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Making the Cut: Receivers of the National Football League

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Abstract

In this paper the prospects of the National Football League, or NFL, are studied in order to determine the relationships between past college statistics, other “measurables,” and how they translate to successful careers in the league. When referring to measurables, this consists of all of the numerical data from each player that should, in theory, help teams get an idea of the players strengths or weaknesses. The data being used comes from an annual scouting combine for NFL teams that is held prior to each season. Information about the player’s college statistics and pre-draft measurables are being compared to several individual player statistics that are commonly indicative of successful careers. The goal is not only to benefit teams in identifying productive players, but also for the young men with dreams of competing at the highest level. It is often difficult to get a concrete idea of what teams are looking for, because many teams having differing opinions about which players will provide the most value. This investigation deals specifically with receivers and analyzing data collected from their past in order to make predictions on future careers. Multiple regression models are necessary due to several important independent variables (measurables) for each dependent variable (player statistics). Analyzing these relationships leads to the construction of several mathematical models which aim to predict the success of future prospective NFL receivers.

Keywords: National Football League, NFL Draft Combine, data, mathematical analysis, statistics in football, multiple regression, prospects, receivers, football, careers, measurables, college statistics, NFL statistics

1 Introduction

American football averages about 16 million views each game [6] and the typical player recieves nearly 2.3 million dollars each year [13]. With this much potential expenditure, coaches and team organizations have honed critical recruiting strategies. Complex analysis of data is only scratching the surface in the National Football League (NFL). The chess-like nature of the game calls for a wide range of skills that vary between individual positions. This project investigates several player characteristics in order to develop a mathematial model that relates those "measurable" traits to career success and longevity. Using statistical data from the past 7 years on 200 players, the research conjectures that there is some correlation between these traits and future success of the NFL player. Onfield productivity is directly related to the length of career a player should expect.

1.1 Motivation

Understanding the game of football through data analysis often comes as a challenge for NFL coaches. Successful coaches report a lifetime of studying the game. Their knowledge propels their careers. Trusting and incorporating statistical analysis into game planning is a risk of team success and job security. Every team in the league has access to the same data and records; however,the NFL is extremely competitive. Therefore, teams' recruiting strategies are well kept secrets. According to [1], one general manager stated, "The point we made with our coaches is: We have all this information but so does everyone else. What advantage does it give us to get it? None. Its what we do with it, the way we use it." Modern technology only increases the amount of data and materials available in forming predictive models. In the same article, Clark claims,"This is the start of something new. There will be more data, more decisions made based on that data, and more evidence of what works. It is an exciting time to be smart in the NFL"[1].

The suitability and completeness of the data directly impacts how well we can predict success of future prospects. Teams, coaches, and players will all benefit from the interpretation of the predictive models. Gaining a competive advantage over opponenents must be the goal of all competitors. Using predictive models could provide the the advantage NFL teams are searching for.

Teams can use this data to to help maximize draft strategies. The NFL Draft is an event in which each team select current prospects to add to their team. These order is predetermined based on the previous season.Each team is only given a short amount of time to make their pick. Teams must have at least primary and secondary choices, in case players are drafted elsewhere. Therefore, they must collect data on as many of the potential recruits as possible. Using predictive models would allow teams to quickly review exactly how they expect each player to produce. Though player productivity is being predicted, it is still not automatic. Coaches are still responsible for putting players in position to excel.

Coaches can use the data collected in playcalling to highlight player abilities and traits. The models would provide them insight to areas each player specializes in. Players would be able to easily identify areas for improvement. Being able to focus their areas of practice and training makes their work much more efficient. Plenty of people are telling them to be bigger, faster, and stronger; but, players need to know how to improve their own particular playstyle.

Fantasy football owners might even be interested in this competitive advantage. Prior to seeing rookies play, it is difficult to gauge them and how they may rank when compared with other players in the NFL. Predicting the success of players and putting them in position to succeed are major responsibilities of every coach, and this goes for fantasy coaches as well. Recognizing expectations of great young players before others in your league should lead to a successful fantasy season.

Narrowing our focus was necessary due to having such a large sample size. The sample size needed to be sufficiently large, however, to suffice the amount of variables being included in our model. Though teams and coaches need information about every position, this research focuses on receivers. Receivers in the NFL have seen a boost in attention in recent years due to a league-wide increase in passing plays. By directly placing more emphasis of the game on receivers, their value to the team is increased. Currently, there is no mathematical model that accurately determines each position's contribution to the success of the team, but coaches' tendencies to value receivers anecdotally point toward the significance of their contributions to team productivity. This makes drafting the right receiver more critical than ever before. The variance of abilities in productive receivers is also of interest. Some may be more effective because of a height or jumping advantage. Others may succeed because of their speed and ability to get in open field. The variety of skills that translate to great receivers make the position particularly difficult to gauge. A mathematical model that accounts for all areas of skill would provide the predictive tool teams need in determining the receiver that provides the best outlook for team success.

2 Background and Related Studies

This section outlines the basic statistical principles that will be analyzed. Observations of similar studies and expert's opinions and insight will also be discussed.

2.1 Multiple Regression

Multiple regression is a common form of predictive analysis. It behaves similarly to linear regression, but allows the modeling of relationships between multiple input variables and a single complex output. Multiple regression allows us to form predictive models in the following form.

$$Y_n = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + ... + \hat{\beta}_n x_n \tag{1}$$

A coefficient $\hat{\beta}_i$ is determined for each input value. The first term, $\hat{\beta}_0$, remains constant regardless of input. Each input value, x_i, represents a specific contribution accounted for in the model by its coefficient $\hat{\beta}_i$. Therefore the combination of these terms depicts their overall effects on the outcome Y_n.

Developing a predictive model provides overall expectations, however analysis of our regression provides further insight. This insight allows us to further improve our model and learn more about important inputs. Beginning with the coefficient of determination (R^2 value) we are able to determine the percentage of variation in the output that is explained by the model. R^2 values determine how well each model predicts the outcome, but do not account for the number of variables used. Too many variables would result in an overfit model which is less predictive. A modified version, called the "Predicted R^2", is more beneficial for this reason. Recording and modeling human actions can be difficult and complex, therefore we can be satisfied with lower R^2 values than normal (40%-50%).This modified value takes into account the amount of variables used as well as the ability of our model to predict the output for each input if it were removed from our sample [12].

For all inputs used in our regression model, we should consider several important values. Minitab calculates the variance inflation factor (VIF). This provides more benefit to the construction of the model than insight for interpretation. The VIF served as an indicator of multicollinearity, or an overfit model. As VIF approaches 5 we should consider removing that input type. Each input type is also assigned a coefficient. This coefficient attempts to indicate the value the output changes with respect to that specific input. A large coefficient could indicate a strong relationship, however it could also indicate a smaller general value for that input type. It is very useful in indicating whether the relation is positive or negative. Another useful value found through Minitab regression is the T-value; which is a proportionalized measure of variance. The p-value is a little more insightful for this set of data. It indicates the probablity of seeing a result as extreme as the one you are getting, or how statistically indicative that input is. Through the interpretation of the data of our multiple regression we are able to determine the statistical significance of the model as well as each individual value.

2.2 Related Studies

There are a couple of public studies of NFL football players that are similar, however most complex data analysis of incoming prospects is held by teams who wish to use that information to give their team the edge. Predictive multiple regression models and other types of data analytics are just now catching up to similar practices used in other sports. According to [1], "Football is still well behind baseball and basketball when it comes to embracing advanced metrics, but teams have made significant progress in recent years. Those who do not adapt will be left behind." Some of the research uses similar models to those we are constructing. In [4], he attempts to relate player data to their draft position. This seems to complicate things even more, due to predicting someone else's predictions of prospects. The input values he uses could also be useful for our model as well. Complex data analyis of football provides so much room for growth of knowledge and the competitive advantage teams need to succeed.

2.3 Key Information

Understanding the abilities that makes receivers successful is important to being able to identify great ones. According to [7] recievers should be able to attack and high point the football. A receiver that goes back to the ball and jumps to catch it will give himself an advantage over the defender. He should also be proficient with his hands and body control. Successful receivers should possess these abilities along with the "measurables" taken from the combine in [4]. Understanding how all of the small details play some part in a successful career and being able to highlight these details in order to better predict careers of future players.

3 Methods and Models

After recognizing several input we can use in forming our models for predicting success. We use several indicators of success so that all styles of successful receivers may be highligted. The models accuracy depends directly on the variables selected for the model. Our variables and reasons for using these are as follows.

3.1 Identifying Outputs

As mentioned above, multiple regression is necessary to relate the large number of inputs to 3 distinct outputs. The 3 outputs are all chosen as a means of indicating player success for each individual season they played in the NFL. They are:

- Touchdowns
- Yards
- Receptions

Touchdowns are the base score of a football game and award 6 points to the team when a player reaches the endzone. Points directly lead to team success and indicate player success as well. Touchdowns are far from the only way to determine the effectiveness and productivity of a player. The number of yards a receiver accumulates indicates his ability to move the offense down the field. Often, tight ends and taller recievers get more attention closer to the endzone. However, they are much less efficient at moving the ball farther down the field. Receptions or catches is the final indicator; it represents a player's to evade defensive players and to catch the ball. In the NFL, yards and touchdowns are important, but a receiver must be able to catch the ball efficiently against the best defenders. It is important to cover all areas of success in order to pinpoint the most productive receivers.

3.2 Inputs

The inputs, or "measurables," attempt to recognize each of these areas of athleticism. Our original inputs are collected from the NFL Scouting Combine[3]. Football is a very physical game in which size tends to matter. Height and weight are used as measurements of prospect size. We also used a variety of quantifiable workouts that measure a receiver's ability to move. Beginning with drills that tests player's agility there is the 3-cone and the shuttle drill. The 3-cone drill requires the participant to move in a triangular pattern from cone to cone. The shuttle drill consists of 2 cones tests the prospect's ability to come to a comlete stop and change direction. The vertical and broad jump are both meausure the athletes ability to jump. A vertical is measured as the maximum height a player leaves the ground upwards when jumping and is crucial to catching balls out of the air. The broad jump is measured as the distance jumped horizontally. The most popular of the workouts, because of its test of pure speed over a short distance, is the 40-yard dash. Each of these workouts relates to the job a receiver must do on Sundays, and attempts to capture all areas that make a receiver successful.

After incorporating the players' raw talent into a model without any other inputs is not the most productive way of predicting player success, but it did give us a strong starting point to build from. The main issue with the data from the NFL combine is the incompleteness of for many players. Players often skip particular events at the NFL combine for a variety of reasons. Some players may be unable to participitate due to injuries while others may feel like the event does not highlight their skillset or improve their draft position. The events are not mandatory and improving draft position is the only goal of individual players. An improved model was developed after incoorporating a more complete source of input categories into our data. These new categories are all taken from past college statistics along with a few categorical predictors. They are:

- Touchdowns (College Success)
- Yards (College Succes)
- Receptions (College Success)
- Years Played (College)

  The number of years an athlete plays college football indicates how much time they were given to accumulate their statistics.
- Conference Classification

Teams play many conference games, and players competing in stronger conferences should be recognized for such.
Categories: SEC, Power 5, Other

- College Position

  Players who were not receivers during their college career can not be expected to have achieved receiving numbers comparable to other players.
  Categories: Wide Receiver, Running Back, Quarterback

Player's college statistics [2] offer more data that incoorporates on field performance into to the predictive models rather than raw ability indicated from combine measurables. Football is a game that requires a great deal of ability to compete effectively, but this is not the only area that should be accounted for. Each individual player is responsible for using their own abilities in real game scenarios. A players knowledge of the game, field vision, and ability to move in pads can all be accounted for by their productivity throughought there college careers. Though there is a wide range of competition in college football, the data collected provides us with knowledge we can use in addition of the players raw abilities.

4 Results and Analysis

After indicating all major inputs that should form the predictive models from other sources the necessary data is recorded in Excel, shown below. Originally our output data was seperated by each player year (Rookie season, 2^{nd} season, etc.). Veteran players have aquired knowledge and an advantage over young players in their Rookie season. The goal is to help us see more clear relationships between our data.

4.1 Data

By recording data from the NFL Combine, other career college statistics, and determining how this data relates to NFL success, would provide teams with the support they need in finding the most beneficial receiver.

1	Player	Combine Year	Height	Wt	40 Time	Vertical	Broad Jum	3-Cone	Shuttle	Years Play	Rec.	Yds	TD	Conf	Total	Pos	TD	Catches	Yards
5	Mike Evans	2014	6.416667	231	4.53	37		7.08	4.26	2	151	2499	17	SEC		WR	56	553	8544.2
6	Amari Cooper	2015	6.083333	211	4.42	33	120	6.71	3.98	3	228	3463	31	SEC		WR	33.25	351.75	4824.8
7	Calvin Ridley	2018	6	189	4.43	31	110	6.88	4.41	3	224	2781	19	SEC		WR	70	448	5747
9	Christian Kirk	2018	5.833333	201	4.47	32.5	115	7.09	4.45	3	234	2856	26	SEC		WR	21	301	4130
10	Jordan Matthew	2014	6.25	212	4.46	35.5	120	6.95	4.18	4	262	3759	24	SEC		WR	29.4	343	4162.2
11	Kevin White	2015	6.25	215	4.35	36.5	123	6.92	4.14	2	144	1954	15	P5		WR	0	33.25	327.25
12	Sammy Watkins	2014	6.083333	211	4.43	34	126	6.95	4.34	3	240	3391	27	P5		WR	39.2	324.8	4999.4
13	Donte Moncrief	2014	6.166667	221	4.4	39.5	132	7.02	4.3	3	156	2371	20	SEC		WR	29.4	280	3560.2
14	Robert Woods	2013	6	201	4.51	33.5	117	7.15	4.47	3	252	2930	32	P5		WR	26.83	402.5	5192.8
15	Eric Page	2012	5.75	186	4.5	30	112	6.95	3.98	3	306	3446	16	Other		WR	0	0	0
16	Brandin Cooks	2014	5.833333	189	4.33	36	120	6.76	3.81	3	226	3272	24	P5		WR	44.8	504	7205.8
17	Davante Adams	2014	6.083333	212	4.56	39.5	123	6.82	4.3	2	233	3031	38	Other		WR	54.6	487.2	5875.8
18	D.J. Foster	2016	5.833333	193	4.57	35.5	117	6.75	4.07	4	222	2458	14	P5		HB	0	39.6667	310.33
19	Curtis Samuel	2017	5.916667	196	4.31	37	119	7.09	4.33	3	172	1286	15	P5		WR	17.5	189	2131.5
20	Dorial Green-Be	2015	6.416667	237	4.49	33.5	119	6.89	4.45	2	87	1278	17	SEC		WR	10.5	119	1646.8
21	Justin Hardy	2015	5.833333	192	4.56	36.5	114	6.63	4.21	4	387	4541	35	Other		WR	15.75	133	1314.3
22	Kenny Golladay	2017	6.333333	218	4.5	35.5	120	7	4.15	2	160	2285	18	Other		WR	28	343	5390
23	Tyler Boyd	2016	6.083333	197	4.58	34	119	6.9	4.35	3	254	3361	21	P5		WR	23.33	354.667	4330.7
24	Josh Reynolds	2017	6.25	194	4.52	37	124	6.83	4.13	3	164	2788	30	SEC		WR	21	140	1771
25	Kendall Wright	2012	5.833333	196	4.49	38.5	121	6.93	4.18	4	302	4004	30	P5		WR	19	339	3858
26	Josh Malone	2017	6.25	208	4.4	30.5	121	7.05	4.19	3	104	1608	14	SEC		WR	3.5	24.5	262.5

Figure 1: College Statistics, Measurable, and Success Indicator Examples in Excel

Using this data we are able to locate individual relationships and attempt to reduce insignificant information. The first step of analysis is to determine whether the data demonstates statistical significance, or not. We begin by testing for randomness in each of the input categories by plotting them in Excel directly to each indicators of success. Interestingly, we notice there is a large decrease in player's productivity with extremely quick 40 times as shown in the tables of Figure 2.

4.2 Analysis

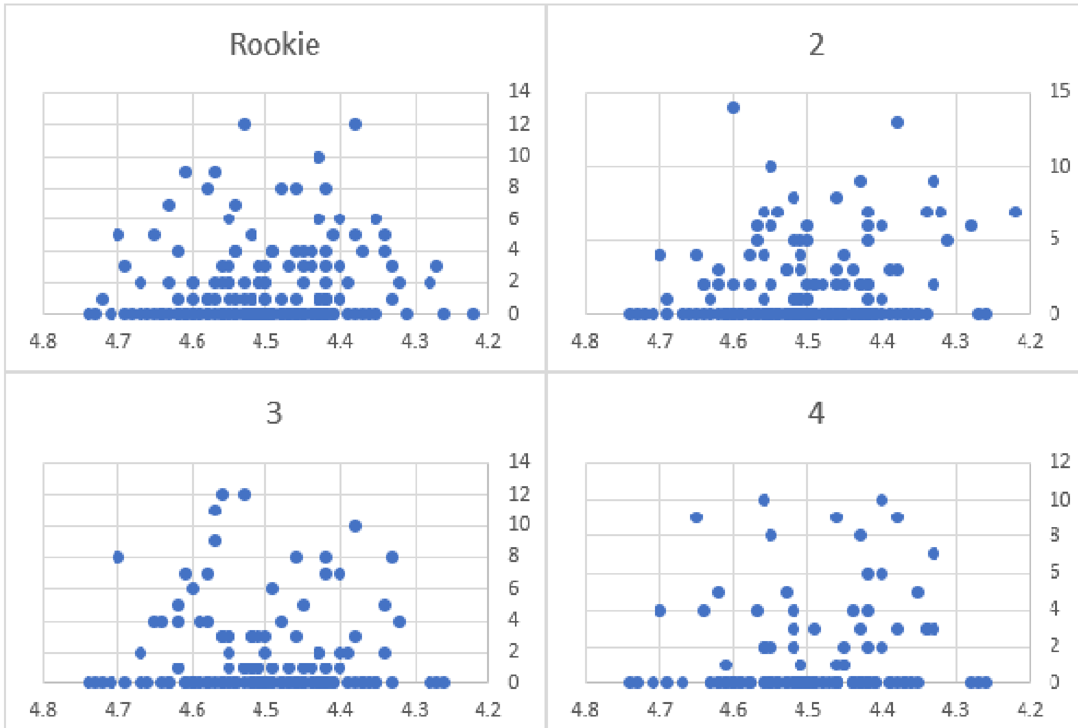

Figure 2: Touchdowns vs. 40-Yard Dash Times

The table does not necessarily indicate that one is too fast for the position; this may be explained by quarterback accuracy. The decrease is clear, but understanding "Why?" is the only way to a solution. Professional quarterbacks are highly skilled, but they cannot be expected to predict where the ball needs to be without spending more time with that quicker reciever. They will be moving faster, but their accuracy depends on a working rapport with their receivers. This helps them target the receiver's catch radius within a shorter time frame. Noticing patterns and constructing ideas about those provide you with reasoning backed by data that should benefit your team. The only input that appeared to be completely insignificant to all values was the shuttle run, therefore it was removed from our research.

After determining individual areas of significance and insignificance we are able to begin constructing our multiple regression models. In order to create a larger data set we proportionalize each players career stats so that they are able to be compared to each other. The data is transferred to Minitab where we were able to compare Predicted R^2 values for all input values using the Best Subset tool located under Stat → Regression →Best Subsets. Using the best subsets tool we are able to directly calculate which inputs combine to form the most predictive regression models. The best model created for each indicator of success is discussed below.

	Term	Coefficient	T-Value	$p-value$	VIF
	Constant	86.9	1.27	0.206	
	3-Cone	8.50	1.29	0.198	1.21
	40 Time	-44.0	-3.46	0.001	1.10
	Height	10.60	1.76	0.081	1.27
	Years Played	-7.71	-4.87	0.000	1.16
Touchdowns	Receptions	0.1226	6.17	0.000	1.52
	Conference				
	Power 5	2.97	1.12	0.266	1.49
	SEC	10.00	3.07	0.003	1.52
	Position				
	QB	18.1	1.52	0.131	1.75
	WR	1.25	0.16	0.870	1.76

Table 1: Equation:Pred. Touchdown= $86.9 + 8.503Cone - 7.71YearsPlayed + 0.1226Rec. - 44.0(40Time) + 0.0Conf_Other + 2.97ConfP5 + 10.00ConfSEC + 10.60Height + 0.0PosHB + 18.1PosQB + 1.25PosWR$

Touchdowns are more important to the team than any other indicator of success. The most important variables used in predicting players number of touchdowns were 3-cone, 40 time, height, years played (college), receptions, conference, and position. The coefficient determines how much the output is predicted to change for that input. Observing the coefficients it is noticed that 40 times have a negative relationship with touchdown productivity. This is not very strange if we think about quicker players having lower 40 times, and being more successful. The 3-cone drill tests a players speed as well, however it does not have the same negative relationship. The P-value for the reciever position is normal. It is relatively high because of most players in this data set being a receiver. Player receptions accounted for the largest proportional variance of this model. The variance inflation factors (VIFS) observed indicate we do not have multicollinearity as they are all below 5. The R^2 value for touchdowns is 32.40% while the "Predicted R^2" value is 22.64%. These are not perfect, however they improved greatly from only using Combine Results.

	Term	Coefficient	T-Value	$p - value$	VIF
	Constant	1229	1.73	0.086	
	3-Cone	86.2	1.24	0.216	1.19
	40 Time	-435	-3.17	0.002	1.15
	Weight	1.157	1.38	0.169	1.23
	Years Played	-77.9	-4.63	0.000	1.17
Receptions	Receptions	1.329	6.45	0.000	1.46
	$Conference$				
	Power 5	40.4	1.44	0.153	1.49
	SEC	87.3	2.52	0.013	1.53
	$Position$				
	QB	227	1.80	0.074	1.75
	WR	37.5	0.47	0.639	1.71

Table 2: Equation: Pred. Receptions= $1229 + 1.157Weight + 86.2(3Cone) - 77.9YearsPlayed + 1.329Rec. - 435(40Time) + 0.0ConfOther + 40.4ConfP5 + 87.3ConfSEC + 0.0PosHB + 227PosQB + 37.5PosWR$

Receptions indicate players abilities to evade defenders and catch the ball. The most predictve inputs we were able to locate in predicting receptions were 3-cone, 40 time, weight, years played (college), receptions, conference, and position. The only input that was changed for the betterment of the model was weight. The T-value of years played and receptions point toward a larger variance. Again there were no VIFs that indicated any sign of multicolliniarity and our model satisfies our expectations of predictions. The R^2 value for receptions is 31.28% while the "Predicted R^2" value is 21.80%.

	Term	Coefficient	T-Value	$p - value$	VIF
	Constant	13604	1.46	0.147	
	3-Cone	1315	1.44	0.151	1.20
	40 Time	-5324	-3.02	0.003	1.10
	Weight	14.9	1.37	0.173	1.22
	Years Played	-1107	-5.03	0.000	1.16
Yards	Yards	1.294	6.66	0.000	1.44
	$Conference$				
	Power 5	597	1.62	0.108	1.50
	SEC	11998	2.63	0.010	1.53
	$Position$				
	QB	2449	1.49	0.139	1.73
	WR	57	0.05	0.957	1.75

Table 3: Equation: Pred. Yards= $13604 + 14.9Weight + 1315(3Cone) - 5324(40Time) - 1107YearsPlayed + 1.294Yards + 0.0ConfOther + 597ConfP5 + 1198ConfSEC + 0.0PosHB + 2449PosQB + 57PosWR$

Yards move the team down the field as well as produce first downs. This directly impacts how well teams play. College yards are not a great indicator of success individually, because of the variance calculated by the T-value. The yards does however improve the overall model. The R^2 value for touchdowns is 34.47% while the "Predicted R^2" value is 25.38%. Singling out player traits and how they translate to the league individually is a waste of information for something as complicated as the skills an NFL receiver must aquire.

5 Conclusion

Teams, coaches, and players can all gain mutual benefit from these predictive models. The models created are imperfect, however do provide significant insight. The knowledge of football we can learn from analyzing the data will only improve as data collection and technology improve as well.

5.1 Future Studies

With a combination of better communication and improvements in data collection technology the predictiveness of future models should only improve. Communication between analytics deptartments of teams and their coaches could help with the goals of both parties. Coaches just need to be able to understand the model and how they can highlight player strengths. They should also be able to communicate ideas of their own and how they relate for more personalized improvements. The analytics departments need information about the best way to go about modeling their data. Ideas about points of emphasis may vary from one coach to another, therefore the two must work together and understand each others field of focus. There are thousands of variables that go into the amount of success a player achieves with their time in the leage. Coach's playcalling obviously has impact on player success. These variables range from the level of play of the team quarterback to the weather a game was played in. Increased identification of variables leads to more dependable predictions

Therefore, improving the model and implementing more complex input variables is a direction for future studies. However, expanding the model to include other positions could be more beneficial on a short term basis. The ideas used here could be maninpulated for the use of analyzing other positions seperately. For each position on a football field there are different indicators of success related to that position. The inputs we use in predicting these would also change per position. Beginning with observing raw talent and college statistics, we could develop similar models for each specific position. The data is available to everyone, but using and trusting the information provided by the data yields a competitive edge for an NFL team.

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