Zach Gilfix

Professor Knudson

Math-394

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Run or Pass: Predicting Play Type in the NFL

Football coaches and athletes have often rejected the use of advanced statistics and analytics to guide a team's decision making. Pittsburgh Steelers head coach Mike Tomlin had this to say on the matter:

"I got a lot of respect for analytics and numbers, but I'm not going to make judgments based on those numbers. The game is the game. It's an emotional one played by emotional and driven men."

This sentiment is shared by many in the industry. Can the use of statistics enable coaches to make better decisions, like it does in virtually every other industry? Even in the sports world, we have seen an increase in the use of statistical analysis, especially in baseball and basketball. As these success stories spill over into the football realm, we expect an increasing, albeit reluctant, acceptance that using numbers to guide on and off-field decisions can and will improve a team's chances of success.

In this paper, we create and examine one possible application of this idea. We create a logistic model that predicts whether a play will be a pass or a run. We incorporate down, distance, score, team, and other variables into the model to determine the probability of the offense throwing or rushing the ball. In practice, this model could be used to help call defensive plays in real-time, and give defenders a better idea of what to expect on the next play.

Basics of Football

This section is for those unfamiliar with football. There are a few concepts to know that will make this paper easier to understand.

First Down/Possessions: At the start of each possession, a team has four downs (plays) to gain ten yards and get a first down. If they get a first down, this process repeats until they score, punt, or turn the ball over. On fourth down, a team can try to pick up a first down (if they fail, the other team takes possession where they fail), kick a field goal for 3 points, or punt the ball down the field and give possession to the other team. The field is 100 yards long, and a team receives 6 points for a touchdown. When we refer to down and distance in the paper, down is what play they are on and distance is how many yards they need for a first down.

Types of plays: A team gains yardage primarily through two types of plays: passes and runs. On a pass play, the quarterback throws the ball to one of his receivers. If the ball is not caught, the pass is incomplete, the clock stops, and the team gains no yards. If caught, the receiver can run with the ball until he is tackled or goes out of bounds. On a run play, the quarterback hands the ball off to a running back who then heads up field until he is tackled or goes out of bounds. Passing plays have more variance in outcome than running plays, which typically go for around 2-5 yards. Leading teams generally want to be more conservative, and rushing/running plays have three traits that make them a safer option. One, the expected gain on the play is less variable. Two, time continues to run after a rushing play, which is desirable for a team who is leading and wants the clock to run down. Thirdly, the risk of turnover is lower for a running team. Pass plays can be caught by the other team, which results in a turnover of possession. We also expect teams to run more in short yardage situations (when the distance to go is small), as the probability of getting a first down is greater with a run than a pass here. When the distance is longer, passes are more likely to gain a first down.

Sacks/Scrambles: A sack is when the quarterback is tackled with the ball as they look for someone to pass to. A scramble is when the quarterback can't find anyone to pass to and/or sees an opening and decides to run with the ball himself.

Literature Review

There is not much in the academic literature that looks at predicting pass versus run in the NFL (National Football League), and we suspect that a lot of work done in this area is likely proprietary and not publicly available**.** There are a number of academic articles (ex. Alamar 2010, Reed et al. 2013) written about the optimal proportion of passing and rushing plays, which have found that passes are underutilized given the average yards gained per pass and the expected change in win probability (passing premium puzzle). Although our research is focused on what the offense *will* do, rather than what they *should* do, this past research, which has found coaches are risk-averse, helps in creating our model. There are some useful works across the sports analytics "blogosphere" that look more specifically at our topic.

Two statisticians at North Carolina State University presented a model to predict run versus pass at JSM 2015. They used play-by-play data from 2000 to 2014 for their models. They made an interesting model decision, running six different logistic regressions, based on time and score. They ran one regression for the first three quarters, and three for the fourth quarter (one each for a winning team, losing team, and a tie game). This has essentially the same effect as interacting time/score on each covariate. The other variables are very similar to the ones we use (although they had access to a few more), which is largely a function of the available data. Their model had an in-sample success rate of 75%.

A similar analysis was done by several members of the Harvard Sports Analysis Collective, who used gradient boosting to predict run vs. pass, with similar variables to the NCSU model. They found team and time effects to be the most important predictors of a play call. Their model had an out-of-sample success rate of about 70%.

Data & Methods

We obtained our data from Brian Burke's (now of ESPN) former site, Advanced Football Analytics, who released NFL play-by-play data from 2002-2012. Our analysis looks at the three seasons from 2010-2012. The data came in raw form, and we used keywords in the play description to determine each play's type. We filtered the data to include only passing and rushing plays (not including 2 point conversions & overtime), and we classified sacks and Quarterback (QB) scrambles as passing plays, since these plays are essentially botched passing plays. After these adjustments we are left with a total of 99,357 plays, 60% passes, 40% rushes.

The variables we use are:

- Down (1st, 2nd, 3rd, or 4th)
- Distance To Go

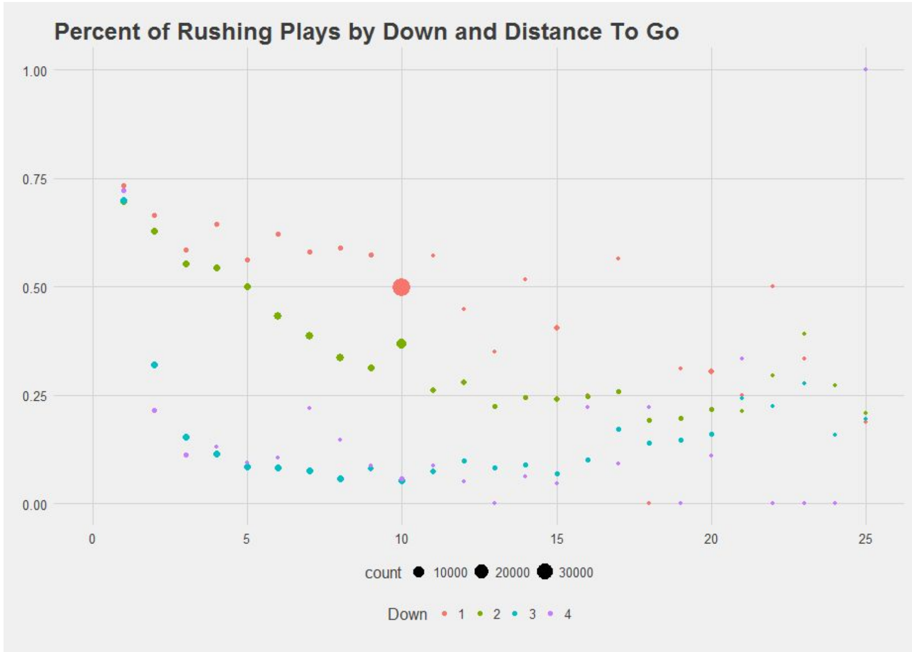
- Yardline (Where the ball is at the start of the play, 100=touchdown)
- Yardline Category (Inside Own 20, Between 20 and 95, 95-100)
- Minutes Played
- Minutes Played Category (First 27 minutes, Final 3 minutes of the first half, second half)
- Offensive Team
- Season (2010, 2011, or 2012)
- Game State (Whether the Offensive Team is losing, tied, or winning)

After conducting exploratory data analysis, we randomly split the data into training and testing sets, putting 60% of the plays in our training set. Next, we fit a logistic model to the training data, which gives us the log-odds of a play being a pass, which we can convert to a more easy-to-understand probability. We can then find the model's success rate in predicting plays from both the training and testing set. We used the *glm* function from the *stats* package in R to fit our model.

Exploratory Data Analysis

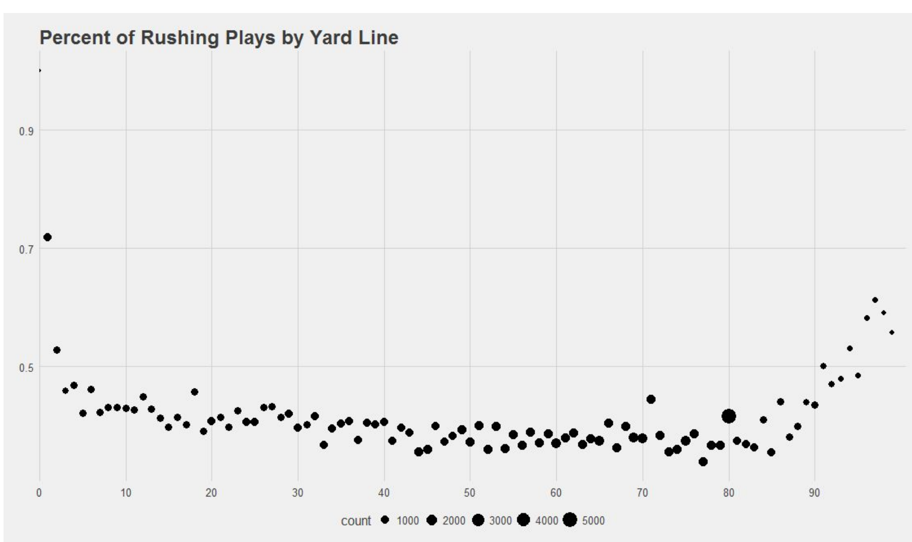
The first step after obtaining and cleaning the data was to perform exploratory data analysis, which enables an examination of how to include the variables in my model. In particular, the time variable was one I expected to be non-linear and EDA helped me decide how to proceed with time in my model.

First, we look at down and distance. These are grouped because these are the two factors we most often think of (together) when we talk about play calling.



From the graph, we can see two clear relationships. One, as the distance required to get a first down increases, the number of running plays decreases fairly steadily within the first ten yards. We also see as down increases, the proportion of passes increases. Less obviously, the relationship between distance to go and % Runs seems to vary by down, and we will test this interaction in our model.

Next, we look at field position. As a team nears the end zone (yard line 0), we expect % Runs to increase, as the number of yards required decrease and play callers become more risk-averse.

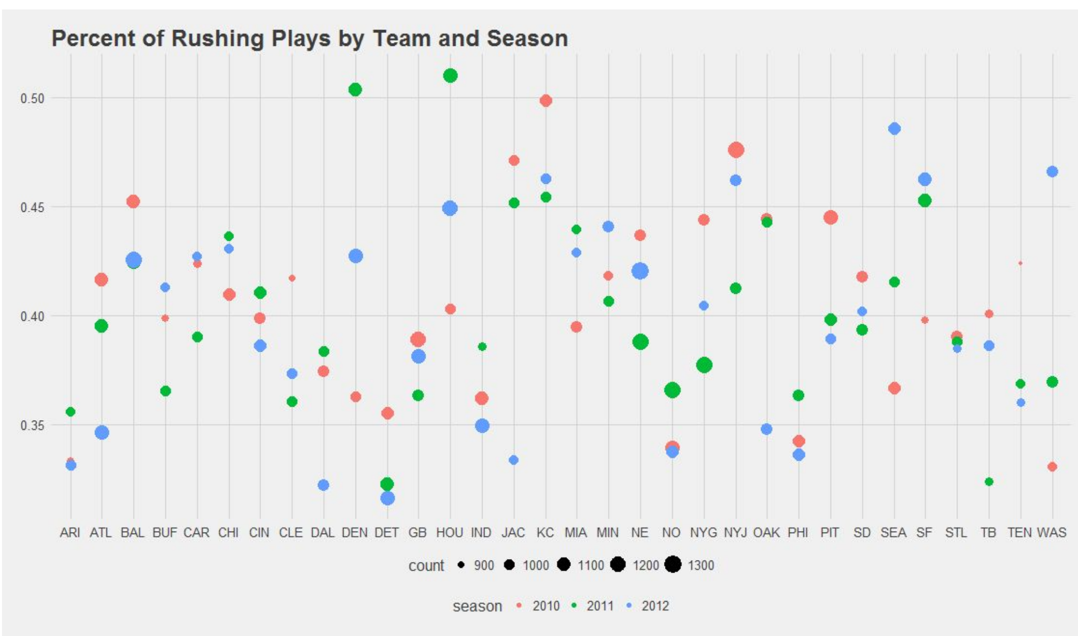


Here we observe a clear non-linear relationship. When a team is within five yards from the endzone (0-5 yards), they rush far more often. From there until their own 20, (5-80 yards), the proportion of passes steadily decreases. Inside their own 20, the number of rushes increases substantially. Due to this nonlinearity, we will make a categorical variable for each of these three groups.

There is not a huge difference in % Runs in each season, but it has been steadily decreasing for the past decade, and we will include it in our model. Below is the mean % Runs for each season in our data set.

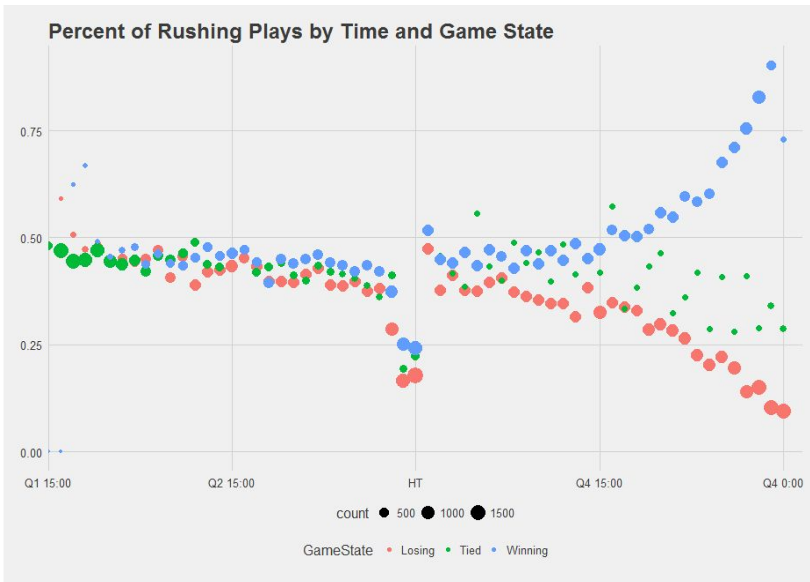
Season	2010	2011	2012
% Runs	40.5%	40.1%	39.7%

We expect to see overall differences in teams, as stronger passing attacks throw more and teams with dangerous ground campaigns rush the ball more.

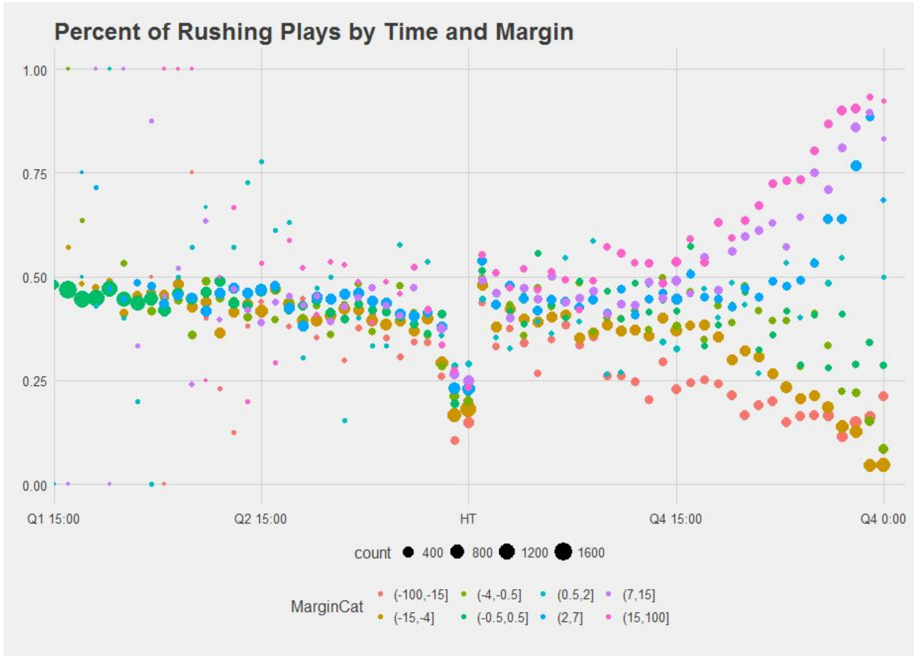


There is a sizable gap between the most run-happy and least run-happy teams. Additionally, we see that there is a lot of season-to-season variability. There are also most likely differences in the ways teams behave in certain situations which we will explore with more interaction later on. There might be another factor at play here. Better teams likely spend more of the game in a winning position, and run the ball more often as a result. We will see if the effect sizes diminish when we control for game state in our model.

Lastly, we examine how play calling changes over the game, and how the game state and margin of lead/deficit influence this.



There are a couple things worth noting here. In the first half, %Run is pretty steady, although the last three minutes of the half produce a sharp decrease in runs. In the second half, we see the divergence in strategy between winning and losing teams. In our model we intend to account for game-state and time effects.



Additionally, when we look at a team's margin of lead/defeat, we see the greater the magnitude of the margin, the further (and earlier) a team moves away from its first half strategy. From here, we take our observations and apply them as we create a formal model.

Model & Results

To create our model, we use backward selection, initially including all of the relevant predictors in our model and then performing F tests with each variable omitted. We find all the variables we initially included to be worthwhile inclusions in our model (at the .05 significance level). Next, we test for, and find several interactions that improved the fit.

Here is the model output (I've included the variable type for ease of reading):

Variable	Type	Coefficient	Odds Ratio
Intercept	NA	2.47***	11.82***
2nd Down	Categorical	-0.34***	.71***
3rd Down	Categorical	-1.41***	.24***
4th Down	Categorical	-0.26*	.77*
Distance To Go	Quantitative	-0.09***	.91***
Distance To Go: 2nd Down	Interaction on Q	-0.04***	.96***
Distance To Go: 3rd Down	Interaction on Q	-0.12***	.89***
Distance To Go: 4th Down	Interaction on Q	-0.23***	.79***
Offensive Team	Categorical	See Below	See Below
Offensive Team: Season	Interaction on C	See Below	See Below
Inside Own 20	Categorical	-4.69***	.01***
Own 20-5	Categorical	-0.75***	.47***
Yardline	Quantitative	-0.25***	.78***
Yardline: Inside Own 20	Interaction on Q	0.30***	1.35***
Yardline: Own 20-5	Interaction on Q	0.25***	1.28***
Time Elapsed	Quantitative	-0.008***	.99***
Time Elapsed: Final 3 Min of 1st Half	Interaction on Q	-0.41***	.66***
Time Elapsed: Second Half (Tie)	Interaction on Q	-0.013**	.99**
Time Elapsed: Second Half (Ahead)	Interaction on Q	0.073***	1.08***
Time Elapsed: Second Half (Behind)	Interaction on Q	-0.053***	.95***
Final 3 Min of 1st Half	Categorical	11.02***	61083***
Second Half (Tie)	Categorical	0.76***	2.13***
Second Half (Ahead)	Categorical	-2.45***	.09***
Second Half (Behind)	Categorical	1.97***	7.17***
Significance: *=.1, **=.05, ***=.01	n=99,357		

Variables with odds ratios above one increase the likelihood that we see a run on the next play. Odds ratios under one increase the likelihood of a pass. A note on the Team variable: Since there are 32 teams, interacting team with season leaves us with 96 different coefficients, so we choose to leave these out of the table. To give you an idea on some of the coefficients, the highest is 0.41 (odds ratio: 1.51) from the 2011 Denver Broncos (Tim Tebow's squad), and the lowest is -0.87 (odds ratio: 0.42) from the 2012 Atlanta Falcons. That Falcons team was the 13th most pass-heavy team and the Broncos were the 2nd most run-heavy team in our data set before we controlled for other factors. All of the team coefficients can be found in the appendix.

When we test out our model, we find the success rates for the training and testing set are both slightly above 69%, which is competitive with the other models discussed earlier and suggests we have not overfit the data.

For every coefficient besides the 4th down and Offense Team, the 95% confidence interval does not contain 0, leading us to reject the null hypotheses that these variables have no effect on a play being a run or a pass. For example, the 95% confidence interval on Distance To Go is -.1085 to -.0802, which tells us with a good deal of certainty that there is an inverse relationship between probability of running the ball and Distance To Go, since the confidence interval does not include (and is not close to) zero.

In the next section, we analyze our results and provide several examples of how the model could be used.

Discussion

In order to assist the reader in understanding the model and provide some practical applications, we will walk through two examples. To find the probability of a run, we first add up the coefficients. This gives us the log odds of a run. Next, we raise e to the power of the log odds (we can remove a log by taking e to the power of the log), which produces the odds. Finally, to determine the probability, we take the odds divided by (1+odds).

Example 1: 2012 New York Giants have a 2nd and 10 at the 15 yard line, and they lead by 10 with 9 minutes to go in the 4th quarter.

Log Odds: 2.47 -.34 +(-.09-.04)(10) -.48 -.75 + (-.25+.25)(15)+ (-.008+0.073)(51)-2.45= .465

Odds: 1.59 Probability: 61% chance of a run

Example 2: 2010 Minnesota Vikings have a 3rd and 5 at the 50 yard line, and they trail by 4 with 5 minutes left in the 3rd quarter

Log Odds: 2.47- 1.41+ (-.09-.12)(5) - .175 -.75 + (-.25+.25)(50)+ (-.008-.053)(40)+ 1.97= -1.385

Odds: .25 Probability: 20% chance of a run

These two examples show how you can plug in the game information we have to find the probability for a given play. In practice, this could be done in a more user-friendly app that take the information and calculates the probability for you. From the examples we can also see the model is more certain about some plays than others, and coaches would need to translate this uncertainty into their play calling.

The coefficients and significance we find from our model meet much of what we saw in our exploratory analysis and intuitively expected. One way the model could be improved is through a deeper analysis of many non-linear factors that go into the game of football. Teams have fairly different passing and running patterns, and these hold up even after controlling for other factors. For higher downs and when the distance to gain a first down is larger, we see more passes. This makes sense because passes are a riskier option that (usually) gain more yards than a run if they are completed. Our game state and time variables also match what we saw earlier. The first half is fairly even in play calling regardless of score, until the final three minutes where it is a race against the clock and teams air the ball out. In the second half we see game state come into play, as leading teams run the ball more and more as the half goes on, and losing teams do the opposite.

Field position is important at the extremes. Runs are much more prevalent inside your own 20 and within five yards from the endzone. We also observe many interactions, reflecting the complex nature of the game. All of these variables make intuitive sense to football fans and do a good job predicting a team's decision. Having access to more data, which teams possess, would allow us to look more closely at individual teams and other less obvious covariates.

Conclusion

In summary, we found all the variables we looked at to be significant, as well as several interactions. Distance and Down play a big role and we see the proportion of runs shrink as both Down and Distance increase. For field position, we find that teams run more when they are near either of the goal lines. In the first half of games, the Game State (winning, tied, and losing) is unimportant and there is a slight downward trend in the percent of runs until the final three minutes, when teams pass much more frequently. In the second half, strategies diverge, and we see winning teams run more as the half goes on and losing teams run less. On the team scale, we observe significant differences in teams' play calling, as some teams resort to the ground game much more than other. After putting these findings into our model, we are able to predict the majority of plays correctly.

With a success rate of just under 70%, our model likely outperforms football "experts" gut instincts and provides a framework and base for future models with more available data to use. Given the size of our dataset and the observed non-linearity in our covariates, the usage of some machine learning techniques would likely improve our success rate. A few obtainable variables that I think would improve the model and be interesting to look at include weather, home team versus away team, dome vs outside, offensive formation, and incorporating previous plays from that game. Teams have access to far more data and knowledge than the general public and can incorporate these and more into an extended model. This is especially true in regards to the tendencies of other teams. Incorporating these variables and more team-specific information could greatly diminish our error rate.

References

http://onlinelibrary.wiley.com/doi/10.1901/jaba.2006.146-05/abstract

http://www.degruyter.com/abstract/j/jqas.2010.6.2/jqas.2010.6.2.1235/jqas.2010.6.2.1235.xml

http://archive.advancedfootballanalytics.com/2010/04/play-by-play-data.html

http://www.eurekalert.org/pub_releases/2015-08/asa-smp080615.php

http://harvardsportsanalysis.org/2016/03/predicting-offensive-play-calling-in-the-nfl/

Appendix

Team Coefficients

	Estimate	Std. Error	z value	Pr(>|z|)	
offTeamARI:season2010	-0.5152868	0.1315413	-3.917	8.95e-05	***
offTeamATL:season2010	-0.3961625	0.1231921	-3.216	0.001301	**
offTeamBAL:season2010	-0.3399445	0.1251573	-2.716	0.006605	**
offTeamBUF:season2010	-0.1372301	0.1323899	-1.037	0.299941	
offTeamCAR:season2010	0.1456407	0.1309767	1.112	0.266156	
offTeamCHI:season2010	-0.3222368	0.1259699	-2.558	0.010526	*
offTeamCIN:season2010	-0.1930098	0.1268347	-1.522	0.128074	
offTeamCLE:season2010	-0.0665341	0.1310036	-0.508	0.611538	
offTeamDAL:season2010	-0.4048245	0.1278084	-3.167	0.001538	**
offTeamDEN:season2010	-0.3035670	0.1285751	-2.361	0.018225	*
offTeamDET:season2010	-0.4253996	0.1287317	-3.305	0.000951	***
offTeamGB:season2010	-0.6705950	0.1224507	-5.476	4.34e-08	***
offTeamHOU:season2010	-0.1769182	0.1280069	-1.382	0.166941	
offTeamIND:season2010	-0.5712897	0.1244696	-4.590	4.44e-06	***
offTeamJAC:season2010	0.0037742	0.1265612	0.030	0.976210	
offTeamKC:season2010	0.0548938	0.1255755	0.437	0.662011	
offTeamMIA:season2010	-0.3213534	0.1277614	-2.515	0.011894	*
offTeamMIN:season2010	-0.1753558	0.1300417	-1.348	0.177511	
offTeamNE:season2010	-0.4612111	0.1266385	-3.642	0.000271	***
offTeamNO:season2010	-0.6427894	0.1268912	-5.066	4.07e-07	***
offTeamNYG:season2010	-0.2705109	0.1283306	-2.108	0.035038	*
offTeamNYJ:season2010	-0.0887801	0.1213169	-0.732	0.464289	
offTeamOAK:season2010	-0.0742604	0.1293819	-0.574	0.565993	
offTeamPHI:season2010	-0.5798615	0.1259444	-4.604	4.14e-06	***
offTeamPIT:season2010	-0.1769712	0.1231197	-1.437	0.150607	
offTeamSD:season2010	-0.2968049	0.1250395	-2.374	0.017611	*
offTeamSEA:season2010	-0.5403624	0.1272091	-4.248	2.16e-05	***
offTeamSF:season2010	-0.1790561	0.1303189	-1.374	0.169446	
offTeamSTL:season2010	-0.2805237	0.1281370	-2.189	0.028579	*
offTeamTB:season2010	-0.3577433	0.1295298	-2.762	0.005747	**
offTeamTEN:season2010	-0.1650852	0.1336679	-1.235	0.216816	
offTeamWAS:season2010	-0.6209430	0.1328124	-4.675	2.93e-06	***

offTeamARI:season2011	-0.3986478	0.1317261	-3.026	0.002475	**
offTeamATL:season2011	-0.3217131	0.1243761	-2.587	0.009692	**
offTeamBAL:season2011	-0.2877388	0.1237451	-2.325	0.020058	*
offTeamBUF:season2011	-0.3800170	0.1293923	-2.937	0.003315	**
offTeamCAR:season2011	-0.3254744	0.1300539	-2.503	0.012328	*
offTeamCHI:season2011	-0.2121804	0.1296609	-1.636	0.101751	
offTeamCIN:season2011	-0.2729666	0.1249428	-2.185	0.028908	*
offTeamCLE:season2011	-0.2617331	0.1291081	-2.027	0.042638	*
offTeamDAL:season2011	-0.4419512	0.1274399	-3.468	0.000525	***
offTeamDEN:season2011	0.4057247	0.1248748	3.249	0.001158	**
offTeamDET:season2011	-0.7809957	0.1286494	-6.071	1.27e-09	***
offTeamGB:season2011	-0.7381254	0.1265294	-5.834	5.42e-09	***
offTeamHOU:season2011	0.1057453	0.1232473	0.858	0.390897	
offTeamIND:season2011	-0.1436852	0.1313165	-1.094	0.273872	
offTeamJAC:season2011	0.1325440	0.1287350	1.030	0.303204	
offTeamKC:season2011	-0.0002988	0.1292386	-0.002	0.998155	
offTeamMIA:season2011	-0.0487193	0.1284528	-0.379	0.704482	
offTeamMIN:season2011	-0.0140519	0.1285364	-0.109	0.912947	
offTeamNE:season2011	-0.7556520	0.1222944	-6.179	6.45e-10	***
offTeamNO:season2011	-0.6475020	0.1210638	-5.348	8.87e-08	***
offTeamNYG:season2011	-0.4918475	0.1216143	-4.044	5.25e-05	***
offTeamNYJ:season2011	-0.3080232	0.1276965	-2.412	0.015859	*
offTeamOAK:season2011	-0.1694408	0.1285125	-1.318	0.187344	
offTeamPHI:season2011	-0.6861358	0.1278179	-5.368	7.96e-08	***
offTeamPIT:season2011	-0.4881068	0.1263530	-3.863	0.000112	***
offTeamSD:season2011	-0.3672337	0.1286802	-2.854	0.004319	**
offTeamSEA:season2011	-0.1326181	0.1272011	-1.043	0.297140	
offTeamSF:season2011	-0.1649624	0.1257518	-1.312	0.189584	
offTeamSTL:season2011	-0.1389247	0.1302915	-1.066	0.286306	
offTeamTB:season2011	-0.4171699	0.1320859	-3.158	0.001587	**
offTeamTEN:season2011	-0.3412345	0.1306021	-2.613	0.008981	**
offTeamWAS:season2011	-0.3111868	0.1283936	-2.424	0.015364	*

offTeamARI:season2012	-0.5497657	0.1312141	-4.190	2.79e-05	***
offTeamATL:season2012	-0.8684856	0.1273344	-6.821	9.07e-12	***
offTeamBAL:season2012	-0.3293457	0.1211083	-2.719	0.006539	**
offTeamBUF:season2012	-0.1421431	0.1298456	-1.095	0.273644	
offTeamCAR:season2012	-0.1854038	0.1297989	-1.428	0.153179	
offTeamCHI:season2012	-0.1615062	0.1283978	-1.258	0.208443	
offTeamCIN:season2012	-0.4999990	0.1253289	-3.989	6.62e-05	***
offTeamCLE:season2012	-0.4276635	0.1306460	-3.273	0.001062	**
offTeamDAL:season2012	-0.4922482	0.1291482	-3.811	0.000138	***
offTeamDEN:season2012	-0.5125032	0.1227506	-4.175	2.98e-05	***
offTeamDET:season2012	-0.5279803	0.1257550	-4.198	2.69e-05	***
offTeamGB:season2012	-0.5706706	0.1227042	-4.651	3.31e-06	***
offTeamHOU:season2012	-0.2045131	0.1233944	-1.657	0.097440	.
offTeamIND:season2012	-0.4139574	0.1247842	-3.317	0.000909	***
offTeamJAC:season2012	-0.3855755	0.1324453	-2.911	0.003600	**
offTeamKC:season2012	0.2581448	0.1293138	1.996	0.045905	*
offTeamMIA:season2012	-0.2150566	0.1290192	-1.667	0.095543	.
offTeamMIN:season2012	-0.1977635	0.1256873	-1.573	0.115613	
offTeamNE:season2012	-0.5921561	0.1190161	-4.975	6.51e-07	***
offTeamNO:season2012	-0.6976853	0.1288690	-5.414	6.17e-08	***
offTeamNYG:season2012	-0.4775124	0.1288012	-3.707	0.000209	***
offTeamNYJ:season2012	-0.0257401	0.1282629	-0.201	0.840947	
offTeamOAK:season2012	-0.3242363	0.1301325	-2.492	0.012717	*
offTeamPHI:season2012	-0.4880411	0.1278669	-3.817	0.000135	***
offTeamPIT:season2012	-0.3761618	0.1288141	-2.920	0.003498	**
offTeamSD:season2012	-0.2818205	0.1287057	-2.190	0.028550	*
offTeamSEA:season2012	-0.0005417	0.1246182	-0.004	0.996532	
offTeamSF:season2012	-0.1826405	0.1234174	-1.480	0.138910	
offTeamSTL:season2012	-0.2817992	0.1303526	-2.162	0.030632	*
offTeamTB:season2012	-0.2751864	0.1286428	-2.139	0.032423	*
offTeamTEN:season2012	-0.4756000	0.1324206	-3.592	0.000329	***
offTeamWAS:season2012	NA	NA	NA	NA	

Drop1 F Tests

```
Model:
IsRun ~ ToGo + Down + GameTimeAndStateCat + minUp + OffTeam:season +
    YardLine + YardCat
                    Df Deviance   AIC   F value    Pr(>F)    
<none>                    70126 70342                        
ToGo                 1    72330 72544 1870.3259 < 2.2e-16 ***
Down                 3    76222 76432 1724.3260 < 2.2e-16 ***
GameTimeAndStateCat  4    73136 73344  638.5431 < 2.2e-16 ***
minUp                1    70161 70375   29.9954 4.348e-08 ***
YardLine             1    70163 70377   31.5184 1.984e-08 ***
YardCat              2    70212 70424   36.7987 < 2.2e-16 ***
OffTeam:season      95    70772 70798    5.7745 < 2.2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Model:
IsRun ~ ToGo * Down + GameTimeAndStateCat * minUp + OffTeam:season +
    YardLine * YardCat
                           Df Deviance   AIC  F value    Pr(>F)    
<none>                          68057 68291                        
ToGo:Down                   3    68248 68476  55.8373 < 2.2e-16 ***
GameTimeAndStateCat:minUp   4    69744 69970 368.7219 < 2.2e-16 ***
OffTeam:season             95    68709 68753   6.0043 < 2.2e-16 ***
YardLine:YardCat            2    68240 68470  80.2040 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```