NBA Prospect Data Analysis

Cade Phillips
Hendrix College

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This thesis is dedicated to
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Abstract

The NBA is currently in an offensive driven era, and when looking at recent and upcoming lottery drafts, the goal of many NBA scouts is to find a positionally fluid, big-scoring, superstar who can be impactful in many different statistical boxes. This can be hard to predict however, and in recent draft classes, there are very few lotteries where the best regarded player today was selected with the number one overall pick. This data analysis research paper attempts to use the statistics that recent lottery draft classes, or top 14 picks in any given draft, have recorded, stretching back to 2011. We then will use this information to make predictions of how the different statistics of each player from the draft class of 2021 changes throughout their NBA careers. The purpose of this statistical analysis is to attempt to find patterns in draftees with the goal being to model the potential futures of the youngest class of NBA players and to improve the research that goes into drafting the league's prospects. This is done using statistical averages from the draft classes 2011-2020, as well as exploring the use of neural networks and machine learning algorithms to discover what statistical patterns we can look for in upcoming NBA draftees.

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Chapter 1

Introduction

Figure 1.1: Steph Curry on Draft Night (2009)[1]

In the last decade of draft picks, there have been many players that have gone on to be all-star level talents and impactful players for their respective franchises. While these are the players any franchise that finds themselves in the lottery are searching for, there have been many swings and misses by teams across the league in the search for the next superstar. While many lottery picks may not make as big of an impact as they were originally thought to when drafted, many go on to define the future of the league, which is now very offensively driven due in most part by players that were drafted in these top 14 spots[6]. Players like Kevin Durant and Steph Curry are just two examples of players who have shifted the NBA into the offensively-driven direction the league finds itself in now, both of whom were lottery picks. Determining which draft prospects have the ability to be these generational, all-star caliber players can be hard to predict however, and in recent draft classes, there are very few lotteries where the best regarded player today was selected with the number one overall pick, as Kevin Durant and Steph Curry were 2 and 7, respectively. Both of these players have grown into the NBA as regrets for teams that passed up on them, as they have been able to shift the entire league into an offensive-driven era by dominating in specific statistical fields or in multiple.

Many players from more recent drafts have been able to fit this mold that players like Durant and Curry have created, which was scouted during their college or pre-NBA careers. This data analysis research paper attempts to use the statistics that recent draft classes have recorded, stretching back to 2011, and use their numbers to predict the future of the most recent draft class of 2021. The goal of this is to help determine what to expect from these young players of multiple positions, and to get a general idea of what the progression of an NBA player looks like based off of these promising young players. To do this, we will attempt to generalize trends set by past NBA lottery picks and find patterns in their statistics. We can look for these patterns we seek by using machine learning tools, to find trends in data using AI. By using the program TensorFlow, we are able to find trends in past draftee's statistics that can help us determine if the draftees from the class of 2021 will be able to reach their ceilings they were scouted for, or only progress to a certain amount. By using both general statistical averages we can find using the datasets of past draft picks as well as using the neural networks and deep learning tools TensorFlow provides, we can attempt to accurately predict the future of some of the NBA's potential future all-stars.

Chapter 2

Background

Figure 2.1: NBA Draft Lottery 1985[2]

In 1984, the NBA chose to move towards a lottery system among the teams that did not make the playoffs. They moved towards this lottery system in an attempt to make the draft selection process less reliable for non-playoff teams, and to de-incentivize tanking, (or purposefully doing bad to get the best draft selection). In previous years, the worst teams participated in a coin flip and the rest of the teams picked in inverse order of their win/loss records, making it easy for low-win teams to seek out upcoming stars in the league. This lottery system would eventually turn into a system which dealt with the 14 teams with the worst records that season, with the worst team records having the most likely chance of getting the number 1 pick[7].

The players typically selected in these lottery selections are the ones that have been scouted out to be the best in their class, and are usually players that are projected to become better than the average NBA player as their career progresses. While there always are players outside of the lottery that become stars and even all-stars in the league, the players with the highest ceiling are usually selected within those first 14 picks. Because of the potentially franchise changing power that these young draftees possess, the NBA has done a lot to continuously de-incentive tanking, such as making the bottom three teams all possess the same 14% chance of landing the number one pick, and giving all of the teams within the lottery an opportunity, even if slim, of landing a higher drafting position than what their win/loss record indicates they should.

2021 NBA DRAFT LOTTERY PROBABILITIES

Percent Chance of Obtaining Each Pick Number:

Team	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10	#11	#12	#13	#14	Top-4 Draft Pick
Houston[1]	14.0	13.4	12.7	11.9	47.9	-	-	-	-	-	-	-	-	-	52.1
Detroit	14.0	13.4	12.7	11.9	27.8	20.1	-	-	-	-	-	-	-	-	52.1
Orlando	14.0	13.4	12.7	11.9	14.8	26.0	7.1	-	-	-	-	-	-	-	52.1
Oklahoma City	11.5	11.4	11.2	11.0	7.4	27.1	18.0	2.4	-	-	-	-	-	-	45.1
Cleveland	11.5	11.4	11.2	11.0	2.0	18.2	25.5	8.6	0.6	-	-	-	-	-	45.1
Minnesota[2]	9.0	9.2	9.4	9.6	-	8.6	29.7	20.6	3.8	0.2	-	-	-	-	37.2
Toronto	7.5	7.8	8.1	8.5	-	-	19.8	33.9	13.0	1.4	0.0	-	-	-	31.9
Chicago[3]	4.5	4.8	5.2	5.7	-	-	-	34.5	36.2	8.5	0.5	0.0	-	-	20.3
Sacramento	4.5	4.8	5.2	5.7	-	-	-	-	46.4	29.4	3.9	0.1	0.0	-	20.3
New Orleans	4.5	4.8	5.2	5.7	-	-	-	-	-	60.6	17.9	1.2	0.0	0.0	20.3
Charlotte	1.8	2.0	2.2	2.5	-	-	-	-	-	-	77.6	13.4	0.4	0.0	8.5
San Antonio	1.7	1.9	2.1	2.4	-	-	-	-	-	-	-	85.2	6.6	0.1	8.0
Indiana	1.0	1.1	1.2	1.4	-	-	-	-	-	-	-	-	92.9	2.3	4.8
Golden State	0.5	0.6	0.6	0.7	-	-	-	-	-	-	-	-	-	97.6	2.4

[1] Oklahoma City has the right to swap Miami's own first-round draft pick for Houston's own first-round draft pick if Houston's own first-round draft pick is not among the first four picks.
[2] Minnesota's own first-round draft pick will be conveyed to Golden State if Minnesota's own first-round draft pick is not among the first three picks.
[3] Chicago's own first-round draft pick will be conveyed to Orlando if Chicago's own first-round draft pick is not among the first four picks.

Figure 2.2: 2021 NBA Draft Lottery Probabilities[3]

As the NBA has continuously trended into an offensively dominated league, the players that are drafted in the lottery are typically players with a high offensive ceiling. Statistically, offense is typically done by filling up the statistics sheet in various different categories. Some of the most important being assists, which is when they pass the ball, putting the catcher in a position to score, rebounds, which allows their team to have possession of the ball and play offense, and simply putting the ball in the basket and scoring points. Because of this, the positions usually taken in the lottery are offensive-oriented guards and forwards, who can score on multiple levels. Centers are taken in the draft as well, but are usually not high picks in the lottery due to the position's tendency to need to be close to the rim and not be relied on to be a big scorer from the 3-point line. So, when analyzing the averages and patterns in the statistics of draftees, it is important to compare those within certain positions to others within their same position.

The players that typically rise through the lottery are players that can potentially play multiple positions because of their size or shooting versatility, so while there are five positions on the court, for the purpose of this research which is to predict players that are destined to be stars in the league, we will only be looking at players classified as Guard, Forward, and Center, to give some flexibility to those who are able to play multiple positions fluidly. While the players typically selected are those with high ceilings and high floors, meaning they have high potential but in the worst case scenario can still at least contribute to a team, there are players that have been taken in past lotteries that were high risk gambles, and in every draft there are usually players that fail to stand out among the rest of their draft class, and their pre-NBA statistics can give us an idea of who those players are.

By comparing this year's draft class, the draft class of 2021, to the last decade of draft picks, we can attempt to predict which of these players will turn out to be franchise changing picks for these low winning teams and which ones will not be able to make an impact in this offensive-oriented league. We will be using many datasets in this research, and using the tools of Python, JupyterNotebook, and pandas, (a Python Data Analysis Library), we can organize each players' points per game, rebounds per game, and assists per game to be used in our analysis, and will make it easier for us to have our data already organized when introducing our machine learning algorithms with TensorFlow.

Chapter 3

Data Analysis

Figure 3.1: 2021 NBA Draft Class[4]

The goal of this data analysis is to accurately determine which players will be good in the current and future NBA. Anyone who watches the NBA today, and in particular anyone who watches the performances of young and progressing lottery picks will tell you that everyone is looking to these players to fill up their stat sheets, especially from players trying to make a name for themselves against the best players in the world. These players are typically drafted to be more than just role players, and have something in their game that shows that they will be able to move the needle for their respective teams in some capacity.

3.1 Trial and Error

In gathering data for this paper, I originally started by gathering the pre-NBA stats for the lottery picks stretching back only to 2015. My original plan for this data analysis was to predict each year of the NBA by drawing averages from only a single draft class' pre-NBA statistics, and finding the average progression of each position to predict the progression of the 2021 draft class. After completing this and finding confusing averages from the data I had, I realized I was making some assumptions that were skewing my data.

My first assumption was that all draft classes are equal in talent, since I was using a single draft class' college numbers vs their NBA numbers at the year they are currently in in the league to predict how this year's draft class will go at that given year. Not only that, but if there was little representation for a certain player position in that draft class, it would make the averages for the players in the 2021 class that I was predicting very dependent on the small sample size I was drawing from. I knew that I would need more data from other draft classes, as well as multiple years of data from the draft classes I was already looking at to more accurately predict the futures for the 2021 class. However, I still wanted this to be relevant to the era the league finds itself in, so I didn't want to delve too far back into draft classes where the players being drafted weren't representative of what is expected in the league today.

After spending some time figuring out what I needed to do to make my data more accurate, I decided to shift my original datasets to ones that represented a specific year that all of the players in that dataset found themselves in for five different draft classes. For example, the dataset representing the rookie year in the league would have nothing but the first year numbers that the lottery players in years 2020, 2019, 2018, 2017, and 2016 were recording in their respective rookie years. Because I needed to expand the years of draft picks I was analyzing, I had to record the college stats for each of these draft classes I was bringing in. So, the data we will be working with contains the college statistics for years 2011-2020, and the following years in the league for these past lottery draft classes.

Yrs in the League	Draft Classes
1	2020, 2019, 2018, 2017, 2016
2	2019, 2018, 2017, 2016, 2015
3	2018, 2017, 2016, 2015, 2014
4	2017, 2016, 2015, 2014, 2013
5	2016, 2015, 2014, 2013, 2012
6	2015, 2014, 2013, 2012, 2011

Figure 3.2: Lottery Drafts Represented in Each Dataset

3.2 Datasets

A few examples of the pre-NBA draft numbers can be seen below, with the draft classes of 2013 and 2020.

	Pk	Tm	Player	College	POS	MP.1	PTS.1	TRB.1	AST.1
0	1	CLE	Anthony Bennett	UNLV	F	27.1	16.1	8.1	1.0
1	2	ORL	Victor Oladipo	Indiana	G	28.4	13.6	6.3	2.1
2	3	WAS	Otto Porter	Georgetown	F	35.4	16.2	7.5	2.7
3	4	CHA	Cody Zeller	Indiana	C	29.5	16.5	8.0	1.3
4	5	PHO	Alex Len	Maryland	C	26.4	11.9	7.8	1.0
5	6	NOH	Nerlens Noel	Kentucky	C	31.9	10.5	9.5	1.6
6	7	SAC	Ben McLemore	Kansas	G	32.2	15.9	5.2	2.0
7	8	DET	Kentavious Caldwell-Pope	Georgia	G	33.9	18.5	7.1	1.8
8	9	MIN	Trey Burke	Michigan	G	35.3	18.6	3.2	6.7
9	10	POR	CJ McCollum	Lehigh	G	31.0	23.9	5.0	2.9
10	11	PHI	Michael Carter-Williams	Syracuse	G	35.2	11.9	5.0	7.3
11	12	OKC	Steven Adams	Pitt	C	23.4	7.2	6.3	0.6
12	13	DAL	Kelly Olynyk	Gonzaga	C	26.4	17.8	7.3	1.7
13	14	UTA	Shabazz Muhammad	UCLA	G	30.8	17.9	5.2	0.8

Figure 3.3: 2013 NBA Lottery Draft Pre-NBA Statistics

	Pk	Tm	Player	College	POS	MP.1	PTS.1	TRB.1	AST.1
0	1	MIN	Anthony Edwards	Georgia	G	33.0	19.1	5.2	2.8
1	2	GSW	James Wiseman	Memphis	C	23.0	19.7	10.7	0.3
2	3	CHO	LaMelo Ball	NaN	G	31.3	17.0	7.6	6.8
3	4	CHI	Patrick Williams	Florida State	F	22.5	9.2	4.0	1.0
4	5	CLE	Isaac Okoro	Auburn	F	31.5	12.9	4.4	2.0
5	6	ATL	Onyeka Okongwu	USC	F	30.6	16.2	8.6	1.1
6	7	DET	Killian Hayes	NaN	G	26.8	12.8	2.3	6.2
7	8	NYK	Obi Toppin	Dayton	F	31.6	20.0	7.5	2.2
8	9	WAS	Deni Avdija	NaN	F	14.3	4.0	2.6	1.2
9	10	PHO	Jalen Smith	Maryland	C	31.3	15.5	10.5	0.8
10	11	SAS	Devin Vassell	Florida State	G	28.8	12.7	5.1	1.6
11	12	SAC	Tyrese Haliburton	Iowa State	G	36.7	15.2	5.9	6.5
12	13	NOP	Kira Lewis Jr.	Alabama	G	37.6	18.5	4.8	5.2
13	14	BOS	Aaron Nesmith	Vanderbilt	F	35.7	23.0	4.9	0.9

Figure 3.4: 2020 NBA Lottery Draft Pre-NBA Statistics

As you can see by the datasets, we have a few different columns for each player that will be relevant to the initial data analysis we will do. Each of the top 14 lottery picks have the averages of their points per game, (PTS.1), rebounds per game, (TRB.1), assists per game, (AST.1), and minutes per game (MP.1). Another relevant column is the position of the player, (POS).

All of these college statistics players recorded are stored in one big dataset, recording the pre-NBA statistics of the top 14 picks in drafts 2011-2020. As stated earlier, we also have several other datasets recording what five sets of lottery picks were recording on their stat sheets at the specific year in their career that the dataset represents. Again, not all of these statistics were recorded at the same year in the NBA, but they were all recorded at the same number of years that all of these players were in the NBA. Since this is organized in this way with five different groups of draft picks, we can use these datasets to attempt to predict what the NBA draft class of 2021 will record in their years in the league up until their most likely "peak age". While this is different for every player, we will be using the average to base this off of, which is roughly 26[8], about 6 years into the league for most modern 19-20 year old draft picks.

Here is our NBA 2021 draft class dataset.

	Pk	Tm	Player	College	POS	MP.1	PTS.1	TRB.1	AST.1
0	1	DET	Cade Cunningham	OKSTATE	G	35.4	20.1	6.2	3.5
1	2	HOU	Jalen Green	GLI	G	32.0	17.9	4.1	2.8
2	3	CLE	Evan Mobley	USC	C	33.9	16.4	8.7	2.4
3	4	TOR	Scottie Barnes	FLORIDAST	F	24.8	10.3	4.0	4.1
4	5	ORL	Jalen Suggs	GONZAGA	G	28.9	14.4	5.3	4.5
5	6	OKC	Josh Giddey	AUSTRALIA	G	32.1	10.9	7.4	7.5
6	7	GSW	Jonathan Kuminga	GLI	F	32.8	15.8	7.2	2.7
7	8	ORL	Franz Wagner	MICHIGAN	F	31.7	12.5	6.5	3.0
8	9	SAC	Davion Mitchell	BAYLOR	G	33.0	14.0	2.7	5.5
9	10	NOL	Ziare Williams	STANFORD	F	27.9	10.7	4.6	2.2
10	11	CHO	James Bouknight	UCONN	G	25.9	13.0	4.1	1.3
11	12	SAS	Joshua Primo	ALABAMA	G	22.5	8.1	3.4	0.8
12	13	IND	Chris Duarte	OREGON	G	34.1	17.1	4.6	2.7
13	14	GSW	Moses Moody	ARKANSAS	G	33.8	16.8	5.8	1.6

Figure 3.5: 2021 NBA Lottery Draft Pre-NBA Statistics

These will be the players we attempt to predict the statistics of in their various years in the league. The way we will start this is by drawing some averages for the progression of past draftees in NBA years with our datasets representing years in the NBA.

3.3 Statistical Analysis Process

We can now begin our statistical analysis. To do this, we need to use the dataset for the year we are trying to predict, and our pre-NBA statistics dataset. The position (POS) of the current player we are iterating through is an important part of this analysis. While most of the teams that are picking players in the draft lottery are teams with bad records, and often will draft based on best talent available rather than team fit, the statistics of players should be averaged and compared with those of the same position. So, if we were looking at a guard, his statistical averages will be stored in a list of Guard (G) averages.

After determining the position of the player, we then divide each of their NBA statistics by the minutes played, to get a good representation of the efficiency of the player. We then find this same player's college statistics and do the same thing. Next, we can divide each of their NBA statistics by their pre-NBA statistics. These numbers will give us an idea of their progression from before the NBA to the NBA. If they are performing worse in the NBA, this will be a value less than 1, and if they are performing as good or better, it will be equal or more than 1. For each player of a certain position, we continue to add up the numbers that represent the progression from pre-NBA to the NBA. After iterating through the entire 42 players in our dataset for that year in the NBA, we divide each of the numbers by how many players of that specific position we iterated through.

In addition to finding these averages, we also record which player was the best from the year we are currently looking at in each position, and the same with which player was the worst. These numbers will represent the floors, or the worst possible outcome, and the ceilings, or best possible outcome, of the progression of each position on the court. In addition to storing these values, we will also record the average amount of minutes that each of these players were playing at that time in their NBA careers, so we have a rough estimate of how much time each of these players will be playing at that specific year in their careers.

After iterating through all of the players in the year we are looking at, we will then go to our 2021 pre-NBA dataset. We start by doing something similar as we did with our previous data set, by dividing each of their points, rebounds, and assists in college by their minutes played in college. We then multiply these numbers by the average progression value that we found for their position, and then multiply that value by the average minutes played by that position in that year. We do the same thing for the ceiling and floor progression values. Pictured below is the data we gathered through this data analysis, which predicts how the 2021 lottery draft picks will perform in their first season of the NBA.

	Player	POS	AVG PTS	AVG REB	AVG AST	CEILING PTS	CEILING REB	CEILING AST	FLOOR PTS	FLOOR REB	FLOOR AST	MP
0	Cade Cunningham	G	11.083391	3.773378	2.355877	17.834039	6.545268	4.667295	6.250530	1.947226	0.259656	24.715625
1	Jalen Green	G	10.919001	2.760424	2.084951	17.569523	4.788206	4.130557	6.157822	1.424498	0.229796	24.715625
2	Evan Mobley	C	6.357441	3.894007	2.189651	8.960463	5.138829	6.936067	4.231275	2.361376	0.798309	18.154545
3	Scottie Barnes	F	7.812265	3.291509	3.906420	12.558375	5.317464	11.149731	4.428243	1.457155	2.059574	23.433333
4	Jalen Suggs	G	9.726229	3.951117	3.710245	15.650260	6.853573	7.350471	5.485152	2.038947	0.408929	24.715625
5	Josh Giddey	G	6.628287	4.966707	5.567293	10.665430	8.615206	11.029523	3.738054	2.563035	0.613606	24.715625
6	Jonathan Kuminga	F	9.060969	4.479663	1.945076	14.565693	7.236939	5.551651	5.136049	1.983153	1.025499	23.433333
7	Franz Wagner	F	7.417237	4.184473	2.236190	11.923360	6.760057	6.382550	4.204329	1.852472	1.178982	23.433333
8	Davion Mitchell	G	8.281213	1.762754	3.971336	13.325116	3.057657	7.867727	4.670229	0.909657	0.437706	24.715625
9	Ziare Williams	F	7.213914	3.364653	1.863225	11.596515	5.435630	5.318029	4.089079	1.489537	0.982344	23.433333
10	James Bouknight	G	9.797684	3.410562	1.196001	15.765237	5.915931	2.369431	5.525450	1.759997	0.131819	24.715625
11	Joshua Primo	G	7.027201	3.255654	0.847218	11.307313	5.647229	1.678448	3.963023	1.680058	0.093377	24.715625
12	Chris Duarte	G	9.788622	2.906333	1.886676	15.750656	5.041299	3.737747	5.520339	1.499793	0.207942	24.715625
13	Moses Moody	G	9.702249	3.697032	1.127953	15.611675	6.412838	2.234621	5.471629	1.907828	0.124319	24.715625

Figure 3.6: 2021 NBA Lottery Draft First Year Predictions Using Statistical Analysis

This simple data analysis can give us a pretty reasonable idea of how each of these players' careers will progress. By doing this same process with our other datasets for other players' statistics at different years in their career, we are able to roughly predict the numbers these draft picks will record. We can also begin to draw some conclusions based on what we have so far. For example, even though the top 3 picks, Cunningham, Green, and Mobley were recording similar points per game, (20.1, 17.9, and 16.4 respectively), we can see that Cunningham and Green are predicted to approach a similar amount of points per game at around 11.5 while Mobley is only predicted 7.7. While Mobley was the only Center taken in this draft, we can also see the average prediction of Forwards points per game is also typically lower than Guards. This is likely due to immediate impact in the NBA for certain positions. Guards seem to be able to make a quicker impact when it comes to scoring points in a game, while those of other positions take longer to develop in their scoring due to the nature of their position. Other positions also may not prioritize scoring as much as a Guard would, so their impact would be seen in the assist and rebound categories, and we can see that Mobley's average prediction is higher in rebounds than both Cunningham and Green.

The following figures represent the statistics of years 2-6 for the 2021 draft class, found with the same methods.

	Player	POS	PTS.1	TRB.1	AST.1	CEILING PTS	CEILING REB	CEILING AST	FLOOR PTS	FLOOR REB	FLOOR AST	MP
0	Cade Cunningham	G	13.961801	4.410393	2.959497	23.098028	6.910918	5.419949	6.445883	2.546206	1.150494	27.820000
1	Jalen Green	G	13.754718	3.226433	2.619155	22.755436	5.055699	4.796655	6.350277	1.862683	1.018187	27.820000
2	Evan Mobley	C	10.002477	5.715464	1.901027	15.535240	7.878408	3.479259	5.822366	4.149606	0.932930	23.107692
3	Scottie Barnes	F	9.407036	3.410052	5.040029	14.168845	5.015224	12.367443	3.494193	1.437247	2.031435	25.992593
4	Jalen Suggs	G	12.252178	4.618137	4.660878	20.269674	7.236446	8.535817	5.656584	2.666141	1.811900	27.820000
5	Josh Giddey	G	8.349685	5.805177	6.993737	13.813495	9.096493	12.808157	3.854882	3.351442	2.718790	27.820000
6	Jonathan Kuminga	F	10.910647	4.640998	2.509521	16.433579	6.825597	6.157971	4.052702	1.956058	1.011488	25.992593
7	Franz Wagner	F	8.931368	4.335177	2.885113	13.452397	6.375821	7.079617	3.317509	1.827163	1.162874	25.992593
8	Davion Mitchell	G	10.431884	2.060339	4.988866	17.258228	3.228473	9.136485	4.816191	1.189474	1.939404	27.820000
9	Ziare Williams	F	8.686540	3.485831	2.403916	13.083637	5.126673	5.898835	3.226569	1.469186	0.968923	25.992593
10	James Bouknight	G	12.342190	3.986327	1.502438	20.418587	6.246423	2.751528	5.698141	2.301384	0.584068	27.820000
11	Joshua Primo	G	8.852198	3.805268	1.064291	14.644839	5.962710	1.949117	4.086882	2.196855	0.413739	27.820000
12	Chris Duarte	G	12.330775	3.396974	2.370077	20.399703	5.322930	4.340500	5.692871	1.961139	0.921359	27.820000
13	Moses Moody	G	12.221970	4.321158	1.416956	20.219699	6.771090	2.594978	5.642638	2.494688	0.550837	27.820000

Figure 3.7: 2021 NBA Lottery Draft Second Year Predictions Using Statistical Analysis

	Player	POS	PTS.1	TRB.1	AST.1	CEILING PTS	CEILING REB	CEILING AST	FLOOR PTS	FLOOR REB	FLOOR AST	MP
0	Cade Cunningham	G	15.778957	4.595850	3.411257	35.559711	8.590438	7.386399	7.584229	2.140854	1.035547	28.057143
1	Jalen Green	G	15.544922	3.362105	3.018962	35.032286	6.284355	6.536963	7.471739	1.566147	0.916459	28.057143
2	Evan Mobley	C	11.176210	6.139088	1.972795	19.679032	8.382058	4.087618	5.363487	4.268441	1.014161	24.169231
3	Scottie Barnes	F	10.114655	3.516897	5.267699	15.024130	7.001536	11.729637	3.944917	1.629004	1.853572	25.800000
4	Jalen Suggs	G	13.846823	4.812330	5.372350	31.205423	8.995077	11.632757	6.655540	2.241696	1.630872	28.057143
5	Josh Giddey	G	9.436414	6.049286	8.061315	21.266053	11.307160	17.455175	4.535656	2.817898	2.447154	28.057143
6	Jonathan Kuminga	F	11.731371	4.786410	2.622882	17.425571	9.528920	5.840396	4.575468	2.217035	0.922927	25.800000
7	Franz Wagner	F	9.603207	4.471007	3.015441	14.264433	8.901006	6.714511	3.745442	2.070942	1.061059	25.800000
8	Davion Mitchell	G	11.789614	2.146976	5.750405	26.569264	4.013070	12.451358	5.666733	1.000112	1.745637	28.057143
9	Ziare Williams	F	9.339962	3.595050	2.512507	13.873414	7.157126	5.594624	3.642771	1.665204	0.884089	25.800000
10	James Bouknight	G	13.948551	4.153952	1.731782	31.434678	7.764455	3.749830	6.704436	1.935008	0.525713	28.057143
11	Joshua Primo	G	10.004330	3.965280	1.226753	22.545918	7.411793	2.656290	4.808628	1.847120	0.372402	28.057143
12	Chris Duarte	G	13.935650	3.539817	2.731864	31.405605	6.616530	5.915308	6.698235	1.648930	0.829305	28.057143
13	Moses Moody	G	13.812684	4.502863	1.633251	31.128487	8.416628	3.536480	6.639131	2.097538	0.495802	28.057143

Figure 3.8: 2021 NBA Lottery Draft Third Year Predictions Using Statistical Analysis

	Player	POS	PTS.1	TRB.1	AST.1	CEILING PTS	CEILING REB	CEILING AST	FLOOR PTS	FLOOR REB	FLOOR AST	MP
0	Cade Cunningham	G	14.449952	3.958082	3.070832	29.353627	6.871969	9.600241	8.997622	2.118996	1.088798	25.570000
1	Jalen Green	G	14.235629	2.895544	2.717686	28.918252	5.027205	8.496214	8.864169	1.550157	0.963586	25.570000
2	Evan Mobley	C	11.006525	6.229894	1.912633	18.520065	8.256318	3.424531	5.283029	4.275125	1.074397	23.806667
3	Scottie Barnes	F	10.597729	3.839995	5.906099	19.560911	7.833860	12.217584	4.322818	1.694851	2.530064	25.368000
4	Jalen Suggs	G	12.680555	4.144521	4.836218	25.759275	7.195662	15.119312	7.895863	2.218808	1.714736	25.570000
5	Josh Giddey	G	8.641618	5.209823	7.256838	17.554580	9.045226	22.686819	5.380919	2.789128	2.572994	25.570000
6	Jonathan Kuminga	F	12.291659	5.226139	2.940753	22.687507	10.661692	6.083354	5.013773	2.306651	1.259764	25.368000
7	Franz Wagner	F	10.061854	4.881760	3.380886	18.571812	9.959134	6.993831	4.104234	2.154653	1.448309	25.368000
8	Davion Mitchell	G	10.796617	1.849039	5.176545	21.932244	3.210277	16.183264	6.722782	0.989901	1.835402	25.570000
9	Ziare Williams	F	9.786037	3.925328	2.817001	18.062718	8.007946	5.827357	3.991728	1.732515	1.206752	25.368000
10	James Bouknight	G	12.773714	3.577506	1.558959	25.948519	6.211219	4.873724	7.953871	1.915252	0.552747	25.570000
11	Joshua Primo	G	9.161701	3.415016	1.104330	18.611076	5.929105	3.452430	5.704761	1.828261	0.391552	25.570000
12	Chris Duarte	G	12.761900	3.048595	2.459238	25.924519	5.292931	7.688237	7.946515	1.632094	0.871951	25.570000
13	Moses Moody	G	12.649291	3.877998	1.470261	25.695766	6.732929	4.596430	7.876396	2.076123	0.521298	25.570000

Figure 3.9: 2021 NBA Lottery Draft Fourth Year Predictions Using Statistical Analysis

	Player	POS	PTS.1	TRB.1	AST.1	CEILING PTS	CEILING REB	CEILING AST	FLOOR PTS	FLOOR REB	FLOOR AST	MP
0	Cade Cunningham	G	14.937597	4.225705	3.228841	29.684956	8.035100	9.047630	4.156843	2.053437	0.614390	25.858621
1	Jalen Green	G	14.716041	3.091325	2.857525	29.244666	5.878097	8.007152	4.095189	1.502197	0.543735	25.858621
2	Evan Mobley	C	12.412919	6.336536	2.165759	20.393490	10.746867	4.268610	7.600933	4.655151	1.062745	24.117647
3	Scottie Barnes	F	9.358954	3.686408	5.775624	20.765856	8.552408	13.096487	4.468148	0.974821	2.398888	23.883333
4	Jalen Suggs	G	13.108487	4.424750	5.085066	26.050032	8.413581	14.249011	3.647838	2.150161	0.967596	25.858621
5	Josh Giddey	G	8.933248	5.562083	7.630240	17.752727	10.576197	21.380914	2.485950	2.702835	1.451897	25.858621
6	Jonathan Kuminga	F	10.854880	5.017111	2.875787	24.085049	11.639619	6.520975	5.182332	1.326708	1.194449	23.883333
7	Franz Wagner	F	8.885718	4.686506	3.306197	19.715829	10.872620	7.496950	4.242215	1.239284	1.373219	23.883333
8	Davion Mitchell	G	11.160972	1.974061	5.442904	22.179804	3.753640	15.251719	3.105882	0.959274	1.035686	25.858621
9	Ziare Williams	F	8.642141	3.768328	2.754769	19.175375	8.742462	6.246563	4.125927	0.996484	1.144185	23.883333
10	James Bouknight	G	13.204791	3.819397	1.639176	26.241412	7.262513	4.593182	3.674637	1.855996	0.311906	25.858621
11	Joshua Primo	G	9.470882	3.645920	1.161153	18.821148	6.932650	3.253700	2.635563	1.771696	0.220946	25.858621
12	Chris Duarte	G	13.192578	3.254724	2.585779	26.217142	6.188798	7.245685	3.671238	1.581599	0.492027	25.858621
13	Moses Moody	G	13.076169	4.140207	1.545914	25.985806	7.872527	4.331849	3.638844	2.011890	0.294159	25.858621

Figure 3.10: 2021 NBA Lottery Draft Fifth Year Predictions Using Statistical Analysis

	Pk	Player	POS	PTS.1	TRB.1	AST.1	COL RANK	NBA RANK	YR 1 RANK	YR 2 RANK	YR 3 RANK	YR 4 RANK	YR 5 RANK
0	1	Karl-Anthony Towns	C	10.3	6.7	1.1	7.0	10.0	9.0	10.0	10.0	10.0	10.0
1	2	D'Angelo Russell	G	19.3	5.7	5.0	9.0	9.0	7.0	8.0	8.0	9.0	9.0
2	3	Jahlil Okafor	C	17.3	8.5	1.3	8.0	2.0	8.0	6.0	3.0	6.0	5.0
3	4	Kristaps Porziņģis	F	18.7	7.8	1.5	8.0	8.0	7.0	8.0	8.0	9.0	8.0
4	5	Mario Hezonja	F	4.6	1.9	1.3	2.0	3.0	3.0	2.0	5.0	5.0	3.0
5	6	Willie Cauley-Stein	F	8.0	6.2	0.9	5.0	3.0	5.0	5.0	8.0	8.0	3.0
6	7	Emmanuel Mudiay	G	17.7	6.0	5.9	9.0	4.0	8.0	7.0	6.0	8.0	4.0
7	8	Stanley Johnson	F	13.8	6.5	1.7	8.0	3.0	5.0	3.0	5.0	4.0	1.0
8	9	Frank Kaminsky	C	10.1	4.6	1.3	6.0	5.0	5.0	6.0	5.0	5.0	6.0
9	10	Justise Winslow	F	12.6	6.5	2.1	7.0	5.0	5.0	7.0	6.0	8.0	8.0
10	11	Myles Turner	C	10.1	6.5	0.6	7.0	8.0	7.0	8.0	8.0	8.0	8.0

Figure 3.11: 2021 NBA Lottery Draft Sixth Year Predictions Using Statistical Analysis

While these numbers give us a good idea of how good these players would be able to do generally within their first six years in the league, we are really only using statistical averages from given years and applying them to each player in the league by position. This becomes apparent in our data, as our third year is somewhat skewed and shows a big jump in points scored by guards, due to the talent of guards in the draft classes from those years represented in the dataset for year 3 in the NBA.

Other than that year in points for guards, everything else also seems like a pretty clear linear progression, as the talent from these lotteries averaged together as a whole is usually a progression from each position. However, not every player will have an obvious linear progression throughout the league, and inversely, there will almost certainly be players that exceed our calculated ceilings in this draft class within their first year. We can attempt to get a better idea of just how much of an impact these players can achieve using machine learning tools.

3.4 Using Machine Learning with TensorFlow

As we move away from our standard data analysis and into deep learning to attempt to predict statistics, we will need to adjust our datasets to help with our machine learning tools. The best way to do this is to implement a ranking system within our data sets for each player.

Ranking players based off of box scores alone is a bit arbitrary, as not all impact on the court is seen on the stat sheet, but for the purposes of this analysis, we can attempt to generalize ranking based on position. For current players with recorded stats for this season, we have about 275 players, according to the season leaders ranking from the NBA[9]. We will divide this into roughly 27 different segments to get a 1-10 ranking, and sort them by points, rebounds, and assists per game.

PTS	TRB	AST	RANK
20.2 +	8.7 +	5.2 +	10
16.2 - 20.1	6.4 - 8.6	3.8 - 5.1	9
13.8 - 16.1	5.4 - 6.3	2.8 - 3.7	8
11.9 - 13.7	4.6 - 5.3	2.2 - 2.7	7
9.6 - 11.8	4.0 - 4.5	1.7 - 2.1	6
7.8 - 9.5	3.4 - 3.9	1.5 - 1.6	5
6.7 - 7.7	2.9 - 3.3	1.2 - 1.4	4
5.4 - 6.6	2.5 - 2.8	1.0 - 1.1	3
4.0 - 5.3	2.0 - 2.4	0.7 - 0.9	2
0 - 3.9	0 - 1.9	0 - 0.6	1

Figure 3.12: Ranking System Using Current NBA Stat Leaders 2021

As always, we also need to consider what each position prioritizes. All positions will prioritize shooting, but it may be even more important to those in the guard position, as they are the facilitators of the offense. Based on the “role” of each position, these are the assumptions we will make when ranking each player by position, where whatever each statistic is multiplied by is the relevant importance of that statistics based on their position.

POS	PTS	TRB	AST
G	x4	x1	x3
F	x3	x2	x2
C	x2	x4	x1

Figure 3.13: Ranking System Weights By Position

Implementing our new ranking system, here are our 2021 pre-NBA statistics, and their rankings based on their pre-NBA recorded numbers.

	Pk	Tm	Player	College	POS	MP.1	PTS.1	TRB.1	AST.1	COL RANK
0	1	DET	Cade Cunningham	OKSTATE	G	35.4	20.1	6.2	3.5	8.0
1	2	HOU	Jalen Green	GLI	G	32.0	17.9	4.1	2.8	8.0
2	3	CLE	Evan Mobley	USC	C	33.9	16.4	8.7	2.4	9.0
3	4	TOR	Scottie Barnes	FLORIDAST	F	24.8	10.3	4.0	4.1	7.0
4	5	ORL	Jalen Suggs	GONZAGA	G	28.9	14.4	5.3	4.5	8.0
5	6	OKC	Josh Giddey	AUSTRALIA	G	32.1	10.9	7.4	7.5	8.0
6	7	GSW	Jonathan Kuminga	GLI	F	32.8	15.8	7.2	2.7	8.0
7	8	ORL	Franz Wagner	MICHIGAN	F	31.7	12.5	6.5	3.0	8.0
8	9	SAC	Davion Mitchell	BAYLOR	G	33.0	14.0	2.7	5.5	8.0
9	10	NOL	Ziare Williams	STANFORD	F	27.9	10.7	4.6	2.2	7.0
10	11	CHO	James Bouknight	UCONN	G	25.9	13.0	4.1	1.3	6.0
11	12	SAS	Joshua Primo	ALABAMA	G	22.5	8.1	3.4	0.8	4.0
12	13	IND	Chris Duarte	OREGON	G	34.1	17.1	4.6	2.7	8.0
13	14	GSW	Moses Moody	ARKANSAS	G	33.8	16.8	5.8	1.6	7.0

Figure 3.14: 2021 NBA Lottery Draft Pre-NBA Statistics with Ranks

The goal of this project is to project the impact of these players in their years up until their "peak", but the problem is that we only have the 2021 draft class' complete pre-NBA statistics, the numbers they were recording that got them drafted, to go off of. I realized with this that I needed to construct multiple TensorFlow models that take in a different set of numbers in each of them to calculate the progression of each of these players.

To do this, I knew I would need more data and I would need to adjust the datasets I had. For each player, I needed to have a rank for them in each of their seasons in the NBA to help calculate what the 2021 class' ranking would be as the years went on, as well as only having input data that was from current players' pre-NBA statistics. So, after pulling more data and adding the rankings to the datasets representing years in the league, Figure 3.14 is the data we will pass through our TensorFlow model.

	Pk	Player	POS	PTS.1	TRB.1	AST.1	COL RANK	NBA RANK	YR 1 RANK	YR 2 RANK	YR 3 RANK	YR 4 RANK	YR 5 RANK
0	1	Karl-Anthony Towns	C	10.3	6.7	1.1	7.0	10.0	9.0	10.0	10.0	10.0	10.0
1	2	D'Angelo Russell	G	19.3	5.7	5.0	9.0	9.0	7.0	8.0	8.0	9.0	9.0
2	3	Jahlil Okafor	C	17.3	8.5	1.3	8.0	2.0	8.0	6.0	3.0	6.0	5.0
3	4	Kristaps Porziņģis	F	18.7	7.8	1.5	8.0	8.0	7.0	8.0	8.0	9.0	8.0
4	5	Mario Hezonja	F	4.6	1.9	1.3	2.0	3.0	3.0	2.0	5.0	5.0	3.0
5	6	Willie Cauley-Stein	F	8.0	6.2	0.9	5.0	3.0	5.0	5.0	8.0	8.0	3.0
6	7	Emmanuel Mudiay	G	17.7	6.0	5.9	9.0	4.0	8.0	7.0	6.0	8.0	4.0
7	8	Stanley Johnson	F	13.8	6.5	1.7	8.0	3.0	5.0	3.0	5.0	4.0	1.0
8	9	Frank Kaminsky	C	10.1	4.6	1.3	6.0	5.0	5.0	6.0	5.0	5.0	6.0
9	10	Justise Winslow	F	12.6	6.5	2.1	7.0	5.0	5.0	7.0	6.0	8.0	8.0
10	11	Myles Turner	C	10.1	6.5	0.6	7.0	8.0	7.0	8.0	8.0	8.0	8.0

Figure 3.15: Section of Year 6 TensorFlow Dataset

This is a small segment of our dataset representing the 6th year of players in the NBA, which we will train our TensorFlow model on. The points, rebounds, and assists per game you see in this dataset are the pre-NBA statistics each player recorded, as well as their pre-NBA ranking (COL RANK), their ranking in their sixth year in the NBA (NBA RANK), and their rankings each of their previous years in the league. For each of our other data sets, representing years 1-5 in the league, they are the same but with however many years they have been in the NBA represented in their past rankings. Now we have our datasets ready to be trained using our TensorFlow model.

We have a single input Tensor with our datasets, so we will be using a Normalized Sequential TensorFlow model. A sequential model takes one single type of input, in this case floating point numbers from each statistical category and ranks, and then sends this input to the hidden layer. Our hidden layer has 64 neurons, all going through non-linear processes to give out output predictions. We train this model through "epochs", or training iteration, in our case, we train our model with 1000 epochs, to ensure enough training has been done to detect patterns and make sound predictions.

To train this model, we will use our TensorFlow datasets we have created, and give them specific inputs, or features. The features we will be putting into our model will be the pre-NBA points, rebounds, and assists per game, as well as each players' college ranking. We will use the column in our data titled "NBA RANK", which is the ranking of the player in the year of the dataset we are looking at, as the labels for our model. This is the column the machine learning tools will be trying to predict, as this is what we would want to predict from our 2021 draft class.

We will need to build many different models to pass our data through. We want a model for each position of each year we are predicting. We want to create models based on position so the rankings being predicted are not having patterns detected from other positions, which have rankings based on different priorities. We need different models for every year as well, as we are inputting a different amount of data every year we try to predict rankings, as our year 6 datasets have nine different columns of data being inputted, our year 5 datasets have eight different columns of data, and so on. So we will need eighteen different TensorFlow models built to predict the rankings of these players throughout their NBA careers.

We will use our trained models on our 2021 draft class to predict their rank, starting with their first NBA year. As we predict the year one rankings, we will add a new column to the dataset, which will represent their first year in the NBA. This is the new dataset we will pass on to our model we build for the second year in the NBA, as this model requires a column for each player's first year rank to predict their second year rank. We will keep adding columns to our 2021 draft class' dataset to match what the model for the year we are trying to predict requires. This will allow us to predict the rankings for each year in the NBA for these young players.

After building all of these models for each position, we have our final dataset using our Normalized Sequential TensorFlow Model, in Figure 3.15.

	Pk	Tm	Player	College	POS	MP.1	PTS.1	TRB.1	AST.1	COL RANK	YR 1 RANK Tensor	YR 2 RANK Tensor	YR 3 RANK Tensor	YR 4 RANK Tensor	YR 5 RANK Tensor	YR 6 RANK Tensor
0	1	DET	Cade Cunningham	OKSTATE	G	35.4	20.1	6.2	3.5	8.0	6.0	7.0	7.0	7.0	8.0	8.0
1	2	HOU	Jalen Green	GLI	G	32.0	17.9	4.1	2.8	8.0	5.0	6.0	7.0	7.0	8.0	8.0
2	3	CLE	Evan Mobley	USC	C	33.9	16.4	8.7	2.4	9.0	9.0	9.0	7.0	7.0	7.0	6.0
3	4	TOR	Scottie Barnes	FLORIDAST	F	24.8	10.3	4.0	4.1	7.0	5.0	6.0	5.0	8.0	6.0	7.0
4	5	ORL	Jalen Suggs	GONZAGA	G	28.9	14.4	5.3	4.5	8.0	6.0	7.0	7.0	6.0	6.0	6.0
5	6	OKC	Josh Giddey	AUSTRALIA	G	32.1	10.9	7.4	7.5	8.0	7.0	9.0	7.0	6.0	4.0	4.0
6	7	GSW	Jonathan Kuminga	GLI	F	32.8	15.8	7.2	2.7	8.0	5.0	6.0	6.0	7.0	6.0	7.0
7	8	ORL	Franz Wagner	MICHIGAN	F	31.7	12.5	6.5	3.0	8.0	6.0	7.0	7.0	8.0	7.0	8.0
8	9	SAC	Davion Mitchell	BAYLOR	G	33.0	14.0	2.7	5.5	8.0	6.0	7.0	7.0	6.0	6.0	6.0
9	10	NOL	Ziare Williams	STANFORD	F	27.9	10.7	4.6	2.2	7.0	7.0	7.0	7.0	8.0	7.0	7.0
10	11	CHO	James Bouknight	UCONN	G	25.9	13.0	4.1	1.3	6.0	5.0	6.0	7.0	7.0	7.0	6.0
11	12	SAS	Joshua Primo	ALABAMA	G	22.5	8.1	3.4	0.8	4.0	5.0	7.0	8.0	7.0	7.0	6.0
12	13	IND	Chris Duarte	OREGON	G	34.1	17.1	4.6	2.7	8.0	5.0	6.0	7.0	7.0	7.0	7.0
13	14	GSW	Moses Moody	ARKANSAS	G	33.8	16.8	5.8	1.6	7.0	5.0	6.0	7.0	7.0	8.0	7.0

Figure 3.16: 2021 NBA Lottery Draft Pre-NBA Statistics with Year 1-6 TensorFlow Ranks

This data gives us many more interesting trends to notice using our machine learning tools. For one, our TensorFlow model predicts that Evan Mobley, a center, will actually have a higher ranking than our top 2 picks, both of which are guards. This is particularly interesting since our past data analysis predicted that he would have a lower ceiling than both Cunningham and Green in his first year, and not be able to score as much as them. However, we can see that it seems as though the center position may be one that has trouble developing over time as his ranking goes steadily down.

Inversely, it seems as though Cunningham and Green will take longer to develop, but by their 5th and 6th years will be both at an 8 rank in their positions. The only other player predicted to reach an 8 by their 6th year is Franz Wagner, in the Forward position.

Chapter 4

Conclusions

Figure 4.1: Draft Lottery Ping Pong Balls[5]

We can graph the future of these players over time to get a general view of their progression, using the ranking system we implemented.

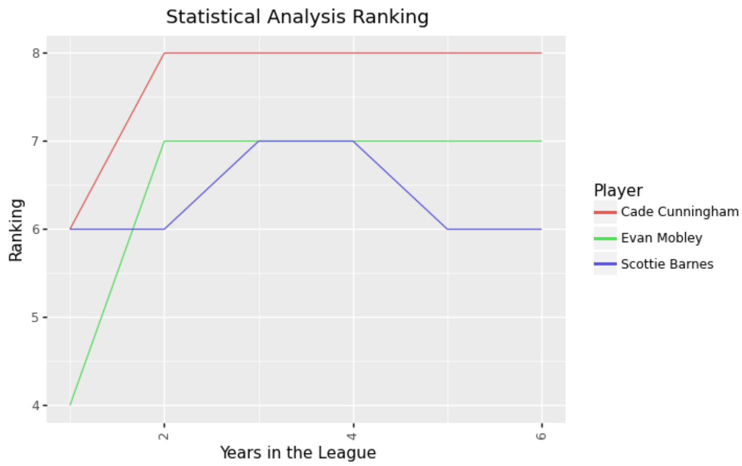

Figure 4.2: Rankings Over Time for First 3 Players of Each Position in 2021 Draft

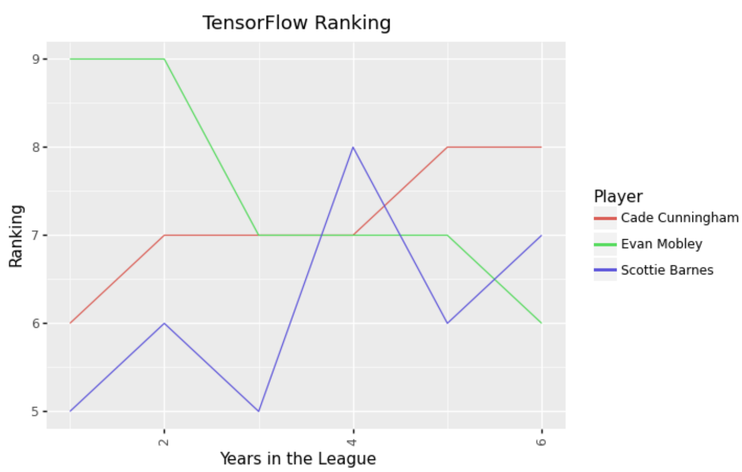

Figure 4.3: TensorFlow Rankings Over Time for First 3 Players of Each Position in 2021 Draft

Figures 4.2 and 4.3 show a comparison of the rank progression for the top three picks of 2021 of each position, with Cade Cunningham at guard, Evan Mobley at Center, and Scottie Barnes at Forward. Using both our statistical analysis and our machine learning tools, we can try and draw some conclusions from our work. For one, it seems as though in both methods, the Guard position has a very linear progression in their time in the league. Based on other examples such as Jalen Green, Chris Duarte, and James Bouknight, they typically progress up to a certain point and hang around that same ranking for their upcoming years. Cunningham and Green are predicted to be the best out of this guard class.

The forward position seems like a position that does notn usually see the same linear progression that the guard position does, and Scottie Barnes is a clear example of that. The forward position is naturally one that demands a lot, as they are asked to impact the game offensively while still being able to defensively anchor the team based on their size and ability to defend close to the rim. We see Kuminga and Wagner also jump around in ranking, but generally being more consistent than Scottie Barnes. Franz Wagner seems to be predicted to be the best out of the lottery's forward class.

The center position, or in particular Evan Mobley as he is the only center in the 2021 draft, seems to be a bit of a wildcard to predict. In our statistical analysis, we can see that Mobley wasn't predicted to make much of an impact right away, but develop quickly into a rank 7 center and stay at that ranking until his sixth year. His TensorFlow predictions seem to be different, almost an opposite, as it is predicted that he starts off very impactful but slowly regresses to a rank 6. If we look back at past lottery draft's, we can see that Centers are slowly taken less than other positions, due to what the position demands from players. Centers are usually not ones to score as often as other positions, and when you are a team that would typically be in the lottery, a team that is looking for the next superstar to score them 20+ points a night, they usually are not looking for a player who is not known for scoring. For our year 6 dataset, containing drafts 2015, 2014, 2013, 2012, and 2011, there were only 17 Centers taken, as compared to the 29 Guards and 24 forwards. This continues to dwindle as our year 1 dataset has 11 Centers, 32 Guards, and 27 Forwards. Centers taken in the lottery are known as big swings, and we can see by the predictions from Evan Mobley, that his impact on the league will be a roll of the dice.

Regardless of position, we can see that we will definitely see some impact from this draft class of 2021, and at this point in time we already have. When beginning this research, this draft class hadn't played any basketball, but we are now about a quarter of the way into the season, and here are the statistics and rankings currently recorded by this draft class.

	Pk	Tm	Player	Yrs	MP.1	PTS.1	TRB.1	AST.1	POS	RANK
0	1	DET	Cade Cunningham	1	31.4	14.1	6.3	4.6	G	8.0
1	2	HOU	Jalen Green	1	30.8	14.0	3.1	2.3	G	7.0
2	3	CLE	Evan Mobley	1	33.8	14.1	8.1	2.6	C	8.0
3	4	TOR	Scottie Barnes	1	35.6	15.3	8.1	3.3	F	8.0
4	5	ORL	Jalen Suggs	1	27.8	12.3	3.4	3.6	G	7.0
5	6	OKC	Josh Giddey	1	29.4	10.4	7.2	5.8	G	8.0
6	7	GSW	Jonathan Kuminga	1	7.2	3.0	1.6	0.4	F	1.0
7	8	ORL	Franz Wagner	1	31.7	13.6	4.3	2.6	F	7.0
8	9	SAC	Davion Mitchell	1	25.6	9.1	2.6	3.4	G	6.0
9	10	NOP	Ziaire Williams	1	18.6	5.0	1.6	0.7	F	2.0
10	11	CHO	James Bouknight	1	1.7	0.3	0.3	0.3	G	1.0
11	12	SAS	Joshua Primo	1	5.2	2.2	0.6	0.4	G	1.0
12	13	IND	Chris Duarte	1	29.8	13.1	4.0	2.0	G	6.0
13	14	GSW	Moses Moody	1	5.9	1.5	0.7	0.2	G	1.0

Figure 4.4: Current NBA Statistics for 2021 Draft Class 1/4 Through the Season

While not all of these players are getting the same opportunity minutes-wise, we can see that they have all started to impact the game well, as the average ranking of these players in the top 5 picks is a 7.66. We can see that Mobley and Giddey have both started the season strong, as the TensorFlow model predicted they would, and Cunningham and Green have both started slightly better than both models predicted they would finish the year with, but are both still playing at the level it was predicted they would eventually reach. Scottie Barnes has been a surprise, as he has been able to make a quicker impact than either models predicted he would in his first year, as he was a surprise pick in the draft[10]. While these statistics are very early, we can see that many of our predictions seem to be shaping up to be true, at least for the players who are given a substantial amount of minutes to record these numbers.

There are many other statistics and factors outside the box scores to consider when drafting young talent, such as heath, leadership abilities, attitude, and team fit, but using statistical analysis and machine learning tools we are able to get an idea of what to expect from these players. There will more than likely continue to be draft surprises, both good and bad, but using information from past draftees can help us get an understanding of the potential some of these young players possess, the potential that got them the notoriety that franchises are looking for. While the league continues to trend in a path established by past lottery picks, we will see what young talents step up and further shift the league, establishing new expectations for future lottery picks' to live up to.

Appendix A

Code Reference

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