplementary for detailed training hyperparameters.

To trade off accuracy and speed, we consider two evaluation protocols. (1) *Single View*: We use only 1 clip per video and the center crop for efficient evaluation, as shown in Table 6. (2) *Multiple Views*: It is a common practice [7, 14, 54] to sample multiple clips per video with several spatial crops to get higher accuracy. For comparison with SOTAs, we use

four clips with three crops (“4×3 Views”) in Table 1.

3.2. Main Results

Comparison with State-of-the-arts. We present our results on **Kinetics-400** in Table 1 and compare our approach with SOTAs trained under various pre-training settings. Our approach outperforms regular video recognition methods while requiring significantly less computation, as shown in the upper table. We also demonstrate superiority over methods that use web-scale image pre-training, such as JFT-300M [44] and JFT-3B [67]. Our model performs better than all JFT-300M pre-trained methods, achieving a higher accuracy (+2.3%) than CoVeR [68]. Surprisingly, our method even outperforms the JFT-3B pre-trained model (**88.6%** *v.s.* 87.2%) despite the latter having almost 3 billion annotated images and a data scale 7.5× larger than ours. We further compare our method with others using web-scale image-language pre-training, such as CLIP [37] and Florence [66]. Despite Florence having a larger dataset (2× more data than the 400M image-text data used in CLIP), our approach still achieves a higher accuracy by 2.1%. Additionally, using only 8 frames and the same CLIP pre-

Method	Top-1 mAP	
ListenToLook [17]	-	89.9
MARL [55]	85.7	90.1
DSANet [59]	-	90.5
TSQNet [60]	88.7	93.7
NSNet [61]	90.2	94.3
BIKE ViT-L	94.7	96.1

Table 2. Comparisons with SOTAs on ActivityNet.

Method	Frames	mAP
MultiScale TRN [71]	-	25.2
STM [20]	16	35.3
SlowFast R101 [14]	16+64	42.5
X3D-XL (312 \uparrow) [13]	16	43.4
ActionCLIP [48]	32	44.3
BIKE ViT-L	16	50.4

Table 3. Comparisons on Multi-label video dataset Charades.

Method	Shot	HMDB	UCF	ANet	K400
VideoSwin [30]	2	20.9	53.3	-	-
VideoPrompt [21]	5	56.6	79.5	-	58.5
X-Florence [34]	2	51.6	84.0	-	-
	1	72.3	95.2	86.6	73.5
BIKE ViT-L	2	73.5	96.1	88.7	75.7
	5	77.7	96.5	90.9	78.2

Table 4. Comparisons on few-shot action recognition across four video datasets.

Method	UCF* / UCF	HMDB* / HMDB	ActivityNet* / ActivityNet	Kinetics-600
GA [33]	17.3 \pm 1.1 / -	19.3 \pm 2.1 / -	-	-
TS-GCN [16]	34.2 \pm 3.1 / -	23.2 \pm 3.0 / -	-	-
E2E [3]	44.1 / 35.3	29.8 / 24.8	26.6 / 20.0	-
DASZL [23]	48.9 \pm 5.8 / -	- / -	-	-
ER [8]	51.8 \pm 2.9 / -	35.3 \pm 4.6 / -	-	42.1 \pm 1.4
ResT [26]	58.7 \pm 3.3 / 46.7	41.1 \pm 3.7 / 34.4	32.5 / 26.3	-
BIKE ViT-L	86.6\pm3.4 / 80.8	61.4\pm3.6 / 52.8	86.2\pm1.0 / 80.0	68.5\pm1.2

Table 5. Comparisons on zero-shot video recognition. * denotes randomly selecting half of the test dataset’s classes for evaluation, repeating the process ten times, and reporting the mean accuracy with standard deviation. For Kinetics-600, we adopt official code [8] to select the 220 new categories outside of Kinetics-400 for evaluation.

training, our model performs on par with the best results of other methods, such as EVL [27], X-CLIP [34], and Text4Vis [58]. When we use more frames as input, our method achieves a new state-of-the-art accuracy of 88.6% under the CLIP pre-training setting.

We also evaluate our method on the untrimmed video dataset, **ActivityNet-v1.3**, to verify its generalizability. We fine-tune the Kinetics-400 pre-trained model with 16 frames, and report the top-1 accuracy and mean average precision (mAP) using the official evaluation metrics. Our approach significantly outperforms recent SOTAs, as shown in Table 2. Furthermore, to demonstrate its effectiveness on smaller datasets, we also evaluate our method on **UCF-101** and **HMDB-51**, achieving top-1 accuracy of 98.8% and 83.1%, respectively. *We include the results in the Supplementary due to space limitations.*

Multi-Label Video Recognition. In addition to the single-label video recognition, we also evaluate our method on multi-label video recognition. We use the **Charades** dataset, which contains long-term activities with multiple actions, and utilize the Kinetics-400 pre-trained ViT-L backbone for training. The results are evaluated using the mAP metric. As shown in Table 3, our BIKE achieves the performance of 50.4% mAP, demonstrating its effectiveness in multi-label video classification.

Few-Shot Video Recognition. We demonstrate the few-shot recognition capability of our method, which refers to

video recognition using only a few training samples. In this experiment, we scaled up the task to categorize all categories in the dataset with only a few samples per category for training. We used a CLIP pre-trained ViT-L/14 with 8 frames for few-shot video recognition, without further Kinetics-400 pre-training. The top-1 accuracy on four datasets is reported in Table 4. Our method shows remarkable transferability to diverse domain data in a data-poor situation. On UCF-101 and HMDB-51, our method outperforms VideoSwin [30] by 42.8% and 52.6%, respectively. In comparison with image-language pre-trained methods, our method outperforms VideoPrompt [21] and X-Florence [34] by 21.1% and 21.9% on HMDB-51, respectively. *See Supplementary for training details.*

Zero-shot Video Recognition. We further evaluate our method in an open-set setting. Table 5 presents the results of zero-shot evaluation on four video datasets using our Kinetics-400 pre-trained model (*i.e.*, ViT-L/14 with 8 frames). There are two major evaluation methods on UCF-101, HMDB-51, and ActivityNet: half-classes evaluation (marked as *) and full-classes evaluation. For fair comparison, we present the results under the half-classes evaluation protocol, which has been widely used in previous works [3, 8, 26, 33]. Additionally, we provide results on the entire dataset for more challenging and realistic accuracy evaluation. *See Supplementary for further details on evaluation protocols.* Our method exhibits strong cross-

Video branch	$g(\cdot \phi_c)$	Top-1(%)	VCS Source	Recognition Source	Top-1	Attributes	Category	Top-1
Baseline: Mean Pool	🔒	76.8				✗	✗	46.2
+ Video Concept Spotting	🔒	78.5 (+1.7)	Word Emb.	Word Emb.	78.1	✓	✗	51.2
+ (Technique) Transf	🔒	78.7 (+1.9)	[CLS] Emb.	[CLS] Emb.	74.7	✓	✓	56.6
+ Frozen label encoder	🔒	78.9 (+2.1)	Word Emb.	[CLS] Emb.	78.5			

(a) The effectiveness of temporal saliency. 🔒 means finetuning category encoder $g(\cdot|\phi_c)$. Transf is the temporal transformer.

(b) Different category embeddings are used for Video Concept Spotting (VCS) and recognition.

(c) The effects of the textual prompt in *Attributes recognition branch* (w/o training).

#Attributes	A	V+A
3	53.4	79.9
5	56.6	80.0
7	57.1	79.7

(d) Study on different number of attributes (w/o training).

Training	A	V	$\xrightarrow{+\Delta\%}$	V+A
✗	56.6	78.9	$\xrightarrow{+1.1\%}$	80.0
✓	69.6	78.9	$\xrightarrow{+2.5\%}$	81.4

(e) The impact of *Attributes branch*. ✓ means fine-tuning the attributes encoder.

	V	$\xrightarrow{+\Delta\%}$	V+A
Baseline	76.8	$\xrightarrow{+2.4\%}$	79.2
Ours	78.9	$\xrightarrow{+2.5\%}$	81.4

(f) The effects of *Attributes branch* to complement *Video branch*.

Lexicon	V	$\xrightarrow{+\Delta\%}$	V+A
IN-1K	78.9	$\xrightarrow{+1.4\%}$	80.3
K400	78.9	$\xrightarrow{+2.5\%}$	81.4

(g) Study on the impact of different lexicon.

Method	T	Backbone	Top-1(%)
VideoPrompt [21]	16	ViT-B/32	76.9
ActionCLIP [48]	8	ViT-B/32	78.4
BIKE (Ours)	8	ViT-B/32	81.4 (+3.0)

(h) Comparison with CLIP-based methods using single-view inference. T is the number of frames.

Backbone	Baseline	\rightarrow V	\rightarrow V+A	V*	\rightarrow V*+A			
ViT-B/32	76.8	$\xrightarrow{+2.1\%}$	78.9	$\xrightarrow{+2.5\%}$	81.4	80.2	$\xrightarrow{+1.7\%}$	81.9
ViT-B/16	79.9	$\xrightarrow{+2.2\%}$	82.1	$\xrightarrow{+1.1\%}$	83.2	83.2	$\xrightarrow{+0.7\%}$	83.9
ViT-L/14	85.2	$\xrightarrow{+0.8\%}$	86.4	$\xrightarrow{+0.1\%}$	86.5	87.4	$\xrightarrow{+0\%}$	87.4

(i) Component-by-component evaluation of our approach using various backbones. Models are fed 8 frames, where * stands for multiple view inference.

Table 6. Ablation studies on Kinetics-400. Models use ViT-B/32 as the backbone, and 8 frames as input, unless otherwise specified. We report top-1 accuracy (%) for a single clip input with 224×224 spatial size. The V and A abbreviations are used for the *Video recognition branch* and *Attributes recognition branch*, respectively. We refer to ImageNet-1K and Kinetics-400 as IN-1K and K400, respectively.

dataset generalization ability and outperforms classic zero-shot video recognition methods.

3.3. Ablation Studies

In this section, we provide extensive ablations to demonstrate our method with the instantiation in Table 6.

The Effect of Temporal Saliency. We investigate the impact of our proposed *Video Concept Spotting* (VCS) mechanism on the performance of the *Video branch*, as shown in Table 6a. We start with a baseline that uses mean pooling to aggregate the features of all frames, without considering temporal saliency. We observe that equipping the baseline with VCS can improve the accuracy by +1.7%. We then introduce a multi-layer (e.g., 6-layers) Transformer encoder with position embedding for sequence features, commonly used in previous methods, and find that it provides an additional 0.2% performance boost. Moreover, freezing the category encoder not only reduces training parameters but also slightly improves performance (+0.2%).

Exploration of Category Embedding for Temporal Saliency and Classification. As mentioned in Section 2.3, CLIP’s textual encoder can generate two types of embeddings: the [CLS] embedding for the entire sentence and the word embedding for each word. Therefore, we can encode the category into these two types of embeddings. The category embedding has two roles in our method: 1) it serves as

a query to determine the temporal saliency, and 2) it calculates similarity with video representation to produce recognition results. We demonstrate the results for three different combinations in Table 6b. We find that the global [CLS] embedding performs better than the word-level embedding for final recognition, but the word-level embedding is necessary for temporal saliency.

Prompt Engineering and Number of Attributes. For both attributes and categories in the *Attributes recognition branch*, we manually define a prompt, i.e., “This is a video about { }”. The results in Table 6c show that the prompt significantly improves accuracy, even without training the attributes encoder. Furthermore, in Table 6d, we observe that the number of attributes has little effect on the performance of the *Attributes recognition* and two-branch recognition.

The Impact of Attributes branch. Table 6e shows that without any training, the *Attributes branch* can be plug-and-played on the *Video branch* to improve the recognition performance. After training the attributes encoder, the *Attributes branch* further boosts performance by an impressive 2.5% on the fusion result. Additionally, we find that the *Attributes branch* can also improve the baseline when fused with it, as shown in Table 6f. By combining the VCS and the *Attributes branch*, we can achieve a remarkable improvement of 4.6% on the baseline.

Attributes Generation with Different Lexicons. In

Sec. 2.2, we use a pre-defined lexicon to obtain attributes. In Table 6g, we explore the impact of different lexicons. We used ImageNet-1K, an image dataset that covers 1000 object categories, as our lexicon to search for potential object attributes. According to the results, this can increase the performance of the *Attributes branch* by 1.4%. We found that using the 400 categories of Kinetics-400 as the lexicon can further improve the results.

Comparison with CLIP-Based Methods. Table 6h presents a comparison between our method and two CLIP-based approaches, VideoPrompt [21] and ActionCLIP [48], both trained with contrastive loss. Despite using fewer frames, our method achieves higher Top-1 accuracy than VideoPrompt. Moreover, using the same ViT-B/32 backbone, our approach outperforms ActionCLIP by 3.0%.

More Evaluation with Different Backbones. Table 6i presents a comprehensive evaluation of the applicability of our method using larger backbones. Our observations are as follows: 1) Despite the greatly improved performance of the baseline with larger backbones, our VCS mechanism still provides consistent, additional gains. This demonstrates the continued necessity of Text-to-Video saliency knowledge for large models. 2) As the absolute accuracy of the *Video branch* increases, the complementing effect of the *Attributes branch* gradually weakens. We conjecture that with larger models, richer representations are learned, leading to reduced bias in learned representations and an increased correlation with the *Attributes branch*, resulting in a reduction in complementary information. 3) Multiple-view evaluation involving more video clips leads to increased performance, reducing the bias of the model itself. For models with a top-1 accuracy of 87.4%, the *Attributes branch* is unable to provide supplementary knowledge. Therefore, the *Attributes branch* is not utilized in our ViT-L/14 models presented in Sec. 3.2.

3.4. Visualization

Figure 3 illustrates the temporal saliency generated by Video Concept Spotting mechanism, highlighting the frame that is most relevant to the category. We also demonstrate the complementarity of the auxiliary attributes generated by our Video-Attribute Association mechanism with the video branch. *See more qualitative results in Supplementary.*

4. Related Works

Video Recognition. Convolutional networks have been the standard backbone architecture in video recognition for a long time. Early works focused on jointly learning spatial and temporal context through parallel branches [14, 15, 42, 47, 50, 52]. Later works developed plug-and-play temporal modules [25, 29, 31, 36, 45, 46, 54, 59, 62] for 2D CNN backbones to improve temporal modeling. Some works also designed dynamic inference mechanisms [51, 53, 55, 56, 60, 61]

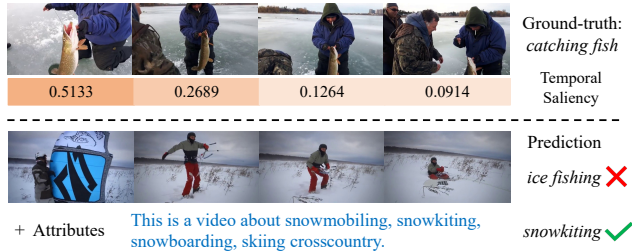


Figure 3. Visualization of (Top) temporal saliency and (Bottom) attributes. Please zoom in for the best view.

for efficient video recognition. Recently, Vision Transformers [10, 18, 28] has emerged as a new trend in image recognition backbones. Transformers have also been adopted for video recognition, such as TimeSFormer [2], ViViT [1], VideoSwin [30], and MViT [11].

Transferring CLIP Models for Video Recognition. CLIP [37] provides good practice in learning the coordinated vision-language models using large-scale image and text pairs. The pre-trained model can learn powerful visual representations aligned with rich linguistic semantics. Initially, some works [12, 32, 57, 70] propose to directly use CLIP for video-text retrieval. Later, a few works also explore the use of CLIP models for video recognition [21, 27, 34, 35, 48, 58, 64], they can be broadly categorized into two lines. The first line [27, 35, 64] follows the unimodal transferring paradigm, where the image encoder of CLIP is used as a strong initialization for the video encoder. The second line [21, 34, 48, 58] provides cross-model learning baselines that directly extend CLIP to video-label matching for video recognition. However, these studies only briefly tap into the knowledge from CLIP. In contrast, our work aims to further explore the bidirectional cross-modal knowledge from CLIP to enhance the cross-model baseline. Our approach introduces auxiliary attributes in the Video-to-Text direction and category-dependent temporal saliency in the Text-to-Video direction, resulting in a more effective and interpretable video recognition.

5. Conclusion

In this work, we introduce a novel two-stream framework called **BIKE** that leverages bidirectional cross-modal knowledge from CLIP models to enhance video recognition. Our approach involves the *Attributes branch*, which utilizes the **Attributes-Category Association** mechanism to generate attributes for auxiliary recognition, and the *Video branch*, which uses the **Video Concept Spotting** mechanism to generate temporal saliency and produce a more compact video representation. Our approach is evaluated on six video datasets, and the experimental results demonstrate its effectiveness.

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