

Atlanta Falcons Win Probability

Shruthi Harve · Week 9 · MSDS456 Assignment 3

OVERVIEW

The Falcons have played decently well over the past 5 seasons, including winning the NFC Championship title in the 2016 postseason. However, we have had a losing record the past 2 seasons. There is room for improvement, and we should take measures to understand what they are from a data perspective. I created a win probability model, upon which we can evaluate the impact of various play outcomes on win probability at an 87% accuracy rate. Although there are some limitations on this model, I believe it will provide foundational guidance on where our shortfalls are. For instance, we may be playing it “too safe” on our fourth downs. In future analyses, we may want to evaluate the impact of going for a fourth down conversion or a touchdown, where we would historically punt or attempt a field goal.

PART 1 – WIN PROBABILITY MODEL

I imported play-by-play data from (Ryurko) in order to analyze the impact of each play in the regular season. Even though Matt Ryan has been the starting QB since 2008, Julio Jones has been on the team since 2011 and I have data available from 2009, I decided to keep only the 2015-2019 seasons to limit analysis to the Dan Quinn era so that we can produce actionable insights. Since the play-by-play data does not indicate the winner of each game, I mapped this value referencing the regular season game data from the same Github site.

In order to factor in the variety of game play indicators, I first needed to check the multicollinearity between them. There is a lot of detail in this dataset and it appears like several of these variables are highly correlated (i.e. pass touchdown vs. touchdown). If I keep all these variables in the model, they will not be as strong as predictors for the dependent variable. Therefore, I will need to

remove a portion of the variables so that the remaining independent variables are less correlated with each other. To do this, I used the Variable Inflation Factors (VIF) method (Bhandari). This was an iterative process, where I would assess the variables with the highest multicollinearity and remove a couple at a time, based interdependencies (i.e. either pass touchdown OR touchdown). I did this until all remaining independent variables had a VIF score under 6.

I then inputted the remaining independent variables into a logistic regression model. I purposely did not include a constant in the model because all the independent variables will never equal 0, rendering the purpose of the constant ambiguous (Grace-Martin). Narrowing down the variables even further based on a 5% significance level was an iterative process as well. Ultimately, the final model produced an Area Under the Curve (AUC) curve score of 85%, which means that using the model is better than a random guess, which has a 50% accuracy rate. In **Appendix A**, I have listed the complete summary of the model as well as a graph of the ROC curve.

I found it interesting that *lateral_reception* as a -1.07 impact to win probability, a large impact especially since win probability is between 0-1. This could be because teams who do a lateral pass/reception are in a desperate state, and just trying to make something happen. Additionally, looking at the coefficients for *fourth_down_failed* (-0.89), *field_goal_attempt* (-0.30), and *punt_attempt* (-0.37), what I deduce is that we should consider “going for it” on 4th downs. This depends on the number of yards to go to achieve 1st down, which we can do in a future analysis. But doing this can improve win probability by 30% over a field goal and 37% over a punt, all else equal. Of course, this is a risky move because failing to convert the 4th down reduces win probability by 89%, all else equal.

PART 2 – GAME SUMMARY

In order to do analysis on an individual game, I merged the predicted win probability from the model into the original play-by-play dataset. This way, I can filter the data to a specific game, while

keeping the same variables used in the model and the predicted win probability for each play within the dataframe.

I decided to look into the 9/15/2019 game against the Philadelphia Eagles, which ended up being a 24-20 win for us. It was an incredibly engaging game, with the Eagles nearly winning in the end. In **Appendix B**, I have plotted our win probability throughout the course of the game. At first glance, it looks like we had the advantage for most of the game, with a win probability of around 90% in the beginning of the second half. Also, we started out with an advantage by having possession on the first drive. This makes sense because teams are more likely to score while on offense, so it brings up a strategic tactic of whether or not a team should start with the ball in the first half or the second half. In this game, the first half was 10-6 favoring the Falcons and the second half was tied at 14-14. Essentially, whoever has first possession of the half has more of an advantage to win that half. I suppose in this game, we played a strong game throughout, even with Philly's additional strength in the second half.

However, there were some dips to our win probability that I wanted to better understand. In our second drive starting around the 6:00 mark, our possession began within our own 5-yard line, which is a difficult position. We were unable to convert a 3rd & 15 from the 20-yard line, despite a completed pass to Davonte Freeman. This drive ended up with a punt from the 25-yard line with about 4:30 left in the 1st quarter. In Part 1, I highlight that the impact of a punt attempt is a -0.37 impact to a team's win probability, which is likely what drove in our probability towards the end of the first quarter. Our probability spiked back up shortly after, when we made an interception; that alone brought up our probability by 0.67 (**Appendix A**).

With about 5:00 the second quarter to go, we see a spike in our win probability. This was driven by a couple things. Firstly, our defense intercepted Wentz again halfway through the quarter (7:30 left) and set us up with decent field position at our own 45-yard line. After a back-and-forth shuffle to gain yards, Ryan threw a deep touchdown pass to Ridley from Philly's 36-yard line on 3rd down & 6th. This

explains the win probability spike to nearly 80% with 5:00 to go. At the end of the second quarter with less than 1:00 left, we see a dip again, driven by an Eagles interception. This was short-lived, however. Even though this interception led to an Eagles field goal making the score 10-6 at halftime, and the Eagles had possession of the ball at the start of the second half, the Eagles special team turned over the ball on a lost fumble during the punt return 10 seconds into the second half. This led to a touchdown pass 2 minutes later, bringing up our win probability to over 85%.

In the second half, we see the Eagles defense start playing more aggressively. This is displayed by two interceptions in the third quarter, indicated by the two dips. Additionally, the declining trend in the fourth quarter was initiated by a sack by Philly defense, leading to a 10-yard loss 3 minutes into the quarter. This leads to the Eagles scoring a rushing touchdown and a 2-point conversion. With 3 minutes left of the game, we were trailing the Eagles 17-20, reflected by the 35% probability in the line plot. Just before the 2-minute warning, we see another spike in our win probability going up to over 65%. This is driven by a pass to Jones on 4th & 3, which led to a touchdown to win the game.

Overall, even though our win probability was above 50% for most of the game, there was room for improvement. Our defense helped us steal possession a handful of times from the Eagles through forced turnovers. However, we threw a few picks that cost us the lead late in the game. Our play call to “go for it” on 4th down and pass to Julio Jones was a smart move that led us to victory. (NFL)

PART 3 – MODEL LIMITATIONS

While the logistic model is more accurate than random selection by 36 percentage points, I was aiming to get the AUC score closer to 90%. This would prove the model to be strong enough for predictions without overfitting the data. It would have been helpful to have data on how many timeouts are remaining for each team. Timeouts are used strategically in the game, and coaches often use them

to deliver expectations to the team or to simply stop the game clock. This variable could indicate that a team with fewer remaining timeouts earlier on in the game is in a desperate state.

Due to the way the messy way the data was structured, I had to filter out the special plays data, including extra points and special teams plays. These plays can have a significant impact on game results. Extra points were considered nearly “guaranteed” points until 2015, when the NFL pushed back the kickoff yard line by 13 yards. According to (Murphy), this amendment has changed strategy for some teams, who may risk a 2-point conversion over the extra point.

Finally, external factors could impact the outcome of the game. While home field advantage is more significant in baseball, it would be interesting to see how significant it is in football. Certain teams are terrible on the road, so I feel this is worth considering in the model. Additionally, weather is not accounted for in the dataset. A particularly cold or rainy game may give the midwestern teams a greater advantage compared to a team from California.

In a future study, I would like to reproduce this graph to include only Atlanta Falcons games. Based on our team’s strengths and weaknesses, what does it take for us to win? What was it about the 2016 season that led us to the Super Bowl, and how can we build on those insights to make that happen again? By filtering the dataset to only Atlanta games, we can also merge in our play calls – perhaps certain plays are more successful on 3rd down than on 2nd down. Some other insights we can consider in relation to play-calling include: rushing vs. passing on 1st down, a short pass to the left vs. a long pass to the right, as well as changing up play call strategy by the defending team.

PART 4 – FUTURE APPLICATIONS

In *Mathletics* chapter 21 “Football Decision Making 101”, Winston goes into the importance of play calling, especially during high pressured situations. In the past, coaches have often gone with their gut, which comes from experience. Nowadays, coaches can consider data-driven insights. One high-

pressured situation that Winston explores is whether a team should attempt to convert a 4th & 5 to a first down or to kick a field goal. In order to compute this, he would define the probability of getting 5 yards as p (or converting to a first down) and the probability of failing to convert as $(1-p)$. He would consider “down”, “yards to go for first down”, and “line of scrimmage yard line”. Based on the Cabot, Sagarin, and Winston (CSW) estimated state values, he would compute the state value of the situation in question, and then compute the estimated value of going for it on a fourth down. (Winston)

We could adopt similar analysis. As stated in Part 1, the benefit of converting a fourth down is significant, improving probability of winning by at least 30%, all else equal. **Appendix C** shows a distribution of fourth down attempts by yards to go for a first down against yards to go for a touchdown. The first scatterplot distribution of play types aligns with what is expected: we punt when we have more yards to go, go for it more when we are closer to a 1st down, etc. What the zoomed in plots show us that we attempt field goals even when we are within 5 yards of the end zone. This game time decision could be a result of the score differential or time remaining in the game. However, I question whether we can attempt to get a touchdown on fourth more frequently if we are within 5 yards of it. Similarly, while we are more likely to pass or run the ball on fourth down when we are 1 yard from a 1st down, we don’t see that same level of aggressive play calling at with 2 yards to go.

Additionally, I understand the decision to punt the ball when we are in the opponent’s side of the field, but perhaps we can go for a conversion when we are in mid-field, since we are out of field goal range. I provided a field goal scatter plot in **Appendix D** for additional context of the outcome of our field goal attempts. At an 87% success rate, our field goals are fairly reliable, but not close to “guaranteed” points. Most of our misses occurred over 20 yards from the end zone and within 10 yards from a first down. Perhaps we could consider going for a conversion in these less-reliable field goal situations in order to risk a higher reward, thereby improving our win percentage.

APPENDIX A

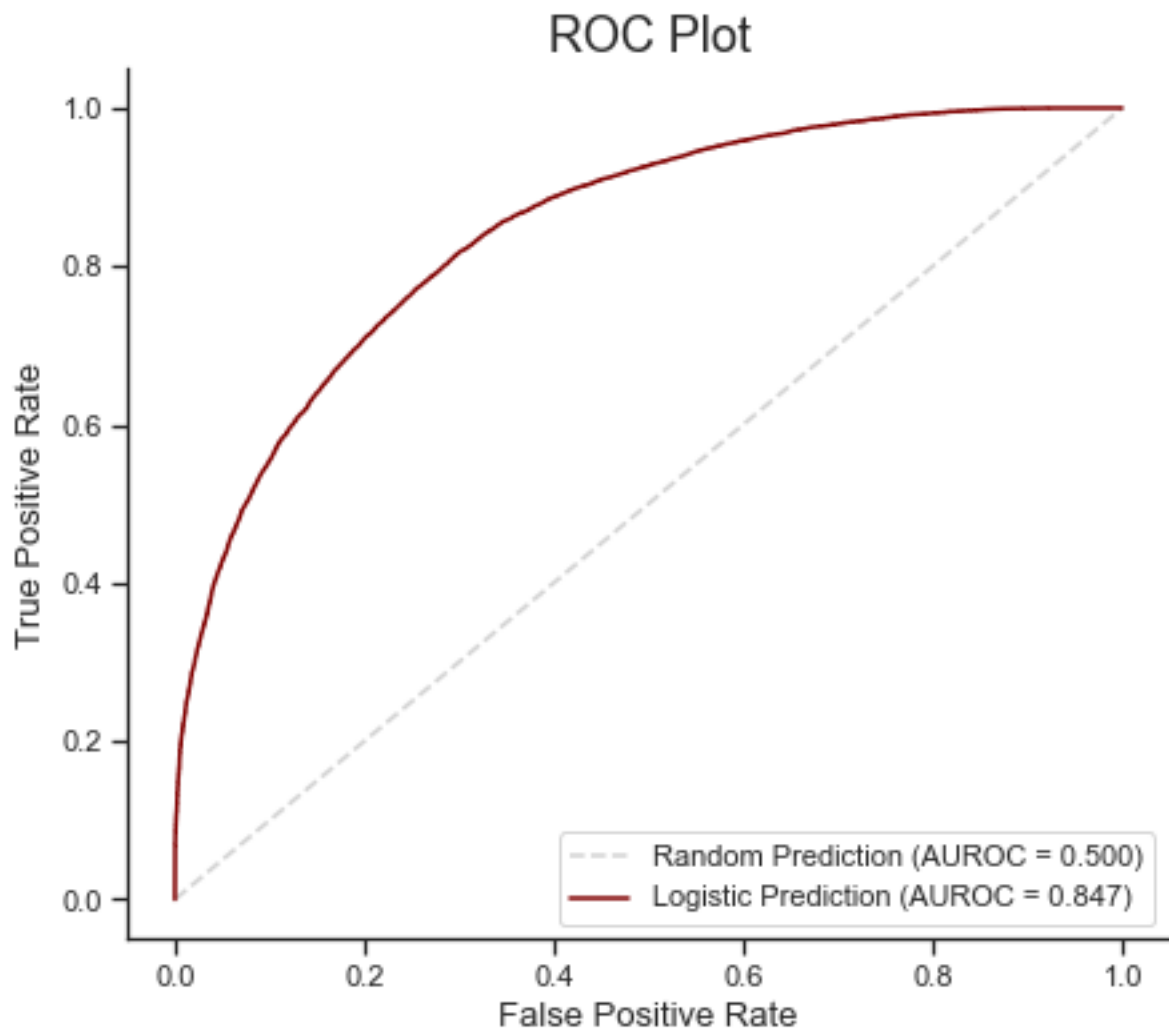
2015-2019 DATA, ALL TEAMS

Logit Regression Results

Dep. Variable:	poswin	No. Observations:	152608			
Model:	Logit	Df Residuals:	152580			
Method:	MLE	Df Model:	27			
Date:		Pseudo R-squ.:	0.3132			
Time:		Log-Likelihood:	-72641.			
converged:	True	LL-Null:	-1.0577e+05			
Covariance Type:	nonrobust	LLR p-value:	0.000			
=====						
	coef	std err	z	P> z	[0.025	0.975]

game_seconds_remaining	0.0003	9.5e-06	33.423	0.000	0.000	0.000
quarter_seconds_remaining	-0.0004	2.91e-05	-14.684	0.000	-0.000	-0.000
yardline_100	-0.0083	0.000	-28.689	0.000	-0.009	-0.008
score_differential	0.1954	0.001	177.005	0.000	0.193	0.198
first_down_rush	0.1648	0.029	5.708	0.000	0.108	0.221
first_down_pass	0.2387	0.026	9.010	0.000	0.187	0.291
first_down_penalty	0.2448	0.048	5.113	0.000	0.151	0.339
third_down_converted	-0.0873	0.030	-2.880	0.004	-0.147	-0.028
third_down_failed	-0.2116	0.024	-8.778	0.000	-0.259	-0.164
fourth_down_failed	-0.9438	0.104	-9.095	0.000	-1.147	-0.740
incomplete_pass	-0.2143	0.022	-9.896	0.000	-0.257	-0.172
interception	-0.6765	0.069	-9.783	0.000	-0.812	-0.541
fumble_forced	-0.3233	0.065	-4.973	0.000	-0.451	-0.196
penalty	-0.1769	0.029	-6.179	0.000	-0.233	-0.121
tackled_for_loss	-0.0795	0.037	-2.147	0.032	-0.152	-0.007
sack	-0.2917	0.041	-7.103	0.000	-0.372	-0.211
pass_touchdown	0.2399	0.050	4.776	0.000	0.141	0.338
rush_touchdown	0.2275	0.070	3.228	0.001	0.089	0.366
return_touchdown	-0.7964	0.216	-3.682	0.000	-1.220	-0.372
field_goal_attempt	-0.2647	0.042	-6.246	0.000	-0.348	-0.182
punt_attempt	-0.3802	0.029	-13.010	0.000	-0.438	-0.323
complete_pass	-0.0794	0.022	-3.587	0.000	-0.123	-0.036
lateral_reception	-1.7616	0.595	-2.963	0.003	-2.927	-0.596
qtr_2	0.3160	0.016	19.632	0.000	0.284	0.348
qtr_3	0.5754	0.021	26.885	0.000	0.533	0.617
qtr_4	0.8752	0.026	33.872	0.000	0.825	0.926
qtr_5	1.2461	0.072	17.215	0.000	1.104	1.388
down_2.0	-0.0602	0.015	-3.883	0.000	-0.091	-0.030

APPENDIX A (cont.)
2015-2019 DATA, ALL TEAMS

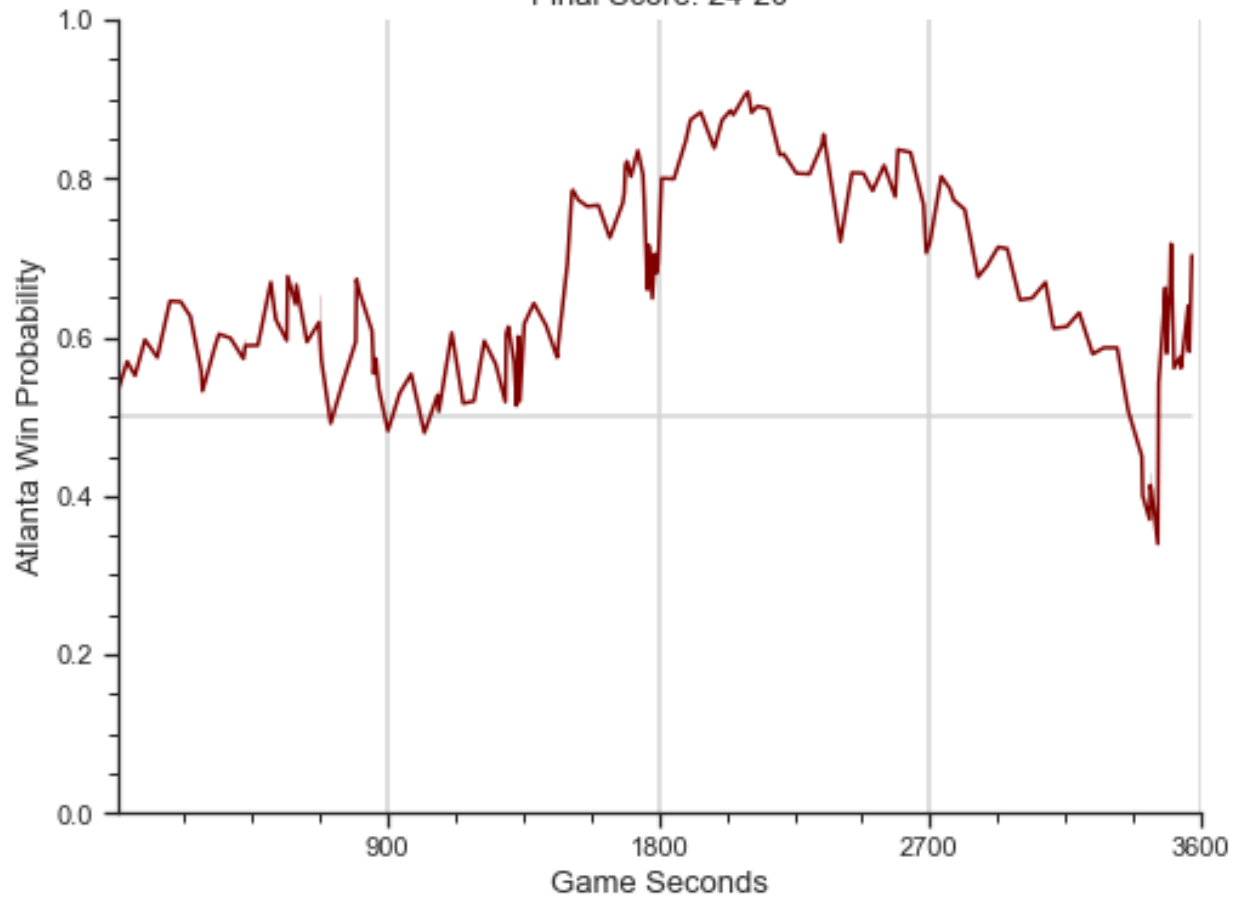


APPENDIX B

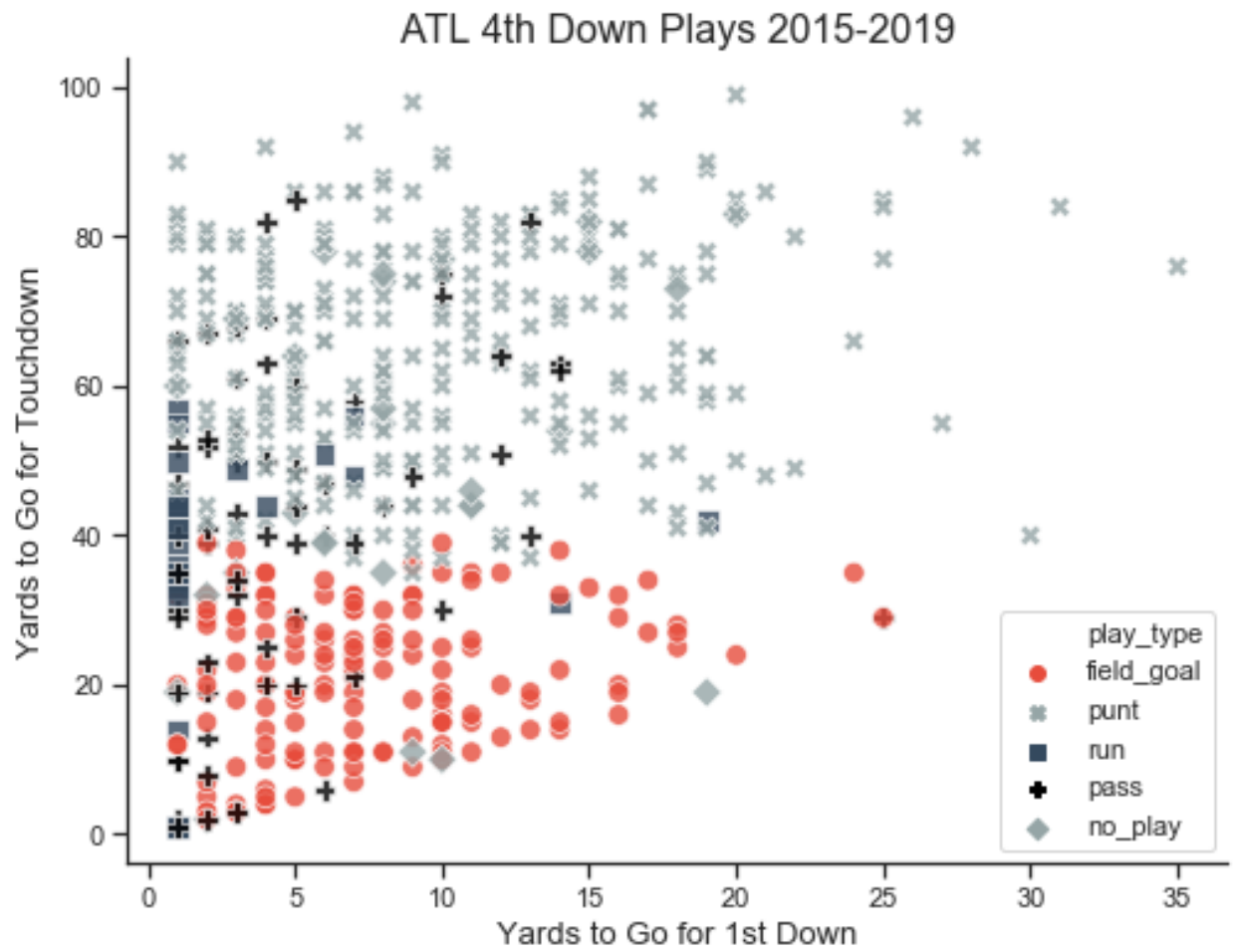
9/15/2019 GAME – WIN PROBABILITY

ATL vs. PHL, 9/15/2019

Final Score: 24-20

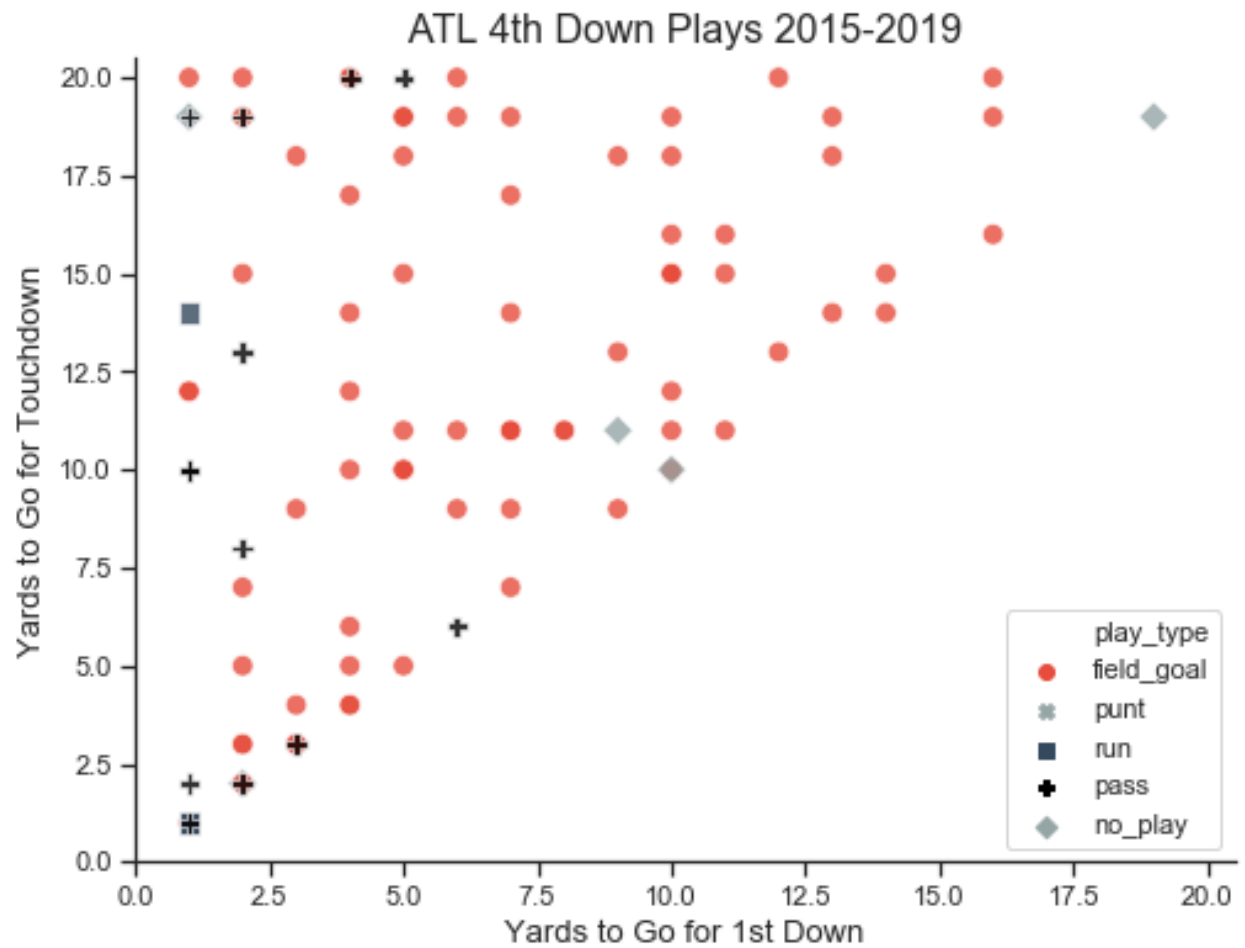


APPENDIX C
2015-2019 ATL 4th DOWN PLAY CALLS



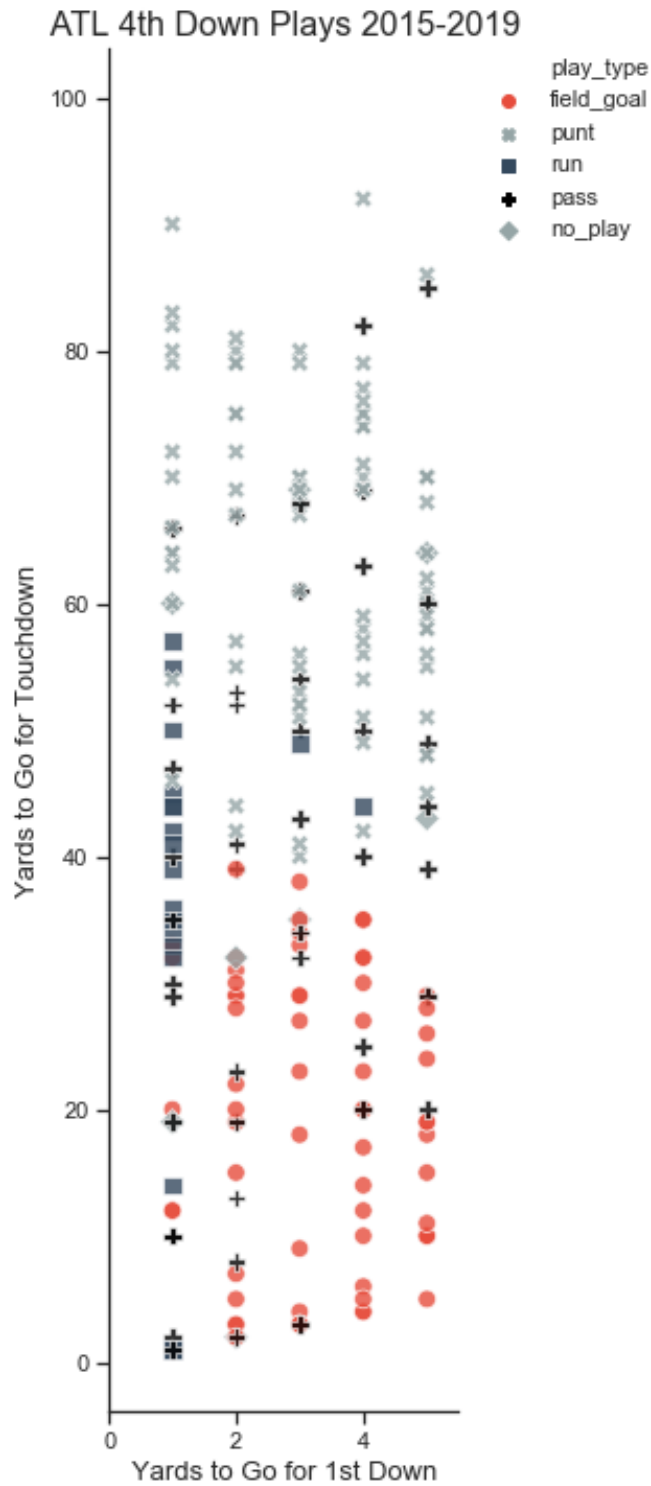
Play Type	Count
Field Goal	161
Penalty	28
Pass	63
Punt	277
Run	26

APPENDIX C (cont.)
 2015-2019 ATL 4th DOWN PLAY CALLS
 (WITHIN 20 YDS OF TOUCHDOWN)



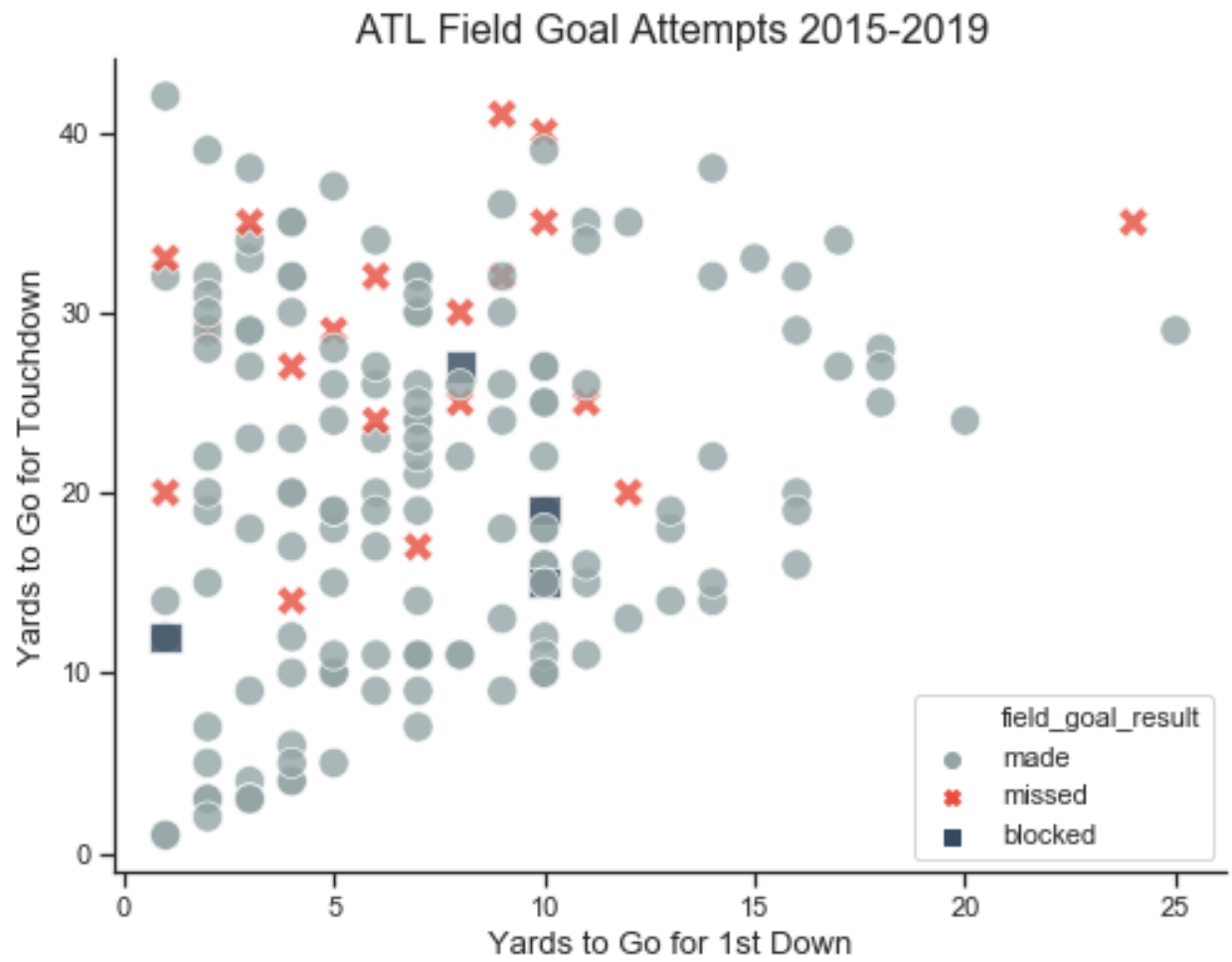
Play Type	Count
Field Goal	80
Penalty	5
Pass	14
Punt	0
Run	5

APPENDIX C (cont.)
 2015-2019 ATL 4th DOWN PLAY CALLS
 (WITHIN 5 YDS OF 1st DOWN)



Play Type	Count
Field Goal	68
Penalty	8
Pass	45
Punt	85
Run	21

APPENDIX D
2015-2019 ATL FIELD GOAL ATTEMPTS



Result	Count
Made	150
Missed	19
Blocked	4

REFERENCES

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[empt](https://qz.com/516768/how-nfl-rule-changes-this-season-are-changing-football-strategy/#:~:text=Under%20the%20new%20rules%20which,league%20to%20miss%2013%20att)
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