DISTRIUBITION-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 since they do not consider (1) class imbalance and (2) class distribution mismatch between labeled and unlabeled data. This paper addresses such a relatively under-explored problem, imbalanced semi-supervised learning, where heavily biased pseudo-labels can harm the model performance. Interestingly, we find that the semantic pseudo-labels from a similarity-based classifier in feature space and the traditional pseudo-labels from the linear classifier show the complementary property. To this end, we propose a general pseudo-labeling framework to address the bias motivated by this observation. The key idea is to class-adaptively blend the semantic pseudo-label to the linear one, depending on the current pseudo-label distribution. Thereby, the increased semantic pseudo-label component suppresses the false positives in the majority classes and vice versa. We term the novel pseudo-labeling framework for imbalanced SSL as Distribution-Aware Semantics-Oriented (DASO) Pseudo-label. Extensive evaluation on CIFAR10/100-LT and STL10-LT shows that DASO consistently outperforms both recently proposed re-balancing methods for label and pseudo-label. Moreover, we demonstrate that typical SSL algorithms can effectively benefit from unlabeled data with DASO, especially when (1) class imbalance and (2) class distribution mismatch exist and even on recent real-world Semi-Aves benchmark.

1 Introduction

Semi-supervised learning (SSL) [9] has shown to be one of the most promising ways to reduce the cost to construct labeled dataset by leveraging unlabeled data [5, 6, 33, 36, 49], and even to push the state-of-the-art supervised learning performances leveraging large-scale data [44, 56, 57]. The common approach of these algorithms is to produce pseudo-labels for unlabeled data based on a model’s prediction and utilize them for regularizing model training [5, 49]. However, most of the SSL methods including state-of-the-art ones heavily rely on the quality of the pseudo-labels [2]. For example, heavily biased pseudo-labels can be obtained from biased predictions [4] in learning with class imbalanced labels [29]. In some other cases, pseudo-labels can extremely be biased when the distribution of the labeled and unlabeled data greatly differs, as shown in Sec. 4. We call such a scenario, class-imbalanced SSL setup, which can further inducing the biased pseudo-labels. Hence, one of the key challenge in imbalanced SSL is to train a model while effectively dealing with the in-the-wild distribution that might come without any prior.

In this work, we first explore a semantic feature similarity-based pseudo-label, we call semantics-oriented pseudo-label (or semantic pseudo-label), which has been known to be less biased to majority classes [48, 27]. However, under imbalanced SSL setup, we observe that using only semantic pseudo-label leads to the reversed bias, which rather degrades the performance on the majorities. In other words, the semantic pseudo-labels show high recall in minority classes with decreased precision, while the traditional linear classifier-based pseudo-labels show high recall in majority classes, but low recall with high precision in the minorities. This complementary property of two different pseudo-labels motivates us to develop a new pseudo-labeling scheme: utilize one pseudo-label to reduce the other’s bias, which provides more balanced supervision to the model rather than only using either kind of the pseudo-label.

Code is available at: https://github.com/ytaek-oh/daso
In this regard, we propose a novel method of blending the two pseudo-labels in a class-adaptive way, coined Distribution-Aware Semantics-Oriented (DASO) Pseudo-label. Although prior works \cite{36,37} explored combining the two pseudo-labels with fixed weight, we find it sub-optimal in imbalanced SSL as demonstrated in Sec. 4.4. To the best of our knowledge, we are the first to blend linear and semantic pseudo-labels class-adaptively, to truly alleviate the bias of pseudo-label, leading to substantial improvements on balanced test criterion under imbalanced SSL. Then, we additionally introduce balanced prototype and semantic alignment loss to learn under balanced feature representation to encourage the model to produce less bias. Our method outperforms the currently proposed re-balancing methods without any prior knowledge of the distribution of the unlabeled dataset.

Our DASO shows consistently favorable performance in various semi-supervised image classification datasets, CIFAR-10, CIFAR-100 \cite{31}, STL-10 \cite{13}, and a newly introduced realistic semi-supervised iNaturalist-Aves dataset \cite{50} with various levels of imbalance ratio for labeled and unlabeled datasets. Our method especially shows favorable performance gain in realistic scenarios when the labeled and unlabeled distribution is different or when the unlabeled data distribution is not known.

The key contributions in our work can be summarized as follows: (1) We propose a novel pseudo-label generation framework called DASO, which adaptively blends the semantic and linear pseudo-labels observing current distribution of pseudo-labels. (2) We provide extensive experiments that show the favorable performance gain of our method over the strong baselines on challenging and realistic setups, especially when the imbalance of the pseudo-labels is severe.

2 Related work

Class-imbalanced learning. Datasets that well capture the dynamic nature of “real-world” exhibits class-imbalanced, or long-tailed label distributions \cite{22,53}. Learning on such real-world datasets has been a great challenge to deep neural networks, since they cannot generalize well to the rare classes \cite{4}. Conventional approaches to learn class-balanced objectives include data re-sampling \cite{1,10,30}, and cost-sensitive re-weighting \cite{7,15}. Another approaches focus on decoupling representation and classifier \cite{27,63}. Recently, margin-based ad-hoc processing method \cite{39} also shown to be effective. Some recent work proposed to use unlabeled data \cite{38,58} in class-imbalanced learning. Unlike all the aforementioned works, we focus on alleviating the bias in pseudo-labels for SSL.

Semi-supervised learning. Semi-supervised learning (SSL) aims to learn from both labeled and unlabeled data. Classical SSL methods generate pseudo-labels from model’s prediction via pseudo-labeling \cite{35}, consistency regularization \cite{40,52} and combinations of them \cite{5,6,33,49} to train unlabeled examples under cluster assumption \cite{9}. However, biased pseudo-labels from either class imbalance or distribution mismatch give inadequate supervision \cite{41} to the model, which poses a potential challenge in SSL. We find that pseudo-label re-balancing methods \cite{26,29,54} and generating pseudo-labels from semantic classifier \cite{23} cannot fully address the bias. In this aspect, we devise a new method that can generate truly balanced pseudo-labels.

3 Proposed method

We first formalize the problem setup in Sec. 3.1. Then, we enlighten the properties of two different pseudo-labels in terms of bias in Sec. 3.2. Finally, based on the observations, Sec. 3.3 describes the novel distribution-aware semantics-oriented (DASO) pseudo-label framework.

3.1 Imbalanced semi-supervised learning

We first define the problem setup and notations. We consider K-class semi-supervised image classification problem 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 \( f = f_\phi \circ f_{\theta}^{\text{enc}} \) consists of a feature encoder \( f_{\theta}^{\text{enc}} \) followed by a linear classifier \( f_\phi \), where \( \theta \) and \( \phi \) are the set of parameters of \( f_{\theta}^{\text{enc}} \) and \( f_\phi \), respectively. The input image \( x \) is paired with one-hot class label \( y \in \mathbb{R}^K \) to learn a supervised loss \( \mathcal{L}_{\text{cls}} \) (e.g., cross-entropy) with prediction \( p = f(x) \). In the while, a pseudo-label \( \hat{p} \in \mathbb{R}^K \) is assigned to each unlabeled image \( u \) from the model to further optimize another objective \( \mathcal{L}_u = \Phi_u(\hat{p}, f(u)) \). \( \Phi_u \) can be implemented with an entropy minimization \cite{20} or consistency regularization framework \cite{34,40,52}. We call \( \hat{p} = \text{PseudoLabel}(p) \) as the online pseudo-label since it is used for learning at the time of generation. Note that PseudoLabel(\cdot) can be any type of pseudo-labeler that takes prediction \( p = f(u) \), depending on the SSL algorithm.

Pseudo-labels can suffer from bias in nature since the target \( \hat{p} \) for \( \Phi_u \) comes from the model prediction, known as confirmation bias in SSL \cite{2}. In this work, we aim to handle the bias in online pseudo-labels caused by long-tailed

\[ \sum_k \hat{p}_k = 1 \text{ where } \hat{p}_k \in [0, 1]. \]
As noted in Sec. 3.1, pseudo-labeling with the final linear classifier, which has been widely adopted by most online imbalanced SSL, which poses a challenge in when learned on both imbalanced \( \mathcal{X} \) and \( \mathcal{U} \) at the same class distribution, while it drops to 35.7% when learned on the same imbalanced \( \mathcal{X} \) but balanced \( \mathcal{U} \). Moreover, \( \{M_k\}_k \), the class prior of \( \mathcal{U} \) is usually not accessible in practice, which poses a challenge in imbalanced SSL literature. Our goal is to obtain a robust pseudo-label under different underlying class distribution of \( \mathcal{U} \), even when the prior knowledge about \( \mathcal{U} \) is not available.

### 3.2 Exploring pseudo-label for imbalanced semi-supervised learning

As noted in Sec. 3.1, pseudo-labeling with the final linear classifier, which has been widely adopted by most online pseudo-label-based algorithms \([5, 49, 55]\), can degrade performances by inducing more biased pseudo-labels. We term this type of pseudo-label as linear pseudo-label for abbreviation. As a result, we explore another way to generate balanced pseudo-labels for imbalanced SSL.

**Semantics-oriented pseudo-labels.** As an alternative to obtaining biased linear pseudo-labels, pseudo-labels can be obtained from similarity-based classifier \([16, 46]\) by measuring the similarity of a given representation to an unlabeled sample in feature space, which we call semantics-oriented pseudo-labels (simply semantic pseudo-labels). Similarity-based classifier has been widely used in few-shot learning \([48]\), noisy label learning \([57]\) and other applications especially for reducing biased predictions \([45, 27]\). As one of the representative works in SSL, USADTM \([23]\) utilizes semantic pseudo-labeling method, attaining the state-of-the-art under several balanced SSL benchmarks. In the following paragraph, we conduct a simple experiment to explore whether semantic pseudo-labels can truly replace the traditional linear pseudo-labels even in the imbalanced SSL scenarios.

**Trade-offs between linear and semantic pseudo-label.** We test two models learned with linear and semantic pseudo-labels, respectively, on long-tailed CIFAR-10 for SSL \([15]\). \( N_1 \) and \( M_1 \), the size of the head class for labeled and unlabeled data is set to 500 and 4000 respectively with the imbalance ratio \( \gamma = 100 \) in both data. We provide more details in Sec. 4.1. We consider FixMatch \([49]\) and USADTM \([23]\), both of which are known to be state-of-the-art methods that leverage linear and semantic pseudo-labels respectively, under balanced benchmarks. We then investigate the properties of pseudo-labels obtained from each and their effect on the balanced test criterion.

From Fig. 1a and 1b, the linear pseudo-labels from FixMatch \([49]\) achieve high recall in majority classes while low recall but high precision in the minorities, suggesting that they are biased towards the head. In contrast, the bias comes reversely in semantic pseudo-label case of USADTM \([23]\), where the actual majority classes are abnormally predicted to the minorities as pseudo-labels, leading to the catastrophic drop in precision of minority pseudo-labels in Fig. 1b. Considering the balanced test accuracy, FixMatch performs poorly on the minorities. USADTM shows relatively increased test accuracy on the tail by virtue of more abundant minority pseudo-labels, but loses accuracy on the head.
significantly. Accordingly, the overall increase in accuracy is limited when only using semantic pseudo-labels. We provide two lessons from the simple experiment in Fig. 1 as summarized by:

1. Semantic pseudo-label is not a complete solution for the imbalanced SSL as the reversed bias towards the tail side incurs, which leads to the limited accuracy gain.
2. The linear and semantic pseudo-label have the complementary property in terms of bias.

These empirical findings motivate us to exploit the only ‘desired’ property for a specific class from linear and semantic pseudo-labels. To this end, we introduce DASO, a new pseudo-labeling framework under imbalanced SSL, which adaptively blends the linear and semantic pseudo-labels based on the current distribution of the pseudo-label. Fig. 1 illustrates efficacy of the proposed method to alleviate the bias across the classes and to improve the overall performance.

### 3.3 Distribution-aware semantics-oriented (DASO) pseudo-label

Our goal is to obtain unbiased pseudo-labels under imbalanced SSL by adaptively blending two complementary linear and semantic pseudo-labels, based on the current distribution. We term the novel framework as Distribution-Aware Semantics-Oriented (DASO) Pseudo-label.

**Framework overview.** Our method consists of two main complementary pseudo-labels. The first one is obtained from a linear classifier followed by any type of traditional pseudo-labeler [49]: \( \hat{p} = \text{PseudoLabel}(p) \) with \( p = f^{\text{enc}}_\theta(z) \), where \( z = f^{\text{mc}}_\theta(u) \) corresponds to a feature in the penultimate layer. In addition, to obtain semantics-oriented pseudo-label \( q \), balanced class prototypical representations \( C \) are constructed and constantly updated using features from \( X \). Then, each feature \( z = f^{\text{mc}}_\theta(u) \) is assigned to the most similar prototype to determine the semantic label. Finally, we blend those two complementary pseudo-labels to obtain the final pseudo-label \( p' \) in such a way that \( q \) is more blended to \( \hat{p} \) as \( \hat{p} \) points to majority classes more, with respect to the current pseudo-label distribution. The debiased pseudo-label \( p' \) is further used to compute \( \Phi_u \) defined in each SSL algorithm.

**Balanced prototype generation.** To setup a semantic similarity-based classifier, we build a set of class prototypes \( C = \{c_k\}_{k=1}^K \) to serve as the reference for assigning semantic pseudo-labels to the samples in \( U \). A naïve way to create a centroid \( c_k \) for class \( k \) is to average all the features over the labeled samples in class \( k \). However, exhaustively computing all the features in class \( k \) is both (1) computationally inefficient and (2) vulnerable to the bias in the labeled dataset. Hence, we build a dictionary of memory queue \( Q = \{Q_k\}_{k=1}^K \) where each key corresponds to class label and \( Q_k \) denotes a queue for class \( k \) with the size \(|Q_k|\). The centroid of features in \( Q_k \) represents the class prototype \( c_k \) for class \( k \) in the while new labeled features enter \( Q \) and some of the old ones are discarded after \( Q \) becomes full at every step: \( c_k = \frac{1}{|Q_k|} \sum_{i \in Q_k} z_i \).

Besides the simple prototype generation process, we introduce two additional tricks over Han et al. [23] for the balanced prototypes. First, instead of setting the size of \( Q_k \) in proportional to the size of class \( k \) (i.e., class frequency), we fix the size of \( Q_k \) for all classes to the same amount. With the equal size of the memory queue over the classes, one can enjoy the balanced effect in the prototypes; the same amount of features contribute to extract the prototype. The second is to adopt momentum encoder \( f^{\text{mc}}_\theta \) for the moderate pace of network parameter update, where \( f^{\text{mc}}_\theta \) shares the same architecture of the original feature encoder \( f^{\text{enc}}_\theta \), but the set of parameters \( \theta' \) is updated by exponential moving average (EMA) of \( \theta \) with momentum ratio \( \rho \), i.e., \( \theta' \leftarrow \rho \theta' + (1 - \rho) \theta \). This prevents high variance in \( C \) across iteration, caused by the abrupt network parameter updates and class-imbalanced labels. We verify the effectiveness of EMA for prototype generation in Sec. 4.3.

**Linear and semantic pseudo-label generation.** In our framework, we obtain the linear pseudo-label of \( u \in U \) using the (potentially biased) classifier: \( \hat{p} = \text{PseudoLabel}(p) \) with \( p = f^{\text{cls}}_\theta(z) \), where \( z = f^{\text{mc}}_\theta(u) \). The semantic pseudo-label \( q \in \mathbb{R}^K \) is generated from a similarity-based classifier, by assigning the most similar prototype along with the balanced prototypes \( C \) to \( z \) in feature space:

\[
q_k = \frac{\exp \left( \text{sim}(z, c_k) / T_{\text{proto}} \right)}{\sum_{k'=1}^K \exp \left( \text{sim}(z, c_{k'}) / T_{\text{proto}} \right)} = \sigma(\text{sim}(z, c_k) / T_{\text{proto}}),
\]

where \( \sigma(\cdot) \) and \( \text{sim}(. , .) \) correspond to softmax activation and cosine similarity respectively, and \( T_{\text{proto}} \) is a temperature hyper-parameter for the prototype-based classifier. In imbalanced SSL, \( \hat{p} \) is biased towards head classes (low recall but high precision in minority classes) and \( q \) is the vice versa.

**Distribution-aware pseudo-label blending.** To obtain unbiased pseudo-labels that are truly helpful to the model, it is necessary for the semantic pseudo-labels to be exploited in the right place. To this end, we design a simple strategy of ‘blending’ linear and semantic pseudo-labels, where we more increase the exposure of the semantic ones to the model in place of the linear ones, as the linear ones make more biased predictions. We take mixup [62] approach on those two
pseudo-labels to alleviate the extreme bias when only using either \( \hat{p} \) or \( q \).

\[
\hat{p}' = (1 - u_k') \hat{p} + u_k' q,
\]

(2)

where \( u = \{u_k\}_{k=1}^{K} \) is the normalized distribution of the current pseudo-labels with \( k' \) as the class prediction from the linear pseudo-label \( \hat{p} \) (i.e., \( k' = \text{argmax}_k \hat{p}_k \)), computed by \( u_k = \frac{1}{\max_i \tilde{m}_i^{1/T_{\text{dist}}}} \left( \tilde{m}_k^{1/T_{\text{dist}}} \right) \), where \( \tilde{m}_k \) corresponds to the frequency of each class in the current pseudo-labels by counting the statistics of the pseudo-labels, and the temperature hyper-parameter \( T_{\text{dist}} \) intercedes the optimal trade-offs between \( \hat{p} \) and \( q \). According to the formulation, when the linear pseudo-label \( \hat{p} \) generates too many majority classes, the more semantic pseudo-label \( q \) which has the opposite property is blended. On the other hand, the resulting pseudo-label \( \hat{p}' \) more favors \( \hat{p} \) in high precision when \( \hat{p} \) predicts the minority classes. Finally, from Eqn. (2), one can exploit the high-precision nature of \( \hat{p} \) for the minorities, while effectively suppress the false positives of \( \hat{p} \) by more attending \( q \) for the majorities.

3.4 Learning DASO framework

Semantic alignment loss. Recent SSL approaches adopt advanced advanced augmentation \([14]\) to fully benefit from the consistency training framework \([6, 49, 55]\). Moreover, the recent progress of representation learning works has demonstrated superior performance in both self-supervised \([8, 19]\) and semi-supervised \([3, 11, 61]\) approaches. Integrating these ideas, we propose to train DASO framework with an additional regularizer called semantic alignment loss \( \mathcal{L}_{\text{align}} \), which imposes consistent assignment of two different views of \( u \) to \( C \) in feature space. The semantic pseudo-label \( q(u) \) in Eqn. (1) from the weakly augmented sample \( u = A_u(u) \) is reused to provide the target for the assignment prediction \( q(s) \) from the advanced augmented one \( u = A_u(s) \) to the cross-entropy loss: \( \mathcal{L}_{\text{align}} = \mathcal{H}(q(u), q(s)) \). Since \( \mathcal{L}_{\text{align}} \) relates the unlabeled examples to the label space through assigning \( C \) constructed from labeled features, the enhanced representation can implicitly guide the classifier \( f_{\hat{p}} \) to produce less biased predictions, as demonstrated in Sec. 4.4.

Total objective. DASO framework can be built upon any existing SSL methods that use \( X \) and \( U \), to generate balanced pseudo-labels on learning both prediction and representation-level objectives:

\[
\mathcal{L}_{\text{DASO}} = \mathbb{E}_{(x,y) \in X} \left[ \mathcal{H}(y, f(x)) \right] + \mathbb{E}_{u \in U} \left[ \lambda_u \Phi_u \left( \hat{p}' , f \left( u(s) \right) \right) \right] + \lambda_{\text{align}} \mathcal{H} \left( q(u) , q(s) \right),
\]

(3)

where \( \mathcal{L}_u \) is for \( X \), \( \mathcal{L}_u \) takes the blended pseudo-labels obtained by DASO into \( \Phi_u \), the objective from the base method for \( U \) (i.e., cross-entropy between pseudo-label and the prediction in case of FixMatch \([49]\)), and \( \mathcal{L}_{\text{align}} \) corresponds to the representation-level objective, respectively.

4 Experiments

In this section, we demonstrate the effectiveness of our framework from a wide range of semi-supervised image classification benchmarks, especially when pseudo-labels of unlabeled data can be heavily biased. First, we describe the experimental setup in Sec. 4.1. From Sec. 4.2 and 4.3, we compare our method with other baseline methods under various scenarios. Finally, Sec. 4.4 conducts ablation study to highlight the contribution of each proposed component to the overall improvements.

4.1 Experimental setup

We present the full details of experimental setup including benchmark information, implementation details with all hyper-parameters and training protocols in Appendix Sec. C.

Datasets. We perform experiments on image classification benchmarks typically adopted in semi-supervised learning literature \([49, 52]\): CIFAR-10/100 \([31]\) and STL-10 \([13]\). For these benchmarks, we first randomly select the same amount of labels per class, and we assume the remaining data to be unlabeled. Then, we vary the size and level of imbalance for both splits, where \( N_1 (M_1) \) and \( \gamma_1 (\gamma_n) \) determine the head class size and imbalance ratio of labeled (unlabeled) data, respectively. Based on the two factors we curate a long-tailed dataset over classes, following the protocol of Cui et al. \([15]\). We specify ‘LT’ here, meaning that each dataset is manipulated in such a way. Moreover, we validate our method on a newly introduced challenging long-tailed Semi-Supervised iNaturalist-Aves (Semi-Aves) dataset \([50]\) where \( U \) contains large non-target class examples.

Baseline methods. First, we consider supervised learning baseline, learning cross-entropy loss for only long-tailed labeled data, named Vanilla. For baseline semi-supervised learning algorithms (i.e., without considering class imbalance),
our DASO is mainly based on FixMatch [49], shows state-of-the-art performance on balanced benchmarks. As one of the semantic pseudo-labeling methods, we also consider the state-of-the-art USADTM [23]. In addition, we compare our algorithm with other re-balancing methods targeted for either labels (i.e., using only labeled data) or pseudo-labels (i.e., learning with both labeled and unlabeled data), and the combination of them. In particular, we consider LDAM-DRW [7]: adopts decision boundary-aware re-weighting strategy, cRT [27]: decouples representation and classifier learning for natural and balanced objective, and logit adjustment (LA) [29]: encourages relative margin on logits depending on class frequency for class re-balancing using only labels. For class re-balancing in pseudo-labels, we consider BOSS [47]: applies re-weighting on consistency term and adaptive confidence threshold based on the pseudo-label distribution, and DARP [29]: adjusts the distribution of biased pseudo-labels to the class prior via solving a convex optimization.

**Training and evaluation.** We have re-implemented all baseline methods considered using Pytorch [43] and conduct experiments under the same codebase, as suggested by Oliver et al. [41]. We train Wide ResNet-28-2 [60] with 1.5M parameters on CIFAR10-LT, CIFAR100-LT, and STL10-LT as a backbone. For training Semi-Aves, we fine-tune the ResNet-34 [24] with 21.3M parameters on ImageNet [17] pre-trained weights provided by the official torchvision library. To evaluate a SSL model, we maintain exponential moving average (EMA) of network parameters at each parameter update. As note, while the similarity-based classifier with prototypes in Sec. 3.3 is only used for generating semantic pseudo-labels in train phase, the class score is measured via learned linear classifier for the inference. We measure the top-1 accuracy of the model on the balanced test data every epoch and finally obtain the median of the accuracy values in the last 20 evaluations, following the standard evaluation protocols [4]. When reporting the performance, we compute the mean and standard deviation of three runs with different random seeds. Experiments on small benchmarks and Semi-Aves are conducted with a Titan Xp GPU (12GB) and four Quadro RTX8000 GPU (48GB × 4), respectively, which take less than 10 and 11 hours each. The codebench will be released later.

### 4.2 Results on CIFAR10-LT, CIFAR100-LT, and STL10-LT.

**Main results.** We extensively evaluate DASO with other baseline methods including semi-supervised learning without considering imbalance (SSL), label re-balancing methods (LB) and pseudo-label re-balancing methods (PB). We report the performance of all baseline methods along with DASO in Table 1. Experiments on the other baseline methods can also be found in Appendix Table 12. We find that all baseline methods even including the recent state-of-the-art methods, FixMatch [49] and USADTM [23], suffer from performance degradation from decreased label size under imbalanced data. On the other hand, our DASO provides substantial performance gain over the baseline FixMatch [49] in all cases. In particular, DASO applied to FixMatch exhibits +14% accuracy gain on STL10-LT with \( N_1 = 150 \). In addition, DASO shows favorable performances in most of the setups compared to the recent pseudo-label re-balancing methods: DARP [29] and BOSS [47]. As note, we demonstrate that DASO can reliably improve the performances on more challenging imbalance scenarios (i.e., \( \gamma_1 \neq \gamma_3 \) and higher imbalance) compared the other PB methods in Table 2. Also
We evaluate DASO on a realistic dataset, we further consider the recent logit adjustment (LA) [39] for re-balancing labels that might be directly applied to the median of the accuracy values in last 20 epochs (Med20 Top1) following the standard in evaluating SSL [41]. More balanced by U contains massive out-of-class examples (Uout) that do not belong to any of the classes in X. The details on the class distribution can be found in Su and Maji [50]. Table 3 shows the results on Semi-Aves dataset. We report in both cases of U = Uin and U = Uin + Uout, where Uin contains examples that shares the class of X. We measure the performances by balanced top-1 accuracy, reporting the one in the best (Best Top1) and at the last epoch (Last Top1). We also report the median of the accuracy values in last 20 epochs (Med20 Top1) following the standard in evaluating SSL [41]. More details can be found in Appendix Sec. C.

In case of U = Uin. As it has the distribution gap in X and U, DARP [29] optimization with the inadequate class prior from X leads to worse performance than the baseline FixMatch [49]. On the contrary, DASO shows the best performance with reliably improving over the baseline FixMatch.

In case of U = Uin + Uout. Since U contains large amount of non-target classes, performance degradation is observed consistently across all baselines, as similar observations are made in [12] [21] [42] [51]. While FixMatch attains the best top1 at a moment, it gradually drops along with the effect from non-target classes in Uout. Among the baselines, DASO

| Algorithm       | γu = 100 | γu = 1 |
|-----------------|----------|-------|
| Mean Teacher    | 52.2 ± 1.09 | 42.3 ± 0.73 |
| w/ DASO (Ours)  | 53.3 ± 1.60 | 75.7 ± 1.19 |
| MixMatch        | 57.3 ± 2.96 | 35.5 ± 1.30 |
| w/ DASO (Ours)  | 60.6 ± 1.15 | 66.7 ± 2.53 |

Table 4: Comparison of accuracy (%) with pseudo-label re-balancing (PB) methods on CIFAR10-LT, CIFAR100-LT, and STL10-LT with more challenging imbalance scenarios. Our method (DASO) consistently improves the baseline FixMatch [49] and shows the best performance among the other PB baselines in most of the setups.

Table 4: Ablation study on Tdist for blending. We select Tdist by 1.5 and 0.3 each.

| Algorithm       | Tdist      | C10 | STL10 |
|-----------------|------------|-----|-------|
| FixMatch        | 68.25      | 55.53 |
| w/ BOSS         | 73.97      | 70.21 |
| w/ DARP         | 74.47      | 68.35 |
| w/ DASO (Ours)  | 75.97      | 64.54 |

Table 3: Comparison of accuracy (%) from DASO upon other classic SSL methods: MeanTeacher [52] and MixMatch [5].
We also conduct an ablation study to understand why the proposed DASO framework can reliably provide performance over the Vanilla, improving the performance in Table 1 by 17%. Note that FixMatch that learned linear pseudo-label shows even lower accuracy on STL10. This shows that using linear pseudo-label on imbalanced data rather harms the model training. Exp 2 is the result when a model is trained with $\mathcal{L}_{\text{align}}$ along with DASO, but $\upsilon_k = 0$ for all $k$. In other words, the model is only trained with linear pseudo-labels of FixMatch + $\mathcal{L}_{\text{align}}$ without using semantic pseudo-labels. Note that the performance of Exp 2 is higher than that of typical FixMatch, and the performance of Exp 5 (our full version method but without $\mathcal{L}_{\text{align}}$) is worse than that of our complete DASO model. This implies that our semantic alignment loss can help improving the model performance with the existence of imbalanced datasets.

Effect of pseudo-label blending. Exp 2, 3, and 4 in Table 6 are the results of our DASO method, but with different pseudo-label blending approaches with constant weights. From Exp 2 and 4, as discussed in Sec. 3.2 due to the bias in the pseudo-labels, using either linear or semantic pseudo-label leads to a marginal performance gain, or even a performance drop. In addition, from Exp 3, blending the pseudo-labels with constant weights (0.5) shows lower performance compared to our final DASO method (with distribution-aware class-wise blending) by a large margin.

Effect of balanced prototype. Exp 6, 7, and 8 in Table 6 shows the results of our DASO method with different design choices in prototype generation explained in Sec. 3.3 balanced prototypes with EMA encoder. When generating a class prototype $C$ with memory queue, using naïve (imbalanced) queuing using an encoder without EMA (Exp 6) leads to the worst performance. In addition, our final DASO model with both balanced queuing using EMA encoder shows the best performance.

Effect of $T_{\text{dist}}$. In Table 4 we show an ablation study results on the temperature hyper-parameter $T_{\text{dist}}$ to compute the weights for pseudo-label blending described in Eqn. (2). 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.
5 Conclusion

In this work, we proposed a novel pseudo-label blending method, distribution-aware semantics-oriented pseudo-label (DASO), to generate less biased pseudo-labels for imbalanced semi-supervised learning. DASO motivates from the interesting observation that linear pseudo-label and semantic pseudo-label biases are complementary across different classes. 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 setups. Despite the simplicity and efficacy of DASO with challenging benchmarks, future researches would explore how to ‘optimally’ balance the trade-off in a theoretically grounded way.

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# Notations

Table 7: Notations and their descriptions used throughout this work.

| Notation | Description |
|----------|-------------|
| DASO     | Distribution-Aware Semantic-Oriented (Pseudo-label) |
| SSL      | Semi-Supervised Learning. |
| $K$      | The number of classes in the labeled dataset. |
| $\mathcal{X}$, $\mathcal{U}$ | Labeled dataset and unlabeled dataset. |
| $N$, $M$      | Total number of examples in labeled dataset and unlabeled dataset. |
| $N_k$, $M_k$ | Number of examples in class $k$ for labeled dataset and unlabeled dataset. |
| $\gamma_l$, $\gamma_u$ | Imbalance ratio for labeled dataset and unlabeled dataset. |
| $\hat{m}$ | Empirical pseudo-label distribution in probability form; $\hat{m} \in [0, 1]^K$. |
| $\sigma(\cdot)$ | Softmax activation. |
| $\mathcal{H}(y, p)$ | Cross-entropy between the target $y$ and prediction $p$. |
| $\text{sim}(\cdot, \cdot)$ | Cosine similarity. |
| $f$ | A classification model; a feature encoder $f_{\text{enc}}^{\theta}$ followed by a linear classifier $f_{\text{cls}}^{\phi}$. |
| $f_{\text{enc}}^{\theta}$ | An EMA encoder (momentum encoder). |
| $\rho$ | Decay ratio for the momentum encoder. |
| $Q$ | A dictionary of memory queue; $\{Q_k\}_{k=1}^K$. |
| $L$ | The maximum queue size for the balanced memory queue. |
| $C$ | A set of class prototypes; $\{c_k\}_{k=1}^K$. |
| $T_{\text{proto}}$ | A temperature factor for the similarity-based classifier. |
| $T_{\text{dist}}$ | A temperature factor for the empirical pseudo-label distribution. |
| $\hat{p}$, $q$ | A linear pseudo-label and semantic pseudo-label. |
| $\upsilon$ | Class-specific mixup factor for the linear and semantic pseudo-label; $\{\upsilon_k\}_{k=1}^K$. |
| $\tilde{p}$ | A blended pseudo-label. |
| $\Phi_u(\cdot, \cdot)$ | A regularizer for $\mathcal{U}$, specified by an SSL algorithm. |
| $\lambda_u$ | A weighting factor for $\mathcal{L}_u$. |
| $\mathcal{L}_{\text{align}}$ | Semantic alignment loss. |
| $\lambda_{\text{align}}$ | A weighting factor for $\mathcal{L}_{\text{align}}$. |
| $P$ | Pre-train steps for applying pseudo-label blending and $\mathcal{L}_{\text{align}}$. |
| $A_w$ | A set of weak augmentations; horizontal flip and/or crop. |
| $A_s$ | A set of strong augmentations; RandAugment [14]. |
| $\mu$ | Unlabeled batch ratio; multiplied to the labeled batch size $B$. |
B Algorithm

Alg. 1 summarizes the blending procedure for linear and semantic pseudo-labels based on the empirical pseudo-label distribution, and Alg. 2 represents the whole DASO framework built upon a typical SSL algorithm whose pseudo-labeler and regularizer correspond to PseudoLabel(·) and \( \Phi_u \).

**Algorithm 1** Distribution-aware pseudo-label blending. \( \hat{p}' \leftarrow \text{Blend}(\hat{p}, q, T_{\text{dist}}) \).

**Input:** Linear pseudo-label \( \hat{p} \in [0, 1]^K \), semantic pseudo-label \( q \in [0, 1]^K \).

**Temperature factor for pseudo-label distribution** \( T_{\text{dist}} \).

**Require:** Empirical pseudo-label distribution \( \hat{m} = \{ \hat{m}_k \}_{k=1}^K \in [0, 1]^K \).

**Output:** Blended pseudo-label \( \hat{p}' \in [0, 1]^K \).

for \( k = 1 \) to \( K \) do

\( v_k \leftarrow \hat{m}_k^{1/T_{\text{dist}}} \) \{Temperature scaling for empirical pseudo-label distribution.\}

\( v_k \leftarrow v_k / \max_k v_k \) \{Normalization for blending.\}

end for

\( k' \leftarrow \arg\max_k \hat{p}_k \) \{Class prediction for linear pseudo-label.\}

\( \hat{p}' \leftarrow (1 - v_{k'})\hat{p} + v_{k'}q \) \{Pseudo-label blending.\}

**Algorithm 2** Distribution-Aware Semantic-Oriented (DASO) Pseudo-label framework.

**Input:** A batch of labeled data \( \mathcal{X}_B = \{ (x_i, y_i) \}_{k=1}^B \) and unlabeled data \( \mathcal{U}_B = \{ u_k \}_{k=1}^B \).

Network for feature encoder \( f_{\theta}^{\text{enc}} \), momentum encoder \( f_{\theta}^{\text{enc}} \), and linear classifier \( f_{\phi}^{\text{cls}} \).

Dictionary of memory queue \( Q = \{ Q_k \}_{k=1}^K \), Momentum decay ratio \( \rho \).

Maximum queue size \( L \), temperature factor for similarity-based classifier \( T_{\text{proto}} \).

Pre-train steps for pseudo-label blending \( P \), current training step \( t \).

**Require:** A set of weak augmentations \( A_{\text{wu}} \) and strong augmentations \( A_{\text{s}} \).

**[Balanced Prototype Generation.]**

Enqueue \( z^{(l)} \) into \( Q_k \), where \( z^{(l)} = f_{\theta}^{\text{enc}}(x) \) and \( k \leftarrow y, \forall (x, y) \in \mathcal{X}_B \).

Dequeue the earliest elements from \( Q_k \) s.t. \( |Q_k| = L, \forall k \in \{1, \ldots, K \} \).

\( c_k \leftarrow \frac{1}{|Q_k|} \sum_{z \in Q_k} z, \forall k \in \{1, \ldots, K \} \). \{A set of balanced prototypes \( C = \{ c_k \}_{k=1}^K \} \}

**[Pseudo-label generation.]**

for \( u \) in \( \mathcal{U}_B \) do

\( z^{(u)} \leftarrow f_{\theta}^{\text{enc}}(A_{\text{wu}}(u)) \), \( z^{(s)} \leftarrow f_{\theta}^{\text{enc}}(A_{\text{s}}(u)) \) \{feature extraction\}

\( \hat{p} \leftarrow \text{PseudoLabel}(f_{\phi}^{\text{cls}}(z^{(u)})), q^{(u)} \leftarrow \sigma(\text{sim}(z^{(u)}, C) / T_{\text{proto}}) \)

\( \hat{p}' \leftarrow \text{Blend}(\hat{p}, q^{(u)}, T_{\text{dist}}) \) if \( t \geq P \) else \( \hat{p} \) \{Blend pseudo-labels after \( P \) train steps.\}

end for

**[Compute losses.]**

\( L_{\text{cls}} \leftarrow \mathbb{E}_{(x, y) \in \mathcal{X}_B} \left[ \mathcal{H} \left(y, \sigma \left(f_{\phi}^{\text{cls}} \circ f_{\theta}^{\text{enc}}(x) \right) \right) \right] \)

\( L_{\text{align}} \leftarrow \mathbb{E}_{u \in \mathcal{U}_B} \left[ \mathbb{I} (t \geq P) \cdot \mathcal{H} \left(q^{(u)}, q^{(s)} \right) \right] \) where \( q^{(s)} \leftarrow \sigma(\text{sim}(z^{(s)}, C) / T_{\text{proto}}) \).

\( L_u \leftarrow \mathbb{E}_{u \in \mathcal{U}_B} \left[ \Phi_u \left( \hat{p}', p^{(s)} \right) \right] \) where \( p^{(s)} \leftarrow f_{\phi}^{\text{cls}}(z^{(s)}) \).

\( L_{\text{DASO}} \leftarrow L_{\text{cls}} + \lambda_u L_u + \lambda_{\text{align}} L_{\text{align}} \)

**[Update parameters.]**

Update \( \theta \) and \( \phi \) to minimize \( L_{\text{DASO}} \) via SGD optimizer.

\( \theta' \leftarrow \rho \theta' + (1 - \rho) \theta \) \{Update the parameters of momentum encoder.\}

\( t \leftarrow t + 1 \)
C Detailed experimental setup

C.1 Datasets

To demonstrate the efficacy of the proposed framework for alleviating imbalance in pseudo-labels, DASO learns on several datasets with *long-tailed* class distribution with respect to labels. For the unlabeled dataset, we do not make any assumptions on the underlying class distribution; we mainly conduct experiments in the case of identical distribution (i.e., $\gamma_l = \gamma_u$), but we also test more realistic scenario where $\gamma_l \neq \gamma_u$ and unlabeled data contain several unknown classes, which can damage the performance of SSL as a special case.

**CIFAR-10 and CIFAR-100.** CIFAR [31] datasets originally have the same number of examples per class; 5000 and 500 examples in $32 \times 32$ sized image for CIFAR-10 and CIFAR-100, respectively. We introduce two parameters, the head class size $N_1$ and imbalance ratio of labels $\gamma_l$ to craft the synthetically long-tailed variants across the level of imbalance and total amount of labels, following the protocol from Kim et al. [29]. The number of examples other than the head class is calculated by $N_k = N_1 \cdot \gamma_l^{\frac{k-1}{K-1}}$ as proposed by Cui et al. [15]. Note that each $N_k$, the number of examples in class $k$ is sorted in a descending order (i.e., $N_1 \geq \cdots \geq N_K$). Similarly, the number of examples per class for the unlabeled dataset can be determined by: $M_k = M_1 \cdot \gamma_u^{\frac{k-1}{K-1}}$ using the labels, and the true labels are thrown away before training. For each trial, we randomly sample the examples for the labeled and unlabeled dataset respectively, controlled by a random seed. We call CIFAR10-LT and CIFAR100-LT for those variants, which consist of labeled and unlabeled splits. We measure the performance on the balanced test dataset, which have $10k$ examples in total.

**STL-10.** To generate STL10-LT, a *long-tailed* variant of STL-10 [13], we follow the same process as explained in above for the labeled dataset. Besides the $5k$ labeled examples, STL-10 contains additional $100k$ unlabeled examples from a similar but broader distribution compared to the labeled dataset. Since the information about the class distribution of the unlabeled dataset is not known, we only construct imbalanced labeled dataset and use the whole $100k$ unlabeled examples for training.

**Semi-Aves.** We also evaluate DASO framework on the Semi-Supervised iNaturalist-Aves (Semi-Aves) dataset [50] to verify that it also performs well in large-scale and more realistic scenarios. Semi-Aves includes $1k$ species of birds sampled from the iNaturalist-2018 dataset [53] with *long-tailed* class distribution. Moreover, only $200$ species are considered in-class, and the other $800$ species correspond to the out-of-class (i.e., novel, open-set) categories for the unlabeled data. For in-class examples, about $4k$ examples are labeled, and the other $27k$ examples are unlabeled ($U_{in}$). Note that the class distribution of labeled data does not match that of $U_{in}$ ($\gamma_l \neq \gamma_u$), as illustrated in Su and Maji [50]. The out-of-class unlabeled data ($U_{out}$) have $122k$ examples in total. Semi-Aves benchmark provides $2k$ images and $8k$ images (i.e., 10 images and 40 images per class) for the validation and test dataset, respectively. Due to the compound effect of (1) long-tailed distribution and (2) predominant novel categories in large-scale, it poses a substantial challenges on SSL algorithms towards practical applications that several previous benchmarks for SSL such as CIFAR [31] and STL-10 [13] might not have considered. We combine the labeled training data and validation data, $6k$ in total, for the labeled dataset in our experiments to guarantee a reasonable baseline performance. As a note, we do not make distinction between $U_{in}$ and $U_{out}$ when learning on the whole unlabeled dataset ($U = U_{in} + U_{out}$).
C.2 Training details

CIFAR10-LT, CIFAR100-LT, and STL10-LT. Following the training protocol suggested in DARP [29], we train a Wide ResNet-28-2 [60] with 1.5M parameters for 250k iterations in both supervised (i.e., using only labels) and semi-supervised (i.e., using both labels and unlabeled data) learning methods, including the re-balancing methods for labels and pseudo-labels. We set the batch size of labeled data as 64, and the network is optimized by Nesterov SGD with momentum 0.9 and weight decay 5e-4. For the methods with using only labels, the base learning rate is set to 0.1 with linear warm-up applied during the first 2.5% of the total train steps, and decays after 80% and 90% of the training phase by a factor of 100, respectively, following [7]. For SSL methods using both labels and unlabeled data, we set the base learning rate as 0.03, which is fixed during the training. We further clarify the details for each method, such as hyper-parameters, in Sec. C.4. For the exponential moving average (EMA) network parameters in evaluating SSL models, the decay ratio (momentum) $\rho$ is set to 0.999 for all SSL methods across all the benchmarks considered here. As suggested by Oliver et al. [41], we measure the performance of the model for every 500 iterations, and report the median test accuracy of the last 20 evaluations.

Semi-Aves. We consider the standard ResNet-34 [24] architecture with 21.3M parameters for training. Due to the inherent challenge of the benchmark, we fine-tune it from the ImageNet [17] pre-trained weights to obtain acceptable performance of the baselines for comparison. For the supervised (Vanilla) method, we train the network for 90 epochs of labeled dataset, while we train 90 epochs of unlabeled data for SSL methods, using a SGD optimizer with momentum 0.9. The base learning rate is set to 0.1 and 0.04 for the Vanilla and SSL method each, with linear warm up for the first 5 epochs and it decays after 30 and 60 epochs, by a factor of 10. We set the labeled batch size as 256. As a pre-processing step, all training images are randomly cropped and re-scaled to $224 \times 224$ size before applying augmentations. For the EMA parameters for evaluating SSL methods, the decay rate is $\rho = 0.9$. The hyper-parameters of the individual method is described in Sec. C.4.

C.3 A test-bed for experiments

To conduct comprehensive experiments on each supervised and semi-supervised baseline algorithms and to effectively study the effect of each re-balancing method of labels and pseudo-labels on each of the SSL algorithms, we construct a single, unified test-bed that includes all the baseline methods considered and the complete DASO framework in this work.

Our new codebench contains label re-balancing methods over supervised learning: simple loss re-weighting and re-sampling based on the class label frequency, LDAM-DRW [7], cRT [27], and logit adjustment [39]; baseline SSL algorithms: PseudoLabel [35], MeanTeacher [52], MixMatch [5], ReMixMatch [6], FixMatch [49], and USADTM [23]; pseudo-label re-balancing: BOSS [47], DARP [29], and our DASO. For the hyper-parameter selection of the SSL algorithms, we mainly follow those from the official FixMatch implementation\(^2\) for FixMatch and the other baseline methods in their work and those from USADTM implementation\(^3\) to ensure an objective comparison. We only make a minor modifications proper to the imbalanced SSL setup.

As a point of reference, we additionally provide a part of experiments conducted in the official DARP implementation\(^4\) in Table 15, whose hyper-parameters and implementation details differ in several aspects (i.e., optimizer, lr, · · ·) to show a validity of the DASO method in different codebase.

Our codebench is designed in a way that re-balancing methods can be applied to a supervised or SSL methods without demanding efforts, and can be easily extended to integrate to new re-balancing and baseline SSL algorithms. Moreover, experiments on the balanced SSL methods can also be conducted by changing options about the dataset configuration.

As suggested by Oliver et al. [41], we expect that the release of this new test-bed can provide researchers in this field with a guideline for easily testing previous works and developing their own new works.

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\(^2\)https://github.com/google-research/fixmatch

\(^3\)https://github.com/taohan10200/USADTM

\(^4\)https://github.com/bbuing9/DARP
C.4 Implementation details

**DASO.** We introduce several hyper-parameters where $T_{dist}$ for scaling the empirical pseudo-label distribution turns out to be the most crucial. $T_{dist}$ is chosen out of $\{0.3, 0.5, 1.0, 1.5\}$ depending on different dataset and the distribution. We present the ablation study on $T_{dist}$ in Table 4. The others are set by: temperature factor for the similarity-based classifier $T_{proto} = 0.05$, the maximum queue size for the balanced prototype $L = 256$, and a weighting factor for the semantic alignment loss ($L_{align}$) $\lambda_{align} = 1$, working well in general across different benchmarks. We do not tune those parameters on different benchmarks or distributions. The ablation study of those parameters compared to the complete DASO framework is provided in Sec. E.1. Moreover, we start applying DASO pseudo-labels and $L_{align}$ after a few pre-training steps $P = 5000$ to avoid unconfident predictions in the early stage of training. For obtaining the empirical pseudo-label distribution $\hat{m}$, we aggregate the class predictions of the final pseudo-labels every 100 iterations on CIFAR10-LT, CIFAR100-LT, and STL10-LT. For semi-aves, we set $P = 20$ epochs and update $\hat{m}$ every epoch. For the momentum ratio $\rho$ of the EMA encoder in prototype generation, we use the same parameter of the one from evaluating SSL models for simplicity. Table 8 summarizes the full list of hyper-parameters of DASO.

| parameter       | CIFAR10-LT | CIFAR100-LT | STL10-LT | Semi-Aves |
|-----------------|------------|-------------|----------|-----------|
| $lr$            | 0.03       | 0.04        |          |           |
| $B$             | 64         | 256         |          |           |
| SGD momentum    | 0.9        | 0.9         |          |           |
| Nesterov        | True       | True        |          |           |
| weight decay    | 5e-4       | 3e-4        |          |           |
| $L$             | 256        | 256         |          |           |
| $\rho$          | 0.999      | 0.9         |          |           |
| $T_{proto}$     | 0.05       | 0.05        |          |           |
| $\lambda_{align}$ | 1.0       | 1.0         |          |           |
| $P$             | 5000 steps | 20 epochs   |          |           |
| $T_{dist}$      | $\{1.5, 0.3\}$ | 0.3         | 0.3      | 1.0       |

For $T_{proto}$ in CIFAR10-LT, we select 1.5 in $\gamma_l = \gamma_u$ cases, and use 0.3 in the case of $\gamma_u = 1$.

**Vanilla CE:** trains with standard cross-entropy loss with using only labeled dataset. The training protocol and hyper-parameters (total iterations, learning rate, optimizer, · · · ) are described in Sec. C.2.

**Re-weighting with Effective Number of Samples [15]:** The weighting factor applied to the cross-entropy loss for each class label is based on the effective number of samples.

$$E_{N_k} = \frac{1 - \beta^{N_k}}{1 - \beta},$$

where $N_k$ corresponds to the number of samples in class $k$, and then the weight for class $k$ is set to be proportional to the inverse of the effective number $E_{N_k}$. $\beta$ is a hyper-parameter, which is set to 0.999 during the experiments.

**LDAM-DRW [7]:** The classifier is trained so that the decision boundary takes up more margin for rare classes, using LDAM loss:

$$L_{LDAM} = -\log \frac{e^{\gamma_k - \delta_k}}{e^{\gamma_k - \delta_k} + \sum_{j \neq y_k} e^{\gamma_j}}, \text{ where } \delta_k \propto \frac{1}{N_k^{1/4}}. $$

Then it adopts deferred re-weighting scheme (DRW) to apply re-balancing algorithm in later stage of training. Following DRW scheme, we apply re-weighting objective after 200k iterations.
cRT [27]: After training the entire network under imbalanced distribution, the classifier is re-trained with the parameters of the feature encoder fixed for a balanced objective. We first train a model in a Vanilla CE scheme. In classifier re-training phase, we simply re-weight the cross-entropy loss with the weights based on the effective number of samples [15] for 100k iterations. The learning rate schedule used for the re-balancing methods is proportionally adjusted (maximum iterations 250k → 100k).

Logit Adjustment (LA) [39]: Logits are adjusted by enforcing a large relative margin between the logits of minority classes and the majority ones in either two ways: post-hoc adjustment or logit-adjusted cross-entropy, based on the class frequency of labels. In our experiments, we adopt the latter strategy. Before measuring cross-entropy for the labeled examples, each logits are adjusted by:

\[ p_k \leftarrow p_k + \tau \log c_k, \]

where \( p = f(x) \) and \( c_k \) denotes the class label frequency value in class \( k \). \( \tau \) is a temperature scaling factor, which is set to \( \tau = 1 \) in the whole experiments.

PseudoLabel [35]: The one-hot pseudo-label \( \hat{p} \) generated from the network prediction \( p = f(u) \) regularizes the unlabeled example. Only the predictions in a pseudo-label with the highest probability value above a certain threshold \( \tau \) contribute to the unlabeled loss. We set \( \tau \) to 0.95.

\[
\Phi_u(\hat{p}, p) = \mathbb{1}\left( \max_k p_k \geq \tau \right) H(\hat{p}, p),
\]

where \( \hat{p} = \text{OneHot}(\arg\max_k p_k) \). We set unlabeled loss weight \( \lambda_u \) as 1 and apply linear ramp-up for the ratio 0.4 of the whole iterations, i.e., \( \lambda_u \) linearly increases starting from 0 and attains the maximum value (\( \lambda_u = 1 \)) at 40% of the total iterations.

MeanTeacher [52]: leverages exponential moving average (EMA) of network parameters \( f^{\text{EMA}} = f^{\phi'}_{\theta'} \circ f^{\phi}_{\theta} \) to enforce consistency for the original predictions of unlabeled images, where \( \phi' \) and \( \theta' \) are the momentum-updating network parameters of the linear classifier and feature encoder, respectively.

\[
\Phi_u(\hat{p}, p) = \| \sigma(\hat{p}) - \sigma(p) \|^2, \text{ where } \hat{p} = f^{\text{EMA}}(u) \text{ and } p = f(u).
\]

We set the EMA decay ratio \( \rho = 0.999 \). \( \lambda_u \) is set to 50, applying linear ramp-up with ratio 0.4.

MixMatch [5]: generates soft pseudo-labels from multiple weakly augmented images with entropy regularization. Then the model learns mixup [62] images and (pseudo-) labels over the whole labeled and unlabeled dataset. For MixMatch, we use the number of augmentations as 2, temperature scaling factor for pseudo-labels as 0.5, and the sampling hyper-parameter from beta distribution for mixup regularization \( \alpha \) as 0.5. We also apply linear ramp-up strategy for \( \lambda_u \), where it attains its maximum value 100 with the ratio of 0.016.

ReMixMatch [6]: adds up two techniques of Augmentation Anchoring and Distribution Alignment over MixMatch [5]. For an unlabeled image, a soft-label is computed from the model prediction of one weakly augmented image, followed by distribution alignment, which scales the prediction by target distribution divided by the average model predictions, and entropy regularization as the same with MixMatch. The soft label corresponds to multiple advanced augmentations of an image for mixup regularization. We use the advanced augmentation as RandAugment [14]. Considering the computational cost, we set the number of advanced augmentations as 2. For other hyper-parameters, we set temperature scaling factor for pseudo-labels as 0.5, and \( \alpha \) as 0.75. The weights for pre-mixup loss and rotation loss are both set to 0.5. For \( \lambda_u \), the linear ramp-up ratio is set to 0.016 with \( \lambda_u = 1.5 \). While the original implementation applies advanced augmentation on labeled images, we rather apply weak augmentations for convenience. Note that we apply distribution alignment (DA) based on the class label distribution as a class prior only when \( \gamma_t = \gamma_u \).
**FixMatch** [49]: One-hot pseudo-labels are generated from weakly augmented images as the same with PseudoLabel [35], then these pseudo-labels provide targets for the predictions from strong augmentations of the same image over standard cross-entropy loss:

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

where \(\hat{p} = \text{OneHot}\left(\arg\max_k p_k^{(w)}\right)\) with \(p^{(w)} = f(A_w(u))\) and \(p^{(s)} = f(A_s(u))\). We use RandAugment [14] for advanced augmentation. For fair comparisons to ReMixMatch [6], we use the unlabeled batch ratio \(\mu\) as 2. For other hyper-parameters, \(\lambda_u\) is set to 1 without applying linear ramp-up strategy.

**USADTM** [23]: combines **unsupervised semantic aggregation** (USA); a triplet mutual information loss for clustering objective in unlabeled data and **deformable template matching** (DTM); assigning a semantic pseudo-label to each unlabeled example solely from a feature-space. The semantic pseudo-label is determined by the agreement of two different distance measure from a sample to each class prototypes constructed from labeled data. The semantic pseudo-label is accepted for measuring the loss only when cosine similarity and L2 distance point to the same prototype with above a certain confidence \(\tau\) in cosine similarity. In our experiments, we use the weighting factor for the mutual information loss \(\alpha = 0.1\) and \(\tau = 0.85\) for the confidence threshold, following Han et al. [23]. We note that Han et al. [23] keeps some confident unlabeled examples to treat them as labeled examples to enforce cross-entropy loss due to the limited labels (i.e., 4 labels per class) in their work. This would also help generally in **imbalanced SSL**, but we do not adopt this strategy in our experiments in order to fairly comparing with other SSL methods focusing on the effect of each pseudo-labeling method.

**BOSS** [47]: This originally proposes to apply three techniques altogether on FixMatch [49] to achieve state-of-the-art performance on CIFAR-10 benchmark under one label per class: **prototype (single-example per class) refining**, **pseudo-label re-balancing**, and **self-training iterations**. We only adopt pseudo-label re-balancing method from the original paper for fairly comparing under **imbalanced SSL**. **Pseudo-label re-balancing** includes adjusting loss-weights and confidence thresholds based on the class distribution of predicted pseudo-labels, on top of the FixMatch loss on unlabeled data:

\[
\Phi_u(\hat{p}, p^{(s)}) = \mathbb{1}\left(\max_k p_k^{(w)} \geq \tau_k\right) \frac{1}{Z} \mathcal{H}(\hat{p}, p^{(s)}),
\]

where \(\tau_k\) is the class-dependent confidence threshold defined as:

\[
\tau_k = \tau - \delta \cdot \left(1 - \frac{\hat{c}_k}{\max_k \hat{c}_k}\right),
\]

and \(\hat{c}_k\) is the number of predicted pseudo-labels in the current batch for class \(k\). We fix \(\delta = 0.25\) during the experiments. Note that the scale of \(\Phi_u\) is adjusted by a factor of \(Z\) to consistently maintain the relative scale of \(\lambda_u\).

**DARP** [29]: Explicitly adjust the predicted class-distribution of pseudo-labels of any SSL algorithms to the given class priors via convex optimization. In our experiments, we use the class prior as the class label frequency in case of \(\gamma_l = \gamma_u\) for CIFAR10-LT and CIFAR100-LT, and in case of Semi-Aves dataset. In other cases, i.e., \(\gamma_l \neq \gamma_u\), we estimate the distribution of unlabeled data (e.g., \(M_k\)) using held-out validation set, following [29]. We start applying DARP at 100k iterations of training with refining pseudo-labels every 10 steps. We use \(\alpha = 2.0\) for removing the noisy entries.
D Detailed analysis

Bias of pseudo-labels. We first take a closer look at bias of pseudo-labels of each method by analyzing per-class recall and precision. We then compare the class-wise test accuracy of each model to evaluate the generalization capability for each class. Fig. 2 and Fig. 3 provide the comparison of FixMatch w/ DASO (ours) and USADTM [23] over baseline FixMatch [49] with respect to the bias of pseudo-labels and the model’s test accuracy, trained on CIFAR10-LT and CIFAR100-LT.

Figure 2: Analysis of bias in pseudo-labels and test accuracy. We consider FixMatch [49] for linear pseudo-labels, USADTM [23] for semantic pseudo-labels, and the proposed FixMatch w/ DASO trained on CIFAR10-LT with $N_1 = 500$ with $\gamma_l = \gamma_u = 100$.

Note that FixMatch and USADTM are the state-of-the-art linear-pseudo label generation and semantic pseudo-label generation methods, respectively. Compared to the linear pseudo-labels, the recall of semantic pseudo-labels on minority classes significantly increased in Fig. 2a and Fig. 3a. However, their precision values are degraded on the minorities in Fig. 2b and Fig. 3b, which means that the semantic pseudo-labels have bias towards the minorities, leading to performance drop on the majority classes as shown in Fig. 2c and Fig. 3c.

In contrary, the pseudo-labels generated from our DASO framework maintains high precision while the recall on the minority classes increased, encouraging high performance on both of majority and minority classes. From the analyses, pseudo-labels from DASO find the trade-off between linear and semantic pseudo-labels with respect to the bias that performs well on the balanced test criterion. Since DASO also aims to keep the prediction of majority classes, the test accuracy drop on the head class is well addressed after applying re-balancing methods.

Figure 3: Analysis of bias in pseudo-labels. We consider FixMatch [49] for linear pseudo-labels, USADTM [23] for semantic pseudo-labels, and the proposed FixMatch w/ DASO trained on CIFAR100-LT with $N_1 = 50$ with $\gamma_l = \gamma_u = 10$. 

We perform the same analysis to compare the different re-balancing methods: DARP [29] and our DASO upon the baseline FixMatch [49] in Fig. 4 and Fig. 5. In CIFAR10-LT case, DASO more attends to increase the prediction of minority classes compared to DARP (Fig. 4a), while the precision values on the minorities decreased on both methods (Fig. 4b). Due to the positively increased accuracy on minority classes with a little performance drop on the majorities, DASO outperforms DARP [19] in the averaged test accuracy over classes.

Figure 4: Analysis of bias in pseudo-labels and test accuracy. We consider FixMatch [49], FixMatch w/ DARP [29], and the proposed FixMatch w/ DASO trained on CIFAR10-LT with $N_1 = 500$ with $\gamma_l = \gamma_u = 100$.

For the CIFAR100-LT experiments as shown in Fig. 5 DARP [29] shows a comparable performance on par with DASO. The overall test accuracy of both methods can be increased by virtue of the positively increased pseudo-labels on the minority classes.

Figure 5: Analysis of bias in pseudo-labels and test accuracy. We consider FixMatch [49], FixMatch w/ DARP [29], and the proposed FixMatch w/ DASO trained on CIFAR100-LT with $N_1 = 50$ with $\gamma_l = \gamma_u = 10$. 

For the CIFAR100-LT experiments as shown in Fig. 5 DARP [29] shows a comparable performance on par with DASO. The overall test accuracy of both methods can be increased by virtue of the positively increased pseudo-labels on the minority classes.
DASO with class distribution mismatch. We present the analyses of bias in pseudo-labels for the other classic SSL algorithms: MeanTeacher [52] and MixMatch [5] in Fig. 6 and Fig. 7 respectively, in case of uniform distribution of unlabeled examples; i.e., $\gamma_u = 1$. In such a case, class distribution mismatch (i.e., $\gamma_l \neq \gamma_u$) can damage the accuracy of the model trained with such a classic SSL algorithms.

From the recall curve in Fig. 6a and Fig. 7a and the precision curve in Fig. 6b and Fig. 7b the pseudo-labels of the baseline SSL algorithms are severely biased towards the head classes, since most of the minority class examples are collapsed to the majority class ones. The uniform class distribution of unlabeled data rather significantly accelerated the bias, to the point where the precision curve is completely reversed; precision value in the majority classes significantly degraded, compared to the recall curve despite learning on the long-tailed labels. Thereby, the model rarely predicts some of the minority class examples for the test dataset in Fig. 6c and Fig. 7c.

We demonstrate that the proposed DASO framework can even completely mitigate such a devastating bias, by just coupling the linear pseudo-labels with the semantic pseudo-labels obtained from the similarity-based classifier. Surprisingly, in MeanTeacher (MT) with DASO case, the tendency of the recall and precision becomes uniform, resulting in a uniform per-class test accuracy in Fig. 6c. When combined with MixMatch [5], DASO also recovers the pseudo-labels on the minority classes significantly. In final, the averaged test accuracy can be more than doubled (i.e., $37.3\% \rightarrow 77.2\%$), as shown in Fig. 7c.

As such, DASO can help alleviate the bias in pseudo-labels, when the distribution between labeled data and unlabeled data substantially differs, without accessing the knowledge about the underlying distribution of unlabeled data. We provide more experimental results of DASO when combined with several baseline SSL algorithms other than FixMatch [49] in Table 12.
Effects on the out-of-class examples. To investigate the effect of learning the model with DASO pseudo-label, we analyze the confidence of predictions on each unlabeled examples after training model with $\mathcal{U} = \mathcal{U}_{in} + \mathcal{U}_{out}$ under Semi-Aves benchmark [50]. Fig. 8 and Fig. 9 visualize the histograms of confidence and entropy values obtained from each of FixMatch [49] and FixMatch w/ DASO, respectively. Since both model do not explicitly learn how to distinguish in-class and out-of-class categories at all, those samples cannot be separated in confidence plot leading to accuracy drop as observed in [21].

![Confidence and Entropy Comparison](image)

Figure 8: Comparisons of DASO and FixMatch [49] on the distribution of confidence values from the predictions of samples in $\mathcal{U}_{in}$ and $\mathcal{U}_{out}$ of Semi-Aves benchmark [50], respectively.

![Confidence and Entropy Comparison](image)

Figure 9: Comparisons of DASO and FixMatch [49] on the distribution of entropy values from the predictions of samples in $\mathcal{U}_{in}$ and $\mathcal{U}_{out}$ of Semi-Aves benchmark [50], respectively.

However, FixMatch w/ DASO, which learned the blending of linear and semantic pseudo-labels can be effective in that the out-of-class examples are further pushed towards the low-confidence region (i.e., higher entropy) compared to the in-class unlabeled examples. For example, more than $10k$ out-of-class examples correspond to the samples with the maximum confidence in Fig. 8a, while about $5k$ examples correspond to the most confident examples with DASO in Fig. 8b. Similar observation can be made in terms of entropy in Fig. 9.

From the observations, we suppose that the reason why the performance of FixMatch can be improved with DASO in presence of large portion of out-of-class examples, i.e., $\mathcal{U} = \mathcal{U}_{in} + \mathcal{U}_{out}$ in Table [5] is that the DASO’s implicit ability to reject more examples corresponding to out-of-class that can cause performance degradation. This point implies the potential application of DASO towards an open-set SSL scenario, where SSL algorithms also observe unlabeled data in a broader class distribution and learning without harmful out-of-class examples would be important.
E Additional experiments

E.1 More ablation study

We conduct several ablation studies on the hyper-parameters included in DASO framework. We consider FixMatch [49] with DASO on CIFAR10-LT with $N_1 = 500$, $\gamma = 100$ (denoted as C10) and STL10-LT with $N_1 = 150$, $\gamma_l = 10$ (denoted as STL10) respectively to evaluate each aspects of DASO. Table 9 compares different values of the maximum queue size $L$ for constructing the balanced prototypes. Table 10 evaluates different temperature factor $T_{\text{proto}}$ for the similarity-based classifier. Finally, Table 11 shows the effect of different loss weights $\lambda_{\text{align}}$ for the semantic alignment loss. We shaded a row that corresponds to the hyper-parameter of the complete DASO framework. We also indicate the best results in bold.

Table 9: Ablation study on $L$, the balanced queue size.

|        | C10 | STL10 |
|--------|-----|-------|
| FixMatch [49] | 68.25 | 55.53 |
| $L = 128$ | 73.77 | 69.17 |
| $L = 256$ | **75.97** | **70.21** |
| $L = 512$ | 75.03 | 69.96 |
| $L = 1024$ | 74.36 | 69.64 |
| $L = 2048$ | 73.50 | 69.99 |

Table 10: Ablation study on $T_{\text{proto}}$ for semantic pseudo-label.

|        | C10 | STL10 |
|--------|-----|-------|
| FixMatch [49] | 68.25 | 55.53 |
| $T_{\text{proto}} = 0.02$ | 73.84 | 68.19 |
| $T_{\text{proto}} = 0.05$ | **75.97** | **70.21** |
| $T_{\text{proto}} = 0.2$ | 70.53 | 66.62 |
| $T_{\text{proto}} = 0.5$ | 52.36 | 60.92 |
| $T_{\text{proto}} = 1.0$ | 46.47 | 57.40 |

Table 11: Ablation study on $\lambda_{\text{align}}$, a weight for $L_{\text{align}}$.

|        | C10 | STL10 |
|--------|-----|-------|
| FixMatch [49] | 68.25 | 55.53 |
| $\lambda_{\text{align}} = 0$ | 70.98 | 61.64 |
| $\lambda_{\text{align}} = 0.5$ | 73.78 | 69.01 |
| $\lambda_{\text{align}} = 1$ | **75.97** | **70.21** |
| $\lambda_{\text{align}} = 1.5$ | 74.57 | 71.51 |
| $\lambda_{\text{align}} = 2$ | 74.57 | 71.12 |

As note, we do not tune the hyper-parameters above ($L$, $T_{\text{proto}}$, $\lambda_{\text{align}}$) depending on different dataset across different imbalance ratio. For example, in STL10-LT case, using $\lambda_{\text{align}}$ value higher than 1 seems effective, but the result 70.21% obtained from $\lambda_{\text{align}} = 1$ already performs well.
E.2 Additional experimental results

DASO with other baseline SSL algorithms. To evaluate the pseudo-labels obtained from DASO itself, we build DASO upon various SSL algorithms, namely MeanTeacher \[52\], MixMatch \[5\], and ReMixMatch \[6\] and compare the performance over that of each baseline SSL algorithm.

Table 12: Comparison of accuracy (%) from DASO applied to the other classic SSL algorithms. DASO consistently improves the performance in most cases.

| Algorithm               | CIFAR10-LT   | CIFAR100-LT | STL10-LT    |
|-------------------------|--------------|-------------|-------------|
|                          | \( \gamma = \gamma_l = \gamma_u = 100 \) | \( \gamma = \gamma_l = \gamma_u = 10 \) | \( \gamma_l = 10, \gamma_u: \text{unknown} \) |
|                         | \( N_1 = 500 \) \( N_1 = 1500 \) | \( N_1 = 50 \) \( N_1 = 150 \) | \( N_1 = 150 \) \( N_1 = 450 \) |
|                          | \( M_1 = 4000 \) \( M_1 = 3000 \) | \( M = 100k \) \( M = 100k \) | \( M = 100k \) \( M = 100k \) |
| PseudoLabel \[55\]      | 47.8 ±1.06 63.4 ±0.81 | 30.7 ±0.18 47.8 ±0.40 | 42.3 ±0.83 60.4 ±1.11 |
| MeanTeacher \[52\]      | 52.2 ±1.09 68.6 ±0.88 | 37.3 ±0.18 52.1 ±0.09 | 38.2 ±0.43 54.6 ±1.17 |
| w/ DASO                 | 53.3 ±1.60 70.7 ±0.59 | 36.5 ±0.24 52.5 ±0.37 | 70.0 ±1.19 78.4 ±0.80 |
| MixMatch \[5\]          | 57.3 ±2.96 65.7 ±0.23 | 42.2 ±0.09 54.2 ±0.47 | 42.4 ±1.69 52.7 ±1.42 |
| w/ DASO                 | 60.6 ±1.15 70.9 ±1.91 | 45.6 ±3.44 55.6 ±0.49 | 52.8 ±2.85 68.4 ±0.71 |
| ReMixMatch \[6\]        | 70.9 ±2.37 77.0 ±0.55 | 52.3 ±0.91 61.5 ±0.57 | 54.4 ±2.15 71.9 ±0.86 |
| w/ DASO                 | 75.3 ±0.46 79.7 ±0.56 | 53.6 ±0.81 62.1 ±0.69 | 70.1 ±2.14 80.9 ±0.55 |

We find that DASO consistently improves the performance even when the underlying class distribution of unlabeled data is not known, i.e. STL10-LT, with substantial gain. For example, DASO raises the test accuracy by +31.8\% in MeanTeacher, trained on STL10-LT with \( N_1 = 150 \). As an exceptional case, MeanTeacher with DASO performs slightly worse than the baseline due to the scarce labels in CIFAR100-LT with \( N_1 = 50 \).

Combination with other re-balancing method. We further consider loss re-weighting scheme as another label re-balancing methods. We adjust the weight of the cross-entropy loss for the labeled data based on the effective number of samples \[15\] in such a way that a loss for an example that corresponds to the minority class labels more contributes to the overall loss.

Table 13: Comparison of accuracy (%) when DASO is further combined with a loss re-weighting scheme as a label re-balancing method.

| Algorithm               | CIFAR10-LT   | CIFAR100-LT | STL10-LT    |
|-------------------------|--------------|-------------|-------------|
|                          | \( \gamma = \gamma_l = \gamma_u = 100 \) | \( \gamma = \gamma_l = \gamma_u = 10 \) | \( \gamma_l = 10, \gamma_u: \text{unknown} \) |
|                         | \( N_1 = 500 \) \( N_1 = 1500 \) | \( N_1 = 50 \) \( N_1 = 150 \) | \( N_1 = 150 \) \( N_1 = 450 \) |
|                         | \( M_1 = 4000 \) \( M_1 = 3000 \) | \( M = 100k \) \( M = 100k \) | \( M = 100k \) \( M = 100k \) |
| FixMatch \[49\] w/ re-weighting \[15\] | 67.8 ±1.13 77.5 ±1.32 | 45.2 ±0.55 56.5 ±0.06 | 56.1 ±2.32 72.4 ±0.71 |
| FixMatch w/ DASO \[15\] w/ re-weighting | 72.2 ±1.28 80.9 ±1.52 | 46.0 ±0.27 58.3 ±0.46 | 58.9 ±2.79 74.7 ±0.55 |
| FixMatch w/ DASO \[15\] w/ re-weighting | 76.0 ±0.37 79.1 ±0.75 | 49.8 ±0.24 59.2 ±0.35 | 70.0 ±1.19 78.4 ±0.80 |
| FixMatch w/ DASO \[15\] w/ re-weighting | 77.3 ±0.86 81.2 ±0.77 | 50.3 ±0.18 60.1 ±0.12 | 70.2 ±1.05 77.8 ±0.58 |

We observe in Table \[13\] that applying loss re-weighting improves performance for both of FixMatch and FixMatch w/ DASO. In that sense, we verify that the performance of DASO can be further pushed by interacting with the other label re-balancing methods.
DASO combined with BOSS. DASO shows a comparable performance with that of BOSS [47], which is another pseudo-label re-balancing algorithm on CIFAR100-LT experiments, as shown in Sec. 4.2. However, we find that the re-weighting scheme in BOSS, which includes re-weighting consistency loss and adjusting confidence threshold across different classes, based on the pseudo-label’s class frequency can also be seamlessly applied to our DASO. Table 14 shows the experimental results when BOSS [47] is combined with our DASO framework upon FixMatch [49].

Table 14: Comparison of accuracy (%) when DASO is combined with another pseudo-label re-balancing method, BOSS [47] on CIFAR100-LT.

| Algorithm          | CIFAR100-LT | CIFAR100-LT | CIFAR100-LT | CIFAR100-LT |
|--------------------|-------------|-------------|-------------|-------------|
|                    | γ = γl = γu = 10 | γ = γl = γu = 10 | γ = γl = γu = 20 | γ = γl = γu = 20 |
| FixMatch [49]      | N_1 = 50, M_1 = 400 | N_1 = 50, M_1 = 400 | N_1 = 50, M_1 = 150 | N_1 = 50, M_1 = 150 |
|                    | 45.2 ± 0.55/56.5 ± 0.06 | 40.0 ± 0.96/50.7 ± 0.25 | 44.0 ± 0.65/53.3 ± 0.43 | 43.6 ± 0.09/52.9 ± 0.42 |
| w/ BOSS [47]       | 50.0 ± 0.39/59.3 ± 0.22 | 44.0 ± 0.65/53.3 ± 0.43 | 43.6 ± 0.09/52.9 ± 0.42 | 43.6 ± 0.09/52.9 ± 0.42 |
| w/ DASO            | 49.8 ± 0.24/59.2 ± 0.35 | 44.0 ± 0.65/53.3 ± 0.43 | 43.6 ± 0.09/52.9 ± 0.42 | 43.6 ± 0.09/52.9 ± 0.42 |
| w/ BOSS+DASO       | 51.5 ± 0.81/60.3 ± 0.50 | 45.8 ± 0.92/53.8 ± 0.14 | 45.8 ± 0.92/53.8 ± 0.14 | 45.8 ± 0.92/53.8 ± 0.14 |

From re-weighting the consistency loss and over-sampling inlier minority classes in pseudo-labels, the performance of DASO can be substantially improved over the one with either BOSS or DASO, which indicates that two re-balancing methods for pseudo-labels are complementary each other.

Experiments under DARP’s protocol. To validate the DASO’s improvement, we further show the results of DASO compared to DARP [29] where the codes are implemented upon the official DARP codebase. We exactly follow the hyper-parameters and training protocols therein, when implementing our DASO framework on FixMatch [49], i.e., uses Adam optimizer with learning rate 0.002.

Table 15: Comparison of accuracy (%) between DARP [29] and DASO built upon the official DARP codebase. It reports balanced accuracy (bAcc) [25] and geometric mean (GM) scores [32] as the performance measure (i.e., bAcc / GM).

| Algorithm          | CIFAR10-LT (γ = γl = γu = 100) |
|--------------------|---------------------------------|
|                    | N_1 = 500, M_1 = 4000. | N_1 = 500, M_1 = 3000. |
| FixMatch [49]      | 67.0 ± 1.76/55.2 ± 5.28 | 73.9 ± 0.36/70.3 ± 0.89 |
| w/ DARP [29]       | 71.6 ± 0.71/67.5 ± 1.31 | 75.6 ± 0.23/73.0 ± 0.22 |
| w/ DASO            | **72.4 ± 0.16/68.2 ± 0.57** | **76.7 ± 0.73/74.4 ± 1.06** |

Table 15 shows the results of DARP [29] and DASO built upon FixMatch [49]. Despite the different environments, DASO consistently outperforms DASO, without thorough tuning of the hyper-parameters in DASO.