Clustering NBA Players Offensively

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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 of 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.

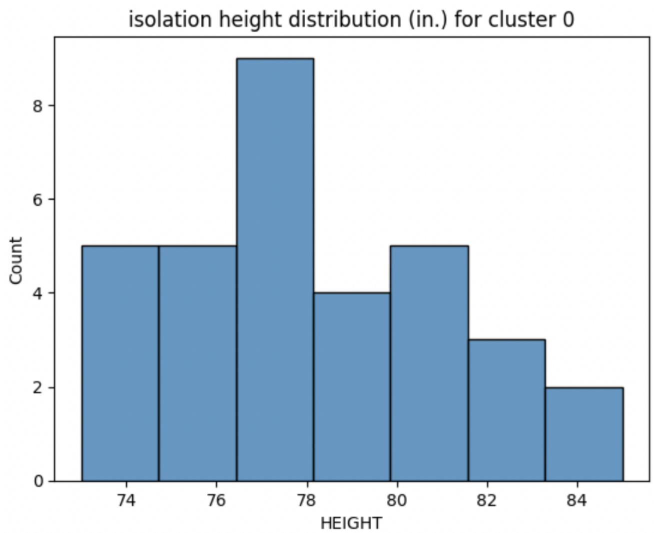
Cluster	**POSS**	**FREQ%**	**PPP**	**PTS**	**FGM**	**FGA**	**FG%**	**EFG%**
0	0-2.5	2.5-12.5	0-.85	0-1.5	0-.6	0-2	0-42	0-42
1	2.5-7	11-22.5	.75-1.25	1.5-7.5	.55-2.4	1.9-5.2	35-60	35-58
2	0-2.5	2.5-12.5	.75-1.75	.75-3	.2-1.2	0-2	39-85	38-105

Table 1: Isolation Cluster Values

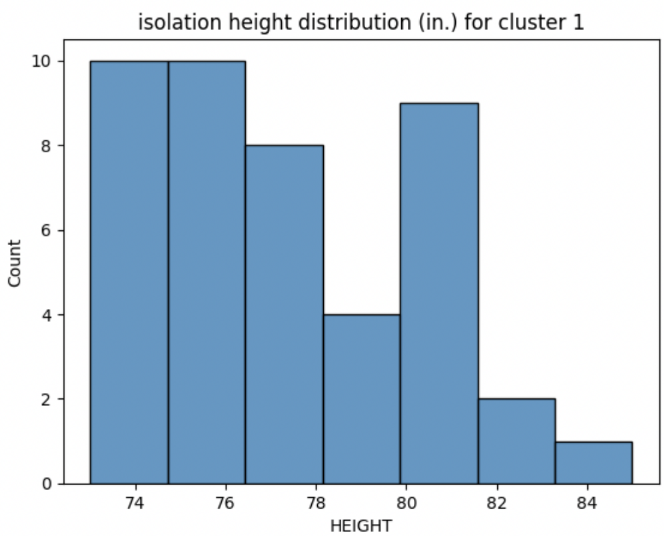
Cluster 0 players attempt isolation plays relatively infrequently, and aren't very productive in such plays. Cluster 1 players attempt a lot of isolation plays, and are moderately efficient at generating points off such possessions. Cluster 2 players don't attempt many isolation plays, but are incredibly 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 0 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 1 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. The fact that cluster 1 players are mostly point guards provides an explanation for why they isolate less than other players, as they are responsible for facilitating plays.

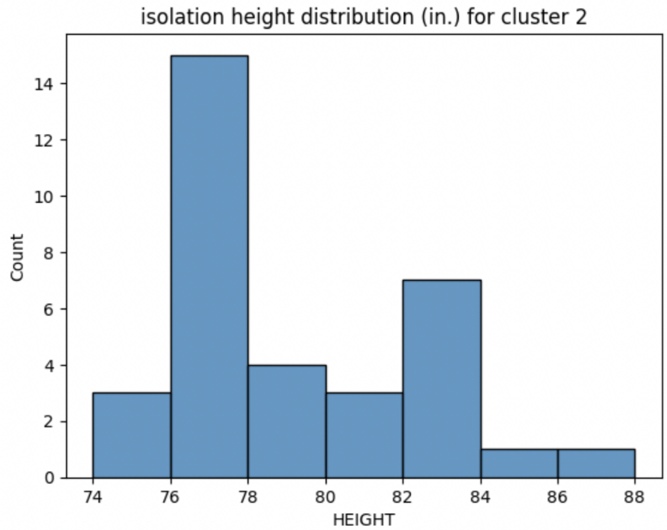
To confirm these identities, the weight and height of the players in each cluster were found. While the mean heights of all the clusters were within the 77-78 inch (6-5 to 6-6) range, there were clear left and right skews in the cluster height distributions that demonstrated the size differences between the different clusters. Cluster 0 players were mostly in the 74-82 inch range (6-1 to 6-8), while shorter players in the <78 inch interval were far more common in cluster 1, confirming the identification of cluster 0 with strong forwards in the 6-6 to 6-9 range (Luka, LeBron, Jayson Tatum) and cluster 1 with shorter, shiftier point guards. Cluster 2 clearly consists of bigs, with a right skew ranging from 78-88 inches (6-5 to 7-3):



The cluster 0 height histogram shows a relatively even distribution, centered around the 74-82 inches.

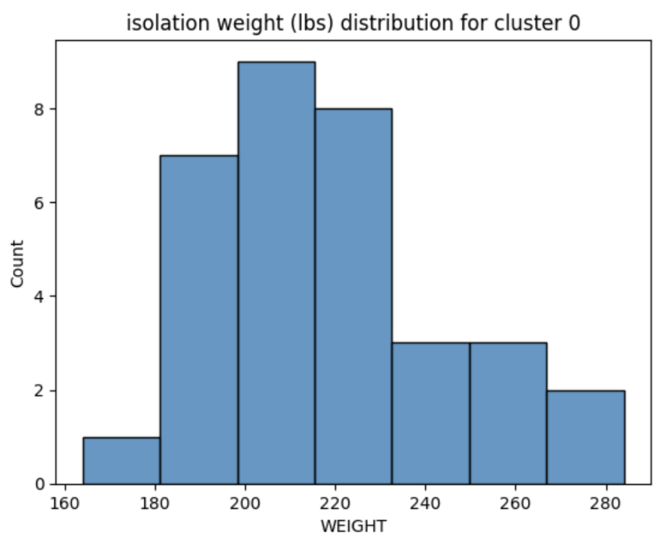


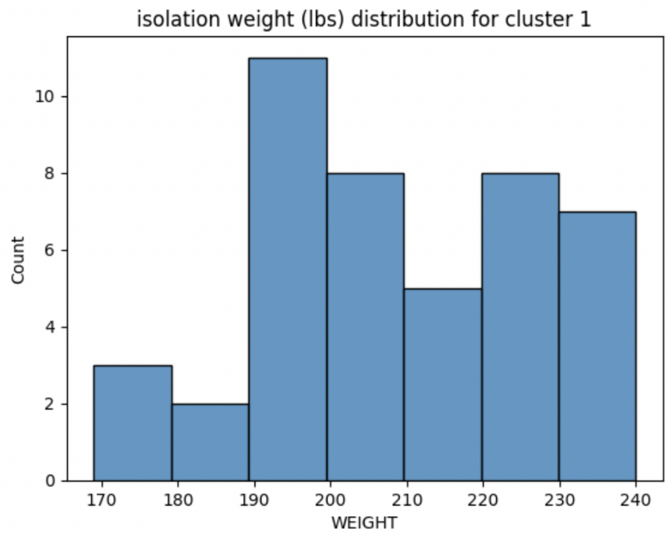
Cluster 1 is dominated by players less than 78 inches tall.

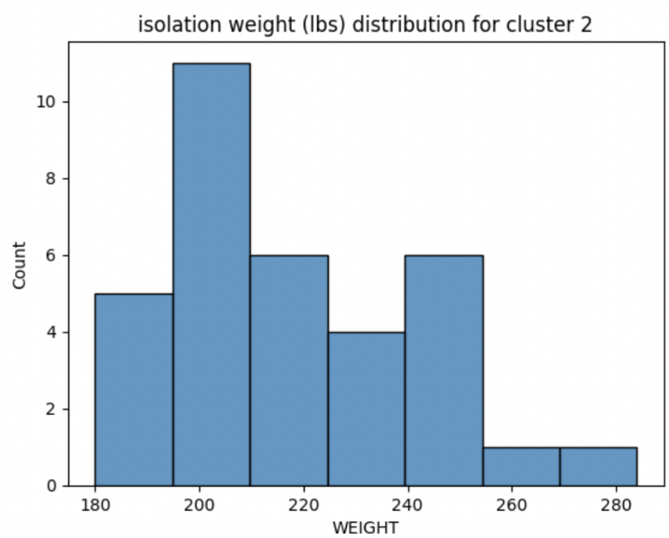


Cluster 2 has a clear right-skew, with a spike in the 82 to 84 inch range.

Weight is distributed along similar lines. Players in clusters 0 and 1 are fairly similar, ranging from 180 to 240 pounds. Cluster 2 players, on the other hand, weigh as much as 280 pounds, with virtually all players 200 pounds or heavier. Such results confirm cluster 2 as consisting of shooting big men, cluster 1 as shifty point guards, and cluster 0 as strong forwards.







Each cluster can then be summarized as follows:

Cluster	Name	Description	Height (in)	Weight (lbs)
0	Strong forward	less efficient, many attempts	74-82	180-240
1	Shifty guard	moderately efficient, few attempts	< 78	180-240
2	Shooting big	highly efficient, few attempts	78-88	200-300

Table 1: Isolation clusters descriptions

Below is a list of a few players in each cluster, in support of the identifications made above.
Cluster 0 players include:

- Luka Doncic
- LeBron James
- Jimmy Butler
- Anthony Edwards
- Kevin Durant
- Brandon Ingram
- DeMar DeRozan
- Jayson Tatum

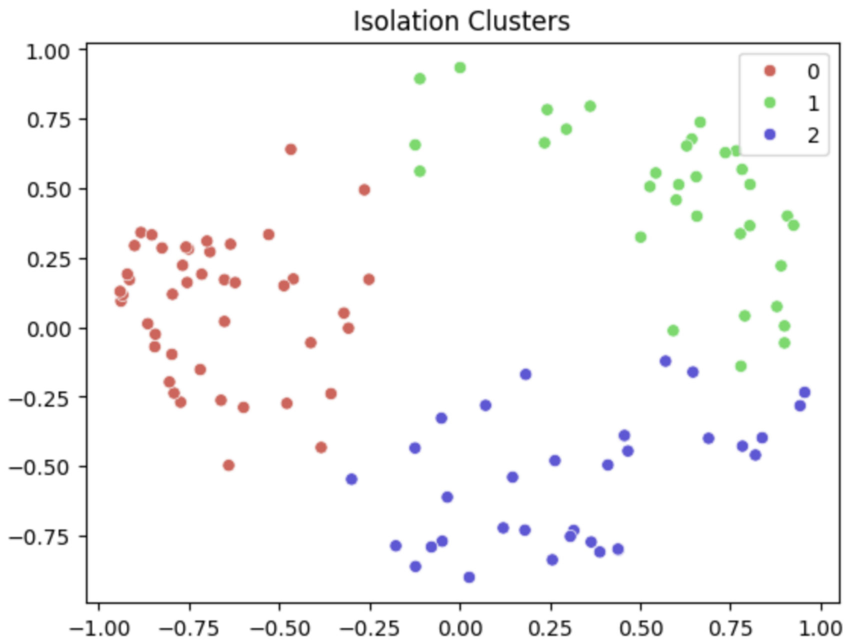
Cluster 1 players include:

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

Cluster 2 players include:

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

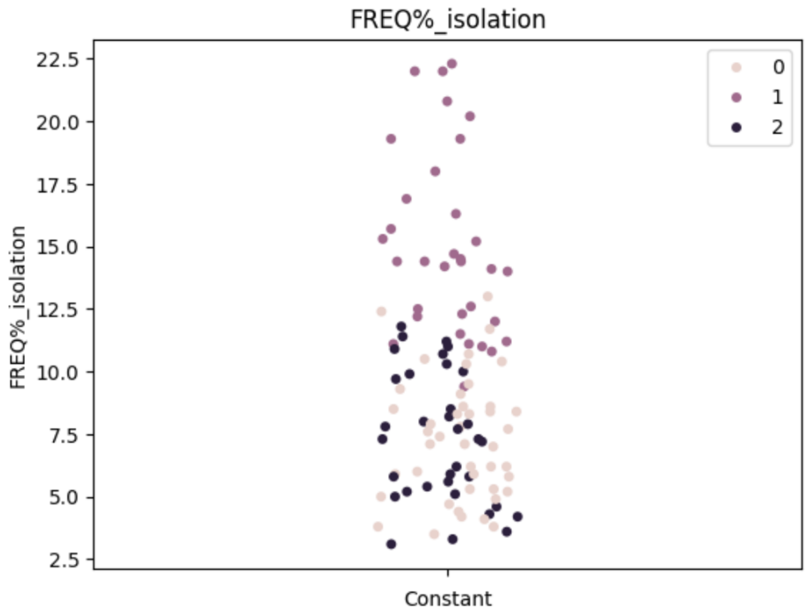
3.1.2 Clusters under PCA



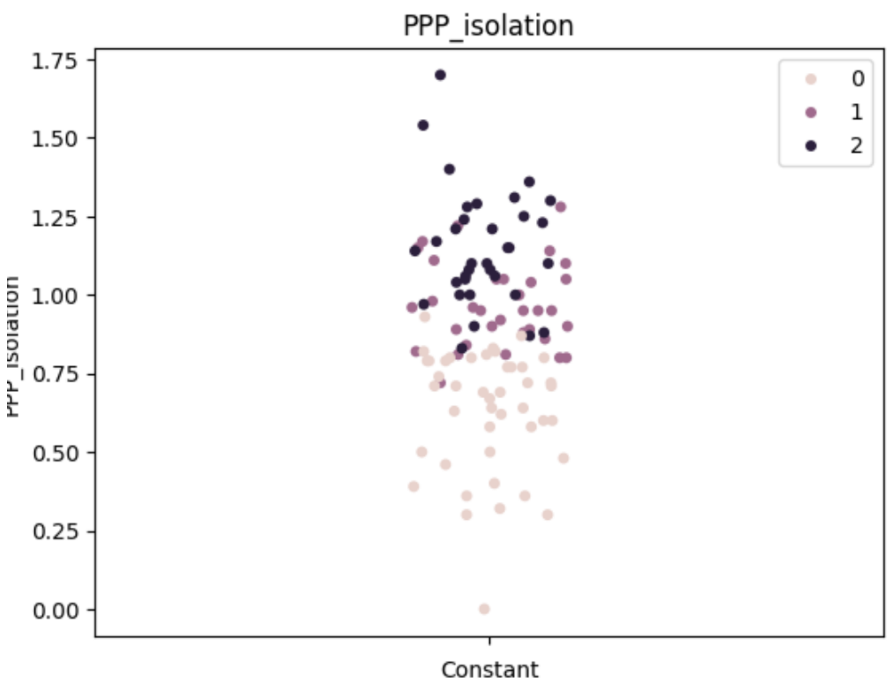
The axes are the two PCA components. It seems like the clustering algorithm is working moderately well for isolation plays.

3.1.3 Variance of clusters with POSS

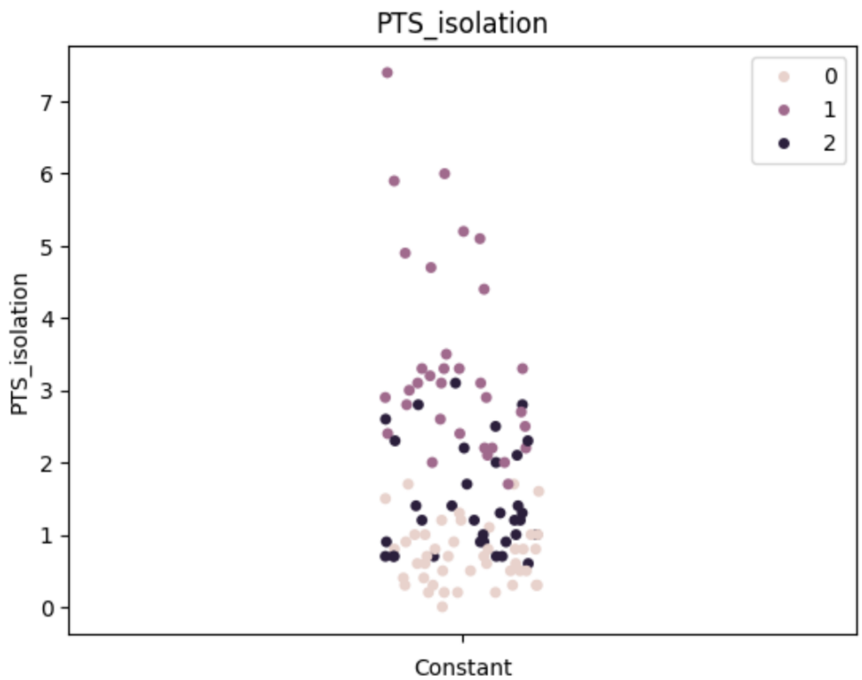
3.1.4 Variance of clusters with FREQ%



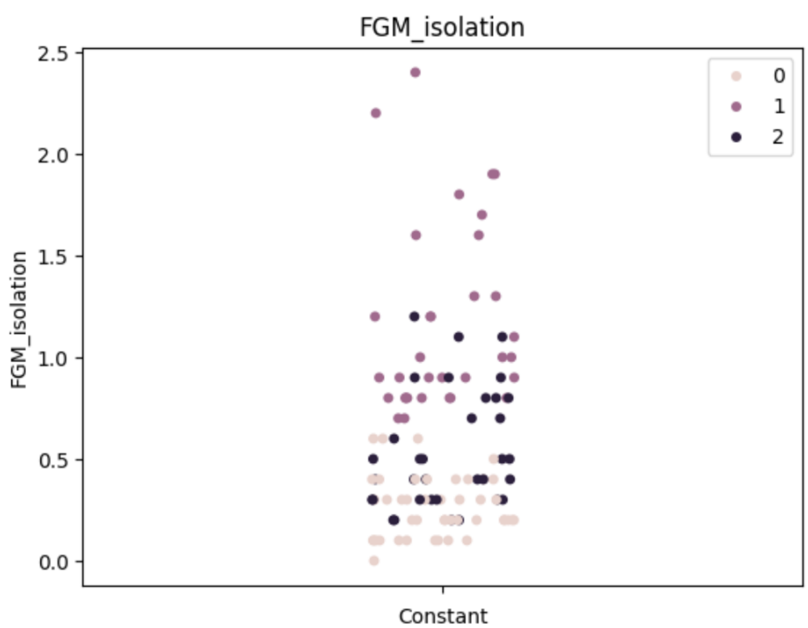
3.1.5 Variance of clusters with PPP



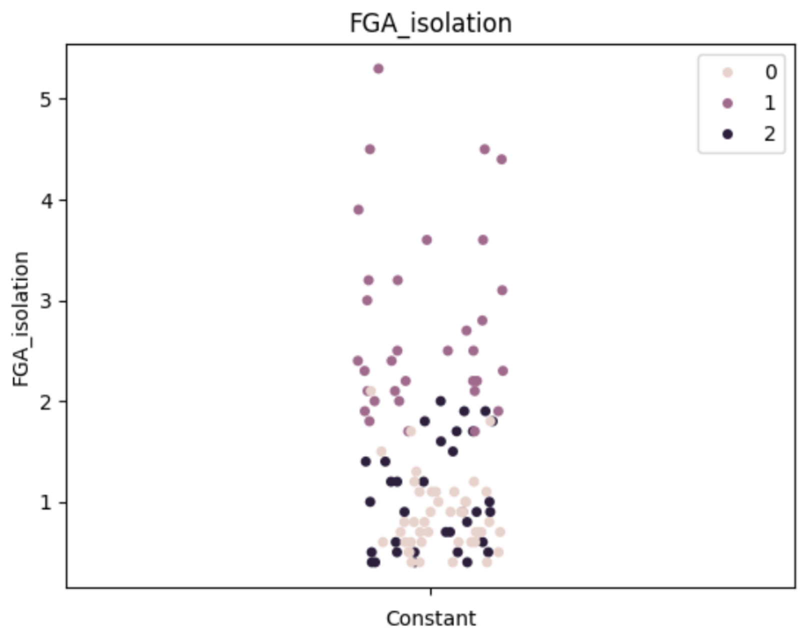
3.1.6 Variance of clusters with PTS



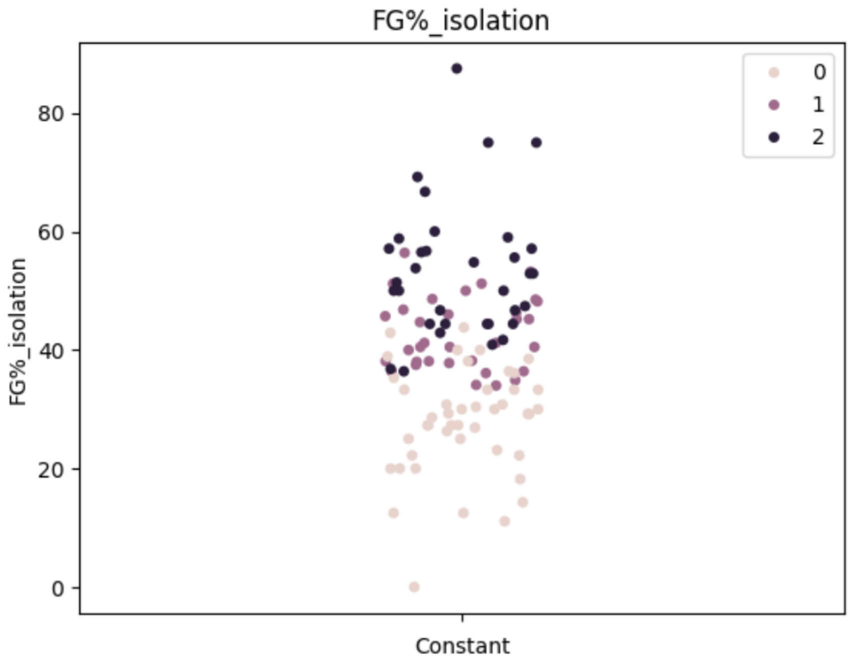
3.1.7 Variance of clusters with FGM



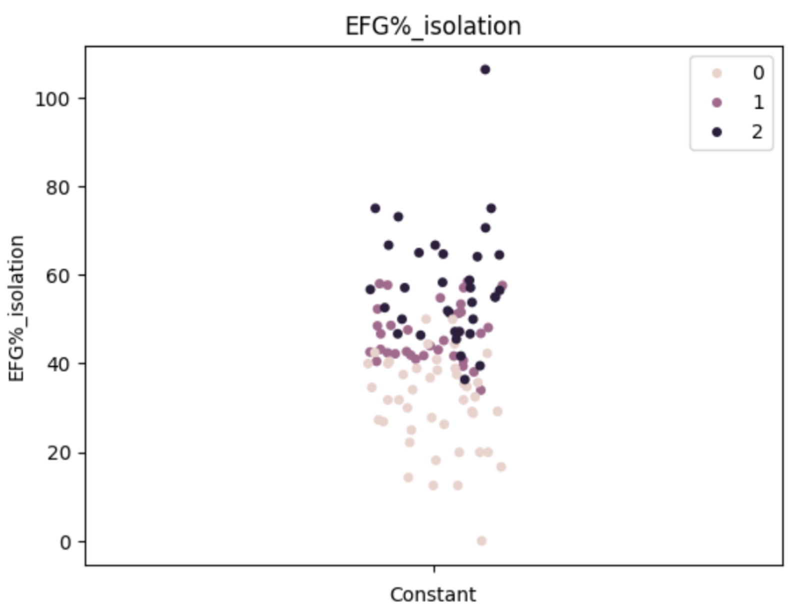
3.1.8 Variance of clusters with FGA



3.1.9 Variance of clusters with FG%



3.1.10 Variance of clusters with EFG%



3.2 Cuts

3.2.1 Describing clusters

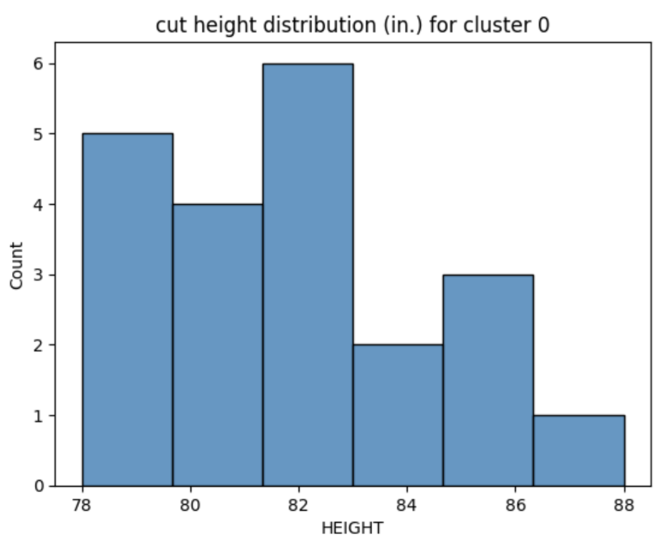
Below are the ranges of each statistic for the cut clusters.

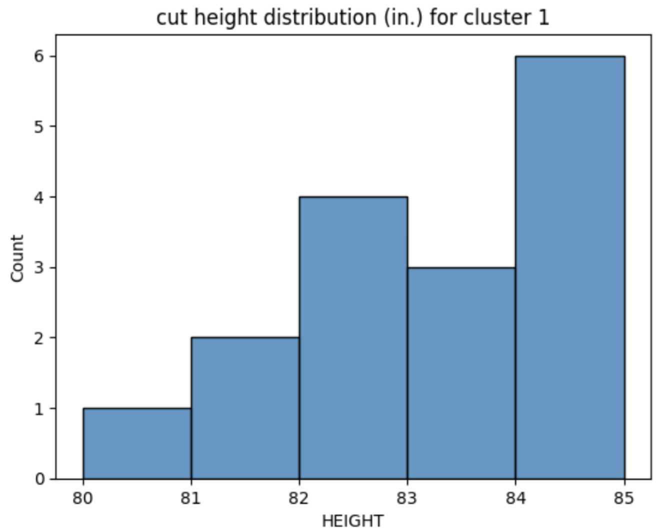
Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	.5-2.4	3.1-11.8	0.83-1.70	0.6-3.1	.2-1.2	.4-2.0	36.4-87.5	36.4-106.3
1	.5-2.4	3.5-13.0	0.00-0.93	0.0-1.7	0.0-.6	.4-2.1	0.0-43.8	0.0-50.0
2	2.1-6.5	9.4-22.3	0.72-1.28	1.7-7.4	0.7-2.4	1.7-5.3	34.0-56.4	34.0-58.5

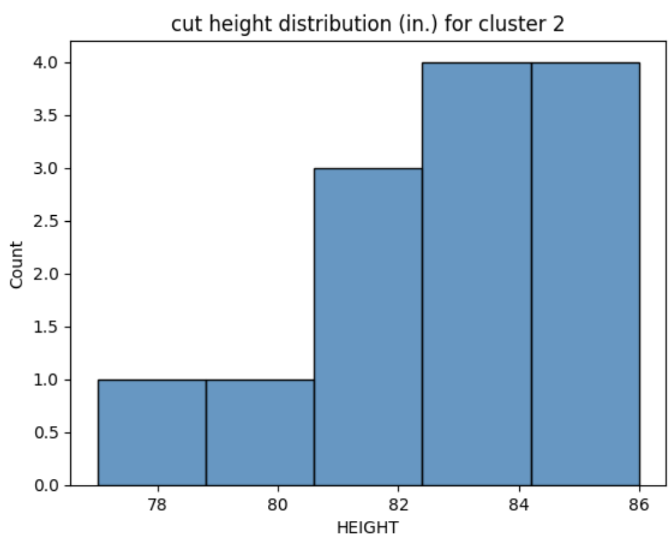
Table 1: Cut Cluster Values

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.

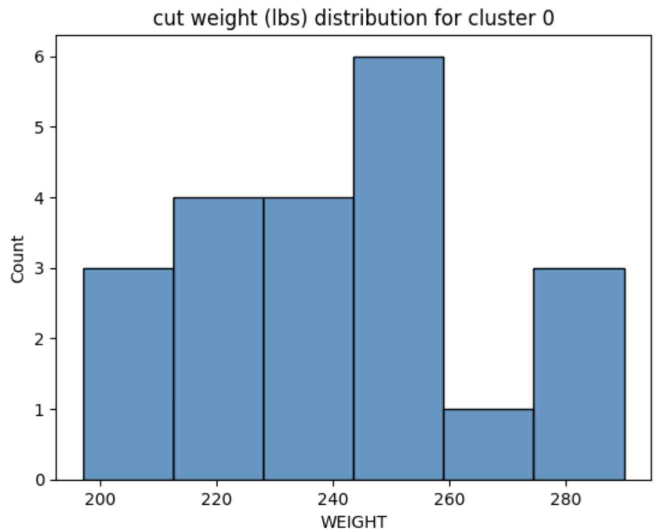
Checking the heights of players in each cluster, we can see that cluster 0 players are generally shorter than cluster 1 and 2 players. The latter two clusters are composed of players with similar heights.

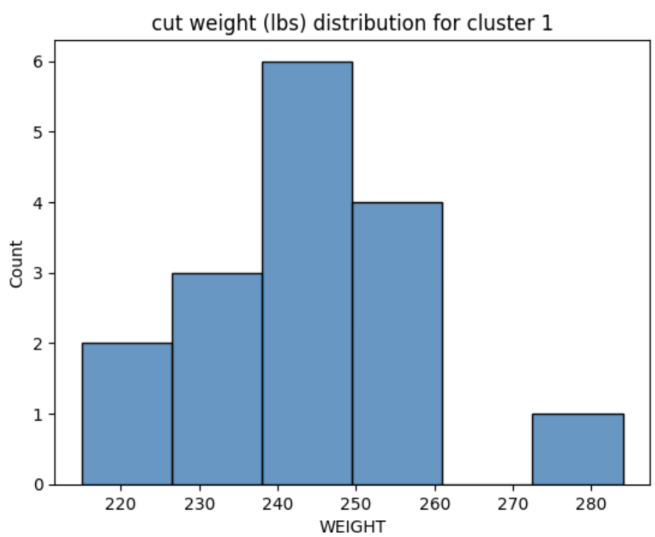


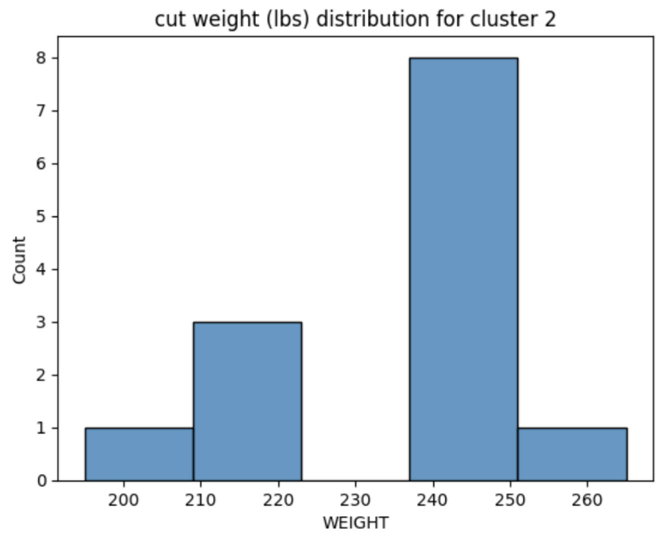




With regard to weights, cluster 2 consists of significantly heavier players than cluster 1.


cut weight (lbs) distribution for cluster 0
Count
0
1
2
3
4
5
6
200
220
240
260
280
WEIGHT


cut weight (lbs) distribution for cluster 1
Count
0
1
2
3
4
5
6
220
230
240
250
260
270
280
WEIGHT



Cluster 0 included:

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

Cluster 1 included:

- Evan Mobley
- Jarrett Allen
- Domantas Sabonis
- Ivica Zubac
- Anthony Davis
- Nikola Jokic
- Rudy Gobert

- Walker Kessler
- Jalen Duren

Cluster 2 includes:

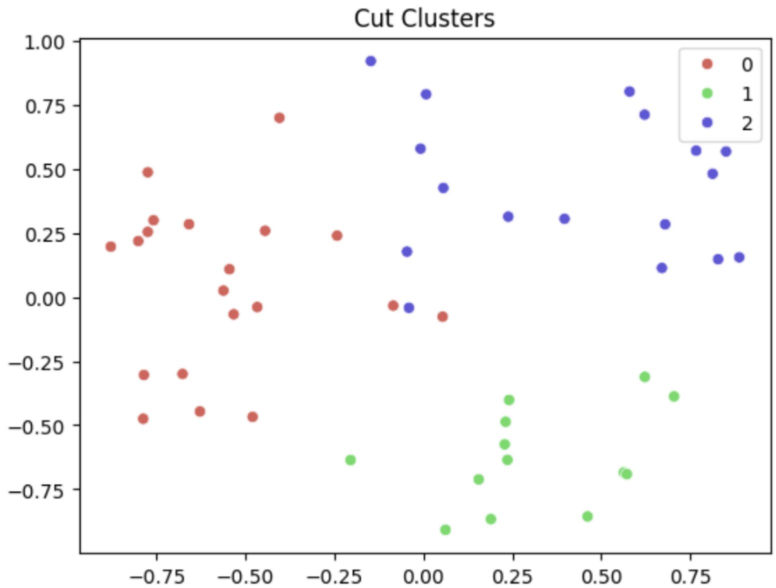
- Giannis Antetokounmpo
- Obi Toppin
- Jonas Valanciunas
- Goga Bitadze
- Kevin Durant
- Kristaps Porzingis
- De'Andre Hunter
- Keldon Johnson

Broadly, cluster 0 seems to be composed of traditional big men who specialize more in traditional post play than perimeter shooting. Cluster 1 includes shooting big men who perform backdoor and baseline cuts with exceptional mobility, shooting, and passing abilities. Finally, cluster 2 players are athletic and versatile, who have a unique combination of skill and size (Kevin Durant, Chet Holmgren), that allows them to finish at the rim extremely efficiently on cuts.

Cluster	Name	Description	Height (in)	Weight (lbs)
0	Traditional post bigs	cut infrequently, strong post play	78-82	200-250
1	Versatile bigs	cut from perimeter often, mobile	82-85	220-260
2	Dynamic wing forwards	skilled and tall, high level finishers	82-86	240-260

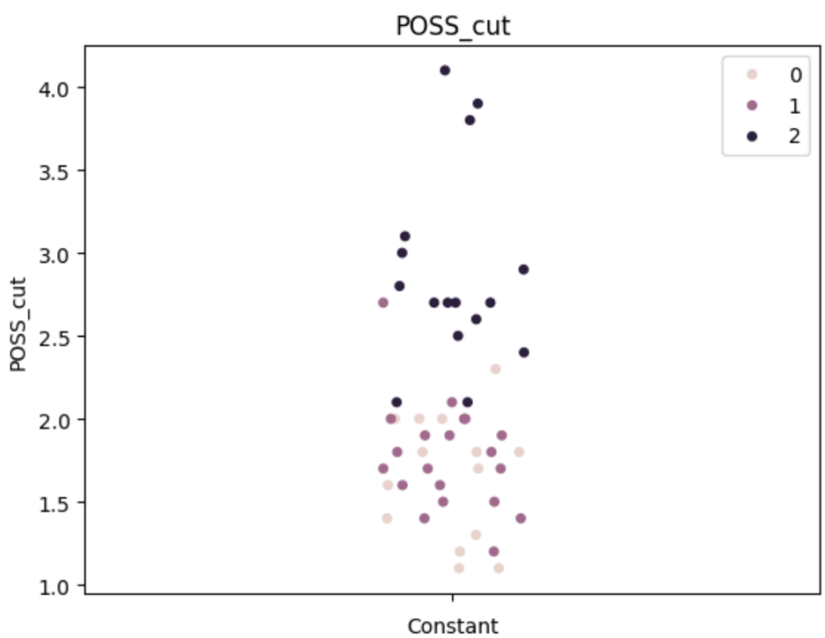
Table 1: Descriptions of cut clusters

3.2.2 Clusters under PCA

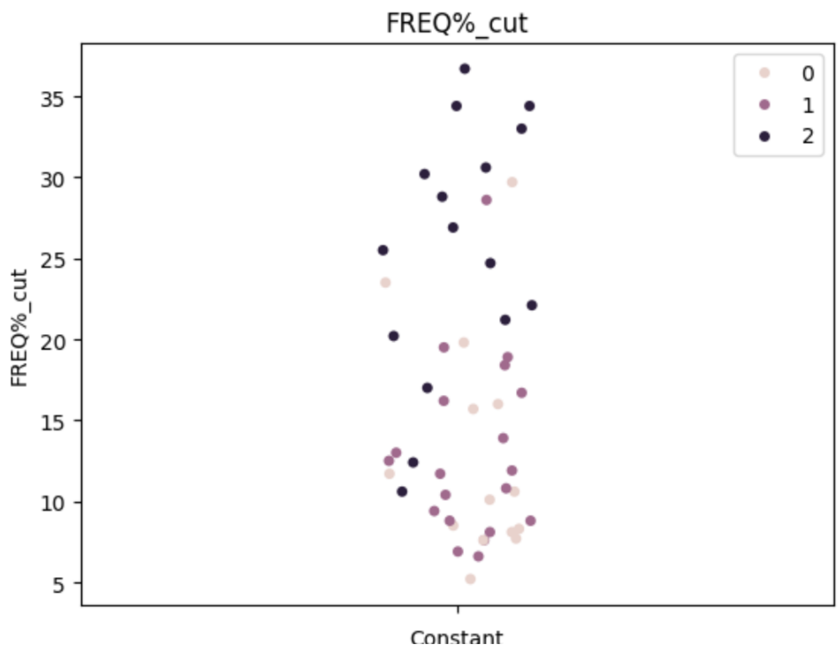


The clustering doesn't appear to be working well on cuts. Let's see how the clusters vary over individual statistics.

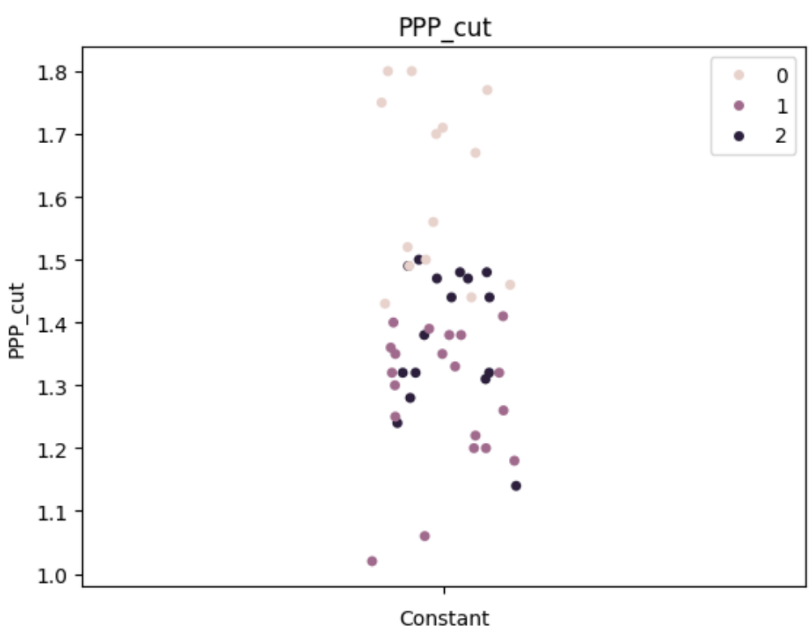
3.2.3 Variance of clusters with POSS



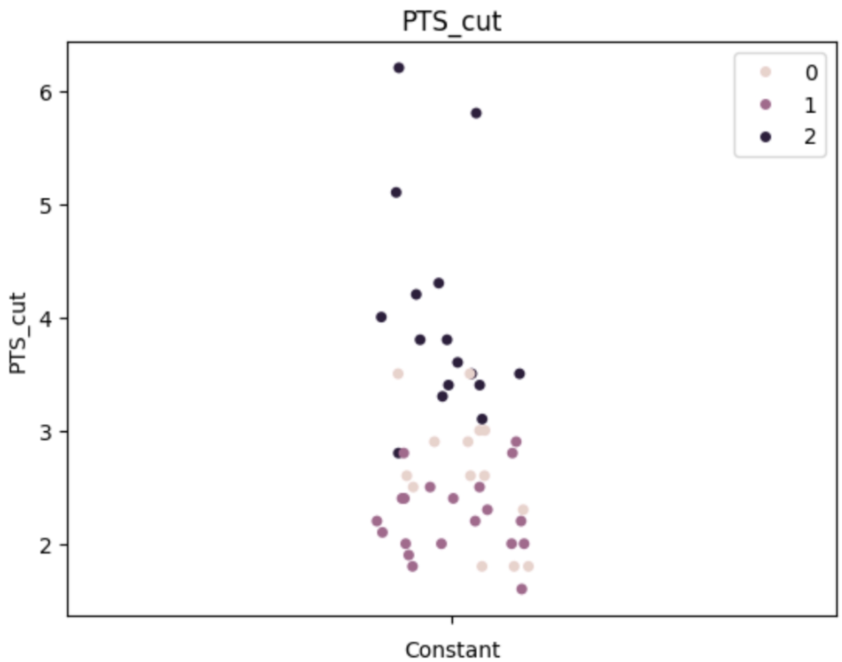
3.2.4 Variance of clusters with FREQ%



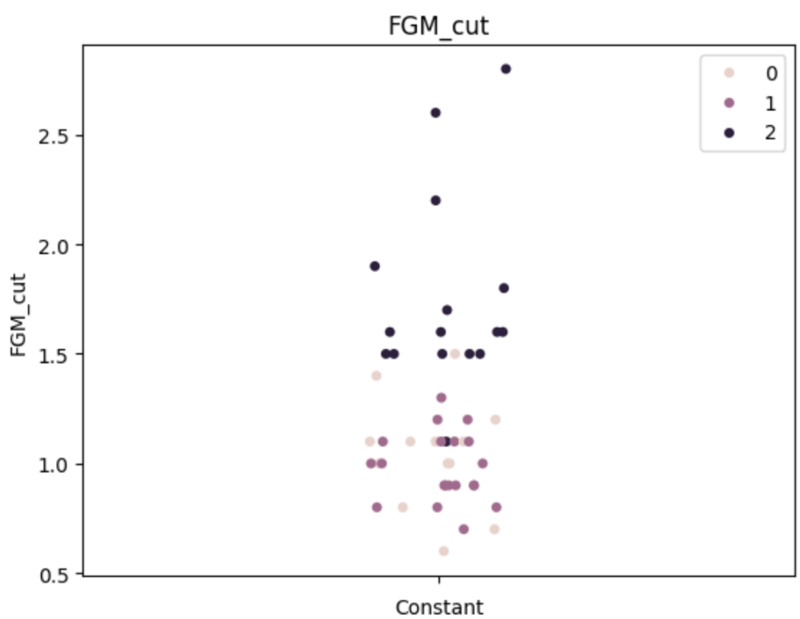
3.2.5 Variance of clusters with PPP



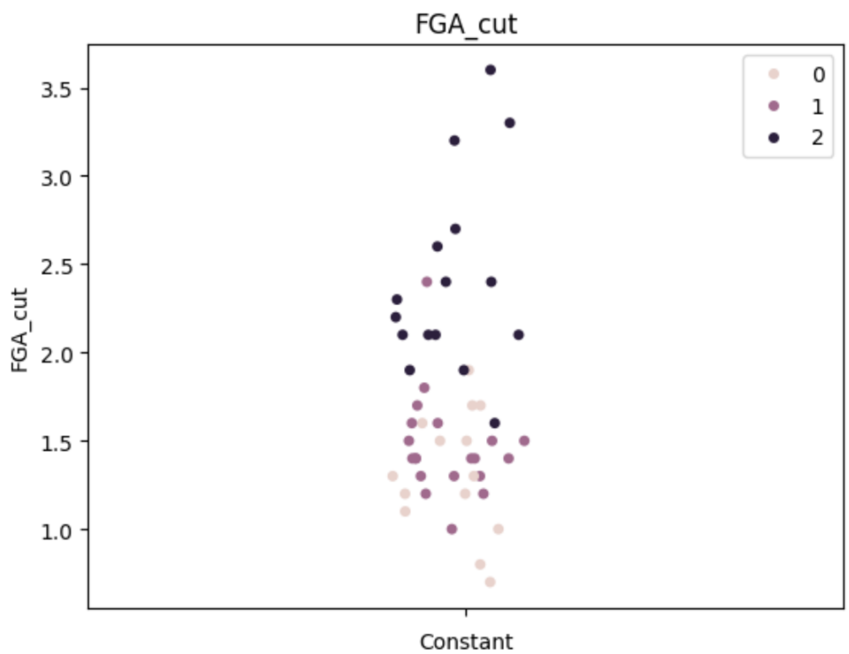
3.2.6 Variance of clusters with PTS



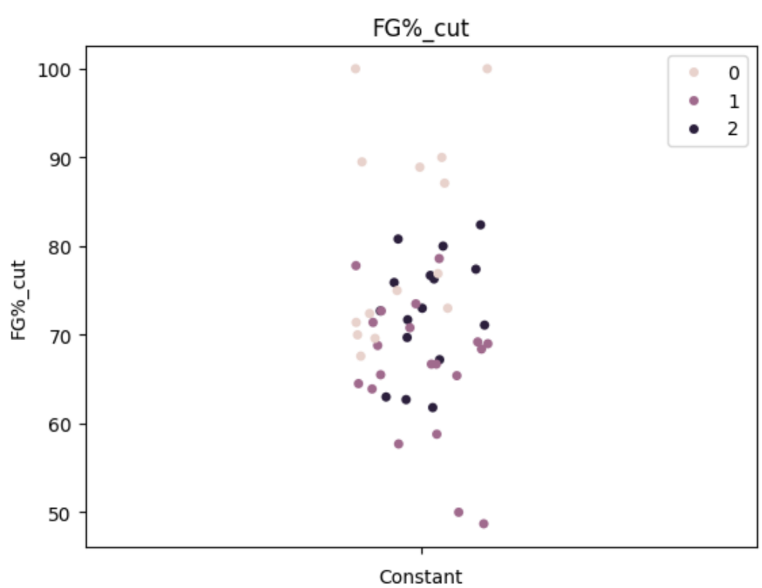
3.2.7 Variance of clusters with FGM



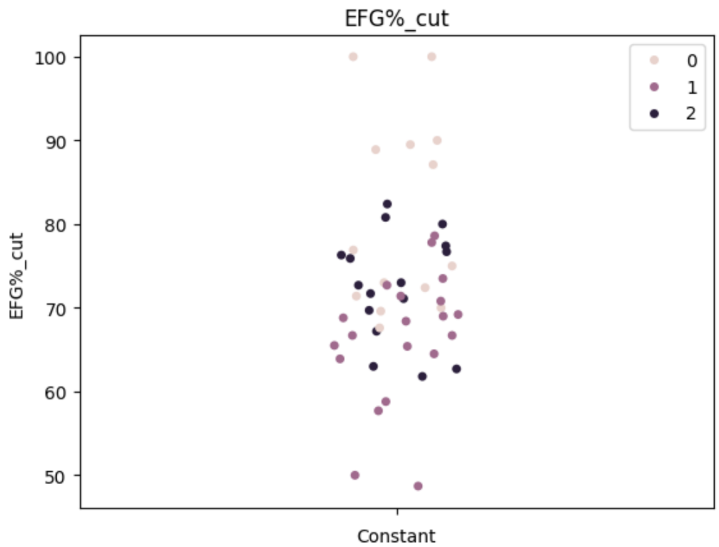
3.2.8 Variance of clusters with FGA



3.2.9 Variance of clusters with FG%



3.2.10 Variance of clusters with EFG%



3.3 Off screen

3.3.1 Describing clusters

The range of values for each cluster are detailed in the following table:

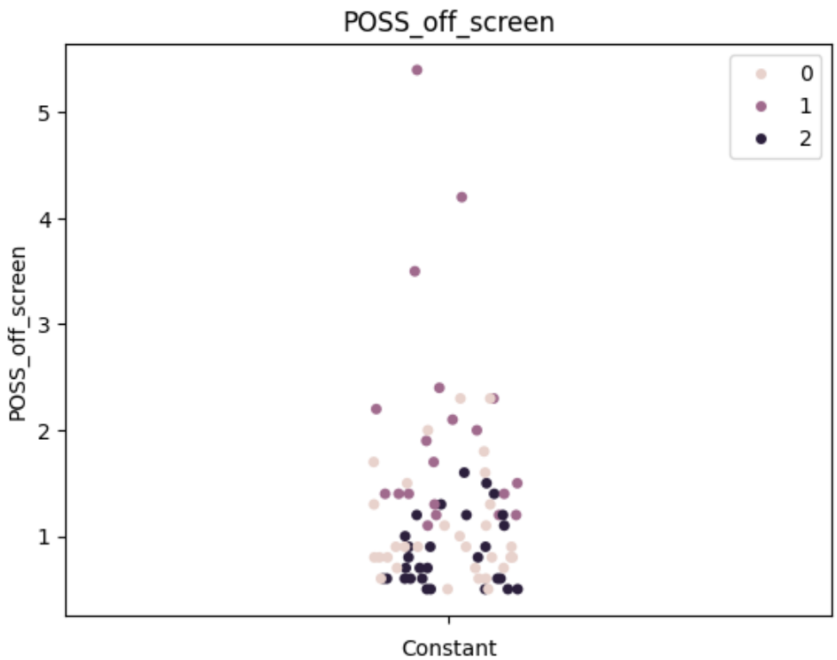
Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	.5-2.3	2.7-18.2	.36-1	.3-1.8	.1-.7	.4-1.8	19-44.4	10-60
1	1.1-5.4	5.4-33.2	.85-1.44	1.1-6.1	.4-2.1	.9-4.7	36.2-61.5	40.6-76
2	.5-1.6	1.8-9.7	1-1.64	.6-1.9	.2-.8	.4-1.4	36.4-75	40.9-87.5

Table 1: Off Screen Cluster Values

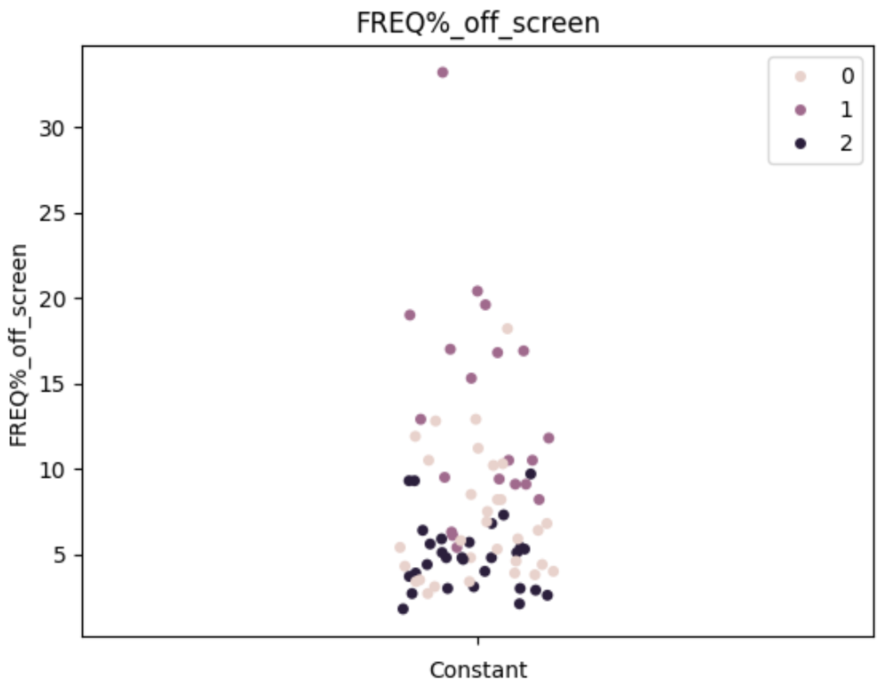
3.3.2 Clusters under PCA

The clusters are visible and clearly delineated under PCA, suggesting KMeans is operating well.

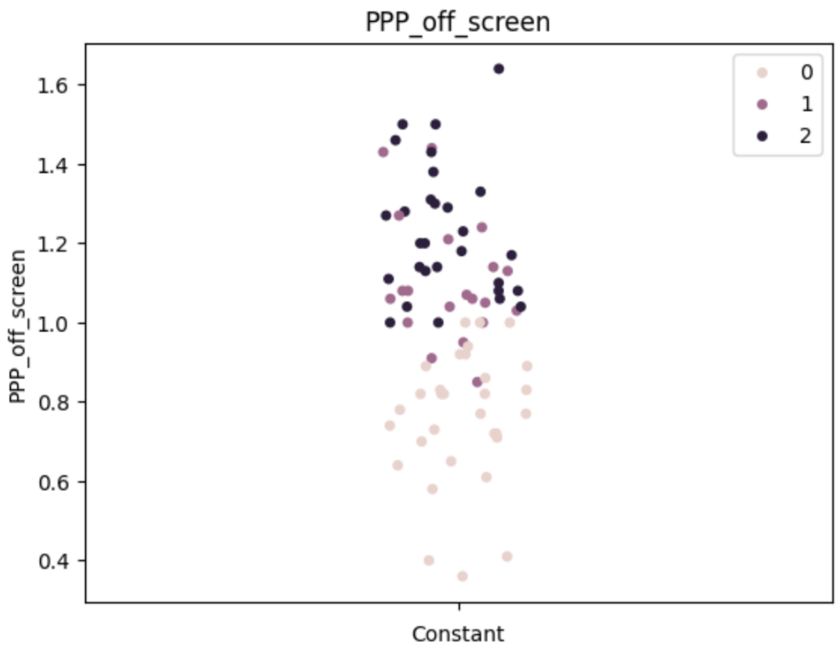
3.3.3 Variance of clusters with POSS



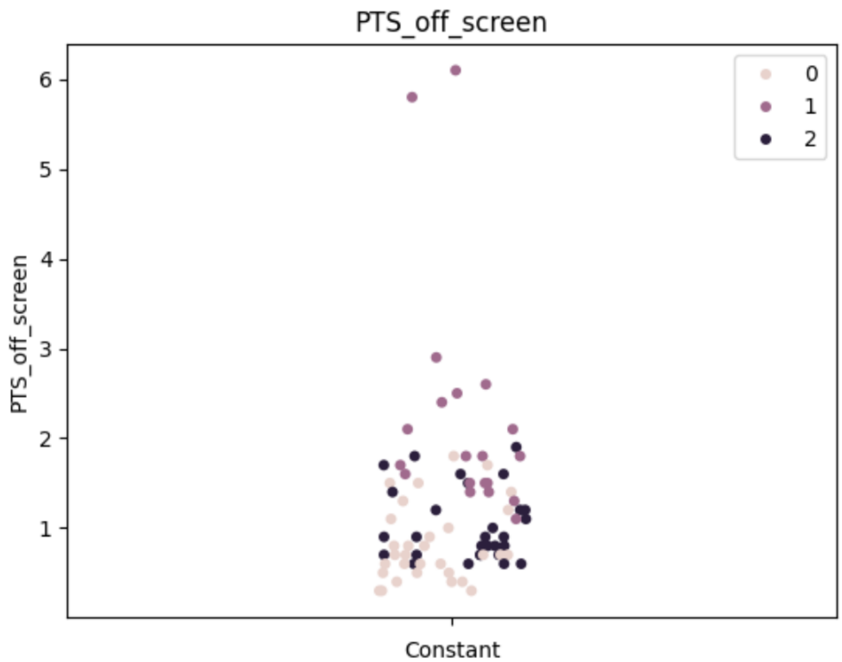
3.3.4 Variance of clusters with FREQ%



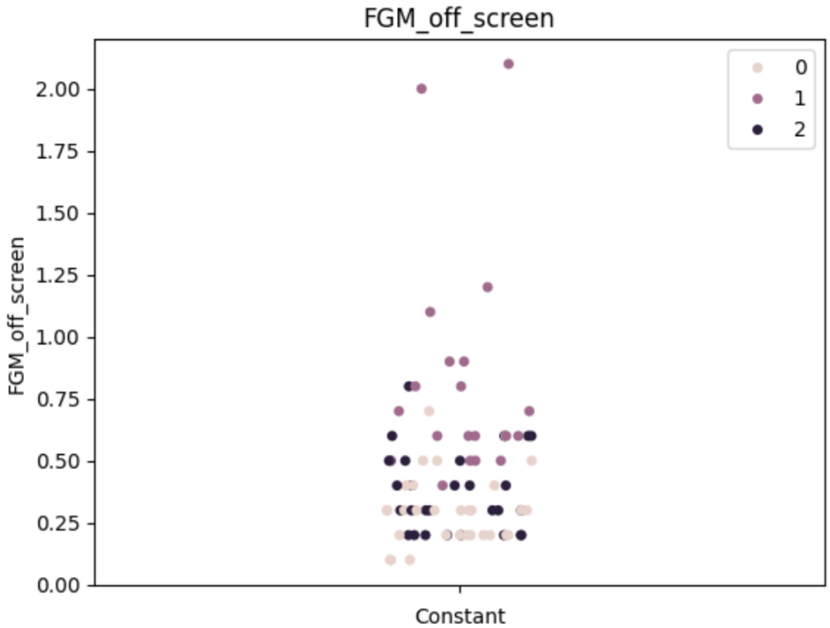
3.3.5 Variance of clusters with PPP



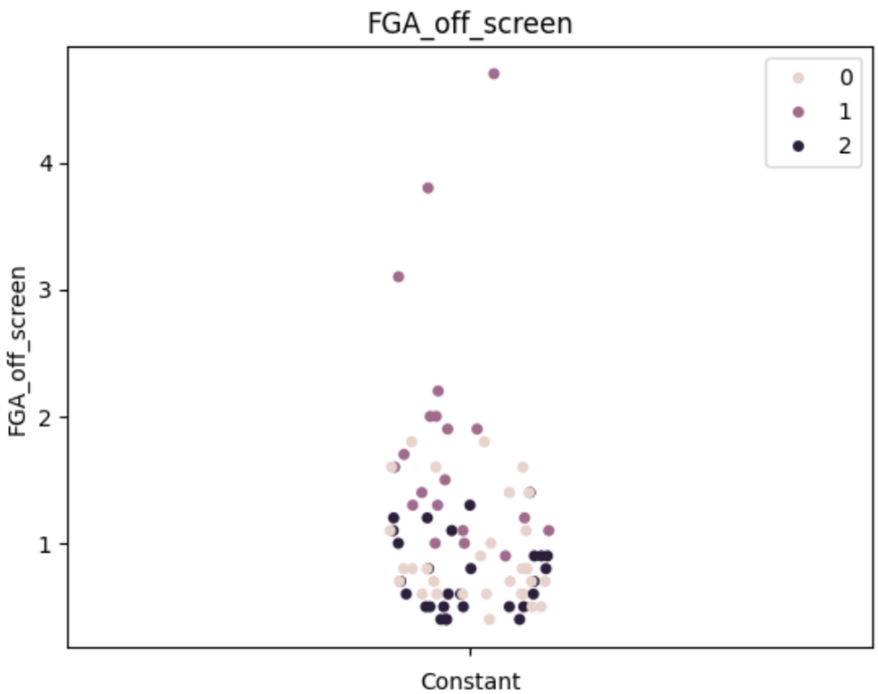
3.3.6 Variance of clusters with PTS



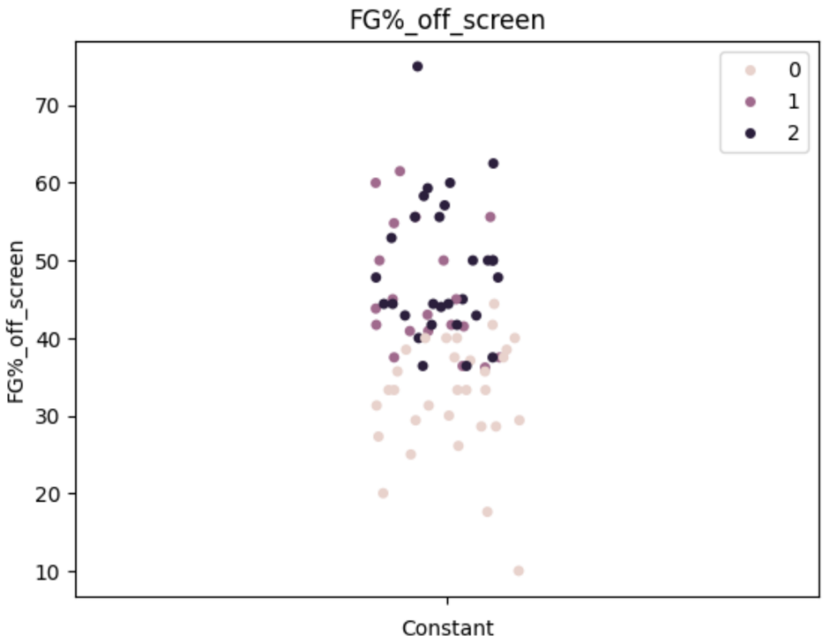
3.3.7 Variance of clusters with FGM



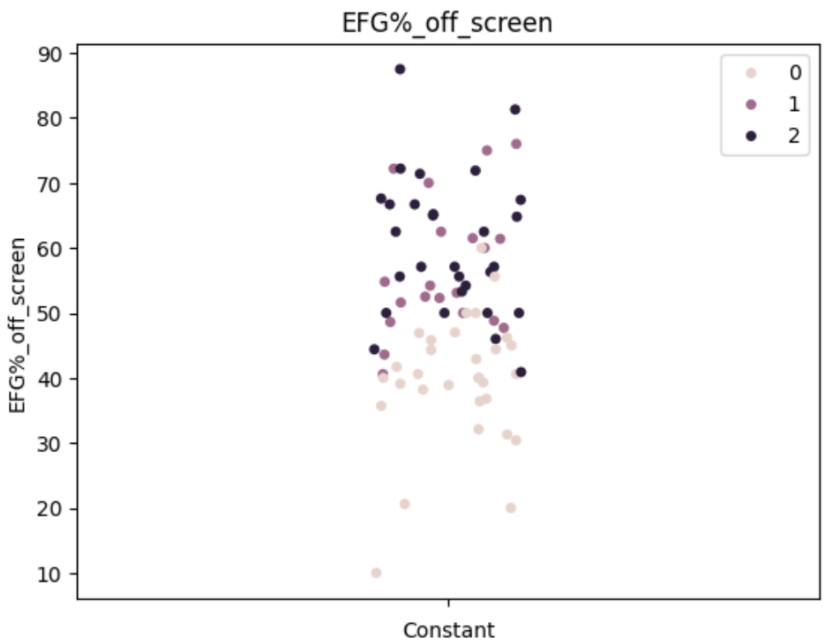
3.3.8 Variance of clusters with FGA



3.3.9 Variance of clusters with FG%



3.3.10 Variance of clusters with EFG%



3.4 Pick and roll ball handler

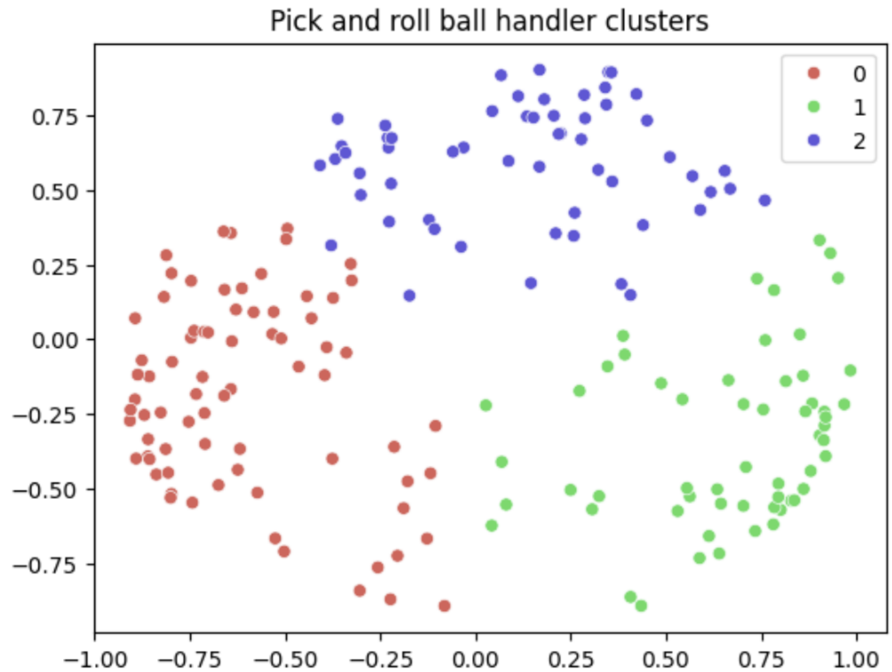
3.4.1 Describing clusters

The clusters range over the following values:

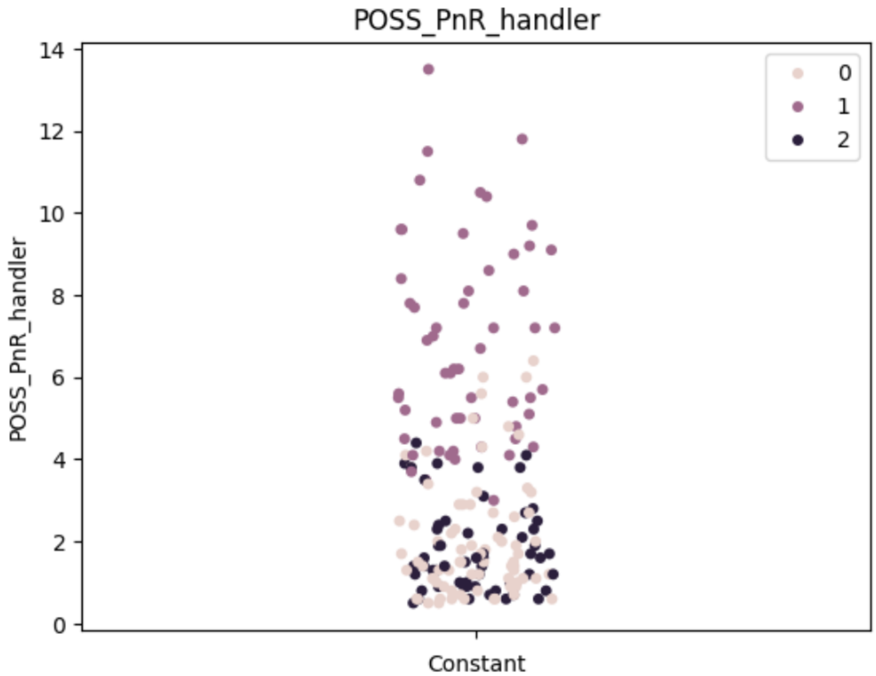
Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	.5-6.4	2.4-42.2	.27-.91	.2-4.5	0.0-1.7	.3-4.7	0.0-50.0	0.0-58.3
1	3-13.5	21.7-57.5	.75-1.24	2.7-13.5	1.1-4.5	2.5-9.8	31.3-65.9	34.4-66.5
2	.5-4.4	3.2-43.9	.78-1.60	.5-4.9	.2-1.8	.4-3.4	36.4-66.7	38.5-77.8

Table 1: Pick and roll ball handler clusters

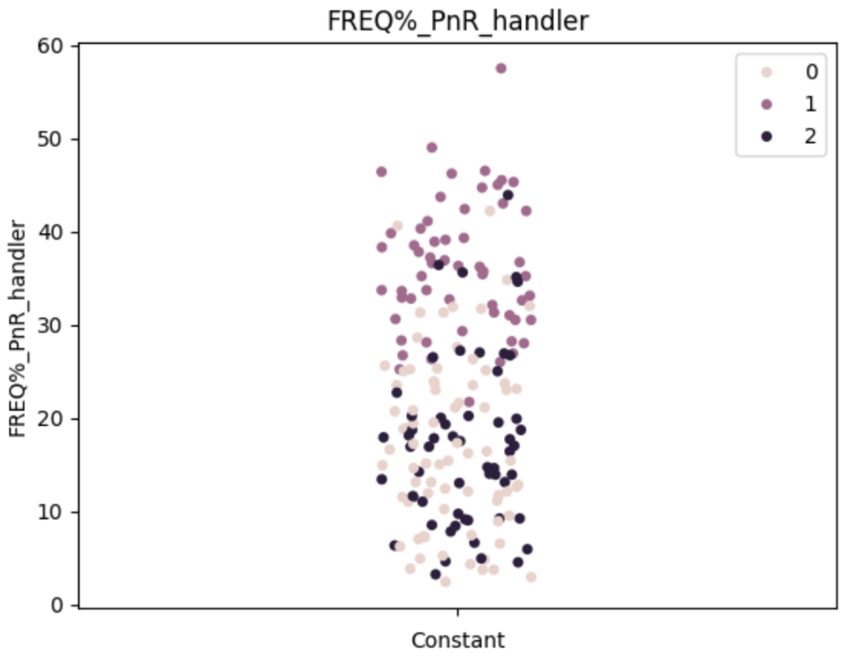
3.4.2 Clusters under PCA



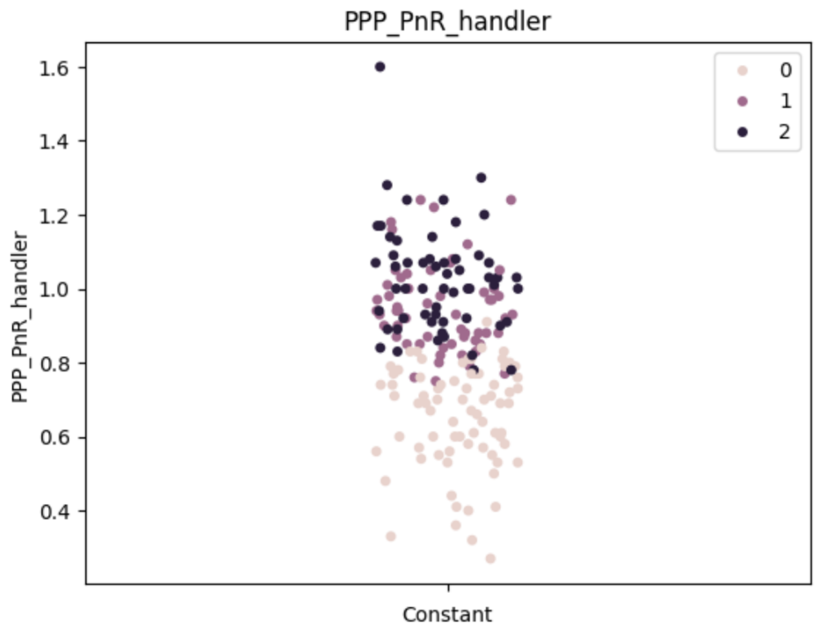
3.4.3 Variance of clusters with POSS



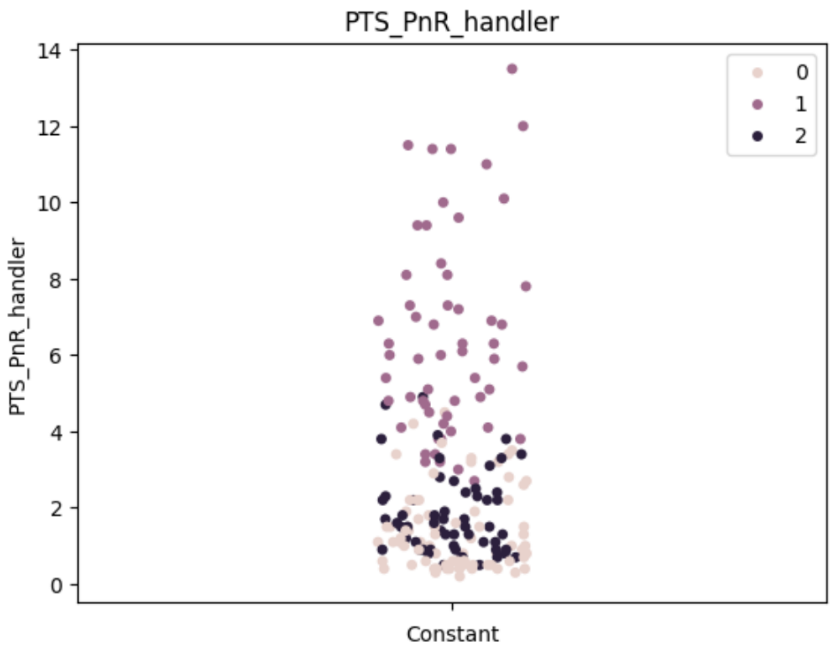
3.4.4 Variance of clusters with FREQ%



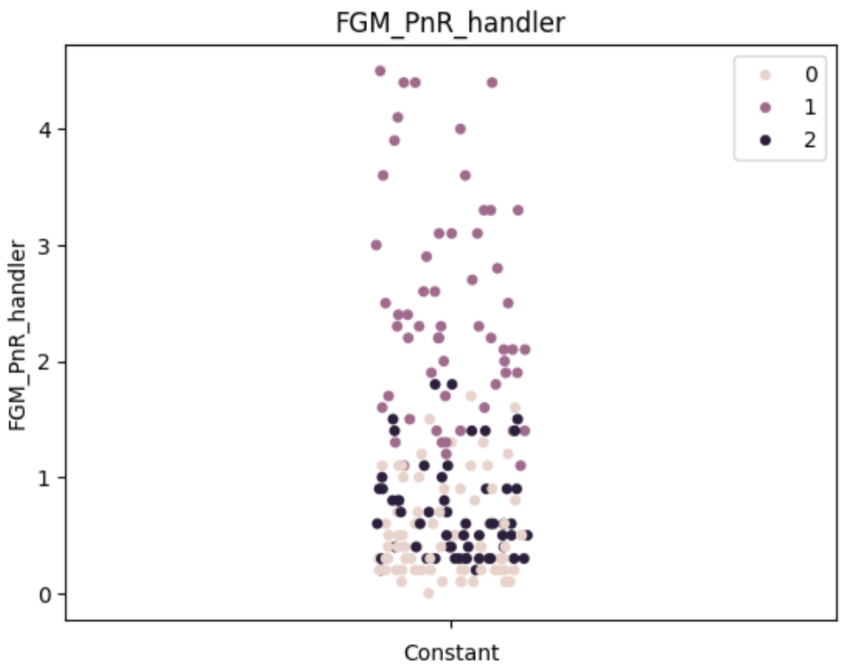
3.4.5 Variance of clusters with PPP



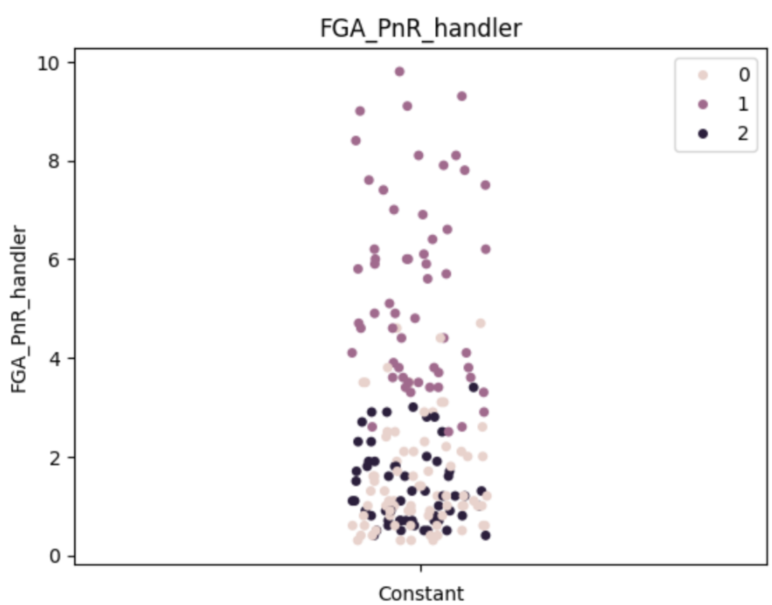
3.4.6 Variance of clusters with PTS



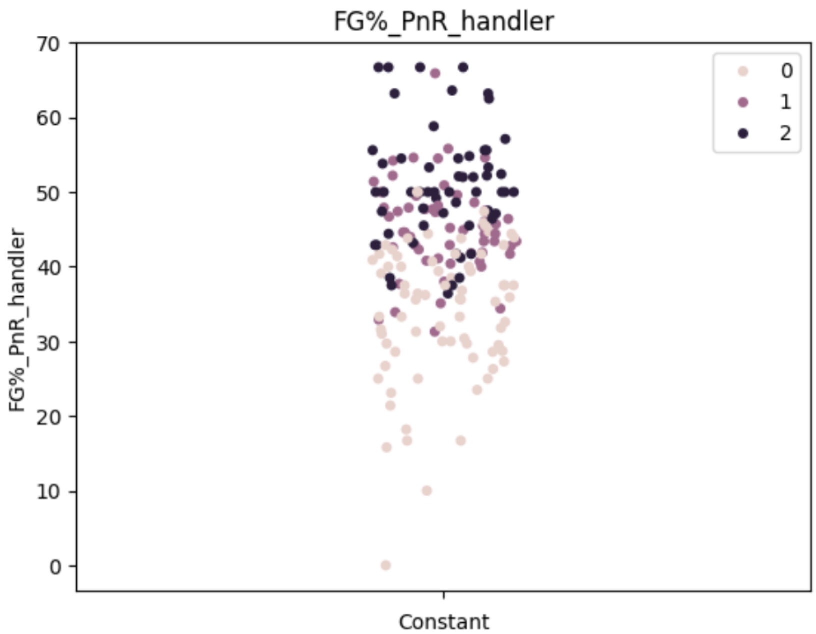
3.4.7 Variance of clusters with FGM



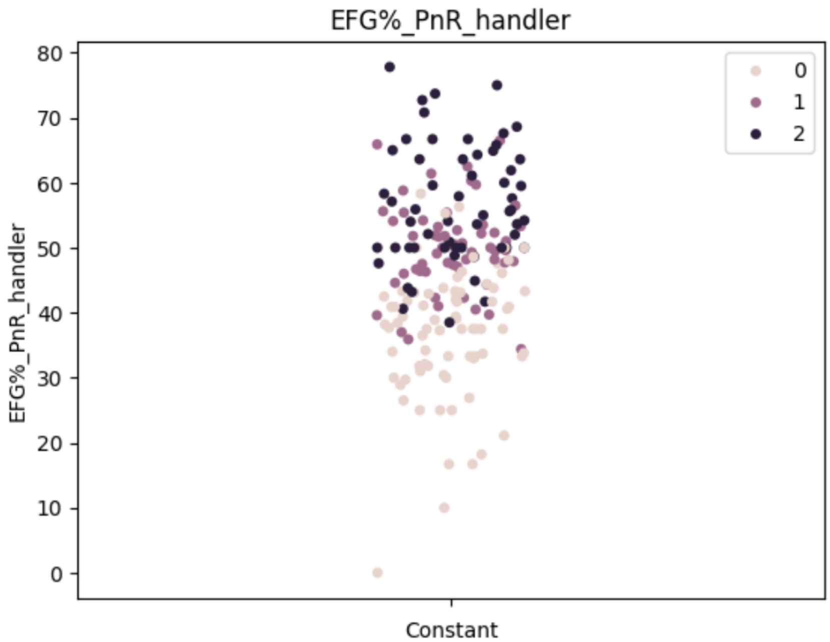
3.4.8 Variance of clusters with FGA



3.4.9 Variance of clusters with FG%



3.4.10 Variance of clusters with EFG%



3.5 Pick and roll roller

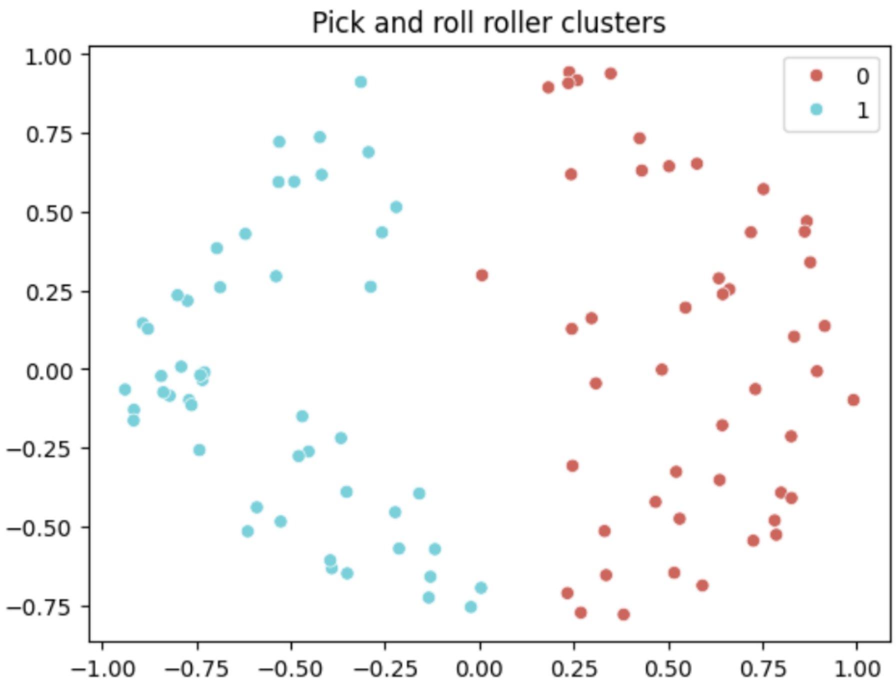
3.5.1 Describing clusters

The clusters range over the following values:

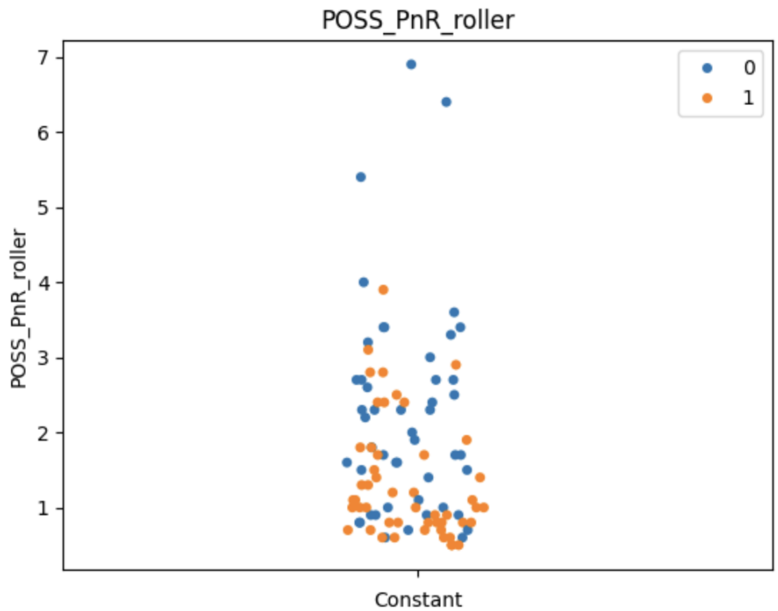
Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	.5-6.4	2.4-42.2	.27-.91	.2-4.5	0.0-1.7	.3-4.7	0.0-50.0	0.0-58.3
1	3-13.5	21.7-57.5	.75-1.24	2.7-13.5	1.1-4.5	2.5-9.8	31.3-65.9	34.4-66.5
2	.5-4.4	3.2-43.9	.78-1.60	.5-4.9	.2-1.8	.4-3.4	36.4-66.7	38.5-77.8

Table 1: Pick and roll ball handler clusters

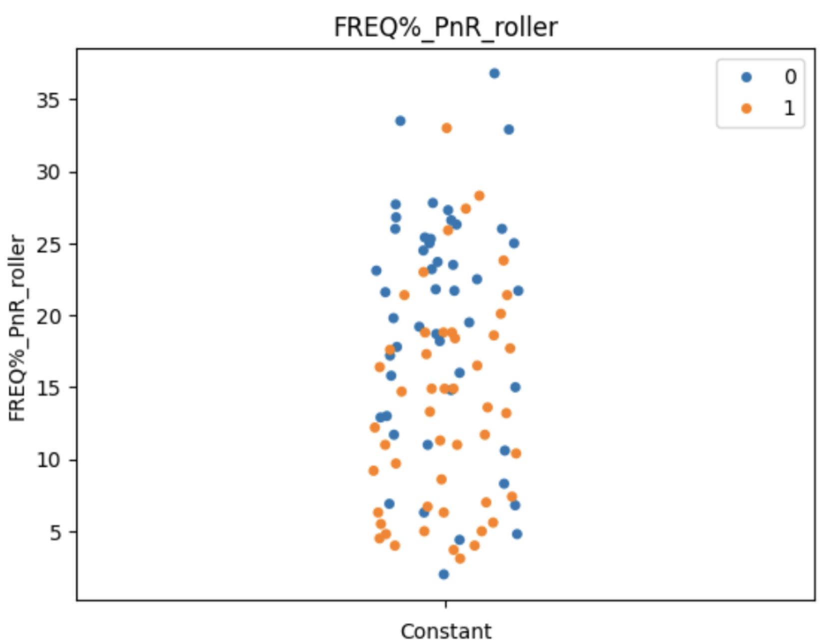
3.5.2 Clusters under PCA



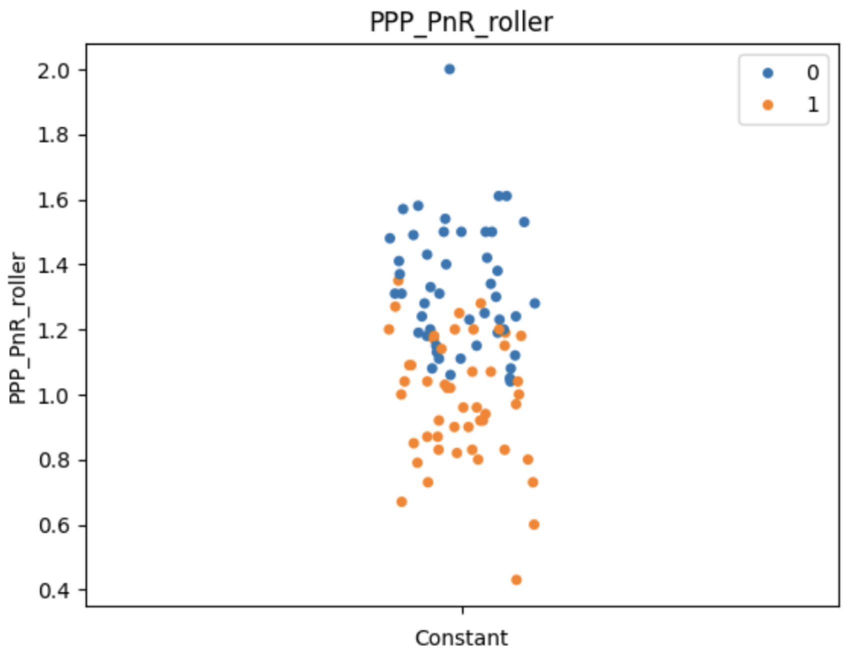
3.5.3 Variance of clusters with POSS



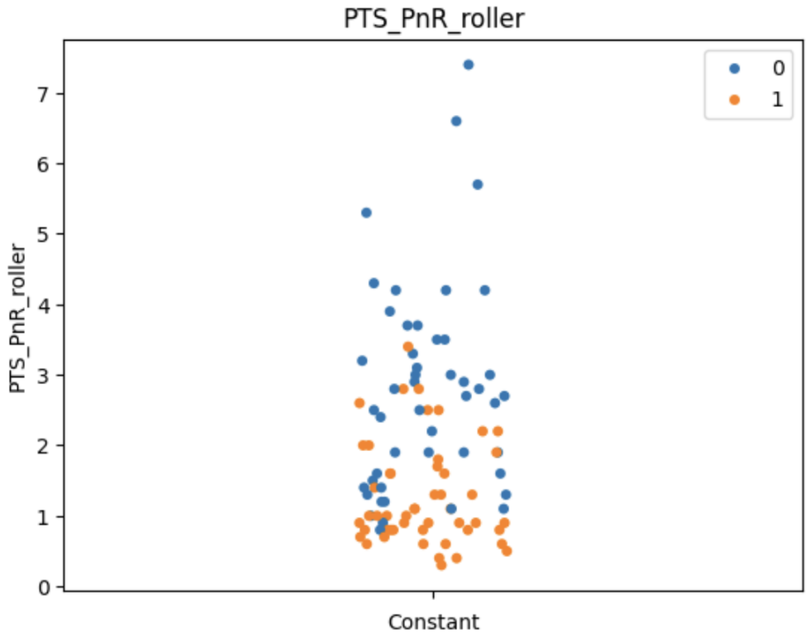
3.5.4 Variance of clusters with FREQ%



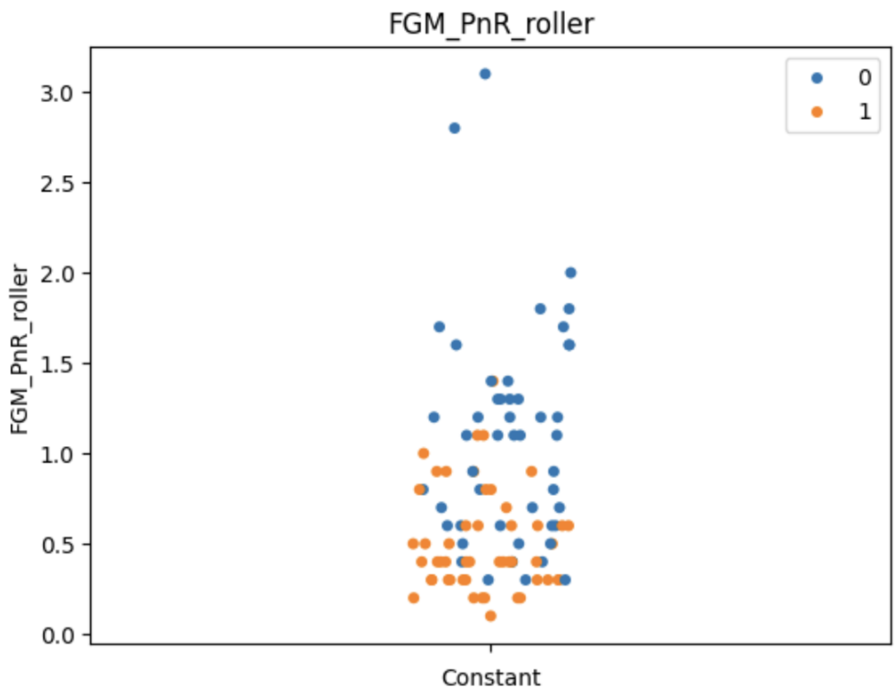
3.5.5 Variance of clusters with PPP



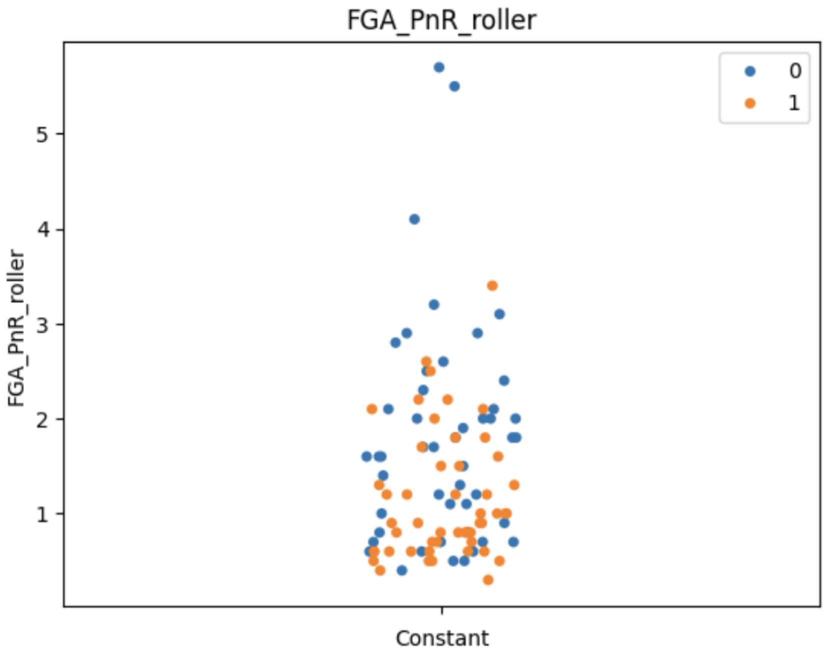
3.5.6 Variance of clusters with PTS



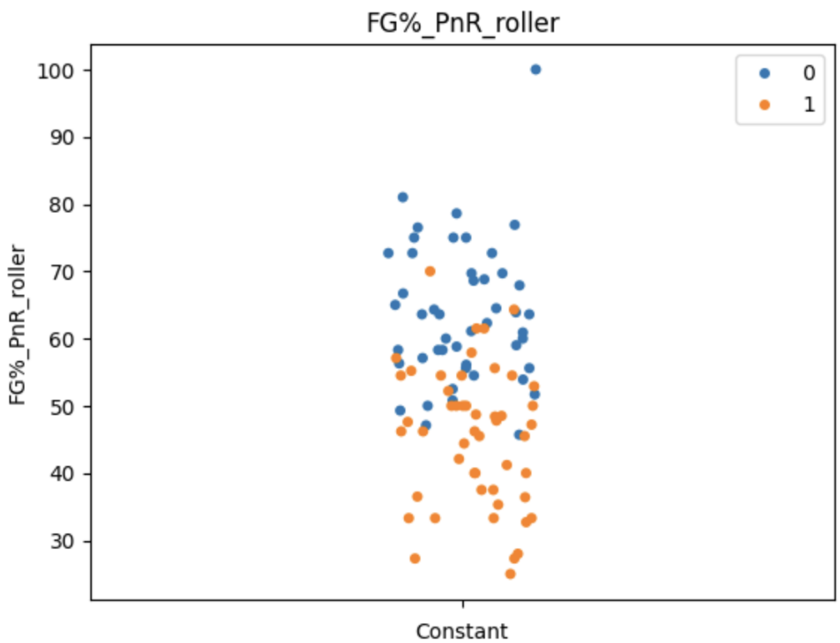
3.5.7 Variance of clusters with FGM



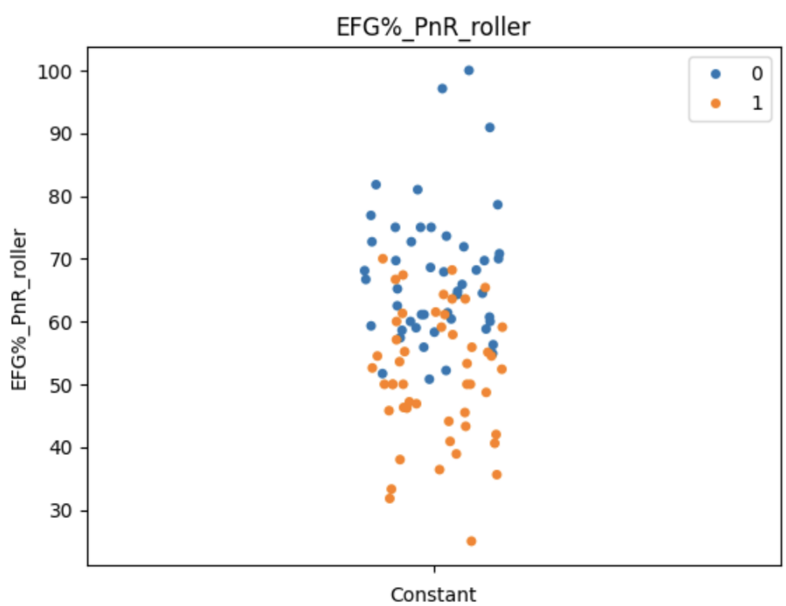
3.5.8 Variance of clusters with FGA



3.5.9 Variance of clusters with FG%



3.5.10 Variance of clusters with EFG%



3.6 Post up

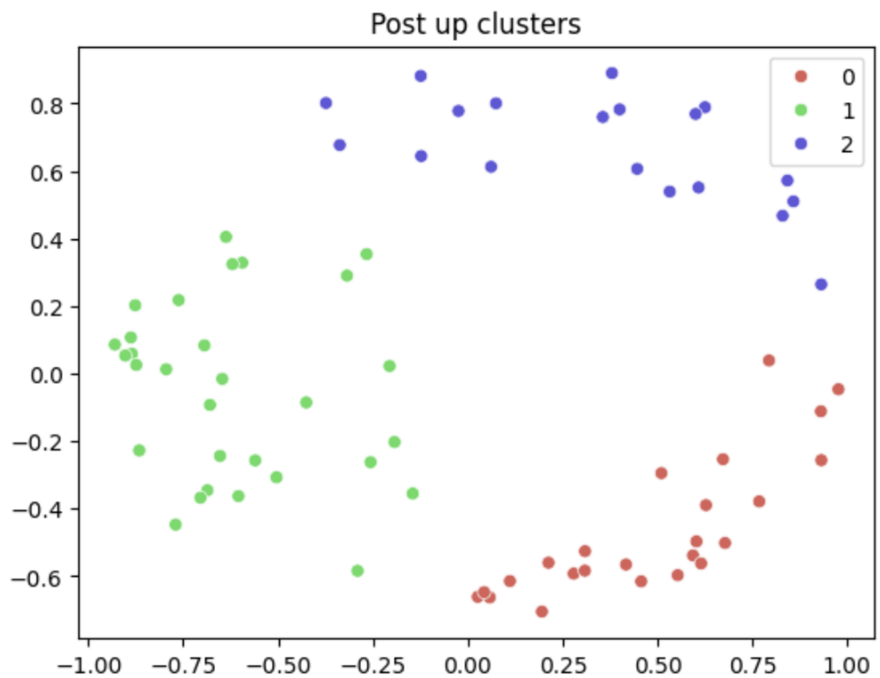
3.6.1 Describing clusters

The clusters occupy the following ranges:

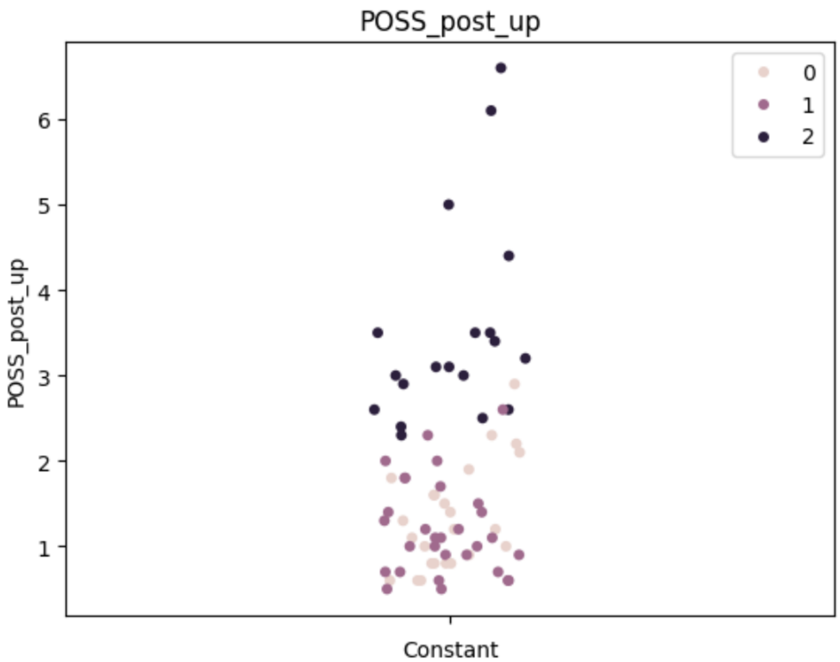
Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	.6-2.9	3.9-13.9	1.03-1.56	.6-3.7	.1-1.3	.2-2.1	42.9-79.2	42.9-79.2
1	.5-2.6	2.8-15.8	.4-1	.2-2.3	0-.7	.3-1.9	14.3-57.1	14.3-57.1
2	2.3-6.6	10.8-25.5	.73-1.21	2.1-7.2	.8-2.8	1.7-5.1	39.5-64.6	39.5-64.6

Table 1: Post up cluster ranges

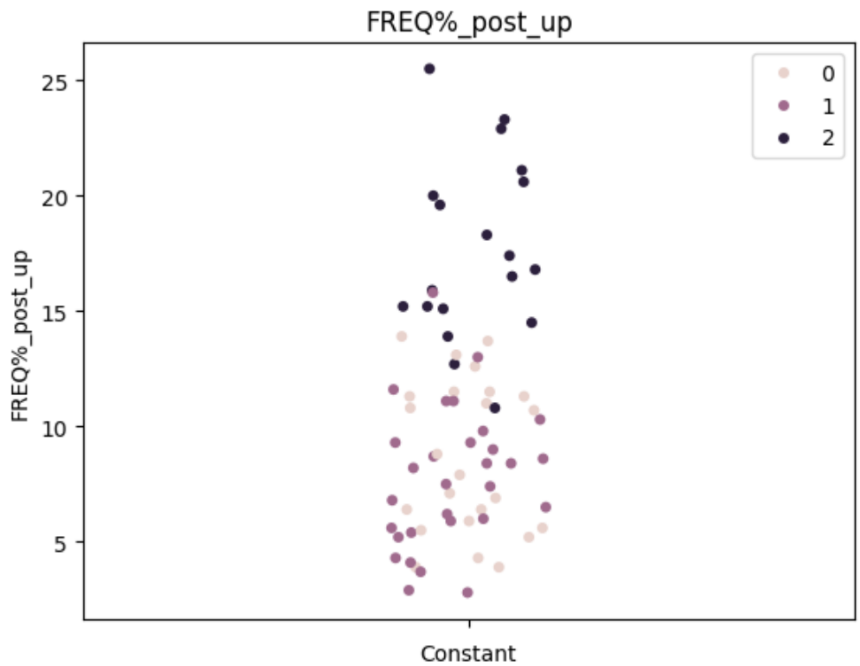
3.6.2 Clusters under PCA



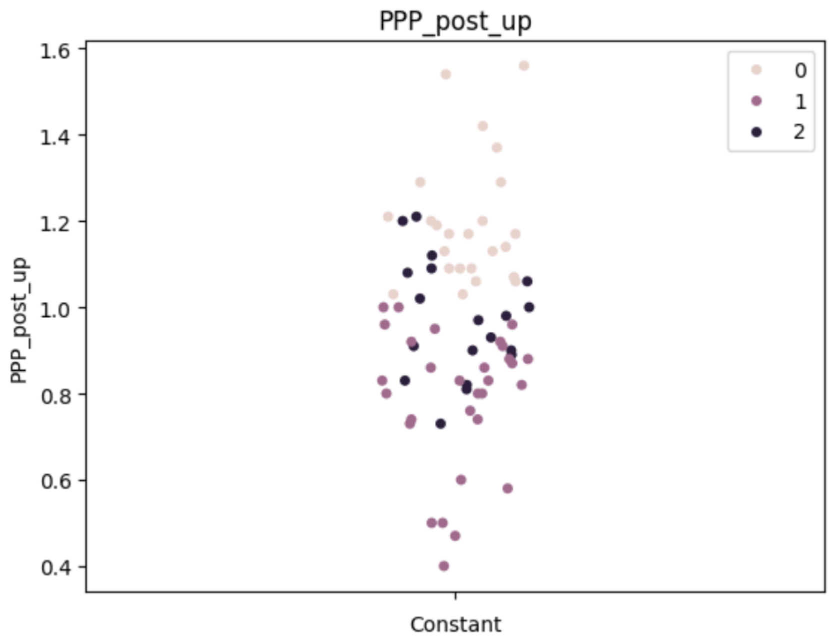
3.6.3 Variance of clusters with POSS



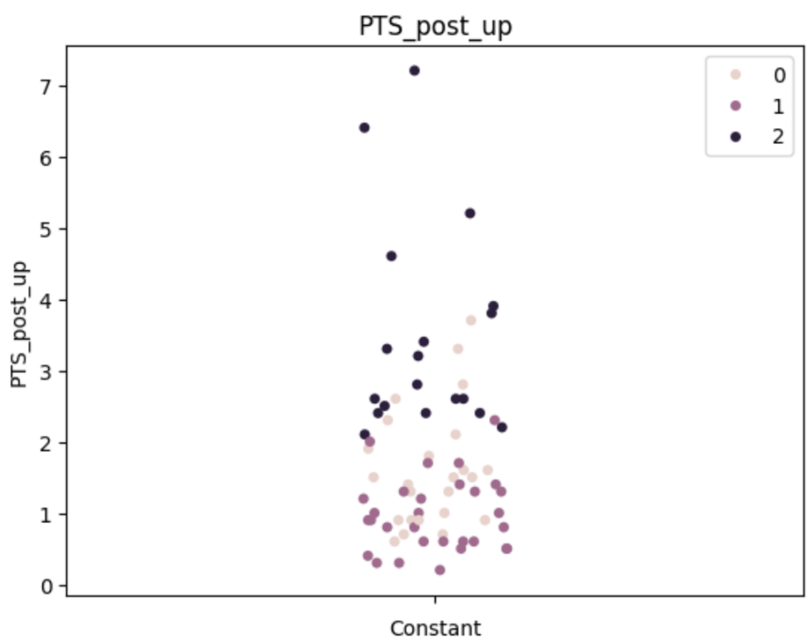
3.6.4 Variance of clusters with FREQ%



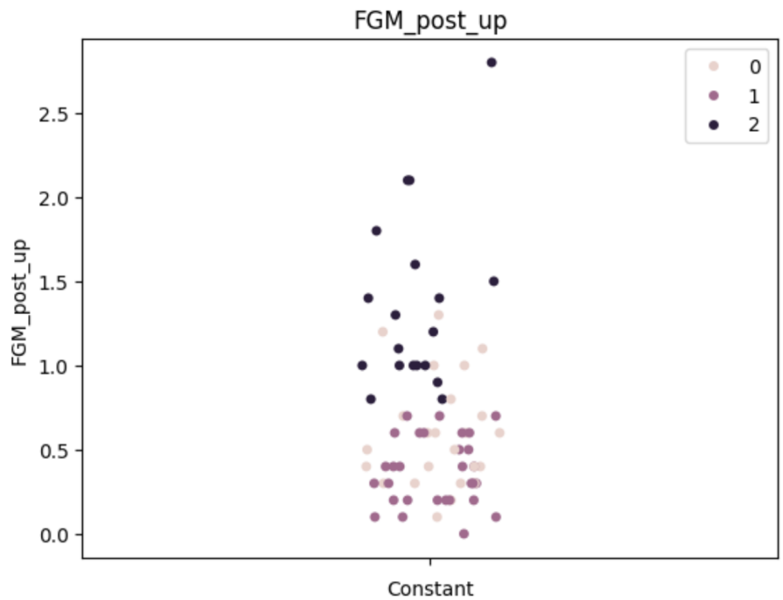
3.6.5 Variance of clusters with PPP



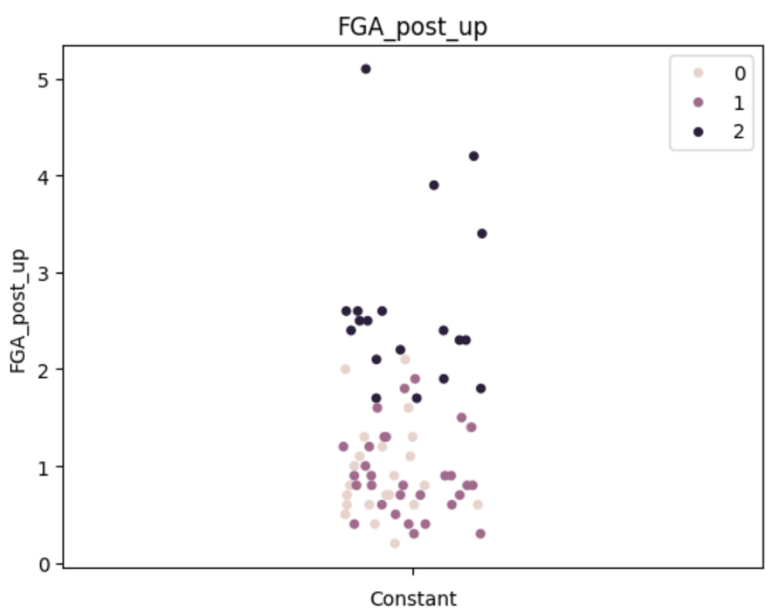
3.6.6 Variance of clusters with PTS



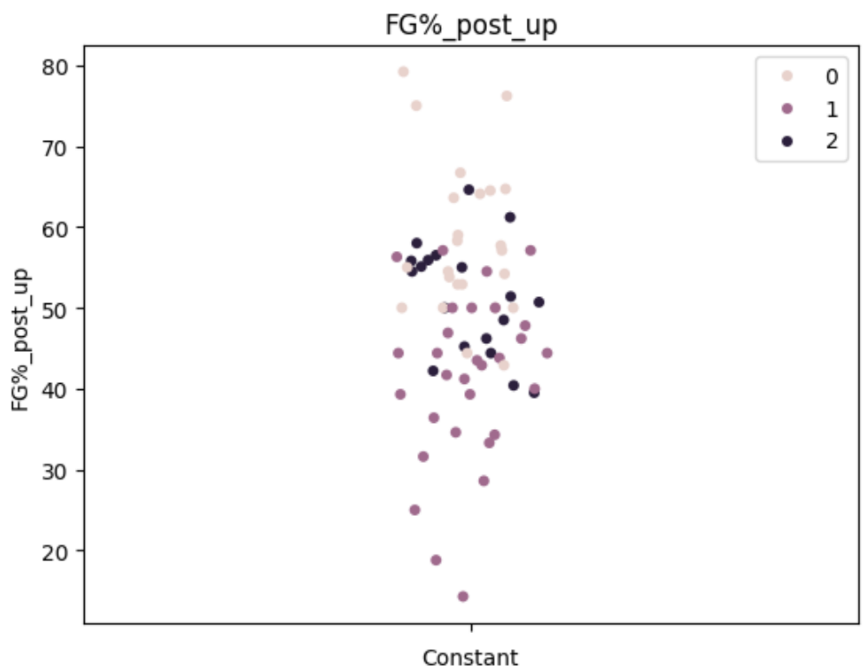
3.6.7 Variance of clusters with FGM



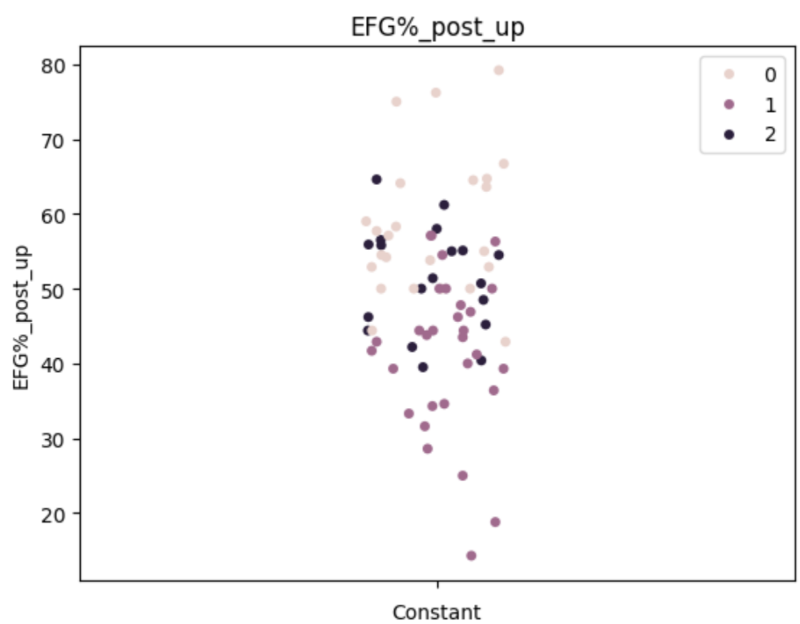
3.6.8 Variance of clusters with FGA



3.6.9 Variance of clusters with FG%



3.6.10 Variance of clusters with EFG%



3.7 Spot up

3.7.1 Describing clusters

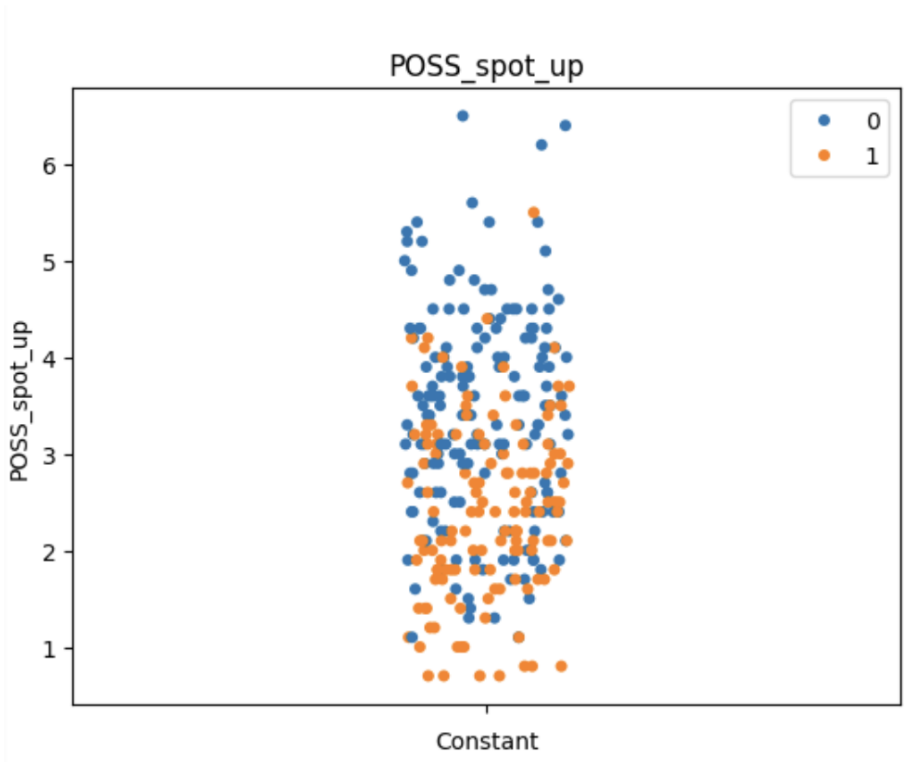
The clusters vary over the following ranges:

Cluster	POSS	FREQ%	PPP	PTS	FGM	FGA	FG%	EFG%
0	1.1-6.5	7-56.2	.88-1.73	1.5-7.7	.5-2.7	1-6	33.8-69.2	45.1-92.3
1	.7-5.5	3.9-70.6	.37-1.13	.4-3.6	.1-1.3	.6-6	14.8-53.3	18.9-64.3

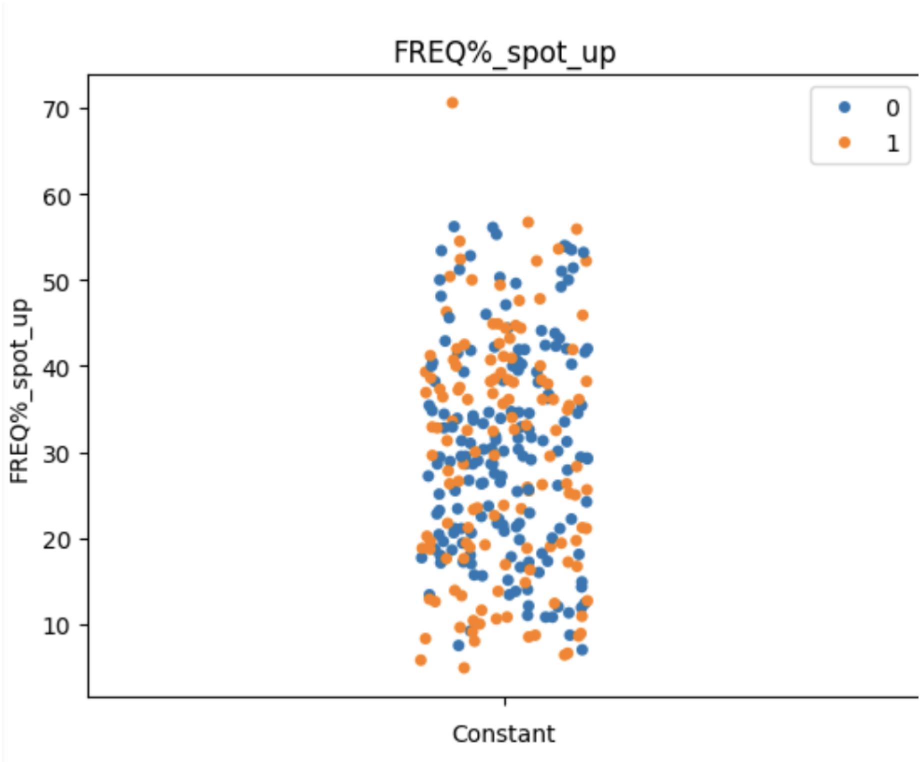
Table 1: Spot up cluster ranges

3.7.2 Clusters under PCA

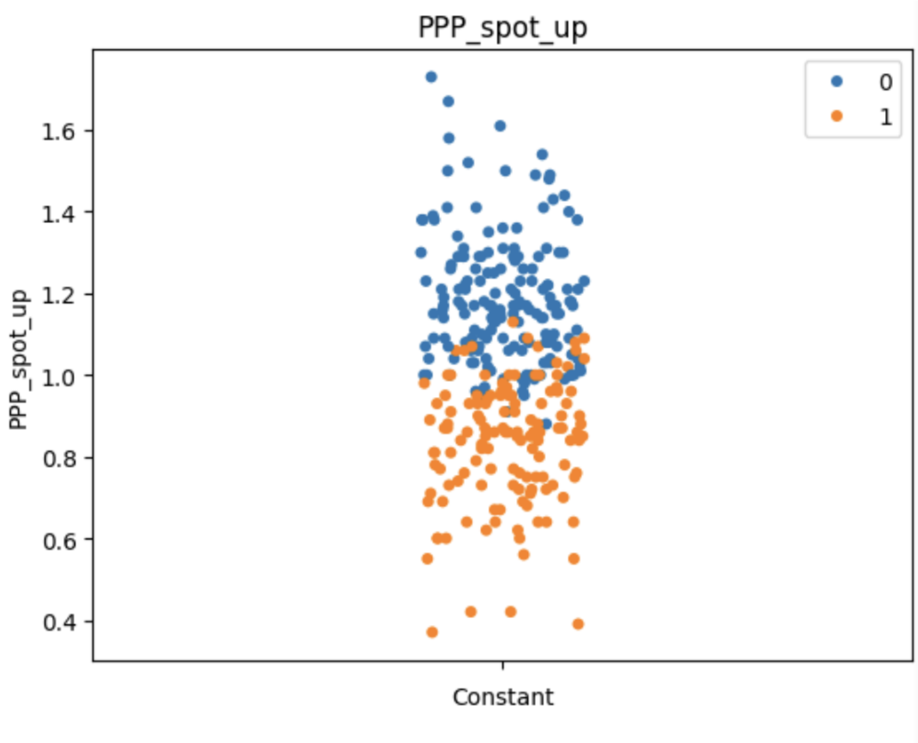
3.7.3 Variance of clusters with POSS



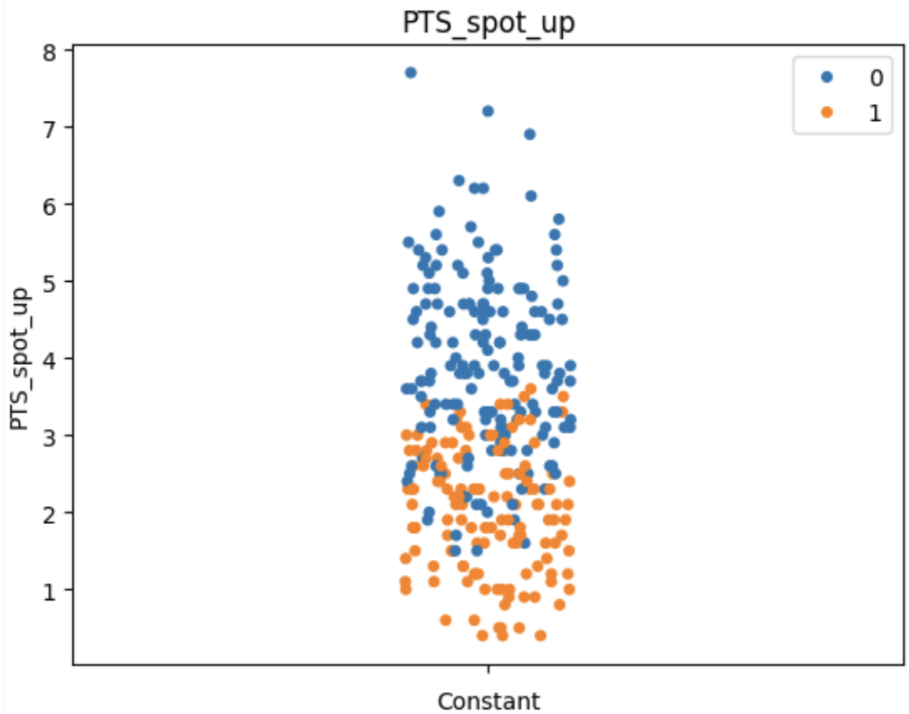
3.7.4 Variance of clusters with FREQ%



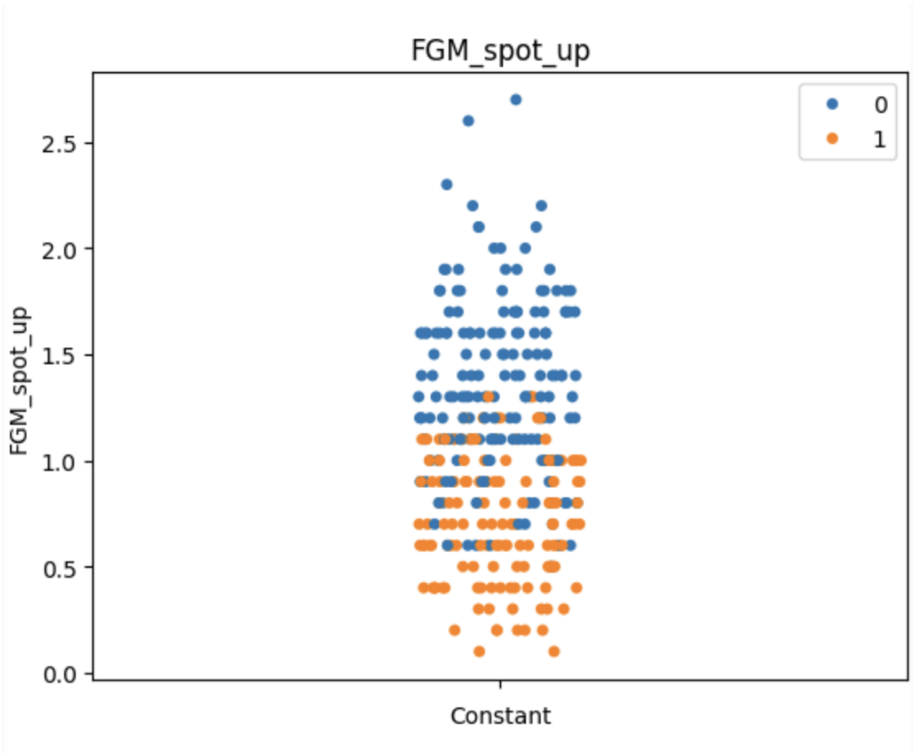
3.7.5 Variance of clusters with PPP



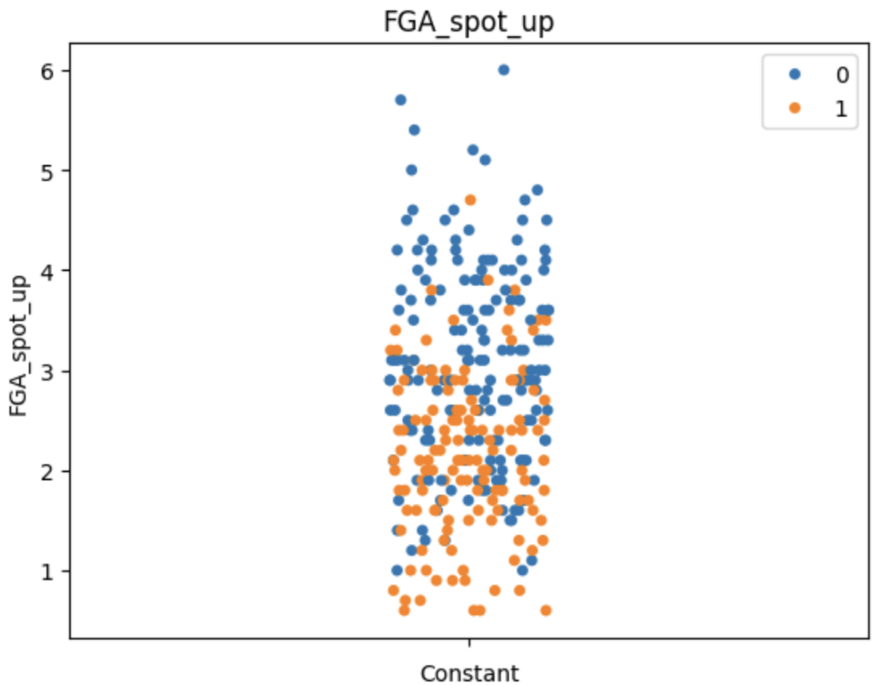
3.7.6 Variance of clusters with PTS



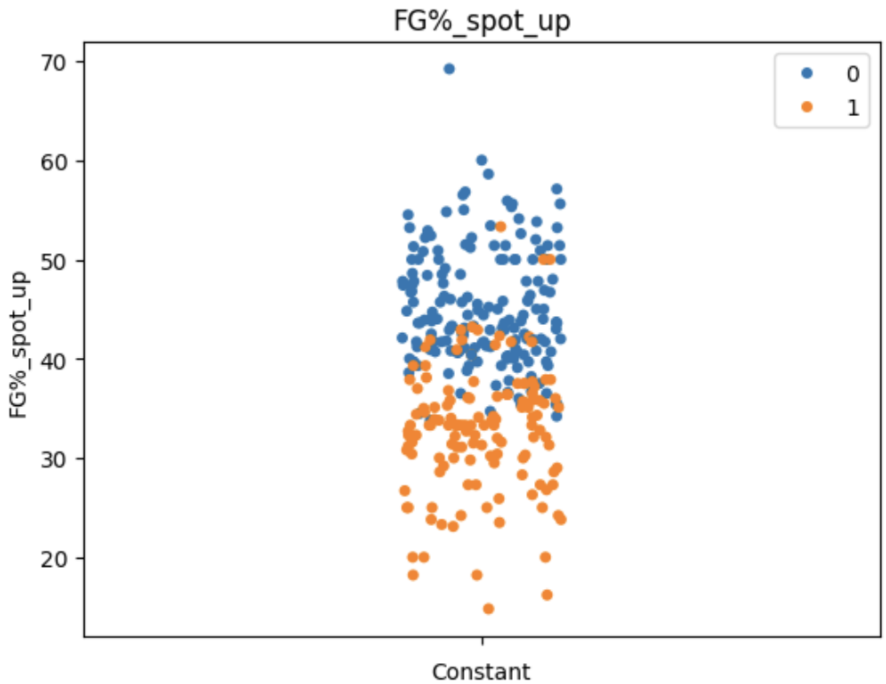
3.7.7 Variance of clusters with FGM



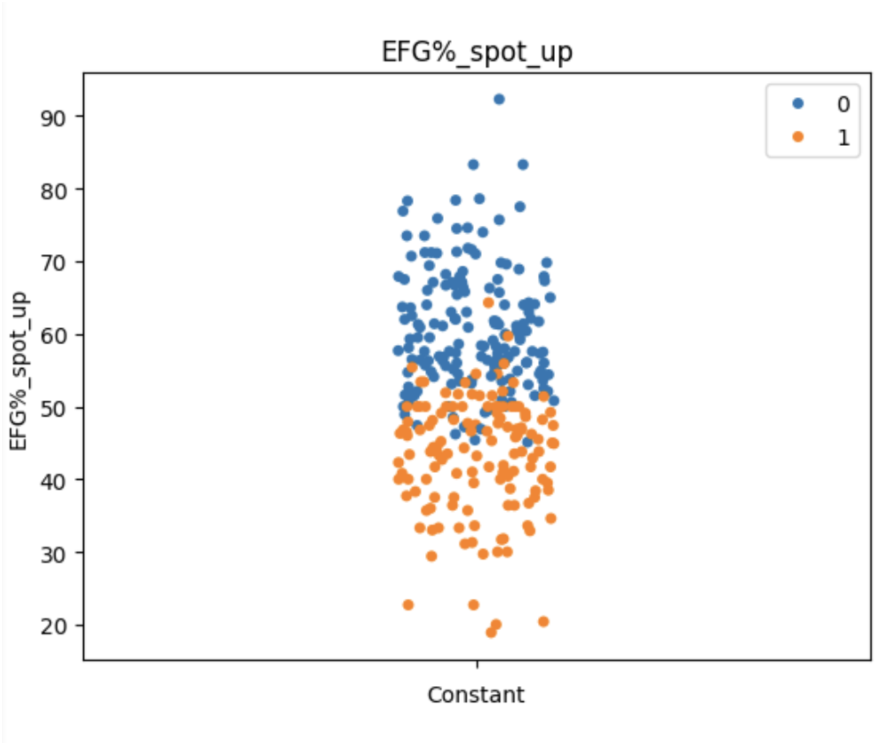
3.7.8 Variance of clusters with FGA



3.7.9 Variance of clusters with FG%



3.7.10 Variance of clusters with EFG%



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

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

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

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

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

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

6 Conclusions

7 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