Augmenting Proposals by the Detector Itself

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Abstract

Lacking enough high quality proposals for RoI box head has impeded two-stage and multi-stage object detectors for a long time, and many previous works try to solve it via improving RPN’s performance or manually generating proposals from ground truth. However, these methods either need huge training and inference costs or bring little improvements. In this paper, we design a novel training method named APDI, which means augmenting proposals by the detector itself and can generate proposals with higher quality. Furthermore, APDI makes it possible to integrate IoU head into RoI box head. And it does not add any hyper-parameter, which is beneficial for future research and downstream tasks. Extensive experiments on COCO dataset show that our method brings at least 2.7 AP improvements on Faster R-CNN with various backbones, and APDI can cooperate with advanced RPNs, such as GA-RPN and Cascade RPN, to obtain extra gains. Furthermore, it brings significant improvements on Cascade R-CNN.\textsuperscript{1}

1 Introduction

Object detection is a fundamental and critical problem in computer vision, which needs to localize and recognize each object in images or videos. With the development of deep learning, current object detectors usually base on convolution neural networks, like FCOS [Tian \textit{et al.}, 2019], ATSS [Zhang \textit{et al.}, 2020], Fast[\text{Girshick, 2015}]/\text{Faster}[\text{Ren \textit{et al.}, 2016}] \text{RCNN}, \text{Cascade R-CNN}[\text{Cai and Vasconcelos, 2018}], \text{DETR}[\text{Carion \textit{et al.}, 2020}] \text{and Sparse R-CNN}[\text{Sun \textit{et al.}, 2020}]. They can be roughly divided into single-, two-, multi-stage and end-to-end methods based on their ways to generate detection results. Single-stage object detectors directly predict bounding boxes and corresponding scores for each location, while two- and multi-stage ones firstly generate proposals by Region Proposal Networks (RPN [\text{Ren \textit{et al.}, 2016}]), then two-stage detectors use a RoI box head to refine the proposals and predict the category for each proposal while multi-stage detectors use multiple RoI box heads to do prediction. Single-, two- and multi-stage methods are dense detectors, so they need to apply non-maximum suppression (NMS) to filter redundant results, while end-to-end methods directly generate detection results without NMS. Typically, performance of multi-stage methods is better than two-stage and one-stage ones, since they apply coarse to fine strategy multi-times which is powerful to generate accurate bounding boxes and can precisely predict the category for each proposal.

For deep learning, if we regard the algorithm as the core of an object detector, then training samples are the power of it. Nearly all experiments on deep learning demonstrate that more training samples, better performance. Furthermore, diversity of training samples is also critical, which means that they need to be distributed evenly in a domain. For two-stage and multi-stage object detectors, the proposals generated by a RPN are the training samples of the RoI box heads, so, proposals’ quality will significantly affect the RoI box head. There are two ways to improve proposals’ quality. One is improving performance of RPN, for example, many detectors place more anchors with different scales and ratios in each location, which makes more anchors match the ground truth to get high recall rate. GA-RPN [\text{Wang \textit{et al.}, 2019}] firstly

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{IoU distribution of original and augmented positive proposals.}
\end{figure}

\textsuperscript{1}All source codes will be released after publication.
estimates anchors’ location and shape, and then refines the estimated anchors to generate proposals. Cascade RPN [Vu et al., 2019] firstly refines the hand-designed anchors, and then aligns features of the refined anchors to process them again. These methods not only improve proposals’ quality, but also make proposals’ intersection over union (IoU) with ground truth more evenly distributed in 0.5 to 1.0, which is critical to proposal diversity. The other is manually generating proposals, for example, IoU Net [Jiang et al., 2018] manually transforms ground truth bounding boxes with a set of random parameters to obtain the proposals whose IoUs are evenly distributed in 0.5 to 1.0.

We hold the idea that the performance bottleneck of two-stage object detector is lacking of high quality proposals. As shown in Figure 1, few original positive proposals whose IoUs are greater than 0.8. However, placing more anchors in each location usually brings little improvements. While GA-RPN and Cascade RPN usually need about 150% extra training costs, because they employ deformable operation [Dai et al., 2017] to align the features for learned or refined anchors during their second step. Meanwhile, manually generated proposals do not match the distribution of proposals generated by the RPN, which may decrease robustness of detectors.

For two-stage object detectors, the outputs of RoI heads naturally contain the characteristics of proposals, inspired by that, we develop a novel and simple method to augment proposals for RoI box head, which is named as APDI, augmenting proposals by the detector itself. APDI takes proposals generated by a RPN as coarse proposals, and then applies a RoI box head to refine them to obtain augmented ones. APDI does not add any parameters or hyper-parameters, but changes the proposals’ generating process, and it only needs little extra training and inference costs. Extensive experiments on MS COCO dataset [Lin et al., 2014] show that APDI can effectively improve performance of two-stage and multi-stage object detectors. Furthermore, with APDI, we can easily integrate the IoU head of IoU Net into a RoI box head, which merely adds subtle extra FLOPs since only an extra Linear layer is added. In this way, we can achieve at least 2.7 AP improvements on Faster R-CNN, and 1.1 AP increments for Cascade R-CNN. Furthermore, it can cooperate with GA-RPN and Cascade RPN and brings at least 4.0 AP improvements on Faster R-CNN. Our main contributions can be summarized as follows:

- We propose a novel and simple method, APDI, which augments proposals by the detector itself and can significantly improve their quality. It can not only be applied on two- and multi-stage object detectors, but also on instance segmentation methods. Furthermore, it can cooperate with GA-RPN and Cascade RPN.
- With APDI, we can easily integrate the IoU head into a RoI box head to predict an IoU score for each instance without manually generated proposals, and obtain big improvements with subtle extra FLOPs.
- On MS COCO dataset, our method achieves at least 2.7 AP and 1.1 AP improvements on Faster R-CNN and Cascade R-CNN, respectively, without any bells and whistles.

2 Related Work

Generating proposals first, then refining proposals and predicting the category for each one has been a popular pipeline in object detection task. This kind of coarse to fine strategy usually brings surprising improvements. R-CNN [Girshick et al., 2014], Fast R-CNN [Girshick, 2015] and Faster R-CNN [Ren et al., 2016] all follow this design philosophy, but they also have some differences. R-CNN and Fast R-CNN employ Selective Search [Uijlings et al., 2013] to generate proposals, while Faster R-CNN designs a RPN which is based on deep learning to generate proposals and achieves joint training.

RPN’s performance greatly surpasses traditional proposal generating methods, like Selective Search and Edge Boxes [Zitnick and Dollár, 2014], and it can get over 90% recall rate when the IoU threshold is 0.5. However, most proposals’ IoUs are distributed in 0.5 to 0.8, which means that the quality of the generated proposals is not good. GA-RPN separates the RPN’s process into two steps. It firstly estimates the location and shape for each anchor, then it uses these learned anchors to match the ground truth. The following procedure is similar as RPN except it needs to align the feature for each learned anchor. GA-RPN greatly improves recall rate since its learned anchors can better match the ground truth than hand-designed anchors. Cascade RPN firstly refines the hand-designed anchors as the anchors of the next step, and then applies Adaptive Convolution to align the features to refine the anchors. Cascade RPN can further improve recall rate of proposals.

Proposals of GA-RPN and Cascade RPN greatly improve quality of proposals, and they bring significant improvements on Faster R-CNN and Cascade R-CNN. However, as Table 1 shows, their AR drop fast with higher IoU thresholds, which means that they lack high quality proposals. Furthermore, they employ deformable operation to align features, which needs about 150% extra training costs because they will encounter the writing lock during gradient computation.

Cascade R-CNN progressively refines proposals stage by stage, so proposals’ quality will be gradually improved during this process since its next RoI head takes the outputs of its previous one as inputs. In this way, Cascade R-CNN obtains diverse training samples for RoI box heads, which is the key factor that it achieves significant improvements over Faster R-CNN. However, it needs about 30% extra training costs since all three RoI box heads need to train, and if we ensemble collected proposals from different RoI box heads to train three heads, it will be a complex and time-consuming problem.

Recognizing detection quality by a model is an important factor, IoU Net proposes an IoU head to predict an IoU score for each detection result, and then uses this IoU score as the ranking keyword to guide the following NMS. In order to train its IoU head, it proposes a manual method which transforms the ground truth into proposals, and keeps their IoUs evenly distributed in 0.5 to 1.0. However, manually generated proposals may not match the distribution of proposals generated by RPN, so the manually generated ones could not directly replace the proposals during training the RoI box head.
Table 1: Comparisons on different region proposal networks.

| Method         | AR\(_{50}\) | AR\(_{60}\) | AR\(_{70}\) | AR\(_{80}\) | AR\(_{90}\) |
|----------------|-------------|-------------|-------------|-------------|-------------|
| RPN            | 92.7        | 88.9        | 78.7        | 46.1        | 8.1         |
| GA-RPN         | 94.8        | 91.8        | 84.8        | 65.1        | 27.6        |
| Cascade RPN    | 94.7        | 92.0        | 86.8        | 73.0        | 36.0        |
| RoI box head   | 93.4        | 90.5        | 85.0        | 73.4        | 45.0        |

Table 1, and we can find that what makes GA-RPN and Cascade RPN success is mainly because their proposals’ quality is higher than RPN, in other words, their AR\(_{70}\), AR\(_{80}\) and AR\(_{90}\) highly surpass those of RPN. However, if we follow the Faster R-CNN’s pipeline to employ the RoI box head to refine the proposals, without any post-processing, we obtain comparable proposals (RoI box head in Table 1) with GA-RPN and Cascade RPN. Therefore, if we directly employ RoI box head to augment the proposals before training, we may obtain comparable performance with complicated RPN, such as GA-RPN or Cascade RPN.

3.2 Box IoU head

IoU Net demonstrates that IoU scores of detection results can guide the NMS and significantly improve the performance. However, it needs manually generated proposals to train its IoU head and takes about extra 15% training and inference costs.

As shown in Figure 3, we integrate the IoU head into RoI box head, which is named as Box IoU head. We assume that proposals with higher IoU will obtain detection result with higher IoU, however, it is not true for original proposals, but is true for APDI. So, the targets of the IoU branch in Figure 3(b) are IoUs of augmented proposals with ground truth.
| Method                  | Backbone    | Schedule | AP  | AP_{50} | AP_{75} | AP_{s} | AP_{m} | AP_{l} |
|------------------------|-------------|----------|-----|---------|---------|-------|-------|-------|
| FCOS [Tian et al., 2019] | ResNet-101 FPN | -        | 41.5 | 60.7    | 45.0    | 24.4  | 44.8  | 51.6  |
| ATSS [Zhang et al., 2020] | ResNet-101 FPN | -        | 43.6 | 62.1    | 47.4    | 26.1  | 47.0  | 53.6  |
| FPN [Lin et al., 2017]  | ResNet-101 FPN | -        | 36.2 | 59.1    | 39.0    | 18.2  | 39.0  | 48.2  |
| Cascade R-CNN [Cai and Vasconcelos, 2018] | ResNet-101 FPN | -        | 42.8 | 62.1    | 46.3    | 23.7  | 45.5  | 55.2  |
| IoU Net† [Jiang et al., 2018] | ResNet-50 FPN | -        | 38.1 | 56.3    | -       | -     | -     | -     |
| Guided Anchoring [Wang et al., 2019] | ResNet-50 FPN | 1x       | 39.8 | 59.2    | 43.5    | 21.8  | 42.6  | 50.7  |
| Cascade RPN [Vu et al., 2019] | ResNet-50 FPN | 1x       | 40.6 | 58.9    | 44.5    | 22.0  | 42.8  | 52.6  |
| DETR† [Carion et al., 2020] | ResNet-50 | -        | 42.0 | 62.4    | 44.2    | 20.5  | 45.8  | 61.1  |
| Sparse R-CNN† [Sun et al., 2020] | ResNet-50 | 3x       | 42.3 | 61.2    | 45.7    | 26.7  | 44.6  | 57.6  |
| Faster R-CNN*           | ResNet-50 FPN | 1x       | 38.3 | 59.5    | 41.4    | 22.3  | 40.7  | 47.9  |
| Faster R-CNN*           | ResNet-50 FPN | 1x       | 41.7 | 59.7    | 45.2    | 24.1  | 44.0  | 52.6  |
| Faster R-CNN*           | ResNet-50 FPN | 3x       | 40.4 | 61.4    | 43.9    | 23.6  | 42.8  | 50.3  |
| Faster R-CNN*           | DCN-50 FPN   | 3x       | 42.2 | 63.3    | 46.0    | 24.8  | 44.4  | 53.2  |
| Faster R-CNN*           | ResNet-101 FPN | 3x       | 42.4 | 63.1    | 46.1    | 25.0  | 45.0  | 53.4  |
| Faster R-CNN+APDI†       | ResNet-50 FPN | 1x       | 42.0 | 60.4    | 45.4    | 24.4  | 44.2  | 53.1  |
| Cascade R-CNN+APDI†     | ResNet-50 FPN | 1x       | 42.8 | 60.2    | 46.1    | 24.9  | 44.8  | 54.3  |
| Faster R-CNN+APDI†      | ResNet-50 FPN | 3x       | 43.5 | 62.4    | 47.0    | 25.6  | 45.6  | 55.1  |
| Faster R-CNN+APDI†      | DCN-50 FPN   | 3x       | 44.9 | 64.0    | 48.3    | 26.7  | 47.0  | 57.0  |
| Faster R-CNN+APDI†      | ResNet-101 FPN | 3x       | 45.2 | 64.2    | 48.5    | 26.9  | 48.0  | 57.0  |

Table 2: Comparisons with state-of-the-art methods on COCO test-dev, the results with symbol ‘*’ are our reimplemented results, and the symbol ‘†’ means the results are reported on COCO val-2017. All settings including ‘1x’ and ‘3x’ training schedules follow the detectron2 unless specially noted. ‘+ADPI’ indicates to apply APDI and Box IoU head on corresponding methods.

There are two reasons for this design. First, it is easily to compute the ground truth for IoU branch. Second, unlike RoI box head+IoU head, the quality of a proposal’s detection result is not known until the proposal is sent into the Box IoU head, which is hard to optimize.

During training, we use BCE as loss function for optimization of IoU scores, and the loss weight is simply set to 1.0, furthermore, all proposals whose IoU is greater or equal to 0.3 need to participate training.

During inference, the detection scores are product of box classification scores and IoU scores. The IoU scores are category-agnostic, which means that each detection has only one IoU score. Therefore, for each detection result, all detection scores for each category need to be calibrated by its IoU score.

4 Experiments

4.1 Dataset and Evaluate Metrics

All our experiments are implemented on the challenging Microsoft COCO 2017 [Lin et al., 2014] dataset. It consists of 118k images for training, train-2017 and 5k images for validation, val-2017. We remove 1021 images with no usable annotations in train-2017 following detectron2, thus 117k images are left. There are also 20k images without annotations for test in test-dev.

We train all our models on train-2017, and report ablation studies on val-2017 and final results on test-dev. All results are subjected to standard COCO-style Average Precision (AP) metrics which include AP (mean of AP over all IoU thresholds), AP_{50}, AP_{75}, AP_{s}, AP_{m}, and AP_{l}, where AP_{50} and AP_{75} are AP for IoU threshold of 50% and 75%, respectively, and AP_{s}, AP_{m}, and AP_{l} are AP for small, medium, and large objects, respectively.

4.2 Implementation Details

All experiments are based on detectron2 [Wu et al., 2019]. And all our codes are deployed on a machine with 8 Tesla V100-SXM2-16GB GPUs and 32 Intel Xeon Platinum 8163 CPUs. Our software environment mainly include Ubuntu 18.04 LTS OS, CUDA 10.1, GCC 7.3, PyTorch [Paszke et al., 2017] 1.6.0 and Python 3.8.5. The other settings follow detectron2 unless specifically noted.

For Cascade R-CNN, we employ the first RoI box head to augment the proposals, and we also replace three RoI box heads.
We apply APDI.  

### 4.3 Results

We apply APDI+ (APDI+Box IoU head) on Faster R-CNN and Cascade R-CNN with ResNet-50 [He et al., 2016], ResNet-101 [He et al., 2016] and DCN-50 [Dai et al., 2017], and report our results on COCO test-dev. It is hard to compare different detectors completely fair due to different settings in training and testing, for example, batch-size, learning rate schedule and iterations, etc. Thus, we reimplement them with various backbones and learning rate schedules, and other settings of them followed detectron2.

As shown in Table 2, with 1x training schedule, APDI+ with ResNet-50 as backbone can achieve 42.0 AP without any bells and whistles, which is 3.7 AP higher than reimplemented Faster R-CNN with the same backbone. And Cascade R-CNN with APDI+ achieves 1.1 AP improvements. Furthermore, with 3x schedule, APDI+ brings at least 2.7 AP improvements on Faster R-CNN with various backbones.

### 4.4 Ablation Study

We report our ablation studies’ results on COCO val2017 dataset. Here, all base models are Faster R-CNN (ResNet-50 FPN) unless specially noted.

| APDI | Box IoU head | AP | AP$_{50}$ | AP$_{75}$ | AP$_{m}$ | AP$_{s}$ |
|------|--------------|----|----------|----------|---------|---------|
| ✓    | ✓            | 37.8 | 58.4 | 41.1 | 22.2 | 41.4 | 48.4 |
| ✓    | ✓            | 39.9 | 59.9 | 43.1 | 23.5 | 43.4 | 52.0 |
| ✓    | ✓            | 36.6 | 56.8 | 39.8 | 21.9 | 40.1 | 46.9 |
| ✓    | ✓            | 41.5 | 60.0 | 44.8 | 24.1 | 44.6 | 54.7 |

Table 3: Comparison results for different components of this paper.

We find that APDI is only slightly slower than standard RPN since APDI is a gradient free method, while GA-RPN and Cascade RPN’s training time is more than twice because of writing lock. And for inference time, APDI is slightly slower than RPN by 12%, while GA-RPN and Cascade RPN bring extra 1.6 AP improvements. To explore underlying reasons, we visualize the distribution of original proposals and augmented positive proposals in Figure 1. We find that the IoUs of the augmented proposals are more evenly distributed in 0.5 to 1.0, while IoUs of the original proposals are mainly distributed in 0.5 to 0.8. Thus, directly applying these unbalanced proposals to train the IoU branch will lead to poor performance according to IoU Net.

**Cascade R-CNN.**

For Cascade R-CNN, as mentioned in Section 4.2, we change the IoU thresholds of its three RoI box heads (change in Table 4), and replace its RoI box heads with three Box IoU heads. In this section, we conduct ablation study for these operations, and report the results in Table 4.

| APDI change | Box IoU head | AP | AP$_{50}$ | AP$_{75}$ |
|--------------|--------------|----|----------|----------|
| ✓            | ✓            | 41.6 | 59.5 | 45.1 |
| ✓            | ✓            | 41.8 | 59.7 | 45.2 |
| ✓            | ✓            | 42.1 | 59.2 | 45.5 |
| ✓            | ✓            | 42.5 | 59.7 | 46.1 |

Table 4: Comparison for different strategies on Cascade R-CNN.
Table 5: Comparison of different RPNs.

| Method     | training time(ms/iter) | inference time(ms/img) | AP  | AP_{50} | AP_{75} | AP_{s} | AP_{m} | AP_{l} |
|------------|------------------------|------------------------|-----|---------|---------|--------|--------|--------|
| RPN        | 189.0                  | 40.5                   | 37.8| 58.4    | 41.1    | 22.2   | 41.4   | 48.4   |
| GA-RPN     | 448.1                  | 69.3                   | 39.6| 58.7    | 43.4    | 21.2   | 43.0   | 52.7   |
| Cascade RPN| 436.4                  | 67.6                   | 40.4| 59.1    | 43.9    | 22.9   | 43.5   | 53.0   |
| RPN+APDI   | 204.3                  | 45.3                   | 39.9| 59.9    | 43.1    | 23.5   | 43.4   | 52.0   |

Table 6: Comparison for different strategies on Faster R-CNN.

| Method   | AP  | AP_{50} | AP_{75} | AP_{s} | AP_{m} | AP_{l} |
|----------|-----|---------|---------|--------|--------|--------|
| None     | 37.8| 58.4    | 41.1    | 22.2   | 41.4   | 48.4   |
| IBBR     | 38.2| 58.5    | 41.6    | 21.9   | 41.2   | 50.1   |
| APDI     | 39.9| 59.9    | 43.1    | 23.5   | 43.4   | 52.0   |

Table 7: Comparison for different RPNs with APDI.

| Method                 | APDI | AP_{bbox} | AP_{mask} |
|------------------------|------|-----------|-----------|
| Mask R-CNN             |      | 38.6      | 35.2      |
| Mask R-CNN✓            |      | 42.0      | 37.0      |
| Cascade Mask R-CNN     |      | 42.2      | 36.6      |
| Cascade Mask R-CNN✓    |      | 43.3      | 37.4      |

Table 8: Comparison on instance segmentation tasks with different methods.

need extra 76% and 71% inference time, respectively. Furthermore, APDI achieves comparable AP with them, so, APDI is a cost-efficient method.

5 Discussion

In this section, we will deeply discuss differences with iterative bounding box regression (IBBR) and the cooperation with improved RPN, like GA-RPN and Cascade RPN. Furthermore, we also try to apply APDI on instance segmentation tasks. All following models are trained on COCO train-2017 and the results are reported on COCO val-2017 dataset. In this section, all base models are Faster R-CNN (ResNet-50 FPN) unless specially mentioned.

5.1 IBBR

IBBR means applying RoI box head several times to refine the bounding boxes during inference, which is similar to APDI in inference. However, the key difference is that APDI works on both training and inference period, but IBBR only works on inference. We apply bounding box regression 2 times for IBBR, and the results are shown in Table 6.

From Table 6, we can conclude that IBBR only brings little gains on Faster R-CNN, and it is beneficial for large instances, but harmful for small ones. Furthermore, experiments in IoU Net [Jiang et al., 2018] show that increasing number of iterations will degrade performance of IBBR. However, APDI surpasses Faster R-CNN on all metrics, mainly because of the well-trained RoI box head by the augmented proposals.

5.2 Cooperation with Improved RPN

APDI tries to augment the proposals generated by RPN, furthermore, we find that APDI can also cooperate well with GA-RPN and Cascade RPN. We directly replace the RPN by them, and keep all other settings unchanged. All results are reported in Table 7, and we can draw a conclusion that GA-RPN or Cascade RPN and APDI are not competitive, but complementary. Moreover, the gains of GA-RPN and Cascade RPN mainly come from AP_{75}, which means that better proposals usually lead to more precise detection results.

Here, we also find that Box IoU head brings 1.6 AP improvements on RPN, while 1.1 AP and 1.0 AP improvements on GA-RPN and Cascade RPN, respectively. It is possibly because there are gaps between IoU distribution of GA-RPN or Cascade RPN and RPN, which bring a large bias for predicting IoU scores.

5.3 Instance Segmentation with APDI

Instance segmentation needs to predict a mask for each instance, and we employ Mask R-CNN[He et al., 2017] as our base model since the mask head’s pipeline is similar to RoI box head. We use the positive refined proposals as inputs of the mask head to save training costs, and other settings are same as Faster R-CNN with APDI and Box IoU head. We also conduct our experiments on Cascade Mask R-CNN.

As shown in Table 8, for instance segmentation, APDI obtains 1.8 AP and 0.8 AP improvements on Mask R-CNN and Cascade Mask R-CNN, respectively. It shows that APDI is also powerful for instance segmentation tasks.

6 Conclusion

In this paper, we propose a novel and simple training method named APDI, which can significantly improve performance with little extra FLOPs. Furthermore, with the help of APDI, we also find that we can integrate IoU head into RoI Box head, which is named as Box IoU head. It is concise and brings big improvements. We hope that the findings could help researchers design more powerful object detector. In our future work, we will deeply explore more advanced cooperation between APDI and improved RPN methods.
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