Proposal Relation Network for Temporal Action Detection

Xiang Wang\textsuperscript{1,2} Zhiwu Qing\textsuperscript{1,2} Ziyuan Huang\textsuperscript{2} Yutong Feng\textsuperscript{2} Shiwei Zhang\textsuperscript{2*} Jianwen Jiang\textsuperscript{2} Mingqian Tang\textsuperscript{2} Changxin Gao\textsuperscript{1} Nong Sang\textsuperscript{1*}

\textsuperscript{1}Key Laboratory of Image Processing and Intelligent Control
School of Artificial Intelligence and Automation, Huazhong University of Science and Technology
\textsuperscript{2}Alibaba Group

\{wxiang, qzw, cgao, nsang\}@hust.edu.cn
\{pishi.hzy, fengyutong.fyt, zhangjin.zsw, jianwen.jjw, mingqian.tmq\}@alibaba-inc.com

Abstract

This technical report presents our solution for temporal action detection task in ActivityNet Challenge 2021. The purpose of this task is to locate and identify actions of interest in long untrimmed videos. The crucial challenge of the task comes from that the temporal duration of action varies dramatically, and the target actions are typically embedded in a background of irrelevant activities. Our solution builds on BMN [10], and mainly contains three steps: 1) action classification and feature encoding by Slowfast [6], CSN [13] and ViViT [1]; 2) proposal generation. We improve BMN by embedding the proposed Proposal Relation Network (PRN), by which we can generate proposals of high quality; 3) action detection. We calculate the detection results by assigning the proposals with corresponding classification results. Finally, we ensemble the results under different settings and achieve 44.7\% on the test set, which improves the champion result in ActivityNet 2020 [17] by 1.9\% in terms of average mAP.

1. Introduction

Action understanding is an important area in computer vision, and it draws growing attentions from both industry and academia because its use in human computer interaction, public security and some other far reaching applications. It includes many sub-research directions, such as Action Recognition [15, 6, 7], Temporal Action Detection [10, 11, 18], Spatio-Temporal Action Detection [12, 8], etc. In this report, we introduce our method for the temporal action detection task in the 6-th ActivityNet challenge [2].

For temporal action detection task, we need to localize and classify the target actions simultaneously. Current mainstream approaches [10, 20, 19] are designed in a two-stage pipeline, i.e., proposal generation and action classification, and have achieved remarkable performance. Therefore, we follow this paradigm to design the solution of this challenge. Moreover, to further improve the performance, we design a proposal relation module to capture the relations among the proposals by non-local operations, and thus can also better model long temporal relationships.

2. Action Recognition and Feature Extraction

In recent years, a large number of deep networks for action recognition are proposed [13, 6, 4]. They have been playing an important role in the development of action detection.

2.1. Slowfast

Slowfast network [6] 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. Channel-separated convolutional network

Channel-Separated Convolutional Network (CSN) [13] aims to reduce the parameters of 3D convolution, and extract useful information by finding important channels simultaneously. It can efficiently learn feature representation
2.3. ViViT

Due to transformer [14] has shown powerful abilities on various vision tasks, we apply the ViViT [1] 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 [5], and then pretrain it on Kinetics700 dataset [3].

2.4. Classification results

Table 1 shows the action recognition results of the above methods on the validation set of ActivityNet v1.3 dataset [2]. 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 with 91.2% Top1 accuracy. We then ensemble all the models and gain the champion result in ActivityNet 2020 with 1.8%.

3. Proposal Relation Network

In the section, we introduce our proposed PRN, as is shown in Figure 1. PRN mainly contains two key modules: data augmentation module and proposal relation module. We will introduce each module in details below, and finally show the detection performance.

3.1. Data augmentation module

Temporal shift operation for action recognition is first applied in TSM [9], and then applied as a kind of perturbations in SSTAP [18] 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. The details are shown in Figure 2.
| Model | Feature | AR@100 | AUC  |
|-------|---------|--------|------|
| BMN   | Slowfast101 | 75.8%  | 68.6%|
| PRN   | Slowfast101 | 76.5%  | 69.3%|

Table 2. Proposal performances on the validation set of ActivityNet v1.3.

| Model | Feature | 0.5  | Average mAP |
|-------|---------|------|-------------|
| BMN   | Slowfast101 | 56.3% | 37.7% |
| PRN   | Slowfast101 | 57.2% | 38.8% |
| BMN   | Slowfast152 | 55.5% | 36.8% |
| PRN   | Slowfast152 | 56.5% | 38.0% |
| BMN   | CSN      | 56.9% | 38.1% |
| PRN   | CSN      | 57.9% | 39.4% |
| BMN   | ViViT    | 55.1% | 36.7% |
| PRN   | ViViT    | 55.5% | 37.5% |
| Ensemble | -    | 59.7% | 42.0% (test: 44.7%) |

Table 3. Action Detection results on the validation set of ActivityNet v1.3. Our PRN shows strong performance on multiple different features.

3.2. Proposal relation module

Recall that temporal action detection is to accurately locate the boundary of the target actions. We explore the associations among proposals to capture the temporal relationships. The non-European space between the proposals makes it difficult to capture directly through the convolutional layer. PGCN [21] first employs GCN to model relations among proposals. However, PGCN suffers from multi-stage training and the adjacency matrix needs to be preset. Our PRN is an end-to-end trained framework, which brings in the power of self-attention [16] to capture interaction relationships among proposals. Specifically, we use the attention mechanism on each proposal to obtain dependencies.

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 PRN and BMN on the validation set of ActivityNet v1.3, which prove that PRN can outperform BMN significantly. Especially, our method significantly improves AUC from 68.6% to 69.3% by gaining 0.7%.

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 PRN, we conduct experiments with different features, as is shown in Table 3. The results show that the proposed PRN can gain 1.3% than BMN in terms of Average mAP. Then we ensemble all the results and reach 42.0% on the validation set and 44.7% on the test set.

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 1.8% drop for detection.

4. Conclusion

In this report, we present our solution for temporal action detection task in ActivityNet Challenge 2021. For this task, we propose a PRN to encode the relations among proposals, which contains data augmentation module and proposal relation module. Experimental results show that PRN can outperform the baseline BMN significantly. We also explore the ViViT model for the challenge, and experimentally show that it is more suitable for action classification than action detection. By fusing all detection results with different backbones, we obtain 44.7% Average mAP on the test set, which gains 1.9% than the champion method in ActivityNet 2020.

5. Acknowledgment

This work is supported by the National Natural Science Foundation of China under grant 61871435 and the Fundamental Research Funds for the Central Universities no.2019kfyXKJC024.

References

[1] Anurag Arnab, Mostafa Dehghani, Georg Heigold, Chen Sun, Mario Lučić, and Cordelia Schmid. Vivit: A video vision transformer. arXiv preprint arXiv:2103.15691, 2021.
[2] Fabian Caba Heilbron, Victor Escorcia, Bernard Ghanem, and Juan Carlos Niebles. Activitynet: A large-scale video benchmark for human activity understanding. In Proceedings of the ieee conference on computer vision and pattern recognition, pages 961–970, 2015.
[3] Joao Carreira, Eric Noland, Chloe Hillier, and Andrew Zisserman. A short note on the kinetics-700 human action dataset. arXiv preprint arXiv:1907.06987, 2019.
[4] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 6299–6308, 2017. 1, 2

[5] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. arXiv preprint arXiv:2010.11929, 2020. 2

[6] Christoph Feichtenhofer, Haoqi Fan, Jitendra Malik, and Kaiming He. Slowfast networks for video recognition. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 6202–6211, 2019. 1

[7] Ziyuan Huang, Shiwei Zhang, Jianwen Jiang, Mingqian Tang, Rong Jin, and Marcelo Ang. Self-supervised motion learning from static images. arXiv preprint arXiv:2104.00240, 2021. 1

[8] Jianwen Jiang, Yu Cao, Lin Song, Ji Lin, Chuang Gan, and Song Han. Tsm: Temporal shift module for efficient video understanding. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 7083–7093, 2019. 2

[9] Tianwei Lin, Xiao Liu, Xin Li, Errui Ding, and Shilei Wen. Bmn: Boundary-matching network for temporal action proposal generation. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 3889–3898, 2019. 1

[10] Zhiwu Qing, Haisheng Su, Weihao Gan, Dongliang Wang, Wei Wu, Xiang Wang, Yu Qiao, Junjie Yan, Changxin Gao, and Nong Sang. Temporal context aggregation network for temporal action proposal refinement. arXiv preprint arXiv:2103.13141, 2021. 1

[11] Lin Song, Shihui Zhang, Gang Yu, and Hongbin Sun. Tac-net: Transition-aware context network for spatio-temporal action detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 11987–11995, 2019. 1

[12] Du Tran, Heng Wang, Lorenzo Torresani, and Matt Feiszli. Video classification with channel-separated convolutional networks. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 5552–5561, 2019. 1

[13] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. arXiv preprint arXiv:1706.03762, 2017. 2

[14] Limin Wang, Yuanjun Xiong, Zhe Wang, Yu Qiao, Dahua Lin, Xiaoou Tang, and Luc Van Gool. Temporal segment networks for action recognition in videos. IEEE transactions on pattern analysis and machine intelligence, 41(11):2740–2755, 2018. 1

[15] Xiaolong Wang, Ross Girshick, Abhinav Gupta, and Kaiming He. Non-local neural networks. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 7794–7803, 2018. 3

[16] Xiang Wang, Baiteng Ma, Zhiwu Qing, Yongpeng Sang, Changxin Gao, Shiwei Zhang, and Nong Sang. Cbr-net: Cascade boundary refinement network for action detection: Submission to activitynet challenge 2020 (task 1). arXiv preprint arXiv:2006.07526, 2020. 1, 2

[17] Xiang Wang, Shiwei Zhang, Zhiwu Qing, Yuanjie Shao, Changxin Gao, and Nong Sang. Self-supervised learning for semi-supervised temporal action proposal. arXiv preprint arXiv:2104.03214, 2021. 1, 2

[18] Mengmeng Xu, Juan-Manuel Pérez-Rúa, Victor Escorcia, Brais Martinez, Xiatian Zhu, Li Zhang, Bernard Ghanem, and Tao Xiang. Boundary-sensitive pre-training for temporal localization in videos. arXiv preprint arXiv:2101.10830, 2020. 1

[19] Mengmeng Xu, Chen Zhao, David S Rojas, Ali Thabet, and Bernard Ghanem. G-tad: Sub-graph localization for temporal action detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 10156–10165, 2020. 1

[20] Runhao Zeng, Wenbing Huang, Mingkui Tan, Yu Rong, Peilin Zhao, Junzhou Huang, and Chuang Gan. Graph convolutional networks for temporal action localization. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 7094–7103, 2019. 3