

# DASO: Distribution-Aware Semantics-Oriented Pseudo-label for Imbalanced Semi-Supervised Learning

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## Abstract

The capability of the traditional semi-supervised learning (SSL) methods is far from real-world application due to severely biased pseudo-labels caused by (1) class imbalance and (2) class distribution mismatch between labeled and unlabeled data. This paper addresses such a relatively under-explored problem. First, we propose a general pseudo-labeling framework that class-adaptively blends the semantic pseudo-label from a similarity-based classifier to the linear one from the linear classifier, after making the observation that both types of pseudo-labels have complementary properties in terms of bias. We further introduce a novel semantic alignment loss to establish balanced feature representation to reduce the biased predictions from the classifier. We term the whole framework as **Distribution-Aware Semantics-Oriented (DASO) Pseudo-label**. We conduct extensive experiments in a wide range of imbalanced benchmarks: CIFAR10/100-LT, STL10-LT, and large-scale long-tailed Semi-Aves with open-set class, and demonstrate that, the proposed DASO framework reliably improves SSL learners with unlabeled data especially when both (1) class imbalance and (2) distribution mismatch dominate.

## 1. Introduction

Semi-supervised learning (SSL) [7] has shown to be promising for leveraging unlabeled data to reduce the cost of constructing labeled data [4, 5, 29, 33, 48] and even boost the performance at scale [42, 57, 58]. The common approach of these algorithms is to produce *pseudo-labels* for unlabeled data based on model's predictions and utilize them for regularizing model training [31, 48]. Although adopted in a variety of tasks, these algorithms often assume class-balanced data, while many real-world datasets exhibit *long-tailed* distributions [3, 16]. With the class-imbalanced data, the class distribution of pseudo-labels from the unlabeled data is significantly biased to the majority classes due to confirmation bias [2], which further biases the model [26].

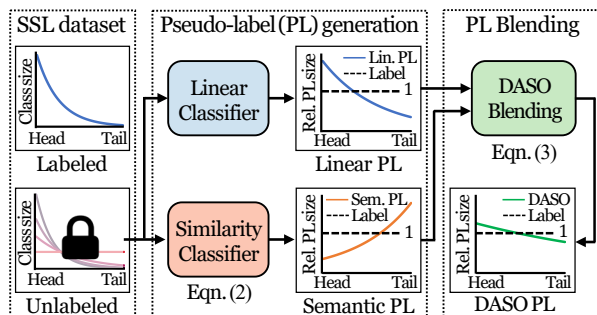


Figure 1. Glimpse of the DASO framework. DASO reduces the overall bias in pseudo-labels (PL) from unlabeled data by blending two complementary PLs from different classifiers. Note that bias is conceptually illustrated as relative PL size (Rel. PL size), meaning that pseudo-label size is normalized by actual label size.

Many methods of handling class-imbalanced labels have been proposed in the supervised learning community, but little interest has been made in re-balancing pseudo-labels in SSL. Recent studies have explored this *imbalanced SSL* setting, where as a reference to the class distribution of unlabeled data, it is often assumed that it is the same as the class distribution of labels [26, 54], or a separate distribution estimate is required [26]. However, the actual class distribution of unlabeled data is unknown without the labels. For example, unlabeled data may have large class distribution gap from labeled data, including many samples in novel classes not defined in the label set [49]. As we elaborate in Sec. 4, the bias of pseudo-labels also depends on such class distribution mismatch between labeled and unlabeled data, and using inaccurate estimates or wrong assumptions about the unlabeled data cannot be helpful under imbalanced SSL.

In this work, we present a new imbalanced SSL method specifically tailored for alleviating the bias in pseudo-labels under class-imbalanced data, while releasing the common assumption that the class distribution of unlabeled data is the same with the label distribution. To this end, as shown in Fig. 1, we observe that semantic pseudo-labels [20] obtained from a similarity-based classifier [47] are biased towards minority classes as opposed to linear classifier-based

pseudo-labels [31, 48] being biased towards head classes. As illustrated in Sec. 3.2, we draw the key inspiration from those complementary properties of two different types of pseudo-labels to develop a new pseudo-labeling scheme.

In this regard, we introduce a generic imbalanced SSL framework termed Distribution-Aware Semantics-Oriented (DASO) Pseudo-label in Sec. 3.3. Building on top of the existing SSL learner, we propose to blend the linear and semantic pseudo-labels in different proportions for each class to reduce the overall bias. This blending strategy can provide a more balanced supervision than using just one kind of pseudo-label. The primary novelty comes from the scheduling of the weights for mixing the pseudo-labels. Specifically, we dynamically adjust the relative weights of semantic pseudo-labels to be blended so that linear pseudo-labels are less biased according to the current class distribution of pseudo-labels. By virtue of such mechanism, without resorting to any class priors for the unlabeled data, DASO reliably brings performance gain even with substantial class distribution mismatch between labeled and unlabeled data.

We further propose a simple yet effective semantic alignment loss to establish balanced feature representation via *balanced* class prototypes, which is the extension of the consistency regularization framework in [48, 56] onto feature space. We align the unlabeled data onto each of the similar prototypes, by consistently assigning two different views of an unlabeled sample in *feature space* to the same prototype. These enhanced feature representations not only help linear classifier produce less biased predictions, but can also be reused for semantic pseudo-labels from similarity-based classifier. We validate the semantic alignment loss is useful under imbalanced SSL, especially helpful for DASO.

The efficacy of DASO is extensively justified with the imbalanced versions of benchmarks: CIFAR-10/100 [28] and STL-10 [10] in Sec. 4. We even test DASO with large-scale long-tailed Semi-Aves [49] with open-set classes in unlabeled data, closely related to real-world scenarios. As such, DASO consistently benefits under various distributions of unlabeled data and degrees of imbalance, demonstrating to be a truly generic framework that works well on top of diverse frameworks such as existing SSL learners and even other re-balancing frameworks for labels and SSL.

The key contributions in our work can be summarized as follows: (1) We propose a novel pseudo-labeling framework, DASO, for debiasing pseudo-labels by class-adaptively blending two complementary types of pseudo-labels observing current class distribution of pseudo-labels. (2) DASO introduces semantic alignment loss to further alleviate the bias from high-quality feature representation, by aligning each unlabeled example to the similar prototype. (3) DASO readily integrates with other frameworks to show significant performance improvements under diverse imbalanced SSL setup, including the most practical scenario.

## 2. Related Work

**Class-imbalanced learning.** Datasets that well capture the dynamic nature of *real-world* exhibit *class-imbalanced*, or *long-tailed* distributions [19, 52]. Learning on such datasets has been a great challenge to deep neural networks, since they cannot generalize well to the rare classes [3]. Conventional approaches to combat the imbalance include data re-sampling [1, 8, 27], cost-sensitive re-weighting [6, 12, 40], and decoupling the representation and the classifier [25, 61]. Recently, learning expert models across classes [53, 55] and re-balancing with the data distribution in loss computation phase [23, 36, 44] are also shown to be effective. On the other hand, [35, 59] leveraged unlabeled data for class-imbalanced learning. Unlike all the aforementioned methods, we focus on alleviating the bias of pseudo-labels in semi-supervised learning due to class imbalanced labels and distribution mismatch between labeled and unlabeled data.

**Semi-supervised learning (SSL).** SSL aims to learn from both labeled and unlabeled data. For unlabeled data, SSL generates targets (*e.g.*, pseudo-labels) from model’s predictions via *pseudo-labeling* [31], *consistency regularization* [37, 50] and combinations of them [4, 5, 29], enforcing *cluster assumption* [7]. However, pseudo-labels can be biased in essence [2] and even become severe under class-imbalanced labels [26]. Some works deal with such issue via loss re-weighting [24, 32, 46], optimization [26], and data re-sampling [54]. However, the distribution of unlabeled data potentially different from the labeled one or even unknown can limit the applicability of such methods. In this aspect, we devise a new method which is able to handle even such challenging but essentially practical scenarios.

## 3. Proposed Method

### 3.1. Preliminaries

**Problem setup.** We consider  $K$ -class semi-supervised image classification that leverages both labeled data  $\mathcal{X} = \{(x_n, y_n)\}_{n=1}^N$  and unlabeled data  $\mathcal{U} = \{u_m\}_{m=1}^M$  to train a model  $f$ . Note that the model  $f = f_{\phi}^{\text{cls}} \circ f_{\theta}^{\text{enc}}$  consists of a feature encoder  $f_{\theta}^{\text{enc}}$  followed by a linear classifier  $f_{\phi}^{\text{cls}}$ , where  $\theta$  and  $\phi$  are the set of parameters of  $f_{\theta}^{\text{enc}}$  and  $f_{\phi}^{\text{cls}}$ . The input image  $x$  is paired with the label  $y$  to learn  $\mathcal{L}_{\text{cls}}$  (*e.g.*, cross-entropy) from prediction  $p = f(x)$ . For the unlabeled data, a pseudo-label<sup>1</sup>  $\hat{p} \in \mathbb{R}^K$  is assigned to learn the unsupervised loss  $\mathcal{L}_u = \Phi_u(\hat{p}, f(u))$ , where  $\Phi_u$  can be implemented via entropy [17] or consistency regularization [30, 50], depending on the SSL learner. For FixMatch [48] as an example, the pseudo-label  $\hat{p} = \text{OneHot}(\arg\max_k p_k^{(w)})$  with  $p^{(w)} = f(\mathcal{A}_w(u))$  provides the target for the prediction  $p^{(s)} = f(\mathcal{A}_s(u))$  with some

<sup>1</sup>In this work, we assume it includes both one-hot form and soft form cases:  $\sum_k \hat{p}_k = 1$  where  $\hat{p}_k \in [0, 1]$ .

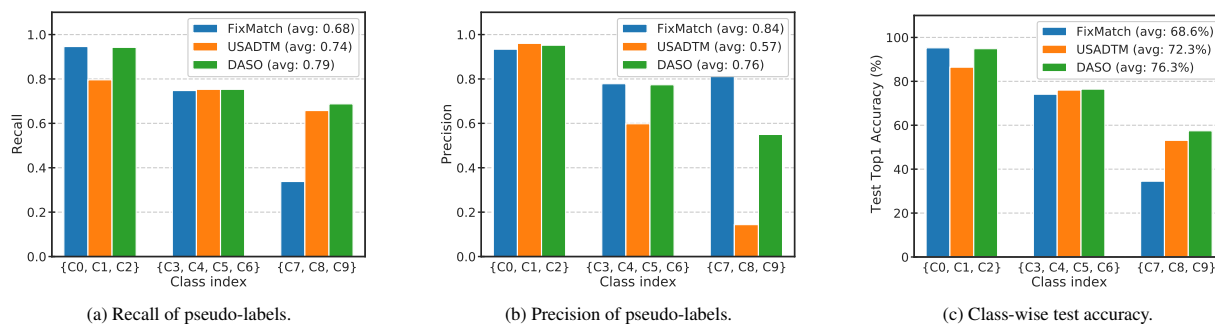


Figure 2. Analysis on recall and precision of pseudo-labels and the corresponding test accuracy. Note that the class index from x-axis is sorted by the class size; C0 and C9 are the head and tail classes, respectively. Although USADTM [20] improves the recall of minority classes, the precision of those classes is significantly reduced. In contrast, DASO improves the recall of minority classes while sustaining the precision, which leads to higher test accuracy of those classes. More analyses with various SSL methods are provided in Appendix E.1.

confident ones to the cross-entropy loss  $\mathcal{H}$  as follows:

$$\Phi_u(\hat{p}, p^{(s)}) = \mathbb{1}\left(\max_k p_k^{(w)} \geq \tau\right) \mathcal{H}(\hat{p}, p^{(s)}), \quad (1)$$

where  $\mathcal{A}_w$  and  $\mathcal{A}_s$  correspond to weak augmentation (e.g., random flip and crop) and advanced augmentation (e.g., RandAugment [11] followed by Cutout [15]), respectively.

**Imbalanced semi-supervised learning.** Let us denote  $N_k$  and  $M_k$  as the number of labeled and unlabeled examples respectively in class  $k$ . The degree of imbalance for each data is characterized by the imbalance ratio,  $\gamma_l$  or  $\gamma_u$ , where we assume  $\gamma_l = \frac{\max_k N_k}{\min_k N_k} \gg 1$  under imbalanced SSL.  $\gamma_u$  is specified in the same way using the actual labels without access during training. It is worth noting that the class distribution of  $\mathcal{U}$  (e.g.,  $\gamma_u$ ) may be either similar to  $\mathcal{X}$ , or significantly divergent in practice, and such varying distributions greatly affect the SSL performances with the same  $\mathcal{X}$  as shown in Table 3. In this regard, our goal is to produce debiased pseudo-labels with class-imbalanced data, while maintaining the performances of SSL algorithms with various, but still *unknown* class distribution of unlabeled data.

### 3.2. Motivation

**Linear and semantic pseudo-label.** Pseudo-labeling based on the linear classifier, which has been widely adopted by most online pseudo-label-based algorithms [31, 48, 56], can produce biased pseudo-labels towards majority classes with class-imbalanced data. Instead of the linear classifier, pseudo-labels can be obtained from similarity-based classifier [13, 45] by measuring the similarity of a given representation (e.g., prototypes [47]) to an unlabeled sample in feature space, which we call simply *semantic pseudo-labels*. As note, similarity-based classifier has been widely adopted for reducing biased predictions [25, 34, 43]. In SSL literature, USADTM [20] utilizes semantic pseudo-labeling method. As following, we conduct a simple experiment to explore each aspect of linear and semantic pseudo-labels.

### Trade-offs between linear and semantic pseudo-label.

As shown in Fig. 2, we compare FixMatch [48] and USADTM [20] using linear and semantic pseudo-label respectively, under *imbalanced* SSL setup. From Figs. 2a and 2b, the linear pseudo-labels from FixMatch achieve high recall in majority classes while low recall but high precision in the minorities, suggesting that actual minority class examples are biased towards head classes. In contrast, for semantic pseudo-labels from USADTM, the actual majorities are biased towards minority classes. This is because the precision of tail classes has decreased significantly in Fig. 2b, while the recall has increased in sacrifice of the recall from head classes in Fig. 2a. Comparing the test accuracy from Fig. 2c, USADTM shows relatively increased overall test accuracy compared to FixMatch by virtue of more abundant minority pseudo-labels, while losing the accuracy on the head. In other words, the overall increase in accuracy is limited when only using semantic pseudo-labels. We provide two lessons from the simple experiment in Fig. 2, as summarized by:

1. Semantic pseudo-labels are *reversely biased towards the tail side*, which lead to the limited accuracy gain.
2. The linear and semantic pseudo-labels have the *complementary properties* useful for reducing the overall bias.

These empirical findings motivate us to exploit the linear and semantic pseudo-labels *differently* in different classes for debiasing. For example, as the linear pseudo-label for a sample  $u$  points to the majorities, more semantic pseudo-label component should contribute to the final pseudo-label to prevent the false positives towards the head, and the vice versa when the linear pseudo-label predicts  $u$  as minority.

We also present the result of our solution, DASO, in Fig. 2, where the recall of the final pseudo-label has increased but the overall pseudo-labels are still not biased towards the minority classes, unlike USADTM. Thanks to such *balanced* pseudo-labels between the head and tail classes obtained by properly blending two pseudo-labels, the overall test accuracy also increased a lot from Fig. 2c.



### 3.3. DASO Pseudo-label Framework

We propose DASO, a generic framework for imbalanced SSL with two novel contributions as (1) distribution-aware blending for the linear and semantic pseudo-labels and (2) semantic alignment loss, which are described as follows.

**Framework overview.** Without loss of generality, we consider DASO built on top of FixMatch [48] for convenience in notations, while DASO can easily integrate with other SSL learners as shown in Tables 1 and 3. First, the linear and semantic pseudo-label,  $\hat{p}$  and  $q^{(w)}$  are produced with a feature  $z^{(w)} = f_{\theta}^{\text{enc}}(\mathcal{A}_w(u))$  from the linear and similarity-based classifier, respectively. Then the final pseudo-label  $\hat{p}'$  is obtained from the distribution-aware blending process using  $\hat{p}$  and  $q^{(w)}$ , and it provides the target to  $\mathcal{L}_u = \Phi_u(\hat{p}', p)$  instead of linear pseudo-label in the existing SSL learner. In case of FixMatch, the prediction of  $u$  corresponds to  $p = f(\mathcal{A}_s(u))$ . For the semantic alignment loss, the semantic pseudo-label  $q^{(w)}$  provides the target for  $q^{(s)}$  to the cross-entropy  $\mathcal{H}$ , where  $q^{(s)}$  is the result of the similarity-based classifier with  $z^{(s)} = f_{\theta}^{\text{enc}}(\mathcal{A}_s(u))$ . Note that we denote  $q^{(w)}$  as  $\hat{q}$  for simplicity, unless confusion arises.

**Balanced prototype generation.** To execute a similarity-based classifier for obtaining the semantic pseudo-label, we first build a set of class prototypes  $\mathbf{C} = \{c_k\}_{k=1}^K$  from  $\mathcal{X}$ , similar to [20]. In detail, we build a dictionary of memory queue  $\mathbf{Q} = \{Q_k\}_{k=1}^K$  where each key corresponds to the class and  $Q_k$  denotes a memory queue for class  $k$  with the fixed size  $|Q_k|$ . The class prototype  $c_k$  for every class  $k$  is efficiently calculated with only small computation overhead by averaging the feature points in the queue  $Q_k$ , where we update  $Q_k$  for all  $k$  at every step by pushing new features from labeled data in the batch and discarding the most old ones after  $Q_k$  has features more than the size  $|Q_k|$ .

The prototype representation can also be imbalanced using class-imbalanced labeled data. To prevent such biased prototypes, we additionally propose *balancing* the prototypes compared to [20] in two ways. First, instead of the size of  $Q_k$  in proportional to the class frequency, we fix the size of  $Q_k$  for all  $k$  to the same amount as  $L$ . By averaging the same number of features from each class, we can compensate for the prototypes especially for the minority classes, with earlier samples remaining in  $Q_k$ . Secondly, we adopt momentum encoder  $f_{\theta'}^{\text{enc}}$  when extracting the features for prototype generation inspired by [21]. Note that  $f_{\theta'}^{\text{enc}}$  has the same architecture with  $f_{\theta}^{\text{enc}}$ , but  $\theta'$  is the exponential moving average (EMA) of  $\theta$  with momentum ratio  $\rho$ , i.e.,  $\theta' \leftarrow \rho\theta' + (1-\rho)\theta$ . This stabilizes the movement of each prototype in feature space across iteration by slowing the pace of network parameter updates. We will verify the effectiveness of such balanced prototypes in ablation study.

**Linear and semantic pseudo-label generation.** We obtain the linear pseudo-label  $\hat{p}$  using the linear classifier followed by softmax activation:  $\hat{p} = \sigma(f_{\phi}^{\text{cls}}(z^{(w)}))$ . The semantic

pseudo-label  $\hat{q}$  is obtained from the similarity-based classifier that measures the per-class similarity of a query feature point  $z$  of either  $z^{(w)}$  or  $z^{(s)}$  to the *balanced prototypes*  $\mathbf{C}$ :

$$q = \sigma(\text{sim}(z, \mathbf{C}) / T_{\text{proto}}), \quad (2)$$

where  $\text{sim}(\cdot, \cdot)$  corresponds to cosine similarity, and  $T_{\text{proto}}$  is a temperature hyper-parameter for the classifier. Note that  $\hat{p}$  is biased towards head classes while  $\hat{q}$  is the vice versa.

**Distribution-aware pseudo-label blending.** In order to obtain the class-specific unbiased pseudo-label, the semantic pseudo-label  $\hat{q}$  should be exploited *differently* across the class. To this end, we propose a novel blending method for the pseudo-labels, where we increase the exposure of the component of semantic pseudo-label in final, as the linear one is more biased to the head classes. Formally, we blend them with a set of distribution-aware weights  $v = \{v_k\}_{k=1}^K$  to reduce the bias that might occur when using either  $\hat{p}$  or  $\hat{q}$ :

$$\hat{p}' = (1 - v_{k'})\hat{p} + v_{k'}\hat{q}, \quad (3)$$

where  $k'$  is the class prediction from  $\hat{p}$ , and each  $v_k$  is derived as  $v_k = \frac{1}{\max_k \hat{m}_k^{1/T_{\text{dist}}}} \left( \hat{m}_k^{1/T_{\text{dist}}} \right)$ . Note that  $\hat{m}$  is the normalized class distribution of the current pseudo-labels, which is the accumulation of  $\hat{p}'$  over a few previous iterations and  $T_{\text{dist}}$  is a hyper-parameter that intercedes the optimal trade-offs between  $\hat{p}$  and  $\hat{q}$ . Overall, in terms of the linear pseudo-label  $\hat{p}$ , the minority pseudo-labels will remain as minority, while the pseudo-labels predicted as majority will be likely to recover the original classes. Note that we dynamically adjust the set of weights  $v$  that determines the relative intensity of  $\hat{q}$  in Eq. (3) based on the current class distribution of pseudo-labels  $\hat{m}$ , making the proposed method flexible to handling various distributions of  $\mathcal{U}$  without resorting to any pre-defined distribution. For example, even under the same prediction of  $\hat{p}$  for the head class, more  $\hat{q}$  is blended when the current model is more biased.

**Semantic alignment loss.** To establish more balanced feature representations, we propose new semantic alignment loss for regularizing the feature encoder  $f_{\theta}^{\text{enc}}$ . It extends the consistency training framework with two asymmetric augmentations  $\mathcal{A}_w$  and  $\mathcal{A}_s$  like [48, 56] onto feature space. In high-level, we align each unlabeled sample  $u$  to the most similar prototype used in the similarity-based classifier, by imposing *consistent assignment* for two augmented views  $\mathcal{A}_w(u)$  and  $\mathcal{A}_s(u)$  to the same  $c_k$  in feature space. Note  $\hat{q}$  is reused to provide the target for  $q^{(s)}$  with the cross-entropy loss  $\mathcal{H}$ :

$$\mathcal{L}_{\text{align}} = \mathcal{H}(\hat{q}, q^{(s)}), \quad (4)$$

where  $q^{(s)}$  is from the similarity-based classifier by passing through  $z^{(s)} = f_{\theta}^{\text{enc}}(\mathcal{A}_s(u))$  to Eq. (2). Since  $\mathcal{L}_{\text{align}}$  relates unlabeled data to the label space through consistently assigning to  $\mathbf{C}$  constructed from labeled features, such enhanced representation can implicitly guide the classifier  $f_{\phi}^{\text{cls}}$

to produce less biased predictions in general, where we validate the efficacy of  $\mathcal{L}_{\text{align}}$  in Secs. 4.4 and 4.5 respectively. **Total objective.** DASO is a generic framework that can easily couple with other SSL algorithms with the modified pseudo-label, where the final DASO objective is as below:

$$\mathcal{L}_{\text{DASO}} = \mathcal{L}_{\text{cls}} + \lambda_u \mathcal{L}_u + \lambda_{\text{align}} \mathcal{L}_{\text{align}}, \quad (5)$$

where both  $\mathcal{L}_{\text{cls}}$  and  $\mathcal{L}_u$  with  $\lambda_u$  come from the base SSL learner, and  $\mathcal{L}_{\text{align}}$  is newly introduced from DASO. Note that  $\mathcal{L}_u$  takes the proposed blended pseudo-label in Eq. (3) instead of the original linear pseudo-label of the learner. We emphasize that DASO is also applicable to traditional SSL algorithms for performance gain without  $\mathcal{L}_{\text{align}}$  due to the absence of  $\mathcal{A}_s$  in the algorithm, as validated in Table 3.

## 4. Experiments

### 4.1. Experimental Setup

To ensure reproducibility, *all* the settings of the proposed DASO and baseline methods are clarified in Appendix C.3, and the self-contained codes will be released later.

**Datasets.** We conduct SSL experiments with various scenarios where the class distribution of unlabeled data is not just limited to the class distribution of labeled data. To accommodate such conditions, we adopt CIFAR-10/100 [28] and STL-10 [10] typically adopted in SSL literature [48]. We make the imbalanced versions by exponentially decreasing the amount of samples per class [12]. Following [26], we denote the head class size as  $N_1$  ( $M_1$ ), and the imbalance ratio as  $\gamma_l$  ( $\gamma_u$ ) for the labeled (unlabeled) data respectively. Note that  $\gamma_l$  and  $\gamma_u$  can vary independently, and we specify ‘LT’ for those imbalanced variants. We also consider Semi-Aves benchmark [49] for practical setup, which is the large-scale collection of bird species with natural long-tailed distribution. Its unlabeled data also show long-tailed distribution, and include large portion of examples in broader categories compared to samples in labeled data (*e.g.*, *open-set*). For more details, see Appendix C.1.

**Baseline methods.** We consider *Supervised* baseline, learning cross-entropy with only labeled data. For using unlabeled data, we mainly adopt *FixMatch* [48] for its simplicity and powerful performances. To extensively validate our proposed method in terms of re-balancing, we mainly compare it with the following re-balancing algorithms on top of *FixMatch*. Note that the results with other baseline SSL algorithms are provided in Table 3 and the Appendix D.3. We consider *logit adjustment* (LA) [36] for balancing labels. Note that LA can also be applied to SSL methods for re-balancing using labels. For re-balancing in unlabeled data similar to our framework, *DARP* [26] and *CReST* [54] are compared. We also experiment with the recently proposed *ABC* [32] that performs single unified re-balancing using both labeled and unlabeled data simultaneously.

**Training and evaluation.** We have re-implemented all the baseline methods using PyTorch [41] and conducted experiments under the same codebase for fair comparison, as suggested by [38]. We train Wide ResNet-28-2 [60] on CIFAR10/100-LT and STL10-LT as a backbone. For training Semi-Aves, we fine-tune the ResNet-34 [22] pre-trained on ImageNet [14]. To evaluate, we use the EMA network with the parameters updating every steps, following [5, 26]. As note, the class score is measured via learned linear classifier at inference time. We measure the top-1 accuracy on the test data every epoch and finally obtain the median of the accuracy values during the last 20 evaluations [5]. When reporting the results, we compute the mean and standard deviation of three independent runs. The codes will be released.

### 4.2. Results on CIFAR10/100-LT and STL10-LT.

As the main results, we first consider the case when the distribution of labeled data and unlabeled data is the same (*e.g.*,  $\gamma = \gamma_l = \gamma_u$ ) in Table 1, which is the ideal case for SSL. In Table 2, we relax such assumption and test imbalanced SSL methods under practical yet challenging scenarios with diverse unlabeled data distributions (*e.g.*,  $\gamma_l \neq \gamma_u$ ).

**In case of  $\gamma_l = \gamma_u$ .** We compare the proposed DASO with several baseline methods, with or without class re-balancing in Table 1. For *Supervised* case, even if Logit Adjustment (LA) [36] is applied, the performances are rather limited compared to even naïve SSL method (*i.e.*, *FixMatch* [48]).

We then compare imbalanced SSL methods: *DARP* [26] and *CReST+* [54] with the proposed DASO on *FixMatch*. Remarkably, DASO shows comparable or even better results in most setups with significant gains compared to baseline *FixMatch*, although *DARP* and *CReST+* even push the predictions of unlabeled data to the label distribution using the assumption  $\gamma_l = \gamma_u$  (*i.e.*, distribution alignment [4]). This verifies the efficacy of DASO for debiasing pseudo-labels, even without resorting to the label distribution.

To validate DASO can reliably benefit from re-balancing labels for debiasing pseudo-labels, we further compare imbalanced SSL methods on label re-balancing *FixMatch* via LA [36] (noted as *FixMatch + LA*). The results show DASO performs the best in most of the setups. It is noticeable that LA with DASO always improves performances compared to both *FixMatch* w/ DASO and *FixMatch + LA* cases.

Finally, we consider *ABC* [32] in the bottom of Table 1. It jointly trains the SSL learner and the auxiliary balanced classifier (ABC) using both labeled and unlabeled data with *linear pseudo-labels*, while the ABC is opted for evaluation. We find that training ABC can readily be extended by just replacing the *linear pseudo-label* for ABC with DASO pseudo-label (3). Finally, DASO can be significantly pushed by combining with ABC [32] (*i.e.*, 13% gain upon *FixMatch* for CIFAR-10). It verifies the flexibility of DASO on any baselines regardless of re-balancing methods.

Algorithm	CIFAR10-LT				CIFAR100-LT			
	$\gamma_l = \gamma_u = \gamma_u = 100$		$\gamma_l = \gamma_u = \gamma_u = 150$		$\gamma_l = \gamma_u = \gamma_u = 10$		$\gamma_l = \gamma_u = \gamma_u = 20$	
	$N_1 = 500$	$N_1 = 1500$	$N_1 = 500$	$N_1 = 1500$	$N_1 = 50$	$N_1 = 150$	$N_1 = 50$	$N_1 = 150$
	$M_1 = 4000$	$M_1 = 3000$	$M_1 = 4000$	$M_1 = 3000$	$M_1 = 400$	$M_1 = 300$	$M_1 = 400$	$M_1 = 300$
Supervised	47.3 $\pm$ 0.95	61.9 $\pm$ 0.41	44.2 $\pm$ 0.33	58.2 $\pm$ 0.29	29.6 $\pm$ 0.57	46.9 $\pm$ 0.22	25.1 $\pm$ 1.14	41.2 $\pm$ 0.15
w/ LA [36]	53.3 $\pm$ 0.44	70.6 $\pm$ 0.21	49.5 $\pm$ 0.40	67.1 $\pm$ 0.78	30.2 $\pm$ 0.44	48.7 $\pm$ 0.89	26.5 $\pm$ 1.31	44.1 $\pm$ 0.42
FixMatch [48]	67.8 $\pm$ 1.13	77.5 $\pm$ 1.32	62.9 $\pm$ 0.36	72.4 $\pm$ 1.03	45.2 $\pm$ 0.55	56.5 $\pm$ 0.06	40.0 $\pm$ 0.96	50.7 $\pm$ 0.25
w/ DARP [26]	74.5 $\pm$ 0.78	77.8 $\pm$ 0.63	67.2 $\pm$ 0.32	73.6 $\pm$ 0.73	49.4 $\pm$ 0.20	58.1 $\pm$ 0.44	43.4 $\pm$ 0.87	52.2 $\pm$ 0.66
w/ CReST+ [54]	<b>76.3</b> $\pm$ 0.86	78.1 $\pm$ 0.42	67.5 $\pm$ 0.45	73.7 $\pm$ 0.34	44.5 $\pm$ 0.94	57.4 $\pm$ 0.18	40.1 $\pm$ 1.28	52.1 $\pm$ 0.21
w/ DASO (Ours)	76.0 $\pm$ 0.37	<b>79.1</b> $\pm$ 0.75	<b>70.1</b> $\pm$ 1.81	<b>75.1</b> $\pm$ 0.77	<b>49.8</b> $\pm$ 0.24	<b>59.2</b> $\pm$ 0.35	<b>43.6</b> $\pm$ 0.09	<b>52.9</b> $\pm$ 0.42
FixMatch + LA [36]	75.3 $\pm$ 2.45	82.0 $\pm$ 0.36	67.0 $\pm$ 2.49	78.0 $\pm$ 0.91	47.3 $\pm$ 0.42	58.6 $\pm$ 0.36	41.4 $\pm$ 0.93	53.4 $\pm$ 0.32
w/ DARP [26]	76.6 $\pm$ 0.92	80.8 $\pm$ 0.62	68.2 $\pm$ 0.94	76.7 $\pm$ 1.13	50.5 $\pm$ 0.78	59.9 $\pm$ 0.32	<b>44.4</b> $\pm$ 0.65	53.8 $\pm$ 0.43
w/ CReST+ [54]	76.7 $\pm$ 1.13	81.1 $\pm$ 0.57	<b>70.9</b> $\pm$ 1.18	77.9 $\pm$ 0.71	44.0 $\pm$ 0.21	57.1 $\pm$ 0.55	40.6 $\pm$ 0.55	52.3 $\pm$ 0.20
w/ DASO (Ours)	<b>77.9</b> $\pm$ 0.88	<b>82.5</b> $\pm$ 0.08	70.1 $\pm$ 1.68	<b>79.0</b> $\pm$ 2.23	<b>50.7</b> $\pm$ 0.51	<b>60.6</b> $\pm$ 0.71	44.1 $\pm$ 0.61	<b>55.1</b> $\pm$ 0.72
FixMatch + ABC [32]	78.9 $\pm$ 0.82	<b>83.8</b> $\pm$ 0.36	66.5 $\pm$ 0.78	80.1 $\pm$ 0.45	47.5 $\pm$ 0.18	59.1 $\pm$ 0.21	41.6 $\pm$ 0.83	53.7 $\pm$ 0.55
w/ DASO (Ours)	<b>80.1</b> $\pm$ 1.16	83.4 $\pm$ 0.31	<b>70.6</b> $\pm$ 0.80	<b>80.4</b> $\pm$ 0.56	<b>50.2</b> $\pm$ 0.62	<b>60.0</b> $\pm$ 0.32	<b>44.5</b> $\pm$ 0.25	<b>55.3</b> $\pm$ 0.53

Table 1. Comparison of accuracy (%) with combinations of re-balancing methods on CIFAR10/100-LT under  $\gamma_l = \gamma_u$  setup. Our DASO consistently improves the performance over all the baselines without or with re-balancing, even with ABC [32] designed for imbalanced SSL. We indicate the best results for each division as bold. More results including new baseline methods are provided in Appendix D.1.

Algorithm	CIFAR10-LT ( $\gamma_l \neq \gamma_u$ )				STL10-LT ( $\gamma_u = N/A$ )			
	$\gamma_u = 1$ (uniform)		$\gamma_u = 1/100$ (reversed)		$\gamma_l = 10$		$\gamma_l = 20$	
	$N_1 = 500$	$N_1 = 1500$	$N_1 = 500$	$N_1 = 1500$	$N_1 = 150$	$N_1 = 450$	$N_1 = 150$	$N_1 = 450$
	$M_1 = 4000$	$M_1 = 3000$	$M_1 = 4000$	$M_1 = 3000$	$M = 100k$	$M = 100k$	$M = 100k$	$M = 100k$
FixMatch [48]	73.0 $\pm$ 3.81	81.5 $\pm$ 1.15	62.5 $\pm$ 0.94	71.8 $\pm$ 1.70	56.1 $\pm$ 2.32	72.4 $\pm$ 0.71	47.6 $\pm$ 4.87	64.0 $\pm$ 2.27
w/ DARP [26]	82.5 $\pm$ 0.75	84.6 $\pm$ 0.34	70.1 $\pm$ 0.22	80.0 $\pm$ 0.93	66.9 $\pm$ 1.66	75.6 $\pm$ 0.45	59.9 $\pm$ 2.17	72.3 $\pm$ 0.60
w/ CReST [54]	83.2 $\pm$ 1.67	87.1 $\pm$ 0.28	70.7 $\pm$ 2.02	<b>80.8</b> $\pm$ 0.39	61.7 $\pm$ 2.51	71.6 $\pm$ 1.17	57.1 $\pm$ 3.67	68.6 $\pm$ 0.88
w/ CReST+ [54]	82.2 $\pm$ 1.53	86.4 $\pm$ 0.42	62.9 $\pm$ 1.39	72.9 $\pm$ 2.00	61.2 $\pm$ 1.27	71.5 $\pm$ 0.96	56.0 $\pm$ 3.19	68.5 $\pm$ 1.88
w/ DASO (Ours)	<b>86.6</b> $\pm$ 0.84	<b>88.8</b> $\pm$ 0.59	<b>71.0</b> $\pm$ 0.95	80.3 $\pm$ 0.65	<b>70.0</b> $\pm$ 1.19	<b>78.4</b> $\pm$ 0.80	<b>65.7</b> $\pm$ 1.78	<b>75.3</b> $\pm$ 0.44

Table 2. Comparison of accuracy (%) for imbalanced SSL methods on CIFAR10-LT and STL10-LT under  $\gamma_l \neq \gamma_u$  setup. For CIFAR10-LT,  $\gamma_l$  is fixed to 100, and  $\gamma_u$  is unknown for STL10-LT. Our DASO consistently shows significant gains on FixMatch [48] without resorting to any class prior under diverse class distribution mismatches between labeled and unlabeled data. We indicate the best results as bold.

**In case of  $\gamma_l \neq \gamma_u$ .** The class distribution of unlabeled data could be either unknown or arguably different from that of the labeled data in real-world (e.g.,  $\gamma_l \neq \gamma_u$ ). To simulate such scenarios, for CIFAR10-LT, we consider two extreme cases for the class distribution of unlabeled data: uniform ( $\gamma_u = 1$ ) and flipped long-tail ( $\gamma_u = 1/100$ ) with respect to the labeled data. For STL10-LT, since we cannot control the size and imbalance of unlabeled data due to unknown labels, we instead set  $\gamma_l \in \{10, 20\}$  with the whole fixed unlabeled data. Table 2 summarizes the results of imbalanced SSL methods under the setups. Note that more comparisons of SSL methods with different re-balancing techniques (i.e., LA [36] and ABC [32]) are presented in Appendix D.2.

Surprisingly, DASO outperforms other baselines by significant margins in most cases. For example, DASO shows 13.6% and 18.1% of absolute gain from FixMatch upon CIFAR-10 ( $\gamma_u = 1$ ) and STL-10 ( $\gamma_l = 20$ ), respectively. Though DARP [26] estimates the distribution of unlabeled data in advance as the prior, the estimation accuracy decreases as using less labels for training. Under  $\gamma_l \neq \gamma_u$ , we evaluate both CReST with self-training only and CReST+

with progressive distribution alignment [54]. Clearly, resorting to the label distributions as the prior for unlabeled data in CReST+ rather harms the accuracy compared to CReST, since the assumption of  $\gamma_l = \gamma_u$  is violated. In particular, when the class distribution of unlabeled data is completely inverted ( $\gamma_u = 1/100$ ), the accuracy loss becomes more severe, resulting in little gain over FixMatch.

By virtue of debiased pseudo-labels from DASO, the abundant minority-class unlabeled samples are correctly used despite class-imbalanced labels. Consequently, the results confirm that conditioning on a certain distribution for unlabeled data (e.g.,  $\gamma_u = \gamma_l$ ) is undesirable in imbalanced SSL, and DASO greatly reduces the bias in presence of distribution mismatch, even without access to the distribution. **DASO on other SSL learner.** To verify DASO is a generic pseudo-labeling framework, we evaluate DASO based on other SSL algorithms including MeanTeacher [50], MixMatch [5], and ReMixMatch [4] in Table 3. As note, MeanTeacher and MixMatch only perform pseudo-label blending (3) without semantic alignment loss (4) due to the absence of  $\mathcal{A}_s$ . For CIFAR10-LT, we set  $\gamma_l = 100$  and for



Algorithm	C10-LT		C100-LT	STL10-LT
	$N_1 = 1500$ $M_1 = 3000$		$N_1 = 150$ $M_1 = 300$	$N_1 = 450$ $M = 100k$
	$\gamma_u = 100$	$\gamma_u = 1$	$\gamma_u = 10$	$\gamma_u : N/A$
Mean Teacher [50]	68.6 $\pm$ 0.88	46.4 $\pm$ 0.98	52.1 $\pm$ 0.09	54.6 $\pm$ 1.17
w/ DASO (Ours)	<b>70.7</b> $\pm$ 0.59	<b>87.6</b> $\pm$ 0.27	<b>52.5</b> $\pm$ 0.37	<b>78.4</b> $\pm$ 0.80
MixMatch [5]	65.7 $\pm$ 0.23	35.7 $\pm$ 0.69	54.2 $\pm$ 0.47	52.7 $\pm$ 1.42
w/ DASO (Ours)	<b>70.9</b> $\pm$ 1.91	<b>73.4</b> $\pm$ 2.05	<b>55.6</b> $\pm$ 0.49	<b>68.4</b> $\pm$ 0.71
ReMixMatch [4]	77.0 $\pm$ 0.55	60.4 $\pm$ 0.70	61.5 $\pm$ 0.57	71.9 $\pm$ 0.86
w/ DASO (Ours)	<b>80.2</b> $\pm$ 0.68	<b>90.5</b> $\pm$ 0.35	<b>62.1</b> $\pm$ 0.69	<b>80.9</b> $\pm$ 0.55

Table 3. Comparison of accuracy (%) from DASO upon other SSL methods: MeanTeacher [50], MixMatch [5], and ReMixMatch [4]. DASO improves the performances in all the setups.

	$\mathcal{L}_{\text{align}}$	C10	STL10
FixMatch	$\times$	68.25	55.53
DASO	$\times$	70.98	61.64
FixMatch	$\checkmark$	73.15	58.51
DASO	$\checkmark$	<b>75.97</b>	<b>70.21</b>

Table 5. Ablation study on pseudo-label blending and semantic alignment loss  $\mathcal{L}_{\text{align}}$ .

	C10	STL10
$v_k = 0$	73.15	58.51
$v_k = 1$	72.35	62.60
$v_k = 0.5$	72.96	64.21
DASO	<b>75.97</b>	<b>70.21</b>

Table 6. Ablation study on the pseudo-label blending strategy with  $\mathcal{L}_{\text{align}}$  applied.

CIFAR100-LT and STL10-LT, we set  $\gamma_l = 10$ . We observe that DASO greatly improves the performances for all the setups, and notably, it achieves  $2.05\times$  accuracy compared to MixMatch and brings 29.1% absolute gain in ReMixMatch on CIFAR10-LT under  $\gamma_u = 1$ . This implies that DASO noticeably helps SSL algorithms in general to benefit from unlabeled data under imbalanced SSL setup. As note, we show the comparison of imbalanced SSL methods built on other SSL learner (e.g., ReMixMatch [4]) in Appendix D.3.

### 4.3. Results on Large-Scale Semi-Aves

We test DASO on a realistic Semi-Aves benchmark [49]. Both labeled data ( $\mathcal{X}$ ) and unlabeled data ( $\mathcal{U}$ ) show long-tailed distributions, while  $\mathcal{U}$  contains large *open-set* examples ( $\mathcal{U}_{\text{out}}$ ) that do not belong to any of the classes in  $\mathcal{X}$ . The results are shown in Table 4. We report both cases:  $\mathcal{U} = \mathcal{U}_{\text{in}}$  and  $\mathcal{U} = \mathcal{U}_{\text{in}} + \mathcal{U}_{\text{out}}$ , where  $\mathcal{U}_{\text{in}}$  contains examples that share the class of  $\mathcal{X}$ . We measure the performances by top-1 accuracy, reporting the one in the final (Last Top1) and the median values in last 20 epochs (Med20 Top1), following [38]. More details on this dataset can be found in Appendix C.1.

**In case of  $\mathcal{U} = \mathcal{U}_{\text{in}}$ .** As it has the distribution gap between  $\mathcal{X}$  and  $\mathcal{U}$ , baseline DARP [26] and CReST [54] with inadequate class prior from  $\mathcal{X}$  show only a slight gain or even unsatisfactory performances compared to FixMatch [48]. In contrary, DASO shows the best performance among the baselines with favorable improvements upon FixMatch.

**In case of  $\mathcal{U} = \mathcal{U}_{\text{in}} + \mathcal{U}_{\text{out}}$ .** Since  $\mathcal{U}$  contains large amount of *open-set* class examples, performance drop is observed consistently across all baselines, as similar observations are

Benchmark	Semi-Aves			
	$\mathcal{U} = \mathcal{U}_{\text{in}}$		$\mathcal{U} = \mathcal{U}_{\text{in}} + \mathcal{U}_{\text{out}}$	
Method	Last Top1	Med20 Top1	Last Top1	Med20 Top1
Supervised	41.7 $\pm$ 0.32	41.7 $\pm$ 0.32	41.7 $\pm$ 0.32	41.7 $\pm$ 0.32
FixMatch [48]	53.8 $\pm$ 0.17	53.8 $\pm$ 0.13	45.7 $\pm$ 0.89	46.1 $\pm$ 0.50
w/ DARP [26]	52.3 $\pm$ 0.48	52.1 $\pm$ 0.48	46.3 $\pm$ 0.70	46.4 $\pm$ 0.61
w/ CReST [54]	52.1 $\pm$ 0.36	52.2 $\pm$ 0.27	43.6 $\pm$ 0.69	43.6 $\pm$ 0.68
w/ CReST+ [54]	53.9 $\pm$ 0.38	53.8 $\pm$ 0.38	45.1 $\pm$ 1.09	45.2 $\pm$ 1.00
w/ DASO (Ours)	<b>54.5</b> $\pm$ 0.08	<b>54.6</b> $\pm$ 0.12	<b>47.9</b> $\pm$ 0.41	<b>47.9</b> $\pm$ 0.38

Table 4. Comparison of accuracy (%) on Semi-Aves benchmark [49]. DASO shows the best performance among state-of-the-art imbalanced SSL methods. Moreover, DASO still performs well in presence of massive open-set class examples  $\mathcal{U}_{\text{out}}$ .

bal.	EMA	C10	STL10
$\times$	$\times$	74.98	68.54
$\checkmark$	$\times$	74.54	70.01
$\times$	$\checkmark$	75.01	69.49
$\checkmark$	$\checkmark$	<b>75.97</b>	<b>70.21</b>

Table 7. Ablation study on balancing prototypes and using EMA encoder on DASO.

	C10	STL10
$T_{\text{dist}} = 0.3$	73.97	<b>70.21</b>
$T_{\text{dist}} = 0.5$	74.47	68.35
$T_{\text{dist}} = 1.0$	74.82	65.96
$T_{\text{dist}} = 1.5$	<b>75.97</b>	64.54

Table 8. Ablation study on  $T_{\text{dist}}$  for DASO. We select  $T_{\text{dist}}$  by 1.5 and 0.3 each.

made in [9, 18, 39]. Among the baselines, DASO shows the best performance with favorable gain. The results suggest that DARP [26] is slightly helpful when both  $\mathcal{U}_{\text{in}}$  and  $\mathcal{U}_{\text{out}}$  are considered altogether for optimization. Concerning CReST and CReST+ [54] with self-training, due to noisy predictions from  $\mathcal{U}_{\text{out}}$  for constructing datasets for the next generation, they rather performs poorly than FixMatch. As such, DASO has superiority in the challenging but practical scenario of long-tailed distributions, even in presence of large amount of open-set examples. To understand this, we further provide the analyses on the confidence plots with or without DASO using each of  $\mathcal{U}_{\text{in}}$  and  $\mathcal{U}_{\text{out}}$  in Appendix E.5.

### 4.4. Ablation Study

We conduct ablation studies to understand why DASO reliably provides improvements to baseline methods. To accommodate both  $\gamma_l = \gamma_u$  and  $\gamma_l \neq \gamma_u$  cases, we consider FixMatch on CIFAR10-LT with  $N_1 = 500$ ,  $\gamma = 100$  (noted as C10) and STL10-LT with  $N_1 = 150$ ,  $\gamma_l = 10$  (noted as STL10) respectively to evaluate each aspect of DASO.

**Component analysis.** Table 5 studies the two major components of DASO: distribution-aware pseudo-label blending and the semantic alignment loss. From the table, both blending mechanism and  $\mathcal{L}_{\text{align}}$  provides significant gain over FixMatch. For example, the blending and  $\mathcal{L}_{\text{align}}$  achieve about 6% and 3% absolute gain, respectively, and combining both shows 15.7% gain in total on STL10. The results confirm that both class-adaptively blending linear and semantic pseudo-labels and the semantic alignment loss are important for reducing bias under imbalanced SSL.

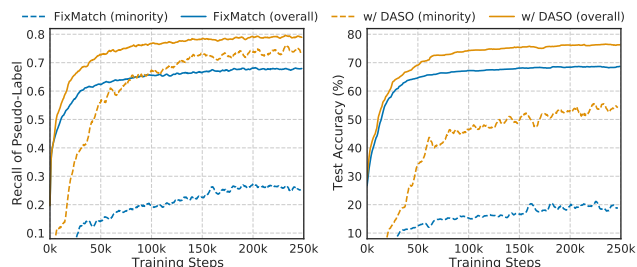


Figure 3. Train curves for the recall of pseudo-labels (left) and the test accuracy (right) on CIFAR10-LT. DASO significantly remedies the bias of pseudo-labels on minority classes, and such unbiased pseudo-labels lead to large gains on the test accuracy.

**Effect of pseudo-label blending.** Table 6 studies the different way of pseudo-label blending on DASO with *constant* weights. Due to the bias in the pseudo-labels, using either linear ( $v_k = 0$ ) or semantic ( $v_k = 1$ ) pseudo-label leads to a marginal gain. In addition, blending them with the same ratio ( $v_k = 0.5$ ) shows the lower performance compared to our final DASO, which demonstrates that distribution-aware class-adaptive blending is crucial for imbalanced SSL.

**Effect of balanced prototype.** Table 7 studies the different design choices of DASO in prototype generation: balanced prototypes (noted as bal.) with EMA encoder (noted as EMA). When generating class prototypes, using class-imbalanced queue without EMA encoder leads to worse performance. In contrary, DASO with both balanced queue using EMA encoder shows the best performance, showing that both correspond to the valid components for the balanced prototypes from imbalanced labeled data.

**Ablation study on  $T_{\text{dist}}$ .** In Table 8, we study the effect of the temperature hyper-parameter  $T_{\text{dist}}$  to compute the weights for pseudo-label blending described in Eq. (3). We empirically find that, for CIFAR-10 and STL-10,  $T_{\text{dist}} = 1.5$  and  $T_{\text{dist}} = 0.3$  show the best performance respectively.

#### 4.5. Detailed Analysis

In this section, we qualitatively analyze how DASO improves the performance under imbalanced SSL setup. We consider FixMatch [48] without and with DASO trained on CIFAR10-LT with  $\gamma = 100$  and  $N_1 = 500$ . Note that Appendix E includes analyses in more various setups.

**Unbiased pseudo-label improves test accuracy.** We visualize the train curves for the recall of pseudo-labels and the test accuracy values in Fig. 3. We denote those for the minorities (e.g., last 20% classes) as dashed lines. From the left of Fig. 3, DASO significantly raises the final recall for the tail classes, which is  $3\times$  compared to that of FixMatch. From the right, both minority and overall test accuracy values in final greatly improved by virtue of the less biased pseudo-labels towards the head classes, which are nearly  $3\times$  and  $9\%$  compared to those of FixMatch, respectively.

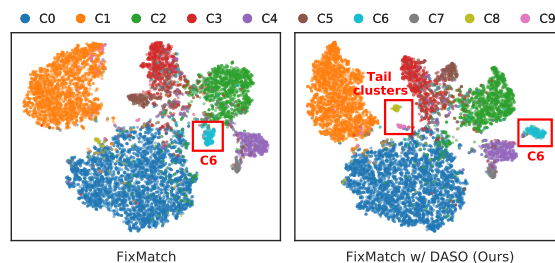


Figure 4. Comparison of t-SNE visualization of unlabeled data from FixMatch (left) and FixMatch w/ DASO (right). Learning with DASO helps the model to establish tail-class clusters in feature space, which can further reduce the biases from the classifier.

**Tail-class clusters are better identified.** To verify the efficacy of reducing the bias, we present t-SNE [51] visualizations of the encoders’ outputs on  $\mathcal{U}$  from FixMatch and w/ DASO respectively. As shown in Fig. 4, tail class examples (e.g., C8 and C9) from FixMatch are scattered to the majority classes. From the right, however, the clusters of tail are clearly recognized as indicated. In addition, the separability of C6 is improved. Thanks to such well identified tail-class clusters from DASO, the actual minority unlabeled examples are correctly leveraged to learn the unbiased model.

## 5. Discussion

**Conclusion.** In this work, we proposed a novel distribution-aware semantics-oriented (DASO) pseudo-label, to generate less biased pseudo-labels for imbalanced semi-supervised learning. DASO adaptively blends the linear and semantic pseudo-labels within each class to mitigate the overall bias across the class. To further push the model to be less biased, we suggest to construct balanced prototypes and learn from semantic alignment loss. We conducted extensive experiments to show the efficacy of our method on various challenging and realistic setups, especially when class imbalance and class distribution mismatch dominates.

**Potential societal impact.** The proposed solution can contribute to solving various social problems attributed to imbalance in real-world, such as gender, racial or religious bias, by improving the fairness of classifiers using unlabeled data. However, the proposed algorithm should be carefully considered as it can be used to raise other fairness issues such as over-balance or discrimination against minorities.

**Limitation and future work.** This study focused on the bias of pseudo-labels to provide correct supervision of unlabeled data. However, even with correct pseudo-labels, the imbalanced but actually unknown class distribution of unlabeled data can also influence the model bias. While we partially resolve the issue by applying other re-balancing methods on DASO, future works should consider comprehensive re-balancing of both labeled and unlabeled data, which can also well address the potentially unknown unlabeled data.



## References

- [1] Shin Ando and Chun Yuan Huang. Deep over-sampling framework for classifying imbalanced data. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases*, pages 770–785, 2017. 2
- [2] Eric Arazo, Diego Ortego, Paul Albert, Noel E O’Connor, and Kevin McGuinness. Pseudo-labeling and confirmation bias in deep semi-supervised learning. In *International Joint Conference on Neural Networks (IJCNN)*, pages 1–8, 2020. 1, 2
- [3] Samy Bengio. Sharing representations for long tail computer vision problems. In *ACM International Conference on Multimodal Interaction*, pages 1–1, 2015. 1, 2
- [4] David Berthelot, Nicholas Carlini, Ekin D. Cubuk, Alex Kurakin, Kihyuk Sohn, Han Zhang, and Colin Raffel. Remix-match: Semi-supervised learning with distribution matching and augmentation anchoring. In *International Conference on Learning Representations (ICLR)*, 2020. 1, 2, 5, 6, 7
- [5] David Berthelot, Nicholas Carlini, Ian Goodfellow, Nicolas Papernot, Avital Oliver, and Colin A Raffel. Mixmatch: A holistic approach to semi-supervised learning. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32, pages 5049–5059, 2019. 1, 2, 5, 6, 7
- [6] Kaidi Cao, Colin Wei, Adrien Gaidon, Nikos Arachiga, and Tengyu Ma. Learning imbalanced datasets with label-distribution-aware margin loss. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32, pages 1567–1578, 2019. 2
- [7] Olivier Chapelle, Bernhard Scholkopf, and Alexander Zien. Semi-supervised learning. *IEEE Transactions on Neural Networks*, 20(3):542–542, 2009. 1, 2
- [8] Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357, 2002. 2
- [9] Yanbei Chen, Xiatian Zhu, Wei Li, and Shaogang Gong. Semi-supervised learning under class distribution mismatch. In *AAAI Conference on Artificial Intelligence (AAAI)*, volume 34, pages 3569–3576, 2020. 7
- [10] Adam Coates, Andrew Ng, and Honglak Lee. An analysis of single-layer networks in unsupervised feature learning. In *International Conference on Artificial Intelligence and Statistics (AISTATS)*, volume 15, pages 215–223, 2011. 2, 5
- [11] Ekin D Cubuk, Barret Zoph, Jonathon Shlens, and Quoc V Le. Randaugment: Practical automated data augmentation with a reduced search space. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. 3
- [12] Yin Cui, Menglin Jia, Tsung-Yi Lin, Yang Song, and Serge Belongie. Class-balanced loss based on effective number of samples. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 9268–9277, 2019. 2, 5
- [13] Piew Datta and Dennis Kibler. Symbolic nearest mean classifiers. In *AAAI Conference on Artificial Intelligence (AAAI)*, pages 82–87, 1997. 3
- [14] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 248–255, 2009. 5
- [15] Terrance DeVries and Graham W Taylor. Improved regularization of convolutional neural networks with cutout. *arXiv preprint arXiv:1708.04552*, 2017. 3
- [16] Qi Dong, Shaogang Gong, and Xiatian Zhu. Imbalanced deep learning by minority class incremental rectification. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, 41(6):1367–1381, 2018. 1
- [17] Yves Grandvalet and Yoshua Bengio. Semi-supervised learning by entropy minimization. In *Advances in Neural Information Processing Systems (NIPS)*, volume 17, pages 281–296, 2005. 2
- [18] Lan-Zhe Guo, Zhen-Yu Zhang, Yuan Jiang, Yu-Feng Li, and Zhi-Hua Zhou. Safe deep semi-supervised learning for unseen-class unlabeled data. In *International Conference on Machine Learning (ICML)*, pages 3897–3906, 2020. 7
- [19] Agrim Gupta, Piotr Dollar, and Ross Girshick. Lvis: A dataset for large vocabulary instance segmentation. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 5356–5364, 2019. 2
- [20] Tao Han, Junyu Gao, Yuan Yuan, and Qi Wang. Unsupervised semantic aggregation and deformable template matching for semi-supervised learning. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 33, pages 9972–9982, 2020. 1, 3, 4
- [21] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 9729–9738, 2020. 4
- [22] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 770–778, 2016. 5
- [23] Youngkyu Hong, Seungju Han, Kwanghee Choi, Seokjun Seo, Beomsu Kim, and Buru Chang. Disentangling label distribution for long-tailed visual recognition. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6626–6636, June 2021. 2
- [24] Minsung Hyun, Jisoo Jeong, and Nojun Kwak. Class-imbalanced semi-supervised learning. *arXiv preprint arXiv:2002.06815*, 2020. 2
- [25] Bingyi Kang, Saining Xie, Marcus Rohrbach, Zhicheng Yan, Albert Gordo, Jiashi Feng, and Yannis Kalantidis. Decoupling representation and classifier for long-tailed recognition. In *International Conference on Learning Representations (ICLR)*, 2020. 2, 3
- [26] Jaehyung Kim, Youngbum Hur, Sejun Park, Eunho Yang, Sung Ju Hwang, and Jinwoo Shin. Distribution aligning refinery of pseudo-label for imbalanced semi-supervised learning. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. 1, 2, 5, 6, 7
- [27] Jaehyung Kim, Jongheon Jeong, and Jinwoo Shin. M2m: Imbalanced classification via major-to-minor translation. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 13896–13905, 2020. 2

- [28] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. *Technical report*, 2009. 2, 5
- [29] Chia-Wen Kuo, Chih-Yao Ma, Jia-Bin Huang, and Zsolt Kira. Featmatch: Feature-based augmentation for semi-supervised learning. In *European Conference on Computer Vision (ECCV)*, volume 18, pages 479–495, 2020. 1, 2
- [30] Samuli Laine and Timo Aila. Temporal ensembling for semi-supervised learning. In *International Conference on Learning Representations (ICLR)*, 2016. 2
- [31] Dong-Hyun Lee. Pseudo-label: The simple and efficient semi-supervised learning method for deep neural networks. In *Workshop on challenges in representation learning, ICML*, 2013. 1, 2, 3
- [32] Hyuck Lee, Seungjae Shin, and Heeyoung Kim. Abc: Auxiliary balanced classifier for class-imbalanced semi-supervised learning. *arXiv preprint arXiv:2110.10368*, 2021. 2, 5, 6
- [33] Junnan Li, Caiming Xiong, and Steven Hoi. Comatch: Semi-supervised learning with contrastive graph regularization. In *IEEE International Conference on Computer Vision (ICCV)*, 2021. 1
- [34] Junnan Li, Caiming Xiong, and Steven Hoi. Mopro: Weakly supervised learning with momentum prototypes. In *International Conference on Learning Representations (ICLR)*, 2021. 3
- [35] Yunru Liu, Tingran Gao, and Haizhao Yang. Selectnet: Learning to sample from the wild for imbalanced data training. In *Mathematical and Scientific Machine Learning*, volume 107, pages 193–206, 2020. 2
- [36] Aditya Krishna Menon, Sadeep Jayasumana, Ankit Singh Rawat, Himanshu Jain, Andreas Veit, and Sanjiv Kumar. Long-tail learning via logit adjustment. In *International Conference on Learning Representations (ICLR)*, 2021. 2, 5, 6
- [37] Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, and Shin Ishii. Virtual adversarial training: a regularization method for supervised and semi-supervised learning. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI)*, 41(8):1979–1993, 2018. 2
- [38] Avital Oliver, Augustus Odena, Colin A Raffel, Ekin Dogus Cubuk, and Ian Goodfellow. Realistic evaluation of deep semi-supervised learning algorithms. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 31, pages 3235–3246, 2018. 5, 7
- [39] Jongjin Park, Sukmin Yun, Jongheon Jeong, and Jinwoo Shin. Opencos: Contrastive semi-supervised learning for handling open-set unlabeled data. *arXiv preprint arXiv:2107.08943*, 2021. 7
- [40] Seulki Park, Jongin Lim, Younghun Jeon, and Jin Young Choi. Influence-balanced loss for imbalanced visual classification. In *IEEE International Conference on Computer Vision (ICCV)*, pages 735–744, 2021. 2
- [41] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 32, page 8026–8037, 2019. 5
- [42] Hieu Pham, Qizhe Xie, Zihang Dai, and Quoc V Le. Meta pseudo labels. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 11557–11568, 2021. 1
- [43] Sylvestre-Alvise Rebuffi, Alexander Kolesnikov, Georg Sperl, and Christoph H Lampert. icarl: Incremental classifier and representation learning. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pages 2001–2010, 2017. 3
- [44] Jiawei Ren, Cunjun Yu, shunan sheng, Xiao Ma, Haiyu Zhao, Shuai Yi, and hongsheng Li. Balanced meta-softmax for long-tailed visual recognition. In *Advances in Neural Information Processing Systems (NeurIPS)*, volume 33, pages 4175–4186, 2020. 2
- [45] Ruslan Salakhutdinov and Geoff Hinton. Learning a non-linear embedding by preserving class neighbourhood structure. In *Artificial Intelligence and Statistics*, pages 412–419. PMLR, 2007. 3
- [46] Leslie N Smith and Adam Conovaloff. Building one-shot semi-supervised (boss) learning up to fully supervised performance. *arXiv preprint arXiv:2006.09363*, 2020. 2
- [47] Jake Snell, Kevin Swersky, and Richard Zemel. Prototypical networks for few-shot learning. In *Advances in Neural Information Processing Systems (NIPS)*, volume 30, pages 4077–4087, 2017. 1, 3
- [48] Kihyuk Sohn, David Berthelot, Chun-Liang Li, Zizhao Zhang, Nicholas Carlini, Ekin D Cubuk, Alex Kurakin, Han Zhang, and Colin Raffel. Fixmatch: Simplifying semi-supervised learning with consistency and confidence. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. 1, 2, 3, 4, 5, 6, 7, 8
- [49] Jong-Chyi Su and Subhransu Maji. The semi-supervised inaturalist-aves challenge at fgvc7 workshop, 2021. 1, 2, 5, 7
- [50] Antti Tarvainen and Harri Valpola. Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In *Advances in Neural Information Processing Systems (NIPS)*, volume 30, pages 1195–1204, 2017. 2, 6, 7
- [51] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(11), 2008. 8
- [52] Grant Van Horn, Oisin Mac Aodha, Yang Song, Yin Cui, Chen Sun, Alex Shepard, Hartwig Adam, Pietro Perona, and Serge Belongie. The inaturalist species classification and detection dataset. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 8769–8778, 2018. 2
- [53] Xudong Wang, Long Lian, Zhongqi Miao, Ziwei Liu, and Stella Yu. Long-tailed recognition by routing diverse distribution-aware experts. In *International Conference on Learning Representations (ICLR)*, 2021. 2
- [54] Chen Wei, Kihyuk Sohn, Clayton Mellina, Alan Yuille, and Fan Yang. Crest: A class-rebalancing self-training framework for imbalanced semi-supervised learning. In *IEEE*

- Conference on Computer Vision and Pattern Recognition (CVPR)*, 2021. [1](#), [2](#), [5](#), [6](#), [7](#)
- [55] Liuyu Xiang, Guiguang Ding, and Jungong Han. Learning from multiple experts: Self-paced knowledge distillation for long-tailed classification. In *European Conference on Computer Vision (ECCV)*, pages 247–263, 2020. [2](#)
- [56] Qizhe Xie, Zihang Dai, Eduard Hovy, Minh-Thang Luong, and Quoc V Le. Unsupervised data augmentation for consistency training. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. [2](#), [3](#), [4](#)
- [57] Qizhe Xie, Minh-Thang Luong, Eduard Hovy, and Quoc V Le. Self-training with noisy student improves imagenet classification. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10687–10698, 2020. [1](#)
- [58] I Zeki Yalniz, Hervé Jégou, Kan Chen, Manohar Paluri, and Dhruv Mahajan. Billion-scale semi-supervised learning for image classification. *arXiv preprint arXiv:1905.00546*, 2019. [1](#)
- [59] Yuzhe Yang and Zhi Xu. Rethinking the value of labels for improving class-imbalanced learning. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. [2](#)
- [60] Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. In *British Machine Vision Conference (BMVC)*, pages 87.1–87.12, 2016. [5](#)
- [61] Boyan Zhou, Quan Cui, Xiu-Shen Wei, and Zhao-Min Chen. Bbn: Bilateral-branch network with cumulative learning for long-tailed visual recognition. In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 9719–9728, 2020. [2](#)

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