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ICT in Business

Exploring the Relationship between Football Players' Performance and Their Market Value

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MASTER'S THESIS

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Abstract

A lot of money is involved with the transfers of top players in the big European football leagues. For various reasons, obtaining a good economic valuation of football players throughout the year is valuable, in other words, not only when a player has just been transferred. The good performance of a player has a positive impact on his club's income. Furthermore, it is relevant to consider how the market value of a player relates to the performance of that player. Both these factors again depend on the various parameters of the player, that might be gleaned from various public sources on the web. In this paper, I demonstrate how market value and performance of La Liga (the Spanish League) players can be modeled using extensive public data sources. According to the results of my model, some players are overvalued or undervalued by the market. In addition, the reasons for these exceptions have been studied.

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Contents

List of Figures

List of Tables

1 Introduction

1.1 Background

European football is the most popular sport in the world [17]. The football clubs in Europe acquire or sell players at a very high transfer fee compared to other countries (e.g. U.S.) [56]. According to accounting's point of view [3], football players' market value is considered to be the most expensive asset for the club's balance sheet. The performance of a player will affect the club's income [23], therefore clubs are willing to spend more money on acquiring good players. The transfer fee of football players are getting higher and higher each year [53]. The UEFA (Union of European Football Associations) Financial Fair Play Regulations[54] were recently implemented strictly, and the break-even assessment was first made during season 2013/14. The motive of this regulation is to prevent professional football clubs from getting into financial problems by spending more than what they earn, which might threaten their long-term survival. Its implementation will definitely affect the behavior of clubs in the transfer market. Nowadays, spending money on overvalued players not only wastes club's money, but also is against UEFA's regulations. It becomes more critical to value football player properly for clubs. Bosman's ruling [4] in 1995 determined a free transfer right within the EU when a player's contract ends, making it even more important for players and agents to

know the suitable value. Therefore, the goal of this research is to study the relationship between the market value and the performance of players.

1.2 Research Questions

The main research question is:

What is the relationship between football players' performance and their market value?

In order to answer the main question, the sub-questions are:

- What is a football player's market value?
- How can the real market value of a football player be determined?
- What are the performance factors?
- How can a football player's performance be evaluated?
- Why are some of the players improperly valued?

1.3 Research Contribution

Incomplete dataset model Not every player has been transferred or is judged by experts. It is impossible to collect market value and assess the performance of all the players. However, there are proxy values (Market Value from Transfer Market[1], Rating from Whoscored.[2]) available for all the players. They are the results of some certain mathematics models which are inaccessible to this research. As a result, the designed model in this research has been built for predicting all the players' real values with the help of proxy values.

More variables introduced Most of previous research is based on the old identified characteristics (total goals, assists, save, etc.) which are very classical indicators for analyzing performance used by media. That is because they are very representative, but this is also the result of the previous undeveloped technology in collecting matches performance data. Since nowadays more detailed data have been collected by advanced technology, this research can be feed by these detailed performance indicators.

[1] http://www.transfermarkt.co.uk/wettbewerbe/national
[2] http://www.whoscored.com/AboutUs

Proposed key performance indicators(KPIs) As more performance variables have been introduced, the complexity of the model will be extremely high. In the literature, there are few quantitative researches on getting the performance indicators. In this paper however, a quantitative research method has been conducted to explore the KPIs for each position. As a quantitative method can reduce the bias caused by people, it is adopted in this research.

The relationship of market value and performance The general relationship between players' market value and performance have been analyzed. In addition, the factors which make the players improperly valued have been revealed as well.

1.4 Research Scope

Opta has collected data from more than 200 professional leagues[3] running in diverse economic environment. Due to the diversity, the distribution of their market data are quite different, e.g. the mean value of each league. As time frame of this study, I have gathered and prepared data only for the Spanish League La Liga in the first half[4] of season 2014/2015.

In this paper, the player's performance is defined as the overall performance of the player in the selected matches, contrary to the previous definition as physical or psychological test results.

1.5 Research Methods

The research problem is proposed and defined based on the literature review. In addition, personal observations on soccer matches also play a part in coming up with a research problem. After the problem is well defined, this research is conducted by a deductive research approach associated with a quantitative analysis to test the hypothesis[20]. Furthermore, the market value should follow the trend of performance and the exceptions of the market value should have some specific reasons.

Literature review is conducted throughout the whole research process. In other words, at each step of the research, the literature review has been carried out for the study of each subtopic. The literature review process is following Mark Saunders et.al [45]

[3]Opta is a performance data provide. According to my email conversations with Opta sales, I got what professional leagues data they have.

[4]With the spring transfer window passed, there is no more transfers in this season.

guidelines. The following key words have been generated: sports data mining, football player, market value, transfer fee, transfer market, performance analysis, athletes performance assessment, etc.. Google scholar[25] is used as the specific search engine for literature review. The literature has been selected before being applied to this research.

Various researches have been conducted in American football, basketball, baseball and hockey, and the most famous research is from Billy Bean [28]. He has defined the process of constructing operational definitions within performance analysis and used them with large objective databases. It helps him to recruit players more efficiently and economically, hence achieve success far in excess of the expectation of his club's financial standing. Billy's success has shown data mining is very useful in the sports area and it can be probably extended to other sports. Added by the fact that there are very limited researches on European football, data mining is the research method for this thesis.

Various research techniques have been applied in this research. Figure 1.1 shows detailed steps of the techniques.

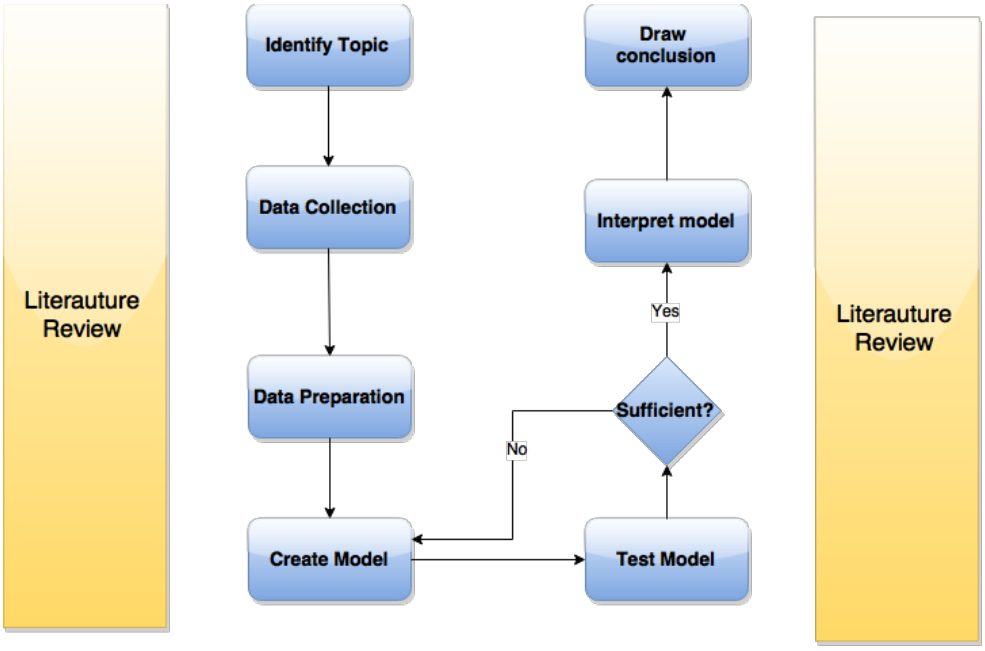


Figure 1.1: Research Techniques

Firstly, the research questions are identified, data sources found out and data observed. Secondly, the data mining technology is selected, on which the model is built. The proper model should be sufficient to solve the problem and consistent to the common sense. Thirdly, the explanations and illustrations are presented. Finally, the conclusion is drawn from the overall process and results.

The adopted tool for this research is R. It [51] is a system for statistics which provides

a programming language for computation, high level graphics, interfaces to other languages and debugging facilities.

1.6 Thesis Outline

The thesis is structured by following the Cross Industry Standard Process for Data Mining [46], and the details are as shown below. (Figure 1.2).

Figure 1.2: Data Mining Process

Chapter 2 - *Problem Statement* is the starting point of this research. It describes how this research topic comes out and what the specific concepts are defined in this research.

Chapter 3 - *Data Preparation* is based on the results from Chapter 2. It shows how data have been collected and pre-processed.

Chapter 4 - *General Model for Real Value* determines the proper machine learning tool and builds the suitable model for predicting incomplete data set.

Chapter 5 - *Market Value* and Chapter 6 - *Performance Analysis* use the model from Chapter 4 to predict the appropriate economic market value of football players and their performance. These two chapters use different parameters to apply to the model.

Chapter 7 - *Market Value vs Performance* has crossed the football player market value and his performance. Also, their general relationship and the other factors have been discussed.

Chapter 8 - *Conclusion* concludes this research and mentions the direction of future study.

2

Problem Statement

The research question has been defined based on the results of literature review and personal observations, which leads to the definition of key concepts - *market value* and *performance*.

2.1 Problem Definition

Matheson's survey of literature in 2003 says that football (or soccer) is undoubtedly considered to be the world's most popular sport [32]. Hundreds of millions of players worldwide have registered with FIFA (Fédération Internationale de Football Association)[16]. Especially, it is the national sport in Latin America, Africa, and most of the countries in Europe. Also, football participation is catching up rapidly in other countries.

Besides playing football for interests or exercise, some people are professional footballers. They can make money by playing in the matches or from endorsements and so on. Successful players or clubs are supported by their fans all over the world, even in the places where very few people actually play football themselves. For instance, in China, more than 1 million users perform actively on Soccer Hupu[1], which is just one of

[1] `http://bbs.hupu.com/`

the famous online football forums in Chinese.

In the same survey of Matheson[32], there is an evidence that football has tremendous economic value which has subsequently attracted much attentions from economists. There are various economic studies on football, like studies on gambling, the labour market of football, econometric analysis of football attendance, etc. [13].

Each piece of player's transfer news has drawn the attention of media, and transfer fee records are reported much higher than previous years. I have looked up the statistics of historical transfer records and there are some interesting findings by only looking at the simple ranking of top 100 transfers in the world [57]. The transfer fee indeed increased a lot in recent years, and highest record "transfer fee" in 2013 is double that in 2008. Particularly, nine out of top ten most expensive transfers in the history happened in recent five years. Generally, the purchasing clubs of these records are clubs in European countries.

According to Forbes 2015 [35], the current value of top clubs is estimated to be billions of dollars, all of which are from the top five Europe Leagues. They are Premier (England), la Liga (Spain), Serie A (Italy), Bundesliga (Germany), Ligue 1 (France). Additionally, Deloitte's report [21] showed that the top 20 most valuable clubs are in the top five most valuable leagues in the world.

Football clubs in Europe are much maturer than those in other continents, as Deloitte's report stated [21]:

"While the potential for growth in markets outside the 'core' European markets remains substantial, the pace of growth at clubs across the 'big five' leagues makes it difficult to see an increase in Money League entrants from outside these leagues in the near future unless they achieve transformational uplifts in their domestic broadcast deals."

The scope of this study is focus on these top five leagues in the world, as players in the following part are all registered in these leagues.

Furthermore, the fans group of European football clubs are very global. According to Forbes[35], Manchester United, which is a famous club of English premier league, has over 600 million followers worldwide. According to the statistic from Hupu[2], the clubs supported by Chinese football fans are all on the most valuable clubs' list, e.g. Real Madrid which has more than $70,000$ supporters on this website.

It is important to realize that not all of these players who have been transferred at a very high fee, have sufficient performance in terms of the money. The most illustrative example is Fernando Torres in 2011. He was transferred from Liverpool to Chelsea at

[2] `http://bbs.hupu.com/9456602.html`

£50 million, which broke the British transfer record in January 2011. However, the performance of Torres was not worth his prohibitive transfer fee paid by Chelsea. This transfer is regarded as one of the worst transfers in the world by media (Daily Mail[3], Independent[4], ESPN[5], etc).

The player's performance is very important to a team's success, which results in the income for the team. A player with high performance deserves a high market value, because he can bring more money to the team. According the case of Torres, it is reasonable to assume that there are some low performers overvalued and waste team much money, while some others may be undervalued. The hypothesis is based on this, which turns out to be

A player's market market is supposed to be in line with his performance. There might be some exceptions due to other market value related factors.

2.2 Research Question

External Factors Which Affect Market Value European football has received less attention from sports data mining, unlike the 'big four' American team sports (football, basketball, baseball and (ice) hockey), for which there are various data mining studies. No extensive scientific research on analyzing the relationship between market value and players' performance has been done. However, sports articles have stated some factors with the limited reason from football experts (football players, coaches, sports journalists, etc.). The following items are the summary of the most common factors from them:

- Squad Status, if this player is a Captain
- Age of players
- Performance Talent
- League Factors
- Image Rights for example Beckham
- Iconic Status for example Ronaldo

[3] http://www.dailymail.co.uk/sport/football/article-3145665/Chelsea-transfers-10-best-10-worst-Premi
html

[4] http://www.independent.co.uk/sport/football/news-and-comment/
the-worst-ever-january-transfer-signings-including-fernando-torres-andy-carroll-and-eric-djembadjemba
html

[5] http://en.espn.co.uk/football/sport/story/233413.html

Narrow down research scope and define research questions Due to the researcher's lack of practical experience on football and connections with football experts, as well as time frame of this research, the qualitative part for modeling market value is not included in this research. After basing the market value model on player performance, the other factors can be figured out by studying the variance of the designed model and the player's real market value. Research on players' performance analysis does not require practical experience, as what Peter Brand has done with baseball [28]. He can find something through out the data and build mathematics model and provide suggestions about finding true baseball diamonds in the rough. My research is conducting the similar approach as Money Ball, to find rules for performance and market market value from the data and present the crossed results. In the end, my research topic is defined as:

" ***What is the relationship between a football player's market value and his performance?***".

2.3 Prior Research

Regarding to the research topic, the definitions of a player's *Market Value* and *Performance* should be clarified and quantified.

2.3.1 Market Value

Market value is represented by Transfer Fee From the accounting point of view [3], football players are intangible assets for a club. In Europe, players are bought or sold for a cash "transfer fee" unlike the wage system of players in the U.S NBA. The football players' market value is considered to be the transfer fee of football player.

Transfer Transfer fee is introduced by a player's transfer. A transfer is the action taken when a player under contract moves between clubs in professional football leagues. This results in the player's registration transfer from one association football club to another. The transfer fee is the money the purchasing club pays to the player's previous club. The player can only be transferred when the transfer window is open and in accordance with the rules set by the governing organizations.

Transfer window is the period when players can be transferred from one club to another and ended with players registering in new clubs via FIFA. It opens twice every year - the winter transfer (Lasting less than 4 weeks) and the summer transfer (Lasting less than 12 weeks) - and is decided by the national associations themselves [16].

A good example of a famous transfer rule is the Bosman Ruling. This rule gave the right to Bosman and all other EU football players to a free transfer at the end of their contracts. However, the provision is that they transfer from a club in one EU Association to a club in another EU Association[4]. Before the issue of Bosman Ruling, even if the contracts had expired, some clubs still had the power to prevent players from joining a club in another country.

A transfer is the action taken under contract moves, so contract length is verdict to players' market value after Bosman Ruling. Amir et.al [3] found that market values are positively and significantly associated with investment in player contracts length. Feess's [15] study found that the significance of long-term effect makes the average contract length higher now, thereby leading to a dramatic increase in transfer fees.

2.3.2 Performance

Define Performance When one speaks of performance, most previous researches have focused on factors which would make a difference in the future. Rampinini [40] believes football is a complex sport which requires the repetition of many disparate actions to assess the physical prowess of players and is very critical the potential performance of players. Krustrup et al.,2006 [26] tested that the mean blood have been observed with individual values above 12 mmol during soccer games, while lactate concentrations of 2–10 mmol under normal condition. William [41] stated that cognition and perception skills are essential determinants to the playing ability when players are confronted with a complex and rapidly changing environment.

The motive for buyer is to acquire a new player to help team to succeed in terms of positions in the League, the champions [9]. In other words, the high transfer fee reflect the new clubs' expectation on the transferred player's high performance to help the team to win more games. As the performance data come from matches which are the most relevant to the market value, the performance in this research can be quantified. Therefore, the performance data in the match are the indicators for the performance analysis. For example, if a player cannot handle his anxiety in the match very well, he will not probably perform well in that game. As a result, this player's performance data will not be good.

Performance Assessment Some papers or media have chosen the best presentable variable by positions to value the player. Brandes [8] measures performance only by the commonly used categories as goals of strikers and assists of midfielders. In addition,

Spanish Leagues la Liga use the total saves to rank the goalkeeper[6]. Unlike the winning points in tennis, football goals are not only from good shots by players, but also it is the result of strong team work. Assessing players with only one most representative performance indicator is an unfair evaluation system, because the passes and other movements are also contribute to the goal. However, with the help of developed video analysis technology, more detailed performance data can be collected which can be included in performance analysis. A fair performance evaluation model should be built with turning the detailed data into assessment results for players' performance.

Evaluating players is quite subjective in soccer. Different people will use different metrics to evaluate for good performance and good players [24]. There are some qualify research on KPIs (Key Performance Indicators) by various positions, such as Hughes et.al have interviewed experts for acquiring the performance indicators by position[24, 12]. However, it need still to find the performance assessment indicator by having the KPIs, because their relationship still needs to be studied.

There is a possible way to discovered this problem by asking football experts to rank players. The number of the interviewed experts should be enough and the experts should have different backgrounds and experience. The final ranking is taken all the experts opinion, which can decrease the bias created by few people. A lot of organization has conducted survey with similar idea by asking the experts to vote for the best players, e.g. FIFA selects the world footballer every year. The votes can be the performance assessment indicator, because a good player will get more votes from the experts.

[6] `http://www.ligabbva.com/4067_estadisticas/index.html`

3 Data

3.1 Data Collection

According to the research question and prior researches, the goal of this research in terms of modeling is to cross examine the performance with the market value in euro amount. The required data should cover these three aspects: the players' basic information (Name, Team, Age, Height, Weight, etc.), market information (transfer fee, former team, the length of the contract, when comes to the team, etc.) and match performance information (on ground time, the actions of the balls, fouls, scores, etc.).

3.1.1 Data Source

The first challenge was to get easy access to the required data in tabular format. I have inquired a lot of online football database webmasters for free data sample. However, due to its high commercial value, there is no free data set available. Most of these websites are buying data from OPTA which is the biggest football data provider and they are using their technology to collect data with the same definitions and same standard for different leagues [1]. Their classic data are detailed into each touch of the ball for each

[1] http://www.optasports.com/en/about/who-we-are/about-opta.aspx

player (shots, passes, key passes, assists, through balls, etc.), which are the ideal data for required performance information. According to OPTA's sales[2], a classic data set for only one historic season just for Premier League is charged at £1750, VAT exclusive and with a significant academic discount. Due to the budget of this research, other methods have been be applied to find the data source.

After an extensive online search and the literature reference tracking [37, 27], I have found the following four useful public tabular data sources, from which the complete data set could be collected. They are Transfer Market[3], WhoScored [4], European football database [5] and Guardian [6].

The market data were from Transfer Market, a website to discuss and learn the latest news from the world of football. In the website, there are transfer news, rumors and also statistics on the market value, e.g. the length of contract, the former clubs.

Transfer fee was gathered from the European Football Database, which is a web database that presents all transfer news in tabular form, by league. It includes basic information of the transferred player and participating clubs in the transfer.

The performance data of the players were collected from the website WhoScored, which has detailed statistics for the top five leagues in Europe accumulated at different scales (powered by OPTA). Details of the offensive, defensive, and pass data have been collected from this website. The chosen performance data were accumulated by each 90 minutes, because it is a normalized version of those data are comparable among players.

As for the real performance assessment indicator, the votes organized by media group - the Guardian were considered, which gathers all the relevant information (name, team, the total votes of player, etc.). The voters consist of sports journalist and the football players themselves. There are 73 judges from 28 nations voting and the more votes a football player gets, the better performance the player has.

3.1.2 Data gathering method

The data of these four data sources present in different formats. I have conducted different methods for downloading the data set.

[2]I have email conversations with OPTA's sales.

[3]http://www.transfermarkt.co.uk/wettbewerbe/national

[4]http://www.whoscored.com/AboutUs

[5]http://www.footballdatabase.eu

[6]http://www.theguardian.com/football/2014/dec/21/how-the-guardian-ranked-the-2014-worlds-top-100-footballers

Web Query Web queries have been conducted for getting data from Transfer Market and Football Database.eu. The data on these two websites rely heavily on front-end formatting, which means we can identify tables with HTML tag. For example transfer table on Football Database.eu. is identified with HTML $< /table >$. Excel web queries [14] can download the tables from these websites directly to the excel sheet by recognizing these HTML tags.

Download Votes on Guardian Media is in an excel file. It can be downloaded directly and easily transferred into ".csv" format which can me processed in R.

Manual Work The performance data from Whoscoard is downloaded by hand. The data are stored in the back-end database which I have no access to, and it is also impossible to scrape data from the web front-end. The only way to get the performance data are to copy and paste the pages manually to the excel sheet.

3.1.3 Data gathering-Start with la Liga

The original research scope was the top five most valuable leagues, but there is a big challenge to collecting performance data. Due to the incomparable pace (the same number of match played in the league) between different leagues, it is impossible to collect consistence data in a short time. In addition, copying and pasting multiple tables on different web pages are very intensive manual tasks, which make collecting harder.

The Reason for Choosing la Liga The Spanish league la Liga[7] is chosen to be the starting point. La Liga ranks 2nd out of the most valuable markets in the world by Forbes [35]. Especially, Real Madrid is the most valuable club in the world, which is from La liga.

In addition, at the first half of season 2014/2015[8], la Liga teams' performance ranking is the most in line with the teams' market value among the top five leagues. The team's performance ranking is the ranking of the team by the accumulated points of its league's competition. The total number of players is different between teams, so the comparable market value of the team (MV) is are the average market value by players, which is

$$MV = Team'sTotalMarketValue/NumbersofPlayers$$

[7] http://www.ligabbva.com/

[8] This research started in January, which is in the middle of leagues competition. The data was collected after the winter transfer window closed, which means the market value is the latest

The market value data for the team are from Transfer Market. The team's ranking come from the official website of each league. According to Figure3.1, la Liga (the red line) shows the best fit on the team performance and team's market value in February 2015.

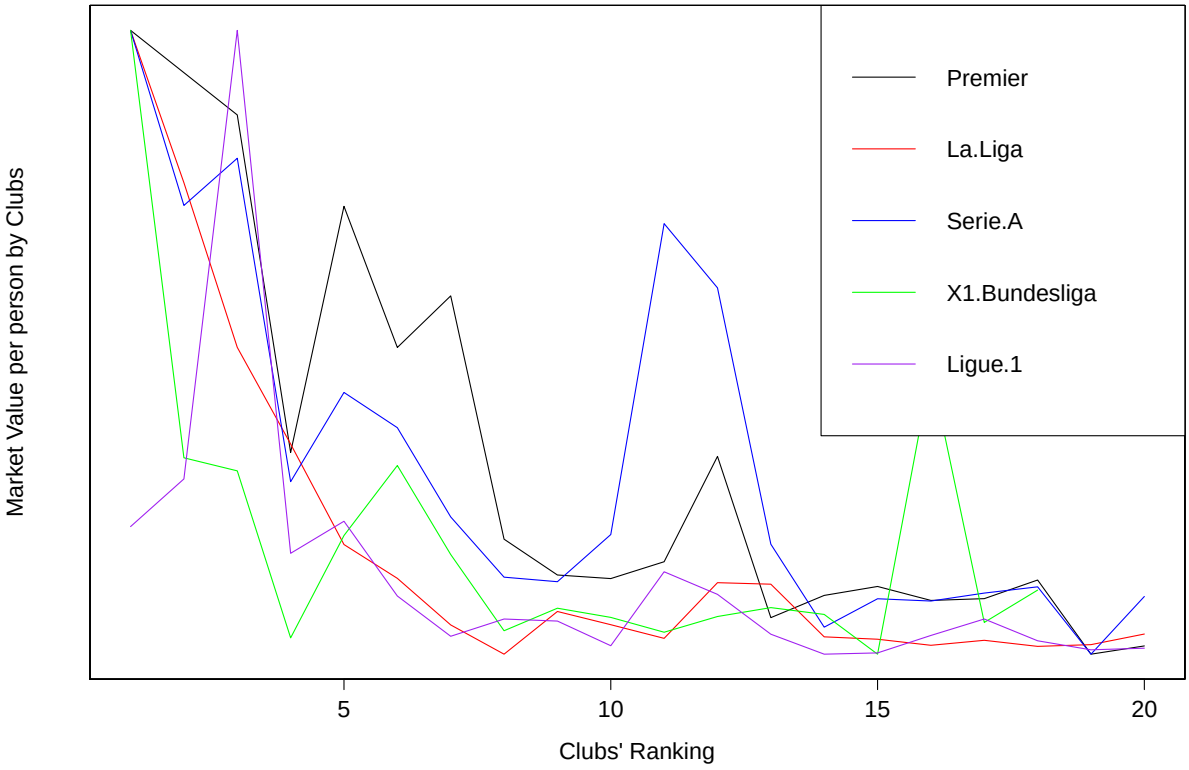


Figure 3.1: Research Techniques

3.2 Data Preparation

Data preparation is essential for data mining, as Zhang et al.[62] have stressed the importance of data preparation in these three aspects: (1) the data is impure in real world; (2) it requires quality data in high-performance mining systems; and (3) high-quality patterns are based on the high quality data. In my case, the collected data set are from four data sources with different formats and there are a lot of missing variables. Thus, before data mining, the data preprocessing has been conducted.

Encoding Some of the files present garbled characters because they are encoding in different format. In order to prevent this situation in the final results, all files have been dealt (open, salve,etc) with UTF – 8 formatting.

3.2.1 Data Merge

Record Linkage The collected data are from four sources, which result in four tables. In order to facilitate the data mining process in this research, the collected data was merged into one data set. This is a record linkage[59] task of finding out the complete information of players in different tables referring. The player's name is considered to be the record, as it is the shared item among all these four data sources. The next task is to choose the right algorithm to match record automatically.

Match Preparation The noise in the collected data has been removed, e.g. the missing observations from Transfer Market and duplicate records from Whoscored.

Players' name are presented quite differently between these tables, e.g. Messi's names is present in Transfer Market as "Lionel Messi", while in Whoscored as "Lionel Messi27, AM(CR),FW". As players' names from Whoscored are presented with other information, it is required to extract them from this attribute. By observing the attribute, it is found that the field before the first comma is the combination of name and age. Every player's age is with two characters because no player is younger than 10 and older than 99 in la Liga. As long as the name and age field is extracted, the names can be got by erasing the last two characters, which is easily to be done with R. It is not hard to pick up that field. In particular, the unlist() function in R can produce a vector which contains all the atomic components occurring in the name. The separation can be identified by commas.

Match Algorithm Matching is necessary to get a cohesive picture especially when this research is extended to more leagues. Distance calculating is chosen as the match algorithm.

- Step 1: Choose the representative variables
- Step 2: Choose the distance
- Step 3: Calculate and compare the distance

The basic information of player is chosen as the representative variables: name, team and age.

Jaro-Winker distance is the chosen distance metric for matching algorithm, given its ability to deal with the approximate match. The Jaro distance is defined as 3.1

$$1 - \frac{1}{3}\left(\frac{w_1 m}{|a|} + \frac{w_2 m}{|b|} + \frac{w_3 m - t}{m}\right) \tag{3.1}$$

$|a|$ indicates the number of characters in a, $|b|$ indicates the number of characters in b, m is the number of character matches and t is the number of transpositions of matching characters. The w_i are weights associated with the characters in a, characters in b and with transpositions. [34]

The best match is the least sum of the distance for name(dn), team(dt) and age(da), which is in Formula 3.2:

$$\min(dn + dt + da)_{ij} \tag{3.2}$$

The above steps can be done with the help of R package stringdist [55]. After getting the matching result, I did the final check and adjusted the unmatched items by hand. The amount of remaining unmatched data set is quite small, which is 29 and it is less than 10% of the whole data set. The data preparation will be more time consuming than data mining [61]. As data match is not the priority of this research and the time frame does not allow me to spend much time on this section, the accuracy of the matching result is larger than 90%, which is sufficient enough to this research.

3.2.2 Data Normalization

The objective functions will not work properly if there is no normalization[18]. e.g. in classification, if one of the features has a broad range of values, the distance between clusters will be affected by this particular feature. Therefore, in order to prevent this error, the range of all features should be normalized in to the same scale.

Furthermore, gradient descent runs much faster with applying feature scaling than without it [22]. The chosen machine learning method is LASSO, and a gradient descent algorithm is proposed to implement LASSO in R 'glment' package [48]. The motivation of using LASSO will be described in the next chapter (Chapter 4).

The numerical data are re-scaling from 0 to 1 by applying the following formula [18]:

$$X_i' = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

X_i' is the scaled result of X_i, which is one of the X. X_{min} is the smallest number of the X. X_{max} is the biggest number of X.

3.2.3 Dealing with missing values

There are a lot of missing values on performance information, which is a problem for the mining process because the common statistical methods and software presume that all variables in a specified model are measured for all cases. The methods to deal with

missing value are known as *listwise deletion* or *complete case analysis* [2]. The default method for virtually all statistical software is *listwise deletion* [2], which is simple to delete cases with any missing data on the variables of interest.

Since every observation has missing values, the default method - delete observations with missing values - of the software cannot be used. The missing value in this case are "not missing not at random (NMAR)" [2], which is generated by the difference of players' position. For example, only goalkeepers have the performance data on savings which presents "NA" for other positions. The performance data are the accumulated counts for the specific movements. When a player does not have that specific movement, it is recorded as 0. All the performance missing data have been convert into number 0.

3.2.4 Type convert

As umerical data are easily to be manipulated by the software and machine learning method, the following variables will be convert into the numerical type.

The variable *contract length* and *in the team since* have been converted from date to the numeric, which in terms of the year. The contract end dates are all on June 30, while *in the team since* varies by players. However, the specific date is not important, so there is no need to put it as the type date. The convert rules are as follows:

$$Contact\ Length = Contract\ Until\ Year - 2015$$

$$Years\ in\ the\ Team = 2015 - Year\ of\ in\ the\ team\ since$$

Market value has been converted from character to the numeric, by converting the text form of describing number into the mathematical form, e.g. set 1 million to 1,000,000.

3.3 Data Set

The required data have been collected and organized, which resulted in a table with 103 variables. On one hand, there are five nominal variables and 98 numerical variables. On the other hand, there are 16 variables for basic information and market information. The performance data is collected with details, so there are 87 variables for player performance. All of the performance data have been accumulated within 90 minutes. The details of each variable described in Appendix A.

4

General Model for Real Value

As stated in the previous chapter, the transfer fee is the market value of football players and the voting result is considered as the players' performance indicator. There are 381 players in la Liga. Not every player has been transferred this season and only top players are on the candidate list of the voting, which are only 33 and 40 players for both subsets. As a result, there is a need to predict the market value and performance indicators for all the players, because this research's scope is for all the players in la Liga.

4.1 Model Preparation

Before modeling the complete list for players' real market value and performance, the machine learning method has been adopted and the relationship between variables been studied.

4.1.1 Machine Learning Method

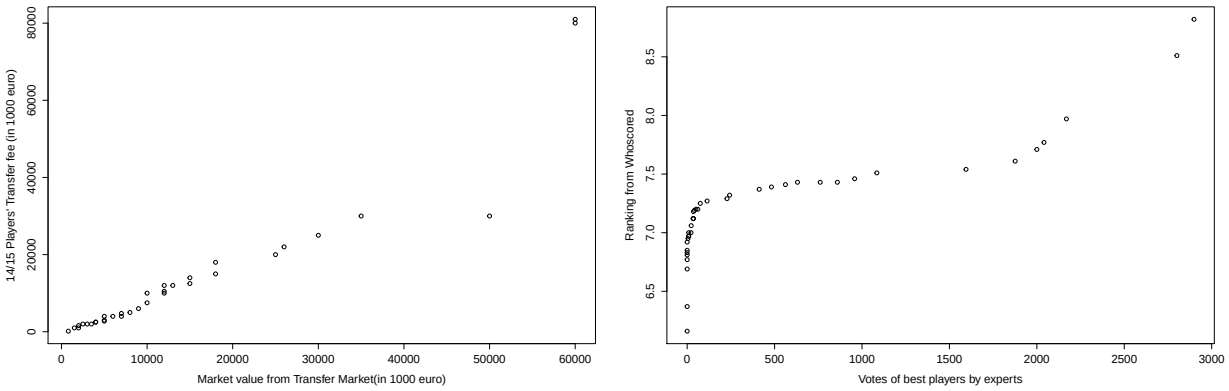
Depending on whether a target variable exists, not exists, or incompletely exists, there are three machine learning approaches: supervised, unsupervised, and semi-supervised learning [33]. Nevertheless, the target list of the data set is incomplete, it seems proper for semi-supervised learning. In reality, I have decided to start the research in the

supervised setting because there is a baseline needed. In addition, there are proxy values exist for both sides. The cross result is good between real and proxy variables. Moreover, the target values - Transfer Fee and Votes - are numerical. Hence, the regression model is the suitable machine learning tool for the research.

4.1.2 Proxy Value

Besides the incomplete list for real market and performance indicators, proxy variables for them have been collected. Market value[1] is a model built by Transfer Market to predict the transfer fee if the player is transferred at this moment, which is adjusted every year. Rating[2] is based on WhoScored's statistical algorithm, which is calculated live during the game. The ratings are scaled from 0-10(10=best). They are based on the models which is not accessible and their relationships with the real value are not revealed as well.

The relations between the proxy values and the real values have been studied. The differences of real value and proxy value have been plotted in Figure4.1, and proxy market value is related to transfer fee. For market value model, the proxy market value can work as independent variables together with other variables to predict the dependent variable. The performance's Q-Q plot failed to tell the relationship between rating and votes. Therefore, rating will not be considered as the dependent variable.



(a) Q-Q plot comparing transfer fees and market value from Transfermarket

(b) Q-Q plot comparing votes FIFA Ballon d'Or and WhoScored rating

Figure 4.1: Comparisson between real and proxy variables for Market value and performace assessment of footbal players.

[1] http://www.transfermarkt.co.uk/jumplist/startseite/wettbewerb/ES1

[2] http://www.whoscored.com/Statistics

4.1.3 Variable Selection

Covariance Covariance test was conducted to study the relationship between all the numerical variables in the data set. A positive covariance would indicate a positive linear relationship between the variables, and vice verse. The covariance value[36] for the whole data set is calculated according to formula 4.1, and the result is coded by color in Figure 4.2.

$$cov(X, Y) = \sum_{i=1}^{n} \frac{(x_i - \bar{x})(y_i - \bar{y})}{n} \tag{4.1}$$

The bright yellow represents a positive linear relationship and the blue stands for a negative linear relationship. The strong linear relationships between variables are in bright colours, and the fade colour zones represent the variables that are independent. According to Figure 4.2, a lot of variables have dependent relationships between each other.

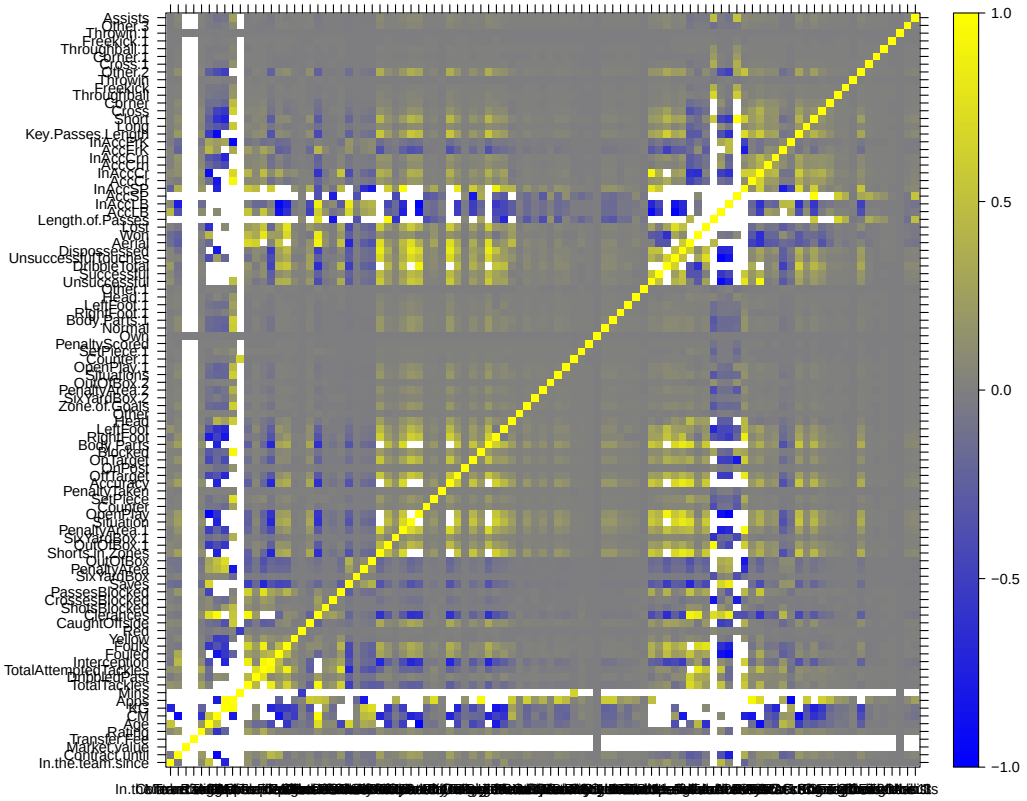


Figure 4.2: Covanriance of all the Variables

Variable Selection It is necessary to conduct the variable selection due to the high covariance between variables. High covariance between variables will cause collinearity

because too many variables are trying to do the same job [22]. The model will be complex and the response time will be longer due to the redundant variables. It also against the principle of Occam's Razor [7] that is the simplest is the best out of the several plausible explanations for a phenomenon.

In addition, due to the lack of observations, the extra variables will add noise to the prediction of the real market value [22]. The models will be built with 33 observations for market value and 40 for performance, but the numbers of the variables are 100 and 87 respectively. This is because the performance-related variables were included to model the market value, but not the other way around. The rationale behind this decision is that performance cannot be influenced by economical variables.

4.2 Choose Suitable Regression Model

Problem Statement The main task is to find a good regression model with variable selection for *Market Value* and *Performance*. More formally, it is assumed that a wide data set with both performance and/or economic related variables, as well as an evaluation function (R^2) can evaluate the quality of the model, with respect to the target variables (real *Market Value* and *Performance*). The task is to find good models such that:

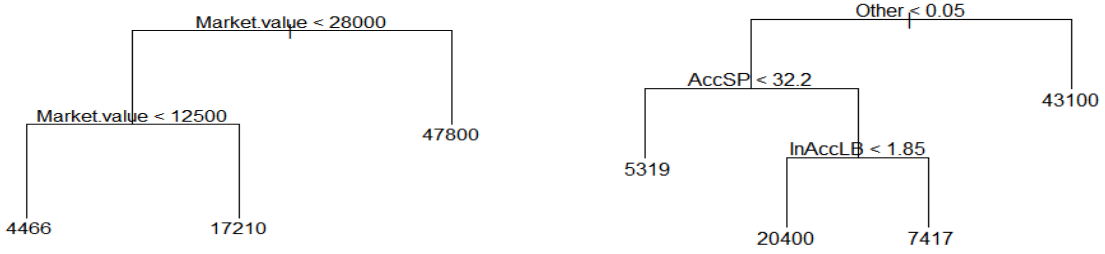
- The score of R^2 is high, where $0 \leq R^2 \leq 1$.
- The complexity of the model (number of variables) is low.
- The models are interpretable for further analysis.

4.2.1 Regression Tree

The data set for estimating *Market Value* has both numeric and nominal independent variables. Most of the regression algorithms have a common constraint that the independent variables must be numerical. Previous research emphasized the impacts of these non-numerical variables on players' market value. Rottenberg [44] stated that dis-economies of scale set in when the difference between teams becomes too great, as rich teams will prefer winning by close margins to winning by great margins. The required model is the one which can deal with nominal variables. Friedman et al [18] has stated that *trees* can naturally handle data of "mixed" type, be good at handling of missing values, be able to deal with irrelevant inputs. Thereupon, the regression tree was firstly applied.

In order to estimate players' market value, a regression tree is built in R with all the variables, including the non-numeric ones (team, nationality, etc). The mechanism of implantation this tree is stated in R "tree" package [42]: "A tree is grown by binary recursive partitioning using the response in the specified formula and choosing splits from the terms of the right-hand-side". Additionally, the most representative variables for market value can be selected out. The explanation of the result is [42]: "The variables are divided into $X < a$ and $X > a$; the levels of an unordered factor are divided into two non-empty groups. The split which maximizes the reduction in impurity is chosen, the data set split and the process repeated. Splitting continues until the terminal nodes are too small or too few to be split".

Figure 4.3 shows the regression trees for predicting real market value. Due to the high correlation between proxy market value and transfer fee, only the proxy market value has been used when applied regression tree with all the variables (Figure 4.3 (a)). In order to find out other significant variables, another regression tree has been built with all the variables excluding the proxy market value (Figure 4.3 (b)).



(a) Real Market Value Tree with Transfer Market's Market Value

(b) Real Market Value Tree without Transfer Market's Market Value

Figure 4.3: Real Market Value by Regression Tree

The task is to predict the real market value with all the representative variable, but the result of regression tree fails to do that. That's because of the tree model's own drawbacks. Friedman said that their ability to extract linear combinations of features and its predictive power are very poor[18]. Nevertheless, the experts believe that *Team*, *Nationality* and *Clubs* have huge impact on players' market value. The significant variables selected by regression tree are numerical ones. Hence, it is reasonable to apply another regression model which can perform predicting well, leaving these nominal variables out.

4.2.2 LASSO

Least Squared Methods There are many regression methods for prediction, and least squared is the most common method among these. This method [1] is a procedure of determining the best fit line to data. The best fitting is reached when the least square of the difference between target value and predict value appears, which equals to formula 4.2.

$$min(S) = \sum_{i=1}^{n}(y_i - f(x_i, \beta))^2 \tag{4.2}$$

y_i is the target value and $f(x_i, \beta)$ is the predict target value.

There are more variables than observations in the sub data set which have real values of *Performance* and *Market Value*. This makes it impossible to apply least squared methods [50] and avoiding over-fitting becomes a real challenge. Moreover, some variables that are correlated with each other. As a a result, the required regression technique can carry out feature selection, and LASSO is recently widely used[52].

LASSO "LASSO" is actually an acronym for *Least Absolute Selection and Shrinkage Operator*. The whole selected variables have been shrunken by setting some coefficients to 0[52]. It tries to retain the good features of both subset selection and ridge regression[3].

By comparing the ordinary linear regression model, LASSO has generated the best optimal model by taking number of the variables and the error of the model into consideration with the help of introducing a criterion. This criterion is subject to a soft-thresholding which would affect the total number of coefficients, and it could be decided by the audience.

LASSO Feature Selection Mechanism LASSO can have better prediction error than linear regression in different scenarios, depending on the choice of threshold. LASSO estimates are defined as the formula 4.3

$$(\hat{\alpha}, \hat{\beta}) = \arg\min \sum_{i=1}^{N}(y_i - \alpha - \sum_j \beta_j x_{ij})^2 \text{subject to} \sum_j |\beta_j| \leq t \tag{4.3}$$

The tuning parameter is $t \geq 0$, which is the threshold mentioned before. For all t, the solution for α is $\hat{\alpha} = \bar{y}$. [52] The bigger t is, the more variables will be included.

[3]Subset selection and ridge regression are two standard techniques for improving the ordinary least square prediction.Both techniques have their own drawbacks

4.3 Apply Lasso Model in R

4.3.1 Model Implementation

In the R package Glmnet, the algorithm of applying LASSO uses cyclical coordinate descent in a path-wise fashion. [48] λ is introduced by transferring the problem into the Lagrangian formulation 4.4

$$\lambda P\alpha(\beta) = \lambda(\alpha \sum_{i=1}^{P} |\beta_i| + \frac{1}{2}(1-\alpha) \sum_{i=1}^{P} \beta_i^2) \tag{4.4}$$

It is able to perform variable selection in the linear model and it can have better accuracy than linear regression in a variety of scenarios, depending on the choice of *lambda* (λ). As λ increases, more coefficients will be zero which means fewer variables are selected and more shrinkage is employed among the non-zero coefficients. With a bound on the sum of the absolute values of the coefficients, it minimizes the usual sum of squared errors.

Fit the model The generalized linear models have been fitted with penalized maximum likelihood. The regularization path is computed for the LASSO or elastic net penalty at a grid of values for the regularization parameter λ. It can deal with all shapes of data, including very large sparse data matrices, which also fits nonlinear models(logistic, Poisson etc) besides linear model. [19]

4.3.2 Proper Model

cross validation Using cross-validation (CV), a suitable value for λ can be chosen. CV[18] is a generally appropriate way to predict the performance of a model on a validation set using computation in place of mathematical analysis. In "R" Package Glment [19], k-fold CV is included in this package for helping decide the suitable λ. The mechanism of k-fold CV is as follows. The data set is divided into k subsets. One of the k subsets used as the test set and the other $k-1$ subsets put together to form a training set. The predicted models are generated by the training set with the test set's inputs. The errors it makes are accumulated as before to give the mean absolute test set error, which is used to evaluate the model. The process has been repeated k times with different test sets. The variance of the resulting estimate is reduced as k increasing [18].

Two significant λs have been proposed within Glment Package with CV. The λ_{min} option refers to value of λ at the lowest CV error, which is the best model to be considered. Sometimes λ_{min} might cause over-fitting, because the error at this value is

the average of the errors over the k folds. The second option offered by Glmnet is to use λ_{1se}. This λ ensures the largest pruning of variables while keeping the minimum standard error, thus creating simpler models. The most suitable threshold is normally between λ_{min} and λ_{1se} subject to other conditions.

Prediction After chosen the right λ, the coefficients of the regression model can be decided with the specific λ. The unknown target can be calculated by applying the decided coefficients.

5 Market Value

5.1 LASSO Real Market Value Model

Because the data set for training the real market value is very small, the k should be small enough to avoid over fitting. The k value for $k-fold$ CV is chosen to be 3 which is the smallest choice for k in Package Glment.

In order to find out the suitable LASSO model for the market value, I have tried different λ values. The chosen model is based on the following criteria: the CV error, the complexity of the model, and the common sense.

5.1.1 Lambda.min model

As is stated in last chapter, λ.min determines the model with the model of least mean squared value. It is ideal to start with this model, which is:

$$\hat{M} = -1,453.19 + 1.01 \cdot Market.value - 5,536.44 \cdot OnPost - 103,099.55 \cdot Corner.1 + 9,514.54 \cdot Assists$$

The predicted real market with λ.min model central tendency table (Table 5.1) shows that the first quarter of the predicted result is negative. In the other word, at least 1/4 of the predictions have negative value. After counting for all the players, there are 142

negative values out of the 381 predicted real market value.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-82,710	-1,434	1,428	4,736	6,617	136,900

Table 5.1: Lambda.min Model for Real Market Value Summary

The negative value means that selling club sells its player for free, and they will give money to the buying club. It is extremely weird and against our common sense that customer getting extra money by taking free product. In addition, there is no trade like this in the transfer records of la Liga in recently five years[1]. Therefore, λ.min model is not the suitable model.

5.1.2 Lambda.1se model

Model built with the significant λ - λ_{1se} is:

$$\hat{M} = 231.26 + 0.89 \cdot Market.value$$

For λ_{1se} model, the coefficient and interception are positive. In that case, the prediction of the real value will be positive. Nevertheless, this model has solved the problem caused by λ_{min} model. As it is too restrictive by only introducing one variable, the λ_{1se} model is considered to be the bottom-line, if there is no better one.

5.1.3 Proper Model

The proper λ must be between λ_{1se} and λ_{min}. According to the models figure(Figure 5.1), for the interval [λ_{1se}, λ_{min}], the mean-squared error will be smaller when λ is closer to λ_{min} (Left black line in the figure).

[1]In addition, I cannot find any transfer records like this, since the complete transfer records can only date back to last 5 years.

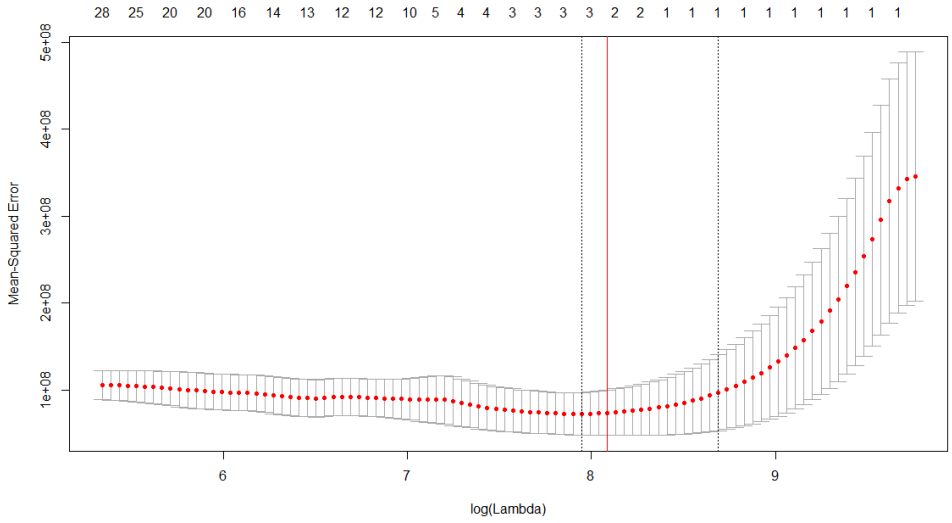


Figure 5.1: LASSO regression for real market value prediction

By taking all practical concerns above into consideration, the criteria for suitable model are: min(λ_{min}-λ) subject to all the predict market values are positive.

The method of finding this value is to traverse the different λ values from λ_{min} to λ_{1se} and predict the model. The experiment stopped when there is no negative market value been predicted.

Based on the above criteria, the threshold is set when $\lambda = 3247.0$. It is the closest model to the best which will never cause negative prediction market value. The red line in Figure 5.1 is the chosen model. It is in the interval of the best model and simple model. The model is:

$$\hat{M} = 231.26 + 0.89 \cdot Market.value + 2723.26 \cdot Assists \tag{5.1}$$

Lockhart et.al said "The usual constructs like p-values,confidence intervals, etc., do not exist for lasso estimate" [30]. As a result, the p-value for the lasso model of market value cannot be provided. However, there is another statistic significant value - *devianceratio* which is the fraction of (null) deviance explained[19]. For the proper model, this ratio is 83.4%, which means the chosen variables can explain 83.4% of the data.

5.2 Market Value Statistic Description

The market value[2] has been collected by applying the suitable model (Formula 5.1) to all the players. Figure 5.2 shows the market value varies from players, which is almost in normal distribution with a peak skewed to the right. The mass of the distribution is concentrated on the left of the figure with the longer right tail [47]. The players with market value distributed on the long tail are the super star players in the league, e.g. Leo Messi, Cristiano Ronaldo.

The threshold for distinguishing star player and average player is at 20 Million Euro, which is the start of the right long tail in Figure 5.2. Only 27 out of 381 players in la Liga has the market value higher than 20 Million Euro. The ratio for the total market value of 27 stars and the total market value of rest average players is 77.9%, but the total number of players in later group is 13 times more than the former one. In addition, the highest market value of player is more than five times higher than the threshold.

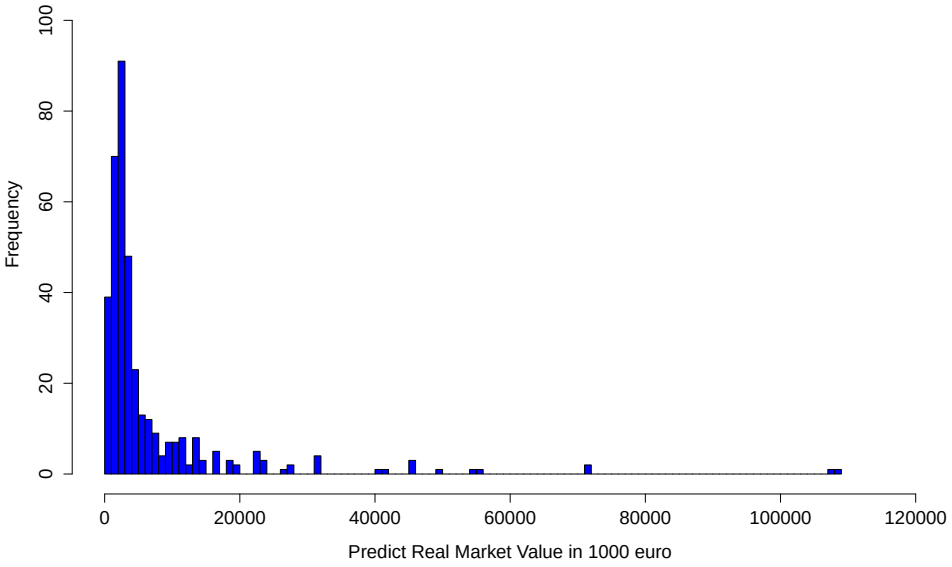


Figure 5.2: Histogram of football player's real market value

[2]If there is no other explanation, *market value* in the following pages refers to the real market value I got by appplying LASSO model.

5.2.1 Relationship between market value and general features

Market Value versus Numerical Variables. In Chapter 2, I have stated players' market value is in relation to players' personal profiles (like age) or market information (e.g. contract duration) from experts' perspective. I have crossed the numerical variables with market value separately in the scatter figure. However, these variables have not created significant difference to market value with large volumes (Figure 5.3). e.g. *Age*, when a player is younger than 20 or older than 33, their market value is significant lower than other ages. However, the number of players in these groups is less than 5% of the whole group of players, which is not sufficient to prove *Age* is the differentiation variable.

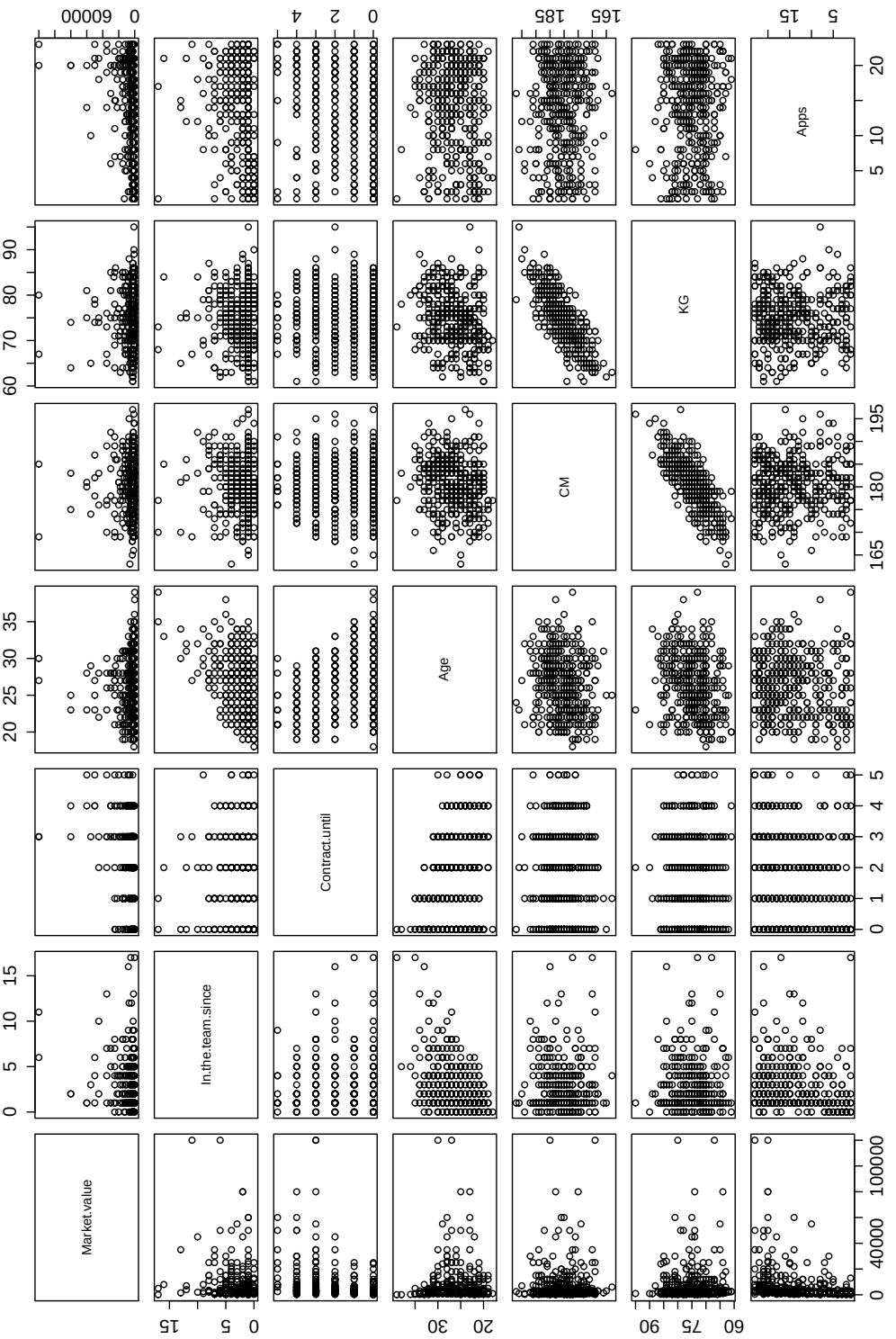


Figure 5.3: Relationship between market value and numerical general features

Market Value versus Nominal Variables. The data set is divided into subgroups by the nominal variable. Because of the right long tail distribution of players' market value, the mean value is heavily influenced by outlying measurements. The median value is always representative of the centre of the data distribution. Hence, median value is the representative for all subgroups.

Market Value versus Position The median of the football players market value shows that there are significant market value difference between football player caused by their positions (Figure 5.4). The players in the strikers positions have the highest market value, while the goalkeepers lowest. The general rule is the market value will increase as the player's position moves forward.

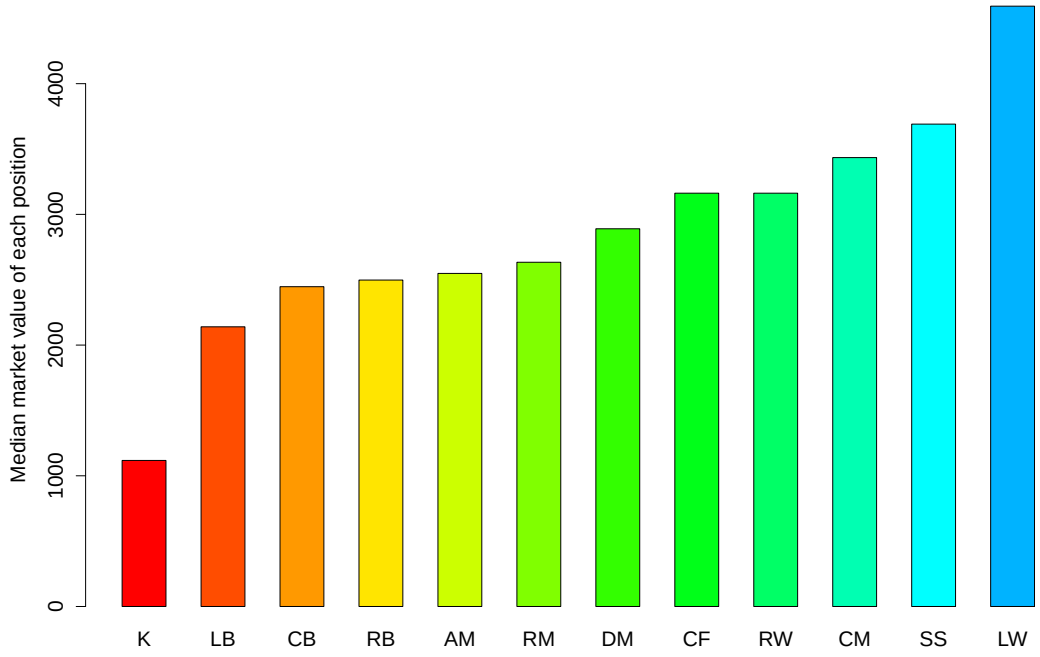


Figure 5.4: Histogram of football player's real market value by positions

5.2.2 Re-category Positions

The *left wings* and *right wings* are the strikers on different side of the play ground. It is very weird that *left wings* has higher market value than the *right wings* in Figure 5.4. I was wondering what makes them such big difference and whether there is a real reason behind.

I have looked into the *left wings* and *right wings* by plotting the distribution diagram for them. Figure 5.5, shows that the *left wings* and *right wings* fit almost the same curve. The total number of the players and the central tendency of these two positions are different, which leads to huge difference on their medians.

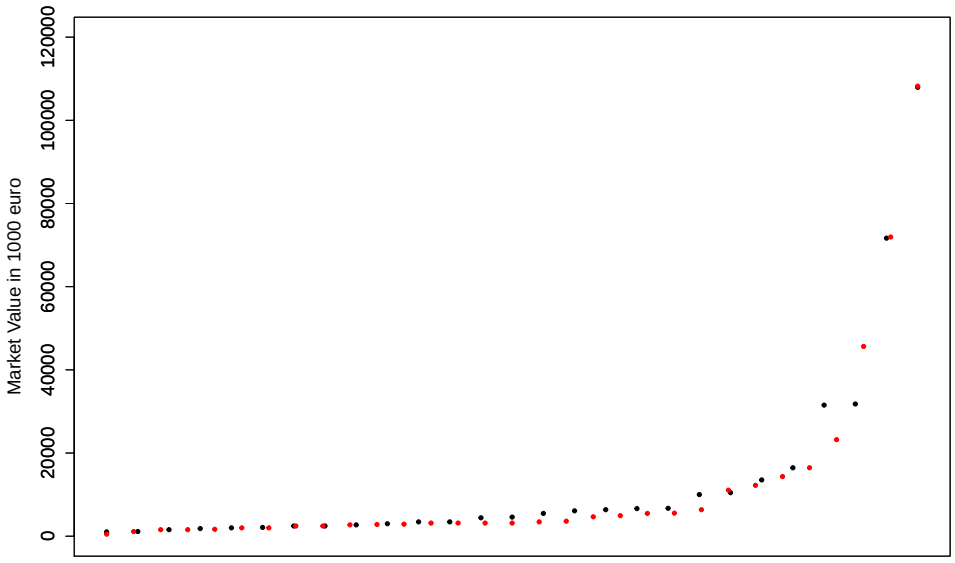


Figure 5.5: Left Wings and Right Wings Market Value Distribution

KS test In statistics, the KS test (Kolmogorov–Smirnov test) is a nonparametric test which can compare the distribution of two samples. It provides a mean of testing whether a set of observations are from some completely specified continuous distribution. [29] KS test has two major advantages[31]:

- The validity of KS test is good with small sample sizes.
- It doesn't depend on the distribution of sample data.

p-value is the significant value in KS test, and normally the threshold for this value is 0.05. When $p < 0.05$, the hypothesis has been rejected and the distributions of the sample data are not the same; when $p > 0.05$, we cannot say the sample data distribute differently. High value of p (1 is the highest value) means the big chance of these two data sets have the same distribution.

The data size of these two positions are 27 and 31, which are all small sample sizes. The distributions of these two samples are still unknown. When the data set is large, the

distributions of these two data sets can be considered to be the continuous distributions, and the distribution functions are LW(mv) and RW(mv). KS test is taken to check whether there is any difference on the distribution of *left wings* and *right wings*. The hypothesis for this test is:

$$H_0 : LW(mv) = RW(mv)$$

The KS-test has been taken in R [10], and the p-value of KS test for *left wings* and *right wings* is 0.88. The hypothesis cannot be rejected, which can prove that the *left wings* and *right wings* have the same distribution.

For the rest positions, not all of them have significant differences as that between each other like *left wings* and *right wings*. The 12 positions have been composed into four significant different categories based on the background knowledge of football, which will be tested in the following paragraph. They are *goalkeepers*(goalkeeper), *defenders* (centre back, left back, right back), *midfielders* (attacking midfield, right midfield, defensive midfield, central midfield),*strikers* (centre forward, right wing, secondary striker, left wing).

KS-test has been taken to test whether there are significant differences between and within the these categories. When considering the market value between the four categories (e.g. test *goalkeeper* and *left wings*), all the $p < 0.001$ which indicates a very significant difference between the four positions. Furthermore, when comparing the market value between specific sub-categories within each group (e.g. comparing various types of defenders amongst each other), the p-values are all larger 0.8, which suggest it make sense to group such very similar sub-categories.

6
Performance Analysis

In Section 2.3.2, the performance analysis should be separated by positions has been explained. The data set has classified positions into 12 categories, however, this classification is too specific. Especially, most players have played in more than one position. Moreover, the whole pool of the data is very small. If subgroups were made into 12 groups, the size of these subgroups would be too small for each subgroup.

Players were classified by positions into *goalkeepers*, *defenders*, *midfielders* or *strikers* from a market value perspective in Section 5.2.2. Also, they are the same categories suggested by Hugh et.al [24], who have carried on a technical analysis of playing positions within elite level international soccer at the European Championships 2004. Therefore, also from literature review perspective, the subgroups for performance analysis are justified.

6.1 LASSO Real Performance Model for Strikers

I have attempted to model the performance over the entire set of players, but failed to find satisfactory results, due to the variance of performance per position. The *strikers* tend to get votes and be selected out due to the bias of voting system. FIFA World Player of the Year (since a few years called the Ballon d'Or) is evaluated with the same

voting mechanism as mentioned in Chapter 3. Moreover, the result of FIFA's[1] ranking is the same as the voting I have used in this research. Although *strikers* only represent 30% of all players, they appear as winners of the FIFA World Player of the Year in 17 out of 24 years.(Figure 6.1) No goalkeeper has ever won the prize. Therefore, I also failed to find an adequate LASSO model for *goalkeepers*, *defenders*, *midfileders*.

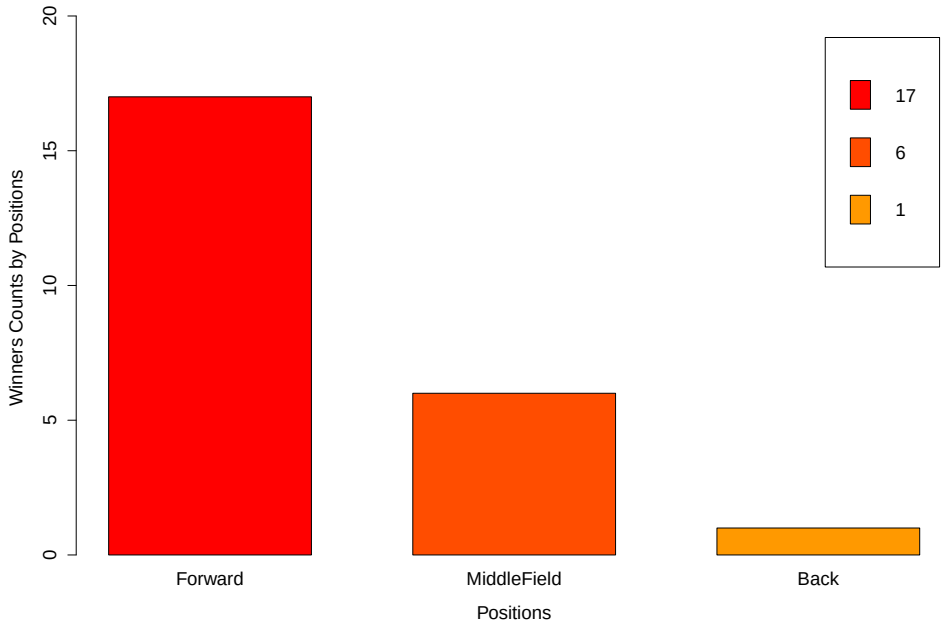


Figure 6.1: FIFA Ballon d'Or winners by position

Only occurring on the *strikers* specifically, it becomes possible to model their performance. In this case, I used LASSO to train the *strikers* with 5-fold cross validation. The threshold for the proper model is λ_{min}. The KPIs for *strikers* have been selected as follows. A good player should have more:

- Shots and Goals in Penalty area ($SP\&GP$);
- Shots on Target (ST);
- Goals from out of Box (GB);
- Dribble successfully (D);
- Assists total (A);

but less:

- Few Fouls (F);

[1]FIFA website.

The model for *strikers* is shown in Formula 6.1.

$$\hat{P} = 0.28 - 0.073 \cdot F + 0.06 \cdot SP + 0.04 \cdot ST + 0.02 \cdot GP + 0.05 \cdot GB + 0.02 \cdot D + 0.08 \cdot A \quad (6.1)$$

The final step is applying this model to predict all the *strikers*. The result of the prediction is *strikers*' performance indicator, which is from -0.22 to 1.02. A player with good performance will be assigned a high score. As is shown in Figure 6.2, The general distribution of *strikers*' performance is almost the same as the normal distribution.

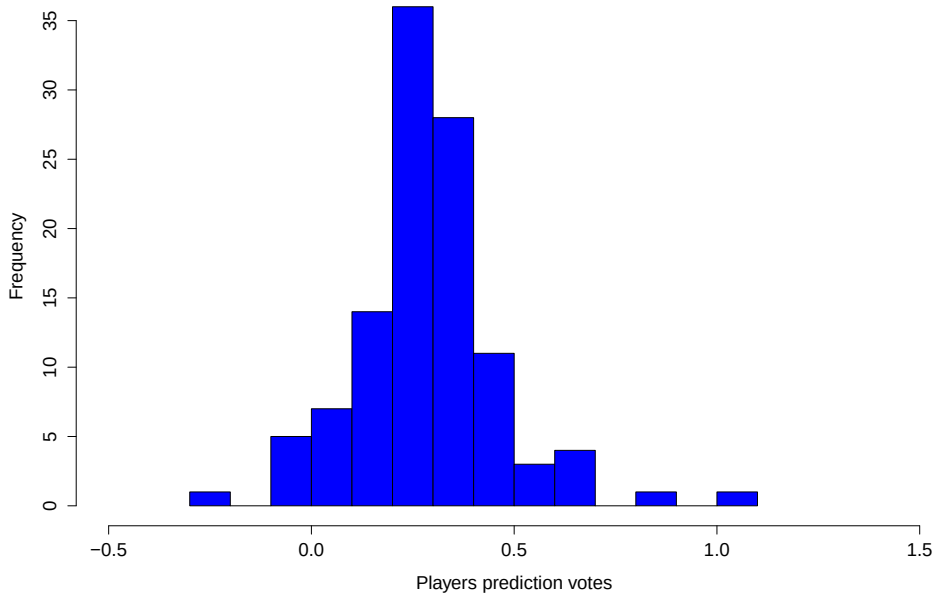


Figure 6.2: General Distribution of strikers' Performance Prediction

From the distribution diagram and the central tendency (Table 6.1) of performance, the top players have much higher performance scores than average players. The difference between the Max and the 3rd Quarter is bigger than the that between the 3rd Quarter and the Min. It means some *strikers* performed much better than the rest of the players.

Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
-0.22	0.20	0.27	0.28	0.36	1.02

Table 6.1: central tendency of *strikers*' Performance Prediction

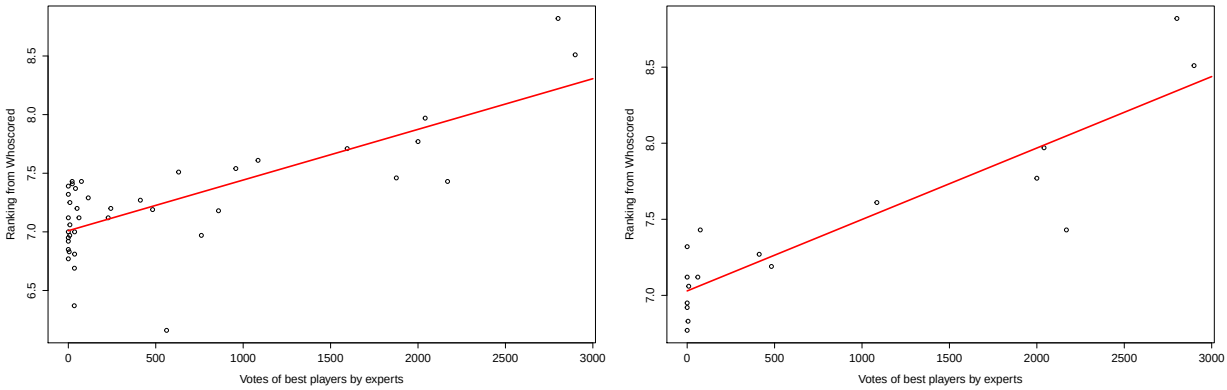
6.2 Models for Goalkeepers, Defenders, Midfielders

6.2.1 Whoscored's Rating as the Target

Except the votes, Whoscored's rating is considered to be the closet value for the players' performance(3.1.1). However, the relationship between rating and votes by experts is still unclear from Q-Q plot in Figure 4.1.

Because *strikers* are favoured by votes, other positions have very few players on the voting list. This cannot justify the relationship between votes and rating for all the players. In order to prove my hypothesis, I have crossed rating and votes twice. The first time is for all the players and the second time is only for *strikers*. Furthermore, I have also analyzed the statistic results of them.

The result of crossing rating with votes for all the players and *strikers* is in Figure 6.3. It is hard to tell a linear relationship due to the fact that most of the observations are around 0 (a). However, an obvious linear relationship appears between rating and votes for *strikers* in the Figure 6.3 (b).



(a) For all the voted players

(b) For voted Strikers

Figure 6.3: Relation between WhoScored Rating and Voting.

F-test F-test[18] is a common test for comparing statistical models which have been fitted to a data set. The purpose of this test is to identify the best fiting model. The p-value is smaller than the significant value in the system (0.05) for both models, which means there is a relationship between votes and rating for all the players [60].

Multiple R-squared [60] R-squared value represents how well the data fit for the crossed model, which ranges from 0 to 1. The high R-squared value(bigger than 0.8) can be considered as the ranking in lines with votes. The low R-squared value (smaller than

0.6) means the two variables cannot represent each other. The multiple R-squared for only crossed *strikers* is 0.8036, however it is 0.5623 of crossing for all the players [18].

According to the above statistic test results, there is a linear relationship between *strikers*' votes and rating. It means rating is able to represent the performance for *strikers*. Thus, rating can be considered as the performance indicators for other positions.

6.2.2 LASSO Models

Rating is the target value of LASSO models for *goalkeepers*, *defenders* and *midfielders*. And the same training processes for the *strikers* have been conducted for these three positions. I used LASSO to train the model with five-fold cross validation. The threshold for the proper model is λ_{min}.

The KPIs for players and the performance prediction model have been studied as follows.

Goalkeepers The *goalkeepers* are responsible for preventing to goal, as a result, a good *goalkeepers* should have more:

- Save in penalty area (SP);
- Fouled (F);
- Successful dribbled pass (S)
- In accurate block (In)

but less:

- Dribbled past (DP);
- Interception (I);
- Accurate free kicks (AF)

It indicates that good *goalkeepers* should stick to their role, while the other actions may distract them. The SP is the determinant variable for *goalkeepers*, and the top *goalkeepers* tend to have more saves in penalty area. The model for *goalkeepers* is as shown in Formula 6.2.

$$\hat{P} = 6.53 - 0.04 \cdot DP - 0.06 \cdot I + 0.01 \cdot F + 0.17 \cdot SP + 0.03 \cdot S + 0.01 \cdot In - 0.1 \cdot AF \quad (6.2)$$

Defenders The *defenders* are responsible for preventing the opposite players close to their box, as a result, a good *defenders* should have more:

- Interceptions (I);
- Shots blocked (SB);
- Short on target (ST);

- Accurate long balls (AL);
- Accurate short passes (AS);
- Total long passes (L).

but less:

- Fouls (F);
- yellow cards (Y);

These KPIs indicate that the block and pass techniques are very critical for the *defenders*. In addition, the fouls and yellow cards will create bad influence on the *defenders* performance, which should be avoided in the matches. The model for *defenders* is shown in Formula 6.3.

$$\hat{P} = 6.82 + 0.04 \cdot I - 0.04 \cdot F - 0.01 \cdot Y + 0.02 \cdot SB + 0.07 \cdot ST + 0.02 \cdot AL + 0.04 \cdot AS + 0.01 \cdot L \quad (6.3)$$

Midfielders The *midfileders* are responsible for organizing offense and defense, as a result, a good *midfileders* should have more:

- Interceptions (I);
- Goals in the zone (GZ);
- Goals by head (GH);
- Aerial won (W);
- Length of passes (LP);
- Accurate free kicks (AK);
- Other assists (OS)

but less: - Unsuccessful touches of ball (UT)

The indicators - *Situation goals* and *goals by body parts* - have slightly positive influence on the player's performance, because the coefficients of these variables are smaller than $e^{-}14$, which are not taken into the model. However, if the *midfileders* have more UT, the performance of these players will be lower than other players, because they are wasting chances. The model for *defenders* is shown in Formula 6.4.

$$\hat{P} = 6.72 + 0.03 \cdot I + 0.11 \cdot GZ + 0.003 \cdot GH - 0.03 \cdot UT + 0.004 \cdot W + 0.05 \cdot LP + 0.02 \cdot AK + 0.03 \cdot OS \quad (6.4)$$

6.2.3 Performance Analysis

After applying these prediction models to the rest of the players by positions, the predicted ratings have been collected, which serve as the performance assessment benchmark. The higher rating score means the better performance of a player. The

distribution diagrams (Figure 6.4) and the central tendency of performance (Table 6.2) have been generated to show the general information of distributions of these three positions.

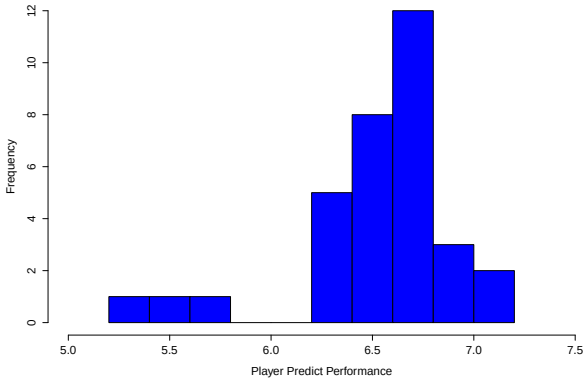
Positions	**Min.**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
Goalkeepers	5.32	6.45	6.64	6.53	6.76	7.14
Defenders	5.67	6.64	6.83	6.82	7.05	7.51
Midfielders	5.99	6.49	6.68	6.72	6.90	7.71

Table 6.2: central tendency of Players' Performance Prediction

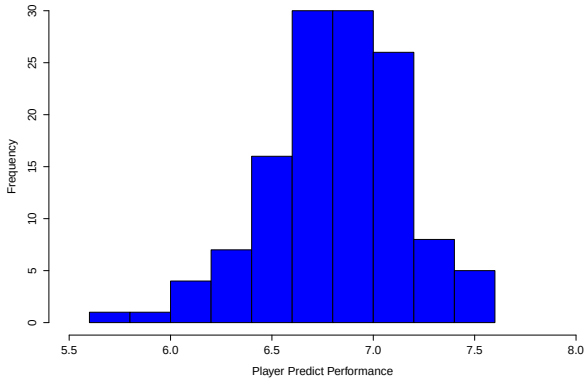
Goalkeepers The general distribution of *goalkeepers* are centred at 6.64 except those of the two bad performance *goalkeepers*. The distance between the Median and the 1st Quarter is 0.2, while the distance between the Max and the Median is 0.5. There aren't much significant difference on *goalkeepers*' performance.

Defenders The general distribution of *defenders* is similar to left-skewed distribution. Most players are performing good enough (the performance around or better than the average). However the Median is extremely close to Mean, which means the poorly performing players (on the left long tail) are much worse the average.

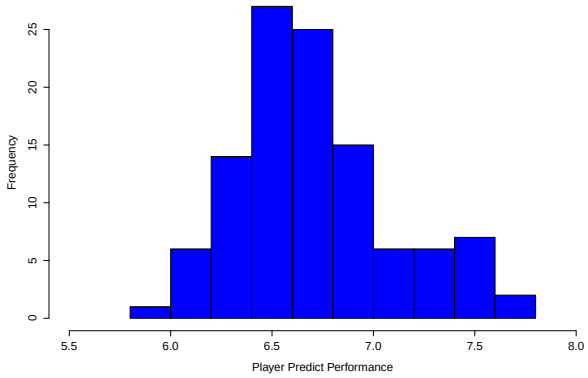
midfilederss The distribution of *midfilederss* more or less resembles a normal distribution. As the right tail has more values than the left side, there is a fact that Median value is smaller than the Mean. It means most players are around the central, but the number of relatively better *midfilederss* is larger than the number of relatively worse performing players.



(a) Goalkeepers



(b) Defenders



(c) Midfielders

Figure 6.4: General Distribution of Players Performance Prediction with WhoScored's Rating

7

Market Value vs Performance

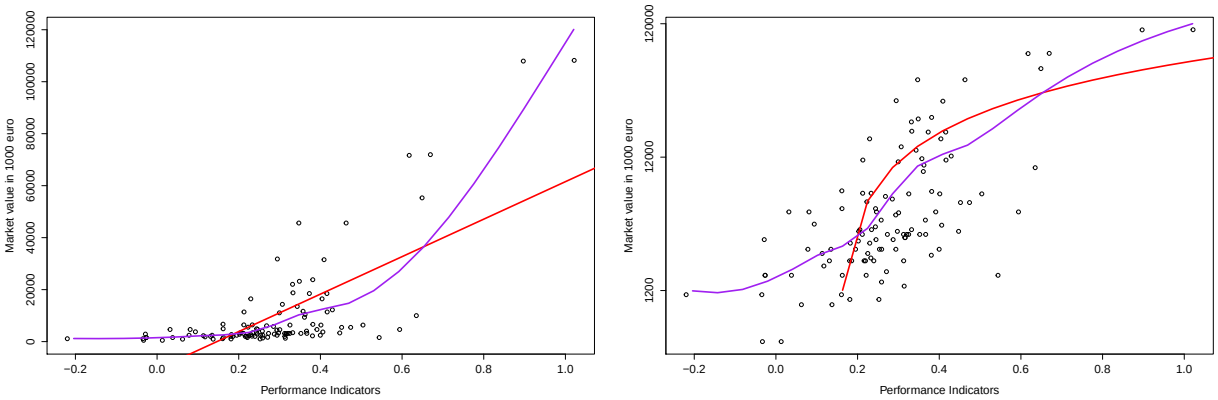
Since the predictions of market value and performance assessments of players have been got, the relation between them can be studied. There are significant differences between the positions, so the relation study is also conducted in different positions.

7.1 Cross Market Value and Performance

In pre-study, the proper parameters for cross model have been defined. Accordingly, based on the cross model result, whether a player is proper valued or not can be defined.

7.1.1 Pre-study

The pre-study started from one position — *strikers*. The crossed result for *strikers* is in (Figure 7.1). The over-all trend of market value follows the trend of performance. The better performance a player has, the higher the market value will be. Apart from the super star players with a very clear linear relationship, most of the players are centred to very low value. It seems that market value has an exponential relationship with the *strikers* performance. The market value has been plotted in logarithm scale in the right figure.



(a) Relation between Market Value and Performance

(b) Logarithm Relation between Market Value and Performance

Figure 7.1: Relation Between Market Value and Strikers Performance Assessments.

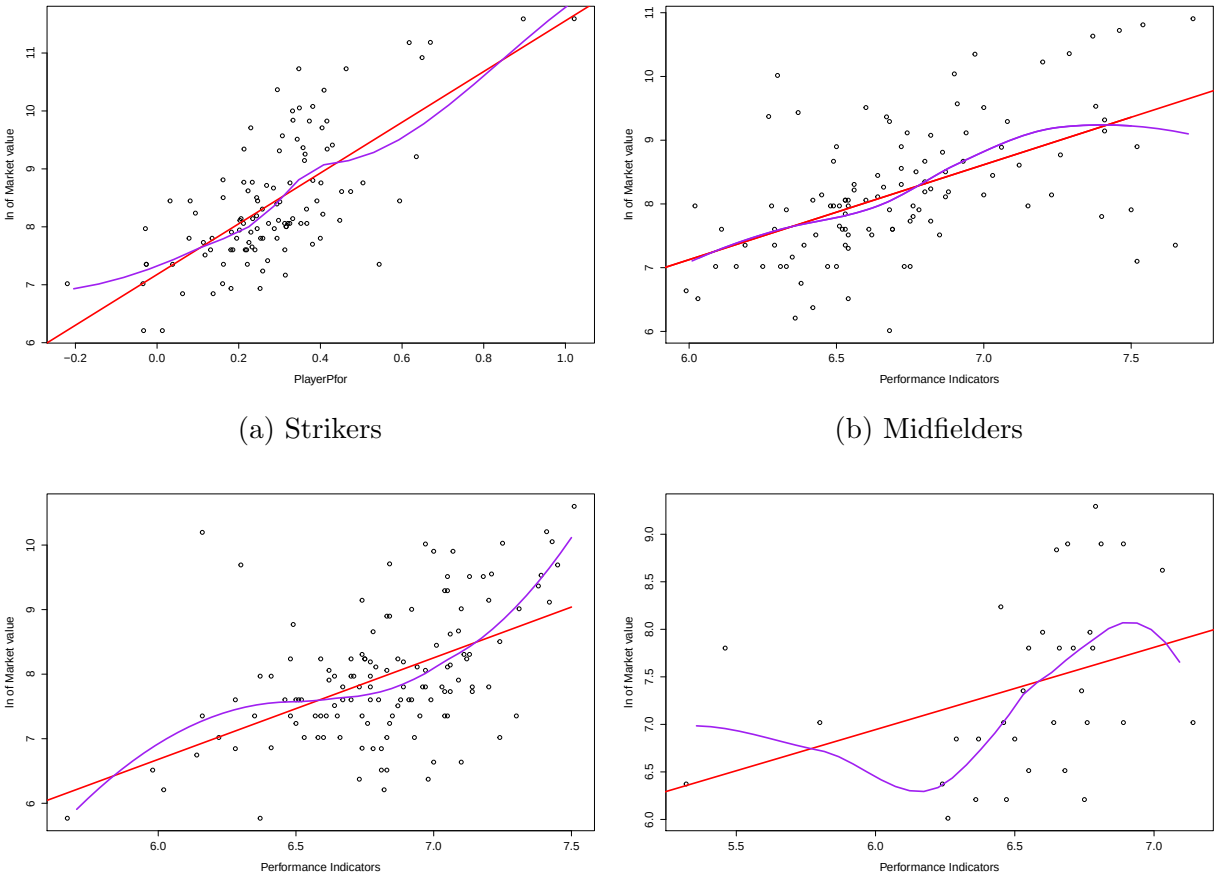
The red line is the simple linear regression fitting[58] and the purple line is polynomial fitting with local regression model by R [11]. It is obvious in Figure 7.1 that the polynomial fitting is the better one for *strikers*. In addition, on a logarithm scale, the polynomial fitting looks like a linear curve (straight line).

The rest of the positions showed the similar plotting results as the *strikers*. Hence, the parameters for building relationship model are the logarithm of market value and the performance indicator.

7.1.2 Market Value Defined by Performance

The process of defining economic market value result is as follows.

Step 1: Fit the data. ***ln*** of market value is mapped to *y-axis*, and performance indicators *x-axis*. Each player is visualized as a small circle in Figure 7.2. After that, the crossed data have been fitted by the linear (red line) and polynomial (purple line) model.



(a) Strikers

(b) Midfielders

(c) Defenders

(d) Goalkeepers

Figure 7.2: Relation between logarithm market value and performance assessments.

Step 2: Choose the proper model. The objective of this research is to study the general relationship between market value and performance. Hence, there is no need for a precise prediction for the market value based on the performance. The complexity of the linear model is much lower than that of the polynomial model. According to Occam's Razor principle[7], the linear model will be the first choice, as long as its grouping for overvalued, propervalued, and undervalued is reasonable.

Step 3: Apply the chosen model. The estimated logarithm of market value ($\hat{M}$) based on performance is predicted by the chosen model. The difference between it and the logarithm of market value (M) has been calculated as $\Delta = ln(M) - ln(\hat{M})$. The smaller the Δ is, the more better the player's market value matches his performance.

Step 4: Determine the threshold. The threshold is to determine how the system tolerate Δ. The value result for players is defined with formular 7.1:

$$\begin{cases} \text{overvalued}, & \Delta > 0.8 \\ \text{undervalued}, & \Delta < -0.8 \\ \text{propervalued}, & -0.8 \leq \Delta \leq 0.8 \end{cases} \tag{7.1}$$

Next, the above steps have been applied for each position.

Strikers The linear model and polynomial model have almost the same division on whether a player is correctly valued. In this case, the linear relationship is considered to be the model of the proper market value regarding to the predicted performance of football players. The model for *strikers* is Formula 7.2.

$$ln(\hat{M}_s) = 7.11 + 4.41 \cdot \hat{P}_s \tag{7.2}$$

Midfielders Due to the same reason as *strikers*, the linear model is chosen to be the best model for *midfielders*, which is Formula 7.3.

$$ln(\hat{M}_m) = -1.81 + 1.49 \cdot \hat{P}_m \tag{7.3}$$

Defenders All of the high performance *defenders* have been overvalued with linear model. It means that the chosen model failed to describe the relationship. Therefore, the polynomial model is considered as the best model in this case.

Unfortunately, the LOESS function does not produce the regression function. That is because LOESS is a non-parametric method which couldn't expressed as a simple equation. The model for *defenders* cannot be written into an equation, but the function is not very important in this case. However, the R package stats for LOESS can predict the result of the polynomial model [39]. The reslut of predicted logarithm of market value by R is in Appendix C.1.

Goalkeepers The distribution of *goalkeepers*' performance and market value is very random, and both models failed to find their relationship. Some *goalkeepers* have the same market value with a big difference on performance, while others have the same performance with a big difference on market value.

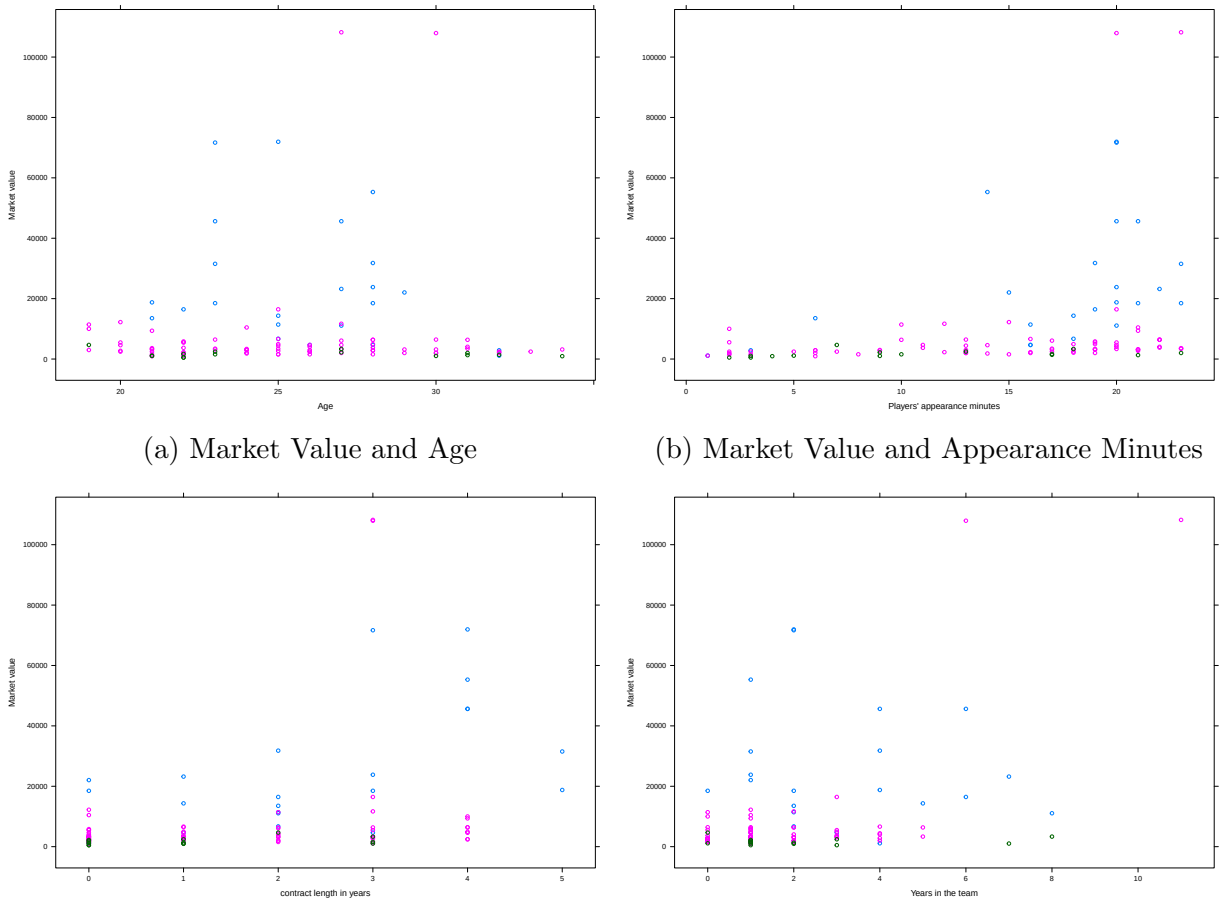
7.2 Value Results observations by Positions

The value results (i.e. overvalued, propervalued, undervalued) can be marked after comparing their Δs to the threshold in 7.1 for *strikers*, *midfielders* and *defenders*. Due to the random relationship between performance and market value, the goal keepers will be studied with another approach.

7.2.1 Value Result versus Characteristics and careers

In this section, the value result will be studied by analyzing market value together with players' characteristics and career details by positions. There seems to be a ceiling for market value, where the top performing players have similar market values but very different performance ratings. The following figures have revealed some additional factors which have impact on players market value. In these figures, the value results have been coded by colours, which are blue (overvalued players), red (propervalued players), green (undervalued players).

Strikers Figure 7.3 has revealed that the improperly valued *strikers* have the special values in age, appearance minutes, contract duration and years stayed in the team.



(a) Market Value and Age

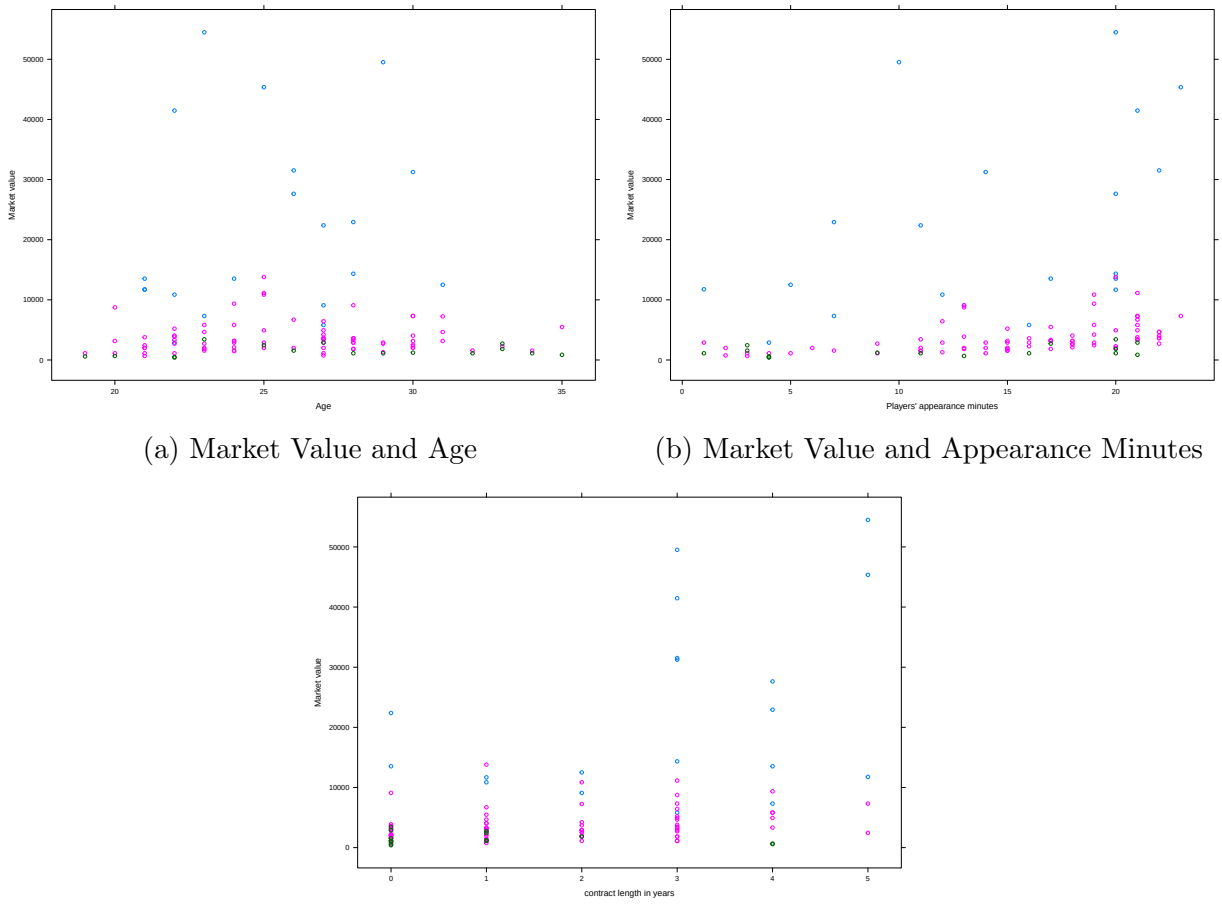
(b) Market Value and Appearance Minutes

(c) Market Value and Contract Duration

(d) Market Value and Years for the team

Figure 7.3: Relation between market value and strikers characteristics and career.

Midfielders Figure 7.4 has revealed that the improperly valued *midfielders* have the special values in age, appearance minutes, and contract duration.



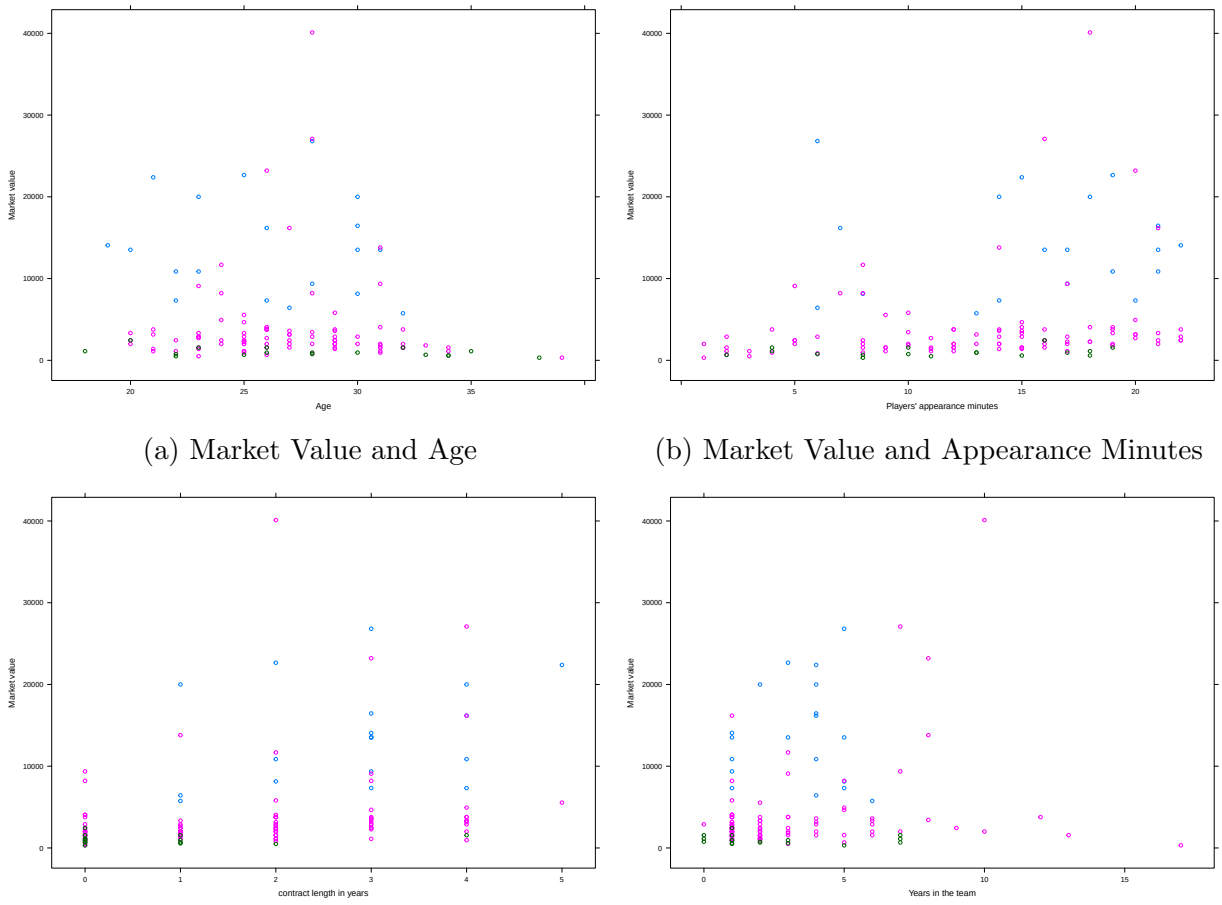
(a) Market Value and Age

(b) Market Value and Appearance Minutes

(c) Market Value and Contract Duration

Figure 7.4: Relation between market value and midfielders characteristics and career.

Defenders Unlike the other two positions, the players with highest value have been properly valued for *defenders*. Figure 7.5 has revealed that the improperly valued *defenders* have the special values in age, appearance minutes, contract duration and years stayed in the team.



(a) Market Value and Age

(b) Market Value and Appearance Minutes

(c) Market Value and Contract Duration

(d) Market Value and Years for the team

Figure 7.5: Relation between market value and defenders characteristics and career.

7.2.2 Analysis for improperly valued players

Strikers, Midfielders, Defenders There are general factors related to the improper valued players: Players' age (**Age**), the contract left for the player (**Con**), the years players have played for this club (**YinT**), the ratio of international players and local players (**InvsLo**), the number of the players from the top 5 club of the League[1] (**Clubs**), and the number of the players from the world top clubs[2] (**PreC**). These factors should be

[1]The top five clubs in la Liga:Real Madrid, FC Barcelona, Atlético de Madrid, Valencia CF, Sevilla FC

[2]The world top clubs are performances well in matches and generate a lot revenue all around the world e.g. Bayern Munich[21]

compared with total number of players for this position in the league (**PinL**) and total number of overvalued players for this position (**Player**) for analysis.

The specific figures of each factor are stated by positions in Table 7.1 and Table7.2, which are separated by overvalued and undervalued players.

Positions	**PinL**	**Player**	**Age**	**Con**	**YinT**	**InvsLo**	**Clubs**	**PreC**
Strikers	111	23	$23-30$	>3	-	14/9	19	18
Midfielders	109	20	$22-31$	>3	-	8/12	18	10
Defenders	128	19	$19-32$	2-5	1-5	13/6	16	10

Table 7.1: Overvalued Players

Positions	**PinL**	**Player**	**Age**	**Con**	**YinT**	**InvsLo**	**Clubs**	**PreC**
Strikers	111	15	$<23>30$	<3	<3	3/12	0	1
Midfielders	109	16	$22-36$	<2	-	8/12	0	1
Defenders	128	17	$18-38$	<2	$1-7$	8/9	1	0

Table 7.2: Undervalued Players

7.2.3 Study for Goalkeepers

Since there is no specific relationship between market value and their performance, I applied the regression tree for *goalkeepers* (Figure 7.6). Market value is considered as the target and all of the rest factors are the independent variables. The variables from regression tree result are regarded as the dominant factors to *goalkeepers* market value.

The appearance is the most important factor for the *goalkeepers*. Only when the goalkeeper has appearance minutes ≥ 17.5, their market value is in relation with their performance. Only less than 1/3 of the *goalkeepers*'s market value depend on their performance. For the rest of the *goalkeepers*, age and weight are the two key indicators. And there is no literature that shows the relationship between the weight and the *goalkeepers* performance.

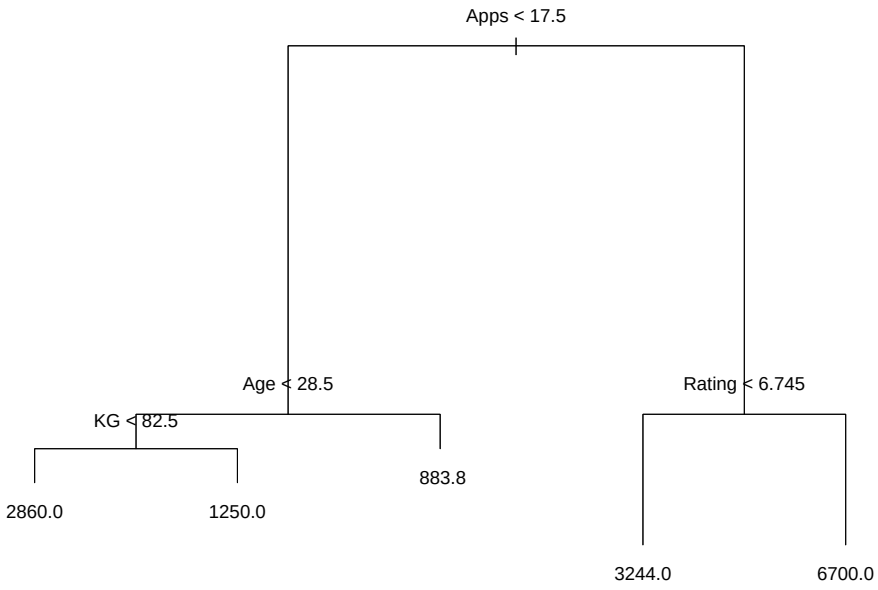


Figure 7.6: Factors Regression Tree for Goal Keepers' Market Value

7.3 Underlying Reasons

Besides the general reasons for the players and clubs, e.g. ages and contracts, there are some other factors effecting players' market value besides footballer themselves, which are super star atmosphere, nationality, club and previous, which have affected players market value.

7.3.1 General Reasons

For all the positions but *goalkeepers*, the older players are most likely to be undervalued. Though the undervalued players in *midfielders* and *defenders* are distributed to all the age groups, the distributions of these players are much more intense for players older than 31 years. Young players also tend to be undervalued. Market value shows the potential performance of the player in the future, however the expectation for the old players is very low because the physical performance will get poorer as the age grow.

The overvalued players always have more playing minutes and a longer contract length. The club knows the player very well and can value him properly. The expectation for the players has shown in their contract length which also affects on their market value. On the contrary, the remaining contract length for undervalued players is very short. On one

hand, when the club does not value a player, the player will not get more appearance opportunity and the club does not want to keep this player. On the other hand, when the club values a player, they prefer to make the player play for them for more years. When a player stays in a team more than 7 years, he is not likely to be improperly valued.

7.3.2 Superstar Players

Superstars Almost all of the overvalued players have very high performance, but the marginal contribution of their performance is lower than their market value. These players are the superstars in the media, e.g. Neymar da Silva, Luis Suárez. Why do these super stars been overvalued?

Rosen [43] who is regarded as the founder of economics superstar player has defined superstars as "the relatively small numbers of people who earn enormous amounts of money and dominate the activities in which they engage". The superstars have the overvalued atmosphere are most due to the marketing value. Normally, high-performance players also bring revenues to the clubs in terms of publicity and merchandise sales.

Attracting Fans Rosen [43] indicates that stars play an important role in promoting fan interest. In 2004, the report [49] from SportFive has stated that 69% of the European soccer fans think that their identification with and affiliation to a team largely depends on the particular players the team engages. The gate revenues can be increased by a star's talent superiority or a star's popularity [6].

According to Rosen [43], audience want to see their favoured players in the ceteris paribus. For example, the movement of the passes are very attractive to the spectators, but these will not be shown in the performance data.

Level of Matches The superstars tend to have longer appearance time than other players. Especially in the big events, the success of tournaments such as the UEFA Cup, the Champions League and the FIFA World Cup, coaches rely more on the stars. Good performance in these important matches is more valuable than that in ordinary matches. Players will be favoured by fans and coaches immediately if they have one key performance indicator in these matches. For example Mario Götze[16] had the final goal in 2014 FIFA World Cup final, which helped the Germany be the champion of and world and made him famous in the world. Consequently, his market value is the second highest among all the German players. However, a lot of players have three goals in matches cannot be known by the public. Even though the overall performance statistics of super stars may not as good as some average players, they tend to shine in important matches.

7.3.3 Nationality

In la Liga, around 58% of the overvalued players are international players, and it is more than that ratio for the whole league. In addition, the international players have a smaller ratio(37%) of undervalued players. Spending money on foreign players brings several extra benefits besides their contribution to win the games as discussed below.

Dramatic Fans Increase Most stars only have loyal local attraction[8], but superstars have fans both domestically and abroad. For example, Leo Messi and Cristiano Ronaldo have fans all over the world. Players from the same place tend to have the same fans group, for instance Spanish players are most likely to be favoured by Spanish people. If the player A is already a team member, the fans will not increase much if the team buys player B who is from the same place as A. Bringing in an international player can dramatically increase the fans' number due to different fans group. For example, Neymar helps Barcelona to gain more fans from Brazil.

Other Revenues Acquiring an international player can help the club to earn extra money besides revenue from tickets. The most important one is revenue from the TV rights. The international player can bring more living chances for the club. Before Sun transferred to PSV, there was no Dutch football league's living match and reports in Chinese media. However, there is more living matches or news for PSV than Real Madrid in Chinese media when Sun was in the PSV. The price of TV rights for Premier League games is extremely high due to the influx of foreign players. Sky Sports and BT Live spending a record £3 billion on TV rights from $2013-16$, which gives each Premier league club an extra £60 million every year[38].

There are also some intangible benefits created by the international transfer that creates revenue. The club will be more famous in the player's home country because of the transferred international player. It can be regarded as a free advertise for the club to foreign land. The transfer of Sun made PSV famous in China, most Chinese people only know PSV other than Ajax. The club products (e.g. the suits) will have more sales and will be easily sponsored by foreign companies.

More Appearance Another possible reason why the international players are easily overvalued is the statistic bias. The statistics of performance is averaged by 90 minutes. The international players have more appearances and movements than local players. Mohr et al.[5] have found that international players performed 28% more high-intensity running (2.43 vs.1.90 km) and 58% more sprinting (650 vs. 410 m) than the local

professional players in the same league. Due to longer appearance time than other players, the average of their performance data is relatively low.

7.3.4 Clubs

All the records of the transfer fee happened in the richest clubs [57]. It seems these clubs have created the inflation of football player market value.

Existing Clubs More than 85% of overvalued players are playing in the richest clubs, while none of undervalued player are working for these clubs except one defender Fernando Navarro from Sevilla.

These clubs have a better ability to increase their financial budget, which enables them to pay the high transfer fee and salary to the superstars. They have generated more revenue from match day including ticket and corporate hospitality sales.

Their TV rights are distributed to more countries and the content covers domestic leagues, cups and European club competitions. In addition, their commercial sources (e.g. sponsorship, merchandising and other commercial operations) are much more than the rest of the clubs.

These clubs have money to buy a lot of stars all over the world. With many stars in the same team, even a superstar player couldn't have much chance to play in the match as well. For example, in 2006-2007, Micheal Owen had very short appearance time. Even though he is worth to his market value, he couldn't have much performance data. Even a super star performs well enough, there is like to be someone else in the same team plays better than him. He will get less attention by teammates, coach or fans than he should have got.

Previous Clubs There is also a finding on previous clubs of the improperly valued players. Most of the overvalued players are transferred from the world most valuable teams, while only one the undervalued players is transferred from top clubs in the world, that is Wellington Silva from Arsenal FC. According to the previous clubs, the inflation of the riches clubs also happens in their second team, e.g. *midfielders* are more from Barcelona B.

Dismissing the contract with players in the top clubs cost more than the rest clubs. The buyer clubs have to pay more to buy the players' remaining contract. [9] That's why most overvalued players are from the riches clubs.

8 Conclusion

In this chapter, the research conclusion will be presented first. And the limitations of this research will be pointed out. At last, the suggestions for the future study will be given.

8.1 Conclusions

The performance of players are related to the income of the team as stated in Chapter 2. Especially under the newly regulations of UEFA, the clubs should spend money wisely. The correct evaluation of players is more important than that of previous years.

Player performance data are hard to acquire and have high commercial value. Therefore, it is difficult to obtain useful data for this research. This research was conducted under a lot of pre-studies on finding out the available useful data source. Record linkage has been used to merge the data from different data sources. The transfer fee is considered as the market value of a player and the votes by experts are as the players' performance assessment.

Real value model As is mentioned in Chapter 4, the target data voting and transfer fee are insufficient. LASSO models have been trained to get the complete list for these two values. Since the transfer fee has a relationship with the market value from Transfer

Market, **the real market model** is based on that variable, which is formula 8.1

$$\hat{M} = 231.26 + 0.89 \cdot Market.value + 2723.26 \cdot Assists \tag{8.1}$$

The players' performance is not in line with the proxy value rating from Whoscored. The reason is the basis of the voting, which favours the strikers. The **real performance model** was only trained for the forward players which is formula 8.2.

$$\hat{P} = 0.28 - 0.073 \cdot F + 0.06 \cdot SP + 0.04 \cdot ST + 0.02 \cdot GP + 0.05 \cdot GB + 0.02 \cdot D + 0.08 \cdot A \tag{8.2}$$

Performance KPIs by positions The performance KPIs have been selected with the LASSO feature selection by positions in Table 8.1. The indicators with '-' in the front have a negative impact on the performance. The observations from the table are as follows. There is a significant difference in the performance indicators between positions. The same indicators create different impacts on positions. For example, more *Interception* is a plus for *midfielders* and *defenders* while it makes the *goalkeepers* performance worse.

Strikers	**Midfielders**	**Defenders**	**Goalkeepers**
Shots in penalty area	Interception	Shots blocked	Saves in penalty area
Goals in penalty area	Goals in the zone	Shot on Target	Fouled
Shots on target	Goals by head	Interceptions	Dribbled pass
Goals from out of box	Aerial won	Accurate long balls	inaccurate block
Dribble successfully	Length of passes	Accurate short passes	-Accurate free kick
Assists total	Accurate free kicks	Long passes	-Interception
-Fouls	Other assists	-Fouls	-Dribbled past
	-Unsuccessful touches	-Yellow cards	

Table 8.1: Overvalued Players

Market value/performance cross results By studying the Spanish league la Liga, the market value is majorly based on the performance of players. The general relationship of market value and performance has been studied. In general, a football player's market value is in a logitism relationship with his performance. As long as a player's performance improves a little, the market value of this player will be multiplied.

The international, young and old players are easily to be improperly valued. The rich clubs tend to overvalue their players, which also affects the market value of their previous players. In addition, the improperly valued players have a significant difference in appearance time and contract length when compared to other players.

8.2 Research limitations

Due to the difficulty of collecting data, this research is conducted with insufficient data. There is only a half season of one league's data which is very limited. Also, the ranking of the club in Section3.1.3 is only for the middle season, the sequence is changed at the end of the season.

The performance and market value use supervised learning to predict the unknown variable. Because of the bias of voting system, among the performance models for all positions, only that of *strikers* is available.

This research is only studied within la Liga. It does not take the leagues differences into consideration. The model has not been verified in different leagues yet. As a result, it cannot represent all the leagues.

Soccer is a highly interactive game based on the combination of complementary player skills. The combination of the players was not taken into consideration in this research. This will result in the inaccuracy prediction on players' performance.

8.3 Future Study

This model is built for evaluating market value of all the players of la Liga based on their performance. Furthermore, the method could be applied to other leagues. As for the performance, the operational model at this point only applies to *strikers*. This can be extended to other positions if a unique model is created for performance across different leagues. As part of future work, I would like to scale up the project to all European leagues.

Even all leagues are covered, this project will keep on dealing with incomplete data because not all players are valued every year (by being transferred), neither are all players' performance evaluated by the voting system. In the future, the semi-supervised methods are considered to solve the tasks of *Performance* and *Market Value* estimation.

Finally, the voting system to assess performance is biased towards *strikers* and well performing players. Hence, there is need to explore other data mining techniques that account for this problem, e.g. an Elo Rating model can be created to evaluate the performance of football players across positions and leagues.

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A

Variable Explanation

Variables	Explanation
Team	Player's team
Player	Player's name
Position	Player's position
Age	Player'sage
Nat.	Player's nationality
Second.Nat.	Player's second nationality
Foot	Player's usually foot play
In.the.team.since	Player's start date of the team
before	For which team player has played before
Contract.until	when will the player's contract end
Market.value	Player's market value from Transfer Market
Rating	Player's rating score by WhoScored
CM	Player's height
KG	Player's weight
Apps	Appearance
Mins	The total minutes played for this season
TotalTackles	Total tackles per 90 minutes
DribbledPast	Total dribbled past per 90 minutes
TotalAttemptedTackles	Total attempted tackles per 90 minutes
Interception	Total interception per 90 minutes

Variables	**Explanation**
Fouled	Total being fouled times per 90 minutes
Fouls	Total fouls per 90 minutes
Yellow	Total yellow cards per 90 minutes
Red	Total red cards per 90 minutes
CaughtOffside	Total caught off side per 90 minutes
Clerances	Total clerances per 90 minutes
ShotsBlocked	Total shots blocked per 90 minutes
CrossesBlocked	Total crosses blocked per 90 minutes
PassesBlocked	Total passes blocked per 90 minutes
Saves	Total saves per 90 minutes
SixYardBox	Saves in six yard box per 90 minutes
PenaltyArea	Saves in penalty area per 90 minutes
OutOfBox	Saves out of box per 90 minutes
Shot.in.Zones	Shots in Zones per 90 minutes
OutOfBox.1	Shot out of Box per 90 minutes
SixYardBox.1	Shot within six yard box per 90 minutes
PenaltyArea.1	Shot in the penalty area per 90 minutes
Situation	Situation Shot per 90 minutes
OpenPlay	Shot Open play per 90 minutes
Counter	Counter Shot per 90 minutes
SetPiece	Set Piece Shot per 90 minutes
PenaltyTaken	Penalty Shot per 90 minutes
Accuracy	Shot accuracy per 90 minutes
OffTarget	Shot off target per 90 minutes
OnPost	Shot on post per 90 minutes
OnTarget	Shot on target per 90 minutes
Blocked	Shot blocked per 90 minutes
Body.Parts	Body Parts Shot per 90 minutes
RightFoot	Right foot Shot per 90 minutes
LeftFoot	Left foot Shot per 90 minutes
Head	Head Shot per 90 minutes
Other	Other Shot per 90 minutes
Zone.of.Goals	Goals from zones per 90 minutes
SixYardBox.2	Goals from six yard box per 90 minutes
PenaltyArea.2	Goals from penalty area per 90 minutes
OutOfBox.2	Goals from out of box per 90 minutes
Situations	Situation goals per 90 minutes
OpenPlay.1	Open play goals per 90 minutes
Counter.1	Counter goals per 90 minutes
SetPiece.1	Set piece goals per 90 minutes
PenaltyScored	Penalty scored per 90 minutes
Own	Own goals per 90 minutes
Normal	Normal goals per 90 minutes

Variables	**Explanation**
Body.Parts.1	Goal by body parts per 90 minutes
RightFoot.1	Goals by right foot per 90 minutes
LeftFoot.1	Goals by left foot per 90 minutes
Head.1	Goals by head per 90 minutes
Other.1	Goals by other parts per 90 minutes
Unsuccessful	Dribble unsuccessful per 90 minutes
Successful	Dribble successful per 90 minutes
DribbleTotal	Dribble total per 90 minutes
UnsuccessfulTouches	Possession loss unsuccessful touches per 90 minutes
Dispossessed	Possession loss dispossessed per 90 minutes
Aerial	Total aerial per 90 minutes
Won	Aerial won per 90 minutes
Lost	Aerial lost per 90 minutes
Length.of.Passes	Total passes per 90 minutes
AccLB	Accurate long balls per 90 minutes
InAccLB	Inaccurate long balls per 90 minutes
AccSP	Accurate short passes per 90 minutes
InAccSP	Inaccurate short passes per 90 minutes
AccCr	Accurate cross passes per 90 minutes
InAccCr	Inaccurate cross passes per 90 minutes
AccCrn	Accurate corner passes per 90 minutes
InAccCrn	Inaccurate corner passes per 90 minutes
AccFrK	Accurate freekicks per 90 minutes
InAccFrK	Inaccurate freekicks per 90 minutes
Key.Passes.Length	Total key passes per 90 minutes
Long	Total key long passes per 90 minutes
Short	Total key short passes per 90 minutes
Cross	Total key cross passes per 90 minutes
Corner	Total key corner passes per 90 minutes
Throughball	Total key through ball per 90 minutes
Freekick	Total key free kick per 90 minutes
Throwin	Total key throw in per 90 minutes
Other.2	Total key other passes per 90 minutes
Cross.1	Corner assists per 90 minutes
Corner.1	Corner assists per 90 minutes
Throughball.1	Throughball assists per 90 minutes
Freekick.1	Free kick assists per 90 minutes
Throwin.1	Thrownin assists per 90 minutes
Other.3	Other assists per 90 minutes
Assists	Assists total per 90 minutes

Table A.1: Variable Explanations

B

R code

In this part, part of Key Process of R code have been provided.

B.1 Data Preparation

B.1.1 Preprocesing

```
# erase last reccord from Transfer Market (empty line)
  dataTF <- dataTF[-nrow(dataTF),]

# erase all duplicate reccords from WhoScored
  dataWS <- unique(dataWS)

# Change Contract.until to numeric
  for(i in 1:nrow(TF)){
  test<-TF$Contract.until[i]
  test <- unlist(strsplit(test, split=""))
  if (length(test)<10)
  {
```

```
    TF$Contract.until[i]<-0
  }else {
    TF$Contract.until[i] <- as.numeric(as.numeric(paste(test[7], test[8], te
  }
}
  TF$Contract.until <- as.numeric(TF$Contract.until)

# Change in the team since into years
  for(i in 1:nrow(TF)){
  test<-TF$In.the.team.since[i]
  test <- unlist(strsplit(test, split="-"))
  if (length(test)<3)
  {
    TF$In.the.team.since[i]<-0
  }else {
    num <- as.numeric(15-as.numeric(test[3]))
    if(num<0 )
    {
      num<-num+100
    }
    TF$In.the.team.since[i]<-num
  }
}
  TF$In.the.team.since <- as.numeric(TF$In.the.team.since)

# Convert Market Value into numbers
  for(j in 1:nrow(MergeMatrix)) {
  test <- MergeMatrix$Market.value[j]
  num <- unlist(strsplit(test, split=" ␣"))[1]
  unit <- unlist(strsplit(test, split="␣"))[2]
  num <- unlist(strsplit(num, split=","))
  if(is.na(num[2])) {
    num<-num[1]
  } else {
    num<-paste(num[1],num[2],sep="")
  }
```

```
  num <- as.numeric(num)
  amatch(unit,"Mill.")
  if(is.na(amatch(unit,"Mill."))) {
    MergeMatrix$Market.value[j]<-num
  } else {
    MergeMatrix$Market.value[j]<-num*10
  }
}
  MergeMatrix$Market.value <-as.numeric(MergeMatrix$Market.value)
#Erase the NA Market Value player
  MergeMatrix <- MergeMatrix[-which(is.na(MergeMatrix$Market.value)),]

# Dealing with Missing Value
  TF[is.na(TF)]<-0
```

B.1.2 Data Match

```
output <- matrix(nrow=nrow(dataWS), ncol=3, dimnames=list(c(), c("aindexWS","
j=1

for(j in 1:nrow(dataWS)){
  aDistName <- stringdist(dataWS$Name[j],dataTF$Player,method="jw")
  aDistTeam <- stringdist(dataWS$Team[j],dataTF$Team,method="jw")
  aDistAge <- stringdist(dataWS$Age[j],dataTF$Age,method="jw")
  aDistHeight <- stringdist(dataWS$CM[j],dataTF$Height,method="jw")
  TotalDist <- aDistName + aDistTeam + aDistAge + aDistHeight
  minDist <- min(TotalDist)
  aIndex <- which(TotalDist == minDist)
  output[j,1] <- j
  output[j,2] <- minDist
  output[j,3] <- aIndex
}
summary(RightMatch)

# Evaluate the matching reslut
RightMatch <- vector(mode="integer", length=nrow(DIndex))
for(j in 1:nrow(DIndex)){
```

```
  if(length(na.omit(DIndex[j,2])) == 0 | length(na.omit(output[j,3])) == 0)
    next
  if (DIndex[j,1]==output[j,1] & DIndex[j,2]==output[j,3]){
    RightMatch[j] <- 1
  }
}
summary(RightMatch)[[4]]/(1-summary(DIndex[,2])[[7]]/nrow(dataWS))
nrow(dataTF)

#sort the data by distance
output[sort.list(output[,2]), ]
```

B.2 LASSO in R

Take the forward players' performance training as an example

```
# Use the package "glment"
library("glmnet")

# Train LASSO model with 5 folders cross validation
cvfit = cv.glmnet(x, y,nfolds=5)

# Plot all the mean squared errors with for all the fitting
plot(cvfit)

# Get the coefficient with the proper lambda value
Coef<- coef(cvfit, s = 0.081740)
Coef[(which(Coef[,1] != 0)),]
```

C Intermediate Results

C.1 Defenders Predicted Logarithm of Market Value

```
x<-as.numeric(Player$Rating)
y<-log(Player$Market.value) # Acctually it is ln,not log
fit<- loess(y~x)
premv <- as.data.frame(predict(fit, interval = "prediction"))

# premv Result is
    predict(fit, interval = "prediction")
1                                7.637719
2                                7.683803
3                                7.729092
4                                7.692301
5                                7.752875
6                                7.884957
7                                8.247011
8                                7.675055
9                                8.223610
```

10	7.590636
11	7.276625
12	7.812882
13	8.118786
14	7.967009
15	8.344933
16	7.276625
17	7.666961
18	7.571646
19	7.766630
20	8.091007
21	7.904617
22	8.648674
23	7.904617
24	9.591489
25	8.579214
26	8.425293
27	8.837744
28	9.432839
29	9.646156
30	8.223610
31	7.613014
32	7.988835
33	7.945675
34	7.709607
35	7.660412
36	7.729092
37	7.740314
38	7.829851
39	8.344933
40	8.091007
41	7.452000
42	7.598582
43	7.700814
44	8.037117
45	8.319634

46	7.573479
47	8.173472
48	5.759453
49	7.598582
50	7.452000
51	8.453852
52	7.692301
53	7.752875
54	7.812882
55	6.868478
56	7.572391
57	7.650818
58	7.578794
59	6.974191
60	7.637719
61	7.607870
62	8.648674
63	7.574909
64	8.223610
65	7.571646
66	8.199363
67	7.666961
68	7.613014
69	8.199363
70	7.766630
71	7.374003
72	7.660412
73	7.766630
74	7.624302
75	7.532592
76	7.594441
77	7.666961
78	7.518462
79	7.554367
80	7.624302
81	7.752875

82	7.573479
83	7.647207
84	7.647207
85	7.924867
86	7.847542
87	7.781239
88	7.666961
89	7.239863
90	7.634060
91	7.603059
92	7.647207
93	7.629683
94	7.700814
95	8.270758
96	7.473687
97	9.701714
98	8.247011
99	9.484831
100	8.012021
101	10.178366
102	7.692301
103	8.247011
104	8.223610
105	8.063615
106	7.692301
107	7.569416
108	8.012021
109	8.319634
110	7.847542
111	7.752875
112	7.532592
113	9.048897
114	8.370919
115	7.554367
116	8.012021
117	7.718945

118	8.684724
119	7.675055
120	9.815510
121	8.453852
122	8.199363
123	8.798165
124	7.576681
125	8.397677
126	8.798165
127	9.093784
128	8.425293