NBA G LEAGUE PLAYER COMPARISONS:

CLASSIFYING UP-AND-COMING BASKETBALL TALENT

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INTRODUCTION

With the recent conclusion of the NCAA March Madness college basketball tournament, the basketball world is shifting its focus to the upcoming NBA draft. Leading up to this event, analysts spend countless hours scouting, holding workouts with notable players, and crunching player statistics to figure out which one will prove to be the best pick. Generally speaking, the majority of players chosen on draft night are from college, with many of the top picks coming fresh off the heels of breakout performances from March Madness. A valuable source for future NBA talent that tends to be overlooked by the mainstream media, however, is the NBA G League, a professional development league where teams send their younger players who need further training and experience. Historically, the NBA G-League has produced notable NBA players, such as 3-point sharpshooter Joe Harris, previous NBA dunk contest winner Derrick Jones Jr., and this year's potential Most Improved Player Christian Wood.

The purpose behind this paper is to outline an algorithm that will help NBA front offices and teams identify G League players who have the most similar play styles to current NBA players to fit their needs. Our algorithm will provide the best and worst NBA player comparisons for any given G League player. By comparing G League players with current NBA players, front offices get an idea of their play style. It is important to note that player comparisons can come from tapes and player highlight reels. Oftentimes, analysts and commentators will discuss how a player visually fits the play style of certain players, as they have the same fadeaway jumper, shooting form, or ball-handling skills of notable NBA players. In contrast, our approach is entirely statistics driven and will automate the tedious task of analyzing hours of footage for each individual player.

DATA COLLECTION

All data was collected from https://www.basketball-reference.com/ by copying the data and formatting it into .csv. For the G League, we used the most recently completed season because it contains relevant prospects for analysis. Although the most recent 2021 season just ended, the regular season and the playoffs were greatly shortened due to the COVID-19 pandemic; thus, we decided to use 2019-2020 season data as teams played more games which provides us with more comprehensive and accurate data. For the NBA, we decided to pull the last three complete seasons of data (2017-2020). This is important because some players often have to sit out significant portions of seasons due to injuries or other personal factors and we did not want these players to be excluded from the search.

For both the G League and NBA, we pulled two types of data sets: *Basic Statistics Per 36 Minutes* and *Advanced Metrics*. The first dataset, *Basic Statistics Per 36 Minutes,* has all of the simple data that is collected during games for each player, such as points (PTS), free throws (FT), and blocks (BLK). This data is then normalized such that the averages are adjusted for players who have different average minutes played; minutes played per-game in basketball are highly variable because players are constantly rotated throughout the game. The second dataset, *Advanced Metrics,* contains metrics that are calculated from the basic statistics of each player with the intent of providing deeper insight into the true performance of a player.

Additionally, we added a “Season” column to the NBA data since we are collecting data from the past three seasons. This column simply denotes which season the data is from so we can differentiate player performances across different seasons.

To summarize, these are the four data sets that we compiled: a single season (2020) of G League basic stats per 36 minutes, a single season (2020) of G League advanced metrics, three seasons (2017-2020) worth of NBA basic stats per 36 minutes, and three seasons (2017-2020) worth of NBA advanced metrics.

DATA CLEANING

After loading datasets into R, we merged both G League datasets into a single data set and repeated the process for the NBA datasets. We then filtered the G League data to only keep players with at least 500 minutes played who are also younger than 24 years old. We set these parameters because to focus on young and relevant G League players who have the most room for future growth. We also checked all four data sets for incomplete entries or other issues but found none. The summary statistics are in the Appendix.

For the NBA data, we only kept players who played more than 1500 minutes in an attempt to focus solely on notable players within the league. We also removed columns that were unnecessary for our project, such as non-numerical data, redundant or overlapping metrics, and data that is not relevant to play style, such as MP or games played (G). We created a row ID by combining a player's name with the season in which they played. As an example, one row is labeled "James Harden 2020" with another row being "James Harden 2019." As a final step, we removed any duplicate rows. This would occur if a player was traded mid-season and played for two teams or more. If this was the case, we only kept the row that contained the highest MP in a single season for that player since it would prove to be the most relevant. These merges and filters resulted in a G League data set with 115 players and 34 metrics, and an NBA data set with 526 players and 34 metrics.

FEATURE GENERATION

We wanted to engineer features that would help characterize playing styles by representing a player's general defensive and offensive capabilities. We created defense (DEF), defensive load (DL), offense (OFF), OFF/DEF (O/D), and usage (USE). Below are their calculations:

- **DEF** = (STL + BLK + DRB + DWS) / PF
- **DL** = (STL% + BLK% + DRB%) / PF
- **OFF** = TS + ORB + OWS + PTS
- **O/D** = OFF / DEF
- **USE** = (2PA + 3PA + FTA + AST% + USG%) / TOV

**See appendix for abbreviations*

Our expectation is that players with a high DEF score have superior defending ability; players with a high DL score are likely the primary or secondary defender on the team; players with a high OFF score have superior scoring ability; players with high O/D are more offensive than defensive; and players with a high USE score are likely the primary or secondary ball shooter and/or distributor on the team. After generation, we scaled both data sets separately with the engineered features. We visually verified prior to scaling that each metric in the datasets were approximately normally distributed.

METHODOLOGY

To begin, we wanted to validate whether we can effectively capture play styles based solely on metrics instead of subjective visual evaluations. Our assumption is that we can find distinct play styles based on this data. To this end, we decided to cluster players using K-means, where K represents the number of clusters into which the data will be grouped.

To find this optimal number of clusters, we generated a scree plot, which is shown below. We found that the “knee” of the scree plot suggests selecting three to five clusters.

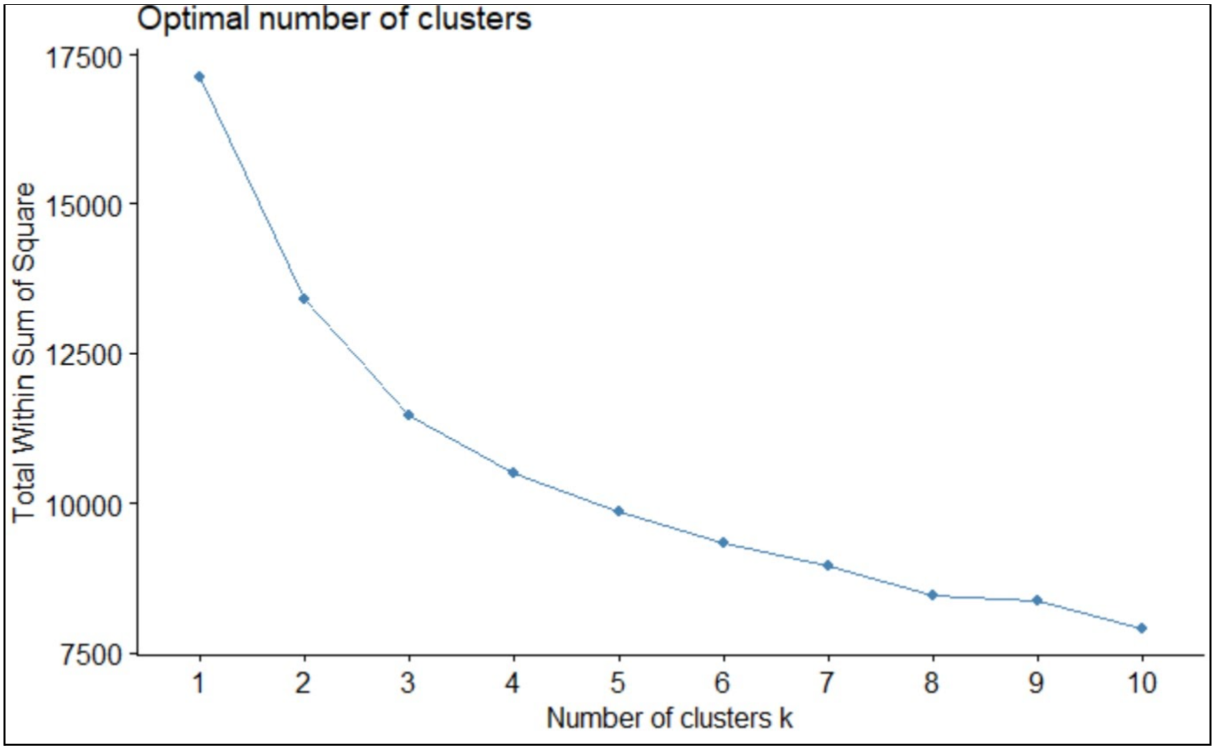

Figure 1: Optimal Number of Clusters for K-Means Clustering

We elected to run K-means clustering with five clusters based on our prior knowledge of the sport. In basketball, there are five players on each team at any given time; consequently, there are traditionally five positions to be filled on each team. These are the Point Guard (PG), Shooting Guard (SG), Power Forward (PF), Small Forward (SF), and Center (C). The PG is typically a smaller player who’s job is to create scoring opportunities for their team. The Point Guard tends to have elite passing ability and ball-handling skills. On the opposite end of the spectrum, the Center is typically the largest and tallest player on the team who exhibits the most physicality. They specialize in getting rebounds, scoring close to the basket, and providing a strong defensive presence. The other three positions are more fluid as their roles are less defined. That being said, the Shooting Guard is meant to specialize in scoring (especially from range), the Power Forward is similar to the Center but has a longer range of shooting and greater technical skill, and the Small Forward is an all-around type of player who is expected to defend both shorter and taller players and score both from close and long range. Thus, we thought it smartest to create five clusters that would hopefully each capture a distinct position. The goodness-of-fit of the model at K=5 was a satisfactory value equivalent to 42.5%.

After deciding on five clusters, we ran K-means and produced the results below in **Figure 2**. We can see five distinct clusters are identified, each possibly representing a single position or a combination of similar positions.

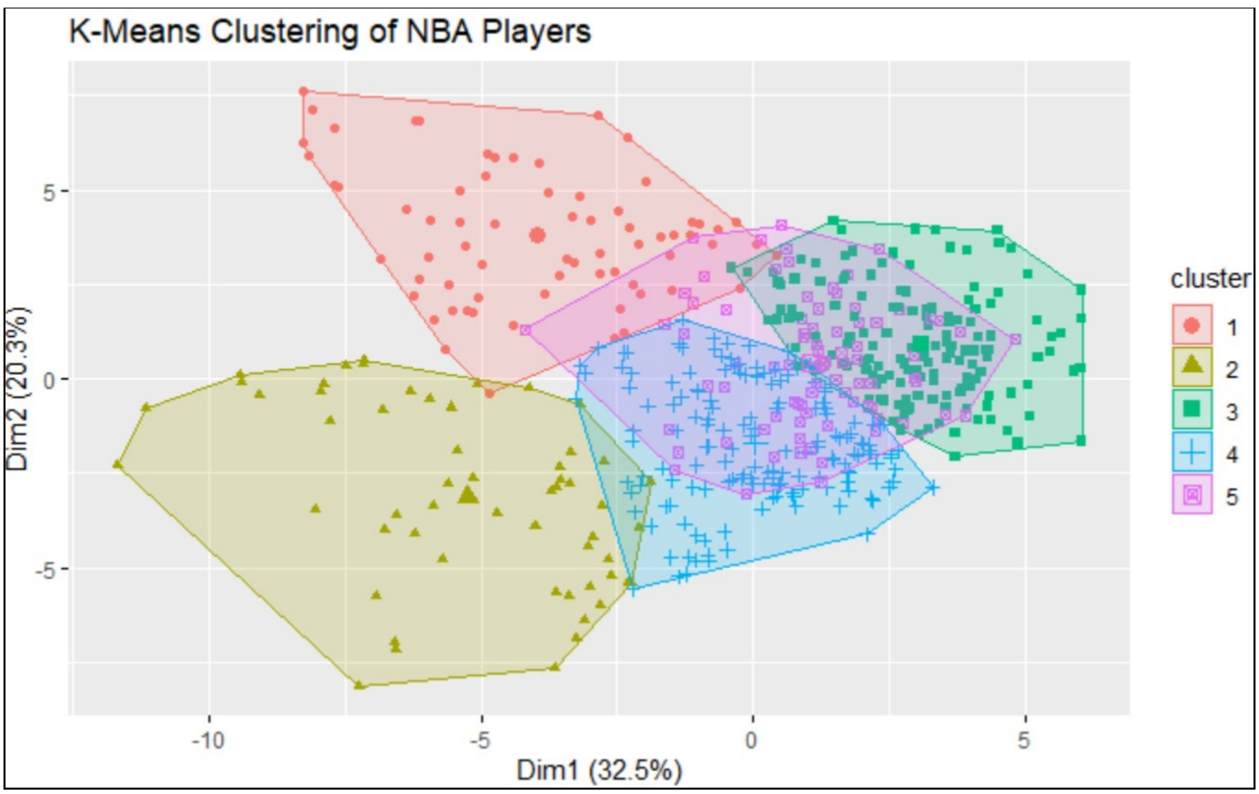

Figure 2: K-Means Clustering

***Legend**: Cluster 1 = C, Cluster 2 = SF/SG, Cluster 3 = PF/C, Cluster 4 = SF/PF, Cluster 5 = PG*

To characterize each cluster, we find which positions occur most in each cluster, and found the following results summarized in **Table 1** below. Upon analyzing the results, it makes sense that we found the PG and C positions to have their own distinct clusters because these two roles are almost polar opposites. However, as mentioned previously, the SF, SG, and PF positions are more fluid in their play styles and roles. Thus, seeing SF-SG, PF-C, and PF-SF combined clusters makes sense because these positions have overlapping play styles (note: the hyphenated position means that a player was listed as playing both positions by their team). It's also important to note that the clusters were organized in a sort of gradient. If we rearrange the positions as C → C-PF → PF-SF → SF-SG → PG, we move from having a cluster that identifies play styles most similar to those of physical and defensive Centers and increasingly becoming more similar to the technical play style of Point Guards.

Cluster	**1**	**2**	**3**	**4**	**5**
Position(s)	C	SF-SG	PF-C	SF-PF	PG

Table 1: Position(s) Within Each Cluster

Now that we have successfully verified that it is possible to identify play styles based solely on metrics, we performed dimensionality reduction on the data because we knew that many of the statistics were redundant. For example, the 2P, 3P, and PTS stats are highly correlated and can likely be summarized with a single metric. Thus, a lot of the information that we have can be compressed down. To achieve dimensionality reduction, we chose to perform principal component analysis (PCA). After running PCA, we generated a PCA scree plot, seen below. The Kaiser Rule[1,2,3] suggests keeping all eigenvectors that have a variance greater than 1, which is represented by the red dotted line in the figure, in which case we would keep the first seven principal components.

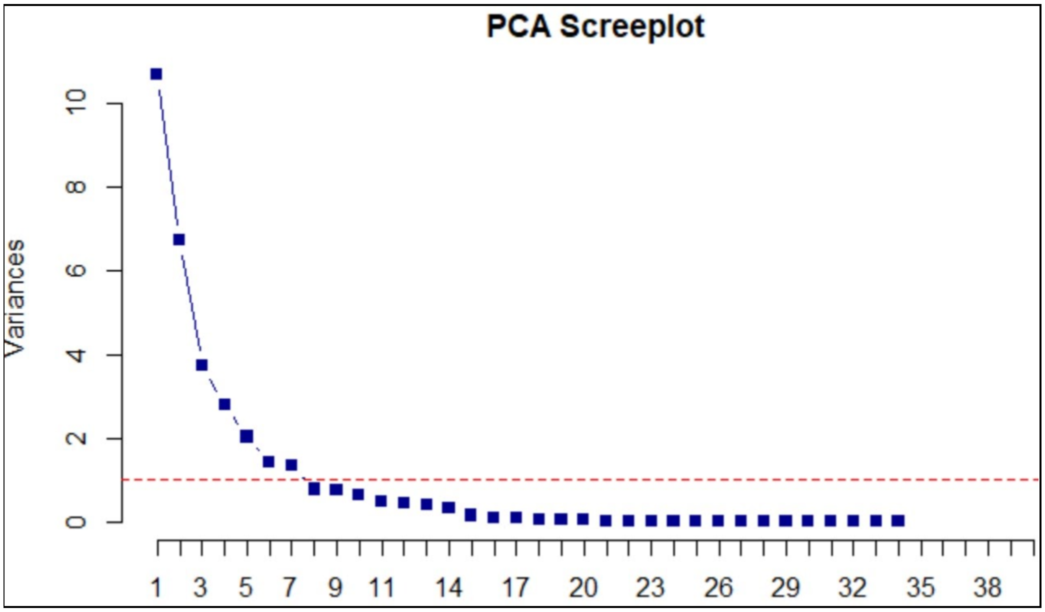

Figure 3: PCA Scree Plot

To verify that seven was a good number of components to keep, we looked at the cumulative percent variance captured by the total number of components, illustrated in **Figure 4** below. A common heuristic suggests keeping "n" components such that at least 90% of the variance of the original data is captured,[2,3] represented by the red dotted line.

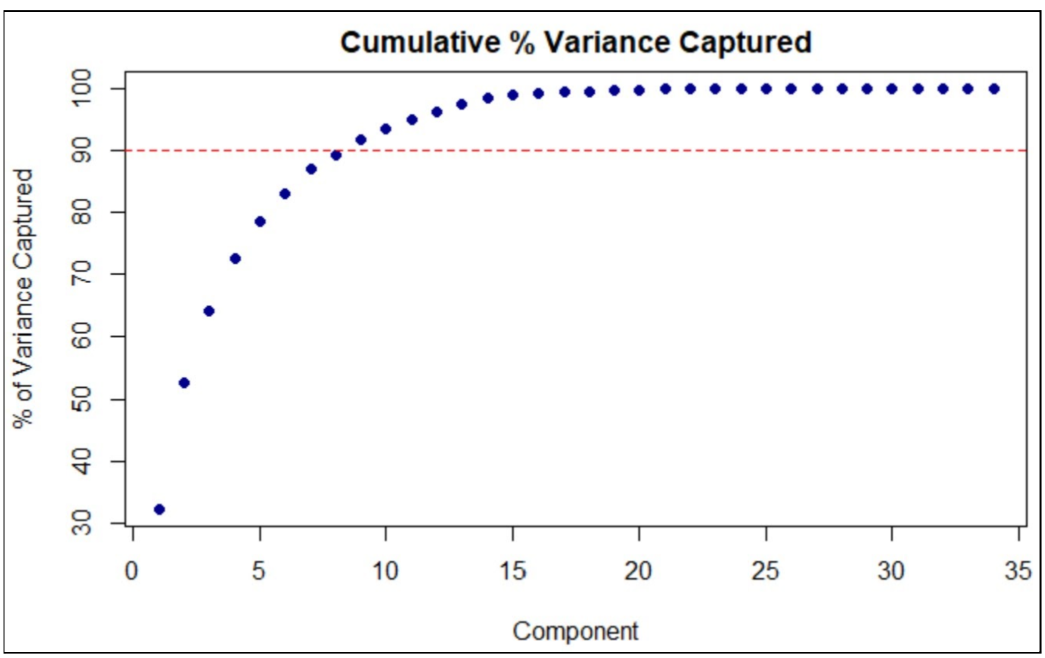

Figure 4: Cumulative Percent Variance Captured

We found that this heuristic suggests keeping nine components. We decided to" split the difference" between the Kaiser Rule suggestion and the cumulative variance heuristic suggestion and kept eight components. We then decided to look at which features are most strongly associated with each component. We looked at the top three features within the top four components, compiled in **Table 2** below. We see desirable results, as all of our engineered features appear, thus validating their importance in our project.

Component	**1**	**2**	**3**	**4**
Top 3 Features (in descending order)	PER OFF 2PA	USE FGA 3PA	STL% STL TOV%	O/D DEF DL

Table 2: Top Features Within Top Four Components
(Engineered Features are Highlighted)

We used the loadings generated by the PCA implemented on the NBA data to perform matrix multiplication across the G League data; this method produced principal component scores for each of the G League players. From here, we created two functions that leveraged cosine similarity with the same general purpose. The first function uses cosine similarity to find the most similar and least similar NBA players for any given G League player. The second function performs the opposite task as it finds the most similar and least similar G League players for any given NBA player. These functions find the most similar and dissimilar players by performing cosine similarity on the PCA scores of the chosen player against the opposing data table and then ranking the cosine similarity scores. The cosine similarity score indicates the degree of similarity on a scale of -1 to 1. The similarity scores were standardized and centered because the range of similarity scores varied widely between players and similarity scores would not be directly comparable.

If we are using the first function, a G League player is chosen and the function looks at the NBA data to find the most similar players. An example is shown in the table below using Talen Horton-Tucker, who was widely recognized as one of the most promising players in the G-League 2020 season:

Most Similar NBA Players to Talen Horton-Tucker	
NBA Player Comparison	**Cosine Similarity Z-Score**
Luka Doncic 2020	2.07
Blake Griffin 2019	2.04
Giannis Antetokounmpo 2020	1.95
Brandon Ingram 2020	1.92
Russell Westbrook 2020	1.89

Least Similar NBA Players to Talen Horton-Tucker	
NBA Player Comparison	**Cosine Similarity Z-Score**
Miles Bridges 2019	-1.64
Kentavious Caldwell-Pope 2020	-1.64
Danuel House 2020	-1.65
Justin Jackson 2018	-1.72
Dante Cunningham 2018	-1.74

Tables 3 and 4: Most/Least Similar NBA Players to Talen Horton-Tucker

These results seem to pass the eye-test — all of the NBA players indicated as "most similar" are known to be the most important players on their team and lead the offense with their offensive prowess, just as is the case with Talen-Horton Tucker on his G League team, the South Bay Lakers.

Next, we show an example using the second function to find G League players that play similarly to the 2020 NBA MVP winner, Giannis Antetokounmpo (or just Giannis, as he is more commonly known):

Most Similar G League Players to Giannis in 2020	
G League Player Comparison	**Cosine Similarity Z-Score**
Deyonta Davis	1.65
Donta Hall	1.64
Marques Bolden	1.60
Kenny Wooten	1.52
Drew Eubanks	1.46

Least Similar G League Players to Giannis in 2020	
G League Player Comparison	**Cosine Similarity Z-Score**
Jawun Evans	-2.03
Trevon Duval	-2.23
Matt Farrell	-2.26
Lamar Peters	-2.61
Marcus Graves	-2.71

Tables 5 and 6: Most/Least Similar G League Players to Giannis in 2020

It is interesting to note that Talen Horton-Tucker does not appear as a comparison for Giannis despite the reverse being true. The most straightforward explanation is that there were more than five G League players more similar to Giannis than Horton-Tucker. However, there is a possibility that our model is simply not robust, so we verified the robustness of our model.

MODEL VERIFICATION

To verify our model, we decided to look at G League players who got called up to play in the NBA this current season (2021). We hypothesized that running our algorithm on a recently promoted player who is now in the NBA (during the 2021 season) against their G League data (from the 2020 season) would yield a high similarity score. Our reasoning is that players who get called up from the G League should retain their play style in the NBA.

To test our hypothesis, we downloaded two new data sets, once again from https://www.basketball-reference.com/. One data set consisted of NBA per 36 minutes data of G League players promoted in 2021, while the other data set complemented the first with the corresponding advanced metrics. After loading in, cleaning, and transforming the data to fit the same exact format as the data from the beginning of our report, we ran the data through our function and returned the standardized similarity scores for each of the players. **Figure 5** below is a box plot of standardized similarity scores for recently promoted G League players.

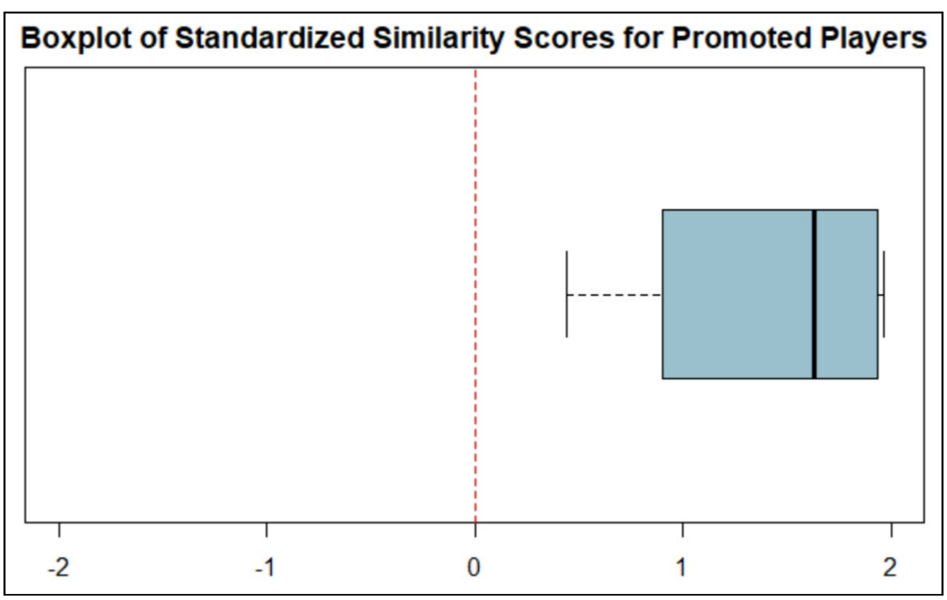

Figure 5: Standardized Similarity Scores of Recently Promoted G Leaguers

The key takeaway from **Figure 5** is that each similarity score is one to two standard deviations above the average similarity score. It provides us with quantitative verification that these recently promoted G League players retain similar play styles after they get called up to the NBA; this provides evidence of a real pattern being recovered by our algorithm instead of fluke results or statistical noise. Lastly, this demonstrates that our algorithm is robust to player data that it has not seen before, as we used an outside data set and produced similar results to our original data set. There is some uncertainty as indicated by the range of the boxplot, but all of it is bounded within the higher range of standardized scores. It's rather significant that none of the players tested above had a standardized similarity score below zero.

CONCLUSION

We successfully developed two accurate and efficient algorithms that identify any given player's most and least similar player comparisons across the two major professional American basketball leagues (NBA and NBA G League). Our functions can be easily used by the scouting office of an NBA team to pinpoint which young G League players show the most potential if they were to be called up to the NBA; it also allows these scouts to quickly understand the player's play style by comparing them to better known players without the scouts having to watch hours of video footage. Alternatively, the algorithm also allows scouts to find all G League players that fit the mould of a known NBA player. All that is required is a player's name and the number of results wanted. Our algorithms were verified using new data that had not been seen before, which yielded promising results that further validated our assumptions.

We initially considered alternative methods for determining similarity between players, such as Euclidean distance. We chose cosine similarity because we were most interested in the ratio between the different metrics in the dataset; we believed that these ratios were more indicative of play style than absolute differences in the metrics (as would have been calculated by Euclidean distance). Additionally, any data project is susceptible to "data snooping"—when statisticians only report relevant and statistically significant results that support a desired narrative. Our methodology took this consideration into account to protect our conclusions against the potential misrepresentation of data. For example, we could have re-ran K-means clustering repeatedly until we found clusters that yielded desirable results for cluster analysis, or chosen an arbitrary number of principal components to keep during PCA that best suited our aims. That being said, we counteracted these possibilities by running K-means clustering 1000 times (nstart=1000) with different starting points and reported only the best result as determined by the function; similarly, we employed the well known Kaiser Rule and 90% heuristic for PCA to determine the number of principal components kept.

REFERENCES

1. Holland, S. M. (2019). PRINCIPAL COMPONENTS ANALYSIS (PCA). *Principal Components Analysis*, 12.

2. Kaiser, H. F. (1960). The Application of Electronic Computers to Factor Analysis. *Educational and Psychological Measurement*, *20*(1), 141–151. https://doi.org/10.1177/001316446002000116

3. Rea, A., & Rea, W. (2016). How Many Components should be Retained from a Multivariate Time Series PCA? *ArXiv:1610.03588 [Stat]*. http://arxiv.org/abs/1610.03588

APPENDIX

GitHub link: https://github.com/bennett2924/gleague-nba

All metrics and their explanations found on https://www.basketball-reference.com/. Below is a list that provides the abbreviation of each Per 36 Minute Statistic:

Per 36 Minutes								
Pos	**G**	**GS**	**MP**	**FG**	**FGA**	**FG%**	**3P**	**3PA**
Position	Games	Games Started	Minutes Played	Field Goals Made	Field Goal Attempts	Field Goal Percentage	3-Point Field Goals Made	3-Point Field Goal Attempts

Per 36 Minutes						
3P%	**2P**	**2PA**	**2P%**	**FT**	**FTA**	**FT%**
3-Point Field Goal Percentage	2-Point Field Goals Made	2-Point Field Goal Attempts	2-Point Field Goal Percentage	Free Throws Made	Free Throw Attempts	Free Throw Percentage

Per 36 Minutes								
ORB	**DRB**	**TRB**	**AST**	**STL**	**BLK**	**TOV**	**PF**	**PTS**
Offensive Rebounds	Defensive Rebounds	Total Rebounds	Assists	Steals	Blocks	Turnovers	Personal Fouls	Points

Below is a list of Advanced Metrics abbreviations and descriptions:

Advanced Metrics		
Abbreviation	**Statistic**	**Explanation**
PER	Player Efficiency Rating	A measure of per-minute production standardized such that league average is 15
TS%	True Shooting Percentage	A measure of shooting efficiency that takes into account 2-point field goals, 3-point field goals, and free throws
3PAr	3-Point Attempt Rate	Percentage of field goal attempts from 3-point range
FTr	Free Throw Attempt Rate	Number of free throw attempts per field goal attempt
ORB%	Offensive Rebound Percentage	An estimate of the percentage of available offensive rebounds a player grabbed while on the floor
DRB%	Defensive Rebound Percentage	An estimate of the percentage of available defensive rebounds a player grabbed while on the floor
AST%	Assist Percentage	An estimate of the percentage of teammate field goals a player assisted while on the floor
STL%	Steal Percentage	An estimate of the percentage of opponent possessions that end with a steal by the player while on the floor
BLK%	Block Percentage	An estimate of the percentage of opponent two-point field goal attempts blocked by the player while on the floor
TOV%	Turnover Percentage	An estimate of turnovers committed per 100 plays
USG%	Usage Percentage	An estimate of the percentage of team plays used by a player while on the floor
OWS	Offensive Win Shares	An estimate of the number of wins contributed by a player due to offense
DWS	Defensive Win Shares	An estimate of the number of wins contributed by a player due to defense
WS	Win Shares	An estimate of the number of wins contributed by a player

NBA Data Summary Statistics:

```
      PER             TS.              X3PAr              FTr               ORB.             DRB.      
 Min.   : 6.40   Min.   :0.4370   Min.   :0.0000   Min.   :0.0700   Min.   : 0.50   Min.   : 5.20  
 1st Qu.:12.60   1st Qu.:0.5370   1st Qu.:0.2577   1st Qu.:0.1732   1st Qu.: 2.00   1st Qu.:10.80  
 Median :15.40   Median :0.5610   Median :0.3805   Median :0.2415   Median : 3.00   Median :14.10  
 Mean   :16.01   Mean   :0.5648   Mean   :0.3671   Mean   :0.2569   Mean   : 4.21   Mean   :15.52  
 3rd Qu.:18.68   3rd Qu.:0.5910   3rd Qu.:0.4840   3rd Qu.:0.3165   3rd Qu.: 5.20   3rd Qu.:18.50  
 Max.   :31.90   Max.   :0.6990   Max.   :0.8820   Max.   :0.7330   Max.   :16.80   Max.   :37.60  

      AST.            STL.             BLK.            TOV.             USG.            OWS        
 Min.   : 4.20   Min.   :0.300   Min.   :0.00   Min.   : 3.70   Min.   : 8.70   Min.   :-2.800  
 1st Qu.: 8.90   1st Qu.:1.100   1st Qu.:0.70   1st Qu.: 9.80   1st Qu.:17.00   1st Qu.: 1.200  
 Median :13.25   Median :1.500   Median :1.20   Median :11.60   Median :20.65   Median : 2.300  
 Mean   :16.40   Mean   :1.554   Mean   :1.66   Mean   :12.05   Mean   :21.12   Mean   : 2.639  
 3rd Qu.:21.90   3rd Qu.:1.900   3rd Qu.:2.00   3rd Qu.:14.00   3rd Qu.:24.70   3rd Qu.: 3.800  
 Max.   :49.80   Max.   :3.500   Max.   :8.40   Max.   :26.80   Max.   :40.50   Max.   :11.600  

      DWS               FGA              FG.              X3PA              X3P.             X2PA      
 Min.   :-0.500   Min.   : 6.2   Min.   :0.3600   Min.   : 0.000   Min.   :0.0000   Min.   : 1.30  
 1st Qu.: 1.400   1st Qu.:11.4   1st Qu.:0.4270   1st Qu.: 3.400   1st Qu.:0.3300   1st Qu.: 6.30  
 Median : 1.900   Median :13.6   Median :0.4520   Median : 5.200   Median :0.3580   Median : 8.70  
 Mean   : 2.094   Mean   :13.9   Mean   :0.4632   Mean   : 5.002   Mean   :0.3451   Mean   : 8.90  
 3rd Qu.: 2.800   3rd Qu.:16.3   3rd Qu.:0.4860   3rd Qu.: 6.700   3rd Qu.:0.3835   3rd Qu.:11.47  
 Max.   : 5.900   Max.   :24.0   Max.   :0.6930   Max.   :12.900   Max.   :0.5710   Max.   :18.80  
                                                                   NA's   :7                       
      X2P.              FTA               FT.              ORB             DRB              AST        
 Min.   :0.3850   Min.   : 0.700   Min.   :0.4490   Min.   :0.200   Min.   : 1.700   Min.   : 1.100  
 1st Qu.:0.4783   1st Qu.: 2.200   1st Qu.:0.7270   1st Qu.:0.700   1st Qu.: 3.600   1st Qu.: 2.100  
 Median :0.5090   Median : 3.300   Median :0.7935   Median :1.000   Median : 4.700   Median : 3.100  
 Mean   :0.5143   Mean   : 3.654   Mean   :0.7788   Mean   :1.395   Mean   : 5.147   Mean   : 3.835  
 3rd Qu.:0.5450   3rd Qu.: 4.575   3rd Qu.:0.8440   3rd Qu.:1.700   3rd Qu.: 6.275   3rd Qu.: 5.200  
 Max.   :0.6990   Max.   :11.800   Max.   :1.0000   Max.   :5.800   Max.   :13.400   Max.   :11.300  

      STL             BLK              TOV              PF              PTS             DEF        
 Min.   :0.200   Min.   :0.0000   Min.   :0.500   Min.   :1.300   Min.   : 7.30   Min.   :1.038  
 1st Qu.:0.800   1st Qu.:0.3000   1st Qu.:1.500   1st Qu.:2.300   1st Qu.:14.00   1st Qu.:2.480  
 Median :1.100   Median :0.5000   Median :2.000   Median :2.700   Median :16.70   Median :3.138  
 Mean   :1.155   Mean   :0.6994   Mean   :2.137   Mean   :2.808   Mean   :17.54   Mean   :3.335  
 3rd Qu.:1.400   3rd Qu.:0.8000   3rd Qu.:2.600   3rd Qu.:3.200   3rd Qu.:20.40   3rd Qu.:3.955  
 Max.   :2.500   Max.   :3.5000   Max.   :5.000   Max.   :5.200   Max.   :35.40   Max.   :8.286  

       DL               OFF              USE               O/D        
 Min.   : 1.791   Min.   : 9.037   Min.   : 1.561   Min.   : 2.494  
 1st Qu.: 5.055   1st Qu.:17.334   1st Qu.: 3.536   1st Qu.: 5.361  
 Median : 6.321   Median :20.940   Median : 4.553   Median : 6.842  
 Mean   : 6.828   Mean   :22.137   Mean   : 4.764   Mean   : 7.203  
 3rd Qu.: 8.152   3rd Qu.:26.064   3rd Qu.: 5.771   3rd Qu.: 8.442  
 Max.   :18.278   Max.   :48.216   Max.   :10.135   Max.   :20.342  
```

G League Summary Statistics:

```
      PER              TS.             X3PAr              FTr              ORB.             DRB.      
 Min.   : 5.90   Min.   :0.4820   Min.   :0.0000   Min.   :0.0210   Min.   : 0.80   Min.   : 6.40  
 1st Qu.:13.15   1st Qu.:0.5600   1st Qu.:0.2345   1st Qu.:0.1200   1st Qu.: 2.50   1st Qu.:11.15  
 Median :15.00   Median :0.5880   Median :0.3900   Median :0.1650   Median : 4.20   Median :14.60  
 Mean   :15.88   Mean   :0.5936   Mean   :0.3688   Mean   :0.1691   Mean   : 5.69   Mean   :15.77  
 3rd Qu.:18.35   3rd Qu.:0.6280   3rd Qu.:0.4990   3rd Qu.:0.2170   3rd Qu.: 7.95   3rd Qu.:20.20  
 Max.   :29.80   Max.   :0.7620   Max.   :0.7110   Max.   :0.4010   Max.   :20.30   Max.   :33.20  

      AST.            STL.            BLK.             TOV.            USG.            OWS      
 Min.   : 1.40   Min.   :0.500   Min.   : 0.100   Min.   : 7.80   Min.   :11.40   Min.   :-2.3  
 1st Qu.: 8.55   1st Qu.:1.300   1st Qu.: 0.800   1st Qu.:11.85   1st Qu.:17.95   1st Qu.:-0.2  
 Median :11.80   Median :1.700   Median : 1.400   Median :14.50   Median :20.60   Median : 0.3  
 Mean   :13.69   Mean   :1.728   Mean   : 2.248   Mean   :14.71   Mean   :20.69   Mean   : 0.3  
 3rd Qu.:18.05   3rd Qu.:2.100   3rd Qu.: 2.950   3rd Qu.:17.20   3rd Qu.:23.85   3rd Qu.: 0.8  
 Max.   :35.40   Max.   :3.500   Max.   :13.100   Max.   :28.80   Max.   :30.20   Max.   : 3.0  

      DWS              FGA             FG.              X3PA             X3P.             X2PA       
 Min.   :0.0000   Min.   : 6.8   Min.   :0.3390   Min.   : 0.000   Min.   :0.0000   Min.   : 3.100  
 1st Qu.:0.6000   1st Qu.:12.0   1st Qu.:0.4250   1st Qu.: 3.250   1st Qu.:0.2943   1st Qu.: 6.600  
 Median :0.8000   Median :14.3   Median :0.4560   Median : 5.500   Median :0.3330   Median : 8.700  
 Mean   :0.8878   Mean   :14.0   Mean   :0.4785   Mean   : 5.191   Mean   :0.3127   Mean   : 8.805  
 3rd Qu.:1.2000   3rd Qu.:16.3   3rd Qu.:0.5205   3rd Qu.: 7.200   3rd Qu.:0.3738   3rd Qu.:10.600  
 Max.   :2.4000   Max.   :19.9   Max.   :0.7040   Max.   :11.800   Max.   :0.6000   Max.   :18.700  
                                                                    NA's   :1                        
      X2P.             FTA              FT.              ORB             DRB              AST       
 Min.   :0.4140   Min.   :0.300   Min.   :0.3330   Min.   :0.30   Min.   : 2.30   Min.   :0.300  
 1st Qu.:0.4925   1st Qu.:1.600   1st Qu.:0.6465   1st Qu.:0.90   1st Qu.: 3.90   1st Qu.:2.100  
 Median :0.5340   Median :2.200   Median :0.7210   Median :1.50   Median : 5.10   Median :2.800  
 Mean   :0.5467   Mean   :2.348   Mean   :0.7168   Mean   :1.97   Mean   : 5.45   Mean   :3.397  
 3rd Qu.:0.5990   3rd Qu.:2.900   3rd Qu.:0.7870   3rd Qu.:2.80   3rd Qu.: 6.85   3rd Qu.:4.550  
 Max.   :0.7090   Max.   :5.700   Max.   :0.9460   Max.   :7.40   Max.   :11.70   Max.   :8.400  

      STL             BLK              TOV              PF              PTS             DEF       
 Min.   :0.300   Min.   :0.0000   Min.   :0.80   Min.   :1.300   Min.   : 9.40   Min.   :1.184  
 1st Qu.:1.000   1st Qu.:0.3000   1st Qu.:2.00   1st Qu.:2.600   1st Qu.:15.25   1st Qu.:2.187  
 Median :1.300   Median :0.6000   Median :2.60   Median :3.000   Median :18.10   Median :2.704  
 Mean   :1.295   Mean   :0.9278   Mean   :2.59   Mean   :3.197   Mean   :17.82   Mean   :2.778  
 3rd Qu.:1.600   3rd Qu.:1.1500   3rd Qu.:3.10   3rd Qu.:3.700   3rd Qu.:20.20   3rd Qu.:3.359  
 Max.   :2.700   Max.   :5.7000   Max.   :5.00   Max.   :5.800   Max.   :29.30   Max.   :5.400  

       DL              OFF             USE              O/D        
 Min.   : 2.441   Min.   :10.39   Min.   :1.035   Min.   : 3.710  
 1st Qu.: 4.948   1st Qu.:17.68   1st Qu.:2.862   1st Qu.: 5.798  
 Median : 5.971   Median :20.32   Median :3.573   Median : 7.869  
 Mean   : 6.374   Mean   :20.68   Mean   :3.633   Mean   : 8.141  
 3rd Qu.: 7.767   3rd Qu.:23.50   3rd Qu.:4.323   3rd Qu.: 9.696  
 Max.   :12.667   Max.   :38.40   Max.   :6.663   Max.   :20.730  
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