Self-paced Resistance Learning against Overfitting on Noisy Labels

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Abstract—Noisy labels composed of correct and corrupted ones are pervasive in practice. They might significantly deteriorate the performance of convolutional neural networks (CNNs), because CNNs are easily overfitted on corrupted labels. To address this issue, inspired by an observation, deep neural networks might first memorize the probably correct-label data and then corrupt-label samples, we propose a novel yet simple self-paced resistance framework to resist corrupted labels, without using any clean validation data. The proposed framework first utilizes the memorization effect of CNNs to learn a curriculum, which contains confident samples and provides meaningful supervision for other training samples. Then it adopts selected confident samples and a proposed resistance loss to update model parameters; the resistance loss tends to smooth model parameters' update or attain equivalent prediction over each class, thereby resisting model overfitting on corrupted labels. Finally, we unify these two modules into a single loss function and optimize it in an alternative learning. Extensive experiments demonstrate the significantly superior performance of the proposed framework over recent state-of-the-art methods on noisy-label data. Source codes of the proposed method are available on https://github.com/xsshi2015/Self-paced-Resistance-Learning.

Index Terms—Convolutional neural networks, self-paced resistance, model overfitting, noisy labels

I. INTRODUCTION

Recently, convolutional neural networks (CNNs) have achieved tremendous success on various different tasks, such as image classification [1] [2] [3] [4] [5], retrieval [6] [7], detection [8] and segmentation [9]. However, most CNNs usually require large-scale high-quality labels to obtain desired accuracy, because deep CNNs are capable of memorizing the entire training data even with completely random labels [10]. This infers that noisy labels might significantly deteriorate the performance of CNNs during training. Unfortunately, noisy labels are pervasive in practice and it is expensive to obtain accurate labeled data.

To tackle noisy labels for effectively and robustly training CNNs, some methods [11] [12] utilize regularization terms for label correction to alleviate the deterioration of deep networks during training, but they often fail to attain the optimal accuracy. Another popular way is to estimate a label transition matrix during training, but they often fail to attain the optimal accuracy. Another popular way is to estimate a label transition matrix, especially for a large number of classes. The third promising direction is to select confident samples based on small-loss distances in order to update networks robustly, without estimating the label transition matrix. MentorNet [14] and Co-teaching [15] are two representative methods. When no clean validation data is available, self-paced MentorNet learns a neural network to approximate a predefined curriculum to provide meaningful supervision for StudentNet, so that it can focus on the samples with probably correct labels. Self-paced MentorNet is similar to the self-training method [16], and it inherits the same inferiority of accumulated errors generated by sample-selection bias. To address the issue, Co-teaching utilizes the memorization effect of deep neural networks [17], which might first memorize training data with correct labels and then those with corrupted labels (please refer to Fig. A1 in the supplemental material), and symmetrically trains two networks, each of which filters corrupted labels and selects the samples with small-loss to update the peer network. However, with the increasing number of training epochs, the two networks will gradually form consensus predictions and Co-teaching will functionally deteriorate to self-paced MentorNet. Although the strategy of “Update by Disagreement” [18] can slow down the two networks of Co-teaching to form consensus predictions, it still cannot prevent the effect of sample-selection bias in many cases [19]. Additionally, when training data is with extremely noisy labels, MentorNet and Co-teaching easily select the corrupt-label data as confident samples so that the networks are overfitted on corrupted labels, thereby decreasing their performance. Moreover, Co-teaching aims to filter corrupt-label training samples and thus might fail to explore their correct semantic information.

To address the performance deterioration of CNNs generated by model overfitting on corrupted labels, and meanwhile explore the correct semantic information of training samples with corrupted labels, in this paper, we propose a novel self-paced resistance framework using a resistance loss to robustly train CNNs on noisy labels, without using any clean validation data. The proposed framework is mainly inspired by: (i) Deep neural networks might first memorize the probably correct-label data and then samples with corrupted labels or outliers [15]; (ii) A curriculum consisting of confident samples can provide meaningful supervision for other training data [14]; (iii) A resisting model overfitted on corrupted labels can reduce the deterioration of model performance. We summarize three major contributions as follows:
We propose a novel resistance loss to significantly alleviate model overfitting on corrupted labels, by smoothing model parameters’ update or attaining equivalent prediction on each class. For clarity, we present the difference between the resistance loss and the traditional cross-entropy loss in Fig. 1.

We propose a novel yet simple framework, self-paced resistance learning (SPRL), by effectively using the memorization effect of deep neural networks, curriculum learning and a resistance loss to robustly train CNNs on noisy labels.

Extensive experiments on four image datasets demonstrate that (i) The proposed framework can prevent the accuracy deterioration of CNNs on noisy labels, leading to superior classification accuracy over recent state-of-the-art methods on multiple types of label noise; (ii) With clean training data only, the proposed method usually obtains better results than standard networks.

The rest of the paper is organized as follows. Section 2 briefly reviews some popular methods to tackle noisy labels; Section 3 introduces the preliminaries on curriculum learning; Section 4 presents the proposed framework, SPRL. Section 5 shows and analyzes experimental results of various methods, and points out the future work; Finally, Section 6 concludes this paper.

II. RELATED WORK

Here, we briefly review some popular statistical learning methods for tackling noisy labels and deep neural networks with noisy labels.

Statistical learning methods. There are numerous statistical learning algorithms to handle noisy labels [20]. They can be roughly categorized into three groups: probabilistic modeling, surrogate losses and noise rate estimation. One popular probabilistic modeling method is [21], which proposes a two-coin model to handle noisy labels provided by multiple annotators. For surrogate losses based methods, [22] proposes an unbiased estimator to provide the noise corrected loss and then presents a weighted loss function for handling class-dependent noisy labels; [23] introduces a robust non-convex loss for tackling the contamination of data with outliers and a boosting algorithm, SavageBoost, to minimize the loss; [24] presents a convex loss modified from the hinged loss and proves its robustness to symmetric label noise. In the noise rate estimation category, [25] designs consistent estimators for classification with asymmetric (class-dependent) label noise; [26] utilizes kernel embeddings onto reproducing kernel Hilbert space for mixture proportion estimation; [27] estimates class proportions when the distributions of training and test samples are different; [27] and [28] introduce class-probability estimators using order statistics on the range of scores. Most of these statistical learning methods are proposed for traditional algorithms on relatively small datasets. Thus they usually fail to obtain promising performance on real applications, especially large datasets.

Deep neural networks with noisy labels. Because deep neural networks are sensitive to noisy labels, a few methods have been proposed to handle noisy labels for robust network training. [29] proposes two robust loss functions for binary classification of aerial image patches to handle omission and wrong location of training labels. [30] [31] [32] investigate noise-tolerant of loss functions under risk minimization. [11] [12] [33] consider the prediction consistency via adding a regularization term for robustly training deep neural networks. This strategy cannot prevent the performance deterioration of CNNs in many cases and it usually fails to obtain optimal accuracy. [34] and [13] estimate a label transition matrix, which summarizes the probability of one class being flipped into another, to correct loss functions, and [35] employs a dimensionality-driven learning strategy to estimate the correct labels of samples during training and adapt the loss function. However, it is difficult to accurately estimate the label transition matrix or the labels of training samples. [36] proposes an iterative learning framework to handle open-set noisy labels. [37] [38] [39] and [40] adopt a small clean dataset to leverage samples with noisy labels; [41] adopts a small clean dataset to assign weights for training samples based on their gradient directions to reduce the effect of corrupted labels. These methods usually require an additional clean dataset to alleviate the overfitting of CNNs on noisy labels. [42] and [43] adopt the confident samples for training by cleaning up corrupted labels, and thus they fail to exploit the semantic information of the samples with corrupted labels. [18] introduces a strategy, “Update by Disagreement”, that updates the parameters of two networks by using the samples with different predictions. This strategy cannot handle noisy labels explicitly, because the disagreement predictions usually contain corrupted labels. MentorNet [14] and Co-teaching [15] are two popular learn-to-teach methods to handle noisy labels. They select confident samples based on small-loss distances to teach the student or other network. [19] extends Co-teaching to alleviate the performance deterioration of deep neural networks. However, these learn-to-teach methods easily select corrupt-label samples as confident ones and then make CNNs be overfitted on corrupted labels in many cases, especially on extremely noisy labels (please refer to Fig. A2 in the supplemental material), thereby...
deteriorating and decreasing the accuracy of CNNs during training. [44] formulates the sample selection from noisy labels as a function approximation problem, and proposes a novel Newton algorithm to solve the problem. However, its selection performance is still far from satisfying on extremely noisy labels.

Similar to previous learn-to-teach methods, the proposed method utilizes the memorization effect of deep neural networks to select confident samples as a curriculum to provide supervision of other training samples. However, unlike previous learn-to-teach methods that are very likely to deteriorate with the increasing number of training epochs, the proposed method can prevent the performance degradation during training. This is because the proposed resistance loss can significantly reduce the effect of corrupted labels by alleviating model overfitting. Additionally, the proposed framework does not require the noise rate and only trains a single network, differing from Co-teaching [15] and its variant [19] that need to know or estimate the rate of label noise and train two networks in a symmetric way. Overall, the proposed method is easy to utilize and can obtain good performance for image classification.

III. PRELIMINARIES ON CURRICULUM LEARNING

Curriculum learning (CL) [45] is a training strategy inspired by the learning process of humans and animals that gradually proceeds easy to difficult samples. CL predetermines the curriculum based on the prior knowledge so that training data is ranked in a meaningful order to facilitate learning. In the following, we briefly introduce three major variants of CL that are related to our proposed method.

Self-paced learning (SPL) [46]: CL heavily relies on the prior knowledge and ignores the feedback of the learner (model); to address this issue, SPL dynamically determines the curriculum based on the learner’s abilities. Given training data $X = \{x_i\}_{i=1}^n$ and the corresponding labels $y = \{y_i\}_{i=1}^n$, where $x_i$ and $y_i$ denote the $i^{th}$ sample and its correct label, respectively. Let $f(\cdot)$ represent a classifier and $w$ be its model parameters. SPL simultaneously selects easy samples and learns model parameters in each iteration by solving the following problem:

$$
\min_{w,v} E(w, v; \lambda) = \sum_{i=1}^{n} v_i L(y_i, f(x_i, w)) - \lambda \sum_{i=1}^{n} v_i, \quad s.t. \ v \in \{0, 1\}^n, \quad (1)
$$

where $L(y_i, f(x_i, w))$ denotes the loss function that calculates the cost between the ground truth label $y_i$ and the estimated label $f(x_i, w)$, $v$ is a binary vector to indicate which ones are easy samples, and $\lambda$ is a parameter to control the learning pace. Eq. (1) is usually solved by an alternative minimization strategy: with fixing $w$, calculating $v$ by $v = \{1 \ L(x_i, f(x_i, w)) < \lambda, \quad 0 \ otherwise. \}$, and then with fixing $v$, updating $w$ by using selected easy samples to train the classifier $f(\cdot)$.

Self-paced curriculum learning (SPCL) [47]: Although SPL can dynamically learn the curriculum, it does not take into account the prior knowledge. Let $\Psi$ be a feasible region encoding the information of a predetermined curriculum. To connect CL with SPL, SPCL [47] employs both the predetermined curriculum obtained by the prior knowledge before training and the learned curriculum during training with the following model:

$$
\min_{w,v} E(w, v; \lambda) = \sum_{i=1}^{n} v_i L(y_i, f(x_i, w)) + G(v, \lambda), \quad s.t. \ v \in \{0, 1\}^n, \ v \in \Psi, \quad (2)
$$

where $v$ is a weight vector to reflect the significance of samples, and $G(\cdot)$ is a self-paced function to control the learning scheme. For example, in SPL, $G(v, \lambda) = -\lambda \sum_{i=1}^{n} v_i$. Similar to Eq. (1), Eq. (2) can also be solved by using an alternative minimization method.

Self-paced MentorNet [14]: Because the learning process of deep neural networks is very complicated, it is difficult to be accurately modeled by the predefined curriculum. To tackle this issue, [14] employs two neural networks, one network called MentorNet $f_m(\cdot)$ and the other called StudentNet $f_s(\cdot)$. MentorNet is to approximate a predefined curriculum in order to compute time-varying weights $f_m(z_i; \Theta^*) \in [0, 1]$ for each training sample, where $\Theta^*$ denotes the optimal parameters in $f_m(\cdot)$, $z_i = \phi(x_i, \tilde{y}_i, w)$ represents the input feature to MentorNet of the $i^{th}$ sample $x_i$, $\tilde{y}_i$ is the noisy label of $x_i$ and $w$ is the parameter of StudentNet $f_s(\cdot)$, which will utilize the learned weights $f_m(z_i; \Theta^*)$ to update $w$. To learn a $\Theta^*$, MentorNet minimizes the following function:

$$
\arg \min_{\Theta} \sum_{i=1}^{n} f_m(z_i; \Theta) l_i + G(f_m(z_i; \Theta); \lambda), \quad (3)
$$

where $l_i$ is the loss between one hot vector $\tilde{y}_i$ of the noisy label $\tilde{y}_i$ and a predicting class probability vector $f_s(x_i, w)$, which is a discriminative function of StudentNet. Similar to SPCL, $G(f_m(z_i; \Theta); \lambda)$ is a self-paced function.

IV. SELF-PACED RESISTANCE LEARNING (SPRL)

Although MentorNet can boost model robustness when no clean validation data is used, it easily selects corrupt-label samples as confident ones and then overfits a model on them. To address this problem, we propose a novel training strategy, SPRL. It employs the memorization effect of deep neural networks to approximate a predefined curriculum in order to provide meaningful supervision for other training samples, and adopts a resistance loss to resist the effect of corrupted labels on the network. For clarity, we present the proposed SPRL framework in Fig. 2.

A. Curriculum Learning using the Memorization Effect

Given $n$ training samples $X = \{x_i\}_{i=1}^n$, $\tilde{y} = \{\tilde{y}_i\}_{i=1}^n$ denotes their corresponding noisy labels, where $x_i$ is the $i^{th}$ training sample, $\tilde{y}_i \in \{1, \cdots, c\}$ is its label and $c$ is the number of classes. To avoid the abuse of symbols, we utilize $f(\cdot)$ to represent an $L$-layer convolutional neural network and $w$ to denote model parameters. Let $P = \{p_i\}_{i=1}^n$ be label predictions of training samples and $B$ represent the index set of selected training data in each mini-batch, where $p_i = f(x_i, w) \in \mathbb{R}^c$ is the label prediction of the sample $x_i$. 


To update model parameters, we adopt the cross-entropy loss function as follows:

$$\min_{\mathbf{w}} \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} -\log(p_{i}[\hat{y}_i]),$$  \hspace{1cm} (4)$$

where $|\mathcal{B}|$ denotes the length of the index set $\mathcal{B}$.

Suppose that we train the network for $T$ epochs in total. When we only utilize Eq. (4) to update model parameters during training, the model performance usually deteriorates after a few epochs, because the network might first memorize the correct and easy samples at initial epochs and then it will eventually overfit on the corrupted labels or outliers [15].

Based on this memorization of deep networks, we first run the correct and easy samples at initial epochs and then it will gradually overfit on corrupted labels for boosting model robustness. It is mainly inspired by: (i) Eq. (7) might smooth the update of model parameters across different epochs in each mini-batch. Because knowledge distillation methods [48] [49] [50] [51] [52] [53] using model predictions as the teacher can also alleviate model overfitting, we present Fig. 3 to illustrate the core idea of the proposed resistance loss and their differences.

Suppose that $p_{i}[j]$ is the label prediction of the sample $x_i$ belonging to the $j^{th}$ class in the $t^{th}$ training epoch, and $p_{t-1}^{-1}[j] \in p_{t-1}^{-1}$ is the label prediction before using $x_i$ to update model parameters in the $(t - 1)^{th}$ training epoch. We propose the resistance loss as follows:

$$\min_{\mathbf{w}} \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} c_{j} p_{t-1}^{-1}[j] \log(p_{i}[j]).$$  \hspace{1cm} (7)$$

Eq. (7) is used to resist model overfitting of CNNs on corrupted labels for boosting model robustness. It is mainly inspired by: (i) Eq. (7) might smooth the update of model parameters; (ii) Eq. (7) tends to make $p_{i}[j] \rightarrow \frac{1}{n} (1 \leq j \leq c)$. Let $p_{i}[j]$ be the label prediction of $x_i$ before using it to update model parameters in the $t^{th}$ training epoch, to better illustrate these two motivations, we present Proposition 1 and show its proof in the following.

**Proposition 1.** Suppose that solving the problem in Eq. (7) with gradient descent, for any two entries $p_{i}[j], p_{i}[k] \in p_{i}$ and $p_{i}^{-1}[j] > p_{i}[k]$. There are only three cases between $p_{i}[j]$ and $p_{i}[k]$ and $p_{i}[j] > p_{i}[k]$: (i) $p_{i}[j] > p_{i}[k]$, (ii) $p_{i}^{-1}[j] > p_{i}[k]$, and (iii) $p_{i}^{-1}[j] \leq p_{i}^{-1}[k] \leq (p_{i}[j] p_{i}[k])^{-1/2}$.

For case (i) and (ii), there exists $p_{i}[j] < p_{i}[k]$ and $p_{i}[j] > p_{i}[k]$ respectively, thereby smoothing the update of model parameters; for case (iii), there exists $p_{i}[j] \leq \frac{p_{i}[j]}{p_{i}[k]} \leq \frac{p_{i}^{1}[j]}{p_{i}[k]}$, upon which each entry in $p_{i}$ tends to be gradually equivalent, i.e. $p_{i}[j] = p_{i}[k] = \frac{1}{c}$, $1 \leq j, k \leq c$.

**Proof.** Let $E(p_{i}) = \sum_{j=1}^{c} -p_{i}^{-1}[j] \log(p_{i}[j])$, taking its derivative with respect to (w.r.t) $p_{i}[j]$, we have:

$$\frac{\partial E(p_{i})}{\partial p_{i}[j]} = -\frac{p_{i}^{-1}[j]}{p_{i}[j]},$$  \hspace{1cm} (8)$$
which means that $\forall E(p_i^t[j]) = -\frac{p_i^{t-1}[j]}{p_i^t[j]}$. Here, the entries in $p_i$ are independent, because Eq. (7) is used as $c$ weighted cross-entropy losses (please refer to Fig. 3a). Note that in this paper, log utilizes $e$ as its base.

If $c = 1$, then $p_i^t[j] = p_i^t[j] + \eta p_i^{t-1}[j]/p_i^t[j]$, where $\eta$ denotes the learning rate. Because $p_i^{t-1}[j] > 0$, $p_i^t[j] > 0$ and $\eta > 0$, $p_i^t[j]$ will gradually approximate to 1, i.e. $-p_i^{t-1}[j] \log(p_i^t[j]) \to 0$.

If $c > 1$, for any two entries $p_i^t[j] > p_i^t[k]$, $1 \leq j, k \leq c$, then when $\eta > 0$, there exists:

$$p_i^t[j] = \frac{p_i^t[j] + \eta p_i^{t-1}[j]}{p_i^t[k] + \eta p_i^{t-1}[k]}$$

Based on Eq. (9), when $\frac{p_i^{t-1}[j]}{p_i^t[k]} < \frac{p_i^t[j]}{p_i^t[k]}$, there exists $p_i^t[j] < p_i^t[k] < p_i^t[j]$, thereby smoothing the update of model parameters. In addition, if $\frac{p_i^{t-1}[j]}{p_i^t[k]} < 1$, there exists $p_i^t[j] < p_i^t[k] < p_i^t[j]$.

When $\frac{p_i^{t-1}[j]}{p_i^t[k]} > \left(\frac{p_i^t[j]}{p_i^t[k]}\right)^2$, i.e., $\frac{p_i^{t-1}[j]}{p_i^t[k]} > \frac{p_i^t[j]}{p_i^t[k]}$, it has $p_i^t[j] > p_i^t[k]$. Eq. (9) equals $p_i^t[j] = \frac{(p_i^t[j])^2 + \eta p_i^{t-1}[j]}{(p_i^t[k])^2 + \eta p_i^{t-1}[k]}$ and $p_i^t[j] < 1$, so they suggest $p_i^t[j] < \frac{(p_i^t[j])^2 + \eta p_i^{t-1}[j]}{(p_i^t[k])^2 + \eta p_i^{t-1}[k]} < p_i^{t-1}[j]$. Thus, $\frac{p_i^{t-1}[j]}{p_i^t[k]} > p_i^t[j] > p_i^{t-1}[j]$, which means model parameters’ update would be smoothed.

When $\frac{p_i^{t-1}[j]}{p_i^t[k]} \leq \left(\frac{p_i^t[j]}{p_i^t[k]}\right)^2$, i.e., $\frac{p_i^{t-1}[j]}{p_i^t[k]} \leq \frac{p_i^t[j]}{p_i^t[k]}$, it has $p_i^t[j] \leq p_i^t[k]$. With an additional constraint $\frac{p_i^{t-1}[j]}{p_i^t[k]} \geq \frac{p_i^t[j]}{p_i^t[k]}$, it means $p_i^t[j] \leq \frac{p_i^{t-1}[j]}{p_i^t[k]} \leq \frac{p_i^t[j]}{p_i^t[k]}$. In this case, each entry in $p_i$ will gradually becomes equivalent, i.e. $p_i[j] = p_i[k]$. With a constraint $\sum_{j=1}^{c} p_i^t[j] = 1$, there will be $p_i[j] = p_i[k] \to \frac{1}{c}$. Therefore, Proposition 1 is proved.

Fig. 4. The loss of Eq. (4) and Eq. (7) change with the number of training epochs by using random 1000 digits from ‘0’ to ‘9’ in MNIST [54] and random 1000 images belonging to 10 categories from CIFAR10 [55]. We first utilize Eq. (4) to train ResNet18 [3] with 100 epochs, and then adopt Eq. (7) to train the network for the subsequent 200 epochs. The loss gradually approaches to $\sum_{j=1}^{c} = 0.1 \times \log(0.1) = 2.303$.

C. Self-paced Resistance Loss

Based on the learned curriculum and the proposed resistance loss, we can obtain the loss function of the proposed framework. Specifically, combining Eq. (5) with Eq. (7), we have:

$$\min_{w, v} E(w, v; \lambda) = \frac{1}{\sum_{i=1}^{c} v_i} \sum_{i=1}^{c} -v_i(\log(p_i^t[j]) + \lambda)$$

$$\mathbf{s.t.} v \in \{0, 1\}^n, \sum_{i=1}^{c} v_i = \delta(t),$$

(10)
where $\gamma(t)$ is a time-dependent weighting function to gradually enhance the weight of model predictions with the increasing number of epochs, so that Eq. (7) is mainly used to prevent model overfitting on corrupted labels. Because deep neural networks might first memorize the correct-label data and then corrupt-label samples, and the noise rate of selected samples usually increases eventually.

There are many choices for $\gamma(t)$. Similar to the popular ramp-up function in $[12]$, we utilize the following function:

$$
\gamma(t) = \begin{cases} 
0 & t \leq T_1 \\
\gamma_{max} e^{-5\|1-\mu\|^2} & T_1 < t \leq T,
\end{cases}$$

where $\mu$ linearly ramps up from 0 to 1 during $T - T_1$ epochs, $\gamma_{max}$ is the maximum of $\gamma(t)$ depending on $m$, e.g. $\gamma_{max} = \gamma_d(10 - \lceil\frac{t}{T_1}\rceil)$. This is because a larger $\gamma_{max}$ is required for a larger noise rate.

The optimization of Eq. (10) is similar to that of Eq. (1) and Eq. (2), and thus we solve it by utilizing an alternative minimization strategy $[46] [47]$. Specifically, it can be divided into two sub-problems:

$$
\min_{v} \sum_{i \in B} -v_i \log(p_i^{t-1}[\tilde{y}_i]) - \lambda v_i,
\quad \text{s.t. } v \in \{0, 1\}^n, \quad \sum_{i=1}^n v_i = \delta(t-1).
\tag{12a}
$$

$$
\min_{w} \sum_{i \in B} -w_i \log(p_i[\tilde{y}_i])
+ \frac{\gamma(t)}{\gamma_d} \sum_{i \in B} \sum_{j=1}^c -p_i^{t-1}[j] \log(p_i[j]),
\tag{12b}
$$

Eq. (12a) is a $v$-subproblem, in which the model parameter $w$ is known, and it aims to learn a curriculum consisting of confident samples; Eq. (12b) is a $w$-subproblem, which consists of a cross-entropy loss to utilize selected confident samples to update model parameters, and a resistance loss to resist model overfitting on CNNs on corrupted labels. We alternatively solve Eq. (12a) and Eq. (12b), i.e. fixing $w$, based on Eq. (12a), we can calculate $v$ as follows:

$$
v_i^* = \begin{cases} 
1 & \text{if } -\log(p_i^{t-1}[\tilde{y}_i]) < \lambda \\
0 & \text{otherwise},
\end{cases}
\tag{13}
$$

Note that in each epoch we might need to adjust $\lambda$ so that $\sum_{i=1}^n v_i = \delta(t-1)$. Then with a fixed $v$, we can update the model parameter $w$ by solving Eq. (12b) via any optimizer, e.g. Adam $[56]$. In summary, we present the detailed procedure to solve Eq. (10) in Algorithm 1.

V. EXPERIMENTS

To evaluate the proposed SPRL, we conduct experiments on four large-scale benchmark datasets: MNIST, CIFAR-10, CIFAR-100 and Mini-ImageNet. We briefly introduce them in the following.

MNIST $[54]$ consists of 70K images with handwritten digits from ‘0’ to ‘9’. There are 60K training and 10K testing images, each of which has a size of $28 \times 28$.

CIFAR-10 $[55]$ contains 60K color images belonging to 10 classes, each of which consists of 6K images. There are 50K training and 10K testing images. Each one is aligned and cropped to $32 \times 32$ pixels.

CIFAR-100 $[55]$ has 60K color images in 100 classes, with 600 images per class. There are also 50K training and 10K testing images. Each image has a size of $32 \times 32$.

Mini-ImageNet $[57]$ is more complex than CIFAR-100. It is composed of 60K color images selected from the ImageNet dataset $[58]$. These images belong to 100 classes, with 600 images per class. We divide them into a training set with 50K images and a testing set containing 10K images, and resize each image to $32 \times 32$.

The images in CIFAR-10, CIFAR-100 and Mini-ImageNet datasets are with the popular augmentation: random translations $(\{\Delta x, \Delta y\} \sim [-4, 4])$ and horizontal flip ($p = 0.5$), and each image in MNIST is only augmented by the random translation $(\{\Delta x, \Delta y\} \sim [-2, 2])$.
A. Implementation Details

We implement SPRL with the PyTorch framework and employ a 13-layer convolutional neural network (ConvNet) [59] [12] or ResNet18 [3] as the backbone network. We adopt the optimizer, Adam [56], to update the network parameters, with initializing the momentum parameters $\beta_1 = 0.9$ and $\beta_2 = 0.999$. By default, we follow [15] to set the maximum learning rate $\eta$ to be 0.001, run the network for $T = 200$ epochs and set the batch size to be 128. When using ResNet18 on MNIST, we choose $\eta = 0.0001$ to avoid exploding gradient. After the first 80 epochs, $\beta_1$ becomes 0.1 and the learning rate linearly decreases to 0 over the following 120 epochs. $T_1$ can be obtained through a validation set. Specifically, we randomly select 10% noisy training data to construct a validation set. $T_1$ is the epoch number, at which the network attains the best validation accuracy, in order to obtain the best model predictions. When the noise rate $\epsilon$ is not known, $m$ is the maximum number of training data whose prediction $p_i[y_i] \geq 0.5$ ($1 \leq i \leq n$) during the first $T_1$ epochs; when $\epsilon$ is known, we can empirically choose $m$ within the range of $[0.5(1-\epsilon)n, 0.8(1-\epsilon)n]$. Additionally, $m$ should satisfy $m \in [0.1n, 0.5n]$, because the noise rate $\epsilon$ is usually smaller than 0.9 and a large $m$ might reduce the effect of curriculum learning. There are many choices for $K$, we set $K = 10$. $\gamma_d$ can be estimated with cross-validation on noisy validation sets. For clarity, we present the detailed parameter settings ($T_1$ and $\gamma_d$) of each experiment in the supplemental materials (Please refer to Tables A3-A4).

B. Experimental Settings

We compare the proposed SPRL with seven state-of-the-art algorithms. We briefly introduce them as follows:

**Standard**: the standard deep neural networks trained on noisy datasets.

**Bootstrap** [11]: which corrects the label by using the weighted combination of predicted and original labels. We adopt hard labels in our experiments because they usually perform better than soft ones.

**F-correction** [13]: which utilizes a label transition matrix to correct model predictions. We employ the forward strategy, which usually yields better performance, and utilize a validation set to estimate the label transition matrix.

**Decoupling** [18]: which updates model parameters using the samples with different predictions of two classifiers.

**MentorNet** [14]: which adopts an additional network to learn an approximate predefined curriculum and employs another network, StudentNet, for classification. We utilize self-paced MentorNet, which is used for the case that no clean validation data is known.

**Co-teaching** [15]: which trains two networks in a symmetric way and each network selects the samples with the small-loss distance as the confident data for the other one.

**Co-teaching+** [19]: which is based on Co-teaching but using the strategy of “Update by Disagreement” [18].

Here, we suppose that the noise rate is known in Co-teaching and Co-teaching+, but the noise rate is unknown in the proposed SPRL. For fairness, we re-implement all the seven state-of-the-art algorithms with the PyTorch framework based on their provided public codes and utilize their default parameter settings. Additionally, they adopt the same backbone networks and training procedure as SPRL.

C. Experiments on Labels with Symmetry and Pair Flipping

Following [13] [15], we corrupt the four datasets manually via a label transition matrix $Q$ that is calculated by $q_{ij} = P_T(y = j | y = i)$, where the noisy label $y$ is flipped from the correct label $y$. Similar to [15], here $Q$ has two representative structures: symmetric flipping (class-independent noise) and pair flipping (class-dependent noise). For clarity, we present the definition of $Q$ with symmetric and pair flipping structures in Eqs. (14a) and (14b), respectively. It is worth noting that for symmetric flipping, the noise rate $\epsilon$ should be smaller than $\frac{1}{1-\epsilon}$, i.e. $\epsilon < \frac{1}{1-\epsilon}$; for pair flipping, $\epsilon < 0.5$ so that more than half of labels are correct. Note that the noise rate $\epsilon$ denotes the ratio of corrupted labels in the whole training data.

\[
Q = \begin{bmatrix}
1 - \epsilon & \epsilon & \cdots & \epsilon \\
\epsilon & 1 - \epsilon & \cdots & \epsilon \\
\cdots & \cdots & \cdots & \cdots \\
\epsilon & \epsilon & \cdots & 1 - \epsilon
\end{bmatrix}
\]  

(14a)

\[
Q = \begin{bmatrix}
1 - \epsilon & \epsilon & 0 & \cdots & 0 \\
0 & 1 - \epsilon & \epsilon & \cdots & 0 \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
\epsilon & 0 & \cdots & 0 & 1 - \epsilon
\end{bmatrix}
\]  

(14b)

1) Experimental Results and Analysis: To better illustrate the strength of the proposed SPRL, we first run all the eight methods with clean training data of the four datasets, and then present their best testing accuracy in Table I. As we can see, SPRL can achieve better or very competitive testing accuracy to the best competitors when using clean training data, and it consistently outperforms Standard, especially for more difficult datasets CIFAR-100 and Mini-ImageNet. A
TABLE II
AVERAGE OF TESTING ACCURACY (%) ON MNIST, CIFAR-10, CIFAR-100 AND MINI-IMAGENET OVER THE LAST TEN EPOCHS. WE BUILT THE BEST RESULTS AND HIGHLIGHT THE SECOND BEST ONES VIA UNDERLINES.

| Method | ResNet18 | | | ConvNet | | |
|--------|----------|----------|----------|----------|----------|----------|
| | $\epsilon = 0.2$ | Symmetry | Pair | $\epsilon = 0.2$ | Symmetry | Pair |
| | | | | | | | |
| MNIST | | | | | | | |
| Standard | 92.69 ± 0.18 | 65.49 ± 0.33 | 24.59 ± 0.18 | 58.00 ± 0.34 | 86.84 ± 0.27 | 60.89 ± 0.59 | 24.80 ± 0.51 | 57.14 ± 0.56 |
| Boostrap | 93.89 ± 0.08 | 66.48 ± 0.63 | 24.38 ± 0.35 | 59.92 ± 0.52 | 91.48 ± 0.16 | 61.05 ± 0.09 | 21.11 ± 0.32 | 55.51 ± 0.72 |
| F-correction | 97.68 ± 0.11 | 92.86 ± 0.14 | 40.93 ± 0.30 | 10.92 ± 0.01 | 87.12 ± 0.15 | 66.36 ± 0.45 | 68.17 ± 0.54 | 57.80 ± 0.64 |
| Decoupling | 92.70 ± 0.64 | 72.60 ± 1.17 | 27.00 ± 0.52 | 11.85 ± 0.36 | 96.26 ± 0.24 | 89.83 ± 0.40 | 71.02 ± 0.39 | 61.22 ± 2.34 |
| MentorNet | 93.51 ± 0.01 | 83.10 ± 0.01 | 24.96 ± 0.01 | 82.15 ± 0.01 | 95.87 ± 0.01 | 92.44 ± 0.01 | 97.95 ± 0.01 | 97.89 ± 0.01 |
| Co-teaching | 99.04 ± 0.02 | 94.69 ± 0.15 | 38.34 ± 1.23 | 87.36 ± 0.39 | 99.56 ± 0.01 | 99.15 ± 0.02 | 97.77 ± 0.03 | 97.25 ± 0.17 |
| Co-teaching+ | | | | | | | | |
| best accuracy among all methods on two different network | | | | | | | | |
| | | | | | | | | |
| Figs. A3-A6), which further illustrate that SRL can obtain | | | | | | | | |
| the best competitors on the four datasets, respectively; for | | | | | | | | |
| the eight methods at different numbers of training epochs | | | | | | | | |
| 2) Parameter Analysis: The proposed SPRL has three | | | | | | | | |
| essential parameters $\gamma_d$, $K$, and $T_1$, where $\gamma_d$ and $K$ determine $\gamma(t)$ and $\delta(t)$, respectively, and $T_1$ determines $m$. Here, we evaluate them by utilizing an easy dataset MNIST, a complex dataset CIFAR-100 and the network ConvNet. Specifically, Figs. 6-7 show testing accuracy of SPRL with different values of $\gamma_d$ on symmetric or pair flipping label noise, including $\gamma_d \in \{0, 1, 5, 10, 50, 100, 300, 500, 1000\}$ on MNIST and $\gamma_d \in \{0, 1, 5, 10, 50, 100, 300\}$ on CIFAR-100. Fig. 8 displays testing accuracy of SPRL with different $K$ within $\{100, 50, 20, 10, 5, 2\}$, and Fig. 9 presents its testing accuracy with different values of $T_1$, like $T_1 \in \{5, 10, 15, 20, 30, 40, 60, 80, 100\}$ on MNIST and $T_1 \in \{5, 10, 15, 20, 30, 40, 60, 80, 100\}$ on CIFAR-100. Fig. 10 displays the effect of different noise rates on the loss function Eq. (12b) during training. Figs. 6-7 suggest that a large weight of the resistance loss (Eq. (7)) can prevent the performance degradation of CNNs on symmetric or pair flipping label noise. Additionally, Fig. 7 also suggests that Eq. (7) with a large weight can boost the model accuracy. When $\gamma_d \geq 50$, SPRL obtains the best or sub-optimal accuracy on MNIST; when $\gamma_d \in \{1, 10\}$, SPRL obtains the best or sub-optimal accuracy on CIFAR-100 with symmetric label noise, and when $\gamma_d \in \{10, 50\}$, it achieves the best or sub-optimal accuracy on pair flipping label noise. However, Fig. 7 illustrates that if $\gamma_d$ is too large, the model accuracy will decrease on CIFAR-100, probably because the
smooth [2] are two popular methods for boosting the model generalization. Here, we utilize Eq. (15) to distill knowledge from previous training epochs and Eq. (16) to smooth labels, and replace Eq. (7) with them in Eq. (10), respectively. They are:

\[
\min_w \frac{1}{|B|} \sum_{i \in B} p_{i}^{t-1} \log \left( \frac{p_{i}^{t-1}}{p_i} \right), \tag{15}
\]

\[
\min_w \frac{1}{|B|} \sum_{i \in B} u_i \log \left( \frac{u_i}{p_i} \right), \tag{16}
\]

where \( w \) denotes model parameters and \( u_i = \{1, \frac{1}{2}, \ldots, \frac{1}{c} \} \in \mathbb{R}^c \).

Fig. 11 shows their performance using ResNet18 as the backbone network on CIFAR-10 and CIFAR-100 with symmetric label noise. It demonstrates the superior performance of Eq. (7) over Eq. (15) and Eq. (16).

D. Experiments on Noisy Labels Generated by CNNs

In practice, labels might be not only symmetric or pair flipping. To further illustrate the strength of the proposed SPRL,
we conduct experiments on noisy labels that are generated by CNNs. Specifically, we uniformly select 4K and 10K images from the training set of CIFAR-10 and CIFAR-100 as labeled data, respectively, and view the remaining images of training sets as unlabeled ones. Next, we only utilize labeled data to train models. Table III presents the accuracy of trained models on training and testing sets of CIFAR-10 and CIFAR-100.

Then we apply trained models on the whole training set and utilize predicting labels as noisy labels. Finally, we run the eight methods by utilizing training data with noisy labels to train models.

Table A4 shows the average accuracy of the eight methods on test sets of CIFAR-10 and CIFAR-100 over the last ten epochs. As shown in Tables III-A4, both SPRL and Co-teaching with noisy labels can consistently outperform ResNet18 and ConvNet with only partially labeled data. However, SPRL always achieves better average accuracy than the best competitor, Co-teaching, on two different deep architectures and datasets, especially on heavy noisy labels, e.g. labels (36.84% noise rate) generated by ResNet18, which is trained with only partially labeled data of CIFAR-10. We also present testing accuracy of the eight methods at different numbers of training epochs in the supplemental materials (please see Fig. A7).

E. Experiments on Real-World Noisy Labels

To further demonstrate the strength of the proposed SPRL on boosting model robustness, we conduct experiments on real-world noisy labels from the datasets Food101 and Clothing1M, respectively. Specifically, Food101 [60] contains 101,000 images belonging to 101 food categories, with 750 training and 250 testing images per category. Training images are with noisy labels, while testing images have clean labels.

Clothing1M [37] contains 1 million clothing images in 14 classes. We utilize training images with noisy labels for model training and 10,000 testing images with clean labels for testing.

Table V displays the average accuracy of Standard, Co-teaching, Co-teaching+ and SPRL on Food101 and Clothing1M over the last ten epochs. It illustrates that SPRL consistently outperforms the best competitors Co-teaching and Co-teaching+ on real-world noisy labels, especially using ResNet18 as the backbone network. Additionally, We show their testing accuracy at different numbers of training epochs in the supplemental materials (please refer to Fig. A8).

Table III: Accuracy (%) of ResNet18 and ConvNet trained by partially labeled data on training and testing sets of CIFAR-10 and CIFAR-100 datasets (4K for CIFAR-10 and 10K for CIFAR-100).

| Network | CIFAR-10 Training | CIFAR-10 Testing | CIFAR-100 Training | CIFAR-100 Testing |
|---------|------------------|------------------|-------------------|------------------|
| ResNet18 | 81.97            | 80.93            | 63.16             | 64.04            |
| ConvNet  | 82.02            | 80.52            | 64.23             | 54.95            |

Table IV: Average of testing accuracy (%) on CIFAR-10 and CIFAR-100 over the last ten epochs by CNN generated noisy labels. We bold the best results and highlight the second best ones via underlines.

| Method      | CIFAR-10 | CIFAR-100 |
|-------------|----------|-----------|
| Standard    | 81.94    | 81.88     |
| Booststrap  | 81.24    | 81.74     |
| F-correction| 83.40    | 81.28     |
| Decoupling  | 79.31    | 78.46     |
| MentorNet   | 81.27    | 80.24     |
| Co-teaching | 82.80    | 82.30     |
| Co-teaching+| 82.26    | 81.75     |
| **SPRL**    | 85.63    | 84.00     |

Table V: Average accuracy (%) of four methods over the last ten epochs on real-world noisy labels.

| Network | Food101 | Clothing1M |
|---------|---------|------------|
| Standard| 71.01   | 74.96      |
| Co-teaching | 71.26  | 74.34      |
| Co-teaching+ | 69.84  | 71.10      |
| **SPRL** | 76.14   | 74.01      |

F. Discussion and Future Work

Experiments on multiple large-scale benchmark datasets and two different backbone network architectures demonstrate that SPRL can significantly reduce the effects of various types of corrupted labels by using the resistance loss to alleviate model overfitting, thus avoiding the performance degradation of CNNs during training. Additionally, experiments on noisy labels generated by CNNs suggest that SPRL can be potentially utilized to further improve the performance of semi-supervised and unsupervised deep methods.

Although SPRL has achieved robust and better accuracy than many state-of-the-art methods, SPRL cannot be directly applied on multi-label datasets with noisy labels, because it calculates the class probability of each sample by using the softmax function, which usually performs poorly on multi-label classification tasks. However, SPRL might be extended to handle multi-label tasks by replacing the softmax function with a sigmoid function. In the future, SPRL might be further improved based on the following two potential directions:
VI. CONCLUSION

In this paper, we propose a novel framework, SPRL, to alleviate model overfitting for robustly training CNNs on noisy labels. The proposed framework contains two major modules: curriculum learning, which utilizes the memorization skill of deep neural networks to learn a curriculum to provide meaningful supervision for other training samples; parameters update, which leverages the selected confident samples and a resistance loss to simultaneously update model parameters and significantly reduce the effect of corrupted labels. Experiments on multiple large-scale benchmark datasets and typical deep architectures demonstrate the effectiveness of the proposed framework, and its significantly superior performance over recent state-of-the-art methods.

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DEEP ARCHITECTURES

Tables A1-A2 present the used network architectures of ResNet18 [3] and ConvNet [59] [12], which are re-implemented with the PyTorch framework. A convolutional layer is represented by ‘conv’; and we display kernel size, stride and padding in brackets, and the number of kernels after the layer is represented by ‘conv’. Additionally, all data layers of ConvNet were initialized following [66].
Table A5 presents the average of testing accuracy (%) of SPRL, Co-teaching and Co-teaching+ on CIFAR-10 and CIFAR-100 using ResNet18 and without using data augmentation.

| Method         | Symmetry | Pair |
|----------------|----------|------|
|                | $\epsilon = 0.2$ | $\epsilon = 0.5$ | $\epsilon = 0.8$ | $\epsilon = 0.45$ |
| Co-teaching    | 78.48 ± 0.18 | 68.59 ± 0.06 | 19.63 ± 0.14 | 67.99 ± 0.31 |
| Co-teaching+   | 74.14 ± 0.22 | 46.69 ± 0.59 | 16.74 ± 0.08 | 45.44 ± 0.32 |
| SPRL           | 84.51 ± 0.12 | 71.91 ± 0.29 | 32.39 ± 0.41 | 79.20 ± 0.14 |

Table A5 shows the settings of two essential parameters $T_1$ and $\gamma_d$ in SPRL. Table A3 shows their values on MNIST, CIFAR-10, CIFAR-100 and Mini-ImageNet when using noisy labels generated by symmetric and pair flipping; Table A4 presents the average of testing accuracy (%) of SPRL, Co-teaching and Co-teaching+ on CIFAR-10 and CIFAR-100 using ResNet18 and without using data augmentation.
displays the values on CIFAR-10 and CIFAR-100 when using noisy labels generated by CNNs.

**Testing Accuracy vs. Training Epochs**

Figs. A1-A4 present testing accuracy of the eight methods at different numbers of training epochs on MNIST, CIFAR-10, CIFAR-100 and ImageNet. It is worth noting that the accuracy of Co-teaching with ConvNet is drastically fluctuating during training on CIFAR-10 and CIFAR-100, while Co-teaching with ResNet18 can achieve stable accuracy on these two datasets. This might be caused by that we set the dropout rate to 0.5 instead of 0.25 in ConvNet. Fig. A5 displays testing accuracy of the eight methods at different numbers of training epochs on CIFAR-10 and CIFAR-100 when using noisy labels generated by CNNs. Fig. A6 presents testing accuracy of Standard, Co-teaching, Co-teaching+ and SPRL on Food101 and Cloth1M with real-world noisy labels at different numbers of training epochs.

**Accuracy of Selected Confident Samples**

Fig. A7 shows the accuracy of selected confident samples of ResNet18, and it suggests that the network might first memorize the probably correct-label data and then corrupt-label samples. Additionally, Fig. A8 presents the accuracy of selected confident samples of Co-teaching on different levels of noisy labels. It infers that the selection accuracy of Co-teaching is significantly decreased on extremely noisy labels.
Fig. A5. Testing accuracy of seven methods with noisy labels generated by CNNs on CIFAR-10 and CIFAR-100 at different numbers of training epochs.

Fig. A6. Testing accuracy of four methods with real-world noisy labels at different numbers of training epochs.

Fig. A7. The accuracy of selected confident samples from CIFAR-10 by using standard ResNet18 with symmetric label noise $\epsilon = 0.5$. Note that we only select 50% training samples as confident ones.

Fig. A8. The accuracy of selected confident samples from CIFAR-10 at different levels of symmetric label noise.

TABLE A3
PARAMETERS FOR SPRL USING SYMMETRIC AND PAIR NOISY LABELS ON MNIST, CIFAR-10, CIFAR-100 AND MINI-IMAGE NET.

| Model       | Symmetry | Pair |
|-------------|----------|------|
| ResNet18    | $\epsilon = 0.2$ | $\epsilon = 0.5$ | $\epsilon = 0.8$ | $\epsilon = 0.45$ |
|             | $T_1$ | $\gamma_d$ | $T_1$ | $\gamma_d$ | $T_1$ | $\gamma_d$ |
| MINIST      | 15 | 300 | 15 | 300 | 15 | 300 | 15 | 300 |
| CIFAR-10    | 20 | 10 | 20 | 10 | 20 | 10 | 20 | 50 |
| CIFAR-100   | 20 | 10 | 20 | 10 | 20 | 10 | 20 | 50 |
| Mini-ImageNet | 15 | 10 | 15 | 10 | 20 | 10 | 10 | 50 |

| Model       | Symmetry | Pair |
|-------------|----------|------|
| ConvNet     | $\epsilon = 0.2$ | $\epsilon = 0.5$ | $\epsilon = 0.8$ | $\epsilon = 0.45$ |
|             | $T_1$ | $\gamma_d$ | $T_1$ | $\gamma_d$ | $T_1$ | $\gamma_d$ |
| MINIST      | 15 | 300 | 15 | 300 | 15 | 300 | 15 | 300 |
| CIFAR-10    | 40 | 5 | 40 | 5 | 40 | 5 | 40 | 50 |
| CIFAR-100   | 40 | 5 | 40 | 5 | 40 | 5 | 40 | 50 |
| Mini-ImageNet | 40 | 5 | 40 | 5 | 40 | 5 | 40 | 50 |

TABLE A4
PARAMETERS FOR SPRL USING NOISY LABELS GENERATED BY CNNS ON CIFAR-10 AND CIFAR-100.

| Model       | ResNet18 | ConvNet |
|-------------|----------|---------|
|             | $T_1$ | $\gamma_d$ | $T_1$ | $\gamma_d$ |
| CIFAR-10    | 10 | 10 | 10 | 10 |
| CIFAR-100   | 20 | 10 | 20 | 10 |