Context-aware Proposal Network for Temporal Action Detection

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Abstract

This technical report presents our first place winning solution for temporal action detection task in CVPR-2022 ActivityNet Challenge. The task aims to localize temporal boundaries of action instances with specific classes in long untrimmed videos. Recent mainstream attempts are based on dense boundary matchings and enumerate all possible combinations to produce proposals. We argue that the generated proposals contain rich contextual information, which may benefits detection confidence prediction. To this end, our method mainly consists of the following three steps: 1) action classification and feature extraction by Slowfast \cite{10}, CSN \cite{20}, TimeSformer \cite{4}, TSP \cite{1}, I3D-flow \cite{7}, VGGish-audio \cite{11}, TPN \cite{33} and ViViT \cite{3}; 2) proposal generation. Our proposed Context-aware Proposal Network (CPN) builds on top of BMN \cite{16}, GTAD \cite{32} and PRN \cite{26} to aggregate contextual information by randomly masking some proposal features. 3) action detection. The final detection prediction is calculated by assigning the proposals with corresponding video-level classification results. Finally, we ensemble the results under different feature combination settings and achieve 45.8\% performance on the test set, which improves the champion result in CVPR-2021 ActivityNet Challenge \cite{26} by 1.1\% in terms of average mAP.

1. Introduction

Recently, the emergence of large-scale datasets \cite{5, 34, 17, 6, 7, 8, 12} and deep models \cite{15, 22, 10} has promoted the development of video understanding, which has a wide range of application prospects in security, surveillance, autonomous driving fields. Video understanding includes many sub-research directions, such as Action Recognition \cite{22, 10, 13, 30}, Action Detection \cite{16, 18, 2, 28, 29, 25, 27, 24, 23}, Spatio-Temporal Action Detection \cite{19, 14}, etc. In this report, we present our competition method for the temporal action detection task in the CVPR-2022 ActivityNet Challenge \cite{5}.

For temporal action detection task, we need to localize temporal boundaries of action instances (i.e., start time and end time) and classify the target categories in the long untrimmed videos. This task is challenging, involving some difficulties such as wide temporal spans of action instances, confusing background and foreground, and limited proposal contextual information. Current mainstream approaches \cite{16, 32, 1, 23, 31} usually adopt "proposal and classification" paradigm, which generates proposals by calculating the boundary probabilities of each time point to combine start points with end points and then classify the proposals. In order to produce high-quality detection results, the generated proposals should precisely cover instance with high recalls and reliable confidence scores. Since proposal-level classification is limited to insufficient instance information, video-level classification has attracted much attention \cite{25, 26}, which leverages the entire video as input to obtain the final results. In this report, we follow this paradigm to design the solution of this challenge. Our main observation is that when predicting the confidence map of dense proposals, the proposals can be mutually inferential, i.e., the confidence of a proposal may be obtained by inference from the surrounding proposals. We thus apply a randomly masking strategy to the proposal features and encourage the model to aggregate context associations for precise proposal confidence prediction. Moreover, to further improve the performance, we apply some data preprocessing techniques, such as too long instance removal, short instance resampling, action instance resize and temporal shift perturbation \cite{28, 15}. Finally, we ensemble some existing methods \cite{16, 32, 18, 26} and achieve 45.8\% mAP on the test set of ActivityNet v1.3 \cite{5}, which improves the champion result in CVPR-2021 ActivityNet Challenge \cite{26} by 1.1\%.
Figure 1. The overall pipeline of our solution in the challenge. Given an input video, we utilize a pre-trained action network to obtain the feature sequence and then perform data pre-processing on the input data. Subsequently, we sample predefined dense proposal features on the input feature sequence and randomly drop some proposal features to encourage the use of contextual information. Finally, post-processing the generated confidence map (including combining with video-level labels) to obtain detection results.

2. Feature Extractor

In recent years, a large number of advanced deep learning algorithms have been proposed for action classification. These methods can act as feature extractors for action detection and also be adopted to generate video-level classifications. In this section, we introduce some deep action classification networks used in our solution.

2.1. Slowfast

Slowfast network [10] was proposed for action classification by combining a fast and a slow branch. For the slow branch, the input is with a low frame rate, which is used to capture spatial semantic information. The fast branch, whose input is with a high frame rate, targets to capture motion information. Note that the fast branch is a lightweight network, because its channel is relatively small. Due to its excellent performance in action recognition and detection, we choose Slowfast as one of our backbone models.

2.2. I3D-flow

Inflated 3D ConvNet (I3D) [7] designs some inflated convolutions to cover different receptive fields, which is based on 2D ConvNet inflation. I3D expands the filters and pooling kernels of deep image recognition networks into 3D shape, making it suitable for spatio-temporal modeling. In our solution, we apply I3D network to extract flow features of ActivityNet v1.3 dataset.

| Model       | Pretrain | Top 1 Acc. | Top5 Acc. |
|-------------|----------|------------|-----------|
| I3D-flow    | K400     | 79.5%      | 93.6%     |
| Slowfast50  | K400     | 85.3%      | 95.8%     |
| Slowfast101 | K400     | 87.1%      | 97.4%     |
| Slowfast152 | K700     | 88.9%      | 97.8%     |
| TPN         | K400     | 87.4%      | 97.1%     |
| TSP         | ANet     | 86.4%      | 97.4%     |
| CSN         | K400     | 90.3%      | 98.1%     |
| ViViT-B/16x2| K700     | 91.2%      | 98.0%     |
| TimeSformer | K600     | 91.1%      | 97.3%     |

Table 1. Action recognition results on the validation set of ActivityNet v1.3 dataset [5]. K400 means pre-training on Kinetics 400 [7]; K700 means pre-training on Kinetics 700 [6]; ANet indicates pre-training on ActivityNet v1.3 dataset [5]. Note that we also use the ActivityNet 2020 champion results [25] and the ActivityNet 2021 champion results [26] for multi-model classification fusion.

2.3. CSN

Channel-Separated Convolutional Network (CSN) [20] aims to reduce the parameters of 3D convolution, and extract useful information by finding important channels si-
multaneously. It can efficiently learn feature representation through grouping convolution and channel interaction, and reach a good balance between effectiveness and efficiency.

2.4. TimeSformer

TimeSformer [4] presents the standard Transformer architecture to video by enabling spatiotemporal feature learning directly from a sequence of frame-level patches. In addition, TimeSformer shows that separate temporal attention and spatial attention within each block leads to the best video classification accuracy.

2.5. TPN

Temporal Pyramid Network (TPN) [33] is a feature pyramid architecture, which captures the visual tempos of action instances. TPN can be applied to existing 2D/3D architectures in the plug-and-play manner, bringing consistent improvements. Considering its excellent spatio-temporal modeling ability, we also use it to extract spatio-temporal features.

2.6. ViViT

Due to transformers [21, 9, 29] have shown powerful abilities on various vision tasks, we apply the ViViT [3] as one of backbones. ViViT is a pure Transformer based model for action recognition. It extracts spatio-temporal tokens from input videos, and then encoded by series of Transformer layers. In order to handle the long sequences of tokens encountered in videos, several efficient variants of ViViT decompose the spatial- and temporal-dimensions of the inputs. We apply the ViViT-B/16x2 version with factorised encoder, which initialized from imagenet pretrained ViT [9], and then pretrain it on Kinetics700 dataset [6].

2.7. Classification results

In addition to the several models mentioned above, we also utilize TSP features [1] and VGGish-audio features [11]. Table 1 shows the action recognition results of the above methods on the validation set of ActivityNet v1.3 dataset [5]. From the results, we can draw several following conclusions: 1) CSN model can outperform slowfast101 by 3.1% with Kinetics400 pretraining on ActivityNet dataset; 2) Transformer based model can indeed obtain better performance than CNN based models. For instance, TimeSformer and ViViT achieve 91.2% and 91.1% Top1 accuracy. 3) The flow feature alone is not as good as the spatio-temporal feature of RGB in performance. We then ensemble all the models and achieve 1.0% performance gain over ActivityNet-2021 champion result.

3. Context-aware Proposal Network

In the section, we introduce our proposed Context-aware Proposal Network (CPN). As is shown in Figure 1, CPN mainly contains two key components: data pre-processing strategies and proposal feature random masking. We will introduce each part in details below, and finally show the detection performance.

3.1. Data pre-processing strategies

In our solution, we mainly used four data pre-processing tricks: too long instance removal, short instance resampling, action instance resize and temporal shift perturbation. Too long instance removal means that we delete training videos where the percentage of action instances is too long (e.g., 98%). The intuition is that these training data lack negative samples (i.e., the IoU between proposal and ground-truth is 0) when generating confidence maps, which may damage the training process.

Short instance resampling denotes that the training video containing short instances is repeatedly sampled, because the recall and localization of the short video instance is low precision, and we hope to alleviate this problem by resampling.
Action instance resize is to obtain and resize action instance by ground-truth annotations, which can simulate the change in the speed of video instances.

Temporal shift operation for action recognition is first applied in TSM [15], and then applied as a kind of perturbations in SSTAP [38] for semi-supervised learning. Here we reuse the perturbation as the feature augmentation. The temporal feature shift is a channel-shift pattern, including two operations such as forward movement and backward movement in the channel latitude of the feature map. This module can improve the robustness of the models.

3.2. Proposal feature random masking

Recall that temporal action detection is to accurately locate the boundary of the target actions. We explore the associations among proposals to capture the contextual relationships. To capture contextual associations among proposals, we randomly mask some proposal features. Specifically, a simple dropout 3d operation is composed on the sampled dense proposal feature maps.

To evaluate proposal, we calculate AR under different Average Number of proposals (AN), termed AR@AN (e.g., AR@100), and calculate the Area under the AR vs. AN curve (AUC) as metrics. Table 2 presents the results of BMN, PRN and CPN on the validation set of ActivityNet v1.3, which prove that CPN can outperform BMN significantly. Especially, our method significantly improves AUC from 68.6% to 69.5% by gaining 0.9%. In addition, compared to PRN, our CPN also has a certain performance improvement.

3.3. Detection results

We follow the “proposal + classification” pipeline to generate the final detection results. Mean Average Precision (mAP) is adopted as the evaluation metric of temporal action detection task. Average mAP with IoU thresholds [0.5 : 0.05 : 0.95] is applied for this challenge.

In order to demonstrate the effectiveness of CPN, we conduct experiments with different features, as is shown in Table 3. The results shows that the proposed CPN can gain 1.5% over BMN in terms of Average mAP when Slowfast101 feature is adopted. Then we ensemble all the results and reach 43.3% on the validation set and 45.8% on the test set. The ensemble strategies mainly contain multi-scale fusion and feature combination. We also used the boundary refinement methods [18, 25] to predict boundaries more accurately.

Moreover, we can find that the Transformer based ViViT shows very strong performance on classification task but unsatisfactory on detection task when compared with the CNN models. The reason may be that the Transformer tends to capture global information by self-attention operation, hence it loses local information which is also important for detection task. Meanwhile, the models perform well on action task may not achieve better performance on the detection task. Slowfast152 exceeds Slowfast101 by 0.8% for classification, but suffers 1.2% drop for detection in our CPN.

4. Conclusion

In this report, we present our solution for temporal action detection task in CVPR-2022 ActivityNet Challenge. For this task, we propose a CPN to leverage rich contextual information among proposals and apply some data preprocessing strategies for high robustness. Experimental results show that CPN can outperform the baseline methods significantly. By fusing all detection results with different backbones, we obtain 45.8% Average mAP on the test set, which gains 1.1% over the champion method in CVPR-2021 ActivityNet Challenge.

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