An Embarrassingly Simple Baseline for Imbalanced Semi-Supervised Learning

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Abstract

Semi-supervised learning (SSL) has shown great promise in leveraging unlabeled data to improve model performance. While standard SSL assumes uniform data distribution, we consider a more realistic and challenging setting called imbalanced SSL, where imbalanced class distributions occur in both labeled and unlabeled data. Although there are existing endeavors to tackle this challenge, their performance degenerates when facing severe imbalance since they can not reduce the class imbalance sufficiently and effectively. In this paper, we study a simple yet overlooked baseline – SimiS – which tackles data imbalance by simply supplementing labeled data with pseudo-labels, according to the difference in class distribution from the most frequent class. Such a simple baseline turns out to be highly effective in reducing class imbalance. It outperforms existing methods by a significant margin, e.g., 12.8%, 13.6%, and 14.6% over previous SOTA on CIFAR100-LT, FOOD101-LT, and ImageNet127 respectively. The reduced imbalance results in faster convergence and better pseudo-label accuracy of SimiS. The simplicity of our method also makes it possible to be combined with other re-balancing techniques to improve the performance further. Moreover, our method shows great robustness to a wide range of data distributions, which holds enormous potential in practice. Code will be publicly available.

1. Introduction

Semi-supervised learning (SSL) has shown great promise in leveraging unlabeled data to improve model performance [2–4,20,31,36,42]. However, standard SSL commonly assumes that both labeled and unlabeled data are well-balanced, which is unrealistic in many real-world applications since data usually present long-tailed distribution. In this paper, we consider a more realistic and challenging setting, Imbalanced Semi-Supervised Learning, where both the labeled and unlabeled data exhibit class-imbalanced distribution. This setting poses great challenges to standard SSL methods since the data imbalance intensifies the issue of confirmation bias, producing biased pseudo-labels towards the majority classes, thus, hurting the generalization performance [34,38].

Many methods have been proposed to tackle the challenge of imbalanced SSL. Some methods solve the problem by refining the class distributions of pseudo-labels [19,34]. CReST [38] re-balances the data distribution and learns the model in several rounds of self-training. More recently, different methods have been proposed to reduce the confirmation bias at the classifier level [12,25,28]. Another branch of research addresses the learning difficulty of each class to solve the class imbalance in different ways [14,22]. However, existing methods cannot sufficiently and effectively reduce data imbalance, hence still suffering from consid-
erable performance degradation as data imbalance strengthens. Besides, some methods are sensitive to the unlabeled data distribution and do not generalize well when class distribution in the labeled data is radically different from that of the unlabeled data.

In this work, we consider a simple but largely overlooked baseline for imbalanced SSL, termed SimiS, which extends the labeled data with pseudo-labels from the unlabeled data to reduce the class imbalance during training. More specifically, we supplement the tail classes of the labeled set according to their difference in class distribution from the head classes, using pseudo-labels. We ask two questions: to what extent this simple method can alleviate the data imbalance problem and how does the performance compare to existing class re-balancing methods?

Through extensive experiments, we show that SimiS is surprisingly effective in reducing data imbalance and already outperforms all existing methods by a significant margin (e.g., over 10%), achieving a new state-of-the-art (SOTA). As shown in Fig. 1, our method presents consistent performance when data imbalance increases, while existing methods suffer a large performance degradation. It also presents faster convergence speed with better pseudo-label accuracy. Despite its simplicity and effectiveness, we further demonstrate two major benefits of SimiS: (1) Our method shows great robustness to a wide range of unlabeled data distributions since the data expansion only depends on the class distribution of the labeled set. We show that our method generalizes well even under reversely distributed unlabeled data (compared to the labeled data distribution), where most existing methods fail to keep the same generalization performance. (2) The simplicity of SimiS also makes it extremely flexible to accommodate different SSL algorithms and class re-balancing techniques. In experiments, we show that SimiS consistently improves the performance when combined with different methods. In particular, combining our method with Logits Adjustment (LA) [26] further pushes the frontier of the SOTA.

To summarize, our contributions are two-fold:

- We demonstrate the importance of reducing the imbalance in labeled data for imbalanced SSL. Based on that, we propose SimiS, a simple baseline to extend labeled data during training that leads to remarkable performance improvement.

- We conduct extensive experiments and show that SimiS significantly outperforms existing methods and achieves a new SOTA. More importantly, our method is robust to different extents of data imbalance and various unlabeled data distributions, whereas existing methods may fail to generalize.

2. Related Work

**Semi-Supervised Learning.** Consistency-based semi-supervised learning (SSL) has demonstrated promising results in recent years [2,3,13,23,24,27,31,33,35,36,39,42]. Earlier work, such as Pseudo-Labeling [24] and Mean-Teacher [33], exploit unlabeled data in self-training with the hard and soft pseudo-labels respectively. Data perturbation [27,39] has been found essential for better generalization of SSL. Meanwhile, many efforts have been put on the study of how to exploit the unlabeled data more efficiently, such as using confidence thresholding to mask out possibly incorrect pseudo-labels [31,36,40,42], and re-weighting of the pseudo-labels [20,30]. More recent works have looked into the debiasing of pseudo-labels [7,34], for generating more accurate pseudo-labels during training. However, a limitation is that previous study all experiments under the class-balanced settings, which is unrealistic since both the unlabeled and labeled data tend to be class-imbalanced.

**Long-tailed Classification.** Except for the widely known re-sampling and re-weighting techniques, there are two branches of work being very effective in long-tailed classification, including the post-hoc normalization of classifier weights [18,37,43,45] and the margin penalty modification of loss function [6,29,32]. In post-hoc normalization methods [18,37,43], the representation from the backbone is learned in the first stage using the original label distribution. Then the scale vector is learned to normalize the weights of the classifier under balanced distribution. They dynamically adjust the margin of samples to the decision boundary [18,37,45], which are found to be correlated to the number of samples in each class. Based on a similar intuition, margin-based loss modification [6,29,32] explicitly encourages larger margins for tail classes during training. Logits Adjustment provides a probabilistic perspective which unified these two lines of work [26]. While being effective in supervised learning, adapting these methods into SSL is difficult due to the existence of unlabeled data.

**Imbalanced Semi-Supervised Learning.** Imbalanced SSL is a pragmatic topic for the deployment of SSL algorithms. Hyun et al. [17] proposed to suppress the loss on minority class. DARP [19] instead proposes to refine pseudo-labels via convex optimization on labeled distribution. A simple solution is proposed in CReST [38], which gradually includes confident unlabeled data to the labeled set, according to the reverse label distribution. Based on the observation of decoupling in long-tailed supervised learning [18,45], ABC [25] proposes to train an auxiliary classifier using balanced label distribution during training, while maintaining the representation learning from the original classifier. Similarly, CoSSL [12] exploits an additional training stage to enhance classifier learning on tail classes with feature blending. DASO [28] adopts a semantic feature classi-
fier to help produce more accurate pseudo-labels. There are other methods trying to solve the problem from debiasing of pseudo-labels [34], re-sampling [15], effective re-weighting [9, 22], and adaptive threshold [14]. In contrast, our method expands the labeled data with pseudo-labels to reduce the class imbalance. While being conceptually similar to CREST [38], SimiS is far more straightforward and simpler. CRESTM [38] expands all classes of the labeled set through several rounds of training, whereas SimiS focus more on the tail classes and performs the expansion in an end-to-end fashion.

3. Method

In this section, we first formulate the problem setting of imbalanced semi-supervised learning (SSL) in Sec. 3.1 and then we introduce our simple baseline SimiS in Sec. 3.2.

3.1. Problem Formulation

In this paper, we focus on class-imbalanced semi-supervised classification tasks. For a $K$-way classification problem, we assume a limited labeled set $\mathcal{D}_L := \{(x_i, y_i)\}_{i=1}^N$, where $x_i$ is a training sample and $y_i \in \{1, \ldots, K\}$ is a class label. There is also an unlabeled dataset $\mathcal{D}_U := \{u_j\}_{j=1}^M$, where $u_j$ is an unlabeled training sample. Denote $N_k$ as the number of labeled sample for class $k$, we have $N = \sum_{k=1}^K N_k$. Without loss of generality, we assume the classes are always sorted by the number of training samples in $\mathcal{D}_L$ in a descending order, i.e., $N_1 > N_2 > \ldots > N_K$. The imbalanced ratio $\gamma_l$ for the labeled set is defined as $N_1/N_K$ and a larger $\gamma_l$ indicates more severe data imbalance.\footnote{Note that we also consider reversed ordered class-distribution in experiments, where $N_1 < N_2 < \ldots < N_K$ and $\gamma_l = N_1/N_K < 1$ and a smaller $\gamma_l$ indicates more severe data imbalance.} Similar to the labeled data, the unlabeled data is also class-imbalanced with a total size of $M$. Its class distribution is usually unknown in practice.

3.2. SimiS: A Simple Baseline for Imbalanced SSL

Existing methods propose various sophisticated techniques to tackle the class imbalance for imbalanced SSL. In contrast, our method is inspired by a simple observation. As shown in Fig. 1 (top), the test accuracy of FixMatch [31] (and other imbalanced algorithms) increases almost linearly as the imbalance ratio of the labeled set decreases. This raises a natural question: would simply reducing the dataset imbalance be an effective way to improve the performance for imbalanced SSL?

To answer that question, in this paper, we introduce SimiS, an extremely simple yet overlooked baseline for imbalanced SSL, which reduces class imbalance of labeled data by leveraging pseudo-labels from unlabeled data during training. Specifically, we supplement the infrequent classes with more pseudo-labels and frequent classes with less pseudo-labels after each training epoch. Given the labeled set $\mathcal{D}_L$ with class marginal distribution $\mathcal{P}_L(y) \in \mathbb{R}^K$, where $\mathcal{P}_L(y = k) = N_k/N$, the unlabeled set $\mathcal{D}_U$ with unknown class marginal distribution $\mathcal{P}_U$, the labeled data expansion is performed in three steps: First, we generate pseudo-labels $\hat{y}_j = \arg \max_k f_\theta(u_j)$ from the model $f_\theta$ and compute the corresponding confidence scores $c_j = \max_k \hat{f}_\theta(u_j)$ for all unlabeled data. Then, the number of pseudo-labels added for class $k$ is computed according to its difference in class marginal distribution from the most frequent class as:

$$S_k = \beta(\mathcal{P}_L(\arg \max_k N_k) - \mathcal{P}_L(k)),$$

where $\mathcal{P}_L(\arg \max_k N_k)$ is the class marginal of the most frequent class and $\beta$ is a hyper-parameter controlling the strength of re-balancing. Finally, we sample the first $S_k$ most confident pseudo-labels to expand the labeled set and start the next training epoch with the expanded set. Ideally, one can set $\beta = N$ to make the expanded labeled set fully uniform. However, this inevitably includes erroneous pseudo-labels as the number of pseudo-labels needed to expand the tail class is often too large. This issue becomes even more notable when the number of required pseudo-labels exceeds the size of the tail class in the unlabeled set, which is arguably the most common case. Therefore, in practice, we modulate it with the number of classes and set $\beta = N/K$ for a good trade-off of class-balancing and pseudo-label quality, which empirically produces the best performance compared to other schemes. The complete algorithm is presented in Algorithm 1.

![Algorithm 1 SimiS algorithm.](image)

This simple method turns out to be a very effective way of reducing data imbalance. As we will shown in Sec. 4.5, the effective imbalance ratio of the expanded labeled set can be reduced by a factor of 10 compared to the original labeled set. The reduction of data imbalance makes our method a strong baseline for imbalanced SSL. In Sec. 4.2,
we demonstrate that SimiS significantly outperforms existing methods in all settings and shows great robustness against a wide range of imbalance ratio and unlabeled data distribution. Moreover, thanks to its simplicity, SimiS can be further enhanced by combining with other re-balancing techniques and achieve even better performance. We empirically verify the superiority of our method lies in the reduction of imbalance ratio of the labeled set. As shown in Fig. 5, the class-wise accuracy of SSL algorithms is positively related to the class marginal of labeled set, regardless of the unlabeled data distribution. This indicates that reducing the imbalance ratio of labeled set is enough to achieve promising performance. Further analysis is in Appendix.

Remark: In fact, the idea of supplementing the labeled set also appears in CReST [38]. The core difference lies in the amount of pseudo-labels added for different classes. CReST samples pseudo-labels to expand labeled data, inversely proportional to the class distribution. While this largely increase the number of data for the tail classes (the sampling rate is 100% for the most infrequent class), it also adds many samples to the head classes. At the end, the expanded new labeled set still suffers from a large imbalance ratio as we will shown in Sec. 4.5. In contrast, our method supplements each class based on the difference between class distribution from the most frequent class. Therefore, the infrequent classes are largely expanded while the most frequent class stay the same, which effectively reduces the data imbalance and leads to improved performance.

4. Experiments

We provide an extensive evaluation of SimiS in this section. Specifically, we present the main comparison and results in Sec. 4.2. Then, the robustness and flexibility of SimiS is evaluated in Sec. 4.3 and Sec. 4.4, respectively. To better understand SimiS, we conduct further analysis in Sec. 4.5 and ablation study in Sec. 4.6.

4.1. Experiments Setup

Baselines. We compare our method with a wide range of imbalanced SSL algorithms, including DARP [19], CReST/CReST+ [38], ABC [25], DASO [28], CoSSL [12], SAW [22], Adsh [14], and DePL [34]. As for the base SSL algorithms, apart from the evaluation on the widely used FixMatch [31] and ReMixMatch [2] in Sec. 4.2, we also test the effectiveness of SimiS with more recent SSL algorithms [1, 4, 36, 42, 44] in Sec. 4.4. All the algorithms and experiments are implemented and conducted under the common codebase USB2 [35] for fair comparison.

Benchmark. We evaluate the algorithms on different settings consisting of diverse datasets. In classic setting, we use WRN-28-2 [41] from scratch and evaluate on CIFAR10-LT [21], CIFAR100-LT [21], and STL10-LT [8]. We use an input size of 32 for all datasets in the classic setting. To construct the long-tailed (LT) class distributions, we randomly choose \( N_k = N_1 \gamma_k^{\frac{k-1}{K-1}} \) and \( M_k = M_1 \gamma_u^{\frac{k-1}{K-1}} \) labeled and unlabeled samples for class \( k \), respectively, where \( \gamma_k (\gamma_u) \) denotes the imbalance ratio. For STL10-LT, we only construct the labeled set and directly use the original unlabeled data as it is already imbalanced. In advanced setting, we adopt an ImageNet-1K [10] pre-trained Vision Transformer [11] as the backbone. More specifically, we train and evaluate ViT-S-P2-32 [35] on CIFAR100-LT [21] with an input size of 32, and ViT-S-P16-224 [35] on FOOD101-LT [5], which is a more realistic dataset with an input size of 224. The advanced setting is more challenging than the classic setting due to the scarcity of labeled data. Apart from these two settings, we provide an evaluation on ImageNet127 [16], which is naturally long-tailed with an imbalance ratio roughly of 286. We randomly select 1% and 10% of samples from each class as labeled data and use a smaller resolution of 112 due to the limited computing resources. We evaluate the algorithms on the balanced test set by default, except ImageNet127 whose test set is also imbalanced. Each experiment is run with three random seeds and we report the averaged best top-1 accuracy. More details on the datasets we used are in Appendix.

Hyper-parameters. Following the common practice [28, 38], for classic setting, we use SGD optimizer with a constant learning rate of 0.03 and a weight decay of 5e-4. We set the batch size for labeled set as 64 and unlabeled set as 128 for FixMatch and 64 for ReMixMatch. We train each algorithm for 256 epochs, with 1024 iterations per epoch. For advanced setting, we mainly use the default setting of USB [35], where AdamW optimizer with different learning rate and layer scale is adopted on different datasets. Specifically, We set the batch size for both labeled set and unlabeled set as 16 for all algorithms. Each algorithm is trained for 200 epochs, with 1024 iterations per epoch. For ImageNet127, we use SGD with an initial learning rate of 0.1 and a cosine scheduler. The labeled batch size is set to 256 and the unlabeled batch size is 512. We train ResNet50 for 200 epochs with 2500 iterations per epoch. The details of hyper-parameters are shown in Appendix.

4.2. Main Results

We compare the performance of SimiS with the baseline methods on classic setting in Tab. 1, advanced setting in Tab. 3, and ImageNet127 in Tab. 2. Our method presents the best performance and outperforms previous methods by a significant margin on both FixMatch and ReMixMatch. On the classic setting, compared to FixMatch, SimiS brings

\[ M_k \text{ is unknown during training and testing.} \]
an average performance improvement of 15.25%, 11.40%, and 14.16% on CIFAR10-LT, CIFAR100-LT, and STL10-LT, respectively. Comparing with the previous best method, our method still shows great superiority in almost all cases. For example, SimiS outperforms ABC [25] by 9.92% on CIFAR10-LT and 9.81% on CIFAR100-LT. Moreover, incorporating Logits Adjustment (LA) [26] in the labeled data loss during the training can further boost the performance, enlarging the performance gap over the previous best to 12.31%, 12.78%, and 7.25% on CIFAR10-LT, CIFAR100-LT, and STL10-LT, respectively.

On the advanced setting, while most of the baselines fail to provide an improvement over FixMatch and some even produce degraded performance, SimiS still significantly improves the average accuracy of FixMatch by 9.96% on CIFAR100-LT and 15.12% and FOOD101-LT. Additionally, although the usage of the pre-trained model already helps mitigate the imbalance issue, we find that SimiS + LA still provides performance improvement in most cases. Similar improvement is also observed for ReMixMatch, where SimiS (+LA) provides a significant improvement over other methods. Notably, although ReMixMatch tends to outperform FixMatch on imbalanced SSL settings with baseline methods, possibly due to Distribution Alignment, FixMatch becomes the better one with SimiS (except STL10-LT), similar to their rankings in balanced set-tings [31, 35], which highlights the importance of reducing imbalance ratio.

On the more realistic dataset ImageNet127 with a class-imbalanced test set, SimiS also outstandingly performs the best (as shown in Tab. 2) in terms of balanced accuracy, e.g., an improvement of 11.81% and 5.04% over ABC with 1% and 10% labels respectively. The margin can be enlarged further with LA. This demonstrates the great potential of SimiS to be applied in realistic situations.

An advantage of SimiS is that it performs consistently across settings with different class imbalance ratios. From Fig. 1, we can see that the model tends to perform less with

| Dataset | CIFAR10-LT | CIFAR100-LT | STL10-LT |
|---------|------------|-------------|----------|
| $N_1$   | 3000       | 1500        | 500      |
| $M_1$   | 30         | 3000        | 4000     |
| $\gamma_1$ | 100      | 100         | 100      |
| $\gamma_6$ | 100      | 100         | 100      |

| Supervised | FixMatch [31] | w/ DARP [19] | w/ cREST [38] | w/ cREST+ [36] | w/ ABC [25] | w/ DASO [28] | w/ CoSSL [32] | w/ SAW [22] | w/ Adsh [14] | w/ DePL [34] |
|------------|---------------|-------------|---------------|---------------|-------------|-------------|-------------|-------------|-------------|-------------|
|            | 63.62 ± 0.40  | 69.2 ± 0.79 | 72.15 ± 0.94  | 73.14 ± 0.65  | 62.52 ± 0.03 | 65.68 ± 0.67 | 57.76 ± 0.39 | 57.56 ± 0.47 | 53.97 ± 0.17 | 66.56 ± 0.42 | 56.29 ± 0.00 |
|            | 10.10 ± 0.10  | 70.35 ± 1.15 | 71.27 ± 0.62  | 71.12 ± 0.42  | 62.16 ± 1.10 | 65.63 ± 0.63 | 56.14 ± 0.46 | 56.40 ± 0.21 | 52.81 ± 0.50 | 63.74 ± 0.54 | 56.03 ± 0.14 |
|            | ± 0.80 ± 0.10 | ± 0.35 ± 0.06 | ± 0.25 ± 0.06 | ± 0.23 ± 0.03 | ± 0.08 ± 0.03 | ± 0.07 ± 0.03 | ± 0.07 ± 0.03 | ± 0.07 ± 0.03 | ± 0.07 ± 0.03 | ± 0.07 ± 0.03 | ± 0.07 ± 0.03 |
|            | 74.10 ± 1.30  | 76.72 ± 0.94 | 76.37 ± 0.84  | 76.20 ± 0.33  | 58.56 ± 0.34 | 60.07 ± 0.24 | 55.43 ± 0.17 | 55.82 ± 0.01 | 61.38 ± 0.15 | 65.52 ± 0.10 | 61.38 ± 0.15 |
|            | 10 ± 2.40     | 10 ± 2.40   | 10 ± 2.40     | 10 ± 2.40     | 10 ± 2.40   | 10 ± 2.40   | 10 ± 2.40   | 10 ± 2.40   | 10 ± 2.40   | 10 ± 2.40   | 10 ± 2.40   |
|            | 15 ± 7.80     | 15 ± 7.80   | 15 ± 7.80     | 15 ± 7.80     | 15 ± 7.80   | 15 ± 7.80   | 15 ± 7.80   | 15 ± 7.80   | 15 ± 7.80   | 15 ± 7.80   | 15 ± 7.80   |

| N         | 1%          | 10%         |
|-----------|-------------|-------------|
| Supervised| 5.82 ± 0.37 | 33.07 ± 0.37|
| FixMatch  | 17.76 ± 0.37| 44.10 ± 0.37|
| w/ cREST  | 21.12 ± 0.37| 45.13 ± 0.37|
| w/ ABC    | 24.76 ± 0.37| 49.13 ± 0.37|
| w/ CoSSL  | 19.59 ± 0.37| 47.23 ± 0.23|
| w/ SimiS  | 36.57 ± 0.37| 54.17 ± 0.37|

| N         |
|-----------|
| 43.93 ± 0.37| 63.71 ± 0.37|
higher $\gamma_l$, and when $\gamma_l = 1/\gamma_u$, compared to $\gamma_l = \gamma_u$. This is also reflected in Tab. 1 and Tab. 3, where most of the baseline methods present a degraded performance for larger $\gamma_l$ and $\gamma_l = 1/\gamma_u$. Intuitively, there are more samples in the unlabeled set of the tail classes in the labeled set when $\gamma_l = 1/\gamma_u$ and the model would learn better if these samples could be utilized correctly during training. By supplementing these samples into the labeled set during training, SimiS surprisingly alleviates the limitations above present in previous methods. For example, SimiS reduces the performance gap when training FixMatch on CIFAR10-LT with $\gamma_l = 100$ and $\gamma_l = 150$ in average from 5.90% to 2.02%, and similarly on other datasets. More importantly, SimiS produces rather consistent results for $\gamma_l = \gamma_u$ and $\gamma_l = 1/\gamma_u$, and usually even better results with $\gamma_l = 1/\gamma_u$, which indicates the robustness of SimiS.

4.3. Robustness to Various Imbalance Distributions

In this section, we empirically verify the robustness of SimiS further from the perspective of training and test distribution on CIFAR10-LT.

**Imbalanced training distribution.** We train FixMatch with SimiS on more diverse imbalance settings and evaluate on the balanced test set of CIFAR10. These imbalance settings are constructed using different combinations of $\gamma_l$ and $\gamma_u$, ranging from $\{1/150, 1/100, 1/50, 1, 50, 100, 150\}$.

**Figure 2.** Accuracy of FixMatch and (b) SimiS on the balanced test set of CIFAR10, trained with different combination of $\gamma_l$ and $\gamma_u$. SimiS performs robustly across different training distributions.

**Figure 3.** Accuracy on test set of different imbalance ratios. We train FixMatch with different algorithms on CIFAR10-LT using (a) $\gamma_l = 100, \gamma_u = 100$, and (b) $\gamma_l = 100, \gamma_u = 1/100$. SimiS performs robustly across different testing distribution.

Fig. 2 shows the heat map of top-1 accuracy on the balanced test set from the models learned on different training distributions. FixMatch performs the best only when $\gamma_l = \gamma_u$, and gradually degrades from the middle to the periphery of the heat map. However, SimiS is consistent across different combinations of imbalance ratios, demonstrating that it is more robust to different training distribution. Comparison with other methods is shown in Appendix.

**Imbalanced test distribution.** We train FixMatch with different imbalanced SSL algorithms on CIFAR10-LT. We use training imbalance of $\gamma_l = \gamma_u = 100$ and $\gamma_l = 1/\gamma_u = 100$, and evaluate on test data of different imbalance ratios. We create the class-imbalanced test set similarly to training set. The accuracy for each imbalance ratio is shown in Fig. 3. One can observe that the accuracy trend of FixMatch and DASO [28] is increasing towards the increase of $\gamma_l$. Although both CReST [38] and ABC [25] alleviate this limitation to some degree, SimiS performs consistently well on all test imbalance ratios and presents smaller performance gaps across imbalance ratios no matter which training distribution is used. The robustness of imbalanced SSL algorithms is usually ignored in previous works and we hope SimiS could inspire more future research on this.

### Table 3. Advanced setting: Top-1 accuracy of imbalanced algorithms with FixMatch and ReMixMatch. The advanced setting is more challenging than the classic setting in terms of number of labels and number of classes, by fine-tuning the pre-trained ViT. We indicate SimiS in gray, the best in **bold**, and the most comparison from previous method in *underline*. Our method is still the best on the advanced setting.
4.4. Flexibility with Different Algorithms

As mentioned earlier, SimiS can be easily integrated into most SSL and imbalanced SSL algorithms for its simplicity. In this section, we evaluate such flexibility with more recent SSL algorithms, including AdaMatch [4], FlexMatch [42], FreeMatch [36], and SoftMatch [1]. The selected SSL algorithms are mainly featured by dynamic and adaptive confidence thresholding for consistency loss. We also verify its compatibility with other imbalanced SSL algorithms, including ABC [25], DASO [28], and CoSSL [12]. Table 4 presents the results on CIFAR10-LT and CIFAR100-LT, which states that SimiS consistently brings significant improvement on different algorithms.

While AdaMatch [4] and FlexMatch [42] perform better than FixMatch [31] on balanced settings, they show inferior performance on imbalanced settings of CIFAR10-LT and CIFAR100-LT. Plugging SimiS into them makes them surprisingly outperform FixMatch (with SimiS) again, except on CIFAR10-LT with $\gamma_u = 1/100$. This indicates that the data distribution of $\gamma = 1/\gamma_u$ might be more destructive for these adaptive thresholding algorithms. FreeMatch [36] and SoftMatch [1] themselves could already produce better performance than some of the imbalanced SSL algorithms with FixMatch. However, interestingly, combining SimiS with them brings less improvement than shown with AdaMatch and FlexMatch. The reason might be FreeMatch and SoftMatch already involve much more unlabeled data into training with their adaptive thresholding mechanism, hence the overall benefit of SimiS is reduced.

SimiS is also compatible with previous imbalanced algorithms since it does not involve any modification of the training part but only focuses on extending the labeled dataset after each training epoch. While SimiS indeed improves the performance of imbalanced SSL algorithms with FixMatch, the performance is generally worse than directly applying SimiS to FixMatch. This is likely due to previous sophisticated imbalanced algorithms limit the ceiling performance of FixMatch.

4.5. More Analysis

We provide more analysis of SimiS with FixMatch on CIFAR10-LT with several important training observations. SimiS can effectively reduce the imbalance ratio of l-
beled data. We first examine the reduced imbalance ratio during training to study to what extent SimiS can alleviate the imbalance. Since CReST [38] shares a similar idea as ours to extend the labeled set with pseudo-labels, we compare the imbalance ratio of the extended labeled set of SimiS and CReST in Fig. 4. When $\gamma_l = \gamma_u$, SimiS could more effectively reduce the imbalance of the labeled set, thus leading to better performance. More interestingly, when $\gamma_l = 1/\gamma_u$, the imbalance ratio is quite different in CReST and SimiS. CReST appends more samples from the head class in the unlabeled set (the tail class of the labeled set), resulting in a reversed extended labeled set that is closer to the actual class distribution of the unlabeled set. From Tab. 1, CReST indeed performs reasonably well when $\gamma_l = 1/\gamma_u$. However, while SimiS presents a class distribution still in descending order as the original labeled set, its performance is surprisingly better than CReST. This motivates us to explore why extending according to the labeled distribution is enough to achieve promising performance.

We do so by training FixMatch with different imbalance ratios in the labeled set, but the same imbalance ratio in the unlabeled set. We fix the size of labeled and the unlabeled set. As shown in Fig. 5, we demonstrate that the class-wise accuracy is positively related to the class distribution of the labeled set, no matter what the class distribution on unlabeled set is. This emphasizes the necessity and sufficiency of reducing the imbalance ratio in the labeled set during training to learn and thus generalize better, which aligns with the intuition of SimiS.

SimiS converges faster with better pseudo-label accuracy. We further plot the training curves of SimiS in Fig. 6, compared to ABC [25] (previous SOTA). SimiS achieves better overall performance, and also outperforms ABC on the minority class as shown in Fig. 6a. Since SimiS better learns each class, it demonstrates robustness to different distributions as shown earlier. Besides, the pseudo-labels generated by SimiS are more accurate than ABC, especially for the minority class, which would alleviate the confirmation bias and lead to better generalization.

4.6. Ablation Study

**Base number $\beta$.** Base number $\beta$ is possibly the most important hyper-parameter in SimiS, since it directly controls the reduced imbalance ratio of labeled set. We evaluate different $\beta$ and find $\beta = N/K$ works the best, as shown in Tab. 5a. Setting it to a large number, such as $M$ and $N$ would falsely extend too much erroneous pseudo-labels into the labeled set, thus impedes the performance, as in CReST. Setting it to a much smaller number $N/K^2$ also improves the performance. But with less samples supplemented, the resulting imbalance ratio might be higher during training.

**Sorting pseudo-labels.** When sampling pseudo-labels to get $\mathcal{D}_U'$, we sort pseudo-labels according to their predicted confidence. We verify different sorting strategies, including random, entropy, and confidence, as shown in Tab. 5b. Surprisingly, random sampling from grouped pseudo-labels already produce good performance, which emphasizes the importance of reducing the imbalance ratio during training. While entropy measures the uncertainty better, directly using confidence presents better performance.

5. Conclusion and Limitations

In this paper, we propose SimiS, an extremely simple baseline for imbalanced SSL. It effectively reduces the imbalance ratio of the labeled data during training by supplementing the pseudo-labels from the unlabeled set into the infrequent classes in labeled set. SimiS not only demonstrates its superior performance on all settings evaluated, but it also presents robustness to different imbalance ratios of labeled and unlabeled data, and flexibility to combine with different algorithms due to its simplicity. SimiS shows excellent potential to solve the data imbalance problem of SSL in practice.

Despite its outstanding performance, a limitation of SimiS is the lack of formal theoretical analysis. Although we empirically find that expanding the labeled set is enough to achieve promising performance and try to explain it from
the marginal ratio perspective, the theoretical guarantee of it still needs to be proved. We hope that SimiS can inspire more work, especially on theoretical sides, and further push the limit of the imbalanced SSL in real deployment.
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A. Theoretical Intuition of SimiS

The objective in SSL is to learn a model that minimizes the KL divergence of $\mathcal{P}(y|x; \theta)$ with the true $\mathcal{P}(y|x)$ on a labeled set with known $\mathcal{P}_L(y)$ and an unlabeled set with unknown $\mathcal{P}_U(y)$. The objective is equivalent to maximize $\log \hat{P}(y|x; \theta)$ on both the labeled set and unlabeled set with $\mathcal{P}_L(x, y)$ and $\mathcal{P}_U(x, y)$:

$$
\theta^* = \arg \max_{\theta} \mathbb{E}_{\mathcal{P}_L(x,y)}[\log \hat{P}(y|x; \theta)] + \mathbb{E}_{\mathcal{P}_U(x,y)}[\log \hat{P}(y|x; \theta)].
$$

The first term corresponds to the Cross-Entropy loss on labeled data:

$$
\mathbb{E}_{\mathcal{P}_L(x,y)}[\log \hat{P}(y|x; \theta)] = \int \mathcal{P}_L(x, y) \log \hat{P}(y|x; \theta) \, dx \, dy
$$

The second term corresponds to the Cross-Entropy loss on unlabeled data with pseudo-labels $\hat{y}$:

$$
\mathbb{E}_{\mathcal{P}_U(x,y)}[\log \hat{P}(y|x; \theta)] = \int \mathcal{P}_U(x, \hat{y}) \log \hat{P}(y|x; \theta) \, dx \, dy
$$

Thus, the second term on the unlabeled set is related the density ratio of pseudo-labels on unlabeled set and the class marginal on labeled set, $\mathcal{P}_U(\hat{y}) / \mathcal{P}_L(y)$. In imbalanced SSL, both $\mathcal{P}_L(y)$ and $\mathcal{P}_U(y)$ is imbalanced. Learning on the class-imbalanced marginal in SSL would result in severe confirmation bias, and thus making $\mathcal{P}_U(\hat{y})$ far away from the true but unknown $\mathcal{P}_U(y)$. To facilitate learning on unlabeled data, it would be intuitive to maintain the ratio roughly to 1.0. Since the model $\hat{P}(y|x; \theta)$ is biased according to $\mathcal{P}_L(y)$, and $\mathcal{P}_U(\hat{y})$ is generated from the model $\hat{P}(y|x; \theta)$, the importance of the class-imbalance in labeled set is further emphasized. This highlights the effectiveness of SimiS, where the imbalance ratio of labeled set is gradually reduced during training, maintaining $\mathcal{P}_U(\hat{y}) / \mathcal{P}_L(y)$ roughly the same, and thus improving performance.

B. Extended Experiments

B.1. Robustness to Training Distributions

In this part, we provide the comparison with more baseline imbalanced SSL algorithms regarding the robustness to different imbalance ratios of training distributions, similar to Fig. 2 of the main paper. These imbalance settings are constructed using different combinations of $\gamma_l$ and $\gamma_u$, ranging from $\{1/150, 1/100, 1/50, 1, 50, 100, 150\}$. Compared with other baseline imbalanced SSL algorithms, SimiS still demonstrates the superior robustness to imbalanced training distributions. This is also related to the performance of SimiS in Fig. 1 of the main paper, where it presents the least performance degradation as the imbalance ratio increases.

B.2. Class Marginal Distribution

In SimiS, we explicitly reduce the imbalance ratio of data according to the difference in class marginal distributions of labeled set. There are other possible marginal distribution we can used to reduce the imbalance ratio, and we conduct an ablation study on this in Tab. 6.

| $\mathcal{P}(y)$ | 100 | 1/100 |
|-----------------|-----|-------|
| $\mathcal{D}_L$ | 88.38 | 88.20 |
| $\mathcal{D}_U$ | 88.04 | 87.72 |
| $\mathcal{D}_U$ | 88.25 | 86.54 |

Table 6. Aligning $\mathcal{P}(y)$ used in Eq. 1. We exploit different marginals including the class marginal of labeled set, oracle unlabeled set, and the estimated unlabeled set. Using labeled set produces the best results.

Specifically, we further validate on two marginals, the estimated $\mathcal{P}_U$ from the expectation of the predicted probability and the oracle $\mathcal{P}_U$, as shown in Tab. 6. The difference of using $\mathcal{P}_L$ and $\mathcal{P}_U$ mainly lies in the setting with $\gamma_u = 1/100$, where using $\mathcal{P}_L$ extends more samples to the minority class of the labeled set, and thus producing better performance.

C. Detailed Experiment Setup

We provide the detailed setup of all experiments in the main paper in this section.

C.1. Datasets

CIFAR10-LT, CIFAR100-LT, and FOOD101-LT. For these original balanced dataset with full annotations, we construct the imbalance labeled set and unlabeled by sampling partial data from the original balanced dataset. We set the number of samples in head class as $N_1$ and $M_1$ for labeled set and unlabeled set, and imbalance ratio as $\gamma_l$ and $\gamma_u$ for them. Then, we sample $N_k = N_1 \gamma_l^{k-1}$ and $M_k = M_1 \gamma_u^{k-1}$ for the remaining classes to ensemble the labeled and unlabeled dataset in SSL.

STL10-LT. STL10 originally contains a labeled set and unlabeled set without labels. For the labeled set, we conduct
the imbalanced sampling similarly as in CIFAR10, and use the original unlabeled set directly in training.

**ImageNet127.** ImageNet127 groups the 1000 classes of ImageNet into 127 classes based on their top-down hierarchy in WordNet. It is a naturally imbalanced dataset with an imbalance ratio of roughly 286. Its most majority class consists of 218 original classes and 277,601 training images, and its most minority class is formed by a single original class with 969 training examples. To construct the labeled set, we randomly sample 1% and 10% samples in each class. The remaining samples are used directly as unlabeled set.

### C.2. Hyper-parameters

#### C.2.1 Classic Setting

We list the hyper-parameters used in classic setting in Appendix C.2.1. We use WRN-28-2 for all datasets in classic setting and an input size of 32. We set labeled batch size as 64, and use a $\mu$ of 2 for FixMatch and 1 for ReMixMatch. We use SGD optimizer with a constant learning rate of 0.03, and the weight decay is set to 5e-4. The evaluation result is from the EMA model with a momentum of 0.999. Running one experiment in classic setting roughly takes 11 hours using a single Nvidia V100.

| Dataset      | CIFAR10-LT | CIFAR100-LT | STL10-LT |
|--------------|------------|-------------|----------|
| Model        | WRN-28-2   | WRN-28-2    | WRN-28-2 |
| Input Size   | 32         | 32          | 32       |
| Labeled Batch size | 64        | 64          | 64       |
| Unlabeled Batch size | 128 (FixMatch), 64 (ReMixMatch) | 128 (FixMatch), 64 (ReMixMatch) | 128 (FixMatch), 64 (ReMixMatch) |
| Optimizer    | SGD        | SGD         | SGD      |
| Learning Rate| 0.03       | 0.03        | 0.03     |
| Weight Decay | 5e-4       | 5e-4        | 5e-4     |
| Training Epochs | 256       | 256         | 256      |
| Iter./Epoch  | 1024       | 1024        | 1024     |
| Model EMA Momentum | 0.999     | 0.999       | 0.999    |

Table 7. Hyper-parameters of classic setting.

#### C.2.2 Advanced Setting

In advanced setting, we mainly follow the hyper-parameters used in USB. We use ImageNet-1K pre-trained ViT-S-P2-32 for CIFAR100-LT and ImageNet-1K pre-trained ViT-S-P16-224 for CIFAR100-LT and FOOD101-LT. The Vision Transformer is trained using AdamW with layer decay. We use a learning rate of 5e-4 and 1e-3 for CIFAR100-LT and FOOD101-LT, and a layer decay of 0.5 for both. The labeled batch size and unlabeled batch size is both set to 64. Running one experiment in advanced setting roughly takes 10 hours using a single Nvidia V100.

| Dataset      | CIFAR100-LT | FOOD101-LT |
|--------------|-------------|------------|
| Model        | ViT-S-P2-32 | ViT-S-P16-224 |
| Input Size   | 32          | 224        |
| Labeled Batch size | 16        | 16         |
| Unlabeled Batch size | 16       | 16         |
| Optimizer    | AdamW       | AdamW      |
| Learning Rate| 5e-4        | 1e-3       |
| Layer Decay  | 0.5         | 0.5        |
| Scheduler    | Cosine      | Cosine     |
| Weight Decay | 5e-4        | 5e-4       |
| Training Epochs | 200       | 200        |
| Iter./Epoch  | 1024        | 1024       |
| Model EMA Momentum | 0.0       | 0.0        |

Table 8. Hyper-parameters of Advanced setting.

#### C.2.3 ImageNet127

On ImageNet127, we train ResNet50 using SGD with an initial learning rate of 0.1 with a cosine scheduler. We set the labeled batch size to 256 and unlabeled batch size 512. Running one experiment on ImageNet127 roughly takes 72 hours using a single Nvidia A100.

![Figure 7](image-url)
| Dataset         | ImageNet127          |
|-----------------|----------------------|
| Model           | ResNet50             |
| Input Size      | 112                  |
| Labeled Batch size | 256                |
| Unlabeled Batch size | 512              |
| Optimizer       | SGD                  |
| Learning Rate   | 0.1                  |
| Scheduler       | Cosine               |
| Weight Decay    | 5e-4                 |
| Training Epochs | 200                  |
| Iter/Epoch      | 2500                 |
| Model EMA Momentum | 0.999             |

Table 9. Hyper-parameters of Advanced setting.