Label Aggregation via Finding Consensus Between Models

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Abstract
Label aggregation is an efficient and low cost way to make large datasets for supervised learning. It takes the noisy labels provided by non-experts and infers the unknown true labels. In this paper, we propose a novel label aggregation algorithm which includes a label aggregation neural network. The learning task in this paper is unsupervised. In order to train the neural network, we try to design a suitable guiding model to define the loss function. The optimization goal of our algorithm is to find the consensus between the predictions of the neural network and the guiding model. This algorithm is easy to optimize using mini-batch stochastic optimization methods. Since the choices of the neural network and the guiding model are very flexible, our label aggregation algorithm is easy to extend. According to the algorithm framework, we design two novel models to aggregate noisy labels. Experimental results show that our models achieve better results than state-of-the-art label aggregation methods.

1 Introduction
Usually, supervised learning tasks require a large amount of labeled samples to train their models. Although several kinds of data sources, such as games and e-commerce platforms, can automatically label their samples with clear rules, there is still a large amount of data need to be manually labeled. However, requesting domain experts to label large datasets is very expensive and time-consuming. An alternative choice is to collect large amount of labels from non-experts.

Recently, there are many works \cite{17, 21} interested in using crowdsourcing to make datasets. Many online platforms, like Amazon Mechanical Turk\textsuperscript{1} and CrowdFlower\textsuperscript{2} provide crowdsourcing services. These platforms split the unlabeled large dataset into small parts and distribute them to a group of registered ordinary workers \cite{22}. Collecting labels from crowdsourcing platform is efficient and cheap, however the non-professional workers usually have low labeling accuracy.

To improve the accuracy, the usual practice is to assign each item to different workers, then aggregate the collected redundant labels into the predicted true labels.

Previous works have proposed many label aggregation methods to infer the true label from the observed noisy labels provided by crowds. The most straightforward way to predict the true label is majority voting. It considers each item independently and takes the most frequent class as the true label. This method does not take the reliability of each worker into consideration, and potentially assumes that all the workers are equally good. However, in actually workers have different degrees of reliability depending on their state of mind, expertise and motivation. A variety of advanced methods have been proposed to overcome this problem. These methods make some assumptions about the behavior of workers and design statistical models to generate the observed noisy labels. These assumptions are represented by model parameters and their relation. They reflect the reliability of workers. Whitehill et al. \cite{22} propose the Generative model of Labels, Abilities, and Difficulties (GLAD) for binary label aggregation. This model can simultaneously infer the true labels, the expertise of workers, and the difficulty of items. Dawid&Skene-EM \cite{2} is a label aggregation method based on Expectation Maximization (EM). Many recent works \cite{25, 26, 7, 14} extend this method and improve its performance. We will briefly introduce the existing label aggregation methods in Section\textsuperscript{2}.

In this paper, we propose a novel label aggregation algorithm which includes a neural network. The neural network is a probabilistic classifier. Given an instance, it can predict the unknown true label, where an instance contains the redundant noisy labels of an item. The challenge is that the corresponding true label of each instance is unknown, the neural network must be trained in an unsupervised way. We need to define a loss function (optimization goal) without any ground truth label. In order to solve this problem we set a guiding model. The training process of our algorithm is to find the consensus between the predictions of the neural network and the guiding model. The loss function is differentiable. Thus our algorithm can be trained using mini-batch stochastic optimization methods, such as SGD, Adam\textsuperscript{8} and RMSProp\textsuperscript{18}. The model parameters of the neural network and the guiding model are updated simultaneously.

Compared with existing label aggregation methods, our al-
algorithm is easy to extend, because there are few limitations in designing the neural network and the guiding model. There are many choices for the architecture of our neural network, e.g., MLP, CNN etc. The only limitation of the guiding model is that it should be differentiable. According to our algorithm, we propose two models, one is a binary label aggregation model based on some delicate assumptions about the behavior of workers, the other is designed to aggregate multiclass noisy labels. Our algorithm can be applied to online settings, because it can be trained using mini-batch stochastic optimization methods. However, in order to fairly compare with state-of-the-art methods, our experiments are conducted on fixed datasets. Experiments on four real-world datasets demonstrate that our models achieve superior performance over state-of-the-art methods.

2 Related Work

Dawid and Skene [2] proposed the conception of confusion matrix to describe the expertise and the bias of a worker. Based on the confusion matrix, they designed an EM algorithm for label aggregation. In the field of crowdsourcing, the confusion matrix is effective and well known. Raykar et al. [14] used noisy labels to train their classification model. Their two-coin model is a variation of the confusion matrix. BCC [7] is the probabilistic graphical model version of Dawid&Skene-EM. It also uses confusion matrix to evaluate workers, and uses Gibbs sampling to perform the parameter estimation. CommunityBCC [19] is an extension of BCC. It divides the workers into worker communities. The workers in the same community have similar confusion matrices. CommunityBCC has better performance than BCC on sparse datasets. BCCWords [15] also extends BCC. Recently Zhou et al. [25,26] proposed the minimax entropy estimator and its extensions. In these model, the authors set a separate probabilistic distribution for each worker-item pair. In most cases, minimax entropy and the extensions outperform Dawid&Skene-EM.

There are several other models for label aggregation. These models do not based on confusion matrix. GLAD [22] is a model that can infer the true labels, the expertise of workers, and the difficulty of items at the same time. It only can used for binary labeling tasks. Liu et al. [11] proposed a model which uses variational inference to approximate the posterior. Zhou and He [24] designed a label aggregation approach which is based on tensor augmentation and completion. Li et al. [12] proposed a general crowd targetting framework, it can target good workers for crowdsourcing.

DeepAgg [3] is a model based on a deep neural network. The model is trained by a seed dataset which contains noisy labels and the corresponding ground truth labels. So it is not an unsupervised approach. DeepAgg has several limitations. It cannot aggregate incomplete data, where many annotators only labeled a few items. Recently, Yin et al. [23] applied Variational Auto-Encoder (VAE) [3] to label aggregation. Their LAA model contains a classifier and a reconstructor. Both the classifier and the reconstructor are neural networks. LAA is an unsupervised model and works well in most case. We will use it as a baseline in our experiments.

3 Methods

3.1 Notation

Let’s start by introducing some notations that will be used throughout the paper. Consider that there are $N$ items labeled by $K$ workers, where each item has $C$ possible classes. $l_{ik} \in [C]$ denotes the label of item $i$ given by worker $k$, where $[C] := \{1, \ldots, C\}$. $I_i$ (instance $i$) denotes the redundant labels for item $i$. $L = \{l_1, \ldots, l_N\}$ is the collection of all the observed labels. Note that each worker may only label a part of the dataset. If item $i$ is not labeled by worker $k$, then the value of $l_{ik}$ is $-1$. $t_i \in [C]$ is the unknown true label of each item $i$. $T = \{t_1, \ldots, t_N\}$ is the collection of all the unknown true labels. For given values of $L$, the goal of label aggregation is to predict the values of $T$.

3.2 Algorithm Framework

In this section, we introduce our novel label aggregation algorithm. This algorithm includes two components: a neural network $g$ and a guiding model $\beta$. The choice of $q$ and $g$ is very flexible. $q$ can be a multilayer perceptron (MLP), a convolutional neural network (CNN), or any other neural networks. In order to apply stochastic optimization, the loss function should be differentiable respect to the model parameters in $g$. This is the only constraint of $g$. Our algorithm is easy to train using any stochastic optimization method.

Definition

In our algorithm, $q$ is a label aggregation neural network. Given an instance $l_i$, it can predict the corresponding unknown true label. $q$ is represented as a probability distribution $g_q(l_i | t)$, where $l_i$ is the input instance (the collected redundant labels for an item) and $\alpha$ denotes the network parameters (e.g., weights, biases, etc.). The network’s output is a C-dimensional vector $g_\alpha(t | c)_{i=1}^C$, the c-th element $g_\alpha(t = c | l)$ is the probability that the true label of the input instance is class $c$.

The noisy labels dataset $L = \{l_1, \ldots, l_N\}$ only contains the observed instances $l_i$, the corresponding true labels $t_i$ are unknown. Label aggregation is to predict these unknown true labels, so this is an unsupervised learning task. In order to train $g$, we define a model $g$ to guide the training. $g$ assumes that an instance $l_i$ is generated from some conditional distributions $g_\beta(l_i | t)$, where $t$ means the unknown true label and $\beta$ denotes the model parameters. It also assumes that the true label $t$ is generated from a prior distribution $g_\beta(t)$. The guiding model $g$ potentially defines a posterior distribution:

$$g_\beta(t | l) = \frac{g_\beta(l | t) g_\beta(t)}{g_\beta(l)}.$$  \hspace{1cm} (1)

We do not make any simplifying assumption about $g_\beta(l | t)$ and $g_\beta(t)$ except that the loss function is differentiable respect to $\beta$.

The optimization goal of this algorithm is to find the consensus between the predictions of $g$ and $q$. That means the neural network distribution $q_\alpha(l | t)$ should be as similar as possible to the posterior distribution $g_\beta(l | t)$. Thus it is reasonable to use Kullback-Leibler divergence, a widely-used
measure of the dissimilarity between two probability distributions, as the loss function:

$$KL(q_\alpha(T|L)||g_\beta(T|L))$$

(2)

where $KL(\cdot)$ is the Kullback-Leibler divergence. We minimize this loss function during the training process. This kind of optimization goal is commonly used in approximate inference and variational inference [1][20]. Thousands of published papers have shown that this optimization goal is effective. Actually, the data log likelihood can be bounded by

$$\log g_\beta(L) = ELBO(q_\alpha(T|L)) + KL(q_\alpha(T|L)||g_\beta(T|L)) \\
\geq ELBO(q_\alpha(T|L))$$

where $ELBO(q_\alpha(T|L)) = \sum_T q_\alpha(T|L) \log \frac{g_\beta(T|L)}{q_\alpha(T|L)}$ is the evidence lower bound (ELBO). Minimizing the KL divergence between $q_\alpha(T|L)$ and $g_\beta(T|L)$ is equivalent to maximizing the ELBO. Neural networks are good at fitting probability distributions. Thus, we can efficiently minimize $KL(q_\alpha(T|L)||g_\beta(T|L))$ and tightly bound the data log likelihood $\log g_\beta(L)$. That’s why our algorithm framework can work well.

We assume that each collected label is independently generated. The instances in $L$ are independent with each other. Plugging $q_\alpha(T|L) = \prod_i q_\alpha(t_i|l_i)$ and $g_\beta(T|L) = \prod_i g_\beta(t_i|l_i)$ into (2), we have:

$$KL(q_\alpha(T|L)||g_\beta(T|L)) = \sum_{i=1}^N -E_{q_\alpha(t_i|l_i)} \left[ \log \frac{g_\beta(t_i|l_i)}{q_\alpha(t_i|l_i)} \right]$$

$$= \sum_{i=1}^N KL(q_\alpha(t_i|l_i)||g_\beta(t_i|l_i))$$

(3)

Equation (3) cannot be directly used to train $q$ and $g$, because the expression of $g_\beta(t|l)$ is unknown. The exact expression of the posterior $g_\beta(t|l)$ may be intractable. Fortunately, it is not necessary to calculate it in our algorithm, we will further rewrite the loss function. Plugging into (3), we have

$$KL(q_\alpha(t_i|l_i)||g_\beta(t_i|l_i)) = -E_{q_\alpha(t_i|l_i)} \left[ \log \frac{g_\beta(t_i|l_i)}{q_\alpha(t_i|l_i)} \right]$$

$$= -E_{q_\alpha(t_i|l_i)} \left[ \log \frac{g_\beta(t_i|l_i)}{q_\alpha(t_i|l_i)} + \log g_\beta(t_i|l_i) \right] + \text{const}$$

$$= KL(q_\alpha(t_i|l_i)||g_\beta(t_i)) - E_{q_\alpha(t_i|l_i)} [\log g_\beta(t_i)] + \text{const}$$

(4)

According to (3) and (4) the loss function is rewritten as

$$F(\alpha, \beta; L) = \frac{1}{N} \sum_{i=1}^N \left\{ KL(q_\alpha(t_i|l_i)||g_\beta(t_i)) - E_{q_\alpha(t_i|l_i)} [\log g_\beta(t_i|l_i)] \right\}$$

(5)

where the constant is ignored and the loss function is rescaled by $1/N$. This will not affect the optimization result. The above is the definition of our label aggregation algorithm. The structure of the algorithm is shown in Figure 1.

**Training**

We are going to solve the following optimization problem

$$\hat{\alpha}, \hat{\beta} = \arg \min_{\alpha, \beta} F(\alpha, \beta; L).$$

The optimization can be performed by using stochastic optimization methods such as SGD, Adam [8] and RMSProp [18]. In our algorithm, we apply mini-batch training that is commonly used in deep learning. The neural network parameters $\alpha$ and the guiding model parameters $\beta$ are trained simultaneously. In mini-batch training,

$$F(\alpha, \beta; L) \approx F(M)(\alpha, \beta; L^{(M)}) = \frac{1}{M} \sum_{i=1}^M \left\{ KL(q_\alpha(t_i|l_i)||g_\beta(t_i)) - E_{q_\alpha(t_i|l_i)} [\log g_\beta(l_i|t_i)] \right\},$$

(6)

where $L^{(M)}$ is a mini-batch sampled from $L$, and $M$ denotes the minibatch size. The gradient of $F(M)(\alpha, \beta; L^{(M)})$ is required to update the model parameters. The unobserved variables $t_i$ are discrete variables that take values from 1 to $C$. Therefore, we have

$$KL(q_\alpha(t_i|l_i)||g_\beta(t_i)) = -\sum_{c=1}^C q_\alpha(c|l) \log \frac{g_\beta(c)}{q_\alpha(c|l)},$$

(7)

$$E_{q_\alpha(t_i|l_i)} [\log g_\beta(l_i|t_i)] = \sum_{c=1}^C q_\alpha(c|l) \log g_\beta(l_i|c),$$

(8)

where $q_\alpha(c|l)$ is the $c$-th element of the neural network output. According to (7) and (8), the values of $F(M)(\alpha, \beta; L^{(M)})$ and the corresponding stochastic gradient $\nabla_{\alpha, \beta} F(M)(\alpha, \beta; L^{(M)})$ can be easily computed. The advantage of using mini-batch training is that it allows our label aggregation algorithm to be used for large datasets and online setting.

**3.3 Label Aggregation Models**

In this section, we will introduce two novel label aggregation models based on the aforementioned algorithm framework. In each model, we need to define $q$ and $g$. 

![Figure 1: Label aggregation via finding consensus between models](image-url)
A Binary Model Based on Worker Ability Assumptions

We take the ability of each worker into consideration and propose a label aggregation model. This model is called NN-WA (NN means neural network and WA means worker ability). In NN-WA, \( q \) is a MLP. It inputs an instance \( l \) and outputs a distribution \( q_\alpha(l|t) \), where \( \alpha \) denotes the network parameters.

Next, we define a guiding model \( g \). As shown in \([7]\) and \([8]\), in order to compute the loss function and its gradient, we need to define \( g_\beta(l|t) \) and \( g_\alpha(l|t) \). In NN-WA, for simplicity, we only consider binary labeling tasks (the number of classes \( C = 2 \)). For each \( c \in \{1, 2\} \), the ability of each worker \( k \) is represented by a single parameter \( \lambda_{ck} \in (-\infty, +\infty) \). We assume that worker \( k \) labels each item \( i \) correctly with the probability

\[
\gamma_\beta(l_{ik} = c|t_i = c) = \frac{1}{1 + e^{-\lambda_{ck}}}, \tag{9}
\]

According to this assumption, we have:

\[
\begin{align*}
\lim_{\lambda_{ck} \to +\infty} g_\beta(l_{ik} = c|t_i = c) &= 1, \\
\lim_{\lambda_{ck} \to -\infty} g_\beta(l_{ik} = c|t_i = c) &= 0, \\
\lim_{\lambda_{ck} \to 0} g_\beta(l_{ik} = c|t_i = c) &= 0.5.
\end{align*}
\]

We can see that the higher the ability of worker \( k \) is, the higher the likelihood for him or her to label the item correctly. When \( \lambda_{ck} = 0 \), he or she just randomly chooses one class. Therefore our assumption is reasonable. According to (9), the conditional distributions that generated instances are defined as

\[
g_\beta(l_i|c) = \prod_{k \in S_i} \left( \frac{1}{1 + e^{-\lambda_{ck}}} \right)^{I(l_{ik} = c)} \frac{e^{-\lambda_{ck}}}{1 + e^{-\lambda_{ck}}} I(l_{ik} \neq c), \tag{10}
\]

where \( S_i \) is a set of workers who have labeled item \( i \). In this model, the prior distribution \( g_\beta(t) \) is fixed during the training process, it has no parameters to be trained. \( g_\beta(t) \) is a multinomial distribution and is estimated by

\[
g_\beta(t|c) = \frac{\sum_i \sum_k I(l_{ik} = c) I(l_{ik} \neq -1)}{\sum_i \sum_k I(l_{ik} \neq -1)}, c \in [C], \tag{11}
\]

where the values of the estimators can be calculated by the result of counting the observed labels. Since \( g_\beta(t) \) is fixed, we introduce a hyperparameter \( \mu \) to constrain the Kullback-Leibler divergence term in the loss function \([5]\). We regard this constrained term as a regularizer. Then, using (7) and (8) the mini-batch loss function used in practice is

\[
\mathcal{L}(M) = -\frac{1}{M} \sum_{i=1}^{M} \left\{ \mu \sum_{c=1}^{C} q_\alpha(c|l_i) \log \frac{g_\beta(c)}{q_\alpha(c|l_i)} + \sum_{c=1}^{C} q_\alpha(c|l_i) \log g_\beta(l_i|c) \right\}. \tag{12}
\]

NN-WA is formally shown in Algorithm 1.

**Algorithm 1** Training of NN-WA, where the model parameters \( \alpha = \{W_1, W_2, b_1, b_2\} \) and \( \beta = \{\lambda_{ck}\} \).

1: for number of training epochs do
2: for number of minibatches do
3: Sampling a minibatch of instances \( \{l_1, ..., l_M\} \).
4: for instance \( i = 1, ..., M \) do
5: \( h = W_2 \tanh(W_1 l_i + b_1) + b_2 \).
6: \( [q_\alpha(t = c|l_i)]_{c=1}^C = \text{softmax}(h) \).
7: for \( c = 1, ..., C \) do
8: Computing \( \log g_\beta(l_i|t = c) \) using (10).
9: end for
10: end for
11: RMSProp updates parameters \( \alpha \) and \( \beta \) using (12).
12: end for
13: end for

A Multiclass Label Aggregation Model

In this section we design a novel label aggregation model. This model can be applied to aggregate multiclass noisy labels. We call it as NN-MC (MC means multiclass). In NN-MC, \( q \) is also a MLP. It is a fully connected neural network with softmax activation function on the last layer.

Now we design a new guiding model \( g \) for NN-MC. Different from NN-WA, we do not delicately make some assumptions about the ability and the behavior of a worker. We design \( g \) from another perspective. Every element in an instance is a independent collected label, so we assumes that in \( g_\beta(l|t = c) \), the \( k \)-th element in an instance is generated by an independent distribution \( \psi_{ck} \). This distribution is defined as

\[
\psi_{ck} = \text{softmax}(\omega_{ck}), \tag{13}
\]

where \( \omega_{ck} \) is a \( C \)-dimensional vector. Then \( g_\beta(l|t = c) \) can be defined as

\[
g_\beta(l_i|t_i = c) = \prod_{k \in S_i} \psi_{ck,l_{i,ik}}, c \in [C], \tag{14}
\]

where \( \psi_{ck,l_{ik}} \) is the \( l_{ik} \)-th element of \( \psi_{ck} \). Since the softmax function is derivable, \( \omega_{ck} \) can be updated by stochastic optimization methods. Just like NN-WA, the prior \( g_\beta(t) \) in NN-MC is fixed and is estimated by (11). The loss function of this model is also defined as (12). NN-MC is illustrated in Algorithm 2.

4 Experiments

4.1 Baselines

We compare our models with Majority Voting and six state-of-the-art baseline methods: Dawid&Skeene-EM \([2]\), Minimax Entropy \([23]\), BCC \([7]\), GLAD \([22]\), MMCE \([26]\), and LAA \([23]\). Dawid&Skeene-EM is a classic generative model for label aggregation. Minimax Entropy is an extension of Dawid&Skeene-EM. This model assumes that the observed labels are generated by a distribution over workers, items, and labels. Bayesian Classifier Combination (BCC) is a Bayesian network using confusion matrix \([2]\). Generative model of Labels, Abilities and Difficulties (GLAD) is a binary label aggregation model. It can simultaneously infer the true labels, the expertise of workers, and the difficulty of items. Minimax
Algorithm 2 Training of NN-MC, where the model parameters $\alpha = \{W_1, W_2, b_1, b_2\}$ and $\beta = \{\omega_{ck}\}$.

1: for number of training epochs do
2: for number of minibatches do
3: Sampling a minibatch of instances $\{l_1, ..., l_M\}$. 
4: for $c = 1, ..., C$ do
5: for $k = 1, ..., K$ do
6: $\psi_{ck} = \text{softmax} (\omega_{ck})$. 
7: end for
8: end for
9: for instance $i = 1, ..., M$ do
10: $h = W_2 \tanh (W_1 l_i + b_1) + b_2$. 
11: $[q_\alpha(t = c | l_i)]_{c=1}^C = \text{softmax}(h)$. 
12: for $c = 1, ..., C$ do
13: $\log g_\beta(l_i | t = c) = \sum_{k \in S_i} \log \psi_{ck,l_i}$. 
14: end for
15: end for
16: RMSProp updates parameters $\alpha$ and $\beta$ using (12) 
17: end for
18: end for

Conditional Entropy Estimators (MMCE) uses an minimax entropy principle to aggregate noisy labels. Label-Aware Autoencoders (LAA) applies variational auto-encoders to label aggregation.

4.2 Datasets

We use four real-world datasets in our experiments. The detailed information of them is shown in Table 1.

Table 1: Datasets

| Dataset | Workers | Items | Labels | Classes |
|---------|---------|-------|--------|---------|
| Adult 13 | 17 | 263 | 1370 | 4 |
| RTE 16 | 164 | 800 | 8000 | 2 |
| Heart 12 | 1002 | 237 | 952 | 2 |
| Age 16 | 165 | 1002 | 10020 | 7 |

Adult 13 is a dataset labeled by Mechanical Turk workers to websites. The web pages are classified into four classes according to the amount of adult content on each web page. RTE 16 is a dataset about recognizing textual entailment. There are 164 workers assign 800 items into 2 classes. The average correct rate of the workers is 83.70%. Heart dataset is provided by 12 medical students. The students judge whether the patients have heart disease based on the physical examination results. These physical examination samples and the corresponding diagnostic results are downloaded from the UC Irvine machine learning repository 5. In order to use Age 4 in our experiments, its labels have been discretized into 7 bins: [0, 9], [10, 19], [20, 29], [30, 39], [40, 49], [50, 59], [60, 100].

4.3 True Label Prediction

After training NN-WA and NN-MC, we use maximum likelihood estimation (MLE) to predict the true label of each item. For NN-WA,

$$\hat{t}_i = \arg \max_{c \in [C]} \prod_{k \in S_i} \left( \frac{1}{1 + e^{-\lambda_{ck}}} \right) I(l_{ik} = c) \left( \frac{e^{-\lambda_{ck}}}{1 + e^{-\lambda_{ck}}} \right) I(l_{ik} \neq c).$$

For NN-MC,

$$\hat{t}_i = \arg \max_{c \in [C]} g_\beta(l_i | t = c) = \arg \max_{c \in [C]} \prod_{k \in S_i} \psi_{ck,t_i},$$

where the values of $\psi$ are computed by $\psi_{ck} = \text{softmax} (\omega_{ck})$. The prediction error rates are computed by comparing the predicted true labels with the ground truth labels. Note that the ground truth labels are only used for evaluation. We do not use them in the training stage.

4.4 Setups

The open source implementations of majority voting, Dawid & Skene EM, Minimax Entropy and MMCE are provided by Zhou [25, 26]. GLAD, LAA and our two label aggregation models are implemented using TensorFlow, which provides GPU acceleration.

We apply MLP as the label aggregation neural network and use the tangent hyperbolic function (tanh) [6] as the activation function. Softmax functions are used as the output of the networks. We use RMSprop [18] as the stochastic optimizer to minimize the loss. In our algorithm, the loss will finally converge to a stable value. As shown in Algorithm 1 and Algorithm 2, we implement MLPs with only 2 layers for NN-WA and NN-MC. Deeper neural networks are also easy to apply in our algorithm. However, limited by the data size, deeper neural networks do not improve the prediction accuracy. We use the likelihood $\prod_l g_\beta(l_i | t_i)$ as the criterion to select the hyperparameter. After training the model and predicting the true label, this likelihood is easy to compute. We test multiple values of $\mu$ and select the value that generates the maximal likelihood. In our experiments, $\mu \in [0.001, 2.0]$.

4.5 Error-Rates of Methods

The prediction error rates of our models and the baselines are illustrated in Table 2. Where GLAD and NN-WA only can aggregate binary noisy labels. The best results are highlighted in bold. NN-WA has the best performance on the Heart dataset. NN-MC outperforms the baselines across the Adult dataset, the Heart dataset and the Age dataset. On the RTE dataset, our models achieve the similar accuracy with GLAD. The results show that our label aggregation algorithm is effective. Our models are more accurate than the baseline methods.

4.6 Further Investigation

Effectiveness of Worker Ability Detection

After training NN-WA, for each class $c$, the ability $\lambda_{ck}$ of each worker $k$ can be detected. In order to evaluate the effectiveness of worker ability detection, we take parameters $\lambda_{ck}$ after training on the Heart dataset. However these parameters are not intuitive and not easy to understand. Therefore, for each class $c \in \{1, 2\}$, we further use equation (9) 

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to compute the predicted accuracy of each worker. The real accuracy of each worker is easy to compute by counting the collected noisy labels and the ground truth labels. Given class \( c \) and worker \( k \), the corresponding real accuracy is computed by

\[
\frac{\sum_i I(l_{ik} = c, gold_i = c)}{\sum_i I(l_{ik} \neq -1, gold_i = c)}
\]

where \( gold_i \) denotes the ground truth label of item \( i \). The results are illustrated in Figure 2. We can see that the prediction is consistent with the reality. In most case, the predicted accuracy and the real accuracy are quite similar which means NN-WA can effectively detect the ability of workers.

**Evaluation of the Trained Parameters in NN-MC**

The trained parameters \( \{\omega_{ck}\} \) in NN-MC can reflect the reliability of each worker. The values of \( \omega_{ck} \) are hard to understand. Given class \( c \) and worker \( k \), we further use equation (13) to compute the distribution \( \psi_{ck} \). Table 3 shows the results on the Adult dataset. Due to limited space, we only illustrate the results of two representative workers. We only care about the diagonal values and omit the other values for clarity. The labeling accuracy of each worker \( k \) is computed by

\[
\frac{\sum_i I(l_{ik} = gold_i)}{\sum_i I(l_{ik} \neq -1)}
\]

We can see that worker \( x \) has higher labeling accuracy, meanwhile, he or she has bigger diagonal values.

This is reasonable, according to the definition of \( \psi_{ck} \), a diagonal value \( \psi_{ck,c} \), \( c \in [C] \) is the probability that the collected label equals the true label and takes value \( c \). The results show that, by learning the model parameters, NN-MC can capture the knowledge of the reliability of workers.

**5 Conclusions**

We present a novel algorithm which aggregates noisy labels by finding consensus between a neural network and a guiding model. According to the algorithm framework, we design two label aggregation models called NN-WA and NN-MC. In our algorithm, there are very few limitations on the choices of the label aggregation neural network and the guiding model. Therefore, our algorithm is very flexible and easy to extend. The experimental results on four real-world datasets show that our models outperform state-of-the-art label aggregation methods.

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