微软亚洲研究院

ICPR 2020
25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

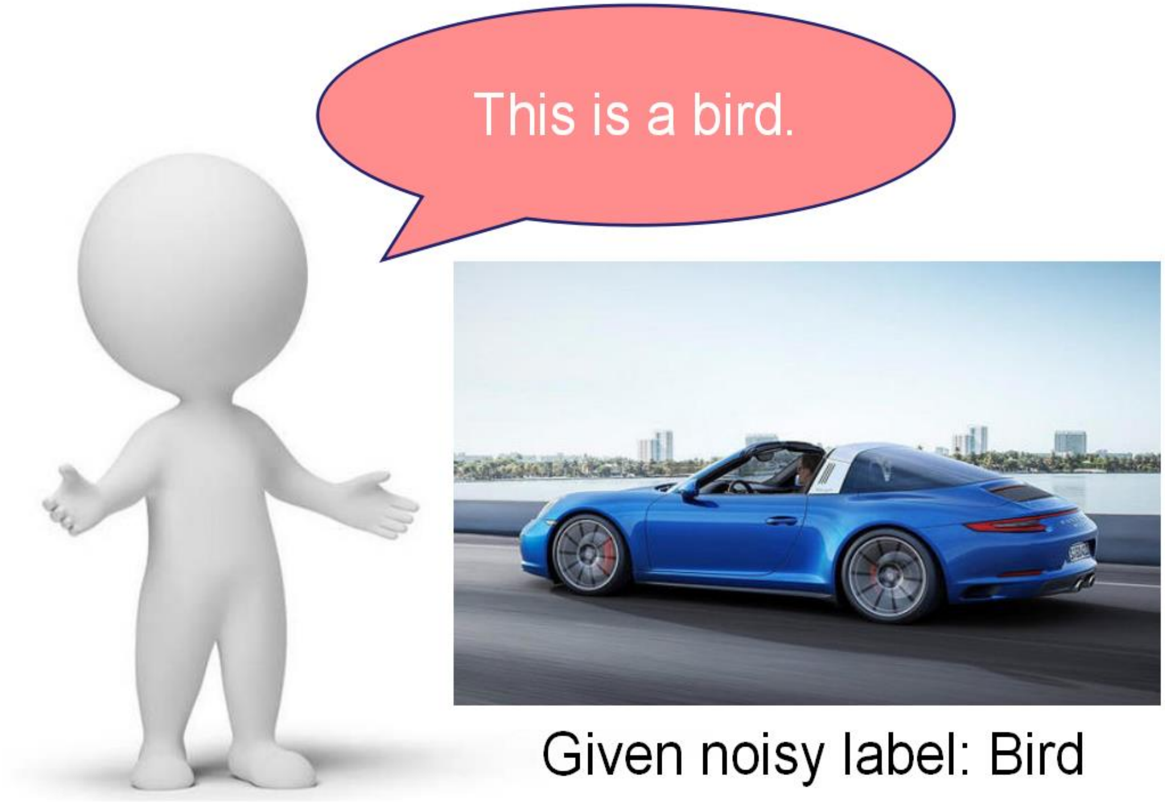
P-DIFF: Learning Classifier with Noisy Labels based on Probability Difference Distributions

Wei Hu, QiHao Zhao, Fan Zhang
Dept. of Computer Science and Technology
Beijing University of Chemical Technology
Beijing, China

Yangyu Huang
Microsoft Research, Asia
Beijing, China
yangyu.huang@microsoft.com

Codes are available on Github:
https://github.com/fistyee/P-DIFF

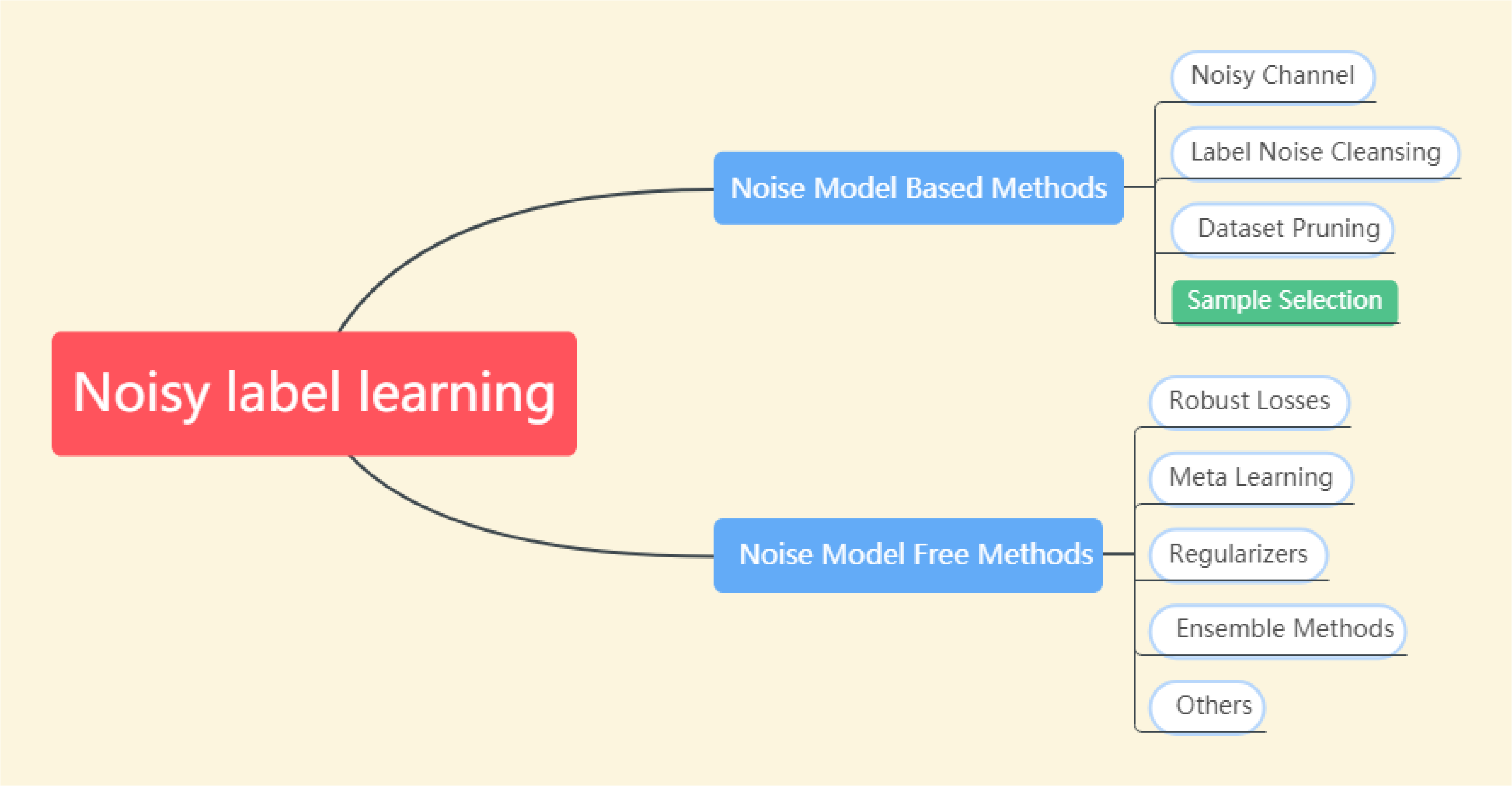
Learning from Noisy Lable



Given noisy label: Bird

Related Work

ICPR 2020
25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021



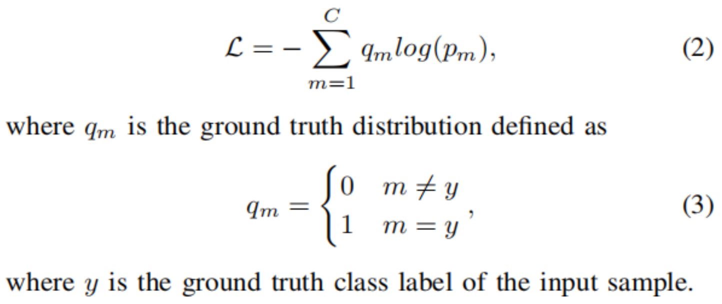
The Proposed P-DIFF Paradigm

- Probability Difference Distributions

Probability Difference

Global Distribution

Probability p_y → Probability Difference δ

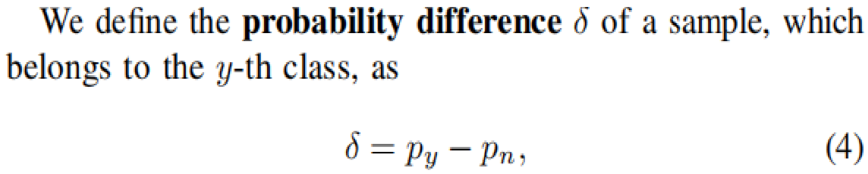


$$\mathcal{L} = -\sum_{m=1}^{C} q_m log(p_m), \quad (2)$$

where q_m is the ground truth distribution defined as

$$q_m = \begin{cases} 0 & m \neq y \\ 1 & m = y \end{cases}, \quad (3)$$

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

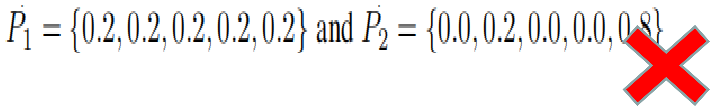


We define the **probability difference** δ of a sample, which belongs to the y-th class, as

$$\delta = p_y - p_n, \quad (4)$$

Global Distribution

We compute the histogram distribution of δ for all input samples, and this global distribution, called $DIST_{all}$, which is just the probability difference distribution.



$\dot{P}_1 = \{0.2, 0.2, 0.2, 0.2, 0.2\}$ and $\dot{P}_2 = \{0.0, 0.2, 0.0, 0.0, 0.8\}$

The Proposed P-DIFF Paradigm

We simply find the smallest bin number x which makes

$$PCF(x) > \tau. \tag{8}$$

According to Equation (7) , the δ values of these samples should be less than 2 · (x − 1)/H − 1, and we can define the threshold $\hat{\delta}$ as

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

we define a dynamic drop rate R(T), where T is the number of training epoch, as

$$R(T) = \tau \cdot \min(\frac{T}{T_k}, 1). \tag{10}$$

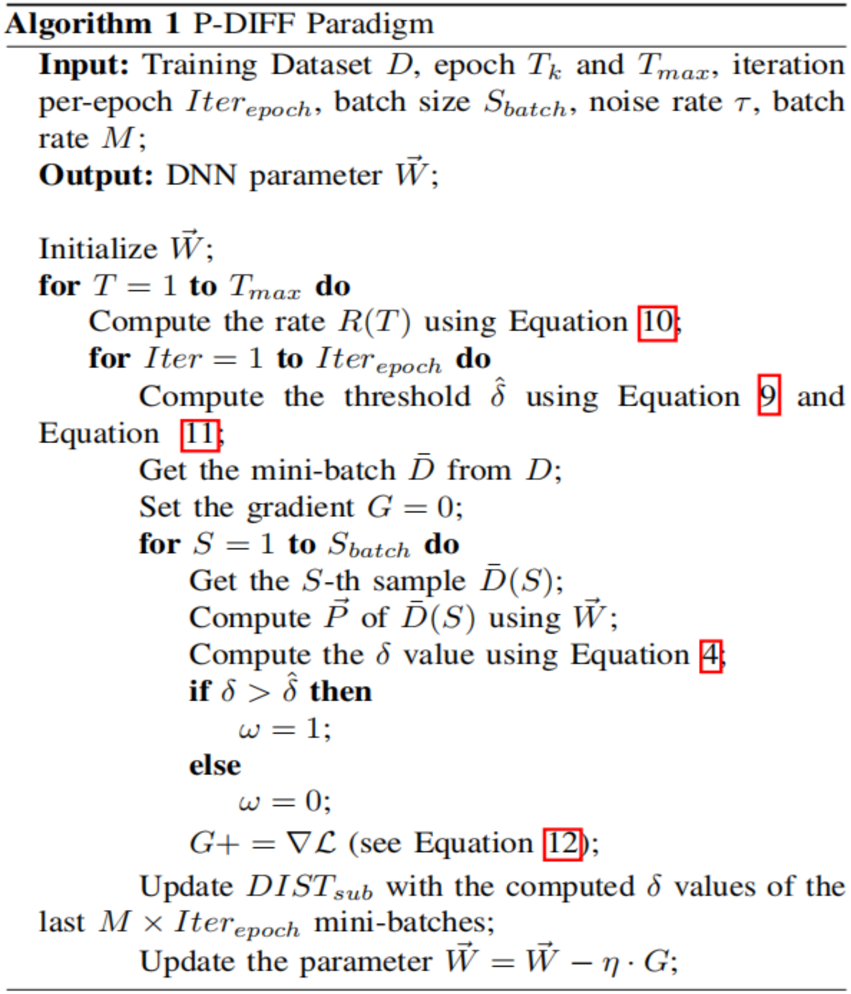
Equation (8) is re-written as

$$PCF(x) > R(T). \tag{11}$$

P-DIFF updates DNN models by redefining Equation (2) as

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

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



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 $\vec{W}$;

Initialize $\vec{W}$;
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 $\bar{D}$ from $D$;
        Set the gradient $G = 0$;
        for $S = 1$ to $S_{batch}$ do
            Get the $S$-th sample $\bar{D}(S)$;
            Compute $\vec{P}$ of $\bar{D}(S)$ using $\vec{W}$;
            Compute the $\delta$ value using Equation 4;
            if $\delta > \hat{\delta}$ then
                $\omega = 1$;
            else
                $\omega = 0$;
            $G+ = \nabla \mathcal{L}$ (see Equation 12);
        Update $DIST_{sub}$ with the computed $\delta$ values of the last $M \times Iter_{epoch}$ mini-batches;
        Update the parameter $\vec{W} = \vec{W} - \eta \cdot G$;
```

Experiments

ICPR 2020
25th INTERNATIONAL CONFERENCE ON PATTERN RECOGNITION
Milan, Italy 10 | 15 January 2021

- Comparison with State-of-the-art Approaches

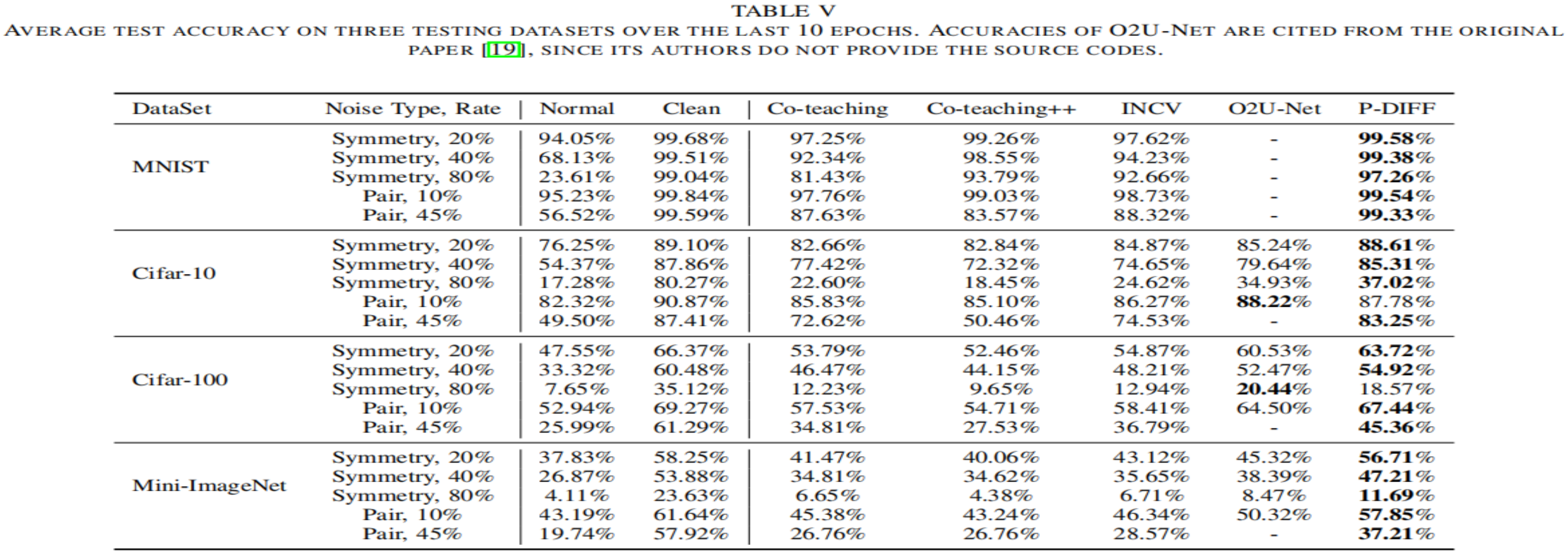


TABLE V
AVERAGE TEST ACCURACY ON THREE TESTING DATASETS OVER THE LAST 10 EPOCHS. ACCURACIES OF O2U-NET ARE CITED FROM THE ORIGINAL PAPER [19], SINCE ITS AUTHORS DO NOT PROVIDE THE SOURCE CODES.

DataSet	Noise Type, Rate	Normal	Clean	Co-teaching	Co-teaching++	INCV	O2U-Net	P-DIFF
MNIST	Symmetry, 20%	94.05%	99.68%	97.25%	99.26%	97.62%	-	**99.58%**
	Symmetry, 40%	68.13%	99.51%	92.34%	98.55%	94.23%	-	**99.38%**
	Symmetry, 80%	23.61%	99.04%	81.43%	93.79%	92.66%	-	**97.26%**
	Pair, 10%	95.23%	99.84%	97.76%	99.03%	98.73%	-	**99.54%**
	Pair, 45%	56.52%	99.59%	87.63%	83.57%	88.32%	-	**99.33%**
Cifar-10	Symmetry, 20%	76.25%	89.10%	82.66%	82.84%	84.87%	85.24%	**88.61%**
	Symmetry, 40%	54.37%	87.86%	77.42%	72.32%	74.65%	79.64%	**85.31%**
	Symmetry, 80%	17.28%	80.27%	22.60%	18.45%	24.62%	34.93%	**37.02%**
	Pair, 10%	82.32%	90.87%	85.83%	85.10%	86.27%	**88.22%**	87.78%
	Pair, 45%	49.50%	87.41%	72.62%	50.46%	74.53%	-	**83.25%**
Cifar-100	Symmetry, 20%	47.55%	66.37%	53.79%	52.46%	54.87%	60.53%	**63.72%**
	Symmetry, 40%	33.32%	60.48%	46.47%	44.15%	48.21%	52.47%	**54.92%**
	Symmetry, 80%	7.65%	35.12%	12.23%	9.65%	12.94%	**20.44%**	18.57%
	Pair, 10%	52.94%	69.27%	57.53%	54.71%	58.41%	64.50%	**67.44%**
	Pair, 45%	25.99%	61.29%	34.81%	27.53%	36.79%	-	**45.36%**
Mini-ImageNet	Symmetry, 20%	37.83%	58.25%	41.47%	40.06%	43.12%	45.32%	**56.71%**
	Symmetry, 40%	26.87%	53.88%	34.81%	34.62%	35.65%	38.39%	**47.21%**
	Symmetry, 80%	4.11%	23.63%	6.65%	4.38%	6.71%	8.47%	**11.69%**
	Pair, 10%	43.19%	61.64%	45.38%	43.24%	46.34%	50.32%	**57.85%**
	Pair, 45%	19.74%	57.92%	26.76%	26.76%	28.57%	-	**37.21%**

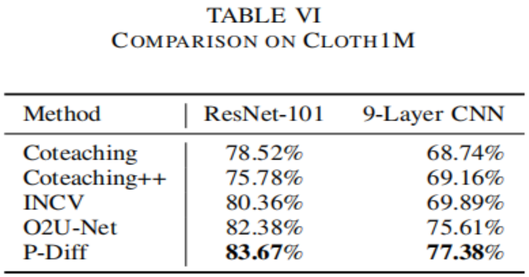


TABLE VI
COMPARISON ON CLOTH1M

Method	ResNet-101	9-Layer CNN
Coteaching	78.52%	68.74%
Coteaching++	75.78%	69.16%
INCV	80.36%	69.89%
O2U-Net	82.38%	75.61%
P-Diff	**83.67%**	**77.38%**

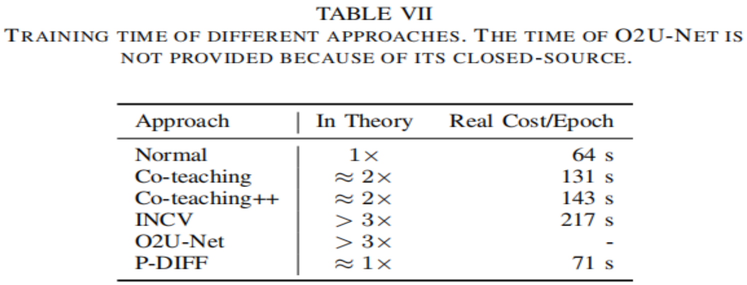


TABLE VII
TRAINING TIME OF DIFFERENT APPROACHES. THE TIME OF O2U-NET IS NOT PROVIDED BECAUSE OF ITS CLOSED-SOURCE.

Approach	In Theory	Real Cost/Epoch
Normal	1×	64 s
Co-teaching	≈ 2×	131 s
Co-teaching++	≈ 2×	143 s
INCV	> 3×	217 s
O2U-Net	> 3×	-
P-DIFF	≈ 1×	71 s