Generating Relative Draft Value in the NBA Draft and Predicting Success from College Basketball

A Major Qualifying Project Report:

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degree of Bachelor of Science

by

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Professor Craig Wills, Major Advisor

# Abstract

# Acknowledgements

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<http://www.nba.com/analysis/rules_history.html>

# 3. Methodology (*Jake)*

## 3.1 Analyze existing basketball player performance metrics

In professional sports, ‘value’ can be quantified in many ways. Some measures look purely at statistical output, whereas others take factors such as contract cost, minutes played, and team wins into account. To contextualize our entire project, which involves measuring the performance of basketball players, we analyzed the common metrics used to evaluate players. These four metrics were Player Efficiency Rating (PER), Win Shares (WS), Value over Replacement Player (VORP) and Fantasy Points (FP).

## 3.2 Feature engineer new player performance metrics addressing shortcomings with existing metrics

After analyzing the existing player performance metrics, we identified potential areas for improvement with different metrics that allowed for a more accurate comparison of players in the same season. These metrics were called Basic Percentile (BP) and Advanced Percentile (AP). Additionally, we created a metric which rewarded recognition rather than statistical output, called Cumulative Individual Accolades (CIA).

## 3.3 Find the highest value picks based on various measures of cost

One of the most important applications of talent evaluation is the NBA Draft. Each of the thirty teams are assigned two picks, generally in inverse order of team wins. A lottery is conducted for the first fourteen picks, to disincentivize intentional losing of games (commonly referred to as ‘tanking’) to obtain a highly talented player with the first pick. The NBA rookie salary scale provides an approximation of the talent level available at each pick, which we use with the performance metrics to find the draft picks which provide the highest output per dollar.

## 3.4 Calculate the approximate value of every pick in the NBA Draft

Another possibility in the NBA Draft is pick trading. Both before and during the draft, teams can swap picks for players or even high picks for multiple lower picks. As such, knowing the value of each position in the draft is critical to teams trying to improve their talent. We use the performance metrics to analyze the drop-off in talent at each pick in the draft.

## 3.5 Create a Jimmy Johnson-style NBA Draft value chart

Pick trading is far more common in the National Football League (NFL) where there are 224 picks between 32 teams. NFL Analyst Jimmy Johnson created a draft chart in the early 1990’s which seeks to quantitatively evaluate the talent available at each pick. We apply this to the NBA and create a value chart which accurately matches past draft pick trades in the NBA.

# 4. Design (*Mike)*

## 4.1 Determining Scope of the Project

The NBA has had extensive changes to its in game rules, restrictions on eligibility and size as an association since its creation. In order to best evaluate a modern day player and produce metrics for their value it was imperative to take careful consideration with which time period of the NBA we would include in our dataset. The question being “how far back do you look?” The time period that was decided on was 1990-present day for the following reasons. The first reason is that all of the major modern rules were implemented in a similar way to how they are now. One exception being the three point line was shortened from 23 feet 9 inches uniformly to 22 feet in 1995 then extended only at the top of the key (corner remained at 22 feet) to 23 feet 9 inches. And the other exception being that the shot clock reset on a hit to the backboard up until 1992. The second reason is because we wanted to capture the Jordan years of the NBA. Although not a definitive time period, the NBA in the 90’s was changing from physical play (as demonstrated by the Detroit Piston “Bad Boys”) to a more offensive and point producing league. Within the 90’s there were many rule changes designed to aid offensive players. The last reason is because by starting at 1990 we would have a dataset containing the three “decades” of basketball, the 90’s (1990-00), the 2000’s (00-10), and this decade (10-present) and this provides an easy timeline to understand for the reader.

## 4.2 Collection and Manipulation of the Data

In order to collect the data for our project we utilized web scraping techniques through the Python package Beautifulsoup. The website that we obtained the information from is Basketball-Reference.com which had all of the data that we thought we would need to collect. To produce our dataset we first iterated through each season and then for each season pulled the information from three tables. Thee three tables were “per-game”, “total” and “advanced.” Each of these tables has every player who played a game in that season within the table. Once all of these tables were saved to local spreadsheets we programmed algorithms that would cumulatively combine the seasons of data so that in the end we had a single spreadsheet with per-game statistics, total statistics, and advanced statistics for every player in every season they played in the NBA since 1990. To produce the cumulative metric we also needed to pull data on all-star selections and seasonal awards. We again utilized basketball-reference as for each year they had tables of award summaries that included all of the players who were selected to the all star game and those were given an award at the end of the year. These awards were transformed into their own respective column where a 1 indicated they achieved that award and a 0 meant they did not.

# 5. Results (*Jake)*

## 5.1 Analyze existing basketball player performance metrics

As discussed in the methods section, a crucial decision in evaluating player value is how ‘performance’ is quantified. The below table lists the top 20 players ranked using the four existing metrics, averaged out over the course of each player’s career.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Player | WS | PER | VORP | FP | AVG |
| LeBron James | 1 | 2 | 1 | 1 | 1.3 |
| Karl Malone | 2 | 4 | 2 | 2 | 2.5 |
| David Robinson | 4 | 1 | 4 | 5 | 3.5 |
| Tim Duncan | 8 | 6 | 9 | 4 | 6.8 |
| Chris Paul | 5 | 7 | 5 | 11 | 7.0 |
| Kevin Durant | 7 | 8 | 15 | 7 | 9.3 |
| Shaquille O’Neal | 14 | 3 | 18 | 3 | 9.5 |
| Michael Jordan | 3 | 11 | 3 | 21 | 9.5 |
| Charles Barkley | 10 | 5 | 6 | 21 | 10.5 |
| Russell Westbrook | 21 | 16 | 8 | 6 | 12.8 |
| Kevin Garnett | 17 | 17 | 12 | 8 | 13.5 |
| John Stockton | 6 | 13 | 19 | 16 | 13.5 |
| Hakeem Olajuwon | 21 | 10 | 17 | 10 | 14.5 |
| James Harden | 12 | 21 | 11 | 17 | 15.3 |
| Clyde Drexler | 16 | 19 | 7 | 21 | 15.8 |
| Stephen Curry | 15 | 21 | 10 | 19 | 16.3 |
| Kobe Bryant | 20 | 15 | 21 | 13 | 17.3 |
| Dirk Nowitzki | 13 | 18 | 21 | 18 | 17.5 |
| Magic Johnson | 9 | 21 | 21 | 21 | 18.0 |
| Dwight Howard | 18 | 21 | 21 | 12 | 18.0 |
| Yao Ming | 21 | 9 | 21 | 21 | 18.0 |
| Allen Iverson | 21 | 21 | 21 | 9 | 18.0 |
| Jason Kidd | 21 | 21 | 16 | 15 | 18.3 |
| Dwyane Wade | 21 | 12 | 20 | 21 | 18.5 |
| Reggie Miller | 11 | 21 | 21 | 21 | 18.5 |
| Scottie Pippen | 21 | 21 | 13 | 21 | 19.0 |
| Larry Bird | 21 | 21 | 14 | 21 | 19.3 |
| Anthony Davis | 21 | 14 | 21 | 21 | 19.3 |
| Gary Payton | 21 | 21 | 21 | 14 | 19.3 |
| Jeff Hornacek | 19 | 21 | 21 | 21 | 20.5 |
| Amare Stoudemire | 21 | 20 | 21 | 21 | 20.8 |
| Patrick Ewing | 21 | 21 | 21 | 20 | 20.8 |

Starting at the top, we can see that there’s a reasonable consensus among the top three players. Beyond that, the metrics begin disagreeing quite significantly. For example, Michael Jordan earns third place in Win Shares and VORP, but doesn’t feature in the top 20 for Fantasy Points. Because Win Shares distributes production by the number of wins the teams accrues, players on successful teams (such as the 90’s Bulls, arguably the greatest team ever) will feature strongly in the WS rankings. Similarly, Magic Johnson’s extremely strong Lakers teams boosts his WS rank to 9, which is the only time he features in these standings.

Extrapolating from this chart, if these metrics disagree so significantly for the absolute best players, it’s likely that mediocre players will also have large disparities in their statistical rankings by each metric.



To investigate just what these statistical disparities might be, we broke down each metric to its mathematical formula, to see their components.

Fantasy Points is the most basic metric – it multiplies each basic ‘counting stat’ by a coefficient and outputs a number representing the volume of statistical output by a player. The coefficients seek to equalize the value of assists, rebounds, and points. FP does not consider the player’s efficiency, or pace of play. Obviously, 20 points in a game ending 74-68 is more valuable than 25 points in a 135-123 game, but FP would rank the latter performance as stronger. By normalizing to pace, the metric would consider the amount of points the player scored per 100 possessions, allowing for a more accurate comparison.

In that case, let’s now move to PER, a stat which is normalized to pace, as well as minutes played. It multiplies counting stats by coefficients and analyzes the proportion of team field goals the player’s assists contribute towards. Additionally, PER subtracts what its creator, John Hollinger, calls “negative accomplishments” such as turnovers, personal fouls, and missed defensive rebounds. PER’s largest flaw is its greatest strength- minutes normalization. Because of limited sample size, the player with the all-time highest PER has only played a few minutes. Adding minimum games or minutes played removes these outliers, but on the other end, players who make significant contributions during their prime, only to decrease in efficiency in their career’s twilight are prone to having a low career average PER.

As such, there is no true ‘best metric’ for evaluating talent. Undoubtedly, every player on this list is a great player in their own right, but such significant difference in the ranking suggests there might be a better way to evaluate talent.

## 5.2 Feature engineer new player performance metrics addressing shortcomings with existing metrics

CIA BP AP

## 5.3 Calculate the approximate value of every pick in the NBA Draft

First, we summed up the total value of each metric of each draft pick.

This graph is oversensitive to extremely good players who come up at particular positions, which makes the graph jagged. In order to provide a more accurate curve, we cluster the draft picks into groups. These groups are 1-3, 4-7, 8-14, 15-30, 31-45, and 46-60. We felt these clusters fall in line with how picks are generally compared to one another

This graph provides a much clearer picture of the values of each metric. Also featured in this graph is the NBA Rookie Salary scale. As there is no mandatory salary for second round picks, we use the league minimum salary. We also display the number of players calculated in each cluster, for context.

Using trendlines, we were able to construct mathematical equations for each metric’s value.

## 5.4 Find the highest value picks based on various measure of cost

First, we use the obvious measure of cost, salary, to divide the pick values by. This shows where the best ‘bang-for-the-buck’ can be found in the NBA draft. We again use the clustering technique to clearly visualize the curves.

As shown, the metrics disagree greatly in where the highest value can be found. Advanced Percentile suggests the early second round has the best value players, but VORP values the top three picks as the superior selections.

## 5.5 Create a Jimmy Johnson-style NBA Draft pick value chart

We created draft value charts for each pick. NFL Analyst Rich Hill used Jimmy Johnson’s chart as a baseline to evaluate draft-pick only trades to create a new draft value chart. With this in mind, we found an assortment of draft-pick only trades in the NBA to evaluate each of the draft charts and select a ‘best’ chart.

|  |  |
| --- | --- |
| Metric | Mean Abs Error |
| VORP | 0.045443858 |
| WS | 0.070661068 |
| FP | 0.081395181 |
| RS | 0.096852287 |
| AVG | 0.112119185 |
| PER | 0.149346209 |
| BP | 0.167310009 |
| AP | 0.198652996 |

Clearly, VORP is the most accurate chart.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| DraftPos | VORP | DraftPos | VORP | DraftPos | VORP | DraftPos | VORP |
| 1 | 3000 | 16 | 1082 | 31 | 390 | 46 | 141 |
| 2 | 2803 | 17 | 1011 | 32 | 364 | 47 | 131 |
| 3 | 2619 | 18 | 944 | 33 | 340 | 48 | 123 |
| 4 | 2446 | 19 | 882 | 34 | 318 | 49 | 115 |
| 5 | 2286 | 20 | 824 | 35 | 297 | 50 | 107 |
| 6 | 2135 | 21 | 770 | 36 | 278 | 51 | 100 |
| 7 | 1995 | 22 | 719 | 37 | 259 | 52 | 94 |
| 8 | 1864 | 23 | 672 | 38 | 242 | 53 | 87 |
| 9 | 1741 | 24 | 628 | 39 | 226 | 54 | 82 |
| 10 | 1627 | 25 | 587 | 40 | 212 | 55 | 76 |
| 11 | 1520 | 26 | 548 | 41 | 198 | 56 | 71 |
| 12 | 1420 | 27 | 512 | 42 | 185 | 57 | 67 |
| 13 | 1327 | 28 | 478 | 43 | 172 | 58 | 62 |
| 14 | 1239 | 29 | 447 | 44 | 161 | 59 | 58 |
| 15 | 1158 | 30 | 418 | 45 | 151 | 60 | 54 |

Compared to the NFL, the NBA follows a different level of apparent talent drop-off.

For the first 20 picks, NBA talent is relatively better than the same draft pick in the NFL. However, after that, the NBA talent continues to decline quickly while the NFL flatlines.

# 6. Methodology for NCAA (*Jake)*

## 6.1 Create a model which predicts various measures of NBA success based on NCAA DI statistics

We designed a series of experiments to examine the ability of machine learning models to predict various success criteria in the NBA. These criteria are as follows:

- Was drafted

- Made NBA (played a regular-season game)

- First round pick

- Lottery pick

All these target values are binary, so this is a classification problem. The models we experimented with were:

- Logistic Regression

- Decision Tree

- Random Forest

- Multi-layer Perceptron (Neural Networks)

# 7. Design for NCAA (*Jake)*

## 7.1 Create a model which predicts various measures of NBA success based on NCAA DI statistics

Once we had a grasp on the value of a player and the expected value from a given draft pick we set out to predict NBA performance for NCAA Division I players. To do this, we first needed to gather statistics about al NCAA Division I players. Using the same methodology to pull data from Basketball-Refernce.com we were able to pull the college data from Sports-Reference.com. We were able to pull data from all NCAA division I teams from 2000 – 2018. But due to the need to lack of identifiers for an NCAA player (the ids used in sports reference are not the same as the ones used in basketball reference) we needed to manually enter where a player was drafted and so we focused on college players from 2010 to 2018. When we were evaluating NBA player performance only in game performance was accounted for, but since predicting NBA readiness and expected performance it is also necessary to consider physical attributes. Thus, we also made sure to collect height and weight measurements for all NCAA players. To further investigate how physical attributes play a role into the probability a college player will reach the NBA we also collected data from the NBA combines from 2010-2018.

After collecting all the data that we needed to we integrated Python with sklearn, a machine learning package, to predict whether or not a player would make the NBA. We defined making the NBA as playing in an official game during the NBA season. This excludes players who were drafted and never played a game, as well as those who signed contracts and were on NBA rosters but failed to play in a game. These distinctions echo the distinctions that are enforced on the sports reference page in order for a college player to be considered having gone on to play in the NBA. We created and ran a logistic regression, decision tree classifier, random forest classifier, MLP classifier, and Zero R model to see which model would be best at predicting whether a player would make the NBA. The Zero R model, predicting every player as never making the NBA, was going to be our baseline. Since the vast majority of NCAA DI players never make the NBA, a model that predicts no one will make the NBA is still correct over 99% of the time. But in order to tell a story worth listening to we needed to predict the players who did end up making the NBA.

A close up of a map

Description generated with high confidenceOnce we had a clean dataset, we used stratified sampling to split the data proportionally based on class value. We also normalized the non-target attributes, to make sure no attribute was being artificially weighed more than another. We tinkered with the parameters for each of the models, until we found the best performing set of parameters for each model. At that point, we ran our experiments on each of the target classes, which were: madeNBA, wasDrafted, firstRound and lotteryPick. We then used sk-learn’s classification\_report to print the resulting precision, recall, accuracy, and f1 score for each of the classes.

In an attempt to improve the prediction ability of our model while also using realistic sub sections of NCAA DI players we broke up our dataset into the following categories to test our model with.

Freshmen only: We decided that it would be appropriate to only look at players who were in their freshmen year because the trend of freshmen being drafted, especially in lottery selections, has been increasing. From our previous work on NBA performance and the expected value of a pick it was appropriate to put an extra consideration on lottery picks. In the 2018 draft 11 of the 15 lottery picks were freshmen, the other four being international player at 3, junior at 10, sophomore at 12, an junior at 13. In the 2017 draft 11 of the 15 lottery picks were also freshmen. The other four being international at 8, sophomore at 12, sophomore at 13, and junior15

Last Year of College: We decided that including the last year a player played would be a good sub section of players to consider as well. This is because this subsection inherently captures a players best season or their

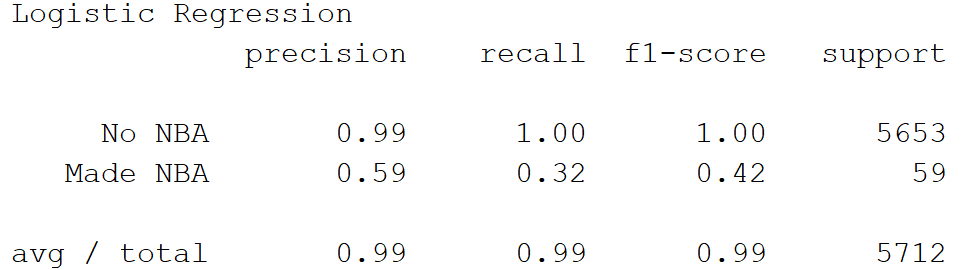
We also ran the model on all of the players in our dataset.

Note: due to an overwhelming amount of empty data points in the combine anthropology and agility datasets we didn’t these metrics. This is due to three main issues, the first is that players who attend the combine rarely perform all the tests, the second is often times the most notable college players rarely perform any of the tests if they attend at all (the vast majority of NCAA players also do not attend) and lastly the combine usually occurs only a month before the NBA draft and by then most scouts/ fans have already decided who they feel are most draft worthy. For these reasons we decided that adding the combine metrics to our machine learning models would negatively affect the model’s ability to predict NBA readiness.

# 8. Results for NCAA (*Mike)*

## 8.1 Using all years of NCAA DI players

### 8.1.1 Predicting whether an NCAA DI player will play an NBA game



53 Misses

13 False Positives

40 False Negatives

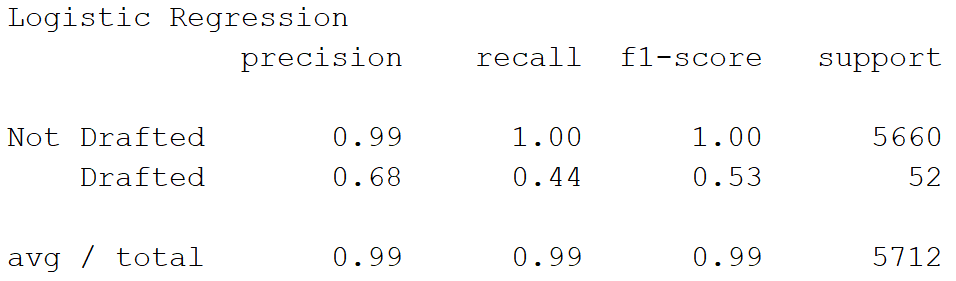
7 ended up playing in the NBA after dataset was collected, 4 are in the G League and the last 2 returned to college expected to be drafted this year ( Juwan Morgan, Jontay Porter)

A close up of a map

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### 8.1.2 Predicting which 2018 NCAA DI players would play an NBA game

### 8.1.3 Predicting whether an NCAA DI player will be drafted



40 misses

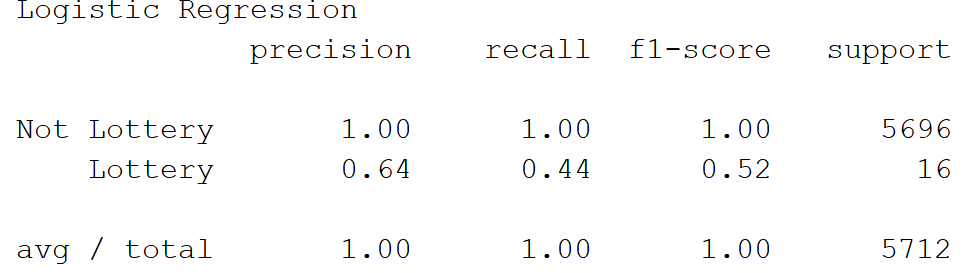
11 False Positive

29 False Negatives

A close up of a map

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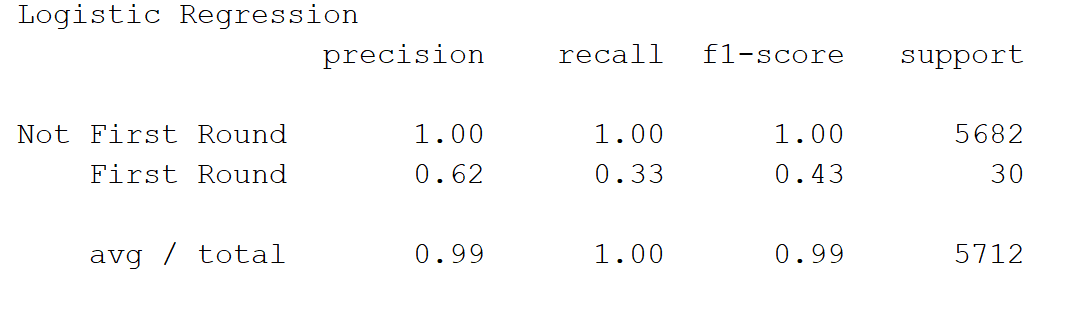
### 8.1.4 Predicting whether an NCAA DI player will be a lottery pick



A close up of a map

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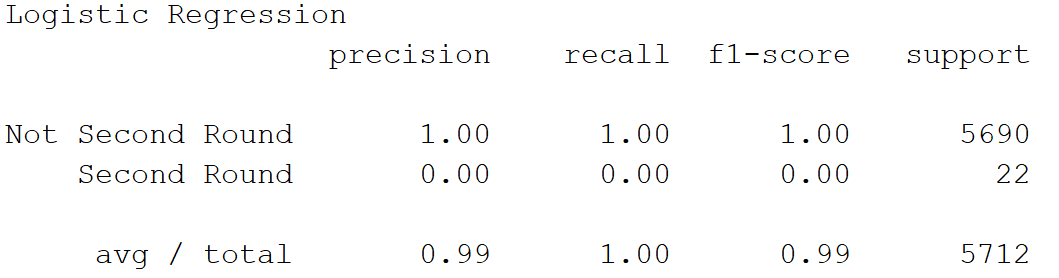
### 8.1.5 Predicting whether an NCAA DI player will be a first round pick



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### 8.1.6 Predicting whether an NCAA DI player will be a second round pick

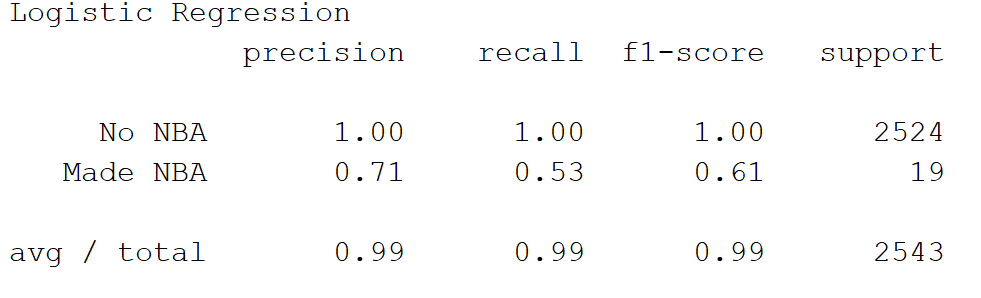


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### 8.2 Using only freshmen year seasons

### 8.2.1 Predicting whether an NCAA DI freshmen will play an NBA game

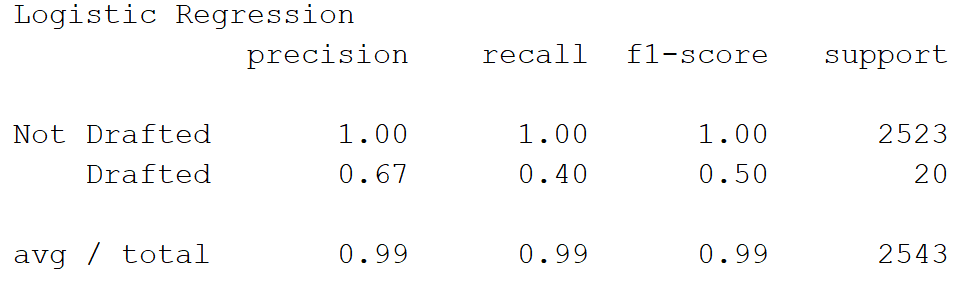


A close up of a map

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### 8.2.2 Predicting which 2018 NCAA DI freshmen would play an NBA game

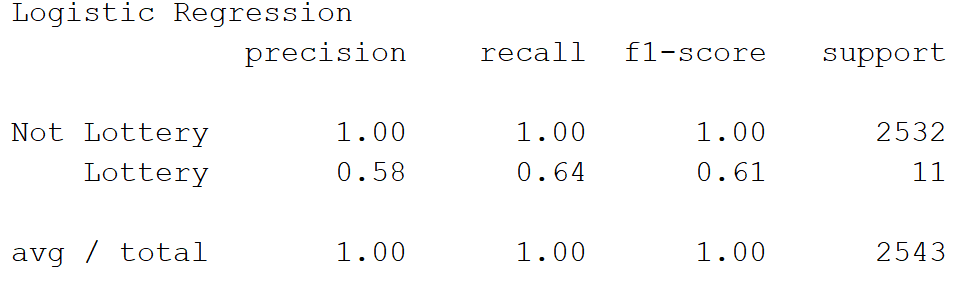
### 8.2.3 Predicting whether an NCAA DI freshmen will be drafted



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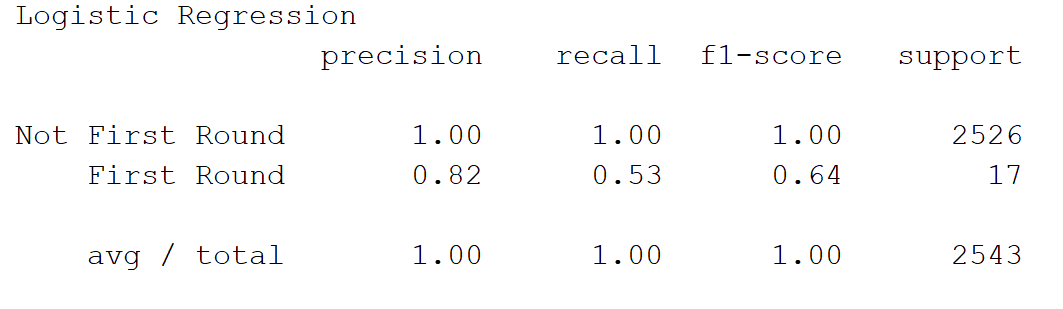
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### 8.2.4 Predicting whether an NCAA DI freshmen will be a lottery pick

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Description generated with very high confidence

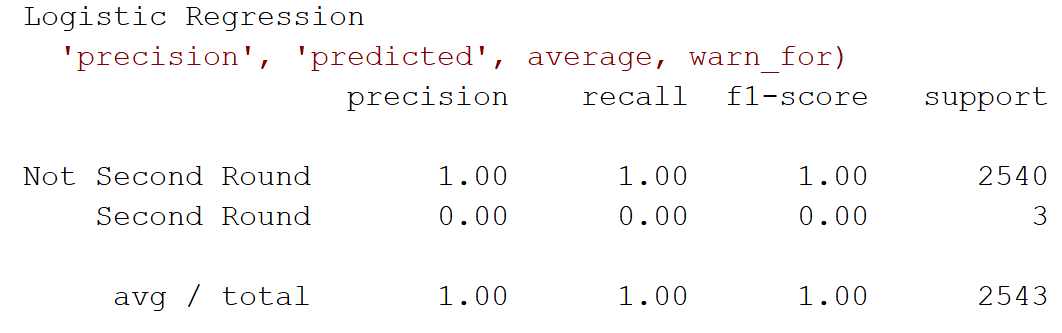
### 8.2.5 Predicting whether an NCAA DI freshmen will be a first round pick



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### 8.2.6 Predicting whether an NCAA DI freshmen will be a second round pick

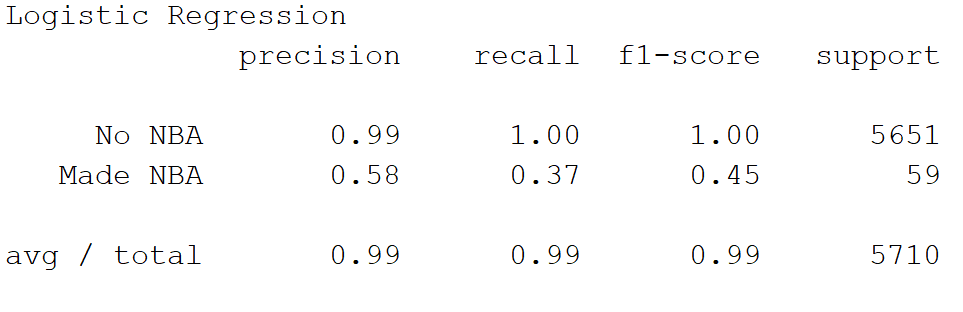


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## 8.3 Using only a player’s last season

### 8.3.1 Predicting whether an NCAA DI player will play an NBA game

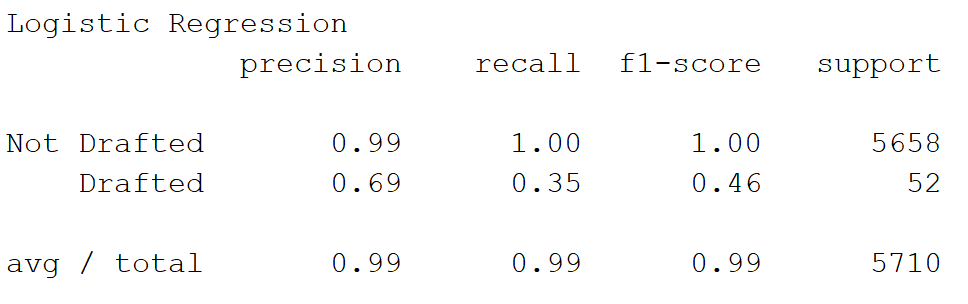


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### 8.3.2 Predicting which 2018 NCAA DI players would play an NBA game

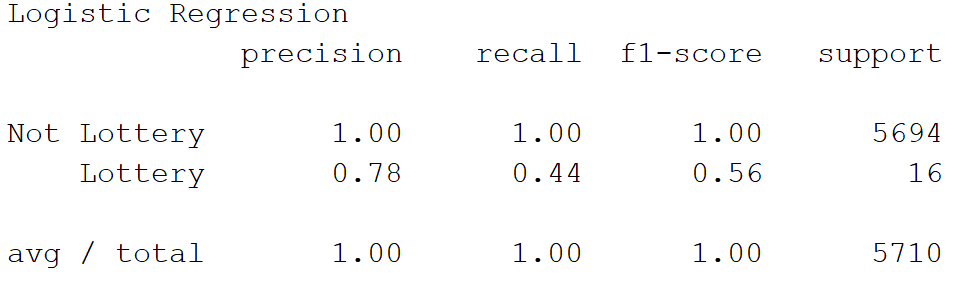
### 8.3.3 Predicting whether an NCAA DI player will be drafted



A close up of a map

Description generated with very high confidence

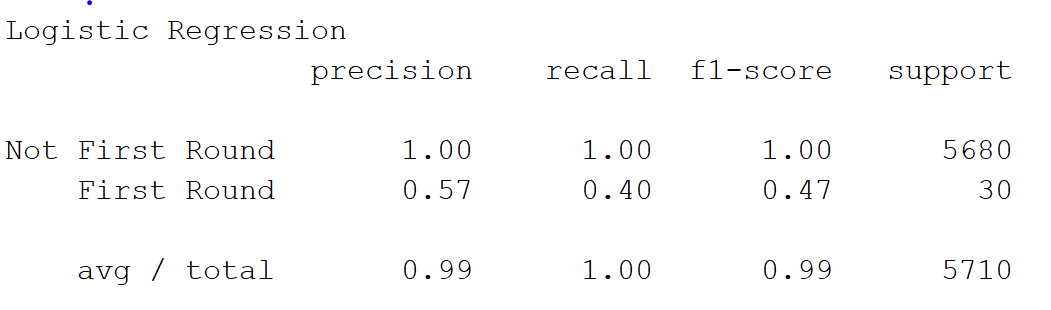
### 8.3.4 Predicting whether an NCAA DI player will be a lottery pick



A screenshot of text

Description generated with very high confidence

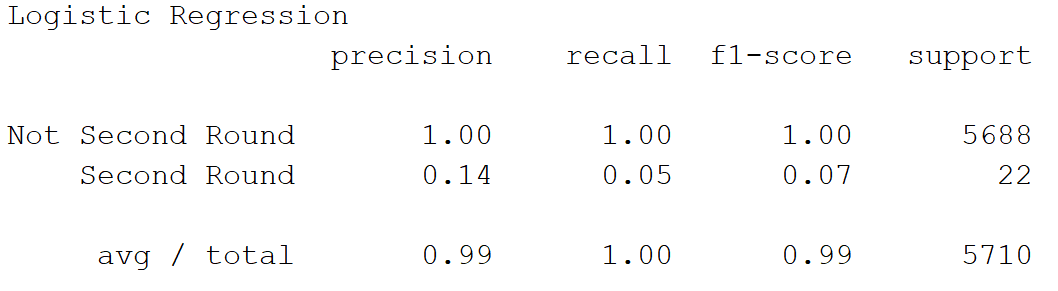
### 8.3.5 Predicting whether an NCAA DI player will be a first round pick



A close up of a map

Description generated with very high confidence

### 8.3.6 Predicting whether an NCAA DI player will be a second round pick



A close up of text on a white background

Description generated with very high confidence

# 9. Discussion *(Mike)*

## 9.1 All Division I Players

Drafted -> Lottery -> NBA -> First -> Second

## 9.2 Freshmen Division I Players

First -> Lottery -> NBA -> Drafted -> Second

## 9.3 Last Year Division I Players

Lottery -> First –> Drafted -> NBA -> Second

Lol why?

## 9.4 Dataset Imperfect

### 9.4.1 NBA / International / G League

### 9.4.2 Returning to College

## 9.5 Needle in a Haystack

# 10. Future Work *(Mike)*

## 10.1 Predicting which current (2019) NCAA DI players will play an NBA game

## 10.2 Comparing Draft Value Across Professional Sports

## 10.3 Considerations for How to Improve Project?