ExMatch: Self-guided Exploitation for Semi-Supervised Learning with Scarce Labeled Samples

Noo-ri Kim, Jin-Seop Lee, and Jee-Hyong Lee*

Sungkyunkwan University, Suwon, South Korea
{pd99j, wlstjq0602, john}@skku.edu

Abstract. Semi-supervised learning is a learning method that uses both labeled and unlabeled samples to improve the performance of the model while reducing labeling costs. When there were tens to hundreds of labeled samples, semi-supervised learning methods showed good performance, but most of them showed poor performance when only a small number of labeled samples were given. In this paper, we focus on challenging label-scarce environments, where there are only a few labeled samples per class. Our proposed model, ExMatch, is designed to obtain reliable information from unlabeled samples using self-supervised models and utilize it for semi-supervised learning. In the training process, ExMatch guides the model to maintain an appropriate distribution and resist learning from incorrect pseudo-labels based on the information from self-supervised models and its own model. ExMatch shows stable training progress and the state-of-the-art performance on multiple benchmark datasets. In extremely label-scare situations, performance is improved by about 5% to 21% for CIFAR-10, CIFAR-100 and SVHN. ExMatch also demonstrates significant performance improvements in high-resolution and large-scale dataset such as STL-10, Tiny-ImageNet, and ImageNet.

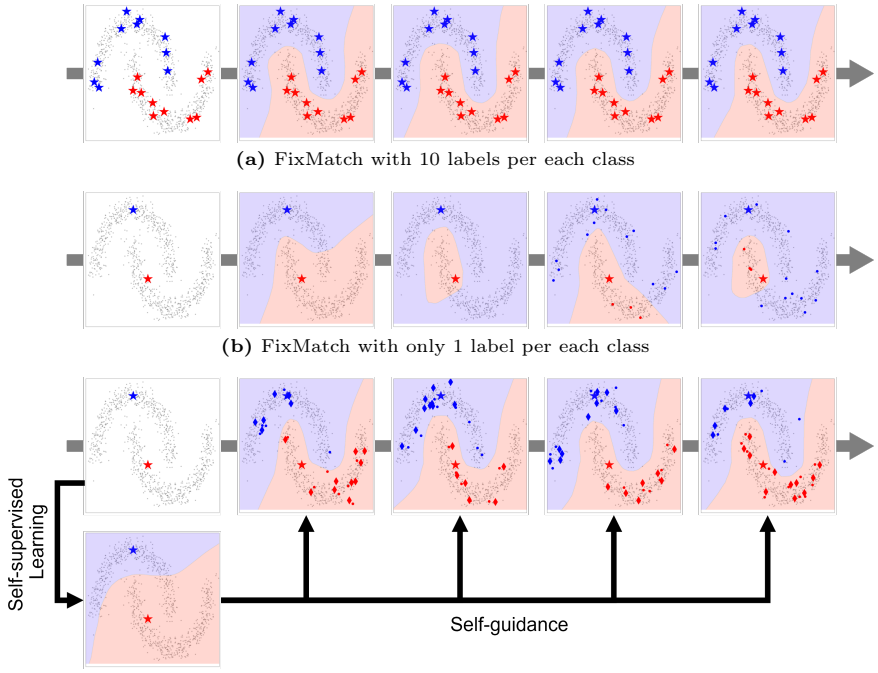
Keywords: Semi-supervised Learning · Scarce Labeled Samples · Self-guided Exploitation · Confirmation Bias

1 Introduction

Semi-supervised learning, which leverages a few labeled samples and a number of unlabeled samples, has evolved rapidly in recent years. With the performance improvement of semi-supervised learning, they are widely used in various fields of machine learning, such as image segmentation [7, 11, 38], object detection [1, 16, 29], text classification [5, 15, 31], and image classification [20, 26, 36]. Semi-supervised learning approaches have shown successful performance when there are a sufficient number of labeled samples, ranging from tens to hundreds [2,3,41].

However, most semi-supervised models showed poor performance when there were only few labeled samples [19]. Figures 1a and 1b show the cases where

* Corresponding author



(a) FixMatch with 10 labels per each class

(b) FixMatch with only 1 label per each class

(c) Our proposed method with only 1 label per each class

Fig. 1: Class boundaries by FixMatch and our proposed method on Moon dataset. Each crescent represents a class in the moon dataset. Labeled samples are represented by star shapes, and unlabeled samples are depicted as grey dots. Colored dots are pseudo-labeled samples. Their colors are the classes of pseudo-labels. In our proposed method, diamond signs denote additionally exploited samples by self-guidance.

each has 10 and 1 labeled samples, respectively. Figure 1a illustrates the class boundary as the training progresses when applying traditional semi-supervised learning method, FixMatch [36] to the moon dataset with 10 labels per each class. Since there are a sufficient number of labeled samples to represent the data distribution, the semi-supervised learning method effectively utilizes unlabeled samples in training, demonstrating accurate class boundaries. Figure 1b shows the class boundary as the training progresses when applying FixMatch to the moon dataset with only one labeled sample per each class. In Fig. 1b, labeled samples are insufficient to represent the data distribution. It can be observed that the model is learning many incorrect pseudo-labels. Consequently, the correctly learned red class region is affected by the wrong pseudo-labels in the next epoch. Due to the repetition of learning incorrect pseudo-labels, the class boundaries become highly unstable and change rapidly.

When the number of labeled samples decreases, it is hard to give exact pseudo-labels to unlabeled samples, so the semi-supervised model would learn from unlabeled samples with unreliable pseudo-labels. Eventually, the efficiency

of semi-supervised learning process may drop. This phenomenon is referred to as confirmation bias [25, 28, 37]. To alleviate this problem, some methods were proposed to obtain more accurate pseudo-labels [4, 14, 18, 19, 26, 30, 40, 44]. However, in situations with scarce labels, where only 1 or 2 labeled samples per class were available, most of them showed poor performance [19]. The main reason for the performance drop is that they heavily depend on the models' own predictions to learn from unlabeled samples. In other words, few labeled samples are too scarce to adequately represent the data distribution, making the model's predictions more inaccurate and obtaining accurate pseudo-labels for unlabeled samples more challenging.

Instead of relying only on models' predictions to obtain accurate pseudo-labels from scarce labeled samples, we propose utilizing unlabeled samples additionally to enhance performance in scenarios with limited labeled samples. For the additional exploitation of unlabeled samples, we utilize the distribution information of feature representation on unlabeled samples. Figure 1c shows the concept of the proposed method. By utilizing not only unlabeled samples but also the distribution information, our proposed method enables learning a wider distribution for each class. The given information guides the selection of unlabeled samples that the model needs to learn additionally during the semi-supervised learning process. Consequently, this self-guidance effectively prevents the learning of incorrect pseudo-labels, leading to a rapid and accurate convergence of the class boundaries.

The proposed method, ExMatch, is a semi-supervised learning approach with self-guided exploitation. To guide the semi-supervised model to consider the distribution information, ExMatch utilizes self-supervised models trained with the given unlabeled samples. Our proposed model choose reliable samples with the confidence of the semi-supervised model and the consistency between the semi- and self-supervised models. The chosen unlabeled samples based on self-guidance are used to additionally train the model to retain appropriate distribution and resist incorrect pseudo-labels. By exploiting chosen unlabeled samples by self-guidance, we can enhance the performance of semi-supervised models in scenarios with limited labeled samples.

We conduct experiments on multiple benchmark datasets [9, 10, 21, 23, 33] under label scarce scenarios and compare them with state-of-the-art methods [14, 18, 19, 26, 36, 39–41, 44]. Our method, ExMatch, shows a big improvement in most of cases. It shows the best performance on CIFAR-10 [21] with 10 labels, CIFAR-100 [21] with 100, 200, 400, and 1000 labels, and SVHN [33] with 10, 20, 40, and 250 labels. Especially in label-scare situations, one labeled sample per class, we improve the performance by 10.2% for CIFAR-10, 21.1% for CIFAR-100, and 5.1% for SVHN compared with their best baselines. Furthermore, ExMatch shows performance improvements of 41.8%, 22.9%, and 20.8% compared to FixMatch in high-resolution and large-scale dataset such as STL-10 [9] with 10 labels, Tiny-ImageNet [23] with 800 labels, and ImageNet [10] with 10k labels, respectively.

2 Related Work

Semi-supervised learning is a machine learning technique using a small number of labeled samples and a large number of unlabeled samples together. Semi-supervised models achieve high performance as they utilizes a large number of unlabeled samples obtained easily. Most semi-supervised learning methods mainly have been proposed based on consistency regularization [22, 35] and pseudo-labeling [24]. Consistency regularization is a method that makes a model trained to predict similar outputs for an image with different augmentations or perturbations. To utilize unlabeled samples, Temporal Ensembling [22], π model [22], Mean Teacher [37], and VAT [32] utilized the consistency regularization. Pseudo-labeling is a type of self-training technique [34, 42] to learn unlabeled samples using high-confident predictions of themselves. Pseudo-label [24] and Noisy Student [42] were proposed based on pseudo-labeling.

With the advance of semi-supervised learning, researchers began to utilize both consistency regularization and pseudo-labeling [2, 3, 14, 18, 19, 26, 30, 36, 39, 41, 44]. Most of them consist of supervised loss, which learns from labeled samples using cross-entropy, and an unsupervised loss, which is based on consistency regularization and pseudo-labeling. For unsupervised learning, each unlabeled sample is augmented using two types of augmentations (e.g. weak and strong augmentation). Then, the model learns from each strong-augmented sample with the paired weak-augmented sample's prediction (pseudo-label). In other words, this process involves learning from labeled samples, propagating labels (pseudo-labels), and learning from unlabeled samples with propagated pseudo-labels.

Recently, most methods have focused on effectively utilizing unlabeled samples. SelfMatch [18] proposed a semi-supervised learning method that utilizes self-supervised models as pre-trained models. CoMatch [26] combines self- and semi-supervised learning techniques to simultaneously learn representations and class probabilities. DoubleMatch [39] uses self-supervised learning to enable utilization of all unlabeled samples. FlexMatch [44] and FreeMatch [40] proposed curriculum pseudo-labeling to consider different learning statuses depending on each class. Less [30] trains self-supervised learning on low-confident unlabeled samples and proposed a class-aware confidence threshold for pseudo-labeling. FlatMatch [14] proposed a regularization method for ensuring consistent learning performance between labeled samples and unlabeled samples.

In the process of semi-supervised learning, there is a critical problem, confirmation bias, that incorrect pseudo-labels gradually increase if incorrect pseudo-labels are propagated [19, 28, 37]. Confirmation bias could be more critical when there are only few labeled samples [19]. To address the problem, previous methods are mainly focused on obtaining accurate pseudo-labels. MixMatch [3] and ReMixMatch [2] used multiple augmentations for pseudo-labeling. CoMatch [26] proposed memory-smoothed pseudo-labeling to assign pseudo-labels by using predictions of similar samples in feature space. Less [30] proposed refining methods for pseudo-label selection. Propagation Regularizer [19] proposed an entropy-based regularizer for accurate pseudo-labels. However, despite these efforts, most methods have still show poor performance in label-scarce environments.

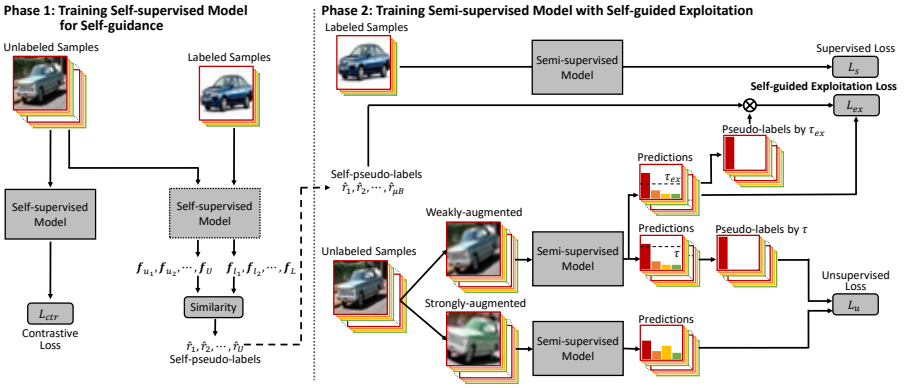


Fig. 2: Overview of ExMatch. Phase 1 is training a self-supervised model for self-guidance. For self-guidance, the model generates self-pseudo-labels reflecting distribution information. Phase 2 is a training semi-supervised model consisting of the supervised loss, the unsupervised loss, and the proposed self-guided exploitation loss. Through the self-guided exploitation loss, the semi-supervised model learns from additional unlabeled samples based on the information from both the self-supervised model and semi-supervised model.

3 Proposed Method

3.1 Overview

In semi-supervised learning, we aim to guide the selection and additional training of unlabeled samples based on the distribution information of the data. When there are only a few labeled samples, such guidance could alleviate the phenomenon where learning is dominated by incorrect unlabeled samples, unlike in Fig. 1b, enabling correct and stable learning, as depicted in Fig. 1c. To achieve this, our proposed method consists of extracting distribution information through feature representations and integrating it into the semi-supervised learning process.

Figure 2 shows an overview of the proposed method, ExMatch. Our proposed method, ExMatch, consists of two phases: (1) obtaining self-pseudo-labels for self-guidance by a self-supervised model; and (2) semi-supervised learning with additional self-guided exploitation. Unlike previous approaches, which either train semi-supervised and self-supervised learning simultaneously [26, 39] or utilize self-supervised models as pre-trained models [18], we decouple self-supervised learning from semi-supervised learning. Because we aim to independently utilize the information obtained through self-supervised learning. By leveraging information from these independent models, we can effectively utilize information from different perspectives.

3.2 Self-supervised Learning for Self-guidance

The first phase is obtaining self-pseudo-labels from the distribution information for self-guidance. To utilize the distribution information, we use SimCLR [6], which is one of successful self-supervised models. SimCLR is a contrastive learning approach that minimizes the distance between feature representations in differently augmented views of a single sample, and maximizes the distance between features representations of other samples. Self-supervised models can be useful in the semi-supervised learning with a few labeled samples because they do not require labeled samples for feature learning.

To obtain self-pseudo-labels, which serve as guidance for semi-supervised learning, we generate feature representations of unlabeled and labeled samples, f_U and f_L, from the self-supervised model, and evaluate cosine similarities between f_U and f_L. Next, each unlabeled sample is given the same label of the nearest labeled sample. We call it self-pseudo-label, $\hat{r}$. We may build a classifier by fine-tuning the self-supervised model with given a few labeled samples, and determine self-pseudo-labels by the classifier. If self-supervised models are fine-tuned with only a few labeled samples, they are prone to overfitting [45]. Furthermore, through fine-tuning, the model will be trained with supervision similar to semi-supervised learning, so the information obtained through both models will become similar. So, instead of fine-tuning the self-supervised model, we take the similarity of the feature representation.

Since self-pseudo-labels are obtained through self-supervised learning, it is very probable that they are independent from pseudo-labels from semi-supervised models. They can provide other additional information that is hard to obtain from semi-supervised learning. We use them as guidance to select unlabeled samples for additional exploitation.

3.3 Semi-supervised Learning with Self-guided Exploitation

The second phase is semi-supervised learning with self-guided exploitation. As mentioned in the previous section, we propose a method for semi-supervised learning models to receive guidance from the distribution information through feature representation of the data. The information is provided through self-pseudo-labels. However, instead of naively using the self-pseudo-labels, our approach considers the confidence of the semi-supervised model and consistency between the trained self-supervised model and the semi-supervised model.

Our semi-supervised model consists of a supervised loss, an unsupervised loss, and a proposed self-guided exploitation loss. The supervised and unsupervised losses are based on FixMatch [36]. The supervised loss is as follows:

$$L_s = \frac{1}{B} \sum_{b=1}^{B} \mathrm{H}\left(y_b, p\left(\alpha\left(x_b\right)\right)\right) \tag{1}$$

where L_s is a cross-entropy loss on weakly-augmented labeled samples. The model p learns a weakly-augmented sample $\alpha(x_b)$ with the given label y_b.

The unsupervised loss L_u is as follows:

$$\begin{gathered} L_u = \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1} \left(\max \left(\boldsymbol{q}_b \right) \geq \tau \right) \mathrm{H} \left(\hat{q}_b, p \left(\mathcal{A} \left(u_b \right) \right) \right) \\ \hat{q}_b = \operatorname{argmax} \left(\boldsymbol{q}_b \right) \\ \boldsymbol{q}_b = p \left(\alpha \left(u_b \right) \right) \end{gathered} \tag{2}$$

where L_u is a masked cross-entropy loss on strongly-augmented unlabeled samples. The model p learns a strongly-augmented sample $\mathcal{A}(u_b)$ with the pseudo-label $\hat{q}_b$ when the maximum of class probability in $\boldsymbol{q}_b$ is above a threshold τ. In Eq. (2), the model learns from strongly-augmented unlabeled samples with pseudo-labels for label propagation.

To make the model robust against confirmation bias, we introduce an additional loss term called self-guided exploitation loss, which additionally trains the model to retain an appropriate distribution and resist incorrect pseudo-labels. To reliably choose pseudo-labeled unlabeled-samples for additional training, we consider not only the confidence of pseudo-labels, but also the consistency between pseudo-labels and self-pseudo-labels. By considering consistency, the model can be guided by the distribution information. The self-guided exploitation loss L_{ex} is as follows:

$$L_{ex} = \frac{1}{\mu B} \sum_{b=1}^{\mu B} \left(\mathbb{1} \left(\hat{q}_b = \hat{r}_b \text{ and } \max \left(\boldsymbol{q}_b \right) \geq \tau_{ex} \right) \cdot \mathrm{H} \left(\hat{q}_b, p \left(\alpha \left(u_b \right) \right) \right) \right) \tag{3}$$

where $\hat{q}_b$ and $\hat{r}_b$ are a pseudo-label and a self-pseudo-label of u_b, respectively. To mitigate noisy labels and utilize the distribution information, the mask consists of consistency between a self-pseudo-label $\hat{r}_b$ and its own pseudo-label $\hat{q}_b$, and its own prediction's confidence $\boldsymbol{q}_b$ as shown in Eq. (3). These conditions allow the model to choose additional unlabeled-samples for exploitation. Finally, the model learns from a weakly-augmented sample $\alpha(x_b)$ using masked cross-entropy.

Unlike the unsupervised loss used for label propagation, the self-guided exploitation loss is designed to guide the model consider the appropriate distribution and resist learning from incorrect pseudo-labels. In other words, it is a retraining process for reliable unlabeled samples. Therefore, we apply weak augmentations to the samples selected through self-guidance, rather than strong augmentations that may deviate significantly from the guidance.

Our overall loss is as follows:

$$L = L_s + \lambda_u L_u + \lambda_{ex} L_{ex} \tag{4}$$

where λ_s, λ_u, and λ_{ex} are weight factors for the supervised loss, the unsupervised loss, and our proposed self-guided exploitation loss, respectively.

4 Experiments

4.1 Experimental Setup

To evaluate semi-supervised models in environments with scarce labeled samples, we compare the proposed method, ExMatch, with UDA [41], FixMatch [36], SelfMatch [18], CoMatch [26], DoubleMatch [39], FlexMatch [44], Propagation Regularizer (PR) [19], FreeMatch [40], and FlatMatch [14]. UDA and FixMatch are the most commonly used as baselines, and SelfMatch, CoMatch, and DoubleMatch are semi-supervised learning methods adopting self-supervised learning. FlexMatch, PR, and FreeMatch are semi-supervised approaches that consider the learning status of each class, and FlatMatch considers the learning status between labeled and unlabeled samples. In environments with scarce labels, the model's performance is strongly effected by the set of labeled samples. Therefore, we re-evaluate all methods based on their original works with the same folds.

To evaluate our proposed method and baselines, we use CIFAR-10/100 [21], and SVHN [33] as benchmark datasets commonly used in semi-supervised learning. Also, we conduct experiments on STL-10 [9], Tiny-ImageNet [23], and ImageNet [10] to demonstrate the effectiveness of our approach with high-resolution and large-scale datasets. Details of datasets are presented in the supplementary material. We select an equal number of labeled samples for each class in all datasets except SVHN, and for SVHN, labeled samples are chosen in according to the original class distribution. All experiments are performed using the same 5 folds. We use the original data as the unlabeled data, and only randomly selected samples as the labeled data.

A Wide ResNet-28-2 [43] architecture is used for CIFAR-10, CIFAR-100, SVHN, and Tiny-ImageNet. For STL-10 and ImageNet, Wide ResNet-37-2 and ResNet-50 are used, respectively. The hyperparameter τ_{ex} is set to 0.6 for ImageNet, and 0.8 for other datasets. The weight of the exploitation loss is set to 0.4 for all datasets. Hyperparameters for the semi-supervised model are set according to the FixMatch [36]. Details of the semi-supervised models are presented in the supplementary material. To obtain self-pseudo-labels, SimCLR [6,17] models with the ResNet-50 [13] are used for all datasets. For SVHN dataset, flip augmentation is not used, and the scale of resize crop is set from 0.8 to 1.0 since it includes digit numbers. All hyperparameters for self-supervised learning are set according to the original works [6, 17]. We present the details of self-supervised models in the supplementary material.

Although we conducted baseline experiments based on the original works, we observed discrepancy in performance compared to the original results. Since all the indices of the labeled samples were not disclosed, we randomly selected labeled samples for the experiments. When labeled data is scarcely given, the performance can vary significantly depending on which samples are chosen [19, 36]. For the fair comparison, in this paper, we fix the indices of randomly selected labeled samples for all the baselines. More details on reproducibility are presented in the supplementary material.

Table 1: Comparison of accuracy for CIFAR-10, CIFAR-100, and SVHN on 5 folds. For a fair comparison, all the baselines are conducted on the same labeled samples for each fold.

Method	CIFAR-10			CIFAR-100			SVHN		
	10	20	40	100	200	400	10	20	40
UDA	56.93 ± 8.17	77.62 ± 7.04	89.41 ± 4.28	24.85 ± 0.85	38.12 ± 0.93	48.62 ± 1.88	12.84 ± 6.29	37.76 ± 20.14	84.90 ± 16.28
FixMatch	60.01 ± 7.41	75.50 ± 10.93	85.57 ± 5.21	24.11 ± 1.50	35.83 ± 1.63	46.04 ± 1.41	13.07 ± 4.48	27.58 ± 14.50	56.65 ± 26.88
SelfMatch	50.60 ± 27.41	77.66 ± 21.78	90.15 ± 4.59	20.71 ± 2.84	32.13 ± 2.57	44.93 ± 1.27	43.07 ± 23.64	73.79 ± 13.16	90.52 ± 6.36
CoMatch	65.10 ± 7.81	88.26 ± 8.29	92.16 ± 4.97	24.19 ± 0.98	32.51 ± 1.15	41.72 ± 2.04	19.51 ± 6.22	27.30 ± 2.79	47.51 ± 6.74
DoubleMatch	54.86 ± 6.83	76.68 ± 9.42	89.91 ± 3.09	20.82 ± 2.66	31.96 ± 1.77	43.31 ± 2.86	29.34 ± 12.65	56.38 ± 10.88	89.04 ± 10.00
FlexMatch	59.06 ± 19.80	**94.62** ± 0.15	94.86 ± 0.05	4.47 ± 0.81	30.59 ± 1.69	46.11 ± 2.83	8.71 ± 0.40	9.93 ± 0.81	32.41 ± 23.12
PR	49.97 ± 17.09	84.53 ± 6.04	90.55 ± 3.15	26.83 ± 1.07	36.22 ± 2.10	47.75 ± 1.43	30.05 ± 20.90	58.34 ± 13.05	74.45 ± 15.18
FreeMatch	66.19 ± 23.58	91.66 ± 7.11	**94.88** ± 0.11	8.08 ± 2.74	29.86 ± 1.68	44.72 ± 1.09	8.84 ± 0.67	29.47 ± 30.37	69.50 ± 17.61
FlatMatch	69.28 ± 17.54	91.59 ± 7.13	94.85 ± 0.11	9.19 ± 3.00	29.47 ± 0.30	47.10 ± 4.47	9.44 ± 0.34	10.99 ± 1.04	34.03 ± 24.99
ExMatch	**72.97** ± 5.91	84.66 ± 3.91	89.78 ± 3.06	**32.49** ± 2.99	**43.71** ± 1.48	**51.13** ± 1.70	**45.25** ± 4.81	**82.07** ± 9.16	**92.97** ± 4.48

4.2 Overall Performance with Scarce Labeled Samples

Table 1 shows the results on CIFAR-10, CIFAR-100, and SVHN. For evaluation, previous studies adopted the median performance of the last 20 checkpoints [2, 3, 26, 36, 39], the best performance in all checkpoints [36, 39], or the performance by model selection [19]. We employ the median performance of the last 20 checkpoints as used in most research. We present the performance with a small number of labeled samples. We present more results with a lager number of labeled samples in the supplementary material.

The proposed method, ExMatch, shows the best performance on CIFAR-10 with 10 labels, CIFAR-100 with 100, 200, and 400 labels, and SVHN with 10, 20, and 40 labels. Especially on CIFAR-10 with 10 labels, CIFAR-100 with 100 labels, and SVHN with 10 labels, we achieve performance improvements of 5.3%, 21.1%, and 5.1% compared with the best baseline models, respectively. Also, compared to FixMatch which is our base method, ExMatch shows improvements. This indicates that self-guided exploitation leads to significant performance improvement in harsh environments to semi-supervised learning, datasets with fewer labeled samples or more classes.

Table 2: Comparison of accuracy for STL-10, Tiny-ImageNet and ImageNet. STL-10 is evaluated on 3 folds, and Tiny-ImageNet and ImageNet are on 1 fold.

Method	STL-10 10 labels	Tiny -ImageNet 800 labels	ImageNet			
			10k labels		100k labels	
			Top-1	Top-5	Top-1	Top-5
FixMatch	38.09	27.48	21.47	38.53	54.43	76.69
ExMatch	**54.01**	**33.77**	**25.94**	**43.99**	**55.95**	**77.58**

On CIFAR-10 dataset, ExMatch shows the best performance and the smallest variance with 10 labels, the most harsh environment. Although learning CIFAR-100 is more difficult than CIFAR-10 due to more classes and fewer unlabeled samples for each class, ExMatch shows a greater performance improvement. Especially on CIFAR-100 with 100 labeled samples, ExMatch achieves a significant improvement of 21.1% compared to the best baseline, PR. Even in the case of class imbalance in SVHN, ExMatch demonstrates superior performance compared to the baselines. Despite being highly influenced by the choice of labeled samples, our approach consistently achieves best performance and shows relatively low standard deviation.

In contrast to the significant performance improvement of ExMatch, methods adopting self-supervised learning, such as SelfMatch, CoMatch, and DoubleMatch, exhibit similar or lower performance compared to FixMatch on CIFAR-10 and CIFAR-100 datasets. On SVHN, they show relatively better performance than FixMatch, but there are performance difference of more than 5% compared to ExMatch. These results indicate that our approach leverages the information from the self-supervised model more effectively.

4.3 Results on Higher Resolution Datasets

To confirm our method is effective with high-resolution datasets and large-scale dataset, experiments are also conducted on STL-10, Tiny-ImageNet, and ImageNet datasets. For STL-10 and Tiny-ImageNet, we respectively sample 1 and 4 labeled samples per class. For ImageNet, we sample 10 and 100 labeled samples per class. Table 2 shows the experimental results. Due to practical challenges arising from high resolution and a larger number of samples, the comparison experiments are conducted exclusively with FixMatch.

Our method exhibits a significant performance improvement of 41.8% on STL-10 and 22.9% on Tiny-ImageNet. On the large-scale dataset, ImageNet, which contains 1000 classes, high resolution, and a substantial number of samples (1.3 million), our method achieves a performance improvement of 20.8% and 2.6%. The experiments shows that our method is also effective to large scale datasets with high resolution images.

Table 3: Ablation study of exploitation conditions and augmentations for CIFAR-10 with 10 labels on 3 folds.

Model	Loss	Acc.
FixMatch	$L_s + \lambda_u \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\left(\max\left(\boldsymbol{q}_b\right) \geq \tau\right) \mathrm{H}\left(\hat{q}_b, p\left(\mathcal{A}\left(u_b\right)\right)\right)$	60.84
M1	$L_s + \lambda_u \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\left(\max\left(\boldsymbol{q}_b\right) \geq \tau \text{ and } \hat{q}_b = \hat{r}_b\right) \mathrm{H}\left(\hat{q}_b, p\left(\mathcal{A}\left(u_b\right)\right)\right)$	64.86
M2	$L_s + \lambda_u L_u + \lambda_{ex} \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\left(\text{True}\right) \mathrm{H}\left(\hat{q}_b, p\left(\alpha\left(u_b\right)\right)\right)$	12.31
M3	$L_s + \lambda_u L_u + \lambda_{ex} \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\left(\max\left(\boldsymbol{q}_b\right) \geq \tau_{ex}\right) \mathrm{H}\left(\hat{q}_b, p\left(\alpha\left(u_b\right)\right)\right)$	29.25
M4	$L_s + \lambda_u L_u + \lambda_{ex} \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\left(\hat{q}_b = \hat{r}_b\right) \cdot \mathrm{H}\left(\hat{q}_b, p\left(\alpha\left(u_b\right)\right)\right)$	56.61
M5	$L_s + \lambda_u L_u + \lambda_{ex} \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\left(\hat{q}_b = \hat{r}_b \text{ and } \max\left(\boldsymbol{q}_b\right) \geq \tau_{ex}\right) \mathrm{H}\left(\hat{q}_b, p\left(\mathcal{A}\left(u_b\right)\right)\right)$	50.07
ExMatch	$L_s + \lambda_u L_u + \lambda_{ex} \frac{1}{\mu B} \sum_{b=1}^{\mu B} \mathbb{1}\left(\hat{q}_b = \hat{r}_b \text{ and } \max\left(\boldsymbol{q}_b\right) \geq \tau_{ex}\right) \mathrm{H}\left(\hat{q}_b, p\left(\alpha\left(u_b\right)\right)\right)$	**74.83**

4.4 Ablation Study

Exploitation Conditions and Augmentations. Table 3 shows the performance with respect to how to guide and how to learn for exploitation. M1 is a model that incorporates the consistency of pseudo-labels and self-pseudo-labels into the unsupervised loss of FixMatch. M2 is a model using all pseudo-labeled unlabeled samples instead of appropriate guiding conditions, M3 is a model that selects and uses unlabeled samples based only on its confidence, without the consistency guidance of the distribution information. M4 is a model that selects and uses unlabeled samples based only on the consistency between pseudo-labels and self-pseudo-labels. M3 and M4 are based on partial conditions of our proposed method, ExMatch. Lastly, M5 is a model that uses strong augmentations instead of weak augmentations in the self-guided exploitation loss.

Simply adding self-pseudo-labels does not lead to significant performance improvement in the model (M1). Since pseudo-labeled samples are inaccurate, using all of them without selection (M2) have a bad effect on model performance. Choosing based on the confidence (M3) is not a good approach because the model is also unreliable. It is not so effective to use unlabeled samples chosen with consistency of pseudo-labels and self-pseudo-labels (M4) because the accuracy of self-pseudo-labels is not so high, either. Despite consisting the same condition as ExMatch, M5 shows lower performance due to the use of strong augmentation.

This demonstrates that we have effectively designed the exploitation loss for consider the information of self-supervised models. As a result, it is evident that simple incorporating self-pseudo-labels into the semi-supervised learning process does not lead to performance improvement. Table 3 confirms that our exploitation conditions are well-designed to achieve performance improvements.

Hyperparameters. To verify the sensitivity of parameters, we perform the experiments with various exploitation weights (λ_{ex}) and exploitation thresholds (τ_{ex}). The exploitation weight is the weight factor of the self-guided exploitation loss, and the exploitation threshold is used in the conditions for self-guidance.

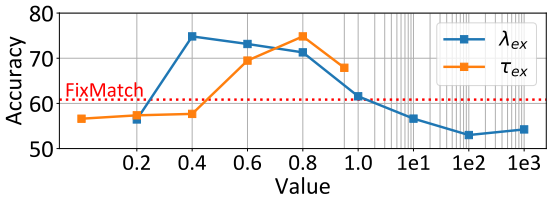


Fig. 3: Accuracy with respect to the weight for exploitation loss, λ_{ex}, and the threshold for exploitation loss, τ_{ex}.

Table 4: Performance depending on self-supervised models. All experiments are evaluated on CIFAR-10 with 10 labels.

	Model	Network	Dataset	Self-pseudo	Accuracy
S1	RotNet	NiN-4	CIFAR-10	Similarity	57.91
S2	SimCLR	WRN-28-2	CIFAR-10	Similarity	71.92
S3	SimCLR	ResNet-18	CIFAR-10	Similarity	74.72
S4	SimCLR	ResNet-50	CIFAR-10	Fine-tuning	67.82
S5	SimCLR	ResNet-50	ImageNet-32	Similarity	74.85
ExMatch	SimCLR	ResNet-50	CIFAR-10	Similarity	74.83

Figure 3 shows the performance of ExMatch with respect to the value of the exploitation weight (λ_{ex}) and the exploitation threshold (τ_{ex}). Looking at the blue line, ExMatch shows the best performance when λ_{ex} is 0.4. It maintains a performance of over 70% when λ_{ex} is between 0.4 and 1.0. Looking at the orange line, ExMatch shows the best performance when τ_{ex} is 0.8. Its performance keeps around 70% under the exploitation thresholds are 0.6 and 0.95.

Self-Supervised Models. We present an ablation study on self-supervised models to examine how they affect the performance of ExMatch. We choose two approaches for self-supervised model training: RotNet [12] and SimCLR; four networks: NiN-4 [27], Wide Resnset-28-2, ResNet-18, and ResNet-50; two datasets for self-supervised model training: CIFAR-10 and ImageNet-32; and two methods for obtaining self-pseudo-labels: similarity and fine-tuning as shown in Tab. 4. S1 is the ExMatch with a simple self-supervised models. S2 and S3 use SimCLR with Wide ResNet-28-2 and ResNet-18, respectively, which are smaller networks compared to the original ExMatch. In S4, instead of utilizing cosine similarity-based self-pseudo-labels, self-pseudo-labels are given by the self-supervised model fine-tuned with scarce labeled samples. The self-supervised models for S5 is trained with ImageNet-32 [8] instead of CIFAR-10.

Despite the limitation of the self-supervised learning method and network size, S1 shows a similar performance to FixMatch. Its accuracy is 57.91% while

Table 5: Analysis of self-guided exploitation on CIFAR-10/100 and SVHN. Accuracy of exploited samples and exploitation ratio are median of the last 20 checkpoints.

	CIFAR-10			CIFAR-100			SVHN		
	10	20	40	100	200	400	10	20	40
Accuracy of All Self-Pseudo-Labels	53.36	65.13	74.46	36.57	43.08	47.99	45.33	65.63	77.21
Accuracy of Exploited Samples	87.87	92.02	93.86	64.27	71.42	76.41	62.54	86.32	93.90
Exploitation Ratio	52.77	66.21	76.85	36.63	45.38	51.79	61.67	73.53	81.07

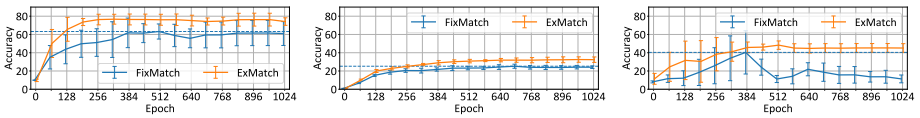
FixMatch is 60.98%. It can be noted that our method still effectively provide additional exploitations, despite the distribution information not being accurate due to the low quality of the self-supervised model. Furthermore, S2 and s3 with a relatively smaller model demonstrates comparable performance to ExMatch, achieving an accuracy of 71.92% and 74.72%, respectively. We adopt self-supervised models fine-tuned on labeled samples to generate self-pseudo-labels for S4, and it achieves a performance of 67.82%. This demonstrates that adopting self-supervised learning is effective, but our approach proves to be more effective. S5 achieves a performance of 74.85% even though the self-supervised model is trained with ImageNet-32, other dataset than CIFAR-10. This provides the possibility of utilizing publicly available pre-trained models, which could lead to a reduction in training costs for self-supervised models.

This result demonstrates additional advantages of our approach. By decoupling the self-supervised model from the semi-supervised model and leveraging information through self-pseudo-labels instead of using the self-supervised model directly, our method provides flexibility and advantages in utilizing self-supervised models with diverse architectures, sizes, and datasets.

4.5 Analysis of Exploitation

We analyze how effectively the proposed self-guided exploitation utilizes unlabeled samples. We evaluate the exploitation by the accuracy of all self-pseudo-labels, the accuracy of exploited samples, and the exploitation ratio as shown in Tab. 5. The accuracy of all self-pseudo-labels is the quality of self-pseudo-labels obtained from the self-supervised model. In other words, it denotes the quality of the distribution information obtained from the self-supervised model. It is evaluated using ground-truth labels that are not used for training. The accuracy of exploited samples refers to the accuracy of unlabeled samples chosen by the conditions in Eq. (3) for self-guidance. The exploitation ratio is the proportion of the chosen unlabeled samples for exploitation.

In Tab. 5, we can know that the accuracy of exploited samples are always much higher than the accuracy of all self-pseudo-labels. This indicates that our



(a) CIFAR-10 with 10 labels **(b)** CIFAR-100 with 100 labels **(c)** SVHN with 10 labels

Fig. 4: Comparisons of learning stability between FixMatch and ExMatch with 1 labeled sample per class on 5 folds.

exploitation conditions are effective in selecting more accurate and reliable samples to guide semi-supervised learning using the distribution information. The ratio of exploited samples is about 36% to 81%, which means that a quite number of unlabeled samples are utilized for additional exploitation. What is interesting is the ratio is linearly proportional to the accuracy of all self-pseudo-labels. As the accuracy increases, so does the ratio, and vice versa. However, the accuracy of exploited samples are kept high.

4.6 Training Stability

We analyze how the self-guided exploitation helps the models stably learn by comparing with FixMatch. Figure 4 shows the accuracy as training progress on CIFAR-10, CIFAR-100, and SVHN with only 1 labeled sample per class. On all datasets, ExMatch demonstrates gradual and stable performance improvements compared to FixMatch. These results show that the self-guided exploitation leads to not only high performance but also high stability in model training.

5 Conclusion

We proposed ExMatch, a semi-supervised learning approach that addressed the performance degradation when a small number of labeled samples were available. By leveraging self-supervised models, ExMatch effectively extracted the distribution information from unlabeled samples. Subsequently, in the semi-supervised learning process, ExMatch learned from unlabeled samples guided by the information to maintain an appropriate distribution and resist learning from incorrect pseudo-labels, which helps alleviate confirmation bias. ExMatch demonstrated stable training progress and achieved state-of-the-art performance on various benchmark datasets with scarce labeled samples.

Acknowledgements. This work was partly supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No.2019-0-00421, AI Graduate School Support Program), the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (RS-2024-00352717), and institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No.2022-0-01045, Self-directed Multi-modal Intelligence for solving unknown, open domain problems)

References

1. Bar, A., Wang, X., Kantorov, V., Reed, C., Herzig, R., Chechik, G., Rohrbach, A., Darrell, T., Globerson, A.: Detreg: Unsupervised pretraining with region priors for object detection. ArXiv preprint **abs/2106.04550** (2021), https://arxiv.org/abs/2106.04550
2. Berthelot, D., Carlini, N., Cubuk, E.D., Kurakin, A., Sohn, K., Zhang, H., Raffel, C.: Remixmatch: Semi-supervised learning with distribution matching and augmentation anchoring. In: 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net (2020), https://openreview.net/forum?id=HklkeR4KPB
3. Berthelot, D., Carlini, N., Goodfellow, I.J., Papernot, N., Oliver, A., Raffel, C.: Mixmatch: A holistic approach to semi-supervised learning. In: Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada. pp. 5050–5060 (2019), https://proceedings.neurips.cc/paper/2019/hash/1cd138d0499a68f4bb72bee04bbec2d7-Abstract.html
4. Chen, H., Tao, R., Fan, Y., Wang, Y., Wang, J., Schiele, B., Xie, X., Raj, B., Savvides, M.: Softmatch: Addressing the quantity-quality trade-off in semi-supervised learning. arXiv preprint arXiv:2301.10921 (2023)
5. Chen, J., Yang, Z., Yang, D.: MixText: Linguistically-informed interpolation of hidden space for semi-supervised text classification. In: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. pp. 2147–2157. Association for Computational Linguistics, Online (2020). https://doi.org/10.18653/v1/2020.acl-main.194, https://aclanthology.org/2020.acl-main.194
6. Chen, T., Kornblith, S., Norouzi, M., Hinton, G.E.: A simple framework for contrastive learning of visual representations. In: Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event. Proceedings of Machine Learning Research, vol. 119, pp. 1597–1607. PMLR (2020), http://proceedings.mlr.press/v119/chen20j.html
7. Chen, X., Yuan, Y., Zeng, G., Wang, J.: Semi-supervised semantic segmentation with cross pseudo supervision. In: CVPR (2021)
8. Chrabaszcz, P., Loshchilov, I., Hutter, F.: A downsampled variant of imagenet as an alternative to the cifar datasets. arXiv preprint arXiv:1707.08819 (2017)
9. Coates, A., Ng, A., Lee, H.: An analysis of single-layer networks in unsupervised feature learning. In: Proceedings of the fourteenth international conference on artificial intelligence and statistics. pp. 215–223. JMLR Workshop and Conference Proceedings (2011)
10. Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: Imagenet: A large-scale hierarchical image database. In: 2009 IEEE conference on computer vision and pattern recognition. pp. 248–255. Ieee (2009)
11. French, G., Laine, S., Aila, T., Mackiewicz, M., Finlayson, G.D.: Semi-supervised semantic segmentation needs strong, varied perturbations. In: 31st British Machine Vision Conference 2020, BMVC 2020, Virtual Event, UK, September 7-10, 2020. BMVA Press (2020), https://www.bmvc2020-conference.com/assets/papers/0680.pdf
12. Gidaris, S., Singh, P., Komodakis, N.: Unsupervised representation learning by predicting image rotations. In: International Conference on Learning Representations (2018), https://openreview.net/forum?id=S1v4N2l0-

13. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition (2015). https://doi.org/10.48550/ARXIV.1512.03385, https://arxiv.org/abs/1512.03385
14. Huang, Z., Shen, L., Yu, J., Han, B., Liu, T.: Flatmatch: Bridging labeled data and unlabeled data with cross-sharpness for semi-supervised learning. In: Oh, A., Naumann, T., Globerson, A., Saenko, K., Hardt, M., Levine, S. (eds.) Advances in Neural Information Processing Systems. vol. 36, pp. 18474–18494. Curran Associates, Inc. (2023), https://proceedings.neurips.cc/paper_files/paper/2023/file/3b11c5cc84b6da2838db348b37dbd1a2-Paper-Conference.pdf
15. Izmailov, P., Kirichenko, P., Finzi, M., Wilson, A.G.: Semi-supervised learning with normalizing flows. In: Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event. Proceedings of Machine Learning Research, vol. 119, pp. 4615–4630. PMLR (2020), http://proceedings.mlr.press/v119/izmailov20a.html
16. Jeong, J., Lee, S., Kim, J., Kwak, N.: Consistency-based semi-supervised learning for object detection. In: Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada. pp. 10758–10767 (2019), https://proceedings.neurips.cc/paper/2019/hash/d0f4dae80c3d0277922f8371d5827292-Abstract.html
17. Khosla, P., Teterwak, P., Wang, C., Sarna, A., Tian, Y., Isola, P., Maschinot, A., Liu, C., Krishnan, D.: Supervised contrastive learning (2020). https://doi.org/10.48550/ARXIV.2004.11362, https://arxiv.org/abs/2004.11362
18. Kim, B., Choo, J., Kwon, Y.D., Joe, S., Min, S., Gwon, Y.: Selfmatch: Combining contrastive self-supervision and consistency for semi-supervised learning. ArXiv preprint **abs/2101.06480** (2021), https://arxiv.org/abs/2101.06480
19. Kim, N.r., Lee, J.H.: Propagation regularizer for semi-supervised learning with extremely scarce labeled samples. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 14401–14410 (2022)
20. Kim, N.r., Lee, J.S., Lee, J.H.: Learning with structural labels for learning with noisy labels. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp. 27610–27620 (June 2024)
21. Krizhevsky, A., Hinton, G., et al.: Learning multiple layers of features from tiny images (2009)
22. Laine, S., Aila, T.: Temporal ensembling for semi-supervised learning. In: 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. OpenReview.net (2017), https://openreview.net/forum?id=BJ6oOfqge
23. Le, Y., Yang, X.: Tiny imagenet visual recognition challenge. CS 231N **7**(7), 3 (2015)
24. Lee, D.H.: Pseudo-label : The simple and efficient semi-supervised learning method for deep neural networks. ICML 2013 Workshop : Challenges in Representation Learning (WREPL) (07 2013)
25. Lee, H.W., Kim, N.r., Lee, J.H.: Deep neural network self-training based on unsupervised learning and dropout. International Journal of Fuzzy Logic and Intelligent Systems **17**(1), 1–9 (2017)
26. Li, J., Xiong, C., Hoi, S.C.: Comatch: Semi-supervised learning with contrastive graph regularization. In: Proceedings of the IEEE/CVF international conference on computer vision. pp. 9475–9484 (2021)
27. Lin, M., Chen, Q., Yan, S.: Network in network. arXiv preprint arXiv:1312.4400 (2013)

28. Liu, L., Li, Y., Tan, R.: Decoupled certainty-driven consistency loss for semi-supervised learning. ArXiv preprint **abs**/ (20), https://arxiv.org/abs/
29. Liu, Y.C., Ma, C.Y., He, Z., Kuo, C.W., Chen, K., Zhang, P., Wu, B., Kira, Z., Vajda, P.: Unbiased teacher for semi-supervised object detection. ArXiv **abs/2102.09480** (2021)
30. Lucas, T., Weinzaepfel, P., Rogez, G.: Barely-supervised learning: semi-supervised learning with very few labeled images. In: Proceedings of the AAAI Conference on Artificial Intelligence. vol. 36, pp. 1881–1889 (2022)
31. Miyato, T., Dai, A.M., Goodfellow, I.: Adversarial training methods for semi-supervised text classification. arXiv: Machine Learning (2017)
32. Miyato, T., Maeda, S., Koyama, M., Ishii, S.: Virtual adversarial training: A regularization method for supervised and semi-supervised learning. IEEE Transactions on Pattern Analysis and Machine Intelligence **41**, 1979–1993 (2019)
33. Netzer, Y., Wang, T., Coates, A., Bissacco, A., Wu, B., Ng, A.Y.: Reading digits in natural images with unsupervised feature learning. In: NIPS Workshop on Deep Learning and Unsupervised Feature Learning 2011 (2011), http://ufldl.stanford.edu/housenumbers/nips2011_housenumbers.pdf
34. Rosenberg, C., Hebert, M., Schneiderman, H.: Semi-supervised self-training of object detection models. 2005 Seventh IEEE Workshops on Applications of Computer Vision (WACV/MOTION'05) - Volume 1 **1**, 29–36 (2005)
35. Sajjadi, M., Javanmardi, M., Tasdizen, T.: Regularization with stochastic transformations and perturbations for deep semi-supervised learning. In: Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain. pp. 1163–1171 (2016), https://proceedings.neurips.cc/paper/2016/hash/30ef30b64204a3088a26bc2e6ecf7602-Abstract.html
36. Sohn, K., Berthelot, D., Carlini, N., Zhang, Z., Zhang, H., Raffel, C.A., Cubuk, E.D., Kurakin, A., Li, C.L.: Fixmatch: Simplifying semi-supervised learning with consistency and confidence. In: Advances in Neural Information Processing Systems. vol. 33, pp. 596–608. Curran Associates, Inc. (2020), https://proceedings.neurips.cc/paper/2020/file/06964dce9addb1c5cb5d6e3d9838f733-Paper.pdf
37. Tarvainen, A., Valpola, H.: Mean teachers are better role models: Weight-averaged consistency targets improve semi-supervised deep learning results. In: Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA. pp. 1195–1204 (2017), https://proceedings.neurips.cc/paper/2017/hash/68053af2923e00204c3ca7c6a3150cf7-Abstract.html
38. Tu, P., Huang, Y., Ji, R., Zheng, F., Shao, L.: Guidedmix-net: Learning to improve pseudo masks using labeled images as reference. ArXiv preprint **abs/2106.15064** (2021), https://arxiv.org/abs/2106.15064
39. Wallin, E., Svensson, L., Kahl, F., Hammarstrand, L.: Doublematch: Improving semi-supervised learning with self-supervision. CoRR **abs/2205.05575** (2022). https://doi.org/10.48550/arXiv.2205.05575, https://doi.org/10.48550/arXiv.2205.05575
40. Wang, Y., Chen, H., Heng, Q., Hou, W., Savvides, M., Shinozaki, T., Raj, B., Wu, Z., Wang, J.: Freematch: Self-adaptive thresholding for semi-supervised learning. arXiv preprint arXiv:2205.07246 (2022)
41. Xie, Q., Dai, Z., Hovy, E., Luong, M.T., Le, Q.V.: Unsupervised data augmentation for consistency training. ArXiv preprint **abs**/ (20), https://arxiv.org/abs/

42. Xie, Q., Luong, M., Hovy, E.H., Le, Q.V.: Self-training with noisy student improves imagenet classification. In: 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020. pp. 10684–10695. IEEE (2020). https://doi.org/10.1109/CVPR42600.2020.01070, https://doi.org/10.1109/CVPR42600.2020.01070
43. Zagoruyko, S., Komodakis, N.: Wide residual networks. In: Proceedings of the British Machine Vision Conference 2016, BMVC 2016, York, UK, September 19-22, 2016. BMVA Press (2016), http://www.bmva.org/bmvc/2016/papers/paper087/index.html
44. Zhang, B., Wang, Y., Hou, W., Wu, H., Wang, J., Okumura, M., Shinozaki, T.: Flexmatch: Boosting semi-supervised learning with curriculum pseudo labeling. Advances in Neural Information Processing Systems **34**, 18408–18419 (2021)
45. Zhang, X., Zhou, L., Xu, R., Cui, P., Shen, Z., Liu, H.: Towards unsupervised domain generalization. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 4910–4920 (2022)