Cycle Self-Training for Semi-Supervised Object Detection with Distribution Consistency Reweighting

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ABSTRACT

Recently, many semi-supervised object detection (SSOD) methods adopt teacher-student framework and have achieved state-of-the-art results. However, the teacher network is tightly coupled with the student network since the teacher is an exponential moving average (EMA) of the student, which causes a performance bottleneck. To address the coupling problem, we propose a Cycle Self-Training (CST) framework for SSOD, which consists of two teachers T1 and T2, two students S1 and S2. Based on these networks, a cycle self-training mechanism is built, i.e., S1→T1→S2→T2→S1. For S→T, we also utilize the EMA weights of the students to update the teachers. For T→S, instead of providing supervision for its own student S1(S2), directly, the teacher T1(T2) generates pseudo-labels for the student S2(S1), which loses the coupling effect. Moreover, owing to the property of EMA, the teacher is most likely to accumulate the biases from the student and make the mistakes irreversible. To mitigate the problem, we also propose a distribution consistency reweighting strategy, where pseudo-labels are reweighted based on distribution consistency across the teachers T1 and T2. With the strategy, the two students S2 and S1 can be trained robustly with noisy pseudo labels to avoid confirmation biases. Extensive experiments prove the superiority of CST by consistently improving the AP over the baseline and outperforming state-of-the-art methods by 2.1% absolute AP improvements with scarce labeled data.

KEYWORDS

• Computing methodologies → Semi-supervised learning settings: Object detection.

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1 INTRODUCTION

With the rapid development of deep learning, large amount of labeled data become the critical component during training process. However, collecting labels is time-consuming and expensive [17], especially for object detection with instance-level annotations. This has encouraged Semi-Supervised Learning (SSL) methods to leverage unlabeled data, such as image classification [1, 12, 20, 32, 43] and object detection [25, 34, 37, 45, 48] tasks. This paper studies the problem of semi-supervised object detection (SSOD) that focuses not only on classification but also localization.

For SSOD, recent mainstream methods are based on pseudo-labeling, which train detectors on labeled data and unlabeled data with pseudo labels jointly to improve detection performance. The pseudo-labeling based model consists of two components: a teacher model and a student model, as shown in Figure 1 (c). The teacher generates pseudo-labels to train the student, and the student updates the knowledge it learned back to the teacher. Also, the teacher can be regarded as the temporal ensemble of the student [25], which generates more stable and accurate pseudo-labels. However, the teacher is tightly coupled with the student due to the exponential
Training Framework. (a) Euclidean distance of weights. (b) Percentage of accurate/inaccurate samples. (c) Teacher-Student framework, we propose to loose the constraint (4) the teacher network $T_2$ generates pseudo-labels for the student network $S_2$; (3) the EMA of the states $T_1$ and $T_2$ are sufficiently consistent, we consider it as a stable instance and increase its influence in the training process via consistency reweighting. As shown in Figure 1 (b), according to our statistics, the accuracy of pseudo labels and the consistency quantification illustrate a strong positive correlation, which means that the pseudo labels with high consistency values can provide more accurate category information. With our proposed strategy, the two student networks $S_1$ and $S_2$ can be trained robustly with noisy pseudo labels to avoid accumulating confirmation biases.

In summary, our main contributions can be summarized as:

- We propose a Cycle Self-Training (CST) framework for semi-supervised object detection, in which a knowledge transferring loop is built to loose the tightly coupling effect of the teacher-student framework.
- A distribution consistency reweighting strategy is proposed to incorporate with our CST framework so that the two student networks can be trained robustly with noisy pseudo labels to avoid the accumulating confirmation biases.
- We conduct extensive experiments on COCO [23] and PASCAL VOC [10] datasets, which validates the effectiveness of our proposed framework. Specifically, the CST framework obtains consistent improvements over the baseline and outperforms the state-of-the-art methods by 2.1% absolute AP improvements with scarce labeled data.

2 RELATED WORK

2.1 Object Detection

Object detection tries to determine the category and location of each object instance appearing in an image. Nowadays, numerous methods to deal with this problem can be roughly divided into two main pipelines: two-stage and one-stage. The two-stage pipeline first uses a Region Proposal Network (RPN) to generate some proposals, which are coarsely localized and categorized into the foreground or not, and then refines the proposals by multi-classification and further regression [4, 6, 7, 30, 36]. The one-stage pipeline omits the region proposals generation process and directly gives the classification and localization results of the anchor boxes [22, 24, 29]. Meanwhile, some one-stage methods formulate bounding box object detection as detecting paired or triplet key-points [8, 9, 18, 39]. Moreover, recent works present a paradigm based on the Transformer [40] structure to detect objects [5, 26, 49], which achieve the state-of-the-art performance on the current object detection datasets. However, both of these works give poor scalability due to the limitation of the quantity of labeled data.

2.2 Semi-supervised Learning (SSL)

In recent years, semi-supervised learning (SSL) has made some great progress by mining the potential of the unlabeled data, which is...
Figure 2: The overview of the cycle self-training (CST) framework with distribution consistency reweighting (DCR) strategy. Labeled and unlabeled images form the training data batch. In each iteration, the teacher T1 (T2) perform pseudo-labeling on weak augmented images to train the student S2 (S1) with strong augmented images. And the student S1 (S2) is utilized to update the teacher T1 (T2) via EMA. Moreover, consistency quantification is performed across the two teachers to reweight unsupervised loss. The final loss is the sum of supervised loss $L_s$ and unsupervised loss $L_u$.

beneficial for the tasks with limited labeled data and abundant unlabeled data. Existing semi-supervised learning approaches are based on the consistency regularization principle or pseudo labeling technique. Dual Student [14] explains the coupling effect of the EMA and replaces the teacher with another student to address this problem. RemixMatch [2] produces distribution alignment and augmentation anchoring to reduce the quantity labeled data. UDA [42] substitutes the traditional noise injection with the high quality data augmentation to improve consistency semi-supervised learning. Fixmatch [33] applies the consistency regularization and introduces artificial labels on weakly augmented unlabeled images. All of these methods leverage the augmentations or perturbations applied to original input images to ensure consistent output predictions. The other kind of methods utilize the pseudo labels by adopting the teacher-student co-training framework. Deep co-training [28] presents a deep adversarial co-training approach and explores the effect on the prediction diversity of the teacher-student models. FixMatch [46] uses unlabeled data by adding additional noise to the student for better learning the knowledge of the teacher model. Noisy Student [43] uses unlabeled data by adding additional noise to the student for better learning the knowledge of the teacher model. FixMatch [46] proposes Curriculum Pseudo Labeling to dynamically leverage unlabeled data with thresholds. SemiMatch [16] generates pseudo-labels between source and weakly augmented target to learn the model again between source and strongly augmented one.

### 2.3 Semi-supervised Object Detection (SSOD)

To avoid the large cost restriction of detection annotations, currently, the semi-supervised learning is applied to object detection task. CSD [13] directly uses the simple flip augmentation to input images based on consistency regularization principle, and the loss function is built on the consistency of the two output predictions. STAC [34] designs a special framework based on both pseudo labels technique and consistency regularization for object detection, including a fixed teacher network for pseudo labels generation and a student network for training with strong augmentations. Unbiased Teacher [25] further explores the teacher-student framework and updates the weights of the teacher network by the EMA technique, which uses Focal Loss [22] to mitigate the class-imbalance issue to some degree. Thus it is also treated as the comparison baseline in most cases. Instant-Teaching [48] leverages Mixup [47] and Mosaic [3] augmentations and proposes a co-rectify scheme to alleviate the confirmation bias [38]. Humble Teacher [37] utilizes plenty of region proposals and soft pseudo labels for training with a light-weighted detection-specific data ensemble algorithm. ISMT [45] proposes an interactive self-training framework and performs NMS operation to fuse the results of the current and historical iteration to improve the quality of pseudo labels. Soft Teacher [44] proposes a mechanism where the classification loss is weighted by the score generated from teacher and a box jittering strategy to select reliable pseudo boxes for regression. Combating Noise [41] treats uncertainty quantification as the soft target and facilitates multi-peak probability distribution. CPL [19] introduces certainty-aware pseudo labels and uses dynamic thresholds to mitigate the class imbalance problem. MUM [15] proposes the Mix and UnMix data augmentation method to generate strongly-augmented images for training, which can be easily equipped on other SSOD methods.

### 3 METHODOLOGY

In this paper, we propose a cycle self-training framework with distribution consistency reweighting strategy to overcome the coupling and the confirmation biases problems. The overall structure of our framework is shown in Figure 2.
3.1 Preliminary

For semi-supervised object detection (SSOD), a set of labeled data \( D_l = \{(x_i^l, y_i^l)\}_{i=1}^{N_l} \) and unlabeled data \( D_u = \{(x_i^u, y_i^u)\}_{i=1}^{N_u} \) are available for training, where \( x \) and \( y \) denote image and ground-truth annotations respectively, i.e., class labels and bounding box coordinates. \( N_l \) and \( N_u \) represent the number of labeled and unlabeled data. And the ultimate goal of SSOD is to improve detection accuracy by training object detectors on both labeled and unlabeled data.

To leverage the unlabeled images, we also adopt the Teacher-Student training paradigm, where the Student is optimized by using the pseudo-labels generated from the Teacher, and the Teacher is updated by gradually transferring the weights of continually learned Student model, similar to recent works [15, 25, 37, 41, 44, 45, 48]. Also, a confidence threshold of predicted bounding boxes is set to filter low-confidence predicted bounding boxes, which are more likely to be false positive samples. Moreover, to address the duplicated boxes prediction issue existing in object detection, we eliminate redundancy by applying non-maximum suppression (NMS) before confidence filtering with threshold \( r \). And different augmentation strategies are adopted for teacher and student model respectively, i.e., weak augmentation for pseudo-labeling of teacher model and strong augmentation for training of student model.

After obtaining the pseudo-labels of unlabeled images from the teacher model, a mixed batch of equal numbers of labeled and unlabeled images are randomly sampled to feed into the supervised branch and unsupervised branch respectively. The final loss \( L \) is the weighted sum of the supervised loss and unsupervised loss,

$$ L = L_s + \alpha L_u, $$

where \( L_s \) and \( L_u \) denote the supervised loss of labeled images and unsupervised loss of unlabeled images respectively, \( \alpha \) is the weight factor to balance these two losses. And the supervised loss and the unsupervised loss are defined as follows:

$$ L_s = \frac{1}{n_l} \sum_{i=1}^{n_l} L_{cls}(x_i^l, y_i^l) + L_{reg}(x_i^l, y_i^l), $$

$$ L_u = \frac{1}{n_u} \sum_{i=1}^{n_u} L_{cls}(x_i^u, y_i^u), $$

where \( L_{cls} \) is the classification loss, \( L_{reg} \) is the regression loss, \( n_l \) and \( n_u \) denote the number of labeled images and unlabeled images in a training batch, \( x_i^l \) and \( y_i^l \) indicate the \( i \)-th labeled image and corresponding ground-truth label, while \( x_i^u \) and \( y_i^u \) denote the \( i \)-th unlabeled image and its pseudo-label from teacher model. Similar to [25], we also do not apply regression loss for unlabeled images since predicted confidence can not show the localization quality.

Besides, our proposed self-training framework can be applied to mainstream object detectors, including two-stage detectors [4, 6, 7, 30, 36] and one-stage detectors [18, 22, 24, 29, 39]. For fair comparisons, we also utilize Faster R-CNN [30] to clarify our method.

3.2 Cycle Self-Training Framework

Our proposed Cycle Self-Training framework consists of three stages, the Burn-In stage, the training stage and the inference stage.

**Burn-In Stage.** In the training stage, the student network is supervised by the pseudo-labels generated from the teacher network. Hence, the quality of pseudo-labels is very important for detection performance. So it is necessary to have a good initialization for both student and teacher networks [25]. In our framework, the students S1 and S2 are initialized with different parameters firstly. Then we only utilize the available labeled images to optimize model \( \theta_1 \) (\( \theta_2 \)) with the supervised loss \( L_s \) for a fixed amount of iterations. After the Burn-In stage, the weights \( \theta_1 \) (\( \theta_2 \)) is copied to both the teacher T1 (T2) and the student S1 (S2), i.e., \( \theta_1 \rightarrow \theta_1', \theta_1 \rightarrow \theta_2', \theta_2 \rightarrow \theta_1' \). Based on the initialized parameters, the models are further trained with the proposed cycle self-training mechanism to improve performance.

**Training Stage.** As analyzed in the previous section, due to the coupling effect, the typical EMA teacher can not provide more meaningful knowledge for student along with the training process, especially in the later stage. To address the issue, an intuitive idea is to loose the coupling between the teacher and the student. Hence, we propose a cycle self-training (CST) framework for semi-supervised object detection, in which a knowledge transferring loop is built to loose the coupling effect of the Teacher-Student framework.

As shown in Figure 2, the proposed CST framework consists of four sub-networks: two teacher networks T1 and T2, and two student networks S1 and S2. To eliminate the coupling effect between T1 and S1, a cycle self-training mechanism is built, i.e., \( S \rightarrow T \rightarrow S \). To further train the teacher networks with the EMA weights of the student networks. By doing so, the advantage of the typical Teacher-Student framework is preserved, i.e., the imbalanced pseudo-labeling biased issue can be alleviated and more stable pseudo-labels can be obtained [25]. For \( T \rightarrow S \), instead of providing supervision for its own student S1 (S2) directly, the teacher T1 (T2) generates pseudo-labels for the student S2 (S1), which looses the coupling relationship and transfers more meaningful knowledge indirectly.

Besides, due to the existence of EMA relationship, the EMA teacher still accumulates the mistakes from its own student and enforces the other student to follow. To overcome this problem, we propose an consistency learning strategy to avoid accumulating biases and collapsing into each other. Specifically, as shown in Figure 2, the pseudo-labels generated from the teacher T1 are measured by the teacher T2 in Distribution Consistency module, which is to perform consistency quantification of classification distribution. Based on the consistency values, each pseudo-label proposal is re-weighted to train the student S2 robustly. More details about the learning strategy will be described in the next section.

**Inference Stage.** At the stage of inference, only the teacher networks are utilized. To illustrate the effect of our framework, we test the single teacher for fair comparisons with the recent state-of-the-art methods. Besides, the teachers T1 and T2 own different parameters, which perform differently for the same categories. So we also report the ensemble results of these two teachers with the Weighted Box Fusion (WBF) [35] method, denoted as CST*.

3.3 Distribution Consistency Reweighting

As analyzed above, although the cycle self-training framework looses the coupling effect, there still exists confirmation bias issue due to EMA. To handle the above noise, a distribution consistency reweighting strategy is proposed, where pseudo-labels are learned
Consistency Quantification. As shown in Figure 3, the EMA teacher T1 generates pseudo-labels for the unlabeled image, including the box coordinates $h_i$ and corresponding classification distributions $\{p_i^1\}$. Then the EMA teacher T2 takes the pseudo boxes as input and predicts classification distribution for each box through its detection head, denoted as $\{p_i^2\}$. Given the predicted distributions from T1 and T2, we can perform consistency quantification by calculating the differences between distributions to assess the quality of all pseudo boxes generated by T1. For comparison, we explore two kinds of quantification styles. And the results are shown in the ablation studies.

- The L1 distance between the predicted distributions from T1 and T2. To make the quantification values more suitable for loss reweighting, we firstly normalize the L1 distance to 0.5 ~ 1 with a sigmoid mapping function. Then a linear normalization is performed so that the quantification values are in the range 0 ~ 1. The specific formula is defined as follows:

$$c_i(p_i^1, p_i^2) = 2 \times (1 - \text{Sigmoid}(||p_i^1 - p_i^2||))$$

(4)

where $c_i$ denotes the quantification value of the $i$th pseudo box, $p_i^1$ and $p_i^2$ are the corresponding distributions from T1 and T2 respectively.

- The JS divergence between the predicted distributions from T1 and T2. Because the JS values are also in the range 0 ~ 1, we only utilize a tunable focusing parameter $\beta = 2$ so that inconsistent instances are further down-weighted. The specific formula is expressed as follows:

$$c_i(p_i^1, p_i^2) = JS(p_i^1, p_i^2)^\beta$$

(5)

Rewighted Loss. After the process of consistency quantification, the values for all pseudo boxes can be acquired. Then the

Algorithm 1 Training procedure of the proposed CST

Require: $(X^l, y^l, X^u)$, pair of labeled images and its annotations, and unlabeled images
Require: $f_{T1}$, $f_{T2}$: teacher object detection model T1 and model T2
Require: $f_{S1}$, $f_{S2}$: student object detection model S1 and model S2
Require: $w()$, $s()$: weak and strong augmentation
Require: $c()$: consistency quantification function
Require: $h()$, $\alpha$: loss function and balancing weight

1: for each iter $\in [1, \text{max\_iterations}]$ do
2: Prepare Data
3: $D \leftarrow w(X^l) + s(X^u)$, $W \leftarrow w(X^u)$, $S \leftarrow s(X^u)$
4: Generate Pseudo Labels
5: $\hat{Y}_u^{S2} \leftarrow f_{T1}(W)$, $\hat{Y}_u^{S2} \leftarrow f_{T2}(W)$
6: Distribution Consistency Quantification
7: $C_{S2} \leftarrow c(\hat{Y}_u^{S2}, f_{T2}(\hat{Y}_u^{S2}))$, $C_{S1} \leftarrow c(\hat{Y}_u^{S2}, f_{T1}(\hat{Y}_u^{S2}))$
8: Compute the Supervised Loss
9: $p_i^{S1} \leftarrow f_{S1}(D)$, $p_i^{S2} \leftarrow f_{S2}(D)$
10: $L_{S1}^{CL} \leftarrow h(p_i^{S1}, Y_i)$, $L_{S2}^{CL} \leftarrow h(p_i^{S2}, \hat{Y}_u)$
11: Compute the Unsupervised Loss
12: $p_i^{mu} \leftarrow f_{S1}(S)$, $p_i^{mu} \leftarrow f_{S2}(S)$
13: $L_{S1}^{SU} \leftarrow h(p_i^{mu}, S_i)$, $L_{S2}^{SU} \leftarrow h(p_i^{mu}, \hat{Y}_u)$
14: Compute the Total Loss
15: $L_{S1} \leftarrow L_{S1}^{CL} + \alpha L_{S1}^{SU}$, $L_{S2} \leftarrow L_{S2}^{CL} + \alpha L_{S2}^{SU}$
16: Update $f_{S1}$ with $L_{S1}$, and Update $f_{S2}$ with $L_{S2}$
17: Update $f_{T1}$ and $f_{T2}$ via EMA
18: end for

foreground box candidates generated from S2 are assigned with corresponding quantification values during the process of label assignment. Based on the assigned values, the foreground classification loss can be re-weighted to mitigate the accumulated biases. Given two box sets $\{x_i^f\}$ and $\{x_i^b\}$, with $\{x_i^f\}$ denoting boxes assigned as foreground and $\{x_i^b\}$ denoting the categories of pseudo boxes generated from teacher T1. $L_{cls}$ is the box classification loss. Including the above distribution consistency reweighting strategy, the whole training process is described in Algorithm 1.

### 4 EXPERIMENTS

#### 4.1 Experimental Settings

Dataset. MS-COCO [23] and PASCAL VOC [10] datasets are used in our experiments following the previous SSDW works. MS-COCO dataset contains 118k labeled images for training with approximate 850k instances of 80 categories. PASCAL VOC 2007 dataset contains 5k labeled images for training with 20 instances of 20 categories,
| Methods      | 1% COCO | 2% COCO | 5% COCO | 10% COCO | 100% COCO |
|-------------|---------|---------|---------|----------|-----------|
| Supervised  | 0.95±0.16 | 1.27±0.15 | 1.84±0.22 | 2.38±0.81 | 3.76±0.32 |
| CSD [13]    | 10.51±0.06 (+1.46) | 13.93±0.12 (+1.23) | 18.63±0.07 (+0.16) | 22.46±0.08 (+1.40) | 38.87±1.24 |
| STAC [34]   | 13.97±0.35 (+4.92) | 18.25±0.25 (+5.55) | 24.38±0.12 (+8.56) | 28.64±0.21 (+7.48) | 39.21±1.58 |
| Instant-Teaching [48] | 18.05±0.15 (+9.00) | 22.45±0.15 (+9.75) | 26.75±0.05 (+8.28) | 30.40±0.05 (+6.54) | 40.20±2.57 |
| ISMT [45]   | 18.88±0.74 (+9.83) | 22.43±0.56 (+9.73) | 26.37±0.24 (+9.70) | 30.53±0.52 (+6.67) | 39.64±2.01 |
| Humble Teacher [37] | 16.96±0.38 (+7.91) | 21.72±0.24 (+9.02) | 27.70±0.75 (+9.23) | 31.61±0.28 (+7.75) | 42.37±4.74 |
| Combating Noise [41] | 18.41±0.10 (+9.36) | 24.00±0.15 (+11.30) | 28.96±0.29 (+10.49) | 34.23±0.20 (+8.57) | 43.20±5.57 |
| Soft Teacher [44] | 20.46±0.39 (+11.41) | 23.34±0.20 (+12.37) | 29.70±0.75 (+12.36) | 35.23±0.14 (+12.14) | 43.37±6.74 |
| CPL [19]    | 19.02±0.25 (+9.97) | 23.34±0.18 (+10.64) | 28.40±0.15 (+9.93) | 32.23±0.14 (+8.37) | 43.30±5.67 |
| MUM [15]    | 21.88±0.12 (+12.83) | 24.84±0.10 (+12.14) | 28.52±0.09 (+10.05) | 31.87±0.30 (+8.01) | 42.11±4.48 |
| Unbiased Teacher [25] | 20.75±0.12 (+11.70) | 24.30±0.07 (+11.66) | 28.27±0.11 (+9.80) | 31.50±0.10 (+7.64) | 41.30±3.67 |
| CST (ours)  | 22.20±0.18 (+13.15) | 26.17±0.15 (+13.47) | 29.75±0.13 (+11.28) | 32.65±0.21 (+8.79) | 42.05±4.42 |
| CST* (ours) | 22.73±0.14 (+13.68) | 26.94±0.10 (+14.24) | 30.83±0.08 (+12.36) | 33.90±0.17 (+10.04) | 43.37±5.74 |

Table 1: The performance (AP%) of different semi-supervised object detection methods for 1%, 2%, 5%, 10% and 100% MS-COCO protocols. All methods use ResNet-50 with FPN as backbone and Unbiased Teacher is treated as baseline for a fair comparison.

| Methods       | 0.5% COCO |
|---------------|-----------|
| Supervised    | 6.83±0.15 |
| CSD [13]      | 7.41±0.21 (+0.58) |
| STAC [34]     | 9.78±0.53 (+2.95) |
| MUM [15]      | 18.53±0.48 (+11.71) |
| Unbiased Teacher [25] | 16.94±0.23 (+10.11) |
| CST (ours)    | 19.20±0.28 (+12.37) |
| CST* (ours)   | 19.65±0.21 (+12.82) |

Table 2: The performance (AP%) of existing SSOD methods with ResNet-50-FPN backbone for 0.5% MS-COCO protocol.

while PASCAL VOC 2012 dataset contains 11.5k labeled images for training with 27k instances. For the experiments on MS-COCO, 0.5%, 1%, 2%, 5% and 10% of the labeled training data are randomly sampled and the remainder is taken as the unlabeled data. In addition, we also use coco-full dataset for the 100% protocol, which is composed of the 118k standard training set of MS-COCO as labeled dataset and the 120k COCO2017 unlabeled data as the unlabeled training set, to further measure the effect of our framework. For the experiments on PASCAL VOC, VOC 2007 dataset is utilized as the labeled training set and VOC 2012 dataset as the unlabeled training set. Moreover, we add the images from COCO dataset that share the same 20 object categories with VOC 2007 dataset to the unlabeled training set as VOC-additional dataset. The detection performance is evaluated on COCO2017-val set for the COCO dataset and VOC 2007-test set for the VOC dataset following the existing works.

Implementation Details. Faster R-CNN [30] with ResNet-50-FPN [11, 21] backbone is involved in our experiments to ensure the fairness and correctness in comparisons followed by the existing works [15, 25, 34, 41, 44, 45]. All hyper-parameters and augmentations are reserved as Unbiased Teacher [25] and the weights of the model are initialized from the pre-trained models on ImageNet [31]. We use an SGD optimizer on 8 GPUs with a learning rate 0.01, a momentum rate 0.9 and a weight decay 0.0001. The batch size is set to 32 in our main experiments compared to other existing methods. For 0.5%, 1%, 2%, 5% and 10% MS-COCO protocols, we adopt 180k training iterations, including 1k, 2k, 6k, 12k and 20k iterations for the initial Burn-in stage that only train the model by labeled data and the rest for the cycle self-training stage. Specially, for 100% (COCO-full) protocol, the Burn-in stage is set to 90k and the total number of training iterations is 360k. For PASCAL VOC dataset and VOC-additional dataset, the Burn-in stage is set to 30k and the whole training iterations are 180k. Following the convention, the confidence score threshold is set to 0.7 for filtering the pseudo labels. For the training loss, we set the weight factor $\alpha = 4$ for the unlabeled data following the Unbiased Teacher [25]. Specially, during the testing process, apart from the detection results produced by the teacher model, we also evaluate the ensemble results of the two teacher models via Weighted Boxes Fusion (WBF) [35], which further improves the performance of our proposed method.

4.2 Comparisons with State-of-the-art

MS-COCO. We first preform the comparative study on MS-COCO dataset to evaluate our CST and CST* method. The results are reported in Table 1. For the 1%, 2% and 5% protocol, our method outperforms all the state-of-the-art methods. Compared to the baseline Unbiased Teacher [25], our CST* achieves 22.73% AP, 26.94% and 30.83% AP with only 1%, 2% and 5% unlabeled data respectively. For 10% and 100% MS-COCO protocols, our CST* improves 2.40%, 2.07% AP over the baseline Unbiased Teacher, which also surpasses most of the methods, including the recent works CPL [19] and MUM [15]. These results show that our proposed CST and CST* is reliable and outstanding in semi-supervised object detection.

In order to illustrate that our CST and CST* can give higher AP results when less labeled data are provided, we conduct the experiment on 0.5% MS-COCO dataset. The evaluation results are shown in Table 2. CST* achieves 19.65% AP and outperforms the best of existing work. The reason is that with less labeled samples, due to the worse pre-trained model in the burn-in stage, the pseudo-labels generated from the teacher become more and more unstable and inaccurate. The gap of the predictions is increased between the
two teachers, so the proportion of reweighted foreground bounding box candidates increases, which facilitates the performance gains caused by distribution consistency reweighting.

**PASCAL VOC.** Then we evaluate our proposed CST and CST* on PASCAL VOC and VOC-additional dataset. As shown in Table 3, our method still preforms better compared to the baseline. For the first protocol, CST* achieves about 51.5% for AP and 78.7% for AP50 improvement over the baseline. For the second protocol, CST* improves from 50.3% to 53.5% for AP and from 78.8% to 80.5% for AP50. These evaluation results indicate that our CST* still achieves the comparable performance on the semi-supervised object detection datasets with less categories. In addition, we find that our CST* preforms better on MS-COCO than PASCAL VOC. This is because PASCAL VOC is so simple due to the less images and categories that probably cause the over-fitting problem. Consequently, this observation confirms our conclusion that unlabeled data with more knowledge and patterns can improve the effect of our method.

### 4.3 Qualitative Results

We give some visual results for comparison, including the supervised method, Unbiased Teacher, our CST and CST*. As shown in Figure 4, these detection results of objects from different categories obviously manifest the superiority of our proposed method. For instance, the chair can be better detected and the cat can be correctly categorized by our CST. Additionally, the figure also shows that the effect of the detection results can be further improved by our CST* method. For example, most of broccoli can be detected by our CST and CST* while less are presented by the Unbiased Teacher. Based on these visualization results, our CST and CST* can achieve more precise classification and accurate localization results.

### 4.4 Ablation Studies

We conduct our ablation studies on 1% MS-COCO dataset to evaluate the effectiveness of each component in our CST framework. Without loss of fairness, we use 16 batch size in our ablation studies because of lower computation and faster training process.

**Effects of Each Component.** Our main contribution contains two components: the Cycle Self-Training (CST) framework and the Distribution Consistency Reweighting (DCR) strategy. To validate the effect of the two components, we take the Unbiased Teacher as the baseline, and then evaluate various component combinations as shown in Table 4. We can observe that adding either of the two components can give a favorable improvement. For the CST component AP gains 1.3% and for the DCR component AP improves 1.1%. By incorporating both of the two components, the performance is significantly boosted to 21.9% compared to the baseline 20.1%.

**Different Consistency Quantification Styles.** Since there are mainly two styles of distribution consistency quantification as mentioned earlier, the experiments with different consistency quantification styles are conducted to verify which style is more compatible with our proposed framework. Table 5 shows the detailed evaluation results while using different styles during training. From the table we can conclude that the L1 distance between the two classification predictions performs better than the JS divergence when treated as consistency quantification style in our framework. The reason is quite likely to be that the L1 distance better balances the weights of different positive samples compared to the JS divergence.

**Different Consistency.** Although we have analyzed the effectiveness of the DCR component, all previous experiments compute the consistency between the two teacher models. Beyond the (T1 ↔
Table 4: Ablation study of different network components.

| CST | DCR | AP (%) |
|-----|-----|--------|
| ✓   | ✓   | 20.1   |
| ✓   | ✓   | 21.4   |
| ✓   | ✓   | 21.2   |

Table 5: Ablation study of consistency quantification style in DCR.

| Quantification Style | AP (%) |
|----------------------|--------|
| JS Divergence        | 21.5   |
| L1 Distance          | 21.9   |

Table 6: Ablation study of different combinations in DCR.

| Combinations for DCR | AP (%) |
|----------------------|--------|
| (T1 ↔ S1), (T2 ↔ S2) | 21.6   |
| (T1 ↔ S2), (T2 ↔ S1) | 21.4   |
| (T1 ↔ T2), (T2 ↔ T1) | 21.9   |

Figure 5: (a) Mean Distance between the features of the same region for different component configurations. (b) KL divergence between the classification predictions of the same region. (c) Training Loss curves of different components.

4.5 Discussions

**Coupling Effect.** To verify our proposed CST framework indeed helps to overcome the tightly coupling effect, we visualize the Euclidean distances between the features of the same regions extracted by the teacher T1 (T2) and the student S2 (S1). Specifically, given the pseudo boxes generated from T1 (T2), we can obtain the aligned features from S2 (S1) through the detection head. Then the mean of Euclidean distances between the features extracted by T1 and S2 is calculated, which is denoted as $D_{T1-S2}$. Similarly, the mean distance $D_{T2-S1}$ and the mean distance $D_{T-S}$ of the teacher-student framework are also provided, as shown in Figure 5 (a). Compared with $D_{T-S}$, the mean distance $D_{T1-S2}$ and $D_{T2-S1}$ are always larger during the training process, which proves that T1(T2) and S2(S1) are not tightly coupled similar to T and S. By doing so, the performance limitation caused by the conventional teacher-student framework can be broken. At the same time, the KL divergence of the classification predictions of the teacher T1 (T2) and the student S2 (S1) is visualized in Figure 5 (b), which also indicates the coupled problem can be alleviated through our CST framework.

**Distribution Consistency Reweighting.** To verify the effectiveness of our proposed distribution consistency reweighting strategy, we present training curves of different component configurations in Figure 5 (c), including the conventional teacher-student framework, the proposed CST framework and the CST framework with distribution consistency reweighting strategy, denoted as $L_{TS}$, $L_{CST}$ and $L_{DCR}$ respectively. We observe that, with our proposed CST framework, the model has lower losses compared with the original teacher-student framework. When we utilize the overall framework, it achieves the lowest losses, which indicates that the model can be trained more robustly with noisy pseudo labels and mitigate accumulating confirmation biases under our proposed method.

5 CONCLUSION

In this paper, we propose a Cycle Self-Training (CST) framework for semi-supervised object detection, in which a knowledge transferring loop is built to loose the tightly coupling effect of the conventional teacher-student framework. Furthermore, a distribution consistency reweighting (DCR) strategy is introduced to be combined with the proposed CST framework to train the student networks robustly with noisy pseudo labels to avoid accumulating confirmation biases. Extensive experiments on MS-COCO and PASCAL VOC datasets demonstrate the effectiveness of our proposed framework. Moreover, the proposed framework is fairly general and can be easily incorporated with existing object detection methods to perform the semi-supervised learning.

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