

# Algorithms for Predicting the NFL Draft

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## Abstract

*Every spring sports networks become engrossed in the task of predicting whom National Football League (NFL) teams will choose as their picks in the draft. Experts are brought in to discuss potential decisions and use a variety of data and information in order to make predictions. This paper reviews the three algorithms used in attempting to predict the first round of the draft: a brute force algorithm that considers the position most commonly selected at each draft pick over the last eight years, Gauss-Jordan, and an algorithm that takes team needs into account in reference to Gauss-Jordan. The goal was to produce an error between Mel Kiper's and Matt Miller's. This paper will discuss the methodology of each algorithm implementation and the final results.*

**Key Words:** Brute force, Gauss Jordan, team needs, quantitative, qualitative, error

## 1. Introduction

The NFL draft is a very publicized, annual event that disposes a lot of attention on football in the spring. Sports networks bring in people considered experts in this field in order to predict which players NFL teams plan to draft. These types of predictions are very popular for sports, which is why attempting to use algorithms to forecast the draft is intriguing.

For this project three algorithms were created with the intent of predicting the NFL draft using players' statistics against historical data. The first step was to determine a value for the predictions of Mel Kiper, sports analyst for NFL.com, and Matt Miller, sports analyst for the Bleacher Report, in order to set a baseline goal.

The algorithms created use statistics farmed for the previous three years top fifty draft picks in order to produce a first round prediction. For each player, combine statistics and college statistics were

gathered, along with college teams' strength of schedule, in order to create quantitative data for the algorithms.

The algorithms were implemented using Mike Mayock's big board and then compared to experts Mel Kiper & Matt Miller's picks from the previous three years. The Gauss-Jordan algorithm resulted in the worst error followed by the brute force algorithm. The team needs algorithm provided our best result, but only after we replaced our Gauss-Jordan results with Mike Mayock's big board.

## 2. Targeted Result

Before any scientific experiment, it is important to set a goal and the measures to use in order to determine whether or not the goal is reached. We decided to measure our success based on prediction errors of the previous three years. We took Mel Kiper and Matt Miller's final mock drafts for each of the last three years and recorded the picks. Next we took the actual picks and put them next to the expert picks in order to realize an error statistic showing how far off each pick was. We did not concern ourselves with whether the pick was higher or lower than expected, only how far off the pick was. (As seen in Figure 1)

Once we farmed these statistics we took their picks and divided them by the total number of picks that year (thirty-two) in order to get an average error. After realizing this statistic, we noted that it did not take into account which picks were exactly correct. Being that the goal is to predict the picks, our team decided we should give more credit for picks that were exactly correct. We then developed the McNamara-Benton Error (MBE). MBE divides the total error by the original thirty-two plus the number of correct picks. This gave the correct picks double the value of any other pick (bottom of Figure 1).

Mel Kiper Jr. 2012				
Pick	Actual	Player	Team	Error
17	17	Dre Kirkpatrick	Bengals	0
18	26	Whitney Mercilus	Chargers	8
19	21	Chandler Jones	Bears	2
20	24	David DeCastro	Titans	4
21	41	Cordy Glenn	Bengals	20
22	31	Doug Martin	Browns	9
23	42	Jonathan Martin	Lions	19
24	11	Dontari Poe	Steelers	13
25	49	Kendall Reyes	Broncos	24
26	43	Stephen Hill	Texans	17
27	35	Courtney Upshaw	Patriots	8
28	19	Shea McClellin	Packers	9
29	25	Don't'a Hightower	Ravens	4
30	27	Kevin Zeitler	49ers	3
31	29	Harrison Smith	Patriots	2
32	34	Coby Fleener	Giants	2
Total Correct: 7				
Total Error: 179				
Average Error: $179/32 = 5.59375$				
McNamara-Benton Error: $179/(32+7)=4.590$				

**Figure 1. Picks 17-32 for Mel Kiper 2012**

After gathering these statistics, we averaged the three years to see how the experts did overall. Next, we averaged Mel Kiper and Matt Miller's three year average and took that as our goal. (Figure 2)

M-B Averages	Mel Kiper	Matt Miller
2012	4.950	6.083
2013	5.725	10.909
2014	6.5	8.1316
3 Year Avg	5.725	8.374533
Our Goal: $(5.725+8.3745)/2 = 7.05$ M-B Average		

**Figure 2. M-B Averages used to determine goal**

### 3. Methodology

#### Brute Force Algorithm

A brute force algorithm is a crude algorithm that works through all possible answers until it finds the right one [1]. In some instances, this algorithm can be successful; but in others there are too many options and brute force is not feasible because its Big-O is linear.

The brute force algorithm created uses NFL.com's big board [2] to choose players based on big board values and typical selection depending on the pick. The algorithm has these typical selections coded in, so when provided a list of the top fifty players for the year it looks at what position is most commonly chosen at the specific draft location, then finds the first player that plays that position and fills the spot.

The algorithm scans through the entire list, placing players depending on position. Once this is done the error is calculated (Figure 3 below).

#### Gauss-Jordan Elimination

Gauss-Jordan is an algorithm used to solve systems of linear equations. Given a number of sets of equations and their answers, (ex.  $3x+4y-7z=5$ ) Gauss-Jordan Elimination uses matrix algebra to determine the values for the given variables.

For our version of Gauss-Jordan elimination we farmed statistics for the top fifty players to go in the draft for each of the past three years. For each position we picked what we thought were their four most important statistics as well as their college strength of schedule. These statistics were then normalized, giving each of them a value from 0-10. The algorithm gives the best result for that statistic in the group a 10 and scales the rest down accordingly. We then broke these players into groups of five and gave them an answer to this based on where they got drafted (Figure 3 below). We decided in order to give them a positively correlated statistic we would take their draft position and subtract it from one-hundred. If a position had more than one set of five, we would average the result of the variable weights (Figure 4 below).

Player	TD		Total		40 time	yd/rush	100-Drafted
	Sched Strength	total/game	yd/game				
Trent Richardson	9.465153971	8.461538	7.011732	9.666667	9.755011		97
Doug Martin	7.082658023	7.076923	5.610766	9.333333	9.820628		69
David Wilson	9.124797407	4.461538	5.217391	9.666667	10		88
Giovani Bernard	7.682333874	10	10	9.833333	9.668874		63
Le'Veon Bell	10	6.538462	6.687371	8.333333	9.521739		52

**Figure 3. RB Statistics**

	X1	X2	X3	X4	X5
RB	8.798318894	11.28123	-14.3459	29.22719	-27.0296

**Figure 4. RB value weights**

Once we used Gauss-Jordan to determine weights for each college statistic based on position, we applied the weights. We took a summation of each statistic times the weight given by this algorithm to determine a player's value.

$$\odot \text{ Player Value} = \sum_{n=0}^4 \text{Stat}_n * \text{Weight}_n$$

We then drafted the players purely on their values. And got the results listed in Figure 5.

### Team Needs Algorithm

Originally we had planned to use our Big Board created by our Gauss-Jordan algorithm and expand upon it to include the selecting team's needs in addition to player values. Each team has obvious needs that they need to replace through the draft. We took their top three needs (according to NFL.com) and gave them a weight. We decided that a team would reach five positions for their first need, three for their second need, and one position down the big board for their third need in that order. If none of these needs were hit within their viable reach-down, then the team would simply draft the most valued player during their time of selection.

After looking at our final results using the Gauss-Jordan Big Board (shown in Figure 5) we had no chance of reaching our original goal. We decided to go back to Mike Mayock's Big Board that we used during our brute force algorithm and apply our Team Needs algorithm to that Big Board. The results were much better than Gauss-Jordan and are listed in Figure 5.

## 4. Results

M-B Averages	Mel Kiper	Matt Miller	Brute	Gauss	Team Needs
2012	4.950	6.083	10.578	12.757	6.428
2013	5.725	10.909	11.253	13.875	9.752
2014	6.5	8.1316	9.76	14.28	8.563
3 Year Avg	5.725	8.374533	10.53	13.63733	8.247
Our Goal: (5.725+8.3745)/2 = 7.05 M-B Average					

**Figure 5. Our results**

The results from testing revealed a disconnect between solid statistics and actual results. As can be seen, our home brewed Big Board (Gauss-Jordan) actually gave us the worst average of all of these. Our prediction that the Team Needs would come largely into play did however work once we went back to the original Big Board. The Team Needs algorithms actually gave us a result that, while not meeting our original goal, beat Matt Miller's mock drafts.

## 5. Conclusion

The contrast between quantitative versus qualitative data became a very obvious issue with regards to making a strong prediction for the NFL draft. We used strictly quantitative data because that is what computers can read, but experts take into account qualitative information (i.e. word of mouth from teams, attitude), which clearly has a strong effect on draft decisions.

In the end, the statistics used in our Gauss-Jordan algorithm did not produce effective correlations to draft order, creating a large error. We were hoping to have a better outcome in order to use our Gauss-Jordan and enhance them using team needs. Our Team Needs algorithm did end up being successful, but only after we used an expert's big board.

Although the results were not what we hoped for, we were able to gain experience with a complex algorithm that is seen often in computer science. This experience will assist in understanding concepts in future classes.

In the future we hope to gather more statistics that provide a positive correlation to enhance the Gauss-Jordan algorithm, along with combining all three algorithms to understand the importance of each with regards to draft picks. Gathering this quantitative data could strengthen our results; but in the end, unless there is a way to

quantify the qualitative information experts take into account, it will be hard to compete with them.

## References

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