An Empirical Study and Analysis on Open-Set Semi-Supervised Learning

Huixiang Luo*, Hao Cheng*, Fanxu Meng, Yuting Gao, Ke Li, Mengdan Zhang, Xing Sun†

Tencent Youtu Lab, Shanghai, China

{luobosirobots,louischeng369,tristanli.sh,winfred.sun}@gmail.com, {rumimeng,yutinggao,davinazhang}@tencent.com

Abstract

Pseudo-labeling (PL) and Data Augmentation based Consistency Training (DACT) are two approaches widely used in Semi-Supervised Learning (SSL) methods. These methods exhibit great power in many machine learning tasks by utilizing unlabeled data for efficient training. But in a more realistic setting (termed as open-set SSL), where unlabeled dataset contains out-of-distribution (OOD) samples, the traditional SSL methods suffer severe performance degradation. Recent approaches mitigate the negative influence of OOD samples by filtering them out from the unlabeled data. However, it is not clear whether directly removing the OOD samples is the best choice. Furthermore, why PL and DACT could perform differently in open-set SSL remains a mystery. In this paper, we thoroughly analyze various SSL methods (PL and DACT) on open-set SSL and discuss pros and cons of these two approaches separately. Based on our analysis, we propose Style Disturbance to improve traditional SSL methods on open-set SSL and experimentally show our approach can achieve state-of-the-art results on various datasets by utilizing OOD samples properly. We believe our study can bring new insights for SSL research.

Introduction

The majority of SSL algorithms are designed assuming that both the labeled and the unlabeled dataset are drawn from the same distribution, which means they share the same classes and no outlier exists in the unlabeled dataset. When it comes to a more realistic setting where the unlabeled dataset contains out-of-distribution (OOD) samples, the performance of many popular SSL algorithms is severely damaged [Oliver et al. 2018; Guo et al. 2020; Yu et al. 2020; Chen et al. 2020]. This setting is firstly introduced by (Yu et al. 2020), and is named as "Open-Set Semi-Supervised Learning" (open-set SSL, illustrated in Figure 1). To mitigate the negative influence of OOD samples, a straightforward approach (Chen et al. 2020; Yu et al. 2020) is to roll back from the open-set SSL setting to the conventional SSL setting by detecting OOD samples at first and filtering them out later. Presuming the ever-present harm to model performance caused by OOD samples, recent studies [Oliver et al. 2018; Yu et al. 2020; Guo et al. 2020] weaken their impact on several levels during training, e.g. data-level, feature-level or loss-level.

However, it is unclear whether directly removing the OOD samples is the best choice for both PL and DACT based SSL methods. In this paper, we deeply study the pros and cons of these two mainstream approaches and analyze the robustness when dealing with OOD samples. We find that: for PL-based methods, the OOD detection module is necessary; for DACT-based methods, this module is not a must. However, to make the method robust to OOD samples, diverse and carefully-searched augmentation strategies are required, and they are often costly to search out.

Besides, the traditional performance upper bound from [Oliver et al. 2018; Yu et al. 2020; Guo et al. 2020] on open-set SSL setting neglects the possible positive outcomes brought by OOD samples. Inspired by the phenomena that the OOD dataset used for pretraining can help boost model performance on downstream tasks on ID datasets, we also exploit the potentialities of OOD samples. In this paper, we

Figure 1: In open-set semi-supervised learning, unlabeled dataset contains OOD samples that do not belong to any labeled single class.
argue that performance boundary can be extended by properly utilizing OOD samples: For DACT, the distribution gap between labeled and unlabeled data is reduced via Style Disturbance; for PL, OOD-style perturbations are added on features of ID samples in a similar way. Experiments on several open-set SSL settings show the advantages of our methods over the others. The contributions of this paper can be summarized as follows:

- We analyze two fundamental SSL methods: Pseudo Labeling (PL) and Data Augmentation based Consistency Training (DACT) on open-set SSL and observe that DACT is more robust than PL. However, requirement for diverse and carefully-searched data augmentation strategies for DACT can be costly. Also, we find there exists a close relationship between DACT on open-set SSL and self-supervised pre-training.
- We propose Style Disturbance to make better use of OOD samples with either PL or DACT based SSL methods. With Style Disturbance, our DACT based methods can surpass SOTA methods on several open-set SSL settings, because style-disturbed samples help reduce the distribution gap between labeled and unlabeled samples. Our method also helps boost the performance of PL-based SSL methods by adding OOD-style perturbations on features of ID samples.

Related Work

Conventional semi-supervised learning.

The goal of semi-supervised learning (SSL) methods is to leverage unlabeled data for performance improvement on labeled data. In conventional semi-supervised learning, pseudo labeling (PL) and consistency regularization are two popular and fundamental methods of many recent SOTA algorithms (Sohn et al. 2020; Kuo et al. 2020; Xie et al. 2020b; Rizve et al. 2021).

**Pseudo Labeling** takes the idea that model trained by labeled data can obtain artificial labels of unlabeled dataset by itself (Lee 2013; Pham et al. 2020; Li et al. 2020). In a narrow sense, PL refers to using “hard” pseudo-labels of samples that satisfy constraints of threshold η (e.g. the maximal class probability ≥ η (Lee 2013)). The hard PL method is closely related to entropy minimization (Lee 2013; Grandvalet and Bengio 2005), a common method forcing the model’s prediction to be in high confidence on unlabeled samples. In a broad sense, methods (Wang and Wu 2020; Pham et al. 2020) using ‘soft’ pseudo-label for supervision also belong to PL-based algorithms.

In addition to model prediction based PL methods, there also exist PL methods (Iscen et al. 2019; Zhu and Ghahramani 2002) based on label propagation.

**Consistency regularization**, another fundamental component in SSL algorithms, is usually implemented by enforcing the model output stable with perturbations during training. The most widely used consistency regularization is Data-Augmentation based Consistency Training (DACT). MixMatch (Berthelot et al. 2019b) applies random horizontal flips and crops several times on a single image, and the average prediction is used for consistency training. ReMixMatch (Berthelot et al. 2019a) requires the model’s prediction of weakly and strongly augmented images to be consistent with each other. UDA (Xie et al. 2020a) leverages CutOut (DeVries and Taylor 2017) and RandAugment (Cubuk et al. 2020) to unlabeled samples. FixMatch (Sohn et al. 2020) follows UDA and ReMixMatch to adopt similar strategies as strong augmentation with samples filtered by the threshold.

Open-set semi-supervised learning

Open-set SSL is a more realistic setting mentioned in (Oliver et al. 2018; Yu et al. 2020), where only ‘dirty’ unlabeled dataset (i.e., dataset has both In-Distribution (ID) and Out-Of-Distribution (OOD) samples) is available. Algorithms (Xie et al. 2020a; Pham et al. 2020; Laine and Aila 2016) for conventional SSL settings tend to filter out OOD samples with a threshold in advance before using dirty unlabeled dataset. UASD (Chen et al. 2020d) ensembles model predictions temporally, and the maximal probability of unlabeled samples are compared with a dynamic threshold to discard OOD samples online. MTCF (Yu et al. 2020) takes the idea of Positive and Unlabeled (PU) learning: OOD detection and model training are performed simultaneously. DS3L (Guo et al. 2020) designs an online ‘soft-weight’ framework (i.e. weight of samples ∈ [0, 1] at loss level) formulated as a bi-level optimization problem. RobustSSL (Zhao et al. 2020b) combines meta-learning with Weighted Batch Normalization to reduce the influence of OOD samples at the feature level. Unlike previous methods handling OOD samples by weight reduction, our method could make better use of them by Style Disturbance.

Self-Supervised Learning

In the field of computer vision, self-supervised learning aims to learn effective visual representations from unlabeled datasets. The common way of self-supervised learning is a 2-step procedure: (1) pretrain a model on large-scale unlabeled datasets containing OOD samples; (2) fine-tune the pretrained model by labeled ID dataset. Recent self-supervised learning algorithms (He et al. 2020; Chen et al. 2020b; Grill et al. 2020; Chen and Hc 2020) that apply multi-view consistency into pretraining achieve great performance on downstream ID tasks, and show a new way of leveraging OOD samples. We also compare DACT based semi-supervised learning and multi-view consistency-based self-supervised learning, analyze the differences and similarities to better understand their relationship.

Pseudo Labeling in open-set SSL

A general PL method first calculates the probability of all the unlabeled data belonging to each class, then carefully picks them out by some threshold(s), such as confidence threshold (Lee 2013; Rizve et al. 2021) and threshold of selected samples per class (Rizve et al. 2021). To test the robustness (i.e., whether the model performance drops after OOD samples are added into unlabeled dataset) of PL on OOD samples, we conduct experiments on several PL-based SSL methods in the open-set SSL setting.
Experiments

Pseudo-Label (Lee 2013), R2-D2 (Wang and Wu 2020) and LabelProp (Iscen et al. 2019). 3 typical PL-based SSL methods are chosen for experiment on CIFAR-10 (Krizhevsky, Hinton et al. 2009) (ID data), with 4 types of OOD data: Tiny ImageNet (TIN) (Deng et al. 2009), LSUN (Yu et al. 2015), Gaussian noise (GN) and Uniform Noise (UN).

Result: As is shown in Table 1 all methods suffer severe performance drop on CIFAR-10. Additional experiments conducted with Pseudo-Label on SVHN or TIN show similar results (refer to the supplementary material for detail). These experiments indicate that PL-based SSL methods are generally not robust on open-set SSL.

Problems of Pseudo Labeling

In this section, we analyze PL methods based on the most widely used threshold: confidence threshold. The reason why PL cannot be robust when dealing with OOD samples are summarized as follows:

• The safe threshold changes when unlabeled ID samples are mixed with OOD samples.

• Unlabeled OOD samples may be labeled wrongly and intensively to several single classes, which causes more severe class-imbalance problems.

• OOD samples may disobey the preconditions of ID tasks differently. The precondition used in this paper is that each sample only belongs to a single class.

Problem of changed threshold: Denote $ID^\eta_{\text{right}}$ as the number of the selected samples whose pseudo labels are right according to threshold $\eta$, and $ID^\eta_{\text{wrong}}$ as number of the selected samples which are wrongly pseudo-labeled. The safe threshold $\eta_{\text{safe}}$ is defined as:

$$\eta_{\text{safe}} := \{\eta \mid ID^\eta_{\text{right}} > ID^\eta_{\text{wrong}}\}. \quad (1)$$

This definition is referred to the setting of learning with noisy labels (Natarajan et al. 2013; Cheng et al. 2020; Zhu, Liu, and Liu 2021; Zhu, Song, and Liu 2021), which indicates that at least, the selected samples have meaningful information. We draw a figure in Figure 2 (a) showing the distribution of training samples’ maximum softmax probability: the safe threshold $\eta_{\text{safe}}$ gets closer to 1 after OOD samples are added in. (b) Number of pseudo-labeled samples per class: the top-2 classes containing most pseudo-labeled ID samples also get the majority of pseudo-labeled OOD samples.

As is illustrated in Figure 2 (b), the top-2 classes containing most pseudo-labeled ID samples also get the majority of pseudo-labeled OOD samples, thus the class distribution is more imbalanced.

Problem of precondition disobedience: In a real-world scenario, samples may not satisfy the rule that each belongs to only one class, which is the precondition of multi-class single-label classification. As is shown in Figure 1 some OOD images may contain objects from several ID classes, while others may just contain objects from none of any ID classes. These images may confuse the classifier differently and make the threshold harder to control. Methods of multi-label learning (Durand, Mehrasa, and Mori 2019) and complementary label learning (Feng et al. 2020) may be helpful to this problem.

Due to the reasons above, OOD samples may cause large performance drop for PL method. Therefore, using OOD detection module to discard OOD samples is a safe and direct way to mitigate their impact, and recent studies (Guo et al. 2020; Chen et al. 2020d; Yu et al. 2020) on open-set SSL all adopt this strategy.

Data Augmentation based Consistency
Training in Open-Set SSL

As a way of consistency regularization, DACT improves model performance by enforcing the model’s output of one training sample stable to its perturbation, which is performed by Data Augmentation (DA) strategy on the image. Recent study (Ghosh and Thiery 2021) shows that: consistency-based SSL methods are more powerful when efficient DA strategies are used for exploiting the geometry of the data manifold. Many SOTA methods on conventional SSL set-
Table 1: Performance of PL-based methods on CIFAR-10. 'Clean' means unlabeled dataset doesn’t contain OOD samples. 5k samples are split from the original training data as validation set; the remaining samples are split into labeled and unlabeled dataset; number of labeled samples is chosen from {1k, 4k}. Each type of OOD dataset contain 10k samples. WRN-28-2 (Zagoruyko and Komodakis 2016), Shake-Shake (Gastaldi 2017) and 13 Layer CNN (Iscen et al. 2019) are used as backbone for Pseudo-Label (Lee 2013), R2-D2 (Wang and Wu 2020) and LabelProp (Iscen et al. 2019) respectively. We use the released codes for experiment and keep all hyper-parameters unchanged.

| Labeled Samples | Unlabeled Samples | Method       | Clean | LSUN | TIN | GN | UN | Mean acc change |
|-----------------|-------------------|--------------|-------|------|-----|----|----|-----------------|
| 1K              | 54K               | Pseudo-Label | 72.14 ± 1.40 | 67.04 ± 0.08 | 66.65 ± 1.63 | 69.09 ± 1.22 | 68.88 ± 2.05 | ↓ 4.23 |
|                 |                   | R2-D2        | 85.95 ± 0.05 | 80.25 ± 0.10 | 79.20 ± 0.06 | 81.80 ± 0.18 | 80.26 ± 0.11 | ↑ 5.54 |
|                 |                   | LabelProp    | 79.38 ± 0.06 | 75.30 ± 1.07 | 75.85 ± 0.89 | 77.80 ± 0.25 | 77.82 ± 0.11 | ↑ 2.68 |
| 4K              | 51K               | Pseudo-Label | 84.84 ± 0.03 | 83.98 ± 0.11 | 83.15 ± 0.03 | 83.97 ± 0.23 | 84.07 ± 0.23 | ↓ 1.04 |
|                 |                   | R2-D2        | 93.97 ± 0.02 | 93.09 ± 0.06 | 92.75 ± 0.11 | 92.58 ± 0.04 | 93.57 ± 0.19 | ↓ 0.97 |
|                 |                   | LabelProp    | 87.67 ± 0.04 | 86.52 ± 0.12 | 85.95 ± 0.08 | 87.44 ± 0.19 | 87.54 ± 0.02 | ↑ 0.80 |

Table 2: Performance of different DA strategies on CIFAR-10 (1k labeled, 55k unlabeled), SVHN (1k labeled, 77k unlabeled) and Tiny-ImageNet (1k labeled, 99k unlabeled, only the last 20 classes are selected as ID classes).

| Dataset  | DataAug (OOD dataset) | Acc   | Mean acc change |
|----------|------------------------|-------|-----------------|
| CIFAR-10 | AA                     | Clean | 88.87 ± 0.66    | ↓ 1.61 |
|          |                        | LSUN  | 86.42 ± 0.21    |     |
|          |                        | GN    | 88.10 ± 0.17    |     |
|          | RA                     | Clean | 81.89 ± 0.43    | ↓ 0.32 |
|          |                        | LSUN  | 81.48 ± 0.65    |     |
|          |                        | GN    | 81.77 ± 0.32    |     |
|          | FA                     | Clean | 88.29 ± 0.25    | ↑ 0.59 |
|          |                        | LSUN  | 88.60 ± 0.22    |     |
|          |                        | GN    | 89.15 ± 0.19    |     |
| SVHN     | AA                     | Clean | 95.54 ± 0.02    | ↑ 0.12 |
|          |                        | LSUN  | 95.49 ± 0.30    |     |
|          |                        | GN    | 95.82 ± 0.05    |     |
|          | RA                     | Clean | 92.07 ± 0.34    | ↓ 0.25 |
|          |                        | LSUN  | 91.40 ± 0.42    |     |
|          |                        | GN    | 92.23 ± 0.35    |     |
|          | FA                     | Clean | 94.85 ± 0.24    | ↑ 0.31 |
|          |                        | LSUN  | 95.19 ± 0.29    |     |
|          |                        | GN    | 95.13 ± 0.51    |     |
| TIN-20   | AA                     | Clean | 54.75 ± 0.05    | ↓ 3.15 |
|          |                        | TIN-180 | 51.40 ± 0.50    |     |
|          | RA                     | Clean | 51.65 ± 0.65    | ↑ 1.70 |
|          |                        | TIN-180 | 53.35 ± 0.35    |     |
|          | FA                     | Clean | 53.15 ± 0.05    | ↑ 0.75 |
|          |                        | TIN-180 | 53.90 ± 0.10    |     |

Table 3: Dimension of learning objective: Denote $D_{ID}$ as ID data, and $D_{OOD}$ as unlabeled OOD samples, the learning objective of DACT on open-set SSL can be written as:

$$w^* = \arg \min_w L_1(w, D_{ID}; w_{ini}) + L_2(w, D_{OOD}; w_{ini}),$$

where $w_{ini}$ is the random initialized weight, $L_2$ is the DA-based consistency loss on OOD samples.

For multi-view consistency-based self-supervised learning, we first train unlabeled samples (OOD samples) via multi-view consistency loss, which is similar to $L_2$ on OOD samples. Then the obtained weight is used to initialize the network for downstream tasks (ID samples). Thus mathematically:

$$w^* = \arg \min_w L_1(w, D_{ID}; w^*_L),$$

s.t.$w^*_L = \arg \min_w L_2(w, D_{OOD}; w_{ini}).$

One can see the difference between Equation (2) and Equation (3) lies in the optimization. In Equation (3), $w^*_L$ serves as a better initialization to help network optimize on
ID samples while in Equation (2), we simultaneously optimize $L_1$ and $L_2$ in one loss function. For traditional open-set ssl settings, the number of ID samples is very small, thus $L_2$ can also help network optimize better without over-fitting to very few ID samples. This is very different with traditional approaches (Yu et al. 2020) that view OOD samples as negative effects to model performance, we show that by utilizing OOD samples properly, they can actually improve model performance and robustness. We further provide more experimental evidence to show the similarity between self-supervised pre-training (Equation (3)) and our DACT approach (2).

**Dimension of experimental phenomena:** We list similar experimental phenomena below:

- DA strategies greatly influence model performance. In self-supervised pretraining, either DA strategies made up of few DAs, or DAs not fit to (downstream) ID tasks result in bad performance (Tian et al. 2020; Xiao et al. 2020; Chen et al. 2020; Zhontar et al. 2021). DA strategies more similar to downstream tasks lead to better performance (Xiao and Guo-Jun 2020; Caron et al. 2020; Chen et al. 2020). In our experiment, we also observe that better DA policies searched for specific datasets show more performance improvement with OOD samples. (e.g., FA on Table 2).

- The distribution gap between the source domain (OOD samples) and target domain (ID samples) is a key factor that may degrade model performance. In transfer learning, the phenomena of negative transfer (Wang et al. 2019; Raghu et al. 2019; Ge et al. 2014; Guo et al. 2018) are usually caused by large distribution gap, which can be calculated quantitatively by metrics such as Maximum Mean Discrepancy (MMD) (Gretton et al. 2007; Long et al. 2013). The same metric could be applied for open-set SSL as well, and we observe the similar phenomena that a larger gap between ID & OOD data would make DACT less robust (e.g., LSUN v.s. GN on Table 2) on OOD samples (refer to the supplementary material for detail).

According to the similarities (learning objective & experimental phenomena) between DACT on open-set SSL and multi-view consistency regularization on self-supervised learning, the explanation of why self-supervised learning works can also apply to DACT on open-set SSL. There are many works explaining why self-supervised learning works can be provided. In (Raphael et al. 2020), a similar metric $\mathcal{D}[a; m; D_{\text{train}}]$ named after ‘diversity’, is used to evaluate the performance of DAs:

$$\mathcal{D}[a; m; D_{\text{train}}] := \mathbb{E}_{D_{\text{train}}} [L_{\text{train}}]$$

where $a$ is a DA strategy, $D_{\text{train}}$ is the augmented training data resulting from $a$, and $L_{\text{train}}$ is the training loss for model $m$ trained on $D_{\text{train}}$.

We also adopt the metric to evaluate the usefulness of DA strategies. We compare the metric between the generally worst strategy AA, and the best DA strategies among {RA, FA} on CIFAR-10, SVHN and TIN datasets. For simplicity, we calculate the expectation of training loss by sampling its value every 400 epochs.

As is shown in Table 3 better DA strategies own higher losses than the worst ones, so the experiment results are in line with the theories: **more diverse DA strategies could bring more useful information to model from OOD samples to improve performance.**

### DACT v.s. PL

Our experiments show that DACT-based SSL methods are far more robust than PL-based methods on open-set SSL. For DACT, a properly chosen DA strategy is the key factor of robustness. However, piles of work are required to search for a robust strategy:

- For a specific dataset, suitable DA methods with proper intensity are required to be selected, in order to construct a good search space.
- Plenty of time and computing resources are necessary to search for a diverse strategy with trial and error.

For lack of abundant domain-specific DA methods in many domains (e.g., videos and medical images (Shorten and Khoshgoftaar 2019; Yun et al. 2020), DACT-based methods might be a costly choice. Despite the fact that PL-based methods are not robust to OOD samples, they are domain-agnostic (Rizve et al. 2021), and usually orthogonal to DACT (Rizve et al. 2021; Cascante-Bonilla et al. 2020), which means they can also

| ID Dataset | OOD dataset | DataAug |
|------------|-------------|---------|
|            |             | AA      | FA      |
| CIFAR-10   | Clean       | 1.17    | 1.27    |
|            | LSUN        | 1.19    | 1.25    |
|            | GN          | 1.06    | 1.13    |
| SVHN       | Clean       | 0.93    | 1.05    |
|            | LSUN        | 0.87    | 0.98    |
|            | GN          | 0.85    | 0.96    |
| TIN-20     | Clean       | 1.12    | 1.23    |
|            | TIN-180     | 1.63    | 1.17    |

Table 3: Loss of different DA strategies on CIFAR-10 with 1k labeled and 54k unlabeled samples.
benefit from diverse DA strategies. In other words, PL-based SSL methods are more general than DACT-based ones, as long as we have a good OOD detection module.

Style disturbance with OOD Samples

Both the success of self-supervised learning (Caron et al. 2020; He et al. 2020; Huang and Belongie 2017) and DACT experiments in Sec. show the possibility of further improving model performance with OOD samples. However, using OOD samples with these methods directly is not safe. As one way trying to transfer knowledge from OOD datasets, self-supervised learning methods may result in the problem of negative transfer (Xiao et al. 2020; Wang et al. 2019; Raghu et al. 2019) because of the distribution gap between ID & OOD samples.

To avoid negative transfer, one safe and efficient way is to use label-invariant perturbations with OOD samples. Neural Style Transfer (NST) algorithms could be adopted as label-preserving DA (Zheng et al. 2019; Yin 2016; Chen and Hsu 2016; Jackson et al. 2019) to use OOD samples. However, applying NST algorithms directly as DA could also hurt model performance (Jackson et al. 2019), since style information correlates strongly with class label in some datasets and removing the correlation by style transfer would lead to a performance drop.

Due to the reasons above, we borrow the idea of AdaIN (Huang and Belongie 2017) and mixup (Zhang et al. 2017), and ‘style’ disturbances of ID samples with OOD ones instead of wild style transfer. The core idea of our method is ‘style disturbance’ (i.e., the ratio of OOD style is far less than that of ID style when mixing them up), and it could be used in either image level (for DACT) or feature level (for PL).

Formulation

Style disturbance for DACT Mathematically, each sample \( x \) could be split into two parts: \( x = (x_{content}, x_{style}) \), where \( x_{content} \) preserves the information of class label and \( x_{style} \) brings variance to the dataset. AdaIN (Huang and Belongie 2017), a real-time arbitrary style transfer method is chosen for style disturbance. The style-disturbed image \( x_{id}^{sd} \) is generated with content of ID image \( x_{id}^{D} \) and style of OOD image \( x_{OOD}^{id} \). To avoid negative effect of artifacts caused by style transfer, \( x_{id}^{sd} \) is further linearly interpolated with \( x_{id}^{D} \):

\[
x_{id}^{sd} = \beta \text{AdaIN}(x_{OOD}^{id}, x_{id}^{D}, \omega) + (1 - \beta)x_{id}^{D}
\]

where both \( \beta \) and \( \omega \in [0, 1] \) control the similarity of \( x_{id}^{sd} \) to \( x_{id}^{D} \). AdaIN is the style-transfer network. The style-disturbed dataset \( D_{SD} \) would be used in the same way as original unlabeled dataset \( D_{U} \) to keep consistency of model predictions with KL-divergence; a standard cross-entropy loss is used for labeled dataset \( D_{L} \). The overall loss function is composed of the UDA loss \( L_{UDA} \), the OOD loss \( L_{SD} \), and the style-disturbed samples \( L_{SD} \). It can be written as:

\[
L_{total} = L_{UDA} + L_{SD} = L_{sup} + L_{unsup} + L_{SD}
\]

where \( \lambda_u \) is the weighting coefficient of consistency loss, \( \phi \) is the model and \( Aug \) is FastAutoAugment (Lim et al. 2019).

Style disturbance for PL For PL-based methods, we implement feature-level style disturbance on both \( D_{U}^{ID} \) and \( D_{L}^{ID} \) based on MixStyle (Zhou et al. 2021), a Domain Generalization method that also combines AdaIN (Huang and Belongie 2017) with mixup (Zhang et al. 2017). Given three batches of input: labeled batch \( B_{L} \), unlabeled ID batch \( B_{U}^{ID} \) and OOD batch \( B_{OOD}^{ID} \), the mixed feature statistics are computed as follows:

\[
\sigma^{sd} = \sigma^{id} + (1 - \rho)\sigma^{ood}
\]

\[
\mu^{sd} = \mu^{id} + (1 - \rho)\mu^{ood}
\]

where \( x^{sd} \) comes from \( B_{L} \) and \( B_{U}^{ID} \), \( x^{ood} \) comes from \( B_{OOD}^{ID} \), \( \rho \in \mathbb{R}^{B} \) are instance-wise weights sampled from the Beta distribution Beta(9, 1), \( \mu^{sd} \) and \( \sigma^{sd} \) are mean and standard deviation computed across the spatial dimension within each channel of each tensor. Finally, the style-disturbed feature \( x^{sd} \) is computed by applying the mixed feature statistics to style-normalized \( x^{id} \):

\[
x^{sd} = \sigma^{sd}\frac{x^{id} - \mu^{id}}{\sigma^{id}} + \mu^{sd}
\]

In practice, whether the MixStyle module is activated or not in the forward pass is according to a probability of 0.5; no MixStyle is applied at test time; gradients are blocked in the computational graph of \( \mu \) and \( \sigma \). After we get style-disturbed dataset \( D_{SD} \), the original labels / pseudo-labels on \( D_{L} \) and \( D_{U}^{ID} \) are applied to \( D_{L}^{SD} \) and \( D_{U}^{SD} \) respectively, and the corresponding loss is \( L_{SD} \). The total loss is:

\[
L_{total} = L_{PL} + \lambda_u L_{SD} = L_{sup}(D_{L}) + L_{unsup}(D_{U}^{ID}) + \lambda_u(L_{sup}(D_{L}^{SD}) + L_{unsup}(D_{U}^{SD}))
\]

Experiments

Because our method of style disturbance is based on both ID & OOD data, OOD samples are required to be sorted out. Since we just want to verify our hypothesis that OOD samples can be useful with style disturbance, the design of OOD detection module is not that important for our method. For DACT, we directly use a simplified detection module of Yu et al. 2020 (refer to supplementary material for details); for PL, we suppose that all OOD samples are picked out perfectly.
### Table 4: Experiments of CIFAR-10 with (1k labeled, 54k unlabeled) and (4k labeled, 51k unlabeled) samples

| Method     | Labeled Samples | Unlabeled Samples | OOD dataset | Mean acc change |
|------------|-----------------|-------------------|-------------|-----------------|
|            | Clean | LSUN | TIN | GN | UN |           |
| **1K**     | 54K   | DS3L | 67.79 ± 0.27 | 69.74 ± 0.08 | 70.10 ± 0.47 | 62.86 ± 0.67 | 62.89 ± 1.65 | ↓ 1.39 |
|            |       | MTCF | 90.67 ± 0.29 | 90.19 ± 0.47 | 89.85 ± 0.11 | 89.87 ± 0.08 | 89.80 ± 0.26 | ↓ 0.74 |
|            |       | Ours | 88.29 ± 0.25 | **91.30 ± 0.36** | **91.10 ± 0.65** | **91.23 ± 0.59** | **91.82 ± 0.04** | ↑ 3.35 |
| **4K**     | 51K   | DS3L | 83.23 ± 0.07 | 82.89 ± 0.69 | 82.58 ± 0.14 | 80.44 ± 0.01 | 80.59 ± 0.03 | ↓ 1.61 |
|            |       | MTCF | 93.30 ± 0.10 | 92.91 ± 0.03 | 93.03 ± 0.05 | 92.83 ± 0.04 | 92.53 ± 0.08 | ↓ 0.48 |
|            |       | Ours | 93.36 ± 0.40 | **94.27 ± 0.21** | **93.84 ± 0.10** | **94.52 ± 0.07** | **94.50 ± 0.13** | ↑ 0.92 |

### Table 5: Performance of Pseudo-Labeling with MixStyle on CIFAR-10 and TIN 20

| ID dataset | OOD dataset | Accuracy | Mean acc change |
|------------|-------------|----------|-----------------|
| CIFAR-10   | Clean       | 55.50 ± 0.73 | ↑ 1.29          |
|            | LSUN        | 57.14 ± 0.74 |               |
|            | TIN         | 56.90 ± 0.70 |               |
|            | GN          | 56.53 ± 0.29 |               |
|            | UN          | 56.60 ± 0.46 |               |
| TIN 20     | Clean       | 46.97 ± 0.45 | ↑ 0.93          |
|            | TIN 180     | 47.90 ± 1.07 |               |

### Experiment setting for DACT Dataset

Experiment results on CIFAR-10 shows great performance of our method, as is listed in Table 4. Compared to previous SOTA methods of MTCF (Yu et al. 2020) and DS3L (Guo et al. 2020), our method outperforms the others not only on classification performance but also on robustness: previous methods avoid disadvantage of OOD samples by reducing their weight, and degradation of model performance is mitigated notably; however, our method tries to take advantages of OOD samples, and improves model performance by 3.35% and 0.92% respectively after using them.

More experiments and analyses are provided in the supplementary material, such as: (1) Analyzing the relationship between DACT robustness and the distribution gap of ID & OOD samples, to show that Style Disturbance does reduce the gap; (2) Implementation details and performances of OOD detection module to show its effectiveness; (3) Ablation studies on Style Disturbance & DACT to better understand the contribution of each module.

### Results and analysis

Experiment results of Style Disturbance with PL and DACT are listed in Table 4 and Table 5 respectively. The results show that: OOD samples can stably boost performance, instead of harming it in Table 1. With the help of OOD samples, Style Disturbance can help boost model performance on both PL and DACT based SSL methods.

Experiment results on CIFAR-10 shows great performance of our method, as is listed in Table 4. Compared to previous SOTA methods of MTCF (Yu et al. 2020) and DS3L (Guo et al. 2020), our method outperforms the others not only on classification performance but also on robustness: previous methods avoid disadvantage of OOD samples by reducing their weight, and degradation of model performance is mitigated notably; however, our method tries to take advantages of OOD samples, and improves model performance by 3.35% and 0.92% respectively after using them.

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### Conclusion

We analyze the robustness of two fundamental SSL methods: PL and DACT, to the more realistic open-set SSL setting. Our observation reveals that: (1) DACT is more robust to OOD samples than PL. However, data augmentation for DACT needs to be diverse and carefully searched. (2) DACT on Open-Set SSL has close relationships with multi-view.
consistency based self-supervised learning in terms of the loss formulation and similar experimental phenomena. (3) OOD samples can be better utilized for PL and DACT by our proposed method Style Disturbance. Experiments on several open-set SSL benchmarks prove that our method achieve
proposed method Style Disturbance. Experiments on several OOD samples can be better utilized for PL and DACT by our consistency based self-supervised learning in terms of the analysis of self-supervision, or what we can learn from a single image.

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More experiments on Pseudo Labeling

Pure Pseudo Labeling on more datasets

We further conduct experiments on Tiny ImageNet (TIN) (Deng et al. 2009) and Street View House Numbers (SVHN) (Netzer et al. 2011) with the basic Pseudo Labeling (PL) based Semi-Supervised Learning (SSL) method. Pseudo-Label (Lee 2013), to verify that PL-based SSL methods are generally not robust on open-set SSL setting.

Experiment setting: For SVHN, 7.3k samples are split from the original training data as validation dataset; the remaining samples are split into labeled and unlabeled dataset; number of labeled samples is 1k. 10k OOD samples are added into unlabeled dataset from the following 4 datasets for each setting: TIN, LSUN (Yu et al. 2015), Gaussian noise (GN) and Uniform Noise (UN).

Implementation detail: We follow the same setting as is mentioned in the main body of the paper.

As is shown in Table 6, Pseudo-Label is also not robust on TIN and SVHN, and it again verifies our point of view.

Pseudo Labeling combined with other SSL methods

We also analyze the PL module in MixMatch (Berthelot et al. 2019b), an SSL algorithm make up of both PL and DACT methods. We compare the model performance before and after removing the PL module to show that PL is not robust to OOD samples.

The PL module of MixMatch is integrated in MixUp (Zhang et al. 2017), a regularization method / augmentation policy widely used in the field of deep learning. MixMatch first puts pseudo-labels on unlabeled samples, then these pseudo-labeled samples are mixed up with labeled samples $D_{l}^{ori}$ in both image level and label level, to generate labeled dataset $D_{l}$ used for training. We argue that $D_{l}$ could suffer from the negative impact caused by pseudo-labeled OOD samples, so we replace $D_{l}$ with $D_{l}^{ori}$ for training.

The open-set SSL experiment is conducted on CIFAR-10 in the same setting as is mentioned in the DACT section of the main paper. The results are listed in Table 6. We can observe that: though replacing $D_{l}$ with $D_{l}^{ori}$ would let model performance drop a little on conventional SSL setting, the performance degradation is mitigated remarkably (by 1.67% and 0.94% respectively) when we do this in open-set SSL setting. The phenomena again indicate that PL is generally not robust to OOD samples in open-set SSL setting.

| ID dataset | OOD dataset | Accuracy | Mean acc change |
|------------|-------------|----------|-----------------|
| SVHN       | Clean       | 92.76 ± 0.32 | ↓ 0.50         |
|            | LSUN        | 92.09 ± 0.37 |               |
|            | TIN         | 91.62 ± 0.44 |               |
|            | Gaussian    | 92.65 ± 0.21 |               |
|            | Uniform     | 92.70 ± 0.15 |               |
| TIN 20     | Clean       | 44.10 ± 0.33 | ↓ 0.53         |
|            | TIN 180     | 43.57 ± 0.61 |               |

Table 6: Performance of Pseudo-Label on SVHN and TIN 20.

Distribution gap measurement

In the field of transfer learning, the distribution change or domain shift caused by many factors (e.g., image quality, modality, style) between the source and target domain can always degrade model performance (Wang and Deng 2018; Csurka 2017). Maximum Mean Discrepancy (MMD) (Gretton et al. 2007) is widely used to measure the distribution gap between domains (Long et al. 2013; Wang et al. 2019b). Our experiment results on open-set SSL also show the variance of model performance in terms of OOD samples. Following studies (Long et al. 2013; Wang et al. 2019b) to measure the gap better by balancing both label and structural information, we adopt MMD and class-wise MMD (Long et al. 2013) together to evaluate the marginal and conditional distribution gap between labeled and unlabeled dataset.

The metric $mmd_{gap}$ is written as:

\[
mmd_{gap} = \left\| \frac{1}{|D_{L}|} \sum_{i=1}^{|D_{L}|} p_{\phi}(y|x_{i}) - \frac{1}{|D_{U}|} \sum_{j=1}^{|D_{U}|} p_{\phi}(y|x_{j}) \right\|_{H}^{2} + \sum_{c=1}^{K} \left\| \frac{1}{|D_{L}|} \sum_{x_{i} \in D_{L}^{c}} p_{\phi}(y|x_{i}) - \frac{1}{|D_{U}|} \sum_{x_{j} \in D_{U}^{c}} p_{\phi}(y|x_{j}) \right\|_{H}^{2}
\]

where K is the number of class in $D_{L}$, $D_{L}^{c}$ is the labeled c-th class dataset, $D_{U}^{c}$ is the c-th dataset pseudo-labeled via maximal probability, $\phi$ is the model, $x$ is the input image and $\phi(x)$ is a 1xK vector representing the probability of $x$ to each class.

Experiment result

We use $mmd_{gap}$ on CIFAR-10 with DACT based SSL method. UDA, to observe the change of performance in terms of distribution gap. Model $\phi$ is trained by $D_{L}$ only. The last columns of Table 6 shows the distribution gap varies with the OOD samples of unlabeled dataset. We notice that the top-1 accuracy of model trained by UDA rises when $mmd_{gap}$ drops, indicating that the distribution gap also results in the change of performance on open-set SSL setting. In a word, a similar phenomenon appears in both the transfer learning and the open-set SSL setting: the model performs better as the distribution gap between $D_{L}$ (target domain) and $D_{U}$ (source domain) gets smaller.
Table 7: CIFAR-10 with 1000 labeled and 54000 unlabeled samples

| Method            | OOD dataset | Mean acc change |
|-------------------|-------------|-----------------|
|                  | Clean | LSUN | TIN | Gaussian | Uniform |      |
| MixMatch          | 90.67 ± 0.29 | 87.03 ± 0.41 | 88.03 ± 0.22 | 84.49 ± 1.06 | 85.71 ± 1.14 | ↓ 4.36 |
| MixMatch (w/o PL) | 90.08 ± 0.29 | 87.93 ± 0.17 | 88.64 ± 0.20 | 86.09 ± 1.27 | 86.90 ± 0.12 | ↓ 2.69 |
| UDA               | 88.29 ± 0.25 | 88.60 ± 0.22 | 88.86 ± 0.37 | 89.15 ± 0.19 | 89.22 ± 0.25 | ↑ 0.67 |
| mmd_gap           | /     | 1.71 ± 0.26 | 1.47 ± 0.26 | 1.20 ± 0.20 | 1.19 ± 0.19 | /     |

Table 8: CIFAR-10 with 4000 labeled and 51000 unlabeled samples

| Method            | OOD dataset | Mean acc change |
|-------------------|-------------|-----------------|
|                  | Clean | LSUN | TIN | Gaussian | Uniform |      |
| MixMatch          | 93.30 ± 0.10 | 91.18 ± 0.33 | 91.25 ± 0.13 | 90.47 ± 0.38 | 91.51 ± 0.35 | ↓ 2.20 |
| MixMatch (w/o PL) | 93.11 ± 0.03 | 91.56 ± 0.02 | 91.98 ± 0.09 | 92.09 ± 0.11 | 91.79 ± 0.24 | ↓ 1.26 |
| UDA               | 93.36 ± 0.40 | 93.56 ± 0.04 | 93.65 ± 0.14 | 93.80 ± 0.08 | 93.84 ± 0.47 | ↑ 0.35 |
| mmd_gap           | /     | 1.85 ± 0.35 | 1.54 ± 0.37 | 1.28 ± 0.32 | 1.26 ± 0.31 | /     |

Table 9: Accuracy(%) for CIFAR-10 and OOD dataset pairs. Following the setup in [Yu et al. 2020], we report the averages and the standard deviations of the scores obtained from three trials. “Clean” means unlabeled dataset doesn’t contain OOD samples.

### DACT robustness and diversity of augmentation strategy

To better understand the relationship between DACT robustness on OOD samples and diversity of DA strategies, we vary the diversity to observe the change of robustness. Fast AugoAugment (FA) is a DA strategy composed of augmentation pairs, and we could use the number of pairs to estimate its diversity roughly. The FA augmentation strategy searched for CIFAR-10 is made up of \( N_{DA} = 493 \) augmentation pairs. We take number of augmentation pairs of this strategy from \( \{8, 62, 493\} \) \( (N_{DA}/2^0 = 493, N_{DA}/2^3 = 62, N_{DA}/2^5 = 8) \) to construct new strategies, so as to vary the diversity of DA strategy. We do experiments on CIFAR-10 (1k labeled, 54k unlabeled) with 10k unlabeled GN samples to observe the performance change before and after using OOD samples. Figure 3 visualizes the experiment result of the above experiment: the model tends to be more robust to OOD samples when the diversity of DA strategy grows larger.

Since AutoAugment (AA) [Cubuk et al. 2018], Fast AutoAugment (FA) [Lim et al. 2019] and RandAugment (RA) [Cubuk et al. 2020] are searched in the same augmentation space, we could use the combinatorial number of all possible augmentation results as a metric to estimate the diversity of these DA strategies roughly. The combinatorial number can be calculated easily: every single DA policy used in AA, FA or RA is in the form of “[policy Name, Intensity, Probability]”, which means each policy is adopted with certain intensity and probability.

- For AA and FA, the DA strategy is made up of many augmentation pairs, e.g., \([N_{1st}, I_{1st}, P_{1st}], [N_{2nd}, I_{2nd}, P_{2nd}]\). Given the augmentation pair number of DA strategy is \( N_{DA} \), then the number of possible augmentation combination is \( 3^{N_{DA}} \).
- For RA, one augmentation combination is chosen \( M \) augmentation policies from 14 types of DA policy with fixed intensity and probability, so the number of possible augmentation combination is: \( \sum_{i=1}^{M} C_{14}^{M} \). \( M \) is set as 2 for RA strategy searched on ImageNet.

Following the main body of the paper, we compare the metric between the generally worst strategy AA, and the best DA strategies among \( \{RA, FA\} \) on CIFAR-10, SVHN and TIN datasets. As
Table 10: Diversity of different DA strategies on SVHN and CIFAR-10 with 1k labeled samples.

| Data | ID dataset | Metric | Mean acc change | Diversity |
|------|------------|--------|-----------------|-----------|
| AA   | CIFAR-10   | 88.87  | 87.26 (-1.61)   | 285       |
| FA   |            | 88.29  | 88.88 (+0.59)   | 1479      |
| AA   | SVHN       | 95.54  | 95.66 (+0.12)   | 120       |
| FA   |            | 94.85  | 95.16 (+0.31)   | 1491      |

Table 11: Diversity of different DA strategies on TIN 20 with 1k labeled samples.

| Data | ID dataset | Metric | Mean acc change | Diversity |
|------|------------|--------|-----------------|-----------|
| AA   | TIN 20     | 54.55  | 51.40 (-3.15)   | 60        |
| RA   |            | 51.65  | 53.35 (+1.70)   | 105       |

is shown in Table 10 and Table 11, the model shows better robustness as the diversity of DA strategies gets larger.

### OOD detection

#### Design of the module

An efficient OOD detection module is important both for robust PL-based SSL methods and better use of OOD samples. The detection module of our DACT & Style Disturbance is a simplified version of previous method (Yu et al. 2020). The two projection heads designed for K-class image classification and OOD sample detection are merged into one (K+1)-class head, and the (K+1)-th class denotes the probability of samples to be OOD. All unlabeled samples are regarded as OOD samples at the beginning of training. To prevent unlabeled samples from being split into ID samples too early, the prediction of original image $p_\phi(y|x)$ in consistency training loss is replaced with $p_\phi^t(y|x)$, the weighted sum of model’s previous predictions $p_\phi^{t-1}(y|x)$ and current prediction $p_\phi(y|x)$:

$$ p_\phi^t(y|x) = \alpha p_\phi^{t-1}(y|x) + (1 - \alpha)p_\phi(y|x) \quad (15) $$

where the momentum hyper-parameter $\alpha \in [0, 1]$ ($\alpha = 0.8$ in experiment). Motivated by momentum update in MoCo (He et al. 2020), previous predictions of $D_U$ are stored in a memory bank. Unlabeled samples are regarded as OOD ones if the (K+1)-th probability of output is the largest after half of total epochs.

#### Performance of the module

We compare our splitting method to existing OOD detection method (Yu et al. 2020) to verify its effectiveness. For simplicity, we only evaluate OOD detection performance on CIFAR-10 setting with 1,000 labeled samples; Since more labeled ID samples will surely make it easier to filter out OOD samples, we do not conduct the CIFAR-10 setting with 4,000 labeled samples here. As is shown in Table 14 as a simplified version of MTCF (Yu et al. 2020), our splitting module performs comparably well.

#### More experiments on the use of OOD samples

**Ablation studies on Style Disturbance & DACT**

To verify the generalization of methods, we turn to TIN with a larger backbone ResNet-50. Using the official implementation of DS3L & MW-Net (Shu et al. 2019) (backbone of DS3L) and MTCF, our experiments show that both methods have unsatisfactory performance. Besides, hardly can I tune hyper-parameters because both methods are very time-consuming and memory-unfriendly, as is shown in Table 13. Also we could not find any references help guide the hyper-parameter tuning procedure for either method on ImageNet or Tiny ImageNet. Consequently, we only make several trials for each method, and report the best result of them. In contrast to the above two methods, ours is much faster and far more robust on OOD samples. As is shown in the 5-th row of Table 12 our method enhances model performance by 2.63%.

The quickly advancing field of Self-Supervised Learning (He et al. 2020; Chen et al. 2020) also motivates us to make better use of OOD samples for better pretrained models. We simply choose MoCo (He et al. 2020), a GPU-friendly method to pretrain the model with both $D_L$ and $D_U$. The pretrained model is then used to initialize the network for subsequent tasks.

We perform an ablation study on TIN to better understand how each module works. We analyze the effect of components in our method and find that each module has an orthogonal contribution to the overall improvements, as is summarized in Table 12. We observe that: (1) Adding 90,000 OOD samples to $D_U$ directly could bring about 1% improvement, and it again verifies the robustness of DACT; (2) Module of style disturbance boosts the performance more than 1.5%; Apart from splitting module, it still contributes about 1% to improvement; Since the splitting module performs in a similar way as another widely-used SSL method Temporal Ensemble (Laine and Aila 2016), it brings roughly 0.5% improvement as well; (3) The pretraining module also shows the value of OOD dataset by enhancing performance for about 1.6%; (4) The combination of all components improves totally 5.8% and shows great advantage on other open-set SSL methods.

#### Why using self-supervised pretraining?

Self-supervised learning shows great performance to use OOD samples to improve model performance on downstream ID tasks. As is discussed in the main body of our paper, DACT on open-set SSL could gain from OOD samples in a similar way as multi-view consistency based self-supervised learning; however, two learning paradigms are quite different from each other in some dimension. For example, the loss function of consistency loss for DACT, and the InfoNCE (Oord, Li, and Vinyals 2018) loss for self-supervised contrastive learning are quite different; the latter aims to pull features of every two samples in the dataset away, while the former tends to draw features from the same class closer. Besides, the use of unlabeled ID data in open-set SSL always show positive influence; in self-supervised learning, however, sometimes taking limited downstream ID data into self-supervised representation learning phase would hurt the final performance (Teng and Huang 2021). Thus the two paradigms also utilize OOD samples differently to some extent, which means they can benefit model performance orthogonally. Experiments in Table 12 and experiments of OpenCoS (Jongjin et al. 2020) also prove this.

#### Implementation of self-supervision module

To obtain better visual representations with OOD samples, Moco v1 (He et al. 2020) is adopted as the self-supervised pretraining module of our method. We implement the pretraining module based on the official implementation of MoCo v1. We take the default hyper-parameter to pretrain the model for 200 epochs, and the pretraining procedure takes about 15 hours on TIN (Deng et al. 2009).

#### Visualization of style-disturbed images

Style-disturbed images of both CIFAR-10 (Krizhevsky, Hinton et al. 2009) and TIN setting are shown in Figure 4 and Figure 5.
Table 12: Ablation studies on Tiny ImageNet.

| Method | Time/trial | Device num | Top-1 acc |
|--------|------------|------------|-----------|
| DS3L   | >1 week    | 8          | 4.50      |
| MTCF   | >2 weeks   | 8          | 29.05     |
| Ours   | <40 hours  | 2          | 65.70±0.16|

Table 13: Comparison of different methods on Tiny ImageNet. The device we used is NVIDIA Tesla V100.

From these images we can observe that the model transfers the style of OOD images to ID images slightly, while the content of image is preserved.

Implementation of other methods

MTCF (Yu et al. 2020): Our implementation is based on the official PyTorch implementation code. For CIFAR-10 setting, we use the experiment result reported in the paper. For TIN setting, we simply replace the dataset, and try to take the default hyper-parameter to train the model. Since it takes too much time to train for a single trial, we just run 2 trials and report the higher result.

DS3L (Guo et al. 2020): Our implementation is based on the official PyTorch implementation code. For CIFAR-10 setting, we modify the ID and the OOD dataset, then directly take the default hyper-parameter to train the model. For TIN setting, we meet a few challenges during training:

- In the data pre-processing process, we find it impossible to apply either global contrast normalization or ZCA-normalization to dataset because of our server’s limited capacity of memory (about 375G). So we have to remove the two steps, and replace them with the common normalization of ImageNet (Deng et al. 2009) as is done in our method.
- Since DS3L takes the MW-Net (Shu et al. 2019) as backbone, we transfer the original ResNet-50 network into the format of MW-Net for training. We also take the default hyper-parameter for training. As it takes too much time to train for a single run, we just run 1 trial and report the result.

From our experiment, we find that the above two methods do not have robust hyper-parameters; Besides, both of the official implementation require a long time to train on a larger dataset. The two problems might be a large obstacle when applying these methods to realistic settings.
| Method | OOD dataset | TIN | LSUN | UN | GN |
|--------|-------------|-----|------|----|----|
|        | Precision   | Recall | Precision | Recall | Precision | Recall | Precision | Recall | Precision | Recall |
| MTCF   | 97.11       | 99.48  | 98.95 | 99.95 | 100 | 100 | 100 | 100 |
| Ours   | 97.22       | 99.65  | 98.20 | 99.34 | 100 | 100 | 100 | 100 |

Table 14: The comparison of precision and recall(%) on OOD detection tasks in CIFAR-10 setting with 1,000 labeled samples.