Predicting NFL Player Outcomes through the Lens of Fantasy Football

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With an estimated 60 million fantasy sports bettors across the US and Canada, the fantasy sports industry is booming (FSGA, 2022). In particular, fantasy football inspires the enthusiasm of American-football fans and invites friendly competition among families and friends every fall. Fantasy football is an online game in which fans can create and bet on fictitious football teams based on real National Football League (NFL) players. The game has been implemented by companies including ESPN, Yahoo! Sports, and DraftKings, which provide users with a platform to manage their team with the help of player insights and weekly player performance projections. Yet, insights are often paywalled and projections can vary widely. The goal of this project is to build a predictive model that predicts weekly fantasy points scored per player, supplementing existing projection sources for traditional league fantasy football. Predictions are complemented by an interactive visualization dashboard that enables fantasy football bettors to analyze patterns in performance and use insights to make decisions about their fantasy team weekly line-up.

Similar work on professional football player predictions has been conducted previously, both at the academic and commercial level. In his paper, Paul Sabin (2021) proposes a hierarchical Bayesian Plus-Minus model to estimate a player's contribution to the team's success using play-by-play and participation data. His approach involves position-specific penalization that focuses on improving upon traditional adjusted plus-minus frameworks. In addition, Wolfson, Addona, and Schmicker (2011) consider the difficulty that NFL teams have in selecting college quarterbacks that will excel at the professional level. They use a logistic regression model to predict a player's likelihood of success in the NFL.

As for commercial literature, Tyler Sidell (2022) explains how IBM Watson and ESPN combine artificial intelligence with fantasy football data to deliver a user-friendly platform for fantasy players. The effort involves using natural language processing and neural networks to help users compare players, evaluate potential trades, or assess the impact of an injury. Lastly, in an interview with ESPN data analyst Mike Clay, Field Yates (2022) inquires about the inner workings of ESPN's weekly player projections. Clay and Yates discuss performance statistics that are most useful in predicting player output and player characteristics that may lead to bursts of high performance.

Data for this project was collected primarily from StatHead.com, which provides information for each player for each game of the season. In addition to player-game level data, injury data was collected from NFL injury reports on the NFL website.

Methods

Before diving into prediction strategies, data on professional football players must first be collected and processed. Data was collected for two groups: the first group consisted of quarterbacks and the second consisted of running backs, wide receivers, and tight ends (henceforth referred to as the running back and receiver group). Data from StatHead.com was downloaded directly from the site and data from the NFL injury reports was collected via web scraping. For the quarterback group, data was collected from the 2000 to 2018 seasons. Across all seasons, 11,660 player-game level instances were available for preprocessing, with 62 columns related to the player, his performance during the game, and characteristics of the game itself. Data for the running back and receiver group was collected from the 2015 to 2018 seasons, with 21,873 player-game level instances and 44 columns containing similar information available for preprocessing. See appendix 1 for a complete list of columns available. The outcome for both groups was fantasy points scored in a given game, defined as the sum of the following:

- 1 point per 25 yards passing (quarterbacks only)
- 4 points per passing touchdown (quarterbacks only)
- -2 points per interception thrown (quarterbacks only)
- 1 point per 10 yards rushing or receiving

- 6 points per rushing or receiving touchdown
- 2 points per two-point conversion
- -2 points per fumble lost

Data Cleaning

First pass data cleaning involved basic string manipulations to accomplish the following: convert player age to a continuous scale, convert draft positions to a numeric scale, extract the month, date, and year of the game, and extract game results including points scored by team and overall result. For players that were signed as free agents, the overall draft pick was substituted as one plus the maximum draft pick for that year.

Data were mostly complete without missing values. Only games where the player participated were included; participation was defined as having a non-missing fantasy point scoring for a given game. For quarterbacks, only games where the player had at least 5 pass attempts were included. The only other missing observations were found in the rates columns (i.e., yards per pass attempt, receiving yards per target) where the denominator was zero. These missing rate values were substituted with zeroes.

Feature Extraction

Feature extraction involved processing each season independently. First, the data were grouped by player and ordered temporally. Then, the data were shifted so that fantasy points scored and game characteristics of the future week would be in line with the player's previous performance measurements. Consequently, the data collected from the last game of the season for each player was dropped. Next, moving averages of previous game performance metrics were calculated to determine each player's performance history. For game weeks below the moving average window, a cumulative average was used. The window of moving averages was tuned for values 2, 3, 4, and 5. Further details discussed in the next section.

Then, for each game, a cumulative average of the performance track record against the opponent was calculated. This measure was incorporated to give a sense of how players of the same position on other teams perform when playing against the upcoming game's opponent. Lastly, the injury data was joined to the player-game level data as an indicator of whether the player had recently recovered from an injury. Injury descriptions were grouped into succinct categories. For instance, finger and wrist injuries were grouped into a more general hand injury category. For a complete list of the injury groupings, see appendix 2.

Preprocessing

To preprocess the data for modeling, the *tidymodels recipe* framework was used. Recipe steps included removing near zero variance predictors, removing correlated numeric predictors, removing predictors that were linear combinations of one another, and centering and scaling all numeric predictors. Correlated predictors were removed to maintain a largest absolute correlation between all variables less than the threshold of 0.9. For regression frameworks, natural cubic splines were fit on all numeric predictors with 3 degrees of freedom to capture nonlinear relationships with the outcome. Also, categorical predictors were dummy encoded. For machine learning frameworks, natural cubic splines were omitted and categorical predictors were one-hot encoded. Preprocessing was performed within each training-validation-test split, see the next section for more details on splits and modeling frameworks

Modeling

For training and tuning, the data were split using a temporal training-validation-test split. For quarterbacks, data from 2000 to 2016 was used as the training set. For running backs and receivers, data from 2015-2016 was used as the training set. For both groups, the 2017 season was used as the validation set and the 2018 season was used as the test set. The training and validation split was used to tune the window of moving averages discussed previously. A linear regression was fit on the training set to tune the optimal window of moving averages on the validation set. The optimal window was selected based on RMSE and was used for downstream modeling. Also, the training and validation splits were combined for further training and hyperparameter tuning.

Four modeling frameworks were explored for both the quarterback group and the running back and receiver group. The first modeling framework was a base linear regression. The second modeling framework was a penalized regression. For the penalized regression, the penalty hyperparameter was tuned to determine the optimal amount of regularization, and the mixture hyperparameter was tuned to determine the optimal proportion of LASSO penalty. The third modeling framework was a random forest model, in which the minimum number of observations in the terminal nodes was tuned from 1 to 5, and the number of predictors considered at each split was tuned from 2 to one fewer than the total number of columns in the processed dataset. The fourth modeling framework was an XGBoost model, in which the minimum number of observations in the terminal nodes was tuned from 5 to 15, the number of predictors considered at each split was tuned from 2 to one fewer than the total number of columns in the processed dataset, the maximum tree depth was tuned from 3 to 8, and the learning rate was tuned. The latter three models were tuned using five-fold cross validation repeated five times.

The *tidymodels* framework was used for tuning all models. For penalized regression, the *glmnet* engine was used, for random forest the *ranger* engine was used, and for XGBoost, the *xgboost* engine was used.

Shiny App

A user-friendly R shiny app was developed to combine fantasy predictions with interactive visualizations. While the predictions are meant to be used exclusively on a weekly basis to determine weekly lineup strategies, the visualization component can be used both for weekly lineup determination and for initial lineup drafting at the beginning of the season. Currently, the app focuses exclusively on quarterbacks.

The app was divided into three tabs: the welcome tab, the exploration tab, and the predictions tab. The welcome tab gives a brief overview of the app functionality. The exploration tab contains four interactive visualizations related to quarterback fantasy scoring. The user can explore how fantasy points are related to past performance, injury type, and team. Multiple filtering options were added for each visualization to allow the user to filter by various attributes, such as season and metric. The exploration tab is primarily useful for high-level overviews and for observing patterns at the season or team level. The predictions tab allows the user to upload a csv file containing information about a quarterback of interest and in return receive a projected fantasy score for the upcoming game. The predictions on this tab are generated using the highest performing model of the four methods discussed previously. In addition, there are two visualizations on the predictions tab to provide some context surrounding the fantasy point projection.

Results

Modeling

After processing the data, 9201 observations with 47 columns were present for the quarterback group and 14,310 observations with 38 columns were present for the running back and receiver group. See appendix 3 for a full list of the variables included in the modeling process. The window of moving averages was tuned as described in the methods section for both position groups (see validation results in appendix 4). As a result, the optimal window was 5 games for the quarterback group and 4 games for the running back and receiver group. The base linear regression, penalized regression, random forest, and XGBoost models were fit on both groups of data as described in the methods section and the resampling and test results are summarized in tables 1 and 2. See appendix 5 for a full summary of the optimal hyperparameters for each model.

Table 1: Model Performance Summary for Quarterbacks

Model	Resampled RMSE	Test RMSE
Base Linear Regression	7.448	8.096

Penalized Linear Regression	7.458	8.130
Random Forest	7.451	8.196
XGBoost	7.446	8.151

With the lowest resampled and test RMSE, the base linear regression performed the best for the quarterback group. For all four modeling frameworks, the resampled RMSE was just over half a point lower than the test RMSE, indicating mild overfitting has occurred.

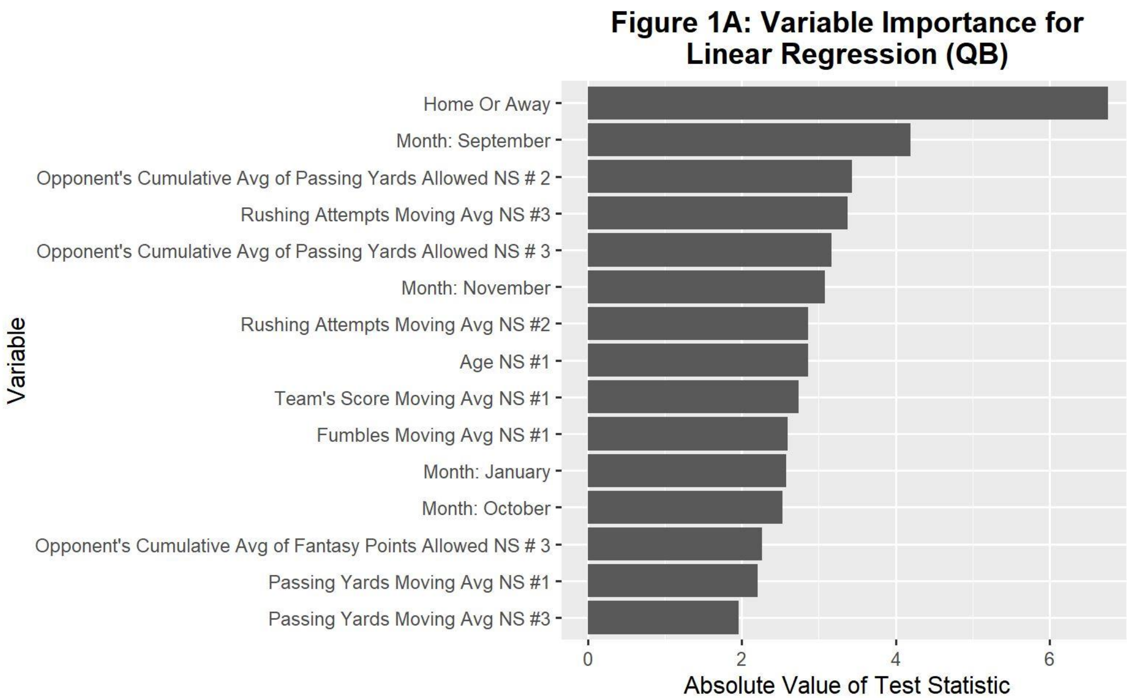
Table 2: Model Performance Summary for Running Backs, Wide Receivers, and Tight Ends

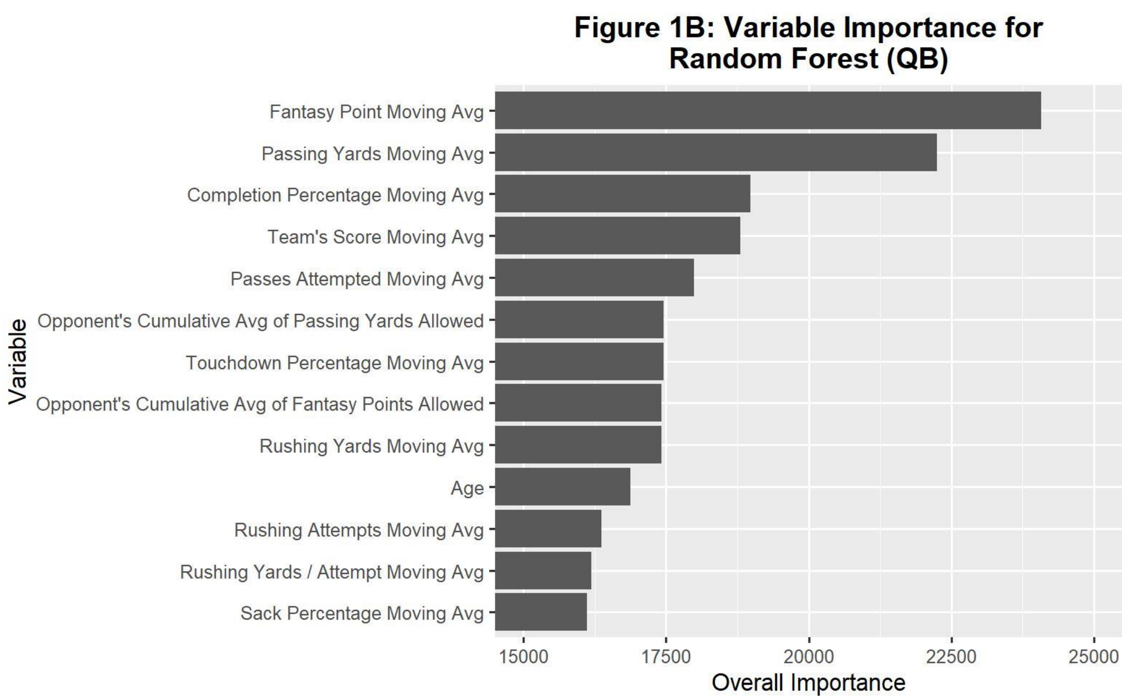
Model	Resampled RMSE	Test RMSE
Base Linear Regression	5.3348	5.5318
Penalized Linear Regression	5.3321	5.5316
Random Forest	5.3692	5.5763
XGBoost	5.3327	5.5447

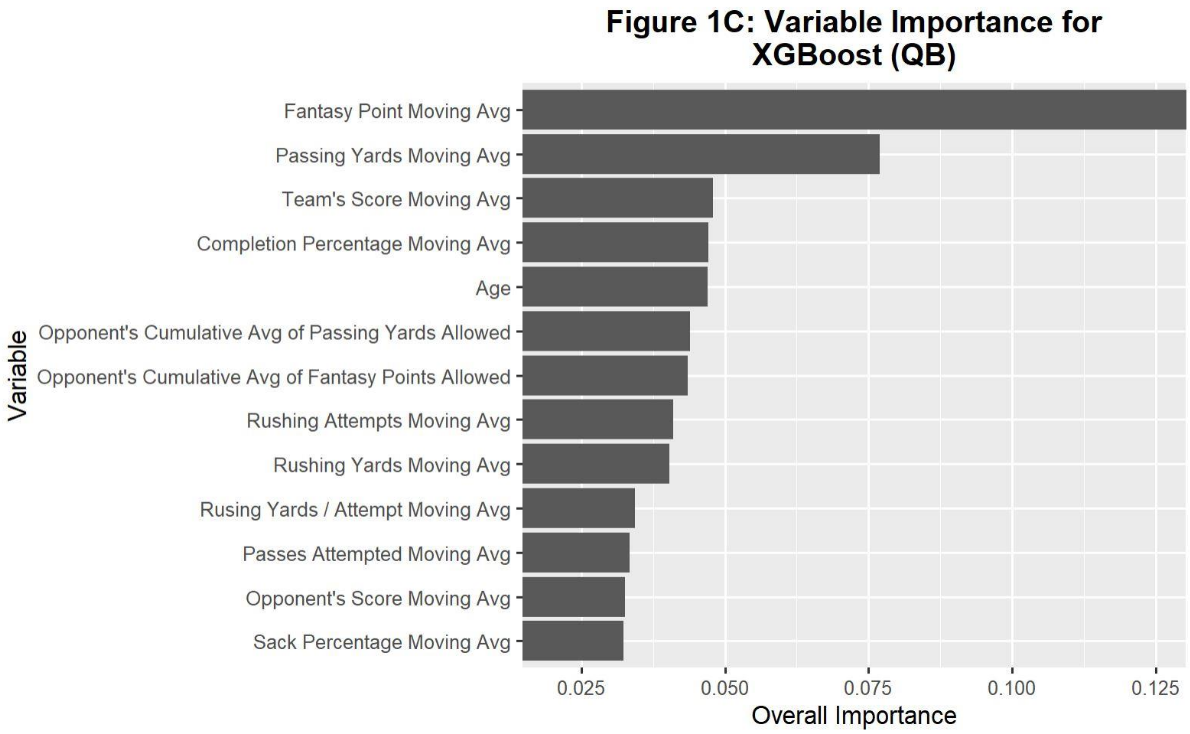
With the lowest resampled and test RMSE, the penalized linear regression performed the best for the running back and receiver group. Although, the base linear regression was a close second. For all four modeling frameworks, the resampled RMSE was a fraction of a point lower than the test RMSE, indicating mild overfitting has occurred, although to a lesser extent than it has occurred for the quarterback group.

Variable importance plots for the base linear regression, random forest, and XGBoost models are shown in figure 1 (A, B, and C) for the quarterback data group. The absolute value of the t-statistic was used as the measure of variable importance for linear regression and the Gini index was used for random forest and XGBoost.

For the base linear regression, the strongest indicator of performance was whether the game was home or away. Oddly enough, the second strongest indicator was whether the upcoming game is scheduled in September. Other important predictors included the historic cumulative average of passing yards and fantasy points allowed by the upcoming opponent, quarterback rushing attempts, quarterback age, overall team score, fumbles, and passing yards. For the random forest and XGBoost models, the top two strongest indicators of performance were player moving average of fantasy points scored and passing yards. Other important predictors included completion percentage, team score, points and yards allowed by the upcoming opponent moving average performance metrics related to rushing and passing.







Variable importance plots for the base linear regression, random forest, and XGBoost models are shown in figure 2 (A, B, and C) for the running back and receiver data group.

For the base linear regression, the strongest indicator of performance was the moving average of rushing attempts, followed by the players' draft round and home or away status. Other important predictors include the month of the game, performance statistics related to receiving, and a moving average of the opponents' total score. For the random forest and XGBoost models, the strongest indicator of performance was moving average of fantasy points scored. Other important predictors included performance metrics related to receiving and rushing, the players' draft round, age, history of rushing and receiving yards allowed by opponent, team and opponent score, and home or away status.

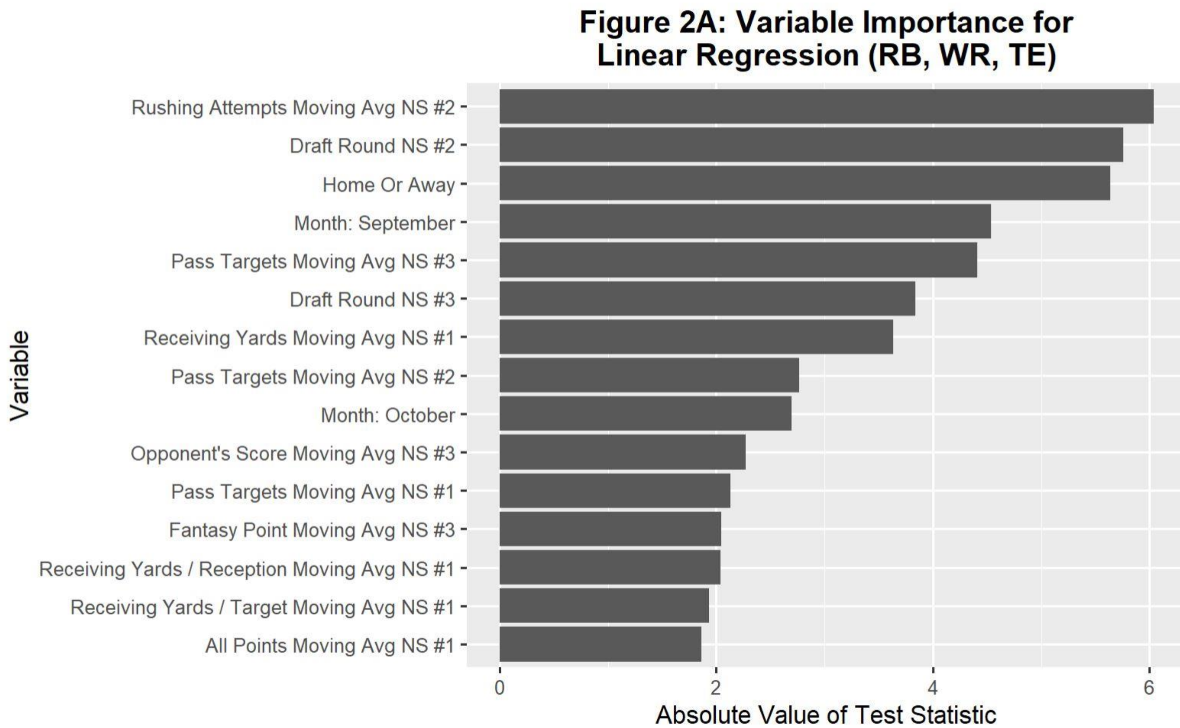


Figure 2A: Variable Importance for
Linear Regression (RB, WR, TE)
Variable
Rushing Attempts Moving Avg NS #2
Draft Round NS #2
Home Or Away
Month: September
Pass Targets Moving Avg NS #3
Draft Round NS #3
Receiving Yards Moving Avg NS #1
Pass Targets Moving Avg NS #2
Month: October
Opponent's Score Moving Avg NS #3
Pass Targets Moving Avg NS #1
Fantasy Point Moving Avg NS #3
Receiving Yards / Reception Moving Avg NS #1
Receiving Yards / Target Moving Avg NS #1
All Points Moving Avg NS #1
0
2
4
6
Absolute Value of Test Statistic

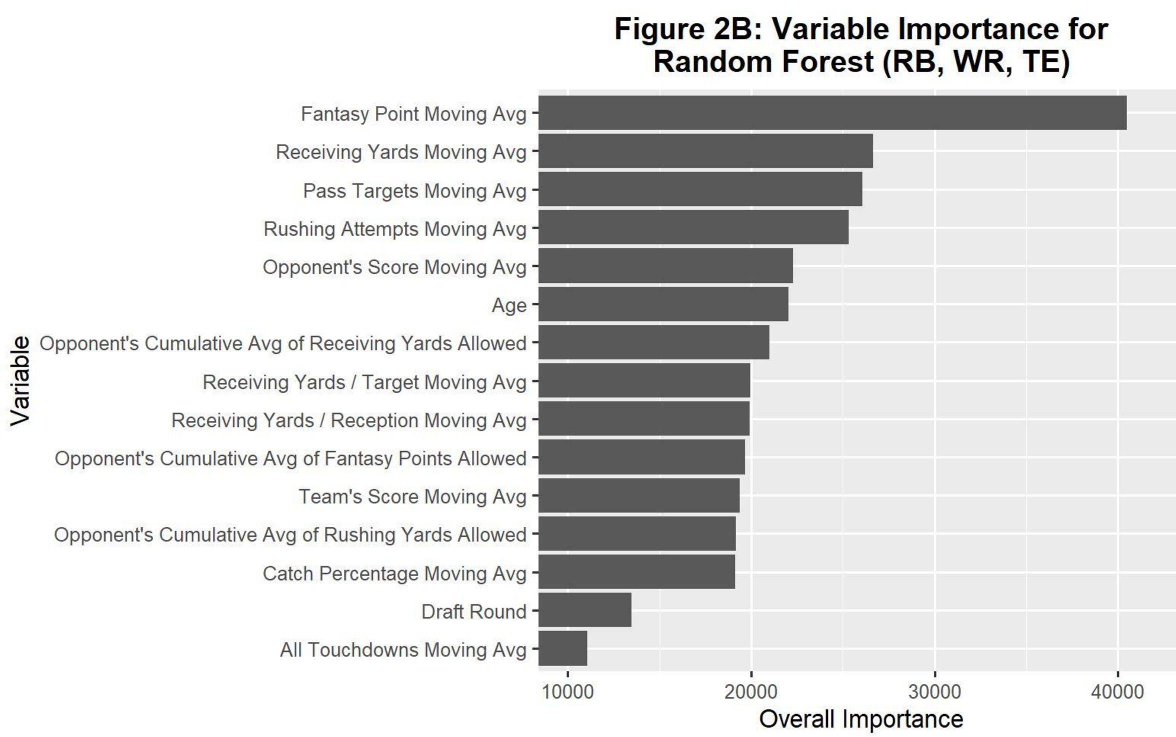
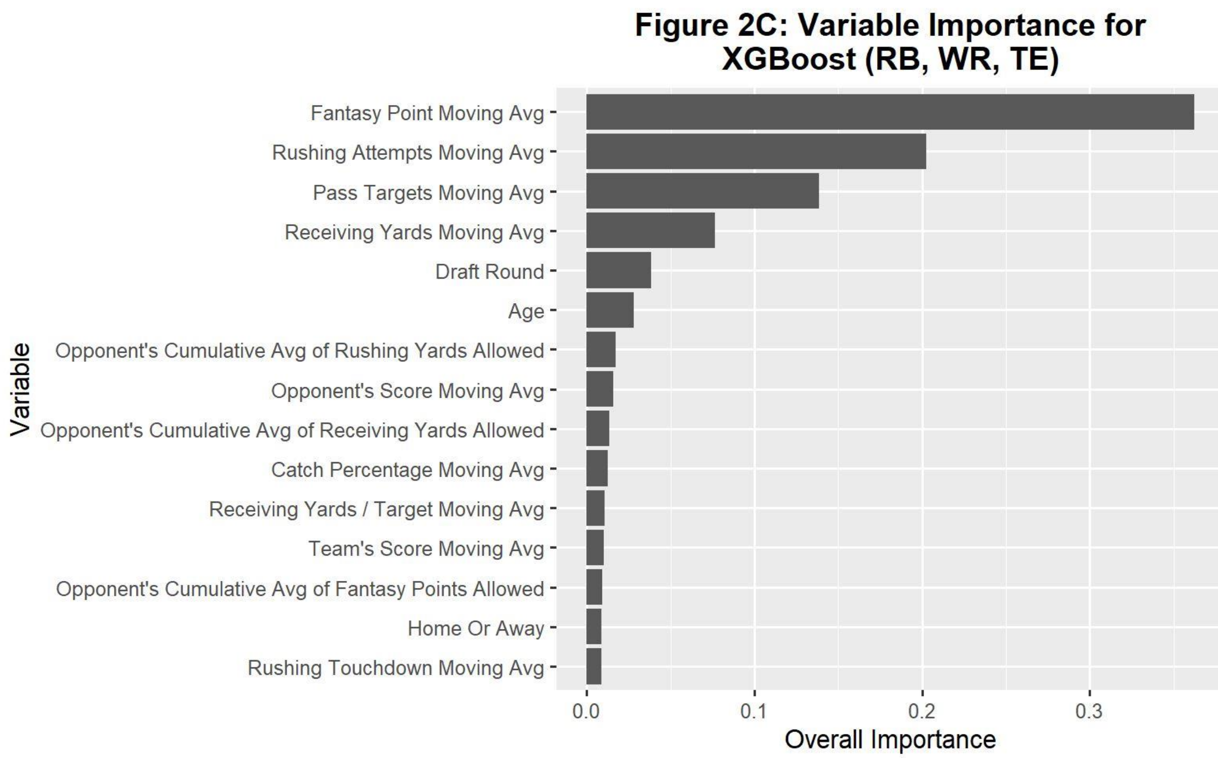
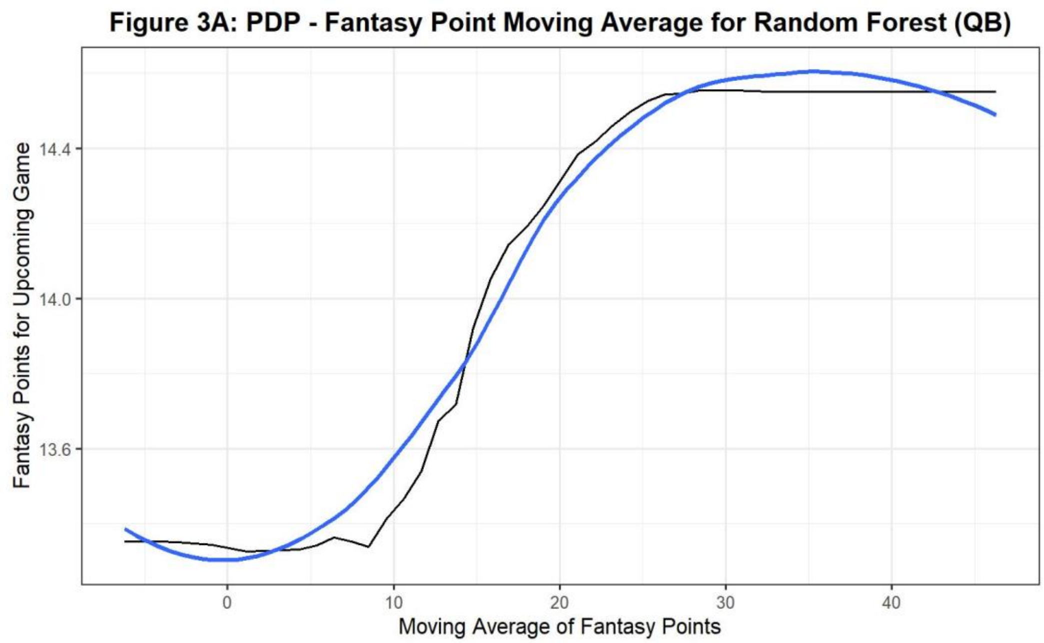
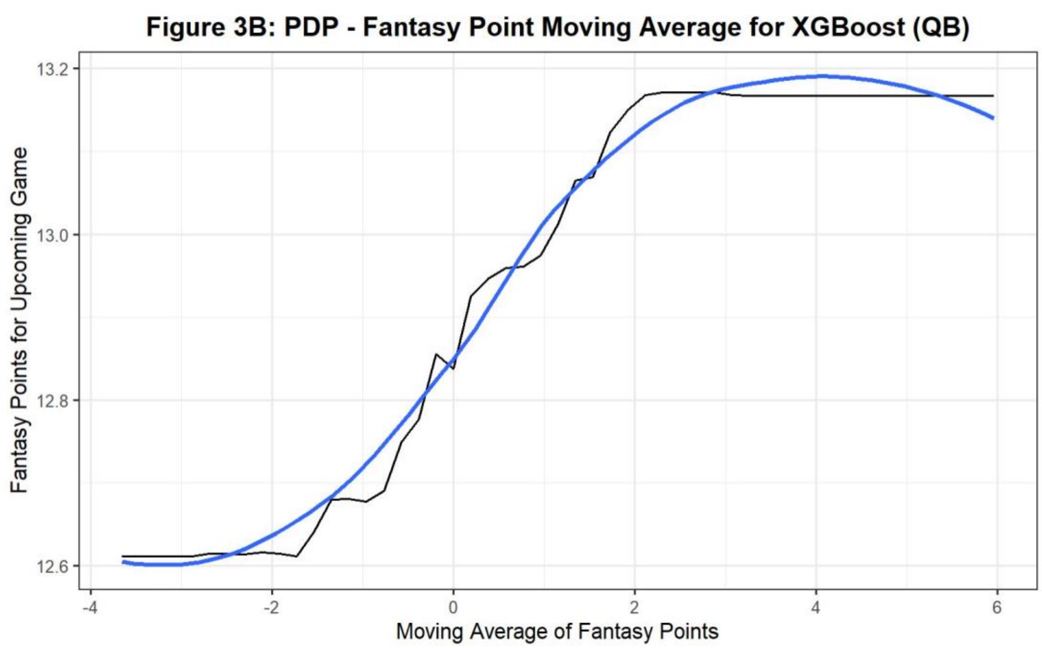


Figure 2B: Variable Importance for
Random Forest (RB, WR, TE)
Variable
Fantasy Point Moving Avg
Receiving Yards Moving Avg
Pass Targets Moving Avg
Rushing Attempts Moving Avg
Opponent's Score Moving Avg
Age
Opponent's Cumulative Avg of Receiving Yards Allowed
Receiving Yards / Target Moving Avg
Receiving Yards / Reception Moving Avg
Opponent's Cumulative Avg of Fantasy Points Allowed
Team's Score Moving Avg
Opponent's Cumulative Avg of Rushing Yards Allowed
Catch Percentage Moving Avg
Draft Round
All Touchdowns Moving Avg
10000
20000
30000
40000
Overall Importance



Partial dependence plots were constructed for the strongest indicator of the random forest and XGBoost models, again for both data groups. Figures 3A and 3B show the relationship between the number of fantasy points scored in an upcoming game and the moving average of fantasy points for the quarterback data group. For both models, there is an approximately cubic or sigmoidal relationship between the predictor and the outcome.





Figures 4A and 4B show the relationship between the number of fantasy points scored in an upcoming game and the moving average of fantasy points for the running back and receiver data group. For both models, there is a sigmoidal relationship between the predictor and the outcome, but for larger values of moving fantasy point averages, the curve is flattened.

Figure 4A: PDP - Fantasy Point Moving Average for Random Forest (RB, WR, TE)

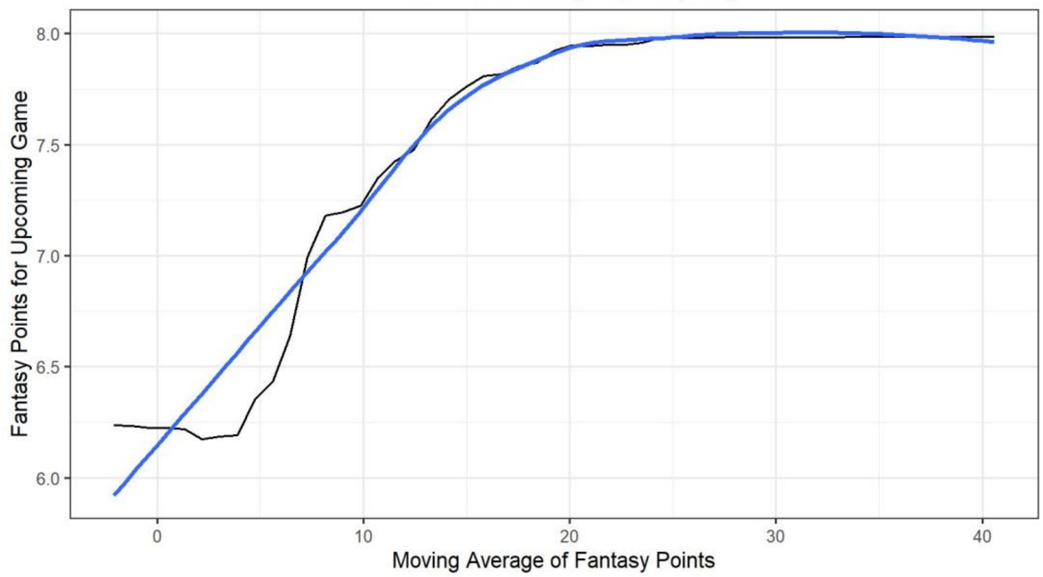
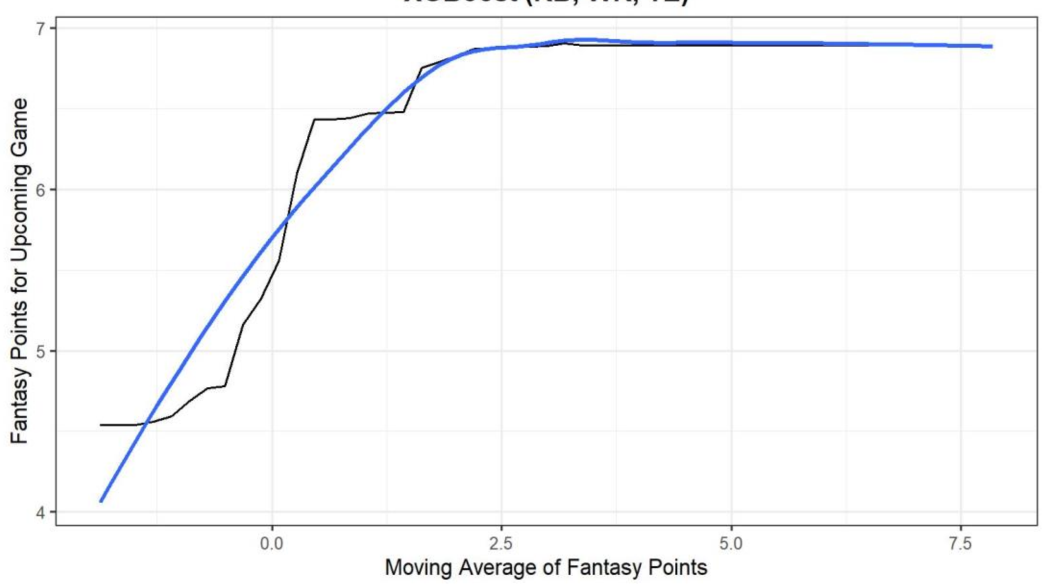


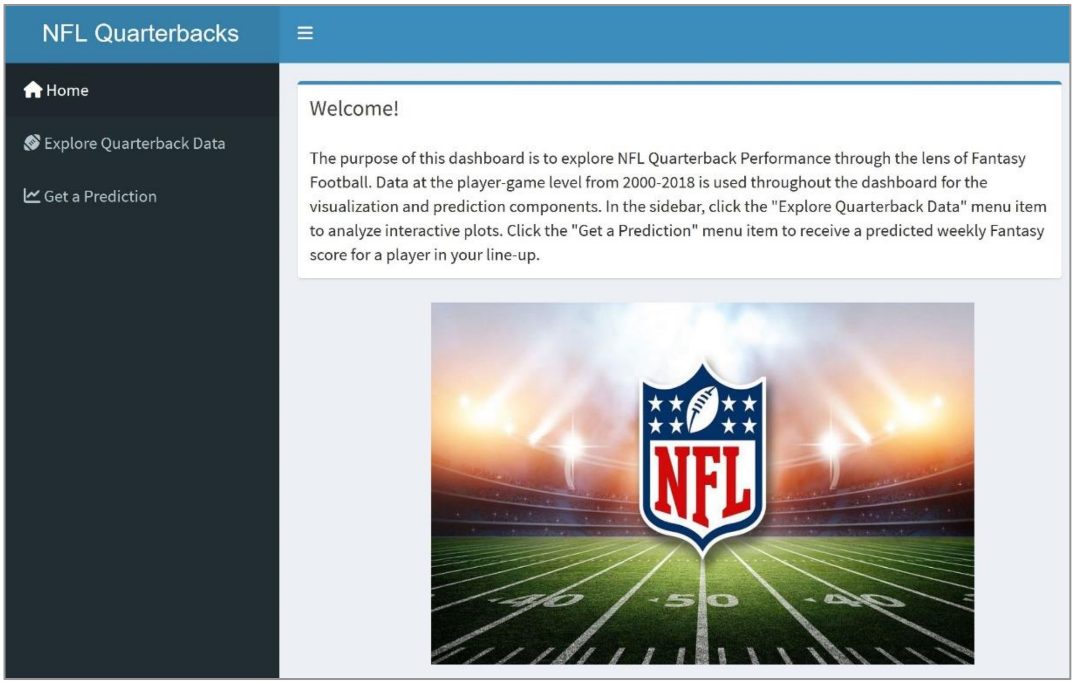
Figure 4B: PDP - Fantasy Point Moving Average for XGBoost (RB, WR, TE)



Shiny App

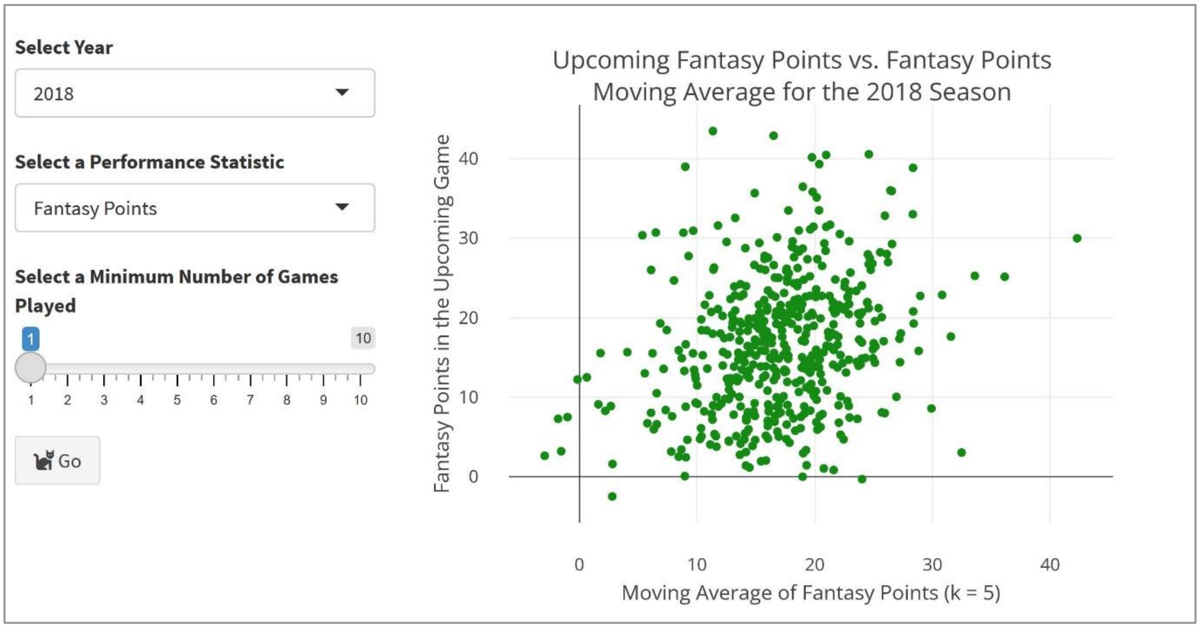
The Shiny app and underlying modeling frameworks serve as a user-friendly platform for fantasy football bettors to analyze patterns in quarterback performance and receive weekly fantasy point predictions. Users are greeted with the welcome page and a brief introduction as shown in figure 5.

Figure 5: Welcome Page of Shiny App



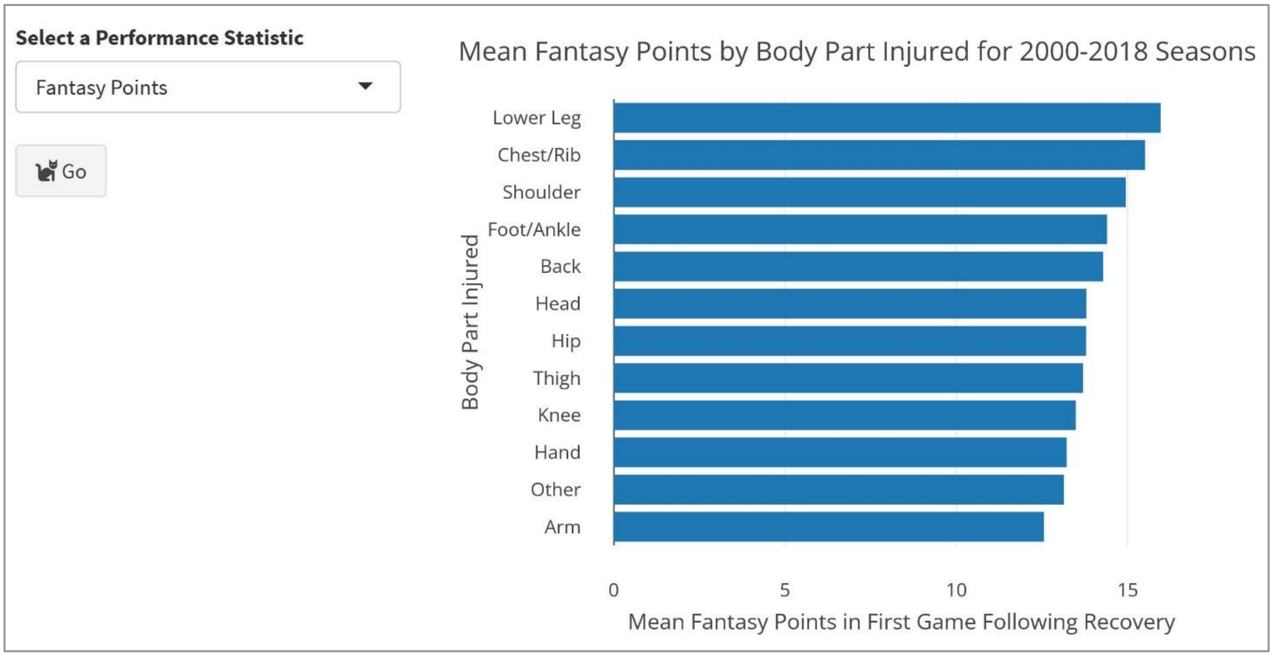
On the exploration tab, the user is presented with four interactive visualizations to analyze performance patterns primarily at the team and season level. The first visualization (see figure 6) is a scatterplot that compares game level instances of player fantasy points scored to his historical moving average of a performance statistic of the user's choice. The user may select from six performance statistics: fantasy points, passes attempted, passes completed, completion percentage, yards gained per pass attempt, and passing yards completed. The user may also select the season to view and can restrict output to only include players that have participated in a minimum number of games. The user can also hover over each observation to see the player name and summary statistics.

Figure 6: Interactive Visualization of Fantasy Points Scored vs. Moving Average Performance History



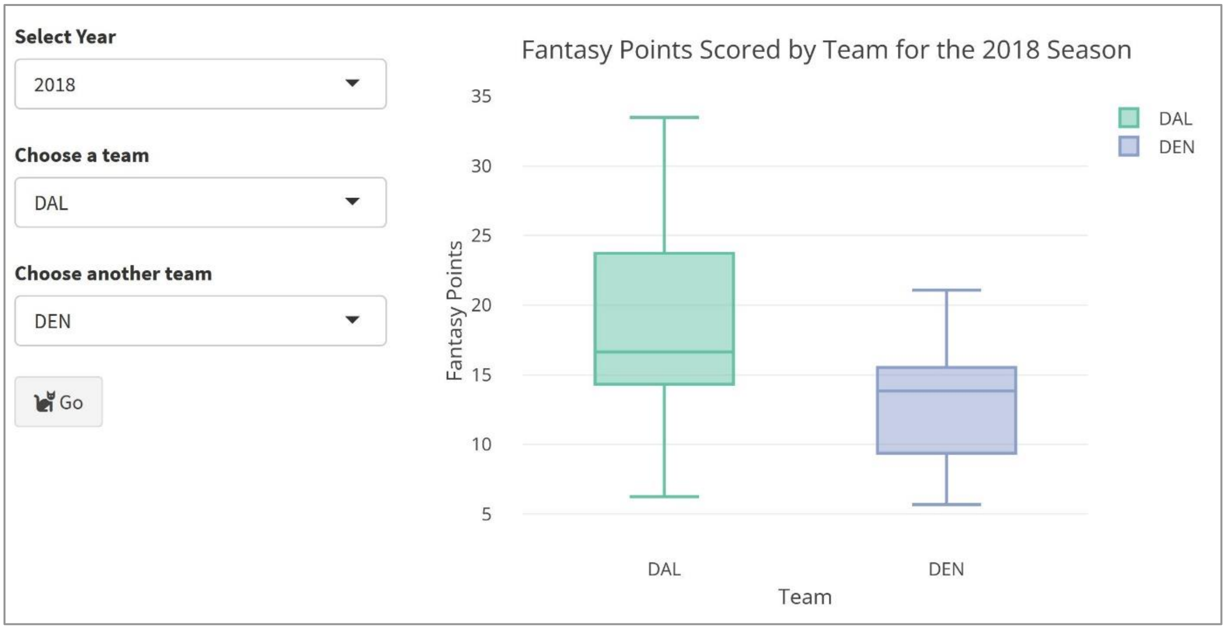
The second visualization (see figure 7) is a bar chart that illustrates the impact of various types of injuries on player performance. The mean fantasy points scored in the game immediately following a player's recovery is grouped by the body part where the injury occurred. The user can select from six different performance metrics to display in the graph, identical to the first visualization. The user can use this graph to weigh the impact of various types of injuries. For instance, a lower leg injury is on average less costly to player performance than an arm injury. Data from all seasons is included in this visualization without the option to filter due to the sparseness of the injury data.

Figure 7: Interactive Visualization of Mean Fantasy Points Scored by Body Part Injured



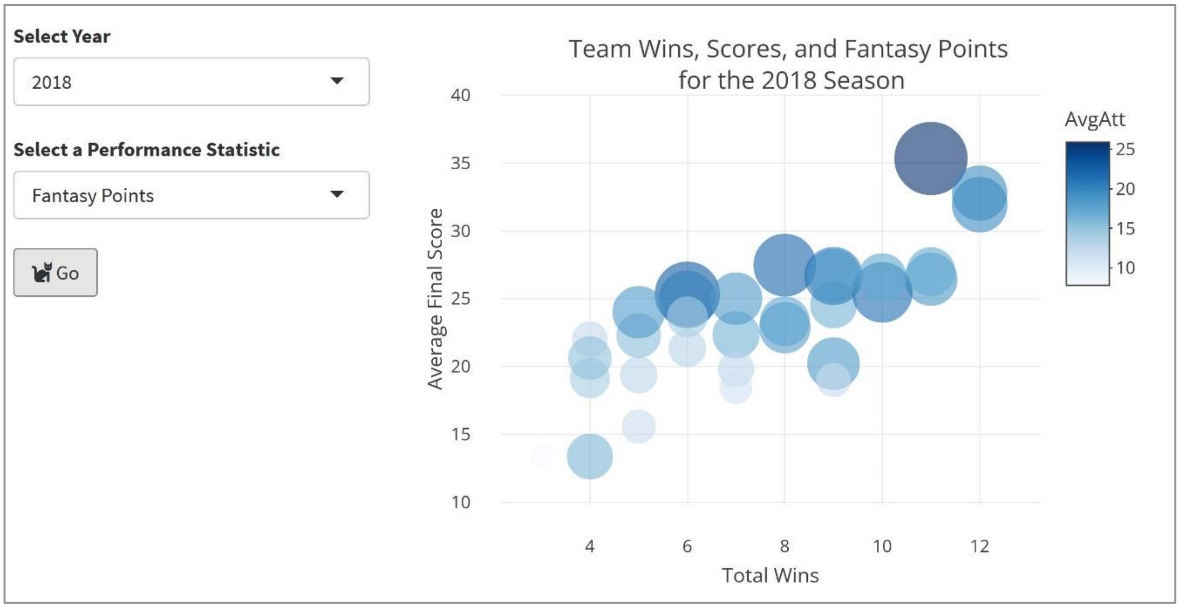
The third visualization (see figure 8) is a side-by-side boxplot that compares the distributions of quarterback performance for two teams of the user's choice. The user can also select the season to be displayed. This plot could be used to help users analyze team level trends in quarterback performance. For example, a user might consider two quarterbacks with similar performance history from two different teams for their weekly line up. However, the distribution of fantasy points scored by quarterbacks on one team might be higher than the other team, so the user may choose to bet on the player from the higher scoring team.

Figure 8: Interactive Visualization of Fantasy Points Scored by Team



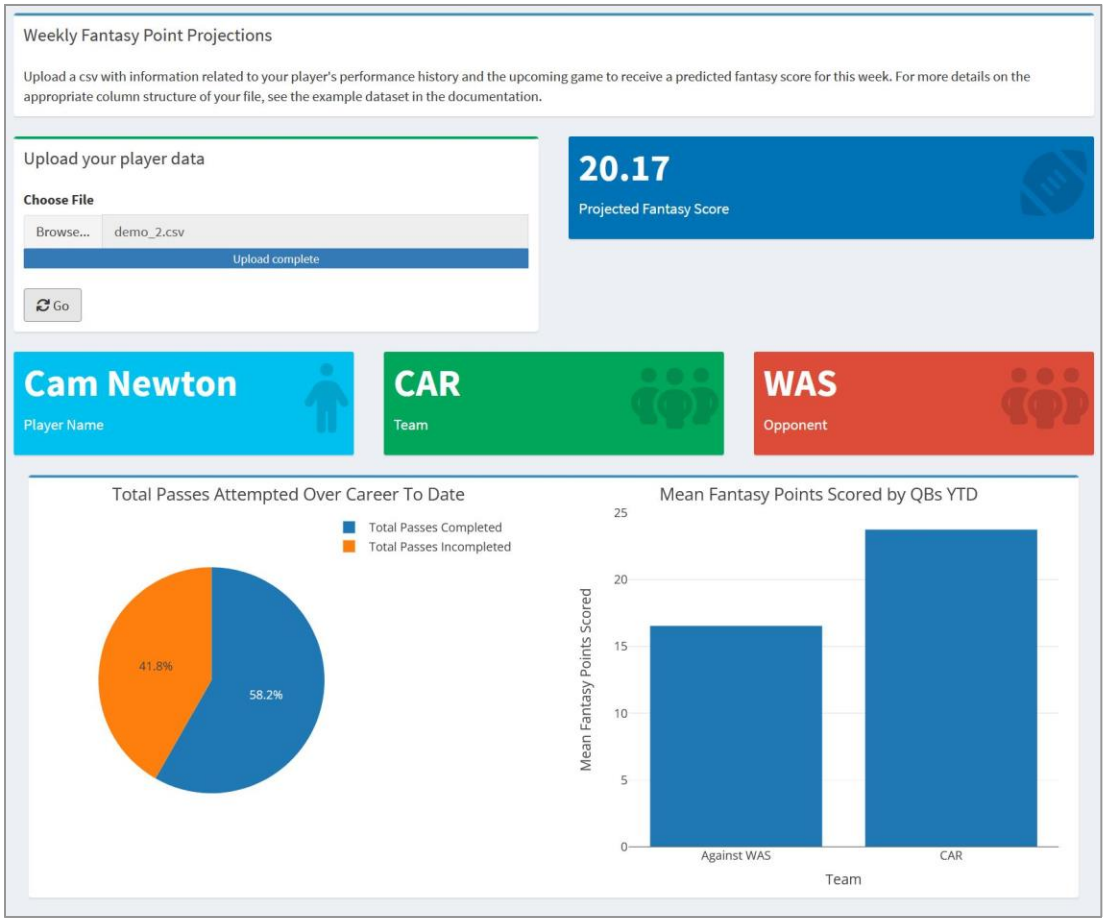
The fourth visualization (see figure 9) plots the average final score achieved by a team vs. the total wins across the season for all teams in the NFL. Each bubble corresponds to one team. The bubbles are sized and colored by a metric of the user's choice, with larger bubbles corresponding to a higher mean score for top players on the team. The user can also filter the data by the season and select from one of six metrics to display on the plot. This plot is primarily useful for observing team and season level trends. The user can compare average quarterback performance by team, and also assess the relationship between game result and overall points scored by a team. The user can hover over the visualization to see summary statistics for each team. In addition to fantasy lineup management, this graph can be used in playoff brackets, in which fantasy fans bet on which teams will make it to the Superbowl. This graph is relevant because fantasy brackets are often played in fantasy leagues.

Figure 9: Interactive Visualization of Fantasy Points, Total Wins, and Average Total Score by Team



Lastly, on the predictions tab (see figure 10), the user can upload a csv file containing information about a player and the upcoming game. After the user hits the "Go" button, a projected fantasy score for the upcoming week will populate. The prediction is generated by the linear regression model. In addition, three value boxes will populate with the player's name, team, and upcoming opponent. An interactive pie chart is displayed on the bottom left corner of the page that breaks down the total passes attempted by the player into percentage completed and incomplete over his career up until the week before the specified game. In the bottom right corner is an interactive bar chart that compares the average fantasy points scored by quarterbacks on the player's team with the average fantasy points scored by other teams that play against the upcoming opponent, season to date. Finally, the user can use the prediction and contextual visualizations to decide if the player is worth including in their weekly lineup.

Figure 10: Player Predictions Tab



Discussion

Overall, the base linear regression and the penalized linear regression outperformed the random forest and XGBoost in both position groups. Mild overfitting occurred for both position groups, indicating the process could be more robust. The most important predictors for the linear regression varied slightly from the most important predictors for the random forest and XGBoost. For the quarterback group, the most important predictors of future fantasy point scoring according to the linear regression included characteristics of the upcoming game, opponent cumulative average of passing yards and fantasy points allowed, and performance statistics related to rushing and passing. According to the random forest and the XGBoost models, the most important indicators included history of fantasy points scored, performance statistics related to rushing and passing, and opponent cumulative average of passing yards and fantasy points allowed. For the running back and receiver group, the most important predictors according to the linear regression included performance statistics related to rushing and receiving, draft round, and upcoming game characteristics. According to the machine learning methods, important predictors included history of fantasy points scored, metrics related to rushing and receiving, draft position, age, and opponent cumulative average of yards allowed.

The limitations of this analysis are primarily related to the data. Firstly, the data were split into training, validation, and test sets using a temporal split. However, the split was not proportional across both data groups. Data from 2017 and 2018 was used for the validation and test sets, respectively, but the quarterback group training data consisted of season data ranging from 2000-2016, whereas the running back and receiver training data consisted only of season data from 2015-2016. In the future, additional data from past seasons could be collected for the running back and receiver group.

Another limitation is related to the injury data. The injury data was sparse for games prior to 2008. As a result, the number of injuries that occurred from 2000-2008 is underestimated.

Future work may include tuning for an expanded moving average window, or exploring a completely cumulative average. Similarly, the number of knots on the natural cubic splines used in the regression models may also be tuned. Additionally, the app may be further developed to include a user interface for the running back and receiver group. Lastly, the data groups could be further decomposed into three groups: quarterbacks, running backs, and wide receivers and tight ends. Three groups might offer a more robust modeling schema because running back game play is focused on rushing, and wide receiver and tight end game play is more focused on receiving.

In conclusion, the shiny dashboard combines interactive visualizations with contextualized predictions to create an engaging and useful tool for fantasy sports bettors to use during the football season. The visualizations offer high level overviews of season and team trends, and may also be used for weekly lineup decisions. The prediction functionality offers a data driven approach to determining the potential value of a player for weekly games. Fantasy sports bettors can use the app to add value to their betting experiences and translate insights into league-winning decisions.

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Appendix

Appendix 1A: Complete list of columns in data prior to processing and feature extraction for quarterbacks
player rank, player name, fantasy points scored, day of game, game number, week number, date, age of player, team name, home or away status, opponent name, game result, passes completed, passes attempted, passes incomplete, completion percentage, passing yards, passing touchdowns, interceptions thrown, pick six, touchdown percentage, intercept percentage, rate, times sacked, yards lost to sacks, sack percentage, yards gained per pass attempt, adjusted yards gained per pass attempt, adjusted net yards gained per pass attempt, yards gained per pass completion, passing targets, reception, receiving yards, receiving yards per reception, receiving touchdowns, catch percentage, receiving yard per target, PPR, DraftKings fantasy points, FanDuel fantasy points, fumbles, fumbles recovered, yards gained for fumbles recovered, fumbles recovered resulting in a touchdown for the recoverer, forced fumbles, rushing attempts, rushing yards, rushing yards per attempt, rushing touchdowns, all touchdowns, extra points made, extra points attempted, extra points percentage, field goals made, field goals attempted, field goal percentage, 2-point conversions made, safeties, all points scored, position, draft round, overall draft pick

Appendix 1B: Complete list of columns in data prior to processing and feature extraction for running backs, wide receivers and tight ends
player rank, player name, fantasy points scored, day of game, game number, week number, date, age of player, team name, home or away status, opponent name, game result, pass targets, receptions, receiving yards, receiving yards per reception, receiving touchdowns, catch percentage, receiving yard per target, PPR, DraftKings fantasy points, FanDuel fantasy points, fumbles, fumbles recovered, yards gained for fumbles recovered, fumbles recovered resulting in a touchdown for the recoverer, forced fumbles, rushing attempts, rushing yards, rushing yards per attempt, rushing touchdowns, all touchdowns, extra points made, extra points attempted, extra points percentage, field goals made, field goals attempted, field goal percentage, 2-point conversions made, safeties, all points scored, position, draft round, overall draft pick

Appendix 2: Injury grouping definitions based on injury description

Words Contained in Original Injury Description	Injury Category
Shoulder	Shoulder
Back	Back
Chest, rib	Chest/rib
Stinger	Stinger
Hamstring, glute, thigh, quadricep	Thigh
Groin, hip	Hip
Calf, fibula, shin, lower leg	Lower leg
Knee	Knee
Foot, achilles, toe, ankle	Foot/ankle
Elbow, arm bicep, forearm	Arm
Hand, wrist, finger, thumb	Hand
Concussion, head, ear	Head
Any other description not included by words above	Other

Appendix 3A: Complete list of columns in data included in the modeling process for quarterbacks

Fantasy points scored in future game (outcome), day of upcoming game, month of upcoming game, home or away status of upcoming game, age of player, position, draft round, overall draft pick, moving average of fantasy points, moving average of overall team points scored, moving average of overall opponent points scored, moving average of passes completed, moving average of passes attempted, moving average of passes incomplete, moving average of completion percentage, moving average of passing yards, moving average of passing touchdowns, moving average of interceptions thrown, moving average of pick six, moving average of touchdown percentage, moving average of interception percentage, moving average of rate, moving average of times sacked, moving average of yards lost due to sacks, moving average of percentage of time sacked when attempting to pass, moving average of yards gained per pass attempt, moving average of adjusted yards gained per pass attempt, moving average of adjusted net yards gained per pass attempt, moving average of yards gained per pass completion, moving average of fumbles, moving average of fumbles recovered, moving average of yards gained for fumbles recovered, moving average of fumbles recovered resulting in a touchdown for the recoverer, moving average of forced fumbles, moving average of rushing attempts, moving average of rushing yards, moving average of rushing yards per attempt, moving average of rushing touchdowns, moving average of all touchdowns, moving average of extra points made, moving average of extra points attempted, moving average of extra points percentage, moving average of 2-point conversions made, moving average of safeties, moving average of all points scored, historical cumulative average of fantasy points allowed by upcoming opponent, historical cumulative average of passing yards allowed by upcoming opponent, whether a recent injury has occurred

Appendix 3B: Complete list of columns in data included in the modeling process for running backs, wide receivers, and tight ends

Fantasy points scored in future game (outcome), day of upcoming game, month of upcoming game, home or away status of upcoming game, age of player, position, draft round, overall draft pick, moving average of fantasy points, moving average of overall team points scored, moving average of overall opponent points scored, moving average of passing targets, moving average of receptions, moving average of receiving yards, moving average of receiving yards per reception, moving average of receiving touchdowns, moving average of catch percentage, moving average of receiving yards per target, moving average of fumbles, moving average of fumbles recovered, moving average of yards gained for fumbles recovered, moving average of fumbles recovered resulting in a touchdown for the recoverer, moving average of forced fumbles, moving average of rushing attempts, moving average of rushing yards, moving average of rushing yards per attempt, moving average of rushing touchdowns, moving average of all touchdowns, moving average of extra points made, moving average of extra points attempted, moving average of extra points percentage, moving average of 2-point conversions made, moving average of safeties, moving average of all points scored, historical cumulative average of fantasy points allowed by upcoming opponent, historical cumulative average of rushing yards allowed by upcoming opponent, historical cumulative average of receiving yards allowed by upcoming opponent, whether a recent injury has occurred

Appendix 4A: Moving average window tuning (validation results) for quarterbacks

Window (k)	Validation RMSE
2	7.426
3	7.466
4	7.445

5	7.407

Appendix 4B: Moving average window tuning (validation results) for running backs, wide receivers, and tight ends

Window (k)	Validation RMSE
2	5.245
3	5.214
4	5.198
5	5.200

Appendix 5A: Optimal hyperparameters for quarterback models

Model	Optimal Hyperparameters
Penalized Linear Regression	$\alpha = 0.9720$ $\lambda = 0.0150$
Random Forest	Minimum node size = 2 Number of randomly sampled predictors considered at each split = 2
XGBoost	Minimum node size = 5 Number of randomly sampled predictors considered at each split = 12 Maximum tree depth = 7 Learning rate = 0.00279

Appendix 5B: Optimal hyperparameters for running back, wide receiver, and tight end models

Model	Optimal Hyperparameters
Penalized Linear Regression	$\alpha = 0.0003$ $\lambda = 0.0150$
Random Forest	Minimum node size = 1 Number of randomly sampled predictors considered at each split = 5
XGBoost	Minimum node size = 10 Number of randomly sampled predictors considered at each split = 24 Maximum tree depth = 4 Learning rate = 0.00214