A Meta Approach to Defend Noisy Labels by the Manifold Regularizer PSDR

Pengfei Chen1, Benben Liao2, Guangyong Chen2∗, Shengyu Zhang2
The Chinese University of Hong Kong1, Tencent2

Abstract

Noisy labels are ubiquitous in real-world datasets, which poses a challenge for robustly training deep neural networks (DNNs) since DNNs can easily overfit to the noisy labels. Most recent efforts have been devoted to defending noisy labels by discarding noisy samples from the training set or assigning weights to training samples, where the weight associated with a noisy sample is expected to be small. Thereby, these previous efforts result in a waste of samples, especially those assigned with small weights. The input \( x \) is always useful regardless of whether its observed label \( y \) is clean. To make full use of all samples, we introduce a manifold regularizer, named as Paired Softmax Divergence Regularization (PSDR), to penalize the Kullback-Leibler (KL) divergence between softmax outputs of similar inputs. In particular, similar inputs can be effectively generated by data augmentation. PSDR can be easily implemented on any type of DNNs to improve the robustness against noisy labels. As empirically demonstrated on benchmark datasets, our PSDR impressively improve state-of-the-art results by a significant margin.

1 Introduction

DNNs have gained a lot of research attention because of their remarkable success in widespread practical applications. The implementation of DNNs on supervised learning tasks always requires a large number of training samples with accurate labels. However, in practical applications, it is too costly to label extensive data correctly, while alternating methods, such as crowdsourcing Yan et al. (2014) and online queries Schroff et al. (2011); Divvala et al. (2014), inexpensively obtain data, but unavoidably yield noisy labels. It is well known that training with noisy labels will degenerate the generalization performance of DNNs, which usually have the high capacity to memorize noisy labels Zhang et al. (2017); Arpit et al. (2017).

During recent years, numerous methods have been proposed to train DNNs robustly against noisy labels. Several methods focus on estimating the noise transition pattern and modifying the loss function accordingly, e.g., forward or backward correction Patrini et al. (2017), S-model Goldberger and Ben-Reuven (2017). However, it is a challenge to estimate the noise transition pattern accurately. An alternative approach is to correct labels using the predictions of DNNs, e.g., Bootstrap Reed et al. (2015). Joint Optimization Tanaka et al. (2018), and D2L Ma et al. (2018), but all of them are vulnerable to overfitting. To improve the robustness, Joint Optimization introduces regularization terms using the prior knowledge of how actual classes distribute over all training data, which is usually unavailable in practical applications.

Intuitively, we can handle noisy labels by selectively training DNNs on the clean proportion of samples Han et al. (2018); Chen et al. (2019) or more generally, on weighted samples Ren et al. (2018); Jiang et al. (2018). The weight can be a real value in the interval \([0, 1]\), or simply drawn

∗Correspondence to: Guangyong Chen <gycchen@tencent.com>.

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from the discrete set \{0, 1\}, where weight 1 is assigned to examples which are believed to be clean. Recently, several methods have been proposed based on this idea, which assign weights to training samples and minimize the weighted training loss. For example, Decoupling [Malach and Shalev-Shwartz, 2017] trains two networks on samples for which the predictions from two networks are different. Reweight [Ren et al., 2018] assumes a clean validation set is given and assigns continuous weights to samples based on the directions of their gradients. MentorNet [Jiang et al., 2018] utilizes a clean validation set to pre-train a teacher network, which provides a sample weighting scheme to train a student network. When it has no access to the clean validation set, MentorNet has to assign weights according to a predefined criterion such as small-loss criterion: treating samples with small training loss as clean ones. Co-teaching [Han et al., 2018] also selects samples based on the small-loss criterion. The novelty of Co-teaching is that two networks are trained simultaneously and each network selects small-loss samples from the mini-batches and uses them to train another network.

The overfitting to noisy labels can be successfully released by the above methods, where the network assigns small weights to noisy labels, and hence the generalization accuracy can be improved. However, the practical implementations of the above methods are hindered by the lack of training samples since noisy samples are likely to be discarded from the training set. Although a sample \((x, y)\) may be noisy with \(y\) being the observed label, the input \(x\) is always valuable.

In this paper, we propose a novel manifold regularizer [Niyogi, 2013] for DNNs, named as Paired Softmax Divergence Regularization (PSDR), to make full use of all training samples regardless of whether the observed labels are clean. Our regularizer is motivated from the assumption widely adopted by the Laplace Eigenmaps (LE) [Belkin and Niyogi, 2003] and the Gaussian Process (GP) [Williams and Rasmussen, 2006], both of which assume that neighboring inputs should have similar outputs and then constrain the functions that should be learned on the training set. To design a manifold regularizer suitable for DNNs, we first clarify three questions as follows.

- How to find its neighboring samples given a specific input?
- How to evaluate the similarity between the outputs of neighboring samples?
- How to implement the regularizer efficiently in DNNs to defend noisy labels?

Thus, our contributions can be summarized by answering the above questions. Firstly, since searching neighboring inputs in the whole training set is quite expensive, we propose to effectively generate neighboring samples of any specific input using the augmentation technique, which is a widely used trick to improve the generalization performance of DNNs. Secondly, we can adopt Kullback-Leibler (KL) divergence to evaluate the similarity between softmax outputs of paired samples generated by data augmentation, because softmax outputs naturally belong to a probability space. Finally, as a flexible regularization loss, PSDR can be easily implemented on any type of DNNs. Experiments verify that our PSDR impressively improves state-of-the-art results by a significant margin. For example, on manually corrupted CIFAR-10 with 40% wrong labels, our performance is nearly as good as training on the clean CIFAR-10.

To systematically evaluate our proposed method, we train DNNs on noisy labels generated by manually corrupting the original ones in benchmark datasets, including CIFAR-10 and CIFAR-100 [Krizhevsky and Hinton, 2009], which have been widely used in the literature [Patrini et al., 2017; Han et al., 2018; Jiang et al., 2018; Ma et al., 2018] for evaluation of DNNs in presence of noisy labels. In the experiments, we leverage PSDR to upgrade three representative baseline methods: F-correction [Patrini et al., 2017], Decoupling [Malach and Shalev-Shwartz, 2017], and Co-teaching [Han et al., 2018]. Empirical results consistently show that our PSDR enables dramatically higher test accuracy, which outperforms extensive state-of-the-art methods [Patrini et al., 2017; Malach and Shalev-Shwartz, 2017; Han et al., 2018; Jiang et al., 2018; Ma et al., 2018] by quite large margins.

2 Method

2.1 Preliminaries

For a \(c\)-class classification, we collect a dataset \(D = \{x_t, y_t\}_{t=1}^n\), where \(x_t\) is the \(t\)-th sample with its observed label as \(y_t \in [c] := \{1, \ldots, c\}\). As discussed previously, the observed label \(y\) may be noisy. Let \(\hat{y}\) denote the latent true label, then we can describe the corruption process of the set \(D\) by
introducing a noise transition matrix $T \in \mathbb{R}^{c \times c}$, where $T_{ij} = P(y = j | \hat{y} = i)$ denotes the probability of labeling an $i$-th class example as $j$. Let $f(x; \theta)$ denote a neural network parameterized by $\theta$, which predicts a probability distribution over all classes for any input $x$. The softmax activation function is implemented on the output layer of the network to ensure $\sum_{i=1}^{c} f_i(x; \theta) = 1$, where $f_i$ denotes the predicted probability for $i$-th class. The aim is to robustly train $f$ on the noisy dataset $D$ by optimizing $\theta$, so that $f$ is able to predict correctly on any testing example $x$. The loss function we use is the widely adopted categorical cross entropy loss, which is denoted as $L_{cce}(f(x; \theta), y)$.

2.2 Generating neighboring samples using data augmentation

Data augmentation is a widely used technique, which can ease the overfitting problem and improve the generalization performance of DNNs. In image classification, a prevalent and effective practice for augmenting image data is to perform geometric augmentations, such as random cropping and horizontal random flipping [Krizhevsky et al. (2012); He et al. (2016); Perez and Wang (2017)]. At each training epoch, for any training example $(x_t, y_t)$, a new input $x'_t$ is randomly generated from $x_t$, and the loss for this example is $L_{cce}(f(x'_t; \theta), y_t)$, where $L_{cce}$ denotes the categorical cross entropy loss, and $\theta$ is the network parameter.

Data augmentation does ease the overfitting problem [Arpit et al. (2017)], but it does not really deal with noisy labels, and the DNNs will unavoidably memorize some wrong samples. Therefore, several specific methods of dealing with noisy labels have been proposed, among which an effective approach is learning to assign weights to training samples and minimizing the weighted training loss

$$L_{\text{supervised}}(x, y; \theta) = \sum_t \omega_t L_{cce}(f(x'_t; \theta), y_t),$$

(1)

where $\omega_t$ is the weight assigned to the $t$-th sample, and $x'_t$ is the random sample generated from $x_t$ by data augmentation. The weight is usually computed in real-time during training [Malach and Shalev-Shwartz (2017); Han et al. (2018); Jiang et al. (2018); Ren et al. (2018)]. Another representative existing method proposes to correct the categorical cross entropy loss using the noise transition matrix $T$ [Patrini et al. (2017)], which can be learned from the noisy dataset, but it is a challenge to estimate $T$ accurately. For example, in F-correction [Patrini et al. (2017)], the loss is

$$L_{\text{supervised}}(x, y; \theta) = \sum_t L_{cce}(T \cdot f(x'_t; \theta), y_t).$$

(2)

To achieve a high test accuracy, most existing methods of defending noisy labels [Patrini et al. (2017); Tanaka et al. (2018); Jiang et al. (2018); Ma et al. (2018)] implement data augmentation in the experiments by default.

2.3 Paired Softmax Divergence Regularization

Compared with normal training, recent state-of-the-art methods achieve impressive robustness when the training set contains noisy labels. However, a remaining issue is the waste of samples - existing methods do not make full use of useful information contained in the distribution of $x$. Even if a sample $(x, y)$ is noisy with $y$ being the wrong label, the input $x$ always makes sense, whose clustering contains some class-dependent information. For example, the images of the same class are ‘close’ to each other in some sense. Intuitively, learning the information contained in the distribution of $x$ should be beneficial to the generalization performance of DNNs.

To make full use of all samples, we propose to add a manifold regularizer, which explicitly encourages the network to predict similarly on neighboring samples. Generally speaking, samples of the same class are nearby, but since the observed labels are noisy, samples with the same label are not guaranteed to be from the same latent true class. An alternative approach is searching neighboring samples in the whole training set for any specific input [Belkin and Niyogi (2003)], but it is quite expensive. Fortunately, for any training example, data augmentation can generate many different neighboring images, which belong to the same class. Therefore, we explicitly penalize the difference between predictions from paired samples generated by data augmentation. Since the output of the network is a probability distribution, we use KL divergence as the penalty. Our proposed PSDR is

$$L_{PSDR}(x; \theta) = \sum_t KL(f(x'_t; \theta) \parallel f(x''_t; \theta)), $$

(3)
where \( x_i \) and \( x_i' \) are two examples randomly generated from \( x_i \) using data augmentation, and the summation is taken over the training set \( D = \{x_i, y_i\}_{i=1}^n \).

PSDR is a flexible regularization loss, which can be easily incorporated in existing training methods by combining \( L_{PSDR} \) with the supervised loss \( L_{supervised} \). In general, we minimize a combined loss

\[
L(x, y; \theta) = L_{supervised} + \alpha \cdot L_{PSDR}. \tag{4}
\]

The specific expression of \( L_{supervised} \) depends on the given training method, which can be simply a normal training procedure, an existing robustly training strategy expressed as Eq. (1), Eq. (2), or any other reasonable formulation. In this way, we can leverage PSDR to upgrade any existing methods of defending noisy labels. As an example, here we show how to improve Co-teaching [Han et al. (2018)] using PSDR in Algorithm 1, which is named as Co-teaching+PSDR. In Co-teaching, samples that have small training loss are selected out for training, which is equivalent to assign weights 1 to small-loss samples and 0 otherwise. Hence, the loss function is given by Eq. (4) with the \( L_{supervised} \) expressed as Eq. (1).

**Algorithm 1 Co-teaching+PSDR**

**INPUT:** epoch \( E_k \) and \( E_{max} \), learning rate \( \eta \), number of steps \( N \), maximum discard ratio \( \tau \), training set \( D \)

1: Initialize two networks \( f_1(x; \theta_1) \) and \( f_2(x; \theta_2) \)
2: for \( e = 1, 2, \ldots, E_{max} \) do
3: Shuffle the training set \( D \)
4: for \( i = 1, 2, \ldots, N \) do
5: Draw mini-batch \( D \) from \( D \), where each sample \( x_i \) in \( D \) is augmented to have \( x_i' \) and \( x_i'' \)
6: Sample \( R(e)\% \) small-loss samples with \( f_1 \): \( D_{f_1} = \{R(e)\% \arg \min_D L_{ccc}(f_1(x_i'), y_i)\} \)
7: Sample \( R(e)\% \) small-loss samples with \( f_2 \): \( D_{f_2} = \{R(e)\% \arg \min_D L_{ccc}(f_2(x_i'), y_i)\} \)
8: \( \theta_1 = \theta_1 - \eta \nabla_{\theta_1} \left( \sum_{D_{f_1}} L_{ccc}(f_1(x_i'), y_i) + \alpha \sum_D KL(f_1(x_i') || f_1(x_i'')) \right) \)
9: \( \theta_2 = \theta_2 - \eta \nabla_{\theta_2} \left( \sum_{D_{f_2}} L_{ccc}(f_2(x_i'), y_i) + \alpha \sum_D KL(f_2(x_i') || f_2(x_i'')) \right) \)
10: end for
11: Update \( R(e) = 1 - \min\{\frac{e}{E_k}, \tau\} \)
12: end for

**OUTPUT:** The trained models, \( f_1(x; \theta_1) \) and \( f_2(x; \theta_2) \)

### 3 Experiments

In this section, we empirically verify the effectiveness of our proposed PSDR. Notably, compared with extensive state-of-the-art methods [Patrini et al. (2017); Malach and Shalev-Shwartz (2017); Han et al. (2018); Jiang et al. (2018); Ma et al. (2018)], PSDR enables the best test accuracy when the training set contains noisy labels. Specifically, we demonstrate that PSDR significantly improves three representative baseline methods: F-correction [Patrini et al. (2017)], Decoupling [Malach and Shalev-Shwartz (2017)], and Co-teaching [Han et al. (2018)], and the improved ones also outperform other baseline methods.

**3.1 Experimental setup**

**3.1.1 Datasets and noise structures**

Our method is verified on the benchmark datasets CIFAR-10 and CIFAR-100 [Krizhevsky and Hinton (2009)], which are widely used in the literature [Patrini et al. (2017); Han et al. (2018); Jiang et al. (2018); Ma et al. (2018)] for evaluation of DNNs in presence of noisy labels. Since the labels in CIFAR-10 and CIFAR-100 are taken as ground truth, the noisy labels are generated by randomly flipping the original ones. Following previous literature [Ren et al. (2018); Han et al. (2018); Jiang et al. (2018); Ma et al. (2018)], we test on two representative types of noise: symmetric noise and
asymmetric noise. As illustrated in Fig. 1 in the symmetric case, all labels can flip uniformly to any other classes, while in the asymmetric case, labels in a class can flip to a single class. The noise ratio $\varepsilon$ denotes the proportion of wrong labels. Note that asymmetric noise with ratio 50% is trivial, hence in the experiments, we test symmetric noise with ratio 20%, 50%, and asymmetric noise with ratio 40%.

### 3.1.2 Compared methods

We investigate the following baselines. (1) 

*F-correction* [Patrini et al. (2017)](https://arxiv.org/abs/1704.05901). It first trains a network to estimate $T$, then modifies the loss function accordingly. (2) 

*Decoupling* [Malach and Shalev-Shwartz (2017)](https://arxiv.org/abs/1701.03971). It trains two networks on samples for which the predictions from the two networks are different. (3) 

*Co-teaching* [Han et al. (2018)](https://papers.nips.cc/paper/7555-the-co-teaching-framework-revisited). It maintains two networks. Each network selects samples of small training loss from the mini-batches and uses them to train another network. (4) 

*MentorNet* [Jiang et al. (2018)](https://arxiv.org/abs/1812.06166). A teacher network is pre-trained, which provides a sample weighting scheme to train a student network. (5) 

*Joint Optimization* [Tanaka et al. (2018)](https://arxiv.org/abs/1809.06625). It updates observed labels using predictions of the network. (6) 

*D2L* [Ma et al. (2018)](https://arxiv.org/abs/1811.03918). For each sample, it linearly combines the original label and the label predicted by the network. The combining weight is computed using the dimensionality of the latent feature subspace [Amsaleg et al. (2017)](https://arxiv.org/abs/1711.09349). In the experiments, standard data augmentation is applied to all methods.

### 3.1.3 Training details

For fair comparisons, all methods are evaluated with the same setup. To ensure that the empirical results are reliable, we repeat each experiment 5 times and report the average test accuracy. Following the official implementation of ResNet [He et al. (2016)](https://arxiv.org/abs/1512.03385) in Keras, we train the ResNet-32 [He et al. (2016)](https://arxiv.org/abs/1512.03385) for 200 epochs with a batch size of 128. We use the Adam optimizer [Kingma and Adam (2015)](https://arxiv.org/abs/1412.6980) with an initial learning rate $10^{-3}$, which is divided by 10 after 80, 120 and 160 epochs, and further divided by 2 after 180 epochs. In the network, we implement $l_2$ weight decay of $10^{-4}$. We use the standard data augmentation: horizontal random flipping and 32 × 32 random cropping after padding 4 pixels around images. In our method, the combining factor $\alpha$ in Eq. (4) is simply set to 1. Although tuning $\alpha$ may result in better performance, we show that $\alpha = 1$ is sufficient for beating all baselines.

### 3.2 Results on CIFAR-10

In Table 1, we report the test accuracy on the clean test set. We show the results for five recent successful baselines, and as an example, we use PSDR to further upgrade three of them. As shown in the table, PSDR consistently enables existing methods to achieve much higher test accuracy. Specifically, Co-teaching+PSDR achieves the best generalization performance under all noise settings, as marked in bold face. For comparison, we also normally train the same ResNet-32 on the original CIFAR-10 without any corruption and report the test accuracy in Table 1 which is 91.55%. Notably, the performance of Co-teaching+PSDR is very close to the clean baseline under symmetric noise with ratio 20% and asymmetric noise with ratio 40%. Even under symmetric noise with ratio 50%, where half of the labels are wrong, Co-teaching+PSDR achieves an impressive test accuracy of 85.4%.
Figure 2: Average test accuracy (5 runs) on CIFAR-10 during training under symmetric noise with ratio 20%, 50%, and asymmetric noise with ratio 40%. We train the ResNet-32 on manually corrupted CIFAR-10 and test on the clean test set. The sharp change of test accuracy results from learning rate change.

Table 1: Average test accuracy (5 runs) on CIFAR-10 under symmetric noise with ratio 20%, 50%, and asymmetric noise with ratio 40%. We train the ResNet-32 on manually corrupted CIFAR-10 and test on the clean test set. The best test accuracy under each setting is marked in bold face. The clean baseline means normal training on the clean CIFAR-10 without corruption.

| Method               | Symmetric          | Asymmetric         |
|----------------------|--------------------|--------------------|
|                      | 20%                | 50%                | 40%                |
| MentorNet            | 88.36 ± 0.46       | 77.10 ± 0.44       | 77.33 ± 0.79       |
| Joint Optimization   | 85.30 ± 0.35       | 79.84 ± 1.18       | 84.34 ± 1.37       |
| D2L                  | 86.12 ± 0.43       | 67.39 ± 13.62      | 85.57 ± 1.21       |
| F-corrrection        | 85.08 ± 0.43       | 76.02 ± 0.19       | 83.55 ± 2.15       |
| F-corrrection+PSDR   | 88.68 ± 0.28       | 82.77 ± 0.52       | 87.25 ± 1.78       |
| Decoupling           | 86.72 ± 0.32       | 79.31 ± 0.62       | 75.27 ± 0.83       |
| Decoupling+PSDR      | 88.89 ± 0.63       | 82.16 ± 1.05       | 84.01 ± 0.69       |
| Co-teaching          | 89.05 ± 0.32       | 82.12 ± 0.39       | 84.95 ± 2.81       |
| Co-teaching+PSDR     | **91.24 ± 0.19**   | **85.40 ± 0.66**   | **90.41 ± 0.37**   |
| Clean baseline       |                    |                    |                    |

In Fig. 2 we show the test accuracy during training. Specifically, we are interested in how PSDR affects the convergence of DNNs, so we plot the accuracy after the first learning rate change at the 80th epoch. As we can see, without PSDR, the networks suffer from severe overfitting to noisy labels, which is indicated by the decrease of test accuracy at the later stage of training (e.g., the dashed green curve in Fig. 2(c)). As shown in the figure, the overfitting is eased by PSDR. For all investigated noise settings and baseline methods, PSDR consistently improves the convergence of DNNs.

3.3 Results on CIFAR-100

In Table 2, we report the test accuracy for CIFAR-100. The observations here are consist with those for CIFAR-10. PSDR consistently improves the generalization performance of investigated baseline methods, and the improved ones also outperform other state-of-the-art methods. As marked in bold face, the best result is achieved by Co-teaching+PSDR. For further comparison, we also normally train the same ResNet-32 on the original CIFAR-100 without any corruption and report the test accuracy in Table 2, which is 67.06%. Impressively, the test accuracy of Co-teaching+PSDR is very close to the clean baseline under symmetric noise with ratio 20%. For other noise settings, Co-teaching+PSDR also significantly outperforms other methods.

To investigate how PSDR affects the convergence of DNNs, we show the test accuracy during training in Fig. 3. As can be seen, PSDR reduces the decrease of test accuracy at the later stage of training, which implies it ease the overfitting to noisy labels. In all experiments, PSDR consistently improves the convergence of DNNs compared with baseline methods.
4 Discussion

4.1 How does smoothness benefit defending noisy labels?

To simplify our presentation, we define the smoothness as predicting similarly on samples of the same class. This assumption has been widely used in manifold learning [Belkin and Niyogi (2003)], but is never adopted to improve the generalization performance of DNNs trained on noisy datasets. As demonstrated empirically in this paper, we find that smoothness on samples of the same class is beneficial to robustness against noisy labels. Without loss of generality, we consider the non-trivial case such that $\forall i, T_{ii}$ is the largest among $\{T_{ij}, j = 1, \cdots, c\}$, which means for samples with actual class $i$, the number of correct labels $i$ is the largest among all labels $\{1, \cdots, c\}$. In this case, if we can enforce smoothness on all samples with actual class $i$, then the network will be very likely to correctly predict class $i$ for these samples since the number of samples with label $i$ is the largest. However, in our setting, the observed labels are noisy, samples with the same label are not guaranteed to be from the same latent true class, so we can’t implement this idea to enforce smoothness according to the observed labels. Moreover, searching neighboring samples of a given input as [Belkin and Niyogi (2003)] is quite expensive. Therefore, we utilize data augmentation, which can generate many different neighboring images, and the generated images are guaranteed to be in the same class.

The idea can be further illustrated in Fig. 4, where we use different colors to indicate the true labels and different shapes to indicate the observed noisy labels. Without any regularization, the theorem on finite sample expressiveness [Zhang et al. (2017)] implies that DNNs can always achieve 0 training error on any finite number of training samples, as illustrated in Fig. 4(a). In this case, the model overfits to the noisy labels, which usually degenerates the generalization performance. On the other

Table 2: Average test accuracy ($\%$, 5 runs) on CIFAR-100 under symmetric noise with ratio 20%, 50%, and asymmetric noise with ratio 40%. We train the ResNet-32 on manually corrupted CIFAR-100 and test on the clean test set. The best test accuracy under each setting is marked in bold face. The clean baseline means normal training on the clean CIFAR-100 without corruption.

| Method              | Symmetric 20% | Symmetric 50% | Symmetric 40% | Asymmetric 20% | Asymmetric 50% | Asymmetric 40% |
|---------------------|---------------|---------------|---------------|----------------|----------------|----------------|
| Clean baseline      | 67.06         |               |               |                |                |                |
| F-correction        | 55.80 ± 0.54  | 43.27 ± 0.72  | 42.25 ± 0.73  |                |                |                |
| F-correction+PSDR   | 60.04 ± 0.49  | 47.38 ± 1.14  | 45.85 ± 0.89  | 60.78 ± 0.52   | 57.43 ± 0.21   |                |
| Decoupling          | 57.55 ± 0.47  | 45.68 ± 0.43  | 43.12 ± 0.42  | 60.78 ± 0.52   | 57.43 ± 0.21   |                |
| Decoupling+PSDR     | 61.84 ± 0.26  | 49.70 ± 0.88  | 46.55 ± 0.36  |                |                |                |
| Co-teaching         | 64.02 ± 0.26  | 57.27 ± 0.36  | 47.67 ± 1.24  | 60.78 ± 0.52   | 57.43 ± 0.21   |                |
| Co-teaching+PSDR    | **66.71 ± 0.44** | **60.78 ± 0.52** | **57.43 ± 0.21** |                |                |                |

As demonstrated empirically in this paper, we find that smoothness on samples of the same class is beneficial empirically in this paper, we find that smoothness on samples of the same class is beneficial to robustness against noisy labels. Without loss of generality, we consider the non-trivial case such that $\forall i, T_{ii}$ is the largest among $\{T_{ij}, j = 1, \cdots, c\}$, which means for samples with actual class $i$, the number of correct labels $i$ is the largest among all labels $\{1, \cdots, c\}$. In this case, if we can enforce smoothness on all samples with actual class $i$, then the network will be very likely to correctly predict class $i$ for these samples since the number of samples with label $i$ is the largest. However, in our setting, the observed labels are noisy, samples with the same label are not guaranteed to be from the same latent true class, so we can’t implement this idea to enforce smoothness according to the observed labels. Moreover, searching neighboring samples of a given input as [Belkin and Niyogi (2003)] is quite expensive. Therefore, we utilize data augmentation, which can generate many different neighboring images, and the generated images are guaranteed to be in the same class.

The idea can be further illustrated in Fig. 4, where we use different colors to indicate the true labels and different shapes to indicate the observed noisy labels. Without any regularization, the theorem on finite sample expressiveness [Zhang et al. (2017)] implies that DNNs can always achieve 0 training error on any finite number of training samples, as illustrated in Fig. 4(a). In this case, the model overfits to the noisy labels, which usually degenerates the generalization performance. On the other
Figure 4: Illustration of decision boundary when trained with noisy labels. The the color red and blue indicate the latent true label, and the shape triangle and circle indicate the observed label. We use the dashed circle to indicate the area of data augmentation for each sample.

Figure 5: Normal training with (i) data augmentation turned off (Normal No Aug.), (ii) data augmentation turned on by default (Normal Aug.), and (iii) PSDR (Normal + PSDR). As an example, we train the ResNet-32 on manually corrupted CIFAR-10 that has symmetric noise with ratio 50%.

hand, with data augmentation, we can generate many neighboring samples of the same class. For illustration, in Fig. 4(b), we use the dashed circle to indicate the area of data augmentation for each input sample. If we can enforce smoothness on the augmented samples, then it is impossible for the DNNs to learn a complex decision boundary that separates nearby samples into multiple classification regions. Since the samples with correct labels are the majority in each class, the network is very likely to correctly predict the actual class.

4.2 PSDR enforces smoothness explicitly

Data augmentation is a widely used technique which eases the overfitting problem and improves the generalization performance of DNNs [Krizhevsky et al. (2012); He et al. (2016); Perez and Wang (2017)]. Traditionally, at each epoch, an augmented sample is randomly generated for each sample in the original training set, and the network is trained on the augmented ones. In this way, for any original sample, various random samples are generated during the whole training process. Since the augmented samples have the same label as the original example, directly training on them enforces smoothness implicitly around original ones.

In Fig. 5 we show the test accuracy of DNNs w.r.t. the number of training epochs. In the experiments, we normally train the DNNs without any specific techniques of dealing with noisy labels. As an example, we train on manually corrupted CIFAR-10 that has symmetric noise with ratio 50%. As shown in the blue curve, without data augmentation, the test accuracy first reaches a high value, then decreases quickly, which implies the network eventually overfit to the noisy labels. This phenomenon is consistent with the finding in [Arpit et al. (2017)], which states that DNNs learn simple patterns first, then memorize noisy labels. The green curve in Fig. 5 shows the test accuracy of the network directly trained on augmented samples. As we can see, data augmentation improves the test accuracy significantly, although overfitting still occurs at the later stage of training.

PSDR further improves the robustness to noisy labels by enforcing smoothness explicitly, as shown in Fig. 5. Recall that in PSDR, the KL divergence between softmax outputs of paired samples generated by data augmentation is directly added to the training loss as a manifold regularization. In this way, PSDR enforces smoothness explicitly. Moreover, PSDR is an unsupervised regularization term, which enables all samples to make sense during training, regardless of whether their labels are clean.
PSDR overcomes the problem of existing methods: many baseline methods do not make full use of all samples, and some of them simply discard the likely noisy samples, which results in lack of training samples, and hence reduces the generalization performance. Fig. 5 demonstrates that with PSDR, even if the network is normally trained without any other specific methods of defending noisy labels, we still can achieve a test accuracy of around 80% on the manually corrupted CIFAR-10 containing 50% wrong labels.

5 Conclusion

In this paper, we present a simple but effective regularization called PSDR, which significantly improves the robustness of DNNs trained with noisy labels. Our method is motivated by the fact that many existing methods do not make full use of all training samples. By encouraging the predictions to be similar for paired samples generated using data augmentation, PSDR enables all training samples from the original training set to make sense in training, regardless of whether their labels are clean. We conduct comprehensive experiments on benchmark datasets under different noise types and noise ratios. Empirical results verify that our PSDR consistently improves existing state-of-the-art methods by a significant margin.

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