No Regret Sample Selection with Noisy Labels

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Abstract—Deep Neural Network (DNN) suffers from noisy labeled data because of the heavily overfitting risk. To avoid the risk, in this paper, we propose a novel sample selection framework for learning noisy samples. The core idea is to employ a “regret” minimization approach. The proposed sample selection method adaptively selects a subset of noisy-labeled training samples to minimize the regret to select noise samples. The algorithm efficiently works and performs with theoretical support. Moreover, unlike the typical approaches, the algorithm does not require any side information or learning information depending on the training settings of DNN. The experimental results demonstrate that the proposed method improves the performance of a black-box DNN with noisy labeled data.

Index Terms—noisy labeled data, adaptive sample selection, regret minimization

I. INTRODUCTION

Deep neural network (DNN) requires a large number of “correctly-labeled” samples for high-performance prediction. In reality, however, it is difficult to guarantee the correctness of the attached labels. As an example, sample sets annotated via crowd-sourcing often contain samples with wrong labels, i.e., noisy-labeled samples. As another example, roughly-collected sample sets contain unnecessarily-labeled samples that are irrelevant to the target class but forcibly labeled. DNN can easily overfit to them and thus they degrade the performance of DNN.

Consider a problem for selecting an optimal subset of training samples (i.e., clean training samples) out of noisy training samples. Fig. 1 shows the most naive way where all possible subsets of the original training samples are prepared and then a DNN is trained by each subset. After the training, by evaluating all of the models, we can find the best model which should be learned with the subset of clean samples only or with just a small number of noisy-labeled samples. This approach, however, is obviously intractable because we need to consider $2^n$ subsets for $n$ training samples.

To avoid this difficulty, we introduce the idea of adaptive expert selection (AES) problem into our subset selection problem. Although AES is not well-known in application-oriented research (e.g., pattern recognition by DNN), it is well-studied in theoretical machine learning research. Fig. 2(a) shows the basic idea of AES. AES is a kind of online multi-stage decision making problem in a game-theoretic scenario, and comprised of three elements: player, exerts, and environment. The player is the user of the system. The player selects one expert $d$ at each stage $t$. Each expert makes its own prediction (or action) $d_t$ to the environment. The environment is like a black-box function and gives the feedback $ℓ_t$ to $d_t$. Finally, the player incurs a loss based on $ℓ_t$ (and $d_t$) at $t$. Assuming a minimization problem, the player needs to select an appropriate expert at each $t$ to minimize the total loss accumulated overall $t \in [1,T]$. (Note that in several problem settings, the player can select multiple experts.)

The solution of AES is not so clear in general because of several reasons. First, the environment is a black-box function. Second, the environment can be time-variant (and even adversarial to the player’s selection). Third, as noted above, AES is an online problem; at stage $t$, we only know the environments before $t$ and do not know the environments after $t$. Those reasons make any statistical estimation of the environment impossible and consequently, it is not easy to guess which expert is the most appropriate at $t$.

In spite of this hurdle, AES still has great theoretical strength; when we employ a specific algorithm on selecting experts, its performance is theoretically guaranteed in terms of regret. Regret is a performance measure of the online machine learning algorithm and often used in theoretical machine learning research. As shown in Fig. 3, the regret indicates the difference between the total loss by the player’s selection and the total loss by the best (fixed) expert. The expert selection algorithm can be seen as an online regret minimization algorithm and therefore its performance is theoretically guaranteed by...
the existence of a regret upper-bounded. The expert selection algorithms, such as Follow-The-Leader, Follow-the-Perturbed-Leader (FPL), Follow-the-Regularized-Leader, etc., have such bounds \[1\].

Our subset selection problem can be reformulated as an AES problem, as shown in Fig. 2 (b). In our case, the player is the user who wants to train a DNN. Each expert corresponds to a subset of training samples. Note that one subset contains a small number of noisy-labeled samples and another subset contains a larger number of them — this means that the goodness of each expert is different. The environment is a DNN which accepts a subset as a batch and updates its internal weights by the samples in the subset. If we treat the epoch as the time index \( t \), the DNN under training is a time-variant environment.

Although the online guess of the best expert at each \( t \) is also difficult for our subset selection problem, we still guarantee the performance of an expert selection algorithm in terms of regret. In other words, if we employ, for example, FPL for subset selection, we can select an appropriate subset at each \( t \) and, consequently, reduce the adverse effect of noisy-labeled samples. For the loss to evaluate the regret (i.e., the feedback from the environment), we introduce “noisiness” loss \( \ell(t) \), which is different from the loss for DNN training. The noisiness loss evaluates the risk of adverse effects by noisy-labeled samples.

Fig. 2 (c) shows the proposed method to solve the subset selection problem (b) as an AES problem. Recalling that we have \( 2^n \) possible subsets, the naive implementation of (b) will encounter the same intractable situation like Fig. 1. The proposed method, however, introduces the adaptive \( k \)-set selection algorithm \[2\], which is derived from the FPL algorithm \[3\], \[4\]. In short, this algorithm and the noisiness loss can derive the most promising subset without listing all \( 2^n \) subsets. The constant \( k \) \( (< n) \) denotes the size of the subset. It should be noted again that the proposed method is an online regret minimization algorithm and thus the performance of the proposed method is guaranteed by the existence of a regret upper-bound.

In addition to the theoretical guarantee, the proposed method has another advantage; that is, the independence of DNN (or even any machine learning) architecture. As shown in Fig. 2 (c), we can consider a DNN as a black box. This means that we can replace it with an arbitrary machine learning framework (e.g., specific DNN, such as ResNet, VGG, and AutoEncoder, and even more classical framework, such as MLP, SVM, and HMM) and therefore the proposed method is a versatile methodology. In fact, we will use a very classical single perceptron with synthetic data for observing the basic performance of the proposed method.

In the remaining of this paper, we first detail the proposed method, including the novel algorithm, called adaptive \( k \)-set selection algorithm and our noisiness loss function. The proposed method can minimize the regret (the difference between the actual total loss and the ideal total loss) and thus the subset by the proposed method is expected to reduce the adverse effect by noisy-labeled samples. Theoretical discussion, such as regret bound of the proposed method, will also be made here.

Second, we experimentally observe the performance of the proposed method by using synthetic toy data and practical image data. In the experiment with the image data, we employ two types of noisy-labeled samples; (typical) noisy-labeled samples and unnecessarily-labeled samples. In the former type, several samples from class A are wrongly labeled as class B and vice versa. In the latter type, several samples from
the non-target class are labeled as A or B. The main contributions of this paper are summarized as follows:

- We propose a novel method for learning from noisy samples. The proposed method is based on a regret minimization approach, called adaptive k-set prediction algorithm. To the authors’ best knowledge, this is the first attempt to show the effectiveness of the regret minimization approach on sample selection for noisy-labeled data.
- The performance of the proposed method is supported by theoretical guarantee in terms of regret for any data distribution and a black-box DNN.
- The proposed method has a large versatility because of its independence from machine learning framework to be trained. The proposed method, therefore, can be applicable to not only various DNN architectures but also any other machine learning framework.
- The experimental results show that the proposed method is effective for improving the training performance of DNN by reducing the adverse effect of noisy-labeled training samples.

II. RELATED WORK

A. Learning from noisy-labeled samples

There are a number of approaches for learning from noisy-labeled data. One of the typical approaches is label correction [3]–[9]. These approaches iteratively and gradually update the noise labels in various ways. As another example, [10] takes an approach of semi-supervised learning by considering identified noise samples as unlabeled data without label correcting. However, all of these approaches focus the samples with noisy-labels. Namely, these approaches have a strong assumption that the noisy-labeled data should belong to one of the target classes. However, our approach does not only focus on noisy-labeled data. For example, some training set main contain unnecessarily-labeled samples irrelevant to the target classes and such noise samples cannot be corrected.

Noise tolerant methods such as [11], [12] aim to raise up the robustness to noise samples. [13] is one of the state-of-the-art approach for noisy-labels which uses two DNN for training and exchange the training-loss information each other, and they empirically showed that the method allows us to select only clean samples. However, these approaches require side information such as noise rate.

To the best of our knowledge, the effectiveness of regret minimization approaches for noisy-labeled data have not been discussed in the literature.

B. Sample selection methods

There are general methods to select good training samples for faster training or noise avoiding [14]–[16]. These approaches attempt to evaluate the importance or influence of training samples for DNN’s parameter update. However, these approaches use some information inside the DNN such as loss information or gradient information. Therefore, while the theoretical guarantees for the performance of sampling are proposed in some literature, we do not sure that the algorithms and the theories can be applied for a DNN learning framework that one wants to use. By contrast, the proposed approach does not require any inside information of a DNN, that is, we can consider the DNN as a black box.

C. Adaptive k-set selection algorithm

Adaptive k-set selection problem is defined as a repeated game between a player and an environment as follows. At each stage $t$, (i) the player provides an $n$-dimensional k-hot vector $d_t$ (i.e., select $k$ elements out of $n$ elements). (ii) the environment returns feedback of $n$-dimensional vector $\ell_t \in [0, 1]^n$. (iii) the player incurs a loss $d_t \cdot \ell_t$. The goal of the player is to minimize the regret:

$$R_T = \sum_{t=1}^{T} d_t \cdot \ell_t - \min_{d \in D} \sum_{t=1}^{T} d \cdot \ell_t$$

where $D$ is all combinations of $n$-dimensional k-hot vectors (i.e., $D = \{d \in \{0, 1\}^n | \sum_{i=1}^{n} d_i = k\}$). Fig. 3 illustrates the definition of the regret. The decision space $D$ of the player contains combinatorially large sets. However, there are several algorithms efficiently work and achieve good upper bound [2], [4], [17], [18]. While the original adaptive k-set selection algorithm is proposed applying for online PCA [2], the extended researches [4], [17], [18] mainly focus on the theoretical analysis and does not show the applicability of real-world tasks.

In our application, the player is a sampling algorithm, and the environment is a DNN. At each epoch $t$, $d_t$ indicates selected samples and update the parameters of the DNN using the selected samples, and $\ell_t$ indicates the “noisiness” of the training samples.

III. OUR APPROACH

A. Basic settings

We consider solving classification problem by a deep neural network which can output the class-wise probability. Let $((x_1, y_1), \ldots, (x_n, y_n))$ be a set of training samples that possibly contains noisy samples. The goal is to obtain a classification model $f$ that achieves high classification accuracy for the set of test samples which does not contain noise samples.

B. Online sample selection framework

The main idea of our work is to consider the above problem as an adaptive k-set selection problem (see detailed settings in Section II-C). Fig. 4(a) illustrates the overview of FPL for selecting a subset of samples. Formally, our online sample selection framework is as follows:

1) At each epoch $t$, we select a promising subset $d_t$ (i.e., $k$ samples) from all possible subsets $D$.
2) Update DNN by learning the samples in the selected subset.
3) Estimate the noisiness of the whole training samples as $n$-dimensional vector $\ell_t \in [0, 1]^n$ by using the updated DNN.
Fig. 4: (a) The direct implementation of FPL for selecting subset of samples. (b) The adaptive k-set selection algorithm, which is totally equivalent to (a).

4) Decide the next subset of samples (i.e., $d_{t+1}$) by an adaptive k-set selection algorithm.

C. Designing noisiness loss functions

To design the loss $\ell$ is an important key of the performance of our algorithm because an adaptive k-set selection algorithm aims to minimize the cumulative loss. In this paper, we attempt to define the “noisiness” of a sample based on the classification behavior of DNN.

We consider the following losses:

- **loss1**: $\ell_{t,i} = \frac{1}{2} (\text{is}(f_i(x_i) = y_i) - p(f_i(x_i)))$

- **loss2**: $\ell_{t,i} = \frac{1}{2} (\text{is}(f_i(x_i) = y_i) (1 - p(f_i(x_i))))$

where $f_i(x_i)$ is the predicted label of $x_i$, $\text{is}(\cdot)$ is a function which returns +1 if $\cdot$ is true and returns -1 otherwise, $p$ denotes the probability (i.e., softmax output) for the predicted label $f_i(x_i)$.

The first noisiness loss (loss1) is designed to evaluate the following straightforward expectation: The samples that are correctly predicted with higher confidence should be cleaner (with a correct label), and the samples that are wrongly predicted with higher confidence should be noisier (i.e., with a wrong label).

By contrast, the second noisiness loss (loss2) is designed so that the samples near the classification boundary should be carefully selected. Roughly speaking, the loss2 gives its loss value in the following order: (correctly predicted with low confidence) < (correctly predicted with high confidence) < (wrongly predicted with low confidence) < (wrongly predicted with high confidence). This loss is motivated by that the noise samples around the classification boundary make an adverse effect for the generalization ability of DNN. In other words, it is expected that DNN itself could avoid the overfitting to noise samples far from the classification boundary.

Note that the FPL-based sample selection algorithm can utilize any noisiness loss functions. This is because it only requires to estimate the loss vector $\ell_t$ but not the underlying function. By this property, we do not need to consider any constraints (e.g., convexity) on designing the function. In Section V-A we will empirically validate the two loss functions defined above.

D. Algorithm implementation with FPL

As shown in Fig. 4 (a), FPL selects the leader (i.e., the optimal subset) by evaluating not only the cumulative loss $\sum_{t} \cdot \ell_{t}$ but also the perturbation $\cdot r_t$, where $r_t$ is a random vector $\mathcal{N}$. This perturbation term is effective to avoid overfitting to the past environment and thus have a tighter regret bound.

We show the pseudo-code of the proposed algorithm in Algorithm 1 when using loss2. The formal procedure of FPL is described as Eq. [5]. As can be seen from Algorithm 1, the proposed method can be easily implemented because it is completely isolated from the DNN architecture.

**Algorithm 1** The proposed sample selection framework (with loss2)

1: **Inputs:**

- $(x_1, y_1), \ldots, (x_n, y_n)$: training samples, $k$, $T$: the number of total epochs, $\sigma, \eta > 0$
2: **Outputs:**

- $f_T$: learned model
3: **Initialize:**

- Set $d_1$ as an $n$-dimensional $k$-hot vector
4: for epochs $t = 1, \ldots, T$ do
5: Obtain $f_t$ by using selected samples indicated by $d_t$
6: Estimate the noisiness of each sample $\ell_{1,t}, \ldots, \ell_{n,t}$ by

\[
\ell_{i,t} = \frac{1 - \text{is}(f_t(x_i) = y_i)(1 - p(f_t(x_i)))}{2} \quad (2)
\]

7: Select $r_t \in \mathbb{R}^n \sim \mathcal{N}(0, \sigma)$
8: Update $d_t$ by

\[
d_{t+1} = \arg \min_{d \in \mathcal{D}} \left( \sum_{t=1}^{T} d \cdot \ell_t + \frac{1}{\eta} d \cdot r_t \right) \quad (3)
\]
9: end for

E. The adaptive k-set selection algorithm

Both of Fig. 4 (a) and Eq. [5] are a direct implementation of FPL. From a practical viewpoint, this direct implementation has a serious problem. Specifically, the set $\mathcal{D}$ in them prevents an efficient computation of the entire algorithm because $|\mathcal{D}| = 2^n$. 
Fortunately, Fig. 4 (a) can be reduced to an equivalent but far more efficient algorithm called an adaptive k-set selection algorithm [4]. Its derivation is very simple: \( \frac{\sqrt{n}}{\eta} \cdot \sum_{\tau=1}^{T} d \cdot \ell_{\tau} + \frac{1}{\eta} \cdot \sum_{\tau=1}^{T} r_{\tau} \). So, if \( d \) has \( k \) 1-elements at the \( k \) minimum elements of the \( n \)-dimensional perturbed cumulative loss vector \( \sum_{\tau=1}^{T} \ell_{\tau} + \frac{1}{\eta} \cdot \sum_{\tau=1}^{T} r_{\tau} \), we can minimize (3). Note that this change only affects Step 8 of Algorithm 1.

IV. THEORETICAL BACKGROUND

A. Theoretical guarantee of the performance

One of the main advantages of the proposed method is that it is supported by a theoretical guarantee of the performance for adaptive k-set selection. As aforementioned in Section II-C, the goal of the adaptive k-set selection problem is to minimize the regret. The regret means the difference between the total loss of the selected k-sets and the most "clean" k-set which is resulted after \( T \) round games. That is, in our scenario, at each epoch, the proposed algorithm aims to select a k-subset of samples competitive with the cleanest k samples resulted after \( T \) epochs. Therefore, if we can define some reasonable loss function to estimate the noisiness of the training samples, the proposed algorithm achieves a high classification performance compared with a model avoiding noise samples.

As bellow, we introduce the theoretical regret bound of the presented FPL-based k-set selection algorithm.

**Theorem 1** ([4]). Let \( k \in \{1, \ldots, n\} \). By setting \( \eta = \frac{1}{\sqrt{kn}} \), the regret of the FPL-based k-set selection algorithm is upper bounded as follows:

\[
R_{T} \leq 2 \sqrt{2Tk \ln \left( \frac{n}{k} \right)}.
\]

Remarkably, the regret has only square root dependence with \( T \). Therefore, this theorem indicates that the selected samples by the proposed algorithm become close to the best k-set samples according to the number of iterated epochs.

Note that the setting of \( \eta = \frac{1}{\sqrt{kn}} \) is theoretically derived to guarantee the worst-case performance (this \( kT \) means the worst cumulative loss of the best k-set). Therefore, in practice, we need to set by controlling the variance \( \sigma \) of the perturbation.

B. Computational efficiency

The computation time of the k-set selection algorithm is upper bounded by \( O(n \log n) \). The major computational cost of the algorithm is to solve Eq. 3 in Algorithm 1. The solution is obtained by sorting the n elements of the perturbed cumulative loss vector \( \sum_{\tau=1}^{T} \ell_{\tau} + \frac{1}{\eta} \cdot \sum_{\tau=1}^{T} r_{\tau} \) and select the top-k elements. FPL-based algorithm has a strong advantage in the computational efficiency compared with the other k-set selection algorithms (e.g., [2], [17], [18] takes \( O(n^2) \)). In fact, it is said that the regret bound of FPL-based algorithm is basically worse than these algorithms. However, in this paper, we emphasize the advantage of the computational efficiency of FPL-based algorithm because \( n \) becomes heavily large for sufficient training of DNN.

V. EXPERIMENTAL RESULTS

In this section, we validate the effectiveness of the proposed method through the experimental demonstrations with several noisy datasets.

A. Toy example with single perceptron

The first experiment is designed to observe the following points:

- What is a good loss for evaluating the noisiness (i.e., probability of the sample has a wrong label) of the training samples?
- Is there a performance difference between the proposed algorithm and simple baselines?

According to these points, we prepare a binary-labeled two-dimensional synthetic dataset. Samples for each class is generated by a Gaussian distribution with the same variance. Its training set contains 1,000 samples and 20% of them have a wrong label (as shown in Fig. 5) and its test set contains correctly-labeled 1,000 samples. For simplicity, we use a perceptron (i.e., single-layer NN) in this experiment. As a simple baseline, we compare with the NN which uses whole training samples at each epoch. In addition, as an ablation study, we observe the performance of NN that uses a randomly-selected subset of samples at each epoch. For each algorithm, the mini-batch size is 1. SGD is used as the optimizer. We set the number of total epochs, \( T \), at 100, \( \eta = \frac{1}{\sqrt{n}} \) and \( \sigma = 1 \times 10^{-5} \). In this experiment, \( k \) is fixed at 0.6n. We compare our sample selection algorithms with the two loss functions, loss1 and loss2.

Fig. 6 shows the training result as learning curves for the training set and the test set. We can see that the learning curves of NN with random k-set sampling and NN with using whole training samples seem very unstable even after 80 epochs. Although their test accuracy scores at the last epoch are not largely different for this toy dataset, our method with both loss1 and loss2 seem to learn more stably than both baselines over epochs. Specifically, the proposed method with loss2 is more stable and achieve a higher test accuracy. By this result, we will employ loss2 in the following experiments.
B. Sample selection for noisy-labeled samples

In this section, we demonstrate the effectiveness of the proposed method for noisy-labels. We used CIFAR10 dataset that has 50,000 training images and 10,000 test images. The number of classes is 10, and each image size is 32 × 32 pixels. We applied symmetric noise [19] to the dataset. Specifically, for randomly chosen a certain percentage (20% or 50%) of training samples, we replaced the original label with one of the different labels (i.e., one of nine labels, in our case). Note that it is assumed that we do not know this noise rate in advance.

For mimicking a practical situation, we split the original training samples into the 45,000 (= n) training samples and the 5,000 validation samples to fix hyper-parameter k. Several validation samples, therefore, have wrong labels. By the validation for the five parameter value candidates \( k \in \{0.5, 0.6, \ldots, 0.9\} \times n \), the best \( k \) is determined and used for test.

To observe the difference of the behavior of the proposed method for different DNN architectures, we employ two popular DNN architectures, 18-layer ResNet (ResNet-18) [20] and MobileNet-v2 [21]. For each DNN architecture, we consider the model trained by whole training samples (i.e., without sample selection) as a baseline. We applied the proposed method to each architecture, respectively. We set the number of total epochs, \( T \), at 200, and \( \eta = \frac{1}{\sqrt{T}} \) and \( \sigma = 1 \times 10^{-5} \) as the previous experiment. For all methods, the learning rate is 0.1 until 100 epochs and then 0.01 until \( T \).

The learning curves for ResNet-18 trained with 20% noise are shown in Fig. 7. The training curves (Fig. 7a) show that the baseline completely overfitted to noise samples. The proposed method with \( k = 0.7n, 0.8n, 0.9n \) seems to overfit some samples with wrong labels. The validation curves (Fig. 7b) indicates that the best model for testing is \( k = 0.6n \), and it achieved the best test accuracy. Moreover, by observing the curve of the validation and test accuracy, the proposed method with \( k = 0.6n \) learned more stably than the others.

Fig. 8 illustrates the two examples of the number of selected times of each sample in \( T \) epochs during training ResNet-18 with 20% noise. We can see that in both case \( k = 0.6n \) and \( k = 0.5n \) the proposed method could avoid high percentage of wrongly-labeled samples and successfully help the training process of DNN to reduce the adverse effect by the wrongly-labeled samples.

The overall results of the testing accuracy scores are shown in Table 4. For each DNN architecture with 20% noisy training samples, the test accuracy of the proposed method is improved by about 3% compared to the baseline. Moreover, when 50% noisy training samples are used for training, the proposed method could show about 10% advantage the baseline. (Note again that each of these best \( k \) can be appropriately decided by the validation accuracy.) From those results, we can conclude that the proposed method, based on regret minimization approach, worked efficiently for different architectures and different noise rate.

C. Sample selection for the training samples with unnecessarily-labeled samples

In the last experiment, we consider the case that training samples contain unnecessarily-labeled samples, which are samples from non-target classes but “accidentally” contained in the training set with target class labels. The basic setting is the same as the previous experiment. We demonstrate the proposed method by CIFAR10 with 50% and 20% noise. For example, 50% noise means that the samples of the first 5 classes (i.e., class 1 to 5) are correctly-labeled data, and the samples of the last 5 classes (i.e., class 6 to 10) are unnecessarily-labeled as any one of class 1 to 5 at random. Therefore, that is a 5-class classification problem. We assume that the target classes are known but the ratio and any property of the unnecessarily-labeled data are unknown. For simplicity, we demonstrate the performance of the proposed method with only MobileNet-v2.

We illustrate the learning curves for 50% noise data in Fig. 9. The baseline completely overfitted to noise samples same as the previous experiments. From the validation accuracy, we could choose \( k = 0.6n \) and achieve the best test accuracy.
TABLE I: Average test accuracy of the last 10 epochs trained with noisy-labeled training samples.

| Architecture | Noise ratio | Whole samples | k = 0.5n | k = 0.6n | k = 0.7n | k = 0.8n | k = 0.9n |
|--------------|-------------|---------------|----------|----------|----------|----------|----------|
| ResNet18     | 20%         | 0.697         | 0.675    | **0.723**| 0.687    | 0.721    | 0.701    |
|              | 50%         | 0.407         | 0.498    | **0.500**| 0.429    | 0.423    | 0.402    |
| MovileNet-v2 | 20%         | 0.565         | 0.539    | 0.556    | 0.580    | **0.598**| 0.571    |
|              | 50%         | 0.323         | 0.359    | **0.425**| 0.364    | 0.380    | 0.366    |

TABLE II: Average test accuracy of the last 10 epochs trained with noisy training samples.

| Architecture | Noise ratio | whole samples | k = 0.5n | k = 0.6n | k = 0.7n | k = 0.8n | k = 0.9n |
|--------------|-------------|---------------|----------|----------|----------|----------|----------|
| MovileNet-v2 | 20%         | 0.641         | 0.538    | 0.594    | 0.653    | **0.663**| 0.658    |
|              | 50%         | 0.436         | 0.407    | **0.472**| 0.418    | 0.453    | 0.453    |

VI. DISCUSSION AND FUTURE WORK

A. For more performance improvement

Through the experiments, the designed loss2 works well for avoiding noise training samples. Future work will focus the theoretical proof for this empirical advantage of loss2 over loss1. Moreover, we will derive more effective loss based on the theoretical proof.

To improve the performance for noisy-labeled samples (i.e., the experiment in Section VI.B), combining with noise correction approaches as described in Section VI may be effective. Most noise correction approaches run some algorithm for identifying noise samples, and appropriately correct them. As shown in Fig. 8 the proposed method may is very suitable for this role.

B. Application to other learning tasks

The proposed method generally works without any assumption for data distribution and DNN architecture. However, in this paper, we consider only a classification task and thus the application filed is limited. DNN is broadly applied for various learning tasks, such as prediction, conversion, generation, compression, etc. Designing a good loss to evaluate a noisiness loss will be an interesting subsidiary topic for those individual task.

Faster training [15], [22] is another interesting application of our approach. The typical approach is to train only “important” training samples for parameter updating of DNN. To estimate the importance of training samples, most methods use some learning information depending on the optimizer. If we can design a loss to evaluate the importance of training samples, the proposed method can be applied for faster training with

We show the number of selected times of each sample in Fig. 10. We can see that the proposed algorithm could avoid more than the half of the noise samples.

Finally, we show the detailed accuracy scores in Table II. The first and most important observation of this result is that the proposed method could improve the performance of DNN also for unnecessarily-labeled dataset. This also shows the versatility of the proposed method. The second observation is that the improvement rates are smaller than the performance improvement in the previous experiment - a possible reason is that the baseline performance is not so degraded in this experiment more than the previous experiment.

This fact suggests that the unnecessarily-labeled samples less affect the generalization ability than noisy-labeled samples.
considering a DNN as a black box. Our regret minimization approach is suitable for the task requiring adaptivity.

VII. CONCLUSION

In this paper, we proposed a novel sample selection framework for learning noisy samples based on a regret minimization approach. We considered the sample selection as an adaptive k-set selection problem. The proposed method is theoretically supported to minimize the regret to select noise samples. Moreover, the proposed method can be easily implemented and does not require little additional computation cost. The experimental results show that the effectiveness of the proposed method for improving the performance of a black-box DNN when given noisy training samples.

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