Overcoming Labeling Ability for Latent Positives: Automatic Label Correction along Data Series

Azusa Sawada and Takashi Shibata
NEC Corpolation, Kanagawa, Japan

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Abstract: Although recent progress in machine learning has substantially improved the accuracy of pattern recognition and classification task, the performances of these learned models depend on the annotation quality. Therefore, in the real world, the accuracy of these models is limited by the labelling skills of the annotators. To tackle this problem, we propose a novel learning framework that can obtain an accurate model by finding latent positive samples that are often overlooked by non-skilled annotators. The key of the proposed method is to focus on the data series that is helpful to find the latent positive labels. The proposed method has two main interacting components: 1) a label correction part to seek positives along data series and 2) a model training part on modified labels. The experimental results on simulated data show that the proposed method can obtain the same performance as supervision by oracle label and outperforms the existing method in terms of area under the curve (AUC).

1 INTRODUCTION

In many applications such as anormaly detection for visual inspection and medical image analysis, automation or support systems need to be developed to reduce labor costs. To construct such systems, it is almost necessary to use machine learning methods, which have substantially improved the accuracy of pattern recognition and classification tasks. In particular, recent sophisticated models, e.g., deep convolutional neural networks (Krizhevsky et al., 2012), can achieve even better accuracy than humans.

In general, however, the performances of the models trained by such machine learning algorithms are still limited by label quality of training data because machine learning techniques usually optimize a model so that the model can infer assigned labels as long as possible. For example, if positive labels are assigned only to the absolutely positive samples (e.g., large tumor after critical phase), the obtained model using this training data recognizes only the large tumor. Therefore, the annotation process is absolutely critical for the performance of the machine learning application.

However, this annotation process usually requires much cost, because accurate labels can be annotated only by specialists for each application, e.g., a medical specialist for cancer detection. Therefore, a machine learning method is highly demanded that can obtain an accurate model from inaccurate labels annotated by non-specialists.

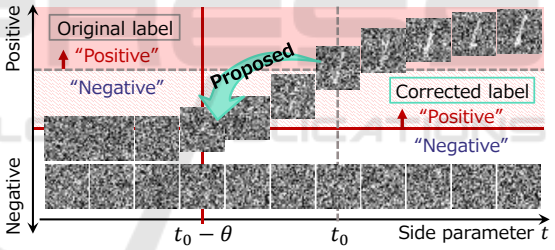

Figure 1: Concept of proposed method. Original labels are insensitive to positives and include some overlooking. Our method corrects labels in upper series to positive as long as there are discriminable differences from lower series images or those remaining negative in upper series.

To address this problem, we consider a way to train models to be as sensitive to positives as they can be without being limited by the insensitive annotation for training datasets. In this paper, we propose a novel framework to seek and learn latent positives missing in negative labeled data by utilizing external information indicating the relationship between data acquired as a series. The concept of the proposed method is shown in Fig. 1. Although original labels are insensitive to positives, our method corrects negative labels to positive ones for data in the upper series, which

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contains original positives, as long as there are discriminable differences from negatives. Our method has two main interacting components: 1) a label correction part to seek positives along data series, and 2) a model training part on modified labels. The former process gives modified labels to the latter one, and the latter process evaluates the separability of labels from the former one by the performance of the trained model.

Although various existing methods(Tanaka et al., 2018) to deal with incorrect labels have been proposed, these cannot find missing positives distributed around a class boundary because they try to correct labels in accordance with consistency in data distribution. Since most of them try to find outliers as mislabeled examples, it is difficult to correct consistent labels such as pseudo labels made by other models.

Contrary to existing approaches, our idea utilizes additional information that is effective to find missing positive data. Specifically, from the relationship between data acquisition conditions, we can guess positive candidates and certainly negative data. For example, in medical diagnosis, X-lay images are captured in the same region in the same patient on different days. If a large tumor is found in the image taken on the last day, a small tumor or sign of it may already exist in previous images. This is less likely to occur for much earlier data. In contrast, the areas labeled as negative in last-day images are certainly also negative in the past images. As a generalization of this situation, we consider data acquired as series that capture common objects under different parameters such as time, lightning conditions, and focus levels as shown in Figure 2. This side parameter and series ID are also to be registered with each data. The separability of positives from negatives increases as the side parameter changes in each series including positives.

The proposed method tries to optimize the model and label correction parameterized by side parameter range, so that it satisfies the requirements of good performance over all data and high sensitivity to latent positives. To the best of our knowledge, this is the first method that can automatically correct the labels using the property of the data series. The experiments on two synthesized datasets show that our method can achieve the same sensitivity as that by supervision by oracle labels from the synthesis model, despite poor given labels.

2 RELATED WORKS

There are many approaches to learn from dataset containing wrong labels, especially related to neural network models recently. These methods are roughly classified into two categories: 1) robust learning under label noise, and 2) label correction.

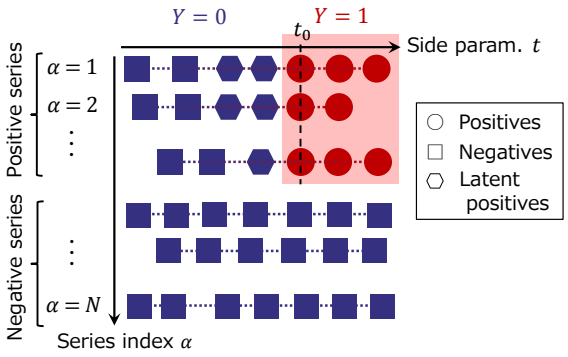


Figure 2: Illustration of data series. Positive series are series including positive data and negative series are series without any positives. Each data has two indices: series index and side parameter index within its series. We assume there are hidden positives near $t = t_0$, the side parameter value corresponding to the first positive in the series.

2.1 Robust Learning under Label Noise

One of the ways to deal with incorrect labels is to surpress the influence of them. Regularlization methods are effective to learn without overfitting to noise (Arpit et al., 2017; Jindal et al., 2016). The methods Backward and Forward in (Patrini et al., 2017) modify loss function to exclude the noise effect from optimization using an estimated label noise model by transition matrix. As similar modeling, linear layer to absorb noise effect is added on top of the network architecture in (Goldberger and Ben-Reuven, 2017; Sukhbaatar et al., 2015). There are also more explicit treatment of noise such as (Wang et al., 2018) detect outliers and assigns small weight to them. These methods will not suit our goal because they just cancel the noise effect without trying to learn missing positives as positive.

2.2 Label Correction

The other approach is to correct wrong label before or during training and use it as target label. They often require an extra dataset with ground truth of pre-identified noisy labels to construct label cleaning model (Veit et al., 2017; Xiao et al., 2015; Vahdat, 2017). In the case that all annotators are non-specialists, however, it is impossible to prepare such clean dataset.

Most of works that don't need small clean dataset use original labels partially. Bootstrap (Reed et al., 2015) replaces the target labels with a combination

of raw target and their predicted labels. D2L (Ma et al., 2018) uses local intrinsic dimensionality to decide when to start using predicted labels for training and increase the weight of prediction as learning epoch. Joint optimization (Tanaka et al., 2018) also learn only from noisy data but it completely replace labels by prediction learned with regularization term.

However, they cannot correct mistakes that are easy for models to fit. It is impossible to find samples to be corrected only by data distribution in the case of such consistent mistakes that all hard positives labeled as negative.

Therefore, we avoid the difficulty in justifying the label correction by utilizing a similarity not in feature space but in side information such as observing conditions. Note that Li et al. (2017) also utilized side information other than the dataset, but it is only used to regularize the learning of clean dataset to cope with its small amount (Li et al., 2017).

3 PROPOSED METHOD

The overview of the proposed framework is shown in Figure 3. As explained in Sec. 1, we assume that the training dataset consists of series with additional labels, side parameter t along each series. The dataset has data $\mathbf{X} = \{X_{\alpha i}\}$, label $\mathbf{Y} = \{Y_{\alpha i}\}$, and side parameter $\mathbf{t} = \{t_{\alpha i}\}$ with two indices α, i ($\alpha = 1, \cdots, N$. $i = 1, \cdots, M_\alpha$) to identify the series and the side parameter point, respectively. The proposed method has two main interacting components: 1) **label controller**: a label correction part to seek positives along data series, and 2) **classifier**: a model training part. The classifier is trained with labels modified by the label controller. The label controller recieves the training result from the classifier to justify current parameter. In this section, the label controller and its parameterization are explained in Sec. 3.1. After that, the concept of the optimization of label control parameter is presented in Sec. 3.2. Finally, the overall picture and optimization procedure of our method are described in Sec. 3.3.

3.1 Label Control along Series

We first explain the details of the label controller that can seek the latent positives along data series.

Missing positive data can be found in negatives from positive series, and this is more likely to happen if their side parameters are close to those of nearby positives as shown in Fig. 2. However, not all negative data in positive series are latent positives that have cognitive differences from other negatives.

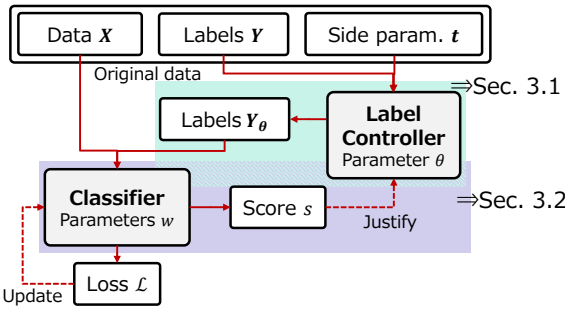


Figure 3: Pipeline of proposed learning framework.

Algorithm 1: Label correction function Q.

Input: $\mathbf{t} = \{t_{\alpha i} | \alpha = 1, \cdots, N.\ i = 1, \cdots, M_\alpha\}$
Input: $\mathbf{Y} = \{Y_{\alpha i} | \alpha = 1, \cdots, N.\ i = 1, \cdots, M_\alpha\}$
Input: θ //label flip threshold
Output: $\mathbf{Y}_\theta$ //controlled labels
  $\mathbf{Y}_\theta \leftarrow \mathbf{Y}$ //initialize output
  for $\alpha = 1$ to N **do**
    if $Y_{\alpha M_\alpha} = 1$ **then**
      $t_0 \leftarrow \min\{t_{\alpha i} | \forall i \text{ s.t. } Y_{\alpha i} = 1\}$
      for all i s.t. $t_{\alpha i} \geq t_0 - \theta$ **do**
        $(\mathbf{Y}_\theta)_{\alpha i} \leftarrow 1$ //overwrite labels as positive
      end for
    end if
  end for

Therefore, we parameterize the label controller by threshold θ corresponding to the threshold for the difference in t. We optimize the threshold θ to achieve proper correction through θ,

$$\mathbf{Y}_\theta = Q(\mathbf{Y}, \mathbf{t} | \theta), \tag{1}$$

where $Q(\cdot|\theta)$ is a label correction function that flips the labels of data in the positive series from negative (i.e., $Y = 0$) to positive (i.e., $Y = 1$) on the basis of the threshold θ as shown in Algorithm 1. Defining the reference point t_0 of the side parameter as the minimum in that of the positive data in each series, the label controller flips labels of negative data that have a side parameter t larger than $t_0 - \theta$ as shown in Fig. 1.

3.2 Threshold Justification for Label Control

Next, we explain how we can justify the threshold θ. We prefer large threshold θ to find more missing positives, but too large θ lead to label flip for absolute negatives. Our method searches for the reasonable θ by checking if θ is too large or not on the basis of the following idea. Let us denote the set of (X, Y) as $\mathcal{D}$ and that of (X, Y_θ) as $\mathcal{D}_\theta$.

When θ exceeds the limit where any positive cues completely disappear from the negatives in positive series, the class overlaps in $\mathcal{D}_\theta$ will increase. Therefore, the limit of reasonable θ enlargement can be detected by the separability of $\mathcal{D}_\theta$ such as Fisher's discriminant ratio, for example. Figure 4 illustrates the dependency of the separability on θ. When θ increases from left to right, negative data next to positives change their labels to positive. As we can see in the upper row, the data is linearly separable only for the smallest θ. Fisher's discriminant ratio, i.e. inter-class variance over inner-class variance, becomes smaller for larger θ because positive class take in data around nearly overlapping region.

On the other hand, the models to use may fit more complex boundaries than that selected by a given separability metric. We should choose θ that suits the model, so that it can perform well on $\mathcal{D}_\theta$ for assumed θ. Actually, model's performance itself reflects the separability of datasets besides the expressibity of the model. In this sense, we can use the performance measure as an adaptive separability score. [1]

In this paper, we use the area under curve (AUC) of the receiver operating characteristic (ROC) curve for the separability score s for $\mathcal{D}_\theta$. This is because AUC can fairly compare $\mathcal{D}_\theta$ among different θs, where class popularity changes.

The two rows in Fig. 4 show the comparison between two models with different expressivities. The separability score s starts to decrease when θ becomes too large for each model to fit the decision boundary. The highly expressive model in the bottom row keeps high s for larger θ than the upper poor model, but finally drops at the largest θ due to excessive label flip. The dependency of s to θ used for training can be found in Fig. 6, which is discussed in Sec. 4.1.2.

3.3 Overall Procedure

Finally, we describe the overall procedure of the proposed method in detail. The proposed method optimizes both classification performance and sensitivity to positives ignored in original labels. This can be expressed as the single minimization problem of classification risk R and the regularization term that enlarges the threshold θ. Let $f_w : \mathcal{X} \to \mathbb{R}$ denote the classifier model parameterized by $\mathbf{w}$,

$$[\hat{\theta}, \hat{\mathbf{w}}] = \underset{\theta, \mathbf{w}}{\operatorname{argmin}} \{R(f_{\mathbf{w}}; \mathcal{D}_\theta) - \beta\theta\}, \tag{2}$$

[1]Note that we should properly regularize the model or evaluate the separability metric on a validation set separated from training data, in the case of highly expressive models such as deep neural networks, which may fit any random labels (Zhang et al., 2017).

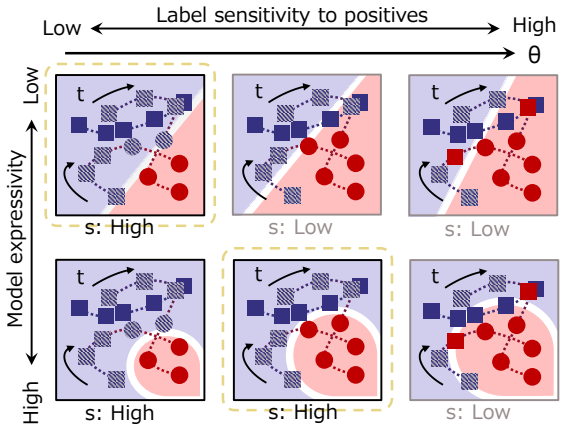


Figure 4: Examples of AUCs in each situation. Squares and circles are negative and positive(or latent positive) data, respectively, and color represents assigned label. Dotted lines link data along series. If the representative power of a model is weak, positives too difficult to classify should not be corrected (θ should not be too large). When the model is strong enough, the resulting AUC is always high. Thus, we prefer larger θ, which means higher sensitivity to positives.

where β is the hyper parameter to balance between classification risk R and the importance of sensitivity expressed by the threshold θ. In this paper, a simple linear form was employed as the regularization term. Our method is not limited to this form and we can select regularization term corresponding to the priority of accuracy or sensitivity. To obtain $\hat{\theta}$ and $\hat{\mathbf{w}}$, we employ an alternating optimization approach by splitting θ update and $\mathbf{w}$ update processes.

θ Updating Process: In the optimization of only θ, we compare risk R before and after a label control. Note that the minimization of the risk R corresponds to the maximization of the performance, which can be regarded as separability score s as described in Sec. 3.2. This optimization for θ is then expressed as follows:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \{R(f_{\hat{\mathbf{w}}}; \mathcal{D}_\theta) - \beta\theta\}, \tag{3}$$

$$\Rightarrow \underset{\theta}{\operatorname{argmax}} \{s(f_{\hat{\mathbf{w}}}, \mathcal{D}_\theta) + \beta\theta\}. \tag{4}$$

Since label correction is discontinuous, a simple implementation of this optimization is a grid search. Here, we assume that original labels are separable enough for the model to lead to satisfying performance. The separability s for the learned model will start to drop after θ exceeds the separable limit, when the label control threshold θ increases. In addition, when starting from small θ, the learning process can be seen as curriculum learning staarting from discrimination of only easier positives when we use neural network models and fine-tune them in each step.

Hence in the proposed method, we increase θ on the grid and stop if the evaluated risk becomes higher for temporally optimized $\mathbf{w}$. Then we tune the model again on the labels corrected by the best θ.

w Updating Process: On the other hand, if θ is fixed, the optimization of $\mathbf{w}$ is the standard supervised learning on corrected labels.

$$\hat{\mathbf{w}} = \underset{\mathbf{w}}{\operatorname{argmin}} R(f_{\mathbf{w}}; \mathcal{D}_{\hat{\theta}}). \quad (5)$$

The risk R can be altered by loss function $\mathcal{L}$ if you need to realize this optimization. In our experiment, we use the cross entropy loss with coefficients inversely proportional to class population ratio.

3.3.1 Implementation Details

We set the initial θ as 0, which corresponds to the original label, and increment it in accordance with a given grid. In each step, we evaluate the separability s on training data, which actually can be altered by a separated validation set to prevent overfitting, after training on the labels controlled with current θ. If the objective is smaller than that in the previous step, the previous value of θ is adopted as reasonable, and the threshold search is finished. As a result, the overall procedure of our method is shown in Algorithm 2. The parameter γ, which is slightly smaller than 1, is introduced to make the stopping condition robust to the probabilistic deviation in s.

Algorithm 2: Learning by proposed method.

Input: $\mathbf{X} = \{X_{\alpha i} | \alpha = 1, \cdots, N.\ i = 1, \cdots, M_\alpha\}$
Input: $\mathbf{t} = \{t_{\alpha i} | \alpha = 1, \cdots, N.\ i = 1, \cdots, M_\alpha\}$
Input: $\mathbf{Y} = \{Y_{\alpha i} | \alpha = 1, \cdots, N.\ i = 1, \cdots, M_\alpha\}$
Input: $\mathbf{w}$ // initial model parameters
Input: binary classifier $f_{\mathbf{w}} : \mathcal{X} \to \mathbb{R}$
Input: θ_{grid} //grid for θ search
Input: β, γ //hyperparameters for optimization
Output: f_w, θ //trained model, label correction range

```
F_before ← −1
initialize objective history
for θ in θ_grid do
    Y_θ ← Q(Y, t|θ)
    w ← TrainModel(f_w, X, Y_θ)
    s ← EvaluateAUC(f_w, X, Y_θ)
    if s + βθ < F_before then
        θ ← θ_before
        break
    else
        F_before ← max(γs + βθ, F_before)
        θ_before ← θ
    end if
end for
Y_θ ← Q(Y, t|θ)
w ← TrainModel(f_w, X, Y_θ)
```

4 EXPERIMENTS

To evaluate the performance of the proposed framework, we generated two types of synthetic datasets . In the first set in Sec. 4.1, we demonstrate the comprehensive results in simplified settings. The second in Sec. 4.2 is a dataset of rather realistic images to evaluate the effectiveness of our method and difficulty for a related work.

4.1 Demonstration on Simple Example

First, we generated point data in two-dimensional (2D) feature space as a simple example. We conducted demonstrative experiments with the dataset and Random Forest (Breiman, 2001), which is a commonly used classifier for pattern recognition tasks.

4.1.1 Synthetic 2-D Point Dataset

The synthetic data model was designed to simply represent our assumption for the dataset structure shown in Fig. 2. We denote the Gaussian distribution with mean μ and covariance matrix Σ by $\mathcal{N}(\cdot|\mu, \Sigma)$ and N-dimensional identity matrix by I_N here.

For all series α, the top data $X_{\alpha 0}$ among $\mathbf{X} = \{\mathbf{X}_{\alpha,\mathbf{i}}\}$ are sampled from the same distribution $p(X|t=0) = \mathcal{N}(X|\mathbf{0}, \sigma^2 I)$ which models the variation of captured objects. Subsequent data in negative series are basically the same. In contrast, in positive series, data start to shift and separate from negative data as a model function $\rho(t)$. Finally, we add noise ε to all data corresponding to observation noise modeled $p(\varepsilon) = \mathcal{N}(\varepsilon|\mathbf{0}, \sigma^2 I_2)$. Resulting data distributions for the negative and positive series are as follows:

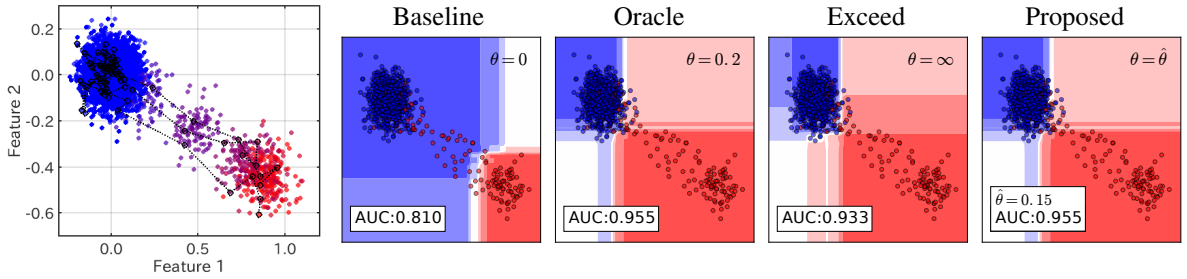
$$\text{Negative series}: \quad p(X|t) = \mathcal{N}(X|\mathbf{0}, 2\sigma^2 I_2), \quad (6)$$

$$\text{Positive series}: \quad p(X|t) = \mathcal{N}(X|\rho(t)\mathbf{v}, 2\sigma^2 I_2), \quad (7)$$

where $\rho(t)$ is the underlying positive appearance emerging from $t = \tau$, and shift direction $\mathbf{v}$ is $(2, -1)/\sqrt{5}$. Parameters are set as $\sigma = 5 \times 10^{-2}$ and $\tau = 0.7$. The generated dataset has 200 series with length 24 for $t = 0$ to 1, half of which are positive series. We keep 20 % of them as the test set. The whole dataset is plotted in Fig. 5(a).

4.1.2 Experiment using Random Forests

In this experiment, we applied our method to a Random Forest classifier (Breiman, 2001) on 2D point



(a) 2D point data (b) Decision surface by each method

Figure 5: (a)Synthesized 2D point data. Positive series were plotted in red if labeled positive and otherwise in intermediate color to indicate separation level. Three series are connected with dotted lines to indicate data structure. (b)Decision surface of each method on synthesized 2D data. Plotted data are only that in test set. Each plot shows one of results for each method.

Table 1: Test performance on 2D point data for each method. All results are averaged over 20 runs. "Acc." means the accuracy.

	Baseline	Oracle	Exceed	Proposed
AUC(%)	81.2(7)	**95.5(3)**	93.3(5)	**95.4(4)**
Acc.(%)	93.2(2)	**95.8(2)**	91(5)	**95.8(3)**

data described above. We compared our method with the following three baselines that are supervised learning using different labels: 1) Baseline: original labels, 2) Oracle: perfect labels made by the knowledge about data generation (upper limit), and 3) Exceed: labels where positive labels are extended over all data in positive series. Original labels was made on the assumption that annotators could find positives after $t \geq 0.9$. In this experiment, the number of trees is set to 8, and the depth of each tree is 3 at most. The optimization parameters are set to $\gamma = 0.99$ and $\beta = 1.0$. Here, each forest is trained 20 times by different random seeds for each method.

The results are summarized in Table 1. Figure 5(b) shows one of resulting decision boundaries. These results show our method has reached almost the same performance as the oracle case in terms of AUC, with the help of series information additional to baseline labels. Furthermore, our method was better than the exceed case, which also uses the series structure for label improvement, which means the threshold search on side information works well.

We also checked the separability score s and resulting performance for each θ value to assess our method. Figure 6 shows measured s on train data and AUC on test data, when trained on labels controlled with different thresholds θ. The evaluation of AUC values used oracle labels for test data, and controled labels for training data. We can see that AUC decreased around the true threshold corresponding to oracle labels for training data, and then our method finds that point. These results show that 1) the AUC is a suitable index for the separability score s in Sec. 3.1, and 2) the proposed procedure in Sec. 3.2 (and

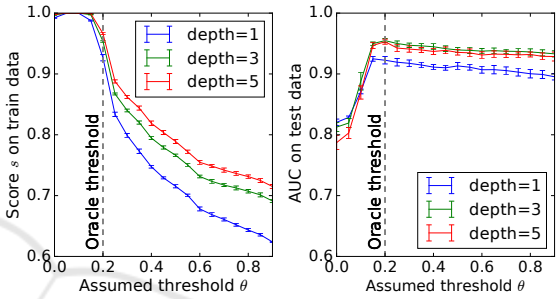


Figure 6: Separability score s and performance for Random Forests trained under label control by different thresholds θ. The parameter depth shown in legend refers to the maximum depth of trees in Random Forests.

Algorithm 2) can correct the label so that the recognition performance becomes high on the test set with labels assigned in the same criterion as the oracle case. Note that our synthetic data are not completely separable for oracle labels, which is why the AUC starts to drop at a larger threshold than the true one.

4.2 Demonstration on Realistic Dataset

For a more realistic example, we generated an image dataset using "1" data of the MNIST handwritten digit dataset to imitate scraches that should be detected in a surface inspection. Positive series are designed to represent images capturing scraches with increasing contrast as lightening condition changes.

4.2.1 Synthetic Scratch Images with Varying Contrast

All data in negative series share the same distribution. Each data in negative series is noise image I_{noise} generated from a simple Gaussian, which can be seen as clean surfaces. On the other hand, the data in positive series are made by overlaying "1" images J on I_{noise} with the fraction of J increasing along series for $t > \tau$. Resulting data distributions for the negative and

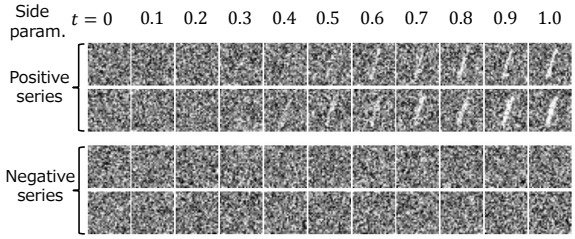


Figure 7: Synthetic image data made by overlaying MNIST "1" data to random noises. Upper two rows are negative series, and the rest are positive series. The side parameter increases from left to right and positive label is assigned to data with $t \geq 0.8$.

positive series are as follows:

$$\text{Negative series}: \quad X(t) = I_{noise}, \tag{8}$$

$$\text{Positive series}: \quad X(t) = I_{noise} + \rho(t) \cdot J, \tag{9}$$

where $\rho(t) = 0.5 \times \max(0, (t-\tau)(1-\tau))$, $0 \leq t \leq 1$ and $\tau = 0.2$ in this experiment. Figure 7 shows examples generated from this model. The train set and test set are made following the seed "1" images from the train set and test set of MNIST dataset.

4.2.2 Experiment using CNN

Next, we evaluated our method applied to a convolutional neural network (CNN) model on synthetic scrach images.

Comparison methods are the same as in the above experiment; 1) Baseline, 2) Oracle, and 3) Exceed. The model used here was a simple CNN with architecture in Table 2. All convolutional layers were set to pad=1 and stride=1 and with batch normalization before ReLU activation. The networks were trained by momentum SGD with minibatch size 40, learning rate 0.001, moment 0.9, and weight decay 0.0005. Optimization parameters of our method are set to $\gamma = 0.99$ and $\beta = 0.2$. For all methods, we ran training 20 times using different random seeds.

We evaluated the model trained by our method in terms of AUC on the test set. In this experiment, we tested AUCs at each point of a series to compare sensitivities to latent positives, using test data generated at a single fraction of J for positive series. In this evaluation, positive series data are all labeled as positive.

As shown in Fig. 8, our method shows high performance over a wider range than the baseline. Moreover, our method achieved almost the same performance as supervision by the oracle labels. In addition, we can see our method obtains slightly better results even than oracle in the separable region. This is due to the existence of overlap between class distributions, and the result by the exceed was affected by more overlaps.

Table 2: CNN architecture used in our experiment.

	layer type	description
in	image	1 channel
1	convolution	3×3, 16 channels
2	convolution	3×3, 16 channels
	pooling, dropout	2×2, drop ratio=0.2
3	convolution	3×3, 32 channels
4	convolution	3×3, 32 channels
	pooling, dropout	2×2, drop ratio=0.2
5	convolution	3×3, 64 channels
6	convolution	3×3, 64 channels
	pooling, dropout	2×2, drop ratio=0.2
7	fully connected	32 units
8	fully connected	2 units
out	softmax	

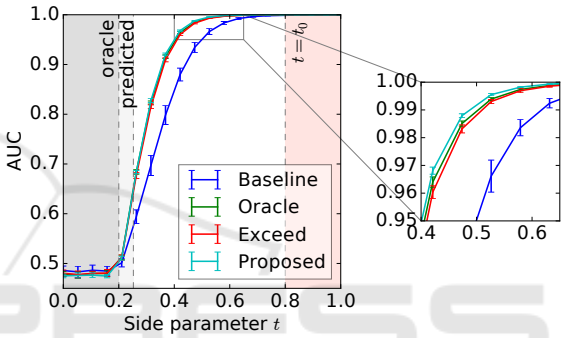


Figure 8: AUCs on test images for proposed and baseline methods.

4.2.3 Comparison with Existing Method

Finally, we compared the proposed method with the existing method (Tanaka et al., 2018) that can learn from incorrect labels, which does not use series information of the data. Figure 9 shows the existing method result applied to base CNN used here. The performance was better than the baseline case but not as good as ours. This is because the existing method modify labels not to find latent positives but to make decision boundary consistent. These results show that 1) the proposed method outperforms the existing method, and 2) the use of the series information is effective for label correction.

5 CONCLUSION

In this paper, we have proposed a learning framework to overcome the limitation of model performance by the annotating ability at preparing training data. The proposed method utilizes the relationship between data observing common objects and corrects

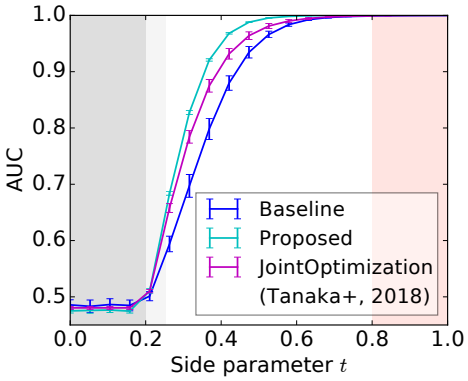


Figure 9: AUCs on test images compared with (Tanaka et al., 2018). The treatment as simple label noise failed to correct labels in the preferable way for our settings.

labels along such series. Experiments on synthesized datasets showed that our method achieved the same performance as supervision by oracle labels, which is the most sensitive to positive data, not limited by given annotation ability.

Our method enables us to get models that can find earlier anomalies than annotators by searching for discriminative cues back to the earlier phase. In addition, this can utilize poor labels made by simple processing such as thresholding or by other classifiers.

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