Clustering NBA Players Offensively

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Contents

1 Objective

The objective of this project is to cluster together NBA players based on their offensive game, as determined by their performance on the following types of plays:

- Isolation
- Cut
- Off screen
- Pick and roll ball handler
- Pick and roll roller
- Post up
- Spot up

The clusters were then used in case studies of two types. The first type explored the clusters a few select players, analyzing strengths and weaknesses in different types of offensive plays. The second type analyzed the cluster compositions of the five lineups in the NBA with the highest offensive rating this season.

Such clusters could be used by a team in a number of ways. If a front office is looking for a hidden gem in free agency to replace a player, they could look at everyone within the cluster associated with the departing player. Strategy-oriented coaches could use the model to craft lineups and plays, and development coaches could use clusters to find appropriate film in the off-season.

2 Methodology

For each play type, the following statistics over the 2023-24 season were collected on a per player basis (averaging over games):

- number of possessions
- frequency
- average points per possession
- total points
- field goals made
- field goals attempted
- field goal percent
- effective field goal percent
- free throw frequency
- turnover frequency
- shooting foul frequency
- and one frequency
- score frequency

For each play type, the corresponding player data was scaled and normalized. Three different types of models were tested: KMeans, spectral clustering with affinity matrix calculated via RBF, and spectral clustering with affinity matrix calculated via nearest neighbors. For each model type, seven different models were trained, one for each play type.

For KMeans, the number of clusters for each play type model was computed via the maximum of silhouette scores over a range from 2 to 20 clusters. The same technique was used for spectral clustering.

Next, all the models were trained. The average of all Davies-Bouldin scores for the KMeans models was computed, and compared to the same averages for the Spectral RBF and nearest neighbor models. The average score was lowest on the KMeans models, leading to it being chosen.

3 Clustering Results

The KMeans models were trained on the following numbers of clusters:

Iso: 3 clusters
Cut: 3 clusters
Off screen: 3 clusters
PnR Handler: 3 clusters
PnR Roller: 2 clusters
Post up: 3 clusters
Spot up: 2 clusters

The average Davies-Bouldin score over all KMeans models was 1.39, indicating a moderately strong clustering. To visualize the clusters (a difficult task, because the feature space is greater than three dimensions), two different techniques were used.

First, PCA on two components was run on the data to project into 2-space, then displayed on a scatterplot with points colored in accordance with their label. The clusters were well visible. **Second**, strip plots were produced to show how the clusters vary over a specific stat.

3.1 Isolation

3.1.1 Describing Clusters

There are three isolation clusters. The seven statistics in which the clustering was most clearly found were:

- number of isolation possessions per game (POSS)
- frequency of isolation plays every game (FREQ%)
- points per isolation possession (PPP)
- average PPG from isolation shots (PTS)
- FGM in isolation per game (FGM)
- FGA in isolation per game (FGA)
- FG% in isolation (FG%)
- EFG% in isolation (EFG%)

The range of values in these statistics for each isolation cluster are listed below.

Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	0-2.5	2.5-12.5	0-.85	0-1.5	0-.6	0-2	0-42	0-42
1	2.5-7	11-22.5	.75-1.25	1.5-7.5	.55-2.4	1.9-5.2	35-60	35-58
2	0-2.5	2.5-12.5	.75-1.75	.75-3	.2-1.2	0-2	39-85	38-105

Table 1: Isolation Cluster Values

Cluster 0 players attempt isolation plays relatively infrequently, and aren't very productive in such plays. Cluster 1 players attempt a lot of isolation plays, and are moderately efficient at generating points off such possessions. Cluster 2 players don't attempt many isolation plays, but are incredibly talented scorers one-on-one.

A quick gut check with the lists of players belonging to each cluster confirms the above analysis. Cluster 2 includes skilled, tall shooting bigs like Nikola Jokic and Chet Holmgren, who can score reliably over any defender. Cluster 1 includes power and small forwards in the 6'6-6'9 range like Jayson Tatum and LeBron, who back down defenders in isolation frequently and can score moderately efficiently on such plays. Finally, cluster 0 includes shifty point guards who can generate space in isolation, but typically take tough shots that result in a basket less frequently than the post moves of players like Jokic.

Cluster 0 players include:

- Cade Cunningham
- Darius Garland
- Dennis Schroder
- Chris Paul
- Collin Sexton
- Jamal Murray
- Josh Giddey

Cluster 1 players include:

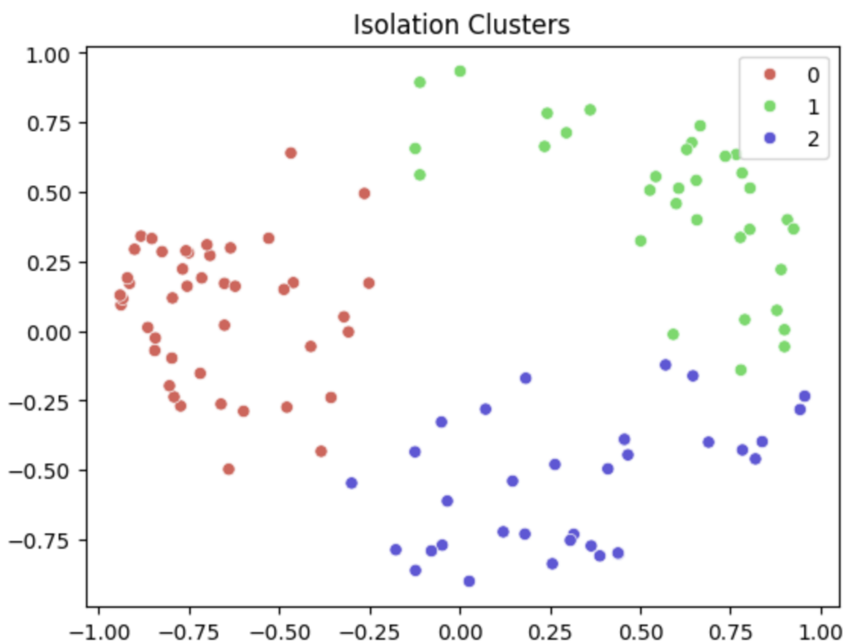
- Luka Doncic
- LeBron James
- Jimmy Butler
- Anthony Edwards
- Kevin Durant
- Brandon Ingram

- DeMar DeRozan
- Jayson Tatum

Cluster 2 players include:

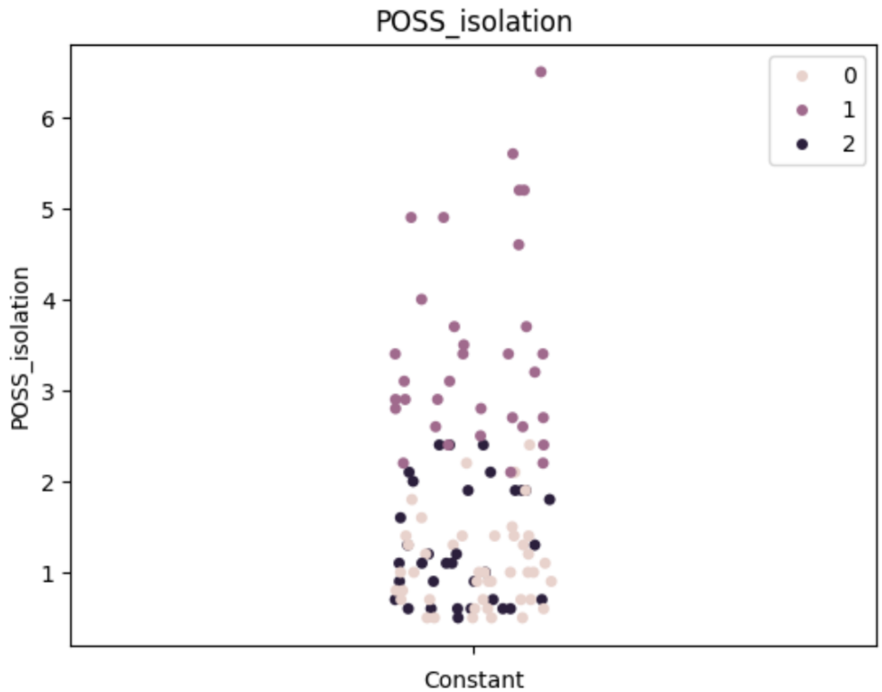
- Jaren Jackson Jr.
- Nikola Jokic
- Bam Adebayo
- Anthony Davis
- Victor Wembanyama
- Chet Holmgren
- Evan Mobley

3.1.2 Clusters under PCA



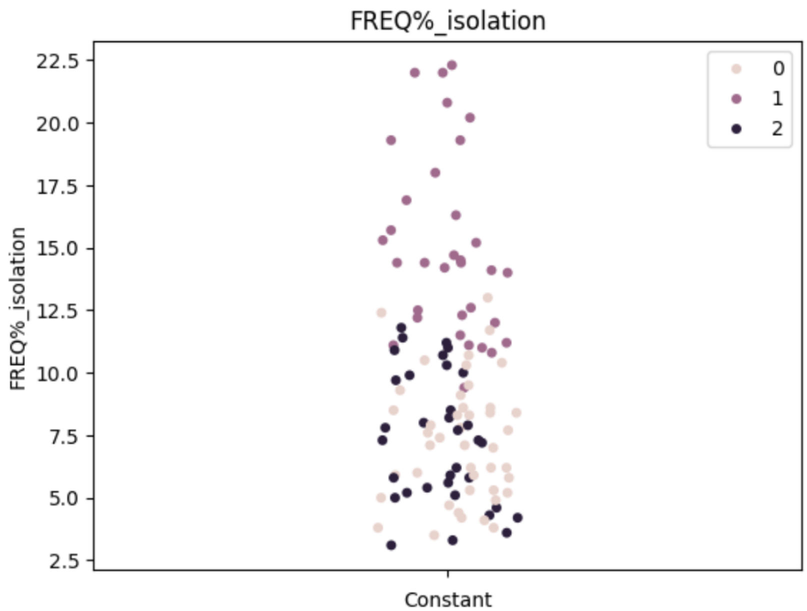
The axes are the two PCA components. It seems like the clustering algorithm is working moderately well for isolation plays.

3.1.3 Variance of clusters with average number of isolation possessions per game



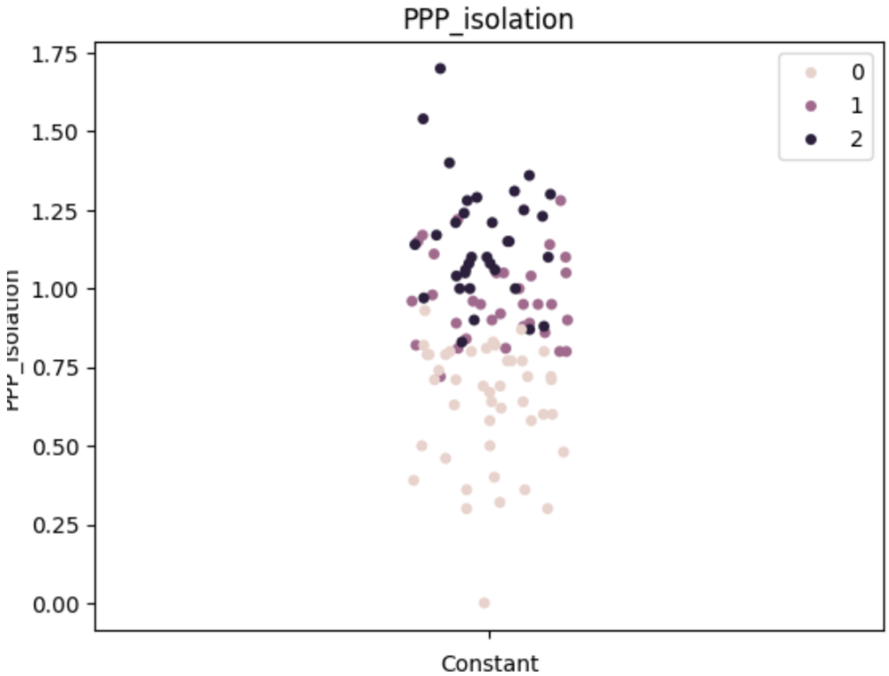
The strip plot doesn't show a very strong clustering (meaning that the model is clustering more heavily over other variables). Cluster 0 and 2 players average between 0 and 2.5 isolation possessions per game, while cluster 1 players average between 2.5 and 7 isolation possessions per game.

3.1.4 Variance of clusters with the average frequency of isolation plays per game



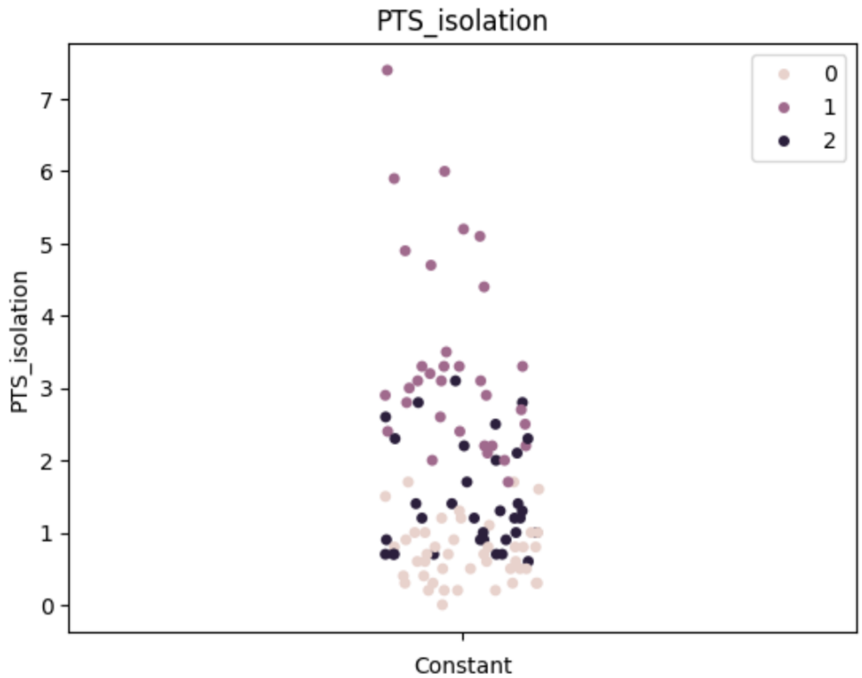
There isn't great clustering here either, but the trend is clear, and similar to that of the last statistic: cluster 1 players attempt a lot of isolation plays (in this case, relative to other types of plays), while a smaller proportion of cluster 0 and 2 players' offensive games come from isolation.

3.1.5 Variance of clusters with points per possession on isolation plays



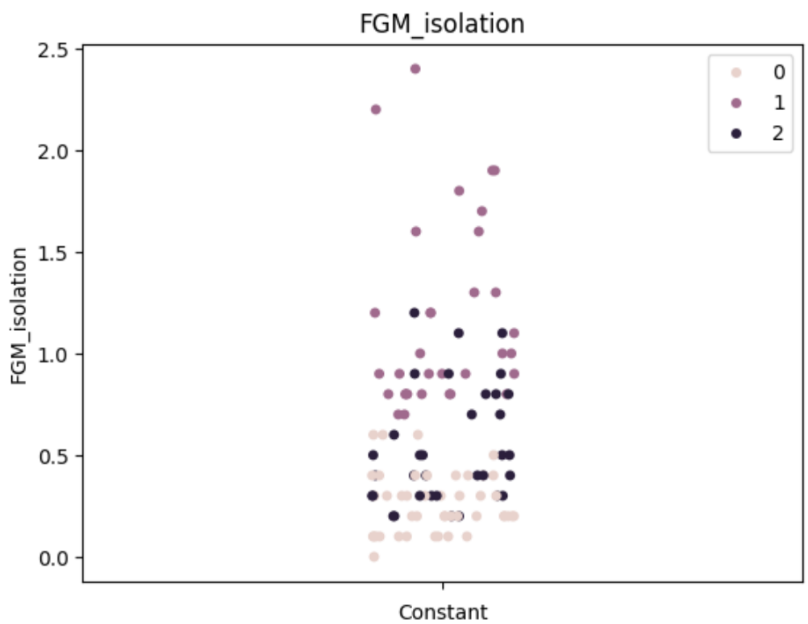
Cluster 0 players are the least productive on isolation plays, scoring between .25 and .75 points per possession. Cluster 1 players are middle-of-the-road, scoring between .75 and 1.25 points per possession. Cluster 2 players, on the other hand, are excellent isolation players who can reliably generate points.

3.1.6 Variance of clusters with average PPG from isolation attempts



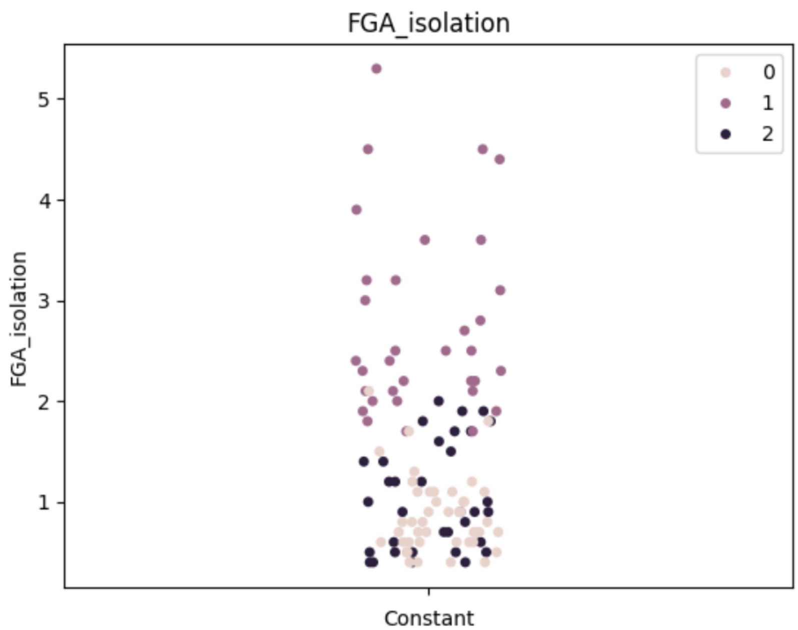
Cluster 0 players generate, on average, between 0 and 1.5 points per game from isolation attempts. Cluster 1 players generate between 2 and 7 points per game from isolation. Finally, cluster 2 players generate between .7 and 3 points per game from isolation.

3.1.7 Variance of clusters with field goals made in isolation



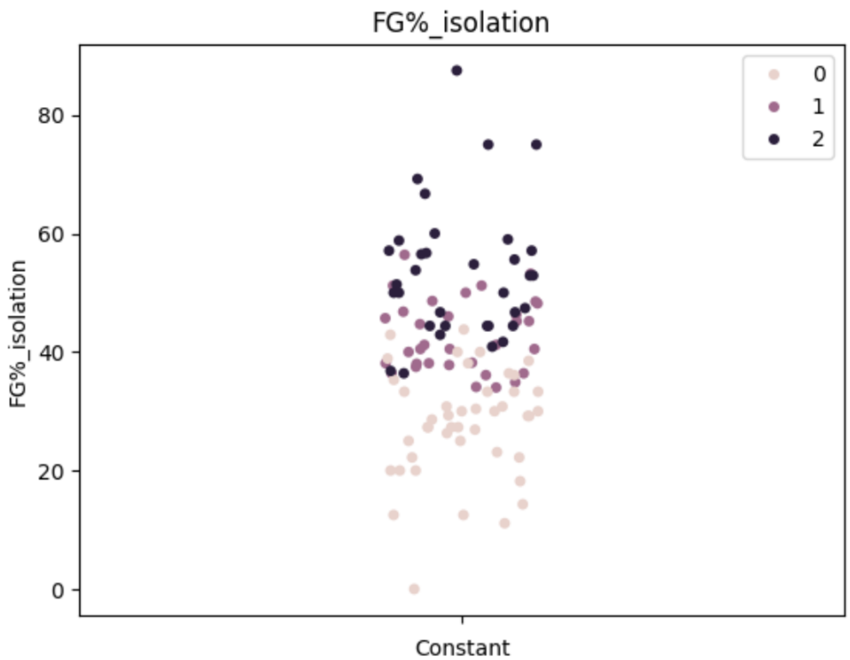
Cluster 0 players average between 0 and .6 field goals made per game in isolation. Cluster 1 players average between .6 and 2.4 isolation field goals per game. Finally, cluster 2 players average between .25 and 1.25 field goals made in isolation per game.

3.1.8 Variance of clusters with field goal attempts in isolation



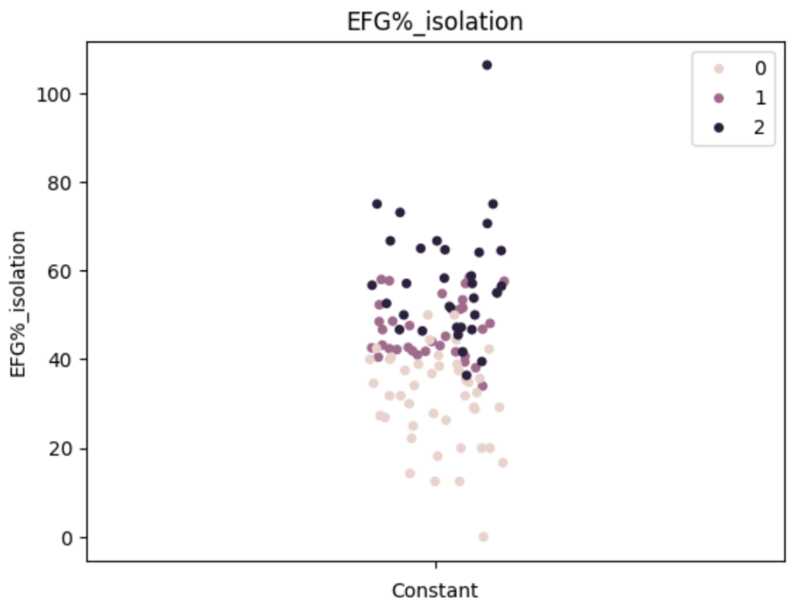
Cluster 0 players attempt between 0 and 2 isolation shot attempts per game. Cluster 2 players attempt a similar range of shot attempts per game. Cluster 1 players attempt a lot of isolation shots per game, ranging from 2 to 5.5. scorers, yet do not attempt as many isolation shots as cluster 1 players.

3.1.9 Variance of clusters with field goal percentage in isolation



Cluster 0 players make between 0 and 41% of their isolation shot attempts. Cluster 1 players make between 38 and 60% of their isolation shot attempts. Cluster 2 players shoot at an extremely efficient rate, making between 40 and 80 percent of their isolation field goal attempts.

3.1.10 Variance of clusters with effective field goal percentage in isolation



The ranges here echo those of the field goal percentage statistic. Cluster 0 players don't shoot efficiently in isolation, at effective field goal percentages between 0 and 43%. Cluster 1 players score at an effective field goal percentage between 39 and 60%. Finally, cluster 2 players are extremely efficient, with an effective field goal percentage between 39 and 100%.

3.2 Cuts

3.2.1 Describing clusters

Below are the ranges of each statistic for the cut clusters.

Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	.5-2.4	3.1-11.8	0.83-1.70	0.6-3.1	.2-1.2	.4-2.0	36.4-87.5	36.4-106.3
1	.5-2.4	3.5-13.0	0.00-0.93	0.0-1.7	0.0-.6	.4-2.1	0.0-43.8	0.0-50.0
2	2.1-6.5	9.4-22.3	0.72-1.28	1.7-7.4	0.7-2.4	1.7-5.3	34.0-56.4	34.0-58.5

Table 1: Cut Cluster Values

Cluster 0 players do not cut very often, yet score extremely efficiently when they do. Cluster 1 players also do not cut very often, and are also inefficient scorers on those few cuts. Cluster 2 players cut to the basket very frequently and score efficiently, although not to the same threshold as cluster 0 players. Relatively infrequent cuts for clusters 0 and 1 indicate that they either predominantly play on-ball or isolate in the low post. Cluster 2 players play off-ball, cut very frequently, and also score efficiently on cuts, suggesting that the cluster is composed of offensively talented big men who can also play on the perimeter. Checking the names of the players in each cluster confirms this analysis. Cluster 0 includes players who are typically most effective when they have time to work with the ball prior to a shot attempt, like Giannis Antetokounmpo, Jonas Valanciunas or Kristaps Porzingis. Cluster 1 includes players who typically operate in the low post, like Jusuf Nurkic or Kevon Looney. Finally, cluster 2 includes the likes of Evan Mobley, Domantas Sabonis, Anthony Davis and Nikola Jokic, offensively efficient big men who can play on any section of the court.

Cluster 0 consists of, among others, the following players:

- Giannis Antetokounmpo
- Obi Toppin
- Jonas Valanciunas
- Goga Bitadze
- Kevin Durant
- Kristaps Porzingis
- De'Andre Hunter
- Keldon Johnson

Cluster 1 included:

- Jusuf Nurkic
- Kevon Looney
- Brook Lopez
- Clint Capela
- Nikola Vucevic
- Marvin Bagley III
- Bam Adebayo
- Alperen Sengun

Cluster 2 included:

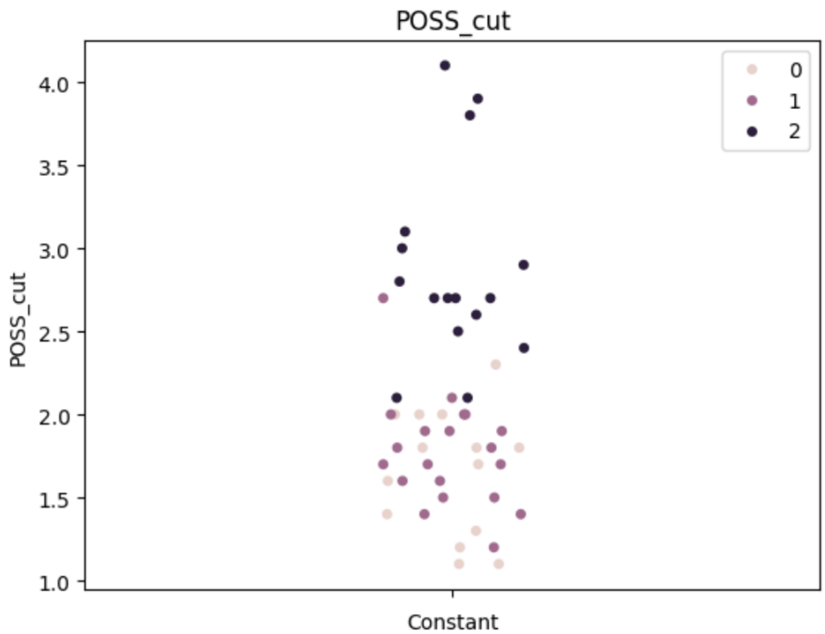
- Evan Mobley
- Jarrett Allen

- Domantas Sabonis
- Ivica Zubac
- Anthony Davis
- Nikola Jokic
- Rudy Gobert
- Walker Kessler
- Jalen Duren

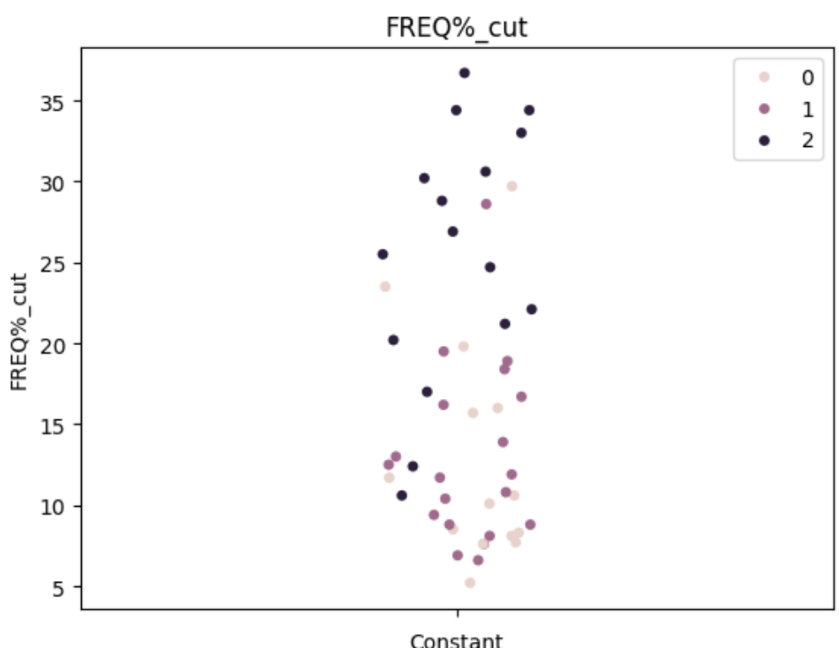
3.2.2 Clusters under PCA

The clustering doesn't appear to be working well on cuts. Let's see how the clusters vary over individual statistics.

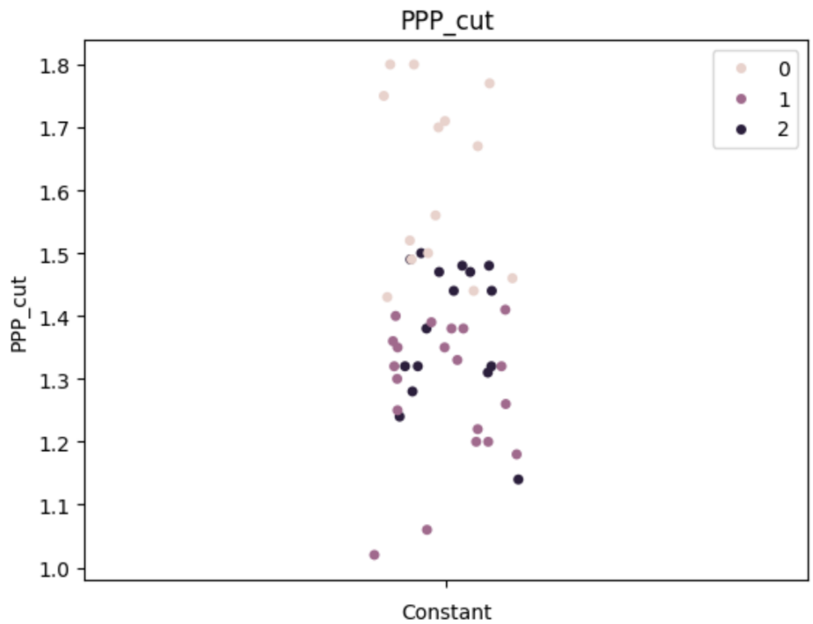
3.2.3 Variance of clusters with average number of cuts per game



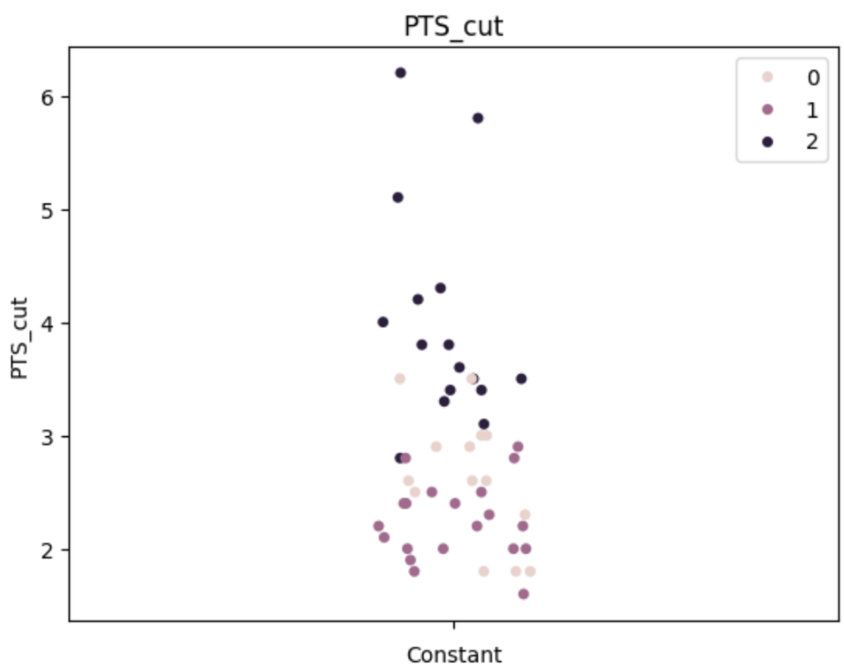
3.2.4 Variance of clusters with frequency of cuts



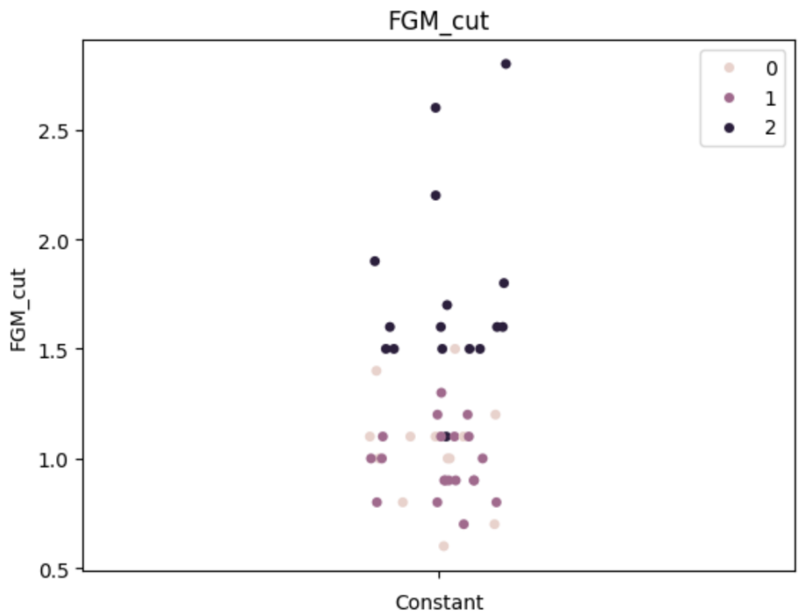
3.2.5 Variance of clusters with points per possession on cuts



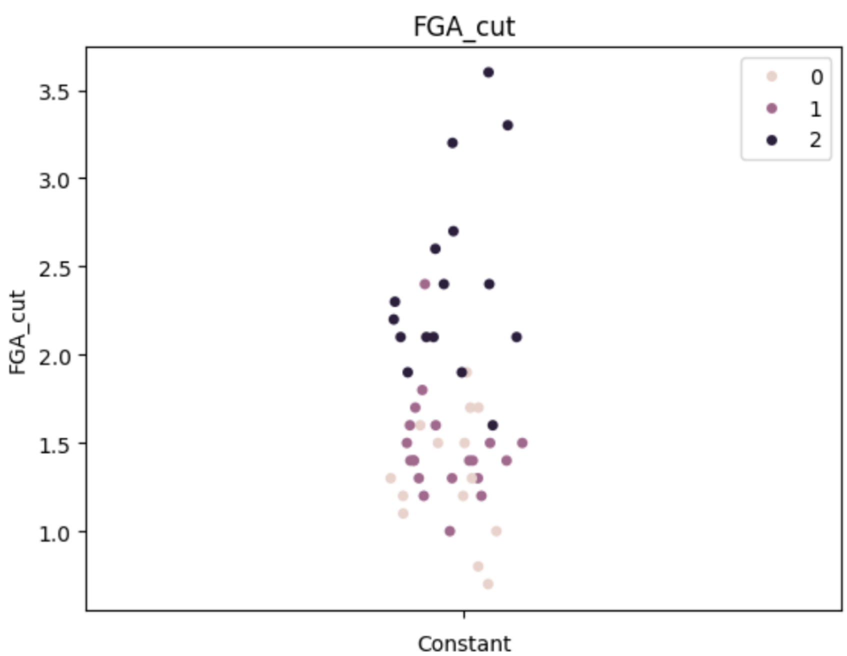
3.2.6 Variance of clusters with PPG from cuts



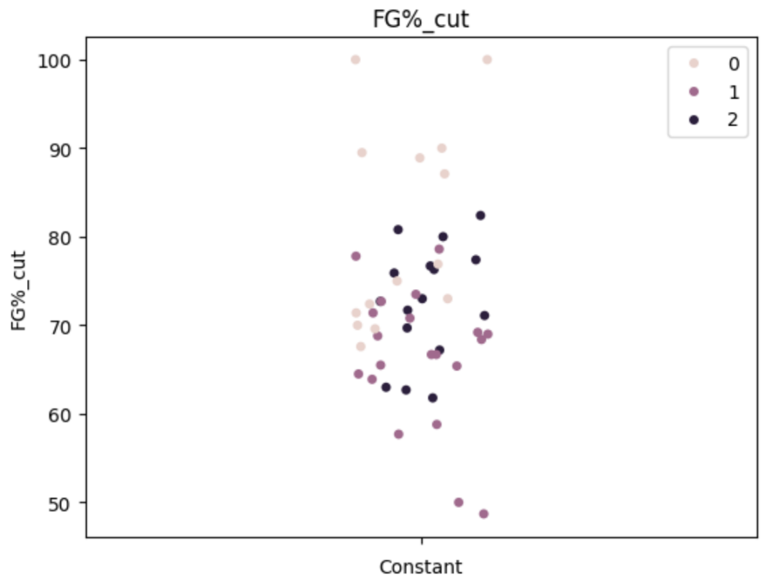
3.2.7 Variance of clusters with FGM from cuts



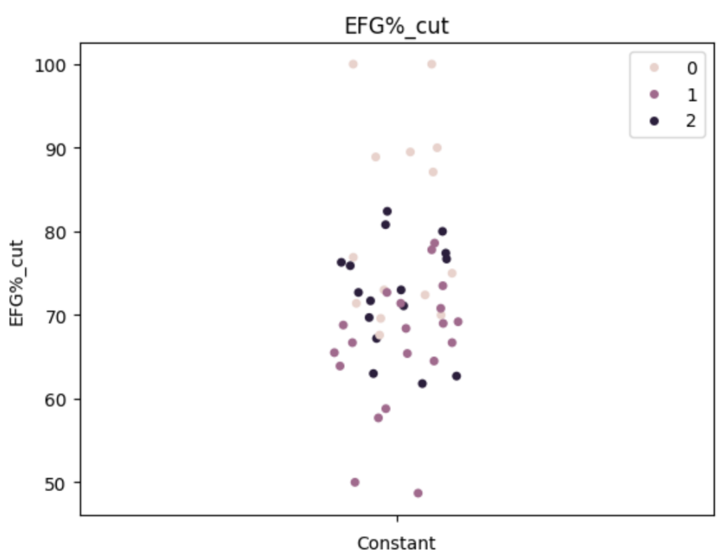
3.2.8 Variance of clusters with FGA from cuts



3.2.9 Variance of clusters with FG% on cuts



3.2.10 Variance of clusters with EFG% on cuts



3.3 Off screen

3.3.1 Describing clusters

3.3.2 Clusters under PCA

3.4 Pick and roll ball handler

3.5 Pick and roll roller

3.6 Post up

3.7 Spot up

4 Analyzing Players

4.1 Case Study A0: Nikola Jokic

4.2 Case Study A1: Anthony Davis

4.3 Case Study A2: Tyrese Haliburton

4.4 Case Study A3: Anthony Edwards

5 Analyzing 2023-24 Lineup Compositions

5.1 Lineups

The top five lineups in the NBA this season in terms of offensive rating (over 100 minutes played together) are:

- Nicolas Batum, Tobias Harris, Joel Embiid, De'Anthony Melton, Tyrese Maxey @ PHI (136.4)
- Myles Turner, Buddy Hield, Bruce Brown, Obi Toppin, Tyrese Haliburton @ IND (134.4)
- Kevin Durant, Eric Gordon, Jusuf Nurkic, Devin Booker, Grayson Allen @ PHX (126.6)
- Brook Lopez, Damian Lillard, Khris Middleton, Giannis Antetokounmpo, Malik Beasley @ MIL (125.2)
- James Harden, Paul George, Kawhi Leonard, Ivica Zubac, Terance Mann @ LAC (122.3)

5.2 Case Study B0: Philly Lineup

Player	Isolation	Cut	Off screen	PnR handler	PnR roller	Post up	Spot up
Batum	INS.	INS.	INS.	INS.	INS.	INS.	0
Harris	1	0	INS.	0	INS.	0	0
Embiid	0	0	INS.	INS.	0	2	0
Melton	1	INS.	2	2	INS.	INS.	0
Maxey	0	INS.	0	1	INS.	INS.	0

Table 1: Philly Lineup Composition

5.3 Case Study B1: Indiana Lineup

Player	Isolation	Cut	Off screen	PnR handler	PnR roller	Post up	Spot up
Turner	INS.	0	INS.	INS.	0	0	1
Hield	INS.	INS.	1	0	1	INS.	0
Brown	2	INS.	INS.	2	INS.	INS.	0
Toppin	INS.	2	INS.	INS.	INS.	INS.	0
Haliburton	2	INS.	INS.	1	INS.	INS.	0

Table 1: Indiana Lineup Composition

5.4 Case Study B2: Phoenix Lineup

Player	Isolation	Cut	Off screen	PnR handler	PnR roller	Post up	Spot up
Durant	0	2	1	2	0	2	0
Gordon	INS.	INS.	INS.	0	INS.	INS.	0
Nurkic	INS.	0	INS.	INS.	1	2	1
Booker	0	INS.	1	1	INS.	0	1
Allen	INS.	INS.	INS.	2	INS.	INS.	0

Table 1: Phoenix Lineup Composition

5.5 Case Study B3: Milwaukee Lineup

Player	Isolation	Cut	Off screen	PnR handler	PnR roller	Post up	Spot up
Lopez	INS.	0	INS.	INS.	0	1	0
Lillard	0	INS.	INS.	1	INS.	INS.	0
Middleton	2	INS.	INS.	0	INS.	0	1
Antetokounmpo	0	2	INS.	2	0	2	1
Beasley	INS.	INS.	INS.	0	INS.	INS.	0

Table 1: Milwaukee Lineup Composition

5.6 Case Study B4: Clippers Lineup

Player	Isolation	Cut	Off screen	PnR handler	PnR roller	Post up	Spot up
Harden	0	INS.	INS.	1	INS.	INS.	0
George	0	INS.	1	2	INS.	0	0
Leonard	0	INS.	0	2	INS.	1	0
Zubac	INS.	1	INS.	INS.	0	0	INS.
Mann	INS.	1	INS.	INS.	0	0	INS.

Table 1: Clippers Lineup Composition

5.7 Lineup Analysis Conclusions

6 Further work

Right now, I'm working on a few different extensions of this project:

- Breaking down most effective combos of clusters in starting lineups
- Graphics to holistically visualize a player's strengths/weaknesses as determined by their cluster
- A similar analysis on 2022-23 data to determine areas of improvement
- A similar analysis, but for player defense against the same types of plays