Projet_Women_FIFA_WC23_Analysis

2024-05-17

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1 Introduction

In today's world, sports are at the center of global culture. To continue to excel, players and teams must find solutions, both physical and tactical. Therefore, statistics will play a crucial role in optimizing performance. Previous studies have shed light on various aspects of football analytics. Collet studied the impact of possession in 2013. More recently Liu analyzed the environmental impact in 2021. However, the realm of soccer remains relatively untapped in terms of data exploration. Understanding the dynamics of offensive and defensive play is pivotal for teams aiming to excel in competitions.

The research gap lies in the need for a comprehensive analysis of football performance using advanced statistical methods, with a focus on data from platforms like StatsBomb. The impact of certain specific aspects of football analytics, such as shot analysis or passing patterns, remains unclear, and a comprehensive understanding of player and team performance is still lacking.

We aimed to address this gap by conducting a detailed analysis of football performance using StatsBomb data. We seeked to identify key performance indicators, assess their impact on match outcomes, and uncover underlying trends and patterns in player and team performance. This report outlines the methodology used for data collection and analysis, presents the findings from the study, and discusses their implications for the future of football analytics.

This report is divided into three parts. In the first section, we conduct an exploratory data analysis to identify certain trends, notably by analyzing shots and goals for each team. Then we seek an optimal statistical model to determine which parameters have the greatest impact on player performance. The last section contains the results of our analysis, including insights into player and team performance derived from StatsBomb data, with graphs examining successful shots and passes.

2 Descriptive data analysis

The package StatsbombR provides the data from 71 national and international competitions, for a total of over 3000 matches. For the sake of this project, we narrow our scope down to the most recent competition available : The FIFA Women's World Cup 2023 and its 64 matches. We begin by interpreting the different variables of this large data set.

The full data set contains 183 variables for analysis, with the majority having a significant proportion of missing values, as they were used to track very specific patterns of play. As an example, the parameter "goalkeeper.shot_saved_to_post" is attributed "True" only if the goalkeeper saved a shot from going inside the goal, by deflecting it onto a post.

2.1 Analysis of successful shots according to country

First, we will look at how the data is stored in the data set. We will do this by plotting the shots of a specific match; we chose Spain-England, which was the final match of the competition.

```
## Warning: Using ‘size‘ aesthetic for lines was deprecated in ggplot2 3.4.0.
## i Please use ‘linewidth‘ instead.
## This warning is displayed once every 8 hours.
## Call ‘lifecycle::last_lifecycle_warnings()‘ to see where this warning was
## generated.
```

```
## Warning: Removed 1 rows containing missing values (‘geom_rect()‘).
```

```
## Warning: Removed 1 rows containing missing values (‘geom_segment()‘).

## Warning: Removed 1 rows containing missing values (‘geom_rect()‘).

## Warning: Removed 1 rows containing missing values (‘geom_point()‘).
## Removed 1 rows containing missing values (‘geom_point()‘).

## Warning: Removed 30 rows containing missing values (‘geom_path()‘).
```

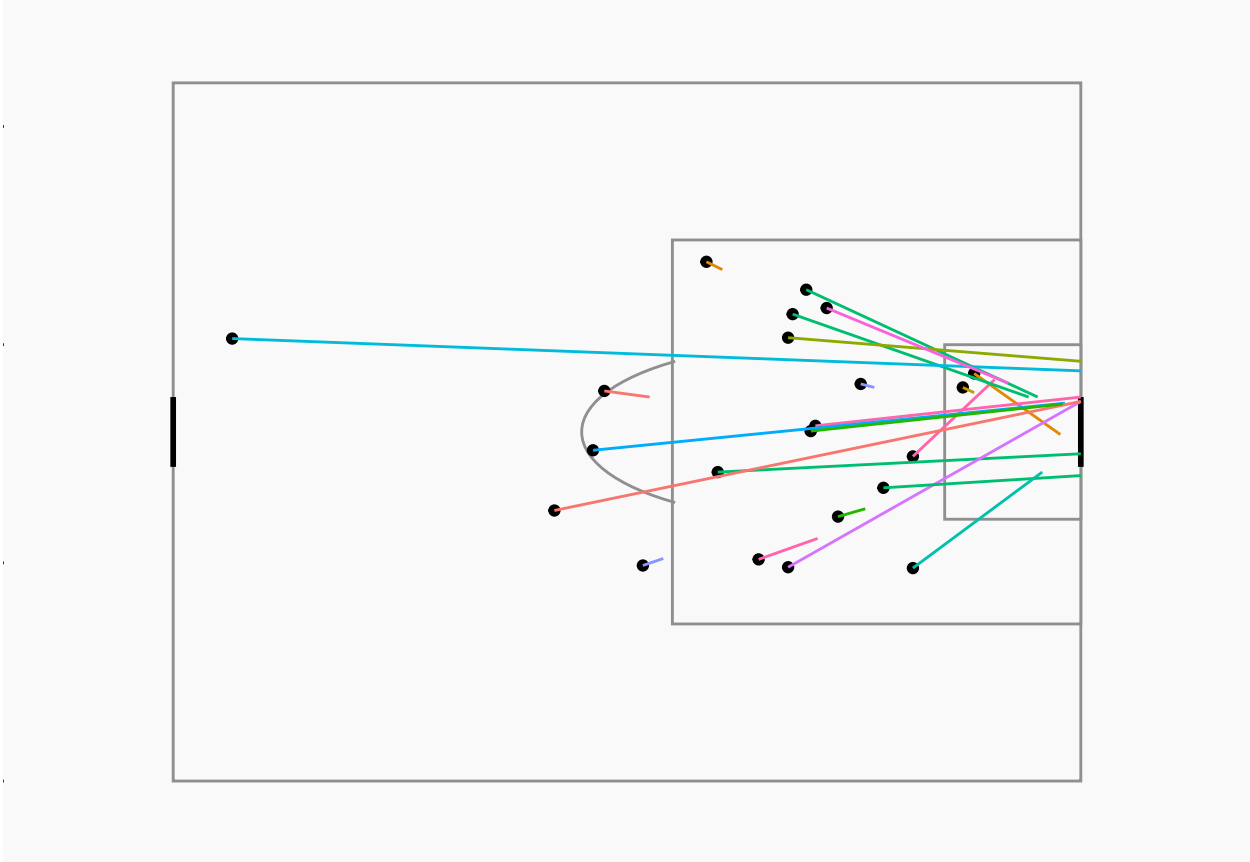


Figure 1: Visualization of the shots of Spain-England on the pitch

We can see that regardless of which team scores, the locations of the players are always tracked the same way : for a given team, the home goal is located at x = 0, which corresponds to the left of this graph, and the opposing goal is located at x = 120. This will allow us to directly use the provided variables, without further formatting the data.

Then, we took a look at the number of goals and shots in all matches for each team.
Figure 2 shows a visualization of these results.

From the above figure, we can already see a big disparity in team success. Some teams, like Vietnam and Haiti, didn't even manage to score a goal over the course of the competition, while Sweden and France were more successful in this aspect. However, simply displaying how much shots and goals a team made provides an incomplete understanding of team effectiveness, and is generally a flawed metric for comparison, as teams that made it further into the competition naturally scored more goals, and had more shots.

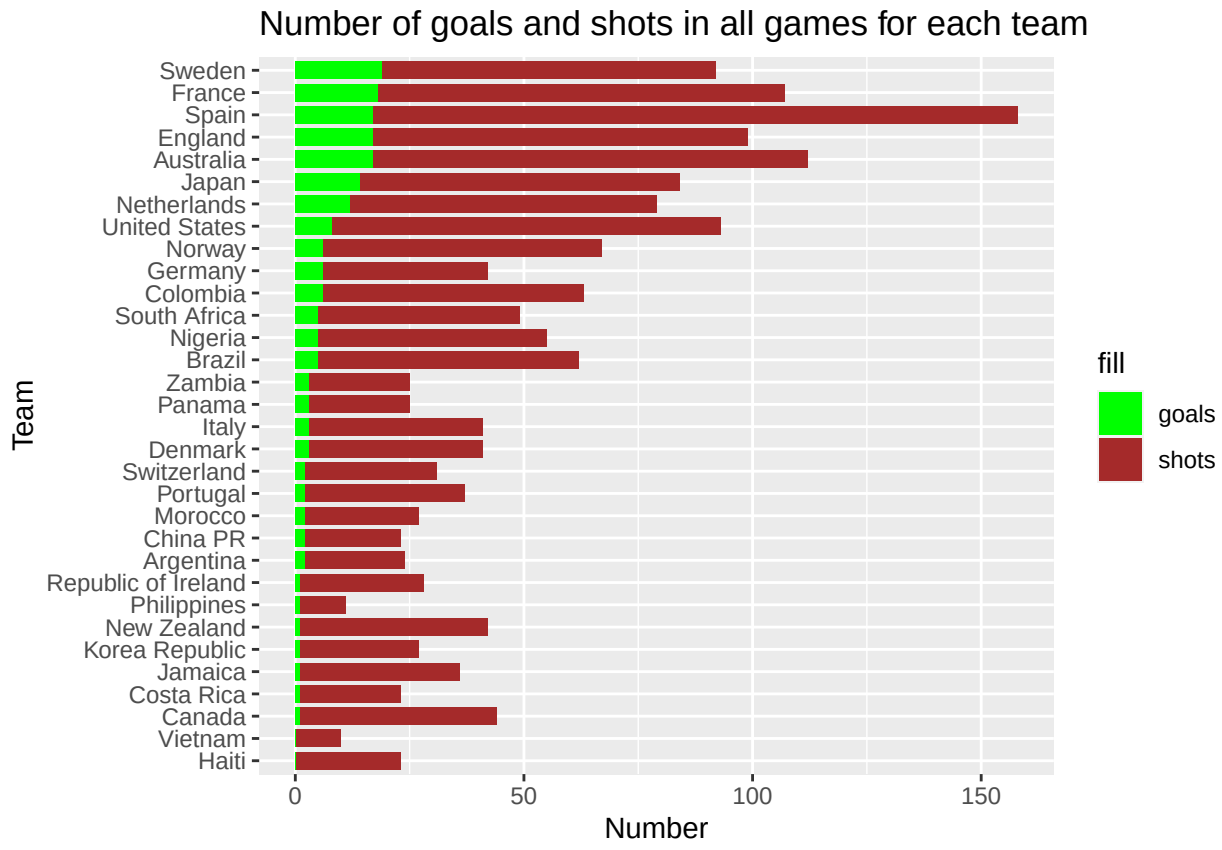


Figure 2: Diagram of the number of goals and shots in all matches for each team

Therefore, we calculated the percentage of shots leading to a goal for every team, and compared them in Figure 3.

From this graph, we are able to identify that Sweden was the most efficient team in scoring by over 2.5%. This is of course very biased, as Sweden finished third in the tournament, only losing one match throughout the entirety of the competition. Keeping that in mind, it is surprising that Spain scores this low on the graph, considering they won the World Cup. It could be that Spain, despite their evident success, was not a very efficient team, or that they had a different playing style than other teams.

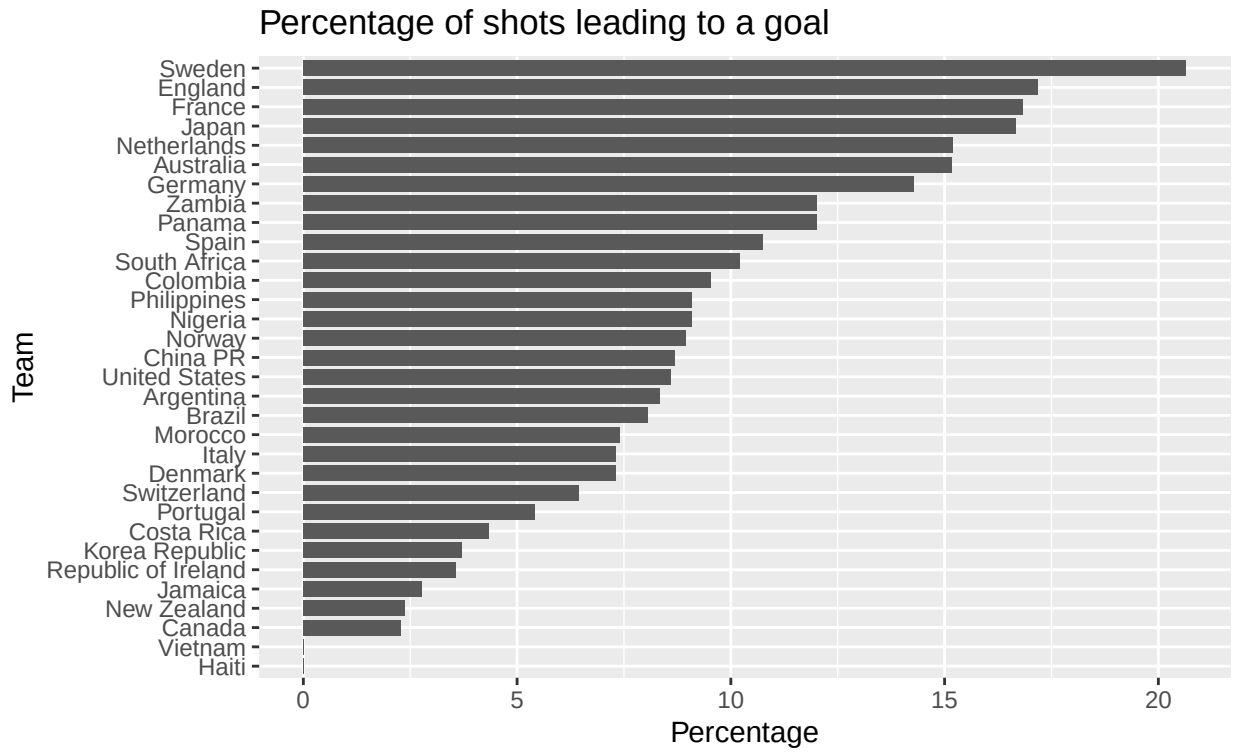


Figure 3: Diagram of the percentage of shots leading to a goal

Next, we wanted to realize the above analyses for singular matches. We chose the four matches played by team France, and created the same graphs for each of their matches. Figure 4 shows the results.

As we can see, there were a huge number of goals in two games : Panama France and Australia France. The first match ended on a exceptional 3-6 score for France, but the former ended on a nil-nil. However, teams went to penalties, and they scored a total of 13, making this observation flawed.

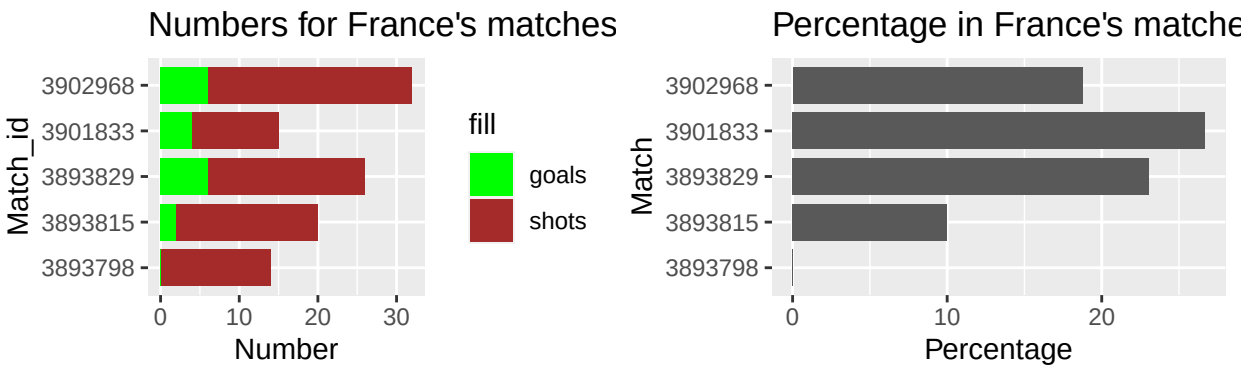


Figure 4: Diagram of the number of shots and goals for each French and percentage

2.2 Analysis of successful shots according to different variables

We first look at the different types of shots in Figure 4. Four different types of shots were differentiated in the data set : “Open Play”, “Penalty”, “Free Kick” as well as “Corner.” A shot was deemed as being “Open Play” if it was taken during regular actions of the game. The “Corner” label only applies to a single shot made by Ireland’s Katie McCabe, and went in. This is something to keep in mind, as it is sure to skew our future models. Other labels are self-explanatory.

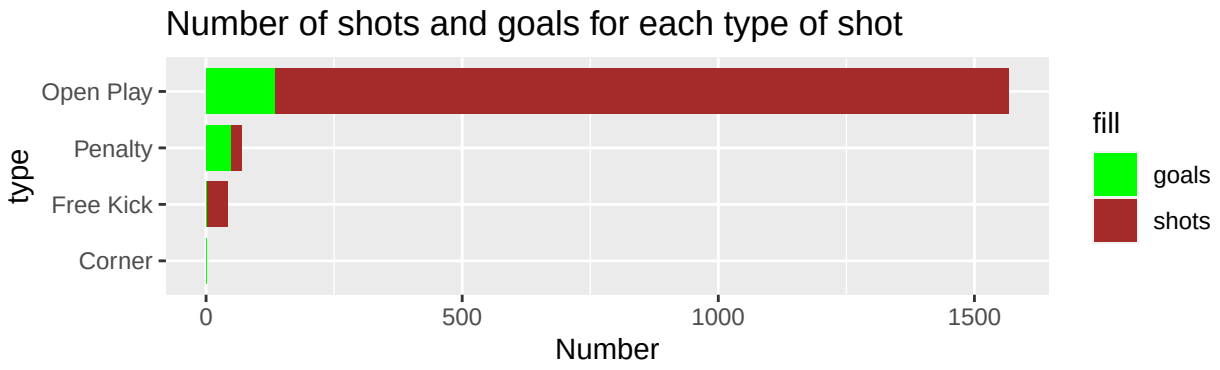


Figure 5: Diagram of the number of shots and goals for each type of shot

Next, we look at the different techniques used by players : how much are being kept a track in the data set, how much were each of them used, and which one produced the most goals.

Figure 5 shows that data set contains seven types of shots, although only three are consistently being used, that is : “Normal”, “Half Volley” and “Volley”. Naturally, the “Normal” shot was the most popular, and hence yielded the mos t goals. A “Lob” was very infrequently done, but could prove effective in the right situation : it seems a good portion of these shots went in.

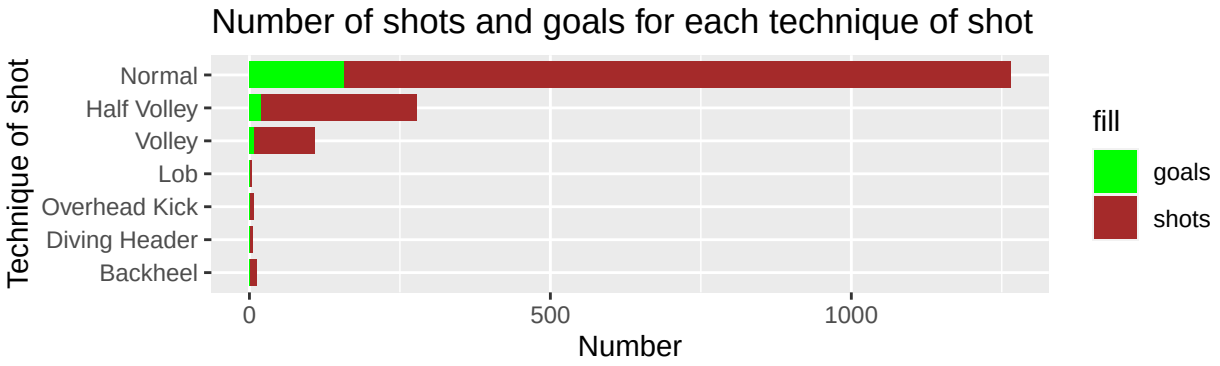
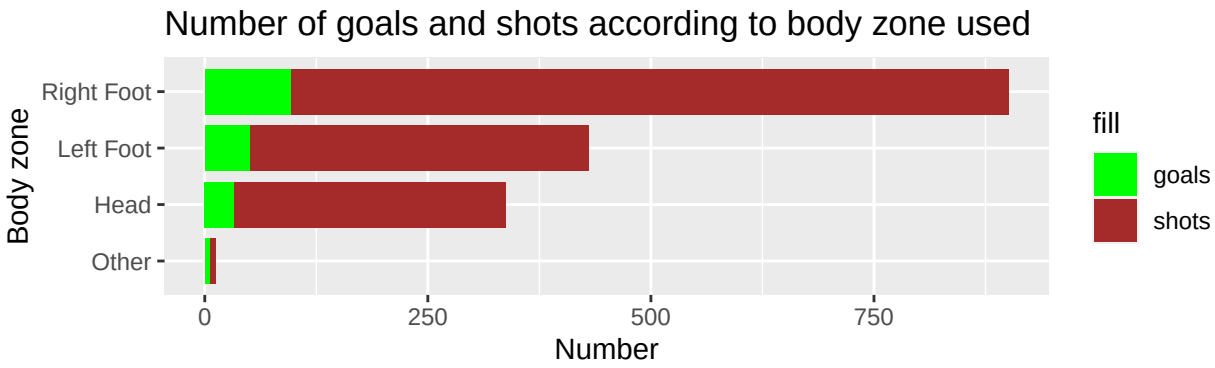


Figure 6: Diagram of the number of shots and goals for each technique of shot

Similarly, we visualize in Figure 6 the different body parts used in shooting.

Unsurprisingly, the right foot was most commonly used, and it seems every body part was equally as effective in scoring, apart from the “Other” body zone.


Number of goals and shots according to body zone used
Body zone
Right Foot
Left Foot
Head
Other
0
250
500
750
Number
fill
goals
shots

3 Models analysis

We wanted to create our own xG model. To do that we developed different models, finding the most relevant variables to predict goals.

We run a logistic regression model: we want the output to be 0 or 1 depending on whether the shot turns into a goal.

3.1 First model : body part, technique, type of shot

The first model keeps the variables studied previously : body part, technique, type of shot.

R^2 for the model without interaction is : 0.144105

R^2 for the model with interaction is : 0.1460338 .

3.2 Our target model : the expected goal variable

We now create a model composed of a single variable: the expected goal given in StatsBomb.

Our goal in creating the different models in this section is to find the most accurate model possible, which can have an R^2 close to this model (with only the expected goal as a variable), i.e. an R^2 close to : 0.262161.

3.3 Model 3 : Adding location.x and location.y

Any player on the field is assimilated as a moving point on a rectangle of size 80x120m. Its horizontal movement - that is, going from one goal post to another - is tracked by the variable location.x, while the vertical movement is associated to location.y. We will now add location.x and location.y to our previously adjusted model.

We test a regression without interaction, and obtain an R^2 of : 0.2054155 .

With interactions, we get an R^2 of : 0.2323348.

In this model, we targeted the main variables to obtain a good model and an R^2 as close to 1 as possible.

3.3.1 Significance of variables ?

We run several tests to see which variables are significant in the model.

```
## Analysis of Deviance Table
##
## Model 1: shot.outcome.name ~ (location.x + location.y + shot.body_part.name +
```

```
##     shot.type.name)^2
## Model 2: shot.outcome.name ~ (shot.body_part.name + shot.technique.name +
##     shot.type.name + location.x + location.y)^2
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      1658     917.76
## 2      1637     891.22 21   26.542   0.1865
```

We see that we can remove the technique because $p - value$>0.05 so we can accept the sub-model with a 95% level.

For this sub-model without the technique variable we obtain an R^2 of : 0.2094726

The R^2 is no greater than for model 3 with interactions: this is normal because the R^2 favors models with many variables.
We should look at other variables such as AIC score, which is minimal for model 3 without interactions.

3.3.2 Comparison of norms

We now want to compare model 3 with and without interaction : the closer the 2-norm is to 0, the better the model.

Norm L2 for the model_3 without interaction is equal to : 4.1435027.

The value for the model_3 with interactions is : 4.2588035.

We find the same results as with the AIC criterion. This is consistent with the fact that R^2 favors models with many variables, so it's better to evaluate with AIC. We can conclude that the model 3 without interaction is best.

We do the same to compare model 1 with and without interaction.

The L2 norms are respectively : 4.6785642 and 4.6786731.

Both models are less accurate than the 3rd one.

3.4 Model 4 : adding the under_pressure variable

We now create a new model like the model_3, but adding a variable : under_pressure.

3.4.1 Test for significance of single variables

First, we test the significance of this new variable.

```
##
## Call:
## glm(formula = shot.outcome.name ~ under_pressure, family = binomial(link = "logit"),
##     data = df_model_4)
##
## Coefficients:
```

```
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -1.94591    0.09486 -20.513   <2e-16 ***
## under_pressureTRUE -0.41957    0.16790  -2.499   0.0125 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1160.9  on 1679  degrees of freedom
## Residual deviance: 1154.5  on 1678  degrees of freedom
## AIC: 1158.5
##
## Number of Fisher Scoring iterations: 5
```

We see that $p_{\text{value}} < 0.05$, so we reject H_0 : playing under pressure is significant.

Estimated coefficients are negative, so playing under pressure reduces the probability of scoring.

Testing the model with only the shot.body_part.name variable gives us a p_{value} of : 0.042.
We reject H_0, the technique variable is significant.

We now want to test the model with only the shot.technique.name variable.

```
##
## Call:
## glm(formula = shot.outcome.name ~ shot.technique.name, family = binomial(link = "logit"),
##     data = df_model_4)
##
## Coefficients:
##                                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)                     -1.657e+01  6.927e+02  -0.024    0.981
## shot.technique.nameDiving Header  8.145e-08  1.277e+03   0.000    1.000
## shot.technique.nameHalf Volley    1.395e+01  6.927e+02   0.020    0.984
## shot.technique.nameLob            1.547e+01  6.927e+02   0.022    0.982
## shot.technique.nameNormal         1.461e+01  6.927e+02   0.021    0.983
## shot.technique.nameOverhead Kick  8.143e-08  1.141e+03   0.000    1.000
## shot.technique.nameVolley         1.389e+01  6.927e+02   0.020    0.984
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1160.9  on 1679  degrees of freedom
## Residual deviance: 1143.9  on 1673  degrees of freedom
## AIC: 1157.9
##
## Number of Fisher Scoring iterations: 15
```

The reference is backheel : all the other techniques are better, we have a lot of values close to 1, we could do a constant sub-model to see if this variable is significant.

We find a p_{value} of 0.009. We reject H_0, the technique variable is significant.

We are now testing the model with only the shot.type.name variable. We also run a sub-model test.

We find a p_{value} of 0.

The variable shot.type.name is significant, we reject H_0.

We do the same with the variable location.x :

We see a p_{value} of : 0. <0.05 so location.x is highly significant.

We check if the variable location.y is significant as well.

The p_{value} is : 0.915. > 0.05 so location.y is not significant.

3.4.2 Testing the complete model

The model is now tested with all the following variables: shot.body_part.name,shot.technique.name,shot.type.name,location.x

We have an R^2 of 0.2054992 which is good, but it's normal because it's a model with many variables.

We also note a low AIC, which is equal to `954.3696823`.

3.5 Model 5 : adding the position of the goalkeeper

We create the same model as above, but adding the position of the goalkeeper.

3.5.1 Does the position of the goalkeeper in x and y improve our results ?

First we test the model with only the location.x.GK variable.

```
##
## Call:
## glm(formula = shot.outcome.name ~ location.x.GK, family = binomial(link = "logit"),
##     data = df_model_6)
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)   23.74030    4.90676   4.838 1.31e-06 ***
## location.x.GK -0.22185    0.04174  -5.315 1.07e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 934.31  on 1620  degrees of freedom
## Residual deviance: 910.15  on 1619  degrees of freedom
##   (59 observations effacées parce que manquantes)
## AIC: 914.15
##
## Number of Fisher Scoring iterations: 5
```

```
## [1] 0.02586437
```

Significant effect of goal position in x because both p_{values} are lower than 0.5.
The AIC value is low, equals to `914.1462437`.

Then we do the same but with the location.y.GK variable.

We find that the variable for keeper position in y is significant as well. AIC is slightly higher than for position in x, it's equal to `937.1556025`.

3.5.2 Complete model

For the model with all the preceding variables and without interaction, we find a very low AIC=`845.3219716`.
We can conclude that this model is really good.

3.6 Keeping all significant variables and removing location.y

Since we found that location.y is not significant, we can remove it from the model.

Without this variable, the AIC is even lower, at `844.5352323`.

We can conclude that we have found our best model for now and it's composed of the variables :

body_part, shot.technique, shot.type, location.x, under_pressure, location.x.GK, location.y.GK.

3.7 Replacing location.y

Seeing as location.y is a very insignificant variable, we now view offense as symmetrical with respect to the axis passing by the center point of the pitch and the penalty spots. We will now refer to location.y as the distance to center, and the new variable will vary from 0 to 40 meters. This hopefully will give more sense to the parameter, as a high distance to center means a player is very off-center.

```
## Warning: Removed 40960 rows containing missing values (‘geom_tile()‘).
```

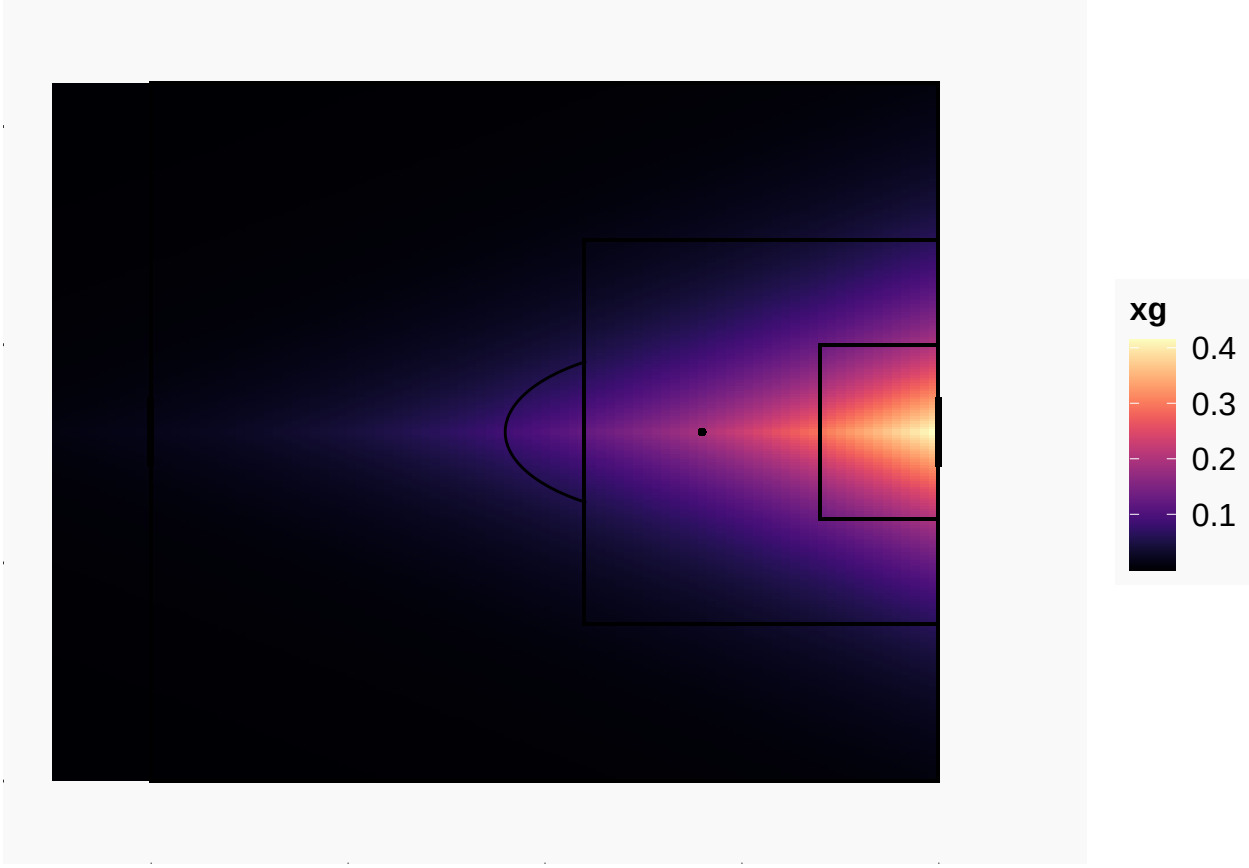
```
## Warning: Removed 65536 rows containing missing values (‘geom_rect()‘).
```

```
## Warning: Removed 65536 rows containing missing values (‘geom_segment()‘).
```

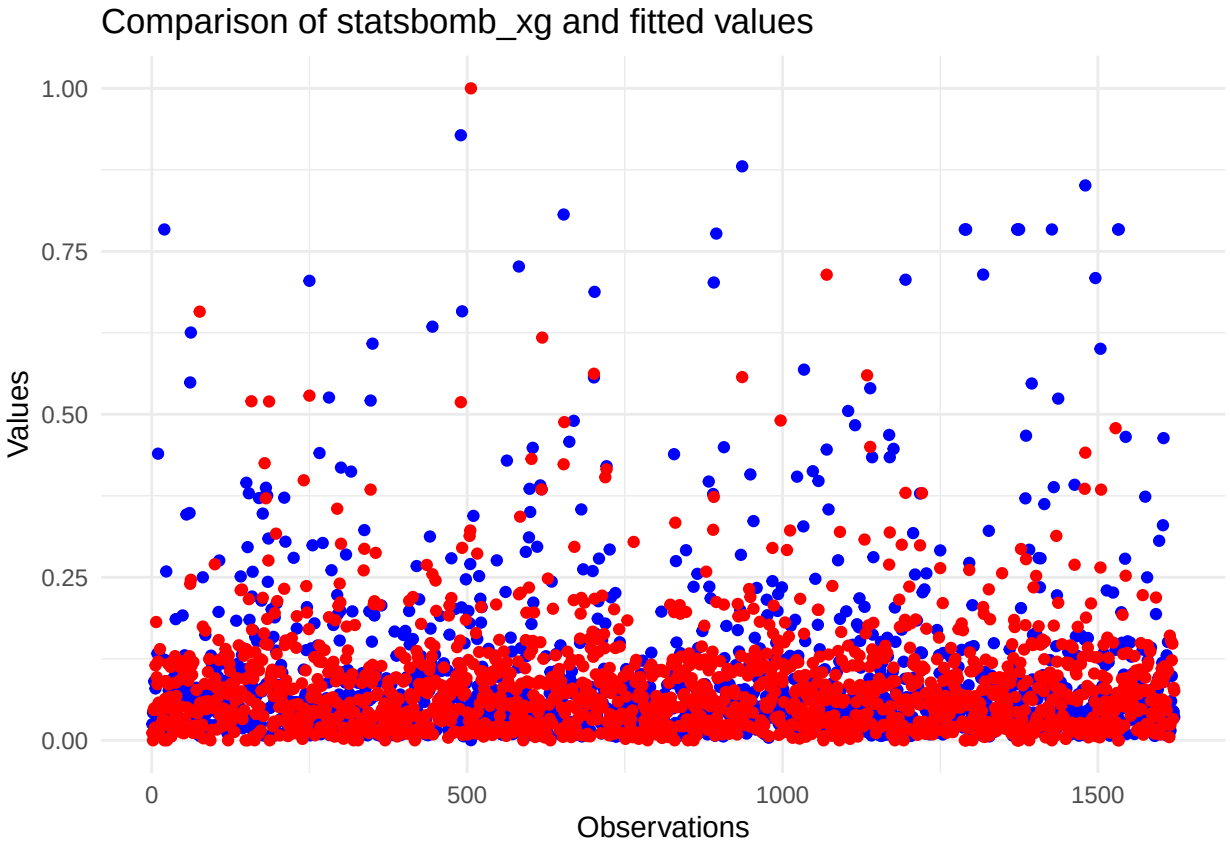
```
## Warning: Removed 65536 rows containing missing values (‘geom_rect()‘).
```

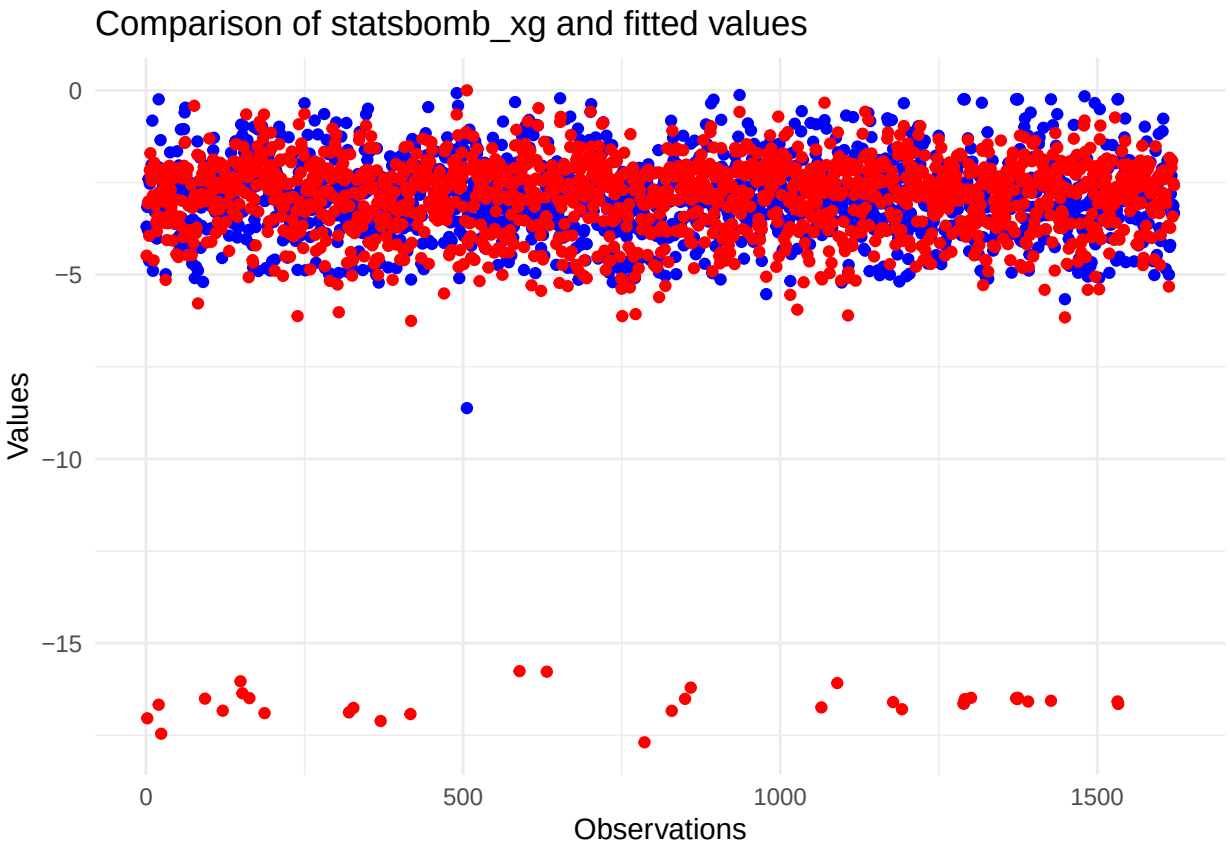
```
## Warning: Removed 65536 rows containing missing values (‘geom_point()‘).
## Removed 65536 rows containing missing values (‘geom_point()‘).
```

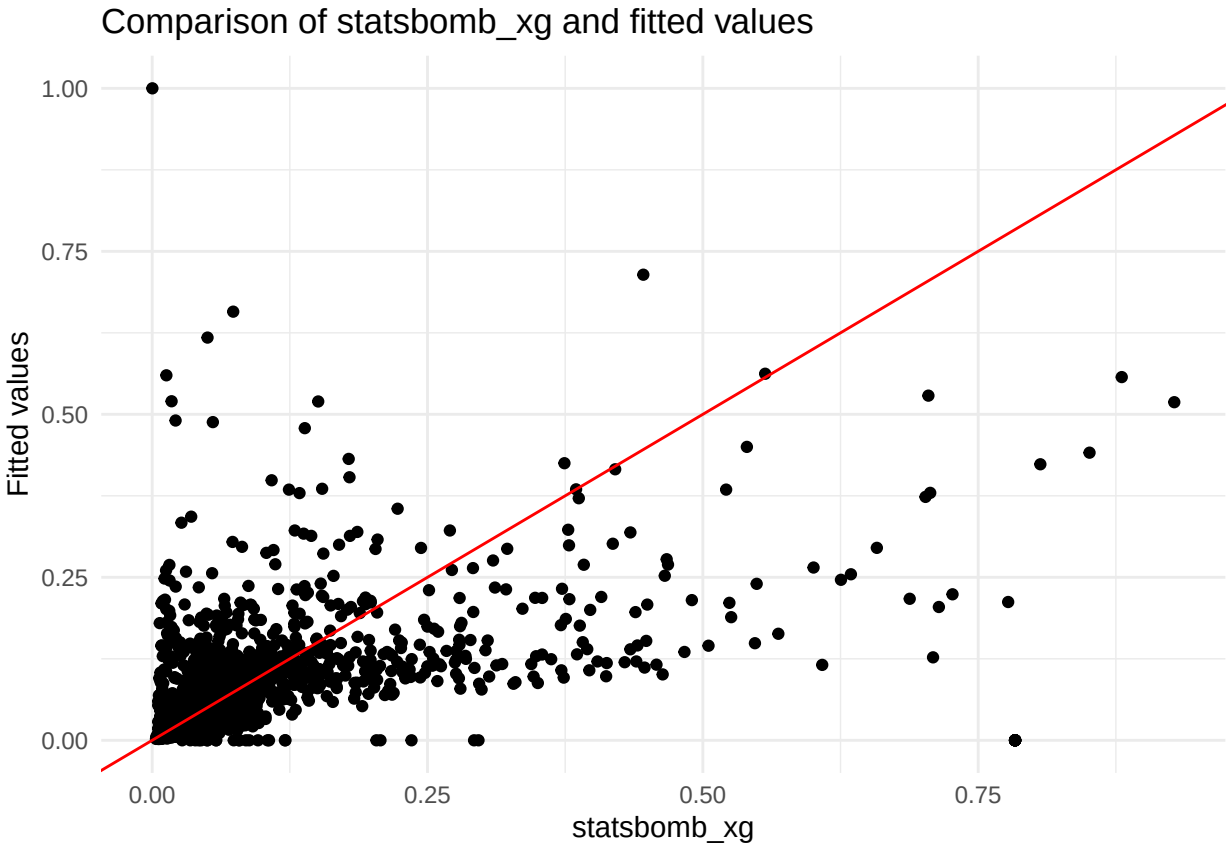
```
## Warning: Removed 30 rows containing missing values (‘geom_path()‘).
```

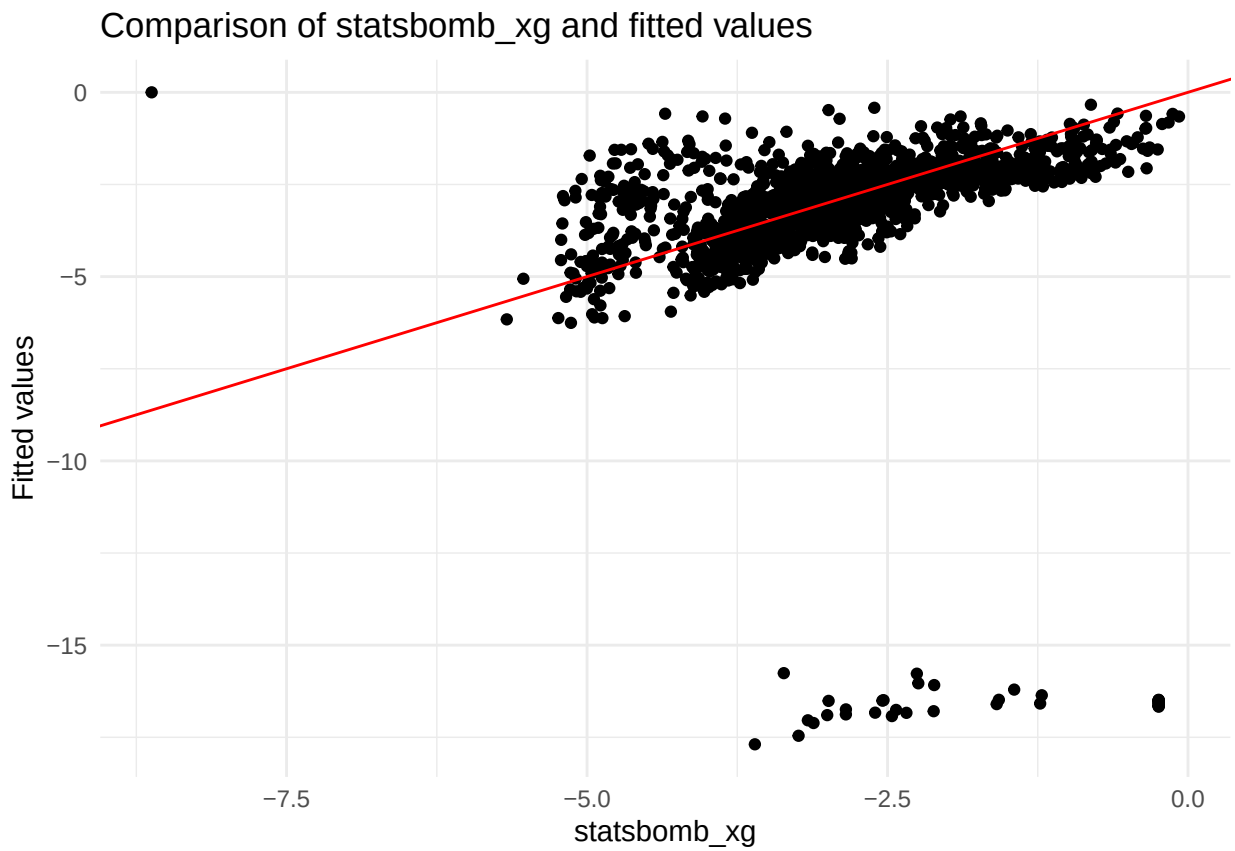


The above heatmap shows what is to be expected : from a very simple model, only using the location as well as the distance to center, we can see that the model expects a player to have better scoring chances with point-blank shots rather than shots outside the penalty area. This is explained by the fact that our data set does not contain many goals made from outside this area.


Comparison of statsbomb_xg and fitted values
1.00
0.75
0.50
0.25
0.00
Values
0
500
1000
1500
Observations


Comparison of statsbomb_xg and fitted values
0
−5
−10
−15
Values
0
500
1000
1500
Observations


Comparison of statsbomb_xg and fitted values
Fitted values
statsbomb_xg
1.00
0.75
0.50
0.25
0.00
0.00
0.25
0.50
0.75



We have a lot of values close to 0, so we do the log to make things clearer.

In log: there's a point (an observation) where we've overestimated the chance of scoring. There are a few points at the bottom right where, on the contrary, we've underestimated the probability, but overall we've got a good prediction based on the Xg of bomb stats.

3.8 Finding our best model with the AIC criterion

```
##
## Call:  glm(formula = shot.outcome.name ~ shot.body_part.name + shot.technique.name +
##     location.x + location.x.GK, family = binomial(link = "logit"),
##     data = df_model_6)
##
## Coefficients:
##                         (Intercept)      shot.body_part.nameLeft Foot
##                             -2.8131                            0.6209
##          shot.body_part.nameOther     shot.body_part.nameRight Foot
##                              1.6863                            0.4945
## shot.technique.nameDiving Header    shot.technique.nameHalf Volley
##                              1.0349                           14.4967
##            shot.technique.nameLob        shot.technique.nameNormal
##                             16.2501                           15.1470
## shot.technique.nameOverhead Kick        shot.technique.nameVolley
##                              0.4921                           14.4811
##                         location.x                    location.x.GK
##                              0.1331                           -0.2488
```

```
##
## Degrees of Freedom: 1620 Total (i.e. Null);  1609 Residual
##   (59 observations effacées parce que manquantes)
## Null Deviance:       934.3
## Residual Deviance: 814.7     AIC: 838.7
```

We can see finally that y-positions are useless even for the goalkeeper, only x-positions are significant.

Our best model is composed of 4 variables : The technique of shot, the body part used and the positions in x for the player and the goalkeeper.