

Impact of Noise in Boosting Methods

Qi Feng, Xiaonan Zhao

Abstract—THIS IS THE abstract.

densely near the misclassified samples. Adaboost has been shown to be very effective in practical (Quinlan, 1996). 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.

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[3] and the recently introduced Deepboost[5] 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

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[2], 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

IV. RESULTS

V. CONCLUSION

VI. ACKNOWLEDGMENTS

REFERENCES

- [1] M. Mohri, A. Rostamizadeh, and A. Talwalkar, *Foundations of machine learning*. MIT press, 2012.
- [2] X. Zhu, X. Wu, and Q. Chen, "Eliminating class noise in large datasets," in *ICML*, vol. 3, 2003, pp. 920–927.
- [3] Y. Freund and R. E. Schapire, "A decision-theoretic generalization of on-line learning and an application to boosting," *Journal of computer and system sciences*, vol. 55, no. 1, pp. 119–139, 1997.
- [4] T. G. Dietterich, "An experimental comparison of three methods for constructing ensembles of decision trees: Bagging, boosting, and randomization," *Machine learning*, vol. 40, no. 2, pp. 139–157, 2000.
- [5] C. Cortes, M. Mohri, and U. Syed, "Deep boosting," in *Proceedings of the 31st International Conference on Machine Learning (ICML-14)*, 2014, pp. 1179–1187.