DST: Data Selection and joint Training for Learning with Noisy Labels

Yi Wei1  Xue Mei1*  Xin Liu2*  Pengxiang Xu1
1College of Electrical Engineering and Control Science, Nanjing Tech University, China
2Beijing Seetatech Technology Co., Ltd
{weiyi,mx,pengxiangxu}@njtech.edu.cn  xin.liu@seetatech.com

Abstract

It is well known that deep learning is extremely dependent on a large amount of clean data. Because of high annotation cost, various methods have been devoted to annotate the data automatically. However, a larger number of sample noisy labels are generated in the datasets, which is a challenging problem. In this paper, we propose a new method called DST for selecting training data accurately. Specifically, DST fits a mixture model to the per-sample loss of the dataset label and the predicted label, and the mixture model is utilized to dynamically divide the training set into a correctly labeled set, a correctly predicted set and a wrong set. Then, the network is trained with these sets in the supervised learning. Due to confirmation bias problem, we train the two networks alternately, and each network establishes the data division to teach another network. When optimizing network parameters, the correctly labeled and predicted sample labels are reweighted respectively by the probabilities from the mixture model, and a uniform distribution is used to generate the probabilities of the wrong samples. Experiments on CIFAR-10, CIFAR-100 and Clothing1M demonstrate that DST is the same or superior to the state-of-the-art methods.

1. Introduction

The remarkable success on training deep neural networks (DNNs) in various tasks relies on a large-scale dataset with the correctly labels. However, labeling large amounts of data with high-quality annotations is expensive and time-consuming. Although there are some alternative and inexpensive methods such as crowdsourcing [36, 39], online queries [4] and labelling samples with the annotator [27] that can annotate the large-scale datasets easily to alleviate this problem, the samples with noisy labels are yielded by these alternative methods. A recent study [40] shows that a dataset with noisy labels can be overfitted by DNNs and leads to poor generalization performance of the model.

As this problem generally exists in the neural network training process and makes models get poor generalization, there are many algorithms developed for Learning with Noisy Labels (LNL). Some of methods attempt to estimate the latent noise transition matrix to express noisy labels and correct the loss function [8, 19, 21]. However, how to correctly construct noise transition matrix is challenging. Some researches modify labels correctly by predictions of models for improving the model performance [23, 26]. Because of training labels from the DNN, the model would easily lead to overfitting under a high noise ratio. The recent research [1] adopts MixUp [41] to address this problem. Another approach reduces the influence of noise on the training process by selecting or weighting samples [24]. Many methods select clean samples with small loss [1, 12]. Co-teaching [9],
Co-teaching+ [38] and JoCoR [34] use two networks to select small-loss samples to train each other.

Despite small-loss is a good method to choose correct samples from the noise samples, the samples which is predicted correctly by the models are ignored in training process. In this work, we propose DST (Data Selection and Joint Training), which can leverage correctly predicted samples and avoid overfitting new labels chosen by the model under a high level of the noise ratio. Compared with other methods using small loss [1,9,38], we propose another method based on two kinds of the loss on each sample to distinguish samples with correctly labels for training networks. We provide experiments to demonstrate the feasibility of our approach, which is superior to many related approaches. Our main contributions are as follows:

- We propose two kinds of the sample loss (1. loss of the label from the dataset; 2. loss of the label predicted by model), which can be used to distinguish correctly labeled and predicted samples. We fit a Gaussian Mixture Model (GMM) dynamically on dataset loss distribution to divide the dataset into correctly labeled samples, correctly predicted samples and wrong samples with wrong labels and predictions.

- We train two networks to generate losses of samples. For each network, we use GMM to get correct samples, which is then used to train another network. This can filter different types of error and avoid confirmation bias in self-training [16].

2. Related Work

In this section, we briefly review existing approaches for LNL.

2.1. Correction model

Correction model is to seek the noisy labels to correct the loss function. One way is to relabel the noisy samples to correct the loss. Some of methods need a set of clean samples to model noisy samples with knowledge graph [18], directed graphical models [35], conditional random field [30] and neural networks [31, 15]. To address the problem of the clean set, Some of methods attemp to relabel samples by network predictions in the process of iteration [26] and [37]. Another way is named loss correction methods, which can modify the loss function during training to make models more robust. Bootstrap [23] modifies the loss by comparing the raw labels with model predictions. Ma et al. [20] use the dimensionality of feature subspaces to improve the Bootstrap. Backward and Forward [21] estimate two noise transition matrix, and Hendrycks et al. [11] use a clean set to improve these matrix for loss correction.

2.2. Division model

Division Model is to reweight training samples or divide them into a clean set and a noisy set to update network parameters [29]. MentorNet [12] trains a mentor network to reweigh the samples which are given to train a student network. Ren et al. [24] use a meta-learning algorithm to reweight samples. Small-loss selection is a common method to extract the clean samples which have smaller loss than noisy samples. Co-teaching [9] trains two networks to obtain the small-loss samples and learn from each other. Co-teaching+ [37] introduces the disagreement data to improve co-teaching. Shen and Sanghavi [25] use one network to select small-loss samples and provide clean samples for another network training. Arazo et al. [1] reweight the samples with the small loss by fitting a mixture model.

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Algorithm 1: DST

1. Input: \( \theta^{(1)} \) and \( \theta^{(2)} \), training dataset \((X',Y')\), GMM initialization parameters \(\gamma\), probability threshold \(r_{\gamma}\), sharpening temperature \(T\), regularization weight \(\lambda_r\), Beta distribution parameter \(\alpha\) for MixUp.

2. \( \theta^{(1)}, \theta^{(2)} \) = Warmup(\(X',Y', \theta^{(1)}, \theta^{(2)}\))

3. while epoch < MaxEpoch do
   4.     \( L_{(1)}, L_{(1)}^{prd} \) = CE(\(X', Y', \theta^{(1)}\))
   5.     \( L_{(2)}, L_{(2)}^{prd} \) = CE(\(X', Y', \theta^{(2)}\))
   6.     \( W_{Y}^{(2)}, W_{Y}^{(2)}_{prd} \) = GMM(\(L_{(1)}, L_{(1)}^{prd}, \gamma\))
   7.     \( W_{Y}^{(1)}, W_{Y}^{(1)}_{prd} \) = GMM(\(L_{(2)}, L_{(2)}^{prd}, \gamma\))
   8.     for \( n = 1, 2 \) do
      9.         for iter = 1 to num_iters do
          10.            From (\(X', Y', W_{Y(n)}^{(n)}, W_{Y(n)}^{(n)}_{prd}\)), Draw a mini-batch \(B = \{ (x_b, y_b, w_b, p_b^{rd}) ; b \in \{1, ..., B\} \}\)
          11.            for \( b = 1 \) to \( B \) do
              12.                \( p_b = \frac{1}{2}(p(x_b; \theta^{(1)}) + p(x_b; \theta^{(2)})\)
              13.                if \( w_b^{rd} \geq r_{\gamma} \) then
                  14.                    \( \tilde{y}_b = w_b^{rd} y_b + (1 - w_b^{rd}) p_b \)
              15.                else if \( w_b^{rd} \geq r_{\gamma} \) then
                  16.                    \( \tilde{y}_b = (1 - w_b^{rd}) y_b + w_b^{rd} p_b \)
                  17.                else
                    18.                    \( w_b^{rd} \sim U(0,1) \)
                    19.                    \( \tilde{y}_b = (1 - \tilde{w}_b^{rd}) y_b + \tilde{w}_b^{rd} p_b \)
               20.            end
          21.            \( \hat{y}_b = \text{Sharpen}(\tilde{y}_b, T) \)
          22.        end
      23.        \( B = \{ (\hat{x}_b, \hat{y}_b) ; b \in \{1, ..., B\} \}\)
      24.        \( \bar{L}_{} = \text{MixUp}(B, \alpha) \)
      25.        \( \bar{L} = \bar{L} + \lambda_r \bar{L}_{seg} \)
      26.        \( \theta^{(n)} = \text{SGD}(\bar{L}, \theta^{(n)}) \)
   8. end
end
```


We use these data to supervise network learning. DST is as in Figure 2, one network can divide the dataset into the correct data and the wrong data to teach the other network. Correctly, each sample must be in one of the following five states:

(i) \( y = y_{real}, \overline{y} = y_{real}, y = \overline{y} \);
(ii) \( y = y_{real}, \overline{y} \neq y_{real}, y \neq \overline{y} \);
(iii) \( y \neq y_{real}, \overline{y} = y_{real}, y \neq \overline{y} \);
(iv) \( y \neq y_{real}, \overline{y} \neq y_{real}, y = \overline{y} \);
(v) \( y \neq y_{real}, \overline{y} \neq y_{real}, y \neq \overline{y} \).

We suppose that small-loss instances are indeed clean and reliable, in other words, DNNs can learn the clean samples and ignore the noisy samples with the prediction close to the real label.
an average probability (i.e. $p = 1/C$). DNN is more likely to predict a samples which is closer in space to the samples learned by DNN. If the noise sample has the close spatial distance to the correct sample learned by DNN and is predicted correctly, this noise sample may have a small loss of the predicted label and a large loss of the raw label (noise label). On the contrary, the noise sample may have the similar losses between the predicted label and the raw label. Therefore, we assume that the $\ell_i$ of the correct predicted samples which are close to the learned samples is lower than the other unlearned samples.

In Figure 3, we observe that DNNs can correct predict some samples with a higher probability for the real label than other labels, meaning that samples with state (iii) have lower $\ell_i^{\text{prd}}$ and higher $\ell_i^{\text{n}}$ than other states. Although samples with state (v) may have the same distribution as (iii), the number of samples with state (iii) is much larger than (v). Similarly, samples with state (i) have lower $\ell_i^{\text{n}}$ than (iv). In the case of asymmetric noise (see Figure 5a), The distribution of $\ell_i^{\text{prd}}$ and $\ell_i^{\text{n}}$ is not regular and hard to be modeled by minimizing the cross entropy. In Figure 5b, the losses are shown when the model is trained with DST for 35 epoches after pre-training. DST can distinguish the samples with state (iii) significantly and use these samples to train networks.

The Gaussian Mixture Model (GMM) [22] is widely used in unsupervised field due to its flexibility. Therefore, we can fit a three components GMM to $\ell_i^{\text{prd}}$ and $\ell_i^{\text{n}}$ by the Expectation-Maximization (EM) algorithm to distinguish correct and wrong samples. Each sample is given a posterior probability $p(y_k|\ell_i^{\text{n}}, \ell_i^{\text{prd}})$ as $w^k_i$ by GMM, where $g_k$ is one of the Gaussian components. We denote that $w^k_i$ is the correctly labeled probability of each sample and $w^{\text{prd}}_i$ is the correctly predicted probability of each sample. Due to the concentrated distribution of $\ell_i^{\text{n}}$ and $\ell_i^{\text{prd}}$, we set the initial means for the Gaussian components. To prevent overfitting, the convergence threshold of EM algorithm depends on the size of the dataset. The training data is divided into a correctly labeled set, a correctly predicted set and a wrong set by setting three thresholds $\tau_k$ on $w^k_i$. In order to address the confirmation bias [28] caused by self-learning, we exploit co-divide [16] which use two networks to generate parameters and teach each other.

### 3.2. Model training

At each epoch, every sample can be relabeled by $w^k_i$ and $\tau_k$. We train only one network at a time and fix another network which can be used to generate a new label for each sample. Given a mini-batch of samples with their corresponding one-hot labels and probability $\mathcal{B} = \{ (x_b, y_b, w^{\text{prd}}_b, w^{\text{n}}_b); b \in \{1, ..., B\}\}$. We reweight the samples with $w^{\text{n}}_b$ and $w^{\text{prd}}_b$ and let the samples compose a new training set $\mathcal{B}$. Then, we exploit MixUp [41] augmentation which mixes two samples with the linear relationship.

To refine the label of each sample, we linearly combine noisy label $y_b$ and prediction average value $p_b$ obtained by two networks. Probabilities $w^{\text{n}}_b$ and $w^{\text{prd}}_b$ guide different samples, respectively. Meanwhile, the wrong sample probability $w^{\text{n}}_b$ is produced by a uniform distribution $\mathcal{U}(0, 1)$ to prevent networks from overfitting to the noisy labels:

$$
\hat{y}_b = \begin{cases} 
    w^{\text{n}}_b y_b + (1 - w^{\text{n}}_b) p_b, & \text{if } w^{\text{n}}_b \geq \tau_r \\
    (1 - w^{\text{prd}}_b) y_b + w^{\text{prd}}_b p_b, & \text{if } w^{\text{prd}}_b \geq \tau_{\text{prd}} \\
    (1 - w^{\text{n}}_b) y_b + w^{\text{n}}_b p_b, & \text{others}
\end{cases}
$$

Figure 3. Distributions of the normalized loss on CIFAR-10 with 50% noise ratio. Top: 15 epoch; bottom: 50 epoch. (a) Distribution of the small-loss method; (b) Distribution of $\ell_i$; (c) Distribution of $\ell_i^{\text{n}}$; (d) Distribution of $\ell_i^{\text{prd}}$. DST with DST for 35 epoches after pre-training. DST can distinguish correct and wrong samples. Each sample is given a posterior probability $p(y_k|\ell_i^{\text{n}}, \ell_i^{\text{prd}})$ as $w^k_i$ by GMM, where $g_k$ is one of the Gaussian components. We denote that $w^k_i$ is the correctly labeled probability of each sample and $w^{\text{prd}}_i$ is the correctly predicted probability of each sample. Due to the concentrated distribution of $\ell_i^{\text{n}}$ and $\ell_i^{\text{prd}}$, we set the initial means for the Gaussian components. To prevent overfitting, the convergence threshold of EM algorithm depends on the size of the dataset. The training data is divided into a correctly labeled set, a correctly predicted set and a wrong set by setting three thresholds $\tau_k$ on $w^k_i$. In order to address the confirmation bias [28] caused by self-learning, we exploit co-divide [16] which use two networks to generate parameters and teach each other.
A sharpening function used by MixMatch [3] is applied on \( \tilde{y}_b \) to adjusting its temperature:

\[
\hat{y}_b^c = \text{Sharpen}(\tilde{y}_b, T) = \tilde{y}_b^c \frac{1}{\sum_{c=1}^C \tilde{y}_b^c} \tag{4}
\]

Where the \( T \) is sharpening temperature. From the sharpening function, we acquire a new training batch \( \hat{B} \) in which each sample has a more refined label. Recently MixUp [41] has been applied in many methods for training DNNs and achieved good result [1, 3]. We follow MixUp to select a pair of samples from the new batch \( \hat{B} \) randomly and mix them linearly:

\[
\begin{align*}
\lambda & \sim \text{Beta}(\alpha, \alpha) \\
\lambda & := \max(\lambda, 1 - \lambda) \\
x' &= \lambda x_1 + (1 - \lambda) x_2 \\
y' &= \lambda \hat{y}_1 + (1 - \lambda) \hat{y}_2
\end{align*}
\]

where \( (x_1, x_2) \) is a pair of two samples and \( (\hat{y}_1, \hat{y}_2) \) is their corresponding labels. We utilize the cross-entropy loss on the MixUp output \( B' \) with \( B \) samples:

\[
\mathcal{L}_x = -\frac{1}{|B|} \sum_{x, y \in B'} \sum_c y'_c \log(p_d(x)) \tag{9}
\]
To prevent the networks from assigning all samples to a single class, we apply the regularization term used in [1, 16, 26], which averages the output of all samples in mini-batch to a mean value $p_{\text{reg}}^c$ (i.e., $p_{\text{reg}}^c = 1/C$) to address issue:

$$L_{\text{reg}} = \sum_c p_{\text{reg}}^c \log \left( \frac{1}{B} \sum_{x \in B} p_{\theta}(x) \right)$$  \hspace{1cm} (10)

Then, we get total loss:

$$L = L_x + L_{\text{reg}}$$  \hspace{1cm} (11)

Subsection 4.2 compares our approach with the state-of-the-art and presents the results of experiments.

4. Experiments

In this section, we first introduce our experiment details, and then compare DST with some state-of-the-arts approaches. We also analyze the impact of MixUp and training with two networks by ablation study.

4.1. Datasets and implementation details

To validate our approach, we use the following benchmark datasets, namely CIFAR-10, CIFAR-100 [14] and Clothing1M [35]. CIFAR-10 with 10 classes and CIFAR-100 with 100 classes contain 50K training images and 10K test images with resolution $32 \times 32$. We follow previous works [17, 26] to generate noise labels with two types: symmetric and asymmetric. Symmetric noise utilizes the random labels to replace the true sample labels for a percentage. Note that there is another label noise criterion [12, 32] in which the true labels is not maintained. In Subsection 4.2, we show the results of both symmetric noise criterions with different levels of noise ranging from 20% to 80%. Asymmetric noise replaces the similar classes with sample labels, which mimic the label noise in real world. We use 40% because more than 50% of the asymmetric noise can cause some classes become theoretically indistinguishable.

We use an 18-layer PreAct Resnet [10]. The networks are trained for 300 epochs with a batch size of 128 by SGD with a momentum of 0.9 and a weight decay of 0.0005. We set the learning rate as 0.02 and reduce it by a factor of 5 per 100 epoch. Before training our method, we use 15 epochs for CIFAR-10 and 30 epochs for CIFAR-100 to pretrain the networks. We set the GMM initial kernel as $(0, 0), (0.5, 0.5), (1, 0)$ and the convergence threshold of EM algorithm as $tol = 20$. The other hyperparameters across all CIFAR experiment are the same $T = 0.5$, $\alpha = 4$ and $\tau = 0.5$.

Clothing1M is a real-world dataset with noisy labels, which consists of 1 million training images from online shopping websites with noisy labels. We use ResNet-50 with ImageNet pretrained weights to train it for 80 epochs. Learning rate is set as 0.02 and reduced by a factor of 2 per 20 epoch.

4.2. Comparison with the state-of-the-arts

We introduce some state-of-the-art methods as follow: (1). Co-teaching+ [9] uses the small loss of samples to train two networks each other; (2). P-correction [37] optimizes the sample labels as the network parameters; (3). Meta-Learning [17] attempts to find the parameters which make model more noise-tolerant by the gradient; (4). M-correction [1] uses BMM to select clean samples and improves MixUp for label noise training; (5). DivideMix [16] models sample loss with GMM and improves MixMatch to achieve excellent performance in label noise training. For the symmetric noise criterion with correct labels (Criterion 1), we compare our method with these baselines using the same network architecture. For another symmetric noise criterion (Criterion 2), the other state-of-the-arts methods with different network architecture are compared with the DST.

Table 1 shows the results on CIFAR-10 and CIFAR-100 in Criterion 1, and the results on CIFAR-10 with 40% asymmetric noise is shown in Table 2. In the tables, "Best" is the best test accuracy across training process and "Last" is the average accuracy of the last 10 epochs. As we can see, the performance of DST is the same or superior to the other baselines. DST works a little worse than DivideMix on CIFAR-100 with 80% noise ratio, but DST achieves comparable performance with DivideMix across the other noise ratios. DST works much better than all other state-of-the-art methods on CIFAR-10 with 40% asymmetric noise ratio. Table 3 shows the comparison in Criterion 2. DST outperforms baselines by a large margin on CIFAR-10 with 80% noise ratio. However, DST has the same problems as Criterion 1 on CIFAR-100 with 80% noise ratio, and our explanation is given in the next paragraph.

In the experiments of CIFAR, due to the existence of noisy labels in the dataset, it is difficult to improves the performance of methods which have achieved very good results. Unfortunately, in the case of high noise ratios, our method can produce a small amount of mistakes leading to the confirmation bias problem, especially in the dataset with more classes like CIFAR-100, in which we have a small gap with the state-of-the-art method [16]. However, DST still outperforms the other methods across all noise ratios.

Table 4 shows the results on Clothing1M dataset. DST obtains 73.67% test accuracy, which is lower than the state-of-the-art [16]. Using a pre-trained network and a small learning rate can easily fits label noise [1]. Therefore, we believe that the data partition ability of DST is well limited. However, compared with Cross-Entropy, DST has a good improvement.

4.3. Ablation study

To understand what makes DST successful, we attempt to remove the MixUp, use one network for self-learning and
| Dataset     | CIFAR-10     |            | CIFAR-100    |            |
|-------------|--------------|------------|--------------|------------|
|             | Method / ratio | 20% | 50% | 80% | 20% | 50% | 80% |
| Cross-Entropy | Best          | 86.8 | 79.5 | 62.7 | 62.1 | 46.7 | 19.8 |
|             | Last          | 82.5 | 57.4 | 26.3 | 61.0 | 36.9 | 9.0 |
| Co-teaching+[38] | Best          | 89.5 | 85.7 | 67.4 | 65.6 | 51.8 | 27.9 |
|             | Last          | 88.2 | 84.1 | 45.5 | 64.1 | 45.3 | 15.5 |
| P-correction[37] | Best          | 92.4 | 89.1 | 77.5 | 69.4 | 57.5 | 31.1 |
|             | Last          | 92.0 | 88.7 | 76.5 | 68.1 | 56.4 | 20.7 |
| Meta-Learning[17] | Best          | 92.9 | 89.3 | 77.4 | 68.5 | 59.2 | 42.4 |
|             | Last          | 92.0 | 88.8 | 76.1 | 67.7 | 58.0 | 40.1 |
| M-correction[1] | Best          | 94.0 | 92.0 | 86.8 | 73.9 | 66.1 | 48.2 |
|             | Last          | 93.8 | 91.9 | 86.6 | 73.4 | 65.4 | 47.6 |
| DivideMix[16] | Best          | 96.1 | 94.6 | 93.2 | 77.3 | 74.6 | 60.2 |
|             | Last          | 95.7 | 94.4 | 92.9 | 76.9 | 74.2 | 59.6 |
| DST         | Best          | 96.1 | 95.2 | 92.9 | 78.0 | 74.3 | 57.8 |
|             | Last          | 95.9 | 94.7 | 92.6 | 77.4 | 73.6 | 55.3 |

Table 1. Comparison with baselines in terms of test accuracy (%) on CIFAR-10 and CIFAR-100 with Criterion 1.

![Graphs showing test accuracy vs. epochs for different methods and noise ratios](image)

| Method     | Best | Last |
|------------|------|------|
| Cross-Entropy | 85.3 | 71.7 |
| P-correction[37] | 88.5 | 88.1 |
| Meta-Learning[17] | 89.2 | 88.6 |
| M-correction[1] | 87.4 | 86.3 |
| DivideMix[16] | 93.4 | 92.1 |
| DST        | **94.3** | **92.3** |

Table 2. Comparison with baselines in terms of test accuracy (%) on CIFAR-10 with 40% asymmetric noise. We implement our method under the DivideMix setting.

Use different modules of the training (i.e., different partition set) to train networks. We set up the experiments on CIFAR-10 in Criterion 1 with noise ratios (20%, 50% and 80%). The results of the experiments are shown in Table 5.

From the results, we clarify some details in the ablation study. First, for DST, two networks are obviously superior to one network. In a high noise ratio, one network can not be trained because of the confirmation bias problem, but two networks address this problem. Second, MixUp is also a good approach to address the confirmation bias problem. In Figure 6, we get the lower accuracy of "Last" when training DST without MixUp across all noise ratios. Finally, Date Selection is very important to DST, especially the module of the correctly predicted training. We guess that the random factors of the wrong samples including the correctly labeled samples replaces the module of the correctly labeled training. In the case of high noise ratio, the correctly labeled set is a small part of the entire training set, which has little effect in the second half of training process. In the low noise ratio, since most samples is in the state (i) introduced in 3.1, the random module of the wrong sample training is almost same as the correctly labeled training. Generally, the correctly labeled training has a improvement on DST, and the module of the correctly predicted training is essential for DST.
5. Conclusion

This paper presents DST on learning with noisy labels. Our method fits a Gaussian mixture model to the cross-entropy loss between the sample and its two labels. Meanwhile, we use two networks to teach each other by the probabilities from GMM. Through many experiments on different datasets, we show that DST can achieve the same or better performance compared with state-of-the-art methods. We further propose to use semi-supervised learning to train the wrong samples generated by GMM. In addition, we are interested in finding a new unsupervised method to improve the capability of data selection.

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Table 3. Comparison with baselines in terms of test accuracy (%) with Criterion 2. Top : CIFAR-10, bottom : CIFAR-100.

| Method | Test Accuracy |
|--------|---------------|
| Cross-Entropy | 69.32 |
| F-correction [21] | 69.84 |
| M-correction [1] | 71.00 |
| Joint-Optim [26] | 72.23 |
| Meta-Learning [17] | 73.47 |
| P-correction [37] | 73.49 |
| DivideMix [16] | 74.76 |
| DST | 73.67 |

Table 4. Comparison with state-of-the-art methods in test accuracy (%) on Clothing1M.

| Method | Test Accuracy |
|--------|---------------|
| Cross-Entropy | 69.32 |
| F-correction [21] | 69.84 |
| M-correction [1] | 71.00 |
| Joint-Optim [26] | 72.23 |
| Meta-Learning [17] | 73.47 |
| P-correction [37] | 73.49 |
| DivideMix [16] | 74.76 |
| DST | 73.67 |

Table 5. Ablation study results in terms of test accuracy (%) on CIFAR-10 in Criterion 1. First, DST is trained without MixUp. Second, DST uses one network to teach itself. Third, DST is trained with the correctly predicted set as the wrong set. Fourth, DST is trained with the correctly labeled set as the wrong set, which has best accuracy at “Last” in 50% noise ratio. Last, DST is trained with all sets as the wrong set.

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