MSAI 349
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Northwestern Football Analytics Detailed Write-up

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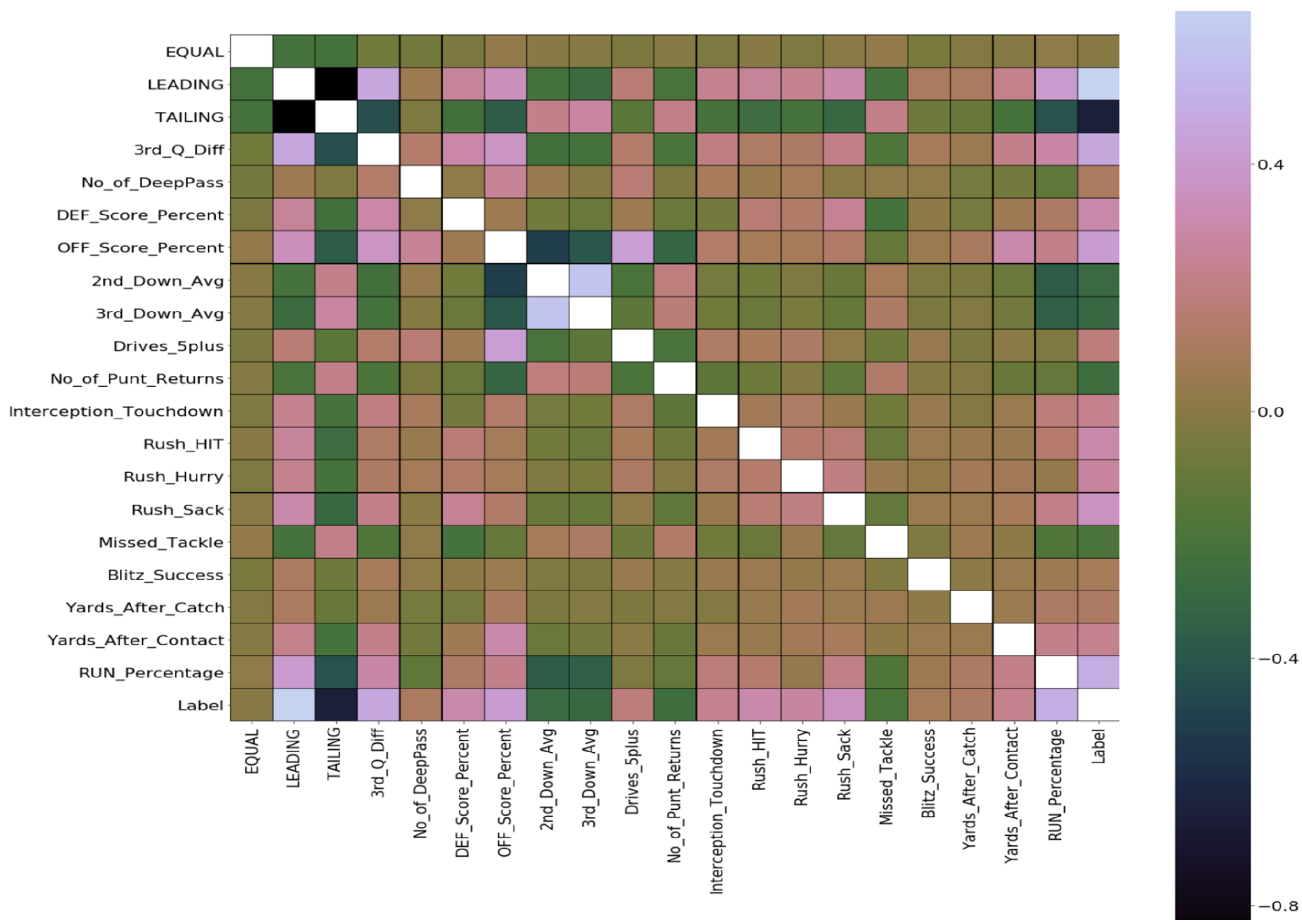
DATA

The data we sourced from profootballfocus.com was already pretty clean, but since it was at the play-level, significant effort went into aggregating the play-level data into game-level features from the available columns. There are also a lot of columns and possible methods of aggregating (# of instances, sum, average, difference, etc.), so we started with a handful of stats Northwestern Football curated for us, and excluded player-level stats and other columns that were exceedingly detailed such as 'time to snap', 'special teams', 'stunts', 'stops', etc.

We processed a total of 519 BIG10 game files into one file with 1038 rows (one row per team) and started with 20 features. We visualized the correlations between the features by using a heatmap:

Figure 1: Feature Correlation Heatmap where lighter colors have a higher correlation



From Figure 1, we dropped features 'Equal', 'no_of_DeepPass', and 'Yards_After_Catch' due to low correlation values.

Table 1: Final Feature List

Feature Name	Description
Leading	if team is leading at halftime
Tailing	if team is tailing at halftime
3rd_Q_Diff	score differential at halftime
Def_Score_Percent	percentage of successful defensive plays
Off_Score_Percent	percentage of successful offensive plays
2nd_Down_Avg	average number of yards left to cover at 2nd downs
3rd_Down_Avg	average number of yards left to cover at 3rd downs
Drives_5plus	number of offensive drives that had more than 4 consecutive plays
No_of_Punt_Returns	number of punt returns
Interception_Touchdown	number of interceptions that resulted in touchdowns
Rush_HIT	number of defensive plays that resulted in a hit on the QB
Rush_Hurry	number of defensive plays that resulted in the QB having to 'hurry'
Rush_Sack	number of defensive plays that resulted in a sack on the QB
Missed_Tackle	count of missed tackles
Blitz_Success	percentage of blitz that were successful
Yards_After_Contact	average yards gained by ballcarrier after first contact
Run_Percentage	percentage of offensive plays that were run instead of thrown

PREDICITVE MODELS

Because our end goal was to be able to determine which features are the most important for victory, we could not use any black-box models. We also want to provide thresholds for the continuous features that change the outcome of the game. Given these constraints, we started with the following models: ZeroR, Decision Tree, Random Forest, Logistic Regression Classifier, Support Vector Classifier, K-Nearest Neighbor, and Gradient Boosting Classifier. We intentionally excluded Naive Bayes Classifier because a lot of these features are dependent on each other, which is a failure-mode of NBC.

For all models, we used a 80:20 training:testing split on the data and 5-fold cross-validation was used for training accuracies.

RESULTS

We used the scikit-learn package for our models, and obtained the following training accuracies prior to hyperparameter tuning (using defaults):

Table 2: Initial Model Accuracies

Model	Initial Train Accuracy (%)
ZeroR	50.13
Decision Tree	78.0
Random Forest	84.0
Logistic Regression	77.0
Support Vector Classifier	76.0
K-Nearest Neighbor	77.0
Gradient Boosting Classifier	85.0

Table 3: Predictive Model Results

Model	Train Accuracy	Test Accuracy
ZeroR	50.13	49.76
Decision Tree	80.34	82.94
Random Forest	**85.90**	**85.71**
Logistic Regression	85.43	83.87
Support Vector Classifier	84.73	84.33
K-Nearest Neighbor	76.86	74.65
Gradient Boosting Classifier	85.55	82.49

To tune the models, we used the GridSearchCV method that helped iterate through many hyperparameter combinations at once. We found that Random Forest and Gradient Boosting classifiers provided the best training and test accuracies of approximately 85%. The results of all of the models we tried included:

ANALYTICS

As expected, the Random Forest model out-performed the Decision Tree model as it is an ensemble method of decision trees. The K-Nearest Neighbor accuracy lacked quite a bit in accuracy in the training set, and we attribute that to not having enough data to compensate for the curse of dimensionality of having 17 features.

On top of just looking at training and test accuracies, an additional way we evaluated the models included the Receiver Operating Characteristic (ROC) metric that shows the true positive rate across the false positive rate. With a higher area under the curve meaning there is higher sensitivity and specificity, we can conclude that Random Forest is the best model based off of this metric.

Figure 2: ROC Plot of all models, we extracted the importance of each feature from the Random Forest model in order of importance:

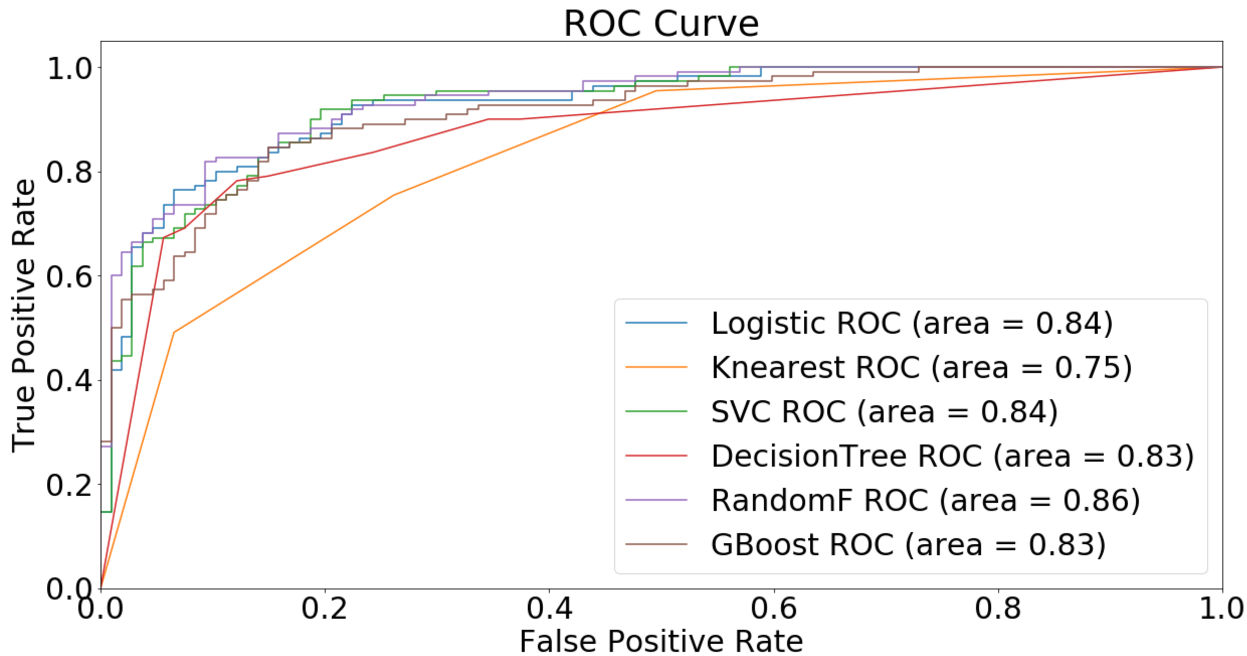
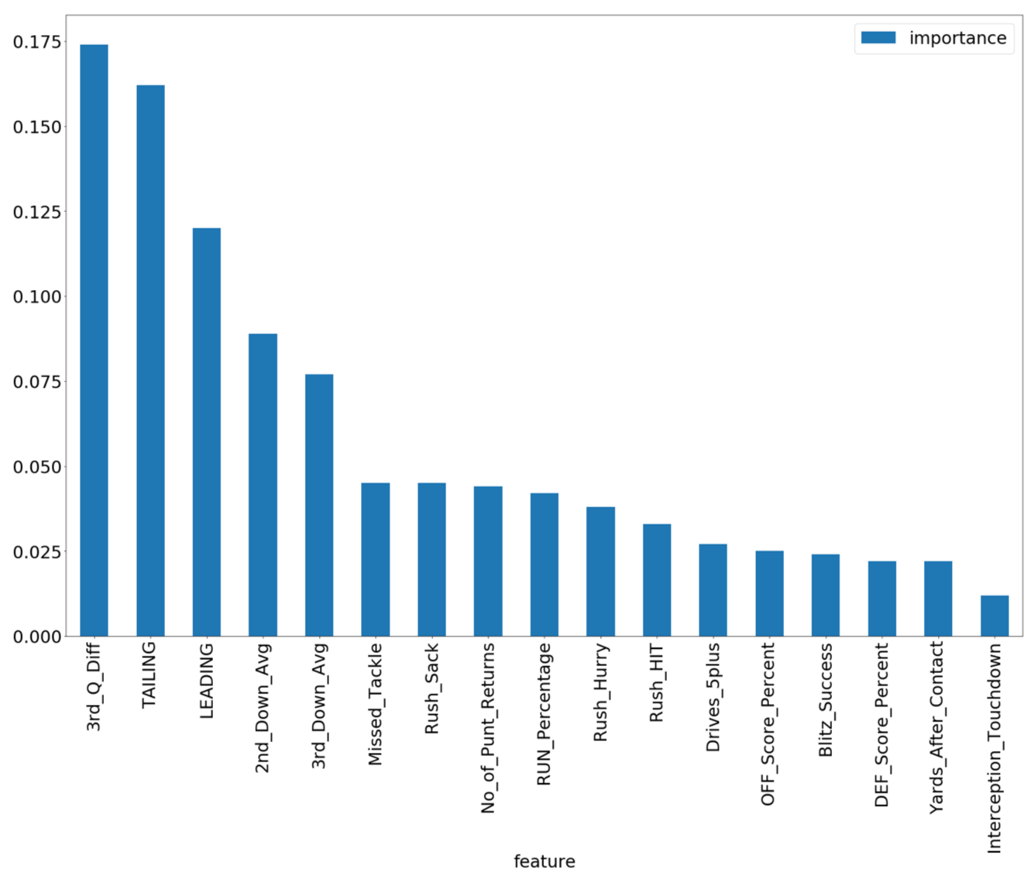


Figure 3: Importance of each Random Forest Feature



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Conclusion & Future Plans

We were satisfied with the accuracies we were able to obtain from the models we tuned, and the Random Forest model performed the best for our purposes. From this model, we were able to identify '3rd_Q_Diff', 'Tailing', 'Leading', '2nd_Down_Avg' and '3rd_Down_Avg' as the most important features contributing to victory.

Moving forward, we want to be able to find threshold values for each of these features. However, since the threshold for a given feature that will change the outcome of the game from a loss to a win varies depending on the values of all of the other features, we aren't able to get a static threshold for each of the features that will ensure victory. Instead, we plan on building out a dynamic analysis tool that takes in values for each feature, predicts the win %, and provides the cutoff thresholds for each feature given the input values. We would also like to be able to built out models specific to each BIG10 team. That way, Northwestern can see what attributes are the most important in order to beat a specific team.

Team Contribution: Vamsi led the charge for the bulk of the data aggregation, and coding of the models. Eric focused on high-level strategies, coordination with NU Football and analysis write-up. Noah assisted with relational and feature analysis and built out the website.