# How Lucky Was Leicester City Winning the Premier League Season 2015/2016?

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## Introduction

The 2015/2016 edition of the Premier League season was truly extraordinary as Leicester City was crowned champions, winning the Premier League for the first time in their history (see figure 1).

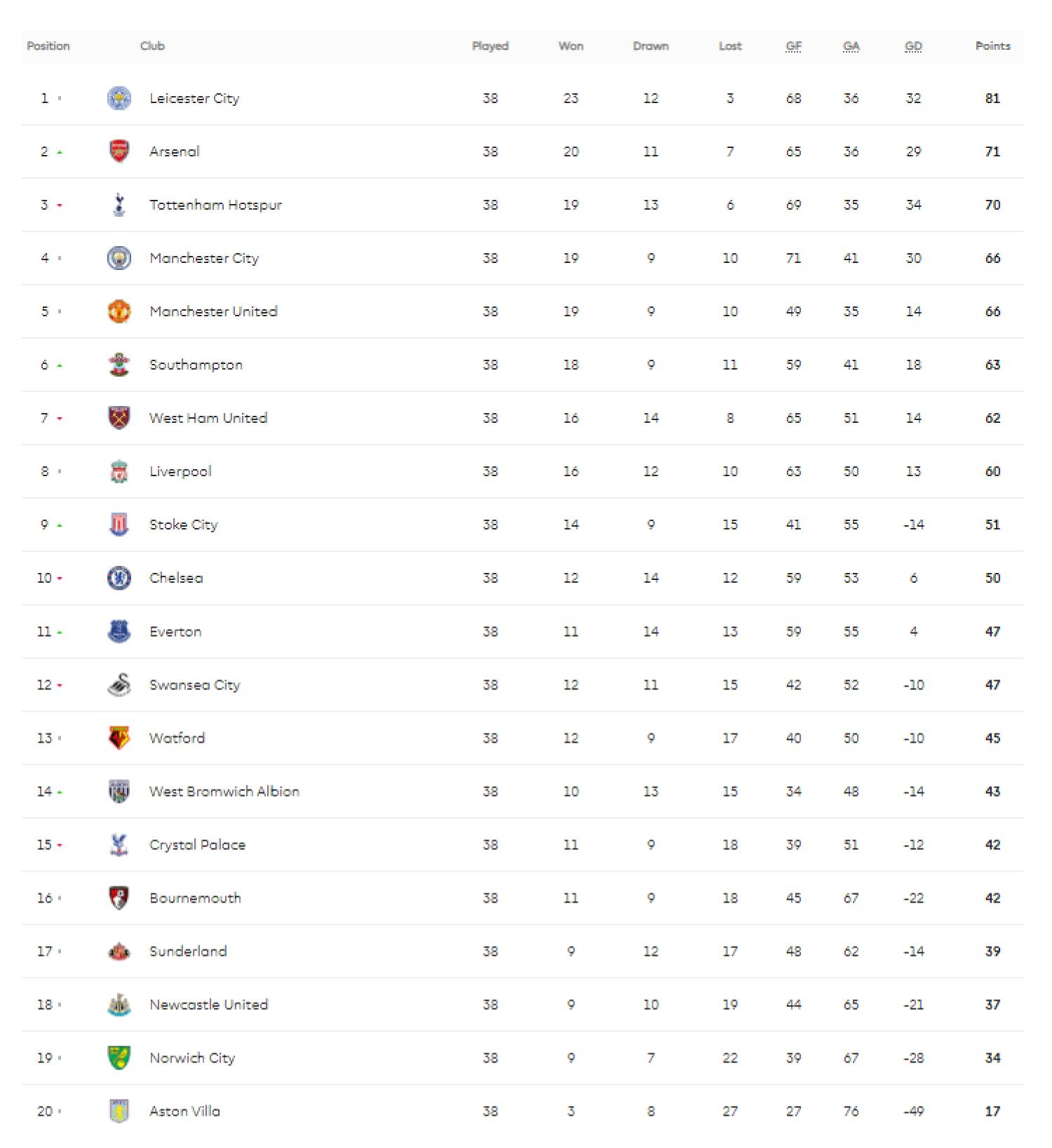


Figure 1: Final table of the 2015/2016 Premier League Season

In the 2014/2015 season, Leicester had finished 14th in the league and the season prior to that they had been promoted to the Premier League. This was truly a remarkable season that no one saw really saw coming. How could this be? And how much was luck involved? Sure, Leicester made some great signings and were fortunate in the sense that all of the top teams really disappointed this season. A couple of facts: Arsenal came closest with 71 points, the lowest ever for a runner-up. Leicester scored a total of 65 goals over 38 matches, averaging 1.71 goals. In comparison, Manchester City scored 102 goals when they won the 2013/2014 season. Leicester ended up with only 81 points, the fourth lowest score for a champion in all 24 seasons of the

Premier League. So how lucky where they? I wanted to investigate how much the element of luck had been on Leicester's side throughout the campaign.

I decided to make a simple Poisson regression model and simulate the season 1000 times to see how many times Leicester would end up on top. To make things simple, I started with a data set containing all the results from the 2015/2016 season. The data consisted of four columns

home: the name of the home team away: the name of the away team yh: the score of the home team ya: the score of the away team

The league consist of 20 teams that play each other two times, home and away for a total of  $20 \cdot 19 = 380$  matches in a season. We will model this as follows: For each game, we assume that the number of goals scored between the home team and away team is independent. We assume that each team has a single parameter that measures its "strength". This is denoted  $\beta_{Leicester}$  and so on for the other teams. If the home team is A and the away team is B, the score (number of goals) for team A will be Poisson distributed with mean  $\lambda$ , such that

$$\ln \lambda = \beta_0 + \beta_{home} + \beta_A - \beta_B,$$

where  $\beta_0$  is the intercept and  $\beta_{home}$  is a home advantage parameter. Similarly, the score (number of goals) for team B will be

$$\ln \lambda = \beta_0 - \beta_A + \beta_B.$$

If two teams have equal strength, i.e.  $\beta_A = \beta_B$ , it follows that  $\exp(\beta_0)$  will give the expected number of goals for the away team and  $\exp(\beta_0 + \beta_{home})$  will give the expected number of goals for the home team.

Hence, the linear predictors are of the form

$$\ln E(Y) = \beta_0 + \beta_{home} x_{home} + \beta_{Leicester} x_{Leicester} + \dots + \beta_{AstonVilla} x_{AstonVilla}$$

Let A be the home team and B the away team. If the score Y is for A, then  $x_{home}=1$ ,  $x_A=1$ ,  $x_B=-1$  and  $x_C=0$ 

for all other teams C. If the score Y is B, then  $x_{home}=0$ ,  $x_A=-1$ ,  $x_B=1$  and  $x_C=0$  for all other teams C.Hence, there are n+1+1=22 covariates. We construct a  $720\times 22$  design matrix X. However, the 20 team covariate vectors are linearly dependent. To work around this problem, we set one of the parameters equal to zero,  $\beta_{AstonVilla}$ . Aston Villas was chosen since it was the team that finished last. The covariate vectors will now be linearly independent. In order to calculate the parameters for the Poisson regression we must use maximum likelihood. For a Poisson regression, we have

$$L(\beta) = \prod_{i=1}^{n} \frac{\lambda_i^{y_i}}{y_i!} e^{-\lambda_i}.$$

The log-likelihood,  $l(\beta)$  then becomes

$$l(\beta) = \sum_{i=1}^{n} y_i (\ln(\lambda_i) - \lambda_i - \ln(y!)).$$

Using our linear predictor and log link  $\eta_i = ln(\lambda_i) = \mathbf{x}_i^T \boldsymbol{\beta}$ , the log-likelihood can be re-written as

$$l(\beta) = \sum_{i=1}^{n} y_i \mathbf{x}_i^T \beta - \sum_{i=1}^{n} e^{\mathbf{x}_i^T \beta} + C,$$

where C = -ln(y!). Differentiating the log-likelihood function gives the score function,

$$s(\beta) = \sum_{i=1}^{n} (y_i - \lambda_i) \mathbf{x}_i$$

We use numerical optimization to solve

$$s(\hat{\beta}) = 0.$$

#### Results

Simulating the season 1000 times produced the following results as shown in figure 2. The second column shows the average number of points over 1000 seasons and the third columns shows the average goal difference.

##		points	goaldif
##	Tottenham	73.562	33.576
##	Leicester	72.873	31.879
##	ManchesterCity	71.538	29.781
##	Arsenal	70.731	28.691
##	Southampton	64.082	18.027
##	WestHam	62.089	14.786
##	${\tt ManchesterUnited}$	61.524	14.247
##	Liverpool	60.732	12.879
##	Chelsea	56.167	5.897
##	Everton	54.797	3.768
##	Swansea	45.822	-10.071
##	Watford	45.757	-9.683
##	CrystalPalace	44.382	-11.932
##	WestBromwich	43.389	-13.717
##	Sunderland	43.180	-14.420
##	Stoke	43.143	-13.932

Figure 2: Average league table of 1000 simulated seasons

Interestingly, this simple model shows that Tottenham has a higher average points score than Leicester City and ends up

on the top of the table. Furthermore, Leicester gets roughly 73 points, which is 8 points lower than they actually got in 2015/2016, a considerable difference. Figure 3 shows the simulated results for each team with the vertical axis showing the number of seasons and the horizontal axis showing their place in the league.

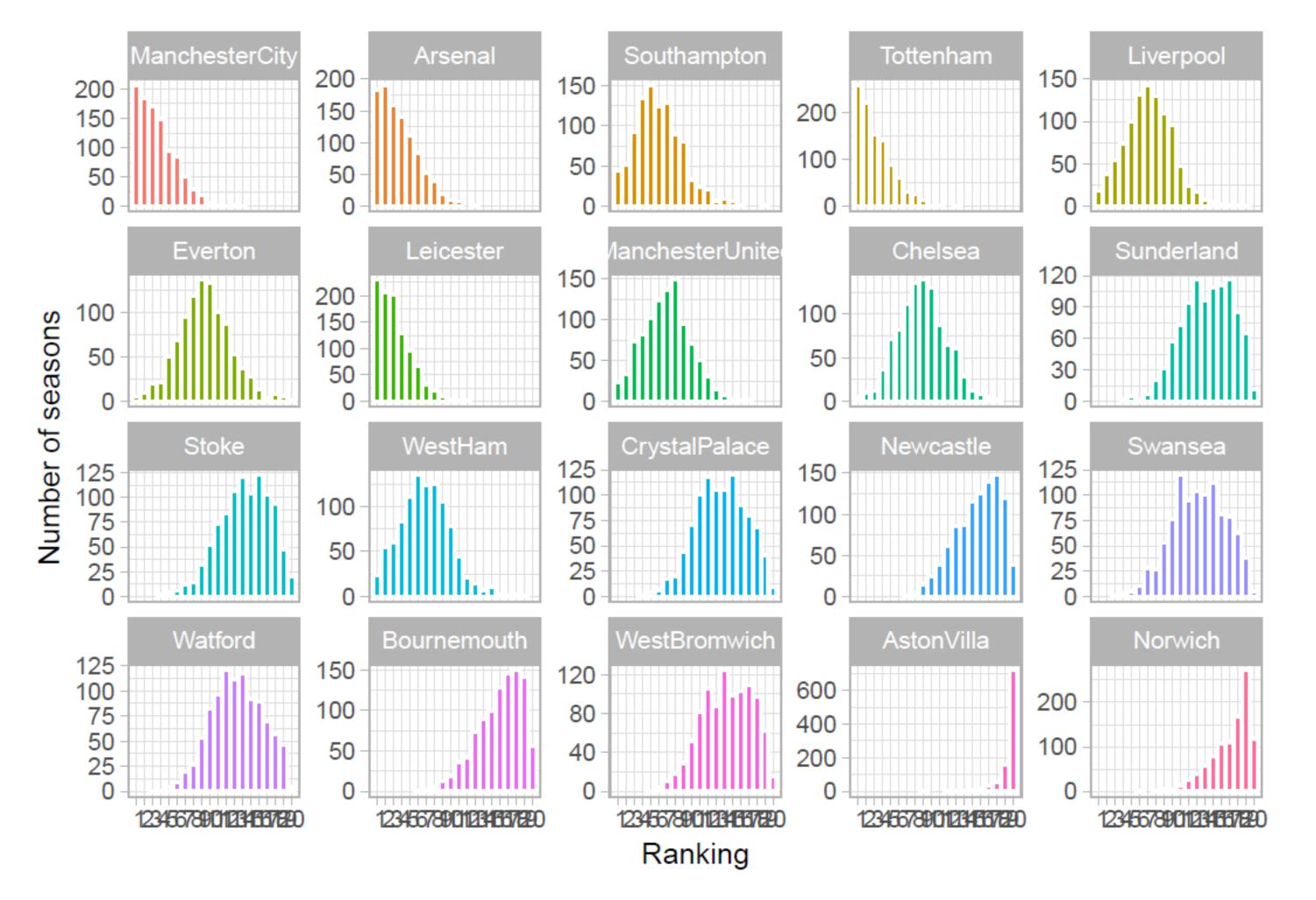


Figure 3: 1000 simulated seasons showing the final standings for each team.

#### Code

## This simple model was made in R

```
generalizedLinearModel <- function(formula, data, contrasts = NULL, ...){</pre>
  # Extract model matrix & responses
  mf <- model.frame(formula = formula, data = data)</pre>
 X <- model.matrix(attr(mf, "terms"), data = mf, contrasts.arg = contrasts)</pre>
 Y <- model.response(mf)
  terms <- attr(mf, "terms")</pre>
  estimate = calc_estimate(X, Y)
  est <- list(terms = terms, model = mf, X=X, Y=Y)
  est$call <- match.call()</pre>
  est$formula <- formula</pre>
  est$estimate = estimate
  class(est) <- 'generalizedLinearModel'</pre>
  return(est)
log.lklh.poisson = function(par,x,y){
  return(sum(y * (x %*% par) - exp(x %*% par)))
calc_estimate = function(X, Y) {
  opt = optim(par = rep(0, 17),
                log.lklh.poisson,
                X = X
                y = Y,
                control=list(fnscale=-1),
                method=c("BFGS"))
  matrix = as.matrix(opt$par)
  rownames(matrix) = colnames(X)
 return(matrix)
final_table = function(input){
  result = data.frame(matrix(OL, nrow=length(levels(input$home)), ncol = 0))
 rownames(result) = levels(input$home)
 result$points = 0
 result$goaldif = 0
 for (i in (1:length(input$home))){
    home = as.numeric(input[i,]$home)
    away = as.numeric(input[i,]$away)
    goal_difference = input[i,]$yh - input[i,]$ya
    result[home, ]$goaldif = result[home, ]$goaldif + goal_difference
    result[away, ]$goaldif = result[away, ]$goaldif - goal_difference
    if(goal_difference > 0){
      result[home, ]$points = result[home, ]$points + 3
    else if(goal_difference < 0){</pre>
      result[away, ]$points = result[away, ]$points + 3
    else{
      result[home, ]$points = result[home, ]$points + 1
      result[away, ]$points = result[away, ]$points + 1
  result = result[(order(-result$points)),]
  return(result)
```