Abstract

We describe our two-stage instance segmentation framework we use to compete in the challenge. The first stage of our framework consists of an object detector, which generates object proposals in the format of bounding boxes. Then, the images and the detected bounding boxes are fed to the second stage, where a segmentation network is applied to segment the objects in the bounding boxes. We train all our networks in a class-agnostic way. Our approach achieves the first place in the UVO 2021 Image-based Open-World Segmentation Challenge.

1. Method

In this section, we present our method for open-world instance segmentation. Our method consists of two stages, the first stage is an anchor-based object detection network that predicts bounding boxes for objects in the images. The second stage consists of a segmentation network, which takes the image and the bounding box as input and segments the object in the bounding box. Thanks to this architecture, we can train the detection network and segmentation network separately on different datasets, instead of following an “end-to-end” training approach. The large input size of segmentation network results in finer and better mask predictions.

1.1. Detection

In this section, we introduce the object detection network we used and the techniques adopted that help to improve the recall of the object detector. An overview of our network architecture is shown in Figure 1.

Baseline. We adopt the Region Proposal Network (RPN) of [20] as our baseline network. Our backbone network consists of a ResNet-50[12] network with the Feature Pyramid Network (FPN) of [15] for multi-scale feature extraction. A classification head and a regression head are used for predicting the “objectness” of the region contents and for bounding box regression, respectively.

Cascade Region Proposal Network (RPN). To further improve the quality of the predicted object proposals, as in [24], we adopt a two-stage cascade architecture for proposal generation. Only one single anchor is used for each location in the feature maps. The predicted bounding boxes from the first stage are used as the input for the second stage. Adaptive convolution is used to solve the misalignment between the anchors and the features throughout the stage. The Focal loss [16] is used for classification and GIoU loss [21] for bounding box regression.

IoU Branch. In addition to the classification and bounding box branches, we use an IoU branch, which predicts the IoU between the predicted bounding boxes and the ground truth bounding boxes. During inference, the objectness score is calculated as the geometric mean of the predicted IoU score and the classification score, as also done in [13, 9] for example.

Decoupled Heads. Decoupled heads have been widely used in previous works [9, 23] and have been demonstrated to be effective to ease the conflict between the classification and regression tasks in object detection. We adopt decoupled heads in our network. Heads across all pyramid levels share the same weights to save memory. We further replace the first convolutional layer of the decoupled heads with deformable convolutional layers [4] and we will show in the later section that this could further improve our results.

Proposal Sampling. Label assignment aims to define positive/negative samples during training. We replace the
Figure 1. Overview of our detection network architecture. DCN stands for Deformable Convolutional neural Network[4].

IoU-based label assignment with the SimOTA label assignment [9] in our network. SimOTA is a simplified version of OTA label assignment [8], which formulates the label assignment as an Optimal Transport (OT) problem and finds the negative/positive samples by measuring their transportation costs to ground truth bounding boxes. Instead of using the Sinkhorn-Knopp algorithm, SimOTA simply takes the top-K candidates that are centered at the center of the ground truth bounding boxes. In addition to this, we adopt different negative/positive label assignment strategies for classification head and regression head. In particular, instead of using one SimOTA for both classification and regression, we use two SimOTAs with different hyperparameters for classification and regression respectively. Compared to the SimOTA for classification, the one for regression assign more positive samples for candidate anchors during training. For the regression head, we loose the selection criterion to generate more positive samples.

Non-maximum suppression (NMS). Non-maximum suppression is used to remove duplicate bounding boxes. We set our NMS threshold to 0.8.

Feature Pyramid Network (FPN). We further add CARAFE [25] blocks in our FPN [15] network for a better feature upsampling.

Backbone. We use the recent Swin-L transformer [18] as our backbone network.

1.2. Segmentation
The segmentation network we used for this challenge is based on the Upernet [27] architecture and the Swin-L transformer [18] as the backbone network. The input consists of images and predicted bounding boxes, the bounding boxes are first used to crop the images to image patches. Then, the image patches are all resized to 512×512 regardless of their height/width ratios.

2. Dataset
2.1. Detection
ImageNet 22k is used to pre-train our backbone network. We then train our detectors on the COCO dataset [17]. Finally, the pre-trained detectors are fine-tuned on the UVO-Sparse dataset and the UVO-Dense dataset [26].

2.2. Segmentation
ImageNet 22k [5] is used to pre-train our backbone network. We then train our segmentation network on a combination of the OpenImage [14], PASCALVOC [6], and COCO [17] datasets. Finally, the pre-trained segmentation networks are fine-tuned on the UVO-Sparse dataset and the UVO-Dense dataset [26].

3. Implementation Details
3.1. Detection
We use MMDetection [1] to train our detectors. For the backbone network, we get the Swin-L transformer pre-trained on ImageNet 22k from 1. All our detectors are trained with Detectron ‘1x’ setting. For data augmentation, we use the basic data augmentation strategy as in [11] for all experiments. The center ratio of both SimOTA samplers are set to 0.25, the top-K number for classification head is set to 10, while the top-K number for regression head is set to 20 to involve more positive samples. Four 3×3 conv layers are used in the classification branch and the regression head, IoU branch shares the same conv layers with the regression branch.

1https://github.com/microsoft/Swin-Transformer
branch. To train the detector with Swin-L transformer backbone, we adopt the AdamW as the optimizer and set the initial learning rate to 1e-4. The batch size is set to 16. After training on COCO, we fine-tune the detector on the combination of UVO-Sparse dataset and UVO-Dense dataset for 6 epochs. All our detectors are trained in the class-agnostic way. Test time augmentation is used during inference to further boost the network performance.

3.2. Segmentation

We use MMSegmentation [2] to train our segmentation network. We use the same backbone network as our detection network. During training, given an image and an instance mask, we first generate a bounding box that envelopes the instance mask, then a 20 pixel margin is added to the bounding box in all directions. We use the generated bounding box to crop the image and resize the image patch to 512×512. Random flipping, random photometric distortion, and random bounding box jitter are used as data augmentation. We adopt ‘poly’ learning rate policy and set the initial learning rate to 6e-5. The batch size is set to 32 and AdamW[19] is used as the optimizer. We first train our network on the combination of the OpenImage [14], PASCALVOC [6] and COCO [17] datasets for 300k iterations, then we finetune the network on the combination of the UVO-Dense and UVO-Sparse datasets for 100k iterations with initial learning rate set to 6e-6. All our segmentation networks are trained in a class-agnostic way, thus, segmenting the object in the cropped path becomes a foreground/background segmentation problem. Only flip test augmentation is adopted during inference.

4. Ablation Study

4.1. Detection

In this section, we ablate the different components in our detection network. We train and evaluate our detectors using COCO train2017/val2017. The results are shown in Table 2.

5. Visualization

We visualize the results predicted by our segmentation network given images and bounding boxes in Figure 2. Our method results in high quality mask predictions.

Table 1. Ablation study on the different components of our method on COCO val2017.

|                      | AR@100 | AR@300 | AR@1000 |
|----------------------|---------|---------|----------|
| Baseline (Res50-FPN RPN) | 44.6    | 52.9    | 58.3     |
| + Casacade RPN        | 61.1    | 67.6    | 71.7     |
| + SimOTA + IoU Branch | 62.6    | 68.1    | 71.7     |
| + Decoupled Head      | 64.5    | 69.8    | 73.1     |
| + Two samplers        | 64.8    | 70.1    | 73.6     |
| + CARAFE              | 65.2    | 70.4    | 73.9     |
| + DCNv2               | 65.6    | 70.8    | 74.2     |
| + Swin-L              | 70.7    | 74.9    | 77.4     |
### 6. Potential Improvements

**More training data.** We only pre-train our detectors on the COCO dataset, while recent works\cite{22} show that pre-training on some large datasets like \cite{22, 14} can further improve the performance of detectors. With more classes and more objects of different shapes and geometries, the detectors might learn a better representation which helps to find more objects and better localize them.

**Data augmentation.** Our detectors are all trained using naive data augmentation like resize, flip, etc. Recent works \cite{10, 7, 3} show that object detectors can largely benefit from strong data augmentation. Adding data augmentation might further improve the performance of our network.

**Misc.** Some hyperparameters are still chosen arbitrarily, including the number of training epochs for fine-tuning on the UVO-Sparse and UVO-Dense datasets and the hyperparameters for label assignment. Tuning these hyperparameters could lead to better performance.

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