The Third Place Solution for CVPR2022 AVA Accessibility Vision and Autonomy Challenge

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Abstract

The goal of AVA challenge is to provide vision-based benchmarks and methods relevant to accessibility. In this paper, we introduce the technical details of our submission to the CVPR2022 AVA Challenge. Firstly, we conducted some experiments to help employ proper model and data augmentation strategy for this task. Secondly, an effective training strategy was applied to improve the performance. Thirdly, we integrated the results from two different segmentation frameworks to improve the performance further. Experimental results demonstrate that our approach can achieve a competitive result on the AVA test set. Finally, our approach achieves 63.008%AP@0.50:0.95 on the test set of CVPR2022 AVA Challenge.

1. Introduction

Instance segmentation applies widely in image editing, image composition, autonomous driving, etc. Instance segmentation is a fundamental problem in computer vision. Deep learning-based methods have achieved promising results for instance segmentation over the past few years, such as Mask R-CNN [8], PANet [10], Tensor-Mask [4], CenterMask [17], SOLO series [15, 16]. Specifically, AVA challenge involves a synthetic instance segmentation benchmark incorporating use-cases of autonomous systems interacting with pedestrians with disabilities [19]. In addition, transformers have made enormous strides in NLP [6, 13]. There are quite a bit of works applying transformers to computer vision [14, 20, 2] because transformers can capture the non-local and relational nature of images. Especially, Swin Transformer [11] has been widely used for many computer vision tasks and achieves successful results, such as detection and segmentation task on COCO.

In order to address the AVA instance segmentation task, firstly we conducted some experiments to test whether previous studies are effective for this task, which can help us employ proper model and data augmentation strategy. Secondly, an effective training strategy is applied to improve the model performance. Finally, we integrated the results from two different segmentation frameworks to improve the performance further.

2. Approach

Our approach mainly includes three parts: segmentation model and data augmentation, training strategy, and model integration. We introduce the segmentation model and data augmentation strategy in Sec.2.1. The training strategy is introduced in Sec.2.2. Moreover, the details of model integration is introduced in Sec.2.3.

2.1. Model and Data

Our segmentation model is Hybrid Task Cascade (HTC) [3] based detector on the CBSwin-Large backbone with CBFPN [9].

Copy-Paste [7], which copies object from one image to another, is particularly useful for instance segmentation. There are only eight categories in AVA challenge, and the number and area of instance per image are small in many cases, so Copy-Paste is a very effective data augmentation for AVA challenge.

2.2. Training Strategy

Firstly, we train the model with Copy-Paste data augmentation. Stochastic Gradient Descent (SGD) is applied to this stage. After the model converged, we use SWA [18] training strategy to finetune the model, which can make the model better and more robust. Adam with decoupled weight decay (AdamW) [12] is applied during the SWA training stage.

Our model architecture and training pipeline are shown in Figure 1.
## 2.3. Model Integration

Mask2Former [5] is a new architecture capable of addressing any image segmentation task, including panoptic, instance and semantic. Mask2Former is very different from the previous instance segmentation framework. In order to combine both advantages of Mask2Former and HTC, we directly trained the Mask2Former in AVA dataset without in-depth research, and integrated the results from HTC and Mask2Former as the final results.

## 3. Experiments

### 3.1. Training Details

We use the AVA2022 train and validation dataset to train and evaluate the model. In the first stage of training, the pre-trained CBSwin-Large model by COCO is applied, we train the model with SGD and initial lr=0.02. Then the SWA training strategy is applied to finetune the model, and the optimizer is AdamW with initial lr=0.0001.

The input images are randomly scaled from 720 to 1620 on the short side and up to 1920 on the long side. Then randomly cropped and padded to [1920, 1080]. Finally, random flip and Copy-Paste data augmentation methods are applied, the augmented images are input to the model for training.

### 3.2. Experimental Results

As shown in Table 1, our approach finally achieves 63.008% AP@0.50:0.95 on the CVPR2022 AVA instance segmentation challenge test set.

### 3.3. Ablation Study

This section elaborates on how we achieve the final result by ablation study to explain our approach. The baseline is HTC-CBSwin-Large, and Copy-Paste is a very effective data augmentation method for this task. In order to improve the recall of the model, Soft-NMS [1] is used on the test stage for all experiments. And test time augmentation(TTA) is also applied, we experiment if add flip horizontal for every image, it can achieve a better score, but for multi scale test with scale factors [0.5,1.0,2.0] or [0.8,1.0,1.2], it can’t bring any improvement. Then we use SWA training strategy to finetune the model, it can bring an improvement of 2.034%. And we also train the Mask2Former in AVA train dataset without in-depth research, we find the segment results of Mask2Former is worse than HTC-CBSwin-Large except category "cane", so we integrate the results from HTC and Mask2Former, it can bring an improvement of 0.405%. Finally, we achieve 63.008% AP@0.50:0.95 on the test set of CVPR2022 AVA instance segmentation challenge.

| Methods | AP@0.50:0.95 | Boost |
|---------|--------------|-------|
| HTC-CBSwin-Large + Soft-NMS + Flip | 58.293% | - |
| HTC-CBSwin-Large + SWA + Soft-NMS + Flip | 59.852% | 1.559% |
| HTC-CBSwin-Large + Copy-Paste + Soft-NMS + Flip | 60.569% | 0.717% |
| HTC-CBSwin-Large + Copy-Paste + SWA + Soft-NMS + Flip | 62.603% | 2.034% |
| HTC-CBSwin-Large + Copy-Paste + SWA + Soft-NMS + Flip + Mask2Former | 63.008% | 0.405% |

Table 1. Experimental results on test set of CVPR2022 AVA Challenge.
4. Conclusion

In this paper, we introduce the technical details of our submission to the CVPR2022 AVA Challenge, including the model and data augmentation strategy, the effective training strategy, and the integration of two different instance segmentation framework. Experimental results demonstrate that our approach can achieve a competitive result on the test set. Finally, our approach achieves 63.008% AP@0.50:0.95 on the test set of CVPR2022 AVA Accessibility Vision and Autonomy Challenge.

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