What Contributes to the Final League Position in the English Premier League?

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Introduction

As a long English Premier League fan, it came to my interest to actually find out what it takes for teams to become the league champion, and what teams should be careful of when wishing not to be relegated from the league. This research is very important, because there could be underlying variables which not many people would expect, to become factors in deciding the league position for teams at the end of the season.

For this research, because the goal is to find underlying factors which could contribute towards the league position, obvious variables such as goals scored for teams will not be considered. The variables that will be looked into in this research are the league position at the end of the season, the average possession teams have in league matches, the average expected goals for teams, clean sheets, and goals conceded.

The final research question of this paper is to find out which model best identifies the final league position for teams in the English Premier League, so the variables we have chosen will be used to find the best model and verify it. For the model, the multiple linear regression model will be used.

The league positions at the end of the season is obviously the most important factor of this research, the average possession of teams in league matches have been chosen as a variable because of the recent style of play in soccer. Many strong teams in the English Premier League have chosen to play and win by possessing the ball as much as they can, so I thought it could be a key factor when deciding the league position. The average expected goals is one of the new terms that have come up in soccer, and is said to be important when winning matches. Expected goals can basically tell us how the teams have played by considering the number of chances teams would have to actually score a goal. It is different from actually scoring a goal because it tells us the likelihood of how which team actually should have scored in matches. The number of clean sheets are the games that teams have went without allowing a goal so it directly relates to the league position, and finally the goals conceded also naturally relates to the league position so it was chosen as well.

The English Premier league data was retrieved from "FootyStats" and the specific season that I will be looking at is the 2018/2019 season.

Website: https://footystats.org/download-stats-csv

Methods

In order to use the multiple linear regression model, some explanation is needed. The multiple linea regression model is shown as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

where more predictors can be added, but for this research only two will be used.

The β_0 is the intercept value of the regression line, β_1 is the change in y with the change in x_1 with the assumption that x_2 stays the same. The β_2 is also the change in y with the change in x_2 with the assumption that x_2 is the same. The multiple linear regression with the right predictors, can be used as a predictor model to predict for the dependent variable y, using the predictors x. In the case of our research, The y is the final league position, and the x is the variables we have chosen.

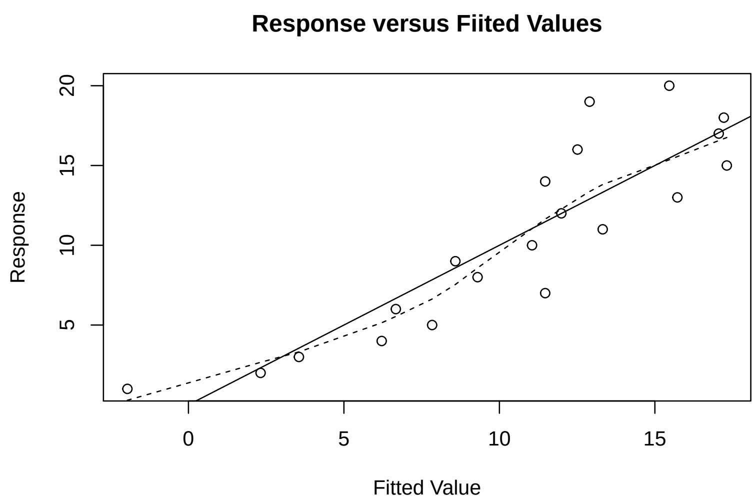
To choose predictors for the final model, each separate variable was scatter plotted with the final league position to look for strong linear relations. Three of them had linear relations which were average possession, expected goals, and goals conceded. The strongest two were chosen which was average possession and expected goals.

Now to check for our model we will need to go through a method called the exploratory data analysis. By making a histogram of the two predictor variables average possession and expected goals, we can check the histogram and see if there are indications for violations. From the histogram of expected goals as plot 1 in the appendix section, a right skew can be seen which might indicate a violation.

Now to check for violations, we will use the residual plots. The residual plots can measure the remaining variability so they can tell us if there are violations. In the case of multiple predictors in the model, we will have to check two conditions in order to look at the residual plot and know how the model is violated.

To check if condition 2 holds, a scatterplot of the predictors can be made and by looking at the relation, it can be seen that it is linear so condition 2 holds.

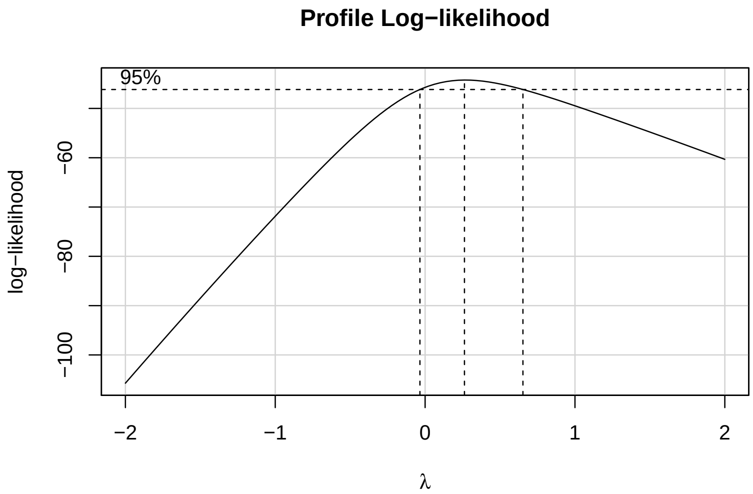
To check if condition 1 holds, a plot of the response against the fitted values can be made to determine the pattern of the plot. In this case for condition 1 to hold the points need to be randomly scattered around the g function. By looking at plot 2 in the appendix, it can be seen that the points are randomly scattered around the g function so we can say condition 1 holds as well.



Plot 2: Response VS Fitted Values

Now we can check the residual plots for possible violations. The residual plots must show no discernible patterns. From looking at plot 3 in the appendix it shows a residual vs fitted value plot. From looking at the plot and the plot of other predictors, it seems to show that there are no violations and assumptions hold. By looking at the normal qq plot as plot 4 in the appendix section, however, the right end of the tail seems to skew up so there might be a mild concern for normality violation.

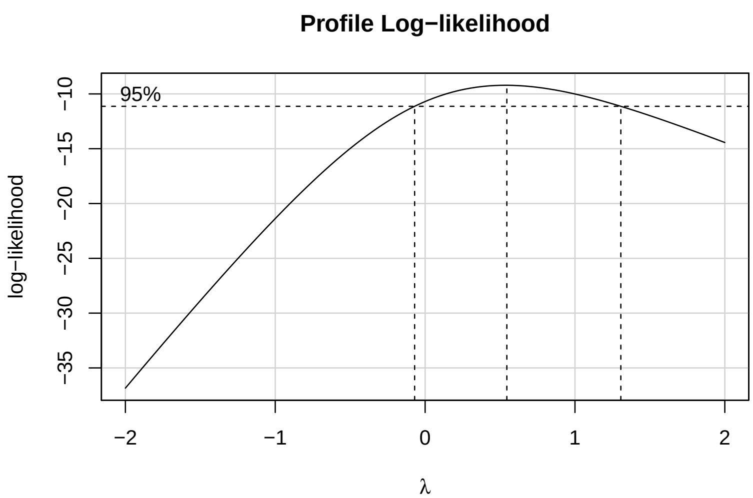
In order to fix this assumed violation of normality, we will just need to transform our Y variable, and a square root transformation seems to be appropriate in this cause. By looking at plot 5, the boxcox plot, the confidence interval does not capture the 1 value, so we will need to fix this by transforming the original model.



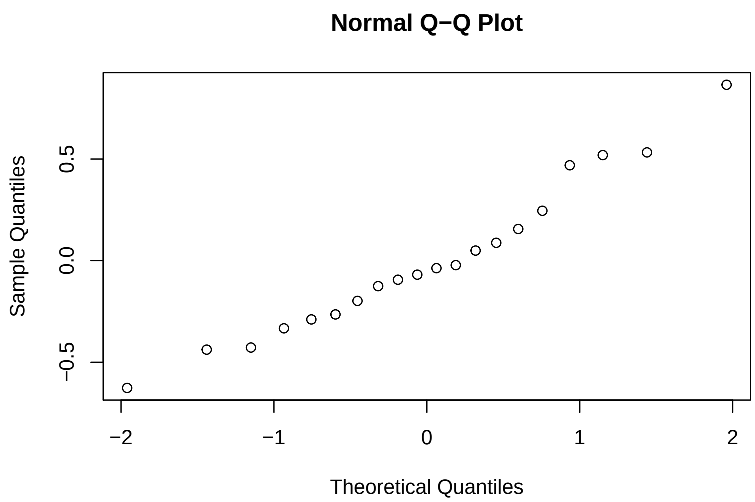
Plot 5: BoxCox Plot of Original Model

Results

As a result of the transformation as explained in the methods section, the new final model have been made by square rooting and transforming only the Y variable. From looking at plot 6, it can be seen that the new confidence interval captures the 1 value in the boxcox plot. The new normal qq plot also seems to show that the dots are more linear and the skew is less than the untransformed version.



Plot 6: BoxCox Plot of Transformed Model



Plot 7: Transformed Model Normal QQ Plot

	Adj R Squared	Average Possession p-value	Expected Goals p-value
Original Model	0.7636	0.111	0.029
Transformed Model	0.847	0.0266	0.0107

Table 1: Numerical Summary of Original Model and Transformed Model

By looking at the summary of the original model and the transformed model, it can be seen that there are many positive changes. The original regression coefficient value was 0.7636 which meant that the model could only explain around 76% of the variability in the model. The transformed model has a value of 0.847 which means it explains more variability. The p-value from the anova test for the predictors also seem to have positively changed where now, the p-value for the predictors have a value less than 0.05 so it can be seen that both predictors are important for the final model and the transformed model shows a much stronger relation than the original model.

Discussion

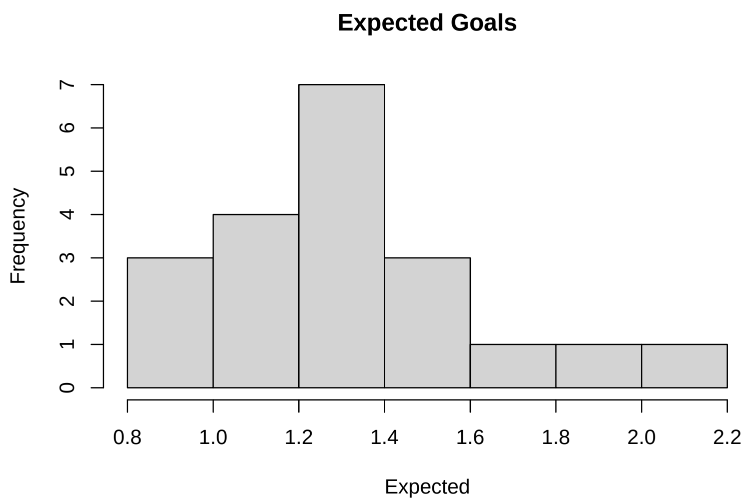
Now that the final transformed model have been made and confirmed as a stronger model than the original one. From this model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \epsilon$$

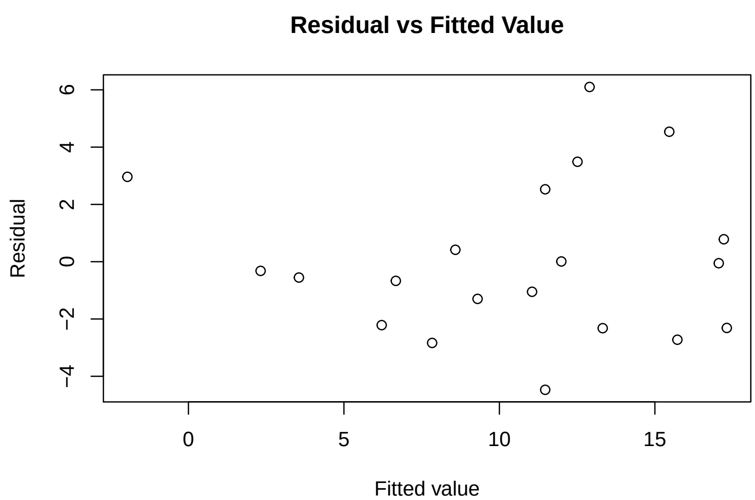
the y now has a root over it, and from the summary the β_0 value is 7.83529, β_1 value is -0.05208 and the β_2 value is -1.627728. This means that with one unit increase in average possession, the league position to square root will decrease by 0.05208 when other predictors remain fixed. In this case, the decrease in league position means lower numbers so that would mean top teams in the league. With one unit increase in expected goals, the league position to square root decreases by 1.627728 with other predictors remaining fixed. When both predictors are 0, the league position to square root would be 7.83529.

The final model seems to show relations and seems to be a good choice to be the best model in predicting the final league position from the data we have. Some of the limitations of this research is that the transformation can never perfectly transform the model. We would just have to be satisfied and move on so we cannot get a perfect final model.

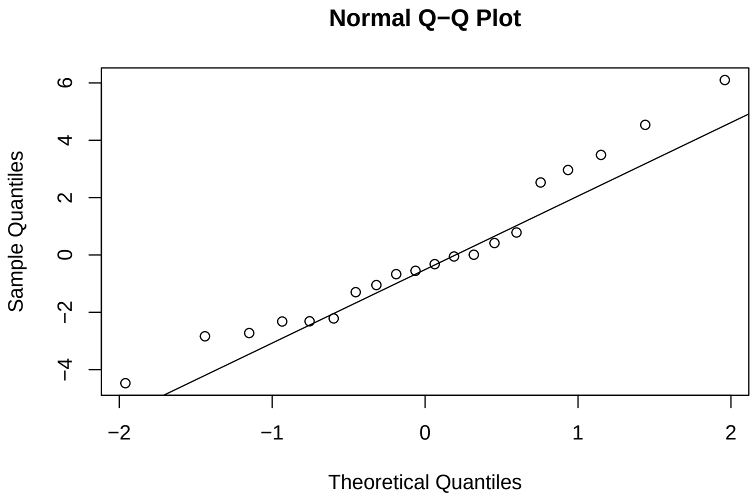
Appendix



Plot 1: Histogram for Expected Goals



Plot 3: Residual VS Fitted Value



Plot 4: Normal QQ Plot for Original Model

Bibliography

All analysis for this report was programmed using 'R Studio'

The packages dplyr, car, carData, openintro, forcats, lme4, purr, readr, stringr, tibble, tidyr, tidyverse were used in this analysis.

Download Soccer / Football Stats Database to CSV: Footystats. Football Stats by FootyStats. (n.d.). Retrieved December 17, 2021, from https://footystats.org/download-stats-csv