NFL Play by Play Predictions

IDS 575: Machine Learning Statistics

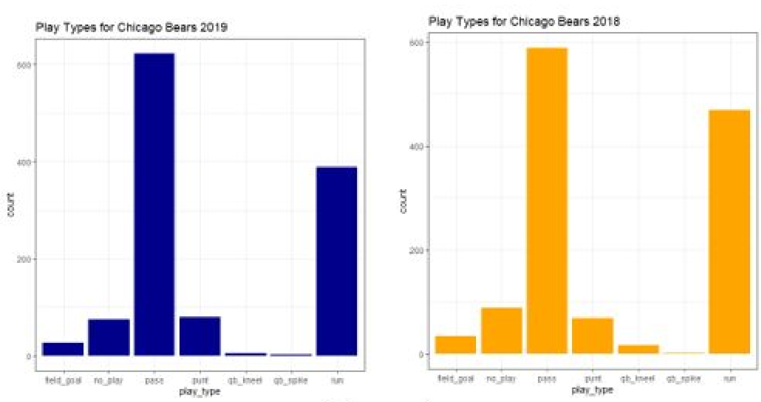
Matt Carey, Danielle Strejc, Emma Van Essen

Abstract

For our final project in Machine Learning Statistics we are going to be using the nflfastR dataset from GitHub that has every single play from the 2018 and 2019 football seasons in the NFL. These datasets consisted of 333 variables with a total of 48,035 rows for 15,995,655 observations for the 2019 season, and 340 variables for 47,875 rows for 16,277,500 observations. The methods we used in the analysis of our models were PCA (Principal Component Analysis) for variable importance, and RF (Random Forest), GLM (Generalized Linear Models), SVM (Support Vector Machines) for model building. Our two models for this report are Passing versus Rushing and Red Zone Scoring. We describe the models used, their accuracies with several evaluation metrics, and the conclusions from those models. From the results, we form recommendations for the Chicago Bears coaching staff.

Introduction

From season to season when it comes to any sport we can see major differences influenced by a slew of different variables that can completely change the course and outcome of a season. In the National Football League, there are stipulations that change drastically every day, and game to game. When looking at the 2019 seasons and information that we obtained through our initial analysis, we learned a lot about what we were searching for, but needed more information to be able to come up with a solid and stable conclusion as to why we came up with the information that we did, and to better clarify and interpret the results of the data. We learned from a single season of informative data that the majority of the time, the Chicago Bears are more likely to go with a Pass rather than a Run (Refer to Figure 1). After further investigating why this was, we knew that we needed some more information to make sure we could accurately breakdown the Chicago Bears front office for the best probabilities in game time situations. We decided that by comparing the 2019 season results to the 2018 season our outcome would be more in depth analysis. The outcome of the Bear's 2018 and 2019 seasons were completely different. In 2018 the Chicago Bears made the playoffs and got the chance to compete for the Wild Card slot to potentially go to the playoffs. Another key difference between these seasons is General Manager Ryan Pace was the 2018 Sports News Executive of the Year for trading for one of the top defensive Edge Rushers in the NFL in Khalil Mack. The previous year the Bears did not have a single All-Pro or Pro Bowler. After the addition, the Bears sent a total of 7 Pro Bowlers and had 4 All-Pro team members. You may be asking yourself why we bring up the Bears defense when our analysis is on passing and rushing and Red Zone outcomes. These defensive moves are important because a stronger defense creates less stress on the offense. It also gives more time to reconstruct an offensive team after releasing Jay Cutler and announcing Mitch Trukisky as their starter, as being drafted the previous year as the 2nd pick in the 1st round of the 2017 draft.

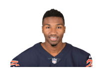
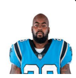
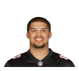
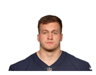


(Figure 1)

Though these are just a few key things, they are absolutely crucial in adding to our analysis of the 2018 and 2019 data. We can see from our analysis and the resulting records of our seasons that there is a correlation between our observations in our model and what happened in those respective seasons. In

2018 the Bears finished the season with a 12-4 record, 5-1 in the division, and made the playoffs. In the 2019 season they finished with a disappointing 8-8 record, 4-2 in the division, and did not make the playoffs that season.

Position Breakdown and Passing/Rushing Total

Position Breakdown 2018 and 2019 Chicago Bears (Players listed are only key impact players for both seasons for our analysis, total team numbers per season found in "Passing/Rushing & Field Goal Totals")	
Quarterback	
2018  *Trubisky: 289/434 (67%) 3,223 Yards, 24TDs/12INTs, 68 Rushes for 421 Yards 3TDs.	**2019**  Mitch Trubisky: 326/516 (63%) 3,138 Yards, 17TDs/10INTs, 48 Rushes for 193 Yards 2TDs.
Wide Receiver	
2018  Taylor Gabriel (67/688 2TDs Receiving, 9/61 Rushing).  Allen Robinson (55/754 4TDs, 1/9 Rushing)  Kevin White (4/92)	**2019**  Taylor Gabriel: (29/353 4TDs Receiving, 3/20 Rushing)  Allen Robinson (98/1,147 7TDs Receiving, 1/2 Rushing)  */+ Cordarrelle Patterson (11/83 Receiving, 17/103 Rushing)
Running Back	
2018  **Jordan Howard:** (250/935 Rushing 9TDs, 20/145 Receiving)  ***/+ Tarik Cohen:** (99/444 3TD Rushing, 71/725 5TDs Receiving)  **Michael Burton:** (1/6 Receiving)	**2019**  **David Montgomery:** (242/889 Rushing 6TDs, 25/185 1TD Receiving)  **Tarik Cohen:** (64/213 Rushing, 79/456 3TDs Receiving)  **Mike Davis:** (126/504 3TDs Rushing, 7/22 Receiving)
Tight End	
2018  **Trey Burton:** (54/569 6TDs)	**2019**  **JP Holtz:** (7/91)
Kicker	

2018

Cody Parkey:
20-29 Yards: 6/6 (100%)
30-39 Yards: 7/10 (70%)
40-49 Yards: 9/12 (75%)
50+ Yards: 1/2 (50%)
Total: 23/30 (76.7%)

2019

Eddy Pineiro:
20-29 Yards: 8/8 (100%)
30-39 Yards: 9/10 (90%)
40-49 Yards: 3/7 (42.9%)
50+ Yards: 2/2 (100%)
Total: 22/27 (81.5%)

Passing/Rushing Totals for Chicago Bears and Opponents
(Combined whole team data for respective seasons, not only top players listed above)

2018 Total

Chicago Bears
Passing: 344/512 (67.2%), 3564 Yrds, 28 TDs, 14 Ints, 6.5 YPA.
Rushing: 468 Rushes for 1938 Yrds, 16 TDs, 4.1 YPA.

TSPS: 421
TSP/Yrds: 1013/5502
TOs/FMBL: 24/10

Opponents Totals
Passing: 377/615 (61.3%), 3515 Yrds, 22 TDs, 27 INTs, 5.3 YPA.
Rushing: 339 Rushes for 1280 Yrds, 5 TDs, 3.8 YPA.

TSPS: 283
TSP/Yrds: 1004/4795
TOs/FMBL: 36/9

2019 Total

Chicago Bears
Passing: 371/580 (64%), 3291 Yrds, 20 TDs, 12 INTs, 5.3 YPA.
Rushing: 395 Rushes for 1458 Yrds, 8 TDs, 3.7 YPA.

TSPS: 280
TSP/Yrds: 1020/4749
TOs/FMBL: 19/7

Opponents Totals
Passing: 362/571 (63.4%), 3554 Yrds,17 TDs,10 INTs, 5.9 YPA.
Rushing: 414 Rushes for 1632 Yrds, 16 TDs, 3.9 YPA.

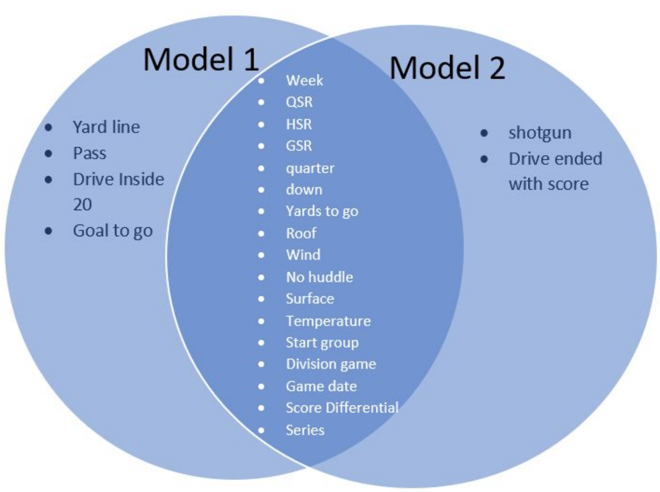
TSPS: 298
TSP/Yrds: 1017/5196
TOs/FMBL: 19/9

*: Indicated player selected for ProBowl
+: Indicated player was selected for 1st Team All-Pro

Abbreviation Definitions:
TSPS – Total Season Points | Yrd -Yards | TDs-Touchdowns| INTs-Interceptions | YPA-Yards per attempt | TOs -Turnovers | FMB – Fumbles | TSP-Total Season Plays | FMBL – Fumbles Lost

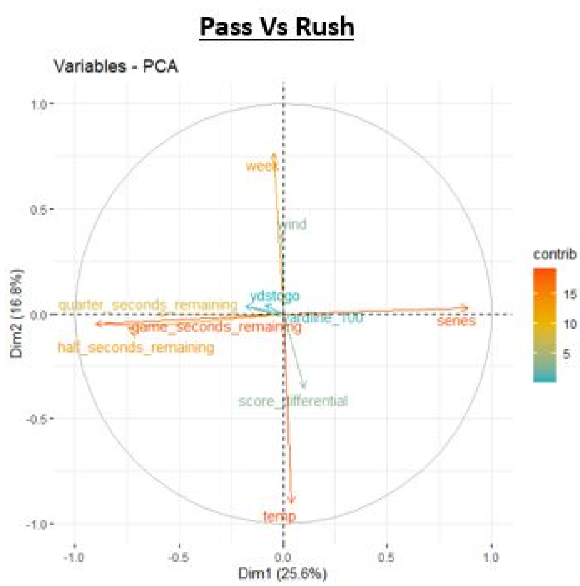
Variable Analysis

To first get a better understanding of the models, we ran our baseline RF that gave us variables that had importance in predicting our output variable. There were hundreds of irrelevant variables or variables that would be leakage, so our first task was to drastically cut our subsets down to 21 for the pass/rush model, and 19 for the red zone model.



To the left is a representation of the variables in each subset. QSR, HSR, GSR is quarter, half, and game seconds remaining. Most variables are applicable for both, but a few, such as the outcome variables, are unique to each model. Model 1 (pass vs rush) includes yard line, drive inside the 20 yard line, and goal to go, and Model 2 (red zone scoring) does not since it is already assumed that the team is within the 20 yard line. This means that we would not learn anything if we kept in variables pertaining to field position since it is fixed essentially in model 2. Shotgun is a formation that the offense takes, and it leads to a pass 72.7% of the time for the Bears in 2019 and 67% in 2018. It is not included in the model that tries to predict passing since we think that would be leakage. Before we get into any analysis, a quick explanation of variables is necessary. Week is week in season from 1-17. There are four downs per drive, which means 4 chances to get a first down and be allowed to continue marching down the field to the end zone. Yards to go is the distance between where the Bears start at the beginning of the play and where the first down marker is. Start group is the time of the game- if a game is on at "prime time" perhaps there are different decisions made compared to if the game is at noon and fewer people are watching. Score differential is the difference in score between the offense and defense at the start of the play. The other variables pertaining to weather or venue are self-explanatory, such as temperature, wind, surface, and roof.

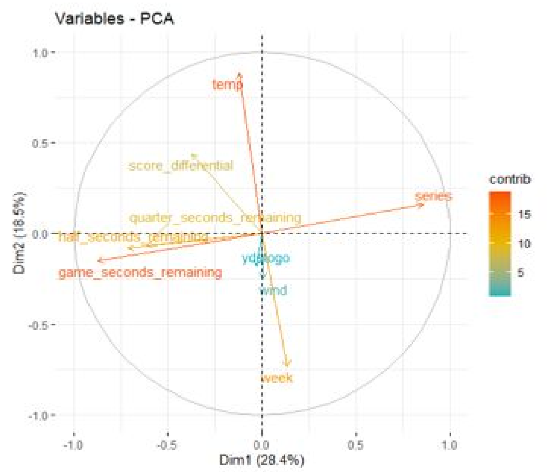
PCA (Principal Component Analysis) - Variable Importance



Once we created our 2 subsets, we decided to examine the PCA of the numeric variables in the models to help us get some understanding regarding our models. In our first PCA model we used 10 variables. We know that with PCA positively correlated variables point to the same direction on the plot, whereas negative ones point opposite directions on a graph. The two biggest sets of variable correlations that we see are "week" versus "temperature" and "series" versus "game seconds remaining." For our Dim2 (16.8%) our biggest factoring variables were "week" versus "temperature." Between the two, "week" is trending towards the positive side of this dimension whereas "temperature" is pointed in the negative direction. We see that both have a very high contribution compared to the rest of the variables shown. Of these two variables, "temperature" has a higher negative contribution for this dimension. This makes sense because regardless of the weather, teams are going to pass and rush the ball. When looking at Dim1 (25.6%) we see that the two variables that factor the most in relation to each other are "series" and "game seconds remaining." For this dimension, "series" is more positively correlated to the model, and "game seconds remaining" is trending towards the negative direction of that dimension. Unlike our Dim1 outcomes, both these variables have the same contribution to the model, just opposite effects. We see that the variables "quarters seconds remaining," "half seconds remaining," "yards to go," "yardline 100," "wind," and "score differential" do not have as much influence on our passing and rushing models.

For our Red Zone scoring model we see very similar outcomes with our Pass vs Rush model. One key takeaway is seeing that "temperature" and "week" are completely flipped in Dim2. Since we know that there are multiple outcomes in the Red Zone, we understand that "temperature" has a major outcome in the Bears game strategy. The plays within the Red Zone for both offense and defensive teams differ from the play calls in the open field at the beginning of those given drives in that series. One big thing we see with a less contributed variable is "score differential." Not only is it flipped completely around in Dim2 moving towards a positive correlation, but the variable contribution is almost double that from the Pass versus Rush model. We can see that this directly applies to in- game situations. If a team is losing a football game, they do not plan on entering the Red Zone to end the drive on a 4th down with a field goal attempt. On the first three plays of the drive they are going to do anything to score a touchdown whether it be by utilizing a pass or rush play. With the same variables as the "Pass Vs Rush Scoring" model, "quarter seconds remaining," "yards to go," and "wind" show very weak contribution to the model.

Red Zone Scoring



Models

We built three models to see which is preferable and gives the best results. We compared our three dataframes: 2018, 2019, and the combined 2018 and 2019. Then we applied an over- under sampling to address the label imbalance. Originally, the ratio of 0:1 for the combined model 1 was about 793:1275, and once we balanced, it looked more like 1074:994. For model 2, the original is 108:827 and once we balanced, it became 483:452. As mentioned earlier, we used subsets of the original data frame that pertained to the specific outcome that we are predicting.

We utilize a 70/30 training/testing split for model 1, and 75/25 for model 2 since there were fewer instances in the model 2 dataframe and we wanted the model to be able to learn from more observations.

We did not worry about different costs associated with predicting the incorrect outcome, since for both models, predicting incorrectly was equivalent for either outcome. A coach is equally worse off predicting a pass when the team rushes the ball as the other way around. We next describe our random forest, SVM and GLM models.

Random Forest Model

The random forest models that we created are meant to be almost a second baseline for further analysis. We received new variable importance scores for each model, and these results informed some of the conclusions that we make. To gauge the accuracy of the random forest we still did test the performance on unseen data, but much of what we received from the RF was the information about splits and variable influence.

The models use the GINI index for splitting as they try to minimize the MSE. The equation for random forest minimizing MSE is: $\frac{1}{N}\sum_{i=1}^{N}(f^{(i)}-y^{(i)})^2$. The Gini index equation is: $1-\sum_{i=1}^{C}(p_i)^2$.

Generalized Linear Models

The goal of our generalized linear models is to predict whether a play was a rush or a pass, and whether a team will score given they were in the red zone. To find the probability, the GLM equation will follow this format:

$$P = \frac{1}{1+e^{-(b_0+b_1x)}}$$

The goal of our two generalized linear models was to find the variables that have high importance in our model and the weights of each variable. In R, we created a full glm with all the variables, and then a null glm and used stepwise regression to find our optimal model using training data. After receiving our best model, we implemented it on our test data and created a confusion matrix to see the accuracy, sensitivity, and the specificity of the models.

The results and the optimal models we received for each dataset are detailed in the experimental results portion in the report.

Support Vector Machine

The goal of a SVM is to find an optimal decision boundary by using the support vectors. The equation looks like this: $\min_{(\xi,w,b)}\ \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}\xi_i$

$$y^{(i)}(w^Tx^{(i)} + b) \geq 1 - \xi_i$$

$$\xi_i \geq 0;\ i = 1,\ldots,m.$$

Radial Basis Kernel: $k(x,y) = \exp(-(\|x-y\|^2/2\sigma^2))$ **Linear Kernel:** $k(x_1,x_2) = x_1 \cdot x_2$

We used the “tune svm” function in R to determine the optimal cost and gamma parameters for the models. In the table below we show our training set sizes. The Red Zone model has fewer observations since there were fewer instances of the Bears being within the 20 yard line on a play, compared to if they passed or rushed the ball. We use a radial kernel for model 1, since that was determined to be optimal for accuracy, and linear was preferable for model 2.

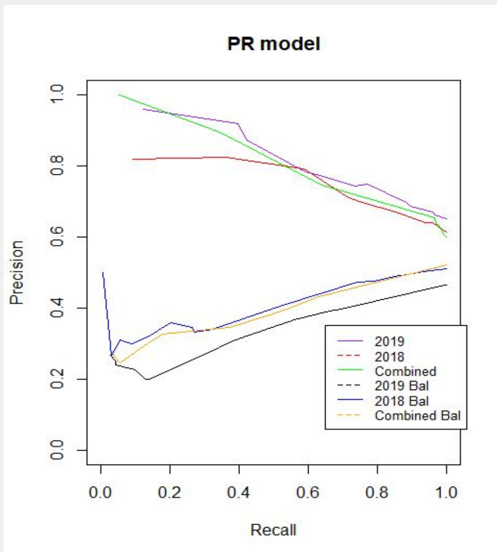
Training Set Size by Model		
	Model 1: Size of training set	**Model 2: Size of training set**
2018	740 x 21	368 x 19
2019	708 x 21	334 x 19
Combined Years	1448 x 21	701 x 19

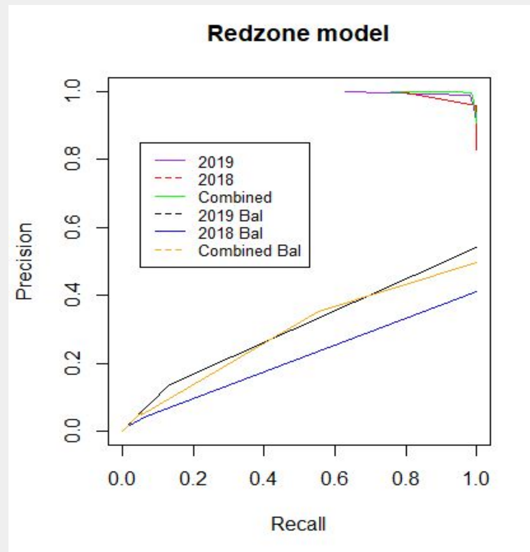
Note that the table only shows the training set for the original dataframe, not the balanced. This is because the two are of identical size.

In the following section we discuss the findings of our models and the different validation metrics we look at.

Experimental Results

Random Forest





For evaluating the random forest model, we use a precision-recall plot since there is label imbalance in the original dataset. We do not see very good results for the PR curve. We also made ROC curves, but those did not fare well either.

The lines in the top right corner of both plots are the original dataset. The balanced lines look much different, which is surprising since in both cases they either improved validation accuracy or kept it at about the same level. We take into account that between the 2018 and 2019 seasons the Bears completely changed the way they ran their offense. Losing a veteran three down back in Jordan Howard between seasons means that the Bears were adapting to a new running game that we can see did not fare as well in their favor between the two seasons. Jordan Howard was let go after the 2018 seasons and the Bears drafted running back David Montgomery to lead the team in the 2019 season.

The tables below detail the accuracy of these random forest models. Overall the testing accuracy is not very high, and balancing gives some improvement, but perhaps random forest models are not the optimal method for predicting the pass or rush outcome.

RF for Model 1- Pass or Run Play		**Evaluation**	
	Size of training set	**Test Accuracy**	**Balanced Test Accuracy**
2018	740 x 21	64.67%	66.56%
2019	708 x 21	67.72%	67.65%
Combined Years	1448 x 21	68.32%	69.44%

For all three models, yards to go is the most significant variable in the random forest. This makes sense, since typically when a team is far from the first down line, they will pass the ball, since that tends to have a higher gain, though it does have a higher risk. The next most significant variables are half and game seconds remaining, score differential, and down. These all make sense since often when time is running out, teams may need to try and score quickly if they are down or if they are up, run the ball and not risk passing the ball.

RF for Model 2- Redzone Score Outcome		**Evaluation**	
	Size of training set	**Test Accuracy**	**Balanced Test Accuracy**
2018	368 x 19	95.08%	96.03%
2019	334 x 19	94.59%	96.50%
Combined Years	701 x 19	96.55%	93.17%

Our second model sees very high test accuracy. The most significant variables are different in order for the three models, but temperature, game start time, wind, week of the season, and game seconds remaining were frequently at the top. There is an issue of high label imbalance that we believe affects our predictions. Start time is likely unimportant, but the other variables make sense as influences to whether or not the Bears are successful on red zone drive.

Generalized Linear Model

Model 1 Experimental Results

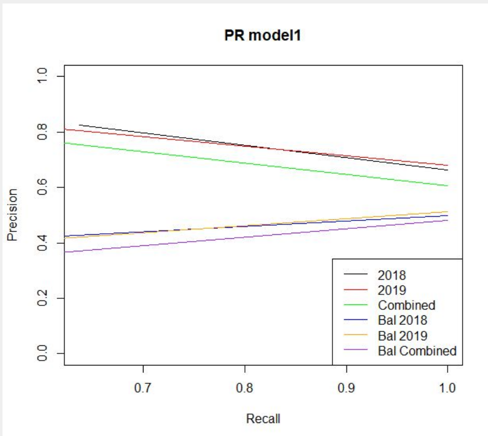
For each model, we reported the optimal model for each dataset, "2018 Play by Play," "2019 Play by Play," as well as a combined dataset with 2018 and 2019 data. We also reported a confusion matrix and PR curves to evaluate the effectiveness of our model on our test data.

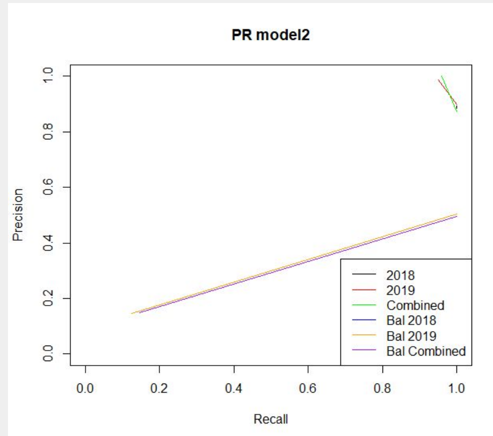
For model 1, the results are is as follows:

Reported Evaluation Measures:

GLM for Model 1- Pass or Run Play			
	Size of training set	**Test Accuracy**	**Balanced Test Accuracy**
2018	740 x 20	0.6472	0.3754
2019	708 x 20	0.6436	0.363
Combined Years	1448 x 20	0.6436	0.3894

PR Curves for Model 1 and Model 2:





Model 1 Analysis:

For model 1, each model's accuracy held at about 60-65%. The models also follow the same trend with relatively high sensitivity and average specificity. This means that the model most accurately predicts passes correctly. We know from our earlier analysis that this information is accurate because the amount of passes outnumber rushing plays. From the optimal models we saw that the down variable has high importance when calculating the probability of the Bears passing or rushing. We see that the variable down is split from second to fourth down and consistently has the highest weight on third down. Third down plays are a team's last attempt to make the first down before having to punt the ball over, or turn over downs on 4th down.

We also created models with the three datasets that utilized the label balance function in R. We saw that the accuracy dropped by 30% in each model. This can be because GLM optimizes deviance, and changing the distribution of the data by balancing it will affect model performance. Therefore, we believe that our current models are optimal given our datasets.

Reported Evaluation Measures:

GLM for Model 2- Redzone Score Outcome			
	Size of training set	**Test Accuracy**	**Balanced Test Accuracy**
2018	368 x 18	0.8525	0.400
2019	334 x 18	0.9796	0.1802
Combined Years	701 x 18	0.991	0.1081

Model 2 Analysis:

To analyze the effectiveness of these models, it is important to look at the confusion matrix as well as the evaluation measures. For model 2, we have high accuracy with our models that are implemented on our test data. We get the lowest accuracy from our 2018 data, but we can account for the low number of instances in our test data. We have the highest accuracy with our 2019 and combined data model. These two both seem to perform well for predicting both drives that ended with and without a score. We feel confident that these models would accurately predict new instances based on the datasets that we used to construct the models.

We also see that the weights for the quarters play a significant role in predicting the outcome of the drive. Between our three models, the surface and whether the stadium is enclosed or not plays a role in the prediction as well. This makes sense because weather can be a significant predictor and having an enclosed stadium removes the issue of wind or temperature.

Support Vector Machine

For SVM, we try two different kernel methods, and determine that a radial kernel gives a better test accuracy for model 1 (pass versus rush) and a linear kernel is preferred for the second outcome (score in the red zone).

Model 1: Below are the tables for the models and the optimal parameters for the SVM. We evaluate the test accuracy and compare results between the three different dataframes.

SVM for Model 1- Pass or Run Play			Evaluation	
	Best Parameters: Gamma, Cost	**Size of training set**	**Test Accuracy**	**AUC**
2018	2, 10	740 x 21	61.12%	0.5392
2019	1, 10	708 x 21	63.04%	0.5594
Combined Years	1, 1	1448 x 21	63.39%	0.5533

Accuracy is not very good, AUC is hardly better than a random guess. We next look at the balanced dataset since there is label imbalance.

Label Balanced- SVM for Model 1- Pass or Run Play			Evaluation	
	Best Parameters: Gamma, Cost	**Size of training set**	**Test Accuracy**	**AUC**
2018	2, 1	740 x 21	79.81%	0.8158
2019	5, 10	708 x 21	81.52%	0.8176
Combined Years	2, 1	1448 x 21	81.94%	0.8193

It appears that balancing has a strong positive impact on the test accuracy for model 1. It also brings the AUC up significantly. This brings to light the importance of balancing a dataframe when there is classifier imbalance.

We think that it may be easier to predict 2019, because in 2019 they had more options to use because of their less experienced offense and that makes it harder to predict which outcome they did for a given play.

They tried more specialty plays since they had a team that was not as good. A specialty play is a “trick” play, that could not be classified as a pass or run necessarily.

Model 2: Below are the tables for the original dataframe and the balanced.

SVM for Model 2- Redzone Score Outcome			Evaluation	
	Best Parameters: Gamma, Cost	Size of training set	Test Accuracy	AUC
2018	.5, 10	368 x 19	97.51%	0.9583
2019	.5, 10	334 x 19	99.00%	0.9944
Combined Years	.5, 10	701 x 19	92.31%	0.7334

Combined AUC is not as good as the separate years since the other two are overfit. We decide to ignore the 2018 and 2019 datasets because they are overfit and have too few observations. Instead we focus on the combined dataframe, where the accuracy and AUC are more realistic. Balancing improves performance, and we believe the test accuracy is as high as it is because this outcome may not be that difficult to predict from the data that the model is given. Whether or not the Bears are able to end a red zone drive with a score relies on a few key variables.

Label Balanced- SVM for Model 2- Redzone Score Outcome			Evaluation	
	Best Parameters: Gamma, Cost	Size of training set	Test Accuracy	AUC
2018	.5, 10	368 x 19	96.72%	0.9717
2019	.5, 10	334 x 19	99.10%	0.9950
Combined Years	.5, .5	701 x 19	96.88%	0.8953

Conclusion and Discussion

The accuracy for pass vs rush may not be very high, but that is not necessarily a bad thing. If it was too easy to predict, teams would all use AI and know the offense’s play before it even happens, which is unrealistic. There is a human component that can not be represented by these models, but seeing that the models can get up to 70-80% accuracy, that shows that there are ways to make predictions from the data.

Key Observations:

- The first thing that we are going to be looking at in our breakdown are plays on 1st and 2nd down.

    - If there are more than 6 yards to go in the open field, the Bears go for a passing play. If you are in the Red Zone go for a running play.
- If there is more than 1:48 left in either half of the game, 70% of the time you are better off throwing the pass than running the football in order to make significant gains.
- If the Bears are losing the game by more than 7 points and the wind is blowing more than 10 mph they are better off running the football. Now in the same scenario if the Bears are losing between 7 - 17 points but there is no wind, better off throwing the pass for better odds at a successful chance at moving the chains and putting another touchdown on the scoreboard and lessen the score differential in the game.
    - If you are in the Red Zone and losing the game by 7 - 17 points you need to go with a win by throwing the football. If you are within the 10 yard line in the Red Zone under the same circumstances, keeping the ball on the ground with a run is better than risking a pass and potentially losing the ball in the End Zone with an interception.
- If there are less than 6 yards to go on any open field play where the temperature is less than 53℉, the best bet is to run the football.
    - If the Bears are within the opponents 40 yard line to the goal and the temperature is less than 53℉, all bets are off and there is an even split between running or passing the football.
- If the Bears are playing on a grass surface and not turf, 78% of the time they are going for a passing play in the Red Zone. This is true for the 1^{st}, 2^{nd}, and 4^{th} quarters of the game. In the 3^{rd} quarter given the situation go for a running play.
- When the game clock is under 27 minutes (they play for 60 minutes in total), the wind is less than 12 mph, the temperature is over 35℉, and you are in the Red Zone, the conditions of the game are good enough to risk putting the ball in the air for a long pass.
- When the Bears get past week 3 in the season and are losing the football game with a temperature hotter than 77℉, if they are in their first 12 series of the game, go for a running play. The Bears knew from what happened in the first 3 weeks of the season that moving forward the rest of the season they needed to change the playbook for the game to incorporate more runs of the football on the ground. As the weeks go on, teams adapt to changes with lineups and make different play calls.

Limitations and Future Considerations

We have a small data frame since when we present for coaches they only care about this season. Aggregating over years more than we have would not make sense since teams are different from year - to - year and coaches change, so our results would be less interpretable if we aggregate across teams or years. We checked to make sure there were not too many coaching/player changes across the two years for the combined dataframe, but this industry moves very quickly and it is common for players and coaches to be brought on or dropped mid-season. Also, as mentioned earlier, this original data frame had over 300 columns. There are many other outcomes that we could predict that would have an impact on the Bears. To have a better understanding of what we wanted to gain insight from this report, we had to start off at square one on what affects the game the most. For us after our initial observations and research it was clear that we needed to look into Passing versus Rushing Plays and Red Zone Scoring.

Our analysis resulted in tons of information regarding Passing versus Rushing Plays and Red Zone Scoring. For future iterations we think that the biggest thing to report would be using this information and adding our own fantasy data results. Even in the world today of NFL Football, fans do not even need to watch a single game to be drawn into the thrill of playing fantasy football with family and friends. Comparing fantasy football in both of our models would be able to give fantasy managers a better insight of players they should play in key position slots such as Running Back, Wide Receiver, and Tight End. Other considerations after looking at our variable importance at the beginning of the report we would learn more about what types of plays were used on third down between passing and rushing to see which ones had a higher success rate for a first down. In games that the Bears were down by 3 - 7 points going into the 3rd and 4th quarter, what were the chances they went for a first down and did not punt the ball? Lastly, we would like to see how the percentage of passing and rushing plays were distributed to the Quarterback, Running Backs, Wide Receivers, and Tight Ends respectively. All of these future iterations would give us the ability to break the game down even further to understand the variable importance in our dataset and how it affects every football game throughout the season broken down by every single play individually.