Refining the Defensive Range AdaptabilitY (DRAY) Score in the NBA

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1 Introduction

In sports like basketball and football, many coaches view the game as a chess match. Teams aspire to gain a competitive advantage based on the player matchups i.e. A faster player matched up against a slower player. Recently, basketball has gone through a revolution called "Small-ball". Typically a team places five players on the court; point guard, shooting guard, strong forward, power forward, and a center. The center and power forward players are usually large, tall, and score efficiently near the basket for two points. However, the skill set of these players does not normally include shooting from behind the three-point arc. Since teams value three point shots, more teams have played smaller players who can defend well at center or power forward positions. This causes a player mismatch because the usually tall center is not typically defending players far away from the basket. The smaller players can use their quickness to get open shots and spread the defense for their teammates to take advantage. Teams have shifted away from traditional player stereotypes and value more players that can defend multiple positions and create these types of mismatches. It has gotten so prevalent in the NBA that the Boston Celtics Head Coach, Brad Stevens, believes there are only three on-court positions: Ball-Handlers, Wings, and Bigs.

There is no current metric or number that effectively measures a player's worth on defense, especially when measuring the impact players have against opponents who play different positions. The one statistic that is used, Plus/Minus, can be frustrating to comprehend. It measures how well a player's team performed while the player was in the game. A positive Plus/Minus would indicate that the player's team outscored the other and vice versa for a negative score. It does not carry much weight due to the fact that a player can have a positive score due to their teammates and if they are offensively better than the other team. As of now, many pundits have to create their own analysis to justify player's defensive skill. However, this leaves many players swept under the rug who might just be overlooked defensively. For my project, I will try to cluster players, using k-means, into the aforementioned new three positions. From there, I intend to refine the DRAY score for each player. The score was created at an NBA Hackathon and it measures how well a player defends multiple positions as well as overall versatility.

2 Background

Senthil Natarajan and Chris Pickard, college students and writers for the Nylon Calculus, first introduced the Defensive Range AdaptabilitY (DRAY) score at a NBA Hackathon [Natarajan and Pickard 2016]. They were tasked with measuring defensive performance and believed that versatility was the most important to gauge. The DRAY score is not normalized and is based off of two major components. First, players are mainly rewarded for minimizing their opponents scoring impact. It does not take steals into consideration or allowing their opponent to receive the ball. Secondly, players were originally divided based on their offensive play-style. To properly evaluate defensive versatility, it is essential to check how certain players defend against different offensive play-styles. The project never released its code but did go through the components step by step in an article.

I wanted to first gather players who played more than forty games in the 2016-2017 season in order to have a large enough sample size. I scraped the data using Python from NBA.com to create multiple dataframes. From that point, there were a couple of differences between my DRAY score and the original. First, they decided to cluster, using a Gaussian Mixture Model, only based on offensive play-style. I wanted to first cluster into the three true-court positions and then find the averages of each offensive play-style within these three positions. Since we differed on what we wanted to cluster, our features also varied. Ball-handlers are typically guard players and are responsible for bringing the ball up-court and distributing the ball to start the offense. Wings play on the sides of the court and make cuts and runs to help open up themselves and other players. Bigs usually play near the basket and have a defensive presence to protect close shots. The features I chose that would correctly cluster those three positions were: Passes Made, Assists, Potential Assists, Drives, Drive Passes, Drive Field Goal Attempts, Front Court Touches, Elbow Touches, Post Touches, Paint Touches, Defended Field Goal Attempts at Rim, Player Height, Rebound Chances, Catch-and-Shoot Attempts, Catch-and-Shoot Three-point Attempts, Shot Attempts Less Than 5ft, 5-10ft, 10-15ft, 15-20ft, 20-25ft, and 25ft+. Each of the features, besides Player Height, was per game and per minute. The drawback from clustering offensive play-styles is that you have to figure out why each player was clustered into each group. In today's NBA, the average number of points are usually close to the basket or three-pointers. [NBA.com] It is easier to divide the positions by the distance they shoot from the basket rather than clustering to find offensive playstyles. The DRAY score also differed as no code or clear definitive equation was introduced.

There have been other findings that use multiple ways to measure defense. One scholarly work uses NBA tracking to see which players play tight defense on-ball versus off-ball. There is another article that uses the tracking to see which players' movements cause their estimate possession value to increase or decrease. Unfortunately, the NBA has removed the tracking data from their website. If the data remained public, it would help introduce and reform metrics due to knowing where players are at all times during a game.

3 Results

The first step was to cluster players into the three true positions by the way they played. Using the features previously mentioned, k-means clustering was performed in Python. Essentially, the algorithm takes k random observations and compares to the rest. The closest observations that match to the k observations join that cluster of points. Since we know that we want three different positions, k can be set to three. Below shows players similarities in each feature while also stating their clustered position by color.

For figure 1 on page 4, we see that Ball-Handlers make most of the passes and assists while also driving to the basket and getting many touches in frontcourt. Big players control much of the elbow, post, and paint touches near the hoop. Similarly, Big players defend and rebound the most shot attempts near the basket due having the most height. Wing players, since they can vary on their playstyle, were in between the two other positions. For example, wings that like to shoot three-pointers are apparent by the amount of blue lines on catch-and-shoot situations. There is a lot of variability for wing players that take frontcourt touches. Overall, when it comes down to shot attempts, it is evident that Big players take many shots less than five feet, but as the distance increases, Wings and Ball-Handlers shoot more from twenty to twenty-five feet. As a reasonableness check, I looked through the cluster to justify each player's clustered position. Stephen Curry, Chris Paul, and Kyrie Irving, bona fide point guards, were found in the Ball-Handler cluster. Big men like Rudy Gobert and DeAndre Jordan were grouped together. Lastly, Wing players included LeBron James and Carmelo Anthony. However the clustering also grouped some players that I was not expecting. For example, DeMarcus Cousins is well known for being a stud offensive Big, but was instead clustered as a Wing. After consideration there are multiple reasons as to why this happened. Cousins takes more jump shots than a traditional Big. He was sixtieth in total in most catch-and-shoot attempts per minute with only fifteen other Big players ahead of him. Another reason has nothing to do with statistics but with his career. During the 2016-2017 season, Cousins was traded from the Sacramento Kings to the New Orleans Pelicans joining another superstar Big, Anthony Davis. Teams do not typically have two Big players together, especially near the basket, fearing that it would cause too much offensive congestion. Since Cousins can shoot three-pointers effectively, the Pelicans can place him on the wing while Davis can create havoc inside. Another example included Giannis Antetokounmpo clustered as a Big even though he plays on the wing. It is well known that Antetokounmpo's' nickname, "Greek Freak", is due to his large hands and long

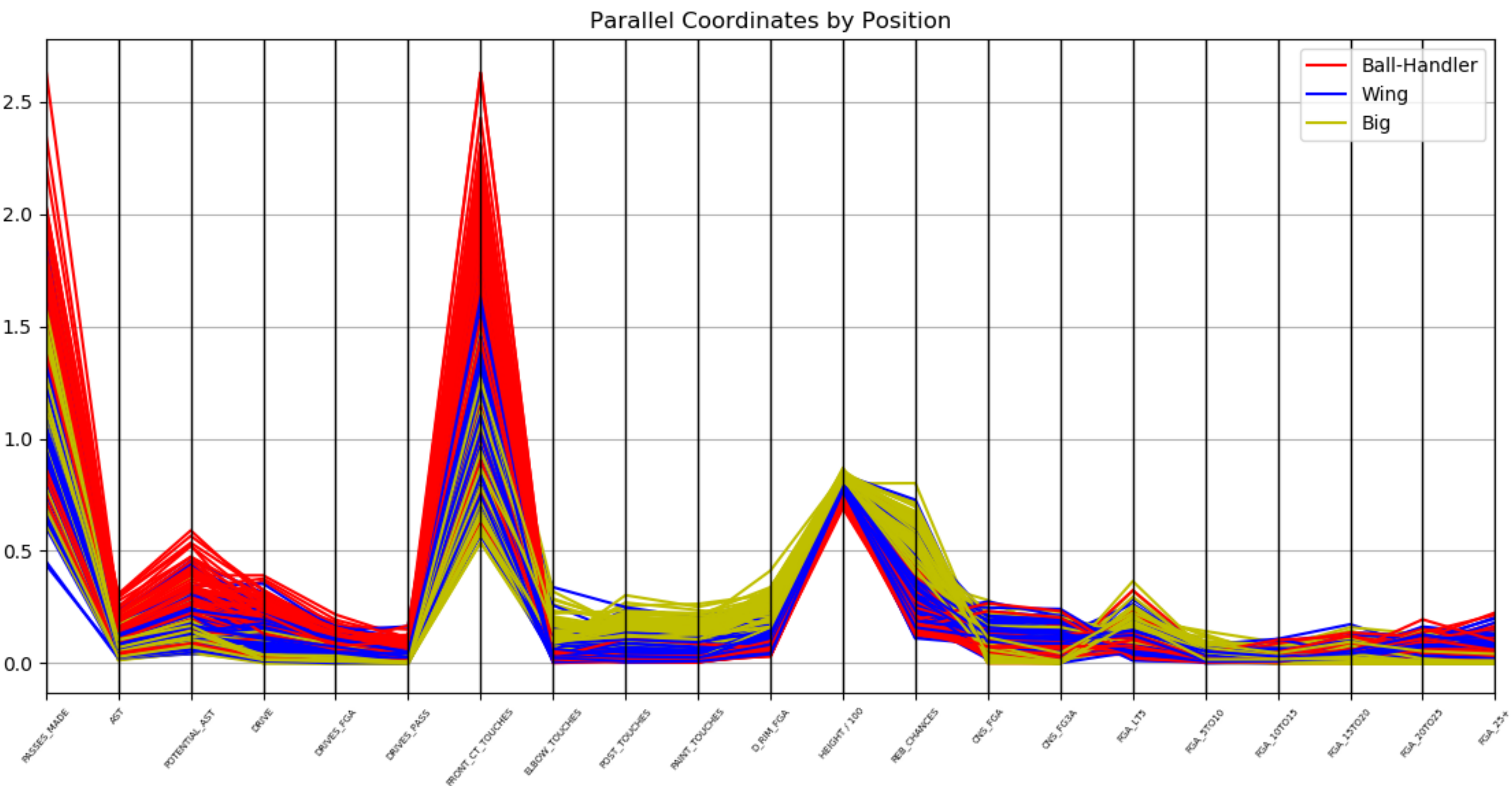

Figure 1: Clustered Features

wingspan. Due to his athleticism, he plays multiple positions for the Milwaukee Bucks. Sometimes he brings the ball up the court as a distributor or sometimes he is a defensive enforcer against Big opponents. Antetokounmpo takes the majority of his shots near the basket due to his size and the fact that he is not a respectable three-point shooter. Since he takes most of his touches less than ten feet away from the basket and defends larger opponents from time to time, he was clustered as a Big. After finding out each player's position, I had to craft a model to find each player's DRAY score. First, I created a table with every player's Defensive Estimated Point Value (EPV) and Offensive point total. Defensive EPV was defined as

$$DEPV = DFGA * PV - DFGM * PV$$

DFGA and DFGM stand for Defended Field Goals Attempted and Made, respectively, while PV is the point value for where the shots are taken from. The Defensive EPV was calculated within five shot ranges: Shots less than 5ft, between 5-10ft, 10-15ft, 15ft to the three-point line, and beyond the three-point line. The number explains the point difference between the maximum amount of points that can be scored on the defender and the actual points scored. DEPV should always be negative, but the more negative it is, the better the overall DRAY will be. Offensive Point Total (OPT) is the total amount of points an offensive player can obtain based off their shot attempts, as defined by:

$$OPT = FGA * PV$$

OPT is calculated within the five shot ranges stated previously. After finding the average OPT by position in each shot range, the next step was to find the OPT for players that could score above average close to the rim or far from the rim. This will create new sub-classes for each position based on their offensive skills. The new offensive positional play-styles that catered to shooting near the rim, included: Big Close, Ball-Handler Penetrate, and Wing Slash. Meanwhile, those that could shoot above average near the three-point line were named Big Stretch, Ball-Handler Perimeter, and Wing Perimeter. Now each player's DRAY can be scored by,

$$\sum[\ (\mathrm{OPT}_r * F_r) - DEPV_r]$$

Since each player defends shots in different spots on the court, there is a frequency, F, assigned to each shot range. So if a player defends 50 percent of their total defended shots in the less than five feet from the rim range, they are getting half the OPT of whoever they are facing in that same range. Subtracting this total by DEPV will get a player's DRAY score in that range as well. The sum of the ranges, r, will get the total DRAY score for that positional play-style. Below we can see the top ten DRAY scores for each position by play-style.

The top performers for Ball-Handlers, Wings, and Bigs were Jrue Holiday, Draymond Green, and Kristaps Porzingis respectfully. These players differ in the way they play but all have unique physical gifts to guard multiple positions and it is highlighted in real-life and by the DRAY.

Table 1: Top Ball-Handlers against Big Close

Position	PLAYER_NAME	BIG CLOSE	Total
Ball-Handler	George Hill	-4.541404	-45.190047
Ball-Handler	CJ McCollum	-4.486499	-45.721061
Ball-Handler	Wilson Chandler	-4.316886	-45.927826
Ball-Handler	Jrue Holiday	-4.121434	-55.090336
Ball-Handler	Damian Lillard	-3.936050	-44.609510
Ball-Handler	Dion Waiters	-3.591126	-41.152165
Ball-Handler	Kemba Walker	-3.547587	-46.102658
Ball-Handler	Mike Conley	-3.257325	-44.155269
Ball-Handler	Derrick Rose	-3.249208	-40.307078
Ball-Handler	Elfrid Payton	-3.065703	-39.655177

Table 2: Top Ball-Handlers against Big Stretch

Position	PLAYER_NAME	BIG STRETCH	Total
Ball-Handler	Jrue Holiday	-13.356836	-55.090336
Ball-Handler	James Harden	-12.835355	-52.231571
Ball-Handler	Kemba Walker	-11.610156	-46.102658
Ball-Handler	Mike Conley	-11.121941	-44.155269
Ball-Handler	Wilson Chandler	-10.904702	-45.927826
Ball-Handler	CJ McCollum	-10.858063	-45.721061
Ball-Handler	George Hill	-10.687189	-45.190047
Ball-Handler	Damian Lillard	-10.664922	-44.609510
Ball-Handler	Patrick Beverley	-10.452875	-39.277922
Ball-Handler	Derrick Rose	-10.213515	-40.307078

Table 3: Top Ball-Handlers against Ball-Handler Penetrate

Position	PLAYER_NAME	BALLH PEN	Total
Ball-Handler	Jrue Holiday	-8.720069	-55.090336
Ball-Handler	James Harden	-8.262713	-52.231571
Ball-Handler	Kemba Walker	-7.074211	-46.102658
Ball-Handler	CJ McCollum	-6.886800	-45.721061
Ball-Handler	Wilson Chandler	-6.883514	-45.927826
Ball-Handler	George Hill	-6.836667	-45.190047
Ball-Handler	Damian Lillard	-6.782674	-44.609510
Ball-Handler	Mike Conley	-6.687993	-44.155269
Ball-Handler	Dion Waiters	-6.123545	-41.152165
Ball-Handler	Derrick Rose	-6.004365	-40.307078

Table 4: Top Ball-Handlers against Ball-Handler Perimeter

Position	PLAYER_NAME	BALLH PER	Total
Ball-Handler	Jrue Holiday	-8.960895	-55.090336
Ball-Handler	James Harden	-8.817814	-52.231571
Ball-Handler	Wilson Chandler	-7.457719	-45.927826
Ball-Handler	CJ McCollum	-7.321152	-45.721061
Ball-Handler	Kemba Walker	-7.298968	-46.102658
Ball-Handler	Damian Lillard	-7.256919	-44.609510
Ball-Handler	George Hill	-7.196048	-45.190047
Ball-Handler	Mike Conley	-7.104142	-44.155269
Ball-Handler	Dion Waiters	-6.700572	-41.152165
Ball-Handler	Derrick Rose	-6.382859	-40.307078

Table 5: Top Ball-Handlers against Wing Slash

Position	PLAYER_NAME	WING SLASH	Total
Ball-Handler	Jrue Holiday	-9.793285	-55.090336
Ball-Handler	James Harden	-9.316167	-52.231571
Ball-Handler	Kemba Walker	-8.121331	-46.102658
Ball-Handler	Wilson Chandler	-7.793418	-45.927826
Ball-Handler	CJ McCollum	-7.781466	-45.721061
Ball-Handler	Mike Conley	-7.707810	-44.155269
Ball-Handler	George Hill	-7.703596	-45.190047
Ball-Handler	Damian Lillard	-7.654929	-44.609510
Ball-Handler	Dion Waiters	-6.987476	-41.152165
Ball-Handler	Derrick Rose	-6.963621	-40.307078

Table 6: Top Ball-Handlers against Wing Perimeter

Position	PLAYER_NAME	WING PER	Total
Ball-Handler	Jrue Holiday	-10.137816	-55.090336
Ball-Handler	James Harden	-10.048022	-52.231571
Ball-Handler	Wilson Chandler	-8.571587	-45.927826
Ball-Handler	Kemba Walker	-8.450404	-46.102658
Ball-Handler	CJ McCollum	-8.387083	-45.721061
Ball-Handler	Damian Lillard	-8.314016	-44.609510
Ball-Handler	Mike Conley	-8.276058	-44.155269
Ball-Handler	George Hill	-8.225143	-45.190047
Ball-Handler	Dion Waiters	-7.774684	-41.152165
Ball-Handler	Patrick Beverley	-7.585678	-39.277922

Table 7: Top Wings against Big Close

Position	PLAYER_NAME	BIG CLOSE	Total
Wing	Draymond Green	-7.528041	-83.236558
Wing	Al Horford	-5.607436	-61.581652
Wing	DeMarcus Cousins	-5.381936	-55.033581
Wing	Paul Millsap	-5.293699	-68.895843
Wing	Andre Roberson	-4.926904	-53.969679
Wing	Kevin Durant	-4.482806	-59.063456
Wing	Kevin Love	-4.334530	-52.040656
Wing	Michael Kidd-Gilchrist	-4.211661	-53.154523
Wing	Serge Ibaka	-4.063979	-48.562071
Wing	James Johnson	-3.960085	-42.987553

Table 8: Top Wings against Big Stretch

Position	PLAYER_NAME	BIG STRETCH	Total
Wing	Draymond Green	-17.471051	-83.236558
Wing	Paul Millsap	-15.231343	-68.895843
Wing	Kevin Durant	-13.510606	-59.063456
Wing	Al Horford	-13.260602	-61.581652
Wing	Michael Kidd-Gilchrist	-12.724209	-53.154523
Wing	Andrew Wiggins	-12.281064	-50.249847
Wing	Andre Roberson	-12.091506	-53.969679
Wing	DeMarcus Cousins	-11.912463	-55.033581
Wing	Kevin Love	-11.604713	-52.040656
Wing	LeBron James	-11.474606	-45.590988

Table 9: Top Wings against Ball-Handler Penetrate

Position	PLAYER_NAME	BALLH PEN	Total
Wing	Draymond Green	-13.622484	-83.236558
Wing	Paul Millsap	-11.169952	-68.895843
Wing	Al Horford	-9.704147	-61.581652
Wing	Kevin Durant	-9.375693	-59.063456
Wing	DeMarcus Cousins	-8.441775	-55.033581
Wing	Andre Roberson	-8.352695	-53.969679
Wing	Michael Kidd-Gilchrist	-8.291708	-53.154523
Wing	Kevin Love	-8.081296	-52.040656
Wing	Andrew Wiggins	-7.864722	-50.249847
Wing	Serge Ibaka	-7.346695	-48.562071

Table 10: Top Wings against Ball-Handler Perimeter

	PLAYER_NAME	BALLH PER	Total
Position			
Wing	Draymond Green	-14.497045	-83.236558
Wing	Paul Millsap	-11.972743	-68.895843
Wing	Al Horford	-10.712291	-61.581652
Wing	Kevin Durant	-10.106518	-59.063456
Wing	DeMarcus Cousins	-9.503519	-55.033581
Wing	Andre Roberson	-9.157940	-53.969679
Wing	Kevin Love	-9.042557	-52.040656
Wing	Michael Kidd-Gilchrist	-8.724369	-53.154523
Wing	Andrew Wiggins	-8.438098	-50.249847
Wing	Serge Ibaka	-8.401637	-48.562071

Table 11: Top Wings against Wing Slash

	PLAYER_NAME	WING SLASH	Total
Position			
Wing	Draymond Green	-14.483219	-83.236558
Wing	Paul Millsap	-12.086710	-68.895843
Wing	Al Horford	-10.485933	-61.581652
Wing	Kevin Durant	-10.312044	-59.063456
Wing	Michael Kidd-Gilchrist	-9.308216	-53.154523
Wing	DeMarcus Cousins	-9.199967	-55.033581
Wing	Andre Roberson	-9.184879	-53.969679
Wing	Andrew Wiggins	-8.876941	-50.249847
Wing	Kevin Love	-8.854184	-52.040656
Wing	Serge Ibaka	-8.164985	-48.562071

Table 12: Top Wings against Wing Perimeter

	PLAYER_NAME	WING PER	Total
Position			
Wing	Draymond Green	-15.634718	-83.236558
Wing	Paul Millsap	-13.141396	-68.895843
Wing	Al Horford	-11.811243	-61.581652
Wing	Kevin Durant	-11.275789	-59.063456
Wing	DeMarcus Cousins	-10.593921	-55.033581
Wing	Andre Roberson	-10.255754	-53.969679
Wing	Kevin Love	-10.123375	-52.040656
Wing	Michael Kidd-Gilchrist	-9.894361	-53.154523
Wing	Andrew Wiggins	-9.637217	-50.249847
Wing	Serge Ibaka	-9.542596	-48.562071

Table 13: Top Bigs against Big Close

	PLAYER_NAME	BIG CLOSE	Total
Position			
Big	Rudy Gobert	-8.545984	-71.743312
Big	Kristaps Porzingis	-7.699154	-82.068330
Big	Tristan Thompson	-6.751163	-64.841091
Big	Anthony Davis	-6.707689	-68.764428
Big	Robin Lopez	-6.606042	-57.180033
Big	Brook Lopez	-6.378538	-55.733064
Big	DeAndre Jordan	-6.258769	-58.255214
Big	Myles Turner	-5.931951	-58.218287
Big	Karl-Anthony Towns	-5.898865	-61.243049
Big	LaMarcus Aldridge	-5.870245	-54.681484

Table 14: Top Bigs against Big Stretch

	PLAYER_NAME	BIG STRETCH	Total
Position			
Big	Kristaps Porzingis	-17.113996	-82.068330
Big	Anthony Davis	-14.469192	-68.764428
Big	Rudy Gobert	-13.989182	-71.743312
Big	Tristan Thompson	-13.494405	-64.841091
Big	Karl-Anthony Towns	-13.163403	-61.243049
Big	Blake Griffin	-12.845039	-55.071091
Big	DeAndre Jordan	-12.165012	-58.255214
Big	Myles Turner	-12.090402	-58.218287
Big	LaMarcus Aldridge	-11.689892	-54.681484
Big	Robin Lopez	-11.571710	-57.180033

Table 15: Top Bigs against Ball-Handler Penetrate

	PLAYER_NAME	BALLH PEN	Total
Position			
Big	Kristaps Porzingis	-13.319083	-82.068330
Big	Rudy Gobert	-11.174513	-71.743312
Big	Anthony Davis	-10.940856	-68.764428
Big	Tristan Thompson	-10.185159	-64.841091
Big	Karl-Anthony Towns	-9.537156	-61.243049
Big	DeAndre Jordan	-9.007890	-58.255214
Big	Myles Turner	-8.874475	-58.218287
Big	Blake Griffin	-8.688544	-55.071091
Big	Robin Lopez	-8.632802	-57.180033
Big	Brook Lopez	-8.559953	-55.733064

Table 16: Top Bigs against Ball-Handler Perimeter

	PLAYER_NAME	BALLH PER	Total
Position			
Big	Kristaps Porzingis	-14.311224	-82.068330
Big	Rudy Gobert	-12.626926	-71.743312
Big	Anthony Davis	-11.920184	-68.764428
Big	Tristan Thompson	-11.230187	-64.841091
Big	Karl-Anthony Towns	-10.591235	-61.243049
Big	Myles Turner	-10.321018	-58.218287
Big	DeAndre Jordan	-10.060948	-58.255214
Big	Robin Lopez	-10.039010	-57.180033
Big	Brook Lopez	-9.570353	-55.733064
Big	Steven Adams	-9.382697	-54.217684

Table 17: Top Bigs against Wing Slash

	PLAYER_NAME	WING SLASH	Total
Position			
Big	Kristaps Porzingis	-14.164014	-82.068330
Big	Rudy Gobert	-11.755211	-71.743312
Big	Anthony Davis	-11.716946	-68.764428
Big	Tristan Thompson	-10.900493	-64.841091
Big	Karl-Anthony Towns	-10.336791	-61.243049
Big	DeAndre Jordan	-9.683627	-58.255214
Big	Blake Griffin	-9.633112	-55.071091
Big	Myles Turner	-9.562588	-58.218287
Big	Robin Lopez	-9.247549	-57.180033
Big	Brook Lopez	-9.182020	-55.733064

Table 18: Top Bigs against Wing Perimeter

	PLAYER_NAME	WING PER	Total
Position			
Big	Kristaps Porzingis	-15.460859	-82.068330
Big	Rudy Gobert	-13.651496	-71.743312
Big	Anthony Davis	-13.009560	-68.764428
Big	Tristan Thompson	-12.279683	-64.841091
Big	Karl-Anthony Towns	-11.715600	-61.243049
Big	Myles Turner	-11.437854	-58.218287
Big	Robin Lopez	-11.082921	-57.180033
Big	DeAndre Jordan	-11.078968	-58.255214
Big	Brook Lopez	-10.533734	-55.733064
Big	Steven Adams	-10.408715	-54.217684

4 Conclusion

Overall, the DRAY score gives a good metric in terms of taking points away as a defender in the NBA. It is highly regarded that Draymond Green is a versatile defensive player and his DRAY score shows us that. Other players that have long wingspan seem to benefit their defense as well. NBA teams can incorporate the score by the way they shape their starting lineups. However, there are some limitations as well. It doesn't measure pick-and-roll defense, which is all about creating mismatches offensively. DRAY also doesn't take into consideration how well offensive players shoot in the five ranges. If more time was allotted, it would be possible to measure each player against each other instead of using league average. With the use of SportsVu, the NBA's data tracking cameras, it would be easier to see players as nodes and where the line up throughout the season. This would eliminate the need for clustering as well as finding league averages. If each player node was colored by their position, it would be easier to track defensive versatility. For my research goals, I feel this is a great to get my feet wet on learning how to use Python and the ins and outs of data scraping.

5 References

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