Mitigating the Mutual Error Amplification for Semi-Supervised Object Detection

Chengcheng Ma\textsuperscript{1,3} Xingjia Pan\textsuperscript{2} Qixiang Ye\textsuperscript{3} Fan Tang\textsuperscript{4} Yunhang Shen\textsuperscript{2} Ke Yan\textsuperscript{2} Changsheng Xu\textsuperscript{1}

\textsuperscript{1}NLPR, Institute of Automation, CAS \hspace{1cm} \textsuperscript{2}YouTu Lab, Tencent \hspace{1cm} \textsuperscript{3}University of Chinese Academy of Sciences \hspace{1cm} \textsuperscript{4}Jilin University

\{machengcheng2017, changsheng.xu\}@ia.ac.cn,
\{noahpan, odysseyshen, kerwinyan\}@tencent.com, qxye@ucas.ac.cn, tangfan@jlu.edu.cn

Abstract

Semi-supervised object detection (SSOD) has achieved substantial progress in recent years. However, it is observed that the performances of self-labeling SSOD methods remain limited. Based on our experimental analysis, we reveal that the reason behind such phenomenon lies in the mutual error amplification between the pseudo labels and the trained detector. In this study, we propose a Cross Teaching (CT) method, aiming to mitigate the mutual error amplification by introducing the rectification mechanism of pseudo labels. CT simultaneously trains multiple detectors with an identical structure but different parameter initialization. In contrast to existing mutual teaching methods that directly treat predictions from other detectors as pseudo labels, we design the Label Rectification Module (LRM), where the bounding boxes predicted by one detector are rectified using the corresponding boxes predicted by all other detectors with higher confidence scores. In this way, CT can enhance the pseudo label quality compared with self-labeling and existing mutual teaching methods, and reasonably mitigate the mutual error amplification. Over two popular detector structures, i.e., SSD300 and Faster-RCNN-FPN, the proposed CT method obtains consistent improvements and outperforms the state-of-the-art SSOD methods by 2.2\% absolute mAP improvements on the Pascal VOC and MS-COCO benchmarks. The code is available at github.com/machengcheng2016/CrossTeaching-SSOD.

1. Introduction

Although the success of supervised deep learning has greatly promoted the development of object detection approaches [26, 34], collecting large amount of labeled data with instance-level annotations is labor-intensive and expensive [19]. One promising solution is to leverage large amount of unlabeled data to improve detection performances.
in a compromised manner, and the essential philosophy behind them is to filter out misclassified bounding boxes by the confidence-thresholding strategy. However, the false pseudo labels can never be rectified and the effectiveness of unlabeled data still remains limited.

To mitigate the mutual error amplification, a promising way is to introduce teacher-student dual detectors, where teacher generates pseudo labels and the student conducts detector training. As the quality of pseudo labels from teacher detector decides the final performance of student detector, a bunch of teacher-student based SSOD methods have attempted to construct teacher detectors to output high-quality pseudo labels, such as pre-training the teacher detectors on the available labeled set [37, 46] and aggregating student detectors following exponential moving average as teachers during the whole training process [27, 41, 51, 54]. However, these methods still have their own shortcoming: the pseudo labels are always fixed [37, 46], and both detectors are soon converged to have highly similar prediction [27, 41, 51, 54], which also leads to the mutual error amplification.

In order to keep improving the quality of pseudo label and prevent the teacher from approximating into the student, an intuitive idea is mutual teaching, where multiple detectors with different parameter initialization are both teacher and student of others. As the training goes, the performance of all detectors are improved together, ensuring the consistent improvement on pseudo label quality to some extent. To the best of our knowledge, no related work has been proposed for SSOD, but the similar idea can be found in the semi-supervised image classification task [33, 47]. However, there is no technique to guarantee the pseudo label quality in existing mutual teaching methods. We implement the mutual teaching for SSOD, and observe that the problem of mutual error amplification still remains.

In this study, we propose a Cross Teaching (CT) method to mitigate the mutual error amplification by introducing the rectification mechanism of pseudo labels. CT simultaneously trains multiple detectors with an identical structure but different parameter initialization. In contrast to existing mutual teaching methods that directly treat predictions from other detectors as pseudo labels, we instead propose the Label Rectification Module (LRM) to rectify the bounding boxes predicted by one detector, using the corresponding boxes predicted by all other detectors with higher confidence scores. Compared with self-labeling methods, LRM takes more reliable information from other detectors to rectify the false bounding boxes, thus escapes the dilemma of being misled by the current detector itself. Besides, in response to the drawback of mutual teaching, LRM can avoid introducing additional misclassified background regions predicted by other detectors. In this way, CT can enhance the pseudo label quality compared with self-labeling and existing mutual teaching methods, and reasonably mitigate the mutual error amplification. To validate the efficacy of CT, we conduct extensive experiments on the Pascal VOC [11] and MS-COCO [25] benchmarks over two popular detector architectures, i.e., SSD300 [26] and Faster-RCNN-FPN [24]. Experimental results show that our CT method obtains consistent and substantial improvements compared with the state-of-the-art SSOD methods. Our main contributions are summarized as:

- Reveal that the performances of self-labeling SSOD methods are hindered by the mutual error amplification between the pseudo labels and the trained detector.
- Propose the Cross Teaching (CT) method to mitigate the mutual error amplification by introducing the rectification mechanism of pseudo labels.
- Conduct extensive experiments to validate the effectiveness of the proposed CT and our method outperforms the state-of-the-art SSOD methods on the Pascal VOC and MS-COCO benchmarks.

2. Related Work

Semi-Supervised Learning (SSL) trains models by leveraging both labeled and unlabeled data, and the general idea can be divided into two groups by recent works [43, 52, 57], i.e., consistency regularization [5, 6, 13, 20, 23, 30, 36, 49] and pseudo-labeling [1, 3, 15, 18, 42, 44]. The first encourages consistent predictions on different augmented versions of the same image, such as virtual adversarial perturbations [30], image mix-up [6, 55], grid-masking [8], and even an ensemble of all popular augmentations [5, 10, 36]. The second explores the way of generating high-quality pseudo labels, such as directly using the teacher model’s predictions [21], utilizing the temporal ensemble of labels [20], measuring similarities between features and prototypes maintained in a memory bank [9, 44], and so on.

Semi-Supervised Object Detection (SSOD) is a significant application of SSL, which leverages limited labeled data and large amount of unlabeled data to train object detectors. [16, 17] follow the self-labeling scheme to generate pseudo labels by the detector itself, which however suffer from the mutual error amplification and finally leads to a degenerate solution. [37, 46] pre-trains a teacher detector on available labeled set and utilize the teacher to annotate the entire unlabeled set in an offline manner. However, the pseudo boxes are generated only once and their quality can largely limit the performance of student detector. [27, 41, 51, 54] utilize the exponential moving average of student detector as teacher to generate pseudo labels in an online manner. However, the teacher predicts similarly with student in the late stage of training and cannot solve the mutual error amplification.

Mutual Teaching proposes to simultaneously train multiple models for tackling the same task, where each of
models takes supervisions from others. However, the existing mutual teaching methods are mostly designed for semi-supervised image classification [33, 47] and noisy label learning [14, 29, 53]. As the pseudo labels in the object detection task contain both regression and classification information, how to effectively adapt the mutual teaching into SSOD still remains to be explored. Besides, the way of enhancing pseudo label quality has not been well studied among existing works.

3. Problem Analysis

3.1. Preliminaries

Under the semi-supervised setting, an object detector \( f \) is trained on a labeled dataset \( D_l = \{ \mathbf{x}_i, y_i \}_{i=1}^{N_l} \) and an unlabeled dataset \( D_u = \{ \mathbf{x}_j \}_{j=1}^{N_u} \). For each labeled image \( \mathbf{x}_i \), the annotation \( y_i \) contains the category and geometric information of all foreground objects. When fed with an image, the classifier \( f_{cls} \) and localization branch \( f_{loc} \) contained in \( f \) output the classification confidence and coordinates of all predicted objects, respectively. The loss function of SSOD is generally written as:

\[
L = L_S + \lambda_U \cdot L_U, \tag{1}
\]

where \( L_S \) indicates the supervised loss on labeled data, and \( L_U \) is the unsupervised loss on unlabeled data weighted by a factor \( \lambda_U \).

3.2. Mutual Error Amplification in Self-Labeling

In each training iteration, the self-labeling SSOD methods [16,17,22,40] utilize the current detector to predict bounding boxes on the unlabeled inputs, then filter out objects of which the confidence score is lower than a preset threshold, and finally train the detector on these pseudo labels. The loss term \( L_U \) in Eq. (1) can be specified as:

\[
L_U = L_{cls}(f_{cls}(A(x^u)), \arg\max_j f_{cls}(x^u)) + L_{loc}(f_{loc}(A(x^u)), f_{loc}(x^u)), \tag{2}
\]

where \( L_{cls} \) denotes classification loss function, and \( L_{loc} \) is the regression loss function. \( A(\cdot) \) denotes the data augmentation function, which can be specified as the identical function \( x = A(x) \), the horizontal flip in CSD [16], and the image mix-up in ISD [17].

To show the limitations of self-labeling SSOD methods, we conduct experiments on Pascal VOC [11] over SSD300 [26], with VOC07 trainval set being \( D_l \) and VOC12 trainval set being \( D_u \), and set confidence threshold as 0.5 (following [16, 17, 40]). The detection performances under different augmentations are reported in Table. 1. Compared with fully-supervised training on VOC07, the mAP increments by self-labeling methods always remain limited (\( \leq 0.46\% \)).

As the core idea of self-labeling is to train the detector on pseudo labels predicted by detector itself, such mechanism will lead to the mutual error amplification (MEA): the incorrect pseudo labels misguide the detector training, and the misguided detector may generate more misclassified pseudo labels in turn. Such mutual error can be amplified during the whole training process. Taking the self-labeling training of SSD300 for example, we report two metrics every 12k iterations, i.e., average pseudo label precision and the number of correct pseudo boxes per batch. As shown in Fig. 3, both metrics keep decreasing, which indicates the existence of MEA. Furthermore, we only select the correct pseudo labels and re-train the detector, which indicates the pseudo label precision being 100% and the error on pseudo labels being eliminated. As a result, the final performance rises up from 72.13% to 74.03% (shown in Table 2), which means that MEA hinders the effectiveness of self-labeling by a 1.9% margin.

It is unrealistic to address MEA by the detector itself. As observed in Fig. 10, pseudo bounding boxes with higher confidence scores are more likely to be classified correctly, so it seems reasonable to improve the pseudo label precision and further enhance detection performance by improving the confidence threshold. However, a higher confidence thresh-

| Method       | \( A(\cdot) \) | Labeled | Unlabeled | mAP\(_{50}\) (\%) |
|--------------|--------------|---------|-----------|------------------|
| Supervised   | identical    | VOC07   | -         | 71.73            |
| SeLa         | identical    | VOC07   | VOC12     | 72.13 (+0.40)    |
| Supervised   | identical    | VOC0712 | -         | 72.37 (+5.64)    |
| Supervised   | HF           | VOC07   | -         | 71.89            |
| SeLa [16]    | HF           | VOC07   | VOC12     | 72.55 (+0.46)    |
| Supervised   | HF           | VOC0712 | -         | 72.76 (+5.37)    |
| Supervised   | MU           | VOC07   | -         | 73.04            |
| SeLa [17]    | MU           | VOC07   | VOC12     | 73.50 (+0.46)    |
| Supervised   | MU           | VOC0712 | -         | 78.83 (+5.79)    |

| Detector     | Method       | Threshold | mAP\(_{50}\) (\%) |
|--------------|--------------|-----------|------------------|
| SSD300       | Supervised   | -         | 71.73            |
| SeLa         | 0.5          | 72.13 (+0.40) |
| SeLa         | 0.8          | 72.12 (+0.39) |
| SeLa (use only TP) | 0.5         | 74.03 (+2.30) |
| SeLa (use true label) | 0.5        | 74.86 (+3.13) |
| Faster-RCNN-FPN | Supervised   | -         | 80.04            |
| SeLa         | 0.7          | 80.63 (+0.59) |
| SeLa (random FP label) | 0.7         | 80.70 (+0.66) |
| SeLa (use true label) | 0.7         | 81.26 (+1.22) |

Table 1. Performances of Self-Labeling (SeLa) over SSD300 on Pascal VOC, implemented with no augmentation (identical), horizontal flip (HF) [16] and mix-up (MU) [17]. Supervised indicates the fully-supervised training. The mAP increments brought by SeLa always seem limited.

Table 2. Analysis on mutual error amplification of Self-Labeling (SeLa) on Pascal VOC. TP/FP denotes the correctly/wrongly classified pseudo boxes. Figures in brackets are performance increments compared with the supervised baseline.
old can also lower the recall of pseudo labels in the early stage of training (in Fig. 3). Such trade-off between precision and recall leads to similar final performances (72.12% for SSD300 shown in Table 2). Besides, when the threshold increases from 0.5 to 0.8 and the label precision keeps 100%, the mAP result drops from 74.03% to 73.59% (in Table 2), which also validates the effect of reducing the recall ratio.

We further attempt to replace the categories of all misclassified bounding boxes predicted by the detector with random categories in each training iteration. Surprisingly, the final detection performances of both SSD300 and Faster-RCNN-FPN can even be improved (shown in Table 2), which indicates that the detector can be misguided more severely by its own mistakes.

Based on the above observations, we conclude that in order to mitigate MEA in self-labeling SSOD methods, it is essential to introduce other detectors with different views for the pseudo label generation.

3.3. Existing Solutions to MEA

Teacher-student based Pseudo-labeling. Some recent works [27, 37, 41, 46, 51, 54] established on the teacher-student based pseudo-labeling scheme can indeed mitigate the MEA problem by introducing another object detector, as one (teacher) detector generating pseudo labels and the other (student) detector conducting training. The approaches of generating pseudo labels can be specified into offline and online.

For offline approaches [37, 46], the teacher detector is pre-trained on available labeled set, then annotates the entire unlabeled set. The student detector is then trained on the labeled set and the unlabeled set with pseudo labels. However, the pseudo labels are generated only once and remain fixed during the semi-supervised training, so the final performance of student is severely limited by pseudo label quality, especially when the teacher detector is not well-trained. For online approaches [27, 41, 51, 54], during the whole process of semi-supervised training, the teacher detector is updated by the exponential moving average of student detector and annotates the unlabeled data in each mini-batch. However, as shown in Fig. 4, the teacher detector predicts similarly with student on same image regions and fails to rectify the misclassified pseudo labels in the later stage of training, which also leads to the MEA problem.

A Conventional Mutual Teaching Solution. In order to address the aforementioned issues, mutual teaching seems like a promising way, where two models are simultaneously trained for the same task. In existing mutual teaching methods, two models with different initialization can generate different predictions on the same images, so they can be teacher and student of each other. To the best of our knowledge, no related work has been proposed for SSOD, but similar idea can be found in semi-supervised image classification [33, 47]. For example, in deep mutual learning (DML) [47], each of classifiers directly treats the predictions from the other as pseudo labels. The objective of DML is to minimize the divergence between two classifiers. In our experiments, we implement the DML and train two SSD300 detectors on Pascal VOC, and report two metrics during the whole training process, i.e., the average pseudo label precision and the average number of correct boxes per batch. As shown in Fig. 3, under the same threshold setting, both metrics keep decreas-
ing and show a similar trend with the self-labeling SSOD method, which indicates that the MEA problem still remains challenging. As a result, how to enhance the pseudo label quality in mutual teaching still remains an open problem.

4. Cross Teaching

4.1. Overview

The overview of our Cross Teaching (CT) method is illustrated in Fig. 5. CT simultaneously trains multiple detectors with an identical structure but different parameter initialization. For simplicity, we here introduce the cross teaching equipped with two detectors $f_A$ and $f_B$. In each training iteration, two detectors are fed with different mini-batches, both of which contain labeled and unlabeled images. The training losses of $f_A$ and $f_B$ are respectively written as:

$$L_A = L^A_S + \lambda_U \cdot L^A_U,$$

(3)

$$L_B = L^B_S + \lambda_U \cdot L^B_U.$$

(4)

Supervised losses. The two detectors $f_A$ and $f_B$ compute supervised losses $L^A_S$ and $L^B_S$ on their corresponding labeled data $\{x^l_A, y^l_A\}$ and $\{x^l_B, y^l_B\}$, respectively. We omit the subscripts $A$ and $B$ in the following section for generality. The supervised loss $L_S$ for SSD is defined in the standard way [26]:

$$L_S = L_{cls}(x^l, y^l) + L_{reg}(x^l, y^l),$$

(5)

where $L_{cls}$ and $L_{reg}$ denote the classification and regression losses, respectively. As for Faster-RCNN, the standard supervised loss $L_S$ [34] is composed of four terms:

$$L_{cls}^{rpn}(x^l, y^l) + L_{reg}^{rpn}(x^l, y^l) + L_{cls}^{roi}(x^l, y^l) + L_{reg}^{roi}(x^l, y^l),$$

(6)

where $L_{cls}^{rpn}$ and $L_{reg}^{rpn}$ denote the losses on RPN and RoI head, respectively.

Unsupervised losses. Both of detectors $f_A$ and $f_B$ calculate unsupervised losses $L^A_U$ and $L^B_U$ on their pseudo-labeled inputs $\{x^u_A, \hat{y}^u_A\}$ and $\{x^u_B, \hat{y}^u_B\}$, respectively. Similar with Eq. (2), the form of unsupervised loss is specified as:

$$L_U = L_{cls}(f_{cls}(A(x^u)), \hat{c}^u) + L_{loc}(f_{loc}(A(x^u)), \hat{b}^u),$$

(7)

where $\hat{c}^u$ and $\hat{b}^u$ respectively denote the object categories and coordinates from the pseudo label $\hat{y}^u$. Specifically, the pseudo label $\hat{y}^u$ is derived from the Label Rectification Module (LRM), which plays a key role in the cross teaching method. We provide the detailed description of LRM in the next subsection.

Inference stage. We utilize both detectors for inference. To report the single detector’s performance, we average the results of two detectors for fair comparisons with other methods in the experiment section. Since the parameters of two detectors are different, the predictions on the same image contain complementary information for each other. So we apply the weighted box fusion [38] to merge the multiple predictions, and annotate the results as cross teaching.

4.2. Label Rectification Module

For clarity, we omit the superscript $u$ in this section. The pseudo label on an unlabeled image is denoted as $\hat{y} = \{(\hat{b}_1, \hat{c}_1), \cdots, (\hat{b}_n, \hat{c}_n)\}$, where $\hat{b}_i$ and $\hat{c}_i$ respectively denote the coordinate and category of $i$-th bounding box. Given an input image, a detector can output predictions $\hat{y} = \{(\hat{b}_1, \hat{c}_1, \hat{p}_1), \cdots, (\hat{b}_n, \hat{c}_n, \hat{p}_n)\}$, with $\hat{p} \in [0.0, 1.0]$ being the confidence score of category $\pi$. By default, the prediction is refined by the non-maximum suppression (NMS) and confidence thresholding ($\hat{p} > \delta$). The detector $f_A$ and $f_B$ compute the unsupervised losses on the pseudo-labeled images $\{x^u_A, \hat{y}^u_A\}$ and $\{x^u_B, \hat{y}^u_B\}$. The goal of LRM is to improve the quality of $\hat{y}^u_A$ and $\hat{y}^u_B$. 

Figure 5. The overview of the Cross Teaching for semi-supervised object detection. Two detectors are simultaneously trained with the help of Label Rectification Module (LRM). Orange and blue boxes are predicted by $f_A$ and $f_B$, respectively.
Figure 6. From left to right: LRM generates the pseudo label $\hat{y}_A$. Orange and blue bounding boxes are predicted by $f_A$ and $f_B$ on the same image, respectively.

Since $\hat{y}_A$ and $\hat{y}_B$ are both generated by LRM in the same way, we only introduce the generation process of $\hat{y}_A$ for clarity. Firstly, we feed the unlabeled image $x_A$ to detector $f_A$ and $f_B$, and obtain the predictions $\overline{y}_A = \{(\hat{b}_i^A, \tau_i^A, \pi_i^A)\} \cdots \{(\hat{b}_n^A, \tau_n^A, \pi_n^A)\}$ and $\overline{y}_B = \{(\hat{b}_1^B, \tau_1^B, \pi_1^B), \cdots, (\hat{b}_m^B, \tau_m^B, \pi_m^B)\}$. Then, for each bounding box in $\overline{y}_A$, LRM finds the best matching box in $\overline{y}_B$ according to the anchor correspondence (for SSD) or the intersection over union score (for Faster-RCNN). Based on the matching bounding box, LRM generates the coordinate and object category in $\hat{y}_A$ according to:

$$\hat{b}_i^A = \begin{cases} (\hat{b}_j^B, \tau_j^B), & \text{if } \pi_i^A < \pi_j^B, \\ (\hat{b}_i^A, \tau_i^A), & \text{otherwise}, \end{cases}$$

(8)

If the best match cannot be found, LRM imitates a bounding box on the same location, of which the category is assigned as background and the confidence score is the same with that predicted by $f_B$ correspondingly. The whole process is illustrated in Fig. 6. We observe that the predictions $\overline{y}_A$ and $\overline{y}_B$ are much different that many bounding boxes remain unmatched when training the Faster-RCNN-FPN detector on MS-COCO, which leads to the missing label issue [50] and hinder the performance of RPN module. To address this issue, we further add all unmatched boxes in $\overline{y}_B$ to the pseudo label $\hat{y}_A$, and similarly for $\hat{y}_B$.

**Discussions.** There are two advantages of LRM. Compared with self-labeling methods, LRM takes more reliable information from other detectors to rectify the false bounding boxes, and escapes the dilemma of being misled by the current detector itself, because the bounding boxes with higher confidence scores are more likely to be classified correctly (shown in Fig. 10). Second, in response to the drawback of mutual teaching, LRM can avoid rejecting the detector’s own prediction which may contains correct bounding boxes, and also avoid introducing additional misclassified background regions predicted by the other detector. To show the improvements on pseudo label quality, we report the two related metrics shown in Fig. 3. It is observed that the proposed LRM can improve both the precision and recall of pseudo labels, compared with self-labeling and mutual teaching methods.

Besides, we shown in Fig. 4 that LRM can prevent both detectors from converging into each other and maintain a higher FP correction ratio than the teacher-student based method. We show the details of pseudo label generating process of self-labeling, teacher-student based pseudo-labeling, mutual teaching, and cross teaching in Fig. 7 for better comparison.

**Extensions.** The proposed CT method can be extended to simultaneously train more than two detectors. To be specific, the coordinate of each object in $\overline{y}_A$ is rectified by the average of predicted coordinates from all other detectors on the corresponding region, while the category is rectified by the major of all predicted categories. The final performance of four detectors can be found in the experiment section.

### 5. Experiments

#### 5.1. Experimental Settings

**Benchmarks.** We evaluate our proposed method Cross Teaching (CT) on two publicly available benchmarks, i.e., Pascal VOC [11] and MS-COCO [25]. As for the former, we take the VOC07 trainval set as labeled and the VOC12 trainval set as unlabeled. The detection performance is evaluated on the VOC07 test set following the VOC style metric (mAP50). As for the latter, we randomly sample 1/2/5/10% of the COCO2017 train set as labeled and take the remaining part as unlabeled. The detection performance is evaluated on the COCO2017 val set following the COCO style metric (mAP50:95). We follow [27, 37] to create five data folds for each protocol, and finally report the mean and standard deviation from five results.

**Implementation details.** We conduct three experiments: SSD300 on VOC, Faster-RCNN-FPN on VOC, and Faster-RCNN-FPN on MS-COCO. To train SSD300 on VOC, we follow CSD [16] and ISD [17] to implement the self-labeling and the proposed CT method based on the Pytorch implementation of SSD3001, and keep the same setting: within a total of 120k iterations, conducting fully-supervised training in the first 12k iterations as a warm-up process, then adjusting $\lambda_U$ in Eq. (1) by ramp-up/down techniques [16, 17, 20, 42]. The

---

1. [https://github.com/amdegroot/ssd.pytorch](https://github.com/amdegroot/ssd.pytorch)
| Model       | Backbone | Method                  | Labeled | Unlabeled | Threshold | mAP$_{50}$ |
|-------------|----------|-------------------------|---------|-----------|-----------|------------|
| SSD300      | VGG-16   | Supervised              | VOC07   | -         | -         | 71.73      |
|             |          | Supervised              | VOC0712 | -         | -         | 77.37 (+5.64) |
|             |          | Self-Labeling           | VOC07   | VOC12'    | 0.5       | 72.13 (+0.40) |
|             |          | CSD [16]                | VOC07   | VOC12     | 0.5       | 72.35 (+0.62) |
|             |          | ISD [17]                | VOC07   | VOC12     | 0.5       | 73.50 (+1.77) |
|             |          | MultiPhase [46]         | VOC07   | VOC12     | -         | 72.30 (+0.57) |
|             |          | CT (ours)               | VOC07   | VOC12     | 0.5       | 73.65 (+1.92) |
|             |          | CT* (ours)              | VOC07   | VOC12     | 0.5       | 74.97 (+3.24) |
|             |          | Supervised + mix-up     | VOC07   | -         | -         | 73.04      |
|             |          | Supervised + mix-up     | VOC0712 | -         | -         | 78.53 (+5.49) |
|             |          | ISD [17]                | VOC07   | VOC12'    | 0.5       | 73.30 (+0.46) |
|             |          | CT + mix-up (ours)      | VOC07   | VOC12     | 0.5       | 74.41 (+1.37) |
|             |          | CT* + mix-up (ours)     | VOC07   | VOC12     | 0.5       | 75.72 (+2.68) |
| Faster-RCNN-FPN | ResNet-50 | Supervised              | VOC07   | -         | -         | 80.04      |
|             |          | Supervised              | VOC0712 | -         | -         | 81.89 (+1.91) |
|             |          | MultiPhase [46]         | VOC07   | VOC12     | 0.7       | 80.64 (+0.60) |
|             |          | UnbiasedTeacher [27]    | VOC07   | VOC12     | 0.7       | 80.69 (+0.65) |
|             |          | CT (ours)               | VOC07   | VOC12     | 0.7       | 80.90 (+0.86) |
|             |          | CT* (ours)              | VOC07   | VOC12     | 0.7       | 81.73 (+1.69) |

Table 3. Experimental results (mAP$_{50}$) on Pascal VOC. Figures in brackets are the absolute mAP improvements compared with the fully-supervised training. The symbol* indicates the merged detection results from all detectors. Best results are highlighted in bold.

| Method                  | 1%          | 2%          | 5%          | 10%         |
|-------------------------|-------------|-------------|-------------|-------------|
| Supervised              | 9.57 ± 0.06 | 13.36 ± 0.19 | 18.85 ± 0.16 | 23.77 ± 0.05 |
| CSD (from [27])         | 10.51 ± 0.06 | 13.93 ± 0.12 | 18.63 ± 0.07 | 22.46 ± 0.08 |
| STAC [37]               | 13.97 ± 0.35 | 18.25 ± 0.25 | 24.38 ± 0.12 | 28.64 ± 0.21 |
| Self-Labeling           | 15.53 ± 0.36 | 19.27 ± 0.16 | 23.75 ± 0.09 | 27.65 ± 0.06 |
| UnbiasedTeacher [27]    | 17.33 ± 0.18 | 20.84 ± 0.02 | 24.90 ± 0.13 | 28.50 ± 0.05 |
| CT (ours)               | 18.15 ± 0.13 | 21.59 ± 0.10 | 25.63 ± 0.04 | 29.11 ± 0.08 |
| CT* (ours)              | **18.94 ± 0.11** | **22.57 ± 0.07** | **26.97 ± 0.04** | **30.67 ± 0.07** |

Table 4. Experimental results (mAP$_{50.95}$) by Faster-RCNN-FPN on MS-COCO. The symbol* indicates the merged detection results from all detectors. Best results are highlighted in bold.

Confidence threshold is set as 0.5. We re-run CSD$^2$ [16] and ISD$^3$ [17] under the same settings. To train Faster-RCNN-FPN on VOC, we notice the differences on hyper-parameters between UnbiasedTeacher$^4$ [27] and the official Detectron2$^5$. Without loss of generality, we adopt the official training hyper-parameters to implement self-labeling and CT, and re-run the UnbiasedTeacher [27]. Within a total of 18k iterations, we take the first 6k iterations as fully-supervised warm-up, and set $\lambda_U$ as 2.0 for the rest. For fair comparisons, we follow [27] to only compute the classification loss in $L_U$ for self-labeling and CT, with confidence threshold being 0.7. To train Faster-RCNN-FPN on MS-COCO, we also adopt the official hyper-parameters of Detectron2$^5$. For all protocols ($1/2/5/10\%$), within a total of 90k iterations, we take the first 10k iterations as fully-supervised warm-up and set $\lambda_U$ as 1.0 for the rest.

5.2. Main Results

Pascal VOC. We evaluate the efficacy of two-detector Cross Teaching (CT) over SSD300 on Pascal VOC as displayed in Table 3. We take the 71.73% mAP of fully-supervised training as the baseline. Under the single detector setting, CT performs the best by showing a 1.92% absolute mAP increment compared with baseline. Besides, we also apply the mix-up augmentation in supervised baseline and our CT method. After such modification, ISD [17] only shows a 0.46% mAP improvement compared with the new baseline (Supervised + mix-up), and CT achieves a 1.37% improvement and still turns out to be the best. When two detectors are utilized in the inference stage, we apply the weight box fusion to merge two detection results. Then the performances of CT further rise (denoted as CT$^*$), achiev-

---

2. https://github.com/soo89/CSD-SSD
3. https://github.com/soo89/ISD-SSD
4. https://github.com/facebookresearch/unbiased-teacher/blob/main/configs/voc/voc07_voc12.yaml
5. https://github.com/facebookresearch/detectron2/blob/main/configs/COCO-Detection/faster_rcnn_R_50_FPN_1x.yaml
6. https://github.com/facebookresearch/detectron2/blob/main/configs/PascalVOC-Detection/faster_rcnn_R_50_FPN_1x.yaml
Figure 8. The visual comparisons among different methods on MS-COCO with 1% labeled data. From top to down: self-labeling, UnbiasedTeacher [27], and cross teaching (ours).

ing both 3.24% and 2.68% absolute improvements without and with mix-up augmentation compared with supervised baseline, and outperform ISD [17] by a 2.2% margin.

Moreover, we benchmark our CT method over Faster-RCNN-FPN in Table 3. In comparison, the mAP gap between supervised VOC07 and supervised VOC0712 becomes much smaller, from 5.64% to 1.91%. Under the single detector setting, CT outperforms the supervised baseline by a 0.86% margin. As for the two-detector scenario, CT can surpass the UnbiasedTeacher [27] by a 1.04% margin. Note that we do not use the regression loss in the computation of unsupervised loss $L_U$, for a fair comparison with UnbiasedTeacher [27].

COCO-standard. We show the performance comparison in Table 4. We adopt the mAP results of CSD [16] and STAC [37] reported in [27]. We observe that CT consistently outperforms the UnbiasedTeacher [27] by about 0.73% when only one detector is utilized in inference stage. After merging the two results from two detectors in CT, the advantage of CT can be increased to 1.61%, 1.73%, 2.07%, 2.17% under the 1%, 2%, 5%, 10% protocol, respectively. Again, we do not use the regression loss in the computation of unsupervised loss $L_U$. The visual comparison among different SSOD methods can be found in Fig. 8.

5.3. Ablation Studies

Pseudo-labeling frameworks. We first study the framework of pseudo label generation. Instead of generating pseudo labels by the detector itself, teacher-student based pseudo-labeling, mutual teaching and our CT method utilize other detectors to generate pseudo labels. We compare the detection performances among these three frameworks by training SSD300 on Pascal VOC. Correspondingly, the proposed CT performs the best as shown in Table 5.

Table 5. Comparison among different pseudo-labeling frameworks. Sup denotes the supervised training on available labeled data. SeLa denotes the self-labeling. TS-offline/online denotes the teacher-student based pseudo-labeling in an offline/online manner.

| Model  | Database | Framework       | mAP (%) |
|--------|----------|-----------------|---------|
| SSD300 | VOC      | Supervised      | 71.73   |
|        |          | SeLa            | 72.13   |
|        |          | TS-offline      | 72.52   |
|        |          | TS-online       | 72.98   |
|        |          | Mutual Teaching | 72.56   |
|        |          | CT (ours)       | 73.65   |

Table 6. Extension from two-detector to four-detector cross teaching. Single denotes the mAP result of each detector. Average denotes the average mAP of all detectors. Merged denotes the mAP of merged predictions by applying the weighted box fusion from all detectors.

| Model  | Database | Index     | Single | Average | Merged |
|--------|----------|-----------|--------|---------|--------|
| SSD300 | VOC      | detector #1| 73.67  | 73.65   | 74.83  |
|        |          | detector #2| 73.63  |         |        |
|        |          | detector #3| 73.80  |         |        |
|        |          | detector #4| 73.73  |         |        |

category labels and coordinates. During the whole training process, we observe that the pseudo label precision for each detector keeps raising from 80.0% to 84.6%, compared with raising from 77.2% to 81.9% in two-detector cross teaching.

6. Conclusion

In this paper, we propose the Cross Teaching (CT) method, with the aim to mitigate the mutual error amplification by introducing the rectification mechanism of pseudo labels. CT simultaneously trains multiple detectors with an identical structure but different parameter initialization, and the proposed Label Rectification Module (LRM) can rectify the wrong pseudo labels predicted by each detector with the corresponding predictions from all other detectors. Extensive results validate the efficacy of CT, with a 2.2% mAP improvement against state-of-the-art SSOD methods.
A. More Ablation Studies

Exponential moving average. As discussed in [27], the exponential moving average (EMA) of a detector can output more conservative and stable predictions than the detector itself, which is commonly used for the pseudo label generation [27, 41, 51, 54]. We follow this common practice in our experiments: we utilize the predictions from the EMAs of other detectors to rectify the pseudo labels predicted by the current detector. According to our experimental results, the EMA strategy can improve the final performance, from 73.36% mAP to 73.65% mAP (cross teaching two SSD300 detectors on Pascal VOC).

Pseudo label rectification strategy. We study four strategies on rectifying the pseudo labels: (a) Cancel the procedure of confidence score comparison. (b) Only utilize the intersection of two predictions from two detectors for each detector’s training, where the intersection includes the matched box pairs predicted with same categories. (c) Only utilize the difference set of two predictions from two detectors for each detector’s training, where the difference set includes the matched box pairs predicted with different categories. (d) Directly treat the prediction from the other detector as pseudo label. As observed in Table. 7, other strategies cannot guarantee the pseudo label quality and lead to bad performances.

B. Cross Teaching Makes Detectors Similar?

Recently, deep co-training [33] has discovered model collapsing phenomenon in the conventional mutual teaching approaches [4, 7, 32, 48] for the semi-supervised classification task, where two classifiers begin approximating into each other and learn similar representations on same images in the middle and late stage of training. The model collapsing phenomenon makes the co-training meaningless because the two classifiers cannot provide different and complementary information for each other. In contrast, we find that such phenomenon does not exist in our cross teaching method. Take the cross teaching of two SSD300 detectors on Pascal VOC for example. During the whole training process, we compute the mean square differences between two features extracted by two detectors on same images from the Pascal VOC database. As shown in Fig. 9 and Fig. 4 in the main manuscript, the two detectors can always learn different representations and output different predictions on same images, so the proposed cross teaching method will not make detectors similar.

C. Other Things We Tried

Noisy Label Learning. The goal of noisy label learning (NLL) is to train accurate models when part of labels in the training set are incorrect, which is similar with noisy pseudo

| Model | Labeled | Unlabeled | Strategy | mAP_{50} |
|-------|---------|-----------|----------|----------|
| VOC07 | -       | -         | (a)      | 73.23    |
| VOC07 | VOC12   | (b)       | 72.56    |
| VOC07 | VOC12   | (c)       | 65.52    |
| VOC07 | VOC12   | (d)       | 72.56    |
| VOC07 | VOC12   | cross teaching | 73.65    |

Table 7. Ablation study on the pseudo label rectification strategy. Best result is highlighted in bold.

Figure 9. The mean square difference between two features extracted by two SSD300 detectors on same images from Pascal VOC during the cross teaching process. Displayed SSD300 layers: 2nd layer (top left), 3rd layer (top right), 4th layer (bottom left), 5th layer (bottom right).

bounding boxes encountered in semi-supervised object detection as discussed in the main manuscript. In the study field of NLL, a bunch of robust loss functions have been recently proposed to mitigate the impact of noisy labels and can successfully improve the classification accuracy, such as generalized cross entropy (GCE) [56], reversed cross entropy (RCE) [45], and normalized cross entropy (NCE) [28]. We take the self-labeling training over SSD300 on the Pascal VOC benchmark for example. For fair comparisons, we replace the conventional cross entropy loss in unsupervised loss term with each of these loss functions, keeping other training settings the same. As shown in Table. 8, none of these loss functions can bring mAP improvements, which indicates that the robust loss functions proposed for NLL still cannot mitigate the mutual error amplification problem in semi-supervised object detection.

Label Smoothing Label smoothing (LR) [39] has been recently proposed to compute cross entropy loss with a weighted mixture of one-hot targets instead of a single one-
hot target, which can prevent the model from becoming over-confident and further improve the classification accuracy [31]. For a K-way classification task, the smoothed target of category $C$ is formulated as

$$y_i = \left\{ \begin{array}{ll}
1 - \epsilon, & \text{if } i = C, \\
\frac{\epsilon}{K-1}, & \text{otherwise}.
\end{array} \right. \quad (9)$$

The parameter $\epsilon$ controls the smoothness (usually set as 0.1). In terms of semi-supervised object detection, for the misclassified pseudo bounding boxes, LR can suppress the weight of incorrect categories by $\epsilon$ and also increase the weight of true categories from 0 to $1 - \epsilon/(K - 1)$, which is likely to alleviate the impact of misclassification. However, the categories of correct classification are similarly being modified, leading to ambiguous targets. As observed in Table 9, such trade-off brought by LR can always hurt the detection performance, and a larger $\epsilon$ leads to a worse result.

### D. Comparison with SoftTeacher [51]

SoftTeacher [51] has been recently proposed to solve the semi-supervised object detection problem, which introduces advanced pseudo-labeling strategies and achieves a good final performance on the MS-COCO benchmark [25]. We make experimental comparisons between our cross teaching method and SoftTeacher. For a fair comparison, we adopt the same data augmentation strategies and training settings according to their official implementation7. Fig. 10 shows that the performance of our cross teaching method can always outperform that of SoftTeacher along the training iterations.

### References

1. Eric Arazo, Diego Ortego, Paul Albert, Noel E O’Connor, and Kevin McGuinness. Pseudo-labeling and confirmation bias in deep semi-supervised learning. In 2020 International Joint Conference on Neural Networks (IJCNN), pages 1–8. IEEE, 2020.
2. YM Asano, C Rupprecht, and A Vedaldi. Self-labelling via simultaneous clustering and representation learning. In International Conference on Learning Representations, 2019.
3. Philip Bachman, Ouais Alsharif, and Doina Precup. Learning with pseudo-ensembles. Advances in neural information processing systems, 27:3365–3373, 2014.
4. Xiang Bai, Bo Wang, Cong Yao, Wenyu Liu, and Zhuowen Tu. Co-transduction for shape retrieval. IEEE Transactions on Image Processing, 21(5):2747–2757, 2011.
5. David Berthelot, Nicholas Carlini, Alex Kurakin, Kihyuk Sohn, Han Zhang, and Colin Raffel. Remixmatch: Semi-supervised learning with distribution matching and augmentation anchoring. In International Conference on Learning Representations, 2019.
6. David Berthelot, Nicholas Carlini, Ian Goodfellow, Nicolas Papernot, Avital Oliver, and Colin A Raffel. Mixmatch: A holistic approach to semi-supervised learning. Advances in Neural Information Processing Systems, 32, 2019.
7. Avrim Blum and Tom Mitchell. Combining labeled and unlabeled data with co-training. In Proceedings of the eleventh annual conference on Computational learning theory, pages 92–100, 1998.
8. Pengguang Chen, Shu Liu, Hengshuang Zhao, and Jiayu Jia. Gridmask data augmentation. arXiv preprint arXiv:2001.04086, 2020.
9. Yanbei Chen, Xiatian Zhu, and Shaogang Gong. Semi-supervised deep learning with memory. In Proceedings of the European conference on computer vision (ECCV), pages 268–283, 2018.

---

7https://github.com/microsoft/SoftTeacher/
[10] Ekin D Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, and Quoc V Le. Autoaugment: Learning augmentation strategies from data. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 113–123, 2019.

[11] Mark Everingham, Luc Van Gool, Christopher KI Williams, John Winn, and Andrew Zisserman. The pascal visual object classes (voc) challenge. International journal of computer vision, 88(2):303–338, 2010.

[12] Aritra Ghosh, Himanshu Kumar, and PS Sastry. Robust loss functions under label noise for deep neural networks. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 31, 2017.

[13] Atin Ghosh and Alexandre H Thiery. On data-augmentation and consistency-based semi-supervised learning. In International Conference on Learning Representations, 2020.

[14] Bo Han, Quanming Yao, Xingrui Yu, Gang Niu, Miao Xu, Weihua Hu, Iovr W Tsang, and Masashi Sugiyama. Co-teaching: robust training of deep neural networks with extremely noisy labels. In Proceedings of the 32nd International Conference on Neural Information Processing Systems, pages 8536–8546, 2018.

[15] Ahmet Iscen, Giorgios Tolias, Yannis Avrithis, and Ondrej Chum. Label propagation for deep semi-supervised learning. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 5070–5079, 2019.

[16] Jisoo Jeong, Seunguei Lee, Jee soo Kim, and Nojun Kwak. Consistency-based semi-supervised learning for object detection. Advances in neural information processing systems, 32:10759–10768, 2019.

[17] Jisoo Jeong, Vikas Verma, Minsung Hyun, Ju ho Kannala, and Nojun Kwak. Interpolation-based semi-supervised learning for object detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 11602–11611, 2021.

[18] Chia-Wen Kuo, Chih-Yao Ma, Jia-Bin Huang, and Zsolt Kira. Featmatch: Feature-based augmentation for semi-supervised learning. In European Conference on Computer Vision, pages 479–495. Springer, 2020.

[19] Alina Kuznetsova, Hassan Rom, Neil Alldrin, J asper Uijlings, Ivan Krasin, Jordi Pont-Tuset, Shahab Kamali, Stefan Popov, Matteo Mallocki, Alexander Kolesnikov, et al. The open images dataset v4. International Journal of Computer Vision, 128(7):1956–1981, 2020.

[20] Samuli Laine and Timo Aila. Temporal ensembling for semi-supervised learning. arXiv preprint arXiv:1610.02242, 2016.

[21] Dong-Hyun Lee et al. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In Workshop on challenges in representation learning, ICML, volume 3, page 896, 2013.

[22] Duo Li, Sanli Tang, Zhizhan Cheng, Shiliang Pu, Yi Niu, Wenming Tan, Fei Wu, and Xiaokang Yang. Rethinking pseudo-labeled sample mining for semi-supervised object detection. 2020.

[23] Junnan Li, Richard Socher, and Steven CH Hoi. Dividemix: Learning with noisy labels as semi-supervised learning. In International Conference on Learning Representations, 2019.

[24] Tsung-Yi Lin, Piotr Dollár, Ross Girshick, Kaiming He, Bharath Hariharan, and Serge Belongie. Feature pyramid networks for object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2117–2125, 2017.

[25] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In European conference on computer vision, pages 740–755. Springer, 2014.

[26] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. Ssd: Single shot multibox detector. In European conference on computer vision, pages 21–37. Springer, 2016.

[27] Yen-Cheng Liu, Chih-Yao Ma, Zijian He, Chia-Wen Kuo, Kan Chen, Pei Zhang, Bichen Wu, Zsolt Kira, and Peter Vajda. Unbiased teacher for semi-supervised object detection. In International Conference on Learning Representations, 2020.

[28] Xingjun Ma, Hanxun Huang, Yisen Wang, Simone Romano, Sarah Erfani, and James Bailey. Normalized loss functions for deep learning with noisy labels. In International Conference on Machine Learning, pages 6543–6553. PMLR, 2020.

[29] Eran Malach and Shai Shalev-Shwartz. Decoupling” when to update” from” how to update”. In Proceedings of the 31st International Conference on Neural Information Processing Systems, pages 961–971, 2017.

[30] Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, and Shin Ishii. Virtual adversarial training: a regularization method for supervised and semi-supervised learning. IEEE transactions on pattern analysis and machine intelligence, 41(8):1979–1993, 2018.

[31] Rafael Müller, Simon Kornblith, and Geoffrey E Hinton. When does label smoothing help? Advances in Neural Information Processing Systems, 32:4694–4703, 2019.

[32] Kamal Nigam and Rayid Ghani. Analyzing the effectiveness and applicability of co-training. In Proceedings of the ninth international conference on Information and knowledge management, pages 86–93, 2000.

[33] Siyuan Qiao, Wei Shen, Zhishuai Zhang, Bo Wang, and Alan Yuille. Deep co-training for semi-supervised image recognition. In Proceedings of the european conference on computer vision (eccv), pages 135–152, 2018.

[34] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. Advances in neural information processing systems, 28:91–99, 2015.

[35] Chuck Rosenberg, Martial Hebert, and Henry Schneiderman. Semi-supervised self-training of object detection models. In Proceedings of the Seventh IEEE Workshops on Application of Computer Vision (WACV/MOTION’05)-Volume 1-Volume 01, pages 29–36, 2005.
Advances in Neural Information Processing Systems, 33, 2020.

[37] Kihyuk Sohn, Zizhao Zhang, Chun-Liang Li, Han Zhang, Chen-Yu Lee, and Tomas Pfister. A simple semi-supervised learning framework for object detection. *arXiv preprint arXiv:2005.04757*, 2020. 2, 4, 6, 7, 8

[38] Roman Solovoyev, Weimim Wang, and Tatiana Gaburseva. Weighted boxes fusion: Ensembling boxes from different object detection models. *Image and Vision Computing*, 107:104117, 2021. 5, 10

[39] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2818–2826, 2016. 9

[40] Peng Tang, Chetan Ramaiah, Yan Wang, Ran Xu, and Caiming Xiong. Proposal learning for semi-supervised object detection. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 2291–2301, 2021. 1, 3

[41] Yihe Tang, Weifeng Chen, Yijun Luo, and Yuting Zhang. Humble teachers teach better students for semi-supervised object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 3132–3141, 2021. 2, 4, 9

[42] Antti Tarvainen and Harri Valpola. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, pages 1195–1204, 2017. 2, 6

[43] Jesper E Van Engelen and Holger H Hoos. A survey on semi-supervised learning. *Machine Learning*, 109(2):373–440, 2020. 2

[44] Ximei Wang, Jinghan Gao, Mingsheng Long, and Jianmin Wang. Self-tuning for data-efficient deep learning. In *International Conference on Machine Learning*, pages 7164–7173. PMLR, 2019. 3

[45] Xingrui Yu, Bo Han, Jiangchao Yao, Gang Niu, Ivor Tsang, and Masashi Sugiyama. How does disagreement help generalization against label corruption? In *International Conference on Learning Representations*, 2018. 2

[46] Zhilu Zhang and Mert R Sabuncu. Generalized cross entropy loss for training deep neural networks with noisy labels. In *32nd Conference on Neural Information Processing Systems (NeurIPS)*, 2018. 9, 10

[47] Xiaojin Jerry Zhu. Semi-supervised learning literature survey. 2005. 2