Multimodal Open-Vocabulary Video Classification via Pre-Trained Vision and Language Models

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Abstract
Utilizing vision and language models (VLMs) pre-trained on large-scale image-text pairs is becoming a promising paradigm for open-vocabulary visual recognition. In this work, we extend this paradigm by leveraging motion and audio that naturally exist in video. We present MOV, a simple yet effective method for Multimodal Open-Vocabulary video classification. In MOV, we directly use the vision encoder from pre-trained VLMs with minimal modifications to encode video, optical flow and audio spectrogram. We design a cross-modal fusion mechanism to aggregate complimentary multimodal information. Experiments on Kinetics-700 and VGGSound show that introducing flow or audio modality brings large performance gains over the pre-trained VLM and existing methods. Specifically, MOV greatly improves the accuracy on base classes, while generalizes better on novel classes. MOV achieves state-of-the-art results on UCF and HMDB zero-shot video classification benchmarks, significantly outperforming both traditional zero-shot methods and recent methods based on VLMs. Code and models will be released.

1 Introduction
Building open-vocabulary models capable of predicting novel visual concepts beyond a fixed set of training classes is of crucial importance in computer vision. Recently, vision and language models (VLMs) that are jointly trained on large-scale image-text pairs, e.g., CLIP [57] and ALIGNS [32], demonstrate impressive transferability on a wide range of visual recognition tasks. Utilizing such strong pre-trained VLMs is becoming a promising paradigm for building open-vocabulary models. Examples include open-vocabulary object detection [23] and image segmentation [21, 41].

In this work, we focus on the challenging task of open-vocabulary video classification via pre-trained vision and language models. We set up open-vocabulary video benchmarks by utilizing two existing large-scale video classification datasets: Kinetics-700 [4] and VGGSound [6]. Concretely, we construct two sets of classes: base and novel. For base classes, we have access to both training and testing videos, which aims at helping the pre-trained VLMs adapt to the video domain. While for novel classes, we only have testing videos, mimicking the real-world challenge of open-vocabulary video classification.

We start with directly fine-tuning the pre-trained CLIP [57], a representative vision and language model, using the training videos from base classes. As shown in Fig. 1a and 1b, we observe that although there is a decent performance improvement on base classes, the accuracy on novel classes decreases significantly. This finding aligns with some recent work studying the generalization of adapting pre-trained VLMs [78].

On the other hand, despite the rich multimodal contents in internet videos, signals such as audio and motion are less explored in recent open-vocabulary models. This is in stark contrast with human

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We conduct extensive experiments and ablation studies on two representative multimodal video datasets: Kinetics-700 [4] and VGGSound [6]. MOV shows clear improvements over CLIP as well as recent VLM adaptation methods [77, 19] on both base and novel classes. MOV also achieves state-of-the-art results on UCF and HMDB zero-shot video classification benchmarks, significantly outperforming both traditional zero-shot methods and recent methods based on VLMs. Furthermore, MOV is scalable with much stronger backbones, indicating its potentials to be incorporated with giant vision and language models.

2 Related work

Vision and language models. Learning a joint embedding space from vision and language modalities has been extensively investigated during the past decade. Early works usually first encode two modalities separately, using hand-crafted descriptors [12] or deep networks [39] for image, and skip-gram text models for language [16]. The cross-modality alignment is then achieved by metric learning [16] or language concepts [40]. Recently, learning vision and language modalities jointly through contrastive learning [24, 53] becomes a promising direction. Impressive performance has been achieved by utilizing stronger encoders for vision [11], language [64] and web-scale pre-training data [31, 57]. CLIP [32] and ALIGN [57] are two representative approaches which shows strong zero-shot performance on various downstream tasks. Despite this strong baseline, adapting

\footnote{We use the term “zero-shot” when we need to align with settings described in some existing works. Otherwise, we would use “open-vocabulary” which we believe is a more precise term.}
pre-trained VLMS to specific vision domains in a more effective way remains critical and is being actively studied. Examples include image classification [77, 78, 19], object detection [23], image segmentation [21, 41] and video action recognition [66, 33]. Our method extends the existing research by adapting pre-trained VLMS to multimodal video and investigating the impact of additional input modalities like flow and audio.

Open-vocabulary video classification. Zero-shot or open-vocabulary video action recognition is a representative task in this domain. Similar to early works of vision and language learning, the video input and labeled texts are encoded with modality-specific pre-trained models such as S3D [70], R(2+1)D [63] for video, Word2Vec [50] for text. Since the generated video and text embeddings are not aligned, various methods have been proposed to bridge the gap by mapping two modalities into a joint embedding space [67, 7, 17, 68, 72, 79], mapping vision modality to language space [2, 3, 25, 71] or mapping language modality to vision space [46, 76]. These joint embedding mapping methods are further extended to audiovisual classification [48, 47, 54]. Our approach shows that we can improve the performance of open-vocabulary video classification by leveraging strong pre-trained VLMS and other modalities like flow and audio.

Multimodal fusion for video. Video is a natural source of multimodal data including motion and audio. Two-stream networks is used to model video and optical flow simultaneously for action classification [58, 65, 15, 14]. Late fusion is adopted [58, 65] and then thoroughly studied [15, 14] on how to better perform spatio-temporal fusion from two modalities. As in the domain of audiovisual fusion, early methods [8] usually adopt straightforward score fusion or stacking input data for early fusion. Later research [36, 69, 13, 52] focus on developing better mid or late fusion strategies to improve the final performance. Different from existing works focusing on a fixed set of classes, we use multimodal fusion to help open-vocabulary models generalize better to novel classes.

3 Methods

An overview of our proposed method is shown in Fig. 2. We next describe each component.
3.1 Modality-Specific Encoding

Given a pre-trained vision and language model, e.g., CLIP [57], we denote its vision encoder as $h_v(\cdot|\theta_v)$ and its language encoder as $g(\cdot|\theta_a)$. For a multimodal video input, we sample $N$ RGB frames $V$ and calculate the corresponding optical flow images $F$, resulting in $V = \{v_1, v_2, \ldots, v_N\}$ and $F = \{f_1, f_2, \ldots, f_N\}$. We also generate the spectrogram image $A$ from the raw audio waveform. More implementation details can be found in Sec. 4. We use the same encoder architecture $h_v(\cdot|\theta_v)$ to extract feature representations for video, flow and audio modalities, denoted as $h_v(\cdot|\theta_v)$, $h_f(\cdot|\theta_f)$, and $h_a(\cdot|\theta_a)$ respectively. Model parameters $\theta_v$, $\theta_f$ and $\theta_a$ are all initialized with the weight $\theta_h$ from the pre-trained VLM. We encode each modality separately as:

$$v = h_v(V|\theta_v), \quad f = h_f(F|\theta_f), \quad a = h_a(A|\theta_a),$$  \hspace{1cm} (1)

where $v$ and $f$ are features from $N$ frames, and $a$ is the representation of a single spectrogram image.

To better aggregate the temporal features of video and flow modalities, we attach temporal fusion networks $\phi_v(\cdot)$ and $\phi_f(\cdot)$, consisting of $L$ transformer layers each, on top of $h_v(\cdot|\theta_v)$ and $h_f(\cdot|\theta_f)$. We denote the input of the $l$-th transformer layer as $z^l$ and the input $z^0$ can be either $v$ or $f$. Then the forward pass of the $l$-th layer in $\phi_v(\cdot)$ and $\phi_f(\cdot)$ can be formulated as:

$$y^l = MSA(LN(z^l)) + z^l,$$  \hspace{1cm} (2)

$$z^{l+1} = MLP(LN(y^l)) + y^l,$$  \hspace{1cm} (3)

where LN stands for layer normalization, MSA represents multi-head self-attention, and MLP means multi-layer perceptron. For audio feature $a$, we simply attach an MLP module upon the backbone. We obtain the temporally fused features as:

$$v_t = \phi_v(v), \quad f_t = \phi_f(f), \quad a_t = MLP(a).$$  \hspace{1cm} (4)

Finally, for the text modality, suppose we have $p$ base classes with labels. We fill each of the class names into $28$ video classification prompts provided by CLIP [57] like “a video of a person doing \{class name\}” and then encode the sentence using the pre-trained language encoder $g(\cdot|\theta_a)$ from VLM. The embedding of each class is averaged over all templates and we denote as $\{B_i\}_{i=1}^p$.

3.2 Multimodal Fusion

We adopt a cross-attention mechanism to leverage multimodal features. Note that despite we can encode all modalities simultaneously, existing video benchmarks usually only contain two most informative modalities, e.g. video and flow for action classification, video and audio for audiovisual classification. Thus our algorithm described here is for fusing one of \{flow, audio\} modality with video modality, as shown in Fig. 2.

For the video modality, we extract the information from other modalities to enhance the performance of video feature. Thus we use $v_t$ as the input for attention query, and $f_t$ or $a_t$ from the other modality as the input for attention key and value. The fused multimodal video feature $v_m$ can be written as:

$$v_t = MCA(LN(v_t), LN(x_t)) + v_t, \quad x_t \in \{f_t, a_t\},$$  \hspace{1cm} (5)

$$v_m = \text{AvgPool}(MLP(LN(v_t)) + v_t),$$  \hspace{1cm} (6)

where MCA denotes multi-head cross-attention, AvgPool denotes temporal average pooling.

For the audio and flow modalities, we aim at incorporating the information from video modality to enhance the generalization ability of the feature. Since the parameters of the temporal fusion network $\phi_v(\cdot)$ for generating the video feature $v_t$ are still trained from scratch on base classes, we choose to directly use the backbone’s output $v$ instead of $v_t$ for better generalization on novel classes. We obtain the fused multimodal flow and audio feature $f_m$ and $a_m$ as:

$$f_t = MCA(LN(f_t), LN(v)) + f_t, \quad a_t = MCA(LN(a_t), LN(v)) + a_t,$$  \hspace{1cm} (7)

$$f_m = \text{AvgPool}(MLP(LN(f_t)) + f_t), \quad a_m = \text{AvgPool}(MLP(LN(a_t)) + a_t).$$  \hspace{1cm} (8)
3.3 Training and Inference on Base Classes

During training, each input multimodal video has a corresponding label \( y \) belonging to the base classes. We would optimize different modalities simultaneously via calculating the video-to-text, flow-to-text and audio-to-text similarity. The training loss function can be formulated as:

\[
L = \alpha \left( -\log \frac{\exp(\text{sim}(v_m, B_y)/\tau)}{\sum_{i=1}^P \exp(\text{sim}(v_m, B_i)/\tau)} \right) + (1 - \alpha)\left( -\log \frac{\exp(\text{sim}(x_m, B_y)/\tau)}{\sum_{i=1}^P \exp(\text{sim}(x_m, B_i)/\tau)} \right), \tag{9}
\]

where \( x_m \in \{f_m, a_m\} \), \( \alpha \) is the weight for balancing two loss terms, \( \text{sim}(\cdot, \cdot) \) is the cosine similarity, \( \tau \) is a pre-defined temperature parameter. During training, we freeze the video encoder and the text encoder to save computation and speed up the training, while for the other two modalities flow and audio, we fine-tune the whole encoder end-to-end. An ablation study on fine-tuning different number of layers can be found in Tab. 6.

For inference on base classes, we compute the probability belonging to the \( j \)-th class by:

\[
P(j) = \frac{\exp(\text{sim}(v_m, B_j)/\tau)}{\sum_{i=1}^P \exp(\text{sim}(v_m, B_i)/\tau)}, \quad j \in \{1, 2, \ldots, p\}. \tag{10}
\]

3.4 Generalization to Novel Classes

Similar to base classes, we obtain the text embeddings for novel classes as \( \{N_j\}^q_{i=1} \), where \( q \) is the number of novel classes. In addition to fused features \( f_m \) or \( a_m \), we also incorporate the video feature \( v \) extracted from the frozen video backbone, followed by a temporal average pooling. Similar to Eq. 10, we compute the probability predictions as (here we only show flow modality for simplicity):

\[
P_f(j) = \frac{\exp(\text{sim}(f_m, N_j)/\tau_f)}{\sum_{i=1}^q \exp(\text{sim}(f_m, N_i)/\tau_f)}, \quad P_v(j) = \frac{\exp(\text{sim}(v, N_j)/(\tau_v))}{\sum_{i=1}^q \exp(\text{sim}(v, N_i)/(\tau_v))}, \quad j \in \{1, 2, \ldots, q\}. \tag{11}
\]

We denote the probability distribution followed by \( \{p_f(j)\}^q_{j=1} \) and \( \{p_v(j)\}^q_{j=1} \) as \( D_f \) and \( D_v \). In our experiments we find the curve of \( D_v \) tends to be much flatter (or have higher information entropy) than \( D_f \) when the temperatures \( \tau_v \) and \( \tau_f \) are both set to the CLIP’s default value of 0.01, resulting in poor performance. We find simply setting \( \tau_v \) to 0.003 while keeping \( \tau_f \) and \( \tau_v \) as 0.01 solves this issue. A detailed ablation study about the temperature can be found in Appendix A.

The final probability predictions for novel classes are calculated by a weighted sum:

\[
P(j) = \beta P_f(j) + (1 - \beta)P_v(j). \tag{12}
\]

4 Experiments

4.1 Data

We describe the details of dataset splits for benchmarking multimodal open-vocabulary video classification and preparing flow and audio modalities.

**Kinetics-700** [4] splits. Kinetics-700 contains around 650k video clips annotated with 700 human action classes. Apart from the visual modality, the optical flow modality plays an important role for distinguishing different action classes. For dataset split, we randomly select 400 classes as base classes and the testing videos of the rest 300 classes are used for novel classes evaluation.

**Kinetics-700 optical flow.** We follow a standard procedure [70, 26, 27] to use the TV-L1 algorithm [75] to extract optical flow in an unsupervised manner. To accommodate for pre-trained vision encoders, we first truncate the vertical and horizontal motion values to \([-20, 20]\), then append a third all-zero channel. Finally we do a shift and scale transformation to map \([-20, 20]\) to \([0, 255]\).

**VGGSound** [6] splits. VGGSound contains around 200k video clips belonging to a total number of 309 classes. Different from other audiovisual datasets like AudioSet [20], VGGSound ensures the source of the sound is visually present inside the same video. Thus we consider this dataset as an excellent test bed for our proposed method. We randomly select 154 base classes for training and leave the rest 155 classes for novel classes evaluation.
VGGSound audio spectrogram. We follow the pre-processing practice of audio spectrogram transformer (AST) [22] to convert waveforms to spectrogram images. First, the raw audio signal is re-sampled to 16kHz and converted to mono channel. We then calculate the log mel spectrogram with 128 frequency bins. The processing Hamming window is 25ms with a hop length set to 10ms. For \( t \) second audio input, the generated 2D spectrogram would have the shape of \( 128 \times 100 t \). We normalize the spectrogram by subtracting the mean pixel value and dividing the standard deviation.

4.2 Implementation

Data augmentation and tokenization. For video, we first randomly sample 16 frames with a stride of 4 from the whole video sequence. We then apply the standard image augmentation used on ImageNet [28, 29] with same augmentation parameters across all frames to keep temporal consistency [56]. For optical flow, we follow the practice of [70, 26, 27] by directly treating it as images and apply the same augmentation with the video. The augmented output tensors have the shape of \((16, 224, 224, 3)\) from both modalities which can be directly fed into CLIP’s vision encoder [57]. For audio, we apply specialized augmentations designed for spectrogram following [22, 52]. As the videos in VGGSound are all 10-second long, the generated spectrogram has a shape of \((128, 100 \times 10)\). We first conduct a random cropping of \((128, 800)\), sampling all frequency bands with a time duration of 8 seconds. SpecAugment [55] is applied subsequently with a time masking range of 192 frames and frequency masking of 48 bins. Finally, to accommodate this single channel output with the pre-trained tokenization layer, we make two necessary changes following [22]: 1) expanding the spectrogram to three duplicated channels, 2) bilinearly interpolating the original positional encoding for spectrogram images with a different resolution.

Network architecture. We adopt CLIP’s ViT-B/16 encoder for video, flow, and audio and the transformer encoder for text. We stack 2 transformer layers for temporal fusion, with an embedding dimension of 512 and 8 attention heads. For the cross-attention head, we use 1 transformer decoder layer with 8 attention heads and an embedding dimension of 512. Query and key-value inputs use separate layer normalization.

Training hyper-parameters. We set all hyper-parameters except for train epochs same for experiments on Kinetics-700 and VGGSound. We use a batch size of 1024 on 128 Cloud TPUv3 cores, AdamW [45] optimizer with a weight decay of 0.05 and an initial learning rate of 1e-4 followed by half-cosine decay [29]. We set the weight \( \alpha \) in Eq. 9 as 0.5. We train 100 epochs on Kinetics-700 and 20 epochs on VGGSound since we observe an overfitting issue with audio modality when trained longer.

Inference hyper-parameters. During inference, for video and flow, we use \( 4 \times 3 \) views following [1, 44] where a video is uniformly sampled into 4 clips temporally, and 3 spatial crops are conducted for each clip. For audio, we use 12 temporal views without spatial cropping. The final score is averaged over 12 views. For novel classes, we set the weight \( \beta \) in Eq. 12 to 0.25.

4.3 Multimodal Open-Vocabulary Video Classification

We evaluate MOV on Kinetics-700 to utilize modalities of video, optical flow and text, and on VGGSound to explore the combination of video, audio, and text.

Comparison baselines. We compare with three baselines: 1) CLIP [57], which directly encodes the video and class names into embeddings with pre-trained encoders. The final prediction is given by comparing similarity scores between video and text embeddings; 2) CoOp [77], which learns continuous text prompt embeddings instead of manually selected templates for better adaptation to downstream tasks; 3) CLIP-Adapter [19], which attaches adapter heads to both video and text encoder. We use the same data, backbone and hyper-parameters as ours introduced in Sec. 4.2 to train (CLIP doesn’t require training) and evaluate all methods.

Results. Tab. 1 shows results on Kinetics-700. We can see that both CoOp and CLIP-Adapter achieve better performance than CLIP on base class prediction. While for novel classes, we observe a large accuracy drop compared with CLIP. The worse performance in harmonic mean of these two methods indicates the loss of the generalization ability outweigh their improvements on base classes. Our proposed MOV shows better performance on base classes, demonstrating the effectiveness of
Table 1: **Open-vocabulary video classification on Kinetics-700** [4]. Modalities are V: Vision, F: Optical Flow and T: Text. MOV obtains the best performance on both base and novel classes, surpassing CLIP [57] by 24.1 and 1.4, respectively.

| method             | modalities | base acc. | novel acc. | harmonic mean |
|--------------------|------------|-----------|------------|---------------|
| CLIP [57]          | V, T       | 51.2      | 56.7       | 53.8          |
| CoOp [77]          | V, T       | 58.9      | 45.7       | 51.5          |
| CLIP-Adapter [19]  | V, T       | 66.5      | 36.2       | 46.9          |
| MOV                | V, F, T    | 75.3      | 58.1       | 65.6          |

Table 2: **Open-vocabulary video classification on VGGSound** [6]. Modalities are V: Vision, A: Audio and T: Text. MOV achieves the best performance on both base and novel classes, surpassing CLIP [57] by 19.9 and 2.7, respectively.

We observe similar trends in experiments on VGGSound in Tab. 2. CoOp and CLIP-Adapter gain improvement in base classes but fail to generalize to novel classes, resulting in a lower harmonic mean of accuracy compared to the CLIP baseline. It is worth noticing that MOV, when fused with the rich audio modality information, shows a 2.7% improvement on novel classes compared with CLIP.

**Backbone scaling.** It is also important to investigate the scalability of MOV with stronger backbones. We experiment with the largest ViT-L/14 model released by CLIP as the vision encoder and a text encoder with embedding dimension increased to 768 and attention heads increased to 12. ViT-L/14 contains $3 \times$ more parameters than ViT-B/16 and we observe around 8% improvement on direct CLIP zero-shot evaluation on Kinetics-700 and 5% improvement on VGGSound, as indicated by results in row 1 and 3 in Tab. 3. Despite this much stronger baseline, MOV still improves 20.5% and 1.6% on Kinetics-700, 19.3% and 2.0% on VGGSound, when compared with row 3 and 4. The nice scaling performance shows that MOV has a great potential to be incorporated into recent giant vision and language models [74, 73].

| method             | backbone | Kinetics-700 base acc. | Kinetics-700 novel acc. | VGGSound base acc. | VGGSound novel acc. |
|--------------------|----------|------------------------|------------------------|-------------------|----------------------|
| CLIP [57]          | ViT-B/16 | 51.2                   | 56.7                   | 48.5              | 48.8                 |
| MOV                | ViT-B/16 | 75.3                   | 58.1                   | 68.4              | 51.5                 |
| CLIP [57]          | ViT-L/14 | 59.6                   | 65.3                   | 52.6              | 34.1                 |
| MOV                | ViT-L/14 | 80.1                   | 66.9                   | 71.9              | 56.1                 |

Table 3: **Scalability of MOV.** MOV scales well with a stronger ViT-L/14 backbone.

### 4.4 Cross-Dataset Transfer

Pre-training an open-vocabulary or zero-shot video classification model on large datasets like Kinetics [4], ImageNet [9] or Sports-1M [34] and evaluating on UCF101 [60] and HMDB51 [38] is the most common paradigm in the literature. Following [3], there are two major evaluation settings. The first is randomly choosing half of the test dataset’s classes and evaluate on the selected subset. To avoid fluctuations brought by randomness, the evaluation is conducted independently for 10 times and we report the mean accuracy with standard deviation from all trials. We donate this setting as UCF$^\dagger$ and HMDB$^\dagger$ in Tab. 4. The second evaluation setting is directly evaluating on the whole dataset,
Table 4: Cross-dataset transfer on UCF and HMDB. We directly evaluate our proposed MOV without any additional training on two classic video action classification benchmarks. In pre-train data, IN is in short for ImageNet. For the text, BERT-ED means BERT [10] encoding of elaborated descriptions collected from Wiki/Diction/WordNet. MOV shows the best performance compared with classic zero-shot video classification methods, as well as CLIP and ActionCLIP, demonstrating a strong cross-dataset generalization ability.

| method       | encoder | pre-train data | text | UCF / UCF | HMDB / HMDB |
|--------------|---------|----------------|------|------------|-------------|
| GA [51]      | C3D [62]| S1M [34]       | W2V  [50]| 17.3±1.1 / - | 19.3±2.1 / - |
| TARN [2]     | C3D [62]| S1M [34]       | W2V  [50]| 19.0±2.3 / - | 19.5±4.2 / - |
| C1WEGAN [46] | I3D [5]| IN, K400 [35]  | W2V  [50]| 26.9±2.8 / - | 30.2±2.7 / - |
| TS-GCN [17]  | GLNet [61]| IN-shuffle [49]| W2V  [50]| 34.2±3.1 / - | 23.2±3.0 / - |
| PS-GNN [18]  | GLNet [61]| IN-shuffle [49]| W2V  [50]| 36.1±4.8 / - | 25.9±4.1 / - |
| E2E [3]      | R(l+1)D [63]| K700 [4]     | W2V  [50]| 48.0 / 35.3 | 32.7 / 24.8 |
| DASZL [37]   | TSM [43]| IN, K400 [35]  | Attributes| 48.9±5.8 / - | - / - |
| ER [7]       | TSM [43]| IN, K400 [35]  | BERT-ED| 51.8±2.9 / - | 35.3±4.6 / - |
| ResT [42]    | RN101 [28]| K700 [4]     | W2V  [50]| 58.7±3.3 / 40.6 | 41.1±3.7 / 34.4 |
| CLIP [57]    | ViT-B/16 [71]| Web [57]    | TSF [64]| 79.9±3.8 / 73.0 | 54.0±4.1 / 46.1 |
| ActionCLIP [66]| ViT-B/16 [11]| Web [57]    | TSF [64]| 82.6±4.1 / 76.2 | 60.8±2.8 / 52.1 |
| MOV          | ViT-L/14 [11]| Web [57]    | TSF [64]| 87.1±3.2 / 80.9 | 64.7±3.2 / 57.8 |

Table 5: Ablation on multimodal fusion. Multimodal fusion improves the performance of using single modality, and the proposed cross-attention mechanism works better than score fusion.

4.5 Ablation Study

Single modality and fusion. We conduct experiments with single modality to understand the capability of each modality as well as the relative improvement brought by different fusion strategies. Results are in Tab. 5. For Kinetics-700, simply using the optical flow as input obtains 54.2% on base classes and 16.8% on novel classes. When using score fusion, compared with video modality, we observe an improvement of 1.2% on novel classes but identical performance on base classes. Equipped with the proposed cross-attention fusion mechanism, we obtain 2.6% improvement on base classes, and 3.5% on novel classes. For VGGSound, the performance of audio only is quite close to video only and the score fusion works quite well for base classes with a 6.5% improvement. Cross-attention further improves the score fusion by 0.7% in base classes and 2.0% on novel classes.
Fine-tuning. We ablate fine-tuning different layers of the encoder for flow and audio modality and show results in Tab. 6. As mentioned in Sec. 3, we use the same ViT-B/16 encoder and same initialization weight for video, flow and audio. We iterate choices of fine-tuning the last 1, 3, 6, 9, and all 12 layers and find the performance increases with increasing number of trainable layers on both modalities. Therefore we adopt the setting of fine-tuning all layers for flow and audio modality.

| trainable layers | modality | accuracy |
|------------------|----------|----------|
| All 12 layers    | Flow     | 54.2     |
| Last 9 layers    | Flow     | 51.6     |
| Last 6 layers    | Flow     | 46.0     |
| Last 3 layers    | Flow     | 38.3     |
| Last 1 layers    | Flow     | 30.5     |

(a) Fine-tuning on Kinetics-700.

| trainable layers | modality | accuracy |
|------------------|----------|----------|
| All 12 layers    | Audio    | 59.5     |
| Last 9 layers    | Audio    | 57.1     |
| Last 6 layers    | Audio    | 50.8     |
| Last 3 layers    | Audio    | 47.8     |
| Last 1 layers    | Audio    | 40.1     |

(b) Fine-tuning on VGGSound.

Table 6: Ablation on fine-tuning different vision encoder layers. We report the performance on base classes of both datasets, and we find the best setting is fine-tuning all layers of the vision encoder.

Per-class accuracy analysis. We analyze and interpret class-wise performance difference between MOV and CLIP baseline which only uses video and text. As illustrated in Fig. 3a, we observe strong gains on classes that require motion understanding, e.g. yawning and long jump. While we also find decreased performance on classes with subtle or ambiguous motions, e.g. look in mirror and geocaching. In Fig. 3b, we observe audio modality can significantly help disambiguate classes sharing similar visual contents, e.g. people nose blowing and people laughing. While for classes being difficult in the audio domain, e.g. sloshing water and wind noise, the performances are degraded.

![Figure 3: Per-class improvement analysis. We show top 20 classes with the most improvement (%) and top 20 classes with the most degradation (%) when compare the proposed MOV with CLIP.](image)

5 Conclusion

We propose a multimodal open-vocabulary video classification method named MOV via adopting pre-trained vision and language models. Our method is motivated by the observation of drastic performance difference when using video, audio and optical flow to generalize to novel classes. We design a cross-modal fusion mechanism to aggregate complimentary multimodal information. Extensive experiments on Kinetic, VGGSound, UCF and HMDB benchmarks demonstrate the effectiveness of our method and the potential of scaling to giant vision and language models.

Limitations: We explore three modalities in VGGSound and Kinetics, which does not fully exploit all information available in multimodal videos. In the future, we plan to further improve the model with more modalities like depth and signals from inertial measurement unit (IMU) sensors.

Societal impact: The proposed method shows better generalization to a wider set of multimodal videos with novel classes, indicating its strong potential for real world applications. We also need to mention that our method is built upon vision and language models pre-trained on large-scale data accumulated automatically from the web with limited manual verification, which may contain biases making them not suitable for some sensitive tasks that or engaging with some social activities.
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## Appendix

### Temperature tuning

As described in Sec. 3.4, in addition to fused flow and audio features of \{f_m, a_m\}, we also incorporate the video feature \(v\) extracted from the frozen video backbone to enhance the generalization to novel classes. We denote the probability distribution followed by \(\{p_f(j)|_{j=1}^{17}\}, \{p_a(j)|_{j=1}^{17}\\) and \(\{p_v(j)|_{j=1}^{17}\\) as \(D_f, D_a\) and \(D_v\). In our experiments we find the curve of \(D_v\) tends to be much flatter (or have higher information entropy) than \(D_f\) and \(D_a\) when the temperatures \(\tau_v, \tau_f, \text{and} \tau_a\) are all set to the CLIP's default value of 0.01. Neglecting this difference and directly combining the scores as in Eq. 12 would lead to poor performance. We address this problem by lowering \(\tau_v\) so that the distribution of \(D_v\) would be more similar to \(D_f\) and \(D_a\). As shown in Tab. 7, adjusting \(\tau_v\) to 0.003 while keeping \(\tau_f, \text{and} \tau_a\) as 0.01 greatly improves the performance by 20% on Kinetics-700 and 16% on VGGSound.

| \(v\) acc. | \(f_m\) acc. | \(\tau_v\) | Final acc. |
|-----------|-------------|---------|----------|
| 56.7 | 30.4 | 0.01 | 38.0 |
| 56.7 | 30.4 | 0.003 | 58.1 |
| 56.7 | 30.4 | 0.0001 | 56.4 |

(a) Tuning \(\tau_v\) on Kinetics-700.

| \(v\) acc. | \(a_m\) acc. | \(\tau_v\) | Final acc. |
|-----------|-------------|---------|----------|
| 48.8 | 24.8 | 0.01 | 35.7 |
| 48.8 | 24.8 | 0.003 | 51.5 |
| 48.8 | 24.8 | 0.0001 | 49.0 |

(b) Tuning \(\tau_v\) on VGGSound.

Table 7: **Ablation on temperature tuning.** Compared with using CLIP’s default temperature of 0.01 (the first row), using a smaller temperature of 0.003 could greatly improve the performance by 20% on Kinetics-700 and 16% on VGGSound.