Stat 139 Final Project: Analyzing The Effects of Environmental and Situational Factors on Yardage in NFL Rushing Plays

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Introduction

Over the past several years, the NFL has grown increasingly interested in statistical analysis and big data, and how statistics can potentially affect how the game is watched and played. And, while they have now begun to collect game data, the NFL still has a shortage of statisticians to actually analyze it. Due to this, the NFL conducts an annual Big Data Bowl, a competition open to the public, where the organization provides game statistics from previous years, and the group with the most accurate predictive model is awarded $75,000 dollars. This year's Data Bowl revolves around the prediction of a rushing play's expected yardage, given a multitude of variables such as, but not limited to, player, offensive formation, and weather.

The dataset from this study is found on the NFL's Kaggle Big Data Bowl website (https://www.kaggle.com/c/nfl-big-data-bowl-2020/data). The dataset contains 23,171 observations of 49 variables, one for each player present in each rushing play from the 2017 and 2018 seasons. Unlike most sports that are played either inside or during warm seasons, football is in the unique position of being a primarily outside sport that also combats the harsh weather conditions that come with Fall and Winter. Potential snowfall or high windspeeds could completely alter how a football team plays the game. In general, the environment a game takes place in may affect a rushing play's yardage. For the purposes of this study, there are six intriguing predictors that may be derived from the dataset that can be deemed "environmental": the game's weather, the game's temperature (deg F), the game's humidity, the game's wind speed (in miles/hour), whether the game was played on turf or grass, and whether or not the offensive team has home-field advantage.

In addition to environmental factors, another interesting aspect to the NFL is how fluid the game is. For example, depending on the quarter, down, yards needed for a first down, yards needed for a touchdown, and current point difference between the offensive team and their opponent, a play could essentially already be decided before it is even run (and the defense could be ready for it). Therefore, the goal of this analysis is to see if rushing plays are best predicted using constant factors (such as environmental factors that persist throughout the game), situational factors, or some combination of both. While situational factors are unknown before the onset of the game, constant factors such as weather can be accurately predicted days before, and therefore could be more assuredly used in pre-game preparations if the analysis deems the factors to be significant predictors. If it is indeed more relevant to use situational factors as predictors, much is revealed about the fluidity of a game and which situations lead to optimal and suboptimal rushing plays.

In order to accomplish this task, separate linear regression models will be run to infer feature significance as well as the strength of the models in explaining the variance in the yardage gained in a play. The first will use only constant factors to predict yardage. The second will only use fluid factors. And the third and subsequent models will build off the first two to try and create the best prediction model for rushing yardage using constant and/or fluid factors.

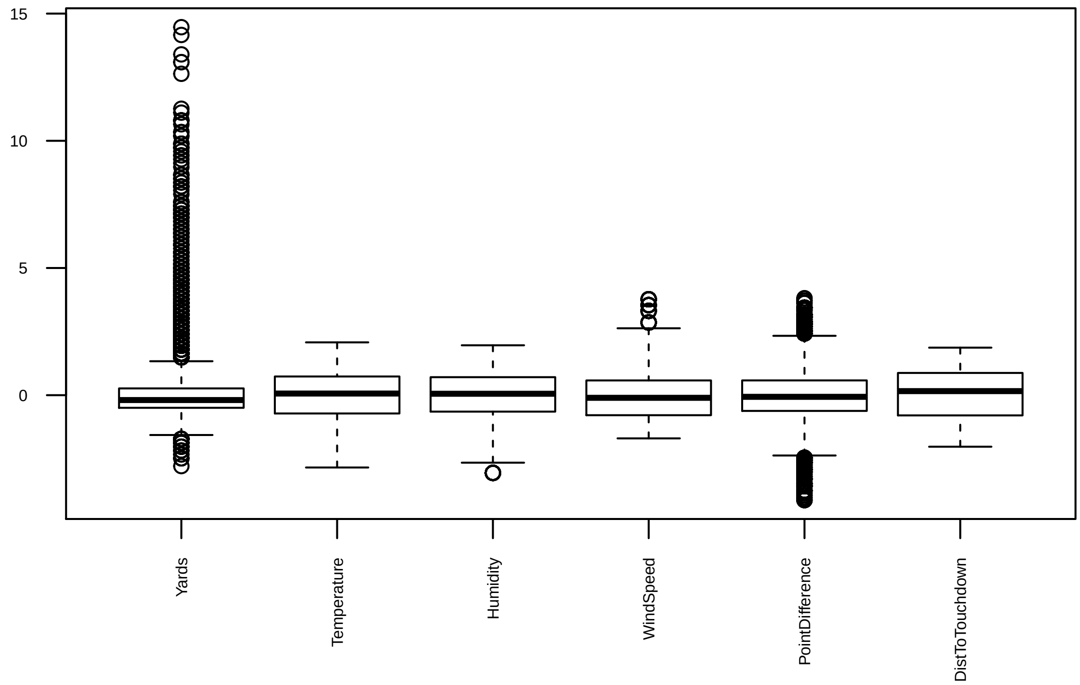
Hypothesis

While no constant, environmental predictors will be significant, at least some of the situational factors will be better, significant predictors of rushing yardage. One reason for this expectation is that, for example, while weather is more likely to predict the frequency of rushing plays, as bad weather will likely limit the ability to pass the ball, players may be trained to be minimally affected by varying weather conditions. On the other hand, situational factors will be better suited to predict rushing outcomes because they are harder to prepare for, and so, have a larger impact on our response variable.

Methods and EDA

Because our data set was large and based on input from various NFL teams, the data contained many NA values, incorrectly inputted data, different string values for factors that represented similar things, and other inaccuracies that had the possibility of skewing our results. Therefore, our first step in our analysis of the data was to clean the data in order to ensure that we had the purest and most efficient data possible. Because this analysis does not take into account the individual attributes of players involved in each play and because the factors we *are* interested in are contained within each of the 22 observations for each play (one for every player involved), we only kept one observation per play by removing any data points with duplicate Play IDs. A few significant alterations to the data set bear mentioning. Many of the observations are missing temperature, wind speed, and weather values (in the given **Temperature**, **WindSpeed**, and **GameWeather** variables, respectively), likely due to them not being manually input with the rest of the data or not recorded at the given game, so we removed all such observations. There were 20 different values for the given **Turf** variable, one for every possible type of surface a game was played on, so to simplify the variable we changed the variable to a "Yes" or "No" binary variable representing whether the turf was artificial or real grass. We also reduced **GameWeather**, which originally had many specific values such as "Heavy lake effect snow" and many values with identical meanings, into five categories, "Clear/Mostly Clear", "Cloudy/Mostly Cloudy", "Fog", "Rain", and "Snow" and sorted the data observation into one of these categories and reduced **WindSpeed**, originally given as a categorical variable with some values representing ranges of wind speeds in a game, into a quantitative variable, averaging over the range to acquire our value if there was a need to.

The variables we are concerned with are our response variable **Yards**, the yardage gained on the play, and our environmental/constant predictors **GameWeather** with "Cloudy/Mostly Cloudy" as the reference group, **Temperature**, **WindSpeed**, **Turf**, **Humidity** (the humidity of the game), and **AtHome** (an indicator for whether or not the offensive team has home-field advantage), and our fluid/situational predictors **Quarter** (a categorical variable representing which quarter the game is in) with the first quarter as the reference group, **Down** (a categorical variable representing the current down) with the first down as the reference group, **Distance** (yards needed for a first down before the play), **PointDifference** (point difference between offensive team and their opponent before the play), and **DistToTouchdown** (yards needed to score a touchdown before the play).



Checking the distributions of the relevant quantitative, nonbinary variables, only the **Yards** variable is heavily skewed (right-skewed), but since there still is a significant left-tail, meaning that this non-normality will not be too damaging to our assumptions of linear regression, and since there are negative values for the **Yards** variable, preventing us from using a logarithmic transformation, the most interpretable transformation, we have chosen to keep the variable as is for better interpretability. Since there may be dependencies among the observations since observations with the same offensive team may not be independent, observations with the same defensive team may not be independent, and observations within the same week of the season may not be independent, our base model for predicting **Yards**, **model.base**, is a standard multiple regression containing grouping variables, **Offense** (with the Arizona Cardinals as the reference group), **Defense** (with the Arizona Cardinals as the reference group), and **Week** (with Week 1 as the reference group), that account for those possible dependencies. Since we wish to use our models to predict **Yards** in future games in future years, it behooves us not to group by game or by year. Thus, for the sake of inference, we assume rushings plays in the same game are independent and rushing plays in the same year are independent (a strong assumption, and an admitted flaw of our models). We then created two new models from our base model. We created a "game-constant" model containing the variables from the base model as well as **GameWeather**, **Temperature**, **Humidity**, **WindSpeed**, **Turf**, and **AtHome** called **model.game_constant**. This "game-constant" model represents the effects of the factors of the game that (relatively) remain the same throughout the entirety of the game on a rushing play's yardage. The second model is the "game-fluid" model containing the variables from the base model as well as **Quarter**, **Down**, **Distance**, **PointDifference**, and **DistToTouchdown** called **model.game_fluid**. This model represents the effects of the factors of the game that are frequently changing on a rushing play's yardage. Based on an analysis of the previous models explained in the **Results** section using features such as predictors' p-values to determine significance, we create a multiple regression model with the significant constant and fluid predictors, as well as our grouping variables, called **model.best** and use that model for further analysis. We then took this version of our model and included quadratic terms for each of the quantitative predictors to evaluate whether they would strengthen the model using an ESS F-test, resulting in a model called **model.best_poly**.

Results

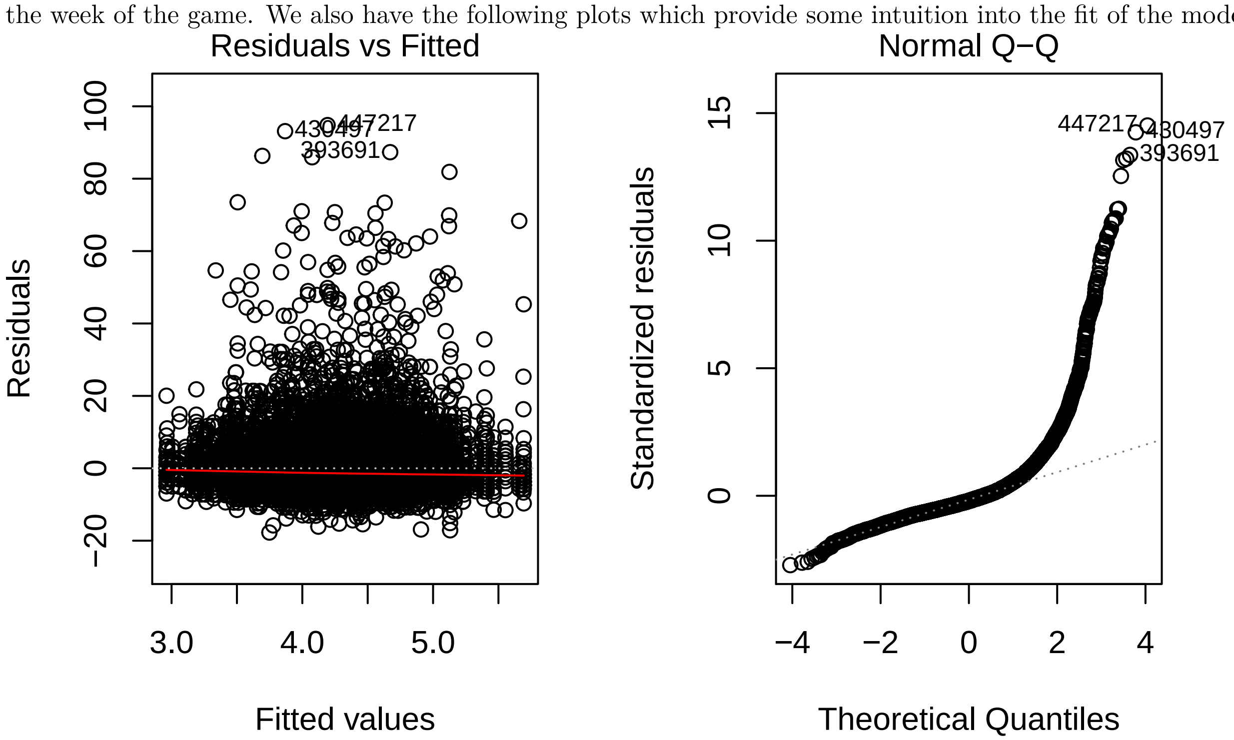
The full summary outputs for the models can be found in Section 2 of the Appendix. Below, we will discuss the relevant results for each of the models in turn, then briefly describe our broad findings.

Model Results

Baseline Model

As previously mentioned, the purpose of our baseline model is to be a barometer that accounts for potential dependencies among the observations of the data so that when we later construct augmented models, we can test whether these augmentations are significant. Thus, we would like to see how well our baseline model does at describing the data at hand.

First of all, we note that the R^2 value is extremely small (0.005127). This is to be expected given that the model attempts to predict the yards of a particular rushing attempt solely through the teams involved and the week of the game. We also have the following plots which provide some intuition into the fit of the model.



From the lefthand plot, we can see that the majority of the observations have a roughly linear relationship with the predictors but there are a number of outliers that occur across all fitted values. This is further demonstrated in the right-hand plot where there appears to be an extremely large right-tail in the residuals and a smaller but still large left-tail as well. This type of distribution is to be expected given the nature of football, since players can simply give up on the play in order to limit large rushing losses to the downside. Again, the fit in the tails is to be expected given that the granularity of predictors used.

Finally, examining the summary output we can see that the magnitudes of the intercepts and coefficients make sense. There are a number of significant predictors but for the purposes of the baseline model which predictors are significant is not relevant.

Overall we can see that our model manages to describe the relevant dependencies in the data that may occur across team offense, defense, and time. Teams with better rushing offenses by other traditional metrics have larger offensive coefficients (such as LAR and KC), and the same holds for teams with better rushing defenses (NO, TEN).

Constant Predictor Model

The R^2 of the constant predictor model is 0.00546, which represents a small improvement over the baseline model. The smallness of the value aligns with our hypothesis, given that adding constant predictors to our baseline model does not offer significant improvement in our model's ability to explain the variance in the **Yard** variable. We would like to see if any of these predictors are statistically significant.

Below we have a table of the additional predictors included in the constant predictor model.

```
##                                 Estimate Std. Error t value Pr(>|t|)
## GameWeatherClear/Mostly Clear  0.054528    0.11960  0.4559    0.648
## GameWeatherRain               -0.016056    0.21775 -0.0737    0.941
## GameWeatherFog                -0.220189    0.52626 -0.4184    0.676
## GameWeatherSnow               -0.214346    0.48985 -0.4376    0.662
## Temperature                   -0.005109    0.00459 -1.1119    0.266
## Humidity                      -0.000302    0.00329 -0.0919    0.927
## WindSpeed                     -0.012521    0.01210 -1.0350    0.301
## TurfYes                        0.210579    0.16225  1.2979    0.194
## AtHomeYes                     -0.094415    0.10829 -0.8718    0.383
```

We can see that the sign of some of these coefficients matches our intuition. For example, in the weather category we have that clear weather increases rushing yards, while adverse conditions such as rain, fog, and snow decrease rushing yards. Others are more perplexing, with rushes at home potentially performing worse than rushes away, and increasing windspeeds affecting rushing yards negatively. We will return to these further in our conclusion.

Overall, we can see that at the $\alpha = 0.05$ level, none of the predictors are statistically significant, again aligning with our original hypothesis.

Fluid Predictor Model

The R^2 value of the fluid predictor model is 0.01793, which represents a large improvement over the baseline. However, we note that our model still explains less than 2% of the variance in the **Yards** variable. Below we list a table of the additional predictors included in the fluid predictor model.

```
##                 Estimate Std. Error t value Pr(>|t|)
## QuarterSecond    0.33865    0.13329  2.5408 1.11e-02
## QuarterThird     0.23411    0.13262  1.7652 7.75e-02
## QuarterFourth   -0.00626    0.13405 -0.0467 9.63e-01
## QuarterOvertime  1.07665    0.54505  1.9753 4.82e-02
## DownSecond       0.18618    0.11121  1.6742 9.41e-02
## DownThird        0.40631    0.19448  2.0892 3.67e-02
## DownFourth      -0.71041    0.52576 -1.3512 1.77e-01
## Distance         0.10328    0.01491  6.9255 4.48e-12
## PointDifference -0.00105    0.00472 -0.2215 8.25e-01
## DistToTouchdown  0.02102    0.00197 10.6808 1.49e-26
```

At the $\alpha = 0.05$ level, the significant predictors are **QuarterSecond** and **QuarterOvertime** (i.e. **Quarter** as a whole), **DownThird** (i.e. **Down** as a whole), **Distance**, and **DistToTouchdown**. Aligning with our hypothesis, all but one (**PointDifference**) of the fluid predictors are significant predictors of a rushing play's yardage.

Combined Model

Our combined model is created by taking the significant predictors from the constant and fluid predictor models. Since there were no significant predictors from the constant predictor model, we end up with a combined model that looks very similar to our fluid predictor model. The R^2 value is 0.01793, which again is a large improvement over the baseline. The table of additional predictors included is as follows:

```
##                  Estimate Std. Error t value Pr(>|t|)
## QuarterSecond     0.33838    0.13328  2.5389 1.11e-02
## QuarterThird      0.23305    0.13253  1.7585 7.87e-02
## QuarterFourth    -0.00995    0.13300 -0.0748 9.40e-01
## QuarterOvertime   1.07596    0.54503  1.9741 4.84e-02
## DownSecond        0.18538    0.11114  1.6679 9.54e-02
## DownThird         0.40492    0.19437  2.0832 3.72e-02
## DownFourth       -0.70945    0.52573 -1.3495 1.77e-01
## Distance          0.10314    0.01490  6.9225 4.58e-12
## DistToTouchdown   0.02102    0.00197 10.6816 1.48e-26
```

The significant predictors here are again **QuarterSecond**, **QuarterOvertime**, **DownThird**, **Distance**, and **DistToTouchdown**.

Quadratic Combined Model

In the quadratic combined model, we use the same predictors as the combined model but also include quadratic terms of the quantitative factors. This gives us an R^2 value of 0.02149, which is a large improvement over the simple combined model; however, this model still does not explain a large amount of the variance in the **Yards** variable. The table of predictors is listed below.

```
##                                   Estimate Std. Error t value Pr(>|t|)
## QuarterSecond                      0.39171   1.33e-01   2.940 3.28e-03
## QuarterThird                       0.22748   1.32e-01   1.719 8.56e-02
## QuarterFourth                     -0.01661   1.33e-01  -0.125 9.00e-01
## QuarterOvertime                    1.02599   5.44e-01   1.886 5.94e-02
## DownSecond                         0.20189   1.17e-01   1.718 8.57e-02
## DownThird                          0.55343   2.16e-01   2.560 1.05e-02
## DownFourth                        -0.51640   5.37e-01  -0.962 3.36e-01
## poly(Distance, 2, raw = T)1        0.16900   3.62e-02   4.667 3.08e-06
## poly(Distance, 2, raw = T)2       -0.00396   1.66e-03  -2.381 1.73e-02
## poly(DistToTouchdown, 2, raw = T)1  0.07604   7.67e-03   9.915 4.08e-23
## poly(DistToTouchdown, 2, raw = T)2 -0.00058   7.71e-05  -7.521 5.66e-14
```

At the $\alpha = 0.05$ level, we have that **QuarterSecond**, **DownThird**, **Distance** (linear and quadratic), and **DistToTouchdown** (linear and quadratic) are all significant. This leads us to conclude that the quadratic terms should indeed be included in our model, a notion supported by an ESS F-test using **model.best_poly** and **model.best** performed in the **Appendix**, which yields a p-value of 8.403e-16, which is very significant and supports keeping the quadratic terms in the model.

To see this model in action, let's take, for example, a game between the New England Patriots and the New York Giants in Week 7 of a future season, where the former team has posession and is going to rush in the second quarter on a second down when they are 5 yards from a first down and 50 yards from a touchdown. As seen in the Appendix, the intercept for **model.best_poly** is -3.066e-01, the coefficient of **OffenseNE** is 1.213e+00, the coefficient of **DefenseNYG** is 1.608e-01, and the coefficient of **Week7** is 1.710e-01. Thus, our predicted yardage for this play is $-3.066e-01+1.213e+00+1.608e-01+1.710e-01+0.39171+0.20189+0.16900(5)-0.00396(5)^2+0.07604(50)-0.00058(50)^2 = 4.9298$.

Conclusion

Discussion

We first note a few overarching observations. As we noted during the data cleaning process, the **Yards** variable has an extremely long right-tail and a non-trivial left-tail as well. This became evident during our analysis since the residuals of our baseline model appeared to have long tails on both sides as well even though we were capturing some dependent effects within the data. As a result, our R^2 values across all models is low in magnitude.

As discussed in the previous section, the inclusion of constant predictors such as environmental factors did not meaningfully affect model quality, and none of the included predictors were statistically significant. By contrast, the inclusion of fluid predictors did affect model quality and also did produce statistically significant predictors. This resulted in our later combined models being dominated by fluid predictors rather than constant predictors.

The quadratic combined model captures some interesting effects of these fluid predictors. The quadratic effects are indeed statistically significant. We will return to the intuition behind these in the next section.

Overall, our hypothesis was that constant predictors such as environmental factors would not have a statistically significant contribution to rushing yards while fluid predictors would. Based on the above results we can see that fluid predictors are indeed more relevant in predicting rushing yards.

Intuitions

Below we will discuss some insights derived from our analysis of constant and fluid predictors.

Constant Predictors

In the discussion of our constant predictor model, we note that some of the predictors had interesting coefficients. Namely, as windspeed increases rushing yardage decreases and being at home decreases rushing yardage as well.

At first glance, the former is interesting because we wouldn't necessarily expect windspeed to negatively affect, or affect at all, the rushing game. However, the negative coefficient can be explained by our not taking into account the direction of the wind in each rushing play. While we would expect the amount of times wind pushes against the offense and the amount of times wind pushes against the defense to be roughly equal, it is possible that in our data set there were more occasions of the wind working against the rushing offense. In future work it would likely be pertinent to account for wind direction for this reason.

Again, at first glance the latter is interesting because we would expect being at home to improve rushing games. However, we can explain the negative coefficient by noting that the disadvantage in playing away comes from communication which more adversely affects the passing game. This suggests that playing at home disproportionately improves the passing game, which comes to the detriment of the rushing game. Again, this is an intuitive explanation but should be verified in future work.

Fluid Predictors

In the quadratic combined model, we see a few interesting results worth discussing.

First, we note that the second quarter coefficient remains significant and positive. This is surprising because any explanations involving the end-of-half should also manifest in the end-of-game scenario. One possible explanation is that at the end-of-half, teams are not facing an imminent win/loss situation and thus are able to maintain a balanced rushing and passing attack, while at end-of-game, teams that are down often resort solely to passing and not rushing, leading to the insignificance of **QuarterFourth**. This is a point that would be interesting to investigate in future work.

Fourth downs not having a significant coefficient make sense given that fourth down is traditionally a passing or punting down. Note that performing above average is not the relevant heuristic to football teams here, but rather whether the rushing attempt converted into a first down.

The quadratic nature of down distance and distance to touchdown appear to follow the same intuition, that on longer distances for both, opposing defenses will be expecting more passing rather than rushing and thus rushing will overperform since it is less likely to convert. At a certain point, however, the probability of converting or scoring on that particular play is so low that defenses optimize for yardage (for field position) and begin defending rushes again. This results in the dual quadratic and significant combination seen in these two predictors.

Challenges in the Data

In addition to the challenges already mentioned in the **Methods and EDA** section, such as many missing values, another issue was the reporting of the stadium type (outdoors, indoors with open roof, indoors with closed roof, etc.) in the dataset. We would have liked to have gotten detailed information regarding this, since the insignificance of the predictors concerning weather, temperature, and humidity could be explained by those factors not mattering in many cases where the stadium was closed off to the outside world. However, the dataset rarely supplied information regarding whether or not an indoor stadium had an open or closed roof for a game, and so, we were unable to take this into account.

Limitations

As previously mentioned, our model is limited by the nature of the data in that the yards variable has very long tails on both sides. This means that our R^2 values are depressed. Additionally, football is naturally a high-variance game with teams often only rushing the ball 25 times per game out of a plethora of different formations and with a variety of different personnel. Attempting to control for these variables is difficult and also results in sample-size issues. The fact that our dataset only includes rushing plays could also be seen as a limitation, since this makes it difficult to conclude recommendations for teams. For example, while we can conclude that rushing on a third down is significantly better than rushing on a first down, we couldn't recommend that a team rush on a third down since that may be inferior to passing on a third down in terms of yardage.

Next Steps

We can extend our base analysis by addressing the concerns presented in the previous Limitations section. It is possible that after controlling for many of these dynamic effects, environmental factors again become relevant in the rushing game. Additionally, acquiring data regarding passing plays should help us make relevant recommendations.

Similarly, we can also work on complementary analysis that brings data to the explanations described in the Intuitions section. Overall we would like to investigate whether the data supports our proposed hypotheses in situations where there are many competing intuitive effects.

Appendix

Section 1: Verification of Issues for Data Cleaning

```r
# Demonstrates that the NA's in the Temperature column occur in
# groups of consecutive indices
which(is.na(data1$Temperature))
```

```
##   [1]  537  538  539  540  541  542  543  544  545  546  547  548
##  [13]  549  550  551  552  553  554  555  556  557  558  559  560
##  [25]  561  562  563  564  565  566  567  568  569  570  571  572
##  [37]  573  574  575 1743 1744 1745 1746 1747 1748 1749 1750 1751
##  [49] 1752 1753 1754 1755 1756 1757 1758 1759 1760 1761 1762 1763
##  [61] 1764 1765 1766 1767 1768 1769 1770 1771 1772 1773 1774 1775
##  [73] 1776 1777 1778 1779 1780 2090 2091 2092 2093 2094 2095 2096
##  [85] 2097 2098 2099 2100 2101 2102 2103 2104 2105 2106 2107 2108
##  [97] 2109 2110 2111 2112 2113 2114 2115 2116 2117 2118 2119 2120
## [109] 2121 2122 2123 2124 2125 2126 2127 2128 2129 2220 2221 2222
## [121] 2223 2224 2225 2226 2227 2228 2229 2230 2231 2232 2233 2234
## [133] 2235 2236 2237 2238 2239 2240 2241 2242 2243 2244 2245 2246
## [145] 2247 2248 2249 2250 2251 2252 2253 2254 2255 2256 2257 2258
## [157] 2259 2260 2261 2262 2263 2264 2265 2266 2267 2268 2269 2270
## [169] 2271 2272 2273 2274 2275 2370 2371 2372 2373 2374 2375 2376
## [181] 2377 2378 2379 2380 2381 2382 2383 2384 2385 2386 2387 2388
## [193] 2389 2390 2391 2392 2393 2394 2395 2396 2397 2398 2399 2400
## [205] 2401 2402 2403 2404 2405 2406 2407 2408 2409 2410 2411 2412
## [217] 2413 2414 2415 2416 2417 2418 2419 2420 2421 2422 2473 2474
## [229] 2475 2476 2477 2478 2479 2480 2481 2482 2483 2484 2485 2486
## [241] 2487 2488 2489 2490 2491 2492 2493 2494 2495 2496 2497 2498
## [253] 2499 2500 2501 2502 2503 2504 2505 2506 2507 2508 2509 2510
## [265] 2511 2512 2513 2514 2515 2516 2517 2518 2519 2520 2521 2522
## [277] 2628 2629 2630 2631 2632 2633 2634 2635 2636 2637 2638 2639
## [289] 2640 2641 2642 2643 2644 2645 2646 2647 2648 2649 2650 2651
## [301] 2652 2653 2654 2655 2656 2657 2658 2659 2660 2661 2662 2663
## [313] 2664 2665 2666 2667 2668 2669 2670 2671 2672 2673 3391 3392
## [325] 3393 3394 3395 3396 3397 3398 3399 3400 3401 3402 3403 3404
## [337] 3405 3406 3407 3408 3409 3410 3411 3412 3413 3414 3415 3416
## [349] 3417 3418 3419 3420 3421 3422 3423 3424 3425 3426 3427 3428
## [361] 3429 3430 3431 3432 3433 3434 3435 3436 3437 3438 3439 3440
## [373] 3582 3583 3584 3585 3586 3587 3588 3589 3590 3591 3592 3593
## [385] 3594 3595 3596 3597 3598 3599 3600 3601 3602 3603 3604 3605
## [397] 3606 3607 3608 3609 3610 3611 3612 3613 3614 3615 3616 3617
## [409] 3618 3619 3620 3621 3622 3623 3624 3625 3626 3627 3628 3629
## [421] 3748 3749 3750 3751 3752 3753 3754 3755 3756 3757 3758 3759
## [433] 3760 3761 3762 3763 3764 3765 3766 3767 3768 3769 3770 3771
## [445] 3772 3773 3774 3775 3776 3777 3778 3779 3780 3781 3782 3783
## [457] 3784 3785 3786 3787 3788 3789 3790 3791 3792 3793 3794 3795
## [469] 3796 3797 3798 3799 3800 3942 3943 3944 3945 3946 3947 3948
## [481] 3949 3950 3951 3952 3953 3954 3955 3956 3957 3958 3959 3960
## [493] 3961 3962 3963 3964 3965 3966 3967 3968 3969 3970 3971 3972
## [505] 3973 3974 3975 3976 3977 3978 3979 3980 3981 3982 3983 3984
## [517] 3985 3986 3987 3988 3989 4601 4602 4603 4604 4605 4606 4607
## [529] 4608 4609 4610 4611 4612 4613 4614 4615 4616 4617 4618 4619
```

```
##  [541]  4620  4621  4622  4623  4624  4625  4626  4627  4628  4629  4630  4631
##  [553]  4632  4633  4634  4635  4636  4637  4638  4639  4640  4641  4642  4643
##  [565]  4644  4645  4646  4647  4648  4649  4650  4651  6017  6018  6019  6020
##  [577]  6021  6022  6023  6024  6025  6026  6027  6028  6029  6030  6031  6032
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##  [625]  6616  6617  6618  6619  6620  6621  6622  6623  6624  6625  6626  6627
##  [637]  6628  6629  6630  6631  6632  6633  6634  6635  6636  6637  6638  6639
##  [649]  6640  6641  6642  6643  6644  6645  6646  6647  6648  6649  6650  6651
##  [661]  6652  6653  6654  7022  7023  7024  7025  7026  7027  7028  7029  7030
##  [673]  7031  7032  7033  7034  7035  7036  7037  7038  7039  7040  7041  7042
##  [685]  7043  7044  7045  7046  7047  7048  7049  7050  7051  7052  7053  7054
##  [697]  7055  7056  7057  7058  7059  7060  7061  7062  7063  7064  7065  7066
##  [709]  7067  7496  7497  7498  7499  7500  7501  7502  7503  7504  7505  7506
##  [721]  7507  7508  7509  7510  7511  7512  7513  7514  7515  7516  7517  7518
##  [733]  7519  7520  7521  7522  7523  7524  7525  7526  7527  7528  7529  7530
##  [745]  7531  7532  7533  7534  7535  7536  7537  7538  7539  7540  7541  7542
##  [757]  7543  7595  7596  7597  7598  7599  7600  7601  7602  7603  7604  7605
##  [769]  7606  7607  7608  7609  7610  7611  7612  7613  7614  7615  7616  7617
##  [781]  7618  7619  7620  7621  7622  7623  7624  7625  7626  7627  7628  7629
##  [793]  7630  7631  7632  7633  7634  7635  7636  7637  7638  7639  7640  7978
##  [805]  7979  7980  7981  7982  7983  7984  7985  7986  7987  7988  7989  7990
##  [817]  7991  7992  7993  7994  7995  7996  7997  7998  7999  8000  8001  8002
##  [829]  8003  8004  8005  8006  8007  8008  8009  8010  8011  8012  8013  8014
##  [841]  8015  8016  8017  8018  8211  8212  8213  8214  8215  8216  8217  8218
##  [853]  8219  8220  8221  8222  8223  8224  8225  8226  8227  8228  8229  8230
##  [865]  8231  8232  8233  8234  8235  8236  8237  8238  8239  8240  8241  8242
##  [877]  8243  8244  8245  8246  8247  8248  8249  8250  8251  8252  8253  8254
##  [889]  8255  8256  8257  8258  8711  8712  8713  8714  8715  8716  8717  8718
##  [901]  8719  8720  8721  8722  8723  8724  8725  8726  8727  8728  8729  8730
##  [913]  8731  8732  8733  8734  8735  8736  8737  8738  8739  8740  8741  8742
##  [925]  8743  8744  8745  8746  8747  8748  8749  8750  8751  8752  8753  8882
##  [937]  8883  8884  8885  8886  8887  8888  8889  8890  8891  8892  8893  8894
##  [949]  8895  8896  8897  8898  8899  8900  8901  8902  8903  8904  8905  8906
##  [961]  8907  8908  8909  8910  8911  8912  8913  8914  8915  8916  8917  8918
##  [973]  8919  8920  8921  8922  8923  8924  8925  8926  8927  8928  8929  9148
##  [985]  9149  9150  9151  9152  9153  9154  9155  9156  9157  9158  9159  9160
##  [997]  9161  9162  9163  9164  9165  9166  9167  9168  9169  9170  9171  9172
## [1009]  9173  9174  9175  9176  9177  9178  9179  9180  9181  9182  9183  9184
## [1021]  9185  9186  9187  9188  9189  9190  9191  9192  9193  9958  9959  9960
## [1033]  9961  9962  9963  9964  9965  9966  9967  9968  9969  9970  9971  9972
## [1045]  9973  9974  9975  9976  9977  9978  9979  9980  9981  9982  9983  9984
## [1057]  9985  9986  9987  9988  9989  9990  9991  9992  9993  9994  9995  9996
## [1069]  9997  9998  9999 10000 10001 10002 10003 10004 10005 10006 10007 10999
## [1081] 11000 11001 11002 11003 11004 11005 11006 11007 11008 11009 11010 11011
## [1093] 11012 11013 11014 11015 11016 11017 11018 11019 11020 11021 11022 11023
## [1105] 11024 11025 11026 11027 11028 11029 11030 11031 11032 11033 11034 11035
## [1117] 11036 11037 11038 11039 11040 11041 11042 11043 11044 11045 11147 11148
## [1129] 11149 11150 11151 11152 11153 11154 11155 11156 11157 11158 11159 11160
## [1141] 11161 11162 11163 11164 11165 11166 11167 11168 11169 11170 11171 11172
## [1153] 11173 11174 11175 11176 11177 11178 11179 11180 11181 11182 11183 11383
## [1165] 11384 11385 11386 11387 11388 11389 11390 11391 11392 11393 11394 11395
## [1177] 11396 11397 11398 11399 11400 11401 11402 11403 11404 11405 11406 11407
```

```
## [1189] 11408 11409 11410 11411 11412 11413 11414 11415 11416 11417 11418 11419
## [1201] 11420 11421 11422 11423 12135 12136 12137 12138 12139 12140 12141 12142
## [1213] 12143 12144 12145 12146 12147 12148 12149 12150 12151 12152 12153 12154
## [1225] 12155 12156 12157 12158 12159 12160 12161 12162 12163 12164 12165 12166
## [1237] 12167 12168 12169 12170 12171 12172 12173 12174 12175 12176 12177 12178
## [1249] 12179 12180 12181 12182 12183 12184 12185 12364 12365 12366 12367 12368
## [1261] 12369 12370 12371 12372 12373 12374 12375 12376 12377 12378 12379 12380
## [1273] 12381 12382 12383 12384 12385 12386 12387 12388 12389 12390 12391 12392
## [1285] 12393 12394 12395 12396 12397 12398 12399 12400 12401 12402 12403 12404
## [1297] 12405 12406 12407 12408 12409 12659 12660 12661 12662 12663 12664 12665
## [1309] 12666 12667 12668 12669 12670 12671 12672 12673 12674 12675 12676 12677
## [1321] 12678 12679 12680 12681 12682 12683 12684 12685 12686 12687 12688 12689
## [1333] 12690 12691 12692 12693 12694 12695 12696 12697 13199 13200 13201 13202
## [1345] 13203 13204 13205 13206 13207 13208 13209 13210 13211 13212 13213 13214
## [1357] 13215 13216 13217 13218 13219 13220 13221 13222 13223 13224 13225 13226
## [1369] 13227 13228 13229 13230 13328 13329 13330 13331 13332 13333 13334 13335
## [1381] 13336 13337 13338 13339 13340 13341 13342 13343 13344 13345 13346 13347
## [1393] 13348 13349 13350 13351 13352 13353 13354 13355 13356 13357 13358 13359
## [1405] 13360 13361 13362 13363 13364 13365 13366 13367 13621 13622 13623 13624
## [1417] 13625 13626 13627 13628 13629 13630 13631 13632 13633 13634 13635 13636
## [1429] 13637 13638 13639 13640 13641 13642 13643 13644 13645 13646 13647 13648
## [1441] 13649 13650 13651 13652 13792 13793 13794 13795 13796 13797 13798 13799
## [1453] 13800 13801 13802 13803 13804 13805 13806 13807 13808 13809 13810 13811
## [1465] 13812 13813 13814 13815 13816 13817 13818 13819 13820 13821 13822 13823
## [1477] 13824 13825 13826 13827 13828 13829 13830 13831 13832 13833 13834 13835
## [1489] 13836 14001 14002 14003 14004 14005 14006 14007 14008 14009 14010 14011
## [1501] 14012 14013 14014 14015 14016 14017 14018 14019 14020 14021 14022 14023
## [1513] 14024 14025 14026 14027 14028 14029 14030 14031 14032 14033 14034 14035
## [1525] 14036 14037 14038 14039 14040 14041 14042 14043 14087 14088 14089 14090
## [1537] 14091 14092 14093 14094 14095 14096 14097 14098 14099 14100 14101 14102
## [1549] 14103 14104 14105 14106 14107 14108 14109 14110 14111 14112 14113 14114
## [1561] 14115 14116 14117 14118 14119 14120 14121 14122 14123 14124 14125 14126
## [1573] 14127 14128 14129 14130 14131 14132 14133 14134 14135 14136 14342 14343
## [1585] 14344 14345 14346 14347 14348 14349 14350 14351 14352 14353 14354 14355
## [1597] 14356 14357 14358 14359 14360 14361 14362 14363 14364 14365 14366 14367
## [1609] 14368 14369 14370 14371 14372 14373 14374 14375 14376 14377 14378 14379
## [1621] 14380 14381 14382 14383 14384 14385 14386 14387 14388 14389 14390 14391
## [1633] 14392 14393 14394 14395 14396 14397 15319 15320 15321 15322 15323 15324
## [1645] 15325 15326 15327 15328 15329 15330 15331 15332 15333 15334 15335 15336
## [1657] 15337 15338 15339 15340 15341 15342 15343 15344 15345 15346 15347 15348
## [1669] 15349 15350 15351 15352 15353 15536 15537 15538 15539 15540 15541 15542
## [1681] 15543 15544 15545 15546 15547 15548 15549 15550 15551 15552 15553 15554
## [1693] 15555 15556 15557 15558 15559 15560 15561 15562 15563 15564 15565 15566
## [1705] 15567 15568 15569 15570 15571 15572 15573 15574 15575 15576 15577 15578
## [1717] 15579 15580 15581 15582 15757 15758 15759 15760 15761 15762 15763 15764
## [1729] 15765 15766 15767 15768 15769 15770 15771 15772 15773 15774 15775 15776
## [1741] 15777 15778 15779 15780 15781 15782 15783 15784 15785 15786 15787 15788
## [1753] 15789 15790 15791 15792 15793 15794 15795 15796 15797 15798 15799 15800
## [1765] 15801 17003 17004 17005 17006 17007 17008 17009 17010 17011 17012 17013
## [1777] 17014 17015 17016 17017 17018 17019 17020 17021 17022 17023 17024 17025
## [1789] 17026 17027 17028 17029 17030 17031 17032 17033 17034 17035 17036 17037
## [1801] 17038 17039 17040 17041 17042 17043 17044 17045 17046 17047 17095 17096
## [1813] 17097 17098 17099 17100 17101 17102 17103 17104 17105 17106 17107 17108
## [1825] 17109 17110 17111 17112 17113 17114 17115 17116 17117 17118 17119 17120
```

```
## [1837] 17121 17122 17123 17124 17125 17126 17127 17128 17129 17130 17131 17132
## [1849] 17133 17134 17135 17136 17137 17138 17139 17140 17141 17426 17427 17428
## [1861] 17429 17430 17431 17432 17433 17434 17435 17436 17437 17438 17439 17440
## [1873] 17441 17442 17443 17444 17445 17446 17447 17448 17449 17450 17451 17452
## [1885] 17453 17454 17455 17456 17457 17458 17459 17460 17461 17462 17463 17464
## [1897] 17465 18976 18977 18978 18979 18980 18981 18982 18983 18984 18985 18986
## [1909] 18987 18988 18989 18990 18991 18992 18993 18994 18995 18996 18997 18998
## [1921] 18999 19000 19001 19002 19003 19004 19005 19006 19007 19008 19009 19010
## [1933] 19011 19012 19013 19014 19015 19016 19017 19018 19515 19516 19517 19518
## [1945] 19519 19520 19521 19522 19523 19524 19525 19526 19527 19528 19529 19530
## [1957] 19531 19532 19533 19534 19535 19536 19537 19538 19539 19540 19541 19542
## [1969] 19543 19544 19545 19546 19547 19548 19549 19550 19551 19552 19553 19554
## [1981] 19555 19556 20898 20899 20900 20901 20902 20903 20904 20905 20906 20907
## [1993] 20908 20909 20910 20911 20912 20913 20914 20915 20916 20917 20918 20919
## [2005] 20920 20921 20922 20923 20924 20925 20926 20927 20928 20929 20930 20931
## [2017] 20932 20933 20934 20935 20936 20937 20938 20939 21151 21152 21153 21154
## [2029] 21155 21156 21157 21158 21159 21160 21161 21162 21163 21164 21165 21166
## [2041] 21167 21168 21169 21170 21171 21172 21173 21174 21175 21176 21177 21178
## [2053] 21179 21180 21181 21182 21183 21184 21185 21186 21187 21188 21189 21190
## [2065] 21191 21192 21193 21479 21480 21481 21482 21483 21484 21485 21486 21487
## [2077] 21488 21489 21490 21491 21492 21493 21494 21495 21496 21497 21498 21499
## [2089] 21500 21501 21502 21503 21504 21505 21506 21507 21508 21509 21510 21511
## [2101] 21512 21513 21514 21515 21516 21517 21518 21519 21520 21521 21522 21523
## [2113] 21524 21525 21526 21527 21528 22020 22021 22022 22023 22024 22025 22026
## [2125] 22027 22028 22029 22030 22031 22032 22033 22034 22035 22036 22037 22038
## [2137] 22039 22040 22041 22042 22043 22044 22045 22046 22047 22048 22049 22050
## [2149] 22051 22052 22053 22054 22055 22056 22057 22058 22059 22060 22664 22665
## [2161] 22666 22667 22668 22669 22670 22671 22672 22673 22674 22675 22676 22677
## [2173] 22678 22679 22680 22681 22682 22683 22684 22685 22686 22687 22688 22689
## [2185] 22690 22691 22692 22693 22694 22695 22696 22697 22698 22699 22700 22701
## [2197] 22702 22703 22704 22705 22706 22707 22708 22709 22710 22711
```

```r
# Demonstrate that there are cases where WindSpeed and WindDirection
# were mixed up while inputting data
unique(data1$WindSpeed[data1$WindDirection == "1" |
  data1$WindDirection == "13" | data1$WindDirection == "8"])
```

```
## [1] SSW E   SE
## 41 Levels:  0 1 10 10-20 10mph 10MPH 11 11-17 12 12-22 12mph 13 13 MPH ... SSW
```

```r
# We dropped the odd weathers like "" and "T: 51; H: 55; W: NW 10 mph"
# and condensed the number of levels
table(data1$GameWeather)
```

```
##
##
##                                                                             1895
##                                                                30% Chance of Rain
##                                                                               52
##                                                                            Clear
##                                                                             2012
##                                                                   Clear and cold
##                                                                               58
##                                                                   Clear and Cool
##                                                                               47
##                                                                  Clear and sunny
```

```
##                                                                           49
##                                                              Clear and Sunny
##                                                                           45
##                                                               Clear and warm
##                                                                           52
##                                                                 Clear skies
##                                                                           96
##                                                                 Clear Skies
##                                                                           90
##                                                                      cloudy
##                                                                           85
##                                                                      Cloudy
##                                                                         5203
##                                                             Cloudy and cold
##                                                                           50
##                                                             Cloudy and Cool
##                                                                           56
## Cloudy with periods of rain, thunder possible. Winds shifting to WNW, 10-20 mph.
##                                                                           43
##                                                   Cloudy, 50% change of rain
##                                                                           47
##                                                       Cloudy, chance of rain
##                                                                           41
##                                     Cloudy, fog started developing in 2nd quarter
##                                                                           50
##                                           Cloudy, light snow accumulating 1-3"
##                                                                           38
##                                                                Cloudy, Rain
##                                                                           50
##                                                                        Cold
##                                                                           52
##                                                          Controlled Climate
##                                                                          570
##                                                                       Coudy
##                                                                           45
##                                                                        Fair
##                                                                          226
##                                                                        Hazy
##                                                                          142
##                                                      Heavy lake effect snow
##                                                                           85
##                                                                      Indoor
##                                                                          281
##                                                                     Indoors
##                                                                          258
##                                                                  Light Rain
##                                                                          126
##                                                               Mostly cloudy
##                                                                          183
##                                                               Mostly Cloudy
##                                                                          828
##                                                                Mostly Coudy
##                                                                           52
##                                                                Mostly sunny
```

```
##                                                                     78
##                                                           Mostly Sunny
##                                                                    269
##                                                     Mostly Sunny Skies
##                                                                     50
##                                                                    N/A
##                                                                     89
##                                                          N/A (Indoors)
##                                                                    494
##                                                             N/A Indoor
##                                                                    192
##                                                               Overcast
##                                                                     98
##                                                           Partly clear
##                                                                     35
##                                                          Partly cloudy
##                                                                     90
##                                                          Partly Cloudy
##                                                                   2094
##                                                         Partly Clouidy
##                                                                     50
##                                                           Partly sunny
##                                                                     98
##                                                           Partly Sunny
##                                                                    244
##                                                           Party Cloudy
##                                                                     37
##                                                                   Rain
##                                                                    859
##                                                        Rain Chance 40%
##                                                                     38
##                                        Rain likely, temps in low 40s.
##                                                                     49
##                                                            Rain shower
##                                                                     54
##                                                                  Rainy
##                                                                     32
##                                                     Scattered Showers
##                                                                     50
##                                                                Showers
##                                                                     40
##                                                                   Snow
##                                                                     91
##                                                           Sun & clouds
##                                                                     44
##                                                                  Sunny
##                                                                   4774
##                                                        Sunny and clear
##                                                                     43
##                                                         Sunny and cold
##                                                                     45
##                                                         Sunny and warm
##                                                                     53
##                                                            Sunny Skies
```

```
##                                                                                       46
##                                                                   Sunny, highs to upper 80s
##                                                                                       50
##                                                                                Sunny, Windy
##                                                                                       36
##                                                                  T: 51; H: 55; W: NW 10 mph
##                                                                                       42
```

Section 2: Model Summaries

```r
summary(model.base)
```

```
##
## Call:
## lm(formula = Yards ~ Offense + Defense + Week, data = data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -17.748  -3.347  -1.306   1.395  94.807
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.253161   0.454010   7.165 8.04e-13 ***
## OffenseATL   0.764040   0.485728   1.573  0.11574
## OffenseBLT   0.912833   0.444542   2.053  0.04005 *
## OffenseBUF   0.249330   0.436250   0.572  0.56765
## OffenseCAR   1.108341   0.447802   2.475  0.01333 *
## OffenseCHI   0.393955   0.437882   0.900  0.36830
## OffenseCIN   0.819984   0.451868   1.815  0.06959 .
## OffenseCLV   1.001659   0.464038   2.159  0.03090 *
## OffenseDAL   1.042760   0.486747   2.142  0.03218 *
## OffenseDEN   0.864984   0.419973   2.060  0.03945 *
## OffenseDET   0.476221   0.507283   0.939  0.34786
## OffenseGB    0.882359   0.458918   1.923  0.05453 .
## OffenseHST   0.517584   0.449149   1.152  0.24918
## OffenseIND   0.512135   0.428214   1.196  0.23172
## OffenseJAX   0.593848   0.456538   1.301  0.19335
## OffenseKC    1.242765   0.439349   2.829  0.00468 **
## OffenseLA    1.354519   0.421006   3.217  0.00130 **
## OffenseLAC   1.112693   0.436456   2.549  0.01080 *
## OffenseMIA   0.619617   0.450626   1.375  0.16914
## OffenseMIN   0.291528   0.535480   0.544  0.58616
## OffenseNE    0.939055   0.423288   2.218  0.02653 *
## OffenseNO    1.310011   0.434392   3.016  0.00257 **
## OffenseNYG   0.892144   0.429003   2.080  0.03758 *
## OffenseNYJ   0.173304   0.443437   0.391  0.69594
## OffenseOAK   0.741375   0.428179   1.731  0.08339 .
## OffensePHI   0.805076   0.427950   1.881  0.05995 .
## OffensePIT   0.643737   0.437494   1.471  0.14119
## OffenseSEA   0.592195   0.425957   1.390  0.16446
## OffenseSF    0.909973   0.429693   2.118  0.03421 *
## OffenseTB    0.125642   0.450266   0.279  0.78022
## OffenseTEN   0.470609   0.427740   1.100  0.27125
```

```
## OffenseWAS   0.303762   0.435275   0.698  0.48527
## DefenseATL  -0.010889   0.452889  -0.024  0.98082
## DefenseBAL  -0.259354   0.390025  -0.665  0.50608
## DefenseBUF   0.158842   0.399472   0.398  0.69091
## DefenseCAR   0.076102   0.427434   0.178  0.85869
## DefenseCHI  -0.486852   0.414977  -1.173  0.24073
## DefenseCIN   0.177404   0.408210   0.435  0.66387
## DefenseCLE  -0.252980   0.395784  -0.639  0.52271
## DefenseDAL   0.148718   0.457225   0.325  0.74499
## DefenseDEN  -0.200681   0.391448  -0.513  0.60819
## DefenseDET   0.474422   0.527381   0.900  0.36835
## DefenseGB    0.116744   0.401411   0.291  0.77118
## DefenseHOU  -0.377909   0.390498  -0.968  0.33318
## DefenseIND  -0.150243   0.394576  -0.381  0.70338
## DefenseJAX   0.199996   0.444286   0.450  0.65261
## DefenseKC    0.290876   0.397810   0.731  0.46467
## DefenseLA    0.620677   0.413830   1.500  0.13367
## DefenseLAC   0.230951   0.405938   0.569  0.56941
## DefenseMIA   0.064910   0.408209   0.159  0.87366
## DefenseMIN  -0.154444   0.495675  -0.312  0.75536
## DefenseNE    0.539596   0.410169   1.316  0.18834
## DefenseNO   -0.417508   0.425487  -0.981  0.32648
## DefenseNYG   0.076584   0.394086   0.194  0.84592
## DefenseNYJ  -0.025843   0.404494  -0.064  0.94906
## DefenseOAK  -0.003168   0.391078  -0.008  0.99354
## DefensePHI  -0.344931   0.425802  -0.810  0.41791
## DefensePIT  -0.051722   0.420628  -0.123  0.90214
## DefenseSEA   0.275598   0.397254   0.694  0.48784
## DefenseSF   -0.108824   0.381692  -0.285  0.77556
## DefenseTB    0.186609   0.416939   0.448  0.65447
## DefenseTEN  -0.459967   0.408030  -1.127  0.25964
## DefenseWAS   0.215291   0.392576   0.548  0.58342
## Week2        0.074484   0.270753   0.275  0.78324
## Week3        0.249645   0.289263   0.863  0.38813
## Week4        0.368789   0.286782   1.286  0.19847
## Week5        0.279875   0.276569   1.012  0.31157
## Week6        0.655664   0.283443   2.313  0.02072 *
## Week7        0.140617   0.274365   0.513  0.60830
## Week8        0.220107   0.283500   0.776  0.43753
## Week9        0.044909   0.290521   0.155  0.87715
## Week10       0.670129   0.285190   2.350  0.01880 *
## Week11       0.352106   0.286749   1.228  0.21949
## Week12       0.475279   0.283518   1.676  0.09368 .
## Week13       0.482269   0.275605   1.750  0.08016 .
## Week14       0.269291   0.279542   0.963  0.33540
## Week15       0.191335   0.277525   0.689  0.49056
## Week16       0.180472   0.272812   0.662  0.50829
## Week17       0.198834   0.270038   0.736  0.46155
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.546 on 19126 degrees of freedom
## Multiple R-squared:  0.005127,   Adjusted R-squared:  0.00107
## F-statistic: 1.264 on 78 and 19126 DF,  p-value: 0.05827
```

```r
summary(model.game_constant)
```

```
##
## Call:
## lm(formula = Yards ~ Offense + Defense + Week + GameWeather +
##     Temperature + Humidity + WindSpeed + Turf + AtHome, data = data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -17.777  -3.336  -1.310   1.420  94.699
##
## Coefficients:
##                                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     3.7030007  0.6661462   5.559 2.75e-08 ***
## OffenseATL                      0.7282949  0.4911874   1.483 0.138165
## OffenseBLT                      0.9006992  0.4475356   2.013 0.044173 *
## OffenseBUF                      0.1971191  0.4484765   0.440 0.660282
## OffenseCAR                      1.1973468  0.4574659   2.617 0.008869 **
## OffenseCHI                      0.4570304  0.4471034   1.022 0.306698
## OffenseCIN                      0.7448637  0.4657648   1.599 0.109787
## OffenseCLV                      0.9916470  0.4663989   2.126 0.033501 *
## OffenseDAL                      0.9663478  0.4898771   1.973 0.048552 *
## OffenseDEN                      0.9327237  0.4301669   2.168 0.030149 *
## OffenseDET                      0.4362593  0.5116768   0.853 0.393888
## OffenseGB                       0.7996195  0.4727227   1.692 0.090754 .
## OffenseHST                      0.4565102  0.4519324   1.010 0.312446
## OffenseIND                      0.4571306  0.4395359   1.040 0.298339
## OffenseJAX                      0.6645541  0.4618419   1.439 0.150189
## OffenseKC                       1.2723521  0.4494711   2.831 0.004648 **
## OffenseLA                       1.4136635  0.4273145   3.308 0.000941 ***
## OffenseLAC                      1.2225762  0.4453883   2.745 0.006057 **
## OffenseMIA                      0.7476284  0.4600129   1.625 0.104129
## OffenseMIN                      0.2332327  0.5401317   0.432 0.665887
## OffenseNE                       0.8942087  0.4365835   2.048 0.040554 *
## OffenseNO                       1.2625641  0.4494352   2.809 0.004971 **
## OffenseNYG                      0.8299621  0.4405398   1.884 0.059585 .
## OffenseNYJ                      0.1523300  0.4539728   0.336 0.737215
## OffenseOAK                      0.8628843  0.4370918   1.974 0.048379 *
## OffensePHI                      0.8929677  0.4380965   2.038 0.041535 *
## OffensePIT                      0.7080615  0.4445359   1.593 0.111219
## OffenseSEA                      0.5333671  0.4399958   1.212 0.225447
## OffenseSF                       1.0123444  0.4374938   2.314 0.020680 *
## OffenseTB                       0.2621085  0.4606185   0.569 0.569338
## OffenseTEN                      0.5423805  0.4354924   1.245 0.212985
## OffenseWAS                      0.3689198  0.4444605   0.830 0.406527
## DefenseATL                     -0.0629211  0.4624189  -0.136 0.891768
## DefenseBAL                     -0.2649115  0.4013508  -0.660 0.509230
## DefenseBUF                      0.0136930  0.4143405   0.033 0.973637
## DefenseCAR                      0.0787647  0.4364609   0.180 0.856792
## DefenseCHI                     -0.4998225  0.4258404  -1.174 0.240517
## DefenseCIN                      0.0075342  0.4227693   0.018 0.985782
## DefenseCLE                     -0.2672110  0.4096099  -0.652 0.514180
## DefenseDAL                      0.0324836  0.4649298   0.070 0.944300
## DefenseDEN                     -0.2176548  0.3989077  -0.546 0.585329
```

```
## DefenseDET                      0.4433975  0.5352508   0.828 0.407459
## DefenseGB                      -0.0550382  0.4192741  -0.131 0.895563
## DefenseHOU                     -0.4771527  0.4031877  -1.183 0.236645
## DefenseIND                     -0.3028528  0.4116499  -0.736 0.461919
## DefenseJAX                      0.2121088  0.4509869   0.470 0.638131
## DefenseKC                       0.2201317  0.4113068   0.535 0.592517
## DefenseLA                       0.6061732  0.4187203   1.448 0.147723
## DefenseLAC                      0.2452016  0.4110093   0.597 0.550792
## DefenseMIA                      0.1101950  0.4162279   0.265 0.791207
## DefenseMIN                     -0.2098379  0.5059760  -0.415 0.678352
## DefenseNE                       0.4218461  0.4224395   0.999 0.318003
## DefenseNO                      -0.5494302  0.4412620  -1.245 0.213098
## DefenseNYG                     -0.0682829  0.4080761  -0.167 0.867113
## DefenseNYJ                     -0.1126995  0.4142592  -0.272 0.785586
## DefenseOAK                      0.0265408  0.3999139   0.066 0.947087
## DefensePHI                     -0.3458714  0.4349629  -0.795 0.426522
## DefensePIT                     -0.0563368  0.4308776  -0.131 0.895975
## DefenseSEA                      0.1286738  0.4132309   0.311 0.755511
## DefenseSF                      -0.0873928  0.3871932  -0.226 0.821431
## DefenseTB                       0.2325696  0.4247219   0.548 0.583986
## DefenseTEN                     -0.4582821  0.4153023  -1.103 0.269828
## DefenseWAS                      0.2123338  0.4021827   0.528 0.597538
## Week2                           0.0959309  0.2770418   0.346 0.729145
## Week3                           0.2573292  0.2934596   0.877 0.380562
## Week4                           0.3202646  0.2908313   1.101 0.270822
## Week5                           0.2965555  0.2818290   1.052 0.292697
## Week6                           0.5991242  0.2905863   2.062 0.039242 *
## Week7                           0.1439080  0.2793273   0.515 0.606423
## Week8                           0.1643227  0.2940212   0.559 0.576250
## Week9                          -0.0395443  0.2981504  -0.133 0.894486
## Week10                          0.5850271  0.3170551   1.845 0.065025 .
## Week11                          0.2518624  0.3042075   0.828 0.407721
## Week12                          0.3791208  0.3020446   1.255 0.209428
## Week13                          0.4124552  0.2865328   1.439 0.150034
## Week14                          0.1835740  0.3103234   0.592 0.554154
## Week15                          0.0819910  0.3029790   0.271 0.786689
## Week16                          0.0568830  0.3019501   0.188 0.850577
## Week17                          0.0403370  0.3157713   0.128 0.898355
## GameWeatherClear/Mostly Clear  0.0545285  0.1196003   0.456 0.648451
## GameWeatherRain                -0.0160555  0.2177548  -0.074 0.941224
## GameWeatherFog                 -0.2201891  0.5262576  -0.418 0.675655
## GameWeatherSnow                -0.2143464  0.4898546  -0.438 0.661702
## Temperature                    -0.0051088  0.0045945  -1.112 0.266177
## Humidity                       -0.0003022  0.0032868  -0.092 0.926745
## WindSpeed                      -0.0125212  0.0120978  -1.035 0.300684
## TurfYes                         0.2105786  0.1622495   1.298 0.194348
## AtHomeYes                      -0.0944153  0.1082930  -0.872 0.383301
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.546 on 19117 degrees of freedom
## Multiple R-squared:  0.00546,    Adjusted R-squared:  0.0009334
## F-statistic: 1.206 on 87 and 19117 DF,  p-value: 0.09298
```

```r
summary(model.game_fluid)
```

```
##
## Call:
## lm(formula = Yards ~ Offense + Defense + Week + Quarter + Down +
##     Distance + PointDifference + DistToTouchdown, data = data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -18.191  -3.246  -1.240   1.392  93.590
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)       0.816520   0.492154   1.659 0.097117 .
## OffenseATL        0.932575   0.483117   1.930 0.053581 .
## OffenseBLT        1.127457   0.442517   2.548 0.010847 *
## OffenseBUF        0.285629   0.433772   0.658 0.510238
## OffenseCAR        1.292935   0.445950   2.899 0.003744 **
## OffenseCHI        0.457234   0.436204   1.048 0.294555
## OffenseCIN        0.907198   0.449422   2.019 0.043544 *
## OffenseCLV        1.017323   0.461490   2.204 0.027506 *
## OffenseDAL        1.169591   0.484168   2.416 0.015715 *
## OffenseDEN        0.905963   0.417534   2.170 0.030035 *
## OffenseDET        0.604821   0.504605   1.199 0.230697
## OffenseGB         0.994809   0.456559   2.179 0.029349 *
## OffenseHST        0.621507   0.446704   1.391 0.164145
## OffenseIND        0.666898   0.426011   1.565 0.117495
## OffenseJAX        0.677429   0.454250   1.491 0.135896
## OffenseKC         1.378311   0.438208   3.145 0.001662 **
## OffenseLA         1.572480   0.421054   3.735 0.000189 ***
## OffenseLAC        1.245776   0.434697   2.866 0.004163 **
## OffenseMIA        0.565916   0.447955   1.263 0.206485
## OffenseMIN        0.394263   0.532516   0.740 0.459080
## OffenseNE         1.229185   0.422893   2.907 0.003658 **
## OffenseNO         1.635849   0.433952   3.770 0.000164 ***
## OffenseNYG        0.918586   0.426603   2.153 0.031311 *
## OffenseNYJ        0.109614   0.440835   0.249 0.803633
## OffenseOAK        0.851176   0.425769   1.999 0.045606 *
## OffensePHI        0.937449   0.426499   2.198 0.027960 *
## OffensePIT        0.758697   0.436129   1.740 0.081943 .
## OffenseSEA        0.665838   0.423725   1.571 0.116108
## OffenseSF         1.025100   0.427300   2.399 0.016449 *
## OffenseTB         0.243676   0.447869   0.544 0.586393
## OffenseTEN        0.592949   0.425295   1.394 0.163271
## OffenseWAS        0.365241   0.432996   0.844 0.398948
## DefenseATL        0.051249   0.451230   0.114 0.909575
## DefenseBAL       -0.240325   0.390324  -0.616 0.538095
## DefenseBUF        0.279328   0.397480   0.703 0.482223
## DefenseCAR        0.086779   0.426265   0.204 0.838683
## DefenseCHI       -0.447871   0.414091  -1.082 0.279455
## DefenseCIN        0.267239   0.405922   0.658 0.510321
## DefenseCLE       -0.143399   0.394230  -0.364 0.716053
## DefenseDAL        0.227360   0.455017   0.500 0.617310
## DefenseDEN       -0.149279   0.389248  -0.384 0.701349
```

```
## DefenseDET       0.511505   0.525228   0.974 0.330132
## DefenseGB        0.218938   0.400110   0.547 0.584251
## DefenseHOU      -0.361988   0.389205  -0.930 0.352346
## DefenseIND      -0.095877   0.393081  -0.244 0.807302
## DefenseJAX       0.204698   0.442069   0.463 0.643336
## DefenseKC        0.407571   0.398447   1.023 0.306369
## DefenseLA        0.677196   0.414453   1.634 0.102285
## DefenseLAC       0.313094   0.404955   0.773 0.439439
## DefenseMIA       0.148219   0.405981   0.365 0.715049
## DefenseMIN      -0.067032   0.493537  -0.136 0.891965
## DefenseNE        0.585049   0.410566   1.425 0.154179
## DefenseNO       -0.383733   0.424922  -0.903 0.366502
## DefenseNYG       0.170654   0.392309   0.435 0.663569
## DefenseNYJ       0.018202   0.402318   0.045 0.963914
## DefenseOAK       0.124407   0.388927   0.320 0.749068
## DefensePHI      -0.330482   0.424643  -0.778 0.436425
## DefensePIT      -0.063561   0.419625  -0.151 0.879605
## DefenseSEA       0.283702   0.395750   0.717 0.473461
## DefenseSF       -0.001420   0.379757  -0.004 0.997018
## DefenseTB        0.230303   0.415306   0.555 0.579217
## DefenseTEN      -0.425202   0.406040  -1.047 0.295024
## DefenseWAS       0.231060   0.390671   0.591 0.554229
## Week2            0.163952   0.269172   0.609 0.542466
## Week3            0.315074   0.287543   1.096 0.273202
## Week4            0.418883   0.285301   1.468 0.142062
## Week5            0.353182   0.275090   1.284 0.199200
## Week6            0.731576   0.281894   2.595 0.009460 **
## Week7            0.187328   0.272784   0.687 0.492263
## Week8            0.318865   0.281934   1.131 0.258073
## Week9            0.156114   0.288933   0.540 0.588990
## Week10           0.790708   0.283599   2.788 0.005307 **
## Week11           0.457380   0.285091   1.604 0.108658
## Week12           0.565841   0.281861   2.008 0.044708 *
## Week13           0.548854   0.273991   2.003 0.045172 *
## Week14           0.349104   0.277958   1.256 0.209146
## Week15           0.317930   0.275962   1.152 0.249303
## Week16           0.306735   0.271269   1.131 0.258179
## Week17           0.265908   0.268521   0.990 0.322056
## QuarterSecond    0.338651   0.133286   2.541 0.011068 *
## QuarterThird     0.234106   0.132620   1.765 0.077539 .
## QuarterFourth   -0.006261   0.134046  -0.047 0.962747
## QuarterOvertime  1.076651   0.545053   1.975 0.048247 *
## DownSecond       0.186182   0.111206   1.674 0.094105 .
## DownThird        0.406306   0.194479   2.089 0.036702 *
## DownFourth      -0.710413   0.525760  -1.351 0.176643
## Distance         0.103283   0.014914   6.925 4.48e-12 ***
## PointDifference -0.001046   0.004722  -0.221 0.824742
## DistToTouchdown  0.021017   0.001968  10.681  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.505 on 19116 degrees of freedom
## Multiple R-squared:  0.01793,    Adjusted R-squared:  0.01341
## F-statistic: 3.966 on 88 and 19116 DF,  p-value: < 2.2e-16
```

```
##
## Call:
## lm(formula = Yards ~ Offense + Defense + Week + Quarter + Down +
##     Distance + DistToTouchdown, data = data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -18.190  -3.249  -1.240   1.395  93.584
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.817001   0.492137   1.660 0.096909 .
## OffenseATL       0.929939   0.482958   1.926 0.054181 .
## OffenseBLT       1.123299   0.442107   2.541 0.011068 *
## OffenseBUF       0.283722   0.433675   0.654 0.512973
## OffenseCAR       1.287380   0.445233   2.891 0.003839 **
## OffenseCHI       0.451116   0.435318   1.036 0.300080
## OffenseCIN       0.904244   0.449213   2.013 0.044134 *
## OffenseCLV       1.015397   0.461397   2.201 0.027769 *
## OffenseDAL       1.165804   0.483854   2.409 0.015988 *
## OffenseDEN       0.905027   0.417502   2.168 0.030193 *
## OffenseDET       0.601202   0.504328   1.192 0.233243
## OffenseGB        0.991985   0.456369   2.174 0.029744 *
## OffenseHST       0.619593   0.446609   1.387 0.165358
## OffenseIND       0.663989   0.425798   1.559 0.118919
## OffenseJAX       0.673488   0.453890   1.484 0.137875
## OffenseKC        1.370669   0.436836   3.138 0.001705 **
## OffenseLA        1.562843   0.418788   3.732 0.000191 ***
## OffenseLAC       1.240131   0.433938   2.858 0.004270 **
## OffenseMIA       0.566542   0.447935   1.265 0.205963
## OffenseMIN       0.390436   0.532222   0.734 0.463205
## OffenseNE        1.220916   0.421230   2.898 0.003754 **
## OffenseNO        1.627365   0.432247   3.765 0.000167 ***
## OffenseNYG       0.915965   0.426428   2.148 0.031727 *
## OffenseNYJ       0.109391   0.440823   0.248 0.804019
## OffenseOAK       0.851145   0.425758   1.999 0.045609 *
## OffensePHI       0.931051   0.425508   2.188 0.028675 *
## OffensePIT       0.751485   0.434901   1.728 0.084014 .
## OffenseSEA       0.662312   0.423415   1.564 0.117784
## OffenseSF        1.024384   0.427277   2.397 0.016518 *
## OffenseTB        0.241266   0.447725   0.539 0.589982
## OffenseTEN       0.590933   0.425187   1.390 0.164600
## OffenseWAS       0.361953   0.432730   0.836 0.402917
## DefenseATL       0.057820   0.450242   0.128 0.897817
## DefenseBAL      -0.230377   0.387720  -0.594 0.552397
## DefenseBUF       0.282645   0.397188   0.712 0.476712
## DefenseCAR       0.094274   0.424909   0.222 0.824418
## DefenseCHI      -0.440309   0.412670  -1.067 0.285996
## DefenseCIN       0.269720   0.405757   0.665 0.506230
## DefenseCLE      -0.140770   0.394041  -0.357 0.720911
## DefenseDAL       0.232042   0.454514   0.511 0.609687
## DefenseDEN      -0.147867   0.389186  -0.380 0.703995
## DefenseDET       0.518773   0.524189   0.990 0.322348
## DefenseGB        0.225009   0.399160   0.564 0.572961
```

```
## DefenseHOU      -0.355790   0.388188  -0.917 0.359394
## DefenseIND      -0.090595   0.392347  -0.231 0.817391
## DefenseJAX       0.209005   0.441630   0.473 0.636035
## DefenseKC        0.418089   0.395596   1.057 0.290589
## DefenseLA        0.688312   0.411391   1.673 0.094318 .
## DefenseLAC       0.320485   0.403568   0.794 0.427130
## DefenseMIA       0.150608   0.405828   0.371 0.710557
## DefenseMIN      -0.060690   0.492693  -0.123 0.901966
## DefenseNE        0.595622   0.407770   1.461 0.144120
## DefenseNO       -0.375011   0.423082  -0.886 0.375426
## DefenseNYG       0.175151   0.391773   0.447 0.654828
## DefenseNYJ       0.020106   0.402216   0.050 0.960133
## DefenseOAK       0.126393   0.388814   0.325 0.745130
## DefensePHI      -0.322942   0.423265  -0.763 0.445485
## DefensePIT      -0.055588   0.418067  -0.133 0.894223
## DefenseSEA       0.289222   0.394954   0.732 0.463999
## DefenseSF        0.001827   0.379465   0.005 0.996158
## DefenseTB        0.235929   0.414518   0.569 0.569252
## DefenseTEN      -0.421142   0.405615  -1.038 0.299154
## DefenseWAS       0.235094   0.390236   0.602 0.546889
## Week2            0.163601   0.269161   0.608 0.543316
## Week3            0.314740   0.287531   1.095 0.273694
## Week4            0.419187   0.285290   1.469 0.141759
## Week5            0.353301   0.275083   1.284 0.199037
## Week6            0.731441   0.281886   2.595 0.009472 **
## Week7            0.185954   0.272706   0.682 0.495320
## Week8            0.320278   0.281855   1.136 0.255835
## Week9            0.154451   0.288829   0.535 0.592828
## Week10           0.790084   0.283578   2.786 0.005339 **
## Week11           0.456774   0.285071   1.602 0.109102
## Week12           0.566257   0.281847   2.009 0.044541 *
## Week13           0.549768   0.273953   2.007 0.044785 *
## Week14           0.348438   0.277935   1.254 0.209978
## Week15           0.317626   0.275952   1.151 0.249738
## Week16           0.307128   0.271257   1.132 0.257547
## Week17           0.265470   0.268507   0.989 0.322828
## QuarterSecond    0.338383   0.133277   2.539 0.011127 *
## QuarterThird     0.233055   0.132531   1.758 0.078680 .
## QuarterFourth   -0.009949   0.133004  -0.075 0.940372
## QuarterOvertime  1.075963   0.545031   1.974 0.048381 *
## DownSecond       0.185377   0.111144   1.668 0.095352 .
## DownThird        0.404920   0.194373   2.083 0.037245 *
## DownFourth      -0.709451   0.525728  -1.349 0.177204
## Distance         0.103140   0.014899   6.923 4.58e-12 ***
## DistToTouchdown  0.021018   0.001968  10.682  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.505 on 19117 degrees of freedom
## Multiple R-squared:  0.01793,    Adjusted R-squared:  0.01346
## F-statistic: 4.011 on 87 and 19117 DF,  p-value: < 2.2e-16

##
## Call:
```

```
## lm(formula = Yards ~ Offense + Defense + Week + Quarter + Down +
##     poly(Distance, 2, raw = T) + poly(DistToTouchdown, 2, raw = T),
##     data = data2)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -18.332  -3.285  -1.172   1.415  94.646
##
## Coefficients:
##                                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        -3.066e-01  5.173e-01  -0.593 0.553348
## OffenseATL                          9.021e-01  4.821e-01   1.871 0.061356 .
## OffenseBLT                          1.058e+00  4.414e-01   2.396 0.016581 *
## OffenseBUF                          2.588e-01  4.329e-01   0.598 0.549950
## OffenseCAR                          1.265e+00  4.445e-01   2.846 0.004434 **
## OffenseCHI                          4.069e-01  4.346e-01   0.936 0.349102
## OffenseCIN                          8.578e-01  4.485e-01   1.913 0.055787 .
## OffenseCLV                          1.019e+00  4.606e-01   2.211 0.027027 *
## OffenseDAL                          1.184e+00  4.830e-01   2.452 0.014220 *
## OffenseDEN                          8.988e-01  4.168e-01   2.157 0.031052 *
## OffenseDET                          5.777e-01  5.034e-01   1.148 0.251177
## OffenseGB                           9.819e-01  4.556e-01   2.155 0.031143 *
## OffenseHST                          5.827e-01  4.458e-01   1.307 0.191232
## OffenseIND                          6.388e-01  4.251e-01   1.503 0.132924
## OffenseJAX                          6.424e-01  4.531e-01   1.418 0.156256
## OffenseKC                           1.335e+00  4.361e-01   3.062 0.002205 **
## OffenseLA                           1.604e+00  4.181e-01   3.838 0.000125 ***
## OffenseLAC                          1.223e+00  4.332e-01   2.823 0.004759 **
## OffenseMIA                          5.231e-01  4.472e-01   1.170 0.242123
## OffenseMIN                          3.577e-01  5.313e-01   0.673 0.500832
## OffenseNE                           1.213e+00  4.205e-01   2.886 0.003908 **
## OffenseNO                           1.599e+00  4.315e-01   3.706 0.000211 ***
## OffenseNYG                          9.495e-01  4.257e-01   2.230 0.025744 *
## OffenseNYJ                          1.195e-01  4.401e-01   0.272 0.785909
## OffenseOAK                          8.232e-01  4.250e-01   1.937 0.052790 .
## OffensePHI                          9.405e-01  4.248e-01   2.214 0.026831 *
## OffensePIT                          7.832e-01  4.342e-01   1.804 0.071290 .
## OffenseSEA                          6.863e-01  4.227e-01   1.624 0.104446
## OffenseSF                           1.011e+00  4.265e-01   2.371 0.017758 *
## OffenseTB                           2.137e-01  4.470e-01   0.478 0.632594
## OffenseTEN                          5.753e-01  4.245e-01   1.355 0.175346
## OffenseWAS                          3.379e-01  4.320e-01   0.782 0.434069
## DefenseATL                          4.501e-02  4.495e-01   0.100 0.920224
## DefenseBAL                         -2.341e-01  3.870e-01  -0.605 0.545326
## DefenseBUF                          2.642e-01  3.965e-01   0.666 0.505230
## DefenseCAR                          9.841e-02  4.242e-01   0.232 0.816537
## DefenseCHI                         -4.644e-01  4.120e-01  -1.127 0.259624
## DefenseCIN                          2.589e-01  4.050e-01   0.639 0.522775
## DefenseCLE                         -1.256e-01  3.934e-01  -0.319 0.749450
## DefenseDAL                          2.430e-01  4.537e-01   0.536 0.592281
## DefenseDEN                         -1.697e-01  3.885e-01  -0.437 0.662181
## DefenseDET                          5.414e-01  5.233e-01   1.035 0.300886
## DefenseGB                           1.880e-01  3.985e-01   0.472 0.637009
## DefenseHOU                         -3.711e-01  3.875e-01  -0.958 0.338297
```

```
## DefenseIND                          -9.828e-02  3.917e-01  -0.251 0.801873
## DefenseJAX                           2.309e-01  4.409e-01   0.524 0.600514
## DefenseKC                            4.055e-01  3.949e-01   1.027 0.304520
## DefenseLA                            6.510e-01  4.107e-01   1.585 0.112975
## DefenseLAC                           3.139e-01  4.029e-01   0.779 0.435831
## DefenseMIA                           1.694e-01  4.051e-01   0.418 0.675830
## DefenseMIN                          -1.200e-01  4.919e-01  -0.244 0.807288
## DefenseNE                            5.753e-01  4.071e-01   1.413 0.157572
## DefenseNO                           -3.542e-01  4.223e-01  -0.839 0.401688
## DefenseNYG                           1.608e-01  3.911e-01   0.411 0.681046
## DefenseNYJ                           2.275e-02  4.015e-01   0.057 0.954822
## DefenseOAK                           1.523e-01  3.881e-01   0.392 0.694757
## DefensePHI                          -3.254e-01  4.225e-01  -0.770 0.441286
## DefensePIT                          -1.702e-02  4.174e-01  -0.041 0.967475
## DefenseSEA                           2.769e-01  3.943e-01   0.702 0.482534
## DefenseSF                           -1.555e-02  3.788e-01  -0.041 0.967254
## DefenseTB                            2.549e-01  4.138e-01   0.616 0.537891
## DefenseTEN                          -4.245e-01  4.049e-01  -1.048 0.294507
## DefenseWAS                           2.099e-01  3.896e-01   0.539 0.589977
## Week2                                1.381e-01  2.687e-01   0.514 0.607331
## Week3                                3.140e-01  2.870e-01   1.094 0.274046
## Week4                                3.929e-01  2.848e-01   1.380 0.167750
## Week5                                3.245e-01  2.746e-01   1.182 0.237332
## Week6                                6.985e-01  2.814e-01   2.482 0.013065 *
## Week7                                1.710e-01  2.722e-01   0.628 0.530018
## Week8                                2.741e-01  2.814e-01   0.974 0.330145
## Week9                                1.231e-01  2.884e-01   0.427 0.669541
## Week10                               7.463e-01  2.831e-01   2.636 0.008402 **
## Week11                               4.260e-01  2.846e-01   1.497 0.134488
## Week12                               5.397e-01  2.814e-01   1.918 0.055113 .
## Week13                               5.253e-01  2.735e-01   1.921 0.054779 .
## Week14                               3.262e-01  2.775e-01   1.176 0.239755
## Week15                               2.909e-01  2.755e-01   1.056 0.290932
## Week16                               2.802e-01  2.708e-01   1.035 0.300848
## Week17                               2.109e-01  2.681e-01   0.787 0.431551
## QuarterSecond                        3.917e-01  1.332e-01   2.940 0.003283 **
## QuarterThird                         2.275e-01  1.323e-01   1.719 0.085578 .
## QuarterFourth                       -1.661e-02  1.328e-01  -0.125 0.900480
## QuarterOvertime                      1.026e+00  5.441e-01   1.886 0.059362 .
## DownSecond                           2.019e-01  1.175e-01   1.718 0.085739 .
## DownThird                            5.534e-01  2.162e-01   2.560 0.010468 *
## DownFourth                          -5.164e-01  5.366e-01  -0.962 0.335873
## poly(Distance, 2, raw = T)1          1.690e-01  3.621e-02   4.667 3.08e-06 ***
## poly(Distance, 2, raw = T)2         -3.959e-03  1.663e-03  -2.381 0.017273 *
## poly(DistToTouchdown, 2, raw = T)1  7.604e-02  7.670e-03   9.915  < 2e-16 ***
## poly(DistToTouchdown, 2, raw = T)2 -5.802e-04  7.714e-05  -7.521 5.66e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 6.494 on 19115 degrees of freedom
## Multiple R-squared:  0.02149,    Adjusted R-squared:  0.01693
## F-statistic: 4.716 on 89 and 19115 DF,  p-value: < 2.2e-16

## Analysis of Variance Table
```

```
##
## Model 1: Yards ~ Offense + Defense + Week + Quarter + Down + poly(Distance,
##     2, raw = T) + poly(DistToTouchdown, 2, raw = T)
## Model 2: Yards ~ Offense + Defense + Week + Quarter + Down + Distance +
##     DistToTouchdown
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1  19115 805997
## 2  19117 808930 -2   -2932.7 34.776 8.403e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```