Unbiased Teacher v2: Semi-supervised Object Detection for Anchor-free and Anchor-based Detectors

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Abstract

With the recent development of Semi-Supervised Object Detection (SS-OD) techniques, object detectors can be improved by using a limited amount of labeled data and abundant unlabeled data. However, there are still two challenges that are not addressed: (1) there is no prior SS-OD work on anchor-free detectors, and (2) prior works are ineffective when pseudo-labeling bounding box regression. In this paper, we present Unbiased Teacher v2, which shows the generalization of SS-OD method to anchor-free detectors and also introduces Listen2Student mechanism for the unsupervised regression loss. Specifically, we first present a study examining the effectiveness of existing SS-OD methods on anchor-free detectors and find that they achieve much lower performance improvements under the semi-supervised setting. We also observe that box selection with centerness and the localization-based labeling used in anchor-free detectors cannot work well under the semi-supervised setting. On the other hand, our Listen2Student mechanism explicitly prevents misleading pseudo-labels in the training of bounding box regression. We specifically develop a novel pseudo-labeling selection mechanism based on the Teacher and Student’s relative uncertainties. This idea contributes to favorable improvement in the regression branch in the semi-supervised setting. Our method, which works for both anchor-free and anchor-based methods, consistently performs favorably against the state-of-the-art methods in VOC, COCO-standard, and COCO-additional.

1. Introduction

Deep learning models have achieved remarkable performance on object detection tasks in recent years, though the strong performance heavily relies on training a network with abundant images with human-annotated labels. To reduce the label supervision for training object detectors, Semi-Supervised Object Detection (SS-OD) methods have been proposed to leverage only limited labeled data but more abundant unlabeled data to improve performance [5, 9, 20, 26, 38]. Existing state-of-the-art SS-OD methods apply self-training techniques, which generate pseudo-labels and enforce the consistency between unlabeled data with different augmentations. Despite the significant improvement, there are still two remaining issues that are left untackled: (1) there is no prior SS-OD work on anchor-free detectors and (2) prior works are ineffective in pseudo-labeling on the bounding box regression.

First, anchor-free detectors have been recently getting more attention in the community of object detection [11, 15, 16, 29, 30, 37, 42], with the promise of achieving competitive accuracy, computational efficiency, and potential generalization to new datasets or environments [37]. In spite of these advances, existing SS-OD works [9, 20, 26] mainly focus on anchor-based detectors (e.g., Faster-RCNN [21] and SSD [19]) but do not empirically verify their effectiveness on anchor-free detectors. In fact, when we adapt recent state-of-the-art SS-OD methods to anchor-free detectors, we observe that, compared with its improvement on anchor-based models, the improvement is much smaller on anchor-free models (see Figure 1a and Table 1). With extensive analysis provided in Section 3.2, we find that some advanced techniques performing favorably in the fully-supervised setting do not work in the semi-supervised setting with limited supervision. For example, the centerness score becomes unreliable for box selection under the semi-supervised setting, and the localization-based labeling method is not robust to the localization noise in pseudo-labels.

Second, following the Teacher-Student framework, the existing SS-OD works [26, 38] apply an unsupervised regression loss with the pseudo-boxes generated from confidence thresholding (i.e., a threshold on the box score). However, we find that this approach inherits some potential issues that can be further addressed. For instance, (1) instead of using one single metric (e.g., box score or box IoU) to jointly represent the quality of four boundaries, the confidence/uncertainty of each boundary should be predicted individually; (2) confidence in the classification branch might not be able to reflect the quality of boundary prediction on
Figure 1. To improve the unsupervised regression loss, we propose (a) Listen2Student, which explicitly compares the prediction uncertainties between the Teacher and the Student and selects these instances where the teacher has lower uncertainty than the student. We then enforce the unsupervised regression loss on these selected regression pseudo-labels. (b) Anchor-free detectors are rapidly developed recently, while adapting the pseudo-labeling method on the anchor-free models results in less improvements compared with the anchor-based detectors.

We demonstrate that our proposed method achieves significant improvements compared to the state-of-the-art SS-OD methods when using both anchor-free and anchor-based detectors on several SS-OD benchmarks, including COCO-standard, COCO-additional, and VOC. We also provide ablation studies to examine the effectiveness of our Listen2Student. We summarize the main contributions as follows:

- We show the generalization of our proposed semi-supervised method on both anchor-based and anchor-free detectors. To the best of our knowledge, we are the first to examine the anchor-free models on SS-OD, and we identify core issues in applying SS-OD methods on anchor-free detectors.

- We explicitly remove misleading instances in regression pseudo-labels by considering relative uncertainty estimation from the Teacher and Student predictions. We provide analyses to verify effectiveness of our approach on anchor-free and anchor-based detectors.

- Based on our empirical study on anchor-free and anchor-based detectors, our method shows favorable improvements against the state-of-the-art methods. With the proposed method, we also bridge the performance gap between anchor-free and anchor-based detectors under the semi-supervised setting.

2. Related Work

Anchor-Free Object Detectors. The development of deep learning models has resulted in significant improvements on object detection tasks. Existing object detectors consist of anchor-based detectors [2, 17, 19, 21, 24, 32] and anchor-free detectors [11, 13, 29, 30, 40, 42]. Specifically, anchor-based detectors predict the box shift and scaling for the pre-defined anchor-boxes, and each predicted box is labeled according to its intersection-over-union (IoU) score to the ground-truth boxes. Based on label assignment (i.e., assign classification labels to predicted instances) and subsampling of foreground-background anchor boxes, the models are then trained to perform object detection. Despite remarkable results that have been achieved, applying anchor-based detectors on new datasets requires experts to tune hyper-parameters [10] related to anchor-boxes, which limits the ability to adapt to new datasets or environments [37]. Alternatively, anchor-free models alleviate these concerns by removing the pre-defined anchor-boxes in detection models. For example, keypoint-based anchor-free detectors eliminated the need for designing a set of anchor boxes by representing a box as two corner points [13], a center point with four extreme points [40], and a center point with the box weight and height [39]. Similarly, FCOS [29] removed...
the pre-defined anchor-boxes and predicted a classification score, distances to four boundaries, and a centerness score for each pixel. Several works improved the performance of the anchor-free model by proposing an adaptive sample selection [37], jointly training the centerness and classification branches with soft-labels [16], soft-selecting the pyramid levels [41], and modeling the boundary uncertainty [15]. In this paper, we use FCOS [29] as our base anchor-free model, since it is publicly available and widely used in existing anchor-free models [15, 16, 37, 41].

**Semi-Supervised Object Detection.** Semi-supervised learning (SSL) for image classification has been rapidly developed and obtained promising results in recent years. Existing SSL image classification works [1, 6, 8, 12, 22, 25, 28, 35, 36] apply input augmentations/perturbations and consistency regularization on unlabeled images to improve the model trained with the limited amount of labeled data. Inspired by these works, several semi-supervised object detection works have been proposed to exploit similar ideas to train object detectors in a semi-supervised manner. For example, CSD [9] apply a left-right consistency loss to enforce prediction consistency between horizontally flipped unlabeled images. Some other works [20, 26, 27, 38] exploit pseudo-labeling, where a model iteratively generates the pseudo-labels of unlabeled data and add the confident predictions into the training data. STAC [26] uses the limited amount of labeled data to train an object detector, which is used to generate the pseudo-labels for unlabeled data in an offline manner. To refine the quality of pseudo-labels, Instant-Teaching [38] proposes a co-rectify scheme to rectify the false prediction between two identical but independently trained models. Humble Teacher [27] applies exponential moving average (EMA) and soft pseudo-labels to improve against the model trained on labeled data only. Unbiased Teacher [20] propose a simple background-weighted loss and box variance filter to improve performance against the supervised baselines. While they can improve the performance in the semi-supervised setting, existing works only present their results on anchor-based detectors. We are thus interested in investigating the generalization of the state-of-the-art methods (i.e., pseudo-labeling) on anchor-free models and improving the performance of anchor-free models for semi-supervised object detection tasks.

### 3. Method

#### 3.1. Background: Semi-supervised Object Detection and Pseudo-labeling

With the goal of learning an object detector in a semi-supervised setting, we assume a set of labeled images $D_s = \{x_i^s, y_i^s\}_{i=1}^{N_s}$ and unlabeled images $D_u = \{x_i^u\}_{i=1}^{N_u}$ are available during training.

In order to address semi-supervised object detection, existing works [20, 26, 38] exploit the pseudo-labeling method. Specifically, this line of works contains two stages: 1) The burn-in stage and 2) the mutual learning stage. In the burn-in stage, with the available labeled data, an initial object detector is trained with the standard supervised losses, $L_{sup} = \sum_i \mathcal{L}(x_i^s, y_i^s)$. In the mutual learning stage, the pretrained object detector is duplicated into a Student and a Teacher model initially. Then, in each training iteration, the Teacher model takes the weakly-augmented unlabeled images as input and predicts the bounding boxes, and the instances with the box score higher than a threshold $\tau$ (i.e., confidence thresholding) are selected as the pseudo-labels.

Based on the pseudo-labels and the same unlabeled image but with a stronger augmentation, the unsupervised loss $L_{unsup}$ is computed and combined with the supervised loss $L_{sup}$ to train the Student model, $\theta_s \leftarrow \theta_s + \gamma \frac{\partial L_{sup} + \lambda_s L_{unsup}}{\partial \theta_s}$, where $L_{unsup} = \sum_i \mathcal{L}(x_i^u, \hat{y}_i^u)$. To refine the quality of the pseudo-labels, the Teacher model weight ($\theta_t$) can be further updated with the Student model weight ($\theta_s$) via Exponential Moving Average (EMA) as shown in [20].

| Methods | Models | 0.5% | 1% | 5% | 10% | 100% |
|---------|--------|------|----|----|-----|------|
| UT [20] | F-RCNN | 14.36 | 18.33 | 26.65 | 29.56 | 37.90 |
| UT [20] | FCOS   | 10.27 | 14.61 | 23.99 | 28.18 | 38.10 |

Table 1. Adaption of Unbiased Teacher [20] to an anchor-free model. The performance is degraded when applying Unbiased Teacher on the anchor-free model (FCOS).
Table 2. While box selection based on box score leads to worse results in semi-supervised learning compared with selecting based on classification scores. (b) Box scores of the anchor-free detectors [29, 37] are defined as the multiplication of the centerness scores and the classification scores, and we find that (c) box scores of pseudo-boxes are dominated by the centerness scores, which are unreliable in semi-supervised setting (see Appendix for further details).

As shown in Figure 1b and Table 1, we observe that simply applying the existing state-of-the-art SS-OD methods [9, 20, 26] on anchor-free detectors obtains much smaller improvements compared with anchor-based detectors. We attribute this to the following two factors.

**Centerness bias issue.** As presented in Figure 2b and Table 2, we notice that selecting the pseudo-boxes based on box scores performs worse than solely relying on classification scores in the semi-supervised setting, while FCOS [29] shows using box scores leads to better results in the fully-supervised setting. We observed that this is because the box scores of some anchor-free detectors [29, 37] are defined as the multiplication of classification scores and centerness scores (see Figure 2a), and the pseudo-boxes selected based on the box scores have relatively high centerness scores but low classification scores (see Figure 2c). This reveals that the box scores are dominated by the centerness scores in the pseudo-labeling mechanism. However, with the limited amount of labels used in the training, the centerness scores are not reliable for reflecting whether a prediction is a foreground instance since there is no supervision to suppress the centerness scores for background instances in the centerness branch\(^1\). As a result, these selected high centerness pseudo-boxes are likely to be the background instances, and adding these false-positive pseudo-boxes in the semi-supervised training degrades the effectiveness of the pseudo-labeling and also aggravates the centerness bias issue.

**Unreliable Label Assignment.** To improve the performance of the fully-supervised anchor-free detector, several works [16, 39] proposed to use soft classification labels, which are weighted based on the bounding box localization as presented in Figure 3a. Similarly, FCOS [29] also presented an advanced label assignment technique, center-sampling, which regards the instances close to the center of the object as foreground instances and improves against the model using the standard label assignment that labels all instances insides ground-truth boxes as foreground and the remaining instances as background. Although the above techniques improve the anchor-free detectors during fully-supervised training, we found that they are not effective or even detrimental during semi-supervised training (see Figure 3b and Table 3). We hypothesize that this is because the pseudo-boxes can have localization noise (either due to the center of the box being shifted or the box has incorrect width and height), and using center-sampling or the Localization-based soft labels makes pixel-wise predictions incorrectly labeled as either foreground (false positive) or background (false negative). For instance, as shown in Figure 3, the precision and recall of center-sampling is much lower than standard for this particular example with reasonable amount of localization noise.

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\(^1\)A similar observation was also made in Generalized Focal Loss [16].
While confidence thresholding has been demonstrated to work well in classification (image-level [25] or box-level [20, 26, 38]), we observed solely relying on the box confidence cannot explicitly prevent misleading instances in the pseudo label for regression, because the Teacher can still provide a regression direction that is contradictory to the ground-truth direction. Similar observations are also found in prior works in knowledge distillation for regression tasks [3, 23].

### 3.3.2 Listen2Student

To address the above concerns and improve the regression branch with the Teacher-Student mechanism, we aim to select the beneficial instances and remove misleading instances for the training of the regression branch. Intuitively, we develop a novel way to use relative prediction information between the Student and Teacher; to our knowledge this is the first instance of moving beyond using just the Teacher’s prediction information. Specifically, as shown in Figure 4, the beneficial instance of boundary prediction is defined as: the instance that satisfies $||\tilde{d}_t - d_g|| \leq ||\tilde{d}_s - d_g||$, where $\tilde{d}_t$ is the Teacher’s regression prediction, $\tilde{d}_s$ is the Student’s regression prediction, and $d_g$ is the ground-truth regression label. As a comparison, the misleading instance of regression is expressed as the instance satisfying $||\tilde{d}_s - d_g|| > ||\tilde{d}_t - d_g||$.

**Uncertainty prediction for regression.** While we were hoping to use ground-truth labels $d_g$ to decide whether the predictions from the Teacher is better or not, in reality, the ground-truth labels are not available for SS-OD. Therefore, we propose to predict the localization uncertainty, which loosely correlates with the error to the ground-truth label (i.e., $||\tilde{d}_t - d_g||$ and $||\tilde{d}_s - d_g||$) for the unlabeled data. As shown in Figure 4, the localization uncertainty of each boundary prediction is derived by adding an additional branch, which has the same output size as the boundary distance regression branch. The localization uncertainty branch is jointly trained with the boundary distance branch, and we use the negative power log-likelihood loss (NPLL) [14]² as the regression loss,

$$
L^{\text{sup}}_{\text{reg}} = \sum_i \eta_i \left( \frac{(d_s - d_g)^2}{2\delta_s^2} + \frac{1}{2} \log \delta_s^2 \right) + 2 \log 2\pi,
$$

where $\eta_i$ is the IoU score between the predicted box and the ground-truth box, and $\delta_s$ is the predicted uncertainty of the Student.

**Relative uncertainties for pseudo-label selection.** With the uncertainty estimation, we first loosely remove the boundaries where student has very small localization uncertainty $\delta_s \leq \sigma_s$. We then propose a selection mechanism which explicitly takes not only the Teacher’s localization uncertainty $\delta_t^i$ but also the Student’s localization uncertainty $\delta_s^i$ into account for the pseudo-label selection. By selecting the beneficial instances where the Teacher has lower localization uncertainty than the Student with a margin $\sigma$, our

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² Listen2Student is not limited to NPLL, and other regression uncertainty estimation methods [7] are also potentially applicable.
unsupervised regression loss is thus defined as

\[
E_{\text{reg}}^{\text{unsup}} = \begin{cases} 
\sum_i \|d_t^i - d_s^i\|, & \text{if } \delta_t^i + \sigma \leq \delta_s^i \\
0, & \text{otherwise}
\end{cases}
\]

(1)

where \(\sigma \geq 0\) is a margin between the localization uncertainties of Teacher and Student. Note that the unsupervised regression loss is computed in the boundary level rather than the box level, so some boundaries of a box are used to computed unsupervised regression loss while the others are not.

The core idea of this mechanism is that the Teacher should only guide the Student with the instances that the Teacher has lower uncertainty than the student, as it indicates that the Teacher has a potentially lower error. By contrast, for the instances, which the Teacher has higher uncertainty than the Student, we should not enforce the loss, as the Teacher is likely to predict worse than the Student and thus mislead the Student for these instances. Based on this selection mechanism, we can explicitly prevent gradients from misleading instances from degrading the performance of the regression branch. Our regression branch can thus gradually be refined and obtain more accurate boundary prediction. It is worth noting that the localization uncertainty branch is an individual branch and only used in the training stage, thus introducing no additional computation during inference.

4. Experiments

4.1. Settings and Implementation Details

**Experimental Settings.** We follow the experimental settings presented in the existing semi-supervised object detection works [20, 26]. Specifically, we use MS-COCO [18] and PASCAL VOC [4] and examine our proposed method on three experimental scenarios, COCO-standard, COCO-additional, and VOC. For COCO-standard, we randomly sample 0.5, 1, 2, 5, and 10% labeled training data as our labeled set, and the remaining data as the unlabeled set. For COCO-additional, we use COCO2017-labeled as labeled set and COCO2017-unlabeled as the unlabeled set. We evaluate on COCO2017-val for both COCO-standard and COCO-additional as in previous works. As for VOC, VOC2007-trainval is used as the labeled set, and VOC2012-trainval and COCO2017-cls are used as the unlabeled set. All trained models in VOC experiment are evaluated on VOC2007-test.

**Model Architecture.** In order to examine the effectiveness of anchor-free models for semi-supervised object detection, we chose FCOS [29] as our base anchor-free models since it is widely adopted in existing anchor-free works [15, 16, 37, 41]. As the existing works mainly focus on anchor-based models and use Faster-RCNN [9, 20, 26] or SSD [9], we also adapt the existing SS-OD methods [9, 20, 26] to the anchor-free model (e.g., FCOS).

**Implementation Details.** Our implementation is based on Detectron2 [31]. To train our model, we use SGD optimizer with the learning rate 0.01, and each batch contains 8 labeled images and 8 unlabeled images unless specified. We use the unsupervised loss weight \(\lambda_u = 3.0\) and classification threshold \(\tau = 0.5\), and we set \(\sigma = 0.1\) as the margin between localization uncertainties of Teacher and Student and \(\sigma_s = 0.5\). We adapt the data augmentation used in Unbiased Teacher and applied the scale jittering used in SoftTeacher [33] without using any geometric augmentation during training, as we empirically find that the scale jittering leads to a significant improvement. More details are listed in the supplementary material.

4.2. Results on Anchor-free Detector

**COCO-standard.** We adapt three anchor-based methods, CSD [9], STAC [26], and Unbiased Teacher [20], to the anchor-free models, and each method was run five times and their means and variances are reported, as presented in Table 4. Our model consistently performs favorably against the baseline methods under different degrees of supervision, and the improvement gap is larger when the level of supervision is lower. Our experiments on VOC and COCO-additional also result in a similar trend as well (see Appendix for experimental results).

4.3. Results on Anchor-based Detector

In addition to the results on the anchor-free model, we are also interested whether our proposed method can generalize to different types of object detectors. Specifically, we apply our unsupervised regression loss on Unbiased Teacher and modify the regression branch to predict the localization uncertainty with an additional branch as we did in Section 3.3. We examine our Listen2Student on the Faster-RCNN for COCO-standard, VOC, and COCO-additional as follows.

**COCO-standard.** As presented in Table 5, compared with the state-of-the-art SS-OD methods [20, 27, 33], our method obtains higher mAP under the cases where 0.5% to 10% data are labeled. Under different batch sizes, we could maintain the improvement gap against existing SS-OD methods and further improve the performance to 35.08 mAP under COCO-standard 10% case. In addition, we also find that the performance gap between the anchor-free and anchor-based detectors is reduced by using our framework, and this verifies the generalization of our proposed Listen2Student to both anchor-free and anchor-based detectors.

**VOC and COCO-additional.** To verify whether our framework can improve the object detector trained with the unlabeled set, we also consider VOC in Table 7 and COCO-additional in Table 8. With VOC07 used as the labeled set, our model can leverage VOC12 to achieve 56.87 mAP, and using VOC12+COCO20cls as the unlabeled set can further improve the model and achieve 58.08mAP. On the
Table 4. Experimental results of the anchor-free model (FCOS-ResNet50) on COCO-standard. * We reimplement and adapt to FCOS-ResNet50. We randomly sample labeled data and run each method 5 times, and we report the mean and standard deviation for each result. We used 8 labeled images and 8 unlabeled images for all results presented in this table.

| Anchor-free detectors on COCO-standard | 0.5% | 1% | 2% | 5% | 10% |
|---------------------------------------|------|----|----|----|-----|
| Supervised                            | 5.42 ± 0.01 | 8.43 ± 0.03 | 11.97 ± 0.03 | 17.01 ± 0.01 | 20.98 ± 0.01 |
| CSD [9]†                              | 5.76 ± 0.55 (±0.34) | 9.23 ± 0.08 (±0.34) | 12.53 ± 0.04 (±0.34) | 18.09 ± 0.08 (±1.08) | 22.06 ± 0.01 (±1.08) |
| STAC [26]†                            | 8.79 ± 0.12 (±0.37) | 11.97 ± 0.12 (±0.54) | 15.50 ± 0.16 (±0.55) | 20.36 ± 0.05 (±3.35) | 24.31 ± 0.02 (±3.33) |
| Unbiased Teacher [20]†                | 10.27 ± 0.13 (±4.85) | 14.61 ± 0.10 (±3.54) | 18.70 ± 0.21 (±5.73) | 23.99 ± 0.12 (±6.98) | 28.18 ± 0.01 (±7.20) |
| Ours                                  | 16.25 ± 0.18 (±0.83) | 22.71 ± 0.42 (±4.28) | 26.03 ± 0.12 (±14.06) | 30.08 ± 0.04 (±13.07) | 32.61 ± 0.03 (±11.63) |

Table 5. Experimental results of anchor-based models (FasterRCNN-ResNet50) on COCO-standard. For a fair comparison, we make the batch size consistent to the baseline methods. †: using labeled/unlabeled batch size 32/32. *: using batch size labeled/unlabeled batch size 8/40, and rest of the results using batch size 8/8. We randomly sample labeled data and run each method 5 times, and we report the mean and standard deviation for each result.

| Anchor-based detectors on COCO-standard | 0.5% | 1% | 2% | 5% | 10% |
|----------------------------------------|------|----|----|----|-----|
| Supervised                             | 6.83 ± 0.15 | 9.05 ± 0.16 | 12.70 ± 0.15 | 18.47 ± 0.22 | 23.86 ± 0.81 |
| CSD [9]                                | 7.41 ± 0.21 (±0.58) | 10.51 ± 0.06 (±1.46) | 13.93 ± 0.12 (±1.23) | 18.63 ± 0.07 (±0.16) | 22.46 ± 0.08 (±1.40) |
| STAC [26]                              | 9.78 ± 0.53 (±2.95) | 13.97 ± 0.35 (±4.92) | 18.25 ± 0.25 (±5.55) | 24.38 ± 0.12 (±5.86) | 28.64 ± 0.21 (±4.78) |
| Humble Teacher [27]                    | - | 16.96 ± 0.38 (±7.91) | 21.72 ± 0.24 (±9.02) | 27.70 ± 0.15 (±9.23) | 31.61 ± 0.25 (±7.74) |
| Instant Teaching [38]                  | - | 18.05 ± 0.15 (±9.00) | 22.45 ± 0.15 (±9.75) | 26.75 ± 0.05 (±8.28) | 30.40 ± 0.05 (±6.54) |
| Unbiased Teacher [20]                  | 14.36 ± 0.09 (±7.53) | 18.33 ± 0.19 (±9.28) | 22.23 ± 0.21 (±9.53) | 26.65 ± 0.31 (±8.18) | 29.56 ± 0.24 (±5.70) |
| ISMT [34]                              | - | 18.88 ± 0.74 (±9.83) | 22.43 ± 0.56 (±9.73) | 26.37 ± 0.24 (±7.90) | 30.53 ± 0.52 (±6.67) |
| Ours†                                 | 17.51 ± 0.24 (±10.88) | 21.84 ± 0.13 (±12.79) | 26.14 ± 0.01 (±13.44) | 30.06 ± 0.14 (±11.59) | 33.50 ± 0.03 (±9.64) |
| SoftTeacher [33]†                      | - | 20.46 ± 0.39 (±11.41) | - | 30.74 ± 0.08 (±12.27) | 34.04 ± 0.14 (±10.18) |
| Ours *                                | 21.02 ± 0.49 (±14.19) | 24.79 ± 0.30 (±15.74) | 28.23 ± 0.05 (±15.53) | 32.05 ± 0.04 (±13.58) | 35.02 ± 0.02 (±11.16) |
| Unbiased Teacher [20]‡                 | 16.94 ± 0.23 (±10.11) | 20.75 ± 0.12 (±11.72) | 24.30 ± 0.07 (±11.60) | 28.27 ± 0.11 (±9.80) | 31.50 ± 0.10 (±7.64) |
| Ours ‡                                | 21.26 ± 0.21 (±14.43) | 25.40 ± 0.36 (±16.35) | 28.37 ± 0.03 (±16.57) | 31.85 ± 0.09 (±13.38) | 35.08 ± 0.02 (±11.22) |

other hand, with the COCO2017-unlabeled set, our model can perform favorably against the object detector trained on COCO2017-train and achieve 44.75 mAP. Note that we train our model for 720k iterations and do not tune the inference threshold (same as SoftTeacher). Training the model longer or tuning the inference threshold can potentially further improve the performance. These results confirm the effectiveness of our framework on improving the existing object detector using the extra unlabeled images.

4.4. Effectiveness of Unsupervised Regression Loss

We compare the methods including 1) our proposed Listen2Student, 2) No unsupervised regression loss, and 3) using confidence thresholding and enforcing L1 loss, as used in existing works [26, 38]. To further understand how these methods contribute to the improvement of bounding box regression, we provide an mAP breakdown from AP55 to AP95 of each method in Table 6. It is worth noting that we only change the unsupervised regression loss across these methods and keep the remaining objective functions and modifications the same across all variants.

We observe that, although the confidence thresholding can improve the easier evaluation metrics (e.g., AP55), it cannot improve or even degrades the results on stricter evaluation metrics (e.g., AP95). This shows that simply using the confidence thresholding cannot prevent misleading pseudo-labels from degrading the performance on extremely precise boundary predictions. In contrast, our Listen2Student shows consistent improvements on all evaluation metrics and leads to favorable results, especially on these stricter evaluation metrics. This empirically confirms that our Listen2Student contributes to the more precise bounding box prediction, as our Listen2Student enforces the boundary-wise unsupervised regression loss, which exploits the pseudo-labels derived by
Table 6. Average precision (AP) breakdown of unsupervised regression methods. We also report the absolute improvement of each unsupervised regression loss method against the model without the unsupervised regression loss.

| Method                  | AP55  | AP60  | AP65  | AP70  | AP75  | AP80  | AP85  | AP90  | AP95  |
|-------------------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| No regression           | 29.71 | 27.34 | 24.64 | 21.38 | 17.55 | 13.27 | 8.33  | 3.45  | 0.35  |
| Confidence Thresholding | +0.89 | +0.85 | +0.43 | +0.55 | +0.41 | +0.05 | -0.11 | -0.33 | -0.03 |
| Listen2Student (Ours)   | +1.07 | +1.25 | +1.56 | +1.67 | +2.09 | +2.34 | +1.61 | +0.23 |

Table 7. Results of the Anchor-based model (Faster-RCNN) on VOC.

| Methods                | Labeled | Unlabeled | AP50  | AP50:95 |
|------------------------|---------|-----------|-------|---------|
| Supervised             | 76.70   | 43.60     |
| STAC [26]              | 77.45   | 44.64     |
| ISMT [34]              | 77.23   | 46.23     |
| Instant-Teaching [38]  | VOC07   | VOC12     | 79.20 | 50.00   |
| Humble Teacher [27]    | 80.94   | 53.04     |
| Unbiased Teacher [20]  | 80.51   | 54.48     |
| Ours                   | 81.29   | 56.87     |
| STAC [26]              | 79.08   | 46.00     |
| ISMT [34]              | 77.75   | 49.59     |
| Instant-Teaching [38]  | VOC12   |            | 79.00 | 50.80   |
| Humble Teacher [27]    | 81.29   | 54.41     |
| Unbiased Teacher [20]  | 81.71   | 55.79     |
| Ours                   | 82.04   | 58.08     |

Table 8. Results of the Anchor-based model (Faster-RCNN) on COCO-additional. *We adapt the scale jitter used in SoftTeacher [33] to Unbiased Teacher and it leads to significant improvement.

| Methods                | mAP  |
|------------------------|------|
| Supervised             | 40.90|
| CSD [9]                | 38.52|
| STAC [26]              | 39.21|
| Humble Teacher [27]    | 42.37|
| Unbiased Teacher* [20] | 44.06|
| SoftTeacher [33]       | 44.50|
| Ours                   | 44.75|

**Limitations and future works.** Although we have shown the improvement and generalization on anchor-free and anchor-based detectors, applying SSOD methods on a large-scale unlabeled dataset (e.g., OpenImage) remains a challenge. We also find that the localization uncertainty estimation for boundary prediction leaves room for improvement to be integrated with the relative thresholding mechanism. There are other challenges such as unseen objects in the unlabeled dataset or domain shift between datasets. While these topics are not our focus in this paper, they are worth exploring in future research.

**5. Conclusion**

In this paper, we examined the existing SS-OD methods on anchor-free models and presented the SS-OD benchmarks on anchor-free detectors. By identifying and addressing the core issues that existed in the pseudo-labeling method on anchor-free detectors, our method can improve against the state-of-the-art methods. We further presented Listen2Student, a novel method that uses relative Teacher/Student uncertainties to explicitly prevent the misleading regression pseudo-labels and select beneficial regression pseudo-labels in a boundary-wise manner. This enables the regression branch to benefit from the use of unlabeled images. In the experiment sections, we examine each method in three different SS-OD tasks and present consistent improvements. We also provide an extensive study to verify the effectiveness and generalization of our proposed Listen2Student mechanism on both anchor-free and anchor-based detectors.

Concerning negative societal impacts, we think it is essential to be aware that there exists the risk that object detection techniques (not just our method) are used in surveillance systems. Also, as this line of works relies on low-labeled data for the model training, this aggravates the risk of data bias toward historically disadvantaged groups.

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