Are soccer team rationals in their transfers ? A game-theoretic approach for soccer clubs transactions

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1 INTRODUCTION

Recently, the sports industry has surrender to data driven analysis in the field and business side, making data analysis a vital part of teams decision-making steps. With the premise that more information can assist win championships, teams, clubs, coach's, managers and athletes search ways to evaluate and improve their performance, given that more winnings implies in increase in the number of fans and monetary revenue [11]. Hence, data driven solutions are been applied in sports from the prediction of matches in soccer and Martial Mixed Arts fights (MMA) [3, 23], passing to more analytic evaluations [24]. In resume, data is everywhere in the sport [11].

Considering a global context, soccer is the most popular sport in the world [15]. Different from other regional sports as Baseball in United States and Rugby in Australia, soccer has a appeal to fans in every part of the globe. Due this fact it has many practitioners and attracts enormous amounts of people to events as FIFA World Cup, continental and intercontinental championships. In financial terms, soccer has one of the biggest monetary movement between all sports [1, 2], produced by ticket sells, TV contracts, marketing, merchandising, uniform sells, sponsors TV channels quotas and also the revenue of players transfers [26]. Better illustrating that, only in Europe in 2016/2017 season, soccer has moved approximately 25 billions of euros [7], showing how big is the sport market.

Between these, athletes transactions is the one which generates most earnings [7], been this majorly induced by multimillionaire proposals. However, this transfers can be influenced by several factors as player performance, age or even by new challenges that athletes are looking for. Nevertheless, to make a transfer complete, a team has also many other variables to consider as adaptation, price and the importance that a player can have for each club, aiming to not idly spend it money.

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Even tough many times teams consider all risk factors before make a transfer, occasionally a player fail in fit a team, turning into a bad investment. In this case there are few options to a club, between then invest in the player waiting time for him to get better and eventually fit in the team, loan or sell the athlete. Illustrating that, we have the 2009 transfer of Kaká' from Milan to Real Madrid. Kaká' which was considered the best player in the world in 2007 when playing in Milan, moved from Italy to Spain with a value of $55,000,000$ euros. Nevertheless, the player do not fit well in Real Madrid, making less that was expected of him, leaving the club without many prestige.

In other case, if a player fit in a team, his utility for the owner club gets bigger, making it possible to hold the player or sell for a higher price. As example of a well made transfer, we have Cristiano Ronaldo, which moved from Manchester United to Real Madrid, also in 2009, arriving with Kaká'. Different from the Brazilian player, Ronaldo not only fit well in the Spanish club, but also turn into a idol, conquering with the club 4 Champions League, and also 4 the title of best player in the world.

Nevertheless, not always a team act as expected, making unlikely transfers, unnecessary buying and selling players. In this cases, clubs make bets, waiting to have a revenue when negotiating a athlete. In this case team do not rightly measure the risk of transferring the player, or the soccer club is not risk averse, which is defined in game theory as an agent (in our case the club) who do not fear lose utility [21].

Given this facts, in this paper we investigate if soccer teams are rationals when making players transactions. We consider a team rational if it make transfers aiming to maximize it benefits, that can be either make money or build a strong team. To accomplish that we use a game theory framework, making a strict evaluation of the values and utilities for each player within a transfers. More specifically, our question over the game are:

- Soccer teams follow the proposed game ?
- What teams are risk averse ?
- What teams have the most advantage when making transfers ?

To address this questions, our proposed methodology consists in a game theoretic approach which models how a team can behavior when making a transfer. To evaluate our game and verify how soccer teams really behavior, was used data collected from SoFIFA [1] and Transfermarkt [2]. With the data gathered from these two websites, was possible to measure a player monetary value, financial situation of the teams involved in the transfer, and player utility for each team, based on his skills of FIFA game data.

[1] https://sofifa.com/
[2] https://transfermarkt.com/

We high-value that with this work, it is possible to assist a team to evaluate it transfer history defining it profile as rational or not. Also it is possible to evaluate future transfers, analyzing how it is possible to maximize it advantage when buying or selling a athlete.

2 PROPOSED GAME

In this work we propose a game of transfer between soccer clubs. Our aim with this work is to evaluate this transfers and verify if the teams transactions are rational. In a player transfer each team has a particular role. Thus, in a simple player transaction, there are a seller team, T_S, which is selling a player p to a buyer team, T_B, i.e. these team are the actual players of this game. Each team has a set of actions attached with a payoff that it can take. This payoffs are measured given the importance of a athlete and the transaction value for a team. Before we define each one of the actions that a team can take, we define the taxonomy of the payoffs bellow:

(1) **Players importance:** The importance a player (p) for the buyer team (i_p^B) and for the seller team (i_p^S).
(2) **Monetary Value:** The monetary value (mv) offered by the team T_B for the team T_S.
(3) **Importance of Value:** The importance of the monetary value offered by the T_B for the team T_S. In this case, it is measure the values importance for the buyer team (i_m^B) and for the seller team (i_m^S). The importance tends to better higher for poor teams, and lower to rich teams.

To understand the payoff model defined in this work, we explain the concepts underneath the transacting of a player. When a player join team, the T_B has a gain in the set of skills available, which is given by the importance of bought player for a team i_p^B. To acquire a player, a team has initially three options: *buy*, *trade* or *loan* the athlete.

When buying a player, a financial compensation is required (mv). Nevertheless, this financial compensation has different meanings for each part evolved in a transfer. For example, consider the transfer of a player p, between two different teams A and B, seller and buyer respectively. Considering that the value of the player in negotiation is 10 million €and the athlete is the most import of team A. If the team B is a rich club, 10 million €is a low value for it transfers, and if the team A is a club with low finances, 10 million €is a high value. Then, although the players importance (i_p^S) for the team A is high, the importance of the money (i_m^S) is higher. And as pointed, the club B is rich, thus, 10 million is a low value, when considering the value of the other players within the team B, and it transactions historic. Hence, the importance of the value for the buyer team (i_m^B) is lower when compared to the seller team. Thus, the importance of monetary value is relative to the financial condition of the team.

To measure i_p^S, i_p^B, i_m^S, i_m^B we use a simple metric, according to each team context. The importance of a player is given by the overall ability of the player in the transfer, divided by the biggest overall ability within a team. The same logic is applied to measure the money importance for each team. The value offered in a player is divided by the most expensive (in financial terms) athlete of the team (buyer and seller). The Equations 1, 2, shows how it measured the player and money importance for each team, respectively.

$$Player\_Importance_A = \frac{Overall}{max(Overall_A)} \tag{1}$$

$$Money\_Importance_A = \frac{Player\_Value}{max(Players\_Value_A)} \tag{2}$$

In trade negotiations, teams aim to exchange two players. This type of negotiation can or can not have a financial compensation attached. Thus, to have a player p, a team offer a other player s plus a monetary value that is variable. To better quantify this value in our model, we measure it by the multiplication of a $\alpha \in (-1, 1)$ parameter to the monetary value (mv) and the money and importance of the money (i_m). Thus, in more complicated trade transfers, it is possible for a team pay back when a expensive player is trade.

We high-value that loan actions where not considered in our game, due the difficult to estimate what is the benefit of loaning a player. In loan transfers, the lending team does not have a visible compensation, given that it will decrease the skill set and the players option in the club. Nevertheless, this is a common practice when a team want to wipe the payroll, give a player more experience or does not consider the athlete part of a season plans, but do not want to break the bond between the club and the player. Hence, it is difficult to model all this situations in our initial model, but this can be considered to future works.

To seller clubs T_S there are four options when negotiating a player: Sell, Trade, Loan and Not Negotiate. The three first options works as the options for the T_B. The last one, of not negotiate, is a option that the seller team has. In this case, the team holds the player, however do not gain any financial compensation. We high-value that in some cases, some players and buyer teams force their transfer when a seller team do not want to negotiate. In this case, the sell/buy action is taken, however, it is not possible to model that it was a forced negotiation, given that it was not measured the will of a player to move from one team to another. Thus, as the payroll, this can be considered as future work.

The Table 1, shows the game proposed in this work. The game models transfers of players between a buyer team T_B and a seller team T_S. It is possible to notice that all the concepts presented above are used to model the game.

3 RELATED WORKS

The aim of this work is to propose a game and verify if soccer teams are rational when making transaction of soccer athletes. To accomplish this our game we use FIFA electronic game series and real transfer data. In this section we evaluate works related to ours in three ways: (*i*) Works that use FIFA Data, (*ii*) Works that evaluate soccer players transfers, and lastly (*iii*) Works that use game theoretic approaches to analyze soccer.

3.1 FIFA Data

FIFA is a game series produced by EA Sports, been a soccer simulator released each year since 1993. Since then FIFA has sold over 260 million copies, and attracts each day more and more players. However, studies using FIFA game data has began more recently, in 2014 by [22], where the author aim to predict soccer matches using machine learning techniques. From that, works as [20], have also

	Actions	Buy	Trade
T_S	Sell	$(mv - i_p^S + i_m^S, i_p^B - mv - i_m^B)$	$(i_p^S - i_s^S - \alpha(mv + i_m^S), i_s^B - i_p^B + \alpha(mv + i_m^B))$
	Not Negotiate	$(i_p^S - i_m^S - mv, i_m^B + mv + i_p^B)$	$(i_p^S - i_s^S - \alpha(mv + i_m^S), i_s^B - i_p^B + \alpha(mv + i_m^B))$
	Trade	$(i_p^S - i_s^S - \alpha(i_m^S + mv), i_m^B + mv - i_p^B)$	$(i_s^S - i_p^S + \alpha(mv + i_m^S), i_p^B - i_s^B - \alpha(mv + i_m^B))$

T_B

Table 1: Game played by two soccer teams when transacting a player

proposed a framework to predict soccer matches using FIFA data and machine learning.

Since then, more and more works have analyzed soccer using FIFA data. The second work of [5], uses FIFA data to make a qualitative analyzes of different game styles. In this work is evaluated teams that has different game styles, prioritizing different skills. In [12], the authors characterize FIFA data attributes and proposes a methodology to identify the evolution in the skills of soccer players this data source.

In [25], the authors present a approach for predicting the potential of professional soccer players. The study of [27] uses the estimated salary given by FIFA data, joined with the players skills to train several supervised machine learning techniques to estimate the wage of a soccer player.

In [13], statistical techniques are applied over FIFA data. The authors use regression method to evaluate the contribution of each player to a team victory. The approach is called Adjusted Plus-Minus (APM), been applied to other sports as hockey and basketball. The work of [19] also estimates the contribution of a player in a match. The main difference from [13] is that a framework is proposed, using data of 20 thousand European championships matches, and FIFA data, assisting in the forecast of a team win probability.

The works of [17, 18], proposes optimization models to maximize the efficiency and efficacy of a team. The work of [17], proposes a stochastic model that aim to ensure the required skills set needed to compose a strong team, respecting constrains of regulations and budget limit. The following work of [18], proposes a more complete linear programming model, using FIFA data players features. The author uses FIFA data to estimate the value and the salary of a player using Simple Moving Average method.

3.2 Soccer Players Transfers

Soccer players transfers as been used as a way to produce revenue and increase a team ability, in this context athletes transactions has been studied in several ways, from sociology to data mining. In this subsection we evaluate some of this works, making a background of works that analyze transfers.

In [26], the author aim to analyze the success of a team according to it transactions. Thus, is used in the methodology transfer data from $2011 - 2015$. The authors modeled the data as a graph, where the nodes are team and the directed links are formed when a Team A sells to a Team B, $A \longrightarrow B$. Through the proposed evaluation, the authors concluded that is possible to win championships avoiding excessive spends, although, money can assist in the assemble of a consistent team.

In [9], the authors evaluated transfers made by countries in FIFA 2018 World Cup. Considering a similar model as [26], the modeled graph has countries as nodes and directed edges to represent transfers between teams of two countries, including clubs with same country. The results shows a heavy tail network, where few countries have most of the accomplished transfers. Besides that, the work shows that countries with a weak economy has the tendency of selling players to Europe and China.

The work of [6], evaluated the transfer market impact in the performance of a National Team in the World Cup. In this paper, the authors shows the evolution of the transfer market and global soccer, evaluating data from 1960 to 2018. In [6, 9], the authors used data from Transfermarkt, resembling to our work. The main difference between the two works, is the evaluated period, where [9], uses data from $1990 - 2018$, and [6] uses a longer period, $1960 - 2018$, and the fact that the first aim do characterize the world transfer network, and the second aim to see the impact of these transactions.

In [10], the author analyze empirically the athletes market in Europe, evaluating aspects as salary and career time. For been centered in Europe, this work analyze the transfers in soccer core, showing how the European leagues works. However, this work is in economy field, not been cleared where the data was gathered, and neither using computational approaches.

3.3 Soccer in Game Theory

In this subsection we analyze game theory applied in soccer. There are several works that use a game theoretic approach to evaluate the economy in the sport. We show the main papers and high-value that any of this works model a game similar to ours.

The work of [16], uses soccer to verify economic theories. In this book the author pass through different game theory concepts use soccer to illustrate. This work do not proposes novelty in the study field, but is a excellent guide to understand game theory and how it can be applied to soccer.

In the proposal of [4], the authors apply a game theoretic approach to verify the behavior of soccer players when taking a penalty shoot. The authors uses data of 300 penalty shoots to verify what is the best strategy to the kicker. Besides that, the authors also verify the satisfaction of goalkeepers when taking a penalty.

In [14], the author evaluates scoring situations in soccer matches. The model proposed by the author are supported by statistics and data collected from the Italian championship. The results shows that in situations of adversarial goal danger, goalkeepers have more chances of winning if protect the near post.

The work of [8], proposes a learning mechanism to assists coach during a soccer matches. The agent act over 11 payoff matrixes, were each matrix represent a player, and learn from this players, maximizing a payoff. The payoffs are measure in dynamic and static ways, been the dynamic payoffs calculated during the game.

Lastly, we high-value that to the best of our knowledge this is the first work to use a game theoretic approach to verify soccer players transfers.

4 METHODOLOGY

In this section, we present the proposed strategy to evaluate the game proposed in section 2. Our aim is to verify if soccer teams are rational in their transfers, quantify what teams are risk averse and which teams take most advantage when negotiating athletes. To accomplish that, we use real transfer data gathered from Transfermarkt [3] to model the importance of money and the price of a player to each team evolved in a transaction. To quantify the player importance for each team we use data gathered from the game FIFA. The game FIFA is soccer simulator, and it data is gathered through several collaborators that watch games and follow the athletes through a year. This data is them joined with players statistics and is used to give each player abilities that better characterize the athlete. Bellow we describe the process to gather and join the collected data.

4.1 Data Gather

To accomplish this work, we gather from the two sites presented bellow. To collect each one of the datasets was develop a web-crawler (with available links), responsible to walk on the pages, download and parse each page. First, it was collected the abilities in SoFIFA page [4], them, using as query the name and birth day of the player (as a way to distinguish athletes with the same name), it was gathered and joined the transfer information about the player.

- **SoFIFA:** It is a major database from the game FIFA. The page has data from 2007 until 2020 FIFA editions, having also updates and users comments about athletes. The data present in the website was used to model the players abilities. More specifically we get the overall ability of the player. [5].
- **Transfermarkt:** Transfermarkt is a website with information of soccer transfers. Between the data present in Transfermakrt there information of the teams there are making a transfer, price, players birth place and countries evolved in negotiation. The collected data was used to measure the importance of the money to the club and the price of a player. [6]

5 EVALUATION

In this section, we compare and discuss the behavior of soccer teams when making players transfers. First we analyze the behavior of teams in specific situations, analyzing also, situations where the proposed game has to evolve. Lastly, we evaluate what is the general behavior of clubs when negotiating players using real transfer data.

5.1 Specific Transfers Analyses

In this subsection we evaluate specific transfers that illustrate different cases where the game is played. We also analyze cases where our proposed model has to evolve aiming to better capture aspects of real life.

We take as example to illustrate the dynamicity of the transfer market the transactions made in the Neymar's history. Neymar have change teams two times in his career. Both of them were Sell-Buy transfers, but each one of them resulted in a different game.

The most common and simple type of transaction is a **Sell-Buy** transfer. In this case a financial compensation is attached to the acquisition of the player, a team takes a player, another takes the money. Nevertheless, we mount the game for all type of situations **Buy-Sell**, **Sell-Trade**, **Not-Negotiate-Buy**, **Not-Negotiate-Trade**, **Trade-Buy** and a **Trade-Trade** transfers, evaluating the best case scenario in each of them in Neymars case.

First, in Table 2, is detailed the transfers in Neymar history. In the table is possible to see the season, teams and market value evolved in the negotiation. As complementary information, which will help us to build the payoff matrix, is also present the athlete overall p_O (in this case Neymar's), the maximum overall of the seller and buyer team, $max(O)^S$ and $max(O)^B$, respectively, which represents the best player in each team. It is also possible to notice the most valuable player in the seller and buyer team, $max(i_m^S), max(i_m^B)$ respectively, which is measured by the monetary value of the athlete given by Transfermarkt. This estimation give to every player, even those who has no transfer, as Messi, a price given his statistics, hence, helping our work in the measure of a athlete monetary importance for a team.

With the data present in Table 2, is measured the values that will be used in the payoff matrix of the Neymar's transfer game. In Table 3, it is possible to see the values that will compose the final payoff matrix of the game. All the values were adjust as pointed in Section 2. The only value measured not pointed before, is the normalization made in the player market value. The necessity of the normalization is to avoid that the payoff be majorly guided by market value, that is biggest value between the terms that compose the payoff. Thus, we normalize the player value by the max reached market value during his career, considering the estimation given by Transfermarkt and actual maximum transfer value. Both values are considered in cases that a player do not have transactions in his career, as pointed before.

Season	T_S	T_S	mv	p_O	$max(O)^S$	$max(O)^B$	$max(i_m^S)$	$max(i_m^B)$
13/14	Santos	Barcelona	88.20	84	84 (Neymar)	94 (Messi)	50 (Neymar)	120 (Messi)
17/18	Barcelona	PSG	220	92	94 (Messi)	87 (Cavani)	120 (Messi)	45 (Cavani)

Table 2: Neymar's transfer history

Season	i_p^S	i_p^B	i_m^S	i_m^B	mv
13/14	1	0.89	1.764	0.735	0.40
17/18	0.97	1.05	1.83	4.88	1

Table 3: Neymar's Game Values

In Tables 4 and 5, it is possible to see the game the values for each of the transfer made by Neymar. The payoffs were calculated according to the values present in Table 3. It is possible to notice that some of the values are still as variable (I_S^B, I_S^S, α), due the fact

[3] https://www.transfermarkt.com/
[4] https://www.sofifa.com
[5] https://www.github.com/lucasgsfelix/SoFIFA-Crawler
[6] https://github.com/lucasgsfelix/Transfermarkt-Crawler

Neymar transaction in real life do not evolve other player. However, we use a range of values within this variables to evaluate what were the best option for the teams, if it were rational and how it could increase their payoff.

Considering the *Sell-Buy* transfer, it is possible to notice that the seller team has a clearly advantage over the buyer team, having a high payoff due the players price. Not-Negotiate it is a bad option for the seller team in this case, given that the team will lose a huge amount of money. Nevertheless, not negotiate it is good for the buyer team, given that it will have a positive payoff. It is worth to highlight that, buying players it is a major investment, when selling Neymar, Santos gain this game, while Barcelona lose. However, after, Barcelona had a gain over Neymar's transfers, making in the end a successful investment, gaining a huge amount of money without selling it main player (Messi).

Another approach that Barcelona could tried to decrease Neymar's price and had a higher payoff, would be trying to trade him for another player. In this case, if Barcelona tried to make a transfer given his best player, it would be a poor decision for both clubs. First Barcelona would lose in quality, and second that Santos would have to repay Barcelona (if the offered player worth more). In the best case scenario, where the two player would have the same value, the seller team would lose the monetary value that it could gain when selling the player. Thus, one option would be offer a player that can be as good as Neymar, but do not has the same market value.

Considering Neymar transfers game, PSG was the most harmed player in this game given that when buying Neymar it had the lowest payoff between all. If PSG considered to give it best player to Barcelona in Neymar place, it payoff would increase ?

Given that the best player in PSG was Edinson Cavani in season 17/18, when Neymar arrived in buyer club, then, considering that it FIFAs overall was 89, his market value was 45 million euros, and the max transfer value in his career was 64.5 million euros. We have $I_S^B = 1$, $I_S^S = 0.94$ and $\alpha = 1 - 0.375 = 0.625$, considering that α is the monetary importance of Cavani's value for Barcelona, minus 1, given a discount in the transfer value. Hence, we have that the *Trade* strategy would give a payoff of $Seller = 0.94 - 0.97 + 0.625 \times (2.83) = 1.73$, $Buyer = 1.05 - 1 - 0.625 \times (5.88) = -3.75$. Thus, if PSG give to Barcelona it best player in exchange to Neymar, the seller club payoff would be -3.75 which would be a high increase in his payoff, however, not sufficient to make it positive. In conclusion, the best option to PSG was to not buy Neymar.

But what is the general behavior in their transfers ? In general team act like Barcelona, making investments or taking poor decisions PSG ? In the next subsection we evaluate the transfer behavior for a transfers dataset.

5.2 Data Evaluation

In this subsection we analyze what is the general behavior of teams when making transfer. To accomplish this study we gather data from Transfermarkt and SoFIFA as pointed in Section 4.

In the end our dataset had about 3025 transactions, with information about players, teams and transfer details. Most of the transfers present in our dataset are from *Sell-Buy* type, them our evaluations are jeopardized by the lack of data of different types. Besides that, one of data sources used in this work, Transfermarkt, do not register transfers attempts and trades, been the last one characterized as sell transactions, hence one future work is to identify trade transfers. Thus, we high-value that this analyzes are limited by the quantity and quality of our data.

In our evaluation we aim to answer the research questions present in Section 1. Thus, answering the first question *Soccer teams follow the proposed game?* Given the limitation of our data, the soccer teams follow the proposed game, making only sell-buy transfers. One of our future works is to gather a bigger quantity of data, with different types of transfer or identify these different transactions. Also, we have to evolve our game to accept loan transfers and try to better specify the payoffs in these cases.

To answer the second question, *What teams are risk averse?* we evaluate all transfer within our dataset, analyzing the teams and countries which make more transactions, considering those with a positive payoff and with a negative.

Our results shows that most of the first place teams, considering the number of transfers ranking, are from Europe, more specifically from Italy, England, Germany, Spain and France, considered to be rich countries [9], which has more power to invest and buy players. Considering a country ranking we have: England, Italy, Germany, France, Spain, Turkey, Belgium, China, Russia e Wales, in this order, as most buyer countries, i.e. less risk averse,. Given that in most of this countries transactions they are willing to pay more to have a player, even if his payoff are negative. As representatives of this groups are: Liverpool, Benfica, Juventus, Ajax, Totteham Hotspurs and most of the famous teams.

The more risk averse countries are given by those teams which all transfers it had a zero or positive payoff, not making risk investments, these team are present in England, Brazil, Argentina, Norway, France, Spain, Portugal, Netherlands, Poland e Chile, in this order, having teams as Botofago (Brazil), Racing (Argentina) and Real Zarragoza (Spain). Nevertheless most of this teams transfers only have sell transactions, making of the teams pointed bellow only partial players in the proposed game (only play the game in one role). This does not mean that the teams do not make buy transactions in real, but it mean that the buy transfers made by the team are not present in the dataset. Thus, to make our analysis more fair we analyze the biggest sellers which also play the game as buyers.

Through Figures 1, 2, it is possible see the risk aversion of the most buyer and seller teams, respectively. When analyzing the buyer teams, we have Italian and English teams. As we can see, most of them has a decrease of utility as it buy more expensive players, given that are other players with a better cost-benefit. However, this is a sign that this teams are not risk averse, in other words, money does not mean that much to team, they rather have a player than keep the money.

When selling players, as we see in Figure 2, it is possible to notice that some teams, even when the players value is big there are a decrease in the utility. This occurs when a team sell a key player to another team, in a force transfer, when the team do not want to sell, but the player force it transaction. In a future work, we can use this strategy to identify forced transactions.

Lastly, we answer the question *"What teams have the most advantage when making transfers ?"* To answer to question, we measure

	Actions	Buy	Trade
	Sell	1.164, -0.245	$1 - I_s^S - \alpha(2.164)$, $0.89 - I_s^B + \alpha(1.135)$
T_S	Not Negotiate	-1.164, 0.245	$1 - I_s^S - \alpha(2.164)$, $0.89 - I_s^B + \alpha(1.135)$
	Trade	$1 - I_s^S - \alpha(2.164)$, 0.245	$I_s^S - 1 + \alpha(2.164)$, $0.89 - I_s^B - \alpha(1.135)$

T_B

Table 4: Neymar transfer game from Santos to Barcelona

	Actions	Buy	Trade
	Sell	1.86, -4.83	$0.97 - I_s^S - \alpha(2.83)$, $1.05 - I_s^B + \alpha(5.88)$
T_S	Not Negotiate	-1.86, 4.83	$0.97 - I_s^S - \alpha(2.83)$, $1.05 - I_s^B + \alpha(5.88)$
	Trade	$0.97 - I_s^S - \alpha(2.83)$, 4.83	$I_s^S - 0.97 + \alpha(2.83)$, $1.05 - I_s^B - \alpha(5.88)$

T_B

Table 5: Neymar transfer game from Barcelona to PSG

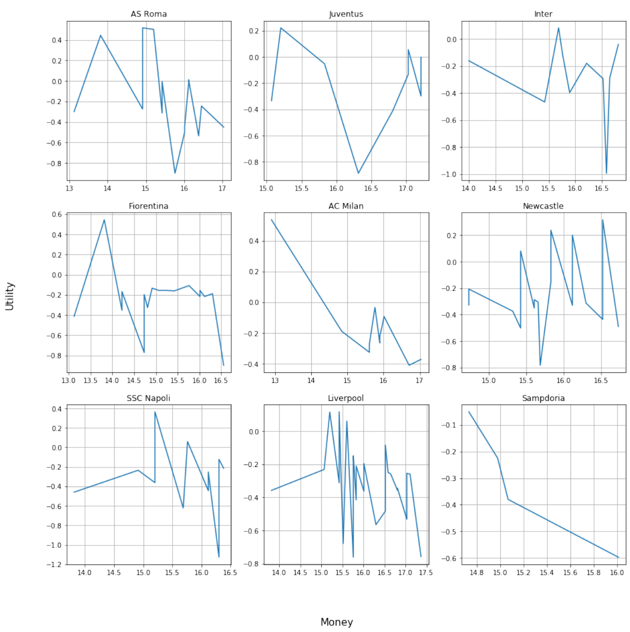

Figure 1: Top buyers risk aversion

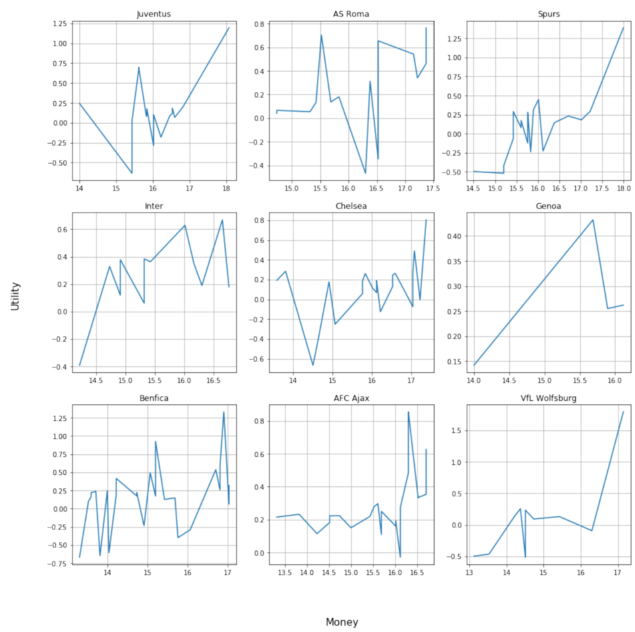

Figure 2: Top sellers risk aversion

for each team the rate of transfers that it made that had a payoff bigger than the other club involved in the transfer. We consider only clubs that had at least one buy and sell transfer. In our evaluations most of teams with a positive punctuation in the game are teams from outside Europe, been distributed between Asia and South America. When considering a country ranking, this can be see more clearly. In Table 6, it is possible to see the top 10 countries that have most positive payoffs in the game.

As we can see from Table 6, three between the five best players in our game are from South America. This players are high-lighted by their type of transfer, working as farm countries [9, 26], were their role in the market are of sell players to bigger countries (most in Europe).

Position(1-5)	Country	Position (6-10)	Country
1	Uruguay	6	Portugal
2	Colombia	7	Austria
3	Netherlands	8	Norway
4	Sweden	9	France
5	Chile	10	Belgium

Table 6: Countries with most punctuation in the game

As pointed before, most of the sell transactions have a higher payoff for the seller team, as this countries play the game selling hence the amount of gathered points are higher. The same works for all the other countries in the ranking most of them works as showcase to bigger European leagues, thus, this countries invest in buying player a very low price and them selling to rich countries for a higher price.

6 CONCLUSION

This work proposes a game theoretic approach to verify if soccer teams are rational in their transfer. To accomplish our work we propose a game, were the players are two teams willing to make a players transaction. One team has the role of seller and another has the role of interested (buyer). In the game each team wants to maximize it payoff, and to verify if this happens in real life, we use a dataset from real transfers and FIFA overall as players importance. Nevertheless, due the lack of data and difficult to gather, was impossible to verify all game states, been able to verify only *Sell-Buy* transfers. However, even with a small amount of data (in type and amount of transfers), it was possible to answer some research question. First we verify if soccer teams follow the game proposed by us. In a short answer, yes, nevertheless, due the lack of data it was not possible to confirm that, given that we do have all the types of transfers. Second, we answer what teams are risk averse, we see that there teams from ever were in the globe, some Brazilian team as Botofogo and Atlético-PR, and even Spanish clubs. Lastly, we analyze what teams have the most advantage when playing the game, in this case, we level up the granularity and evaluate by country, were we could see that South American and European countries takes the most advantage.

As future works, we aim to gather a bigger amount of data, per team, aiming to collect complete team a make a better model. Another work is to expand the game, making present loan transfers. We high-value the potential of this game for future proposals, been possible to make models to better understand the soccer transfers.

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