LEARNING FROM SMALL AMOUNT OF MEDICAL DATA WITH NOISY LABELS: A META-LEARNING APPROACH

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ABSTRACT

Computer vision systems recently made a big leap thanks to deep neural networks. However, these systems require correctly labeled large datasets in order to be trained properly, which is very difficult to obtain for medical applications. Two main reasons for label noise in medical applications are the high complexity of the data and conflicting opinions of experts. Moreover, medical imaging datasets are commonly tiny, which makes each data very important in learning. As a result, if not handled properly, label noise significantly degrades the performance. Therefore, we propose a label-noise-robust learning algorithm that makes use of the meta-learning paradigm. We tested our proposed solution on retinopathy of prematurity (ROP) dataset with a very high label noise of 68%. Our results show that the proposed algorithm significantly improves the classification algorithm’s performance in the presence of noisy labels.

Index Terms— deep learning, label noise, robust learning, meta-learning, retinopathy of prematurity

1. INTRODUCTION

Compared to its alternatives, deep networks are considered to have an impressive ability to generalize. Nonetheless, these powerful models are still prone to memorize even complete random noise. Preventing undesired memorization of data becomes an even more important step in the presence of label noise.

Medical data is much more complicated than other standard real-world datasets and requires a high level of expertise. However, even for the experts, it is hard to correctly label data. For example, on the ROP dataset annotated by three experts, there exists 27% of conflict [1]. Another work on the ROP dataset validates the same observation with eight experts [2]. To cope with label noise, one can simply remove suspicious samples and train the network with clean data. However, medical datasets are commonly small due to the expensive cost of collecting and annotating data. Also, there are privacy concerns too. Therefore, it is crucial to make the best use of each data during training networks in the medical data domain. As a result, label-noise-robust learning is a very critical milestone for obtaining trustworthy automated diagnosis systems.

There are various approaches against label noise in the literature [3]. Some works model the noise as a noisy channel between model predictions and given labels [4]. However, this is a probabilistic approach and requires a large amount of data to converge to the optimal solution, which is not the case in medical datasets. Another trend is to increase the effect of clean samples on learning by either picking only confidently clean samples [5]. These methods are inclined to continuously learn from easy samples since they are more confidently regarded as noise-free. As a result, their learning rate is low, and they miss the valuable information from hard informative samples. One simplified approach is to cleanse noisy labels iteratively during training [6]. Nevertheless, these methods are prone to re-label outliers, which are very hard to differentiate from correctly labeled hard informative samples.

All of the methods above are tested on either toy datasets (MNIST, CIFAR10 etc.) with random synthetic noise or massive datasets collected from the web. However, the medical domain is more difficult since the noise is not merely random synthetic noise, and the amount of data is much smaller than datasets collected from the web. Some pioneer works in the field of learning from medical data with noisy labels are [7,8], in which they used conventional learning approaches. However, in recent years, meta-learning approaches are shown to be very effective, especially in small datasets. Meta-learning approaches commonly have two training loops: 1) conventional training loop that trains the base classifier with conven-
tional machine learning techniques 2) meta training loop that optimizes meta-parameters (e.g. hyper parameters) to make conventional learning more effective. Our meta-parameters are noisy labels, and the meta-learning objective is to provide noise-robust learning to the base classifier.

In this work, we followed the methodology of [9], which employs a meta-learning approach and has given the current state-of-the-art result on training in the presence of noisy labels. Our algorithm is tailored to make the best use of a small verified clean data (we call this data meta-data) to extract noise-free knowledge from the noisy training data. The proposed framework adopts the meta-learning framework with two learning objectives as conventional training and meta training. In the conventional training stage, the base classifier is trained on training data with their predicted soft labels (instead of given noisy labels). In the meta training stage, soft-labels are generated according to meta-objective. It can be said that our meta objective seeks optimal soft-labels for each noisy data so that base classifier trained on them would give the best performance on clean meta-data. Our algorithm differs from label noise cleansing methods in a way that it is not searching for clean hard-labels but rather searching for optimal soft-labels that would provide the most noise-robust training. In order to verify the performance of the proposed algorithm it is tested on extremely noisy ROP dataset, which is illustrated in Figure 1.

2. THE PROPOSED METHOD

2.1. Problem Statement

In supervised learning we have the clean dataset, which consists of data instances and corresponding hard-labels. In hard-label representation, each instance belongs to only one class. In the presence of the label noise, we have the same data instances but with corrupted labels. Therefore, in the presence of the label noise, we are training network on noisy dataset while aiming to obtain the best classifier for clean dataset. However, training on noisy data directly would yield a suboptimal model for clean dataset. As a result, one needs to consider the existence of noisy labels when training on an imperfect dataset.

Both clean and noisy datasets are defined over hard label space \( Y^h \). Differently, in this work, we are seeking optimal label distribution, which is defined over soft-label space \( Y^s \). Unlike hard-labels, soft-labels have non-zero values for all classes, which lets them to define not only the corresponding class but also the similar classes. For example, in a digit classification task, "1" is more similar to "7" than "0". We can express this relation with soft-labels but not with hard-labels. Therefore, soft labels contain more information about the data, which is better for training. As a result, unlike aiming to find noise-free hard-labels in \( Y^h \), our algorithm seeks optimal soft-labels in \( Y^s \).

2.2. Learning with the Proposed Method

There are two consecutive stages in training: meta training and conventional training. In the first stage, a small MLP network is trained on meta objective to find optimal soft labels. In the second stage, the base classifier is trained on these soft-labels. These two stages are repeated consecutively during the training.

2.2.1. Meta training

Overall flowchart of meta-training stage is illustrated in Figure 2. First, we generate soft-label predictions. In the first epoch, label predictions are set as \( \hat{y} = K \ast y \) where \( K \) is a large number such as 10. In the later epochs, label-predictions are updated iteratively. Afterward, we calculate updated model parameters \( \theta \) by using these labels with stochastic gradient descent (SGD) optimizer as follows

\[
\hat{\theta} = \theta^{(t)} - \alpha \nabla_{\theta} L_{KL}(f_{\theta}(x), \hat{y}^{(t)}) \bigg|_{\theta^{(t)}} \tag{1}
\]

We used KL-divergence loss \( L_{KL} \) as loss function since it is a defacto loss function for soft-labels. Then using these updated parameters, we calculate the loss on meta-data. Since meta-data consists of clean hard labels, we used categorical cross-entropy loss \( L_{cce} \) to calculate meta-loss. Then we back-propagated the meta loss all the way back for updating soft-labels. This is more like asking the question; what would be the initial label predictions so that the base classifier trained on it (\( \hat{\theta} \)) would give the minimum loss on clean meta-data. Intuitively, the answer is the noise-free soft labels of the corresponding data. Therefore, our meta-objective is to find the least noise-affected soft-label representation of data. Label predictions are updated with SGD on the meta loss, which is calculated over meta-data.

\[
\hat{y}^{(t+1)} = \hat{y}^{(t)} - \nabla_{\hat{y}} \beta L_{cce}(f_{\hat{\theta}}(x), \hat{y}) \bigg|_{\hat{y}^{(t)}} \tag{2}
\]

2.2.2. Conventional training

At this point we have the soft-label predictions. Therefore, we train the base classifier on these soft-labels instead of given noisy labels. Same as before, we used KL-divergence loss \( L_{KL} \) for loss function. Furthermore, soft-labels can peak at multiple locations, but we want our network prediction to peak at only one value. Therefore, we defined entropy loss \( L_e \) as follows, which forces network predictions to peak at only one value.

\[
L_e(f_{\theta}(x)) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{C} f_{\theta}^j(x_i) \log(f_{\theta}^j(x_i)) \tag{3}
\]
Finally, we train base-classifier by using these two loss functions with SGD as follows

\[ \theta^{(t+1)} = \theta^{(t)} - \lambda \nabla_{\theta} \left( L_{KL}(f_{\theta}(x), \hat{y}^{(t+1)}) + L_{c}(f_{\theta}(x)) \right) \bigg|_{\theta^{(t)}} \]

Notice that we have three different learning rates \( \alpha, \beta \) and \( \lambda \) for each step.

### 2.3. Overall Algorithm

It is empirically shown that, under the presence of the noise, deep networks first learn clean representations of data, and only afterward they start to overfit the noise. Therefore, we begin by training network on noisy data with classical cross-entropy loss as warm-up training. At the end of warm-up training, our model leverages 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 meta-objective to lead in the wrong direction. After warm-up training, we employ our proposed algorithm, as explained in Section 2.2.

### 3. EXPERIMENTS

#### 3.1. Dataset

We collected 1947 retina images with 640x480 resolution from potential ROP patients. Each image is labeled by the same three experts to one of the following categories: normal, pre-plus and plus. From these 1947 images, only on 622 images all three experts gave the same label, which is 32% of the dataset. We randomly picked 200 images as meta-data and 300 images as test-data from these 622 images. Remaining 1447 images are considered to be unreliable since there is no consensus on the labels by three experts. Therefore, these images are used as noisy training data. We used majority voting on training data annotations to determine training labels. For preprocessing, we resized all images to 256x256 and the center crop 224x224. For data augmentation purposes, we used a random horizontal flip.

#### 3.2. Pre-Training

We used ResNet50 architecture with model parameters pre-trained on the ImageNet dataset. Our dataset is considerably small; therefore, we applied transfer learning by further pre-training network on a different but similar dataset. We used diabetic retinopathy (DR) dataset that has 35k high-resolution retina images [10]. A clinician has rated the existence of diabetic retinopathy on a scale of 0 to 4 as follows: no diabetic retinopathy (0), mild (1), moderate (2), severe (3), proliferative DR (4). Since we are not interested in classifying DR, but rather pre-train network to learn useful representation mapping, we converted dataset to binary classification task as: diabetic retinopathy (0) and no diabetic retinopathy (1). This dataset consists of high-resolution images with varying sizes. Therefore, we first resized all the images to 1024x1024 and then cropped 224x224 around the center of the retina image. On the resulting dataset, we trained our model for one epoch. Afterward, we replaced the final layer of the classifier with randomly initialized 2048x4 fully connected layer and softmax layer to match our ROP dataset labels.
### Table 1: Train and test accuracies on ROP dataset.

| Method                        | Train  | Test  |
|-------------------------------|--------|-------|
| Cross Entropy (no pre-train)  | 100.0% | 86.3% |
| Cross Entropy (pre-train on DR) | 100.0% | 90.3% |
| **Proposed algorithm**        | **86.23%** | **91.4%** |

3.3. Training Procedure

After pre-training on DR dataset, we employed our proposed algorithm. Stochastic gradient descent optimizer with momentum 0.9 and weight decay $10^{-4}$ is used for base classifier. We initialized learning rate as $10^{-3}$ and set it to $10^{-4}$ and $10^{-5}$ at $10^{th}$ and $20^{th}$ epochs. Total training consists of 30 epochs, in which first 10 epochs are warm-up training and rest is meta-training. During the whole training we used batch size of 16. We set the hyper-parameters as $K = 10, \alpha = 0.5, \beta = 4000$.

3.4. Evaluation of the results

In order to show the effectiveness of our algorithm, we compare its performance to classical learning with cross-entropy loss. We made three different runs, and results are provided in Table 1. First, we directly train the model on the ROP dataset without any pre-training on the DR dataset. This run achieved 86.3% test accuracy, which is moderate but the worst performance in the leaderboard. Secondly, we pre-trained the network on the DR dataset and then move to conventional training with cross-entropy on the ROP dataset. This run resulted in 90.3%, which is 4% more than the previous run. Increase in the performance shows the effectiveness of pre-training on the DR dataset. Finally, we employed our learning framework. Our proposed algorithm gives the best performance with 91.4%. Another important observation is, in conventional cross-entropy loss both networks manage to get 100% training accuracy. Considering that labels are extremely noisy, this is an undesired behavior that means the network is overfitting the data. On the other hand, in our algorithm, training accuracy is stuck at 86.23%. Therefore, we can conclude that our algorithms prevents model to overfit the noise.

4. CONCLUSION

In this work, we proposed a meta-learning based label noise robust learning algorithm. Our algorithm is especially effective in the case of small data with label noise, since it can successfully leverage the noise-free information from the noisy training data by using very small clean meta-data. We tested our proposed algorithm with the ROP dataset with extreme label noise ratio of 68%, where we managed to get best test accuracy of 91.4%.

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