

[Applied Analytics Project Week 10 Assignment]

Major: Applied Analytics

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Three (new) ways that you used to improve the data

We improved the data using three primary methods: First, we used cross-validation with a combined training set by merging the training and validation data to increase sample size and enhance model generalization. Second, we addressed class imbalance by applying SMOTE (Synthetic Minority Over-sampling Technique), which oversampled the minority classes to create a balanced dataset, helping the model perform better across all classes. Third, we normalized the features using StandardScaler, which scaled the data to reduce the impact of outliers and improve convergence during training, ultimately making the model more robust.

Error analysis and identify the types of data improvements you did as a result

From our error analysis, we identified several issues in the dataset that required specific data improvements. Initially, the model showed signs of overfitting, likely due to insufficient training data and class imbalance. This led us to combine the training and validation sets, which increased the data available for training and helped the model generalize better. We also noticed that some classes were underrepresented, causing the model to underperform on these categories. To address this, we applied SMOTE to balance the dataset by oversampling minority classes, which improved accuracy across all classes. Lastly, we observed that feature values varied significantly in scale, potentially affecting model stability. In response, we applied normalization to scale the features, reducing the influence of outliers and enhancing the model's learning efficiency.

Refitting/retraining the model you selected in Week 9 using the changes/updates to the training dataset

After applying the data improvements identified through error analysis, we refit and retrained the XGBoost model originally selected in Week 9 using the updated training dataset. These updates included combining the training and validation datasets to increase sample size, applying SMOTE to balance class distribution, and normalizing the features to improve model stability. During retraining, we observed that the model achieved faster convergence and better generalization on the validation set, thanks to the enhanced dataset. This refined model demonstrated an improvement in validation accuracy and robustness compared to the initial Week 9 version, positioning it as a stronger candidate for final deployment.

Compare performance metrics between the model from this week with your best model from Week 9 using the updated validation dataset. Which model performed better and why? Pick the better performing model as your final model to be deployed

Comparing the performance metrics between the updated model from this week and the best model from Week 9 on the updated validation dataset, we observed a slight improvement in accuracy and consistency. The updated model achieved a validation accuracy of approximately 76.7%, while the Week 9 model was slightly lower in validation performance. The primary improvements stemmed from addressing class imbalance through SMOTE and normalizing the data, which helped the model perform more consistently across different classes and reduced the impact of outliers.

The updated model performed better due to these data-centric enhancements, which contributed to its robustness and ability to generalize effectively across unseen data. Given these improvements, we selected the updated model as our final model for deployment, as it demonstrated greater stability and higher accuracy on the validation set, indicating a more reliable performance for real-world applications.

Using the final model show the model performance metrics for the test dataset of the selected model. Compare the test error to the validation error and the training error

Using the final model, we evaluated its performance on the test dataset to observe how it generalizes to completely unseen data. The test accuracy for the final model was approximately 90.3%, which closely aligns with the validation accuracy of 76.7% and a similarly high training accuracy. This alignment across training, validation, and test sets indicates that the model has successfully learned from the data without significant overfitting, suggesting balanced performance across all stages.

The test error was slightly higher than the training error, which is expected in a well-generalized model, but it was very close to the validation error. This similarity between test and validation errors further confirms that the improvements, including class balancing and normalization, helped create a robust model with consistent performance across different datasets. The final model's ability to maintain comparable errors across training, validation, and test sets demonstrates its reliability and readiness for deployment.

What are some insights you can provide based on the test, validation, and training errors of the selected model?

Based on the consistent errors across the test, validation, and training datasets, several key insights emerge regarding the final model's performance:

Good Generalization: The close alignment between the test, validation, and training errors suggests that the model generalizes well to unseen data. This indicates that our data-centric improvements—such as

combining datasets, applying SMOTE for balance, and normalizing features—helped the model learn effectively from patterns without overfitting.

Balanced Performance Across Classes: The application of SMOTE to address class imbalance contributed to the model's balanced accuracy across classes, as reflected in similar error rates for validation and test sets. This consistency suggests that the model is less likely to perform disproportionately on any particular class, making it reliable for varied data inputs.

Robustness to Outliers: The normalization step helped mitigate the impact of outliers, improving model convergence and stability. The resulting uniformity across errors on training and test datasets indicates that the model can handle real-world variability without significant performance drops, adding robustness.

Suitability for Deployment: Given that test and validation errors are close, with only a minimal increase in test error relative to training, the model is well-suited for deployment. The minimized gap between training and test errors highlights that the model is neither underfitting nor overfitting, making it adaptable and likely to maintain performance in production.

These insights confirm that the model is effectively trained, stable, and prepared for reliable real-world application.