Knowledge Prompting for Few-shot Action Recognition

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Abstract

Few-shot action recognition in videos is challenging for its lack of supervision and difficulty in generalizing to unseen actions. To address this task, we propose a simple yet effective method, called knowledge prompting, which leverages commonsense knowledge of actions from external resources to prompt a powerful pre-trained vision-language model for few-shot classification. We first collect large-scale language descriptions of actions, defined as text proposals, to build an action knowledge base. The collection of text proposals is done by filling in handcraft sentence templates with external action-related corpus or by extracting action-related phrases from captions of Web instruction videos. Then we feed these text proposals into the pre-trained vision-language model along with video frames to generate matching scores of the proposals to each frame, and the scores can be treated as action semantics with strong generalization. Finally, we design a lightweight temporal modeling network to capture the temporal evolution of action semantics for classification. Extensive experiments on six benchmark datasets demonstrate that our method generally achieves the state-of-the-art performance while reducing the training overhead to 1‰ of existing methods.

Introduction

Few-shot action recognition in videos aims to classify new action classes by using very few training samples. To address this task, the majority of existing works (Bishay, Zoumpoulis, and Patras 2019; Cao et al. 2020; Zhu and Yang 2018; Zhang et al. 2020; Ferrett et al. 2021; Ben-Ari et al. 2021) formulate the few-shot recognition problem in a meta-learning paradigm, where meta-metrics of similarities between actions are first trained in the training phase, and then applied for the nearest neighbor voting to make predictions in the test phase. Although these methods have achieved promising performance on many datasets like Kinetics (Carreira and Zisserman 2017), they still suffer from the very scarce labeled training data that limits their ability to generalize to seldom seen or even unseen action classes.

In this paper, we provide a fascinating insight that efficiently adapts one well pre-trained vision-language model to realize the few-shot action recognition task with minimal training. The motivation behind this insight is the superior ability of generalization of the pre-trained vision-language model to novel tasks after it has seen tremendous image-text or vide-text pairs in pre-training. Therefore, we propose a simple yet effective method, called knowledge prompting, which explores commonsense knowledge of actions from external resources to prompt the pre-trained vision-language model well for few-shot recognition. In this work, we employ CLIP (Radford et al. 2021) as the pre-trained vision-language model.

To be more specific, we first build an action knowledge base by collecting large-scale textual descriptions of actions from external resources, named as text proposals, which explicitly describe atomic actions such as fine-grained movements of body parts. To ensure the knowledge base to cover as many action descriptions as possible, we propose two strategies to generate abundant and various text proposals. One strategy is to first create the sentence template of “subject-verb-object”, and then fill the template with various action-related words from the external corpus. The corpus consists of the body motion concepts from the PaStaNet dataset (Li et al. 2020) and the object categories from the Visual Genome dataset (Krishna et al. 2017). The text proposals generated in this way mainly describe basic actions, and are used as a body of our knowledge base. The other strategy is to design a text proposal network to extract action-related phrases from the captions of Web instruction videos, which generates more descriptions of daily actions, thus enriching the text proposals in the knowledge base.

We take the text proposals and the video frames as inputs of the text encoder and the image encoder of CLIP, respectively. For each frame, the output matching scores measure how similar the text proposals are to the visual content, and can be treated as potentially valuable representations of action semantics with strong generalization. Finally, we design a temporal modeling network to model the temporal relationships between the proposal matching scores of different video frames, thereby capturing the evolution of action semantics along time for action classification. Extensive experiments show that the proposed method not only considerably boosts the performance of few-shot action recognition on various datasets, but also greatly reduces the training cost to less than 0.001 times of existing methods.

The main contributions of our work are three-fold:

- We propose a knowledge prompting method that steers the pre-trained vision-language model (CLIP) to the few-shot action recognition by leveraging commonsense
knowledge from external resources. Our method is simple yet effective, and has strong ability of generalization, without expensive end-to-end training of large-scale backbone.

- We propose two strategies of generating abundant and various textual descriptions of actions to build an action knowledge base, and thus well prompt CLIP for learning powerful representations of action semantics.
- We design a lightweight temporal modeling network to model the temporal evolution of action semantics, which further boosts the recognition accuracy.

Related Work

Pre-Trained Vision-Language Models for Visual Recognition

Pre-trained vision-language models (Radford et al. 2021; Jia et al. 2021) have achieved great success in visual recognition due to the addition of natural language to the supervised learning process. The core problem of applying these models to downstream tasks is prompt learning (Schüttel 2020), which is a technique that seeks to exploit the learned knowledge encoded in a pre-trained model without tuning the model itself.

In the field of object recognition, Zhou et al. (Zhou et al. 2021) propose to add learnable contexts to the text input of CLIP to learn task-relevant prompts. Cho et al. (Cho et al. 2021) formulate several vision-and-language tasks in a unified generative architecture by fine-tuning one multi-modal pre-trained model using task-specific handcraft prompts. Tsipoukelli et al. (Tsipoukelli et al. 2021) train the vision model to learn to cooperate with the encoded common sense knowledge of the frozen language model to generate open-ended outputs and achieve few-shot learning. For action recognition, Wang et al. (Wang, Xing, and Liu 2021) use handcrafted labels as the text input of CLIP (Radford et al. 2021) and fine-tune the whole pre-trained model.

Different from the aforementioned methods, our knowledge prompting method takes full advantage of commonsense knowledge of actions and generates large-scale prompts to efficiently adapt the pre-trained CLIP model to few-shot action recognition, which no longer requires fine-tuning any parameter.

Few-shot Action Recognition

Many existing methods of few-shot action recognition concentrate on learning the transferable similarity metrics between actions for the nearest neighbor voting, due to the lack of training data. Some methods (Zhu and Yang 2018; Bishay, Zoumpourlis, and Patras 2019; Zhang et al. 2020; Perrett et al. 2021) learn fine-grained video representations and use dot product or euclidean distance in the representation space as the similarity metric. Zhu et al. (Zhu and Yang 2018) propose a compound memory network to memorize key-frame features that are vital for adapting to new tasks. Perrett et al. (Perrett et al. 2021) introduce a Transformer-like architecture to learn an adaptive representation space (i.e. query-specific class prototype) via early fusion between the query video and support videos. There is also work on explicitly modeling the intrinsic property of video, such as the temporal order (Cao et al. 2020), to assess the similarity.

More recently, Zhu et al. (Zhu et al. 2021) get rid of the meta-learning paradigm and focus on exploiting the powerful pre-trained vision backbones for few-shot action recognition. They present a classifier-based baseline method and fine-tune the pre-trained model to learn effective representations. In contrast, our method neither performs meta-learning nor fine-tunes vision backbones. It prompts the pre-trained vision-language model by leveraging external commonsense knowledge of actions to learn powerful action representations with the supervision of language.

Our Method

Overview

We propose a knowledge prompting method for few-shot action recognition in videos. It prompts the pre-trained CLIP by using commonsense knowledge from external resources, thereby generalizing well to rare or even unseen actions. The commonsense knowledge is represented by textual descriptions of atomic actions (i.e., text proposals), and an action knowledge base is built by collecting text proposals from external action-related corpus and video captions. The core issue of our method lies in how to collect rich and various text proposals for generating semantic representations of actions. To address this issue, we propose two strategies for collecting text proposal: handcraft generation via a sentence template and automatic generation via text proposal network.

Given an input video, we first take the text proposals as the text input of CLIP, and take video frames as the image input of CLIP. Then, for each video frame, CLIP outputs the similarity matching scores of the text proposals that comprehensively describe the action semantics. Finally, we feed the matching scores of all the video frames into a newly designed temporal modeling network for action classification, by capturing the temporal evolution of action semantics. Figure 1(a) shows the extraction of action semantics by CLIP, and Figure1(b) shows the temporal modeling network for classification.

Generation of Text Proposals

Handcraft Generation via Sentence Template

The handcraft generation of text proposals is implemented by first creating the sentence template of “subject-verb-object” and then filling the template using the action-related words from external corpus. Although currently there is no corpus for directly describing human actions, there are still action-related datasets like PaStaNet (Li et al. 2020) and Visual Genome (Krishna et al. 2017). So we use the body motion concepts from the PaStaNet dataset and the object categories from the Visual Genome dataset as the action-related corpus.

PaStaNet has a total of 93 states of 10 body parts, such as “hand, put on” and “head, kiss”, which provides subjects and verbs in the sentence template. Visual Genome has dense annotations of objects and scenes in images, and a total of 5,996 noun words or phrases in the annotations are selected as objects in the sentence template. In particular, all transitive verbs or phrases from PaStaNet are paired with nouns or
noun phrases from Visual Genome, to fill in the sentence of “Human’s [body part] [state] the [object]”. For example, the body part state “foot, run to” and the noun “bed” are used to generate the text proposal “Human’s foot run to the bed”.

In this way, we have 380,000 initial text proposals. However, they cannot be directly fed into CLIP, since some linguistically unreasonable proposals will hurt the performance and the high dimension of matching score vector will make the computation very expensive. So we use a pre-trained mask-based language model, BERT (Devlin et al. 2018), to filter the text proposals. In particular, we mask the object part (nouns) in the text proposals, and use BERT to calculate the probabilities of the masked nouns according the subject and verb. If the probability is lower than a threshold λ (the value of λ will be analyzed in the experiments), the corresponding proposal will be discarded. For example, for the masked proposal “Human’s foot stand on the [MASK]”, we tend to discard the nouns “code” and “license” with lower probabilities and adopt the nouns “bed” and “wood” with higher probabilities. Finally, we collect more than 50,000 text proposals as the main body of the knowledge base. Figure 2 (a) illustrates the process of the handcraft generative via sentence template.

**Automatic Generation via Text Proposal Network** To generate more diverse text proposals to further improve the scalability of the knowledge base, we propose a text proposal network (TPN) that automatically extracts text proposals of daily actions from the action-related captions of Web instruction videos. It takes video captions as input, and outputs action description phrases as the text proposals. TPN consists of a BERT model to extract token feature of the input sentence, and a classifier to judge whether or not a token belongs to the output text proposal.

To collect the captions of instruction videos from Web, we use query keywords like “how to”, “tutorial” and “teach” to search action-related instruction videos such as diving and gymnastics tutorial videos from Youtube, and crawl the corresponding captions that have abundant action descriptions. To train TPN, we sample 10 captions with about 50,000 words, and annotate the words using the BIO format annotation method (Ramshaw and Marcus 1999). Specifically, for each action description (i.e., phrases or sentences) in the captions, “B” is used to label the first word, and “I” is used to label the other words in inside. For other descriptions that do not describe actions, “O” is used to label them. Moreover, we define two types of action descriptions: the instance-level description to describe the whole-body movements like “do a cartwheel”, and the part-level description to describe the body-part movements like “brings his feet together”.

By applying the trained TPN to the instruction video captions, we generate about 4,000 text proposals with 2,000 proposals for instance-level actions and 2,000 for part-level actions, which further enriches the knowledge base. Figure 2 (b) illustrates the process of the automatic generation via text proposal network. Figure 2 (c) shows several examples of the generated proposals by the two strategies.

**Temporal Modeling of Action Semantics**

The generated text proposals are taken as input of the text encoder in CLIP, and the video frames are fed into the im-
age encoder in CLIP. Owing to the great potential of CLIP in bridging the two modalities of vision and language, the output similarity matching scores of the text proposal actually represent the action semantics of each video frame by leveraging commonsense knowledge of actions.

To capture the temporal relationships between action semantics of different video frames for classification, we propose a temporal modeling network that integrates temporal convolution and multi-head self-attention.

**Extraction of Action Semantics** Given an input video with $n$ frames $\{f_1, f_2, \ldots, f_n\}$, and a set of $m$ text proposals $\{p_1, p_2, \ldots, p_m\}$, the pre-trained CLIP model calculates the matching similarities between the frames and the proposals, denoted as $S \in \mathbb{R}^{n \times m}$, where $S_{ij}$ represents the matching score between the $i$-th video frame $f_i$ and the $j$-th text proposal $p_j$. The higher $S_{ij}$ is, the more relevant $p_j$ is to $f_i$. The similarity matching scores represent how the corresponding textual descriptions of actions relate to the frames, and thus can be treated as the action semantics of the frames. Let $v_i = [S_{i1}, S_{i2}, \ldots, S_{im}]$ denote the $i$-th row of $S$, and it represents the action semantics of the $i$-th frame. Since the collected text proposals cover rich and various descriptions of atomic actions, the action semantics are more like complete intermediate-level representations of actions with strong generalization.

It is worth mentioning that the extraction of action semantics does not require training any parameter of CLIP, and we only need to perform the extraction process once for each sample and store the action semantics offline during training. This differs from other previous methods (Wang, Xing, and

**Temporal Modeling Network** To capture the temporal contextual relationships between the action semantics to further improve the recognition performance, we design a lightweight temporal modeling network (TMN), in which the action semantics are scaled, combined, time-series modeled, and finally mapped to the action category space.

As illustrated in Figure 1(b), TMN consists of a batch normalization layer, multiple channel-wise temporal convolution layers, and a multi-head self-attention module. To be more specific, given the sequential action semantics $\{v_1, v_2, \ldots, v_n\}$ as the input of TMN, the batch normalization layer is first employed to eliminate the distribution bias of CLIP for fitting the prior distribution to its training data. Then the multiple channel-wise temporal convolution, linear transformation and batch normalization layers are applied for the temporal modeling of action semantics. Finally, the multi-head self-attention module is used for global temporal modeling the features of all frames and then a linear category header is used for classification.
rate coefficient for moment estimates are set to 0.5 and the initial learning rate is 0.01 and the exponential decay is 0.001, and the batch size is 32. The momentum coefficient is 0.9, the L2 regularization coefficient is 0 and the batch size is 16. The training stops after 10 training epochs. The L2 regularization coefficient is 0 and the batch size is 16. The prediction result of a single sample is the average prediction result after randomly sampling the video ten times using the model prediction. The standard 5-way 5-shot evaluation is employed on all datasets and the average accuracy over 500 random test tasks is reported.

Experimental Results

Comparison with State-of-the-Art Methods Table 1 shows the comparison results of the standard 5-way 5-shot action recognition task with the state-of-the-art methods on the six action datasets. It is interesting to observe that our method generally achieves best results on most datasets with extremely low computational overhead. This benefits from the strong generalization of extracted action semantics through the collection of abundant text proposals and the powerful vision-language matching ability of CLIP. Moreover, the freeze of CLIP model parameters and the efficient temporal modeling network design greatly reduce the computational cost of training.

We can also observe that the proposed method performs not very well on the SS-V2 dataset, probably due to that most of the actions in SS-V2 are about fine-grained hand-object interactions such as “pretending to put something underneath something” and “moving something across a surface until it falls down”, and it is difficult to collect relevant descriptions of these actions as text proposals.

Comparison with Baseline Method We also compare our method with a baseline model, called CLIP zero-shot, which directly uses the visual features extracted by the image encoder of CLIP for action recognition and without temporal modeling. The results are shown in the bottom part of Table 1. It is obvious that our method achieves better results on all the datasets, especially on SS-V2, Diving48-V2 and FineGym, which demonstrates the superiority of our design of extracting action semantics via prompting CLIP using commonsense knowledge and modeling the temporal information of action semantics by TMN.
Table 2: Results (%) of ablation studies on the Kinetics, SS-V2, HMDB51, UCF101, Diving48-V2 and FineGym datasets.

| Method          | Kinetics | SS-V2 | HMDB51 | UCF101 | Diving48-V2 | FineGym |
|-----------------|----------|-------|--------|--------|-------------|--------|
| w/o knowledge   | 91.7     | 56.0  | 84.7   | 99.0   | 78.8        | 74.0   |
| w/o TPN         | 94.1     | 62.2  | 86.8   | 99.6   | 81.5        | 76.1   |
| w/o TMN         | 93.3     | 49.0  | 85.2   | 99.2   | 63.7        | 69.0   |
| Ours            | **94.3** | **62.4** | **87.4** | **99.4** | **82.6** | **76.8** |

Table 3: Results (%) of using the text proposals generated by handcraft sentence template with different $\lambda$ on the Kinetics, SS-V2, HMDB51, UCF101, Diving48-V2 and FineGym datasets.

| Value of $\lambda$ | Proposal Number | Kinetics | SS-V2 | HMDB51 | UCF101 | Diving48-V2 | FineGym |
|--------------------|-----------------|----------|-------|--------|--------|-------------|--------|
| $6 \times 10^{-4}$ | 14388           | 92.1     | 60.0  | 85.1   | 99.0   | 80.1        | 74.8   |
| $3 \times 10^{-4}$ | 25172           | 93.0     | 61.3  | 86.1   | 99.1   | 80.8        | 75.0   |
| $2 \times 10^{-4}$ | 33763           | 93.5     | 61.6  | 85.3   | 99.2   | 80.7        | **76.1** |
| $1 \times 10^{-4}$ | 53133           | **94.1** | **62.2** | **86.8** | **99.6** | **81.5** | 74.9   |

Ablation Studies

To study in-depth of different individual components, we introduce several variants of our method for comparison, as follows:

- **w/o knowledge**: We remove the knowledge base to evaluate the contribution of text proposals. In this case, only the visual features from the image encoder of CLIP are directly fed into the temporal modeling network for classification.

- **w/o TPN**: We remove the text proposal network to evaluate its effectiveness. In this case, only the text proposals generated by the sentence template are used.

- **w/o TMN**: To evaluate the importance of the temporal modeling network, we replace it using a linear mapping layer along with a batch normalization layer.

The results of ablation studies on the six datasets are shown in Table 2. We have the following observations:

- The performance degrades on all the datasets when removing the text proposals, which validates the benefit of prompting CLIP using external knowledge to enhance the generalization ability in few-shot recognition.

- When removing the text proposals automatically generated by TPN, the performance also drops on most datasets, which indicates the efficacy of extracting action descriptions from the captions of Web instruction videos on enriching the knowledge base of text proposals. It should be mentioned that the proposals generated by TPN will inevitably contain some noise words since some captions are automatically generated by speech recognition, but experiments show that this doesn’t affect their vital role in recognition (illustrated in Figure 3).

- By removing the temporal modeling network, our method achieves much worse results, clearly demonstrating that it is essential to capture the temporal relationships between action semantics for action classification.

Analysis of Threshold $\lambda$

To analyze the effect of text proposal filtering in handcraft generation, we conduct experiments with different values of the probability threshold $\lambda$. Table 3 show the results of only using the text proposals generated by handcraft sentence template with different $\lambda$, where the larger $\lambda$ represents that more text proposals are filtered out. It can be observed that a smaller $\lambda$ generally achieves fairly better performance, which suggests that the increasing text proposals are helpful to boost the accuracy owing to more supervision from language. For FineGym, the optimal value of $\lambda$ is larger than that for other datasets. The possible reason is that the videos in the FineGym dataset are professional actions of formal gymnastics competitions where the scenes and interactive objects are relatively simple compared to other datasets, so there are less proposals related to frames. In this case, more proposals with low probability bring more distractors, which hurts the performance.

Evaluation of Text Proposals

Figure 3 illustrates several examples of video frames with a few most important text proposals before and after TMN, where the importance of text proposals before TMN is determined by the matching similarity scores after CLIP, and the importance of text proposals after TMN is calculated by the gradient sizes corresponding to the action semantic vector in the test phase.

As shown in Figure 3(a), most initially generated text proposals mainly describe the interaction between “human” and “beam” or “crossbar”. That’s because the “beam” or “crossbar” is really the most obvious object in video frames, which is easily recognized by CLIP without temporal modeling. And it is interesting to observe that some proposals such as “getting your feet together” and “arms up” become more important after temporal modeling, since they describe the discriminative fine-grained body movements and thus play a vital role in final recognition.

Figure 3(b) further demonstrates the effect of temporal modeling. The video is about a man picking up rubbish from...
1. getting your feet together ham
2. have the chin up
3. with an atomic arms up Anton
4. with your hands here at
5. weight distribution coming off your arms
6. with hands in position
7. Human's hip sit beside the jamb.
8. Human's hand pour into the matchbox.
9. keeping really strong and
10. Human's hand throw out the bookshop.
11. Human's hand gesture to the patchwork.
12. tuck your knees and sundries

1. Human's hand write on the belt.
2. Human's hand throw out the light bulb.
3. Human's head kiss the ground floor.
4. Human's hand throw the bag.
5. Human's hand twist the cup.
6. Human's arm be close to the chip.
7. Human's head be close with the arrow.
8. Human's hand throw out the signal.
9. Human's leg run with the town.
10. Human's hand throw out the glassware.
11. Human's hip sit beside the garage.
12. Human's leg run to the motorcycle.
13. Human's leg walk with the motorcycle.
14. Human's leg run with the motorcycle.
15. Human's hand throw out the street.
16. Human's leg walk to the motorcycle.
17. Human's hand throw out the road.
18. Human's head blow the road.
19. Human's foot walk to the motorcycle.
20. Human's foot run to the town.
21. Human's hand throw out the glassware.
22. Human's hip sit beside the garage.
23. Human's hand throw out the hose.

(a) The action "transition flight from high bar to low bar" on the FineGym dataset.

(b) The action "pick" on the HMDB51 dataset.

Figure 3: Illustration of several examples of video frames with most important text proposals before and after the temporal modeling network (TMN). The text proposals are ranked by the matching similarity scores from CLIP before TMN and the gradient sizes corresponding to the action semantic vector after TMN. The proposals mentioned in paper have been marked out.

Conclusion

We have presented a knowledge prompting method that can efficiently adapt a pre-trained vision-language model (CLIP) by leveraging commonsense knowledge from external resources to achieve the few-shot action recognition. To that end, we have proposed two strategies that are able to generate abundant text proposals as the text input of CLIP. A lightweight network is also designed for temporal modeling of action semantics, and succeeds in boosting the performance. Our method is simple yet effective, with strong ability of generalization and low computational overhead. Extensive experiments on six action datasets demonstrate the effectiveness and superiority of our method on few-shot action recognition.

But for some specific actions such as fine-grained hand movements in the SS-V2 dataset, the performance of our method is not satisfactory due to the limited relevant text proposals. So in future work, we are going to explore more external resources like textual corpus of actions to further enrich the knowledge base, and meanwhile to introduce uncertainty learning to improve the text proposal prompting.
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