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Analysis of what makes an Euroleague team successful through player clustering

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Abstract

Technology has revolutionized many industries and sport is no exception, looking for ways to improve your team, taking advantage of any resource.

The goal of data analysis is to find a solution to the questions we ask ourselves. So far, coaches have relied solely on intuition, but data is an opportunity to move away from cognitive biases and get closer to reality.

This work is done in the context of a basketball team that competes in the Euroleague and asks what type of players it should have to maximize its chances of becoming champion. To be able to do this, player data from the last 5 years has been collected and ’clustering’ is performed, which is a machine learning technique that groups the players who have similar characteristics.

Apart from this, this clustering has other applications like finding a similar substitute for a player who is going to another team or to see an evolution from the five traditional positions in basketball.

Resum

La tecnologia ha revolucionat moltes indústries i l'esport no és cap excepció, buscant constantment maneres de fer millorar al teu equip, aprofitant qualsevol recurs.

La intenció de l'anàlisi de dades es trobar solució a preguntes que ens realitzem. Fins ara, s'ha confiat únicament amb la intuició, però les dades són una oportunitat per allunyar-se dels biaixos cognitius i apropar-se a la realitat.

Aquest treball es realitza en el context d'un equip de bàsquet que competeix a la Eurolliga i es pregunta quina tipologia de jugadors ha de tenir per maximitzar les seves possibilitats d'esdevenir campió. Per poder-ho dur a terme, es recopilen les dades dels jugadors dels últims 5 anys i es realitza 'clustering', una tècnica de machine learning que agrupa els jugadors que tenen característiques semblants.

A part d'això, el clustering té altres aplicacions com trobar un substitut semblant d'un jugador que marxa a un altre equip o veure l'evolució de les tradicionals cinc posicions del bàsquet.

Resumen

La tecnología ha revolucionado muchas industrias y el deporte no es una excepción, buscando constantemente maneras de hacer mejorar a tu equipo, aprovechando cualquier recurso.

La intención del análisis de datos es encontrar solución a preguntas que nos realizamos. Hasta ahora, se ha confiado únicamente en la intuición, pero los datos son una oportunidad de alejarse de los sesgos cognitivos y acercarse a la realidad.

Este trabajo se realiza en el contexto de un equipo de baloncesto que compite en la Euroliga y se pregunta qué tipología de jugadores debe tener para maximizar sus posibilidades de convertirse en campeón. Para poderlo llevar a cabo, se recopilan los datos de los jugadores de los últimos 5 años y se realiza 'clustering', una técnica de Machine Learning que agrupa a los jugadores que tienen características similares.

A parte de esto, el clustering tiene otras aplicaciones como encontrar un sustituto parecido a un jugador que se va a otro equipo o ver la evolución de las tradicionales cinco posiciones en baloncesto.

Acknowledgements

Firstly, I would like to thank my thesis advisor Prof. Josep Ramon Morros for the weekly feedback and the predisposition. Every time I have had any doubt he has given me great advice to keep going.

Special thanks to Adrià Arbués who has been a mentor to me since I started with Basketball Analytics, has also helped during the project, and has contributed with a lot of free resources to the basketball community.

I would also like to thank Fran Camba, whose work has boosted my curiosity in player clustering, and Nacho Gámez for his contribution with the scraping of play-by-play and shot chart scraped Euroleague data.

I want to thank the Sports Analytics community to share their knowledge online and especially, the ones who participated in the talks I chaired.

Contents

List of Figures

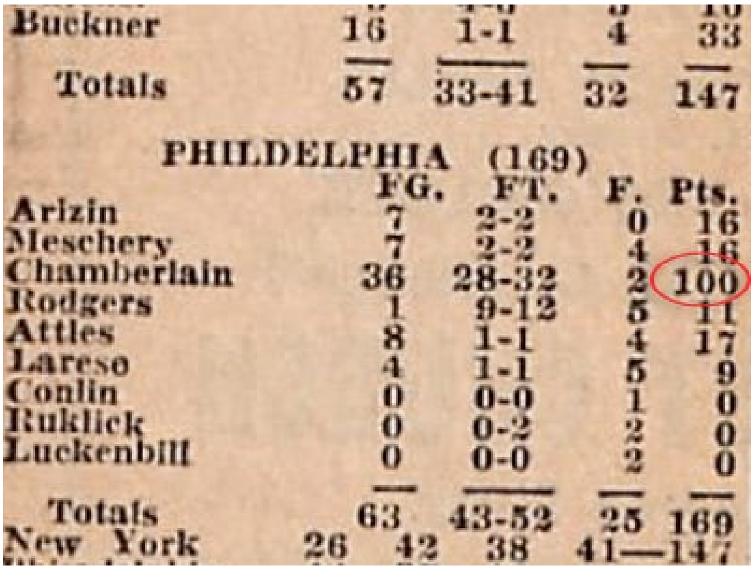
List of Tables

1 Introduction

So far, teams have relied on the experience and intuition of the coaching staff, but something new has emerged, Data Analytics can be used to make better decisions. It can reveal trends and metrics that can be used to increase the efficiency of your team.

When a basketball coach watches a game, he/she tries to analyze the strengths and weaknesses of a team. Here is an example: it can happen that, one player scores 20 points, the conclusion may be that this player is the best scorer of the team. But after that, a stat shows up saying that it is his career-high and this season, he is only averaging 2 points a game, so the conclusion that this player was the best scorer would have been wrong. As Ben Falk said in the Thinking Basketball podcast [1], ”A human can watch and analyze a game better than data will ever be able to, but data can analyze all games”.

We have available data for a long time ago (see Figure 1). In the beginning, points and fouls were only captured in the box score [1], but as time has gone by, we have much more.



Buckner	16	1-1	4	33
Totals	57	33-41	32	147
PHILDELPHIA		(169)		
	FG.	FT.	F.	Pts.
Arizin	7	2-2	0	16
Meschery	7	2-2	4	16
Chamberlain	36	28-32	2	100
Rodgers	1	9-12	5	11
Attles	8	1-1	4	17
Larese	4	1-1	5	9
Conlin	0	0-0	1	0
Ruklick	0	0-2	2	0
Luckenbill	0	0-0	2	0
Totals	63	43-52	25	169
New York	26	42	38	41—147

Figure 1: Old box score from the Wilt Chamberlain’s 100 point game in 1962.

In the United States, they have evolved a lot from the box score, having tracking data and a team of professionals helping the coaching staff. In Europe, Sports Analytics is starting but some teams are already applying it.

This is why during the 2020 lockdown due to COVID-19, I started an initiative of Basketball Analytics talks with experts on the field to learn **how** they apply this science to their teams.

Part 1 [2]

[1] A box score is a structured summary of the results from a sports competition

- Fran Camba: how to characterize a player numerically to then cluster
- Jorge Lorenzo: draw tactical conclusions during the game in a professional team
- Sergi Oliva: from the origin of boxscore to player tracking, taking control of your own analysis

Part 2 [3]

- Adrià Arbués: what is clustering and how to apply it
- Luis Clausín: how data can reduce the impact of cognitive biases on decision making
- Jesús Mayoral: the use of advanced statistics to sign players

Part 3 [4]

- Lluís Riera: Euroleague analysis to prepare for the season
- Rafael Jiménez: statistics in the ”minicopa” + analysis with FEB data
- Víctor Solanes: Application of the 4 Factors from Dean Oliver in a u18 team

These talks, and especially the ones from Fran and Adrià were a starting point for this project. They talked about clustering, which is an unsupervised Machine Learning technique that groups items with similar characteristics. So I decided to try this technique with player data from the Euroleague, the top-tier European professional basketball club competition.

1.1 Statement of purpose

Every Summer some teams sign some top players that make the team a championship contender. Sometimes these expectations end up being true, others not, triggering a disappointing season.

But, can Machine Learning help in the decision-making of signing players to improve their chances of becoming champions?

This can be done by looking at the past seasons. We have taken the last 5 seasons played, from the 14-15 to the 18-19, due to COVID-19 the 19-20 season had no champion. First, research has to be done about what data is there available. Then, build a database with relevant player stats for every season.

Once this is done, we can process to do the player clustering to analyze what type of players do the last Euroleague champions have in common.

1.2 Requirements and specifications

Requirements

- Although we can not access to the official Euroleague's database, the stats are published online, so web scraping can be done to get them and be able to have our own database.
- Velocity in execution is not something essential, but something to keep in mind
- The results from the clustering have to be clear so that the analysis can be done properly

Specifications

- As this is a proof of concept, no specifications are needed

1.3 Methods and procedures

This project uses some work developed by other authors. The parts of extraction, transformation and clustering have been done using Python 3.7.

Within Python the following libraries have been used:

- Pandas [5] 1.1.4 for data manipulation: slicing, filtering, indexing...
- BeautifulSoup [6] 4.9.3 for Web Scraping which is a technique to extract data from websites.
- Scikit-learn [7] 0.24.0 that provides tools for predictive data analysis, in this project it has been used for the clustering
- Numpy [8] 1.17.2 that adds support for large, multi-dimensional arrays and matrices.

Google Data Studio has been used to create a dashboard to visualize the results with interactive graphics.

1.4 Work plan

The Gantt chart of the project was first created with the Project Proposal and Work Plan, but the theme of the project was not clear yet, so the Gantt chart has ended up being completely different.

In the following weeks, the project was defined and with the Project Critical Review, a much better Gantt chart was created.

This last chart has been followed pretty well, but there was a minor setback because I did not consider a week or two to clean the data, which I would talk about in Chapter 3.

This has been the final Gantt chart (Figure 2):

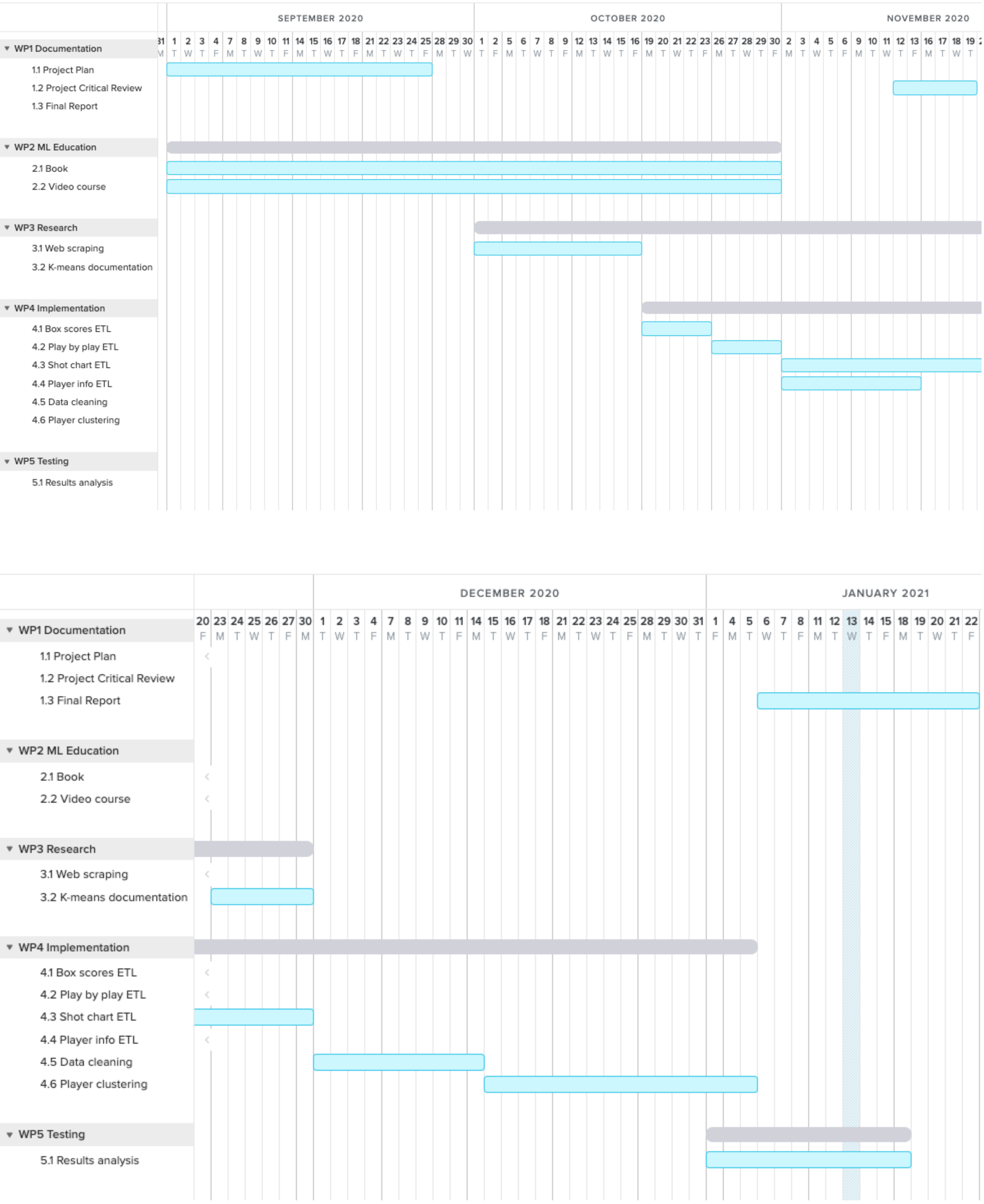


Figure 2: Final Gantt chart

2 State of the art

2.1 Sports Analytics

It is difficult to know when Sports Analytics was born, but the book, and later movie, ”Moneyball” [9] made this science known with the story based on real events of how the Oakland Athletics, a low-budget baseball team, used sabermetrics[2] to prioritize personnel decisions in professional sports. Billy Beane, the General Manager, signed players that fit his system. He was very criticized but he was successful, and he revolutionized baseball’s modern era, and now every major professional sports team in the US has an analytic expert or even an analytics department.

Why is Sports Analytics useful?

Luis Clausín, in one of the talks I chaired, explains the work of Michael Lewis in his book ”The Undoing Project”[10]. He talks about these emotional influences and patterns that make us unable to properly interpret the information we receive, called **cognitive biases**. The book talks about the research of Daniel Kahneman and Amos Tversky[11], they studied the fact that when we face a decision, like making a player play or not, we tend to fall on mental **heuristics**, which are mental shortcuts that we use to make quick intuitive decisions, and may lead to misjudgments.

Then, biases are the result of judgmental heuristics. Some types of heuristics are:

- **Availability Heuristic**: The most accepted, recent, or readily available information and data are selected with priority by our brain.

- **Affect Heuristic**: The reliance on a “good” or “bad” feeling in making a decision. Basically, trusting your intuition to make quick judgment calls.

- **Representative Heuristic**: The use of stereotypes to judge the likelihood that something belongs to certain group.

Some types of biases:

- **Confirmation Bias**: The tendency to favor, seek, interpret, and remember information that confirms one’s beliefs or hypotheses.

- **Overconfidence Bias**: The overestimation of the confidence with which we trust our own decisions or positions

- **Novelty Bias**: The tendency to prefer something just because it is new.

[2] the application of statistical analysis to baseball records, especially to evaluate and compare the performance of individual players.

Heuristics and cognitive biases are mental limits [12]. Apart from that, we have time and resource limits. Many front office decision-makers do not have the time or resources to watch all the games from all the candidates when signing a player.

Sports analytics is useful because it gives you more information with less time and, as stats are numbers without emotions, they can prevent us from falling back to cognitive biases. Some real use cases are:

- Opponent team and player analysis
- Team performance analysis
- Sports science: physical performance and medical decision-making
- Fan insights and engagement analysis
- Revenue optimization
- Real time decisions.

2.2 Basketball Analytics

In 2003, *Basketball On Paper - Rules and Tools for Performance Analysis* [13] was published, it is considered the basic book for anyone who wants to start in the world of advanced statistics. Some of the metrics used by the writer, Dean Oliver, are still used now.

To do any analysis, we first need data, more data means more information (unless we have useless data). Basketball Analytics has evolved as different and more completed **data sources** have been available: [14]

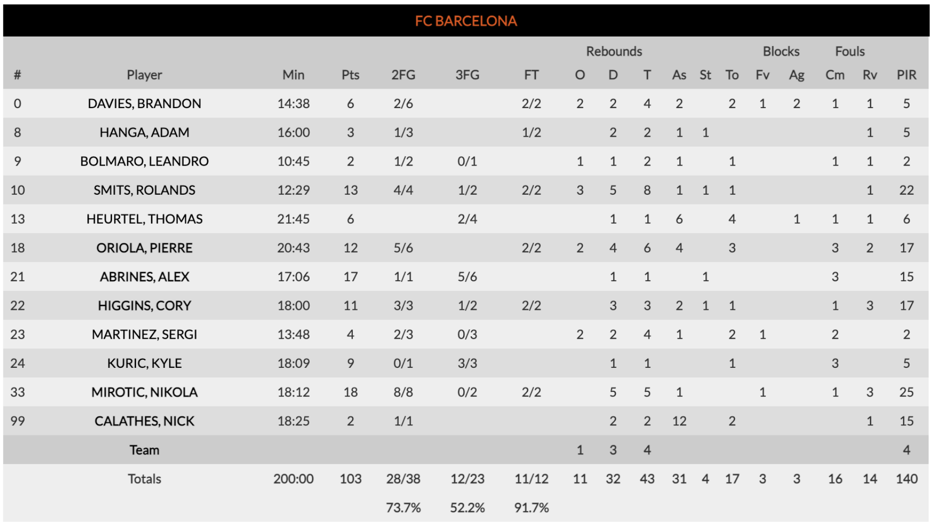
2.2.1 Box score

A box score is a structured summary of some stats collected during the game. Traditionally, it contains the minutes played, made and missed shots, rebounds, assists, steals, blocks, turnovers and fouls (see Figure 3).

It represents 24 rows of data per game approx., one row per player, and team totals. It requires no processing. But the problem is that there is no context provided and it is purely based on the outcome, meaning it can not be known how these things that are in there occurred.

Even with this basic form of data that had been in the industry for a lot of years, there have been many changes in the last 20 years because people tried to figure out smarter ways to use it to affect some change in the sport.

Maybe the most relevant of them, the change that has been the biggest attributed to analytics is



FC BARCELONA

							Rebounds						Blocks		Fouls		
#	Player	Min	Pts	2FG	3FG	FT	O	D	T	As	St	To	Fv	Ag	Cm	Rv	PIR
0	DAVIES, BRANDON	14:38	6	2/6		2/2	2	2	4	2		2	1	2	1	1	5
8	HANGA, ADAM	16:00	3	1/3		1/2		2	2	1	1					1	5
9	BOLMARO, LEANDRO	10:45	2	1/2	0/1		1	1	2	1		1			1	1	2
10	SMITS, ROLANDS	12:29	13	4/4	1/2	2/2	3	5	8	1	1	1				1	22
13	HEURTEL, THOMAS	21:45	6		2/4			1	1	6		4		1	1	1	6
18	ORIOLA, PIERRE	20:43	12	5/6		2/2	2	4	6	4		3			3	2	17
21	ABRINES, ALEX	17:06	17	1/1	5/6			1	1		1				3		15
22	HIGGINS, CORY	18:00	11	3/3	1/2	2/2		3	3	2	1	1			1	3	17
23	MARTINEZ, SERGI	13:48	4	2/3	0/3		2	2	4	1		2	1		2		2
24	KURIC, KYLE	18:09	9	0/1	3/3			1	1			1			3		5
33	MIROTIC, NIKOLA	18:12	18	8/8	0/2	2/2		5	5	1			1		1	3	25
99	CALATHES, NICK	18:25	2	1/1				2	2	12		2				1	15
	Team						1	3	4								4
	Totals	200:00	103	28/38	12/23	11/12	11	32	43	31	4	17	3	3	16	14	140
				73.7%	52.2%	91.7%											

Figure 3: Barcelona's box score of the game against Alba Berlin

the rise of the 3-point shot. Nowadays, teams shoot a lot more threes than they used to.

Analysts realized that **3 is bigger than 2**, which is obvious, by a significant 50% margin, so instead of taking a long 2-point shot, it is better to step back and shoot a 3-pointer. In Figure 4 we see this change reflected:

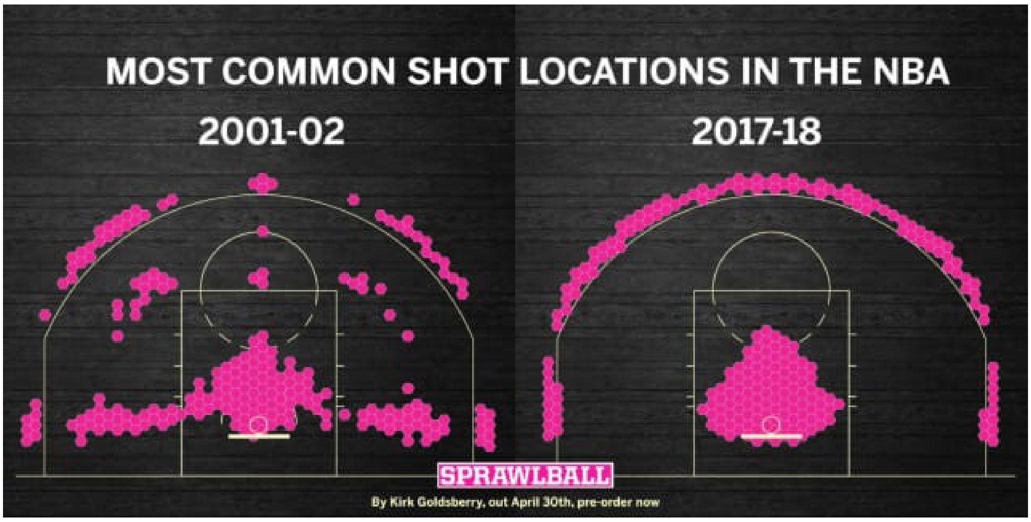


Figure 4: Graphic from the book SprawBall by Kirk Goldsberry

Looking at rebounding numbers, coincidentally, the days that the team played the worst, the players would rebound (on offense) the best. Another realization was that if there are more misses because the team is not playing well, there are more opportunities to rebound the ball and then players will rebound the ball more. So the great second revolution was that instead of looking at totals **it is better to look at percentages**, to be aware of opportunities. See the example in Table 1.

Player	Shots made	Shots taken	%
A	5	20	20%
B	4	5	80%

Table 1: Simple efficiency example

Although player A has scored more points, he has taken way more shots (more opportunities) than B, so player B has been more efficient than player A.

These two realizations made this started being called *Advanced Analytics*.

From the box score, the concept of *possessions* was born. A team has the possession when they are playing offense. The formula to calculate it is:

$$\texttt{Possessions} = 0.96 \times [(Field\,Goal\,Attempts) + (Turnovers) + \\ 0.44 \times (Free\,Throw\,Attempts) - (Offensive\,Rebounds)]$$

One of the things that was a challenge with the box score data source is that **context matters**. Rebounding is not the same against smaller and lazy opponents than against taller and active opponents.

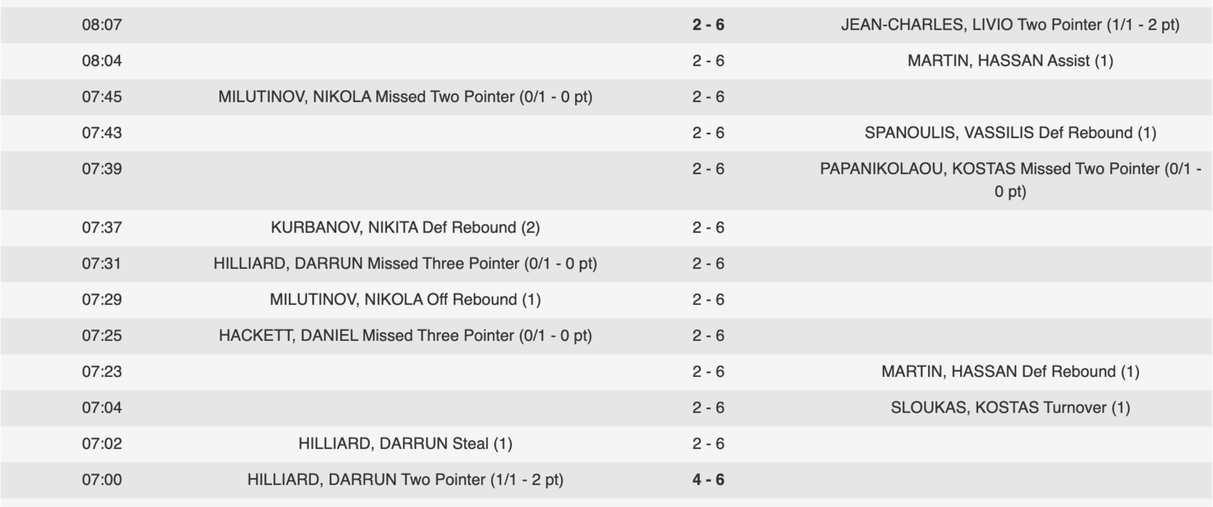
Advanced Analytics opened the door to some people from different disciplines getting into basketball teams and being able to keep improving.

2.2.2 Play-by-play

A play-by-play is defined as reporting on every action as it occurs on the game chronologically (see Figure 5).

The data is still outcome-based and it is not so much data, just 400 rows of data per game which are the number of events that happen. But there is some context in terms of knowing who is on the court when an event happens, which was the score, the time left... so we can understand better.

With this information, we can do **lineup optimization**: understanding which groups of players play better together, which are the players we have on the court when we are effective. Also, be able to identify if two players perform well together.



08:07		**2 - 6**	JEAN-CHARLES, LIVIO Two Pointer (1/1 - 2 pt)
08:04		2 - 6	MARTIN, HASSAN Assist (1)
07:45	MILUTINOV, NIKOLA Missed Two Pointer (0/1 - 0 pt)	2 - 6	
07:43		2 - 6	SPANOULIS, VASSILIS Def Rebound (1)
07:39		2 - 6	PAPANIKOLAOU, KOSTAS Missed Two Pointer (0/1 - 0 pt)
07:37	KURBANOV, NIKITA Def Rebound (2)	2 - 6	
07:31	HILLIARD, DARRUN Missed Three Pointer (0/1 - 0 pt)	2 - 6	
07:29	MILUTINOV, NIKOLA Off Rebound (1)	2 - 6	
07:25	HACKETT, DANIEL Missed Three Pointer (0/1 - 0 pt)	2 - 6	
07:23		2 - 6	MARTIN, HASSAN Def Rebound (1)
07:04		2 - 6	SLOUKAS, KOSTAS Turnover (1)
07:02	HILLIARD, DARRUN Steal (1)	2 - 6	
07:00	HILLIARD, DARRUN Two Pointer (1/1 - 2 pt)	**4 - 6**	

Figure 5: Play-by-play of a CSKA Moskow-Olympiacos Piraeus game

Another advancement was about all those things that coaches call intangibles, meaning things that do not get reflected in the stat sheet because technically the player is not responsible for the outcome, but he/she has helped to make this happen.

With this, we can start looking at, not only how many rebounds the player gets or what defensive rebound percentage the player has, but also what happens when this player is on the court. So maybe his effect is not by getting the ball but by making his teammates get the ball.

The challenge with play-by-play data is that we know the what and when in terms of context, but we do not know the how or the why. We still do not know the process that led to something happening.

2.2.3 Player tracking

Tracking is a technology able to identify every player (and the ball) on the court at every moment through video (Figure 6). Currently, it is only used in the NBA, this is why it is considered the most advanced basketball league in Analytics.

From tracking data, analysts receive large files that give essentially x, y, and z positions of every player at 25 frames per second rate. That equates to a million rows of data per game, so the available data has increased exponentially, and so the techniques that they have to use.

With this huge dataset of just positions, they can figure out what actions and what type of situations are happening in the game: what is a pass, a dribble, a particular play a team is running, and other tactical situations. This provides rich contextual information and it is not only based on the outcome but also what route the player took to get to that outcome and even where were the other players and how were they moving when it happened.

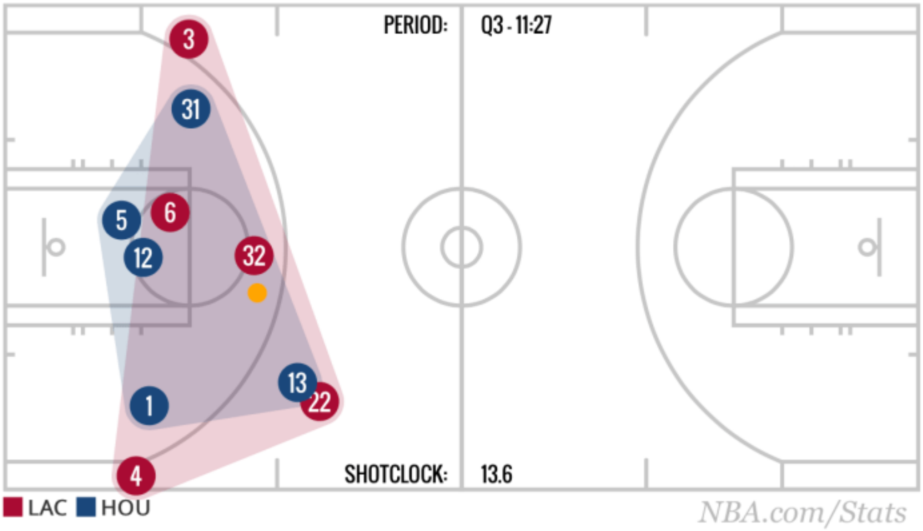


Figure 6: Player tracking of a Clippers-Rockets game

Knowing the context allows analysts to have a conversation with coaches in a sense that apart from identifying the problem, they can provide tools to find the solution. For example, when not finding a particular important shot in the game, being able to identify which situations have led to that, which situation has not led to that but we are okay with, or which situations we are not taking advantage of that could lead to that.

The available jobs in basketball nowadays have changed significantly because knowing how to do Machine Learning techniques over this dataset is required.

The most interesting advance is being able to quantify and analyze trade-offs. Basketball is a game of trade-offs, coaches make a bet on what they are trying to do, strengthening one part of the game by probably weakening another part. For example, defensively in a particular situation, what is better for the team, to put two defenders to cover the ball or isolate the player in a 1-on-1?

2.3 Machine Learning

Second Spectrum is the Official Tracking Provider for the NBA, among other leagues, not only they have developed the software to get files with the position of the players in the court, but also they have implemented ML algorithms to get insights.

As Rajiv Maheswaran, the CEO and Co-Founder of Second Spectrum explained in his TED talk [15], they implemented *classification* to identify tactical situations that occur in basketball, for example, a pick and roll[3]. Classification is a supervised learning technique that after introducing

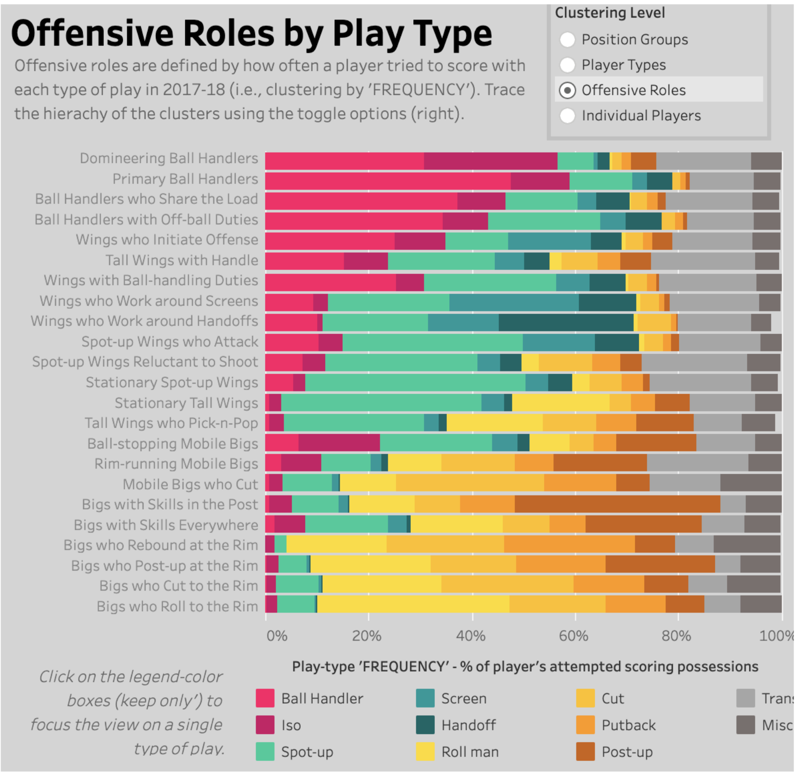
[3] offensive play in which a player sets a screen for a teammate with the ball and then moves toward the basket

labeled data from previous games, like these files but with the added information of what is a pick and roll and what is not, can identify what is a pick and roll and what is not for future games. This is called *spatiotemporal pattern recognition*.

With spatiotemporal pattern recognition, they are also able to quantify how good or how bad a shot is by looking at every shot taken and its situation: where the shot is, what is the angle to the basket, where are the defenders standing, which shot type it is, and more. With this information, they build a model that predicts what is the likelihood that this shot would go in under these circumstances. They can know the quality of the shot and the quality of the shooter.

2.4 Player Clustering

There have been other projects which have used clustering. Todd Whitehead used [16] the NBA play-type data[4] from the 17-18 season to define 23 different offensive roles and created a few Tableau dashboards to describe the groups that were formed (see Figure 7). His goal was to see how basketball has evolved from the classic five positions.



Offensive Roles by Play Type

Offensive roles are defined by how often a player tried to score with each type of play in 2017-18 (i.e., clustering by 'FREQUENCY'). Trace the hierachy of the clusters using the toggle options (right).

Clustering Level
○ Position Groups
○ Player Types
● Offensive Roles
○ Individual Players

Click on the legend-color boxes (keep only') to focus the view on a single type of play.

Domineering Ball Handlers
Primary Ball Handlers
Ball Handlers who Share the Load
Ball Handlers with Off-ball Duties
Wings who Initiate Offense
Tall Wings with Handle
Wings with Ball-handling Duties
Wings who Work around Screens
Wings who Work around Handoffs
Spot-up Wings who Attack
Spot-up Wings Reluctant to Shoot
Stationary Spot-up Wings
Stationary Tall Wings
Tall Wings who Pick-n-Pop
Ball-stopping Mobile Bigs
Rim-running Mobile Bigs
Mobile Bigs who Cut
Bigs with Skills in the Post
Bigs with Skills Everywhere
Bigs who Rebound at the Rim
Bigs who Post-up at the Rim
Bigs who Cut to the Rim
Bigs who Roll to the Rim
0%
20%
40%
60%
80%
100%
Play-type 'FREQUENCY' - % of player's attempted scoring possessions
Ball Handler
Iso
Spot-up
Screen
Handoff
Roll man
Cut
Putback
Post-up
Trans
Misc

Figure 7: Graphic with the 23 offensive roles by the frequency of type of play

[4] The NBA's individual play-type data are provided by Synergy using a proprietary, real-time, video-indexing, statistical engine that logs every play of every game.

Samuel Kalman and Jonathan Bosch presented this work [17] in the MIT Sloan Sports Analytics Conference. One of the goals is the same as the project before but with the addition that it also provides insight into which combination of player types yield the most effective basketball performance. They used box score and play-by-play data from ten NBA seasons (2009-2018).

Adrià Arbués [18], used Euroleague data focusing on shooting with the goal of, through clustering, being able to spot different types of group players.

This was done by splitting the court in 14 regions (see Figure 8, and then seeing how players perform at each zone by mapping it in tetradecagons (14 side polygon), where all the vertices' orientation correspond to a different type of spatial shot.

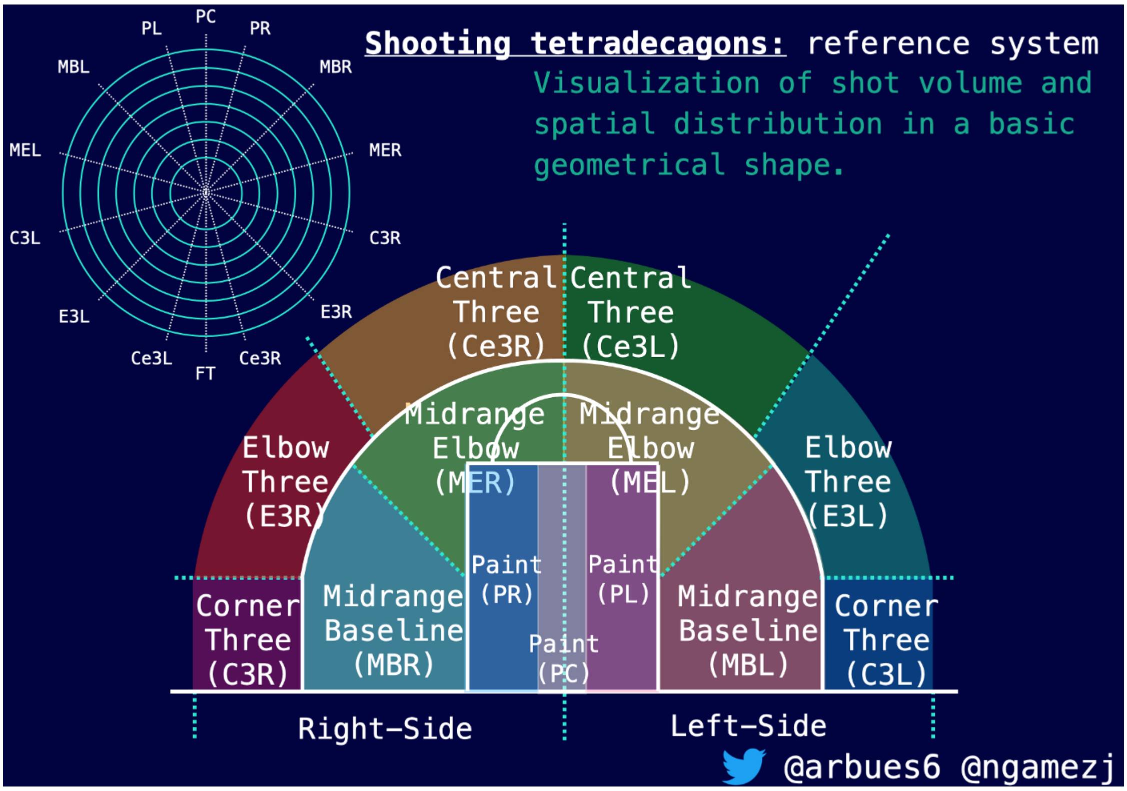


Figure 8: Reference system for mapping shots in “Shooting tetradecagons” by Adrià Arbués

3 Methodology/project development

Note: The code is available on GitHub: github.com/dmolins/euroleague-clustering

3.1 Data collection

In every analysis, we need data. Sometimes data is provided and other times techniques have to be used to take this data. Because of this, an ETL (Extraction, Transformation and Loading of the data) process has been followed.

3.1.1 Extraction

In order to do a consistent analysis, data from 4 different resources will be gathered: box score, play-by-play, shot chart, and player info.

1. **Box score**

   In this case Web Scraping has been used to take the data from Basketball Reference [19], which is a very popular and reliable website where we can find these stats averaged for every player during the whole season.Web Scraping refers to the extraction of data from a website. This information is collected and then exported into a format that is more useful for the user. We do it using Python and export the data into CSV files.

2. **Play-by-play**

   The play-by-play data gives us more information. In this case, thanks to Nacho Gámez, we already have CSV files that have been built from the Euroleague website [20].

3. **Shot chart**

   It is another data source that gives information about the shots made or miss by every player and its position on the floor (see Figure 9). Like the play-by-play data, thanks to Nacho Gámez's work, we already have the CSV files.

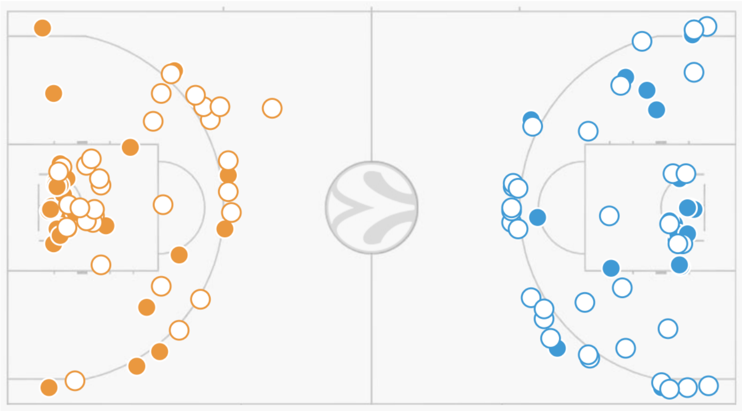
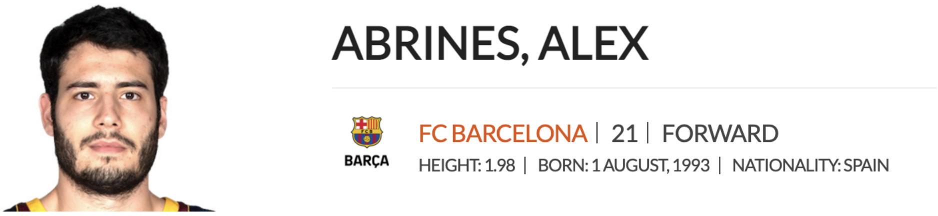


Figure 9: Example of a complete shot chart of a game

4. **Player info**

   The resources mentioned give us information about the games, but we also need information about the players: height, nationality, age and position (see Figure 10). We can access this information also on the Euroleague website, which has been scraped.



ABRINES, ALEX

BARÇA

FC BARCELONA | 21 | FORWARD

HEIGHT: 1.98 | BORN: 1 AUGUST, 1993 | NATIONALITY: SPAIN

Figure 10: Information about Alex Abrines from Euroleague's website

3.1.2 Transformation

The goal is to take relevant data to do the clustering, so this phase consists of transforming the data extracted into relevant and structured data for the analysis.

To explain it, it is better to start from the end. In Figure 11 we can see the table used to cluster the players, a fact table called stats, which contains information from games (box score, play-by-play, and shot chart). The player_info table has not been used but it has been taken in case it is needed in the future.

With the stats collected in the stats table we have information about the player's role, his scoring efficiency, how many possessions he finishes when he is on the court, his playing style and his

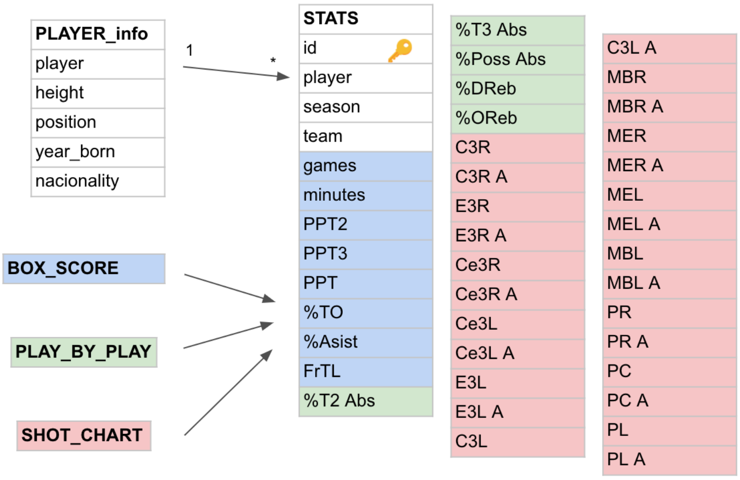


Figure 11: Final table showing the source of every parameter

shooting preferences. The meaning of every stat, every parameter for the clustering, will be explained below.

But to arrive here, previously some transformations have to be done.

1. **Box score**

   Directly from the CSV files obtained, the box_score table (Figure 12) is built.

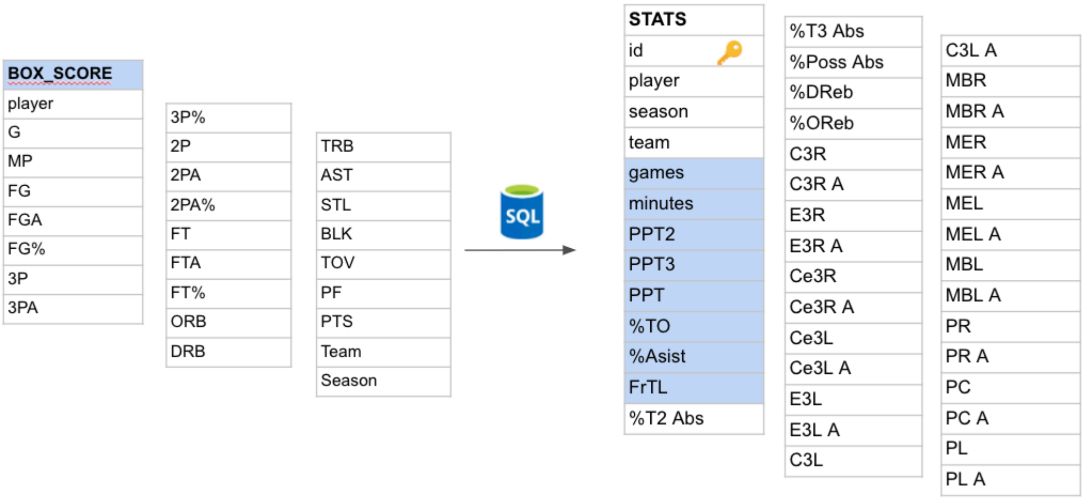


Figure 12: Box score’s contribution to the stats table

To get the stats that we want, we use the following formulas:

Games played:

$$games = G$$

Minutes per game:

$$minutes = MP$$

The points the player added per 2 point shot attempted:

$$PPT2 = \frac{2 \times 2P}{2PA}$$

The points the player added per 3 point shot attempted:

$$PPT2 = \frac{3 \times 3P}{3PA}$$

The points the player added per shot attempted, taking into account 2 and 3-pointers:

$$PPT = \frac{2 \times 2P + 3 \times 3P}{FGA}$$

Turnover rate, meaning the percentage of the possessions the player finishes that end up with a turnover:

$$\%TO = \frac{TOV \times 100}{FGA + FTA \times 0.44 + AST + TOV}$$

Assist rate, same concept for assists:

$$\%Asist = \frac{AST \times 100}{FGA + FTA \times 0.44 + AST + TOV}$$

Frequency of free throw shooting, meaning how many free throws the player scores compared to his/her field goals attempts:

$$FrTL = \frac{FT}{FGA}$$

2. **Play-by-play**

   For the play-by-play data we previously have to process the data that we get from the CSV files, these are the most relevant columns the files have:

   - Codeteam → (p.e: BAR for FC Barcelona)
   - Player → who did the action

- Playinfo → type of play (Two Pointer, Defensive Rebound, Foul, Substitution...)
- Game → game identifier

From this data source, information about the usage of a player will be obtained by how many of each stat the player had (_j) and how many the team had when the player was on the court (_e). The stats that represent usage are shots attempted(2 and 3-pointers, T2A and T3A), free throw shooting (TL) and turnovers (TO).

Apart from this, rebounding ability is also measured by summing up the rebounds, defensively and offensively, a player had (_j) and the available rebounds the player he could have got when he was on the court (_t).

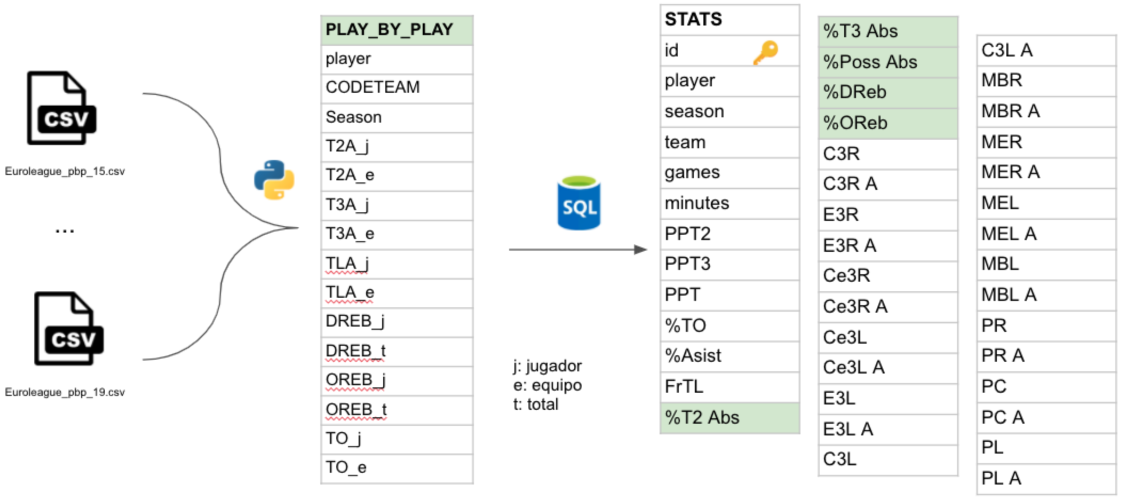


Figure 13: Play-by-play's contribution to the stats table

With these stats, the play_by_play table can be built, and from it we can get the stats that are going to be used in the clustering (see Figure 13):

The percentage of two-point shots absorbed, meaning the percentage of two-point shots a player took out of ones the team took when he was on the court:

$$\%T2Abs = \frac{T2A_j \times 100}{T2A_e}$$

The percentage of three-point shots absorbed, same concept for 3 point shots:

$$\%T3Abs = \frac{T3A_j \times 100}{T3A_e}$$

The percentage of possessions absorbed, same concept for possessions:

$$\%PossAbs = \frac{(T2A_j + T3A_j + TLA_j \times 0.44 + TO_j - OREB_j) \times 100}{T2A_e + T3A_e + TLA_e \times 0.44 + TO_e - OREB_t}$$

The percentage of defensive rebound, the defensive rebounds the player took out of the total he could have got:

$$\%DReb = \frac{DREB_j \times 100}{DREB_t}$$

The percentage of offensive rebound, same concept for the offensive ones:

$$\%OReb = \frac{OREB_j \times 100}{OREB_t}$$

3. **Shot chart**

This one is more tricky. The CSV files give information of every shot taken with:

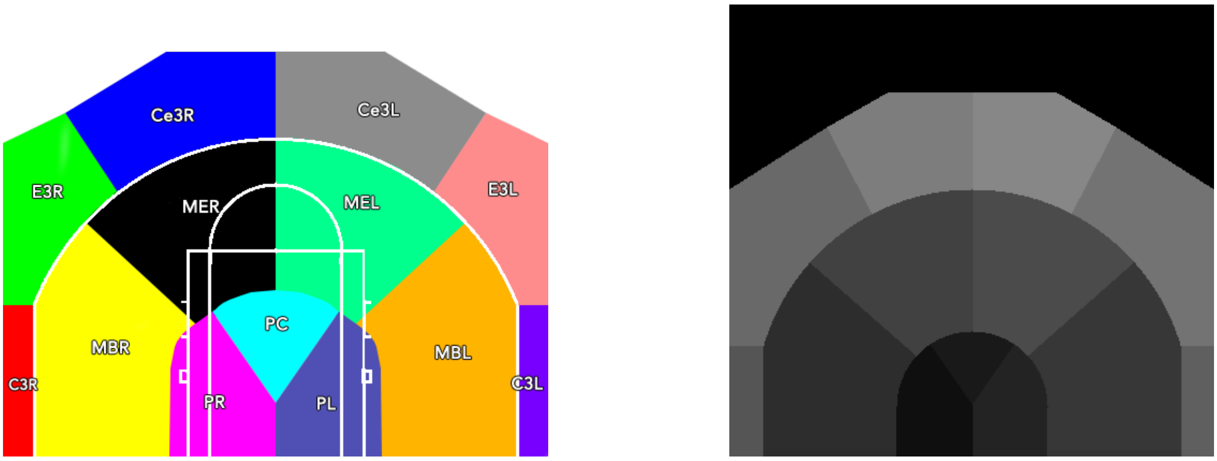
- The player who took the shot
- Type of shot: two/three-pointer made/missed or free throw
- The points added with the shot (0, 1, 2 or 3)
- The position of the shot, with coordinates (in cm) on the x (COORD_X) and y-axis (COORD_Y)

For the coordinates, the origin is under the rim, and as you go further, COORD_Y increases. Shots taken from the left (as if you see it from the court) have COORD_X > 0, and from the right, < 0.

Although the files give a shot zone, I think this can be improved, so an image has been created with other regions defined very close to the one Adrià Arbués created [21].

The image in Figure 14a is a representation done with Photoshop from the created image Figure 14b, which has been created with Python to be extremely precise. The grey-scale image has been created superposing polygons so that each zone in this image has a unique label.

Every shot region has an acronym, following the guide in table 2:



(a) With shot region names

(b) Grey-scale

Figure 14: Shot regions

Digit	Meaning	Digit	Meaning	Digit	Meaning
3	3-pointer	C	Corner	R	Right
M	mid-range	E	Elbow	L	Left
P	paint	Ce	Central	C	Central
		B	Base-line		

Table 2: Shot regions achronim guide

To know the shots made and attempted per game for every player and every shot region, a Python script has been created that goes shot by shot identifying the region and adding it to the player who took it. The process is as follows: first, the coordinates (x,y) are converted from cm to pixels in the image (X,Y). Then, as all the pixels of a given region of the image have the same label, it is possible to know the region from where the shot was thrown by simply taking the value of the pixel at position (X,Y). With this information, the shot_chart table is built as shown in Figure 15:

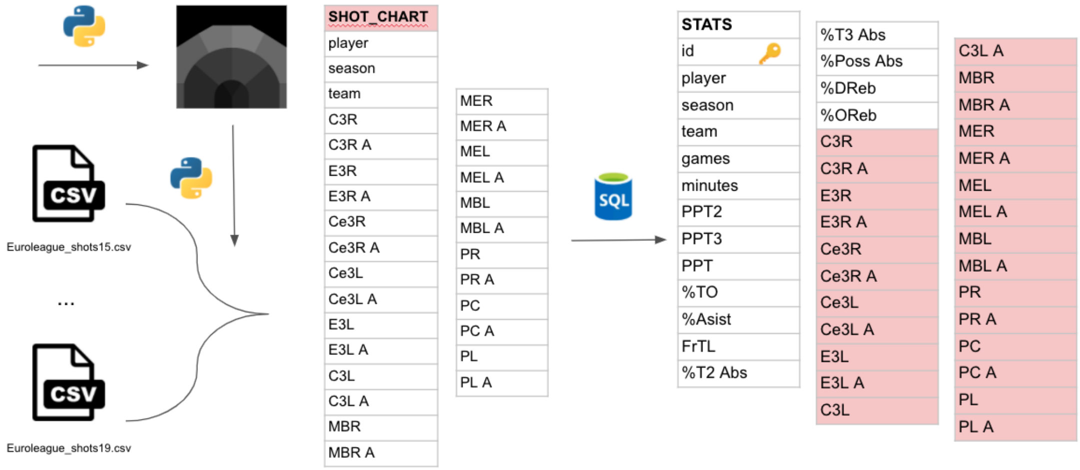


Figure 15: Shot regions

So for example, MBR stands for the made shots in the Mid-range Baseline Right region, and MBR_A for the attempted shots in the same region.

4. **Player info**

   No transformation is required for player information, just importing it to an SQL table.

3.1.3 Loading

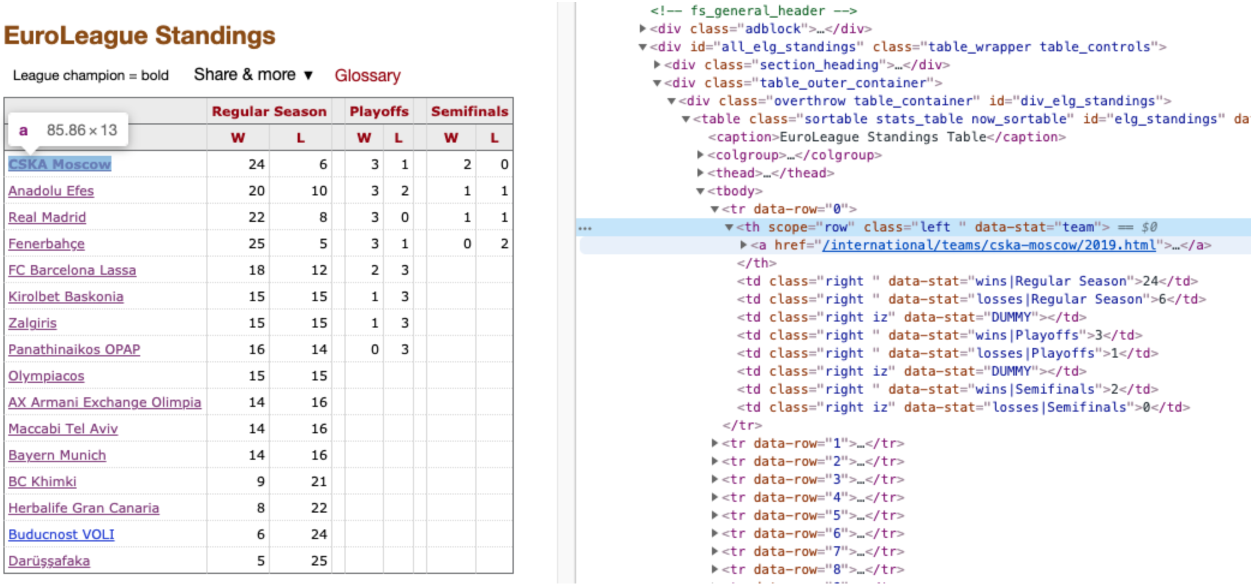
SQL has been used to join the box_score, play_by_play, and shot_chart tables into a view, which has been stored in a local server.

3.2 Web Scraping

Web Scraping has been used to extract the box scores and player info from websites, so in this chapter, the process will be briefly explained.

First, the data source has to be inspected to be able to understand, through the HTML code, how the web is structured. In Figure 16 we see the Basketball-Reference page for the 18-19 Euroleague season, we can see that the links for every team who competed that season are stored in a table (table class=”sortable stats_table now_sortable” id=”elg_standings” data-cols-to-freeze=”1”).

A connection has to be made with the website that wants to be scraped and then parse the HTML



EuroLeague Standings

League champion = bold   Share & more ▾   Glossary

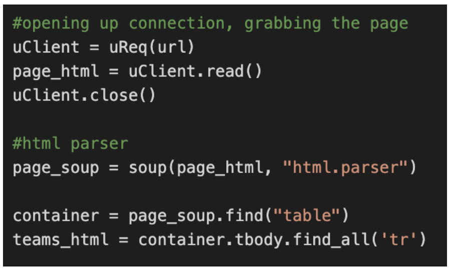
a 85.86 × 13

	Regular Season		Playoffs		Semifinals	
	W	L	W	L	W	L
CSKA Moscow	24	6	3	1	2	0
Anadolu Efes	20	10	3	2	1	1
Real Madrid	22	8	3	0	1	1
Fenerbahçe	25	5	3	1	0	2
FC Barcelona Lassa	18	12	2	3		
Kirolbet Baskonia	15	15	1	3		
Zalgiris	15	15	1	3		
Panathinaikos OPAP	16	14	0	3		
Olympiacos	15	15				
AX Armani Exchange Olimpia	14	16				
Maccabi Tel Aviv	14	16				
Bayern Munich	14	16				
BC Khimki	9	21				
Herbalife Gran Canaria	8	22				
Buducnost VOLI	6	24				
Darüşşafaka	5	25				

```
      <!-- fs_general_header -->
     ▶<div class="adblock">…</div>
     ▼<div id="all_elg_standings" class="table_wrapper table_controls">
       ▶<div class="section_heading">…</div>
       ▼<div class="table_outer_container">
         ▼<div class="overthrow table_container" id="div_elg_standings">
           ▼<table class="sortable stats_table now_sortable" id="elg_standings" da
               <caption>EuroLeague Standings Table</caption>
             ▶<colgroup>…</colgroup>
             ▶<thead>…</thead>
             ▼<tbody>
               ▼<tr data-row="0">
...              ▼<th scope="row" class="left " data-stat="team"> == $0
                   ▶<a href="/international/teams/cska-moscow/2019.html">…</a>
                  </th>
                  <td class="right " data-stat="wins|Regular Season">24</td>
                  <td class="right " data-stat="losses|Regular Season">6</td>
                  <td class="right iz" data-stat="DUMMY"></td>
                  <td class="right " data-stat="wins|Playoffs">3</td>
                  <td class="right " data-stat="losses|Playoffs">1</td>
                  <td class="right iz" data-stat="DUMMY"></td>
                  <td class="right " data-stat="wins|Semifinals">2</td>
                  <td class="right iz" data-stat="losses|Semifinals">0</td>
                </tr>
               ▶<tr data-row="1">…</tr>
               ▶<tr data-row="2">…</tr>
               ▶<tr data-row="3">…</tr>
               ▶<tr data-row="4">…</tr>
               ▶<tr data-row="5">…</tr>
               ▶<tr data-row="6">…</tr>
               ▶<tr data-row="7">…</tr>
               ▶<tr data-row="8">…</tr>
```

Figure 16: HTML code of Basketball Reference website

page into a container using Beautiful Soup, as can be seen in Figure 17.



```
#opening up connection, grabbing the page
uClient = uReq(url)
page_html = uClient.read()
uClient.close()

#html parser
page_soup = soup(page_html, "html.parser")

container = page_soup.find("table")
teams_html = container.tbody.find_all('tr')
```

Figure 17: First steps for Web Scraping

After that, you have to go directly to the information you want to get using functions like `find` or `find_all` taking as a parameter the element where the information is. Figure 17, shows that every team is stored inside a row of the table (tr).

Once we have the information we want, it is stored in a DataFrame using the pandas' library that allows us, when it is finished, to export the data into a CSV file.

3.3 Data Cleaning

Cleaning the data is essential to get at least acceptable results. After gathering all the data, there was a complete revision to assure that the data did not have any mistakes. Some mistakes were found and made me step back to correct them. The origin of these mistakes can be found in the ETL process or even in the data sources.

A remarkable bug that was found was that there were some cases that the values obtained were not being coherent and it was because of the collected data from the Euroleague website. It was found that there were cases that the same player was named differently in different games. For example, for some games, we had stats from Alex Abrines and for other games, from Alejandro Abrines, so this was interpreted as two different players. As a solution, both ”players” were summed up and saved with the name of Alex Abrines.

3.4 Clustering

Once we have the data structured and cleaned, we can proceed to do the clustering. Python and the Scikit-learn library have been used. First, the connection with the SQL server is done to get the stats table, and the parameters that are going to be used are introduced into a NumPy matrix.

The algorithm used to do the clustering has been the K-means algorithm [22]. K-means clusters data by trying to separate samples in n groups of equal variance. It requires the number of clusters to be specified.

After trying with a different number of clusters, the results were not being adequate.

It was observed that players were falling into clusters that they did not fit. What these players had in common was that they played for very few minutes. As a solution, the query was filtered by the players that played more than 5 minutes per game because those who did not, their stats were not reliable for being a very small sample that introduces noise. There were also removed those players who played less than five games.

K-means clustering is ”isotropic” in all directions of space [23] and therefore tends to produce more or less round (rather than elongated) clusters. In this situation, leaving variances unequal is equivalent to putting more weight on variables with smaller variances. This is why standardizing the parameters before clustering was tried.

These two adjustments made improve the results and, after testing the clustering with a different number of clusters, the best results have been fixing this value to 10.

3.5 Visualization

To interpret the results, visualizing them with graphics can help. The program Google Data Studio has been used to do so, seeing the difference between clusters and understanding what characteristics does a player need to have to be in a particular cluster. The dashboard created is available for anyone to see it and be able to interact with it:

https://datastudio.google.com/s/j1yrSOAvW0Y

Here are some of the used graphics:

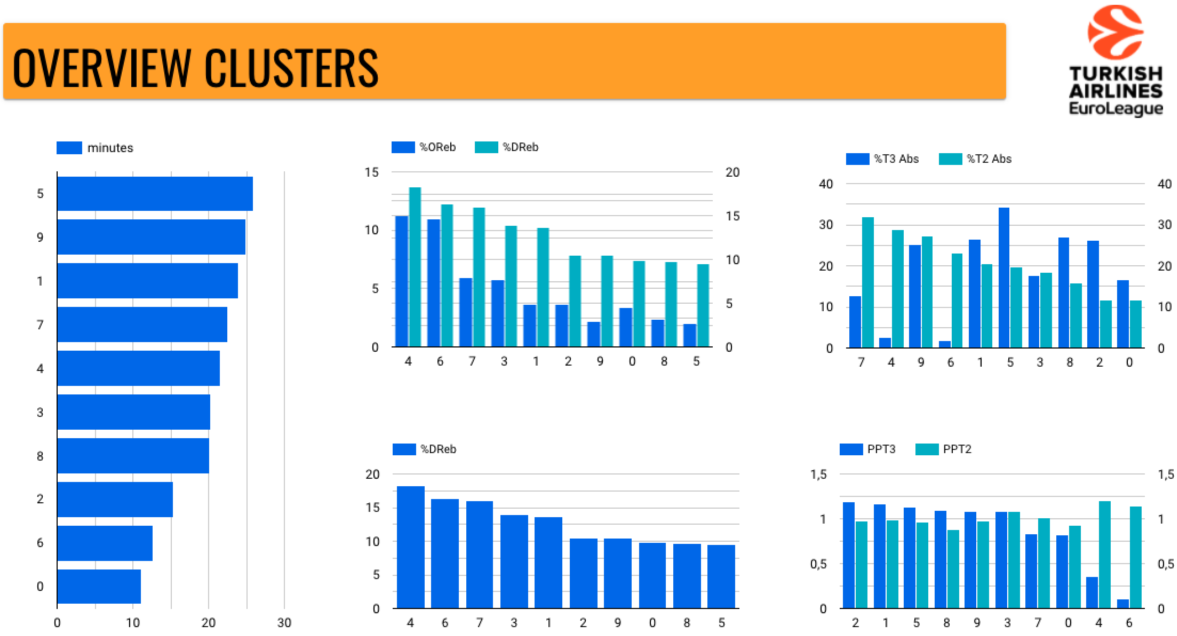
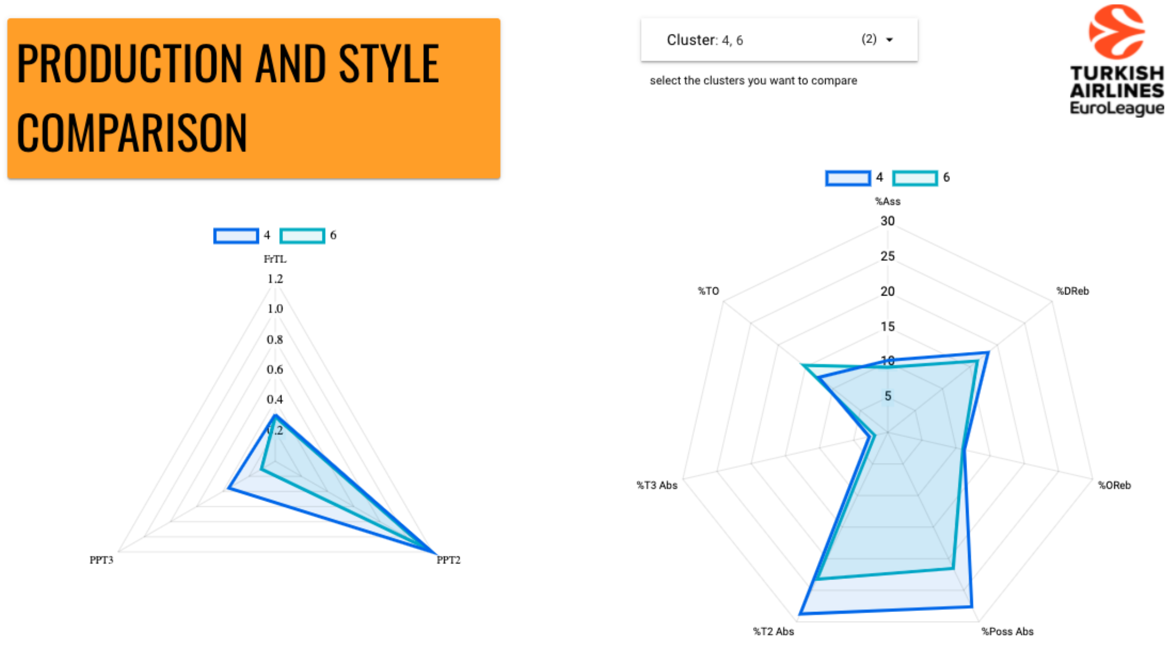


Figure 18: Clusters overview page

In Figure 18 there is an overview of all the clusters that allow us to see the main difference between them. If it is not very clear what distinguished two specific clusters, on another page, there is the possibility to see it with more detail. For example, in Figure 19 we use this page to compare clusters 4 and 6:



PRODUCTION AND STYLE COMPARISON

Cluster: 4, 6 (2)

select the clusters you want to compare

Figure 19: Production and style comparison for clusters 4 and 6

4 Results

The results from the clustering have finally been satisfactory, with 10 differentiated groups. To understand the results (see Table 3), basketball knowledge is required.

ID	Cluster name	Characteristics	Some players
0	Secondaries	few minutes, low %Poss, high %Ass	Balbay, Vezenkov, youngsters
1	3-point spot-up forwards	high 3 pointers from corners, few paint shots, rebound	Datome, Micov, Thompkins
2	3-point specialists	few minutes, high %T3 Abs, low in anything else	Mahnmoutoglu, Taylor, Bertrans
3	3&D	low shooting volume but efficient, rebound	Claver, Kurbanov, Kuzminskas, Blazic
4	Top bigs	high rebound, high volume paint shots, no 3FG	Tomic, Shengelia, Vesely
5	Star exteriors	very high %T3 Abs, especially above the break, high minutes, high usage	Llull, Doncic, Spanoulis
6	Second unit bigs	low minutes and usage, high rebound, high %TO	Diop, Dorsey, Slaughter
7	Mid-range forwards	high mid-range volume, low %Ass, low 3FG	Printezis, Gentile, Jankunas
8	Second sword exteriors	low %T2 Abs, high volume and efficiency in 3FG	Carroll, Rudy, Abrines
9	Ball-dominant guards	High minutes, %Ass and %Poss, mid-range	Calathes, Heurtel, De Colo

Table 3: Results player clustering

0. **Secondaries**
   In this group, there are players who play the least minutes and have a secondary role in their teams. In the minutes they play, their first option is to play for the team, this is why

they finish few possessions, and a lot of them end up with an assist to another teammate. Young players in their first season are common to be here.

1. **3 point spot-up forwards**
   Here we have those players who can stretch the floor because of their efficient 3 point shot, specially from the corners. In offense they are usually opened, this is why their strength is not the offensive rebound.

2. **3 point specialists**
   It has been seen the importance of the 3 point shot in modern basketball, so there are players who can make it to a top league with that being their only strength. They play few minutes and they do what they know. Consequently, they do not dribble to the basket so they do not score near the rim or receive fouls to get to the free throw line.

3. **3&Ds**
   3&D is a concept given for those players who can do a little bit of everything, we can find players that can play in multiple traditional positions because of their versatility. They have a low shooting volume but they are efficient. They also help in rebounding.

4. **Top bigs**
   In this cluster we find those players who move close to the basket and they can score and rebound a lot. They finish strong at the rim, this is why they are fouled a lot.

5. **Star exteriors**
   In this group there are the type of players that usually receive more attention. They are the most used in terms of minutes played and shooting volume. They shoot a lot of threes, specially above the break (3 point shots that are not from the corners).

6. **Second unit bigs**
   Similar to the top bigs cluster, but with the difference that these players shoot less and are less efficient, so they are not as skilled as the other cluster. This also shows in the fact that they turn the ball over a lot.

7. **Mid-range shooters**
   Although these players can shoot from 3, their strength is the mid-range shot. As their focus is on scoring, they give few assists.

8. **Second sword exteriors**
   Players from this cluster are outside scorers who do not finish much in the paint and do not play a lot of minutes but are key in terms of scoring from 3 and play-making.

9. **Ball-dominant guards**

> Here we find those players who dominate rhythm of the game. They can score from inside and outside, they use a lot the mid-range area, but their strength is assisting to other teammates.

As ten clusters have been fixed, there is not a cluster with one of the traditional five positions (point-guard, shooting-guard, small-forward, power-forward, and center), even if the number of clusters is fixed to five, these traditional positions do no appear. On the other hand, it can be seen that these new roles (better said than positions) focus more on the player's production and efficiency, although the bigs (clusters four and six) can be distinguished from others.

Furthermore, it is interesting to see that few players are in the same cluster for all of the five seasons. This can be because they can develop or get older so their style and production changes, also if a player changes from one team to another, he may play a different role there. In Table 4 there is the example of Luka Doncic's evolution.

Season	Cluster	Info
15-16	Secondary	First season in Euroleague with 16 years old
16-17	Second sword exterior	He starts to play regularly being important for the team
17-18	Exterior star	He wins the MVP award[5] and helps Madrid winning the Euroleague. Next year he goes to the NBA

Table 4: Luka Doncic's evolution

Once the clusters are done, can we see clusters on the last champions that other teams do not have? Do these teams have a specific number of players of a specific cluster that other teams do not? The champions from the last five seasons have been compared between each other and also compared to the other teams. In Figure 20 there are graphics done with Google Data Studio that show the number of players from each cluster of the last 3 Euroleague champions.

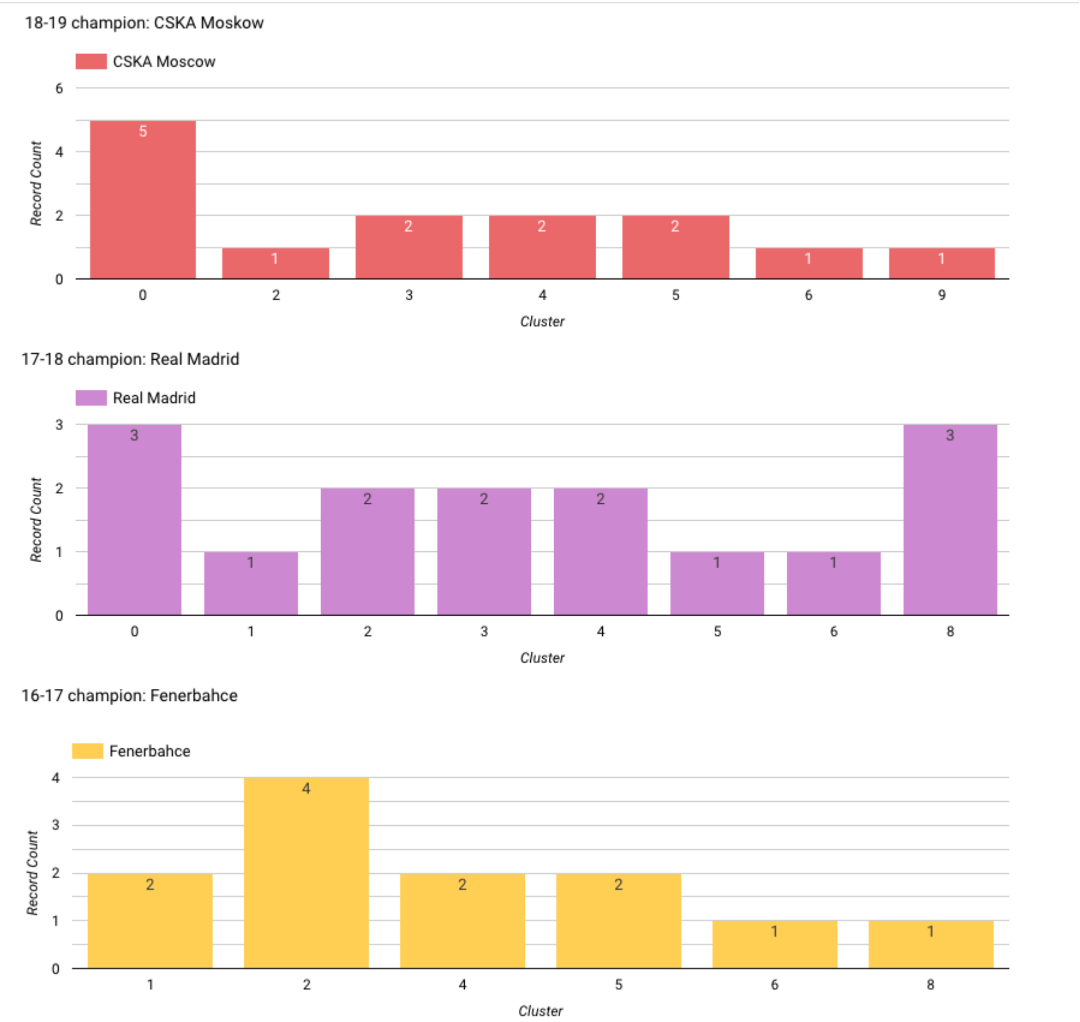


Figure 20: Clusters of the last 3 Euroleague champions

We can conclude, only by watching Figure 20 that a championship team must have at least two players from cluster 4 (Top bigs), one or more player from cluster 2 (3 point specialists), at least one player from cluster 5 (exterior stars)... but many other teams who were not champions have these type of players, so this clustering is not conclusive to define a team champion.

5 Budget

This project has lasted four months, so all of the costs will be estimated monthly and finally multiplied by four.

All of the software used is Open Source and no raw materials have been used. The only material used is the computer which is a MacBook Pro (13-inch, 2017, Two Thunderbolt 3 ports) that had a price of 1500€, taking into account that a computer can last 4 years, the cost for one month is:

$$Monthly PC Cost = \frac{1500}{4} = 375EUR$$

The place to work has been a coworking space in Barcelona, where it is all included (WiFi, lighting, printer, and more). This adds up a cost of 300€ monthly for a fixed desk. As it is close to home and the talks I chaired were online, no transportation was needed.

Finally, wages. In this project, there has been a mentor as a Senior Engineer and me as a Junior Engineer. The mentor has worked one hour per week for the weekly meetings with a salary of 60€/hour and I have worked 20 hours per week for 10€/hour. To get the cost from the salary, a 33% of social security benefits adds up.

$$Monthly Senior Engineer Cost = (60 \times 1 hour \times 4 weeks) \times 1.33 = 319.2EUR$$

$$Monthly Junior Engineer Cost = (10 \times 20 hour \times 4 weeks) \times 1.33 = 1064EUR$$

Then the costs for this project are (see Table 5):

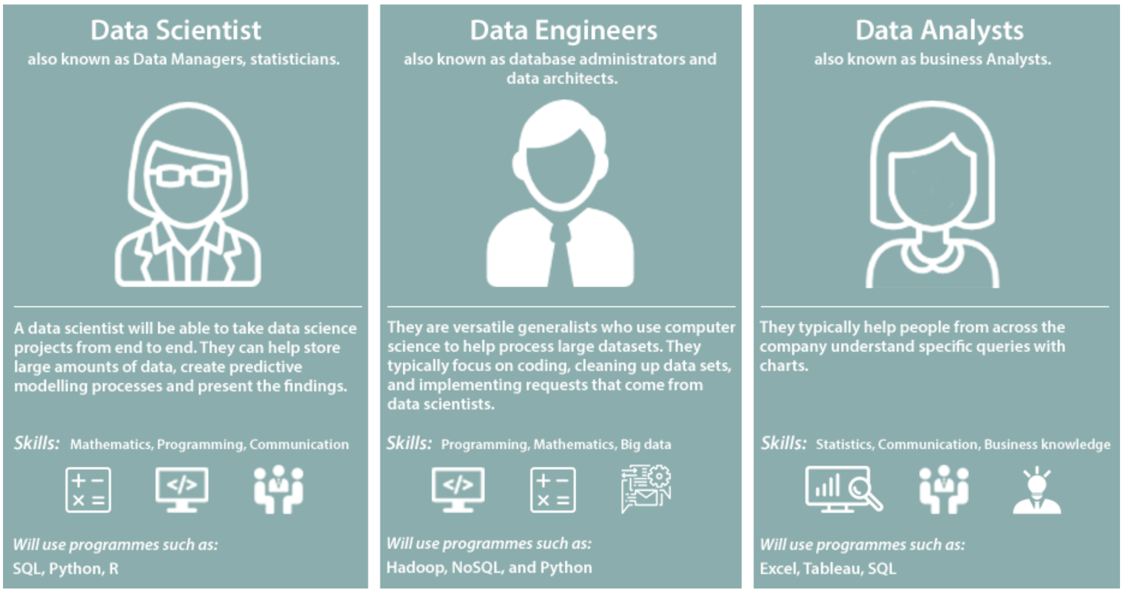
Item	Cost
Computer	375EUR
Senior Engineer	319.2 EUR
Junior Engineer	1064 EUR
Coworking space	300 EUR
Total (monthly)	2058.2EUR
TOTAL COST (4 months)	8232.8 EUR

Table 5: Costs of the project

6 Conclusions and future development

6.1 Conclusions

This project has involved all the parts of analysis, from the data extraction to the final intepretations. With it, it has allowed me to learn a little bit from every step of the process: what a Data Engineer (ETL process and Data Cleaning), a Data Scientist (ML techniques, although they do way more than that), and Data Analyst (visualization and final analysis) do. In Figure 21 these jobs with more detail are shown.



Data Scientist
also known as Data Managers, statisticians.

A data scientist will be able to take data science projects from end to end. They can help store large amounts of data, create predictive modelling processes and present the findings.

Skills: Mathematics, Programming, Communication

Will use programmes such as:
SQL, Python, R

Data Engineers
also known as database administrators and data architects.

They are versatile generalists who use computer science to help process large datasets. They typically focus on coding, cleaning up data sets, and implementing requests that come from data scientists.

Skills: Programming, Mathematics, Big data

Will use programmes such as:
Hadoop, NoSQL, and Python

Data Analysts
also known as business Analysts.

They typically help people from across the company understand specific queries with charts.

Skills: Statistics, Communication, Business knowledge

Will use programmes such as:
Excel, Tableau, SQL

Figure 21: Jobs in the data field and its characteristics

Although the results may not help to find the type of players that make a Euroleague team champion, other applications have been found. When a player goes to another team or retires, this can be helpful to find a replacement with similar skills so that the coach does not need to change the way the team plays.

Another possible application could be to identify teams with similar players. So when a particular strategy has worked against one team, if we face another one with similar players, the same strategy can work against them.

With this, it has also been proven that basketball has evolved and traditional positions are not as defined as before. I do not think they do not exist anymore, because some clusters are very related to these positions but it is true that new types of players can be found. This information can help coaches boost their team's performance by being aware of their players' strengths and weaknesses.

Once this is coming to the end, now that I look behind I would have done some things differently. I did not expect the original data to have mistakes. Anyway, I should have planned to invest time in analyzing it beforehand. So the two weeks I dedicated to clean the data would probably have been less. Furthermore, the 'timing' of each Work Package was not as I expected, the project has made me understand that, more or less, it is 50% to get the data and structure it, 20% to clean it, 10% to apply clustering, and 20% to analyze the results.

Personally, I have enjoyed this project a lot, it has allowed me to put together my two passions: basketball, which has been for a long time, and data, which is "new" for me. This work has made me realized that this is what I want to do in the future but this is just the beginning, so I have to learn and experience a lot to arrive at that point.

6.2 Future work

Even though the results obtained are not enough to know which players a team needs to have to become champion, it does not mean that it is impossible to know using clustering. I would like to continue this project by trying other methods like K-means with a lot of clusters (more than 20), applying PCA before clustering, or trying other algorithms like DBSCAN or Gaussian mixture model. Also, with more data, a better analysis can be done. The same process can be applied using play-type or tracking data, which hopefully, will be available in Europe soon.

It is said that the NBA is way more physical than in Europe, and the way is played is different, so it would be interesting to do the same for other leagues and compare the resulting clusters. Besides, some prospects from Europe decide to go to the NBA after playing in the Euroleague, so another future work could be to analyze if they play the same way or also predict how well a player from Europe could do in the NBA.

References

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