Impact of Noise in Boosting Methods

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***Abstract*—THIS IS THE abstract.**

I. Introduction

The fundamental idea of ensemble methods is to construct a combination of weak base classifiers that are diverse and result in a high accuracy. Multiple ensemble methods, including boosting[], bagging[], and decision tree ensemble[], are being introduced in the past 20 years. Boosting algorithms took a significant place in ensemble methods. Adaboost[1] and the recently introduced Deepboost[2] are typical boosting algorithms with a good experimental result without overfitting the training set. They both have good theoretical learning bound and benefit directly from minimizing the learning bound.

Boosting algorithms maintains a set of weights over the original training set S, and adjust these weights each iteration. They utilize the base classifiers and create a combination of these classifiers with a complex classifier that typically has a good performance. Boosting increases weight of samples that are mislabeled by the base classifier and decreases weight of samples that are correctly labeled during each iteration. Therefore, the algorithm will keep focus on the misclassified samples. As we shall discuss later, noise is typically distributed densely near the misclassified samples. Adaboost has been shown to be very effective in practical[3]. Since Adaboost is a special case of Deepboost by setting $\lambda = 0$ and $\beta = 0$, Deepboost will always out performs Adaboost. Therefore, both of these boosting algorithm will have a good performance in practical. However, the experimental robustness of these algorithms have not been tested before.

Our work is to test the robustness of boosting algorithms with experiments by introducing realistic noise into the training dataset. Finally, an explanation of the results is given based on the theoretical learning bound from both algorithms.

II. Realistic Noise

The impact of noise in the performance of an algorithm is regarded as the robustness. In Dietterich's work[4], multiple levels of noise are added to sample dataset to test the robustness of Adaboost. However, the noise introduced was by reverting labels in training data randomly without replacement with a fraction r. This makes the noise in the training dataset unrealistic. Many other publications have used different procedure to add noise into the training data The procedure is to set each training sample's label to a random class with probability r. Both of these procedures are adding noise with a uniform distribution over the entire training data.

However, in actual datasets noise are not distributed with a uniform fashion across the entire dataset. In Xingquan et al.'s work[5], a general method to eliminate noise from training data is introduced. In this algorithm, noise identification is based on the majority and non-objection schemes, which is founded on the assumptions that noise is distributed according to the distribution of empirical errors. The denser the classification errors, the denser the noise in training set. More generally, realistic noise distribution should not be uniform

over the entire training dataset, but with a relation to the classification error.

Following the definition of Adaboost, the distribution $D_t(i)$ updated during each iteration of Adaboost is a perfect simulation of the training error distribution after round t. Since $D_t(i)$ is updated with according to the loss function, the distribution would be updated with a higher level where empirical errors are denser. Therefore, the distribution from Adaboost after T rounds(finished) would be suitable for introducing realistic noise.

III. Methods

We tested Adaboost and Deepboost on the UCI dataset, ionosphere[6]. We randomly split the data to two parts; 80% for the training data and 20% for testing.

A. Adaboost

B. Deepboost

Following the work from Cortes et al. [2], we use the H_1^{stumps} as the base classifier for Deepboost. The Rademacher complexity of H_1^{stumps} can be bounded by its growth function. It is trivial to see that

$$\Pi_{H_1^{stumps}}(m) \leq 2md,$$

since there are $2m$ distinct threshold functions for each dimension with m points. Therefore,

$$\mathfrak{R}_m(H_1^{stumps}) \leq \sqrt{\frac{2\log(2md)}{m}}.$$

By now, we have the notation from Deepboost

$$\Lambda_j = \lambda \cdot \mathfrak{R}_m(H_1^{stumps}) + \beta.$$

where we conducted experiments for $\lambda \in \{10^{-i} : i = 3, \cdots, 7\}$ and $\beta \in \{10^{-i} : i = 3, \cdots, 7\}$ as well, and optimize the training error on these experiments.

We optimize the parameter by minimizing the 10-fold cross validation, and then measure the error by testing data.

In all of our experiments, the number of iterations was set to 50. We also test the result for 100 rounds, but the test error remains basically the same. As we shall see, in some experiments the training error decreases vastly and reaches to zero after 40 iterations.

IV. Results

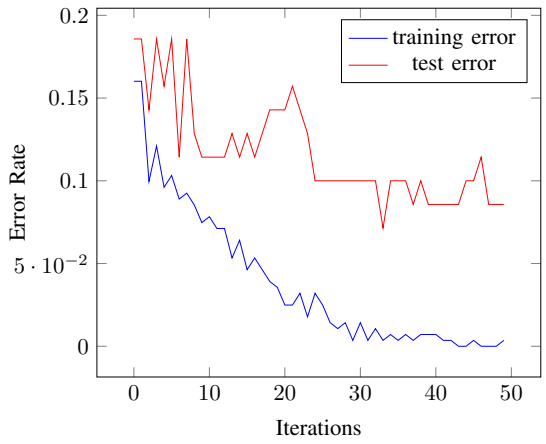

Fig. 1. Adaboost running on Ionosphere.

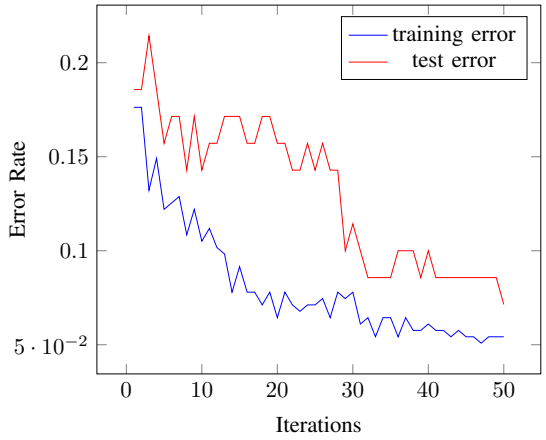

Fig. 2. Adaboost running on Ionosphere.

Observe that

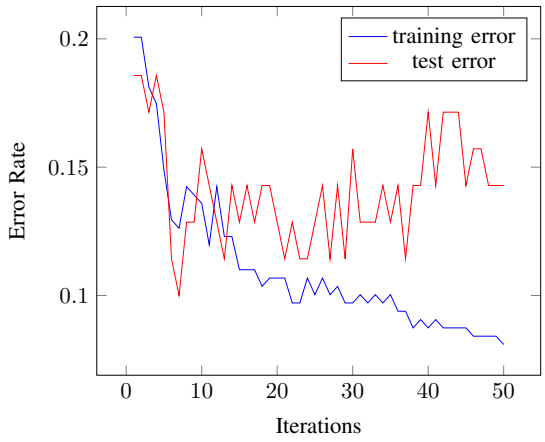

Fig. 3. Adaboost running on Ionosphere.

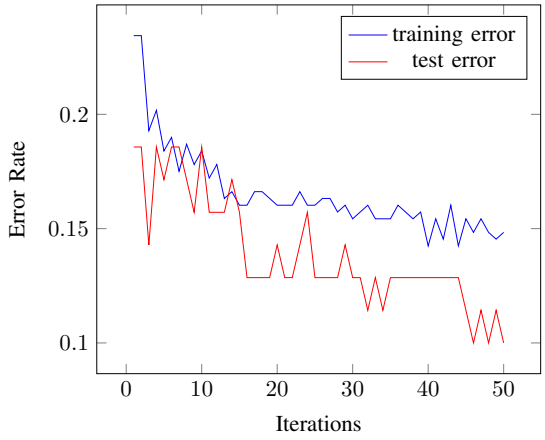

Fig. 4. Adaboost running on Ionosphere.

V. Conclusion

VI. Acknowledgments

References

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