MALIS Project3 Report: Multi-Class AdaBoost

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1. Introduction

The primary objective of this project is to extend the digit classification problem from Project2 by implementing a multi-class AdaBoost model using perceptrons as weak learners. The goal is to demonstrate how the AdaBoost algorithm extends to handle multi-class classification using the SAMME (Stagewise Additive Modeling using a Multi-class Exponential loss function) algorithm.

2. Understanding Multi-Class AdaBoost

AdaBoost is a machine learning ensemble method that combines multiple weak classifiers to form a strong classifier. While the traditional AdaBoost algorithm is designed for binary classification, the SAMME extension generalizes it to multi-class problems, requiring the addition of a factor $\log(\text{num\_class} - 1)$ in the computation of the weak learner's contribution.
The algorithm works by iteratively training weak learners, calculating their errors on the training data, and updating the weights assigned to each data point. Misclassified points are assigned higher weights, ensuring that subsequent chosen learners are the ones performing good at difficult examples. This process helps create a collection of learners that complement each other by addressing different areas of the training space.
Furthermore, each learner is associated with a coefficient, which is higher for learners with lower error. The final model is a weighted linear combination of the weak learners.

3. Model Architecture and Implementation

To use the perceptron as a weak learner, we extended our previous implementation to a multiclass perceptron. We created a function, `train_weak_learners`, which generates a specified number of weak learners and trains them for a given number of epochs. To introduce variability among the learners, we used a variable learning rate centered around a specified value α, and we made sure that each learner was trained on a shuffled version of the data.

Once the learners are ready, we create an AdaBoost model, train it, and validate its performance on the validation data. This process is repeated for several models, each with an increasing number of learners, to analyze the effect of boosting.

Finally, the model with the highest validation accuracy is selected as the best model, and its performance is evaluated on the test set.

4. Results and Analysis

Initially, we encountered a problem in achieving low accuracy for individual perceptrons when using a low number of epochs alone. To address this issue, we significantly reduced the training size, which solved the problem. However, the performance of the boosting model remained suboptimal, even with a high number of learners. To improve performance, we separated the training data for individual perceptrons from the data used for boosting, ensuring that more data was allocated for the boosting process. This adjustment led to a notable improvement in the performance of the model.

We observed that when the individual accuracy of the perceptrons was high, the best models were those with a small number of learners. In contrast, when the accuracy of the perceptrons was lower, the best models were those with a higher number of learners. By carefully tuning the number of learners and the training size, we were able to boost the performance of perceptrons with accuracy around 60% to a final accuracy of approximately 90%.

5. Conclusion

This project demonstrated the importance of diversity among weak learners for boosting performance. Sufficient training data allocation is critical, and the effect of boosting is most notable when learner accuracy is between 50% and 70%. Additionally, smaller datasets require fewer perceptrons to build the best model, highlighting the need to tailor the ensemble size to the data.

Tonia was in charge of `MultiClassPerceptron` and `training_weak_learner`
Tarek was in charge of `SAMME`
The main function and the overall strategy were made by both of us.
Chatgpt was used in the project, particularly in transforming high-level ideas into code, and in the making of the report.