MetaLabelNet: Learning to Generate Soft-Labels from Noisy-Labels

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Real-world datasets commonly have noisy labels, which negatively affects the performance of deep neural networks (DNNs). In order to address this problem, we propose a label noise robust learning algorithm, in which the base classifier is trained on soft-labels that are produced according to a meta-objective. In each iteration, before conventional training, the meta-objective reshapes the loss function by changing soft-labels, so that resulting gradient updates would lead to model parameters with minimum loss on meta-data. Soft-labels are generated from extracted features of data instances, and the mapping function is learned by a single layer perceptron (SLP) network, which is called MetaLabelNet. Following, base classifier is trained by using these generated soft-labels. These iterations are repeated for each batch of training data. Our algorithm uses a small amount of clean data as meta-data, which can be obtained effortlessly for many cases. We perform extensive experiments on benchmark datasets with both synthetic and real-world noises. Results show that our approach outperforms existing baselines.

Index Terms—deep learning, label noise, noise robust, noise cleansing, meta-learning

I. INTRODUCTION

Computer vision systems have made a big leap recently, mostly because of the advancements in deep learning algorithms [1]–[3]. In the presence of large scale data, deep neural networks are considered to have an impressive ability to generalize. Nonetheless, these powerful models are still prone to memorize even complete random noise [4]–[6]. In the presence of noise, avoiding memorizing this noise and learning representative features becomes an important challenge. There are two types of noises, namely: feature noise and label noise [7]. Generally speaking, label noise is considered to be more harmful than feature noise [8]. In this work, we address the issue of training DNNs in the presence of noisy labels.

Various approaches of classification in the presence of noisy labels are summarized in [7], [9]. The most natural solution is to clean noise in the preprocessing stage by human supervision. However, this is not a scalable approach. Furthermore, in some fields, where labeling requires a certain amount of expertise, such as medical imaging, even experts may have contradicting opinions about labels [10]. Therefore, a commonly used approach is to cleanse the dataset with automated systems [11], [12]. In general, instead of noise cleansing in the preprocessing stage, these methods iteratively correct labels during the training. However, these algorithms tackle the problem of differentiating hard informative samples from noisy instances. As a result, even though they provide robustness up to some point, they do not fully utilize the information in the data, which upper-bounds their performance.

In this work, we propose an alternative approach for label correction. Instead of finding and correcting noisy labels, our algorithm aims to generate a new set of soft-labels in order to provide noise-free representation learning. To this end, we propose a reciprocal learning framework, where two networks (MetaLabelNet and the classifier network) are iteratively trained over the feedbacks coming from their peer network. In this context, MetaLabelNet acts like a teacher and learns to produce soft-labels to be used in training for the classifier network. For training MetaLabelNet, a meta-learning paradigm is deployed, which consists of two stages. Firstly, updated classifier parameters are calculated by using soft-labels that are generated by MetaLabelNet. Secondly, the cross-entropy loss on meta-data is calculated by using these updated classifier parameters. Finally, calculated cross-entropy loss on meta-data is backpropagated for the MetaLabelNet.

After updating MetaLabelNet, the base classifier is trained by using the soft-labels generated by the MetaLabelNet with the updated parameter set. These steps are repeated consecutively for each batch of data. As a result, MetaLabelNet plays the role of ground truth generator for the base classifier. What differs our approach from the classical teacher-student framework is the usage of meta-learning in the training of MetaLabelNet. Instead of training on the direct feedback coming from the base classifier, we set a meta-objective which deploys two iterations of the classifier network. For training MetaLabelNet, a meta-objective seeks for soft-labels such that gradients from classification loss would lead network parameters in the direction of minimizing meta loss. Our algorithm differs from conventional label noise cleansing methods in a way that it does not search for clean hard-labels but rather searches for optimal labels in soft-label space to minimize meta-objective. Our contribution to the literature can be summarized as follows:

- We propose a novel label noise robust learning algorithm that uses meta-learning paradigm. The proposed meta-objective aims to reshape the loss function by modifying soft-labels, so that learned model parameters are the least noise affected. Our algorithm is model agnostic and can easily be adopted by any gradient-based learning architecture at hand.
- To the best of our knowledge, we propose the first algorithm that can work with both noisily labeled and unlabeled data. The proposed framework is highly independent of the training data labels. As a result, it can be applied to unlabeled data in the same manner as labeled data.
- We performed extensive experiments on various datasets and various model architectures with synthetic and real-
world label noises. Results show the superior performance of our proposed algorithm over state-of-the-art methods.

The remainder of the paper is organized as follows. In Section II, we present related work from the literature. The proposed approach is explained in Section III and experimental results are provided in Section IV. Finally, Section VI concludes the paper by further discussions on the topic.

II. RELATED WORK

In this chapter, first the related works from the field of deep learning in the presence of noisy labels are presented. Afterward, methods from the meta-learning literature and their usage on noisily labeled data are analyzed. Finally, approaches that make use of both noisily labeled data and unlabeled data are investigated.

Learning with noisy labels: There are various approaches against label noise in the literature [9]. Some works model the noise as a probabilistic noise transition matrix between model predictions and noisy labels [17]–[18]. However, matrix size increases exponentially with an increasing number of classes, making the problem intractable for large scale datasets. Some researchers focus on regularizing learning by robust loss functions [19]–[23] or overfit avoidance [24]. These methods generally rely on the internal noise robustness of DNNs and aim to improve this robustness further with the proposed loss function. However, they do not consider the fact that DNNs can learn from uninformative random data [4]. One line of works focuses on increasing the impact of clean samples on training by either picking only clean samples [25]–[28] or employing a weighting scheme that would up-weight the confidently clean samples [29], [30]. Since these methods focus on low loss samples as reliable data, their learning rate is low and they mostly miss the valuable information from hard samples. One popular approach is to cleanse noisy labels iteratively during training [11], [12]. These approaches mainly employ expectation-maximization so that with better classifier better cleansing is provided, and with better labels a better classifier is obtained. Our approach is similar to these approaches in the sense that iterative label correction is employed. However, rather than variations of expectation-maximization, our approach uses meta-learning for label correction. Moreover, we are not interested in finding clean labels but soft-labels that would result in a minimum loss on meta-objective.

Meta learning with noisy labels: Meta-learning aims to utilize the learning for a meta task, which is a higher-level learning objective than classical supervised learning, e.g., knowledge transfer [31], finding optimal weight initialization [32]. As a meta-learning algorithm, MAML [32] seeks optimal weight initialization by taking gradient steps on the meta objective. This idea is used to find the most noise-robust weight initialization in [33]. However, their algorithm requires to train ten models simultaneously with two learning loops which is computationally infeasible for most of the time. Three particular works using the MAML approach worth mentioning are [34]–[36], in which authors try to find the best sample weighting scheme for noise robustness. Their meta-objective is to minimize the loss on the noise-free meta-data. Therefore, the weighting scheme is determined by the similarity of gradient directions in the noisy training data and clean meta-data. Unlike these methods, our algorithm does not seek for optimal weighting scheme, but rather optimal soft-labels that would provide the most noise robust learning for the base classifier. The logic behind our meta approach is visualized in [37]. Similar to our work, [37] also uses a meta-objective to update labels progressively. However, they formalize the label posterior with a free variable that does not depend on instances. Differently, we used an SLP network to interpret soft-labels from feature vectors of each instance, which provides a much more stabilized learning, as illustrated in Figure 4. Furthermore, [37] can only generate labels for given noisy labels, while our proposed algorithm can generate labels for unseen new data and unlabeled data as well.

Learning from both noisily-labeled and unlabeled data: Some works attempt to use semi-supervised learning techniques on noisily labeled dataset by removing labels of potentially noisy samples [38], [39]. Iteratively, unlabeled dataset is updated so that noisy samples are aggregated in the unlabeled dataset and clean samples are aggregated in the labeled dataset. However, these works do not use an additional unlabeled data in combination with noisily labeled data. They rather generate various combinations of unlabeled-subsets from the given labeled data. Differently, during training of MetaLabelNet, our proposed framework does not require training data labels but only meta-data labels. Therefore, the proposed algorithm can be used on unlabeled data in combination with noisily labeled data. To the best of our knowledge, our proposed algorithm is the first one to work with both noisily labeled and unlabeled data.

III. THE PROPOSED METHOD

In this section, we will first give a formal definition of the problem. Afterward, the proposed algorithm is described, and further analyses are provided to support the claim.

A. Problem Statement

In supervised learning we have a clean dataset \( S = \{ (x_1, y_1), ..., (x_N, y_N) \} \in (X, Y^h) \) drawn according to an unknown distribution \( \mathcal{D} \), over \( (X, Y^h) \) where \( X \) represents the feature space and \( Y^h \) represents the hard-label space for which each label is encoded into one-hot vector. The aim is to find the best mapping function \( f : X \rightarrow Y^h \) that is parametrized by \( \theta \).

\[
\theta^* = \arg\min_{\theta} R_{l, \mathcal{D}}(f_{\theta})
\]

where \( R_{l, \mathcal{D}} \) is the empirical risk defined for loss function \( l \) and distribution \( \mathcal{D} \). In the presence of the noise, dataset turns into \( S_n = \{ (x_1, \tilde{y}_1), ..., (x_N, \tilde{y}_N) \} \in (X, Y^h) \) drawn according to a noisy distribution \( \mathcal{D}_n \), over \( (X, Y^h) \). Then, risk minimization results in a different parameter set \( \theta^*_n \).

\[
\theta^*_n = \arg\min_{\theta} R_{l, \mathcal{D}_n}(f_{\theta})
\]
where $R_l, D_n$ is the empirical risk defined for the same loss function $l$ and noisy distribution $D_n$. Therefore, in the presence of the noise aim is to find $\theta^*$ while working on noisy distribution $D_n$. Both $D$ and $D_n$ is defined over hard label space $Y^h$. In this work, we are seeking optimal distribution $D$, which is defined over $(X, Y^s)$, where $Y^s$ represents the soft-label space. Since non-zero values are assigned to each classes, soft-labels can encode more information about the data.

Throughout this paper, we represent given data labels by $y$ and generated soft-labels by $\hat{y}$. While $y$ is in over hard-label space, $\hat{y}$ is in soft-label space. $D_m$ represents the meta-data distribution. $N$ is the number of training data samples, and $M$ is the number of meta-data samples, where $M << N$. $N_b$ represents the number of data in each batch and it is same for both training data and meta-data. We represent the number of classes as $C$, and superscript represents the label probability for that class, such that $y^j_i$ represents the label value of $i^{th}$ sample for class $j$.

B. Training

The full pipeline of the proposed framework is illustrated [figure 1]. Overall, training consists of two phases. Phase-1 is the warm-up training, which aims to provide a stable initial point for phase-2 to start on. After the first phase, the main algorithm is employed in the second phase that concludes the training. Each of the training phases and their iteration steps are explained in the following.

1) Training Phase-1

It is commonly accepted that, in the presence of noise, deep neural network firstly learn useful representations and then overfit the noise [5], [6]. Therefore, before employing the proposed algorithm, we employ a warm-up training for the base classifier on noisy training data with conventional cross-entropy loss. At this stage, we leverage the useful information from the data. This is also beneficial for our meta-training stage. Since we are taking gradients on the feedback coming from the base classifier, without any pre-training, random feedbacks coming from the base network would cause MetaLabelNet to lead in the wrong direction. Furthermore, we need a feature extractor for training in phase-2. For that purpose, the trained network at the end of warm-up training is cloned, and its last layer is removed. Then, this clone network, without any further training, is used as the feature extractor in phase-2.

2) Training Phase-2

This phase is the main training stage of the proposed framework. There are three iteration steps, which are executed on each batch of data consecutively. The first two iterations steps are the meta-training step, in which we update the parameters of MetaLabelNet. Afterward, in the third iteration step, base classifier parameters are updated by using the soft-labels generated with the updated parameters of the MetaLabelNet. These three steps are executed for each batch of data consecutively. The following subsections explain training steps in detail.

**Meta Training Step:** Firstly, data instances are encoded into feature vectors with the help of a feature extractor network $g(.)$.

$$v = g(x)$$

Then, depending on these encodings, MetaLabelNet $m_\phi(.)$ generates soft-labels.

$$\hat{y} = m_\phi(v)$$

Using these generated labels, we calculate posterior model parameters by taking a stochastic gradient descent (SGD) step on the classification loss.

$$\hat{\theta} = \theta(t) - \nabla_\theta L_c(f_\theta(x), \hat{y}^{(t)}) |_{\theta(t)}$$

and

$$L_c(f_\theta(x), \hat{y}^{(t)}) = \frac{1}{N_b} \sum_{i=1}^{N_b} l_c(f_\theta(x_i), \hat{y}_i^{(t)})$$

where $x_i \in D_n$ and $\hat{y}_i^{(t)} = m_\phi(v_i)$ is the corresponding predicted label at time step $t$. Adapted from [37], we choose the classification loss $l_c$ as KL-divergence loss as follows

$$l_c = KL(f_\theta(x_i)||\hat{y}_i)$$

Following, we calculate the meta-loss with the feedback coming from updated parameters.

$$L_{meta}(f_\theta(x), y) = \frac{1}{N_b} \sum_{j=1}^{N_b} l_{ccee}(f_\theta(x_j), y_j)$$

where $x_j, y_j \in D_m$ and $l_{ccee}$ represents the conventional categorical cross-entropy loss. Finally, we update MetaLabelNet parameters with SGD on the meta loss.

$$\phi^{(t+1)} = \phi^{(t)} - \beta \nabla_\phi L_{meta}(f_\theta(x), y) |_{\phi^{(t)}}$$

Mathematical reasoning for the meta-update is further presented in Section III-D

**Conventional Training Step:** In this phase, we train the base network on two losses. The first loss is the classification loss, which ensures that network predictions are consistent with estimated soft-labels.

$$L_c(f_\theta(x), \hat{y}^{(t+1)}) = \frac{1}{N_b} \sum_{i=1}^{N_b} l_c(f_\theta(x_i), \hat{y}_i^{(t+1)})$$

Notice that this is the same loss formulation with Equation 5 but with updated soft-labels $\hat{y}_i^{(t+1)} = m_\phi^{(t+1)}(v_i)$. Moreover, inspired from [11], we defined entropy loss as follow.

$$L_e(f_\theta(x)) = -\frac{1}{N_b} \sum_{j=1}^{N_b} C \sum_{j=1}^{C} f^j_\theta(x_i) \log(f^j_\theta(x_i))$$
Fig. 1: The overall framework of the proposed algorithm. $x_n, y_n$ represents the training data and label pair. $x^j_n, y^j_n$ represents batches of training data and label pair. The training consists of two phases. In the first phase (warm-up training), the base classifier is trained on noisy data with the conventional cross-entropy loss. This is useful to provide a stable starting point for the second phase. Training phase-2 consists of 3 consecutive steps, which are repeated for each batch of data. In the first iteration step, classification loss for model predictions is calculated with soft labels produced by MetaLabelNet. Then, updated classifier parameters $\hat{\theta}$ is calculated by SGD. In the second iteration step, the cross-entropy loss for meta-data is calculated using the updated classifier parameters $\hat{\theta}$. Then, updated MetaLabelNet parameters $\hat{\phi}$ is calculated by taking an SGD step on this cross-entropy loss. In the third iteration step, new soft-labels are produced by updated MetaLabelNet parameters $\hat{\phi}$. Then, classifier parameters $\theta$ is updated by the classification loss (with newly generated soft labels) and entropy loss. Feature extractor is the pre-softmax output of the base classifier’s duplicate trained at the warm-up phase of the training.

training loop to saturate. Finally, we update base classifier parameters with SGD on these two losses.

$$\theta^{(t+1)} = \theta^{(t)} - \lambda \nabla_\theta \left( L_c(f_\theta(x), \hat{y}^{(t+1)}) + L_c(f_\theta(x)) \right)_{\hat{\theta}^{(t)}} \quad (13)$$

Notice that we have two separate learning rates $\beta$ and $\lambda$ for MetaLabelNet and the base classifier. Training continues until the given epoch is reached. Since meta-data is only used for the training of MetaLabelNet, it can be used as validation-data for the base classifier. Therefore, we used meta-data for model selection. The overall training for phase-2 is summarized in Algorithm 1.

C. Learning with Unlabeled Data

The presented algorithm in Figure 1 uses training data labels $y_n$ only in the training phase-1 (warm-up training). The training phase-2 is totally independent of the training data labels. Therefore, training phase-2 can be used on the unlabeled data in the same way as the labeled data. As a result, if there exists unlabeled data, warm-up training is conducted on the labeled data. Afterwards, the proposed Algorithm 1 is applied to both labeled and unlabeled data in the same manner.

D. Reasoning of Meta-Objective

We can rewrite the update term for MetaLabelNet as follow.

$$-\beta \nabla_\phi L_{meta}(f_\phi(x), y)_{\hat{\phi}^{(t)}} \quad (14)$$

$$= -\beta \frac{\partial L_{meta}(f_\phi(x), y)}{\partial \theta} \frac{\partial \theta}{\partial \phi}_{\hat{\phi}^{(t)}} \quad (15)$$

$$= -\beta \frac{\partial L_{meta}(f_\phi(x), y)}{\partial \theta} \frac{\partial \theta}{\partial \phi} \left( -\frac{\partial L_c(f_\theta(x), \hat{y}^{(t)})}{\partial \theta} \right)_{\hat{\phi}^{(t)}} \quad (16)$$
where $\hat{y}^{(t)} = m_\phi(x)$ is a fixed encoder for which no learning occurs. All derivatives of $\phi$ are taken at time step $t$. Therefore, we drop the notation $\phi^{(t)}$ from now on.

$$= \frac{\beta}{N_b} \sum_{j=1}^{N_b} \frac{\partial l_{cce}(f_\theta(x), y_j)}{\partial \phi} \frac{\partial y_j}{\partial \phi} \left( -\frac{1}{N_b} \sum_{i=1}^{N_b} \frac{\partial l_{c}(f_\theta(x), \hat{y}_i^{(t)})}{\partial \phi} \right)$$

$$= \frac{\beta}{N_b N_b} \sum_{j=1}^{N_b} \sum_{i=1}^{N_b} \frac{\partial l_{c}(f_\theta(x), \hat{y}_i^{(t)})}{\partial \phi} \frac{\partial l_{cce}(f_\theta(x), y_j)}{\partial \phi}$$

Let

$$S_{ij}(\theta, \hat{\theta}, \phi^{(t)}) = \frac{\partial l_{c}(f_\theta(x), y_j)}{\partial \phi} \frac{\partial l_{c}(f_\theta(x), \hat{y}_i^{(t)})}{\partial \phi}$$

Then we can rewrite meta update as

$$\phi^{(t+1)} = \phi^{(t)} + \frac{\beta}{N_b} \sum_{j=1}^{N_b} \sum_{i=1}^{N_b} S_{ij}(\theta, \hat{\theta}, \phi^{(t)})$$

In this formulation $\frac{1}{N_b} \sum_{j=1}^{N_b} S_{ij}(\theta, \hat{\theta}, \phi^{(t)})$ represents the similarity between the gradient of the $ij$th training sample subjected to model parameters $\theta$ on predicted soft-labels $\hat{y}_i^{(t)}$ at time step $t$, and the mean gradient computed over the batch of meta-data. As a result, the similarity is maximized when the gradient of $i$th training sample is consistent with the mean gradient over a batch of meta-data. Therefore, taking a gradient step subjected to $\phi$ means finding the optimal parameter set that would give the best $\hat{y} = m_\phi(x)$ such that produced gradients from training data are similar to gradients from meta-data. As a result, the presented meta-objective reshapes the loss function by changing soft-labels so that that resulting gradient updates would lead to model parameters with the minimum loss on meta-data. Therefore, our meta-objective aims to reshape the classification loss function by changing soft-labels to adjust gradient directions for least noise affected learning (Figure 2).

### IV. Experiments

We conducted comprehensive experiments on three different datasets. In this section, firstly the description of the used datasets is provided. Secondly, the experimental setup used during the trials is described. Thirdly, results on these datasets are presented and compared to state-of-the-art methods.
optimizer with weight decay of $10^{-4}$ is used for MetaLabelNet. SLP with the size of NUM FEATURES x NUM CLASSES is used for MetaLabelNet architecture. For model selection we used the meta-data and evaluated the final performance on test data. Dataset specific configurations are as follows.

1) CIFAR10
We use an 8-layer convolutional neural network with 6 convolutional layers and 2 fully-connected layers. The batch size is set to 128. $\lambda$ is initialized as $10^{-2}$ and set to $10^{-3}$ and $10^{-4}$ at $40^{th}$ and $80^{th}$ epochs. $\beta$ is set to $10^{-2}$. Total training consists of 120 epochs, in which the first 44 epochs are warm-up. For data augmentation, we used a random vertical and horizontal flip. Moreover, we pad images 4 pixels from each side and random crop 32x32 pixels.

2) Clothing1M
In order to have a fair comparison, we followed the widely used setup of ResNet-50 [2] architecture pre-trained on ImageNet [44]. The batch size is set to 32. $\lambda$ is set to $10^{-3}$ for the first 5 epochs and to $10^{-3}$ for the second 5 epochs. $\beta$ is set to $10^{-3}$. Total training consists of 10 epochs, in which the first epoch is warm-up training. All images are resized to 256x256, and then central 224x224 pixels are taken. Additionally, we applied a random horizontal flip.

3) WebVision
Following the previous works [43], we used inception-resnet v2 [45] network architecture with random initialization. The batch size is set to 16. $\lambda$ is set to $10^{-2}$ for the first 12 epochs and to $10^{-3}$ for the rest. $\beta$ is set to $10^{-3}$. Total training consists of 30 epochs, in which the first 14 epochs are warm-up training. All images are resized to 320x320, and then central 299x299 pixels are taken. Furthermore, we applied a random horizontal flip.

C. Results on CIFAR10
We conduct tests with synthetic noise on CIFAR10 dataset and comparison of results to baseline methods is presented in Table 1. Our algorithm manages to give the best results on all levels of feature-dependent noise and achieves comparable performance for uniform-noise. Given training data labels are not used in Algorithm 1 but they are used during the warm-up training. As a result, noisy-labels affect initial weights for the base model. In feature-dependent noise, labels are flipped to the class of most resemblance. Therefore, even though it degrades the
overall performance, the classifier model still learns useful representations of data. This provides a better initialization for our algorithm. As shown in Figure 3, performance is boosted around 10% for feature-dependent noise and 5% for uniform noise. Moreover, even though initial performance after warm-up training is worse for feature-dependent noise at 40% noise ratio, it manages a better final performance. From these observations, we can conclude that the proposed algorithm performs better as the noise gets related to the underlying data features. This is an advantage for real-world scenarios since noisy labels are commonly related to data attributes. We showed this further on noisy real-world datasets in the next sections.

In Figure 4, we compared the stability of the produced labels [37]. This observation is consistent with the higher performance of our proposed algorithm.

![Mean Absolute Difference](image)

**Fig. 4:** Comparison of the stability of the produced labels with [37]. Lines indicates the mean absolute difference between produced labels in consecutive epochs. Shaded region indicates the variance in the differences.

**D. Results on Clothing1M**

Clothing1M is a widely used benchmarking dataset to evaluate performances of label noise robust learning algorithms. State of the art results from the literature are presented in Table I where we managed to outperform all baselines. Our proposed algorithm achieves 78.20% test accuracy, which is 3.5% higher than the closest baseline.

| noise type | 20  | 40  | 60  | 80  |
|------------|-----|-----|-----|-----|
| Cross Entropy | 82.55±0.80 | 76.31±0.75 | 65.94±0.44 | 38.19±0.81 |
| SCE [23] | 81.36±2.27 | 78.94±2.22 | 72.20±2.24 | 51.47±1.58 |
| GCE [22] | 84.98±0.30 | **81.65±0.30** | **74.59±0.46** | 42.53±0.24 |
| Bootstrap [27] | 82.76±0.36 | 76.66±0.72 | 66.33±0.30 | 38.35±1.83 |
| Forward Loss [17] | 83.24±0.37 | 79.69±0.49 | 71.41±0.80 | 31.53±2.75 |
| Joint Opt. [11] | 83.64±0.50 | 78.69±0.62 | 68.83±0.22 | 39.59±0.77 |
| PENCIL [12] | 83.86±0.47 | 79.01±0.62 | 71.53±0.39 | 46.07±0.75 |
| Co-Teaching [28] | **85.82±0.22** | 80.11±0.41 | 70.02±0.50 | 39.82±2.62 |
| MLNT [33] | 83.32±0.45 | 77.59±0.85 | 67.44±0.45 | 38.83±1.76 |
| Meta-Weight [36] | 83.59±0.54 | 80.22±0.16 | 71.22±0.81 | 45.81±1.78 |
| MSLG [37] | 83.03±0.44 | 78.28±1.03 | 71.30±1.54 | **52.43±1.26** |
| **Ours** | 83.35±0.17 | 79.03±0.26 | 70.60±0.86 | 50.02±0.44 |

**TABLE I:** Test accuracies for CIFAR10 dataset with varying level of uniform and feature-dependent noise. Results are averaged over 4 runs.

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**E. Results on WebVision**

Table III shows performances on WebVision dataset. As presented, our algorithm manages to get the best performance on this dataset as well.

| method | acc  | Top1 | Top5 |
|--------|------|------|------|
| MLC [46] | 71.10 | 52.43 | 78.42 |
| Joint Opt. [11] | 72.23 | 58.10 | 80.42 |
| MetaCleaner [48] | 72.50 | 59.03 | 81.36 |
| SafeGuarded [49] | 73.07 | 61.59 | 82.76 |
| MLNT [33] | 73.47 | 62.54 | 83.02 |
| PENCIL [12] | 73.49 | 62.86 | 83.35 |
| **Ours** | 78.20 | 87.48 | 92.50 |

**TABLE III:** Test accuracies on WebVision dataset. Baseline results are taken from [43].

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**V. ABLATION STUDY**

In this chapter, we analyze the effect of individual hyper-parameters on the overall performance.

**A. Warm-Up Training Duration**

Figure 6 presents results for different durations of warm-up training. We observed that it is beneficial to train on noisy data as warm-up training until a few epochs later the first learning rate decay. Because, during this duration training is mostly resilient to noise. After that, the base model starts to overfit the noise. As warm-up training gets longer and longer, the base model overfits the noise even more, which leads to poor model initialization for our algorithm. But even then,
Fig. 5: Test accuracies for different levels of feature-dependent noise for varying amount of meta-data on CIFAR10.

| # meta-data | 0.5k | 1k  | 2k  | 4k  | 8k  | 12k | 14k |
|-------------|------|-----|-----|-----|-----|-----|-----|
| Test Accuracy | 76.13 | 77.71 | 76.95 | 77.60 | 77.44 | 77.61 | 78.20 |

TABLE IV: Test accuracies for varying number of meta-data for Clothing1M dataset.

as soon as we employ the proposed algorithm, test accuracy increases significantly and ends up in a small margin of best performance. On the other hand, if we finish warm-up training early (such as 20th epoch), overall performance decreases significantly.

This is due to less stabilized initial model parameters. Alternatively, if we finish warm-up training exactly at the epoch of learning rate decay (40th epoch), it still gives a sub-optimal performance. Therefore, we advise employing warm-up training until a few epochs later the first learning rate drop and then continue training with Algorithm 1.

B. \( \beta \) Value

We used Adam optimizer for the MetaLabelNet and observed that best values of \( \beta \) is in between \( 10^{-2} \) to \( 10^{-3} \). As the dataset gets simpler (e.g. CIFAR10), \( 10^{-2} \) results in better performance. On the contrary, \( 10^{-3} \) provides better performance for more complex datasets (e.g. Clothing1M, WebVision).

C. MetaLabelNet Complexity

We observed that increasing MetaLabelNet complexity does not contribute to the overall performance. Three different configurations of multi-layer-perceptron (MLP) network with one hidden layer are tested as follows: 1) Sole MLP network 2) Additional batch-normalization layers 3) Additional batch-normalization and dropout layers. None of the configurations manages to get better accuracy than the proposed MetaLabelNet architecture. Our MetaLabelNet is a single, fully-connected layer with the same size as the last fully-connected layer of the base classifier. This is logical because input features to MetaLabelNet are extracted from the last layer before the fully-connected-layer of the base classifier. Therefore, keeping the same configuration as the last layer of the base classifier leads to the easiest interpretation of the extracted features.

D. Meta-Data Size

Figure 5 and Table IV shows the impact of meta-data size for CIFAR10 and Clothing1M datasets. Around 1k meta-data suffices for top performance in both datasets, which is around 100 samples for each class. It should be noted that Clothing1M is 15 times bigger than CIFAR10 dataset; nonetheless, they require the same number of meta-data. So, our algorithm does not demand an increasing number of meta-data for an increasing number of training data.

E. Unlabeled-Data Size

Labels of the training data are not used in the proposed Algorithm, but they are required for the warm-up training. Therefore, even though unlabeled-data’s size does not directly affect training, it indirectly affects by providing a stable starting point. We removed labels of a certain amount of training data and conducted warm-up training only on the labeled part. Afterward, the whole dataset is used for training with Algorithm 1. Figure 7 shows the impact of unlabeled-data size for different levels of feature-dependent noise on CIFAR10 dataset. As illustrated, our algorithm can give top accuracy even up to a point where 72% of the training data (36k images) is unlabeled. Secondly, Table V presents results for Clothing1M dataset. For comparison, we trained an additional network with the classical cross entropy method only on labeled data samples and measured the performances. Even in the extreme case of 900k unlabeled data, which is 90%
of the training data, our algorithm manages to achieve 75.23% accuracy, which is higher than all state-of-the-art baselines.

VI. CONCLUSION

In this work, we proposed a meta-learning based label noise robust learning algorithm. Our algorithm is based on the following simple assumption: optimal model parameters learned with noisy training data should minimize the cross-entropy loss on clean meta-data. In order to impose this, we employed a learning framework with two steps, namely: meta training step and conventional training step. In the meta training step, we update the soft-label generator network, which is called MetaLabelNet. This step consists of two sub-steps. On the first sub-step, we calculate the classification-loss between model predictions on training data and corresponding soft-labels generated by MetaLabelNet. Then, updated classifier model parameters are determined by taking a stochastic-gradient-descent step on this classification-loss. On the second sub-step, meta-loss is calculated between model predictions on meta-data and corresponding clean labels. Finally, gradients are backpropagated through these two losses for the purpose of updating MetaLabelNet parameters. This meta-learning approach is also called taking gradients over gradients. As a result, our meta objective seeks for soft-labels such that gradients from classification loss would lead network parameters in the direction of minimizing meta loss. Then, in the conventional training step, the classifier model is trained on training data and soft-labels generated by updated MetaLabelNet. These steps are repeated for each batch of data. To provide a reliable start point for the mentioned algorithm, we employ a warm-up training on noisy data with classical cross-entropy loss before the learning framework mentioned above. The presented learning framework is highly independent of training data labels, allowing unlabeled data to be used in training. We tested our algorithm on benchmark datasets with synthetic and real-world label noises. Results show the superior performance of the proposed algorithm. For future work, we intend to extend our work beyond the noisy label problem domain and merge our method with self-supervised learning techniques.

In such a setup, one can put effort into picking up the most informative samples. Later on, by using these samples as meta-data, our proposed meta-learning framework can be used as a performance booster for the self-supervised learning algorithm at hand.

VII. ACKNOWLEDGEMENTS

We thank Dr. Erdem Akagündüz for his valuable feedbacks during the writing of this article.

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