Towards Realistic Long-Tailed Semi-Supervised Learning: Consistency Is All You Need

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Abstract

While long-tailed semi-supervised learning (LTSSL) has received tremendous attention in many real-world classification problems, existing LTSSL algorithms typically assume that the class distributions of labeled and unlabeled data are almost identical. Those LTSSL algorithms built upon the assumption can severely suffer when the class distributions of labeled and unlabeled data are mismatched since they utilize biased pseudo-labels from the model. To alleviate this issue, we propose a new simple method that can effectively utilize unlabeled data of unknown class distributions by introducing the adaptive consistency regularizer (ACR). ACR realizes the dynamic refinery of pseudo-labels for various distributions in a unified formula by estimating the true class distribution of unlabeled data. Despite its simplicity, we show that ACR achieves state-of-the-art performance on a variety of standard LTSSL benchmarks, e.g., an averaged 10% absolute increase of test accuracy against existing algorithms when the class distributions of labeled and unlabeled data are mismatched. Even when the class distributions are identical, ACR consistently outperforms many sophisticated LTSSL algorithms. We carry out extensive ablation studies to tease apart the factors that are most important to ACR’s success. Source code is available at https://github.com/Gank0078/ACR.

1. Introduction

Semi-supervised learning (SSL) is an effective way of using unlabeled data to improve the generalization of deep neural networks (DNNs) [1, 10, 16] when only a limited amount of labeled data is accessible [3, 23, 29, 31]. The core idea of most SSL algorithms is to generate pseudo-labels for unlabeled data and select confident ones to train models. Recent progress on SSL has revealed promising performance in various tasks, such as image recognition [29] and text categorization [35, 39]. However, most existing SSL algorithms assume the datasets are class-balanced, i.e., each class is associated with an equivalent number of samples in both labeled and unlabeled datasets. In contrast, class distributions in many real-world tasks are long-tailed [6, 19, 33, 38, 44]. It is well known that classifiers trained on long-tailed datasets tend to be biased towards majority classes, leading to low test accuracy on minority classes [20, 37, 45].

To improve the performance, many long-tailed semi-supervised learning (LTSSL) algorithms have been proposed to generate unbiased pseudo-labels. They pursue class-balanced classifiers using techniques including resampling [18], re-weighting [17], label smoothing [36], and pseudo-label alignment [14, 34]. These algorithms have shown strong generalization for the minority class by assuming the class distributions of labeled and unlabeled data are almost identical. However, this assumption is frequently violated in real-world applications, for instance, if the labeled and unlabeled data are collected from different tasks. The unlabeled data may have a large class distribution gap from labeled data, and using the erroneous assumption can severely deteriorate the performance [17, 25].

Contribution. This paper studies the under-explored yet practical LTSSL problem, i.e., learning from unlabeled data of unknown class distributions. Notably, we start with three representative types of class distributions of unlabeled data, i.e., consistent, uniform, and reversed, as illustrated in Figures 1a to 1c. We then propose a new simple algorithm to effectively use unlabeled data through the adaptive consistency regularizer (ACR), which is built upon one of the most popular SSL algorithms FixMatch [29]. Concretely, ACR is developed based on two findings: i) to learn a class-balanced classifier, it is helpful to generate pseudo-labels biased appropriately toward the minority class, whereas ii) to learn a better feature extractor, the accuracy of pseudo-labels is critical. Those two findings seem to contradict. We thus present a two-branch network, including a balanced branch and a standard branch, to resolve this con-
Specifically, ACR learns a class-balanced classifier via imposing consistency between its predictions and the adjusted outputs of the standard classifier. The adjusted outputs are designed to be appropriately biased toward the minority class. However, for the second finding, it is observed that the accuracy of pseudo-labels produced by the standard classifier varies as the class distribution of unlabeled data changes. We resolve this difficulty by refining the original pseudo-labels to match the true class distribution of unlabeled data and enhance their accuracy. Importantly, ACR realizes the adaptive refinery of pseudo-labels for various distributions in a unified formula by estimating the true class distribution.

We demonstrate the effectiveness of the proposed approach under various realistic LTSSL scenarios by varying the class distributions of unlabeled data. Despite its simplicity, the proposed algorithm improves recent LTSSL algorithms in all test cases, e.g., our method improves DARP [14], CReST [34], DASO [25] with up to 10.8%, 11.2%, and 7.2% absolute increase on the test accuracy, respectively. Nevertheless, more importantly, in addition to three types of representative class distributions, i.e., consistent, uniform, and reversed, we also test our method under many other class distributions. As expected, our method significantly improves the performance when the class distributions are mismatched between labeled and unlabeled data.

2. Related Work

Semi-supervised learning. A popular class of Semi-supervised learning (SSL) algorithms use unlabeled data to improve the performance via learning to predict the pseudo-labels produced by the model, which can be viewed as a self-training process [2, 3, 23, 31]. Recent SSL algorithms [2, 29] combine pseudo-labeling and consistency regularization, which encourages similar predictions between two different views of an image, to improve the robustness of DNNs. As a representative approach, FixMatch [29] achieves significantly more superb performance than many other SSL algorithms in the image recognition task. Hence, the performance of SSL algorithm is quite sensitive to the quality of pseudo-labels. However, most existing SSL algorithms assume balanced class distributions of labeled and unlabeled data, resulting in poor generalization of the minority class due to biased pseudo-labels. Recently, Fixmatch has been frequently used as the base model for performance improvement under long-tailed class distribution. Long-tailed semi-supervised learning. Long-tailed semi-supervised learning (LTSSL) has received significant attention for its practicality in many real-world tasks. For instance, DARP [14] and CReST [34] propose eliminating biased pseudo-labels generated by the model by distribution alignment to refine pseudo-labels according to the class distribution of labeled data. ABC [18] uses an auxiliary balanced classifier trained by down-sampling majority classes to improve the generalization. CoSSL [9] designs a novel feature enhancement module for the minority class using mixup [42] to train balanced classifiers. Although these algorithms can significantly enhance performance, they assume identical class distributions of labeled and unlabeled data. A recent work, DASO [25], proposes to handle this issue by employing a dynamic combination of linear and semantic pseudo-labels based on the current estimated class distribution of unlabeled data. It is noted that the accuracy of semantic pseudo-labels in DASO relies on the discrimination of learned representations. However, long-tailed class distribution negatively impacts representation learning, reducing the reliability of semantic pseudo-labels. We also demonstrate the gain of pseudo-labels F1 of our method ACR compared to DASO in Figure 1d.

3. The Proposed Method

In this section, we first introduce the problem setup. Next, we present the ACR algorithm for handling unknown class distribution of unlabeled data.

3.1. Preliminaries

Problem setup. In LTSSL, we have a labeled dataset $D^l = \{(x_i^{(l)}, y_i^{(l)})\}_{i=1}^N$ of size $N$ and an unlabeled dataset $D^u$.
Formally, the objective function is given as follows:

$$
\ell_{\text{con}} = \sum_{j=1}^{M} M(x_j^{(u)}) \ell \left( f(A(x_j^{(u)})), q_j \right),
$$

where $q_j$ is the pseudo-label of $x_j^{(u)}$ predicted by $f$, the sample masks $M(x_j^{(u)}) := \mathbb{I} \left( \max \left( \delta(f(x_j^{(u)})) \right) \geq \rho \right)$ selects unlabeled samples whose predicted confidence is higher than a predefined threshold $\rho$ ($\rho = 0.95$ for FixMatch). Here, $\delta(\cdot)$ is the softmask function and $\mathbb{I}(\cdot)$ is the indicator function. To generate another view for each sample, $A(x_j^{(u)})$ represents the specific augmentation scheme for $x_j^{(u)}$, such as Cutout [8] and RandomAugment [5]. Incorporating the consistency regularizer improves the model’s robustness to spurious feature patterns. Additionally, it is worth noting that FixMatch includes all labeled data as part of unlabeled data without using their ground-truth labels, and we follow this practice in this work.

### 3.2. Adaptive consistency regularizer

Latterly, two-stage algorithms have been prevalently inspired by the empirical finding that long-tailed datasets suffer a more significant negative impact on classifier learning than representation learning [13, 43]. Therefore, two-stage algorithms discover class-balanced classifiers using various techniques such as re-sampling [13] and label smoothing [11], based on the feature extractor trained in the first stage. However, two-stage algorithms are computationally expen-
sive for SSL [18, 36]. We thus employ a double-branch network with a standard branch and a balanced branch to emerge the training of the standard classifier and a class-balanced classifier. For the standard branch, we employ FixMatch, which optimizes the standard cross-entropy on labeled data to learn good feature representations (denoted by $f$). For the balanced branch (denoted by $\tilde{f}$), we optimize the balanced softmax [22,28] which is an improved version of standard cross-entropy:

$$L_{b\text{-labeled}} = - \sum_{i=1}^{N} \log \frac{\tilde{f}_{y(i)}(x_i^{(l)}) + \tau \log \pi_{y(i)}}{\sum_{c=1}^{C} \tilde{f}_{c}(x_i^{(l)}) + \tau \log \pi_{c}}, \quad (3)$$

where $\pi_{c}$ is an estimate of class prior $P(y = c)$ which is approximated by the empirical frequency on the training samples, and $\tau$ is a scaling parameter that affects the intensity of logit adjustment. Through minimizing Equation (3), $\tilde{f}$ can predict more balanced predictive probabilities. For both the standard and balanced branches, the consistency regularizer is employed, e.g., the balanced branch jointly optimizes Equation (3) and Equation (2). Ultimately, those two branches are jointly learned with a shared feature extractor. The diagram of ACR is summarized in Figure 2.

Can the double branch network handle unknown class distributions of unlabeled data? We respond to this question with two findings: i) pseudo-labels biased towards minority classes can benefit the classifier learning, whereas ii) pseudo-label distribution that approximates the true distribution helps learn better feature extractor. Inspired by the first finding, we propose to apply a simple logit adjustment (a.k.a post-hoc logit adjustment [22]) to the output of the standard classifier $f$ whose predictions are initially biased towards majority classes. The refined logits are used to generate pseudo-labels which will be treated as targets for the balanced branch. Specifically, the pseudo-label of the $j$-th unlabeled data $x_j^{(u)}$ used in the consistency regularizer in the balanced branch is generated by:

$$\tilde{q}(x_j^{(u)}) = \arg \max \ f \left( x_j^{(u)} \right) - \tau \cdot \log \pi. \quad (4)$$

So that the consistency regularizer for balanced branch is:

$$L_{b\text{-con}} = \sum_{j=1}^{M} \text{dist} \left( \tilde{f}(A(x_j^{(u)})), \tilde{q}_j \right). \quad (5)$$

**Refining pseudo-labels in a unified formula.** Inspired by the second finding, we strive for accurate pseudo-labels of unlabeled data for the standard branch. We empirically find that the standard branch can produce high quality of pseudo-labels and their overall distribution matches the true distribution in the consistent setting but are biased towards majority classes in the other two scenarios, with different degrees. Fortunately, we overcome this difficulty by a simple dynamic logit adjustment in a unified formula. Specifically, ACR automatically changes the intensity of logit adjustment, which is controlled by the scaling parameter $\tau$, according to the unlabeled data class distribution estimate.

To estimate the true class distribution, we first craft three anchor distributions, including the class distribution of labeled data ($\pi_{con}$), a uniform distribution ($\pi_{uni}$), and a reversed class distribution of the labeled data ($\pi_{rev}$). We take the pseudo-labels produced by the balanced branch to estimate the distribution and calculate its distance to each anchor distribution. Specifically, let $\pi^{est}$ be the estimate distribution from the model, we calculate the bidirectional KL-divergence, which is a symmetric distance measure as:

$$\text{dist}_{\text{con}} = \frac{1}{2} \left( D_{KL}(\pi_{con} \| \pi^{est}) + D_{KL}(\pi^{est} \| \pi_{con}) \right)$$

$$\text{dist}_{\text{uni}} = \frac{1}{2} \left( D_{KL}(\pi_{uni} \| \pi^{est}) + D_{KL}(\pi^{est} \| \pi_{uni}) \right) \quad (6)$$

$$\text{dist}_{\text{rev}} = \frac{1}{2} \left( D_{KL}(\pi_{rev} \| \pi^{est}) + D_{KL}(\pi^{est} \| \pi_{rev}) \right),$$

where $D_{KL}(p||q) = \sum_{c=1}^{C} \pi_{c} \log \left( \frac{\pi_{c}}{\pi_{c}^{est}} \right)$. In our implementation, the model is trained for several iterations of warm-up before estimating the class distribution to prevent inconsistent results. We update $\pi^{est}$ using an exponential moving average with the predicted class distribution of unlabeled data in each mini-batch. Finally, the anchor distribution corresponding to the smallest of the three distances calculated above is closest to the true class distribution of unlabeled data. Based on the distances to anchor distributions, ACR can adaptively handle various class distributions of unlabeled data in a unified formula that adjusts the scaling parameter $\tau$ as follows:

$$\tau(t) = \frac{2 \cdot \text{dist}_{\text{con}}^{(t-1)}}{\text{dist}_{\text{con}}^{(t-1)} + \text{dist}_{\text{uni}}^{(t-1)} + \text{dist}_{\text{rev}}^{(t-1)}}, \quad (7)$$

where $t$ is the training iteration. $\text{dist}_{\text{con}}^{(t-1)}$ represents the average distance between the predicted distribution at iteration $t - 1$ and the consistent anchor distribution. The other two distances are defined likewise. From Equation (7), it is easy to derive that i) when the class distributions of labeled and unlabeled data are consistent, $\text{dist}_{\text{con}}^{(t-1)}$ should be much larger than $\text{dist}_{\text{uni}}^{(t-1)}$ so that $\tau$ will almost approach 0. The pseudo-labels for the standard branch are largely depend on its output. ii) In uniform setting, it yields a moderate value of $\tau$ which is below 1. iii) On the contrary, for the reversed cases, $\text{dist}_{\text{uni}}^{(t-1)}$ will be quite larger than $\text{dist}_{\text{con}}^{(t-1)}$, and as a result, $\tau$ will be larger than other two cases but less than 2, which means the pseudo-labels will be more biased towards minority classes. As expected, empirical results as depicted in Figure 4d coincides with our analysis. Ultimately, we maximize the consistency between the standard branch’s outputs and refined pseudo-labels by the adaptive $\tau$ in Equation (7).
3.3. Sample mask generation

To utilize pseudo-labels that are likely to be correct for calculating consistency regularizer, the most popular way is to select unlabeled samples with high predictive confidence. We follow this principle but introduce another complementary term to further enhance the quality of pseudo-labels. We take the balanced branch for an example, and its consistency regularization loss is modified to:

\[
\mathcal{L}_{b\text{-}con} = \sum_{j=1}^{M} \tilde{M}(x_j^{(u)}) \ell \left( \tilde{f}(A(x_j^{(u)})), \tilde{q}_j \right),
\]

\[
\tilde{M}(x_j^{(u)}) = \mathbb{1} \left( \max \left( \delta(f(x_j^{(u)})) \right) \geq \rho \right) \lor \mathbb{1} \left( \max \left( \delta(f(x_j^{(u)})) - \tau \cdot \log \pi \right) \geq \rho \right),
\]

where \(\delta(\cdot)\) denotes the softmax function. In this way, we can select more samples for the minority classes by considering the balanced branch’s output. The consistency regularizer \(\mathcal{L}_{con}\) for the standard branch can be written likewise, which can pick more examples that fit the true distribution. We can obtain more confident samples through the newly constructed sample mask, which is beneficial for consistency loss to work. Considering that the output logits from each branch have been well aligned with the target after a training period, both the original and the adjusted logits are trustworthy. We demonstrate the effect of the new sample mask selection principle in Section 4.5.

Overall, each branch of the network has two losses to minimize, i.e., the classification loss and the consistency loss, which can select more samples for the minority classes by considering the balanced branch’s output. The consistency regularizer \(\mathcal{L}_{con}\) for the standard branch can be written likewise, which can pick more examples that fit the true distribution. We can obtain more confident samples through the newly constructed sample mask, which is beneficial for consistency loss to work. Considering that the output logits from each branch have been well aligned with the target after a training period, both the original and the adjusted logits are trustworthy. We demonstrate the effect of the new sample mask selection principle in Section 4.5.

4. Experiments

We conduct extensive experiments to demonstrate the effectiveness of the proposed method under various class distributions of unlabeled data.

4.1. Experimental setup

The experiments we conducted are based on widely used datasets, including CIFAR10-LT [15], CIFAR100-LT [15], STL10-LT [4], and ImageNet-127 [9]. Recall that parameter \(\gamma_u\) is used to control the imbalance ratio of the labeled dataset, and we can decide the number of labeled samples for class \(c\) as \(N_c = N_1 \cdot \gamma_u \cdot \frac{M_c}{M}\) once \(N_1\) is given. Likewise, given the imbalance ratio of unlabeled dataset \(\gamma_u\) and \(M_1\) (or \(M_C\) in the reversed setting), we set \(M_c\) as we did for the labeled dataset.

- **CIFAR-10-LT**: Following DASO [25], we test our method under \(N_1 = 500, M_1 = 4000\) and \(N_1 = 1500, M_1 = 3000\) settings. We report results with imbalance ratios \(\gamma_l = \gamma_u = 100\) and \(\gamma_l = \gamma_u = 150\). For uniform and reversed settings, we fix \(\gamma_l = 100\) and adjust \(\gamma_u \in \{1, 1/100\}\) to simulate various class distribution of unlabeled data.

- **CIFAR-100-LT**: We test our method under \(N_1 = 50, M_1 = 400\) and \(N_1 = 150, M_1 = 300\) settings. The imbalance ratio is set to \(\gamma_l = \gamma_u = 10\) and \(\gamma_l = \gamma_u = 20\). With a fixed \(\gamma_l = 10\), we also test our method under \(\gamma_u \in \{1, 1/10\}\) for the uniform and reversed unlabeled data class distributions.

- **STL10-LT**: Since ground-truth labels of unlabeled data in STL-10 are unknown, we conduct experiments by controlling the imbalance ratio of labeled data. We follow the settings by DASO and set \(\gamma_1 \in \{10, 20\}\).

- **ImageNet-127**: ImageNet127 is a naturally long-tailed dataset, so we do not need to construct the datasets manually. Following CoSSL [9], we down-sample the image size to \(32 \times 32\) and \(64 \times 64\) due to limited resources.

Following previous work [9, 26], we implement our method using Wide ResNet-28-2 [41] on CIFAR10-LT, CIFAR100-LT, and STL10-LT, and ResNet-50 on ImageNet-127. Following FixMatch, we train the network for 500 epochs with 500 mini-batches in each epoch, with a batch size of 64, using standard SGD with momentum [24, 27, 30]. We use a cosine learning rate decay [21] which sets the learning rate to \(\eta \cos \left( \frac{T \pi}{T} \right)\), where \(\eta\) is the initial learning rate, \(t\) is the current training step, and \(T\) is the total number of training steps. Considering the imbalanced test set in ImageNet-127, we set \(\tau = 0.5\) for the balanced softmax defined in Equation (3), while for other datasets, we fix \(\tau = 2\). To demonstrate the superiority of our approach, we compare with many existing LTSSL algorithms, including DARP [14], CReST [34], DASO [25], ABC [18], TRAS [36]. We measure the performance of all methods using top-1 accuracy on the test set. We report each method’s mean and standard deviation of three independent runs in our experiments.

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

We first evaluate the performance when the class distributions are consistent (i.e., \(\gamma_l = \gamma_u\)) in Table 1. Subsequently, in Table 2 and Table 3, we report results when the unlabeled data class distribution is uniform or reversed (e.g., \(\gamma_u = 1\) or \(\gamma_u = 1/100\)).

**In case of \(\gamma_l = \gamma_u\)**: We compare our approach ACR with several state-of-the-art LTSSL methods: DARP [14], CReST+ [34], and DASO [25]. Results are reported in Table 1. Without exception, ACR consistently outperforms existing methods by a large margin, even though most of
DASO achieves a noticeable improvement. However, its adjustment (LA) and auxiliary balanced classifier (ABC), performace of our method. By further combing with logit assumption that labeled and unlabeled data share the same these methods are particularly developed based on the assumption that labeled and unlabeled data share the same class distribution. This observation verifies the superior performance of our method. Further combing with logit adjustment (LA) and auxiliary balanced classifier (ABC), DASO achieves a noticeable improvement. However, its performance is still 3.7% below ACR on average.

In case of \( \gamma_l \neq \gamma_u \). In real-world datasets, the class distribution of unlabeled data is likely to be significantly inconsistent with labeled data. Therefore, we consider uniform and reversed class distributions, e.g., \( \gamma_u = 1 \) or \( \gamma_u = 1/100 \) for CIFAR10-LT. On the STL10-LT dataset, due to the unknown ground-truth labels of the unlabeled data, we can only control the imbalance ratio of labeled data. The results are summarized in the Table 2 and Table 3.
It can be seen that our method achieves the best results when the class distributions of unlabeled data are inconsistent. For example, ACR obtains 15.6% and 20.1% absolute performance gains over FixMatch under $\gamma_u = 1$ and $\gamma_u = 1/100$ on CIFAR10-LT, respectively. Similarly, the CIFAR100-LT results show that our method outperforms DASO by an average of 9.3% accuracy increase. For STL10-LT, ACR achieves the best results with averaged 6.8% accuracy gain compared with DASO, even if the unlabeled data distribution is unknown. Generally speaking, empirical results under unknown class distributions of unlabeled data on three datasets justify that ACR can effectively utilize unlabeled data to alleviate the negative impact of class imbalance.

### 4.3. Results on ImageNet-127

ImageNet127 is initially introduced in previous work [12] and is applied to LTSSL by CRest [34], which groups the 1000 classes of ImageNet [7] into 127 classes based on the WordNet hierarchy. Compared with other datasets, we do not need to construct the dataset artificially because it naturally follows a long-tailed class distribution with an imbalance ratio $\approx 286$. Following CoSSL [9], we downsample the original images to smaller sizes of $32 \times 32$ or $64 \times 64$ pixels using the box method from the Pillow library and randomly select 10% training samples to form the labeled set. It is worth noting that the test set of ImageNet-127 is also long-tailed, so we set the scaling parameter $\tau = 0.5$ in balanced softmax to reduce the bias of the classifier towards the minority class. The results are summarized in Table 4. We can see that ACR achieves superior results for both image sizes $32 \times 32$ and $64 \times 64$ with 11% and 9.5% absolute improvement on test accuracy compared with TRAS [36], respectively. The results show that our method can successfully apply to tasks with long-tailed test datasets.

### 4.4. Results under more class distributions

To examine the performance of our method in more imbalanced scenarios, we conduct additional experiments on CIFAR-10-LT by fixing $\gamma_l = 100$ while varying the imbalance ratio of unlabeled data $\gamma_u$ from consistent to reversed by a step size 20. We set $N_1 = 500$ and $M_1 = 4000$ ($M_C = 4000$ in reversed setting) and compare the performance with DASO w/ LA [25]. The results are reported in Figure 3. It can be easily observed that our method ACR consistently outperforms DASO in all test cases. Overall, the performance gain becomes increasingly significant as the class distribution of unlabeled data changes from consistent to reversed. This demonstrates the capability of our method to handle various realistic LTSSL problems adaptively.

#### 4.5. Systematic analysis of the proposed method

To better understand our method, we conduct extensive ablation studies. Due to limited space, we defer more detailed analysis to supplementary material.

### Distribution estimation

Figure 4 illustrates the bidirectional KL-divergence for different unlabeled data distributions and the $\tau$ values during the training. From Figures 4a to 4c, we can observe that distance between the estimated and the true distributions is small under three different settings so that our method can accurately determine the underlying distribution of unlabeled data. It implies that the balanced classifier has a strong generalization ability.

#### Scaling parameter $\tau$

Our model’s accurate distribution discrimination ability benefits the proposed adaptive consistency regularizer, which adjusts the value of scaling parameter $\tau$ in Equation (7) to handle various unlabeled data class distributions. Figure 4d displays the dynamic values of $\tau$ under three settings. We can see that $\tau$ increases from a minimal value for consistent to a relatively large value for reversed setting, showing good adaptability of our method.

### Visualization

Moreover, we visualize the learned representations of ACR using the t-distributed stochastic neighbor embedding (t-SNE) [32] and compare them with the previous method DASO. Figure 5 illustrates the comparison results on test set under uniform and reversed settings. It can be seen from the figure that the representations obtained by ACR allow for clearer classification boundaries.

Additionally, we conduct many ablation studies on the critical components of ACR on CIFAR10-LT and CIFAR100-LT. Detailed results are reported in Table 5.

### Impact of sample mask principle

To verify the effect of the mask generation principle, we perform ablation experiments to compare our principle with a standard mask generation strategy based on the confidence of the pseudo-labels used as the targets in the consistency loss. With an averaged 1.7% improvement on CIFAR100-LT, it clearly shows the superiority of our sample mask generation principle.

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**Table 5. Ablation studies of our proposed ACR algorithm.** Con, Uni, and Rev represent consistent, uniform, and reversed for short.
Impact of adaptive LA on the standard branch. ACR adjusts the intensity of LA applied to pseudo-labels in consistency loss according to the current distribution of unlabeled data. When the intensity of LA applied to the standard branch is fixed (we set $\tau = 2$ in Equation (7) in this experiment), the performance decreases in all three settings on CIFAR100-LT dataset, especially in consistent and uniform settings. Also, the performance in consistent setting decreases 4.8% on CIFAR10-LT, showing the importance of developing an adaptive LA strategy for the standard branch.

Impact of LA on the balanced branch. To study the influence of LA on the balanced branch, we remove the LA in the consistency loss. The results reflect an averaged 0.4% slightly drop in accuracy on CIFAR100-LT. However, the performance decreases significantly (3.4%) on CIFAR10-LT, indicating the necessity of LA for the balanced branch.

Impact of balanced softmax. We replace the balanced softmax with standard cross-entropy to study its impact on performance. The results indicate a 0.2% drop indicating that balanced softmax is not quite sensitive for CIFAR100-LT. However, for CIFAR10-LT, the performance penalty in the consistent setting exceeds 7.3%.

Impact of labeled data in the unlabeled set. Following FixMatch [29], we include all labeled data as part of unlabeled data without their labels when constructing the unlabeled set. So when we exclude labeled data from the unlabeled set during the training, the results decrease dramatically, particularly for reversed setting on CIFAR10-LT.

5. Conclusion

This paper presents a simple and effective method by minimizing the adaptive consistency regularizer (ACR) for long-tailed semi-supervised learning with unknown class distributions of the unlabeled data. Our main idea is to i) benefit classifier learning by generating pseudo-labels that are properly biased towards minority classes while ii) benefit representation learning by generating pseudo-labels whose distribution approximates the true class distribution. We implement our idea in a double-branch network and realize ACR through on-the-fly distribution estimation and a novel dynamic logit adjustment. We empirically show that our method significantly outperforms all competing methods under various scenarios, offering a solid baseline for future studies in this task.
References


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A. More Experimental Details

Our experiments are run on NVIDIA GeForce RTX 3090. In the implementation of the proposed method, we use PyTorch 1.12.0 and Torchvision 0.13.0.

Datasets. In our experiments, we compare the proposed algorithm ACR with existing state-of-the-art methods on several datasets under various unlabeled data class distributions, e.g., consistent, uniform, and reversed.

- CIFAR-10-LT and CIFAR-100-LT: There are 5000 and 500 samples in CIFAR-100 and CIFAR-100 originally, with the image size of 32×32. The entire CIFAR dataset can be downloaded from [https://www.cs.toronto.edu/kriz/cifar.html](https://www.cs.toronto.edu/kriz/cifar.html). We need to manually construct the imbalanced dataset according to N₁, M₁ (Mₖ for reversed), and the imbalance ratio as we describe in our paper. We calculate the top-1 accuracy for measuring the performance of each method.

- STL10-LT: STL-10 includes 5000 labeled samples and 100k samples without labels initially, so ground-truth labels of unlabeled data in STL-10 are unknown. We train the model with a long-tailed labeled dataset constructed artificially and the whole 100k unlabeled data. The image size of each sample is 96×96, and the dataset can be downloaded at [https://cs.stanford.edu/acoates/stl10/](https://cs.stanford.edu/acoates/stl10/).

- ImageNet-127: ImageNet-127 is a naturally long-tailed dataset. The dataset can be downloaded from [https://image-net.org/download-images](https://image-net.org/download-images). Following CoSSL [9], we use the image size of 32 × 32 and 64 × 64 for training.

B. Pseudo-code for Our ACR Algorithm

Algorithm 1 summarizes the whole framework of the proposed ACR. We also include the source code for ACR in the supplementary.

C. Additional Experimental Results

In this section, we report more results to show the effectiveness of ACR and detailed analysis to help better understand the approach.

More results compared with DASO. To further illustrate the superior performance of our method in the case of uniform and reversed class distributions of unlabeled dataset, we combine our ACR with DASO w/ LA and DASO w/ ABC on three datasets. The results are reported in Table 6 and Table 7. As we can see, ACR significantly outperforms competing methods with an average 7.9% performance gain, indicating the strong performance of ACR.

More settings on CIFAR100-LT. We evaluate our proposed algorithm ACR under more types of class distributions of unlabeled data on CIFAR100-LT dataset. The result is illustrated in Figure 6a. In this experiment, we fix γ_l = 20 and vary γ_u from consistent to reversed by a step size of 5. We set N₁ = 50 and M₁ = 400 (M_C = 400 for reversed), and compare the performance with DASO w/ LA. It can be seen that ACR outperforms DASO w/ LA in all settings, showing the superior performance of ACR when dealing with various unlabeled class distributions.

Algorithm 1 Adaptive Consistency Regularizer (ACR)

**Input**: labeled dataset D² and unlabeled dataset D⁰, standard classifier 𝑓 and balanced classifier ℓ̃, class prior of labeled dataset π, estimated unlabeled dataset class distribution π̃, number of iterations in each epoch K, scaling parameter τ, three anchor distributions.

**Require**: Strong augmentations A.

Calculate the distance between π̃ and three anchor distributions and obtain the adaptive τ(t) according to Equation (7)

**for** k = 1 to K **do**

\[\{(x_i^{(l)}, y_i^{(l)})\}_{i=0}^{B-1} \leftarrow \text{Sample a batch of labeled data}\]

\[\{(x_j^{(u)}, y_j^{(u)})\}_{j=0}^{B-1} \leftarrow \text{Sample a batch of unlabeled data}\]

\[q(x_j^{(u)}) \leftarrow \arg \max f(x_j^{(u)}) - τ(t) \cdot \log π\]

\[q(x_j^{(u)}) \leftarrow \arg \max f(x_j^{(u)}) - τ \cdot \log π\]

Update estimated class distribution π̃ according to pseudo-labels ℓ̃(x_j^{(u)})

Generate sample masks M̃ for standard and balanced branch respectively based on Equation (8)

\[L_{\text{labeled}} \leftarrow \sum_{i=0}^{B-1} ℓ(f(x_i^{(l)}), y_i^{(l)})\]

\[L_{\text{b-labeled}} \leftarrow \sum_{i=0}^{B-1} ℓ(f(x_i^{(l)}), y_i^{(l)})\]

\[L_{\text{con}} \leftarrow \sum_{j=0}^{B-1} M(x_j^{(u)})\ell\left(f(A(x_j^{(u)})), q(x_j^{(u)})\right)\]

\[L_{\text{b-con}} \leftarrow \sum_{j=0}^{B-1} M(x_j^{(u)})\ell\left(f(A(x_j^{(u)})), q(x_j^{(u)})\right)\]

\[L_{\text{total}} = L_{\text{labeled}} + L_{\text{con}} + L_{\text{b-labeled}} + L_{\text{b-con}}\]

**Update** ℓ and f based on \(\nabla L_{\text{total}}\) using SGD

![Figure 6](image-url) (a) More settings (b) τ values

Figure 6. (6a): More realistic LTSSL settings on CIFAR100-LT. (6b): The adaptive τ values when training CIFAR100-LT.
Adaptive $\tau$ values on CIFAR100-LT. We investigate the adaptive change of $\tau$ values on CIFAR100-LT dataset in Figure 6b. We can see that the scaling parameter $\tau$ increases its value from consistent to reversed settings, which coincides with observation on CIFAR100-LT illustrated in the main paper.

**Confusion matrices on test set.** We compare ACR and DASO [25] under uniform and reversed unlabeled data class distributions by calculating their confusion matrices in Figure 7. We have two key observations: 1) ACR achieves higher overall accuracy for classes and 2) ACR significantly improves the minority class accuracy. On the contrary, DASO produces biased predictions toward the majority class.

**Precision and Recall of pseudo-labels.** In this experiment, we investigate the quality of pseudo-labels generated by our method. The results are illustrated in Figure 8. Interestingly, ACR produces pseudo-labels of high quality in both uniform and reversed settings. As we can see, ACR significantly improves the precision and recall of pseudo-labels compared with DASO w/ LA, showing the effectiveness of the proposed adaptive logit adjustment.

**What if the target distribution is more imbalanced?** We fix the labeled data imbalance ratio as $\gamma_l = 100$ and design the unlabeled data to be more class-imbalanced. Results in Figure 9 indicate that our method (ACR) consistently outperforms DASO by large margins, showing its capability to generalize to various target distributions.

**Fine-grained results.** Here, we report the fine-grained accuracy on the test set in Table 8. ACR achieves impressive improvements on few-shot classes compared with previous state-of-the-art method (DASO) at the cost of negligible drop under the consistent setting. For other settings, ACR outperforms DASO in all cases, indicating its strong generalization ability for both head and tail classes.

Table 6. Test accuracy of DASO combined with LA or ABC and our proposed ACR under uniform and reversed class distributions, i.e., $\gamma_l \neq \gamma_u$, on CIFAR10-LT and STL10-LT datasets. The $\gamma_l$ is fixed to 100 for CIFAR10-LT, while it is set to 10 and 20 for STL10-LT dataset. The best results are in **bold**.

Table 7. Test accuracy on CIFAR100-LT dataset under uniform and reversed class distributions. DASO combines LA and ABC to enhance its re-balancing ability. The best results are in **bold**.

Figure 7. The confusion matrices of the test set for DASO and ACR on CIFAR-10-LT dataset in uniform and reversed settings.
labeled data is not enough for model fine-tuning. Moreover, by generating high-quality pseudo-labels, methods based on FixMatch leverage unlabeled data more effectively than self-supervised learning.

Table 10. Performance comparison between SSP and FixMatch. The labeled imbalance ratio $\gamma_{l}$ is fixed 10 and 100 for CIFAR10-LT and CIFAR100-LT, respectively.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>CIFAR10-LT</th>
<th>CIFAR100-LT</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{l}$</td>
<td>100</td>
<td>1</td>
</tr>
<tr>
<td>SSP</td>
<td>64.9</td>
<td>70.6</td>
</tr>
<tr>
<td>FixMatch</td>
<td>77.5</td>
<td>81.5</td>
</tr>
</tbody>
</table>

Effect of the class imbalance ratio and the amount of labeled data. We illustrate the performance by varying the imbalance ratio and amount of labeled data in Figure 9 and Table 9, respectively. ACR outperforms DASO in all cases even under very high class imbalance ratios. Also, more results can be found in Figure 3 (main paper) and Figure 6a. Concerning the amount of labeled data, ACR improves DASO by an average 4.7% test accuracy.

Table 9. Accuracy on two datasets with various amount of labeled data (e.g., 0.5× means a half of the initial labeled data is used).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>CIFAR10-LT</th>
<th>CIFAR100-LT</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>D'</td>
<td>$</td>
</tr>
<tr>
<td>DASO</td>
<td>66.6</td>
<td>77.3</td>
</tr>
<tr>
<td>Ours</td>
<td>73.9</td>
<td>80.3</td>
</tr>
</tbody>
</table>

Self-supervised pre-training baseline. Following [40], we train SimCLR using all data and fine-tune the model on the labeled set. We find that its performance is even worse than FixMatch (8.8% accuracy drop). This is because the limited