P-DIFF: Learning Classifier with Noisy Labels based on Probability Difference Distributions

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Abstract—Learning deep neural network (DNN) classifier with noisy labels is a challenging task because the DNN can easily overfit on these noisy labels due to its high capability. In this paper, we present a very simple but effective training paradigm called P-DIFF, which can train DNN classifiers but obviously alleviate the adverse impact of noisy labels. Our proposed probability difference distribution implicitly reflects the probability of a training sample to be clean, then this probability is employed to re-weight the corresponding sample during the training process. P-DIFF can also achieve good performance even without prior-knowledge on the noise rate of training samples. Experiments on benchmark datasets also demonstrate that P-DIFF is superior to the state-of-the-art sample selection methods.

I. INTRODUCTION

DNN-based classifiers achieve state-of-the-art results in many researching fields. DNNs are typically trained with large-scale carefully annotated datasets. However, some datasets are difficult to obtain for classification tasks with large numbers of classes. Some approaches [1], [2], [3], [4] provide the possibility to acquire large-scale datasets, but inevitably result in noisy/incorrect labels, which will adversely affect the prediction performance of the trained DNN classifiers.

To solve this problem, some approaches try to estimate the noise transition matrix to correct mis-labeled samples [5], [6], [7], [8]. However, this matrix is difficult to be accurately estimated, especially for classification with many classes. Other correction methods [9], [10], [11], [12] are also proposed to reduce the effect of noisy labels. Recently, some approaches focus on selecting clean samples, and update the DNNs only with these samples [13], [14], [15], [16], [17], [18], [19], [20].

In this paper, we propose P-DIFF, a novel sample selection paradigm, to learn DNN classifiers with noisy labels. Compared with previous sample selection approaches, P-DIFF provides a stable but very simple method for evaluating sample being noisy or clean. The main results and contributions of the paper are summarized as follows:

1) We propose the P-DIFF paradigm to learn DNN classifiers with noisy labels. P-DIFF uses a probability difference strategy, instead of the broadly utilized small-loss strategy, to estimate the probability of a sample to be noisy. Moreover, P-DIFF employs a global probability distribution generated by accumulating samples of some recent mini-batches, so it demonstrates more stable performance than single mini-batch approaches. P-DIFF paradigm does not depend on extra datasets, phases, models or information, and is very simple to be integrated into existing softmax-loss based classification models.

2) Compared with SOTA sample selection approaches, P-DIFF has advantages in many aspects, including classification performance, resource consumption, computation complexity. Experiments on several benchmark datasets, including a large real-world noisy dataset cloth1M [21], demonstrate that P-DIFF outperforms previous state-of-the-art sample selection approaches at different noise rates.

II. RELATED WORK

Learning with noisy datasets has been widely explored in classification [22]. Many approaches use pre-defined knowledge to learn the mapping between noisy and clean labels, and focus on estimating the noise transition matrix to remove or correct mis-labeled samples [5], [6], [7].

Recently, it has also been studied in the context of DNNs. DNN-based methods to estimate the noise transition matrix are proposed too [23], [24], [25], [26], [27] use a small clean dataset to learn a mapping between noisy and clean annotations. [9], [10] use noise-tolerant losses to correct noisy labels. [11] constructs a knowledge graph to guide the learning process. [8] proposes a human-assisted approach which incorporates an structure prior to derive a structure-aware probabilistic model. Local Intrinsic Dimensionality is employed in [12] to adjust the incorrect labels. Rank Pruning [28] is proposed to train models with confident samples, and it can also estimate noise rates. However, Rank Pruning only aims at binary classification. [29] implements a simple joint optimization framework to learn the probable correct labels of training samples, and to use the corrected labels to train models. [30] proposes an extra Label Correction Phase to correct the wrong labels and achieve good performance. Yao et al. [31] employ label regression for noisy supervision.

Some approaches attempt to update the DNNs only with separated clean samples, instead of correcting the noisy labels. A Decoupling technique [14] trains two DNN models to select samples that have different predictions from these two models. Weighting training samples [32], [33], [34] is also applied
to select clean samples. Based on Curriculum learning [53], some recent proposed approaches select clean training samples by using some strategies. However, these approaches usually require extra consumption, such as reference or clean sets [20], extra models [13], [56], [37], [15], [17], [38], or iterative/multi-step training [16], [19].

In the paper, we proposed a very simple sample selection approach P-DIFF. Compared with previous approaches, reference sets, extra models, and iterative/multi-step training are not required in P-DIFF.

III. THE PROPOSED P-DIFF PARADIGM

Samples with incorrect label are referred as noisy samples, and their labels are referred as noisy labels. Noisy labels fall into two types: label flips where the sample has been given a label of another class within the dataset, and outliers, where the sample does not belong to any of the classes in the dataset. In some papers, they are named as closed-set and open-set noisy labels. As most of previous works [13], [15], [11], [9], [39], [12], [19], [17], we also address the noisy label problem in a closed-set setting. Actually, experiments in Section III-C on the large real-world dataset Cloth1M [21] demonstrate that P-DIFF is capable to process open-set noisy labels too.

Our P-DIFF is also a sample selection paradigm. The key of selecting samples is an effective method to measure the possibility that a sample is clean. Some recently proposed methods [13], [15], [20], [17] employ the small-loss strategy to select clean samples. Different from those approaches, P-DIFF selects the clean samples based on the probability difference distributions. The probability difference distribution is computed with the output of the softmax function, and is presented as follows.

A. Probability Difference Distributions

![Fig. 1. DIST and the corresponding performance results at different training epochs.](image)

Following previous sample selection approaches, such as O2UNet [19], we also remove potential noisy labels to achieve better performance, although noisy and real hard samples may not be distinguished in some cases. Our sample selection strategy is based on two key strategies: Probability Difference and Global Distribution.

1) Probability Difference: The softmax loss is widely applied to supervise DNN classification, and can be considered as the combination of a softmax function and a cross-entropy loss. The output of the softmax function is $\hat{p} = (p_0, p_1, \ldots, p_C)$, where $C$ is the class number. As for an input sample, $p_m \in [0, 1]$ is the predicted probability of belonging to the $m$-th class, and

$$p_m = \frac{e^{\tilde{W}_m^T \bar{x} + \bar{b}_m}}{\sum_{j=1}^C e^{\tilde{W}_j^T \bar{x} + \bar{b}_j}},$$

where $\bar{x}$ denotes the feature of the input sample computed with DNNs. $\tilde{W}$ and $\bar{b}$ are the weight and the bias term in the softmax layer respectively. The cross-entropy loss is defined as

$$\mathcal{L} = - \sum_{m=1}^C q_m \log(p_m),$$

where $q_m$ is the ground truth distribution defined as

$$q_m = \begin{cases} 0 & m \neq y \\ 1 & m = y \end{cases},$$

where $y$ is the ground truth class label of the input sample.

Generally, as training a DNN classifier, $p_y$ is encouraged to be the largest component in $\hat{p}$ for an input sample belonging to the $y$-th class. However, if the sample is wrongly labeled, enlarging $p_y$ would lead to adverse effects on the robustness of the trained classifier. The small-loss strategy has been proven to be an effective way to select clean samples [13], [15], [20], [17]. However, the small-loss strategy cannot select appropriate clean samples in some cases. For example, $\tilde{P}_1 = \{0.2, 0.2, 0.2, 0.2, 0.2\}$ and $\tilde{P}_2 = \{0.0, 0.2, 0.0, 0.0, 0.8\}$ are the output values of two training samples, and $y = 1$. It is clear that the $\mathcal{L}$ values of these two samples are equal because of the same $p_y = 0.2$, but the second sample has much higher probability to be wrongly labeled.

We define the probability difference $\delta$ of a sample, which belongs to the $y$-th class, as

$$\delta = p_y - p_n,$$

where $p_n$ is the largest component except $p_y$ in $\hat{p}$, so $\delta \in [-1, 1]$. Ideally, the $\delta$ value should be 1 for a clean sample. If the sample is a label flip noisy sample, we can also ideally infer that $p_y = 0$ and $p_n = 1$ ($\delta = -1$), where $n$ is the correct label. Although we cannot achieve such results in real training, it inspires us to select clean samples according to $\delta$ values.

It is clear that $\delta_1 = 0.0$ and $\delta_2 = -0.6$ of two samples mentioned above, which indicates that the second sample has higher probability to be noisy. Experiments in Section IV-B verify the effectiveness of $\delta$, compared with only $p_y$. 
2) Global Distribution: Furthermore, only considering samples in one mini-batch [13], [15], [20] reduces the stabilization of sample selection, and a global threshold is not applied too since the loss values are rapidly changed especially in early epochs. P-DIFF adopts a selection method based on a $\delta$ histogram. We compute the histogram distribution of $\delta$ for all input samples, and this global distribution, called $DIST_{all}$, is just the probability difference distribution. We divide the entire range $[-1, 1]$ of the distribution into $H$ bins. We set $H = 200$ in our implementation. Let $PDF(x)$ be the ratio of samples whose $\delta$ fall into the $x$-th bin as

$$PDF(x) = \frac{1}{N} \sum_{i=1}^{N} \begin{cases} 1 & \text{if } \left[ H \cdot \frac{\delta_i + 1}{2} \right] = x \\ 0 & \text{else} \end{cases}, \quad (5)$$

where $N$ is the number of training samples. $PDF(x)$ means the probability distribution function of $DIST_{all}$. We then define the probability cumulative function of $DIST_{all}$ as

$$PCF(x) = \sum_{i=1}^{x} PDF(i). \quad (6)$$

Moreover, given the $x$-th bin, we can get its value range as

$$\delta \in (2 \cdot \frac{x - 1}{H} - 1, 2 \cdot \frac{x}{H} - 1). \quad (7)$$

We perform an experiment to show this distribution. The experiment setting is presented in the Section V. We train a normal DNN model with Cifar-10. Figure 1 shows a probability difference distribution of the DNN at different training epochs. This distribution $DIST_{all}$ is employed in our P-DIFF paradigm to learn classifier with noisy labels. In theory, the distribution $DIST_{all}$ should be computed in each mini-batch training, but it is time-consuming if the number of samples is large. In our implementation, only the $\delta$ values of samples belonging to recent $M$ mini-batch samples are stored to generate the distribution $DIST_{sub}$. If $M$ is too small, $DIST_{sub}$ cannot be considered as a good approximation of $DIST_{all}$. However, a large $M$ is not appropriate too, because the $\delta$ values of far earlier training samples cannot approximate their current values (discussed in Section IV-C).

B. Learning Classifier with Noisy Labels

The basic idea of P-DIFF paradigm is trying to select clean samples based on the $DIST_{all}$. As discussed in the Section III-A the samples with larger $\delta$ have higher probability of being clean during training, and they should have higher rate to be selected to update the training DNN model. The remaining problem is to find a suitable threshold $\delta$.

Given a noise rate $\tau$ and a distribution $DIST_{all}$, P-DIFF drops a certain rate ($\tau$) of the training samples that fall into the left part of $DIST_{all}$. We simply find the smallest bin number $x$ which makes

$$PCF(x) > \tau. \quad (8)$$

Therefore, all samples falling into left of the $x$-th bin will be dropped in training. According to Equation 7 the $\delta$ values of these samples should be less than $2 \cdot (x - 1)/H - 1$, and we can define the threshold $\hat{\delta}$ as

$$\hat{\delta} = 2 \cdot \frac{x - 1}{H} - 1. \quad (9)$$

However, at the beginning of training process, the DNNs do not have the ability to classify samples correctly, so we cannot drop training samples with the rate $\tau$ throughout the whole training process. We know the DNNs will be improved as the training iteration increases. Therefore, similar with Co-teaching [15], we define a dynamic drop rate $R(T)$, where $T$ is the number of training epoch, as

$$R(T) = \tau \cdot \min(T_k, 1). \quad (10)$$

We can see that all samples are selected at the beginning, then more and more samples are dropped as $T$ gets larger until $T = T_k$ (a given epoch number), and the final drop rate is $\tau$. Therefore, Equation 5 is re-written as

$$PCF(x) > R(T). \quad (11)$$

P-DIFF updates DNN models by redefining Equation 2 as

$$L = -\omega \sum_{m=1}^{C} q_m \log(p_m), \quad (12)$$

where $\omega$ is the computed weight of the sample. We set $\omega = 1$ if $\delta > \hat{\delta}$, or $\omega$ is set to 0.

Algorithm 1 gives the detailed implementation of our P-DIFF paradigm with a given noise rate $\tau$.

C. Training without a given $\tau$

Similar with Co-teaching, a given noise rate $\tau$ is required to compute $R(T)$ in P-DIFF (Algorithm 1). If $\tau$ is not known in advance, it can be inferred by using the validation set as [13], [6]. However, the rate inferred using the validation set cannot always accurately reflect the real rate in the training set. We further explore the method for learning classifiers without a pre-given noise rate $\tau$.

According to the algorithm described above, the key of P-DIFF is to find a suitable threshold $\hat{\delta}$ to separate clean and noisy training samples. Based on the definition $\hat{\delta} = \hat{p}_y - \hat{p}_n$, we can reasonably infer that 0 might be a candidate. Considering the gradually learning problem (see Equation 10), we compute the threshold as

$$\hat{\delta} = \min(T_k, 1) - 1. \quad (13)$$

In other words, all samples are employed to learn the classifier in the beginning, and with the increase of the training epoch number, some samples will be dropped. At last, only samples with $\delta > 0$ are selected as clean samples to update the DNNs.
Algorithm 1 P-DIFF Paradigm

Input: Training Dataset $D$, epoch $T_k$ and $T_{max}$, iteration per-epoch $Iter_{epoch}$, batch size $S_{batch}$, noise rate $\tau$, batch rate $M$;
Output: DNN parameter $\tilde{W}$;

Initialize $\tilde{W}$;
for $T = 1$ to $T_{max}$ do
  Compute the rate $R(T)$ using Equation 10
  for $Iter = 1$ to $Iter_{epoch}$ do
    Compute the threshold $\hat{\delta}$ using Equation 9 and Equation 11
    Get the mini-batch $\tilde{D}$ from $D$;
    Set the gradient $G = 0$;
    for $S = 1$ to $S_{batch}$ do
      Get the $S$-th sample $\tilde{D}(S)$;
      Compute $\tilde{P}$ of $\tilde{D}(S)$ using $\tilde{W}$;
      Compute the $\delta$ value using Equation 4
      if $\delta > \hat{\delta}$ then
        $\omega = 1$;
      else
        $\omega = 0$;
      end if
      $G + \nabla L$ (see Equation 12);
    end for
    Update $DIST_{sub}$ with the computed $\delta$ values of the last $M \times Iter_{epoch}$ mini-batches;
    Update the parameter $\tilde{W} = \tilde{W} - \eta \cdot G$;
  end for
end for

1) Noise Rate Estimation: DNNs memorize easy/clean samples firstly, and gradually adapt to hard/noisy samples as training epochs become large. When noisy label exists, DNNs will eventually memorize incorrect labels. This phenomenon, called Noise-Adaptation phenomenon, does not change with the choice of training optimizations or networks. DNNs can memorize noisy labels, so we cannot only trust $\delta = 0$. In the section, we further propose a noise rate estimation technique to achieve better performance.

According to the definition of $\delta$, the $\delta$ value should be encouraged to be close to 1 or -1 for clean and noisy samples respectively. Therefore we propose a value $\zeta$ to evaluate the performance of the learned classifier as

$$\zeta = \sum_{x=1}^{H} \left( \left| 2 \frac{x - 1}{H} - 1 \right| \cdot PDF(x) \right).$$

In fact, $\zeta \in [0, 1]$ is the expected value of $|\delta|$ in the distribution $DIST_{all}$. According to the Noise-Adaptation phenomenon and the P-DIFF paradigm, a high $\zeta$ should indicate that the DNN model currently mainly memorizes correct labels. Therefore, we can reasonably infer that the proportion of noisy samples in all samples with $\delta > \hat{\delta}$ is small, and the noise rate $\tau$ can be estimated based on the above inference.

We firstly train the DNN model until $T = T_k$ ($\hat{\delta} = 0$), then $\zeta$ is computed for each mini-batch. Once $\zeta$ is larger than a threshold (discussed in Section IV-D), all samples with $\delta < 0$ are regarded as noisy samples to estimate the noise rate $\tau$. With the estimated $\tau$, the threshold $\hat{\delta}$ is then computed by using Equation 9 instead of Equation 13, and we train DNNs by using the method with the given noise rate $\tau$ as Algorithm 1.

If $\zeta$ is always less than the threshold, we estimate $\tau$ in the end of training by regarding all samples with $\delta < 0$ as noisy samples.

IV. EXPERIMENTS

We verify the effectiveness of P-DIFF on 4 benchmark datasets: MNIST, Cifar10, Cifar100, and Mini-ImageNet [41], which are popularly used for evaluation of noisy labels in previous works. Furthermore, we also perform experiments on a large real-world noisy benchmark Cloth1M [21]. For the fair comparison, we use 9-layer [15] and ResNet-101 CNNs in experiments. All models are trained by using the SGD optimizer (momentum=0.9) with an initial learning rate 0.001 on a TitanX GPU. The batch size is set to 128. We fix $T_{max} = 200$ to train all CNN classifiers, and fix $T_k = 20$ in our P-DIFF implementations. Caffe [42] is employed to implement P-DIFF. Following other approaches, we corrupt datasets with two types of noise transition matrix: Symmetry flipping and Pair flipping.

![Fig. 2. DIST_{all} (Yellow), DIST_{clean} (Green) and DIST_{noise} (Red) at different training epochs. The DNNs are trained with given noise rates. The corresponding thresholds $\delta$ and the performance results can also be seen in the figure.](image)

A. Probability Difference Distribution in Training

We firstly perform an experiment to show the probability difference distribution throughout the training process. In the experiment, Cifar-10 is corrupted by using Symmetry flipping with 50% noisy rate. To better illustrate the effectiveness of P-DIFF, as shown in Figure 2, we present three types of distributions: $DIST_{all}$, $DIST_{clean}$ and $DIST_{noise}$. These distributions are built by using $\delta$ values of all samples, clean samples, and noisy samples respectively. Therefore, we can conclude that $DIST_{all} = DIST_{clean} + DIST_{noise}$. 

To further demonstrate the effectiveness of $\delta$, we train the DNNs (abbreviated as P-DIFF) with some noisy datasets as shown in Table I. We also employ P-DIFF paradigm to train the DNN (abbreviated as P-DIFF$_{m1}$) but using $p_y$ instead of $\delta$. Comparing the performance of P-DIFF and P-DIFF$_{m1}$ in Table I, we can see that the probability difference $\delta$ plays the key role to achieve satisfied performance, especially on Pair Flipping datasets.

To evaluate P-DIFF without given noise rates, we perform another experiment on the same noisy dataset, but train the DNN by using the method presented in Section III-C. DIST$_{all}$, DIST$_{clean}$, and DIST$_{noise}$ are also presented in Figure 3. The figure shows $\delta$, $\zeta$, and the performance results too. We can see that most of clean and noisy samples are separated clearly by using P-DIFF.

### TABLE I

| DataSet | Noise Type, Rate | P-DIFF$_{m1}$ | P-DIFF |
|---------|-----------------|---------------|--------|
| Cifar-10 | Symmetry,20%    | 85.59%        | 88.61% |
|         | Symmetry,40%    | 82.74%        | 85.31% |
|         | Pair,10%        | 83.69%        | 87.78% |
|         | Pair,45%        | 73.47%        | 83.25% |

### C. Effect of $M$

$M$ indicates the rate of recent batch number used to generate the distribution DIST$_{sub}$. To demonstrate the effect of $M$, we perform some experiments on Cifar-10 with different $M$ value. Table II gives the comparison result. We can observe that only using samples in one mini-batch (as [13, 15, 17]) cannot achieve satisfied performance. Meanwhile, a large $M$ is also not preferred as discussed in Section III-A2, which can be observed from the table too. According to our experiments on several datasets, setting $M = 20\%$ can achieve good results in all experiments. Actually, we can observe that $M$ is not a very sensitive parameter for achieving good performance.

### TABLE II

| $M$ | Symmetry,20% | Symmetry,40% | Pair,10% | Pair,45% |
|-----|--------------|--------------|----------|----------|
| 0%  | 87.71%       | 81.37%       | 84.87%   | 74.23%   |
| 5%  | 88.35%       | 83.09%       | 86.32%   | 77.95%   |
| 10% | 88.79%       | 85.64%       | 88.28%   | 81.27%   |
| 20% | 88.61%       | 85.31%       | 87.78%   | 83.25%   |
| 50% | 88.13%       | 84.14%       | 87.34%   | 78.04%   |
| 100%| 88.38%       | 85.13%       | 87.67%   | 78.48%   |

### D. Effect of $\zeta$

We also perform several experiments to evaluate the effect of $\zeta$ in Equation 14 when the noise rate is not given. $\zeta$ is employed in P-DIFF to reflect the degree of convergence of the model, which can be observed in Figure 3. According to the results shown in Table III $\zeta$ is not a very sensitive parameter for achieving good performance too, as long as the value is not close to 1.0. Therefore, we set $\zeta = 0.9$ in all our experiments.
TABLE III
AVERAGE TEST ACCURACY ON FOUR CIFAR-10 TESTING DATASETS OVER THE LAST 10 EPOCHS WITH DIFFERENT ζ VALUES.

| ζ   | Symmetry 20% | Symmetry 40% | Pair 10% | Pair 45% |
|-----|--------------|--------------|----------|----------|
| 0.5 | 87.71%       | 78.35%       | 82.39%   | 81.49%   |
| 0.8 | 88.28%       | 84.27%       | 85.38%   | 83.86%   |
| 0.85| 87.37%       | 84.93%       | 85.65%   | 86.24%   |
| 0.90| 86.61%       | 85.74%       | 87.43%   | 86.73%   |
| 0.95| 86.22%       | 84.49%       | 86.94%   | 83.24%   |
| 1.0 | 86.19%       | 84.13%       | 86.32%   | 87.52%   |

E. Experiments without a Given τ

To evaluate P-DIFF without a given noise rate τ, we train the DNNs on benchmarks again, but by using the method presented in Section III-C. Moreover, we apply P-DIFF to train DNNs with clean training datasets to demonstrate its effectiveness. The results are shown in Table IV. From the table, we can see that our estimated τ_{est} are very close to the real rates in many cases, especially when the corresponding ζ value is high. This phenomenon also proves that the ζ can be applied to evaluate the performance of the DNNs trained with P-DIFF.

To verify the effectiveness of ζ, Table V presents the test accuracy results (abbreviated as TA1, and TA = TA if ζ < 0.9) without considering ζ (using Equation 13). TA should be equal to TA1 if ζ cannot exceed a threshold 0.9 throughout the training process. As shown in the table, the performance of DNNs can be further improved if the noise rates can be estimated with ζ. We also observed that P-DIFF can deal with clean datasets and achieved good results too.

By comparing with the results in Table VI, it is surprising that the DNNs trained without a given noise rate even achieve better performance than the DNNs trained with correct given noise rates. More exploration should be conducted to find the reason behind this phenomenon.

F. Comparison with State-of-the-art Approaches

We compare the P-DIFF with four outstanding sample selection approaches: Co-teaching [15], Co-teaching+ [17], INCV [18], and O2U-Net [19].

Co-teaching: Co-teaching simultaneously trains two networks for selecting samples. We compare Co-teaching because it is an important sample selection approach.

Co-teaching+: This work is constructed on Co-teaching, and heavily depends on samples selected by small-loss strategy. Therefore, it is suitable to compare with P-DIFF for comparison.

INCV: This recently proposed approach divides noisy datasets and utilizes cross-validation to select clean samples. Moreover, the Co-teaching strategy is also applied in the method.

O2U-Net: This work also compute the probability of a sample to be noisy label by adjusting hyper-parameters of DNNs in training. Multiple training steps are employed in the approach. Its simplicity and effectiveness make it to be a competitive approach for comparison.

As the baseline, we also compare P-DIFF with the DNNs (abbreviated as Normal) trained with the same noisy datasets by using the classic softmax loss. The DNNs (abbreviated as Clean) trained only with clean samples (For example, only 80% clean samples are used for a Symmetry-20% noisy dataset) are also presented as the upper bound. We corrupt datasets with 80% noise rate to demonstrate that P-DIFF can deal with extremely noisy datasets. Table V reports the accuracy on the testing sets of four benchmarks. We can see that the DNNs trained with P-DIFF are superior to the DNNs trained with these previous state-of-the-art approaches.

We further perform experiments on a large-scale real-world dataset Cloth1M, which contains 1M/14k/10k train/val/test images with 14 fashion classes. Table VII lists the performance results. Though P-DIFF addresses noisy problem in the closed-set setting, it can also achieve good results on real-world open-set noisy labels.

1) Comparison on Computational Efficiency: Compared with these approaches, P-DIFF also has advantages in resource consumption and computational efficiency, since other approaches require extra DNN models or complex computation to achieve good performance. Table VII shows the training time of these approaches for comparison. All data are measured with the 9-Layer CNNs trained on Cifar-10 with 40% symmetry noise rate. Furthermore, P-DIFF only requires an extra small memory to store the distribution, so it costs fewer memory than other noise-free approaches too.
V. CONCLUSION

Based on probability difference and global distribution schemes, we propose a very simple but effective training paradigm P-DIFF to train DNN classifiers with noisy data. According to our experiments on both synthetic and real-world datasets, we can conclude that P-DIFF can achieve satisfied performance on datasets with different noise type and noise rate. P-DIFF has some parameters, such as $M$ and $\zeta$, but we can conclude that the performance of our paradigm is not sensitive to them according to our experiments. Since P-DIFF only depends on a Softmax layer, it can be easily employed for training DNN classifiers. We also empirically show that P-DIFF outperforms other state-of-the-arts sample selection approaches both on classification performance and computational efficiency.

Recently, some noise-tolerant training paradigms [30], [29] which employ the label correction strategy to achieve good performance, and we will investigate this strategy in P-DIFF to further improve the performance in the future.

REFERENCES

[1] R. Fergus, L. Fei-Fei, P. Perona, and A. Zisserman, “Learning object categories from internet image searches,” Proceedings of the IEEE, vol. 98, no. 8, pp. 1453–1466, 2010.

[2] S. K. Divvala, A. Farhadi, and C. Guestrin, “Learning everything about anything: Webly-supervised visual concept learning,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 3270–3277.

[3] J. Krause, B. Sapp, A. Howard, H. Zhou, A. Toshev, T. Duerig, J. Philbin, and L. Fei-Fei, “The unreasonable effectiveness of noisy data for fine-grained recognition,” in European Conference on Computer Vision. Springer, 2016, pp. 301–320.

[4] L. Niu, W. Li, and D. Xu, “Visual recognition by learning from web data: A weakly supervised domain generalization approach,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 2774–2783.

[5] A. Menon, B. Van Rooyen, C. S. Ong, and B. Williamson, “Learning from corrupted binary labels via class-probability estimation,” in International Conference on Machine Learning, 2015, pp. 125–134.

[6] T. Liu and D. Tao, “Classification with noisy labels by importance reweighting,” IEEE Transactions on pattern analysis and machine intelligence, vol. 38, no. 3, pp. 447–461, 2016.

[7] N. Natarajan, I. S. Dhillon, P. K. Ravikumar, and A. Tewari, “Learning with noisy labels,” in Advances in neural information processing systems, 2013, pp. 1196–1204.

[8] B. Han, J. Yao, G. Niu, M. Zhou, I. Tsang, Y. Zhang, and M. Sugiyama, “Masking: A new perspective of noisy supervision,” in NIPS, 2018.
[9] G. Patrini, A. Rozza, A. K. Menon, R. Nock, and L. Qu, “Making deep neural networks robust to label noise: A loss correction approach,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), 2017, pp. 2233–2241.

[10] A. Ghosh, H. Kumar, and P. Sastry, “Robust loss functions under label noise for deep neural networks,” in AAAI, 2017, pp. 1919–1925.

[11] Y. Li, J. Yang, Y. Song, L. Cao, J. Luo, and L.-J. Li, “Learning from noisy labels with distillation,” in ICCV, 2017, pp. 1928–1936.

[12] X. Ma, Y. Wang, M. E. Houle, S. Zhou, S. M. Erfani, S.-T. Xia, S. Wijewickrema, and J. Bailey, “Dimensionality-driven learning with noisy labels,” in ICML, 2018.

[13] L. Jiang, Z. Zhou, T. Leung, L.-J. Li, and L. Fei-Fei, “Mentornet: Learning data-driven curriculum for very deep neural networks on corrupted labels,” in International Conference on Machine Learning, 2018, pp. 2309–2318.

[14] E. Malach and S. Shalev-Shwartz, “Decoupling "when to update" from "how to update",” in Advances in Neural Information Processing Systems, 2017, pp. 966–970.

[15] B. Han, Q. Yao, X. Yu, G. Niu, M. Xu, W. Hu, I. W. Tsang, and M. Sugiyama, “Co-teaching: Robust training of deep neural networks with extremely noisy labels,” in NIPS, 2018.

[16] Y. Wang, W. Liu, X. Ma, J. Bailey, H. Zha, L. Song, and S.-T. Xia, “Iterative learning with open-set noisy labels,” in CVPR, 2018.

[17] X. Yu, B. Han, J. Yao, G. Niu, I. W. Tsang, and M. Sugiyama, “How does disagreement help generalization against label corruption?” in ICML, 2019.

[18] P. Chen, B. Liao, G. Chen, and S. Zhang, “Understanding and utilizing deep networks trained with noisy labels,” in ICML, 2019.

[19] J. Huang, L. Qu, R. Jia, and B. Zhao, “O2o-net: A simple noisy label detection approach for deep neural networks,” in Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 3326–3334.

[20] M. Ren, W. Zeng, B. Yang, and R. Urtasun, “Learning to reweight examples for robust deep learning,” in International Conference on Machine Learning, 2018.

[21] T. Xiao, T. Xia, Y. Yang, C. Huang, and X. Wang, “Learning from massive noisy labeled data for image classification,” in 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2015.

[22] B. Frénay and M. Verleysen, “Classification in the presence of label noise: a survey,” IEEE transactions on neural networks and learning systems, vol. 25, no. 5, pp. 845–869, 2014.

[23] T. Xiao, T. Xia, Y. Yang, C. Huang, and X. Wang, “Learning from massive noisy labeled data for image classification,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 2691–2699.

[24] S. Sukhbaatar, J. Bruna, M. Paluri, L. Bourdev, and R. Fergus, “Training convolutional networks with noisy labels,” in ICLR, 2015.

[25] J. Goldberger and E. Ben-Reuven, “Training deep neural-networks using a noise adaptation layer,” in ICLR, 2017.

[26] A. Veit, N. Alldrin, G. Chechik, I. Krasin, A. Gupta, and S. J. Belongie, “Learning from noisy large-scale datasets with minimal supervision.” in CVPR, 2017, pp. 6575–6583.

[27] D. Hendrycks, M. Mazeika, D. Wilson, and K. Gimpel, “Using trusted data to train deep networks on labels corrupted by severe noise,” in NIPS, 2018.

[28] C. G. Northcutt, T. Wu, and I. L. Chuang, “Learning with confident examples: Rank pruning for robust classification with noisy labels,” in Proceedings of the Thirty-Third Conference on Uncertainty in Artificial Intelligence, ser. UAI’17, AUAI Press, 2017. [Online]. Available: http://auai.org/uai2017/proceedings/papers/35.pdf

[29] D. Tanaka, D. Iken, T. Yamasaki, and K. Aizawa, “Joint optimization framework for learning with noisy labels,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5552–5560.

[30] J. Han, P. Luo, and X. Wang, “Deep self-learning from noisy labels,” in Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 5138–5147.

[31] J. Yao, H. Wu, Y. Zhang, I. W. Tsang, and J. Sun, “Safeguarded dynamic label regression for noisy supervision.” AAAI, 2019.

[32] J. Friedman, T. Hastie, and R. Tibshirani, The elements of statistical learning. Springer series in statistics New York, NY, USA:, 2001, vol. 1, no. 10.

[33] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, “Focal loss for dense object detection,” IEEE transactions on pattern analysis and machine intelligence, 2018.

[34] M. P. Kumar, B. Packer, and D. Koller, “Self-paced learning for latent variable models,” in Advances in Neural Information Processing Systems, 2010, pp. 1189–1197.

[35] Y. Bengio, J. Louradour, R. Collobert, and J. Weston, “Curriculum learning,” in Proceedings of the 26th annual international conference on machine learning, ACM, 2009, pp. 41–48.

[36] J. Li, Y. Wong, Q. Zhao, and M. S. Kankanhalli, “Learning to learn from noisy labeled data,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 5051–5059.

[37] K.-H. Lee, X. He, L. Zhang, and L. Yang, “Cleannet: Transfer learning for scalable image classifier training with label noise,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 5447–5456.

[38] J. Shu, Q. Xie, L. Yi, Q. Zhao, S. Zhou, Z. Xu, and D. Meng, “Meta-weight-net: Learning an explicit mapping for sample weighting.” 2019.

[39] A. Valdat, “Toward robustness against label noise in training deep discriminative neural networks,” in Advances in Neural Information Processing Systems, 2017, pp. 5596–5605.

[40] D. Arpit, S. Jastrzêbowski, N. Ballas, D. Krueger, E. Bengio, M. S. Kanwal, T. Maharaj, A. Fischer, A. Courville, Y. Bengio et al., “A closer look at memorization in deep networks,” in ICML, 2017.

[41] O. Vinyals, C. Blundell, T. Lillicrap, D. Wierstra et al., “Matching networks for one shot learning,” in Advances in neural information processing systems, 2016, pp. 3630–3638.

[42] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell, “Caffe: Convolutional architecture for feature embedding,” in Proceedings of the 22Nd ACM International Conference on Multimedia, ser. MM ’14, New York, NY, USA: ACM, 2014, pp. 675–678. [Online]. Available: http://doi.acm.org/10.1145/2647905.2647989