Statistical Assessment of Soccer Players

by

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A thesis submitted to the Faculty of Graduate and Postdoctoral
Affairs in partial fulfillment of the requirements
for the degree

Master of Science

in

Mathematics and Statistics

Carleton University
Ottawa, Ontario

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ABSTRACT

This thesis examines the use of neural network modelling and ordinal logistic regression on a single season of data (2015-16) to score or rank soccer players. These scores and ranks are then compared with ones from FIFA EASports that are based on a much more extensive data set that includes more variables as well as historical data. Using repeated measures one-way ANOVA and subsequent multiple comparison testing, we conclude that a neural network model with ten nodes in one hidden layer is able to generate scores statistically similar to FIFA EASports, while ordinal logistic regression cannot. We confirm this result by also examining the ranks obtained by both the neural network model and the ordinal logistic regression model. Spearman rank correlations are also examined and confirm that a neural network with 10 nodes in one hidden layer also generates ranks statistically similar to FIFA EASports. We also demonstrate the use of association rule mining on one team's data from the 2015-16 season to identify players and combinations thereof that are associated with winning (or not winning) a match. Analyses are based on data from the Italian Serie A League 2015-2016 season.

Acknowledgements

These past couple of years have proven to be the hardest period of my life so far. I could not be here without the help of the people around me. I have been surrounded by the kindest people. I want to thank my parents for their support without any hesitation. I want to thank my brother and sister who have always been there for me. I want to thank Gray Barski and Shintara Hagiwara for many discussions about this research and for their moral encouragement.

Last but not the least, I want to thank my supervisor, Dr. Mills. She supported me during this hard time and never gave up on me. I am blessed with being her student.

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1. Introduction

Soccer is the world's largest grossing sport with annual revenues within some leagues surpassing the GDP of some small countries. In the last 30 years the development and implementation of data analytics in soccer has become increasingly popular. Predictive models from quantitative measurements have been shown to provide useful inferences that have not been available traditionally from experts within the sport. With the world-wide popularity of soccer, there exists significant incentive to perform such analyses since the rewards are potentially quite large. However, due to the dynamic nature of the sport, data analysis on a sport like soccer is quite challenging.

The results of this work can be used for different purposes. These analyses can be used by coaches, managers, players and agents. Also, these types of statistical analysis can be used by video game companies, betting organizations, and fans. It must be mentioned that this work can be used for other sports as well. Soccer is dynamic; players' decisions are evolving sequentially and contingent upon other players' choices amongst other phenomena. Although an immense amount of data is tracked and published, many of these sources are not free or readily available to the public. One firm that provides datasets is Opta [1]. Opta is one of the largest companies that provide data for other parties. They also have their own analytical team and prepare analytical inferences for different parties such as betting

companies. Obtaining an accessible and suitable dataset is quite difficult; the task requires an immense amount of resources to gather and compile such a data set. The data that is readily available to the public is generally expressed in raw form and requires substantial manipulations, organization, and computational techniques in order to be brought into a form which allows for statistical inference. Statistical predictive modelling will be highly dependent upon obtaining a suitable data set. The statistical problem in mind must not only be well defined by the researcher but also, the methods and procedures used to attempt to solve the problem must be tailored in a manner that addresses the previous constraints.

This thesis explicitly considers the following questions:

- 1.) Can we use statistical learning methods to duplicate the FIFA rankings from EA Sports' 2016 players' rankings? (We did not have access to the formulae, or the complete data set implemented within that system).
- 2.) Can we find a methodology that provides insight into players or combinations of players that increase the chance of a team winning a match? Similarly, can we find a methodology that identifies players or combinations of players that decrease the chance of a team winning a match? One way of describing this objective in simpler qualitative terms is attempting to find a methodology that would identify a player or a set

of players whose presence (or absence) makes a difference on winning a game.

We are interested in investigating whether statistical machine learning can address these questions. To conduct our research we will use data from Italian Serie A League for the 2015-2016 season [2]. Chapter 2 of this thesis provides a literature review summarizing relevant contributions to soccer analytics that exist within the academic literature. Chapter 3 discusses the dataset used and associated data wrangling. Chapter 4 presents methodological procedures proposed to address the research questions. The first section has the primary goal of examining methods for finding and assessing the accuracy of scoring/ranking models based on event data. Two different models proposed in this section are Neural Networks(NNET) and Ordinal Logistic Regression(ORM). We compare our results to those from the scores of EA Sports' FIFA 2015-16. The second section is concerned with methodology for finding a player or set of players that are associated with winning (or not winning) a match. For this objective, association rule mining is proposed. Chapter 4 concludes the explanation of the methodologies with a discussion of the relative utility of each methodology. Chapter 5 presents the results of each methodological procedure implemented within this thesis. Finally, Chapter 6 provides conclusions, a discussion about possible alternative methodologies, and motivates future research.

2. Literature Review

This chapter presents a review of the literature relevant to the research questions posed in this thesis. Sarmento et al [3] published a paper that systematically reviewed and organised the literature on match analysis in

adult male football in an attempt to identify the most common research topics, to characterise their methodologies, and to systematise the evolutionary tendencies on this topic. It contained a review of 53 papers and categorized them into four (4) categories:

1. Empirical studies with predominantly descriptive analysis.
2. Comparative studies with predominantly comparative analysis according to the different functional positions of the players.
3. Empirical studies with predominantly comparative analysis based on the different competitive levels.
4. Empirical studies with situational - match status, quality of opposition and match location.

Table 1: Empirical studies with predominantly descriptive analysis.

Study	Sample	Movement Category	Procedure
Barros et al. (2007)	55 players of First Brazilian Division	Standing/walking/jogging, low-speed running, moderate-speed running, high-speed running, sprinting.	Video analysis of the activity of players.
Di Salvo et al. (2007)	300 players of Spanish Premier League	Standing/walking/jogging, low-speed running, moderate-speed running, high-speed running, sprinting.	Computerised match analysis system (AMISCO)

Rampinini, Coutts, Castagna, Sassi, and Impellizzeri (2007)	20 players of a successful team that participated in a major European National League	Standing, walking, jogging, running, high-speed running, sprinting.	Computerised match analysis system (ProZone)
Di Salvo, Benito, Calderon, Di Salvo, and Pigozzi (2008)	62 goalkeepers of English Premier League	Walking, jogging, running, high-speed run, sprinting and total distance.	Computerised match analysis system (ProZone)
Bradley, Di Mascio, Peart, Olsen, and Sheldon (2010)	110 players of European successful teams	Standing, walking, jogging, running, high-speed running, sprinting.	Computerised match analysis system (ProZone)
Gregson, Drust, Atkinson, and Di Salvo (2010)	485 players of the English Premier League	Total high-speed running (expressed as both high speed running distance completed with the respective players team in possession and without possession), high-speed running distance, total sprint distance.	Computerised match analysis system (ProZone)
Vigne, Gaudino, Rogowski, Alloatti, and Hautier (2010)	388 players of the Italian Series A	Walking, jogging, speed below the anaerobic threshold, speed above the anaerobic threshold, sprint.	Computerised match analysis system (SICS)
Carling (2011)	21 players of French League 1 division	Total distance covered in: low-to-moderate intensity; high intensity; very high intensity.	Computerised match analysis system (AMISCO)
Castellano, Blanco-Villaseñor, and Álvarez (2011)	434 players of Spanish Premier League	Standing/walking/jogging, low-speed running, moderate-speed running, high-speed running, very high-speed running, sprinting.	Computerised match analysis system (AMISCO)
Robinson, O'Donoghue, and Wooster (2011)	180 players of the English Premier League	Path changes of: 45° to 135° to the left; 45° to 135° to the right; more than 135° to the left or the right.	Computerised match analysis system (ProZone)

Table 2: Comparative studies with predominantly comparative analysis according to the different functional positions of the players.

Study	Sample	Categories of player positions	Analysed variables	Main results
Barros et al. (2007)	55 players of First Brazilian Division.	Central defenders, external defenders, central midfielder, external midfielder, forwards.	Distances covered at different intensities.	The distances covered by external defenders, central midfielders and external midfielders were greater than forwards. The forwards covered greater distances than central defenders.
Bloomfield et al. (2007)	55 of the English Premier League.	Defenders, midfielders and forwards.	Purposeful movements (PM).	The specific position on the field had a significant influence on %PM time spent sprinting, running, shuffling, skipping and standing still. The position had no significant influence on the %PM time spent performing

				movement at low, medium, high or very high intensities.
Di Salvo et al. (2007)	300 of Spanish Premier League.	Central defenders, external defenders, central midfielder, external midfielder, forwards.	Distances covered at different intensities.	Midfield players covered a significantly greater total distance than the groups of defenders and forwards. The shortest distance was covered by central defenders.
Rampinini et al. (2007)	20 players of a successful team that participated in a major European National League.	Centre-back, fullback, midfielder, forward.	Match activities, match distances, other match analysis measures.	Difference of all variables between player positions
Di Salvo et al. (2009)	563 of the English Premier League.	Central defenders, external defenders, central midfielder, external midfielder, forwards.	High-intensity running activity.	The total high-intensity running was dependent upon playing position with the external midfielders completing the highest and lowest distance, respectively.
Dellal et al. (2010)	3540 players of French League 1 division.	Central defenders, fullbacks, central defensive midfielders,	Physical parameters (distances covered in high intensity and	In the offensive phase, the forwards covered about 4 times

		wide midfielders, central attacking midfielders, forwards.	sprinting, of ground duels or heading duels won. Technical parameters (successful passes, total duration of individual ball possession, number of touches per individual possession).	more the total distances in sprinting than central defenders and full backs. Midfielders performed successful passes ranging from 75% to 78%, whereas lower values were found for the forwards (71%) and central defenders (63%), respectively
Di Salvo et al. (2010)	717 players of Champions League teams.	Central defenders, external defenders, central midfielder, external midfielder, forwards.	Total number of sprints and total sprint distance covered.	Differences were found in most of the analysed variables depending on the specific position on the field. Wide midfielders performed a higher number of sprints in all five distance categories than all other positions.
Vigne et al. (2010)	388 players of the Italian Series A.	Defenders, midfielders and forwards.	Distances covered at different intensities.	The midfielders covered significantly

				more distance than players in other positions. For midfielders, the number of displacements of 2–40 m and the number of sprints covering between 2 and 9 m and between 30 and 40 m are considerably greater than for other positions.
Dellal et al. (2011)	5938 of the English Premier League and of Spanish Premier League.	Central defenders, fullbacks, central defensive midfielders, wide midfielders, central attacking midfielders, forwards.	Distances covered at different intensities. Technical parameters.	English Premier League and Spanish Premier League teams present differences in various physical and technical aspects of match play, suggesting that cultural differences may exist across professional soccer leagues and playing positions.

Table 3: Empirical studies with predominantly comparative analysis based on the different competitive levels.

Study	Sample	Number of considered levels	Strategies used to established the levels	Results
O'Donoghue et al. (2001)	72 players of the English Championships	Three	Elite, amateurs and semi-professional players	Semi-professional players performed more discrete movements than the other players. Amateur players performed a significantly lower number of periods of high-intensity activity than elite and amateur players. However, the duration of the periods of high-intensity activity performed by amateur players was significantly longer than those performed

				by the other groups of players.
Hughes and Franks (2005)	116 matches of the 1990 (Italy) and 1994 (USA) World Cup	Two	Successful teams (quarterfinalists) and unsuccessful teams (first round losers)	For successful teams, longer passing sequences produced more goals per possession than shorter passing sequences. For unsuccessful teams, neither tactic had a clear advantage.
Rampinini et al. (2009)	186 players of the Italian Series A	Two	Successful teams (ranked in the first five positions) vs. less successful teams (ranked in the last five positions)	The players from the more successful teams covered greater total distance with the ball and very high-intensity running distance and also had more involvements with the ball, completed more short passes, successful short passes, tackles, dribbling, shots, and

				shots on target compared to the less successful teams.
Bradley et al. (2010)	110 players of European successful teams	Two	Elite domestic players (that played in teams that compete in one of the strongest Leagues in the world) vs. Elite international players (that played in teams ranked in the Top 10 of the FIFA	No statistical significant differences were found between the groups for high intensity running distance, mean recovery time or maximal running speed.
Lago-Ballesteros and Lago-Peñas (2010)	380 matches of the Spanish Premier League	Three	According to the final ranking	Top teams had a higher average of goals for total shots and shots on goal than middle and bottom teams. Bottom teams needed a higher number of shots for scoring a goal than the other groups of teams. Middle teams showed a lower

				value in assists and ball possession than top teams.

Table 4: Empirical studies with situational - match status, quality of opposition and match location.

Study	Sample	Categories	Variable	Results
Lago and Martín (2007)	170 games of the Spanish First league	Winning, drawing, losing Home vs. away Reference team	Percentage of team possession	The teams that played at home had more possession than the teams playing away. When losing, teams playing at home had more possession than when they were drawing or winning. The worse the opposing team, the higher was the percentage of ball possession.
Taylor et al. (2008)	40 games of a professional English team	Winning, drawing, losing	Technical Behaviours	At winning: teams performed

		Home vs. away Home vs. away Strong vs. weak		more interception, clearance and aerial challenge and fewer crosses, passes and dribbles. At losing: teams made more crosses, dribbles and passes and fewer clearances and interceptions. Playing at home, performed more crosses and shots, but fewer interceptions and tackles. When they played against strong opponents, they performed more passes and less dribbling.
Lago (2009)	27 games of the Spanish first League	Winning, drawing, losing Home vs. away Strong vs. weak	Percentage of team possession	Possession was greater when losing than when winning or drawing. Playing against strong opponent teams has been associated

				with a decrease in time of possession. The possession was not influenced by the venue of the game.
Lago et al. (2010)	27 players of the First Spanish League	Winning, drawing, losing Home vs. away Strong vs. weak	Work rate	Playing against strong opponent teams has been associated with a decrease in time of possession. The possession was not influenced by the venue of the game. Players covered greater distances when they played against strong opposition.
Lago-Peñas and Dellal (2010)	380 games of the Spanish First league	Winning, drawing, losing Home vs. away Strong vs. weak	Percentage of team possession	The best ranked teams maintained a high percentage of possession and their pattern of play was more stable. Time

				of possession was greater when teams were losing and when they played at home. Playing against strong opponents is associated with a reduction in time of possession.
Lago-Peñas, Lago-Ballesteros, et al. (2011)	172 players of the Spanish First league	Winning, drawing, losing Home vs. away Strong vs. weak	Work rate	The elite players performed less high intensity when winning than when losing. The teams playing at home covered greater distances at low intensity than the teams playing away. Players covered a greater distance walking and jogging when playing against stronger teams
Castellano et al. (2011)	434 players of the Spanish First league	Winning, drawing, losing Home vs. away	Work rate	The total distance covered by players at

		Strong, medium and weak		different intensities during the effective time of play was higher when playing at home, when the reference team was losing and when the opponent team was strong.

These research papers mostly show that there are high-intensity activity patterns in elite domestic and elite international players. The soccer players were assessed by the 10- x 5-m shuttle run test (10 x 5 SRT) on a soccer field in a soccer season. These studies also showed that there are differences between different competitive levels. The professional players who play for more successful teams cover greater total distances with the ball and at very high-intensity running, have a higher average number of goals for total shots on target, higher number of passes, tackles, dribbling and shots on target compared to less successful teams. [4]

There are also studies that focus on the fatigue of the players and the effect of substitutions. These studies show that the performance of players does not change with the short recovery between matches. Di Salvo et al [5] use factorial linear mixed modeling to show the intensity activity of players is related to the position they play. Christopher Carling [6] used Friedman's

repeated-measures analysis of variance on ranks test to assess differences in means in performance measures across separate time intervals. Follow-up univariate analyses using Tukey pairwise multiple comparison procedures were performed where appropriate. By using tracking data , they show that the covered distance during different periods of the match was higher in the first half than second half of a match. But the skill-related measures revealed no significant decline between halves. Also analysis of players' performance suggested that their performance did not change when competing in successive matches within a short time period.

Lyons et al [7] mostly focused on predicting and finding the most effective way of playing, using multidimensional data instead of just one-dimensional data.

Albin Tenga et al [8], using Norwegian elite soccer matches, were trying to examine the effect of playing tactics on achieving score-box possession by assessing opponent interactions. Using multiple logistic regression, they found that, for the main variable "team possession type", counterattacks were more effective than elaborate attacks when playing against an imbalanced defence (odds ratio: 2.69; 95% confidence interval: 1.64 to 4.43) but not against a balanced defence (odds ratio: 1.14; 95% confidence interval: 0.47 to 2.76).

Other studies examined, for each team, ball possession and the probability of scoring a goal. The first of these studies was by Reep et al [9], followed by

the work of Mike Hughes et al [10], which was influenced by the earlier work of Reep and Benjamin [11]. But instead of finding how to score or how the goals were scored, Mike Hughes et al looked into the passing and shots in the soccer game and their effect on the quality and quantity of scoring.

The study by Carlos Lago-Peñas et al [12] identified the soccer game-related statistics that best discriminated home and visiting teams according to team quality.

Using the Kolmogorov-Smirnov test, only the variables possession, gains of possession and losses of possession were found to follow a Normal distribution. They used either a t-test or a Mann-Whitney U test, depending on the variable distribution, to identify univariate differences between the game-related statistics of home and away teams.

Using discriminant analysis, they were able to identify variables useful for discriminating between winning, drawing, and losing teams. They used all the games in 2008-2009 season of the Spanish pro league (380 matches).

They used variables such as: total shots, shots on goal, effectiveness ($\text{Effectiveness} = \text{Shots on goal} \times 100 / \text{Total shots}$), assists, crosses, offsides committed and received, corners, ball possession, crosses against, fouls committed and received, corners against, yellow and red cards, and venue.

They used univariate (t-test) and multivariate (discriminant) analyses of data and concluded that winning teams had averages that were significantly higher for the following game statistics: total shots ($p <$

0.001), shots on goal ($p < 0.01$), effectiveness ($p < 0.01$), assists ($p < 0.01$), off-sides committed ($p < 0.01$), and crosses against ($p < 0.01$). Losing teams had significantly higher averages for the variables crosses ($p < 0.01$), off-sides received ($p < 0.01$), and red cards ($p < 0.01$). Using discriminant analysis, they concluded the following: the variables that discriminate between winning, drawing, and losing teams were the total shots, shots on goal, crosses, crosses against, ball possession and venue. [13]

Utilizing data from the 2001-2002 FA Premiership season, Horn et al [14] found that, for the central area just outside the penalty area, 86% of the passes in this area go to the penalty area and therefore result in a shooting opportunity. In a similar study, Taylor and Williams [15] found how important it was in the 2002 World Cup finals for the winning side to retain possession. They reported that gaining possession in the defensive area resulted in more attempts on the goal, which was related to more goals and in a way means better defending and not giving the opponents the opportunity to score or attempt to score a goal.

In a similar study, Pollard [16] defined a variable called "Yield" which represents the number of actions that were successfully performed in the match. It was suggested that unsuccessful teams have a lower yield attribute. However, this variable is not very reliable for a soccer match, where the result of the entire game can turn at the last minute just by a mistake.

Another article by Carlos Lago-Peñas and Alexandre Dellal [17] studied how longer possession time can result in more scoring and therefore result in winning. A standard multiple regression was used to examine how much ball possession was explained by contextual variables (match status, match location, quality of opposition and by the level of the team.

In a study on the performance of players, Radu S. Tunaru et al [18] examined how the form of a player can affect winning the Premier league championship in season 2003-2004. In this study they used an Opta Index [1] for the players and showed how the transfer value of Thierry Henry, who was playing for Arsenal in the 2003-4 season, changed throughout the season and how his performance affected his market value, as shown in Figures 1 and 2.

Figure 1: Opta Index Scores for Thierry Henry over season 2003-04 when playing for Arsenal Football Club [18]

Figure 2: The evolution of Thierry Henry's financial value over season 2003-04 [18]

In the same study [18] they noted the number of injured players the rivals of Arsenal for the championship- Manchester United (ManU)- had for that season. It is very clear that, for the second half of the season, ManU's number of injured players was high. Thus it was possible that, along with the Thierry Henry's form for the second part of the season, another reason that ManU could not compete with Arsenal and lost the championship was their high number of injured players together with not having good substitutes to play in the injured players' positions [18]. Figure 2 shows the player's market value after each game he played in that season. Figure 1 and Figure 2 are not necessarily correlated but when his Opta index is high, his market value increased as well.

Figure 3: The evolution of injuries for Manchester United in season 2003-04

3. Study Data and Exploratory Data Analyses

3.1. Data

Data for this thesis was gathered from the official Italian League Website [2]. The data set used was for the 2015-16 season for the professional Italian football league known as Serie A. There were 591 players listed on 20 different teams playing in the league. They played 38 games throughout the entire season - 19 games at home and 19 away games. The information included time spent on the field for each game throughout the season for all the players that played in the Italian professional Serie A league in the season of 2015-16. Other information that was included were Assists, Goals scored, Position of the players, Yellow cards, Red cards, Clean sheet, Win/Lose/Draw table, and the result of the games.

3.1.1. Definition of the Variables

Assists are recorded for the last player who passed the ball for the goal scorer to score a goal.

Clean sheet means a team does not concede any goals in a match.

Positions are divided into Defence, Midfielder, and Striker.

Yellow cards and Red cards: Yellow cards represent a warning. If a player gets two yellow cards in one match, it becomes a red card and the player

must leave the field; their team must play the rest of the game with a player short. a direct red card is when the foul is usually harsh and harmful to the other player. In the data sets made for the yellow card and red card, we have been combined results in such a way that if a player gets a red card without getting a yellow card, instead of recording a one in the yellow card column, a two was entered in the table since two yellow cards have the same weight as one red card.

3.1.2. Structure of the Data Sets

The datasets for Clean sheet, Yellow cards and Red cards, Time played, Goals Scored and Assists had the same structure. The first column was the name of the player, the second column was the team they played on, and the rest of the columns are the teams that they played against in the season. For instance, for the Time Played Table, the numbers represent the minutes played by a player in each game.

3.1.3. Data Wrangling

The first table that needed preparation was the Results table. The Results table has the form below:

Table 5: The structure of Results table

	A	B	C
A		Number-Number	Number-Number
B	Number-Number		Number-Number
C	Number-Number	Number-Number	

A, B and C are the names of the teams. For any game, the column represents the home team and the row represents the away team. The first number is the number of goals that the home team scored, and the second number is the number of goals that the away team scored.

Based on the Results table, a few other tables were generated. The Win/Lose/Draw table and the Clean Sheet table were generated from this table. The Win/Lose/Draw table was made based on the difference of the two numbers in Table 5. A positive number means that the home team won the game, a negative means the away team won the game, and zero means that the game was a tie. For a win, all the winning players in that match were assigned a value of one, for a loss they were assigned -1, and for a draw they were assigned zero.

As explained earlier, if a team does not concede any goals in a match they have a clean sheet. If they had a clean sheet, in the Clean Sheet table, all the players on that team were assigned a value of 1, otherwise they are assigned a value of zero.

Before starting work with the data, some minor changes had to be made. There were some players on the squad for each team that never got the chance to play at any time in the entire season therefore, all the variables for those players were zero. As a result, these players were removed from the data set.

3.2. Exploratory Data Analyses

3.2.1. Descriptive Statistics

The team with the largest number of Clean sheets (CS) was Juventus (22 games out of 38 games); Napoli and Fiorentina (with 15 and 14 Clean sheets, respectively) were next highest. It must be noted that, in the 2015-16 season, Juventus won the league and Napoli was in second place.

For each position, the list of the Top Ten players is presented, based on each variable.

3.2.1.1. Defenders

In the following tables, the top 10 defenders based on each of: time played, number of assists, number of goals, and warning cards are shown.

Time played

Table 6: Top Ten Defenders - playing time

	Player	Team	Overall CS	Overall Assists	Overall Cards	Overall Goals	Overall Time
1	ELSEID HYSAJ	Napoli	15	2	5	0	3441
2	FRANCESCO ACERBI	Sassuolo	11	0	3	4	3426
3	MARIO RUI	Empoli	12	2	8	0	3425
4	RAUL ALBIOL	Napoli	15	1	10	1	3408
5	L. BONUCCI	JUVENTUS	22	1	6	2	3325
6	GIANCARLO GONZALEZ	Palermo	10	0	10	0	3311
7	GONZALO RODRIGUEZ	Fiorentina	14	0	7	4	3309
8	EMILIANO MORETTI	Torino	6	1	4	1	3268
9	FEDERICO PELUSO	Sassuolo	11	1	11	1	3237
10	SIME VRSALJKO	Sassuolo	11	4	10	0	3226

Goals

Table 7: Top Ten players with highest number of Goals

	Player	Team	Overall clean sheet	Overall Assist	Overall Cards	Overall Goals	Overall Time
1	EROS PISANO	Verona	0	0	6	5	3069
2	FRANCESCO ACERBI	Sassuolo	11	0	3	4	3426

3	GONZALO RODRIGUEZ	Fiorentina	14	0	7	4	3309
4	L.DIGNE	Roma	8	3	4	3	2924
5	LEONARDO BLANCHARD	Frosinone	7	1	4	3	2577
6	LUCA ROSSETTINI	Bologna	13	1	12	3	2686
7	LUCA ANTONELLI	Milan	11	1	5	3	2483
8	ALEX	Milan	11	1	2	3	2118
9	MARCOS ALONSO	Fiorentina	14	4	8	3	2479
10	ERVIN ZUKANOVIC	Sampdoria	7	0	6	3	1409

Overall Assists

Table 8:Top Ten players with Assists

	Player	Team	Overall Clean Sheet	Overall Assist	Overall Cards	Overall Goals	Overall Time
1	CRISTIAN ANSALDI	Genoa	12	4	4	0	2132
2	DANIEL PAVLOVIC	Frosinone	7	4	5	0	2036
3	SIME VRSALJKO	Sassuolo	11	4	10	0	3226
4	BRUNO PERES	Torino	6	4	9	2	2745
5	ANDREA RISPOLI	Palermo	10	4	2	0	1511
6	MARCOS ALONSO	Fiorentina	14	4	8	3	2479
7	L.DIGNE	Roma	8	3	4	3	2924
8	FABRIZIO CACCIATORE	Chievo	12	3	6	1	2444
9	FAOUZI GHOULAM	Napoli	15	3	3	0	3066
10	ADAM MASINA	Bologna	13	3	10	2	2820

Warning Cards

Table 9: Top Ten Defenders with highest number of warning cards

	Player	Team	Overall clean sheet	Overall assists	Overall cards	Overall Goals	Overall time
1	MAURICIO	LAZIO	12	0	15	0	2050
2	LARANGEIRA DANILO	UDINESE	9	0	13	0	3122
3	FELIPE	UDINESE	9	1	13	1	2241
4	LEONARDO BLANCHARD	FROSINONE	7	1	12	3	2577
5	ALJAZ STRUNA	PALERMO	10	0	12	1	1915
6	BOSTJAN CESAR	CHIEVO	12	0	11	1	2870
7	KALIDOU KOULIBALY	NAPOLI	15	0	11	0	3039
8	FEDERICO PELUSO	SASSUOLO	11	1	11	1	3237
9	KAMIL GLIK	TORINO	6	0	11	0	3162
10	RICCARDO GAGLIOLO	CARPI	8	0	11	1	2792

3.2.1.2. Midfielders

In the following tables the top 10 Midfielders based on: time played on the field, number of assists, number of goals, warning cards are displayed.

Time played

Table 10: Top Ten Midfielders based on time on the field

	Player	Team	Overall clean sheet	Overall assists	Overall cards	Overall Goal	Overall time
1	MAREK HAMSIK	NAPOLI	15	11	0	6	3362
2	FRANCO VAZQUEZ	PALERMO	10	7	11	8	3343
3	MARTEN DE ROON	ATALANTA	11	2	11	1	3270
4	DIEGO LAXALT	GENOA	12	4	3	3	3261
5	FRANCESCO MAGNANELLI	SASSUOLO	11	1	8	1	3241
6	P. POGBA	JUVENTUS	22	12	10	8	3184
7	PIOTR ZIELINSKI	EMPOLI	12	4	7	5	3175
8	BORJA VALERO	IORE	14	6	5	5	3157
9	TOMAS RINCON	GENOA	12	5	9	3	3102
10	RADJA NAINGGOLAN	ROMA	8	1	12	7	3084

Goals

Table 11: Top Ten Midfielders with highest number of Goals

	Players	Team	Overall clean sheet	Overall assist	Overall cards	Overall Goal	Overall time
1	JOSIP ILICIC	IORE	14	5	2	13	1984
2	MIRALEM PJANIC	ROMA	8	12	12	9	2700
3	FRANCO VAZQUEZ	PALERMO	10	7	11	8	3343
4	ROBERTO SORIANO	SAMP	7	4	7	8	2953
5	P. POGBA	JUVENTUS	22	12	10	8	3184
6	ALESSANDRO FLORENZI	ROMA	8	3	4	7	2865

7	RADJA NAINGGOLAN	ROMA	8	1	12	7	3084
8	EMANUELE GIACCHERINI	BOLOGNA	13	0	7	7	2288
9	VALTER BIRSA	CHIEVO	12	7	4	6	2401
10	SUSO	GENOA	12	1	4	6	1211

Overall Assists

Table 12: Top Ten Midfielders based on Assists

	Player	Team	Over all clean sheet	Over all assist	Over all cards	Over all Goal	Over all time
1	MIRALEM PJANIC	ROMA	8	12	12	9	2700
2	P. POGBA	JUVENTUS	22	12	10	8	3184
3	MAREK HAMSIK	NAPOLI	15	11	0	6	3362
4	RICCARDO SAPONARA	EMPOLI	12	10	8	5	2719
5	BONAVENTUR A	MILAN	11	8	7	6	2811
6	VALTER BIRSA	CHIEVO	12	7	4	6	2401
7	FRANCO VAZQUEZ	PALERMO	10	7	11	8	3343
8	BORJA VALERO	FIORE	14	6	5	5	3157
9	FEDERICO VIVIANI	Verona	0	6	6	3	1688
10	TOMAS RINCON	GENOA	12	5	9	3	3102

Warning Cards

Table 13: Top Ten Midfielders with highest number of warning cards

	Player	Team	Over all clean sheet	Over all assist	Over all cards	Over all Goal	Over all time
1	LORENZO LOLLO	CARPI	8	1	14	3	2223
2	FERNANDO	SAMP	7	2	14	4	3054
3	MIRALEM PJANIC	ROMA	8	12	12	9	2700
4	RADJA NAINGGOLAN	ROMA	8	1	12	7	3084
5	JORGINHO	NAPOLI	15	4	12	0	3051
6	MIRKO GORI	FROSINONE	7	0	11	0	2269
7	DANILO SODDIMO	FROSINONE	7	2	11	1	1886
8	AMADOU DIAWARA	BOLOGNA	13	1	11	0	2897
9	MARTEN DE ROON	ATALANTA	11	2	11	1	3270
10	GIUSEPPE VIVES	TORINO	6	1	11	1	2709

3.2.1.3. Strikers

In the following, the top 10 Strikers based on: time played on the field, number of assists, number of goals, and warning cards are shown.

Time played

Table 14: Top Ten Forwards based on time on the field

	Player	Team	Overall clean sheet	Over all assist	Over all cards	Over all Goal	Over all time
1	CARLOS BACCA	MILAN	11	2	2	18	3316
2	MANUEL PUCCIARELLI	EMPOLI	12	3	2	6	3220
3	GONZALO HIGUAIN	NAPOLI	15	2	3	36	3090
4	DANIEL CIOFANI	FROSINONE	7	1	1	9	3039
5	77 CYRIL THEREAU	UDINESE	9	3	4	11	2950
6	ALEJANDRO GOMEZ	ATALANTA	11	7	6	7	2946
7	JOSE' CALLEJON	NAPOLI	15	7	4	7	2934
8	MOHAMED SALAH	ROMA	8	6	3	13	2838
9	MASSIMO MACCARONE	EMPOLI	12	5	4	13	2778
10	NIKOLA KALINIC	FIORE	14	3	5	12	2727

Goals

Table 15: Top Ten Forwards based on Goals scored

	Player	Team	Over all clean sheet	Over all assist	Over all cards	Over all Goal	Over all time
1	GONZALO HIGUAIN	NAPOLI	15	2	3	36	3090
2	P. DYBALA	JUVENTUS	22	9	1	19	2547
3	CARLOS BACCA	MILAN	11	2	2	18	3316
4	MAURO ICARDI	INTER	15	4	1	16	2699
5	LEONARDO PAVOLETTI	GENOA	12	3	5	14	2118
6	MOHAMED SALAH	ROMA	8	6	3	13	2838

7	MASSIMO MACCARONE	EMPOLI	12	5	4	13	2778
8	LORENZO INSIGNE	NAPOLI	15	10	2	12	2682
9	ANDREA BELOTTI	TORINO	6	4	4	12	2646
10	NIKOLA KALINIC	FIORE	14	3	5	12	2727

Overall Assists

Table 16: Top Ten Forwards based on Assists

	Player	Team	Overall clean sheet	Over all assist	Over all cards	Over all Goal	Over all time
1	LORENZO INSIGNE	NAPOLI	15	10	2	12	2682
2	P. DYBALA	JUVENTUS	22	9	1	19	2547
3	D.PEROTTI	ROMA	8	7	2	3	1275
4	RICCARDO MEGGIORI NI	CHIEVO	12	7	10	5	1712
5	JOSE' CALLEJON	NAPOLI	15	7	4	7	2934
6	ALEJANDRO GOMEZ	ATALANTA	11	7	6	7	2946
7	MIROSLAV KLOSE	LAZIO	12	7	3	7	1442
8	A. MORATA	JUVENTUS	22	7	6	7	1554
9	MOHAMED SALAH	ROMA	8	6	3	13	2838
10	EDIN DZEKO	ROMA	8	6	6	8	2070

Warning Cards

Table 17: Top Ten Forwards based on Warning cards

	Player	Team	Over all clean sheet	Over all assist	Over all cards	Over all Goal	Over all time
1	FEDERICO DIONISI	FROSINONE	7	4	12	9	2580
2	DOMENICO BERARDI	SASSUOLO	11	6	11	7	2257
3	RICCARDO MEGGIORINI	CHIEVO	12	7	10	5	1712
4	10 RIGHT MATT	BOLOGNA	13	3	9	8	2257
5	MAURICIO PINILLA	ATALANTA	11	2	9	5	1412
6	NICOLA SANSONE	SASSUOLO	11	4	8	7	2520
7	SIMONE ZAZA	JUVENTUS	22	0	8	5	721
8	14 DRIES MERTENS	NAPLES	15	5	7	5	1192
9	MARKO LIVAJA	EMPOLI	12	0	7	1	672
10	EDIN DZEKO	ROME	8	6	6	8	2070

3.2.1. Visualization

3.2.1.1. Parallel Coordinates

In order to have a better understanding of how the players performed, a parallel coordinates plot was constructed.

The lines represent all the players for a particular position. The colour scheme we have implemented is to bring attention to players with notable

characteristics. For instance, if a player is coloured differently than yellow it indicates that the player achieved either the highest or lowest value of a certain variable. If two or more players tie for the highest (lowest) value for a particular variable, they are colour-coded the same.

To better understand this graph (since other graphs are too busy) an example with 10 players is presented below.

Figure 4: Parallel Coordinates example

Ggobi is an interactive tool within R that can be used to better understand Ggobi we can hover over a point and identify the player associated with that reading. In the parallel coordinates plot above, the defender M. Wague is highlighted in yellow and we can follow his performance on different attributes. For instance, he has the second highest number of warning cards

amongst all the defenders, he did not score any goals that season and also, he is ranked fourth among his team mates in overall time played on the field. This graph will be used later in the association rule mining section.

Defenders

Figure 5: Parallel Coordinates for Defenders

Midfielders

Figure 6: Parallel Coordinates for Midfielders

Strikers

Figure 7: Parallel Coordinates for Strikers

3.2.1.2. Findings Based on the Parallel Coordinates Plots

With parallel coordinates, we can examine players based on their performance. Recall, if a striker gets a lot of warning cards, it can be troublesome for the team at some point during the season because five (5) yellow cards in different matches or a red card or (2 yellow cards) in a match will result in the player being banned for the next game, resulting in the team being unable to play that player in the next game. Another reason that a striker receives warning cards may be due to the style of game play and tactics used by a team. Usually this type of game play and style requires a striker who is always pressuring the opponent's defenders, thereby causing them to make mistakes.

Another use of parallel coordinates is to examine the overall performance of the players, variable by variable.

From Figures 4-6, it is obvious that, among all 20 teams in the league, only one team had no clean sheets - the team (Frosinone) with the silver color legend. Note that their strikers have not scored many goals - only nine (9) goals in total (Federico Dionisi). In the entire season the team scored only 35 goals, compared to Roma which was the highest scoring team with 83 goals.

Later in the research parallel coordinates will be used to show the performance of a player compared to his teammates.

4. Methodologies

In this chapter, we outline the methodologies proposed to address our research questions.

4.1. Scoring/Ranking Players

The first question was: Can we duplicate the EA Sports' FIFA 2015-16 players' scorings/rankings (since we did not have access to the formulae or the complete data set implemented within the system)?

The two methods we propose are Neural Networks Regression and Ordinal Logistic Regression.

4.1.1. Neural Network Regression

A multiple regression model is a linear combination of $p - 1$ predictors such that

$$E\{Y_i\} = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_{p-1} X_{i,p-1}.$$

A Neural Networks regression model is used to model the response variable as a nonlinear function of various linear combinations of the predictor variables. It is a nonlinear statistical model that contains many more parameters than a linear statistical model. One of the major shortcomings of neural networks regression modelling is that it will usually be over-parameterized - there are parameters that are uninterpretable. On the other hand, neural network regression models often perform better in predicting future responses than regression models.

The simplest but at the same time the most widely-used neural network model, the single-hidden-layer, feedforward neural network, is described below. This model is also referred to as a single-layer perceptron. In this neural networks model, there is one hidden layer with m nodes in the hidden layer and the i th response $Y_i = 1, \dots, n$, is modeled as a nonlinear function g_Y of m derived predictor values $H_{i0}, H_{i1}, \dots, H_{i,m-1}$:

$$Y_i = g_Y(\beta_0 H_{i0} + \beta_1 H_{i1} + \dots + \beta_{m-1} H_{i,m-1}) = g_Y(\mathbf{H}_i' \boldsymbol{\beta}) \quad (1)$$

where

$$\boldsymbol{\beta}_{m \times 1} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{m-1} \end{bmatrix} \text{ and } \mathbf{H}_{i,m \times 1} = \begin{bmatrix} H_{i0} \\ H_{i1} \\ \vdots \\ H_{i,m-1} \end{bmatrix} \text{ and } H_{i0} = 1 \quad (2)$$

The j^{th} predictor value H_{ij} , $j = 1, \dots, m-1$ for the i^{th} observation is a nonlinear function g_j of a linear combination of the original $p-1$ input predictor variables and the bias term, i.e.,

$$H_{ij} = g_j(\mathbf{X}_i' \boldsymbol{\alpha}_j) \quad j = 1, \dots, m-1 \quad (3)$$

where:

$$\boldsymbol{\alpha}_{j,p \times 1} = \begin{bmatrix} \alpha_{j0} \\ \alpha_{j1} \\ \vdots \\ \alpha_{j,p-1} \end{bmatrix} \text{ and } \mathbf{X}_{i,p \times 1} = \begin{bmatrix} X_{i0} \\ X_{i1} \\ \vdots \\ X_{i,p-1} \end{bmatrix}$$

and $X_{i0} = 1$. Note that $\mathbf{X}_i'$ is the i^{th} row of the $\mathbf{X}$ input matrix of predictor variables.

Equations 1 and 3 together form the neural network model:

$$Y_i = g_Y(\mathbf{H}_i' \boldsymbol{\beta}) = g_Y[\beta_0 + \sum_{j=1}^{m-1} \beta_j g_i(\mathbf{X}_i' \boldsymbol{\alpha}_j)] \quad (4)$$

The functions $g_Y, g_1, \dots, g_{m-1}$ are called activation functions in the neural networks literature. To completely specify the neural network model, it is necessary to identify the m activation functions. A common choice for each of these functions is the logistic function:

$$g(Z) = 1/(1 + e^{-Z}) = [1 + e^{-Z}]^{-1} \quad (5)$$

This function is flexible and can be adapted to a variety of circumstances.

Use of n (5) for each of $g_Y, g_1, \dots, g_{m-1}$ in (4) yields the specific neural network model to be discussed in this section:

$$\begin{aligned} Y_i &= [1 + \exp(-\mathbf{H}_i' \boldsymbol{\beta})]^{-1} \\ &= f(\mathbf{X}_i, \alpha_1, \dots, \alpha_{m-1}, \boldsymbol{\beta}) \end{aligned}$$

where $\boldsymbol{\beta}, \alpha_1, \dots, \alpha_{m-1}$ are unknown parameter vectors, $\mathbf{X}_i$ is a vector of known constants.

Neural networks model $f(\mathbf{X}_i, \alpha_1, \dots, \alpha_{m-1}, \boldsymbol{\beta})$ is a special case of a nonlinear regression model. Recall, however, that these models are generally over-parameterized and use of standard estimation methods will result in fitted models that generally have poor

predictive ability. This is analogous to leaving too many unimportant predictors in a linear regression model.

Note that because the logistic activation function is bounded between 0 and 1, it is necessary to scale Y_i so that the scaled value Y_i^{sc} also falls within these limits. This can be accomplished by using:

$$\frac{Y_i - Y_{min}}{Y_{max} - Y_{min}}$$

where Y_{min} and Y_{max} are the minimum and maximum values, respectively, of the response variable. It is also common practice to center and scale each of the predictors to have mean 0 and standard deviation 1. In our work, the response variable is overall player performance rankings from EA Sports' FIFA 2015-16 season. The predictor variables used are, for each player, playing time, goals scored, assists, and warning cards.

The reason that Neural Network (NNET) was chosen, is that this machine learning model has not been examined for use in this context before and also NNET addresses the non-linearity of the problem. Moreover, NNET does not have assumptions and it can be used for almost any type of modeling.

There are other choices for activation functions g for NNET such as: Rectified linear unit (ReLU), Exponential linear unit (ELU) and Tanh. As mentioned before, we used a logistic activation function since it can capture the non-linearity of the relationship between response and predictor variables.

4.1.2. Ordinal Logistic Regression

4.1.2.1. Multiple Logistic Regression Model

Following Kutner et al in [19], when the response variable is binary, we consider that the response variables Y_i are independent Bernoulli random variables with expected values $E\{Y_i\} = \pi_i$ where π_i represents the probability of $Y_i = 1$. Then

$$E\{Y_i\} = \pi_i = \frac{\exp(\beta_0 + \beta_1 X_i)}{1 + \exp(\beta_0 + \beta_1 X_i)}$$

It is simple to extend the equation above to more than one predictor variable. In extending the simple logistic regression model, we simply replace $\beta_0 + \beta_1 X_i$ by $\beta_0 + \beta_1 X_i + \dots + \beta_{p-1} X_{p-1}$. To simplify the formulae, we use matrix notation:

$$\boldsymbol{\beta}_{p \times 1} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{bmatrix}, \quad \mathbf{X}_{n \times p} = \begin{bmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \\ \vdots \\ \mathbf{X}_n \end{bmatrix}, \quad \mathbf{X}_{i \times p} = \begin{bmatrix} 1 \\ X_{i1} \\ X_{i2} \\ \vdots \\ X_{i,p-1} \end{bmatrix}, \quad i=1, \dots, n$$

With this notation, the simple logistic response function extends to the multiple logistic response function as follows:

$$E\{Y_i\} = \pi_i = \frac{\exp(\mathbf{X}_i' \boldsymbol{\beta})}{1 + \exp(\mathbf{X}_i' \boldsymbol{\beta})}$$

and

$$E\{Y\} = \pi = \frac{\exp(X'\beta)}{1 + \exp(X'\beta)}$$

The logit transformation is:

$$\pi' = \log_e \left(\frac{\pi}{1 - \pi} \right)$$

and gives the logit response function in the form of a linear predictor:

$$\pi' = X'\beta$$

The multiple logistic regression model can therefore be stated as follows:

Y_i are independent Bernoulli random variables with expected values $E\{Y_i\} = \pi_i$ where

$$E\{Y_i\} = \pi_i = \frac{\exp(X'_i\beta)}{1 + \exp(X'_i\beta)}$$

where the observations X are considered to be known constants. Alternatively, if the X are random, $E\{Y_i\}$ is viewed as a conditional mean, given the values of $X_{i1}, \dots, X_{i,p-1}$.

Like the simple logistic response function, the multiple logistic response function is monotonic and sigmoidal in shape with respect to $X'\beta$ and is almost linear when π is between 0.2 and 0.8. The X predictor variables may be quantitative or qualitative and represented by indicator variables. This flexibility makes the multiple logistic regression model very attractive.

4.1.2.2. Ordinal Logistic Regression

Following Winship and de Mane [20] and Liu et al [21], an ordinal logistic regression model is a generalization of a binary logistic regression model when the outcome variable has more than two ordinal levels. It estimates the probability of being at or below a specific outcome level, conditional on a collection of explanatory variables.

The ordinal logistic model can be expressed as a latent variable model [22] [23].

Consider a set of observations n and vectors $X_1, X_2, \dots, X_{p-1}$ that represent our predictor variables and responses $Y_1, Y_2, \dots, Y_k$ where Y_i is an ordinal variable $1, \dots, k$. We fit a coefficient vector β of length p and a set of thresholds $\theta_1, \dots, \theta_k$ where $\theta_1 < \theta_2 < \dots < \theta_k$ is always true.

These thresholds divide the real number line into k disjoint segments, corresponding to the k responses [24]. Now the model becomes

$$\Pr(Y \leq i | \mathbf{X}) = \frac{1}{1 + e^{-(\theta_i - \beta' \mathbf{X})}}.$$

Assuming the latent variable model Y^* exists, it will be determined as

$$Y^* = \beta' \mathbf{X} + \varepsilon$$

where ε is distributed $N(0,1)$ conditioned on $\mathbf{X}$. The values of the observed ordinal variable Y fall within the regions divided by the cut points (thresholds). For example, $Y = 0$ if $Y^* \leq \theta_1$. and

$$y = \left\{ \begin{array}{ll} 1 & \text{if } y^* \leq \theta_1 \\ 2 & \text{if } \theta_1 < y^* \leq \theta_2 \\ 3 & \text{if } \theta_2 < y^* \leq \theta_3 \\ \vdots & \vdots \\ k & \text{if } \theta_{k-1} < y^* \leq \theta_k \end{array} \right\}$$

We then find the conditional distribution of Y as

$$\begin{aligned} P(Y = k|\mathbf{X}) &= P(\theta_{k-1} < Y^* \leq \theta_k|\mathbf{X}) \\ &= P(\theta_{k-1} < \boldsymbol{\beta}'\mathbf{X} + \varepsilon \leq \theta_k) \\ &= \Phi(\theta_k - \boldsymbol{\beta}'\mathbf{X}) - \Phi(\theta_{k-1} - \boldsymbol{\beta}'\mathbf{X}) \end{aligned}$$

where Φ is the cumulative distribution function of the standard normal distribution.

The log-likelihood of the model for a single training example $\mathbf{x}_i, y_i$ can now be written as:

$$\text{loglikelihood}(\boldsymbol{\beta}, \boldsymbol{\theta}|\mathbf{x}, y) = \sum_{j=1}^k [y_i = j] \log [\Phi(\theta_j - \boldsymbol{\beta}'\mathbf{X}) - \Phi(\theta_{j-1} - \boldsymbol{\beta}'\mathbf{X})]$$

4.1.2.3 Comparison of scoring and ranking methods

To compare the two proposed scoring methods with the FIFA EASports scoring, we use repeated measures one-way ANOVA and, if we conclude there are differences, employ multiple comparison methods to assess the differences. To compare the three ranking methods, we use Spearman correlations and inter-rater reliability methods (IRR).

4.2. Methodology to address the second research question: Association rule mining

The second research question was: Is there a way to find if a player playing in a match increases the chance of winning for his particular team? Furthermore, can we find the combinations of players that are associated with a team winning (or losing)? In order to answer these questions, we employ association rule mining.

It is most often applied to binary-valued data $X_j \in \{0,1\}$, where it is referred to as “market basket” analysis. In that context the observations are sales transactions, such as those occurring at the checkout counter of a store. The variables represent all of the items sold in the store. For observation i , each variable X_j is assigned one of two values; $x_{ij} = 1$ if the j^{th} item is purchased as part of the transaction, whereas $x_{ij} = 0$ if it was not purchased. In any row, those variables that frequently have joint values of one represent items that are frequently purchased together. More generally, the basic goal of association rule analysis is to find a collection of prototypes X -values $v_1, \dots, v_L$ for the feature vector X , such that the probability density $\Pr(v_l)$ evaluated at each of those values is relatively large. In this general framework the problem can be viewed as “mode finding” or “bump hunting.” As formulated, this problem is impossibly difficult. A natural estimator for each $\Pr(v_l)$ is the fraction of observations for which $X = v_l$. For problems that involve more than a small number of values, the number of observations for which $X = v_l$ will nearly always be too small for reliable estimation.

In order to have a tractable problem, both the goals of the analysis and the generality of the data to which it is applied must be greatly simplified.

An association rule is a rule such that “If a customer buys Item A and Item B, they often buy C as well”

$$i.e. A \text{ and } B \Rightarrow C$$

4.2.1. The Apriori Algorithm

The Apriori algorithm uses three key components to determine how a rule is a good rule. These components are: support, confidence and lift. The idea is to only look at the highly probable sets and combine them; otherwise, since the number of items are high, it makes it impossible to inspect all combinations of items. The Apriori algorithm uses the fact that if an itemset is infrequent, then all the combinations of that itemset with other itemsets must also be infrequent.

Below are definitions of support, confidence and lift that are used to examine rules that are found.

The first key component is support:

$$Support(A, B, C) = \left(\frac{Number\ of\ items\ containing\ A, B\ and\ C}{Total\ number\ of\ baskets} \right) \times 100\%$$

$$= P(A \cap B \cap C)$$

Only those sets exceeding a specified level of support are considered as candidates for further analysis. This will reduce the number of rules and combinations.

The second key component is confidence:

$$\begin{aligned} \text{Confidence}(\text{rule}) &= \left(\frac{\text{Support}(A, B, C)}{\text{Support}(A, B)} \right) \times 100\% \\ &= P(C|A \cap B) \end{aligned}$$

By setting the confidence of a rule fairly high and restricting the rules to combinations of A and B only with sufficient support, still the desired results have to actually hold high confidence.

The last component is lift of a rule of the form $A \text{ and } B \Rightarrow C$:

$$\begin{aligned} \text{Lift}(\text{rule}) &= \left(\frac{\text{Confidence}(A, B, C)}{\text{Confidence}(A, B)} \right) \times 100\% \\ &= \frac{P(C|A \cap B)}{P(C)} \end{aligned}$$

In short, after restricting the results to things that occur often enough (support) and looking at how confident the rule would hold (confidence), interesting rules are the ones that really result in significant “improvement” (lift).

If we go back to the research question, we are interested to find out which player or set of players is most associated with a team winning (or losing) a match.

5. Results

5.1. Scoring/Ranking Players Based on Performance during the 2015-16 Season

The variables used in the analyses were:

- the number of clean sheets during the entire season
- the number of goals scored
- the number of assists
- the total time they spent on the pitch
- the number of warning cards

It is already known [25] that the more warning cards a player has, the greater the potential of having a negative effect on team performance, either as result of being

banned from a game or even being sent off during the same match if the player gets two (2) yellow cards in the same match or one (1) red card, (which will also result in being banned from the next match). In some cases, based on the intensity of the foul, a player can even get banned for a few matches.

We used two methods to score (and subsequently rank) players. We compared the results with a reference method - the best available was for FIFA from EASports, which is a football video game [26]. We tested to determine if either or both of these methods could duplicate the FIFA EASports scoring.

5.1.1. Preparation of the Data for Scoring and Ranking

First, we needed to remove players for whom there was no record in EASports, since they were not ranked by FIFA [26]. Goalkeepers are not included in our analysis so they were removed as well from the dataset. This reduced the number of players to 544. We also noted that there were players for whom there were no readings for the variables. Removing them reduced the dataset to 489 players. These 489 players all played at least one minute during the season and their EASports FIFA ranking existed. In the following we discuss how our scoring models were built.

5.1.1.1. *Predictor Variables*

We began by examining relationships among the predictor variables. Including variables that are highly correlated with each other may result in unstable models due

to multicollinearity. The Performance Analytics package in R [27] was used to obtain Figure 20, the chart of the correlation matrix for the variables. From this visualization, we found the correlation between Overall Time and Total cards was 0.69 and between Overall goals and Overall assists was 0.55.

Figure 8:Chart of Correlation Matrix for predictor variables

5.1.2. Scoring Players: Using Neural Networks

As mentioned before, the predictor variables for this model were:

- Overall time played during the season
- Total number of goals scored by the player
- Total number of warning cards received by the player (Combination of red cards and yellow cards. Each red card was treated as equivalent to two yellow cards)
- Total Clean sheets for the entire season
- Total number of assists by the player for the entire season
- Indicator of position played. Two indicator variables were used in order to define position- the first was the defender indicator; the second was the midfield indicator. If both were zero the player was a striker.

5.1.2.1. Building the Model

The first attempt to build the model used a Neural Network with a single hidden layer with two nodes in the hidden layer and did not define any starting weights in the code, hence the starting weights were randomly chosen.

The results were as follows:

Sum Square of Errors (Model 1) = 10974.57

Summary Statistics from fitted predictions:

Table 18: The summary of NNET Model1 with two hidden nodes and no initial assigned weights

Min	73.83
1st Quarter	73.83
Median	73.83
Mean	73.83
3rd Quarter	73.83
Max	73.83

These results indicated that all of the predictions were 73.83; this did not seem reasonable and the sum of squares for error (SSE) was very high. The residuals plot below (Fig. 21) showed the poor fit of this initial model.

Figure 9: Residual Plot using 2 hidden Nodes with for NNet Model1 and random initial weights

The second attempt used the final weights from this first model as a starting point and built a model again with two nodes in the hidden layer. The results were follows:

Table 19: The summary of NNET Model2 with two hidden nodes with starting weights from the NNET Model1

Min	73.83
1st Quarter	73.83
Median	73.83
Mean	73.83
3rd Quarter	73.83
Max	73.83

As shown in Table 19, the results were still not good. This second model shows the same SSE for as Model 1 (=10974.57). The corresponding plot of residuals (Fig. 9) demonstrated that there were many predictions that were far from the EASports' scorings.

Figure 10: Residual Plot for NNET Model2 using 2 hidden nodes with initial weights from NNet Model1

The next attempt added more nodes to the hidden layer. It consisted of ten (10) hidden nodes, without predefining any starting weights. The results were as follows:

Table 20: The summary of NNET Model3 with ten nodes in hidden layer and no initial starting weights

Min	58.99
1st Quarter	71.86
Median	73.17
Mean	73.83
3rd Quarter	75.41
Max	83

Figure 11: Residual Plot for NNET Model3 with ten nodes in hidden layer and no initial starting weights

In NNET Model3 we note that the distribution of errors appeared random and there were no obvious trends or systematic patterns in the plot. The SSE Model 3=4908.264 has improved substantially.

Re-running the analysis but with starting weights obtained from the final weights of NNET Model3, we obtained NNET Model4. This model resulted in the same SSE (=4908.264) as Model3.

The result of the model is as follows:

Table 21: The summary of NNET Model4 with 10 nodes in the hidden layer and starting weights from NNET Model4

Min	52.94
1st Quarter	71.89
Median	73.44
Mean	73.83
3rd Quarter	75.55
Max	86.69

The residual plot in Figure 11 shows randomness with most readings around zero.

Figure 12: Residual Plot for NNET Model4

Using NNET Model4 we obtained the following table of predicted scores for the players:

Table 22: Players with EASports score and prediction from NNET Model4

Player	Team	FIFA Rating	Predicted Value
GONZALO HIGUAIN	NAPOLI	86	86.69
P. POGBA	JUVENTUS	86	85.30
P. DYBALA	JUVENTUS	81	84.26
L. BONUCCI	JUVENTUS	83	83.40
MIRALEM PJANIC	ROMA	84	82.92
M. MANDZUKIC	JUVENTUS	82	82.61
A. MORATA	JUVENTUS	80	82.46
MAURO ICARDI	INTER	80	82.31
P. EVRA	JUVENTUS	81	82.12
LORENZO INSIGNE	NAPOLI	82	82.03

A. BARZAGLI	JUVENTUS	85	81.95
JUAN CUADRADO	JUVENTUS	81	81.90
CLAUDIO MARCHISIO	JUVENTUS	84	81.26
ALEX SANDRO	JUVENTUS	82	81.09
S. LICHTSTEINER	JUVENTUS	82	81.04
MAREK HAMSIK	NAPOLI	82	80.95
G. CHIELLINI	JUVENTUS	86	80.89
SAMI KHEDIRA	JUVENTUS	81	80.57
CARLOS BACCA	MILAN	82	80.49
JOSE' CALLEJON	NAPOLI	81	80.15
HERNANES	INTER	80	79.98
SIMONE ZAZA	JUVENTUS	79	79.93
RAUL ALBIOL	NAPOLI	81	79.84
JOSIP ILICIC	FIORE	80	79.78
EDER	SAMP	79	79.65
JORGINHO	NAPOLI	79	79.55
RICCARDO SAPONARA	EMPOLI	78	79.48
MIRANDA	INTER	85	79.43
ELSEID HYSAJ	NAPOLI	77	79.37
I.PERISIC	INTER	81	79.35
MIROSLAV KLOSE	LAZIO	79	79.35
DANIELE RUGANI	JUVENTUS	78	79.30
EL SHAARAWY	ROMA	79	79.19
KALIDOU KOULIBALY	NAPOLI	80	79.16
JEISON MURILLO	INTER	79	79.16
MOHAMED SALAH	ROMA	80	79.16
FRANCESCO ACERBI	SASSUOLO	79	79.12
S. STURARO	JUVENTUS	77	79.01
ADEM LJAJIC	ROMA	79	78.99
HERNANES	JUVENTUS	80	78.93
FAOUZI GHOULAM	NAPOLI	78	78.66
ALLAN	NAPOLI	80	78.61
BORJA VALERO	FIORE	82	78.61
D.PEROTTI	ROMA	79	78.52
GONZALO RODRIGUEZ	FIORE	81	78.38
KWADWO ASAMOAH	JUVENTUS	79	78.31
MASSIMO MACCARONE	EMPOLI	75	78.26
ALEJANDRO GOMEZ	ATALANTA	78	78.21

MARIO LEMINA	JUVENTUS	76	78.19
FEDERICO BERNARDESCHI	FIORE	77	78.17
BONAVENTURA	MILAN	80	78.17
MARCELO BROZOVIC	INTER	78	78.10
VICTOR IBARBO	ROMA	78	78.06
KINGSLEY COMAN	JUVENTUS	78	78.01
VALTER BIRSA	CHIEVO	75	78.01
ADAM MASINA	BOLOGNA	73	78.00
MARCOS ALONSO	FIORE	75	78.00
VICTOR IBARBO	ROMA	78	77.96
FERNANDO LLORENTE	JUVENTUS	80	77.94
R. PEREYRA	JUVENTUS	80	77.91
MARIO RUI	EMPOLI	76	77.85
FRANCO VAZQUEZ	PALERMO	80	77.84
EDIN DZEKO	ROMA	80	77.74
RICCARDO MEGGIORINI	CHIEVO	75	77.72
MARTIN CACERES	JUVENTUS	80	77.69
DAVIDE ASTORI	FIORE	79	77.67
SIMONE PADOIN	JUVENTUS	74	77.64
GARY MEDEL	INTER	81	77.62
MATTIA DESTRO	BOLOGNA	76	77.60
SIME VRSALJKO	SASSUOLO	77	77.60
DOMENICO BERARDI	SASSUOLO	81	77.56
LUCA ANTONELLI	MILAN	77	77.54
DRIES MERTENS	NAPOLI	81	77.54
TOMAS RINCON	GENOA	75	77.54
FACUNDO RONCAGLIA	FIORE	75	77.53
MANUEL PUCCIARELLI	EMPOLI	73	77.49
GERVINHO	ROMA	80	77.40
MAURICIO ISLA	JUVENTUS	75	77.30
RODRIGO PALACIO	INTER	79	77.23
LEONARDO PAVOLETTI	GENOA	75	77.22
PIOTR ZIELINSKI	EMPOLI	74	77.16
FEDERICO PELUSO	SASSUOLO	73	77.11
ANDREA BELOTTI	TORINO	75	77.10
LUIS MURIEL	SAMP	75	77.04
ALBERTO PALOSCHI	CHIEVO	77	77.00
CYRIL THEREAU	UDINESE	77	77.00

BOSTJAN CESAR	CHIEVO	77	76.92
NICOLA SANSONE	SASSUOLO	77	76.89
ARMANDO IZZO	GENOA	74	76.89
DANIEL CIOFANI	FROSINONE	72	76.82
DUSAN BASTA	LAZIO	79	76.81
STEVAN JOVETIC	INTER	80	76.78
MATIAS VECINO	FIORE	75	76.77
MARTEN DE ROON	ATALANTA	76	76.75
DIEGO LAXALT	GENOA	73	76.69
BOUKARY DRAME'	ATALANTA	74	76.68
MASSIMO GOBBI	CHIEVO	73	76.66
DANIELE GASTALDELLO	BOLOGNA	76	76.62
ANTONIO CANDREVA	LAZIO	81	76.61
FELIPE MELO	INTER	79	76.60
LUCA ROSSETTINI	BOLOGNA	74	76.57
ALESSIO ROMAGNOLI	MILAN	76	76.54
YUTO NAGATOMO	INTER	74	76.49
FELIPE ANDERSON	LAZIO	79	76.46
GEOFFREY KONDOGBIA	INTER	76	76.46
MILAN BADELJ	FIORE	78	76.39
FRANCESCO TOTTI	ROMA	79	76.39
SENAD LULIC	LAZIO	77	76.33
P.KONE	FIORE	75	76.31
MANOLO GABBIADINI	NAPOLI	78	76.31
M'BAYE NIANG	MILAN	75	76.26
ALEX TELLES	INTER	76	76.22
A.IONITA	Verona	74	76.20
LUCAS CASTRO	CHIEVO	75	76.16
LUCAS BIGLIA	LAZIO	81	76.11
MAURICIO	LAZIO	78	76.11
FABRIZIO CACCIATORE	CHIEVO	72	76.09
LEANDRO PAREDES	EMPOLI	74	76.04
FRANCESCO MAGNANELLI	SASSUOLO	76	76.01
DANILO D'AMBROSIO	INTER	74	75.99
LORENZO TONELLI	EMPOLI	78	75.97
A. RUDIGER	ROMA	76	75.93
PAOLO CANNAVARO	SASSUOLO	75	75.88
NICOLAS BURDISO	GENOA	76	75.82

C.TELLO	FIORE	78	75.81
EMILIANO MORETTI	TORINO	77	75.80
OSCAR HILJEMARK	PALERMO	72	75.77
MARCO PAROLO	LAZIO	80	75.71
GREGOIRE DEFREL	SASSUOLO	73	75.68
ADAM LJAJIC	INTER	79	75.66
LARANGEIRA DANILO	UDINESE	76	75.66
SEBASTIAN DE MAIO	GENOA	76	75.64
MARCO BORRIELLO	CARPI	74	75.62
FABIO QUAGLIARELLA	TORINO	78	75.60
KEITA	LAZIO	77	75.50
CRISTIAN ANSALDI	GENOA	79	75.49
FEDERICO DIONISI	FROSINONE	72	75.46
NENAD TOMOVIC'	FIORE	75	75.42
LUCA TONI	Verona	74	75.41
EMANUELE GIACCHERINI	BOLOGNA	77	75.38
ALFRED DUNCAN	SASSUOLO	73	75.32
MARIOS OIKONOMOU	BOLOGNA	75	75.23
ANTHONY MOUNIER	BOLOGNA	76	75.19
ROBERTO SORIANO	SAMP	76	75.14
SIMONE PEPE	CHIEVO	76	75.14
M.BISEVAC	LAZIO	77	75.13
JURAJ KUCKA	MILAN	77	75.04
SAPHIR TAIDER	BOLOGNA	73	74.96
ANTONIO DI NATALE	UDINESE	77	74.94
C.IMOOBILE	TORINO	79	74.93
SANTIAGO GENTILETTI	LAZIO	77	74.91
WESLEY HOEDT	LAZIO	75	74.90
ANDREA MASIELLO	ATALANTA	73	74.89
ANDREA MASIELLO	ATALANTA	73	74.89
FRANCO BRIENZA	BOLOGNA	75	74.89
I.ABATE	MILAN	77	74.84
MATIAS FERNANDEZ	FIORE	76	74.84
RICCARDO MONTOLIVO	MILAN	79	74.83
BLERIM DZEMAILI	GENOA	72	74.83
JONATHAN BIABIANI	INTER	77	74.82
MAXIMILIANO MORALES	ATALANTA	76	74.82
FREDY GUARIN	INTER	79	74.78

MAURICIO PINILLA	ATALANTA	76	74.77
GABRIEL PALETTA	ATALANTA	77	74.77
IVAN RADOVANOVIC	CHIEVO	73	74.76
MANUEL PASQUAL	FIORE	72	74.76
FABIO QUAGLIARELLA	SAMP	78	74.74
LUIZ ADRIANO	MILAN	79	74.71
KHOUMA BABACAR	FIORE	75	74.69
ANDREA COSTA	EMPOLI	74	74.67
KOSTAS MANOLAS	ROMA	83	74.65
PERPARIM HETEMAJ	CHIEVO	75	74.63
MAURO ZARATE	FIORE	76	74.59
VINCENT LAURINI	EMPOLI	71	74.55
DANILO CATALDI	LAZIO	73	74.54
DUVAN ZAPATA	UDINESE	77	74.54
NICOLA RIGONI	CHIEVO	72	74.54
LUCA SILIGARDI	Verona	73	74.50
FILIP DJORDJEVIC	LAZIO	79	74.50
RADJA NAINGGOLAN	ROMA	83	74.43
ALESSANDRO FLORENZI	ROMA	79	74.43
L.CIGARINI	ATALANTA	76	74.42
DAVIDE SANTON	INTER	75	74.41
BRUNO FERNANDES	UDINESE	75	74.40
JASMIN KURTIC	ATALANTA	74	74.39
DOMENICO MAIETTA	BOLOGNA	73	74.35
MATTEO POLITANO	SASSUOLO	69	74.35
OMAR EL KADDOURI	NAPOLI	77	74.34
FELIPE	UDINESE	73	74.33
ANTONIO FLORO FLORES	SASSUOLO	72	74.33
MAXI LOPEZ	TORINO	77	74.28
ALEX	MILAN	79	74.25
FERNANDO	SAMP	70	74.22
FEDERICO VIVIANI	Verona	73	74.20
MARCEL BUCHEL	EMPOLI	71	74.16
JUAN JESUS	INTER	75	74.13
ALEX FERRARI	BOLOGNA	67	74.13
IAGO FALQUE	ROMA	78	74.10
GIUSEPPE ROSSI	FIORE	78	74.08
LUCA RIZZO	BOLOGNA	71	74.08

ROBERTO INGLESE	CHIEVO	70	74.08
GODFRED DONSAH	BOLOGNA	73	74.07
RICCARDO GAGLIOLO	CARPI	71	74.07
DIEGO PEROTTI	GENOA	79	74.06
ALJAZ STRUNA	PALERMO	67	74.04
ANTONIO DI GAUDIO	CARPI	72	74.03
SUSO	GENOA	75	74.03
GIAMPAOLO PAZZINI	Verona	74	74.00
AMAURO	TORINO	74	74.00
L.DIGNE	ROMA	77	73.99
ACHRAF LAZAAR	PALERMO	73	73.99
S.FLOCCARI	BOLOGNA	73	73.98
KEISUKE HONDA	MILAN	77	73.98
DAVID LOPEZ	NAPOLI	76	73.90
ALESSANDRO GAMBERINI	CHIEVO	77	73.88
MARCO D'ALESSANDRO	ATALANTA	69	73.84
KEVIN LASAGNA	CARPI	71	73.83
P.WSZOLEK	Verona	72	73.81
VLAD CHIRICHES	NAPOLI	76	73.79
A.CERCI	GENOA	77	73.79
EDER	INTER	79	73.78
MATTIA DE SCIGLIO	MILAN	75	73.77
ALESSANDRO MATRI	LAZIO	77	73.75
L.PASCIUTI	CARPI	71	73.73
EMMANUEL BADU	UDINESE	74	73.72
SALIH UCAN	ROMA	73	73.7
SERGEJ MILINKOVIC-SAVIC	LAZIO	75	73.70
SIMONE MISSIROLI	SASSUOLO	75	73.70
K.STROOTMAN	ROMA	80	73.65
GAETANO LETIZIA	CARPI	72	73.63
S.SABELLI	CARPI	67	73.62
JAKUB BLASZCZYKOWSKI	FIORE	78	73.61
PANAGIOTIS KONE	UDINESE	75	73.54
PANAGIOTIS TACHSIDIS	GENOA	74	73.53
EZEQUIEL MUNOZ	GENOA	72	73.53
DANIELE BASELLI	TORINO	78	73.51
DARIO DAINELLI	CHIEVO	74	73.50
SERGE GAKPE'	GENOA	74	73.49

PONTUS JANSSON	TORINO	75	73.49
GERMAN DENIS	ATALANTA	75	73.48
GERMAN DENIS	ATALANTA	75	73.48
ANDREA BERTOLACCI	MILAN	76	73.48
MATTEO BRIGHI	BOLOGNA	70	73.47
ABDOULAY KONKO	LAZIO	75	73.46
IBRAHIMA MBAYE	BOLOGNA	68	73.44
MATO JAJALO	PALERMO	72	73.43
MARCO BORRIELLO	ATALANTA	74	73.42
LEONARDO BLANCHARD	FROSINONE	71	73.42
BRUNO PERES	TORINO	80	73.39
NICOLAS FREY	CHIEVO	72	73.37
STEFANO MAURI	LAZIO	79	73.37
SERGIO PELLISSIER	CHIEVO	72	73.36
SINISA ANDELKOVIC	PALERMO	74	73.35
KAMIL GLIK	TORINO	82	73.35
R.ALVAREZ	SAMP	77	73.32
ANDREA RISPOLI	PALERMO	64	73.26
J.DE GUZMAN	CARPI	76	73.24
LORENZO LOLLO	CARPI	71	73.22
STEFAN RADU	LAZIO	79	73.21
MARKO LIVAJA	EMPOLI	69	73.21
MARIO BALOTELLI	MILAN	79	73.18
SIMONE ROMAGNOLI	CARPI	70	73.15
JUANITO GOMEZ	Verona	73	73.13
DIEGO FALCINELLI	SASSUOLO	69	73.08
MIRKO VALDIFIORI	NAPOLI	76	73.06
IVAYLO CHOCEV	PALERMO	70	73.05
U.EMANUELSON	Verona	74	73.05
CHRISTIAN MAGGIO	NAPOLI	75	73.02
CRISTIAN ZACCARDO	CARPI	73	72.99
DANIELE CROCE	EMPOLI	74	72.99
DANIELE CROCE	EMPOLI	74	72.99
ANDREA LAZZARI	CARPI	72	72.97
RAMAN CHIBSAH	FROSINONE	68	72.97
SAMUELE LONGO	FROSINONE	69	72.96
ROBIN QUAISON	PALERMO	73	72.95
OGENYI ONAZI	LAZIO	75	72.88

AFRIYIE ACQUAH	TORINO	73	72.84
SILVAN WIDMER	UDINESE	75	72.82
GORAN PANDEV	GENOA	74	72.82
SERGIO FLOCCARI	SASSUOLO	73	72.82
EDENILSON	UDINESE	74	72.81
JERRY MBAKOGU	CARPI	73	72.81
V.REGINI	NAPOLI	71	72.80
K. BOATENG	MILAN	77	72.80
A. TABACCHI	BOLOGNA	67	72.78
ALEKSANDAR TRAJKOVSKI	PALERMO	67	72.74
LUCA RIGONI	GENOA	73	72.74
ANDREA POLI	MILAN	75	72.72
RICARDO KISHNA	LAZIO	75	72.70
MARTIN MONTOYA	INTER	78	72.69
MATTEO MANCOSU	BOLOGNA	70	72.68
A.FLORO FLORES	CHIEVO	72	72.67
IVAN STRINIC	NAPOLI	73	72.67
RAFAEL MARQUEZ	Verona	76	72.65
LUCA PAGANINI	FROSINONE	65	72.64
OLIVIER NTCHAM	GENOA	64	72.63
FEDERICO BARBA	EMPOLI	71	72.62
ANGELO PALOMBO	SAMP	71	72.62
MARCO ZAMBELLI	EMPOLI	68	72.61
DANIELE DE ROSSI	ROMA	82	72.59
S.GAKPE	ATALANTA	74	72.57
R.FREULER	ATALANTA	67	72.56
B.CRISTANTE	PALERMO	72	72.55
ALESSIO CERCI	MILAN	77	72.53
J.OBI	TORINO	72	72.53
RODRIGO AGUIRRE	UDINESE	67	72.53
GIAMPIERO PINZI	CHIEVO	73	72.53
ANDREA RANOCCHIA	INTER	77	72.53
DANIEL PAVLOVIC'	FROSINONE	65	72.51
ERICK PULGAR	BOLOGNA	68	72.50
MARCO BENASSI	TORINO	75	72.48
CHRISTIAN ZAPATA	MILAN	76	72.46
LORENZO PELLEGRINI	SASSUOLO	65	72.44
GUILHERME	UDINESE	74	72.44

GERMAN DENIS	ATALANTA	75	72.44
GERMAN DENIS	ATALANTA	75	72.44
RAFFAELE BIANCO	CARPI	69	72.44
SUSO	MILAN	75	72.43
ISAAC COFIE	CARPI	71	72.40
LEVAN MCHEDLIDZE	EMPOLI	71	72.39
N.SPOLLI	CHIEVO	74	72.39
ROMULO	Verona	73	72.39
IVAN PIRIS	UDINESE	75	72.37
GUGLIELMO STENDARDO	ATALANTA	74	72.37
M.WAGUE	UDINESE	73	72.34
GILBERTO	FIORE	69	72.33
JOAQUIN CORREA	SAMP	71	72.32
U. COSIC	EMPOLI	68	72.32
A. FARNERUD	TORINO	72	72.29
J.ZUNIGA	BOLOGNA	72	72.27
J.MENEZ	MILAN	81	72.27
NIGEL DE JONG	MILAN	77	72.24
T. MATAVZ	GENOA	72	72.22
GIUSEPPE VIVES	TORINO	74	72.22
LORENZO CRISSETIG	BOLOGNA	71	72.21
ALEKSANDAR TONEV	FROSINONE	67	72.21
TINO COSTA	GENOA	76	72.20
STIPE PERICA	UDINESE	70	72.17
ISSA CISSOKHO	GENOA	73	72.17
DANILO SODDIMO	FROSINONE	68	72.16
GASTON BRUGMAN	PALERMO	68	72.16
FRANCESCO LODI	UDINESE	73	72.14
DANILO AVELAR	TORINO	75	72.13
FILIPPO FALCO	BOLOGNA	64	72.12
ANDREA CONTI	ATALANTA	67	72.11
LUCA RIGONI	PALERMO	73	72.10
GIOVANNI MARCHESE	GENOA	74	72.08
DANIELE CROCE	EMPOLI	74	72.07
DANIELE CROCE	EMPOLI	74	72.07
PAOLO SAMMARCO	FROSINONE	68	72.06
KARIM LARIBI	SASSUOLO	69	72.05
EROS PISANO	Verona	72	72.04

DANIELE VERDE	FROSINONE	69	72.02
GIOVANNI PASQUALE	UDINESE	69	72.01
NENAD KRSTICIC	SAMP	72	72.00
MARQUINHO	UDINESE	76	72.00
PAWL WSZOLEK	SAMP	72	72.00
RAFFAELE MAIELLO	EMPOLI	66	71.99
MATTEO FEDELE	CARPI	67	71.97
NICOLO' CHERUBIN	ATALANTA	72	71.96
MATTEO BIANCHETTI	Verona	71	71.95
DIEGO CAPEL	GENOA	75	71.93
GIANPAOLO BELLINI	ATALANTA	68	71.92
JUAN ITURBE	ROMA	77	71.92
F.HELANDER	Verona	73	71.91
ALBERTO GRASSI	ATALANTA	70	71.90
ALESSANDRO FRARA	FROSINONE	67	71.89
EDOARDO GOLDANIGA	PALERMO	70	71.87
G.MONACHELLO	ATALANTA	66	71.84
MIRKO GORI	FROSINONE	66	71.84
MASSIMILIANO CARLINI	FROSINONE	67	71.82
NICOLAS CASTILLO	FROSINONE	73	71.81
DAVIDE BIONDINI	SASSUOLO	70	71.81
J.SALA	SAMP	72	71.80
JURAJ KUCKA	GENOA	77	71.79
ARCHIMEDE MORLEO	BOLOGNA	70	71.79
LUCA MARONE	CARPI	70	71.78
EVANGELOS MORAS	Verona	74	71.77
DAVIDE BRIVIO	ATALANTA	72	71.76
MATTIA CASSANI	SAMP	72	71.75
MICHEL MORGANELLA	PALERMO	67	71.73
G.SILVA	GENOA	70	71.73
MANUEL ITURRA	UDINESE	74	71.72
ANTONIO NOCERINO	MILAN	72	71.71
ALEANDRO ROSI	FROSINONE	70	71.68
CRISTIAN RAIMONDI	ATALANTA	67	71.65
K.CONSTANT	BOLOGNA	71	71.64
GIULIO MIGLIACCIO	ATALANTA	71	71.63
ENZO MARESCA	PALERMO	74	71.61
M.MANCOSU	CARPI	70	71.60

GENNARO SARDO	CHIEVO	66	71.56
CARLOS CARMONA	ATALANTA	74	71.56
WALLACE	CARPI	67	71.55
S.VERDI	CARPI	71	71.55
MAICON	ROMA	77	71.50
JOSE' MAURI	MILAN	72	71.48
MARCELLO GAZZOLA	SASSUOLO	66	71.47
MATIAS SILVESTRE	SAMP	73	71.47
M.CRIMI	CARPI	66	71.45
R. FIAMOZZI	GENOA	65	71.45
L.ANTEI	SASSUOLO	71	71.44
LUCA BITTANTE	EMPOLI	67	71.43
R.MARTINHO	CARPI	72	71.43
L.MARONE	Verona	70	71.42
GABRIEL SILVA	CARPI	70	71.40
JACOPO SALA	Verona	72	71.37
EMIL HALLFREDSSON	Verona	74	71.37
EDGAR BARRETO	SAMP	73	71.32
L. DE SILVESTRI	SAMP	76	71.23
EDSON BRAAFHEID	LAZIO	72	71.22
PHILIPPE MEXES	MILAN	77	71.15
ALESSANDRO GAZZI	TORINO	74	71.09
Z.KUZMANOVIC	UDINESE	74	71.09
FRANCELINO MATUZALEM	Verona	71	71.00
FEDERICO MATTIELLO	CHIEVO	71	71.00
CESARE BOVO	TORINO	75	70.99
NIKLAS MOISANDER	SAMP	74	70.99
PEDRO PEREIRA	SAMP	65	70.98
DAVID IVAN	SAMP	67	70.96
CRISTIAN MOLINARO	TORINO	75	70.88
EMERSON	ROMA	68	70.86
THOMAS HEURTAUX	UDINESE	77	70.85
EMANUELE TERRANOVA	SASSUOLO	70	70.84
ABDELHAMID EL KAOUTARI	PALERMO	73	70.82
B.DJIMSITI	ATALANTA	62	70.80
STEFAN DE VRIJ	LAZIO	81	70.79
LORENZO ARIAUDO	SASSUOLO	71	70.78
MARCELO ESTIGARRIBIA	ATALANTA	73	70.72

A.CODA	SAMP	70	70.69
ROBERTO CRIVELLO	FROSINONE	67	70.68
RODRIGO ELY	MILAN	70	70.67
BOSKO JANKOVIC	Verona	73	70.66
ROBERT GUCHER	FROSINONE	70	70.63
DODO	SAMP	73	70.56
ROBERTO VITIELLO	PALERMO	72	70.55
ERVIN ZUKANOVIC	SAMP	71	70.55
T.CIONEK	PALERMO	70	70.54
FABIO DAPRELA	PALERMO	67	70.51
E.ZUKANOVIC	ROMA	74	70.46
M.DOMIZZI	UDINESE	73	70.42
MATTEO CIOFANI	FROSINONE	68	70.37
M.FARES	Verona	65	70.32
DAVIDE ZAPPACOSTA	TORINO	76	70.29
E.SUAGHER	CARPI	70	70.26
DAVIDE BERTONCINI	FROSINONE	61	70.25
GASTON SILVA	TORINO	70	70.24
LEANDRO GRECO	Verona	72	70.22
F.POLI	CARPI	68	70.14
ANDREA RANOCHIA	SAMP	77	70.12
NICOLAS SPOLLI	CARPI	74	70.12
NIKOLA MAKSIMOVIC	TORINO	80	70.08
LEANDRO CASTAN	ROMA	79	70.07
ROBERT ACQUAFRESCA	BOLOGNA	68	70.06
PIERLUIGI GOLLINI	Verona	70	70.00
IGOR BUBNJIC	CARPI	72	69.94
VASSILIS TOROSIDIS	ROMA	76	69.93
ADRIANO RUSSO	FROSINONE	67	69.92
O.KRAGL	FROSINONE	66	69.88
ANTE REBIC'	FIORE	69	69.83
MICHELE CAMPORESE	EMPOLI	67	69.81
DJAMEL MESBAH	SAMP	71	69.80
A.REBIC	Verona	69	69.78
VASCO REGINI	SAMP	71	69.76
MICHELANGELO ALBERTAZZI	Verona	67	69.75
MOBIDO DIAKITE	SAMP	75	69.64
FRANCO SIGNORELLI	EMPOLI	68	69.36

ASSANE GNOUKOURI	INTER	69	69.06
T.COSTA	FIORE	71	69.04
GILBERTO	Verona	69	69.00
LUIGI GIORGI	ATALANTA	67	68.90
KAMIL WILCZEK	CARPI	70	68.81
RONALDO	EMPOLI	62	68.61
F.DAPRELA	CARPI	67	68.38
SAMUEL SOUPRAYEN	Verona	70	67.94
S.LONGO	FROSINONE	69	67.89
EMIL KRAFTH	BOLOGNA	67	67.76
F.ZUCULINI	BOLOGNA	70	66.84
M.ZAMBELLI	EMPOLI	68	66.78
ALEXANDER MERKEL	UDINESE	68	66.69
N.NINKOVIC	CHIEVO	68	66.49
M.TROTTA	SASSUOLO	68	66.30
D.FURMAN	Verona	66	66.00
FEDERICO BONAZZOLI	SAMP	62	65.12
SADIQ	ROMA	63	63.69
LUCA MARTINELLI	EMPOLI	63	63.00
ALEJANDRO RODRIGUEZ	SAMP	66	62.80
ANTONINO LA GUMINA	PALERMO	58	60.32
A.BENTIVEGNA	PALERMO	57	57.18
A. FAVILLI	JUVENTUS	53	52.94

It must be mentioned that to get Table 22 above, the Neural Network algorithm was repeated 1000 times for each number of hidden nodes ranging from 1 to 10. This was performed in order to find the number of nodes in the hidden layer that generated the lowest SSE. Additionally, the algorithm was also run with more than 10 nodes in the hidden layer, just to see what the best number of nodes in the hidden layer might be.

Below are some players for whom there were substantial differences from their FIFA scores. The young star Paulo Dybala from Juventus was bought from Palermo for 40M € when he was only 21 years old. At the time he was showing promise of becoming a talented player. During his first season he scored 19 goals and had 9 assists, therefore indicating this money was well spent. Our scoring results are based solely on the 2015-16 season and score him higher than his EASports FIFA score. That latter score is based on historical data and does not capture his improved performance.

Another player chosen for further examination was Gonzalo Higuain. One should note that the predicted score for Higuain of 86.69 from the Neural Network model was almost equivalent to the score generated from the EASports' scores which was 86. However, Higuain was chosen because of his phenomenal performance - during the 2015-2016 season, Higuain set a record for most goals scored by a player in a single season.

The next player is Georgio Chiellini. He is one of the best defenders among the squad, based on the FIFA scores. But the model shows a drop of five points for the 2015-2016 season. This may be related to the fact that he was injured most of the season and he could not play as much as other defenders.

The summary of the NNet Model4 model is presented as follows:

a 7-10-1 network with 91 weights

options were - linear output units

b->h1	i1->h1	i2->h1	i3->h1	i4->h1	i5->h1	i6->h1	i7->h1	
1240.26	-218.78	3.04	8.05	-0.08	20.85	-43.53	811.11	
b->h2	i1->h2	i2->h2	i3->h2	i4->h2	i5->h2	i6->h2	i7->h2	
-1.05	-5.21	-0.58	0.65	-0.47	-3.86	-0.13	-0.14	
b->h3	i1->h3	i2->h3	i3->h3	i4->h3	i5->h3	i6->h3	i7->h3	
0.44	0.71	0.14	-0.50	0.04	8.78	0.16	0.15	
b->h4	i1->h4	i2->h4	i3->h4	i4->h4	i5->h4	i6->h4	i7->h4	
-9089.44	778.71	1103.25	-36.60	-271.64	13.45	-1658.13	6201.93	
b->h5	i1->h5	i2->h5	i3->h5	i4->h5	i5->h5	i6->h5	i7->h5	
3570.27	-248.25	-1.72	129.72	-267.57	-1.49	962.44	256.75	
b->h6	i1->h6	i2->h6	i3->h6	i4->h6	i5->h6	i6->h6	i7->h6	
3.22	-1.68	-0.09	-0.45	0.01	10.89	0.24	-2.54	
b->h7	i1->h7	i2->h7	i3->h7	i4->h7	i5->h7	i6->h7	i7->h7	
18057.61	-1302.12	0.12	2417.71	8.97	-162.30	-6314.37	-14233.21	
b->h8	i1->h8	i2->h8	i3->h8	i4->h8	i5->h8	i6->h8	i7->h8	
9.04	-0.38	-0.24	-0.11	-0.15	0.00	-0.20	0.50	
b->h9	i1->h9	i2->h9	i3->h9	i4->h9	i5->h9	i6->h9	i7->h9	
-6385.25	973.10	-114.36	-662.79	-0.08	-127.10	1711.25	-717.58	
b->h10	i1->h10	i2->h10	i3->h10	i4->h10	i5->h10	i6->h10	i7->h10	
-0.94	-12.51	0.04	0.41	-0.53	-2.19	-0.41	-0.20	
b->o	h1->o	h2->o	h3->o	h4->o	h5->o	h6->o	h7->o	h8->o
35.12	-14.38	-46.39	33.33	5.43	-3.04	23.50	9.41	-8.79
h9->o	h10->o							
-14.20	8.64							

5.1.3. Scoring/Ranking Model: Using Ordinal Regression Modelling

The same data set was used for ordinal regression modelling as for Neural Network modelling. The function “orm” (Ordinal Regression Model) in the R package rms was used.

As per Leard [28] there are four assumptions that must hold in order to perform ORM. First, the dependent variable must be measured at ordinal levels. The

second assumption is that the predictor variables must be continuous, ordinal or categorical. The third assumption is that there should not be any multicollinearity among the predictor variables. Lastly, we require the assumption of proportional odds. This requires that each predictor variable has an identical effect at each cumulative split of the ordinal dependent variable (parallelism) [28]. The last assumption has been tested using the Brant Package and none of the variables reached our significance level hence [29] all assumptions are met, and we can continue with the model. (The threshold for this analysis was 0.05.)

H0: The assumption of parallelism holds

H1: The assumption of parallelism does not hold

Variables	P-value
Omnibus	0.003
Overall Clean Sheet	0.07
Overall Assists	0.54
Overall Cards	0.30
Overall Goal	0.27
Overall time	0.82

The summary of the ORM is

Min	-2.87
1st Quarter	-0.62
Median	0.19
Mean	0.36
3rd Quarter	1.08
Max	6.82

The latent variable results using ORM are shown in the table below:

Table 23: Ordinal Regression Model compared to FIFA Score

Player	Team	FIFA Rating	Latent Variable	Transferred Values
P. DYBALA	JUVENTUS	81	6.82	85.95
GONZALO HIGUAIN	NAPOLI	86	6.56	85.07
P. POGBA	JUVENTUS	86	6.09	83.49
LORENZO INSIGNE	NAPOLI	82	5.06	79.99
MAREK HAMSIK	NAPOLI	82	4.74	78.90
M. MANDZUKIC	JUVENTUS	82	4.47	77.98
MAURO ICARDI	INTER	80	4.40	77.73
A. MORATA	JUVENTUS	80	4.30	77.39
JOSE' CALLEJON	NAPOLI	81	4.04	76.51
CARLOS BACCA	MILAN	82	3.95	76.19
JUAN CUADRADO	JUVENTUS	81	3.82	75.76
MASSIMO MACCARONE	EMPOLI	75	3.73	75.45
I.PERISIC	INTER	81	3.60	74.99
L. BONUCCI	JUVENTUS	83	3.49	74.63
MIRALEM PJANIC	ROMA	84	3.44	74.47
RICCARDO SAPONARA	EMPOLI	78	3.36	74.20
ALEJANDRO GOMEZ	ATALANTA	78	3.33	74.08
MOHAMED SALAH	ROMA	80	3.29	73.95
JOSIP ILICIC	FIORE	80	3.28	73.93
BORJA VALERO	FIORE	82	3.27	73.90
SAMI KHEDIRA	JUVENTUS	81	3.23	73.75
P. EVRA	JUVENTUS	81	3.15	73.49
FRANCO VAZQUEZ	PALERMO	80	3.15	73.48

LEONARDO PAVOLETTI	GENOA	75	3.01	72.99
BONAVENTURA	MILAN	80	3.00	72.96
A. BARZAGLI	JUVENTUS	85	2.95	72.79
ALLAN	NAPOLI	80	2.88	72.58
MANUEL PUCCIARELLI	EMPOLI	73	2.86	72.49
VALTER BIRSA	CHIEVO	75	2.75	72.13
CYRIL THEREAU	UDINESE	77	2.71	71.98
ANTONIO CANDREVA	LAZIO	81	2.68	71.89
ALEX SANDRO	JUVENTUS	82	2.65	71.78
MARCELO BROZOVIC	INTER	78	2.63	71.70
DOMENICO BERARDI	SASSUOLO	81	2.59	71.59
MIROSLAV KLOSE	LAZIO	79	2.55	71.44
PIOTR ZIELINSKI	EMPOLI	74	2.52	71.35
MATTIA DESTRO	BOLOGNA	76	2.51	71.30
CLAUDIO MARCHISIO	JUVENTUS	84	2.51	71.30
FELIPE ANDERSON	LAZIO	79	2.49	71.23
NICOLA SANSONE	SASSUOLO	77	2.43	71.04
DIEGO LAXALT	GENOA	73	2.41	70.98
TOMAS RINCON	GENOA	75	2.40	70.94
RICCARDO MEGGIORINI	CHIEVO	75	2.38	70.87
S. LICHTSTEINER	JUVENTUS	82	2.33	70.71
ELSEID HYSAJ	NAPOLI	77	2.33	70.70
FEDERICO BERNARDESCHI	FIORE	77	2.32	70.65
FAOUZI GHOULAM	NAPOLI	78	2.31	70.63
ANDREA BELOTTI	TORINO	75	2.30	70.59
JORGINHO	NAPOLI	79	2.30	70.58
DRIES MERTENS	NAPOLI	81	2.22	70.32
OSCAR HILJEMARK	PALERMO	72	2.22	70.31
MARCOS ALONSO	FIORE	75	2.21	70.27
G. CHIELLINI	JUVENTUS	86	2.21	70.27
MIRANDA	INTER	85	2.21	70.27
RAUL ALBIOL	NAPOLI	81	2.15	70.09
EDIN DZEKO	ROMA	80	2.15	70.08
SIMONE ZAZA	JUVENTUS	79	2.14	70.03
GONZALO RODRIGUEZ	FIORE	81	2.12	69.97
GREGOIRE DEFREL	SASSUOLO	73	2.07	69.80

STEVAN JOVETIC	INTER	80	1.95	69.42
FEDERICO DIONISI	FROSINONE	72	1.95	69.39
ALBERTO PALOSCHI	CHIEVO	77	1.94	69.38
ADAM MASINA	BOLOGNA	73	1.92	69.30
RODRIGO PALACIO	INTER	79	1.91	69.28
JEISON MURILLO	INTER	79	1.88	69.17
ROBERTO SORIANO	SAMP	76	1.86	69.10
DANIEL CIOFANI	FROSINONE	72	1.86	69.08
SIME VRSALJKO	SASSUOLO	77	1.80	68.90
MARIO RUI	EMPOLI	76	1.76	68.74
DANIELE RUGANI	JUVENTUS	78	1.75	68.71
FRANCESCO ACERBI	SASSUOLO	79	1.74	68.70
HERNANES	JUVENTUS	80	1.72	68.63
ALESSANDRO FLORENZI	ROMA	79	1.72	68.61
MANOLO GABBIADINI	NAPOLI	78	1.67	68.44
R. PEREYRA	JUVENTUS	80	1.65	68.39
S. STURARO	JUVENTUS	77	1.65	68.37
LUCA ROSSETTINI	BOLOGNA	74	1.64	68.36
ADAM LJAJIC	INTER	79	1.61	68.26
LUCAS BIGLIA	LAZIO	81	1.59	68.19
MARIO LEMINA	JUVENTUS	76	1.59	68.17
KALIDOU KOULIBALY	NAPOLI	80	1.58	68.15
SENAD LULIC	LAZIO	77	1.58	68.13
EMANUELE GIACCHERINI	BOLOGNA	77	1.57	68.11
ALFRED DUNCAN	SASSUOLO	73	1.56	68.06
C.TELLO	FIORE	78	1.55	68.05
GARY MEDEL	INTER	81	1.55	68.05
KWADWO ASAMOAH	JUVENTUS	79	1.54	68.00
DAVIDE ASTORI	FIORE	79	1.53	67.98
KEITA	LAZIO	77	1.51	67.90
MARTEN DE ROON	ATALANTA	76	1.50	67.87
MATIAS VECINO	FIORE	75	1.50	67.86
ANTHONY MOUNIER	BOLOGNA	76	1.47	67.76
LUCAS CASTRO	CHIEVO	75	1.46	67.75
FABRIZIO CACCIATORE	CHIEVO	72	1.45	67.69
M'BAYE NIANG	MILAN	75	1.43	67.62
FRANCO BRIENZA	BOLOGNA	75	1.42	67.59

SIMONE PADOIN	JUVENTUS	74	1.41	67.55
LUIS MURIEL	SAMP	75	1.41	67.55
CRISTIAN ANSALDI	GENOA	79	1.35	67.36
RADJA NAINGGOLAN	ROMA	83	1.34	67.34
L.DIGNE	ROMA	77	1.34	67.33
FRANCESCO MAGNANELLI	SASSUOLO	76	1.34	67.31
FEDERICO PELUSO	SASSUOLO	73	1.33	67.30
EDER	SAMP	79	1.33	67.29
DANIELE GASTALDELLO	BOLOGNA	76	1.31	67.24
D.PEROTTI	ROMA	79	1.30	67.20
FACUNDO RONCAGLIA	FIORE	75	1.29	67.17
DUVAN ZAPATA	UDINESE	77	1.27	67.10
MASSIMO GOBBI	CHIEVO	73	1.27	67.07
MARTIN CACERES	JUVENTUS	80	1.26	67.07
KINGSLEY COMAN	JUVENTUS	78	1.25	67.03
FERNANDO LLORENTE	JUVENTUS	80	1.22	66.92
LUCA ANTONELLI	MILAN	77	1.21	66.89
MARCO PAROLO	LAZIO	80	1.19	66.81
MILAN BADELJ	FIORE	78	1.16	66.72
LEANDRO PAREDES	EMPOLI	74	1.16	66.70
LUIZ ADRIANO	MILAN	79	1.14	66.64
KHOUMA BABACAR	FIORE	75	1.14	66.64
ARMANDO IZZO	GENOA	74	1.13	66.60
BRUNO FERNANDES	UDINESE	75	1.12	66.57
EMMANUEL BADU	UDINESE	74	1.09	66.47
FELIPE MELO	INTER	79	1.08	66.45
FILIP DJORDJEVIC	LAZIO	79	1.08	66.44
GEOFFREY KONDOGBIA	INTER	76	1.07	66.42
BOSTJAN CESAR	CHIEVO	77	1.07	66.41
MAURICIO PINILLA	ATALANTA	76	1.06	66.39
KOSTAS MANOLAS	ROMA	83	1.05	66.35
DANILO D'AMBROSIO	INTER	74	1.04	66.30
KEISUKE HONDA	MILAN	77	1.02	66.23
BLERIM DZEMAILI	GENOA	72	1.01	66.21
RICCARDO MONTOLIVO	MILAN	79	1.00	66.17

JURAJ KUCKA	MILAN	77	1.00	66.17
PAOLO CANNAVARO	SASSUOLO	75	0.97	66.08
NICOLA RIGONI	CHIEVO	72	0.97	66.07
ALESSIO ROMAGNOLI	MILAN	76	0.97	66.06
MAURICIO ISLA	JUVENTUS	75	0.97	66.06
FERNANDO	SAMP	70	0.96	66.05
SAPHIR TAIDER	BOLOGNA	73	0.96	66.02
ALEX TELLES	INTER	76	0.93	65.92
EL SHAARAWY	ROMA	79	0.93	65.92
MATTEO POLITANO	SASSUOLO	69	0.92	65.91
ALEX	MILAN	79	0.92	65.90
ANTONIO DI NATALE	UDINESE	77	0.92	65.89
A. FAVILLI	JUVENTUS	53	0.91	65.87
MATIAS FERNANDEZ	FIORE	76	0.90	65.84
LORENZO TONELLI	EMPOLI	78	0.90	65.83
GODFRED DONSAH	BOLOGNA	73	0.89	65.78
SEBASTIAN DE MAIO	GENOA	76	0.88	65.76
BRUNO PERES	TORINO	80	0.87	65.73
ACHRAF LAZAAR	PALERMO	73	0.86	65.69
ROBERTO INGLESE	CHIEVO	70	0.86	65.68
I.ABATE	MILAN	77	0.85	65.65
NICOLAS BURDISO	GENOA	76	0.84	65.62
S.FLOCCARI	BOLOGNA	73	0.83	65.58
KEVIN LASAGNA	CARPI	71	0.83	65.58
JONATHAN BIABIANY	INTER	77	0.82	65.55
MAXIMILIANO MORALES	ATALANTA	76	0.82	65.54
SUSO	GENOA	75	0.81	65.52
MAURO ZARATE	FIORE	76	0.81	65.52
JASMIN KURTIC	ATALANTA	74	0.81	65.51
YUTO NAGATOMO	INTER	74	0.77	65.40
ANTONIO DI GAUDIO	CARPI	72	0.77	65.38
L.CIGARINI	ATALANTA	76	0.76	65.36
ANDREA COSTA	EMPOLI	74	0.75	65.31
PERPARIM HETEMAJ	CHIEVO	75	0.70	65.15
DIEGO PEROTTI	GENOA	79	0.69	65.12
ANDREA MASIELLO	ATALANTA	73	0.68	65.08
ANDREA MASIELLO	ATALANTA	73	0.68	65.08
NENAD TOMOVIC'	FIORE	75	0.67	65.06
ALESSANDRO MATRI	LAZIO	77	0.67	65.04
DANIELE BASELLI	TORINO	78	0.66	65.01

DANILO CATALDI	LAZIO	73	0.65	64.99
LUCA RIZZO	BOLOGNA	71	0.65	64.97
MARIOS OIKONOMOU	BOLOGNA	75	0.64	64.95
SERGIO PELLISSIER	CHIEVO	72	0.64	64.93
VINCENT LAURINI	EMPOLI	71	0.63	64.91
ANDREA RISPOLI	PALERMO	64	0.63	64.90
MANUEL PASQUAL	FIORE	72	0.62	64.89
GERMAN DENIS	ATALANTA	75	0.62	64.86
GERMAN DENIS	ATALANTA	75	0.62	64.86
SIMONE PEPE	CHIEVO	76	0.62	64.86
GAETANO LETIZIA	CARPI	72	0.61	64.86
DAVIDE SANTON	INTER	75	0.61	64.83
EMILIANO MORETTI	TORINO	77	0.61	64.83
FREDY GUARIN	INTER	79	0.58	64.75
WESLEY HOEDT	LAZIO	75	0.57	64.71
LARANGEIRA DANILO	UDINESE	76	0.57	64.71
SERGE GAKPE'	GENOA	74	0.56	64.69
MARCEL BUCHEL	EMPOLI	71	0.56	64.67
ALESSANDRO GAMBERINI	CHIEVO	77	0.55	64.65
MARCO D'ALESSANDRO	ATALANTA	69	0.52	64.55
MARCO BORRIELLO	ATALANTA	74	0.52	64.55
A.CERCI	GENOA	77	0.51	64.51
ALEKSANDAR TRAJKOVSKI	PALERMO	67	0.51	64.50
JAKUB BLASZCZYKOWSKI	FIORE	78	0.51	64.50
DAVID LOPEZ	NAPOLI	76	0.51	64.50
A. RUDIGER	ROMA	76	0.50	64.46
JERRY MBAKOGU	CARPI	73	0.50	64.45
GABRIEL PALETTA	ATALANTA	77	0.49	64.44
ANDREA BERTOLACCI	MILAN	76	0.49	64.43
ANTONIO FLORO FLORES	SASSUOLO	72	0.49	64.43
IVAN RADOVANOVIC	CHIEVO	73	0.49	64.43
MATTIA DE SCIGLIO	MILAN	75	0.48	64.40
GIUSEPPE ROSSI	FIORE	78	0.47	64.36
DIEGO FALCINELLI	SASSUOLO	69	0.46	64.34
SIMONE MISSIROLI	SASSUOLO	75	0.46	64.33
BOUKARY DRAME'	ATALANTA	74	0.45	64.30

GERVINHO	ROMA	80	0.43	64.24
DOMENICO MAIETTA	BOLOGNA	73	0.43	64.24
LEONARDO BLANCHARD	FROSINONE	71	0.42	64.20
DANIEL PAVLOVIC'	FROSINONE	65	0.41	64.16
DUSAN BASTA	LAZIO	79	0.38	64.06
EDER	INTER	79	0.38	64.05
LUCA PAGANINI	FROSINONE	65	0.38	64.05
SILVAN WIDMER	UDINESE	75	0.37	64.04
OMAR EL KADDOURI	NAPOLI	77	0.37	64.02
MATTEO BRIGHI	BOLOGNA	70	0.35	63.95
MAURICIO	LAZIO	78	0.34	63.94
SERGEJ MILINKOVIC- SAVIC	LAZIO	75	0.34	63.92
SINISA ANDELKOVIC	PALERMO	74	0.33	63.90
IVAYLO CHOCHEV	PALERMO	70	0.33	63.89
RICCARDO GAGLIOLO	CARPI	71	0.33	63.88
ROBIN QUAISSON	PALERMO	73	0.32	63.87
SIMONE ROMAGNOLI	CARPI	70	0.32	63.87
MATO JAJALO	PALERMO	72	0.31	63.84
PAOLO SAMMARCO	FROSINONE	68	0.31	63.83
MARCO BORRIELLO	CARPI	74	0.30	63.80
FELIPE	UDINESE	73	0.30	63.77
CRISTIAN ZACCARDO	CARPI	73	0.28	63.73
OGENYI ONAZI	LAZIO	75	0.28	63.73
LORENZO LOLLO	CARPI	71	0.28	63.72
DANIELE CROCE	EMPOLI	74	0.27	63.68
DANIELE CROCE	EMPOLI	74	0.27	63.68
JUAN JESUS	INTER	75	0.26	63.64
ABDOULAY KONKO	LAZIO	75	0.25	63.63
LUCA RIGONI	GENOA	73	0.24	63.59
PANAGIOTIS TACHTSIDIS	GENOA	74	0.24	63.57
FRANCESCO LODI	UDINESE	73	0.23	63.56
DARIO DAINELLI	CHIEVO	74	0.23	63.56
L.PASCIUTI	CARPI	71	0.23	63.55
VLAD CHIRICHES	NAPOLI	76	0.20	63.44
ALEX FERRARI	BOLOGNA	67	0.20	63.44
EDENILSON	UDINESE	74	0.19	63.42
RAFFAELE BIANCO	CARPI	69	0.19	63.42

FRANCESCO TOTTI	ROMA	79	0.19	63.41
DANIELE DE ROSSI	ROMA	82	0.17	63.36
SANTIAGO GENTILETTI	LAZIO	77	0.16	63.30
AFRIYIE ACQUAH	TORINO	73	0.13	63.22
MARIO BALOTELLI	MILAN	79	0.13	63.22
EZEQUIEL MUNOZ	GENOA	72	0.13	63.21
KAMIL GLIK	TORINO	82	0.11	63.15
MARCO BENASSI	TORINO	75	0.11	63.15
NICOLAS FREY	CHIEVO	72	0.11	63.14
STEFAN RADU	LAZIO	79	0.10	63.11
C.IMOOBILE	TORINO	79	0.08	63.03
ALJAZ STRUNA	PALERMO	67	0.08	63.03
ISAAC COFIE	CARPI	71	0.07	63.02
GIUSEPPE VIVES	TORINO	74	0.07	63.02
ANTE REBIC'	FIORE	69	0.07	63.01
CHRISTIAN ZAPATA	MILAN	76	0.06	62.99
SERGIO FLOCCARI	SASSUOLO	73	0.06	62.98
LORENZO PELLEGRINI	SASSUOLO	65	0.06	62.98
OLIVIER NTCHAM	GENOA	64	0.06	62.97
MAXI LOPEZ	TORINO	77	0.06	62.96
CHRISTIAN MAGGIO	NAPOLI	75	0.04	62.89
GORAN PANDEV	GENOA	74	0.03	62.88
ALESSIO CERCI	MILAN	77	0.03	62.88
A.FLORO FLORES	CHIEVO	72	0.03	62.86
IBRAHIMA MBAYE	BOLOGNA	68	0.01	62.82
MATTEO MANCOSU	BOLOGNA	70	0.01	62.81
ANDREA CONTI	ATALANTA	67	0.00	62.79
MARCO ZAMBELLI	EMPOLI	68	0.00	62.77
FEDERICO BARBA	EMPOLI	71	0.00	62.77
M.BISEVAC	LAZIO	77	-0.01	62.73
FABIO QUAGLIARELLA	TORINO	78	-0.03	62.68
EDGAR BARRETO	SAMP	73	-0.03	62.68
MIRKO VALDIFIORI	NAPOLI	76	-0.03	62.66
IVAN PIRIS	UDINESE	75	-0.05	62.61
MARKO LIVAJA	EMPOLI	69	-0.07	62.54
MARTIN MONTOYA	INTER	78	-0.07	62.53
IVAN STRINIC	NAPOLI	73	-0.07	62.52
IAGO FALQUE	ROMA	78	-0.08	62.49
ANDREA RANOCCHIA	INTER	77	-0.08	62.49

J.ZUNIGA	BOLOGNA	72	-0.08	62.49
DANILO SODDIMO	FROSINONE	68	-0.11	62.40
GUGLIELMO STENDARDO	ATALANTA	74	-0.12	62.36
ERICK PULGAR	BOLOGNA	68	-0.14	62.31
NICOLO' CHERUBIN	ATALANTA	72	-0.14	62.28
ISSA CISSOKHO	GENOA	73	-0.15	62.27
STEFANO MAURI	LAZIO	79	-0.15	62.26
RICARDO KISHNA	LAZIO	75	-0.19	62.14
FABIO QUAGLIARELLA	SAMP	78	-0.19	62.12
T. MATAVZ	GENOA	72	-0.19	62.12
ROBERT ACQUAFRESCA	BOLOGNA	68	-0.19	62.11
CRISTIAN MOLINARO	TORINO	75	-0.21	62.07
M.WAGUE	UDINESE	73	-0.21	62.05
ALEANDRO ROSI	FROSINONE	70	-0.21	62.04
L. DE SILVESTRI	SAMP	76	-0.22	62.02
G.SILVA	GENOA	70	-0.23	62.00
EDOARDO GOLDANIGA	PALERMO	70	-0.23	61.98
TINO COSTA	GENOA	76	-0.23	61.98
GABRIEL SILVA	CARPI	70	-0.24	61.97
GIANPAOLO BELLINI	ATALANTA	68	-0.24	61.97
V.REGINI	NAPOLI	71	-0.24	61.95
GILBERTO	IORE	69	-0.24	61.95
J.MENEZ	MILAN	81	-0.25	61.92
DAVIDE BRIVIO	ATALANTA	72	-0.25	61.90
ASSANE GNOUKOURI	INTER	69	-0.26	61.90
HERNANES	INTER	80	-0.26	61.89
DAVIDE BIONDINI	SASSUOLO	70	-0.26	61.88
U. COSIC	EMPOLI	68	-0.26	61.87
MICHEL MORGANELLA	PALERMO	67	-0.27	61.86
GIAMPIERO PINZI	CHIEVO	73	-0.27	61.86
N.SPOLLI	CHIEVO	74	-0.31	61.71
T.COSTA	IORE	71	-0.31	61.70
GASTON BRUGMAN	PALERMO	68	-0.32	61.69
ARCHIMEDE MORLEO	BOLOGNA	70	-0.32	61.68
EROS PISANO	Verona	72	-0.32	61.67
MAICON	ROMA	77	-0.32	61.67
A. TABACCHI	BOLOGNA	67	-0.34	61.63

MATTIA CASSANI	SAMP	72	-0.34	61.63
JOAQUIN CORREA	SAMP	71	-0.34	61.62
LEVAN MCHEDLIDZE	EMPOLI	71	-0.35	61.59
DIEGO CAPEL	GENOA	75	-0.35	61.58
MIRKO GORI	FROSINONE	66	-0.36	61.56
FEDERICO VIVIANI	Verona	73	-0.36	61.54
GIOVANNI MARCHESE	GENOA	74	-0.36	61.53
MATIAS SILVESTRE	SAMP	73	-0.37	61.52
S.SABELLI	CARPI	67	-0.37	61.51
LUCA BITTANTE	EMPOLI	67	-0.38	61.46
ANDREA POLI	MILAN	75	-0.39	61.46
A.IONITA	Verona	74	-0.39	61.44
ENZO MARESCA	PALERMO	74	-0.40	61.41
K.CONSTANT	BOLOGNA	71	-0.41	61.39
ALBERTO GRASSI	ATALANTA	70	-0.41	61.38
LORENZO CRISSETIG	BOLOGNA	71	-0.41	61.36
MARCELLO GAZZOLA	SASSUOLO	66	-0.42	61.34
M.TROTTA	SASSUOLO	68	-0.42	61.33
GIAMPAOLO PAZZINI	Verona	74	-0.44	61.27
ERVIN ZUKANOVIC	SAMP	71	-0.45	61.25
R. FIAMOZZI	GENOA	65	-0.45	61.24
P.KONE	FIORE	75	-0.46	61.20
GENNARO SARDO	CHIEVO	66	-0.47	61.17
CESARE BOVO	TORINO	75	-0.48	61.14
DANIELE CROCE	EMPOLI	74	-0.48	61.13
DANIELE CROCE	EMPOLI	74	-0.48	61.13
EMIL KRAFTH	BOLOGNA	67	-0.49	61.10
STIPE PERICA	UDINESE	70	-0.49	61.10
FILIPPO FALCO	BOLOGNA	64	-0.49	61.10
RAFFAELE MAIELLO	EMPOLI	66	-0.49	61.09
FEDERICO MATTIELLO	CHIEVO	71	-0.51	61.03
ROBERTO CRIVELLO	FROSINONE	67	-0.51	61.03
DODO	SAMP	73	-0.52	61.01
CRISTIAN RAIMONDI	ATALANTA	67	-0.52	61.01
G.MONACHELLO	ATALANTA	66	-0.52	61.00
RAMAN CHIBSAH	FROSINONE	68	-0.53	60.98
EDSON BRAAFHEID	LAZIO	72	-0.53	60.98
L.ANTEI	SASSUOLO	71	-0.54	60.93
MANUEL ITURRA	UDINESE	74	-0.54	60.92
MATTEO CIOFANI	FROSINONE	68	-0.54	60.92

R.FREULER	ATALANTA	67	-0.56	60.86
ABDELHAMID EL KAOUTARI	PALERMO	73	-0.58	60.79
NIKLAS MOISANDER	SAMP	74	-0.59	60.78
PHILIPPE MEXES	MILAN	77	-0.59	60.76
THOMAS HEURTAUX	UDINESE	77	-0.60	60.74
RODRIGO AGUIRRE	UDINESE	67	-0.61	60.69
Z.KUZMANOVIC	UDINESE	74	-0.62	60.66
S.GAKPE	ATALANTA	74	-0.63	60.64
F.ZUCULINI	BOLOGNA	70	-0.63	60.63
STEFAN DE VRIJ	LAZIO	81	-0.64	60.59
NIKOLA MAKSIMOVIC	TORINO	80	-0.64	60.58
DAVIDE ZAPPACOSTA	TORINO	76	-0.64	60.58
GERMAN DENIS	ATALANTA	75	-0.65	60.58
GERMAN DENIS	ATALANTA	75	-0.65	60.58
KARIM LARIBI	SASSUOLO	69	-0.65	60.57
SUSO	MILAN	75	-0.65	60.56
MICHELE CAMPORESE	EMPOLI	67	-0.66	60.53
LUCA RIGONI	PALERMO	73	-0.67	60.50
GIULIO MIGLIACCIO	ATALANTA	71	-0.67	60.50
M.MANCOSU	CARPI	70	-0.67	60.48
S.VERDI	CARPI	71	-0.68	60.47
EVANGELOS MORAS	Verona	74	-0.68	60.44
LUCA TONI	Verona	74	-0.70	60.39
LUCA MARTINELLI	EMPOLI	63	-0.70	60.38
M.ZAMBELLI	EMPOLI	68	-0.71	60.35
EMANUELE TERRANOVA	SASSUOLO	70	-0.72	60.33
CARLOS CARMONA	ATALANTA	74	-0.72	60.31
NIGEL DE JONG	MILAN	77	-0.73	60.29
K. BOATENG	MILAN	77	-0.73	60.29
ALESSANDRO FRARA	FROSINONE	67	-0.74	60.25
JURAJ KUCKA	GENOA	77	-0.75	60.21
RONALDO	EMPOLI	62	-0.76	60.20
P.WSZOLEK	Verona	72	-0.76	60.20
ALEKSANDAR TONEV	FROSINONE	67	-0.76	60.19
M.CRIMI	CARPI	66	-0.77	60.16
B.DJIMSITI	ATALANTA	62	-0.77	60.16
LORENZO ARIAUDO	SASSUOLO	71	-0.77	60.15

ROBERT GUCHER	FROSINONE	70	-0.77	60.14
FRANCO SIGNORELLI	EMPOLI	68	-0.79	60.08
ANTONINO LA GUMINA	PALERMO	58	-0.81	60.02
N.NINKOVIC	CHIEVO	68	-0.81	60.01
JUAN ITURBE	ROMA	77	-0.81	60.01
VASCO REGINI	SAMP	71	-0.82	59.98
T.CIONEK	PALERMO	70	-0.83	59.95
SADIQ	ROMA	63	-0.83	59.93
JOSE' MAURI	MILAN	72	-0.85	59.89
DAVID IVAN	SAMP	67	-0.89	59.75
R.ALVAREZ	SAMP	77	-0.89	59.74
ADRIANO RUSSO	FROSINONE	67	-0.93	59.61
O.KRAGL	FROSINONE	66	-0.93	59.61
F.POLI	CARPI	68	-0.94	59.58
ANTONIO NOCERINO	MILAN	72	-0.94	59.57
ANDREA RANOCHIA	SAMP	77	-0.94	59.56
LUCA MARONE	CARPI	70	-0.95	59.52
MARCELO ESTIGARRIBIA	ATALANTA	73	-0.96	59.51
IGOR BUBNJIC	CARPI	72	-0.97	59.48
LUIGI GIORGI	ATALANTA	67	-0.98	59.45
RODRIGO ELY	MILAN	70	-0.99	59.42
PEDRO PEREIRA	SAMP	65	-0.99	59.40
SAMUELE LONGO	FROSINONE	69	-1.00	59.39
PANAGIOTIS KONE	UDINESE	75	-1.01	59.33
VASSILIS TOROSIDIS	ROMA	76	-1.01	59.32
FABIO DAPRELA	PALERMO	67	-1.02	59.31
ROBERTO VITIELLO	PALERMO	72	-1.02	59.30
R.MARTINHO	CARPI	72	-1.03	59.27
GASTON SILVA	TORINO	70	-1.03	59.26
MARQUINHO	UDINESE	76	-1.04	59.24
E.ZUKANOVIC	ROMA	74	-1.04	59.22
E.SUAGHER	CARPI	70	-1.08	59.11
M.DOMIZZI	UDINESE	73	-1.09	59.06
B.CRISTANTE	PALERMO	72	-1.09	59.06
MASSIMILIANO CARLINI	FROSINONE	67	-1.10	59.05
GUILHERME	UDINESE	74	-1.11	58.99
KAMIL WILCZEK	CARPI	70	-1.12	58.95
MATTEO FEDELE	CARPI	67	-1.14	58.88
LEANDRO CASTAN	ROMA	79	-1.15	58.88

WALLACE	CARPI	67	-1.16	58.82
ANDREA LAZZARI	CARPI	72	-1.17	58.81
A.BENTIVEGNA	PALERMO	57	-1.17	58.80
NICOLAS CASTILLO	FROSINONE	73	-1.17	58.79
GIOVANNI PASQUALE	UDINESE	69	-1.20	58.70
K.STROOTMAN	ROMA	80	-1.20	58.70
VICTOR IBARBO	ROMA	78	-1.20	58.70
ADEM LJAJIC	ROMA	79	-1.20	58.68
VICTOR IBARBO	ROMA	78	-1.20	58.68
EMERSON	ROMA	68	-1.22	58.63
JUANITO GOMEZ	Verona	73	-1.22	58.62
ALESSANDRO GAZZI	TORINO	74	-1.22	58.61
MOBIDO DIAKITE	SAMP	75	-1.24	58.55
DJAMEL MESBAH	SAMP	71	-1.25	58.51
NICOLAS SPOLLI	CARPI	74	-1.26	58.48
PONTUS JANSSON	TORINO	75	-1.27	58.45
DANIELE VERDE	FROSINONE	69	-1.28	58.43
SALIH UCAN	ROMA	73	-1.28	58.42
J.DE GUZMAN	CARPI	76	-1.30	58.35
DANILO AVELAR	TORINO	75	-1.30	58.35
NENAD KRSTICIC	SAMP	72	-1.30	58.34
ALEXANDER MERKEL	UDINESE	68	-1.31	58.32
FEDERICO BONAZZOLI	SAMP	62	-1.32	58.27
ALEJANDRO RODRIGUEZ	SAMP	66	-1.33	58.23
S.LONGO	FROSINONE	69	-1.35	58.19
F.HELANDER	Verona	73	-1.36	58.14
DAVIDE BERTONCINI	FROSINONE	61	-1.39	58.03
LUCA SILIGARDI	Verona	73	-1.40	58.02
ANGELO PALOMBO	SAMP	71	-1.41	57.99
F.DAPRELA	CARPI	67	-1.44	57.87
J.OBI	TORINO	72	-1.44	57.87
AMAURO	TORINO	74	-1.54	57.53
A.CODA	SAMP	70	-1.56	57.48
LEANDRO GRECO	Verona	72	-1.57	57.44
J.SALA	SAMP	72	-1.57	57.43
PAWL WSZOLEK	SAMP	72	-1.62	57.27
MATTEO BIANCHETTI	Verona	71	-1.67	57.11
L.MARONE	Verona	70	-1.75	56.82
JACOPO SALA	Verona	72	-1.77	56.77

A. FARNERUD	TORINO	72	-1.77	56.74
SAMUEL SOUPRAYEN	Verona	70	-1.84	56.50
EMIL HALLFREDSSON	Verona	74	-1.98	56.03
BOSKO JANKOVIC	Verona	73	-2.23	55.18
U.EMANUELSON	Verona	74	-2.25	55.12
M.FARES	Verona	65	-2.29	54.98
MICHELANGELO ALBERTAZZI	Verona	67	-2.42	54.55
RAFAEL MARQUEZ	Verona	76	-2.46	54.41
ROMULO	Verona	73	-2.49	54.29
A.REBIC	Verona	69	-2.52	54.20
PIERLUIGI GOLLINI	Verona	70	-2.58	54.01
GILBERTO	Verona	69	-2.72	53.51
FRANCELINO MATUZALEM	Verona	71	-2.75	53.42
D.FURMAN	Verona	66	-2.87	53.01

The ordinal regression model gives results in the interval $[-2.87, 6.82]$. These were linearly transformed to map to scores in the same range, $[53, 86]$, as those of FIFA EASports using 3.4 for the slope value and 62.77 for the intercept term. These converted scores were compared to the FIFA EASports scores for each player. The resulting SSE for ORM was 56,444.2, which is substantially higher than that of the Neural Network model⁴. (the k value for this ORM model is equal to the number of players that are assessed, i.e., 489)

Paulo Dybala is ranked first amongst all players using Ordinal Logistic Regression model results (NNet Score = 84.26, ORM score = 85.95). When viewing this player's rank difference between the two proposed models, we note that it is quite small. Moreover, it should be noted that for many of the top-

rated players there exists a small difference between the ranks assigned by the two models. It is worth mentioning that the ORM does yield intuitive results. For instance, Dybala can be considered as having had a great season with the most impact of any player for his team by obtaining 19 goals and nine assists. These values gain even greater significance when considering the total number of goals Juventus scored -Dybala's goals make up almost one third of the entire number of goals scored by Juventus during the 2015-16 season. A similar story is conveyed when analyzing the actual performance of Higuain (NNet Score =86.69, ORM score = 85.07) as he scored 36 goals and two assists. When analyzing which position each model greatly values, one can see that, for each model, the top 20 players are primarily Strikers. (It should be noted that this type of modelling behavior - that allocates a ranking preference to strikers- is similar to other ranking models that have been developed in previous years [31][32] i.e. the more goals you score the better player you are.)

5.1.4. Comparison of Methods for Scoring and Ranking

5.1.4.1. Repeated measures one-way ANOVA for Comparing Scoring

Methods

The original scoring was from FIFA EASports. They release the scores of all players, every year based on many factors such as their pace, ability to score,

heading ability, defence, etc.. It must be kept in mind that these scores are heavily based on performance in many previous years.

The SSE for the best Neural Net model was 4908.264. This value is more than ten times smaller than the SSE of 56,444.2 generated from the ORM model. This suggests that Neural Net model4 performs better with regard to duplicating the FIFA scoring of players. One of the reasons may be the fact the ORM is generally used as a ranking model - not a predictive scoring model. The ORM, Neural Net and FIFA scores were further analyzed via a repeated measure One-Way ANOVA.

In this test, the treatments are the three different scoring methods and by using this test we are controlling for the correlation of the scores on the same player.

Table 24: Repeated measures One-Way ANOVA Model

Response transformation matrix			
	scoreFactor1	scoreFactor2	
Score-orm	-1	-1	-1
Score-nnet	0	1	1
Score-ea	1	0	0

Sum of squares and products for the hypothesis:

	scoreFactor1	scoreFactor2
scoreFactor1	47893.37	47893.67
scoreFactor2	47893.67	47893.67

Multivariate Tests: scoreFactor

	Df	test stat	approx F	num Df	den Df	Pr(>F)
Pillai	1	0.91629	2665.34	2	487	< 2.22e-16
Wilks	1	0.08371	2665.34	2	487	< 2.22e-16
Hotelling-Lawley	1	10.94595	2665.34	2	487	< 2.22e-16
Roy	1	10.94595	2665.34	2	487	< 2.22e-16

Univariate Type III Repeated-Measures ANOVA Assuming Sphericity

	Sum Sq	num Df	Error SS	den Df	F value	Pr(>F)
(Intercept)	7298708	1	22454	488	158623.1	< 2.2e-16
scoreFactor	31929	2	6170	976	2525.3	< 2.2e-16

Assuming sphericity holds, we conclude that the three scoring methods are not all the same.

5.1.4.1.1. Multiple comparisons for Comparing Scoring Methods

We proceed to use Tukey's HSD test to determine which pairs of scores differ, The results are as follows:

Table 25: Tukey multiple comparisons of means; 99% family-wise confidence level

Scores	Difference	Lwr	Upr	P Adj
NNET-ORM	9.90E+00	9.4270185	10.366179	0
EA-ORM	9.90E+00	9.4269571	10.366118	0
EA-NNET	-6.13E-05	-0.469642	0.469519	0.999999

The TukeyHSD results show the pair-wise differences of scores of the three score sets at a 1% level of significance family-wise. The Difference column provides mean differences. The “Lwr” and “Upr” columns provide lower and upper 99% confidence bounds, respectively. The “P Adj” column shows the p-values adjusted for the number of comparisons made. As there are three sets of scores, three possible pair-wise comparisons are obtained. The results show that NNET and EASports(FIFA) do not give significantly different results but that ORM results differ significantly from both of NNET and EASports (FIFA).

Recall that we must assess the sphericity assumption of the fitted models. When checking the sphericity, the Mauchly test was applied to the three sets of scores.

Table 26: Mauchly test for sphericity

	Test Statistic	p-value
ScoreFactor	0.75221	7.7334e-31

Based on these results in Table 26, the assumption of sphericity is invalid and hence the use of the parametric ANOVA and Tukey’s HSD is not supported.

5.1.4.2. Multiple Comparisons of Scoring Methods

Given the results above, a multiple comparison analysis was performed to assess for pairwise differences in the model scores. Multiple pairwise-comparison testing using the Wilcoxon signed-rank test was performed. The null hypothesis for the Wilcoxon signed-rank test is that the median difference between pairs of observations is zero. Note that this is different from the null hypothesis of the parametric paired t-test, which is that the mean difference between pairs is zero. For each of the pairwise groups, we find that the Wilcoxon signed-rank test using Benjamini and Hochberg [30] (BH) yields results that allow the null hypothesis to be rejected for the EA vs. ORM and the NNETModel4 vs. ORM comparisons. Thus we conclude that ORM differs from EASports and NNETModel4 but that NNETModel4 and EA are not significantly different.

Table 27: Pairwise comparisons using Wilcoxon rank sum test
*p-value adjustment method: BH

Column1	EASports	NNET
NNET	0.36	
ORM	<2e-16	<2e-16

5.1.4.2.2. Spearman's rank correlation

Using FIFA EASports, NNETModel4, and the ORM scores, the players were ranked and the three sets of ranks were examined for correlation. The Spearman Correlation test yields results that indicate that, in each pairwise case, the null hypothesis is rejected at a type I error level of .01, where the null hypothesis is that there is no correlation between ranking methods. Hence, there exists evidence that suggests the models' ranks are correlated. It also should be noted that the values for the Spearman Correlation coefficients are .593 for the EA - ORM pair, .699 for the EA - NNET Model4 pair, and .843158 for the NNET Model4 - ORM pair.

5.1.4.2.3. Inter-Relater Reliability Analysis

Performing an Inter-Relater Reliability (IRR) analysis using the "irr" package in R on the pairwise combinations of the model scores' rankings with Cohen's Kappa statistic

$$\kappa = \frac{p_o - p_e}{1 - p_e} = 1 - \frac{1 - p_o}{1 - p_e}$$

where:

p_o = the relative observed agreement among raters.

p_e = the hypothetical probability of chance agreement

yields result that suggest that when comparing the three ranking methods, the highest similarity (the Kappa measure) is between NNET Model4 and EASports rankings and also the ORM and NNET Model4 are more similar than ORM and EA rankings.

The results are as follows:

Cohen's Kappa for 2 Raters (Weights: unweighted) ORM and NNET

Subjects = 489

Raters = 2

Kappa = 0.0129

Cohen's Kappa for 2 Raters (Weights: unweighted) ORM and EASports

Subjects = 489

Raters = 2

Kappa = 0.00284

Cohen's Kappa for 2 Raters (Weights: unweighted) NNET and EASports

Subjects = 489

Raters = 2

Kappa = 0.0114

5.1.5. Summary of ORM/NNET Findings

Given the results above, it appears that NNET Model4 is better at generating players' scores similar to those from EA Sports. NNET Model4 had a substantially lower SSE than ORM. ORM seems to produce, on average, lower scores than NNET Model4 whereas NNET Model4 yields results that are almost identical to the EA Sports' scores. It should also be noted that the number of explanatory variables utilized in both the NNET Model4 and ORM are rather few and simplistic in some sense.

5.2. Association rule mining

In this section, the purpose was to suggest a methodology to address the second objective of the thesis - to find a player or group of players who had the greatest impact on a team winning (or not winning) a match. Since data from all of the teams could produce a vast number of rules, only the champions for the 2015-16 season (Juventus) were considered for discussion to address objective 2 of this thesis.

Each team has 10 players on the field (not including the goalkeeper) at the same time. If they used all three substitutes during the match, at most 13 players could play on a team in any one match. To consider a rule as beneficial, the lift associated with a rule must be higher than 1. We consider the resulting rules and examine their interpretations.

5.2.1. Data preparation

To do association rule mining, we needed to create a binary matrix and then employ the *apriori* function in the AruleViz package in R. For the matrix, the columns represented players and each row represented a game. There were a few players that played only one or two matches the entire season and were sold to other teams; they were removed from the data set since including them

resulted in many non-useful rules. This reduced the number of players in the analysis to 25.

The data set was divided into a submatrix for each team; that submatrix contained information on all games played by that team, home and away. Only the champions of the 2015-16 season are written-up in this thesis.

We examined which players fell within the rules most often in games that the team won and which players were playing (or not playing) when the team lost. Various values for support and confidence were used in performing these analyses but, for the sake of illustration, only some of the results are provided in this thesis.

These derived rules have direct interpretation and can be used to help identify players that provide the team with a high level of performance. Moreover, further inference can be drawn from these rules with respect to determining how important each player's position is for a specific matchup between two teams. Players work as a team in soccer and hence some can produce opportunities that lead to goals for other players. In some cases, a player may be good at destroying the opponent's in-game tactics and hindering them from playing their usual system.

5.2.2. Results: Association rule mining

We now consider the association rule mining results. The purpose was to demonstrate a methodology that would find the best player(s) in terms of winning games. We also are interested in detecting players associated with games that were not won. For purposes of this write-up we considered only the Juventus team.

Table 24 below shows the rules for winning games and Table 25 shows the rules for losing games. The tables were sorted by lift from the maximum to minimum.

We transformed the data into transactional data format and in this section we consider only games played by Juventus. A column was added to delineate if the match was won using:

$$\begin{cases} \text{if } win = 1 & \text{match was won} \\ \text{if } win = 0 & \text{match was tied/lost} \end{cases}$$

We used the *apriori* function from the AruleViz package in R. In the *apriori* function we can define a right-hand side (rhs) as the event for which we wish rules. Thus, setting *rhs* to be win=1 finds rules for winning matches. We can repeat a similar procedure to obtain rules for matches that result in a loss or a tie.

In this analysis only the players on one team were considered, since the data that was available was too little and it was not possible to find out if a player is performing better (or worst) against a certain team.

5.2.2.1. Rules for winning

Below we examine the top 10 rules for a win for Juventus (support ≥ 0.6 and confidence ≥ 0.7). In examining rules, we used various levels for support and confidence.

For when $rhs = "win=1"$, rules sorted in order of *lift* are:

Table 28: Top rules for Juventus winning

lhs	rhs	Support	Confidence	lift	count
{A. BARZAGLI=1}	{win=1}	0.625	0.8064516	1.112347	25
{P. DYBALA=1, A. MORATA=1}	{win=1}	0.6	0.8	1.103448	24
{L. BONUCCI=1, P. DYBALA=1, A. MORATA=1}	{win=1}	0.6	0.8	1.103448	24
{A. MORATA=1}	{win=1}	0.675	0.7941176	1.095335	27
{P. POGBA=1, A. MORATA=1}	{win=1}	0.625	0.78125	1.077586	25
{L. BONUCCI=1, A. MORATA=1}	{win=1}	0.625	0.78125	1.077586	25
{P. DYBALA=1}	{win=1}	0.65	0.7647059	1.054767	26
{L. BONUCCI=1, P. DYBALA=1}	{win=1}	0.65	0.7647059	1.054767	26
{L. BONUCCI=1}	{win=1}	0.675	0.75	1.034483	27
{P. POGBA=1}	{win=1}	0.65	0.7428571	1.024631	26
{L. BONUCCI=1, P. POGBA=1}	{win=1}	0.6	0.7272727	1.003135	24

The highest lift belongs to A. Barzagli playing in a match – a lift of 111.2347%. A rule that has a lift equal to 1.1123 indicates that the chance of winning a game will increased by 11%, using that combination of players.. Support is an indication of how frequently the items (i.e. player or group of players) appear in the data. Moreover, confidence shows the proportion of times the condition (e.g. winning) has occurred, given that player or group of players. Barzagli is a

defender, nicknamed “The Wall” because he is a strong defender and opponents have problems passing through him. He is known to be fast [31] and he can clear crosses and also, he is a good tackler, which helps him to get the ball back or clear a dangerous attempt.

It must also be mentioned that a 10% increase in the chance of winning a soccer match is very significant and it can impact whether a team wins the championship at the end of the season. You can follow Barzagli’s performance in the Figure 11:

Figure 13: Overall performance of A. Barzagli

The next group of rules, Rules 2-6, all involve A. Morata playing in a match. He was usually one of the two strikers in the 3-5-2 formation [33][34] or playing as a substitute for Mario Mandzukic.

The second highest lift (110.3448%) is associated with Dybala and A. Morata playing together in a match. This lift means having these two players play

together results in a 10% increase in the chance of winning a match. They are both strikers. Dybala's playing style has more dribbling, winning one-on-one challenges, and creating spaces for other strikers; Morata is more of a striker who needs space to score goals. This rule indicates these two players have a good understanding of each other's movement and playing style since both are among the top assist's players on the team. In total, in 2015-16 they created 16 goals (assists) and scored 26 goals.

The third rule, with the same lift as the second rule above, adds L. Bonucci to the pairing of P. Dybala and A. Morata. L. Bonucci was one of the best defenders in the 2015-16 season [35]. Also, because of his passing accuracy and ability to make plays from the defense line, he was a valuable player in the squad and works well with the Dybala/Morata pairing. However, having Bonucci paired with the other two does not change the chance of winning.

Rule 4, with a lift of 109.5335%, quantifies the effect of Morata alone on a match win. Morata by himself can increase the chance of winning by 9.5% but when he is paired with Bonucci or Pogba in the other rules, the lift decreases.

Rules 5 and 6 have the same lift – 107.7586% - and both involve pairing Morata with either P. Pogba or L. Bonucci. Pogba is the only Midfielder that appears in these top 10 rules. He had the most assists in the 2015-16 season (12 assists) and, among midfielders, was the top scorer with 8 goals. He was sold to Manchester United the following season for the record signing (at the time) of €105 M.

If we go further, in the last three rules, the rules are Bonucci and Pogba alone and a combination of two of them. It can be observed that the combination of the two players would decrease lift and therefore, the chance of winning a match. Now let us consider further the players that appear in these rules.

A. Barzagli is a defender who played 2877 minutes in the season, making him the third highest in the timetable for the Juventus squad. He received only two yellow cards and scored once during the 2015-16 season. One of his strong abilities is that he is a solid defender that any Goalkeeper can rely on. His tackles are clean - he received only two yellow cards during the entire season - and he is one of best players who can clear balls in the air (high balls). This ability can be useful for the set pieces which are mostly crossed balls which are high.

L. Bonucci is considered as one of the best defenders in the world from the critics' point of view. One of his abilities is making successful long passes during matches and he has one of the highest passing accuracy rates among all players in the five major leagues in Europe. (Premier League, La Liga, Bundesliga, Serie A, League One). With his ability a team can plan to start their strategy from the back lines and go deep gradually and, if the opposing team is pressuring to get the ball back with their strikers, he can make long passes to relieve the pressure from the back line and help the team to play according to their game plan and

force their game plan on their opponent. Therefore, he can be a treasure to any coach and having him in the squad cannot be anything but beneficial. He is a good player who has been playing regularly - he was one of the top players in the time on the field table (Table 1) with 3325 minutes out of 3420 minutes in 38 games during the season (without counting injury times).

Figure 14: Overall performance of L. Bonucci

He had only six yellow cards, one assist, and 2 goals during the season. Additionally, Juventus made 22 clean sheets during the season, which is a Serie A Record for the most clean sheets in one season [36].

P. Pogba is the second player on the time table for the Juventus squad in the 2015-16 season. He is young and promising player; in the 2015-16 season he was only 22 years old. He made 12 assists (highest number of assists that season) and scored eight goals which, for a Midfielder, is consider high. P. Pogba

can be considered a regular player for the squad but it should also be mentioned that he was sold at the end of the season to Manchester United- one of the top teams in the Premier League- for the record signing of 105M symbo;€, which made him the most expensive player of all time in the pre-season of 2016-2017.

Figure 15: Overall performance of P. Pogba

P. Dybala was bought for this 2015-16 season as a young star Striker who had good dribbling abilities and was good at scoring. This season was his first season playing with the squad. He played 2547 minutes in that season - 4th highest play time - and scored 19 goals - the highest scorer for Juventus in that season.

Figure 16: Overall performance of P. Dybala

A. Morata is another young Striker in the Juventus squad. He was usually played as a substitute but, because of his abilities and his pace, he had potential to be a game-changer in most of the games. He scored seven times in the season and had seven assists and six yellow cards. Although he only played 1554 minutes in the entire season, he stood 4th in the squad in the Overall scores table and 3rd in total number of assists.

Figure 17: Overall performance of A. Morata

5.2.2.2. Rules for Losses or Ties:

Using “ $win = 0$ ” (lost or tied matches) with support ≥ 0.2 and confidence ≥ 0.6 gives the following top rules for Juventus, by lifts:

Table 29: Top rules for Juventus not winning

lhs	rhs	Support	Confidence	lift	Count
{CLAUDIO MARCHISIO=0, SAMI KHEDIRA=0}	{win=0}	0.2	0.72	2.64	8
{SAMI KHEDIRA=0, KWADWO ASAMOAH=0, DANIELE RUGANI=0}	{win=0}	0.225	0.69	2.51	9
{SAMI KHEDIRA=0, DANIELE RUGANI=0}	{win=0}	0.225	0.64	2.33	9
{SAMI KHEDIRA=0, KWADWO ASAMOAH=0}	{win=0}	0.225	0.6	2.18	9

Due to the small number of games that Juventus did not win that season, we obtain only four rules. The first rule indicates that if two of the best midfielders (Marchiso and Khedira) are not playing, the lift=264%, meaning the chance of not winning the game increases by 164%. This suggests that the rest of the midfielders of Juventus simply are not able to cover those positions.

The next three rules with highest lift all involve Khedira not playing and, in all three cases, the lift exceeds 2, meaning at least a doubling of the chance of not winning a game if he is not playing.

In the second highest lift rule, there are two other players (Asamoah and Rugani) whose absence from play is strongly associated with the team not winning a match. The first player is Kwadwo Asamoah. He usually plays on the left wingback. He was injured most of the 2015-16 season so his playing time was

low compared to other players in his position. The other players who could play in his position were Alex Sandro and Patrice Evra. Alex Sandro was usually playing forward wing because Juventus did not have enough players for that position. As a matter of fact he was the only player who could fit in that position because he is left-footed and has good dribbling ability and his crosses have high accuracy. Therefore, he was played as left winger more than left back winger. Hence, the only real option for the coach was Patrice Evra. Even though he was an experienced defender, since he was over 30 years old, he did not perform well for the entire season. The last other player in Rule 2 was Daniele Rugani. At the time of his purchase, he was a young promising defender and he was considered heir to Barzagli who was near the end of his career and needed more rest time for recovery. For more clarity, Rugani was new on the squad and the approach of the head coach for young and new players is to wait until they are synched with the team and the playing style and then the coach brings them into the squad slowly by letting the young players play in less important matches. It can be concluded that by letting them play in those matches, they gain experience in a real match and also, they can learn from other players. (Examples of players introduced in this way are Bonucci or Barzagli.) Therefore, it is hard to conclude he was irreplaceable player or that his presence was crucial for the team to win even though, whenever he was playing, Juventus was on the winning side.

Applying *apriori* can help us find players that are synched together and have a good understanding of each other's game play and game style as well as finding

crucial players for the squad i.e. players who can help the team to win their matches.

Now we examine further the players mentioned in these rules.

Kwadwo Asamoah is a left wing back. He only played 609 minutes in the entire season. (In that season he had a knee injury that took a long time for recovery.)

He had one assist and received one yellow card. The rules suggest that whenever he was not playing there was at least a doubling of the chance the team did not win. One of his characteristics is that he does not do show-offs like dribbling or similar things; he is a team player.

Figure 18: Overall performance of K. Asamoah

D. Rugani is a Central Defender. In the previous season as a Defender he did not receive a single warning card. Even though he was only 21 years old, he showed maturity in his game style. He was bought as a starlet, and since he has just joined the squad, he needs time to get used to the game style of the team and to synch

with other players. As a consequence he did not play many games as a regular at the beginning of the season. He played a total of 1242 minutes and only received two yellow cards and did not score or assist. However his not playing is strongly associated with Juventus not winning the match- more than a doubling of the probability of losing.

Figure 19: Overall performance of D. Rugani

Claudio Marchisio accrued 2030 minutes of game play in the 2015-2016 season, ranking him among the top ten players in terms of highest amount of game play. One should note that he did not score any goals in this large amount of playing time and only incurred two assists. This is perhaps due to his playing style, in conjunction with his position as a midfielder, which is mostly concerned with connecting the defensive line to the attacking line. We see that when Marchisio and Khedira were not playing, there is an increase of 164% in the probability of Juventus losing.

Figure 20: Overall performance of Claudio Marchisio

Another noteworthy midfielder is Sami Khedira who scored 5 goals and assisted 4 times. One of Khedira's primary duties is to help the attackers when they are applying pressure in regards to scoring a goal. Another duty Khedira takes on is helping relieve the pressure being applied by opposing teams to his team's defense.

Figure 21: Overall performance of Sami Khedira

6. Conclusions

This thesis explicitly considered the following questions:

1.) Can we duplicate the FIFA rankings from EA Sports' 2015-16 players' rankings?

2.) Can we find a methodology that provides insight into players or combinations of players that increase the chance of a team winning a match?

Similarly, can we find a methodology that identifies players or combinations of players that decrease the chance of a team winning a match?

The research performed within this thesis was organized into three segments:

1. Data gathering and manipulation

2- Neural Network and Ordinal Regression Modelling of player scoring and comparison with EASport's FIFA scoring and ranking

3-Association Rule Mining for finding rules for winning (losing) team play

The most time-consuming part of this research involved data wrangling.

However, as stated in the introduction, this was initially anticipated since in much applied research, data preparation is notorious for being a time-consuming endeavour. Moreover, in this particular situation, a variety of different modelling techniques and approaches required that the data be brought into alternate forms in order to conduct the analyses.

To address the first problem of duplicating the FIFA EASports' scoring of players, we employed two methods- neural networks and ordinal logistic regression. Both methods were used to score and subsequently rank players. We note that we had only data for 2015-16 but that FIFA EASports' scoring of players is based on years of historical data. Even so, we were able to obtain a fairly realistic scoring method using Neural Network modelling. In the case of ordinal logistic regression, initially the model generated a latent variable score for the players and then a linear transformation was implemented to map these to player scores. The results of both methods were compared against FIFA EASports scoring. From our results, it is apparent that, as far as replicating the FIFA EASports method, the Neural Network model⁴ outperformed ordinal logistic regression.

We found that ORM was insufficient for replicating EA Sports' FIFA ratings. This perhaps could be due to the rather limited number of explanatory variables. Perhaps a greater array of variables containing predictive information could yield more robust model results when attempting to generate scores similar to those obtained from EA Sports'. The explanatory variables utilized within this research are some of the most readily available and commonly known variables pertaining to player performance. Another reason for the discrepancy between the ORM and EA Sports' ratings could be attributable to the linear transformation applied to the original fitted values from the ORM. With this in mind, perhaps another transformation would map the fitted values more closely to the values from the EA Sports ratings.

Taking into consideration how substantially different the original fitted values from the ORM before the linear transformation are to the rankings from EA Sports', one could perhaps state that the overall modelling methodology is not effective in generating similar scores between the two models.

The second part of this research focused on demonstrating a methodology that would find the player(s) associated with a team winning (or not winning) games. We presented results for Juventus but other teams could be analyzed using the same method. Association rule mining proved to be a useful endeavour for gaining insight into this research question.

In regards to the use of Association Rule Mining, one could possibly further the analysis by utilizing weighted Association Rule Mining. This would be conducted by having weighted values for each variable associated with a player which would allow for more intuitive rules than the binary transaction data Association Rule Method implemented within this research.

Overall, the results within this research have demonstrated that analysing historical data can help us obtain information that is helpful for gaining a greater understanding of the underlying factors and phenomena related to player and team performance.

There is a need to develop models that can handle game data that is sampled at a high frequency. This places emphasis on the model's ability to handle and process raw data and convert it quickly into a reliable form from which inference can be drawn *during a game* for on-demand/in-game analytics that seek to inform a team's choice. As shown by this thesis, the data does contain information that is useful for extracting inference. Therefore, if the nature of these hypothetical models could be developed so that in-game actions could be analyzed and processed rapidly, then the output from these models could be used to influence and alter game outcomes as the games are being played. This might bring an unprecedented level of demand for informative analytic models like those presented in this research.

It would seem intuitive to suggest that one of the ways to bring live analysis into a working form is to use live tracking data with a Convolutional Neural Network and other machine learning techniques that allow for a more automatic approach to conducting inference. By automatic, we simply mean that the statistician's expertise would be more heavily allocated towards the construction of the model *a priori*. This would lead to situations where one could derive characteristics about the game-play of opponents in a short time-span and therefore allow for the implementation of appropriate tactics to hinder or nullify an opponent's performance. An example of the legitimacy of these suggestions is depicted in sports like basketball and hockey where such

analyses are occurring on relatively smaller scales. Given the similar dynamic nature of these sports with soccer, it would appear that the existence and development of these methodologies suggest the possibility of similar methods being developed for soccer.

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