Point-Teaching: Weakly Semi-Supervised Object Detection with Point Annotations

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Abstract. Point annotations are considerably more time-efficient than bounding box annotations. However, how to use cheap point annotations to boost the performance of semi-supervised object detection remains largely unsolved. In this work, we present Point-Teaching, a weakly semi-supervised object detection framework to fully exploit the point annotations. Specifically, we propose a Hungarian-based point matching method to generate pseudo labels for point annotated images. We further propose multiple instance learning (MIL) approaches at the level of images and points to supervise the object detector with point annotations. Finally, we propose a simple-yet-effective data augmentation, termed point-guided copy-paste, to reduce the impact of the unmatched points. Experiments demonstrate the effectiveness of our method on a few datasets and various data regimes. In particular, over the strong semi-supervised baseline method Unbiased Teacher, our detector achieves significant improvements of 9.1 AP with 0.5% fully labeled data on MS COCO and 2.5 AP₅₀ with fully labeled data on the Pascal VOC07 dataset. When using 30% fully labeled data from MS-COCO, our method outperforms previous state-of-the-art weakly semi-supervised method Point DETR by 3.4 AP. We believe that our proposed framework can largely lower the bar of learning accurate object detector and pave the way for its broader applications.

Keywords: Point-supervised, Semi-supervised, Object Detection, Instance Segmentation

1 Introduction

Great progress has been achieved in object detection and segmentation in recent years [12,3,14,6,7]. Accurate object detectors can be trained using large fully-labeled datasets [8,9]. However, annotating large-scale object detection datasets are extremely expensive and time-consuming, as it requires the annotators to find all the objects of interest in the images and to draw a tight bounding box/segmentation mask for each of them.

How to train object detectors with fewer annotations has attracted increasing attention. Weakly supervised object detection (WSOD) methods [10,11,12,13,14,15] reduce the cost via replacing the box annotations with cheaper annotations, e.g., image-level categories, point clicks and squiggles. Semi-supervised object detection (SSOD) methods [16,17,18,19,20] train object detectors with a small amount of fully-labeled images and large-scale unlabeled images. However,
although both ways can reduce the annotation cost, the performance of the trained detectors is still far behind the fully-supervised counterpart.

In this paper, we aim to train object detectors with considerably fewer annotations while achieving comparable performance with the fully-supervised counterpart. To achieve this goal, there are two key problems: 1) what annotation formats to use and 2) how to train object detectors with such annotations. A cheap but effective annotation format for object detection should be 1) simple to annotate, 2) convenient to store and use, 3) localization-aware. Among various weak formats, point click annotation stands out as it meets all the requirements. Point click provides a stronger prior of object location compared with image-level category annotation. Meanwhile, it does not require detailed and expensive location information such as object bounding box or segmentation masks, thus being considerably more time-efficient. According to [21] a box annotation takes 7 seconds while a point annotation takes 0.8-0.9 seconds. To achieve the best balance of detection performance and annotation cost, we adopt mixed annotation formats to construct the training dataset. In the following, we use point annotated setting to represent such a dataset which comprises a small number of fully annotated images and massive point annotated images. Under this setting, we are able to obtain abundant annotations in a relatively cheaper manner [22][23].

To fully utilize both the limited box annotations and abundant point annotations, we propose a novel weakly semi-supervised object detection framework, termed Point-Teaching. Inspired by Mean Teacher [24] and Unbiased Teacher [18], we construct a Student model and a Teacher
model with the same architecture. In each training iteration, weakly augmented point-labeled images are fed to the Teacher model to generate reliable pseudo bounding boxes. The Student is then optimized on fully labeled and pseudo labeled images with strong augmentation. The Teacher is updated via Exponential Moving Average (EMA) of the Student. Within this basic framework, we propose three key components tailored for point annotations. First, we propose the hungarian-based point matching method to generate pseudo labels for point annotated images. A spatial cost and a classification cost are introduced to find the bipartite matching between point annotations and predicted box proposals.

We further propose multiple instance learning (MIL) approaches at the level of images and points to supervise the object detector with point annotations. Inspired by previous WSOD works \cite{12,13,14,15}, we perform image-wise MIL via treating the whole image as a bag of object proposals. These proposals are aggregated for predicting all presented classes in the image, supervised by image-level labels during the training. To leverage the location information of point annotations, we propose point-wise MIL, which selects the highest detection score proposal with the same class label as the only positive and suppresses the rest proposals as negatives around the given point annotation. Finally, we propose the point-guided copy-paste augmentation strategy. The motivation is that there still exist some point annotations that have not been matched any proposals after the point matching. To further utilize those unmatched points, we maintain an online object bank and paste same-class objects to unmatched point annotations during the training. The point-guided copy-paste makes the distribution of generated pseudo labels closer to that of the ground truth.

Experiments demonstrate the effectiveness of our method on different datasets and various data regimes. In particular, using fully-labeled VOC07 and point-labeled VOC12, Point-Teaching achieves comparable performance (83.0 vs. 83.5 AP) with supervised learning on the fully-labeled VOC07&12. Over the strong semi-supervised baseline method Unbiased Teacher \cite{18}, our detector achieves significant improvements of 9.1 AP with 0.5% fully labeled data on MS COCO and 2.5 AP\textsubscript{50} with fully labeled data on VOC07 dataset. When using 30% fully labeled data from MS COCO, our method outperforms previous state-of-the-art weakly semi-supervised method Point DETR \cite{25} by 3.4 AP.

Our main contributions are summarized as follows:

\begin{itemize}
  \item We propose a simple and effective training framework for weakly semi-supervised object detection, termed \textbf{Point-Teaching}, which integrates point annotations into semi-supervised learning. The key components of Point-Teaching include Hungarian-based point-matching approach, image-wise and instance-wise MIL loss, and point-guided copy-paste augmentation.
  \item Extensive experiments are conducted on MS-COCO and VOC datasets to verify the effectiveness of our method. Point-Teaching significantly outperforms the existing methods \cite{18,25} and greatly narrows the gap between weakly semi-supervised and fully-supervised object detectors.
  \item We further extend Point-Teaching from WSSOD to weakly semi-supervised instance segmentation (WSSIS) and weakly-supervised instance segmentation (WSIS), setting a strong baseline for the two challenging tasks.
\end{itemize}
2 Related Work

Fully-supervised object detection. With the large-scale fully annotated detection datasets [8,9], existing modern detectors have obtained great improvements in the object detection task. These detectors can be divided into three categories: two-stage detectors [1,26], one-stage detectors [2,27,4] and the recently end-to-end detectors [28,29,30]. Faster RCNN is a popular two-stage detector that first generates region proposals and then refines these proposals in the second stage. Unlike two-stage detectors, one-stage detectors, such as YOLO [2] and FCOS [4], directly output dense predictions of classification and regression without refinement. Recently, DETR [28] introduces the transformer encoder-decoder architecture to object detection and effectively removes the need for many hand-craft components, e.g. predefined anchors and non maximum suppression (NMS) post-processing. Despite the great success, these detectors are trained with large amounts of expensive fully-labeled data. Therefore, a lot of work has been proposed to reduce the annotation cost.

Weakly-supervised object detection. There exist many WSOD works that focus on training object detector with weakly-labeled data. Most previous studies have two phases: proposal mining and proposal refinement. The proposal mining phase is formulated as the MIL problem to implicitly mine object locations with image-level labels. The proposal refinement phase aims at refine the object location with the predictions from the proposal mining phase. WSDDN [12] proposes a two-stream network to simultaneously perform region selection and classification. The region level scores from these two streams are then element-wise multiplied and transformed to image-level scores by summing over all regions. Following WSDDN [12], ContextLocNe [13] introduces context information. OICR [14] presents a multi-stage refinement strategy to avoid the MIL detector be trapped into the local minimum. PCL [31] proposes to refine instance classifiers by clustering region proposals in an image to different clusters. MIST [15] proposes a multiple instance self-training framework. OIM [32] effectively mining all possible instances by introducing information propagation on spatial and appearance graphs. However, propagating image-level weak supervision to instance-level training data inevitably involves a large amount of noisy information and the performance of these methods are limited.

Semi-supervised object detection. Besides WSOD, SSOD addresses the problem by using large amount of unlabeled data, together with a small set of labeled data. One popular SSOD technique is consistency regularization, which aims to regularize the detector’s prediction with an image of different augmentations. CSD [16] enforces the detector to make consistent predictions on an input image and its horizontally flipped counterpart. ISD [33] proposes an interpolation-based method for SSOD. Another emerging SSOD approach is pseudo labeling, where a teacher model is trained on labeled data to generate pseudo labels on unlabeled data, and a student model is then trained on both labeled and pseudo labeled data. STAC [17] pre-trains a model on labeled data and fine-tunes it on both labeled and unlabeled data iteratively. Instance-Teaching [19] introduces a co-rectify scheme for alleviating confirmation bias of pseudo labels. Unbiased Teacher [18] proposes a class-balance loss to address the class imbalance issue in pseudo-labels and refine the teacher model via Exponential Moving Average (EMA).
Weakly semi-supervised object detection. Image-level annotation is a kind of weak annotation compared to box annotation. However, it is not optimal for object detection since the lack of instance-level information. Recently, point supervision \cite{34, 25, 35, 21} has been employed in WSSOD. Papadopoulos et al. \cite{35, 21} collect click annotation for the PASCAL VOC dataset and train an object detector through iterative multiple instance learning. UFO\textsuperscript{2} \cite{34} proposes a unified object detection framework that can handle different forms of supervision simultaneously, including box annotation and point annotation. Point DETR \cite{25} extends DETR \cite{28} by adding a point encoder and thus can convert point annotations to pseudo box annotations. In this paper, we follow this setting and introduce several methods for improving the performance of point-based WSSOD.

3 Method

3.1 Preliminaries

Problem definition. In this work, we study weakly semi-supervised object detection under the point annotated setting, in which the dataset consists of a small set of fully annotated images \( D_F = \{ (I_i, \hat{b}_i) \}_{i=1}^{N_F} \) and a large set of point annotated images \( D_P = \{ (I_i, \hat{p}_i) \}_{i=1}^{N_P} \). \( N_F \) and \( N_P \) are the number of fully labeled and point labeled images respectively. \( I_i \) denotes fully or point labeled images. For fully annotated images, the annotation \( \hat{b}_i \) includes box coordinates \((\hat{b}_{x1}, \hat{b}_{y1}, \hat{b}_{x2}, \hat{b}_{y2})\) and class label \( \hat{b}_{l} \). For point annotated images, the annotation \( \hat{p}_i \) includes point location \((\hat{p}_{x1}, \hat{p}_{y1}, \hat{p}_{x2}, \hat{p}_{y2})\) and class label \( \hat{p}_{l} \). For point annotated images, we only need to randomly annotate one point for each object instance, thereby the annotation cost can be greatly reduced.

3.2 Overall Architecture

For a fair comparison, we take Faster RCNN with FPN \cite{1} and ResNet-50 backbone \cite{36} as our baseline object detector. Compared to the original Faster RCNN network \cite{1}, we add two additional parallel branches to the RCNN head, termed Objectness-I branch and Objectness-P branch, respectively. The Objectness-I branch is used to suppress the likelihood of inconsistent classification predictions with image-level annotations, and is optimised with image-wise MIL loss. The Objectness-P branch is developed to measure the quality of pseudo boxes at point level, and is supervised with point-wise MIL loss.

The training pipeline of Point-Teaching is represented in Fig. 2. Inspired by Mean Teacher \cite{24} and Unbiased Teacher \cite{18}, there are two models with the same architecture, a Student model and a Teacher model. In each training iteration, weakly augmented point-labeled images from the dataset \( D_P \) are firstly fed to the Teacher for reliable pseudo labels; the Student is then optimized by labels from fully-labeled dataset \( D_F \) and pseudo labels generated from the Teacher with strong augmentation; Finally, the Teacher is updated by EMA of the Student. Different from the original Unbiased Teacher \cite{18}, there are three key components within the proposed framework: hungarian-based point matching strategy, point supervision with image-wise and instance-wise MIL loss, and point-guided copy-paste augmentation.
Fig. 2: The training process of Point-Teaching. In each training iteration, the Teacher model first generates pseudo box annotations for the point-labeled images with weak augmentation. The Student model is then trained on fully-labeled images with weak augmentation and point-labeled images with strong augmentation. The Teacher model is gradually updated by the student model via EMA. Image-wise MIL loss constructs a bag containing all predicted boxes, and the number of positive boxes in the bag is uncertain. The point-wise MIL loss constructs a bag for each annotated point, and there is only one positive box in these bags.

3.3 Point Matching

In order to find the best matching between the annotated points and the predicted boxes, i.e., to choose the best box prediction for each point annotation, we propose a simple point matching method, termed hungarian-based point matching. Specifically, we design two types of matching costs between annotated points and predicted boxes: a spatial cost and a classification cost. For the spatial cost, we consider two factors: 1) Predicted boxes that share the same class label with the given point annotation should have a low cost. 2) Predicted boxes with point annotations inside lead to a low cost. For the classification cost, higher confidence scores of the Classification branch and Objectness-P branch lead to a lower cost.

Formally, the cost matrix $L_{\text{match}} \in \mathbb{R}^{N_p \times N_b}$ is defined as:

$$L_{\text{match}}(i, j) = \left(1 - \mathbb{1}[\hat{p}_i \text{ in } b_j] \cdot \mathbb{1}[\hat{p}_i^l = b_j^l]\right) + \left(1 - \sigma(s_{j,\hat{p}_i}) \cdot \sigma^P(s_{j,1}^P)\right),$$

(1)

where $i$ is the index of the annotated points, and $j$ is the index of the predicted boxes. $L_{\text{match}}(i, j)$ denotes the matching cost between the annotated point $\hat{p}_i$ and the predicted box $b_j$. $N_p$ is the number of annotated points, and $N_b$ is the number of predicted boxes. $\hat{p}_i^l$ indicates the class label of the annotated point $\hat{p}_i$, $b_j^l$ indicates the class label of the predicted box $b_j$. We use $s \in \mathbb{R}^{N_b \times (C+1)}$ and $s^P \in \mathbb{R}^{N_b \times 2}$ to denote the outputs of Classification and Objectness-P branches, respectively, where $C$ denotes the number of categories excluding background. $\sigma(\cdot)$ represents the softmax function.
operation on the Classification output along the second dimension. $\sigma^P(\cdot)$ represents the softmax operation on the Objectness-P output along the second dimension.

Once the cost matrix is defined, the point matching problem could be mathematically formulated as a bipartite matching problem as:

$$\hat{\pi} = \arg\min_{\pi \in \mathcal{S}_{N_b}} \sum_i^{N_p} \mathcal{L}_{\text{match}} (i, \pi(i)),$$

where $\pi \in \mathcal{S}_{N_b}$ indicates a permutation of $N_b$ elements. This optimal assignment can be solved with the Hungarian algorithm [37].

### 3.4 MIL Loss for Images and Points

In this section, we present the overall loss function $\mathcal{L}$ of Point-Teaching framework.

$$\mathcal{L} = \mathcal{L}_{\text{det}} + \lambda_1 \mathcal{L}_{\text{mil}}^{I} + \lambda_2 \mathcal{L}_{\text{mil}}^{P}. \quad (3)$$

As shown in Eq. (3), the overall loss $\mathcal{L}$ consists of three parts: $\mathcal{L}_{\text{det}}$, $\mathcal{L}_{\text{mil}}^{I}$ and $\mathcal{L}_{\text{mil}}^{P}$, respectively. $\mathcal{L}_{\text{det}}$ represents the losses of the original object detector, e.g. classification loss and regression loss in RPN and ROI head of Faster RCNN. $\mathcal{L}_{\text{mil}}^{I}$ is image-wise MIL loss, which is proposed in WSDDN [12]. $\mathcal{L}_{\text{mil}}^{P}$ is our proposed point-wise MIL loss, which is defined below. $\lambda_1$ and $\lambda_2$ are hyper-parameters used to balance these three loss terms.

**Image-wise MIL loss.** Given the point annotations, we can easily obtain image-level labels $\{\hat{\phi}_c, \ c = 1, \cdots, C\}$. Image labels can help improve the performance of object detection in two ways. First, for categories that do not present in the image, the image-level supervision could help decrease the confidence score of the corresponding predicted boxes. Second, it helps detect the objects of the categories that present in the image.

Taking hundreds of predicted boxes as a bag, we only know the class labels of the entire bag and do not know the individual class label of each predicted box. Let us denote by $s, s^I \in \mathbb{R}^{N_b \times C}$ the output of Classification branch and Objectness-I branch, respectively; $\sigma^I(\cdot)$ the softmax operation on the first dimension. We share ROI features of box proposals with two fully-connected layers and then produce two score matrices $\sigma (s), \sigma^I (s^I) \in \mathbb{R}^{N_b \times C}$ by Classification branch and Objectness-I branch, respectively. Then the element-wise product of the two score matrix is a new score matrix $X^s \in \mathbb{R}^{N_b \times C}$, which can be formulated as: $X^s = \sigma (s) \odot \sigma^I (s^I)$. Finally, a sum pooling is applied to obtain image-level classification scores:

$$\phi_c = \sum_{i=1}^{N_b} X^s_{i,c} = \sum_{i=1}^{N_b} \left[ \sigma (s_{i,c}) \odot \sigma^I (s^I_{i,c}) \right]. \quad (4)$$

Based on the obtained image-level labels and image-level classification scores, the introduced image-wise MIL loss is defined as the sum of binary cross-entropy loss across all categories:

$$\mathcal{L}_{\text{mil}}^{I} = - \sum_{c=1}^{C} \left( \hat{\phi}_c \log(\phi_c) + (1 - \hat{\phi}_c) \log(1 - \phi_c) \right), \quad (5)$$
where $C$ is the number of categories, $\hat{\phi}_c \in \{0, 1\}^C$ is the image-level one-hot labels, and $\phi_c$ denotes the predicted image-wise classification scores.

**Point-wise MIL loss.** To perform multiple instance learning at point level, we construct a bag with part of the predicted boxes for each annotated point, as shown in Fig. 2. For example, the constructed bag $\Psi_i$ for the annotated point $\hat{p}_i$ consists of those predicted boxes that enclose point $\hat{p}_i$ and have the same class label as $\hat{p}_i$. In other words, $\Psi_i = \{b_j \mid 1[\hat{p}_i \text{ in } b_j] \cdot 1[\hat{p}_i^j = b_i^j]\}$, in which $\hat{p}_i^j$ denotes the class label of annotated point $\hat{p}_i$, and $b_i^j$ denotes the class label of the predicted box $b_j$. Unlike the bag of image-wise MIL loss, there is only one positive box proposal inside $\Psi_i$, defined as the best predicted box corresponding to the annotated point $\hat{p}_i$. Assuming we know how to calculate the bag-level confidence score $\varphi_i$ for bag $\Psi_i$, we can define the proposed point-wise MIL loss as:

$$L_{mil}^P = -\sum_{i=1}^{N_p} \log(\varphi_i),$$

(6)

where $N_p$ denotes the number of annotated points, and $L_{mil}^P$ is the sum of the binary cross-entropy loss for all annotated points.

Next, we explain how to compute the bag-level confidence score $\varphi_i$ corresponding to bag $\Psi_i$. To help find out the best box proposal inside $\Psi_i$, we add the Objectness-P branch. This branch performs binary classification to predict whether the box is the best prediction inside bag $\Psi_i$, and its output is denoted as $s^P \in \mathbb{R}^{N \times 2}$. Since there should be only one positive box inside the bag $\Psi_i$, we use a slightly different way to compute $\varphi_i$. As shown in Eq. (7):

$$\varphi_i = \frac{1}{|\Psi_i|} \left[ \sigma(s_k, \hat{p}_i^k) \odot \sigma^P(s_{k,1}^P) \odot \prod_{m \neq k} \sigma^P(s_{m,0}^P) \right],$$

(7)

in which $\sigma(\cdot)$ and $\sigma^P(\cdot)$ denote softmax operation as described earlier, $|\Psi_i|$ indicates the number of predicted boxes in bag $\Psi_i$. Comparing Eq. (4) and Eq. (7), we can find that the element-wise multiplication before accumulation is different. Taking the $k^{th}$ predicted box in bag $\Psi_i$ as an example. In addition to multiplying the positive confidence score of the two branches (i.e., $\sigma(s_k, \hat{p}_i^k) \cdot \sigma^P(s_{k,1}^P)$), we also multiply the negative confidence scores of the Objectness-P branch of the remaining boxes in bag $\Psi_i$ (i.e., $\prod_{m \neq k} \sigma^P(s_{m,0}^P)$). With the help of negative confidence scores, the proposed point-wise MIL loss can encourage that each bags have and only have one positive box with the highest positive confidence score, while the positive confidence score of remaining boxes is suppressed. The pseudo-code of point-wise MIL loss based on PyTorch is provided in the supplementary.

### 3.5 Point-Guided Copy-Paste

During the point matching, we observe that $\sim 6\%$ of the annotated points are not matched with any predicted boxes, and these unmatched points usually correspond to difficult instances to be detected (e.g. instances from minority classes). Ignoring these unmatched points may cause the class imbalance of the generated pseudo boxes. The confirmation bias in pseudo boxes further reinforces
Table 1: Comparison of our proposed Point-Teaching with other SSOD (without point-level labels) and WSSOD (with point-level labels) methods on COCO val. set. All these models use R50-FPN as the backbone network. Point-Teaching are trained with a batch size of 64 (32 fully-labeled images and 32 point-labeled images) and 180k iterations. Note that the upper bound of 100% fully supervised model is 40.2 AP [39].

| Method         | Type     | 0.5%    | 1%      | 2%      | 5%      | 10%     | 30%     |
|----------------|----------|---------|---------|---------|---------|---------|---------|
| Supervised     | FSOD     | 6.83 ± 0.15 | 9.05 ± 0.16 | 12.70 ± 0.15 | 18.47 ± 0.22 | 23.86 ± 0.81 | 31.99 ± 0.82 |
| CSD [16]       | SSOD     | 7.41 ± 0.21 | 10.51 ± 0.06 | 13.93 ± 0.12 | 18.63 ± 0.07 | 24.46 ± 0.08 | -       |
| STAC [17]      | SSOD     | 9.78 ± 0.53 | 13.97 ± 0.35 | 18.25 ± 0.25 | 24.38 ± 0.12 | 28.64 ± 0.21 | -       |
| Instant-Teaching [19] | SSOD | - | 18.05 ± 0.15 | 22.45 ± 0.15 | 26.75 ± 0.05 | 30.40 ± 0.05 | -       |
| Unbiased Teacher [18] | SSOD | 16.94 ± 0.23 | 20.16 ± 0.12 | 24.16 ± 0.07 | 27.84 ± 0.11 | 31.39 ± 0.10 | -       |
| Point DETR [25] | WSSOD    | -       | -       | -       | 26.2    | 30.4    | 34.8    |
| Point-Teaching | WSSOD    | 26.02 ± 0.09 | 28.34 ± 0.02 | 30.18 ± 0.08 | 33.15 ± 0.07 | 35.18 ± 0.09 | 38.20 ± 0.10 |

the imbalance issue. To alleviate the impact of these unmatched points, we propose a simple data augmentation strategy termed point-guided copy-paste. Different from naively copying ground-truth boxes from one labeled image to another unlabeled image like Simple Copy-Paste [38], we maintain a dynamic object bank as depicted in Fig. 2, which will be updated with ground truth object patches (cropped based on box annotation) from fully labeled images and pseudo object patches from point labeled images during each training iteration. For each unmatched point after the point matching stage, we randomly select an object patch with the same class label from the object bank, and paste the selected patch near the point on the original image. The effectiveness of point-guided copy-paste augmentation is verified in Sec. 4.3.

4 Experiment

4.1 Datasets

We benchmark our proposed method on the large-scale dataset MS-COCO [8] and PASCAL VOC [40]. Following [25], we synthesize the point annotations by randomly sampling a point inside the annotated box. Then we discard the box annotations of point-labeled images. Specifically, there are two experimental setting:

1. **COCO-standard**: We randomly selected 0.5%, 1%, 2%, 5%, 10% and 30% from the 118k labeled images as the fully-labeled set, and the remainder is used as the point-labeled set. Model performance is evaluated on the COCO2017 val set.

2. **VOC**: We use the VOC07 trainval set as the fully-labeled training set and the VOC12 trainval set as the point-labeled training set. Model performance is evaluated on the VOC07 test set.

4.2 Implementation Details

We implement our proposed Point-Teaching framework based on the Detectron2 toolbox [39]. For fair comparison with existing works [17,19,18], we take Faster RCNN with FPN [1] as our object
Table 2: Ablation study of proposed point matching strategy

(a) Comparison of the effectiveness of the point location on the COCO val. set. ‘random’ and ‘center’ indicate the annotation location on objects.

| Point Location | $AP_{50:95}$ | $AP_{50}$ |
|----------------|--------------|-----------|
| random         | 25.18        | 48.26     |
| center         | 25.19        | 48.28     |

(b) Comparison of detection accuracy on the COCO val. set by varying the point matching methods when selecting pseudo box annotations.

| Point Matching | $AP_{50:95}$ | $AP_{50}$ |
|----------------|--------------|-----------|
| None           | 20.2         | 36.5      |
| Hungarian      | 25.2         | 48.3      |

detector and ResNet-50 [36] as backbone. The feature weights are initialized by the ImageNet pretrained model. Our method mainly contains three hyperparameters: $\tau$, $\lambda_1$ and $\lambda_2$, which indicates the score threshold of the pseudo boxes, the loss weight of image-wise MIL loss and the loss weight of point-wise MIL loss, respectively. We set $\tau = 0.05$, $\lambda_1 = 1.0$ and $\lambda_2 = 0.05$ unless otherwise specified.

We use $AP_{50:95}$ (denoted as AP) as evaluation metric. On Pascal VOC, the models are trained for 40k iterations on 8 GPUs and with batch size 32, which contains 16 box-labeled images and 16 point-labeled images respectively. Other training and testing details are same as the original Unbiased-Teacher [18].

4.3 Ablation Study

When conducting ablation experiments, we choose 1% MS-COCO protocol and take a quick learning schedule of 90k iterations and a smaller batch size of 32, containing 16 box-labeled images and 16 point-labeled images, respectively.

Effects of point location. We verify the effectiveness of point annotation location to Point-Teaching between two point location schemes: center point and arbitrary point on objects. As shown in Table 2a when using center point on objects as our annotation, Point-Teaching achieves 25.2 AP. While we randomly sample point inside the box annotation, the performance only slightly drops 0.01% AP, showing that Point-Teaching is insensitive to the location of point annotation.

Effects of point matching. We explore the impact of our proposed Hungarian-based point matching method on the model performance. In this experiment, we set the loss weights of $\lambda_1$ and $\lambda_2$ to 0. As shown in Table 2b when point matching is not used, the model reaches 20.2 AP, as reported in Unbiased-Teacher [18]. Taking point annotations into consideration and using our proposed Hungarian matching, the model reaches 25.2 AP, which improves the AP with 5.0 absolute points.
Table 3: Ablation study of loss weight and score threshold

| (a) Varying the loss weight $\lambda_1$ of image-wise MIL loss on COCO val. set | (b) Varying the loss weight $\lambda_2$ of point-wise MIL loss on COCO val. set | (c) Comparison of detection accuracy on the COCO val. set when varying the score threshold $\tau$ |
| --- | --- | --- |
| $\lambda_1$ | $\lambda_2$ | AP$_{50:95}$ | AP$_{50}$ | $\lambda_1$ | $\lambda_2$ | AP$_{50:95}$ | AP$_{50}$ | $\tau$ | $\lambda_1$ | $\lambda_2$ | AP$_{50:95}$ | AP$_{50}$ |
| 0.5 | 25.0 | 47.9 | 0.025 | 25.9 | 49.6 | 0.01 | 26.2 | 50.7 |
| 1.0 | 0 | 25.7 | 49.0 | 0.05 | 26.0 | 49.9 | 0.05 | 1.0 | 0.05 | 26.3 | 50.4 |
| 1.5 | 25.0 | 48.5 | 0.1 | 25.7 | 49.8 | 0.1 | 26.2 | 50.0 |
| | | | 0.15 | 25.4 | 48.8 | 0.15 | 26.2 | 49.9 |

**Loss weight $\lambda_1$ of image-wise MIL loss.** We conduct experiments to explore the effect of loss weight $\lambda_1$ of image-wise MIL loss. In these experiments, we use Hungarian-based point matching and set the loss weight $\lambda_2$ of point-wise MIL loss to 0. As shown in Table 3a, when loss weight $\lambda_1$ reaches 1.0, the model achieves the highest AP. If not specified, in other experiments, we will set $\lambda_1$ to 1.0 by default.

**Loss weight $\lambda_2$ of point-wise MIL loss.** We conduct experiments to explore the effect of loss weight $\lambda_2$ of point-wise MIL loss. In these experiments, we use Hungarian-based point matching and set the loss weight $\lambda_1$ of image-wise MIL loss to 0. As shown in Table 3b, when loss weight $\lambda_2$ reaches 0.05, the model achieves the highest AP. If not specified, in other experiments, we will set $\lambda_2$ to 0.05 by default.

**Score threshold $\tau$.** The score threshold $\tau$ is used to filter out low quality pseudo boxes. We conduct experiments to explore the effect of score threshold $\tau$. When conducting these experiments, we use Hungarian-based point matching and set the loss weights of $\lambda_1$ and $\lambda_2$ to 1.0 and 0.05 respectively. As shown in Table 3c, when $\tau$ reaches 0.05, the model achieves the highest AP. If not specified, in other experiments, we set $\tau$ to 0.05 by default.

**Factor-by-factor experiment.** We conduct a factor-by-factor experiment on our proposed Hungarian-based point matching, image-wise MIL loss, point-wise MIL loss and point-guided copy-paste. As shown in Table 4, each element of our proposed Point-Teaching has a positive impact on the performance of the model. When all these elements are combined, the model reaches the highest performance, i.e., 27.3 AP.

### 4.4 Comparison with State-of-the-art Methods

We verify our method with previous studies on COCO-standard dataset. As shown in Sec. 4, our method consistently surpass all previous SSOD models (CSD, Instance Teaching, Unbiased...
Table 4: The effect of each element proposed in this work. H. PM indicates hungarian-based point matching, I. MIL denotes image-wise MIL loss and P. MIL indicates point-wise MIL loss, P. CP indicates point-guided copy-paste augmentation.

| H. PM | I. MIL | P. MIL | P. CP | AP | AP50:95 |
|-------|--------|--------|-------|-----|----------|
| ✓     | ✓      | ✓      | ✓     | 20.2| 25.2     |
| ✓     | ✓      | ✓      |       | 25.2|          |
| ✓     | ✓      | ✓      |       | 25.7| 26.0     |
| ✓     | ✓      | ✓      |       | 26.0|          |
| ✓     | ✓      | ✓      | ✓     | 26.3|          |
| ✓     | ✓      | ✓      | ✓     | 26.3|          |
| ✓     | ✓      | ✓      | ✓     | 27.3|          |

Table 5: Comparison of our proposed Point-Teaching with other SSOD methods on Pascal VOC dataset. The unlabeled or point-labeled images are VOC12 trainval set. The Unbiased Teacher reports AP with COCO evaluation protocol in their paper, which leads to poor performance. For a fair comparison, we report Unbiased Teacher results based on the default Pascal VOC evaluation protocol.

| Method               | Labeled     | Pseudo-labeled | AP50 | AP50:95 |
|----------------------|-------------|----------------|------|---------|
| Supervised VOC07     | None        | 72.6           | 42.1 |
| Supervised VOC07&12  | None        | 83.5           | 56.4 |
| CSD [16]              | VOC07       | VOC12          | 74.7 | -       |
| STAC [17]             | VOC07       | VOC12          | 77.5 | 44.6    |
| Instant-Teaching [19] | VOC07       | VOC12          | 79.2 | 50.0    |
| Unbiased Teacher [18] | VOC07       | VOC12          | 80.5 | 54.5    |
| Point-Teaching        | VOC07       | VOC12          | 83.0 | 54.6    |

Teacher) and WSSOD models (Point DETR) in all data regimes that 0.5% to 30% data are fully-labeled. The results also indicate that Point DETR [25] suffers larger performance drop with fewer fully-label data, e.g. Point-Teaching outperforms Point DETR [25] by 6.95 AP under 5% COCO labeled data.

We also conduct experiments on VOC07&12 dataset. As represented in Table 5 our methods achieves 83.0 AP50, 2.5 AP50 improvement against the Unbiased Teacher. Moreover, Point-Teaching is only 0.5 AP50 and 1.8 AP below the fully-supervised model trained on VOC07&12 dataset, which demonstrates Point-Teaching has fully-supervised-level capacity.

4.5 Extensions: Weakly Semi-Supervised Instance Segmentation

In order to demonstrate the generality of Point-Teaching, we extend our framework to weakly semi-supervised instance segmentation. In this experiment, Mask RCNN with ResNet-50 backbone is used as our detector and only fully-labeled data has box and mask annotations. As shown
Table 6: Point-Teaching for weakly semi-supervised instance segmentation on COCO val. set. Results are reported with mask AP_{50:95}. All models are trained with a batch size of 32 (16 fully-labeled images and 16 point-labeled images) and 180k iterations.

| Method                  | Backbone | COCO Labeled Setting |
|------------------------|----------|----------------------|
|                        |          | 1%       | 2%   | 5%   | 10%  |
| Supervised (AP^{mask}) | R50-FPN  | 10.8     | 14.5 | 18.7 | 22.6 |
| Point-Teaching (AP^{mask}) | R50-FPN | 23.5     | 25.9 | 30.7 | 33.3 |

Table 7: Point-Teaching for weakly-supervised instance segmentation on COCO val. set. Results are reported with mask AP_{50:95}.

| Method                  | Backbone | COCO Labeled Setting |
|------------------------|----------|----------------------|
|                        |          | 30%                  |
| Supervised (AP^{mask}) | R50-FPN  | 22.1                 |
| Point-Teaching (AP^{mask}) | R50-FPN | 28.0 (↑5.9)          |

In Table 6, Point-Teaching significantly improve the performance in all data regimes. This result indicates that Point-Teaching can benefit from only a small amount of mask annotations. Thus, it is a promising approach to reduce the annotation cost in weakly semi-supervised instance segmentation task.

4.6 Extensions: Weakly Supervised Instance Segmentation

We further extend our framework to weakly supervised instance segmentation. In this scenario, we supervise the instance segmentation training with only box and point annotations. Specifically, we train Mask RCNN with ResNet-50 under 30% COCO labeled setting. The whole training pipeline contains two stage. In the first stage, we use proposed Point-Teaching framework to get a well-trained teacher model. In the second stage, we fix the teacher model with zero EMA update rate and use the proposed hungarian-based point matching method to generate pseudo bounding boxes, and the student model is supervised with both annotated and pseudo-annotated boxes with three additional loss terms, e.g. point loss, project loss [41,42] and pairwise loss [42]. More details about loss functions can be found in the supplementary materials. As shown in Table 7, Point-Teaching achieves 28.0 mask AP without mask annotation, outperforming the supervised baseline by 5.9 AP.
5 Conclusion

In this work, we presented Point-Teaching, a novel weakly semi-supervised framework for object detection and instance segmentation. It can effectively leverage point annotation with the proposed hungarian-based point matching strategy, image-wise MIL loss, point-wise MIL loss, and point-guided copy paste augmentation. Extensive experiments are conducted to show its superiority over previous works in all data regime settings.

In the future, we would explore Point-Teaching without handcrafted point annotations (e.g. points generated by unsupervised learning), which will further reduce the annotation cost while maintaining competitive detection performance.

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