CaSP: Class-agnostic Semi-Supervised Pretraining for Detection & Segmentation

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Abstract

To improve instance-level detection/segmentation performance, existing self-supervised and semi-supervised methods extract either very task-unrelated or very task-specific training signals from unlabeled data. We argue that these two approaches, at the two extreme ends of the task-specificity spectrum, are suboptimal for the task performance. Utilizing too little task-specific training signals causes underfitting to the ground-truth labels of downstream tasks, while the opposite causes overfitting to the ground-truth labels. To this end, we propose a novel Class-agnostic Semi-supervised Pretraining (CaSP) framework to achieve a more favorable task-specificity balance in extracting training signals from unlabeled data. Compared to semi-supervised learning, CaSP reduces the task specificity in training signals by ignoring class information in the pseudo labels and having a separate pretraining stage that uses only task-unrelated unlabeled data. On the other hand, CaSP preserves the right amount of task specificity by leveraging box/mask-level pseudo labels. As a result, our pretrained model can better avoid underfitting/overfitting to ground-truth labels when finetuned on the downstream task. Using 3.6M unlabeled data, we achieve a remarkable performance gain of 4.7% over ImageNet-pretrained baseline on object detection. Our pretrained model also demonstrates excellent transferability to other detection and segmentation tasks/frameworks. Code will be released at https://github.com/dvlab-research/Entity.

1. Introduction

Deep learning [15, 17, 18, 23, 42, 45–47] has enabled instance-level detection (object detection [11, 12, 39], instance segmentation [14, 30], etc.) methods to achieve previously unattainable performance. This remarkable success cannot be divorced from the availability of datasets with instance annotations such as COCO [29], Cityscapes [8] and Open Images [22]. However, annotating instances is laboriously expensive due to the great intricateness needed for annotating instance-level bounding boxes, masks, and/or semantic classes. Due to such a limitation, the datasets in instance-level detection domain are relatively small in scale, compared to other domains. Also because of this, instance-level detection models generally have degraded generalization performance in real-world applications [7, 32, 33, 41].

To counteract the adverse effects of annotation constraints, many have attached importance to leveraging unlabeled images to improve instance-level detection [8, 29]. Unlike labeled data that can provide explicit and indisputable supervision signals, the extraction of training signals from unlabeled data remains very much an open issue. The two popular approaches for learning from unlabeled data are self-supervised and semi-supervised learning. Self-supervised methods [5, 13, 16, 38, 53, 56] usually rely on training signals like the relative distances...
between the augmented samples of a positive/negative pair, while semi-supervised strategies [19, 25, 37, 43, 48, 51, 58, 62] directly leverage the pseudo labels generated by a detector pretrained on ground-truth labels. In terms of task specificity, these two approaches are at the two extreme ends of the spectrum — self-supervised learning utilizes hardly any task-specific training signals from unlabeled data, whilst semi-supervised learning utilizes too much of them. Consequently, the model tends to underfit/overfit (depending on the amount of task specificity in the training signals) the ground-truth labels of downstream task during the finetuning or final-training stage. This motivates us — is there a good middle ground between the two extremes that has a more optimal amount of task specificity?

In instance-level detection/segmentation tasks, the datasets usually have two types of annotations: localization-based annotations (e.g., boxes, masks) and class labels for those annotations. While semi-supervised methods utilize the information from both kinds of annotations to do pseudo labeling on unlabeled data, we argue that such a practice is not optimal for (pre)training and it hurts downstream-task performance. Given the pseudo labels that closely mimic ground-truth labels, the model is likely to take an easier optimization path and potentially arrive at a less-favorable local optimum, when being finetuned on the downstream task. To mitigate the issue, we can disregard either one of the annotation types for the purpose of pseudo labeling. A related example is the conventional practice of pretraining the model on ImageNet [10] with just image-level class labels. Conversely, the approach of using localization-based annotations (while ignoring class labels) has not been explored previously, which we believe is a promising direction given the nature of detection/segmentation tasks.

To this end, we propose a novel learning framework called CaSP (Class-agnostic Semi-supervised Pretraining). CaSP is a framework consisting of three cascaded training stages, where each stage employs a specific variant of training data. Concretely, we first train a labeling detector on class-agnostic annotations and then use it to generate pseudo labels on unlabeled images. After that, we pretrain the target detector on the class-agnostic pseudo labels. Finally, we train the target detector on class-specific ground-truth annotations for the downstream task. Unlike semi-supervised methods that jointly use labeled and unlabeled data within the same training stage, these two data variants are assigned separately to the different stages of CaSP, as shown in Figure 1. This decoupling strategy provides the model with a good initial solution (learned from unlabeled data) that guides it to maintain a good generalization performance, when being finetuned on the downstream task.

In our experiments, we evaluate our method and investigate the upper bound of model performance using multiple large-scale unlabeled data splits that have different dataset scales, consisting of images from COCO unlabeled [29], Places365 [60], and Open Images [24]. Through extensive experiments, we demonstrate that our method can obtain consistent performance gains when using different unlabeled splits ranging from 0.12M to 3.6M images. Owing to the superior effectiveness of our method at consuming large-scale unlabeled data, we are the first successful attempt to improve detection/segmentation performance using an unlabeled dataset with an enormous amount of 3.6M images, in the history of semi-supervised object detection. Moreover, the pretrained class-agnostic model demonstrates excellent transferability to other instance-level detection and segmentation tasks/frameworks. The contributions for this paper are threefold:

- We propose a novel class-agnostic semi-supervised pretraining framework for instance-level detection/segmentation tasks. By leveraging class-specific pseudo labels and cascaded training stages, it achieves a more optimal amount of task specificity in the training signals extracted from unlabeled data.
- We conduct extensive ablative and comparative experiments on object detection, demonstrating the effectiveness of our method. To the best of our knowledge, we are the first to use unlabeled data at an unprecedented scale of 3.6M for semi-supervised object detection.
- We demonstrate that our pretrained model can significantly improve the performance on other instance-level detection/segmentation tasks (instance segmentation, keypoint detection, entity segmentation, panoptic segmentation) and frameworks.

2. Related work

**Instance-level detection/segmentation.** Instance-level detection tasks, including object detection [9, 11, 12, 27, 28, 34, 39, 50], instance segmentation [4, 14, 30, 36, 57, 59], and key point detection [14, 44, 55, 61], require detecting objects with different instance-level representations such as bounding box, pixelwise mask, and keypoints. Recently, there have been works on class-specific panoptic segmentation [1, 6, 26] and class-agnostic entity segmentation [35] that perform dense image segmentation by treating all segmentation masks as instances.

Most of instance-level detection research works generally focus on designing more advanced architectures or detection methods that work well on existing labeled datasets. Instead, we aim to design a training framework that better utilizes unlabeled images, without modifying the underlying architecture or method. This helps us understand how far current methods can scale with the help of large-scale unlabeled data.
Semi-supervised detection. Semi-supervised learning approaches mainly focus on two directions for instance-level detection. One is about the consistency-based methods [19, 48], which are closely related to self-supervised approaches. They usually construct a regularization loss by designing some contrastive pretext task [5, 13, 16, 38, 53, 56]. Another direction is on pseudo labeling [25, 37, 43, 51, 58, 62]. As the name implies, they leverage a pretrained detector to generate pseudo labels on unlabeled images. The pseudo labels are usually almost identical to the ground-truth labels. Thus, both two types of labels can be used for joint training with similar losses. Our framework is also based on pseudo labeling, but we use pseudo labels in the pretraining stage (not the final training stage) and we use class-agnostic pseudo labels (not class-specific ones).

Class-agnostic detection and segmentation. Class-agnostic localization [20, 35, 39, 40, 52] has been widely used in detection and segmentation. One of the most prominent examples is the two-stage detector [39]. It mainly has a class-agnostic region proposal network (RPN) and a detection head. RPN predicts numerous high-quality class-agnostic proposals for further classification and localization refinement. Inspired by this design, our method decouples semi-supervised learning into pretraining and finetuning stages, which use class-agnostic and -specific labels, respectively. Such a design allows the model to detect/segment objects comprehensively in the pretraining stage. As demonstrated by recent works on open-world detection/segmentation [20, 35, 40], it can improve the model’s generalization on unseen objects.

Besides the benefits shown by existing works, in this paper, we present the first evidence that class-agnostic training can significantly bridge the quality gap between pseudo labels and human (ground-truth) labels. This is important because the quality of pseudo labels directly impacts the effectiveness of pretraining.

3. Methodology

Fig. 2 provides an overview of the proposed Class-agnostic Semi-Supervised Pretraining (CaSP) framework. The framework consists of three training stages, including Early/Late Pretraining and Finetuning. First, we use the labeled data but with class-agnostic annotations to train a labeling detector in the Early Pretraining stage. The labeling detector then predicts class-agnostic pseudo labels on unlabeled images. After that, numerous unlabeled images with their pseudo labels are used to pretrain a target detector in the Late Pretraining stage. Finally, we finetune the pretrained target detector on the labeled dataset with class-specific annotations.

In the following sections, we first introduce the entire process of our training framework. After that, we explain in detail our proposal to adopt data annotations at Entity level for pretraining, as an alternative to the common practice of using object-level annotations. This annotation adoption is to enable our framework work more effectively for instance-level segmentation tasks such as panoptic segmentation. Finally, we describe the base detection framework used for the pretraining stages in this paper.
| Train data      | Num | $\text{AP}^{\text{det}}$ | $\text{AP}^{\text{det-a}}$ |
|----------------|-----|---------------------------|---------------------------|
| Ground-truth   | 118k| 41.0                      | 41.9                      |
| Pseudo labels  | 123k| 35.9                      | 40.0                      |

Table 1. COCO val2017 validation results from training on ground-truth and pseudo labels, across class-specific ($\text{AP}^{\text{det}}$) and class-agnostic ($\text{AP}^{\text{det-a}}$) tasks. ‘Num’ is the number of training images. $\text{AP}^{\text{det}}$ and $\text{AP}^{\text{det-a}}$ indicate the class-specific and -agnostic object detection mAPs respectively.

### 3.1. Pretraining

#### Why Class-Agnostic Pretraining?

We first study the feasibility of class-agnostic detection for pretraining, by contrasting it to the conventional class-specific detection task, in terms of class-agnostic [35] and class-specific [29] AP evaluation metrics respectively. Through this study, we find that the class-agnostic task can effectively close the AP gap between training on pseudo labels and ground-truth annotations. Table 1 shows that the validation performance gap between training on either ground-truth or pseudo labels, for both class-specific and -agnostic settings on COCO validation set [29]. The ground-truth-unlabeled AP gaps of class-specific and class-agnostic models are 5.1% (41.0-35.9) and 1.9% (41.9-40.0) respectively. The much smaller gap indicates that the class-agnostic pseudo labels have much a better quality than the class-specific ones, thus enabling the model to closely approach the mAP of training on ground-truth labels. In many cases, class-agnostic pseudo labels can eliminate the ambiguities caused by confusing predefined classes such as cyclist and person, while generalizing well to other kinds of objects unseen in $D^t$ [35]. We argue that such properties of class-agnostic pseudo labels are more useful for pretraining, compared to prematurely learning classification-aware features through the class-specific labels of downstream task.

#### Preliminaries.

The three stages in CaSP framework is largely based on the conventional object detection training process which we first briefly introduce here. Conventionally, given the input images $I$ and their ground-truth annotations $Y$ from the human-labeled training dataset $D^t$, the detection model denoted as $h_*$ is trained with the composite detection loss: $L_{\text{det}} = L_{\text{cls}}$ (classification loss) + $L_{\text{loc}}$ (localization loss). The detection model $h_*$ is learned through a function $\mathcal{H}(\cdot)$ that determines the neural network hypothesis spaces, depending on the task at hand. Next, we provide the details of the three stages of CaSP framework.

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1. We use FCOS [50] with ResNet50 backbone, a popular one-stage detector, to explore the performance gap between using class-aware and -agnostic labels. We follow its 36 epoch training setting widely adopted in detectron2 [54] or mmdetection [2].

### Early Pretraining

The goal of this stage is to train a labeling detector on $D^t$ to generate high-quality class-agnostic pseudo labels $D^p$ from the unlabeled dataset split $D^u$. To keep the training and inference consistent, we train the labeling detector on the class-agnostic annotations obtained from $D^t$. We directly remove class information from the annotations in $D^t$ using the class-agnostic conversion function $\alpha(\cdot)$ and regard each label as a class-free “object”. To train the labeling detector, we use a recent class-specific detection framework (see Sec. 3.4) and replace its multi-class classifier with a binary classifier. Given the labeled dataset $D^t$, the labeling ‘L’ detector $h_L$, is trained as follows:

$$h_L = \arg\min_{h \in H(L)} \sum_{(I, Y) \in D^t} L_{\text{det}}(h(I), \alpha(Y)),$$

where $L_{\text{det}}$ is the class-agnostic version of $L_{\text{det}}$ and $H(L)$ indicates the neural network hypotheses conditioned on the labeling detection task.

Once the training is done, we apply the labeling detector to the unlabeled images and then filter the prediction results using merely a single (constant) score threshold $\delta$. Without semantic class labels in the prediction results, class-agnostic pseudo labels avoid the long-tail problem suffered by in class-specific predictions. As a result, there is no need for a complicated strategy that applies class-dynamic score thresholds as in existing works [25,37,43,51,58,62]. Given the labeling detector $h_L$ and $\delta$, our class-agnostic pseudo-label process to obtain the pseudo labels $Y^p$ and pseudo-label dataset $D^p$ is represented by the following:

$$Y^p_i = \{y_j \mid h_L(I^u_i)[\text{score}(y_j) > \delta] \text{ s.t. } I^u_i \in D^u\}, \quad (2)$$

$$D^p = \{(I^u_i \in D^u, Y^p_i \in Y^p) | Y^p_i \neq \emptyset\}, \quad (3)$$

where ‘$p$’ indicates the association with pseudo labels and $\text{score}(\cdot)$ returns the objectness score of any prediction.

### Late Pretraining

We pretrain our target detector only on the pseudo-label dataset $D^p$. We do not make use of any ground-truth dataset in this stage, which is different from the existing semi-supervised approaches that carry out joint training on ground-truth training and unlabeled dataset splits. Given that, we do not require a divide-and-conquer strategy to handle different dataset splits, such as applying different loss weights to noisy pseudo labels and clean ground-truth labels. To obtain the pretrained target ‘T’ detection model $h_T$, we perform Late Pretraining as follows:

$$h_T = \arg\min_{h \in H(T)} \sum_{(I^p, Y^p) \in D^p} L_{\text{det}}(h(I^p), [Y^p]), \quad (4)$$

where $[\cdot]$ transforms $Y^p$ to binary training targets.
3.2. Finetuning

With the pretrained target detection model $h_T$ from Late Pretraining, we fine-tune it for the downstream task using the class-specific ground-truth annotations of $D^t$. Instance-level detection/segmentation tasks are typically class-specific tasks. Thus, the output channel of target detector’s semantic classifier should be adapted to the number of pre-defined classes for the downstream task at hand. There are two ways to initialize multi-class classification layer: (1) random initialization; (2) initialize each output channel with the one from the pretrained class-agnostic classification layer. We empirically find these two strategies produce similar results. The finetuning process to obtain the final ‘F’ downstream-task model $h_F$ is represented by:

$$h_F = \arg\min_{h \in \mathcal{H}(F; h_T)} \sum_{(I_i, Y_i) \in D^t} L_{\text{det}}(h(I_i), Y_i),$$

(5)

where $\mathcal{H}(F; h_T)$ indicates that the neural network hypotheses are conditioned on both the task ‘F’ and pretrained model $h_T$. Our approach of pretraining on only unlabeled data makes the detector less prone to overfitting to the downstream task’s images and ground-truth labels, since they have not been exposed to the model in Late Pretraining.

3.3. From Objects to Entities

Pretraining on large-scale unlabeled data is a costly process. Therefore, it is favorable to design our CaSP framework such that its pretrained model can serve a good range of downstream tasks that expand beyond detection and also include segmentation. Instance segmentation and panoptic segmentation are two popular instance-level segmentation tasks that require more fine-grained visual information for predicting pixelwise masks for each instance.

We draw inspiration from Entity Segmentation [35] on how to boost the applicability and usefulness of our CaSP framework. Instead of just focusing on objects, we propose to perform pretraining based on the semantically-meaningful and -coherent mask regions known as Entities, that include not just object regions but also stuff regions such as sky and road. With this, even the unlabeled images with little-to-no object regions can still provide substantial pseudo-label training signals through the stuff regions for pretraining purposes. Furthermore, stuff regions have close relationships with objects, and thus we hypothesize that the pretraining on stuff pseudo labels is beneficial to the downstream task even if the task is purely object-oriented.

3.4. Base Detector

Following Entity Segmentation, we adopt the CondInst [49], a popular instance segmentation framework, as our base detector for labeling and target detectors. This framework has two parts: a dense one-stage detector FCOS for detection and a segmentation head for mask prediction. The FCOS has a backbone, FPN neck, and a detection head. The detection head has three output branches: the classification, regression, and kernel branch. The first two branches perform instance-level classification and regression to achieve object detection. Whereas, the kernel branch generates dynamic convolution weights which are used to convolve with high-res feature maps to generate binary instance masks within the segmentation head. Overall, the CondInst base detector is trained with the following:

$$\mathcal{L}_e = \mathcal{L}_{\text{det}}^{(a,c)} + \mathcal{L}_{\text{seg}},$$

(6)

where $\mathcal{L}_{\text{seg}}$ is usually the dice loss between predicted segmentation mask and ground truth. We choose $\mathcal{L}_{\text{det}}^{(a,c)}$ as class-agnostic $\mathcal{L}_{\text{det}}$ or class-specific $\mathcal{L}_{\text{det}}$ depending on the detector and training stage described in subsection 3.1 and 3.2.

Note that the network modules in CondInst are fairly independent of each other. That suggests that we can use our pretrained target detector to initialize the model of any instance-level detection/segmentation frameworks in a highly versatile manner. E.g., we can easily initialize the backbone and FPN neck of Mask R-CNN with our CondInst target detector pretrained with Late Pretraining.

4. Experiments

Datasets. MS-COCO [29] is used as the main evaluation dataset. In addition to MS-COCO train2017 and val2017 splits, we curate 3.6 million unlabeled images from COCO unlabeled [29], Places365 [60], and Open Images [24]. To better demonstrate the data scalability of CaSP, we construct four unlabeled data subsets (tiny, small, base, large) with 120K, 660K, 1.74M, and 3.66M images respectively. Unless specified, we report the experimental results from using tiny as the unlabeled subset, which has nearly the same scale as train2017.

Training Setup. For fair comparisons with other methods (some may require less training time), we train all models to reach their respectively upper-bound performances, by increasing the number of training epochs accordingly.
Table 2. Impact of pretraining data choice. $AP^e$ and $AP^p$ indicate the APs for class-specific object detection and instance segmentation tasks. Their class-agnostic counterparts have names appended with ‘-a’. $AP$ and $PQ$ are the evaluation metrics of class-agnostic entity detection and panoptic segmentation. ‘G’ and ‘P’ indicate whether ground-truth (train2017) or pseudo labels (unlabeled data) are used as pretraining data, while ‘A’ and ‘S’ indicate whether class-agnostic or class-specific labels are used for pretraining. Note that all the results here are obtained via COCO val2017.

Unless specified, we train with 60 and 36 epochs in the Late Pretraining and Finetuning stages for CaSP to achieve the upper-bound performance. Upper-bound performance evaluation is the preferred way to gauge the true performance of different methods that may require different training costs. We apply either weak data augmentation (conventional multi-scale training) or strong data augmentation (jittering of scale, brightness, contrast, etc. [58]) to the unlabeled images before generating pseudo labels.

**Implementation.** We adopt the Condinst [49] framework with Swin Transformer Tiny (T) backbone [31] as our base model. Please refer to our supplementary file for the detailed hyper-parameter settings for the pretraining and finetuning stages.

### 4.0.1 Experimental Results

**Pretraining Data.** Table 2 shows the impact of the choice of pretraining data on the downstream task performances after the Finetuning stage. From the first two rows, we observe that ImageNet pretrained model and the model pretrained on class-agnostic ground-truth labels suffer from the worst downstream performances. Whereas, in the last three rows, the models that leverage pseudo labels ‘P’ for pretraining consistently achieve stronger downstream performances. It can also be clearly seen that using class-agnostic labels ‘A’ during pretraining is better than using class-specific labels ‘S’, resulting in a downstream $AP^e$ gap of 1.0% (48.1-47.1). Class-agnostic pretraining helps to prevent the model from overfitting to the ground-truth labels during Finetuning. In particular, Entity-based pretraining data provides the best overall downstream task performance, while strongly raising the downstream PQ performance by 1.2% (43.7-42.5) due to the inclusion of both object and stuff elements.

**Upper-Bound Performance.** We investigate the number of training epochs required to achieve the upper-bound performance in both the Late Pretraining and Finetuning stages. Table 3 shows the pretrained model performance under different numbers of Late Pretraining epochs. When increasing the number of epochs from 12 to 48, the performance of pretrained model improves from 38.4 to 40.2 in terms of class-agnostic AP$^e$. The improvement saturates after 40 epochs. Table 4 shows the downstream object detection performance AP$^e$. E× indicates the E×12 training epochs. E.g., 1× and 5× represent 12 and 60 training epochs, respectively. The ‘F’ and ‘LP’ represent the Finetuning and Late Pretraining.

Table 5. The relationship between the performance of Early-Pretraining labeling detector and the performance of Late-Pretraining target detector. The different columns correspond to the various backbones used by the labeling detector. The Late-Pretraining target detector is always based on Tiny backbone.
### Table 5. Comparison with the state-of-the-arts under the setting of train2017 set with 118k images. The ‘unlabeled images’ means the number of unlabeled images we use. The ‘Aug’ indicates whether to use strong or weak data augmentation. In the column of ‘mAP’, the left part is the baseline performance of using only train2017, and the right part is the performance of using both train2017 and unlabeled dataset. → indicates the performance gain and ‡ refers to the same set of unlabeled images.

| Setting | Type               | Unlabeled Images | Model          | Aug  | AP_det   |
|---------|-------------------|------------------|----------------|------|----------|
|         | MoCo-v2 [3]       | 1.28M            | R-50-FPN       | Strong | 39.7     |
|         | DenseCL [53]      | 1.28M            | R-50-FPN       | Strong | 39.7     |
|         | DetCo [56]        | 1.28M            | R-50-FPN       | Strong | 38.9     |
|         | DetCon [16]       | 1.28M            | R-50-FPN       | Strong | 41.6     |
|         | PreDet [38]       | 50.00M           | R-50-MaskRCNN  | Strong | 44.9     |
| Semi-supervised | Proposal learning [48] | 0.12M           | R-50-FPN       | Strong | 37.4     |
|         | STAC [43]         | 0.12M            | R-50-FPN       | Strong | 39.5     |
|         | Self-training [62]| 2.90M            | R-50-FPN (SimCLR) | Strong | 41.1     |
|         | Soft Teacher [58] | 0.12M            | R-50-FPN       | Strong | 40.9     |
|         | CaSP (ours)       | 1.74M            | Swin-T-FCOS    | Strong | 46.8     |
|         |                  | 3.66M            | Swin-T-FCOS    | Weak   | 46.8     |

### Table 7. The ablation study on the effect of score threshold on late-pretraining target detector. The δ is the score threshold of the labeling detector used to make pseudo labels on unlabeled images.

| score threshold (δ) | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 |
|---------------------|-----|-----|-----|-----|-----|
| Late-pretraining (AP_det) | 39.6 | 40.2 | 39.8 | 39.5 | 39.0 |

### Table 8. The ablation study on data augmentation. The ‘LP’ and ‘F’ represent the Late Pretraining and Finetuning stages. The ‘weak’ and ‘strong’ refer to weak and strong data augmentation. (A, B) indicate the class-agnostic AP_det and class-specific AP_dets.

| Setting | Num  | Late-Pretrain (AP_dets) | Finetune (AP_dets) |
|---------|------|------------------------|--------------------|
| Tiny    | 123K | 40.2                   | 48.2               |
| Small   | 660k | 40.7                   | 48.8               |
| Base    | 1.74M | 41.4               | 49.7               |
| Large   | 3.66M | 42.0               | 50.6               |

### Table 9. The ablation study on unlabeled splits with different dataset scales.

Dataset scale, the performances of the models from Late Pretraining and Finetuning stages improve consistently. We also notice that the class-agnostic performance of the Late-Pretraining model correlates well with the performance of the Finetuning model. This is unsurprising considering the substantial task similarity between Late Pretraining and Finetuning.

**State-of-the-art Comparison.** In Table 6, we compare the performance of CaSP on the downstream object detection task with those of state-of-the-art methods. Remarkably, our method achieves the most significant performance gains even though our model is based on an already strong baseline with the powerful Swin-Tiny backbone. With strong data augmentation and 1.74M unlabeled images,
we obtain 50.8 $\text{AP}^\text{det}$ with 4.0% improvement over the ImageNet-pretrained baseline. Furthermore, by increasing the number of unlabeled images to 3.66M, we observe an even bigger performance gain of 4.7% that leads to 51.5 $\text{AP}^\text{det}$. Since there is no obvious sign of performance saturation, we believe that using a super-scale unlabeled dataset (larger than our 3.66M one) can potentially bring the model performance to a much greater height. With the same Swin-T backbone and similar 1.74M unlabeled images, Soft Teacher [58] merely achieves a 2.5% gain, despite its relatively significant 3.6% gain with another backbone and 120K unlabeled images. The reason has twofold. Unlike CaSP that decouples pretraining and finetuning, Soft Teacher performs joint training and that requires it to be particular about the scale of unlabeled data, in order to achieve a good balance between the contributions from labeled and unlabeled data. Using an unlabeled dataset larger than expected can spoil such a balance. On the other hand, Self-training [62] performs much worse than ours, even with a large amount of 2.9M unlabeled images. This is due to the premature use of class/downstream-specific labels in the pseudo-labeling stage, potentially causing the model overfit easily to ground-truth labels in the final training stage. Whereas, CaSP mitigates such a problem by completely not allowing the model train on labeled images and class-specific labels during Late Pretraining.

Initialization Strategy. Here, we study the effects of including/excluding the multiple parts (backbone, neck, head, and classifier) of the pretrained model from Late Pretraining for initializing the Finetuning model. As shown in Table 10, the main source of improvement (+3.8%) comes from backbone initialization, while the other parts provide smaller improvements. This ablation study motivates us to transfer our pretrained model to other instance-level detection/segmentation tasks that may not use the downstream frameworks as ours.

Generalization to Other Frameworks/Tasks. Table 11 shows the strong performance improvements resulted from initializing the downstream models with a single model $h_T$ pretrained with CaSP, on various instance-level detection/segmentation tasks. Some frameworks like Mask R-CNN have heads that are incompatible with those of

Table 10. Ablation study on the initialization strategy. The pretrained model is divided into four parts here. $\circ$ indicates the part’s pretrained weights is not being used, while $\checkmark$ indicates otherwise.

| Task | Type | Framework | Pretrained w/ | Task Perf. |
|------|------|-----------|---------------|------------|
| DET  | E    | FCOS [50] | ImageNet Ours | 46.8       |
|     | P    | RetinaNet [28] | ImageNet Ours | 42.8       |
|     | P    | FPN [27]  | ImageNet Ours | 44.0       |
| INS  | E    | CondInst [49] | ImageNet Ours | 41.9       |
|     | P    | Mask R-CNN [14] | ImageNet Ours | 42.8       |
| Entity | E    | CondInst [49] | ImageNet Ours | 35.1       |
| Point | P    | Mask R-CNN [14] | ImageNet Ours | 66.8       |
| Panop| P    | PanopticFPN [21] | ImageNet Ours | 39.5       |

Table 11. Overall performance evaluation on mainstream instance-level detection/segmentation tasks with Swin-Tiny backbone. “E” and “P” indicate initializing the framework with entire or part of our pretrained model. “ImageNet” and “Ours” refer to ImageNet and our pretrained weights. “Task Perf” refers to the task-specific evaluation metrics, including $\text{AP}^\text{det}$ for object detection, $\text{AP}^\text{seg}$ for instance segmentation, $\text{APE}$ for key-point detection, $\text{AP}^\text{seg}$ for entity segmentation, and PQ for panoptic segmentation.

Our CondInst base detector. Using just our FPN backbone pretrained weights to initialize Mask R-CNN, we achieve 2.7 $\text{AP}^\text{seg}$ and 1.0 $\text{AP}^\text{point}$ improvements on instance segmentation and keypoint detection. This demonstrates the strong generalization ability of our semi-supervised pretraining method.

5. Conclusion

This paper proposes a novel class-agnostic semi-supervised pretraining framework to improve instance-level detection/segmentation performance with unlabeled data. To extract the training signals with a more optimal amount of task specificity, the framework adopts class-agnostic pseudo labels and includes three cascaded training stages, where each stage uses a specific variant of data. By pretraining on a large amount of class-agnostic pseudo labels on unlabeled data, our pretrained model has strong generalization ability and is equipped with the right amount task-specific knowledge. When fine-tuned on different downstream tasks, the model can better avoid overfitting to the ground-truth labels and thus can achieve better downstream performance. Our extensive experiments show the effectiveness of our framework on object detection with different unlabeled splits. Moreover, the pretrained class-agnostic model demonstrates excellent transferability to other instance-level detection frameworks and tasks.

Limitation. Our framework depends heavily on a reliable labeling detector that is trained on COCO, a dataset with high-quality annotations. However, there are many widely-
used datasets with incomplete/partial annotations (e.g., Open Images, Objects365) that may corrupt the labeling detector. As for how to train a robust labeling detector with incomplete annotations, we leave it for future work.
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