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Statistical analysis of sports data

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Abstract

Keywords :

Acknowledgements

Introduction

Can mathematics help your favorite football team to win ? What if, by using statistics, you were able to identify performance indicators for a team ? These are real questions and by using machine learning methods, it is possible to answer them.
The point of our project is to study what kind of actions can lead to a high number of points at the end of a tournament. To do so, we created a data set based on data from the website *whoscored.com*.

When a team plays a game, it wins a number of points, according to the outcome of the meeting. The team receives three points for a win, one point for a draw, and zero for a defeat. The aim of a club is to maximize its number of points at the end of the season.
We chose to study the number of points and not the number of goals because a high number of goals does not necessarily mean a high number of points. For example, a team can score ten goals in a game and win, and then lose the three following games, goalless. Its number of points will only be three while its number of goals will be ten. Another team, wining its four meetings, scoring only once by game, will have four goals and twelve points. The ranking at the end of a season is based on the number of points and not the number of goals, thus, the second team will have a better ranking.

We divided the study into three different parts. First we had an exploratory analysis to discover our data, in order to find some interactions and have a first idea what the main variables are. Then we used variable selection methods based on regression to keep a reasonable number of variables. Finally we implemented the machine learning algorithm, Random Forest, to have another idea of the main variables, by using importance score of this method.

1 Data presentation

1.1 The website : *WhoScored.com*

The website *WhoScored.com* is managed by a team of football analysts and software developers from London. It gathers football statistics, mainly from European divisions, with a lot of different variables. More than 500 tournaments, 15,000 teams and 250,000 players teams are represented. For some tournaments, detailed statistics are available.

When detailed statistics are available, we have around 80 variables for each tournament. These variables are the averages over a game. For example, the number of passes will not be the total number of passes during the season, but this number divided by the number of games.

1.2 The variables

Here we only study the team statistics (not player or referee statistics). This data is split into three main categories : `offensive`, `defensive` and `passing`.

1.2.1 `Offensive` statistics

`Offensive` data refers to actions from the players when they are in an offensive strategy. There are five `offensive` data : shots, goals, dribbles, possession loss and aerial duels. For the aerial duels and the dribbles, we only know if the action was successful or unsuccessful. Shots and goals data are more detailed. We have statistics on the zones of the football field where shots and goals have been tempted. We can only find the type of situation of these shots and goals, the accuracy of these actions and the players body parts used to shoot.

1.2.2 `Defensive` statistics

`Defensive data` refers to actions from the players when they are in a defensive strategy. They do not control the game anymore. They try to prevent the other team from scoring. There are eight `defensive` data points : tackles, interception, fouls, cards, off-sides, clearances, blocks and saves. They are less detailed than `offensive` data, and thus less variables are available.

1.2.3 `Passing` statistics

`Passing` data refers to all the passing actions between players during the game. They are divided into three types of passing : passes, key-passes and assists.
Assists are passes that are immediately followed by a goal.
Key passes are important passes which can lead to assists and then to a goal.
The third type of pass, just called `passes` are all the other kind of passes during the game.

1.3 Our data

At first, we tried to work only with the data from the French tournament, the "*Ligue 1*". We only had 20 teams to study, which meant 20 individuals only. It was not enough to study statistics on it, in front of the large number of explanatory variables. Two options were available :

- Gather data from several last seasons, which did not satisfy the rules of independence necessary for the implementation of statistical methods. Most of the teams keep a similar composition and a similar playing style over the years. Using data from several successive years would have made individuals dependant.
- Use data from different tournaments

We chose to use data from different tournaments, from six different countries : France's Ligue 1, Spain's LaLiga, the German Bundesliga, the Italian Serie A, England's Premier League and Argentina's Superliga. The data from all six tournaments is from the 2018-2019 season. The data set is composed of 124 independent teams and

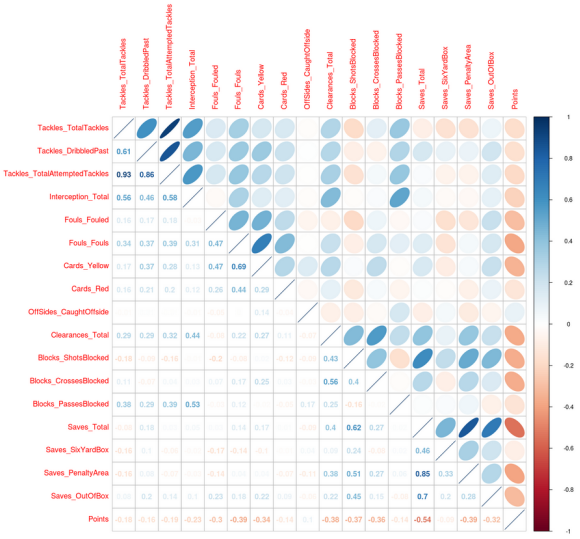
86 variables.

To study the number of points at the end of a tournament, each team has to have played the same number of games. In the `Superliga` tournament from Argentina, each team plays 25 games, while in `Ligue 1` in France, each team plays 38 games. The number of points for a french team will be higher than for an argentinean team. Since the data set was composed of averaged values, we multiplied the values for each team by the number of games played.

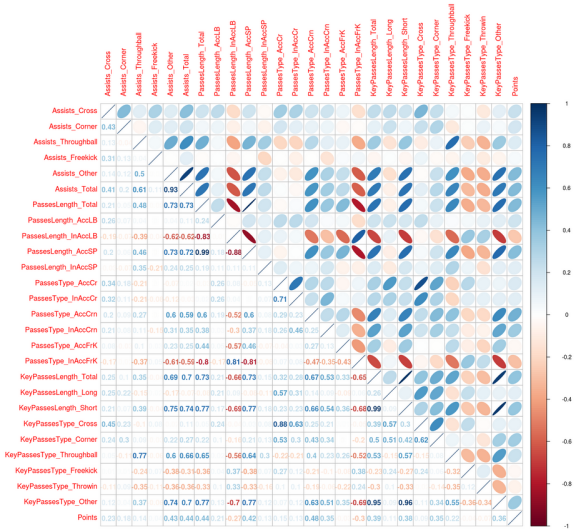
2 Exploratory analysis

2.1 Analysis of the correlations between variables

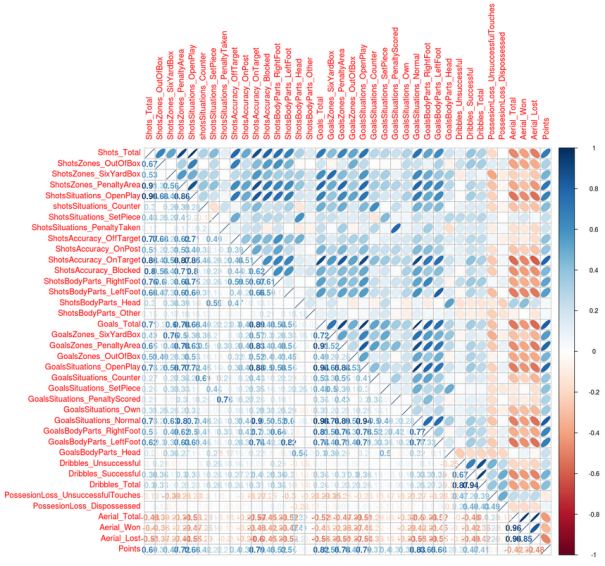
The aim of this section is to carry out a qualitative analysis of the data. We use the `corrplot` package ([Wei and Simko, 2017]) to display correlation matrices. Indices of the correlation matrices are computed on each data set (`offensive`, `defensive` and `passing`) and displayed in the lower triangular part of each plot for more readability.



(a) `Defensive` data



(b) `Passing` data



(c) `Offensive` data

Figure 1: Correlation matrices of `offensive`, `defensive` and `passing` data

We sought to identify some correlated variables and particularly which variables are correlated with the number of points at the end of a tournament.
In Figure 1, we represent on the same graph the real correlation coefficient between each variable and an ellipse standing for this coefficient. A red ellipse means that two variables are negatively correlated, whereas a blue one means that they are positively correlated. The thinner the ellipses, the more correlated the variables are.

In Figure 1a, we note some highly correlated variables. This is the case for `TotalTackles` and `TotalAttemptedTackles`, because `TotalTackles` is included in `TotalAttemptedTackles`. The same phenomenon is observed with `SavesTotal` and `SavesPenaltyArea`, with the same explanation.
About `Points`, our interest variable, there is no highly correlated variable. `SavesTotal` is softly negatively correlated to the number of points.

Several `passing` variables are correlated negatively, as we can see in Figure 1b. Those variables are `PassesLength_AccSP` (Accurate Short Passes) and `PassesLength_InAccLB` (Inaccurate Long Balls) ; `PassesLength_InAccLB` (Inaccurate Long Balls) and `PassesLength_Total` ; `PassesType_InAccFrK` (Inaccurate Freekicks) and `PassesLength_AccSP` (Accurate Short Passes) ; `PassesType_InAccFrK` (Inaccurate Freekicks) and `PassesLength_Total`. Each variable is the "opposite" of the other, which can explain why they are negatively correlated. For example, when a team spends the game doing short passes, it does not do long passes.
There are positively correlated variables as well. These include `KeyPasssesType_Other` with `KeyPassesLength_Total` and `KeyPassesLength_Short`, or `Assists_Other` with `Assists_Total`.
The `Points` variable is slightly positively correlated with `PassesType_AccCrn`, `PassesLength_Total`, `Assists_Total`. It is also slightly negatively correlated to `PassesType_InAccFrK` and `PassesLength_InAccLB`.

The variable `Points` is positively correlated to assits variables and lightly negatively correlated to inaccurate passes.
Finally, the last correlation graph, Figure 1c represents the correlation matrix of `offensive` data. As with the other matrices, some variables are positively correlated. `Aerial_Total`, `Aerial_Loss` and `Aerial_Won` are closely correlated, they must carry the same information. The same phenomenon is observed for `Dribbles_Successful`, `Dribbles_Unsuccessful` and `Dribbles_Total`. Then `Shots_Total` is positively correlated to `ShotsSituations_OpenPlay` and `ShotsZone_PenaltyArea`, which are the most common types of shots during a game. Some other variables are positively correlated, they have narrow blue ellipses. There are very few negative correlations, and they are weak.
`Points` is positively correlated with `Shots_Total`, `ShotsAccuracy_OnTarget`, `Goals_Total`, `GoalsZones_PenaltyArea`, `GoalsSituations_OpenPlay` and `GoalsSituations_Normal`. It makes sense, and it is quite trivial. Having a high number of shots or goals in game, means that the team had the ball and had goals opportunities, which is helpful to win.

The three corrplots in Figure 1 allowed us to discover the data set and its three different parts (`defensive, offensive, passing`). Interactions with the variable to be explained, `Points`, are numerous for `passing` and `offensive` data, but are rare for `defensive` data. To win a tournament, a team must be in offensive and not defensive positions. It should be scoring goals, not trying to avoid taking them.

2.2 Principal Component Analysis

Another way to analyse our data is to compute a Principal Component Analysis (PCA) to obtain a display of individuals and variables on the same plane. We chose this method because it provides a good representation of individuals and variables by maximizing the variance between variables ([Wikistat, 2016]).
This linear dimensionality reduction method converts correlated variables into a basis of linearly uncorrelated variables, called principal components.

In this method, variables and individuals are projected on principal planes, as we can see on the Figure 2. Such graphs make it possible to see links between variables. Two variables which are close on a principal plane are strongly and positively correlated, in regard to the main variables carried by this plan. In contrast, two variables which are radially opposed are strongly but negatively correlated.

On a factorial map, we can also see the links between individuals and variables by using a biplot display such as we see in Figure 2. Individuals which are close to an arrow tip have a high value of the variable associated to this arrow.

In Figure 2, we have computed the PCA on the entire data set excluding `Points`. `Points` is displayed on the factorial map but has not been used to compute the PCA, since it is a quantitative supplementary variable. That is why the arrow is a red dotted line. Even if `Points` is a supplementary variable, it is highly correlated with the first dimension : it is almost horizontal. We can say that the first principal axis stands for the number of points and hence for the teams rank.

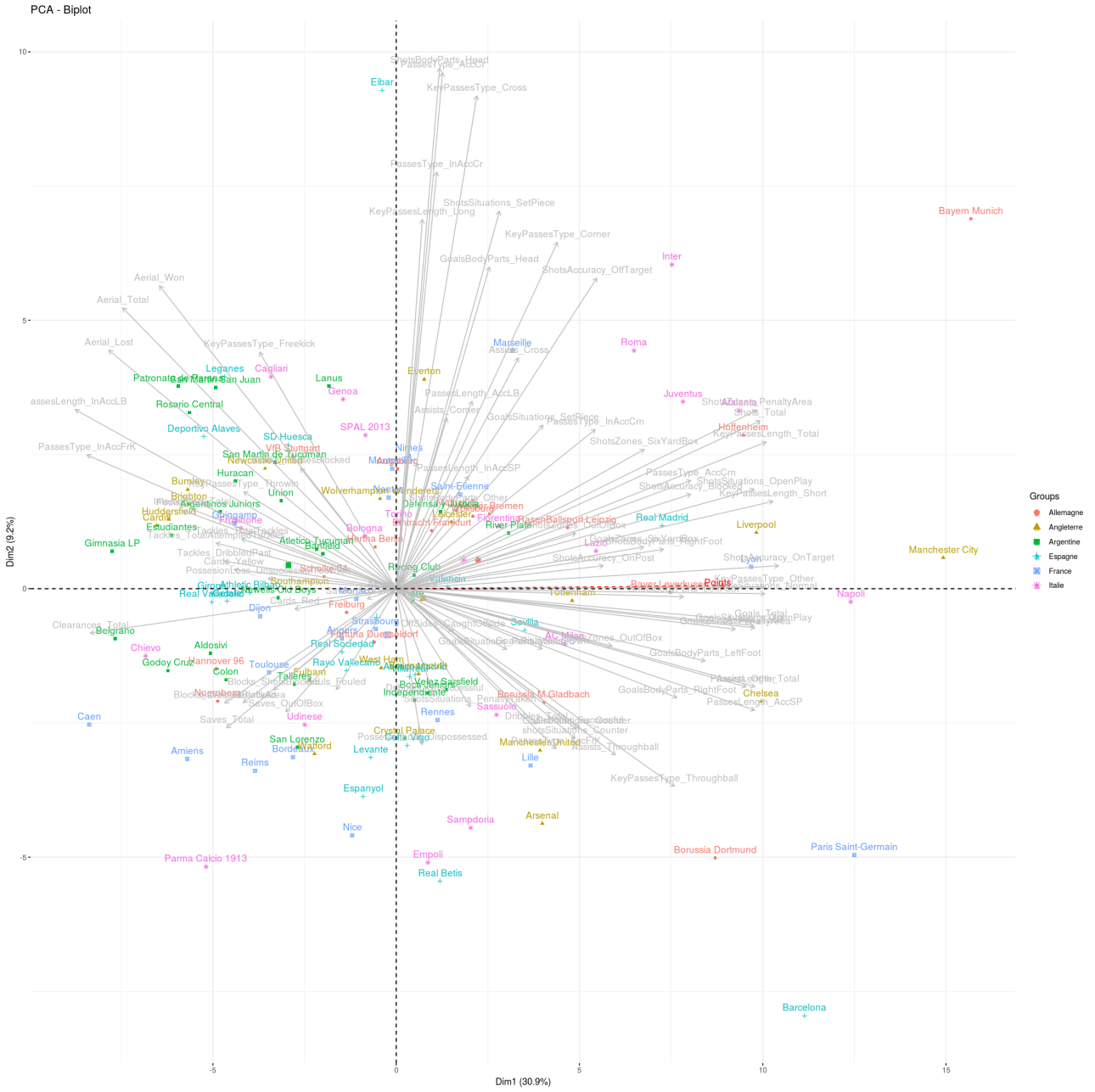


Figure 2: PCA biplot

There are two types of variables that are opposite along the first axis. Variables related to aerial duels, fouls, tackles and ball losses (among others) are displayed on the left, whereas variables related to passes length, shots and goals are displayed on the right. It should be noted that these last variables, correlated to `Points` according to the PCA, are logically influential on the number of points of a team. To have a lot of points, a team needs to score goals and construct its game, especially thanks to the numerous and short passes. In contrast fouls, cards and inaccurate actions will lead to few points.

Then, teams have been plotted by color according to their countries. We can see that teams of each country, excepting Argentina, are spread all along the horizontal axis. On the right of the map, we find the best team (or at least the second best team) of each tournament (Bayern Munich, Manchester City, Napoli, Paris Saint-Germain and Barcelona) excepting the Argentina. On the left of the graph, low-performing teams, excepting for Argentina, are plotted. The center of the biplot gathers teams in the middle of the ranking.
We notice that all the Argentina teams are displayed on the left of this graph, maybe because they do not play the same football as in Europe. It can be explained by the fact that it is the only non European team in our data set.

By seeing this graph, the best teams of the tournaments can be considered as outliers. Eibar and Parma Calcio 1913 are also outliers from the "middle" teams.

2.3 Clustering

In this part we try to gather teams or variables in homogeneous clusters. Two elements of the same cluster have more similarities than two elements of two different clusters. Similarity criterion can be computed using distances, dissimilarities or homogeneity criterion.
An easy way to interpret method is Hierarchical Cluster Analysis (HCA). This is an iterative method based on a distance measure between an individual and a cluster, as explained in [Bridges Jr, 1966]. Starting with one cluster per individual, at each step of the algorithm the two closest clusters are grouped together. At the end we obtain only one cluster containing all the individuals and we can visualize all the "sub-clusters" on a dendrogram, as in Figure 4.

2.3.1 Teams clustering

To create individual clusters, we started from the results of the PCA. Thanks to the PCA, the dimensions of individuals coordinates are already reduced, and then, it is easier to cluster the football clubs. To create clusters, we need to know how many clusters we want to keep. To do so, we use Figure 3 which represents the mean decrease of distance between two clusters for each new grouping. An optimal number of clusters maximize the jump between two consecutive bars on graph 3. Here two or three clusters are optimal but clustering football teams into only three clusters will not be precise enough. We notice that 5 clusters also provide a large jump. Hence we choose 5 as the optimal number of clusters.

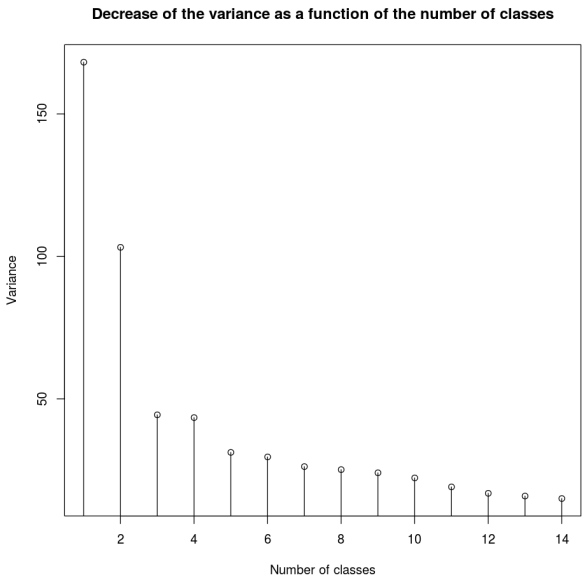


Figure 3: Decrease of the variance

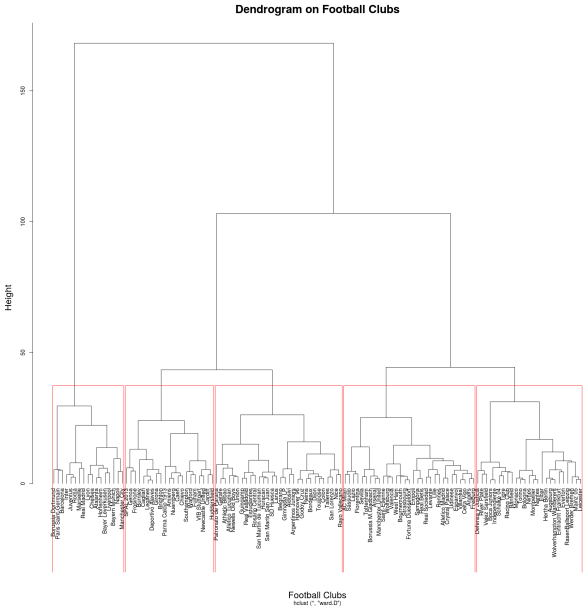


Figure 4: Dendrogram on individuals

Knowing the optimal number of clusters, we are able to divide individuals in 5 clusters, as it is shown in Figure 4. Football clubs seem to be gathered according to their performances. On the left of the dendrogram are the best clubs and on the right the weaker. To have a more precise idea on the characteristics of each cluster, we plot the PCA biplot where we add the clusters. It is Figure 5.

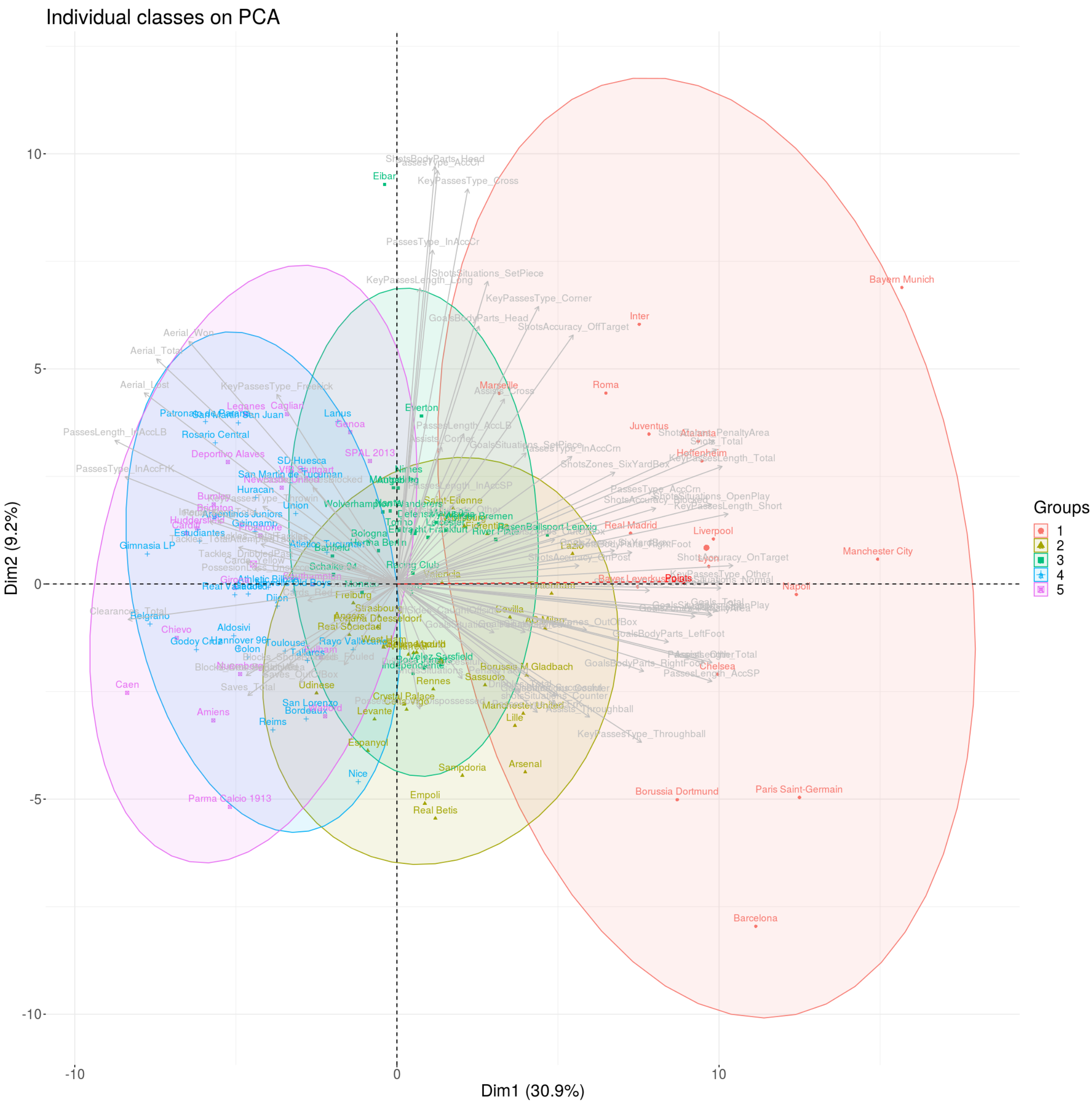


Figure 5: Individuals clusters PCA biplot

Since the first dimension is highly linked to the number of points of a team, as mentioned in Part 2.2, we can clearly visualize the first cluster, in red, composed of the best teams. This cluster is the most spread out because each team seems to have its pwn characteristics. Good teams seem to often be good, but in different ways. The separation is obvious for the top of the ranking, as evidenced by the PCA biplot and the dendrogram (Figure 4) because this cluster is linked to the others only at the end. The other clusters are more or less mixed up. The divisions are fuzzy.

2.3.2 Variables clustering

To create a dendrogram for variables, we compute the Spearman correlation coefficients between each variables. Then the dendrogram is built using the Ward distance method applied to the correlation coefficients.

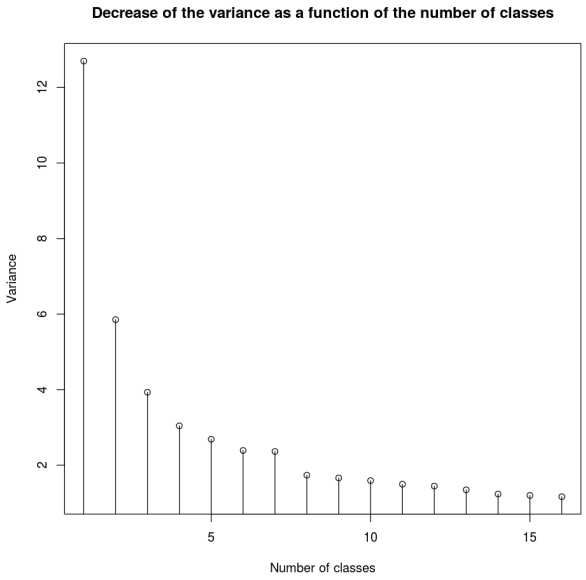


Figure 6: Decrease of the variance

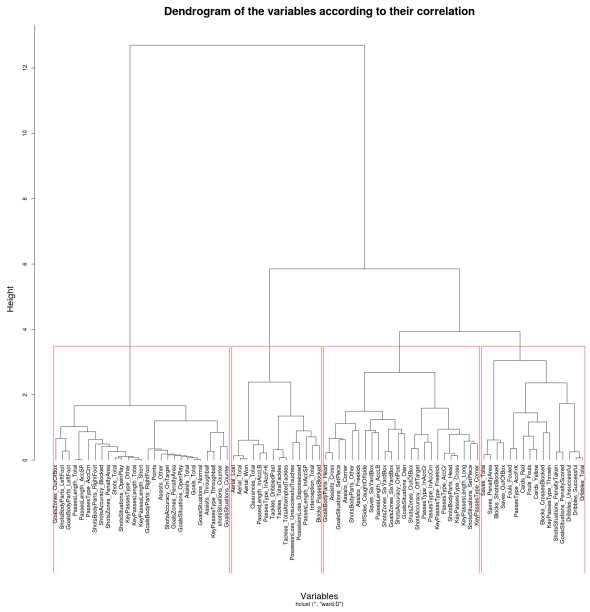


Figure 7: Dendrogram on variables

Analysing Figure 6, we can choose to split the variables into 3, 4 or 8 clusters. Since we want to obtain a precise gathering of variables, we choose to keep 8 clusters, as shown on the Figure 7.
We can see a cluster gathering aerial duels and long passes (clearances for example). Another clustering gathers actions happening after fouls like corners and free kicks. These clusters contain variables negatively correlated with the number of points. Another cluster, the first rectangle on the left, is relatively different from the others because it is separated very early on the dendrogram. It is related to actions that are important to score goals (key passes, assists...) and hence to goals themselves.
The other clusters do not allow us to draw any useful conclusions.

On the Figure 8 we see the 8 clusters of variables perfectly separated. This is therefore the main interest of the PCA, namely to separate the variables as much as possible in order to have the greatest possible variance, while reducing the size of individuals.

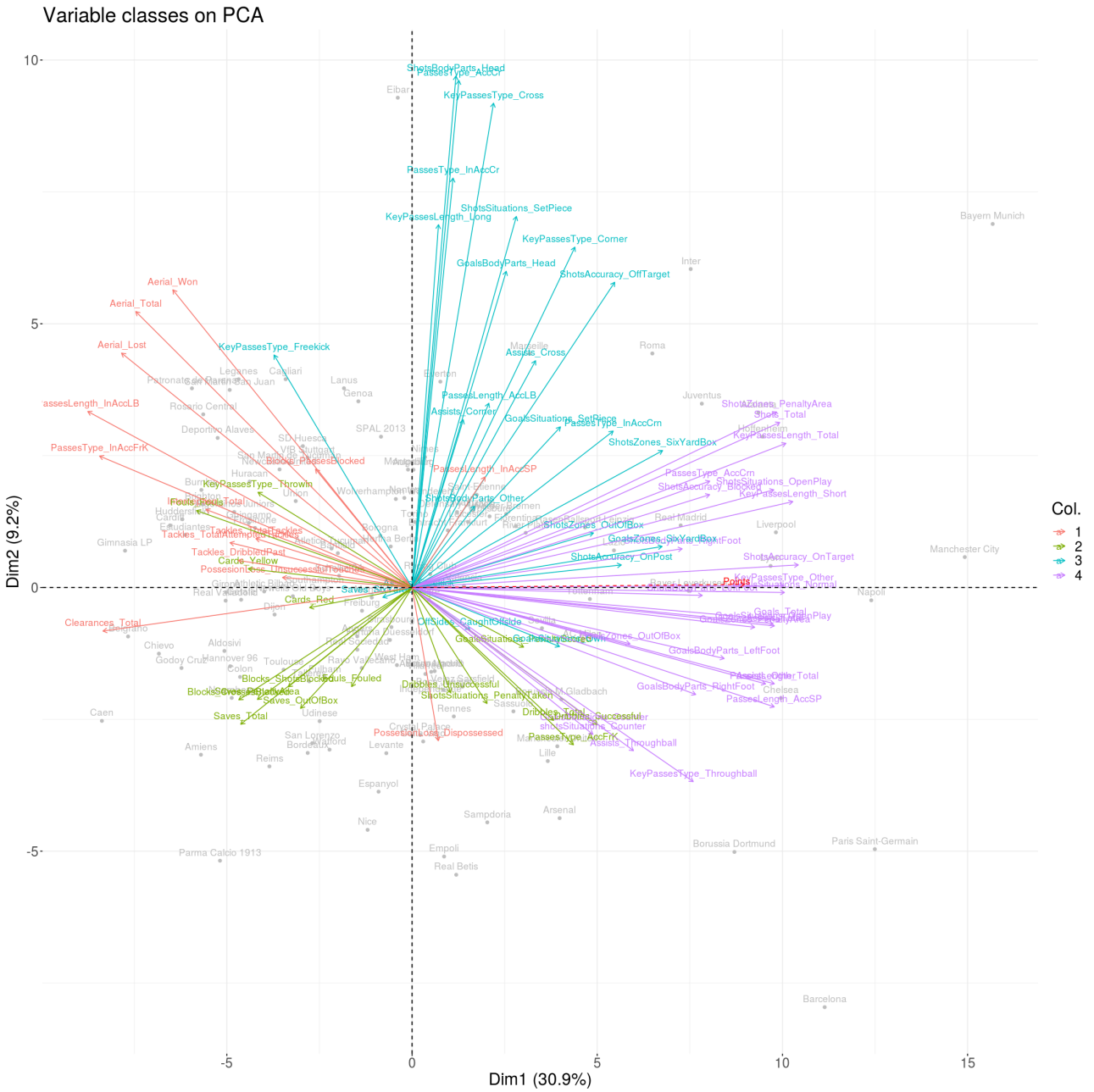


Figure 8: Variables clusters PCA biplot

2.3.3 Total classification

It is possible to visualize clusters on variables and individuals. To do so, we can use a `heatmap`. On Figure 9, each cell stands for the contribution of an individual to a variable. The whiter a cell, the more positively influenced by this variable the individual is. For instance, we an see a dark green cell between `ShotsBodyParts_LeftFoot` and `Barcelona`. It makes sense because Messi plays for Barcelona, and he is left-footed.
On the bottom left corner are the whiter cells. It corresponds to good ranked clubs, hence, these variables lead to a good ranking. Next to those variables, there are deep pink cells. The corresponding variables are negatively influential on the ranking. There are aerial duels and inaccurate actions, for example.

Figure 9: Heatmap on the two dendrograms

For the two next sections, we decided to remove variables related to goals, assists and key passes. They are directly linked to the number of points and thus to the ranking. We want to identify which actions during the game are the most relevant to the outcome of a championship.

3 Variable selection and regression

3.1 Bayesian Information Criterion

The Bayesian Information Criterion, also named *BIC*, is a criterion used to select a model among a finite set of models. The finite set of models is composed of the complete model and every possible combination with different numbers of variables ([Zhang, 2016]). A good model minimizes the criterion.
The BIC is defined as

$$BIC = ln(x)k - 2ln(\hat{L})$$

where

- $\hat{L}$ is the maximized value of the likelihood function;
- x is the observed data;
- n is the number of individuals;
- k is the number of parameters estimated by the model.

To select variables, we worked stepwise. At each iteration, the models tries to add a variable to the model and checks if one variable can be removed.

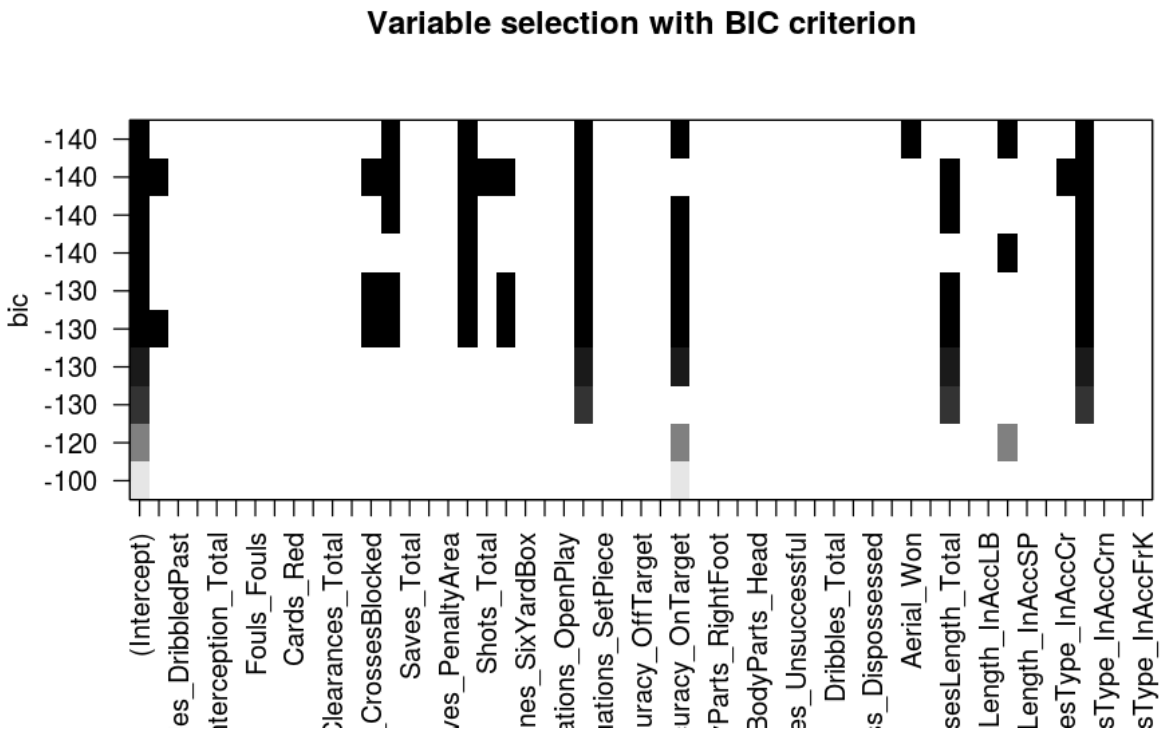


Figure 10: BIC Criterion

The variables selected are those allowing the lower BIC. The best model according to this criterion includes the black variables at the top. There are 7 variables left.

3.2 Lasso and ElasticNet

Our data set is composed of a number of explanatory variables (actions) really close to the number of individuals (football teams). A classical regression will lead to estimators with high variance.
A solution can be to use regularization methods, by introducing penalization criterion in the optimisation problem. Let us consider a linear model with n observations :

$$Y_i = \theta_0 + \theta_1 X_i^1 + \theta_2 X_i^2 + ... + \theta_p X_i^p + \epsilon_i$$

where $Y_i \in \mathbb{R}$ and $X_i \in \mathbb{R}^p$. We assume that the variables ϵ_i are independent and identically distributed, centered and with a variance σ^2.
We can rewrite this equation using matrix $\mathbf{X}$ with general term X_i^j (we set $X_i^0 = 1 \forall i$) and the vectors θ and $\mathbf{Y}$. We want to minimize $\|\mathbf{Y} - \mathbf{X}\theta\|^2$. The classical least squares estimator, in the case of the matrix $\mathbf{X}$ is of full rank, is :

$$\hat{\theta} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Y}$$

In our case, since the number of explanatory variables is greater than the number of individuals, the matrix $\mathbf{X}$ is not of full rank. That is why we introduce the LASSO regression, where the optimisation problem can be written as :

$$\min_{\theta} L(\theta) = \|\mathbf{Y} - \mathbf{X}\theta\|^2 + \lambda \sum_{i=1}^{p} |\theta_i| \tag{1}$$

With this method we obtain sparse solutions, which means that several coefficients θ_i are set to 0. In other words, some variables are not used to explain the target variable Y. That is why we can say that LASSO regression is a variable selection method.
The parameter λ in equation 1 has to be chosen by us. To help us find the better value of λ, we used a cross-validation method.
For example, in Figure 11, some coefficients are put to 0, and when $\lambda = 0.018$, we have less than 10 coefficients left.

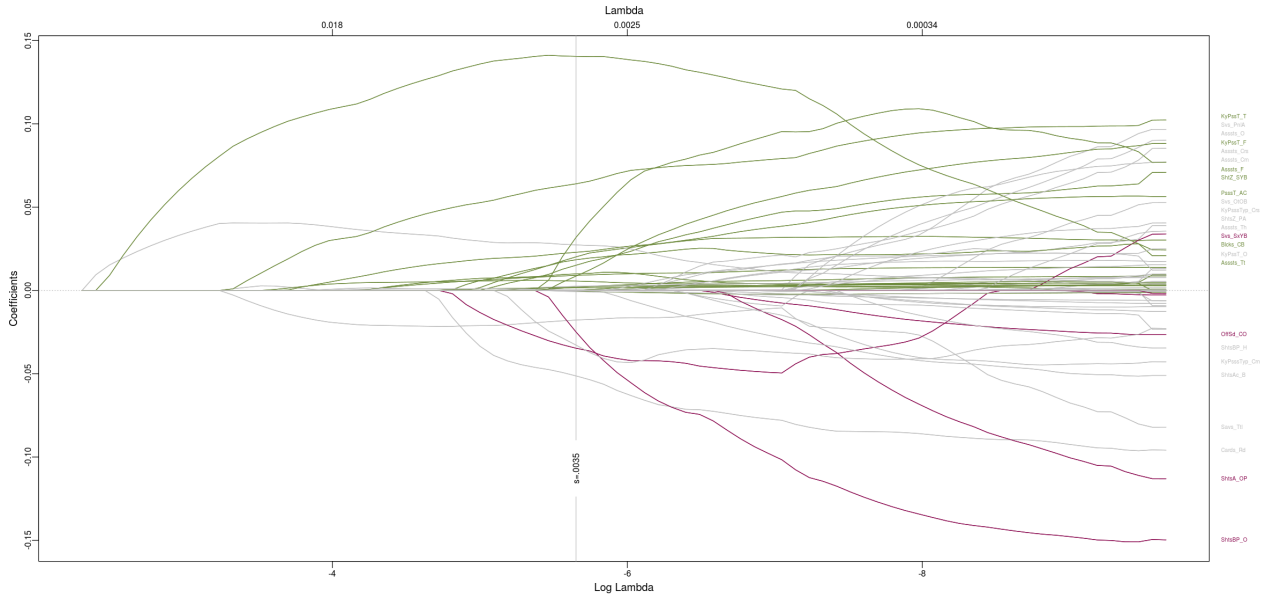


Figure 11: Lasso regression on the data set

Another regularization method in regression, called Ridge regression consists in minimizing :

$$\min_{\theta} L(\theta) = \|\mathbf{Y} - \mathbf{X}\theta\|^2 + \lambda \sum_{i=1}^{p} |\theta_i|^2 \tag{2}$$

This method do not lead to sparse solutions but it prevents parameters θ_i from taking high values. This is not a variable selection method.

LASSO and Ridge regressions combined form the ElasticNet method, which can be written, as explained in [Zou and Hastie, 2005] :

$$\min_{\theta} L(\theta) = \|\mathbf{Y} - \mathbf{X}\theta\|^2 + \lambda \left(\alpha \sum_{i=1}^{p} |\theta_i| + (1-\alpha) \sum_{i=1}^{p} |\theta_i|^2 \right) \tag{3}$$

ElasticNet method is a good compromise between sparse solutions and solutions with enough non-zero parameters. There is not as much null coefficients as in the LASSO regression, but we keep a reasonable number of explanatory variables.

3.3 Results comparison

3.3.1 Methods comparison

Using different methods, we obtained different results. The best method seems to be ElasticNet. It keeps around 20 variables, which is a good number. If we want to reduce the dimension, we can remove the variables with a coefficient close to 0, but keeping all of them allows a larger study.

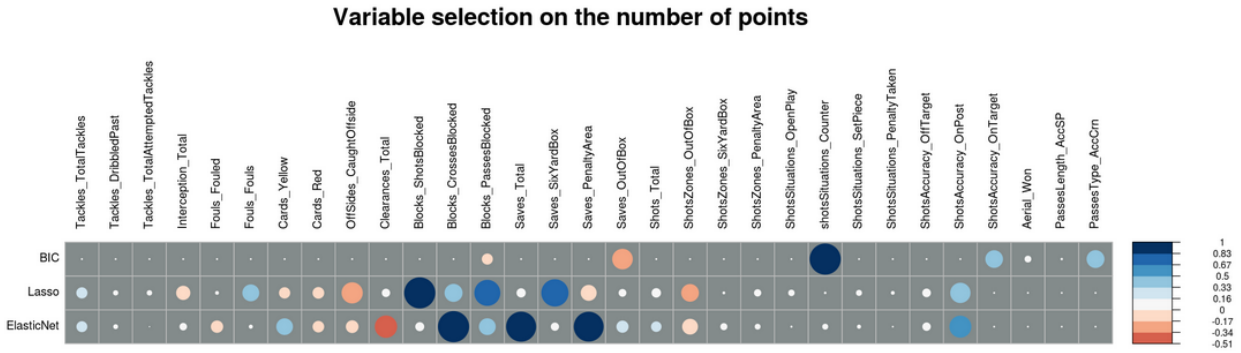


Figure 12: Variables kept according to the method

Based on ElasticNet, crosses blocked, saves and particularly saves in penalty area are highly positively correlated to the number of points at the end of the tournament. `ShotsAccuracy_OnPost` has also a high positive correlation. `Clearances_Total` is negatively correlated to the number of points. We had already seen it in part 2.1, and it is confirmed.
LASSO and ElasticNet only retain the variables with small non-zero coefficients: these are those in the defensive category. This is maybe because offensive data have coefficients way bigger : in this case the $L1$-penalty predominates and enforces these variables to 0. We can discuss on the relevance of LASSO and ElasticNet for variable offensive selection, but this is a good way to identify which defensive actions have an influence on the outcome of a tournament.

3.3.2 Differences between tournaments

The data set is composed of data from six different countries. We have already seen in Part 2.2 that Argentina's teams play differently from European teams. We applied variable selection methods in regression to data from each country to observe possible differences.

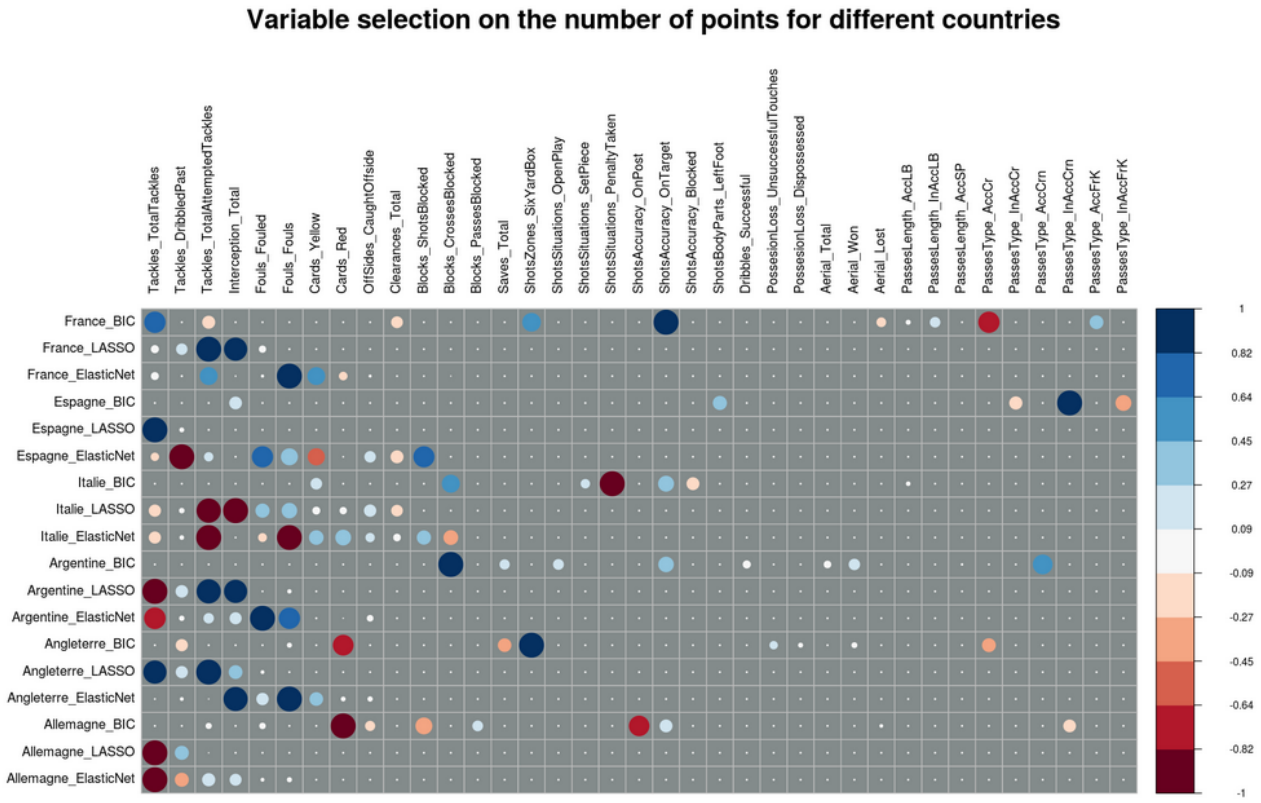


Figure 13: Variables kept according to the country

In Figure 13, we can note some differences. For some countries (France, Spain, England), tackles are positively correlated to the number of points while for Germany and Argentina, they are negatively correlated. Winning points in France is highly positively correlated with `ShotsAccuracy_OnTarget`. This variable does not have any effect in the other countries.

4 Machine learning methods

In the next subsections, we will compare three machine learning algorithms (Random Forest, Support Vector Machine and eXtreme Gradient Boosting) in variable selection. To compare theses methods we will use the importance of features, computed by the `caret` package. Classical SVM and XGB methods do not provide variable importance but `caret` package computes it, based on the area under the ROC or the value of the t-statistic of each variable, depending on the form of the regression method.

4.1 Random Forest

4.1.1 Classification and Regression Tree

A Classification and Regression Tree (CART) is a non parametric algorithm which aims in constructing a binary decision tree, easy to interpret.
Figure 14 is an example of a tree computed with the number of points as target variable.
Its construction is detailed in [Loh, 2011]. For each node, the algorithm chooses the explanatory variable which minimizes the sum of heterogeneities of the two son nodes, and the threshold which best divides these two son nodes. The heterogeneity of the node κ is defined by

$$D_\kappa = \sum_{i \in \kappa} (y_i - \overline{y_\kappa})^2$$

On the tree represented in Figure 14, we can see several nodes. Each node represents a variable which splits individuals according to a threshold. For example, the root (first node on top of the tree) in Figure 14 stands for `ShotsAccuracy_OnTarget` with its threshold 165.

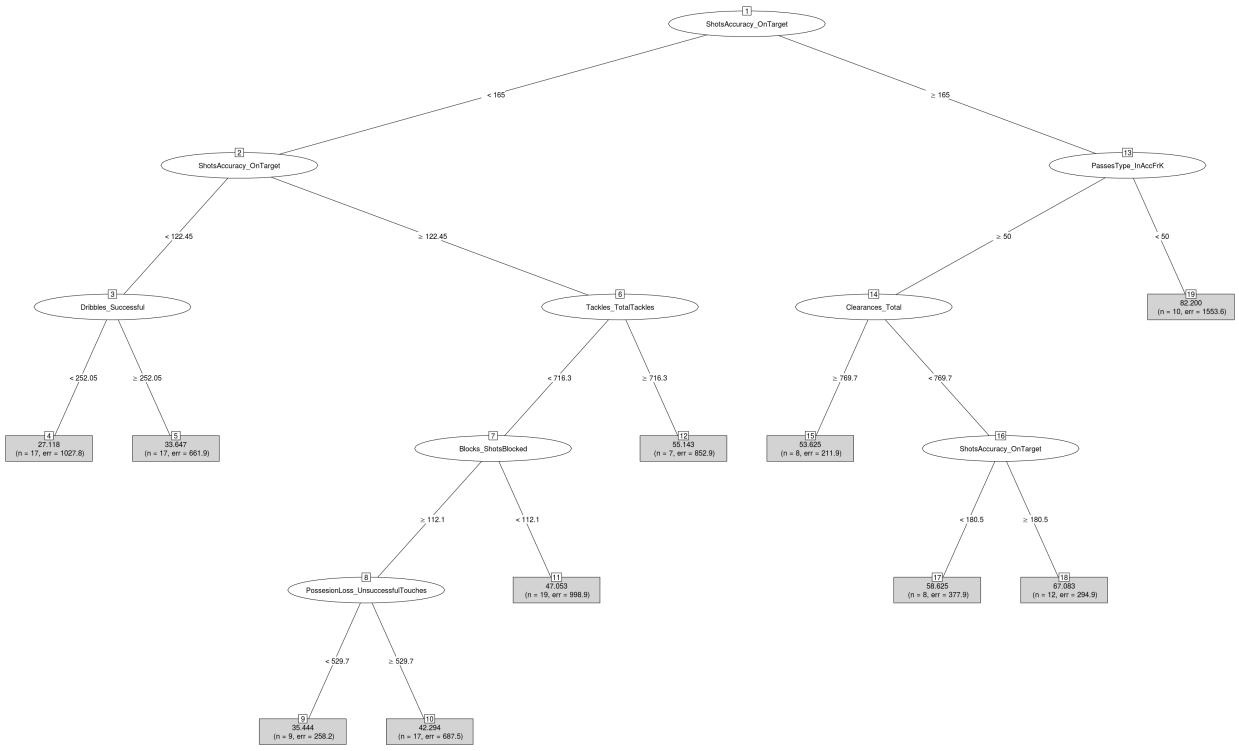


Figure 14: Example of a tree used in Random Forest algorithm

A variable can be selected to split several nodes. In Figure 14, the variable `ShotsAccuracy_OnTarget` is used three times to split three nodes. Thus, this variable has an important effect on the number of points.

4.1.2 Feature selection using Random Forest

Random Forest is an aggregation method based on *bagging* applied on CARTs ([Breiman, 2001]). To construct each CART, the algorithm starts by sampling individuals by a *bootstrapping* method, i.e randomly with replacement. The CART model is then adjusted to this bootstrap sample. In order to reduce variance of the model, before splitting each node according to heterogeneity criterion, algorithm selects randomly a set of explanatory variables among all of them. This procedure reduces correlation between trees.

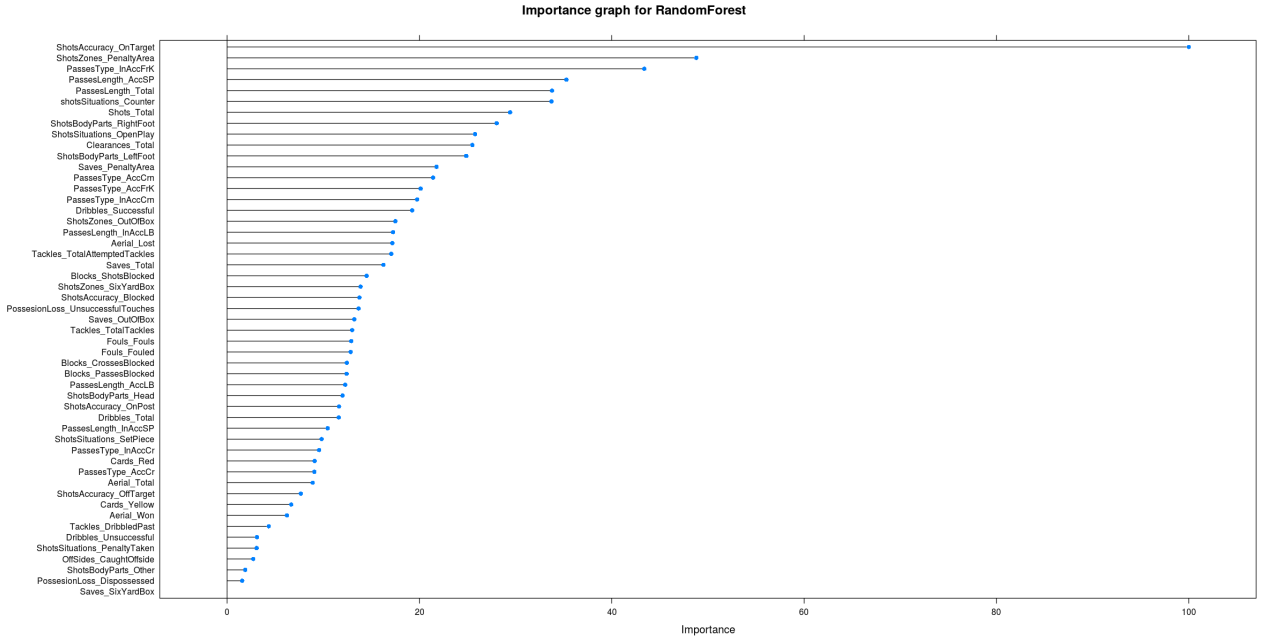


Figure 15: Variable importance based on Random Forest

Figure 15 shows the decrease of importance of the 30 most important features of our data set, for the prediction of the number of points.

There are 6 variables that stand out from the others : `ShotsAccuracy_OnTarget`, `ShotsZones_PenaltyArea`, `PasseType_InAccFrk`, `PassesLength_AccSP`, `PassesLength_Total`, `shotsSituations_Counter`.

The root mean squared error of this model is 9.95. This is the lowest error found considering the three machine learning methods implemented.

4.2 Support Vector Machine

A support Vector Machine (SVM) constructs one or a set of hyperplanes in a high dimensional space. Hyperplanes are chosen to maximize the margin. The margin is the separation between the hyperplane and its closest value. It was first defined for classification, but can be adapted easily to regression problems. `caret` provides an importance measure calculated as explained earlier.

In Figure 16, we can pick the 7 most important variables. They are `ShotsAccuracy_OnTarget`, `ShotsZones_PenaltyArea`, `PassesLength_Total`, `PassesLength_AccSP`, `Shots_Total`, `ShotsSituations_OpenPlay`, `PasseType_AccCrn`.

The root mean squared error of this model equals to 12.68.

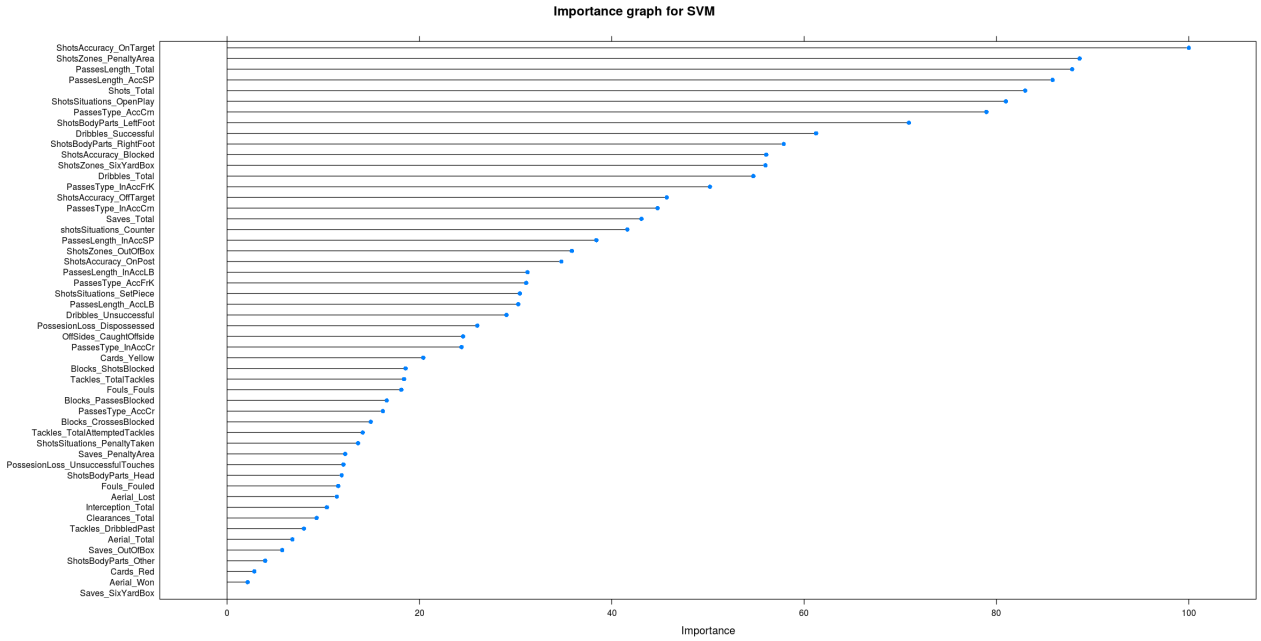


Figure 16: Variable importance based on SVM

4.3 XGBoost

`eXtreme Gradient Boosting` is an optimized version of `Gradient Boosting` algorithm. *Boosting* is a supervised learning method in which several methods from a model set are sequentially aggregated.
At each step, the algorithm add to the combination a new model adapted from the previous one. In the new model, more importance is given to observations that were missajusted on the previous model.

There are several *boosting* methods but the most famous is `Gradient Boosting` [Friedman, 2002]. At each step the new model is constructed in the direction of the gradient of the loss function. This gradient is approximated by a Regression Tree.
`XGBoost` [Chen and Guestrin, 2016] is an improved version of Gradient Boosting in particular because it requires the adjustment of more parameters. The major changes are an additional penalization in the loss function and an approximation of the gradient by a Taylor development. It can also be computed on GPU.

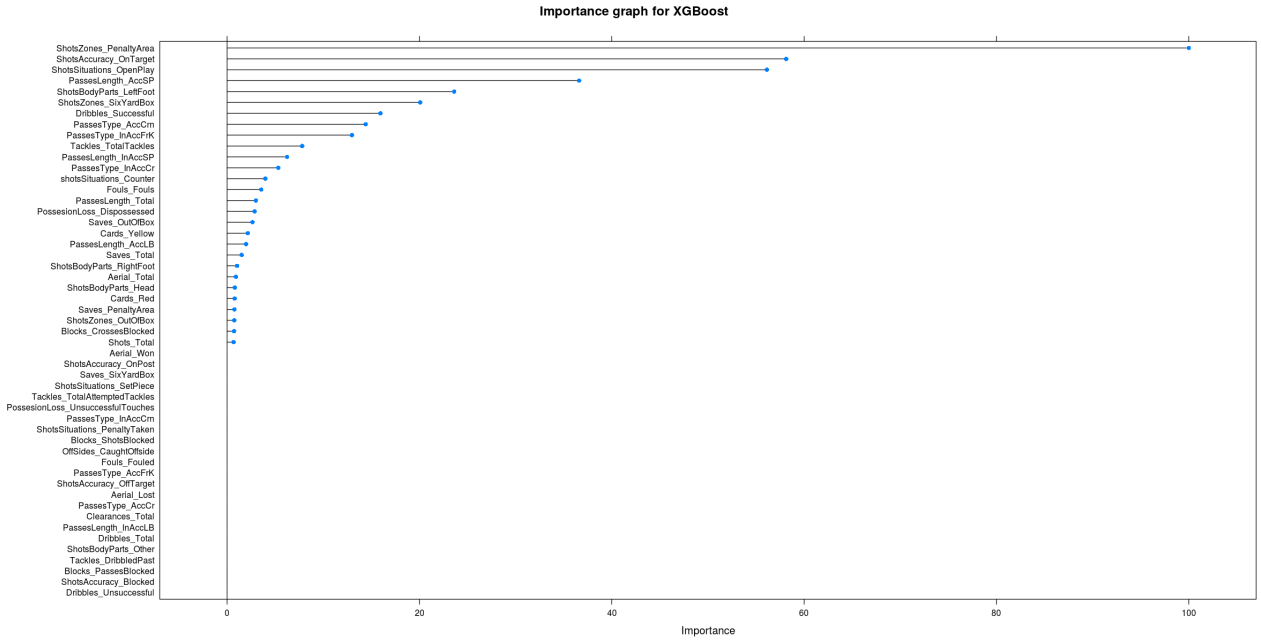


Figure 17: Variable importance based on XGboost

We computed importance of features for `XGBoost`, as we can see in Figure 17. We notice 6 variables really important : `ShotsZones_PenaltyArea`, `ShotsAccuracy_OnTarget`, `ShotsSituations_OpenPlay`, `PassesLength_AccSP`, `ShotsBodyParts_LeftFoot` and `ShotsZones_SixYardBox`.
The model fitted has a root mean squared error of 10.37.

4.4 Comparison of the machine learning results

The three machine learning methods highlighted different main variables.

Figure 18: Comparison of the main variables

In Figure 18 we can identify `ShotsAccuracy_OnTarget`, `ShotsZones_PenaltyArea` and `PassesLength_AccSP` as the three main variables, identified by all three methods. They represent the number of shots on target, the number of shots from the penalty area and the number of accurate short passes. The total pass length and the number of shots from the open play also seem important.

Regarding root mean squared error as a performance indicator of these three methods, we can say that Random Forest is better than XGBoost, which is better than SVM. What's more, Random Forest is the fastest algorithm.

Conclusion

The aim of the study of the data set from *whoscored.com* was to highlight the main variables leading a team to the head of a tournament. It was also to find out the characteristics of the best teams and see if they are specific to the country.

The first step of this study, exploratory analysis, was necessary to discover our data set and to have a first sight of interactions and redundancy between variables. We noticed that the number of points of a club was highly correlated to `offensive` and `passing` statistics.
Then we computed a PCA to obtain another representation of our variables and individuals, by maximizing variance. According to the PCA biplot, we identified the best teams of each championship as outliers. First axis of this PCA was highly linked to the number of points. Teams spread along this axis : good teams on the one hand and bad teams on the other hand. Teams of middle ranking are rearranged along this axis.

For the second and third parts of this project, we decided to remove variables directly linked to goals, assists and key passes. Variable selection methods applied on the entire data set would have highlighted these variables, but it is obvious that a team needs to score goals to win matches. By not considering these features, we emphasized the number of accurate short passes, of penalties, and of shots on target. Short passes testify a built-up game and interaction between players. When a team is able to construct its game, it is leading the game. The importance of the number of penalties reflects the fact that good teams are more likely to get fouled in the penalty area, and then be able to shoot penalties. Obviously, to score goals, it is necessary to shoot on target.

LASSO and ElasticNet selected main variables from `defensive` data. They selected variables related to saves, like passes or shots blocked, have a positive influence on the number of points, unlike clearances.

References

[Breiman, 2001] Breiman, L. (2001). Random forests. *Machine learning*, 45(1):5–32.

[Bridges Jr, 1966] Bridges Jr, C. C. (1966). Hierarchical cluster analysis. *Psychological reports*, 18(3):851–854.

[Chen and Guestrin, 2016] Chen, T. and Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages 785–794. ACM.

[Friedman, 2002] Friedman, J. H. (2002). Stochastic gradient boosting. *Computational statistics & data analysis*, 38(4):367–378.

[Loh, 2011] Loh, W.-Y. (2011). Classification and regression trees. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 1(1):14–23.

[Wei and Simko, 2017] Wei, T. and Simko, V. (2017). *R package "corrplot": Visualization of a Correlation Matrix*. (Version 0.84).

[Wikistat, 2016] Wikistat (2016). Analyse en Composantes Principales — Wikistat. [En ligne; Page disponible le 23 septembre 2019].

[Zhang, 2016] Zhang, Z. (2016). Variable selection with stepwise and best subset approaches. *Annals of translational medicine*, 4(7).

[Zou and Hastie, 2005] Zou, H. and Hastie, T. (2005). Regularization and variable selection via the elastic net. *Journal of the royal statistical society: series B (statistical methodology)*, 67(2):301–320.