Miquel Villaró Cañizal

Mathematical Engineering
on Data Science

The Apriori Algorithm and Basketball. Using Machine Learning to Quantify, Predict, and Relate Basketball Players' Impact on Professional Level

MENTIONS AND ACKNOWLEDGEMENTS

First of all, I would like to express my gratitude towards everyone who has provided anything positive to this project and, without whom, I could not have come all this way.

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ABSTRACT (English)

Measuring the impact of a basketball player on his/her team is one of the most burdensome unknowns in the sport's data analytics world. In this project Machine Learning is used through the Apriori Algorithm applied to FC Barcelona's basketball team to identify the most efficient sets of players and the relationship between them. Furthermore, a statistic is assigned to measure the impact of the players in each game phase and a predictive model is established to forecast their performance in the Final 4 of the 2021-2022 season.

RESUMEN (Spanish)

Medir el impacto que tiene un jugador de baloncesto en su equipo es una de las mayores incógnitas en el ámbito de analítica de datos del deporte. En este proyecto se trata el uso de Machine Learning mediante el Algoritmo Apriori aplicado al FC Barcelona de baloncesto para identificar los conjuntos de jugadores más eficientes y las relaciones entre ellos. Además, se atribuye una estadística que calibra el impacto de los jugadores en cada fase del juego y se establece un modelo predictivo sobre la actuación de los mismos en la Final a 4 de la temporada 2021-2022.

RESUM (Catalan)

Mesurar l'impacte que té un jugador de bàsquet en el joc del seu equip és una de les grans incògnites en l'àmbit de l'analítica de dades de l'esport. En aquest treball es tracta la utilització de Machine Learning a través de l'Algoritme Apriori aplicat al FC Barcelona de bàsquet en competició d'Eurolliga per a identificar els conjunts de jugadors més eficients i les relacions entre ells. A més a més, també s'atribueix una estadística que mesura l'impacte dels jugadors en cada fase del joc i s'estableix un model predictiu sobre l'actuació d'aquests en la Final a 4 de la temporada 2021-2022.

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1. Context

Nowadays, European basketball is starting to make a technological leap linked to data analytics. New stats and ways to see matches and sources of information appear all the time, and Europe is trying to reach the American analytical level in order to attract new players and sponsors to their leagues and provide higher-level information to major clubs. Furthermore, there are very few stats that can encompass more than one player (and the entire team) to make a specific evaluation. A basketball coach must be aware of the importance of having the most optimal players on the court throughout the entire match, in order to be able to control the pace and achieve victory. This project focuses on a recent methodology that can be implemented to help find the most optimal players..

Basketball is a 5-on-5 sport that is mostly decided in 1-on-1 and 2-on-2 situations. However, each player on the court affects the game in a positive or negative way. A player can affect the game directly (scoring points, grabbing rebounds, etc.) or indirectly (defensive intimidation, outside shot threat, etc.). To this day there is no metric in basketball that can measure this impact of each player (or group of players) on the game. The closest approach is the +/- metric, which individually keeps track of the scoreboard when the player is on the court. This project introduces a new way to assess the offensive impact of each player, specifically in the case of FC Barcelona players in different phases of the game at the highest level of European basketball.

2. Objectives

The project assesses the application of Machine Learning (specifically the Apriori algorithm) to the extent of being able to identify, predict and evaluate the impact of each player (and group of players) in different stages of the game. After an extensive data gathering on FC Barcelona’s Euroleague 21-22 season, the most and least efficient sets of players in the team are extracted, both at a general level and play-type level.

This approach provides an illustrative tool that helps coaches make choices about how the team should play according to the players on the court (and also the other way around: to choose the players who must be on the court according to the way in which the coach wants to play).

This information is also used to have a new point of view when evaluating the season, both at an individual and collective level, and to make a prediction about which (sets of) players will be more or less efficient against a particular rival or situation.

3. Methodology

3.1. Data gathering

To carry out the project, a deep data gathering process was performed by re-visualizing all of FC Barcelona's matches in the top European competition. Since basketball is a complex sport, plays have not been taken into account individually, but the game has been classified in phases (1vs1, outside shot, inside ball...), and the most important aspects have been collected in view of the proposed objectives. The data collected is the following:

- Players on court (Point Guard, Shooting Guard, Small Forward, Power Forward, Center) following this preference list (from PG to C) ordered by verticality:
  - Calathes, Jokubaitis, Laprovittola, Ubal, Villar, Higgins, Exum, Kuric, Bonilla, Abrines, Caicedo, Martinez, Hayes-Davies, Mirotic, Smits, Oriola, Sanli, Davis, Nnaji.
- Point differential with which the phase starts.
- Type of phase played:
  - Phase 1: 1vs1.
  - Phase 2: Pick, hand-off (2vs2 game).
  - Phase 3: Outside shot (2 or 3 points).
  - Phase 4: Inside shot or pass to a cut (intention to score in the paint).
  - Phase 5: Fast break or quick transition.
- Success of the phase:
  - 0→The phase ends unsuccessfully:
    - Bad/blocked shot.
    - Turnover or deflection (e.g. deflected pass which goes out of bounds).
  - 1→The phase ends successfully:
    - It ends in a score (1, 2, 3 or 4 points).
    - It gets a desirable shot opportunity.
    - The defense must commit a violation to stop the attack (foul, etc.).
- Points achieved (0, 1, 2, 3, 4) and quarter in which it is played (1, 2, 3, 4 or 5 in case of overtime).
- If the phase is played in clutch time (close endings):
  - It's cut down to when the differential is between -6 and +6 (2 possessions) and there are 5 minutes or less left in the game. In case of overtime, the differential is not taken into account, the 5 minutes it lasts are clutch-time.
  - Elimination games are clutch-time throughout the entire match (QFG5, F4).
    - 0 → The phase is not in clutch time.
    - 1 → The phase is in clutch time.
- Rival, court (home or away) and competition (regular season or playoffs).

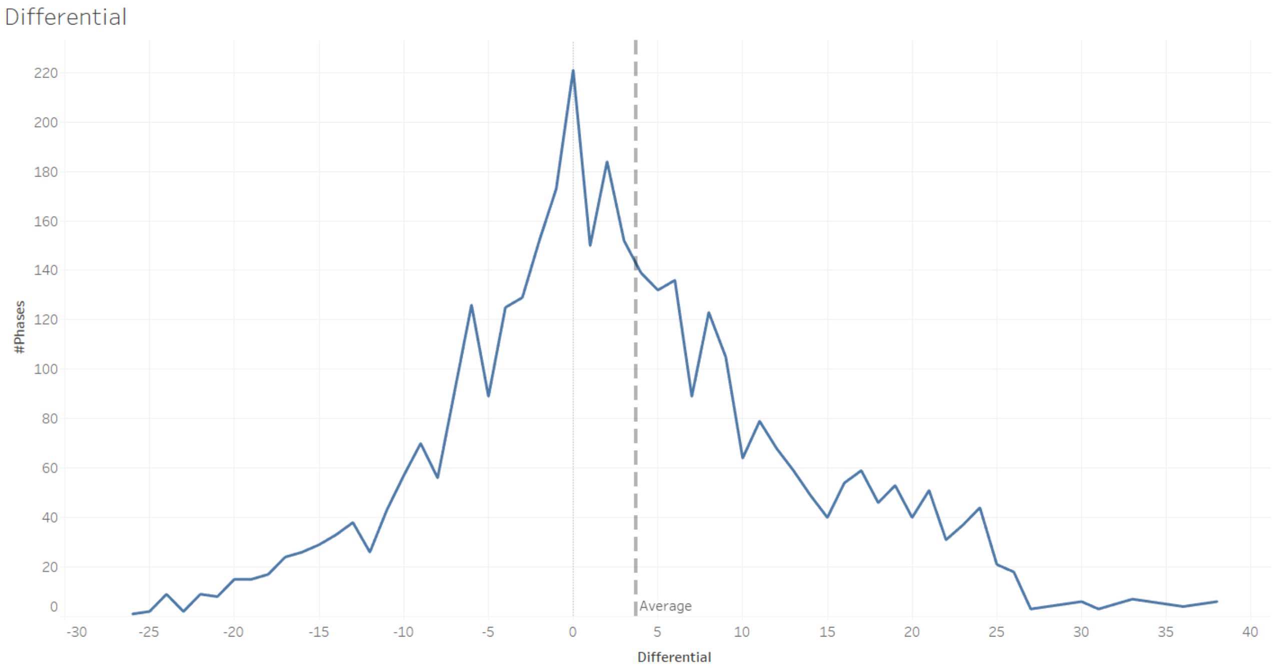
4. Preliminary study

The database collected and worked with consists of 3642 phases, in which there are 20 different players participating in 39 matches (including regular season, playoffs and Final 4). As you can see in this analysis, an aspect that is rarely taken into account in the usual statistics gains importance: this aspect being the psychological weight (differential, clutch, terrain, play-offs...).

In order to be able to have an opening view of the database (in *.csv* format), the visualization tool *Tableau* was used (which will later be used for the display of final data and its analysis). This platform allows you to easily start observing various aspects which are important for coaches: players with more or less prominence, general season analysis, predominant playstyle, clutch time performance, etc.

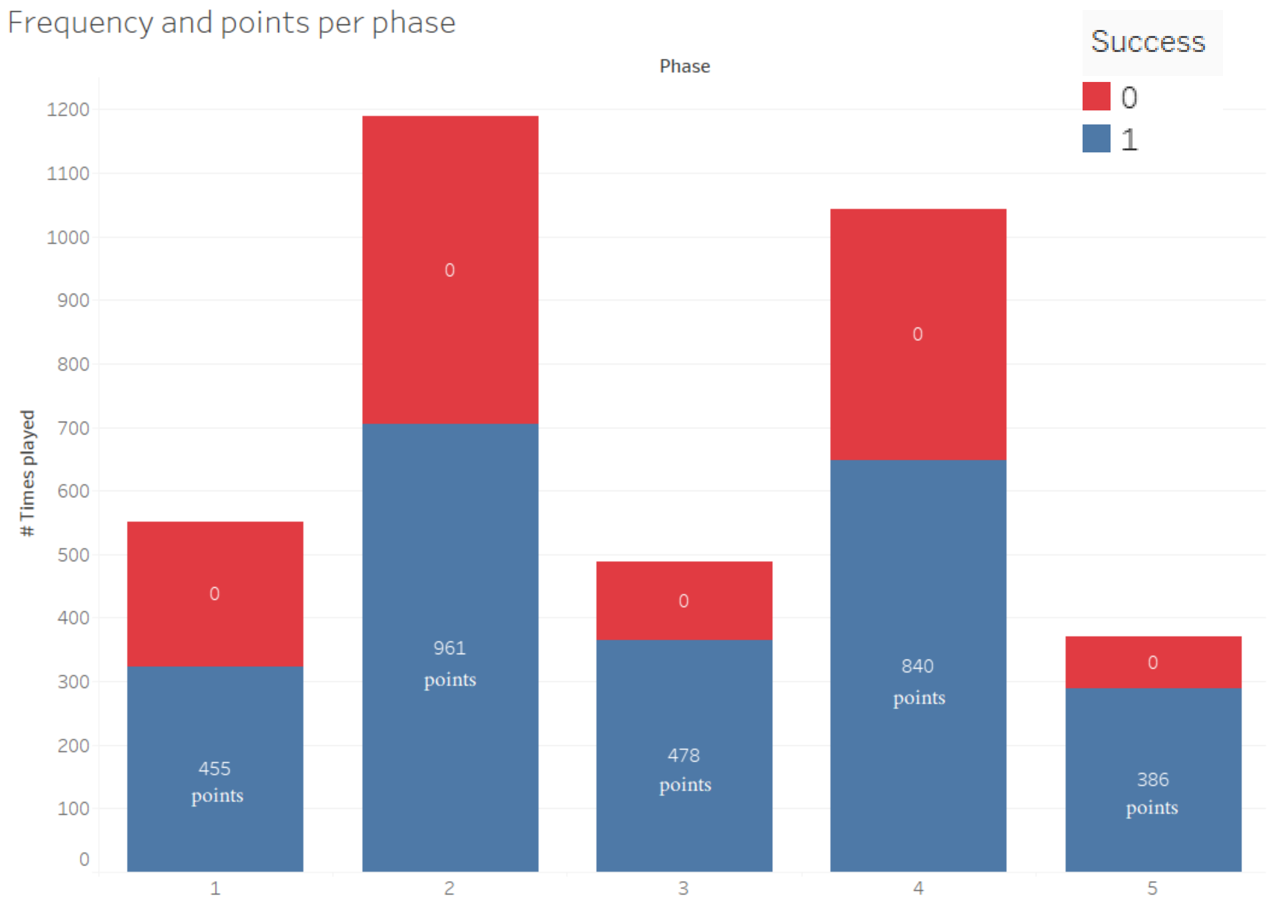
Here are some of the highlights represented in charts:

Chart 4.1*: Differential distribution*



This graph allows us to see the dominance that FC Barcelona has had throughout the Euroleague season. With an average of +3.7, and a negatively skewed distribution, you can see Barcelona's tendency to go ahead in the scoreboard, which is very complicated at the highest European level.

***Chart 4.2**: Frequency bar plot and points per phase*



In this graph you can see the number of times that each type of phase has been played throughout the season, together with the success and number of points it has provided.

It can be seen that phase 2 and 4 plays are by far the most used, which is usual because modern European basketball is very much based on 2vs2 play with pick & roll/pop (almost essential in any tactic), and in Europe the low post game doesn't go as unnoticed as in the NBA.

On the other hand, it can be seen that phases 3 and 5, despite being very effective, they have not been played that much. In the case of phase 5 it can be explained, since to start a fastbreak and/or transition you must force an offense's mistake, which makes it less dependent on the team.

In the case of phase 3, however, it is an aspect that can be worked on. Barça has very good shooters like Kuric, Abrines, Laprovittola and even in power forwards like Mirotic, but Barça did not want to "take risks" in this sense and preferred to play more with post-game plays.

Moreover, analyzing the phases that Barça has decided to play in clutch-time (decisive moments), it can be seen that they don't only follow predominant phases 2 and 4, but phase 3 is used half as often despite being the most more effective for the team (except for the phase 5 for the reasons previously stated).

Chart 4.3: *Frequency of phases in clutch time*

Phase frequency in clutch time

Phase	
4	126
2	103
1	78
3	60
5	34

Another interesting aspect is the individual performance in clutch-time. Before further analysis, here is the success (in quantity) of the players in each position in clutch time (the numbers represent the number of successful/failed plays)

Chart 4.4: *Success quantification in clutch time (Point Guards)*

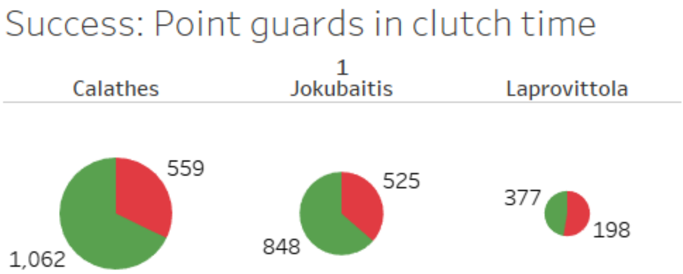


Chart 4.5: *Success quantification in clutch time (Shooting Guards)*

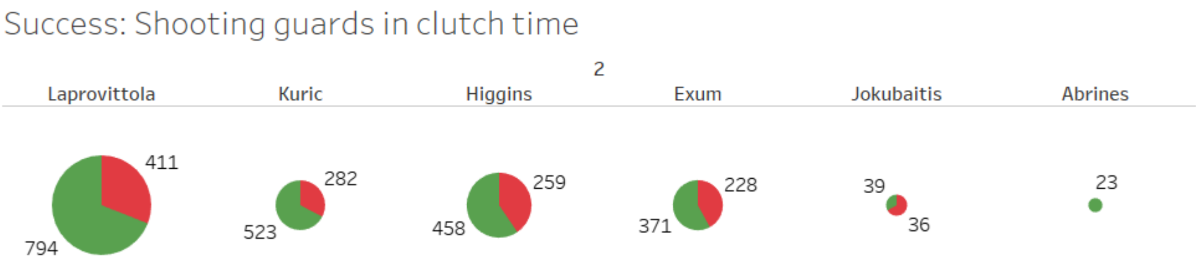


***Chart 4.6:** Success quantification in clutch time (Small Forwards)*

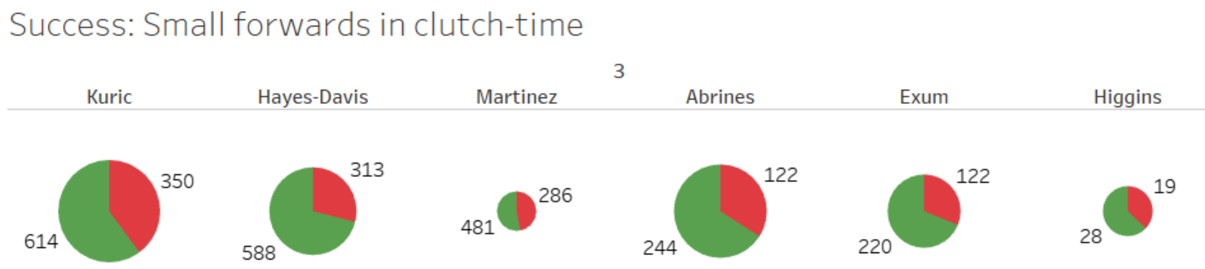


***Chart 4.7:** Success quantification in clutch time (Power Forwards)*

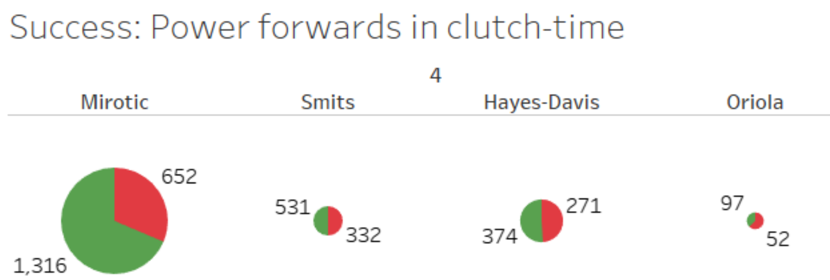
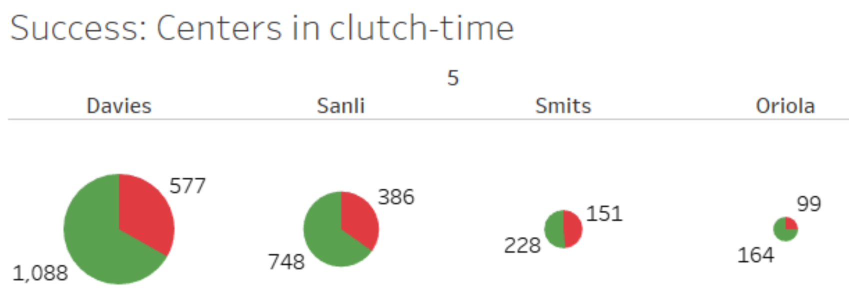


***Chart 4.8:** Success quantification in clutch time (Centers)*



From these charts it can be deduced that the players who have had the most success in clutch-time are Calathes (PG), Laprovittola (SG), Kuric (SF), Mirotic (PF) and Davies (C). This, however , does not mean that they are the most successful players in this phase of the match. This aspect is discussed later.

As mentioned before, the success of players in these positions is taken into account here. Interestingly and as an example, although Kuric is the most successful player at the wing position, in the semi-final decisive match against Real Madrid he only played 1 minute. In the final part of the project we also deal with this topic.

5. Analysis

To carry out the main analysis, the initial database was split into several according to the following classification:

- Overall success (all successful phases).
- Overall failure (all unsuccessful plays).
- Successful scoring (all plays ending in points → objective analysis).
- Unsuccessful scoring (all plays that do not end in points → objective analysis).
- Phase *x* (1, ..., 5) successfully (all *x* phases played successfully).
- Phase *x* (1, ..., 5) without success (all *x* phases played without success).
- Clutch success (all successful clutch-time plays).
- Clutch failure (all plays in clutch time without success).

5.1. The Apriori Algorithm

It's an algorithm used for frequent itemsets mining and learning association rules in relational databases. It uses Machine Learning in order to quantify several parameters (*support, lift*...) based on, among others, the frequency of the sets in the database and the coincidences between them to give as output relations between these (independence, degree of dependence, etc.).

The algorithm follows the data mining technique *join* and *prune* [1]:

1. **Join**: given an amount of K-itemsets, generate (K+1)-itemsets by joining each item with itself.
2. **Prune**: analyzes the frequency of each itemset in the database. If the candidate does not have the minimum support, it is classified as infrequent and removed.

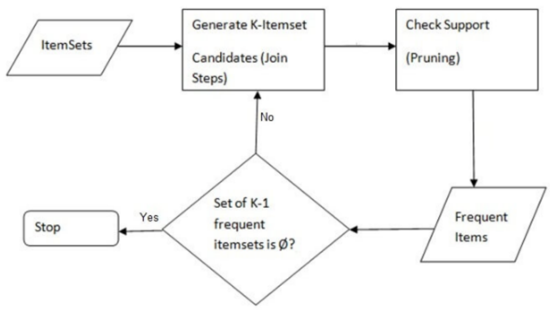


Image 5.1.1: *Apriori Algorithm Methodology*

A parameter is entered that represents the minimum support that is used as a threshold to decide which itemsets are removed in the process. This project uses *min_support = 0.05*, which is also its default value.

In this case, it is used to give information about which players (consequent set), added to those already on the court (antecedent set), maximize/increase the probability of success (or failure) according to the type of dataset being observed (phase type, clutch-time, etc.).

5.1.1. Example

An example result is the following (successful phase 2, regardless of positions):

Table 5.1.1: *Association rule - Successful phase 2 (position-less)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Laprovittola, Exum, Calathes)	(Mirotic)	0.061882	0.608939	0.057585	0.930556	1.528160	0.019902	5.631285

This result can be interpreted the following way:

- Antecedents / consequents: Sets of players and their appearance ratio in the database (support).

- Confidence: Probability that when a successful phase 2 occurs (in this case) where the antecedent set is present, the consequent set is also present. That is to say, if a successful phase 2 with Laprovittola, Exum and Calathes happens, Mirotic will also be there with a 93% probability.

- Lift: Measures how different the antecedent and the consequent of the relationship appear compared to if they were independent. In other words, it represents the same as the confidence attribute, but the popularity of the playersets is taken into account.
    - Range of values: [0, inf)
    - Lift = 1 → Independent sets, no correlation
    - Lift > 1 → High probability
    - Lift < 1 → Low probability

- Leverage: Calculates the difference between the frequency of the antecedent and the consequent together and the frequency if they were independent.
    - Range of values: [-1, 1]
    - Leverage = 0 → Independent sets

- Conviction: The higher it is, the greater the interest in the association (the more dependent the consequent is of the antecedent)
    - Conviction = inf → Maximum correlation
    - Conviction = 1 → Independence, no correlation

As a conclusion of the example, if players Calathes, Laprovittola and Exum are on the court, and the coach wants to play in phase 2 (high pick, hand-off...), in order to increase and maximize the probability of success now he knows Mirotic must also be on the court.

5.2. Position dependency

One way to do the analysis is by considering the positions of the players. Below are the top 3 relationships between players in some phases of the game with this aspect in mind. The complete data and results are accessible in Appendix #2.

It should be noted that the fact that players appear in the most important relationships does not mean that they are the most suitable for that type of phase. This aspect is discussed later on.

Table 5.2.1: *Association rules - Overall success (position-wise)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.061023	0.341212	0.057155	0.936620	2.744980	0.036333	10.394213
(Escorta_Laprovittola, Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.061453	0.565535	0.057155	0.930070	1.644584	0.022402	6.212849
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.066609	0.341212	0.061453	0.922581	2.703835	0.038725	8.509347

Table 5.2.2:. *Association rules - Scoring (position-wise)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.067335	0.331662	0.063754	0.946809	2.854740	0.041421	12.564756
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.072350	0.331662	0.068052	0.940594	2.836003	0.044056	11.250358
(Escorta_Laprovittola, Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.068052	0.570201	0.063754	0.936842	1.643004	0.024951	6.805158

Table 5.2.3:. *Association rules - Phase 1 without success (position-wise)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Escorta_Higgins, Aler_Hayes-Davis)	(Base_Calathes)	0.061404	0.456140	0.061404	1.000000	2.192308	0.033395	inf
(Escorta_Higgins, Aler_Hayes-Davis, Alerpivot_...	(Base_Calathes)	0.057018	0.456140	0.057018	1.000000	2.192308	0.031010	inf
(Escorta_Higgins, Aler_Hayes-Davis)	(Alerpivot_Mirotic, Base_Calathes)	0.061404	0.333333	0.057018	0.928571	2.785714	0.036550	9.333333

Table 5.2.4:. *Association rules - Phase 1 with success (position-wise)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.068085	0.334752	0.065248	0.958333	2.862818	0.042457	15.965957
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.073759	0.334752	0.069504	0.942308	2.814945	0.044813	11.530969
(Escorta_Laprovittola, Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.069504	0.541844	0.065248	0.938776	1.732557	0.027588	7.483215

***Table 5.2.5:**. Association rules - Phase 3 without success (position-wise)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Pivot_Davies, Aler_Martinez)	(Escorta_Kuric)	0.072581	0.338710	0.064516	0.888889	2.624339	0.039932	5.951613
(Alerpivot_Mirotic, Pivot_Sanli, Escorta_Lapro...	(Base_Calathes)	0.072581	0.419355	0.064516	0.888889	2.119658	0.034079	5.225806
(Pivot_Davies, Escorta_Exum)	(Aler_Kuric)	0.064516	0.354839	0.056452	0.875000	2.465909	0.033559	5.161290

***Table 5.2.6:**. Association rules - Phase 4 with success (position-wise)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Aler_Abrines)	(Base_Calathes)	0.069444	0.489198	0.066358	0.955556	1.953312	0.032386	11.493056
(Escorta_Higgins, Aler_Hayes-Davis, Base_Calat...	(Alerpivot_Mirotic)	0.055556	0.586420	0.050926	0.916667	1.563158	0.018347	4.962963
(Aler_Abrines, Base_Calathes)	(Alerpivot_Mirotic)	0.072531	0.586420	0.066358	0.914894	1.560134	0.023824	4.859568

***Table 5.2.7:**. Association rules - Clutch time without success (position-wise)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Aler_Abrines, Base_Jokubaitis)	(Escorta_Higgins)	0.062937	0.237762	0.062937	1.0	4.205882	0.047973	inf
(Base_Jokubaitis, Escorta_Exum)	(Aler_Kuric)	0.055944	0.314685	0.055944	1.0	3.177778	0.038339	inf
(Aler_Exum, Pivot_Sanli)	(Escorta_Laprovittola)	0.055944	0.426573	0.055944	1.0	2.344262	0.032080	inf

We can see that, obviously, the position in which each player takes, affects the impact of each of them. An example is Kuric, which appears as a consequent set as a SG and SF in the top unsuccessful phase 3 relationships. However, almost all players already have a defined position from which they do not vary much, provided that each has their own player profile and role to get the most out of it (perimeter players like Exum and Hayes-Davis or post players like Mirotic and Smits are exceptions due to their offensive and defensive versatility). Between players who have participated the most (Mirotic, Calathes, Laprovittola) it's easier to identify relationships and that is why the main ones relate them to each other. However, players with less prominence (Exum and Higgins playing half the season, for example) are already seen as particularly influential players in some phases of the game.

The fact that some relationships have *confidence = 1* and *conviction = inf* means that in all successful (or unsuccessful) phases in which the antecedent set has participated, the consequent set was also there. That is, in the context of the database, they always occur together. For example, all of the unsuccessful clutch-time plays that have been played with Jokubaitis (PG) and Abrines (SF) have happened with Higgins (SG).
The disadvantage of this analysis is that some players who are more versatile than the rest (Exum, Mirotic, Smits, etc.) can change positions more easily and their impact is not much reflected in the results (they are analyzed as 2 different players in 2 different positions).
With that said, the same analysis is performed without considering the players' position.

5.3. Position independency

Following the same procedure as in the previous section, with the Apriori algorithm, it has been possible to extract the most transcendent relationships between players in each phase of the game, regardless of their position.

With these results, some changes can be distinguished with respect to the position-dependent results. An example is the following:

***Table 5.3.1**: Association rules - Overall success (position-less)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Calathes, Exum, Laprovittola)	(Mirotic)	0.061882	0.608939	0.057585	0.930556	1.528160	0.019902	5.631285
(Calathes, Sanli, Laprovittola)	(Mirotic)	0.079502	0.608939	0.071336	0.897297	1.473543	0.022925	3.807704
(Abrines, Mirotic)	(Calathes)	0.069618	0.456382	0.061023	0.876543	1.920637	0.029251	4.403309

Disregarding the position variable, players like Sanli and Abrines now appear in the relationships, which means they have more of a role in success than it seemed (even considering that Abrines has been injured mid-season).

The rest of the results, as in the previous section, can be found in Appendix 2. With this, however, little more information can be extracted compared to what has already been mentioned.

The results so far give quite relevant information, seeing players who are much more present in some phases of the game than in others. Even so, the players with the most playing time (Mirotic, Calathes) appear more in all types of association rules because they are arguably the best players on the team and can bring more effectiveness to the game, whichever the phase is.

5.4. Interactive program

With all the information obtained so far and using the same tools, it has been possible to create an interactive tool with *Python* which, given 1, 2 or 3 players, outputs the players that would increase the efficiency according to the type of phase of the game with them on the court. It can do so regardless of the positions or with them in mind, and the code is accessible via the GitHub repository:

https://github.com/mikivillaro10/TFG

In the next page there are 3 outputs from the relationships interactive program:

Case 1:
- Position-dependent
- Phase 2
- Player #1: Calathes (PG)
- Player #2: Laprovittola (SG)
- Player #3: Davies (C)

```
Seleccioni P en cas de joc posicional o N en cas de joc no posicional: P
Seleccioni una fase de joc de les indicades prèviament: 2

IMPORTANT!
Màxim 3 jugadors! En cas de no introduir jugador, prèmer ENTER
Seleccioni el base de la llista prèvia: Calathes
Seleccioni l'escorta de la llista prèvia: Laprovittola
Seleccioni l'aler de la llista prèvia:
Seleccioni l'aler-pivot de la llista prèvia:
Seleccioni el pivot de la llista prèvia: Davies

Millors jugadors per maximitzar èxit en fase 2 :
['Alerpivot_Mirotic']
```

Figure 5.4.1: *Case 1 output*

Case 2:
- Position-independent
- Phase 1
- Player #1: Laprovittola
- Player #2: Mirotic
- Player #3: Hayes-Davis

```
Seleccioni P en cas de joc posicional o N en cas de joc no posicional: N
Seleccioni una fase de joc de les indicades prèviament: 1
Seleccioni el jugador 1 de la llista prèvia: Laprovittola
Seleccioni el jugador 2 de la llista prèvia: Mirotic
Seleccioni el jugador 3 de la llista prèvia: Hayes

Millors jugadors per maximitzar èxit en fase 1 :
['Sanli']
```

Figure 5.4.2: *Case 2 output*

Cas 3:
In case there is not enough data to identify relationships between the specified players, the output is as follows:

```
Seleccioni P en cas de joc posicional o N en cas de joc no posicional: N
Seleccioni una fase de joc de les indicades prèviament: 5
Seleccioni el jugador 1 de la llista prèvia: Jokubaitis
Seleccioni el jugador 2 de la llista prèvia: Abrines
Seleccioni el jugador 3 de la llista prèvia: Sanli
Not enough data on this playerset
```

Figure 5.4.3: *Case 3 output*

This last case is due to the lack of data on the specified set and phase, since it is very specific (unless it's a very usual phase and set) and the algorithm also uses the parameter (min_support) which removes relationships with a very low *support* (0.05). Basically, despite having collected almost 4000 phases (should have been more due to the elimination of the Russian teams from the competition), the separations in small databases make the analysis very specific and cause that for some sets there is not sufficient data.

6. Player Score

6.1. Calculation

With all this information, these relationships and parameters will be used in order to achieve a numerical result that can really quantify the presence and importance of each player (and group of players) when on the court, classifying it by phases. As mentioned at the beginning of the project, the impact of a player or group of players on the court is difficult to measure, since it involves many variables that are not quantifiable, but the algorithm helps to get closer in this sense.

To calculate the score of (groups of) players the parameter **lift** is used. *Lift* is a variable that, as explained before, measures the maximization/increase of success probabilities (or not) of the antecedent set added to the consequent set. The greater it is, the higher the probability of the existence of an intersection between both playersets (they appear together, either in success or failure phases).
Another reason for which this parameter is used is because it takes into account the proportion of the subsets in the database. This is also true with the *leverage*, but because of their respective formulas [2], *lift* finds stronger associations between less frequent groups, while *leverage* prioritizes relationships between more frequent sets [3]:

$$\mathrm{lift}(\boldsymbol{M_1} \to \boldsymbol{M_2}) = \frac{\mathrm{confidence}(\boldsymbol{M_1} \to \boldsymbol{M_2})}{\mathrm{support}(\boldsymbol{M_2})}$$

$$\mathrm{levarage}(A \to C) = \mathrm{support}(A \to C) - \mathrm{support}(A) \times \mathrm{support}(C)$$

With this in mind, the impact of a player (or group) can be measured according to which relationships it appears in as a variable that maximizes/minimizes the probability of success. With the data collected and normalizing the *lift* parameter, a score can be achieved for each subset that measures its impact on the court.

For each player in the corresponding database, the relations in which it appears in the consequent set are taken and the proportional part of the *lift* of the relationship. That is, if the player is part of a consequent group of 3 players, ⅓ from the *lift* of the relationship is added to his individual score.

The same methodology is followed in groups of players. For example, if a group of 2 players appears in a 3-player consequent set, ⅔ from the *lift* is added to the group's score.

Since each dataset (phases, clutch time, overall and scoring) is split into success and unsuccess, the calculation applied to the "successful" datasets gives a positive *score* for each (set of) players, and the same applied to the unsuccessful datasets gives another *score*, which is interpreted as negative, for each (set of) players. The final score is given by the following calculation:

positive_score - negative_score

What we want to measure with this calculation is the value that the (set of) player has when appearing as a consequent set. That is, if a player appears many times as a maximizer, the more it means a positive impact (or negative if we do it in non-success) for the team, because it helps more groups of players to reach success (or non-success).

In this way, for each (set of) players, their weight is taken into account when maximizing the success/failure probabilities according to each type of play at specific moments in the match.

6.2. Individual results

The individual results are the following:

***Table 6.2.1**: Individual scores - Phases 1, 3, 5 and clutch time*

Phase 1		Phase 3		Phase 5		Clutch time	
Player		Player		Player		Player	
Laprovittola	15.12	Mirotic	18.25	Smits	6.27	Davies	39.06
Exum	4.62	Higgins	14.92	Jokubaitis	4.71	Laprovittola	28.43
Smits	2.16	Exum	8.80	Oriola	2.63	Mirotic	27.42
Oriola	0.25	Laprovittola	6.54	Sanli	1.96	Jokubaitis	26.41
Sanli	0.13	Calathes	4.47	Higgins	1.14	Exum	24.96
Martinez	-0.74	Abrines	2.37	Martinez	-10.53	Kuric	22.29
Hayes-Davis	-0.87	Davies	1.93	Abrines	-12.67	Calathes	22.26
Abrines	-1.00	Hayes-Davis	-3.27	Hayes-Davis	-12.99	Hayes-Davis	12.82
Calathes	-2.19	Oriola	-3.99	Kuric	-15.47	Abrines	1.03
Kuric	-3.64	Smits	-4.14	Calathes	-18.24	Oriola	0.00
Mirotic	-6.38	Martinez	-6.90	Exum	-22.80	Higgins	-0.62
Jokubaitis	-7.01	Jokubaitis	-7.16	Laprovittola	-28.61	Sanli	-1.02
Davies	-12.55	Kuric	-10.34	Davies	-30.13	Martinez	-8.10
Higgins	-33.75	Sanli	-15.26	Mirotic	-39.35	Smits	-9.84

Of these we can highlight a few aspects:

- Higgins is the player with the worst score in phase 1 despite being a player who stands out for his 1vs1 skills. This doesn't mean the algorithm has calculated it wrong, since it must not be forgotten that the IMPACT of the player is measured in this type of play, whether he has played 1v1 or his teammate has.
  In other words, the numbers represent the IMPACT of each player according to each type of phase. It doesn't mean they are good or bad 3 (Phase 3) or 1vs1 (Phase 1) shooters, but they affect the team in one way or another when you want to play that type of phase.
- As a comparison, in the initial analysis the players with the most success in clutch-time were *Calathes, Laprovittola, Kuric, Mirotic* and *Davies*. These 5 players have the individual ratings in rankings #1, #2, #3, #6 and #7, and now we can check that players like *Jokubaitis* and *Exum* have a similar impact to these players in clutch-time.

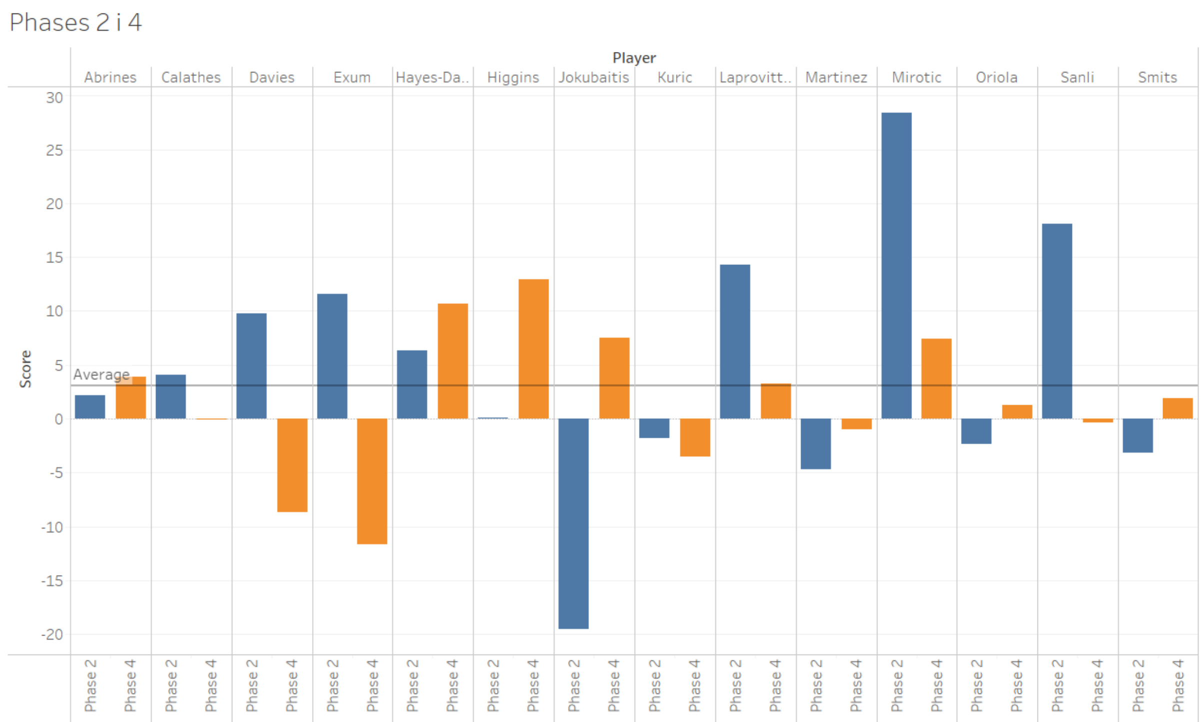


***Chart 6.2.1**: Individual scores - Phases 2 and 4*

Here we can remark the negative impact of *Davies* in phase 4 (despite being a very technical interior player in the 1vs1 at the low post) and *Jokubaitis* in phase 2, despite being a point guard who mostly plays the pick & roll. As previously mentioned, it should be borne in mind that the number gives a statistic of the impact, not of the performance of each player.

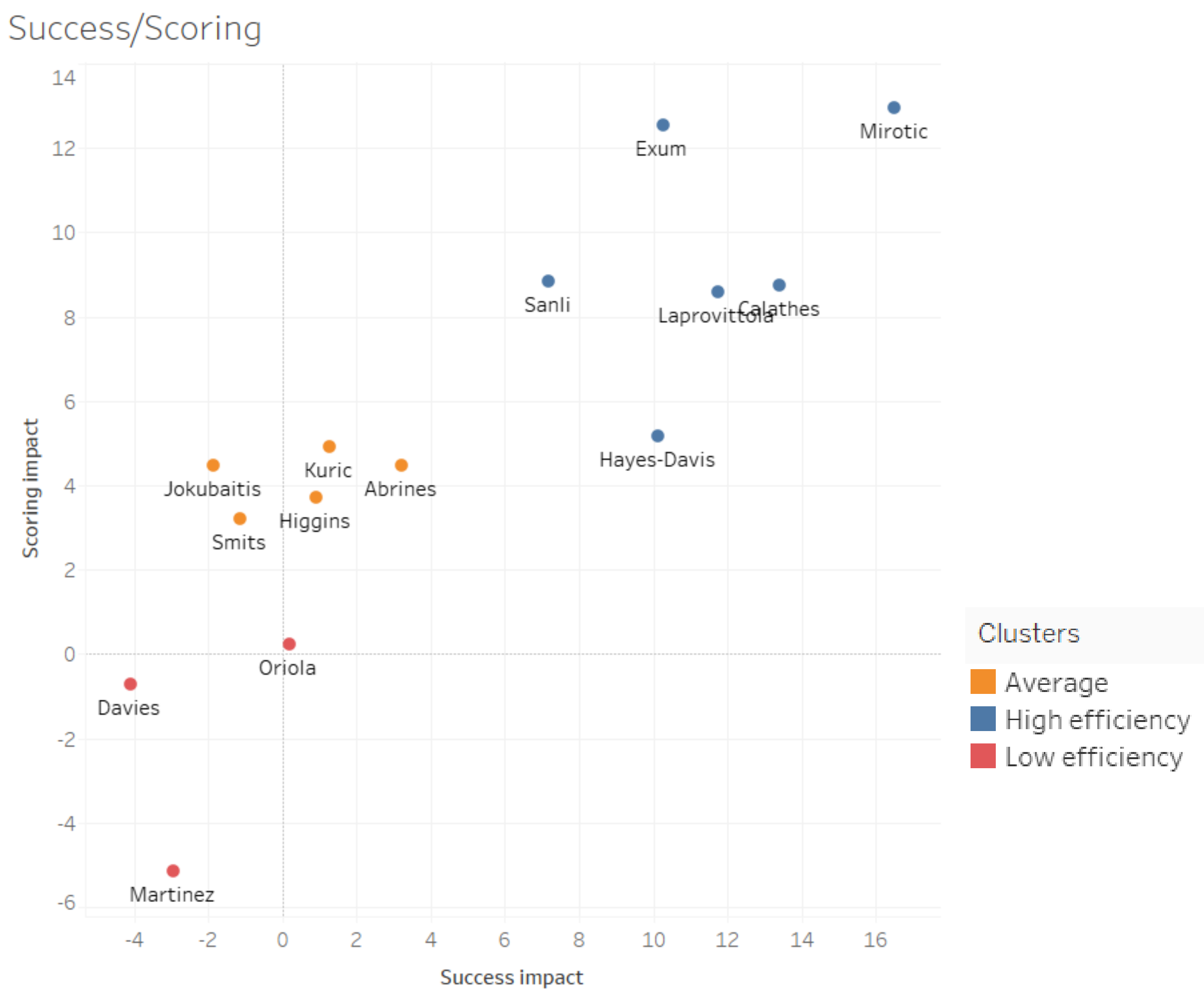


Chart 6.2.2: *Impact on scoring and success scatter-plot*

In this *scatter plot* we can see the comparison of each player in his contribution to success (X axis) and scoring (Y axis). The colors are determined by the clustering algorithm K-Means [4] (using the graphical tool Tableau), which distinguishes 3 clearly identified groups (efficient, average and inefficient).

It's interesting to see how players *Sanli* and *Davies* are so far apart in this chart. They are 2 completely opposite center styles but each effective in their own way. However, looking at the results of the entire season, Sanli has had a much more positive impact than Davies.

It's also worth noting the "not very outstanding" numbers of Jokubaitis, despite winning the prize for the most promising player of the Euroleague (Rising Star).

6.3. Results by pairs

The most prominent pairs of players by game phase (positively and negatively) are included:

Table 6.3.1: *Scores by pairs - Phases 1, 2, 3*

Phase 1

Pairs	
Calathes,Exum	7.71
Laprovittola,Mirotic	7.44
Calathes,Laprovittola	6.30
Laprovittola,Kuric	4.76
Hayes-Davis,Sanli	4.13
Laprovittola,Sanli	4.06
Laprovittola,Hayes-..	4.05
...	
Higgins,Hayes-Davis	-6.79
Calathes,Kuric	-6.84
Higgins,Davies	-7.15
Higgins,Kuric	-7.29
Calathes,Higgins	-12.22
Higgins,Mirotic	-13.03

Phase 2

Pairs	
Mirotic,Davies	11.19
Hayes-Davis,Mirotic	9.10
Calathes,Davies	8.52
Laprovittola,Mirotic	7.80
Mirotic,Sanli	7.43
Calathes,Mirotic	7.18
Exum,Sanli	5.62
...	
Exum,Davies	-2.46
Mirotic,Smits	-3.11
Jokubaitis,Davies	-3.17
Jokubaitis,Higgins	-3.34
Jokubaitis,Martinez	-3.47
Jokubaitis,Kuric	-3.52

Phase 3

Pairs	
Mirotic,Davies	6.13
Higgins,Mirotic	5.52
Laprovittola,Mirotic	5.29
Calathes,Mirotic	4.89
Exum,Mirotic	4.58
Laprovittola,Exum	4.34
Calathes,Exum	4.02
...	
Hayes-Davis,Sanli	-4.24
Kuric,Hayes-Davis	-4.32
Jokubaitis,Kuric	-4.81
Laprovittola,Hayes-..	-4.83
Laprovittola,Sanli	-5.16
Calathes,Sanli	-7.96

Table 6.3.2: *Scores by pairs - Phases 4, 5, clutch time*

Phase 4

Pairs	
Calathes,Hayes-Davis	7.77
Hayes-Davis,Mirotic	6.38
Higgins,Hayes-Davis	5.87
Jokubaitis,Mirotic	4.24
Calathes,Laprovittola	3.20
Calathes,Sanli	2.79
Higgins,Kuric	2.65
...	
Exum,Davies	-2.92
Mirotic,Davies	-3.40
Exum,Mirotic	-3.58
Calathes,Mirotic	-3.68
Calathes,Exum	-4.46
Calathes,Davies	-6.56

Phase 5

Pairs	
Exum,Sanli	3.91
Calathes,Hayes-Davis	2.86
Jokubaitis,Exum	2.71
Martinez,Davies	2.67
Calathes,Higgins	2.58
Jokubaitis,Davies	2.19
Martinez,Smits	2.00
...	
Laprovittola,Abrines	-7.96
Calathes,Laprovittola	-9.48
Laprovittola,Mirotic	-10.96
Mirotic,Davies	-12.18
Exum,Davies	-12.94
Calathes,Mirotic	-14.51

Clutch time

Pairs	
Calathes,Davies	19.56
Mirotic,Davies	17.29
Laprovittola,Higgins	15.75
Laprovittola,Mirotic	15.40
Laprovittola,Davies	14.42
Kuric,Hayes-Davis	14.40
Hayes-Davis,Mirotic	13.10
...	
Martinez,Davies	-2.12
Hayes-Davis,Smits	-2.17
Laprovittola,Abrines	-2.77
Higgins,Hayes-Davis	-2.94
Higgins,Smits	-2.97
Laprovittola,Sanli	-3.12

It can be seen that, comparing these to the individual results, the players influence on their pairs' impact contributes to their partner having more or less impact on the game. For example, Jokubaitis is the player with the worst contribution in phase 2 and, in the pairs table, he is also part of the worst. The same can be said for Mirotic (in a positive way) in Phase 3.

In the end, the graphical representation that gives a more general view of each player's contribution to the team is the one that shows their impact score on success and scoring. The same goes for couples.

As mentioned above, it can be seen that players with good individual scores contribute to combinations of players which have the same tendency in every phase of the game. For example, *Mirotic* is part of the success of the couples with whom it is formed, while *Davies* has the opposite effect. It relates to the previous chart where *Mirotic* ranks as the most impactful player in success and scoring and *Davies* as the second worst in this regard:

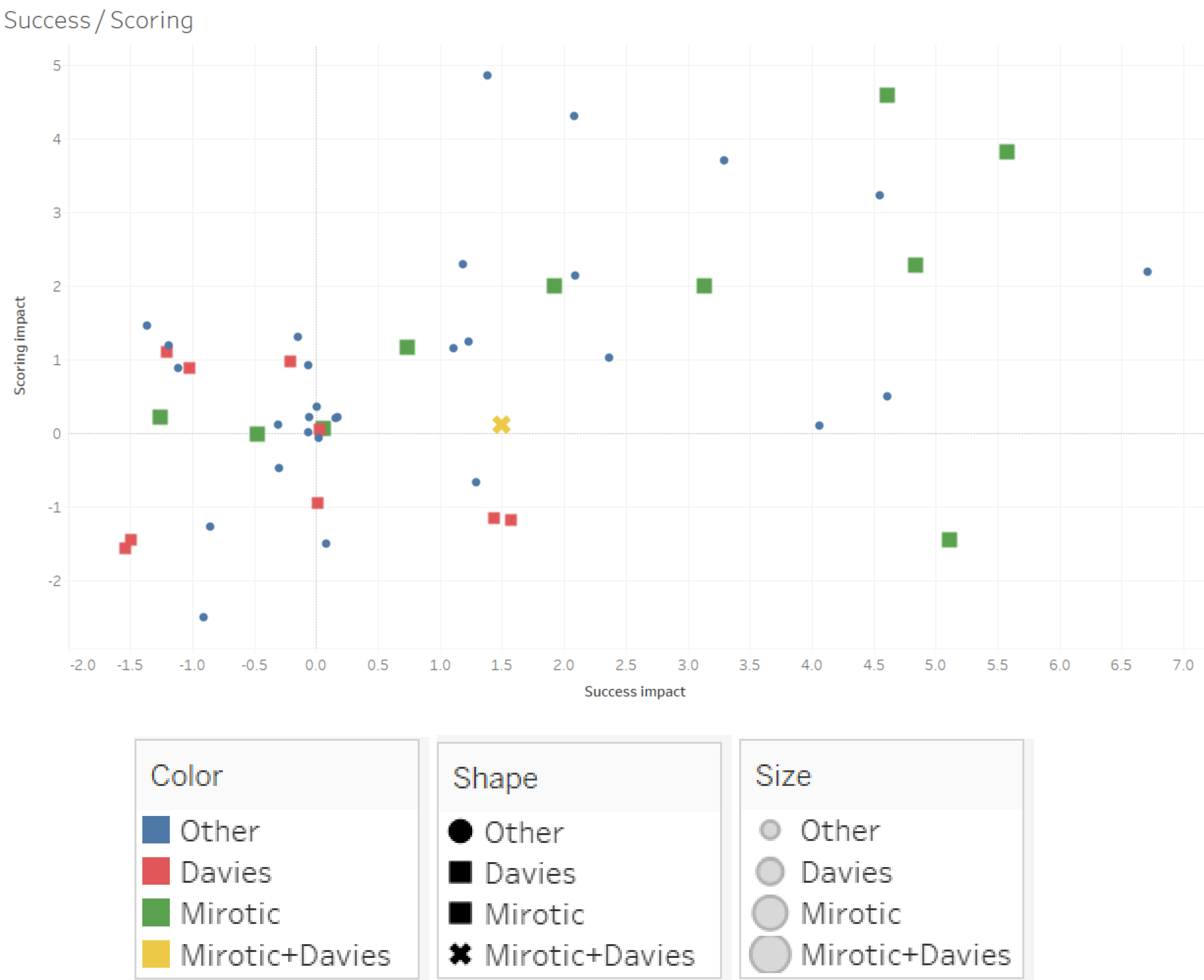


Chart 6.3.1: *Impact in success and scoring: Mirotic-Davies comparison*

The combination of both players is located in the center of the union between the two datapoint clusters (between the 2 pair groups), which shows that the contribution to the good impact of this couple (*Mirotic* + *Davies*) is thanks to *Mirotic* instead of *Davies*.

6.4. Results by trios

Then, the results are escalated to groups of 3 to see each contribution. It can be checked that the number distribution (range) lowers in variance and standard deviation, as the more players form a group, the fewer participation phases there will be (fewer relationships).

Table 6.4.1*: Scores by trios - Phases 1 and 2*

Phase 1

Trios	
Laprovittola,Kuric,Mirotic	1.947
Laprovittola,Hayes-Davis,Mirotic	1.868
Calathes,Exum,Davies	1.677
...	
Calathes,Higgins,Mirotic	-2.341
Calathes,Hayes-Davis,Mirotic	-2.433
Calathes,Kuric,Mirotic	-2.940

Phase 2

Trios	
Calathes,Mirotic,Davies	2.902
Calathes,Higgins,Mirotic	1.658
Exum,Mirotic,Sanli	1.606
...	
Calathes,Laprovittola,Sanli	-0.048
Calathes,Exum,Mirotic	-0.117
Calathes,Mirotic,Sanli	-0.394

Table 6.4.2*: Scores by trios - Phases 3 and 4*

Phase 3

Trios	
Calathes,Laprovittola,Exum	1.478
Calathes,Laprovittola,Davies	1.355
Jokubaitis,Mirotic,Davies	1.324
...	
Calathes,Hayes-Davis,Sanli	-1.710
Kuric,Hayes-Davis,Davies	-2.165
Calathes,Laprovittola,Hayes-Da..	-2.255

Phase 4

Trios	
Higgins,Hayes-Davis,Mirotic	1.569
Calathes,Hayes-Davis,Mirotic	1.561
Calathes,Higgins,Hayes-Davis	1.366
...	
Calathes,Exum,Mirotic	-1.196
Calathes,Exum,Davies	-1.365
Exum,Mirotic,Davies	-1.534

Table 6.4.3*: Scores by trios - Phase 5 and clutch time*

Phase 5

Trios	
Calathes,Hayes-Davis,Mirotic	2.171
Exum,Mirotic,Sanli	1.482
Hayes-Davis,Mirotic,Davies	1.391
...	
Calathes,Laprovittola,Mirotic	-2.979
Calathes,Mirotic,Davies	-3.383
Exum,Mirotic,Davies	-3.573

Clutch time

Trios	
Calathes,Mirotic,Davies	7.094
Calathes,Laprovittola,Higgins	6.745
Laprovittola,Higgins,Mirotic	5.831
...	
Jokubaitis,Laprovittola,Kuric	-1.166
Calathes,Laprovittola,Kuric	-1.312
Laprovittola,Abrines,Davies	-1.525

As in the previous section, the "trios" of players who have had more or less impact in terms of success and scoring throughout the season are obtained:

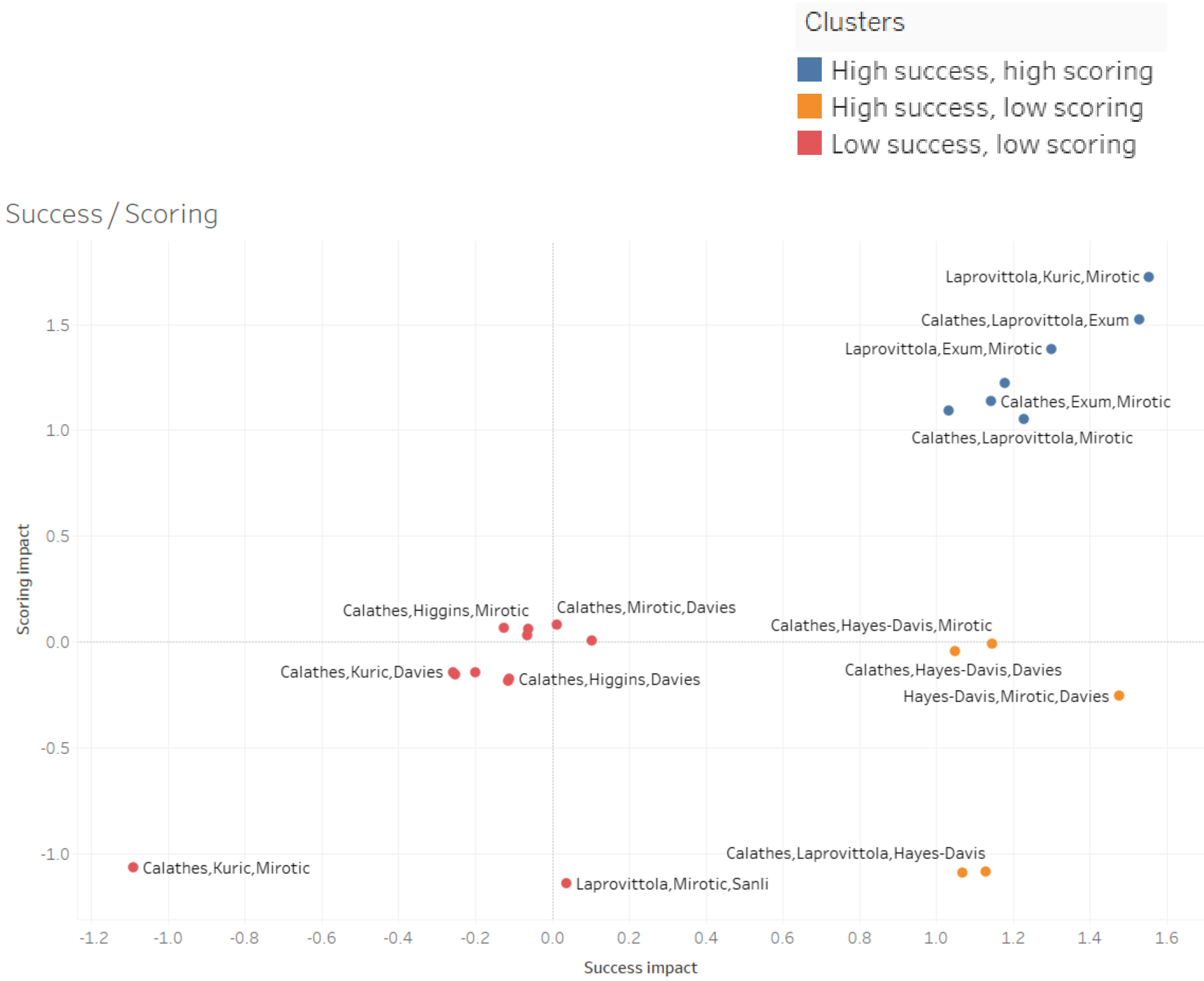


***Chart 6.4.1**: Trios' impact scatter plot (success and scoring)*

Here are some highlights:

1. *Calathes* and *Mirotic* (the two most important players and with the most playing time on the team) impact the game much more positively when they are with *Exum* on the court than when they are there with *Kuric*.
2. The groups are combinations of the same players among themselves, except *Mirotic* and *Calathes* who, as they are the ones who play the most, can be quantified in relation to almost everyone else (*Laprovittola* and *Kuric* too but to a lesser extent).

6.5. Results by foursomes

Finally, we can analyze the most efficient groups of 4. From this section, however, we can only extract them from the clutch database. This is because, when the match has a close ending or is directly a knockout match, there are much fewer rotations and the variety of players decreases. So, the algorithm's set of possible items is smaller and it is easier to find larger relationships (*support* considerably greater).

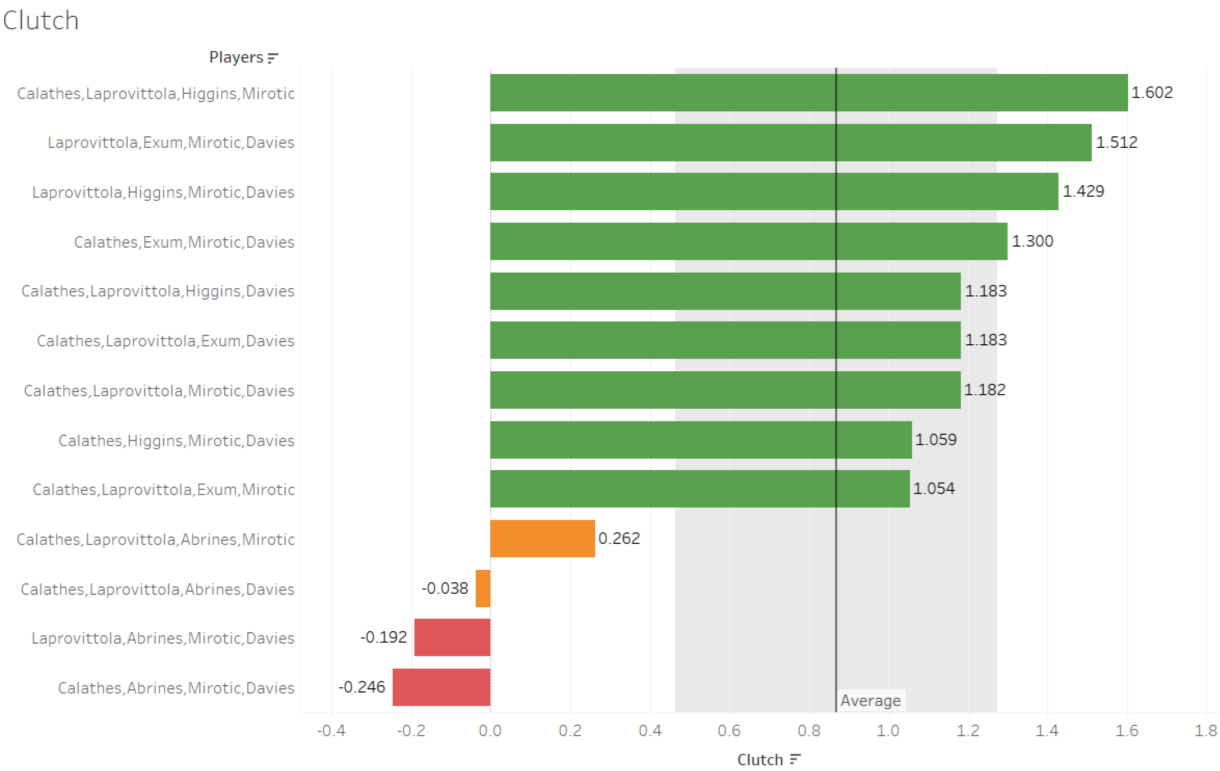


***Chart 6.5.1**: Scores by foursomes - Clutch time*

In this case, the difference between the sets with positive clutch-time impact and those with zero or negative impact is the player Abrines. If we look again at his clutch time results in smaller subsets, we see that he individually has a score of 1,02. The lowest rated players (Smits, Martinez, Sanli) do not appear in these 4-sets, as there is not enough data on them at this phase of the game, but there is on Abrines, who has a clearly negative impact at this time of the game.

7. Predictions

Finally, the scores can also be used to make a prediction of the players' performance in the final stretch of the season. The respective *scores* have been used to do so with respect to the Final 4 (F4) in Belgrade, where FC Barcelona faces Real Madrid and Olympiacos.

To make the predictions, the data taken into account is the data corresponding to this game (similar variables) before the F4. In these two cases, they are these:

- Games against Madrid || Clutch time plays
- Games against Olympiacos || Clutch time plays

These are the variables chosen because the teams are the same and the games are decisive, so it has a much greater psychological weight and all its integrity is clutch time.

Below is a comparison of the prediction results with the match's individual performance metrics: the **PIR**, **+/-** (Score differential while the player is on the court) and the **minutes played**, all collected from the competition's official app *Euroleague Mobile* [5]. Also, being a final phase, it's equally important that, when playing, the team finds success and scores as much as possible, so a combination of both scores (Success and Score) will be used.

The criterion for assigning whether the predicted score is correct or not is as follows:

Table 7.1: *Prediction correctness criterion*

Score	+/- i PIR	Prediction correctness
High	High	Correct
High	Low	Incorrect
Low	High	Incorrect
Low	Low	Correct

If a player's performance is predicted correctly and he plays more or less minutes than he should (low score and many minutes / high score and few minutes), it is marked with an orange background, to indicate that the prediction is correct but he has not played the amount of time he should have played.

For both predictions, the scores scaled to foursomes of players have been computed, which can be found in Appendix 3.

7.1. Semi-final vs Real Madrid

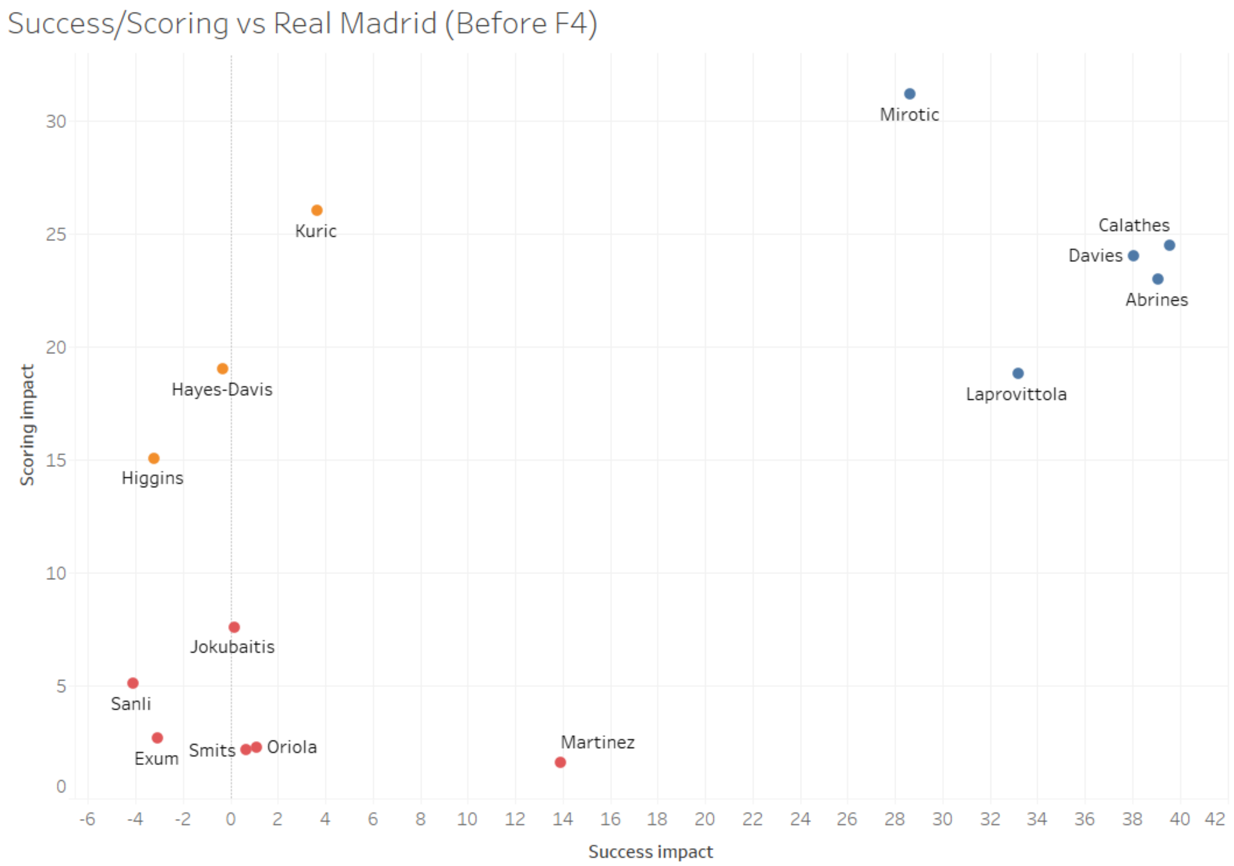
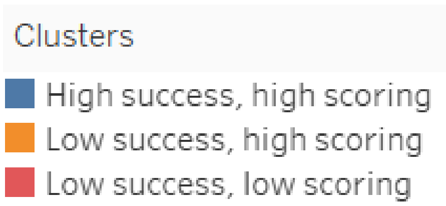


Chart 7.1.1: *Individual scores vs Real Madrid (before the F4)*

We can highlight that, unlike the previous section, the algorithm classifies *Abrines* as one of the reference players in this context while before he was the negative factor. The difference between the two classifications is the database: in this section the 2 F4 matches are not taken into account (182 stages of difference).



It should be noted that FC Barcelona has played 3 more times against Real Madrid this season (Copa del Rey + ACB (national league)), but these are not taken into account in this analysis because the only context considered is the Euroleague one:

Table 7.1.1: *Comparison: algorithm prediction and semi-finals performance*

Player	Success	Scoring	Total	Minutes	PIR	+/-
Calathes	39.59	24.48	65.07	28:57	14	+12
Davies	38.04	24.03	62.07	23:02	12	+2
Abrines	39.07	22.98	62.05	16:41	-1	-4
Mirotic	28.64	31.17	59.81	32:10	39	+5
Laprovittola	33.18	18.82	52	28:55	13	+8
Kuric	3.66	26.04	29.7	02:05	-1	+5
Hayes-Davis	-0.3	19.02	18.99	08:21	3	-6
Martinez*	13.89	1.58	15.47	0:00	0	0
Higgins	-3.23	15.07	11.84	11:29	-1	-15
Jokubaitis	0.16	7.60	7.76	10:01	6	-16
Oriola*	1.10	2.28	3.38	0:00	0	0
Smits	0.68	2.16	2.84	04:19	1	-2
Sanli	-4.13	5.12	0.99	11:49	-1	-5
Exum	-3.06	2.66	-0.4	22:11	4	+1

*Did not play

As a conclusion, it can be said that the algorithm works correctly. Despite having some exceptions, it correctly predicts player performance and impact results (at an individual level).

Playing time correctness:

- Kuric should have played more.
- Higgins should have played less.
- Jokubaitis should have played less.

7.3. 3rd place game vs Olympiacos

The same parameters are taken into account (clutch time + matches against Olympiacos), including the match against Real Madrid in the semi-finals.

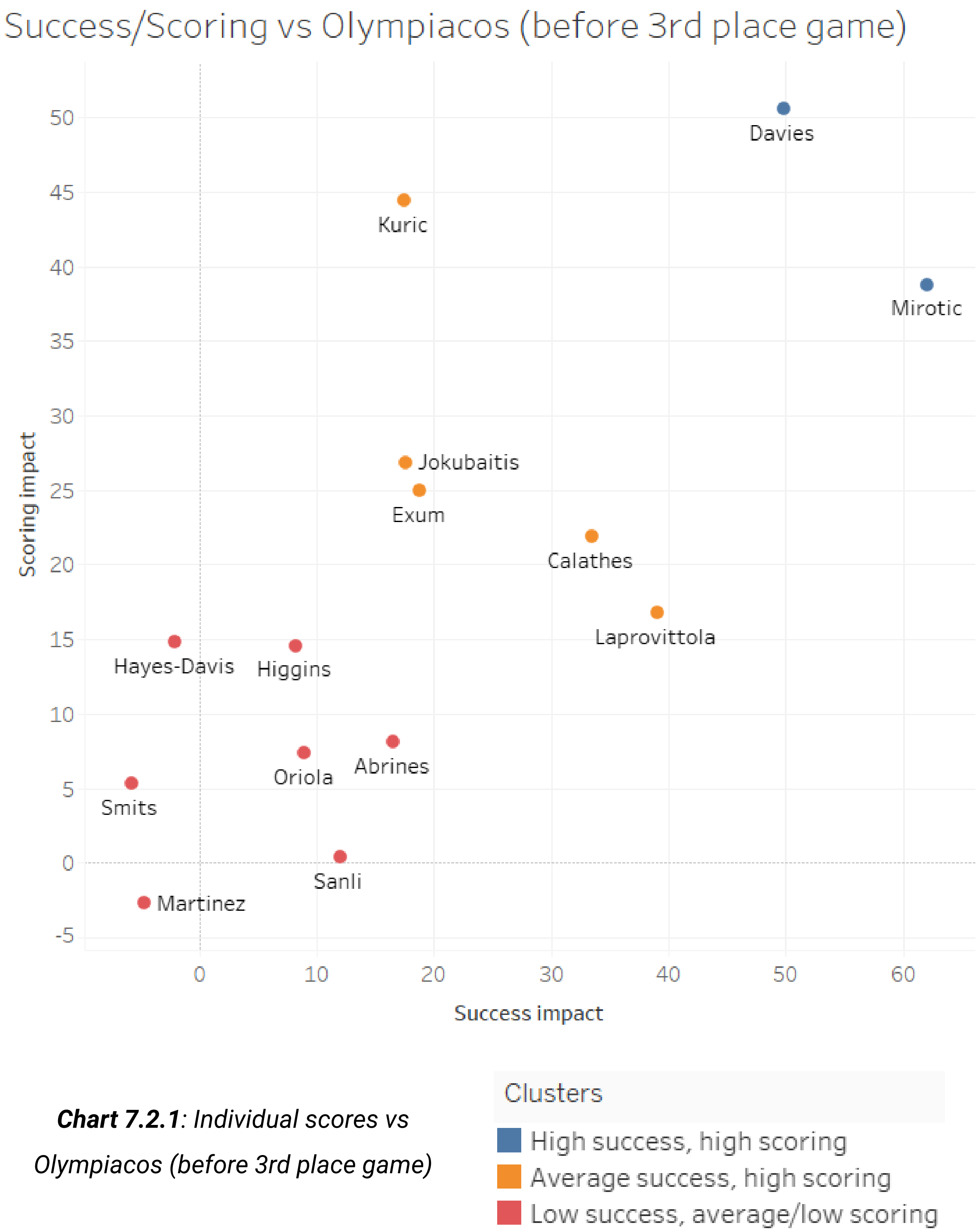


***Chart 7.2.1**: Individual scores vs Olympiacos (before 3rd place game)*

Table 7.2.1: *Comparison: algorithm prediction and 3rd-place game performance*

Player	Success	Scoring	Total	Minutes	PIR	+/-
Mirotic	62.08	38.79	100.87	25:37	27	+17
Davies	49.79	50.60	100.39	12:56	12	-8
Kuric	17.49	44.42	61.91	16:31	-3	+7
Laprovittola	39	16.82	55.82	11:16	1	+10
Calathes	33.45	21.91	55.35	26:54	24	+15
Jokubaitis	17.62	26.86	44.48	13:06	2	-5
Exum	18.84	24.97	43.81	09:34	5	-6
Abrines	16.51	8.10	24.61	19:48	8	+11
Higgins	8.25	14.60	22.85	22:10	4	-3
Oriola*	8.98	7.36	16.34	00:00	0	0
Hayes-Davis	-2.02	14.81	12.79	15:04	-1	-6
Sanli	11.98	0.39	12.37	27:04	16	+18
Smits*	-5.79	5.34	-0.45	00:00	0	0
Martinez*	-4.67	-2.69	-7.36	00:00	0	0

*Did not play

In this case the approach was appropriate, as the 2 players with the worst scores didn't play. The algorithm has failed on only 3 players: *Abrines* and *Sanli* (underrated) and *Davies* (overrated). It has made an accurate prediction about the rest of the players, and the following can be corrected from the playing time:

- Laprovittola should have played more.
- Jokubaitis should have played less.
- Higgins should have played less.
- Hayes-Davis should have played less.

In total for the two matches, the algorithm predicted the individual impact of the players with an *accuracy* of 78.26% (18 correct, 5 incorrect).

8. Final conclusions

Assessing the impact a player (or set of players) has is essential for any professional basketball team. The goal was to obtain a quantification, a statistic of this essential aspect that would allow players to be classified according to the impact they have in various phases of the game.

Specifically, FC Barcelona has the problem of being the best team in Europe during the regular season, but the playoff format and subsequently the final 4 hurts it in this sense, because it forces players and coaches to make very transcendent decisions in just 40 minutes of play and the impact each player has becomes much more important.
The proposed method for an approximation of this statistic has given good results.

First of all, the relationships (association rules) between sets of players have been identified, which has shown that there are sets of players that, at first glance (without numerical data), appear to be playing correctly when in fact it's the opposite, and vice versa. It was possible to verify the great impact that the best players of the team have (*Mirotic, Calathes, Laprovittola*) in all phases of the game, and the appearance as key factors of success (or failure) of some players with more specific roles (*Abrines, Higgins*) in more specific phases.

Afterwards, the scores for each player (and set) have been calculated and the surprising impact that some players have, either in some specific phase of the game or when they are playing with teammates or others, has been observed. Obviously, the best players on the team are still indisputable, but it can be identified that they will perform better or worse in a phase of the game depending on who their teammates are on the court (*Kuric, Exum, Higgins…*) regardless of their specialty. For example, *Higgins* is a 1v1 specialist and has a very negative impact on the phase 1 game.

The individual scores were then used to predict the performance of the team before the Final 4. It has given good results, correctly calculating the players' impact with an accuracy of 78.26%, regardless of whether they have played more or less minutes.

Finally, all this information can be used by FC Barcelona to decide how to renew the squad at the end of the season. Depending on the coach's playstyle, some phases will be played more than others, and will need to be played by players with a more positive impact on them. **The algorithm has a lot of potential, different approaches and a high level of reproducibility**, and not only at the highest European level, but also in any competition and context.

Even so, after this extensive analysis one might think that a basketball player is too unpredictable to be able to predict his behavior, since much of the sport is reading what the opposing team is doing at the time of doing every play to be able to attack and defend in the most optimal way possible. But each team and, above all, each player, has a specific way of playing, an "algorithm" that tries to resolve defenses with varying attacks but on the same basis specified in their capabilities.
In the end, a player is not a number, but you can round it off.

WEBGRAPHY

[1] *Apriori Algorithm In Data Mining: Implementation With Examples - Software Testing Help*, 13 June, 2022, https://www.softwaretestinghelp.com/apriori-algorithm/#:~:text=The%20steps%20followed%20in%20the,each%20item%20in%20the%20database.

[2] *Association Rules - Mlxtend*. https://rasbt.github.io/mlxtend/user_guide/frequent_patterns/association_rules/

[3] *What is the difference between lift and leverage? - BigML* https://support.bigml.com/hc/en-us/articles/207310225-What-is-the-difference-between-lift-and-leverage-

[4] Garbade, Dr Michael J. "Understanding K-Means Clustering in Machine Learning." *Medium*, 12 Sept. 2018, https://towardsdatascience.com/understanding-k-means-clustering-in-machine-learning-6a6e67336aa1

[5] "Euroleague Basketball Mobile App." *Euroleague Basketball*, https://www.euroleaguebasketball.net/euroleague-basketball-app/

APPENDIX 1

DATA GATHERING

A1.1. Data sources and collection

- Gerard Solé (partner and sports commentator at DAZN who has given me game access)

- Subscription to Barça TV+

- YouTube

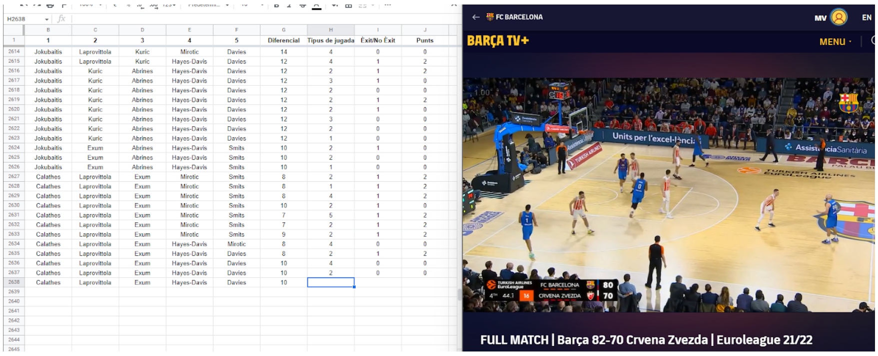


Image A1.1.1. *Example of data collection*

* Matches against Russian teams prior to their disqualification are included.

Phase: Attempt to find an advantage to get a good shot

- The type of phase depends on how you want to end it.
- <u>The phase type is not equivalent to how the play ends</u>. In other words, if a player tries a 1v1 and ends up passing the ball for a 3-point shot, *the play is of phase 1, not phase 3*. Even so, if the same move is made with the <u>intention</u> to give the ball in this shot, it would be phase 3.
  Another example is a pick with a defensive switch where the ball is given inside <u>to play a 1v1 in the low post</u>. This is a *phase 4* case.
- If a move is started with PHASE 4 (for example), but <u>no advantage is taken and the phase is changed</u> , this first phase was not successful, as the desired completion was not achieved. The success of the next phase (still within the same play) will depend on how it ends.
  An example of this case would be an inside ball to *Davies*, who messes up and is forced to pass it out to *Exum*, who plays a 1-on-1 because there are 5 seconds left on the shot clock.
- In case there are 2 phases in the same play (for example, a play that gives the possibility of an inside ball and an open shooter at the same time) and the intention is not clear, the <u>completion</u> is the factor taken into account.
- Defensive court turnovers after a rebound count as an *unsuccessful phase 5* (transition) <u>if a high probability of transition is cut</u>. Similarly, fouls taken on defensive rebounds count as a *successful phase 5* if they interrupt a clear transition (same as tactical fouls).
- Fouls received in clutch time to stop the clock and force free throws are not counted as a phase, as well as fouls received and turnovers without having started any play.
- If a phase is repeated in the same play, this is only counted once.

A1.2. A phase that doesn't end in a score is successful? And if it ends in free throws?

I have discussed this matter with 3 people:

- Joan Miquel Villaró (Level 2 coach and women's basketball manager at *CB Solsona*)
- Jordi Ribas (Superior coach and statesman at LEB Or's *Bàsquet Lleida* (2nd national league))
- Marc Maset (Superior coach at *UE Mataró*'s junior national team, statesman of UNI Girona (1st women's league team) and staff member at Joventut de Badalona)

The first two differentiate between achieving success and scoring. They claim that a play can be successful and, in addition, end in points scored or not. You can also find that the defense fouls you because they don't know how to defend the attack and they are late in their closeouts. Scoring from the free throw line (or having the chance to do so) is already considered a good option. They clearly differentiate between a successful choice and points earned. If the phase gets you a good shot but the shooter misses, the phase is successful, but a more effective shooter will be searched.
As a summary, the phase is successful if it gives you the option to score.

On the other hand, Marc is closer to the approach I had initially. In a professional league like the Euroleague, what matters to you in the end is whether you score or not, since it is your main goal, much before just getting a shooter open. If a player takes a bad shot and makes it, it will be more valuable than a player who shoots alone but misses it.
As a summary, the phase is successful if you score.

Considering all this, and adding that if it's all reduced to whether you get the basket or not you lose a lot of information, I decided to meet both criteria and separate the column *Success* and *points achieved*, to then be able to do the subsequent analysis more subjectively and fulfilling the two perspectives.
In addition:

- If the phase ends in a normal foul (no free throw penalty), the phase is considered successful because the defense had to foul to stop it.
- If it ends in an offensive foul, it will be considered an unsuccessful phase, since it has the same value as losing the ball (turnover).

A1.3. Interpretation of phases after offensive rebound

Case 1: The shot is immediately after the rebound (maximum one dribble)

- It's not considered a new phase, it's included in the previous one that generated this rebound.

Case 2: The shot is not immediately after the rebound (pass to outside shooter, multiple dribbles...)

- It is considered a new phase.
- Many times, when an offensive rebound is taken, the centers/forwards look for an outside shooter. This is considered phase 3.

A1.4. Examples of phases

Attached below is an example for each type of phase in the multiple regular season games of FC Barcelona in the Euroleague. It contains the opponent, the court in which they play (home or away), the quarter and the time left to finish it:

Transition cut by a foul after a defensive rebound (successful phase 5)

- Maccabi (away), 2nd quarter, 3:32 remaining

Successful phase 1

- Zalgiris (home), 3rd quarter, 8:20 remaining

Unsuccessful phase 1

- Panathinaikos (away), 3rd quarter, 0:12 remaining

Successful phase 2

- Olimpia Milano (away), 2nd quarter, 4:40 remaining

Unsuccessful phase 2

- Baskonia (local), 4th quarter, remaining 9:30

Successful phase 3

- Efes (away), 3rd quarter, remaining 9:40

Unsuccessful phase 3

- Crvena Zvezda (away), 1st quarter, 2:20 remaining

Successful phase 4

- ASVEL (away), 3rd quarter, 4:05 remaining

Unsuccessful phase 4

- UNICS (home), 2nd quarter, 5:32 remaining

Successful phase 5

- Bayern (home), 3rd quarter, 1:55 remaining

Unsuccessful phase 5

- Real Madrid (home), 2nd quarter, 3:05 remaining

Play without phase (not included)

- CSKA (home), 3rd quarter, 6:40 remaining

APPENDIX 2

RESULTS: RELATIONSHIP TABLES

Below are the resulting tables with the top 5 association rules for each analyzed database.

A2.1. Position dependency (PD)

Table A2.1.1: *Association rules - Success (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.061023	0.341212	0.057155	0.936620	2.744980	0.036333	10.394213
(Escorta_Laprovittola, Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.061453	0.565535	0.057155	0.930070	1.644584	0.022402	6.212849
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.066609	0.341212	0.061453	0.922581	2.703835	0.038725	8.509347
(Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.066609	0.565535	0.061023	0.916129	1.619933	0.023353	5.180159
(Alerpivot_Mirotic, Aler_Exum)	(Escorta_Laprovittola)	0.073055	0.341212	0.066609	0.911765	2.672137	0.041682	7.466266

Table A2.1.2: *Association rules - Failure (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.102662	0.495817	0.088213	0.859259	1.733015	0.037312	3.582349
(Alerpivot_Mirotic, Aler_Exum)	(Base_Calathes)	0.063878	0.425095	0.054753	0.857143	2.016356	0.027598	4.024335
(Alerpivot_Mirotic, Aler_Exum)	(Escorta_Laprovittola)	0.063878	0.312548	0.053232	0.833333	2.666261	0.033267	4.124715
(Escorta_Higgins, Base_Calathes)	(Alerpivot_Mirotic)	0.102662	0.495817	0.082890	0.807407	1.628437	0.031988	2.617871
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.068441	0.312548	0.054753	0.800000	2.559611	0.033362	3.437262

Table A2.1.3: *Association rules - Scoring (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.067335	0.331662	0.063754	0.946809	2.854740	0.041421	12.564756
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.072350	0.331662	0.068052	0.940594	2.836003	0.044056	11.250358
(Escorta_Laprovittola, Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.068052	0.570201	0.063754	0.936842	1.643004	0.024951	6.805158
(Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.072350	0.570201	0.067335	0.930693	1.632221	0.026081	6.201392
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.103152	0.570201	0.095272	0.923611	1.619800	0.036455	5.626465

Table A2.1.4: *Association rules - No scoring (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Aler_Exum)	(Escorta_Laprovittola)	0.065004	0.330365	0.056545	0.869863	2.633035	0.035070	5.145616
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.119768	0.521817	0.103295	0.862454	1.652791	0.040798	3.476523
(Escorta_Higgins, Base_Calathes)	(Alerpivot_Mirotic)	0.105076	0.521817	0.087711	0.834746	1.599692	0.032881	2.893623
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.064114	0.330365	0.053428	0.833333	2.522462	0.032247	4.017809
(Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.064114	0.521817	0.053428	0.833333	1.596985	0.019973	2.869101

Table A2.1.5: *Association rules - Successful phase 1 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.099379	0.549689	0.096273	0.968750	1.762359	0.041646	14.409938
(Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.086957	0.549689	0.083851	0.964286	1.754237	0.036052	12.608696
(Escorta_Laprovittola, Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.074534	0.549689	0.071429	0.958333	1.743409	0.030458	10.807453
(Pivot_Smits, Alerpivot_Mirotic)	(Base_Calathes)	0.062112	0.431677	0.059006	0.950000	2.200719	0.032194	11.366460
(Pivot_Sanli, Alerpivot_Mirotic, Escorta_Lapro...	(Base_Calathes)	0.083851	0.431677	0.077640	0.925926	2.144951	0.041443	7.672360

Table A2.1.6: *Association rules - Unsuccessful phase 1 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Escorta_Higgins, Aler_Hayes-Davis)	(Base_Calathes)	0.061404	0.456140	0.061404	1.000000	2.192308	0.033395	inf
(Alerpivot_Mirotic, Aler_Hayes-Davis, Escorta_...	(Base_Calathes)	0.057018	0.456140	0.057018	1.000000	2.192308	0.031010	inf
(Escorta_Higgins, Aler_Hayes-Davis)	(Alerpivot_Mirotic, Base_Calathes)	0.061404	0.333333	0.057018	0.928571	2.785714	0.036550	9.333333
(Escorta_Higgins, Aler_Hayes-Davis)	(Alerpivot_Mirotic)	0.061404	0.517544	0.057018	0.928571	1.794189	0.025239	6.754386
(Escorta_Higgins, Aler_Hayes-Davis, Base_Calat...	(Alerpivot_Mirotic)	0.061404	0.517544	0.057018	0.928571	1.794189	0.025239	6.754386

Table A2.1.7: *Association rules - Successful phase 2 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.068085	0.334752	0.065248	0.958333	2.862818	0.042457	15.965957
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.073759	0.334752	0.069504	0.942308	2.814945	0.044813	11.530969
(Escorta_Laprovittola, Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.069504	0.541844	0.065248	0.938776	1.732557	0.027588	7.483215
(Alerpivot_Mirotic, Aler_Exum)	(Escorta_Laprovittola)	0.085106	0.334752	0.079433	0.933333	2.788136	0.050943	9.978723
(Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.073759	0.541844	0.068085	0.923077	1.703584	0.028119	5.956028

Table A2.1.8: *Association rules - Unsuccessful phase 2 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Pivot_Smits, Escorta_Laprovittola)	(Alerpivot_Mirotic)	0.059794	0.470103	0.053608	0.896552	1.907139	0.025499	5.122337
(Alerpivot_Mirotic, Aler_Exum)	(Base_Calathes)	0.076289	0.385567	0.068041	0.891892	2.313196	0.038627	5.683505
(Alerpivot_Mirotic, Escorta_Laprovittola, Aler...	(Base_Calathes)	0.063918	0.385567	0.055670	0.870968	2.258927	0.031026	4.761856
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.105155	0.470103	0.090722	0.862745	1.835225	0.041288	3.860677
(Pivot_Smits, Escorta_Laprovittola)	(Base_Calathes)	0.059794	0.385567	0.051546	0.862069	2.235847	0.028492	4.454639

Table A2.1.9: *Association rules - Successful phase 3 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.090659	0.615385	0.087912	0.969697	1.575758	0.032122	12.692308
(Aler_Exum)	(Escorta_Laprovittola)	0.087912	0.351648	0.085165	0.968750	2.754883	0.054251	20.747253
(Alerpivot_Mirotic, Aler_Exum)	(Escorta_Laprovittola)	0.074176	0.351648	0.071429	0.962963	2.738426	0.045345	17.505495
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.068681	0.351648	0.065934	0.960000	2.730000	0.041782	16.208791
(Base_Calathes, Aler_Exum)	(Alerpivot_Mirotic)	0.068681	0.615385	0.065934	0.960000	1.560000	0.023669	9.615385

Table A2.1.10: *Association rules - Unsuccessful phase 3 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Pivot_Davies, Aler_Martinez)	(Escorta_Kuric)	0.072581	0.338710	0.064516	0.888889	2.624339	0.039932	5.951613
(Pivot_Sanli, Alerpivot_Mirotic, Escorta_Lapro...	(Base_Calathes)	0.072581	0.419355	0.064516	0.888889	2.119658	0.034079	5.225806
(Pivot_Davies, Escorta_Exum)	(Aler_Kuric)	0.064516	0.354839	0.056452	0.875000	2.465909	0.033559	5.161290
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.096774	0.451613	0.080645	0.833333	1.845238	0.036941	3.290323
(Aler_Martinez, Base_Jokubaitis)	(Escorta_Kuric)	0.072581	0.338710	0.056452	0.777778	2.296296	0.031868	2.975806

Table A2.1.11: *Association rules - Successful phase 4 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Aler_Abrines, Alerpivot_Mirotic)	(Base_Calathes)	0.069444	0.489198	0.066358	0.955556	1.953312	0.032386	11.493056
(Escorta_Higgins, Aler_Hayes-Davis, Base_Calat...	(Alerpivot_Mirotic)	0.055556	0.586420	0.050926	0.916667	1.563158	0.018347	4.962963
(Aler_Abrines, Base_Calathes)	(Alerpivot_Mirotic)	0.072531	0.586420	0.066358	0.914894	1.560134	0.023824	4.859568
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.149691	0.586420	0.134259	0.896907	1.529463	0.046477	4.011728
(Escorta_Laprovittola, Aler_Hayes-Davis, Base ...	(Alerpivot_Mirotic)	0.066358	0.586420	0.058642	0.883721	1.506977	0.019728	3.556790

Table A2.1.12: *Association rules - Unsuccessful phase 4 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.098734	0.506329	0.083544	0.846154	1.671154	0.033552	3.208861
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.060759	0.329114	0.050633	0.833333	2.532051	0.030636	4.025316
(Escorta_Laprovittola, Aler_Exum)	(Base_Calathes)	0.060759	0.427848	0.050633	0.833333	1.947732	0.024637	3.432911
(Pivot_Davies, Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.060759	0.506329	0.050633	0.833333	1.645833	0.019869	2.962025
(Pivot_Sanli, Aler_Hayes-Davis)	(Alerpivot_Mirotic)	0.065823	0.506329	0.053165	0.807692	1.595192	0.019837	2.567089

Table A2.1.13: *Association rules - Successful phase 5 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.083333	0.392361	0.083333	1.000000	2.548673	0.050637	inf
(Alerpivot_Mirotic, Base_Calathes, Aler_Exum)	(Escorta_Laprovittola)	0.072917	0.392361	0.072917	1.000000	2.548673	0.044307	inf
(Alerpivot_Mirotic, Aler_Exum)	(Escorta_Laprovittola)	0.086806	0.392361	0.083333	0.960000	2.446726	0.049274	15.190972
(Alerpivot_Mirotic, Aler_Kuric, Escorta_Higgins)	(Base_Calathes)	0.059028	0.468750	0.055556	0.941176	2.007843	0.027886	9.031250
(Aler_Hayes-Davis, Base_Calathes)	(Alerpivot_Mirotic)	0.107639	0.531250	0.097222	0.903226	1.700190	0.040039	4.843750

Table A2.1.14: *Association rules - Unsuccessful phase 5 (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Escorta_Exum)	(Pivot_Davies, Aler_Kuric)	0.072289	0.168675	0.072289	1.0	5.928571	0.060096	inf
(Alerpivot_Mirotic, Escorta_Exum)	(Aler_Kuric)	0.072289	0.253012	0.072289	1.0	3.952381	0.053999	inf
(Pivot_Davies, Escorta_Exum, Alerpivot_Mirotic)	(Aler_Kuric)	0.072289	0.253012	0.072289	1.0	3.952381	0.053999	inf
(Pivot_Davies, Aler_Exum)	(Escorta_Laprovittola, Alerpivot_Mirotic)	0.060241	0.289157	0.060241	1.0	3.458333	0.042822	inf
(Aler_Exum)	(Escorta_Laprovittola)	0.120482	0.397590	0.120482	1.0	2.515152	0.072579	inf

Table A2.1.15: *Association rules - Success in clutch time (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Alerpivot_Mirotic, Base_Calathes, Aler_Higgins)	(Pivot_Davies, Escorta_Laprovittola)	0.054264	0.348837	0.054264	1.0	2.866667	0.035334	inf
(Aler_Abrines, Alerpivot_Mirotic, Escorta_Lapr...	(Pivot_Davies, Base_Calathes)	0.108527	0.410853	0.108527	1.0	2.433962	0.063938	inf
(Pivot_Davies, Aler_Exum)	(Alerpivot_Mirotic, Escorta_Laprovittola, Base...	0.096899	0.414729	0.096899	1.0	2.411215	0.056712	inf
(Alerpivot_Mirotic, Aler_Exum)	(Escorta_Laprovittola, Base_Calathes)	0.147287	0.437984	0.147287	1.0	2.283186	0.082777	inf
(Pivot_Davies, Aler_Exum)	(Escorta_Laprovittola, Base_Calathes)	0.096899	0.437984	0.096899	1.0	2.283186	0.054459	inf

Table A2.1.16: *Association rules - Failure in clutch time (PD)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Aler_Abrines, Base_Jokubaitis)	(Escorta_Higgins)	0.062937	0.237762	0.062937	1.0	4.205882	0.047973	inf
(Base_Jokubaitis, Escorta_Exum)	(Aler_Kuric)	0.055944	0.314685	0.055944	1.0	3.177778	0.038339	inf
(Pivot_Sanli, Aler_Exum)	(Escorta_Laprovittola)	0.055944	0.426573	0.055944	1.0	2.344262	0.032080	inf
(Alerpivot_Mirotic, Aler_Higgins)	(Escorta_Laprovittola)	0.062937	0.426573	0.062937	1.0	2.344262	0.036090	inf
(Base_Calathes, Pivot_Davies, Alerpivot_Miroti...	(Escorta_Laprovittola)	0.062937	0.426573	0.062937	1.0	2.344262	0.036090	inf

A2.2. Position independency (PI)

Table A2.2.1: *Association rules - Success(PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Exum, Calathes, Laprovittola)	(Mirotic)	0.061882	0.608939	0.057585	0.930556	1.528160	0.019902	5.631285
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.079502	0.608939	0.071336	0.897297	1.473543	0.022925	3.807704
(Mirotic, Abrines)	(Calathes)	0.069618	0.456382	0.061023	0.876543	1.920637	0.029251	4.403309
(Calathes, Laprovittola)	(Mirotic)	0.216588	0.608939	0.186076	0.859127	1.410860	0.054188	2.775986
(Higgins, Calathes)	(Mirotic)	0.114740	0.608939	0.098410	0.857678	1.408480	0.028540	2.747721

Table A2.2.2: *Association rules - Failure (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Higgins, Calathes)	(Mirotic)	0.111787	0.543726	0.089734	0.802721	1.476333	0.028952	2.312836
(Higgins, Calathes, Davies)	(Mirotic)	0.063878	0.543726	0.050951	0.797619	1.466950	0.016218	2.254529
(Calathes, Laprovittola)	(Mirotic)	0.199240	0.543726	0.154373	0.774809	1.424999	0.046041	2.026165
(Calathes, Laprovittola, Davies)	(Mirotic)	0.082890	0.543726	0.063878	0.770642	1.417335	0.018809	1.989354
(Sanli, Calathes)	(Mirotic)	0.108745	0.543726	0.082129	0.755245	1.389017	0.023002	1.864204

Table A2.2.3: *Association rules - Scoring (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Exum, Calathes, Laprovittola)	(Mirotic)	0.068052	0.615330	0.063754	0.936842	1.522505	0.021879	6.090616
(Mirotic, Abrines)	(Calathes)	0.070917	0.449857	0.063754	0.898990	1.998392	0.031851	5.446418
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.068768	0.615330	0.061605	0.895833	1.455860	0.019290	3.692837
(Calathes, Laprovittola)	(Mirotic)	0.210602	0.615330	0.182665	0.867347	1.409565	0.053075	2.899824
(Sanli, Calathes)	(Mirotic)	0.126791	0.615330	0.108883	0.858757	1.395605	0.030864	2.723467

Table A2.2.4: *Association rules - No scoring (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Higgins, Calathes, Davies)	(Mirotic)	0.063224	0.566785	0.052538	0.830986	1.466139	0.016704	2.563186
(Higgins, Calathes)	(Mirotic)	0.113980	0.566785	0.094390	0.828125	1.461091	0.029788	2.520521
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.079697	0.566785	0.065450	0.821229	1.448924	0.020278	2.423294
(Calathes, Laprovittola)	(Mirotic)	0.210151	0.566785	0.169635	0.807203	1.424178	0.050524	2.247003
(Sanli, Calathes)	(Mirotic)	0.127783	0.566785	0.101514	0.794425	1.401633	0.029088	2.107332

Table A2.2.5: *Association rules - Successful phase 1 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Exum, Calathes, Davies)	(Mirotic)	0.052795	0.596273	0.052795	1.000000	1.677083	0.021315	inf
(Exum, Calathes, Laprovittola)	(Mirotic)	0.074534	0.596273	0.071429	0.958333	1.607205	0.026986	9.689441
(Exum, Laprovittola)	(Mirotic)	0.121118	0.596273	0.108696	0.897436	1.505075	0.036476	3.936335
(Exum, Calathes)	(Mirotic)	0.145963	0.596273	0.130435	0.893617	1.498670	0.043401	3.795031
(Sanli, Calathes)	(Mirotic)	0.145963	0.596273	0.130435	0.893617	1.498670	0.043401	3.795031

Table A2.2.6: *Association rules - Unsuccessful phase 1 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Mirotic, Hayes-Davis, Higgins)	(Calathes)	0.057018	0.456140	0.057018	1.000000	2.192308	0.031010	inf
(Higgins, Calathes, Kuric)	(Mirotic)	0.092105	0.583333	0.083333	0.904762	1.551020	0.029605	4.375000
(Mirotic, Higgins, Kuric)	(Calathes)	0.096491	0.456140	0.083333	0.863636	1.893357	0.039320	3.988304
(Mirotic, Higgins)	(Calathes)	0.184211	0.456140	0.157895	0.857143	1.879121	0.073869	3.807018
(Higgins, Calathes)	(Mirotic)	0.184211	0.583333	0.157895	0.857143	1.469388	0.050439	2.916667

Table A2.2.7: *Association rules - Successful phase 2 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Exum, Calathes, Laprovittola)	(Mirotic)	0.070922	0.578723	0.066667	0.940000	1.624265	0.025622	7.021277
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.075177	0.578723	0.068085	0.905660	1.564928	0.024578	4.465532
(Calathes, Laprovittola, Davies)	(Mirotic)	0.085106	0.578723	0.075177	0.883333	1.526348	0.025924	3.610942
(Calathes, Laprovittola)	(Mirotic)	0.207092	0.578723	0.181560	0.876712	1.514907	0.061711	3.417021
(Mirotic, Abrines)	(Calathes)	0.068085	0.425532	0.059574	0.875000	2.056250	0.030602	4.595745

Table A2.2.8: *Association rules - Unsuccessful phase 2 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Exum, Calathes, Laprovittola)	(Mirotic)	0.065979	0.507216	0.055670	0.843750	1.663491	0.022204	3.153814
(Martinez, Davies)	(Jokubaitis)	0.072165	0.470103	0.059794	0.828571	1.762531	0.025869	3.091065
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.068041	0.507216	0.055670	0.818182	1.613082	0.021158	2.710309
(Calathes, Laprovittola)	(Mirotic)	0.195876	0.507216	0.156701	0.800000	1.577236	0.057349	2.463918
(Sanli, Calathes)	(Mirotic)	0.098969	0.507216	0.078351	0.791667	1.560806	0.028152	2.365361

Table A2.2.9: *Association rules - Successful phase 3 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Exum, Calathes, Laprovittola)	(Mirotic)	0.065934	0.648352	0.063187	0.958333	1.478107	0.020438	8.439560
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.096154	0.648352	0.090659	0.942857	1.454237	0.028318	6.153846
(Calathes, Laprovittola)	(Mirotic)	0.208791	0.648352	0.189560	0.907895	1.400312	0.054190	3.817896
(Higgins, Calathes)	(Mirotic)	0.126374	0.648352	0.112637	0.891304	1.374724	0.030703	3.235165
(Calathes, Laprovittola, Davies)	(Mirotic)	0.090659	0.648352	0.079670	0.878788	1.355419	0.020891	2.901099

Table A2.2.10: *Association rules - Unsuccessful phase 3 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Exum, Laprovittola)	(Mirotic)	0.080645	0.483871	0.072581	0.900000	1.860000	0.033559	5.161290
(Martinez, Smits)	(Kuric)	0.080645	0.701613	0.072581	0.900000	1.282759	0.015999	2.983871
(Sanli, Smits)	(Kuric)	0.080645	0.701613	0.072581	0.900000	1.282759	0.015999	2.983871
(Martinez, Davies)	(Kuric)	0.072581	0.701613	0.064516	0.888889	1.266922	0.013593	2.685484
(Oriola, Jokubaitis)	(Kuric)	0.064516	0.701613	0.056452	0.875000	1.247126	0.011186	2.387097

Table A2.2.11: *Association rules - Successful phase 4 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Mirotic, Abrines)	(Calathes)	0.075617	0.489198	0.072531	0.959184	1.960729	0.035539	12.514660
(Calathes, Abrines)	(Mirotic)	0.081790	0.635802	0.072531	0.886792	1.394761	0.020529	3.217078
Higgins, Hayes-Davis, Calathes)	(Mirotic)	0.058642	0.635802	0.050926	0.868421	1.365866	0.013641	2.767901
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.066358	0.635802	0.057099	0.860465	1.353353	0.014908	2.610082
(Calathes, Laprovittola)	(Mirotic)	0.211420	0.635802	0.179012	0.846715	1.331727	0.044591	2.375955

Table A2.2.12: *Association rules - Unsuccessful phase 4 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Calathes, Laprovittola, Davies)	(Mirotic)	0.111392	0.56962	0.088608	0.795455	1.396465	0.025156	2.104079
(Exum, Calathes, Davies)	(Mirotic)	0.068354	0.56962	0.053165	0.777778	1.365432	0.014228	1.936709
(Calathes, Laprovittola)	(Mirotic)	0.210127	0.56962	0.162025	0.771084	1.353681	0.042333	1.880080
(Higgins, Calathes)	(Mirotic)	0.098734	0.56962	0.075949	0.769231	1.350427	0.019708	1.864979
(Sanli, Calathes)	(Mirotic)	0.098734	0.56962	0.075949	0.769231	1.350427	0.019708	1.864979

Table A2.2.13: *Association rules - Successful phase 5 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Mirotic, Higgins, Kuric)	(Calathes)	0.059028	0.468750	0.055556	0.941176	2.007843	0.027886	9.031250
(Sanli, Laprovittola, Calathes)	(Mirotic)	0.090278	0.586806	0.079861	0.884615	1.507510	0.026886	3.581019
(Exum, Calathes, Laprovittola)	(Mirotic)	0.083333	0.586806	0.072917	0.875000	1.491124	0.024016	3.305556
(Higgins, Calathes)	(Mirotic)	0.104167	0.586806	0.090278	0.866667	1.476923	0.029152	3.098958
(Sanli, Calathes)	(Mirotic)	0.128472	0.586806	0.111111	0.864865	1.473853	0.035723	3.057639

Table A2.2.14: *Association rules - Unsuccessful phase 5 (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Laprovittola, Abrines)	(Mirotic, Calathes)	0.060241	0.433735	0.060241	1.0	2.305556	0.034112	inf
(Higgins, Davies)	(Mirotic, Calathes)	0.060241	0.433735	0.060241	1.0	2.305556	0.034112	inf
(Mirotic, Kuric, Exum)	(Davies)	0.072289	0.469880	0.072289	1.0	2.128205	0.038322	inf
(Exum, Sanli)	(Laprovittola)	0.060241	0.506024	0.060241	1.0	1.976190	0.029758	inf
(Hayes-Davis, Mirotic, Sanli)	(Laprovittola)	0.060241	0.506024	0.060241	1.0	1.976190	0.029758	inf

Table A2.2.15: *Association rules - Successful in clutch time (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Higgins, Laprovittola, Calathes)	(Mirotic, Davies)	0.054264	0.534884	0.054264	1.0	1.869565	0.025239	inf
(Mirotic, Laprovittola, Abrines)	(Davies)	0.116279	0.624031	0.116279	1.0	1.602484	0.043717	inf
(Higgins, Laprovittola, Calathes)	(Davies)	0.054264	0.624031	0.054264	1.0	1.602484	0.020401	inf
(Mirotic, Calathes, Laprovittola, Abrines)	(Davies)	0.108527	0.624031	0.108527	1.0	1.602484	0.040803	inf
(Mirotic, Higgins, Laprovittola, Calathes)	(Davies)	0.054264	0.624031	0.054264	1.0	1.602484	0.020401	inf

Table A2.2.16: *Association rules - Unsuccessful in clutch time (PI)*

antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
(Abrines, Jokubaitis)	(Higgins)	0.062937	0.307692	0.062937	1.0	3.250000	0.043572	inf
(Hayes-Davis, Martinez)	(Davies)	0.055944	0.559441	0.055944	1.0	1.787500	0.024647	inf
(Mirotic, Calathes, Davies, Abrines)	(Laprovittola)	0.062937	0.587413	0.062937	1.0	1.702381	0.025967	inf
(Exum, Calathes, Laprovittola)	(Mirotic)	0.097902	0.762238	0.097902	1.0	1.311927	0.023277	inf
(Higgins, Calathes, Kuric)	(Mirotic)	0.062937	0.762238	0.062937	1.0	1.311927	0.014964	inf

APPENDIX 3

RESULTS: FOURSOMES' PREDICTIONS BEFORE THE FINAL 4

A3.1. Semifinal vs Real Madrid

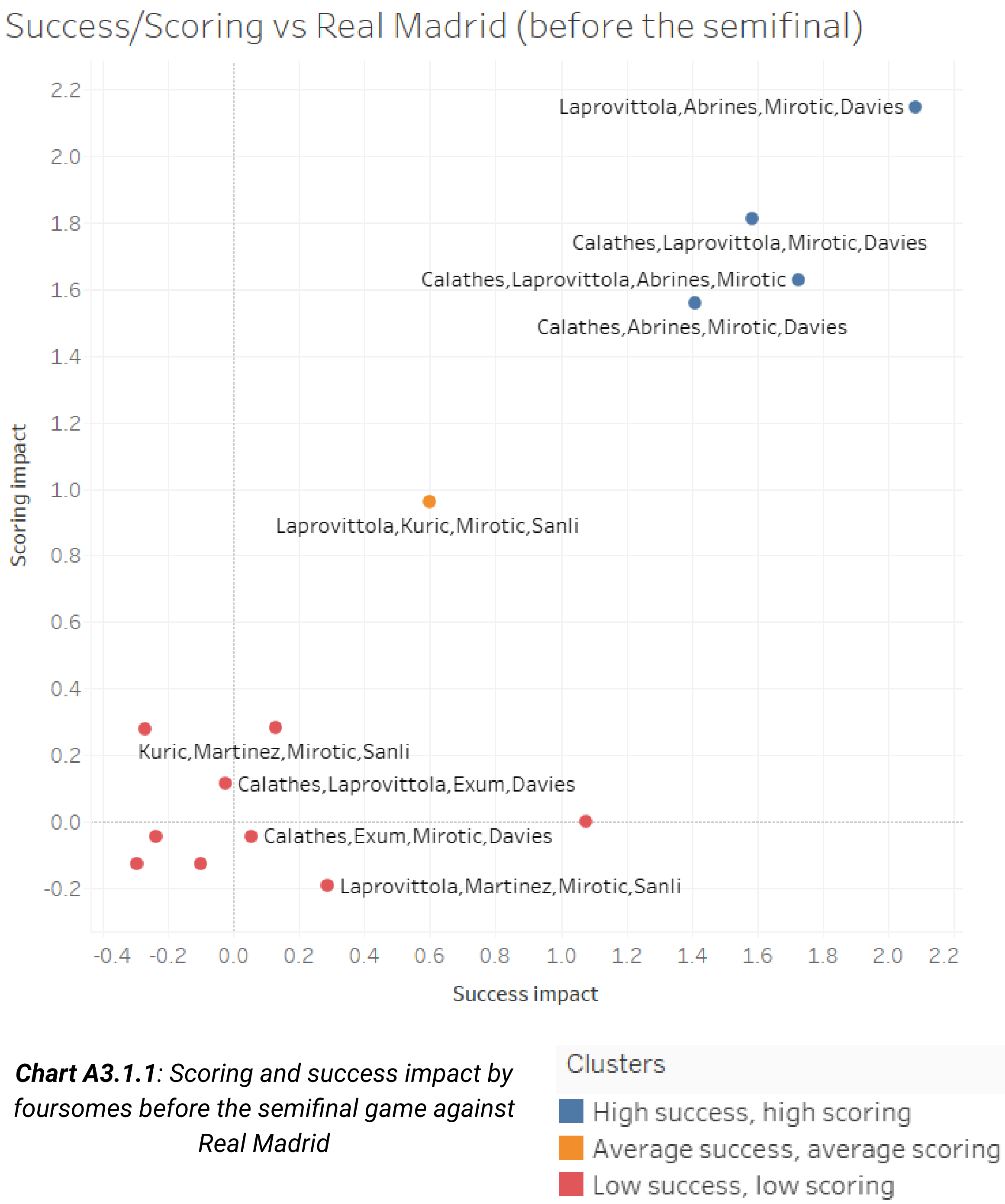


***Chart A3.1.1**: Scoring and success impact by foursomes before the semifinal game against Real Madrid*

A3.2. 3rd-place game vs Olympiacos

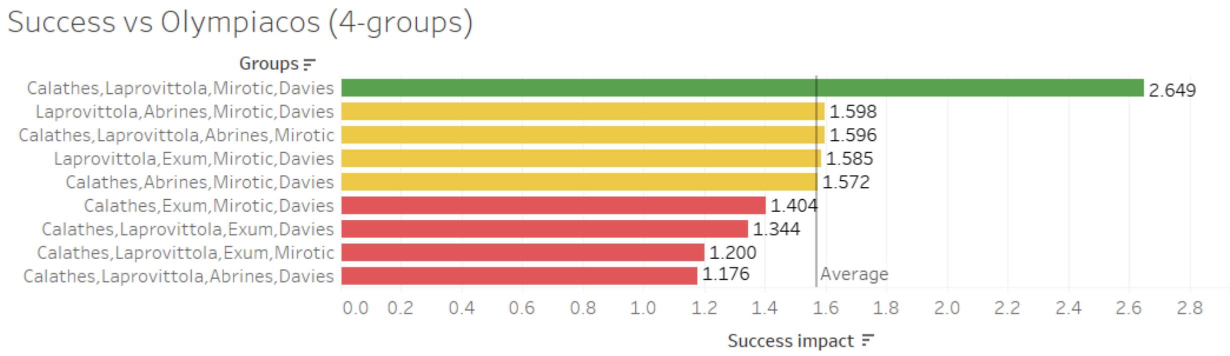


Chart A3.2.1: *Success prediction (by foursomes) in the 3rd-place game vs Olympiacos*

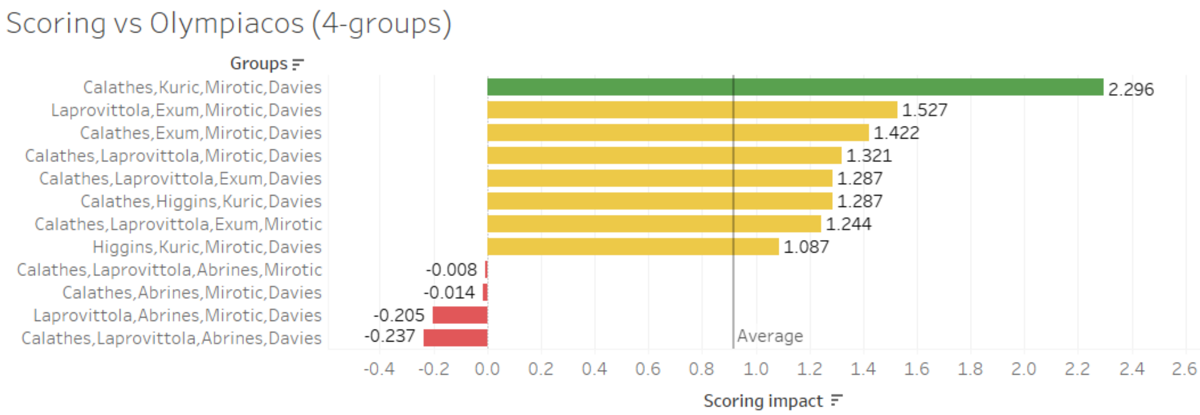


Chart A3.2.2: *Scoring impact prediction (by foursomes) in the 3rd-place game vs Olympiacos*