



Football Transfer Market Data Analysis

Data Science Final Project - January 2024

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Introduction

This project is based on the 'Football Data from Transfermarkt Football (Soccer) data' on Kaggle, scraped from [Transfermark website](#).

This project is done in two main parts. One part, the first part is related to the analysis of football data and drawing graphs and obtaining information based on the available data.

In the second part, it is about building machine learning models and building a comprehensive data set to predict the price of football players based on their performance in 2023.

The data came from: <https://www.kaggle.com/datasets/davidcariboo/player-scores> by <https://www.kaggle.com/davidcariboo>

These data are included with this shape. Some of them were used in the first part and some others were used in the second part.

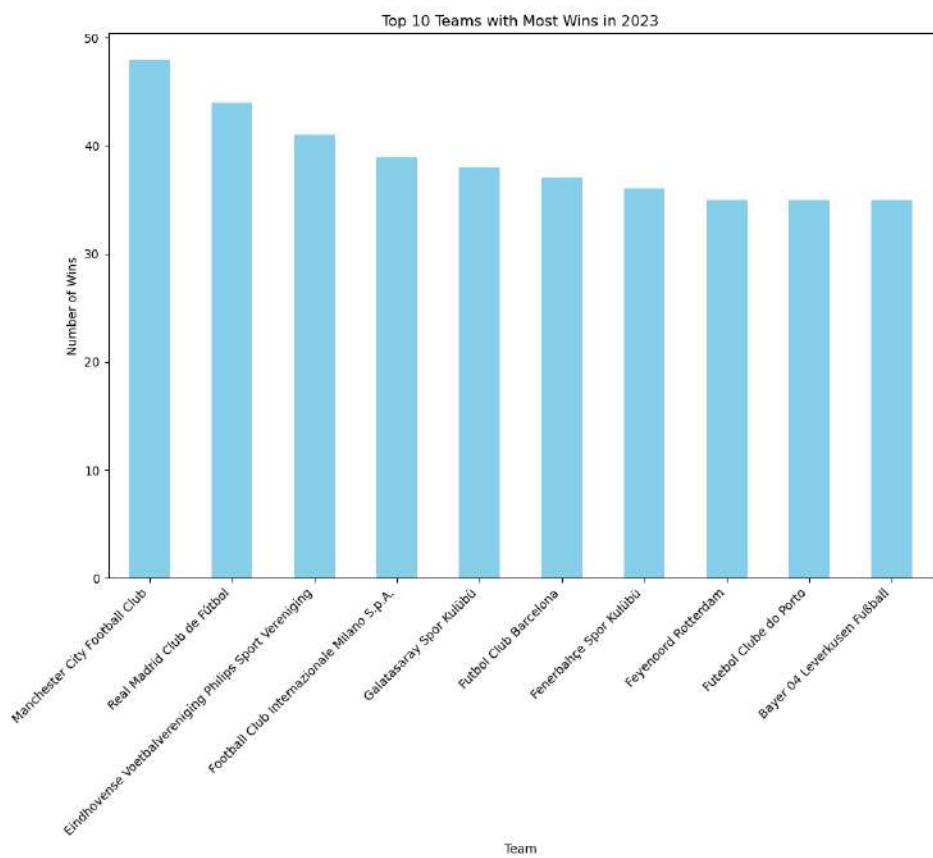
Data Frame	Rows	Columns
appearances_df	1524941	13
clubs_df	426	17
club_games_df	132390	11
competitions_df	43	10
games_df	66195	23
game_events_df	681952	10
game_lineups_df	2304615	9
players_df	30396	23
player_valuations_df	464869	5

1. Football data analysis

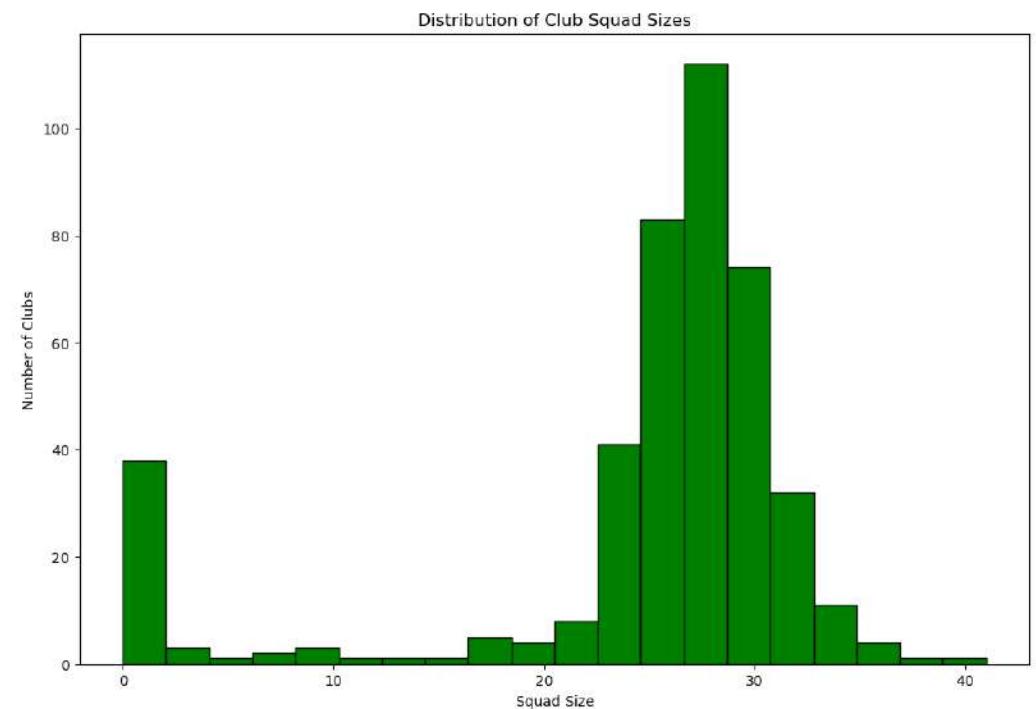
In this part of the project, some questions were asked and their answers were found in the data set, and relevant analyzes and graphs were drawn.

Which team has won more in the year 2023?

The team with the most wins in 2023 is Manchester City Football Club with 48.0 wins.



Visualizing Club Squad Sizes

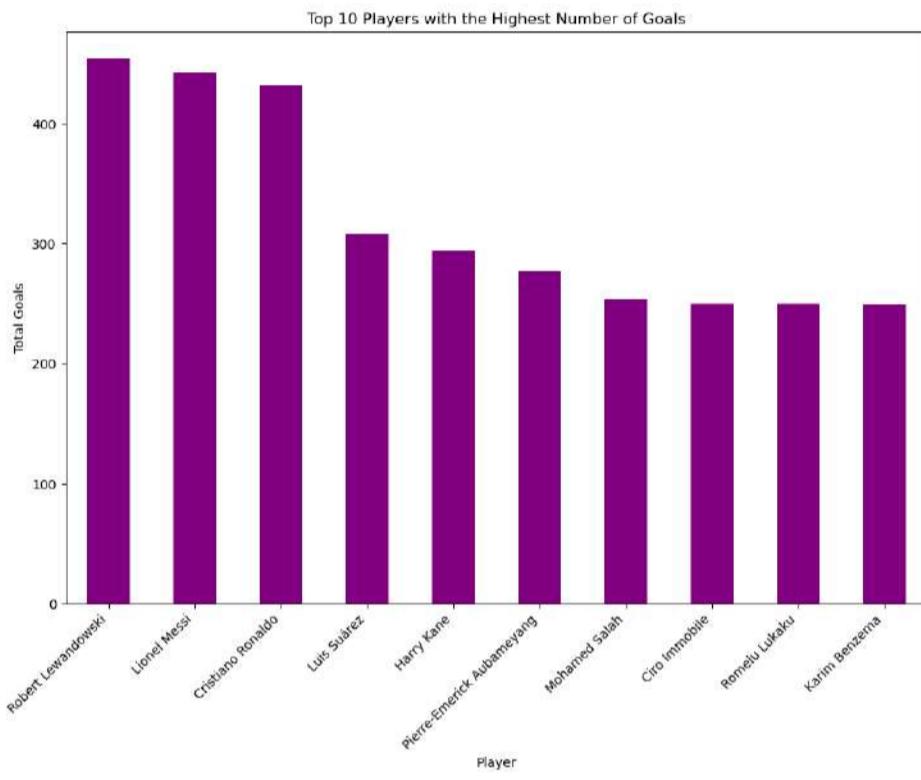


- According to the result of the plot, most teams have a squad size of 25 to 30.

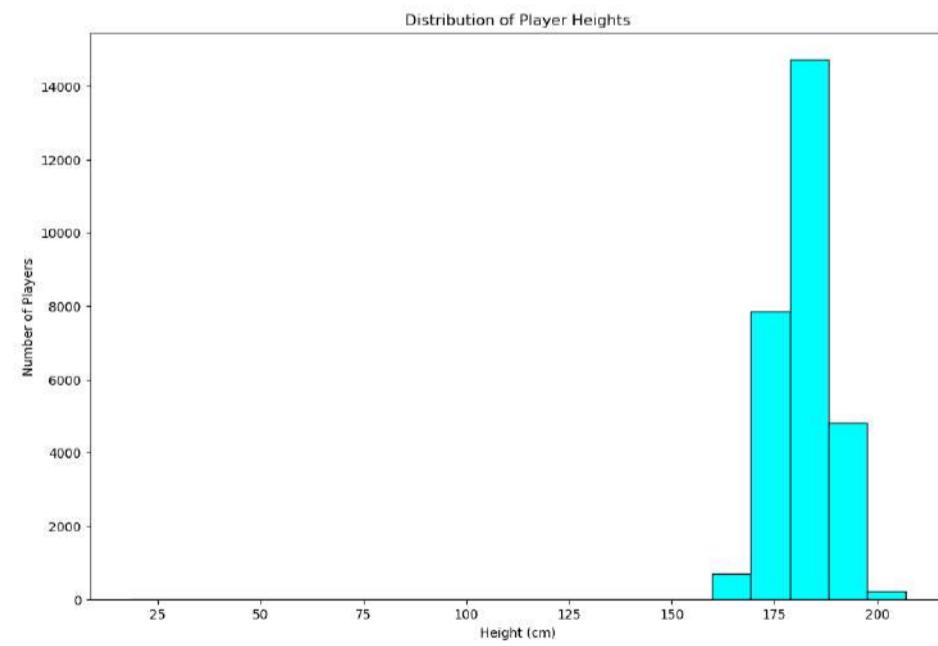
Which player has the highest number of goals in a Match?

The player with the highest number of goals is Arkadiusz Milik with 6 goals.

Highest number of goals in domestic leagues

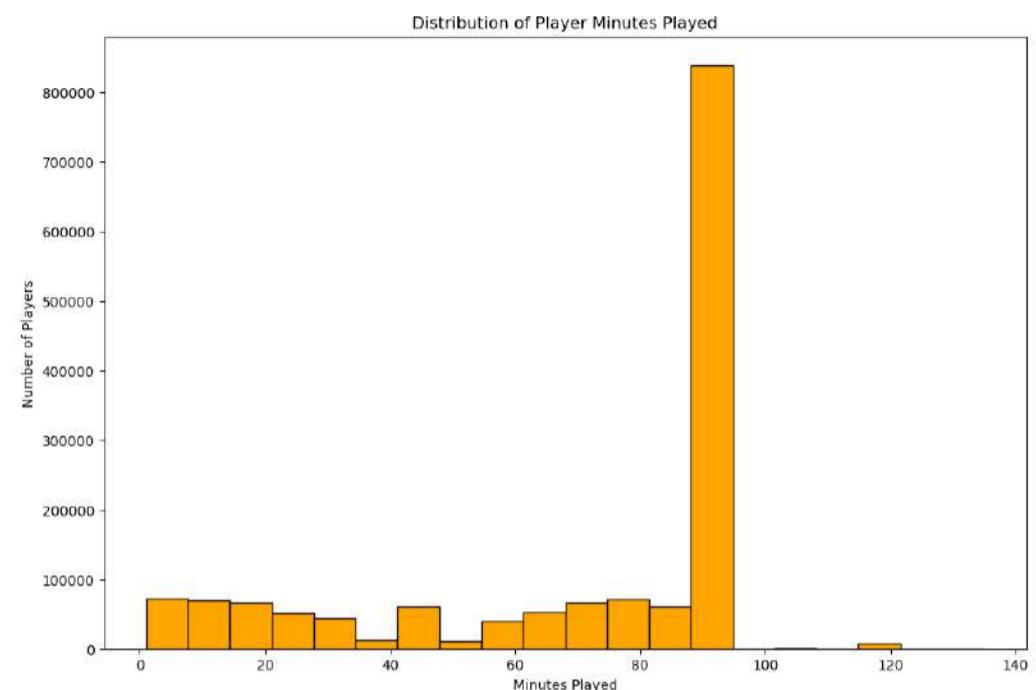


Player height distribution



- As can be seen, most players have the height between 175 and 185.

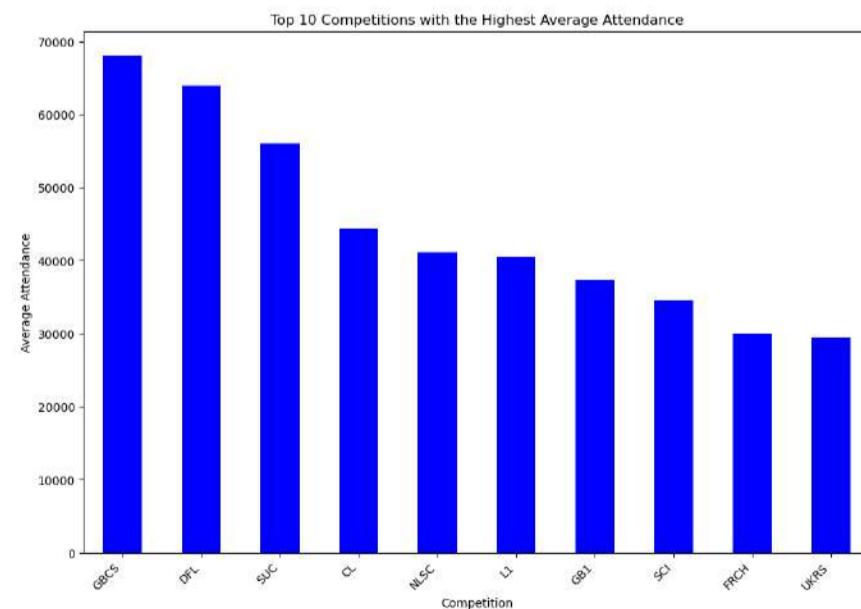
Visualizing Player Minutes Played



- As expected! Because in football we have 3 substitutions (in 90 minutes), so the majority of players play 90 minutes.

Which competition had the highest average attendance?

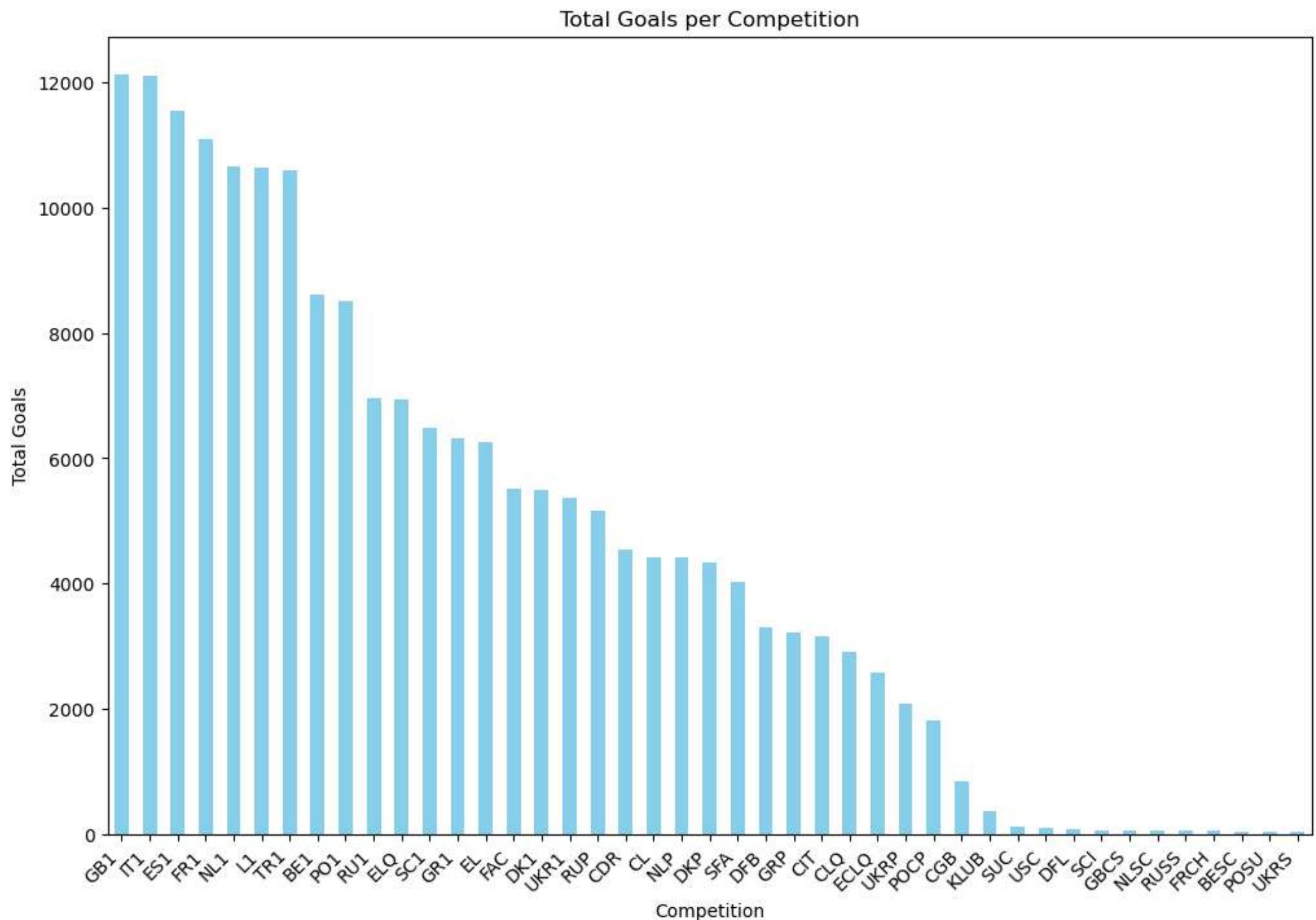
The competition with the highest average attendance is GBCS.



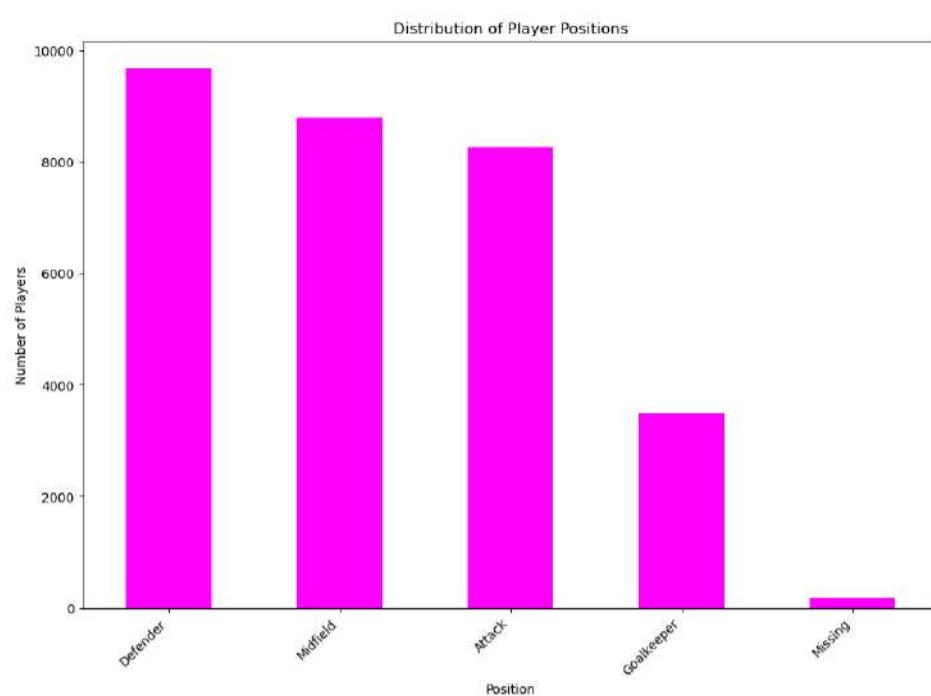
- in this plot, 10 competitions with the highest average attendance have been shown.

Which competition had the highest total number of goals scored?

The competition with the highest total number of goals scored is GB1.



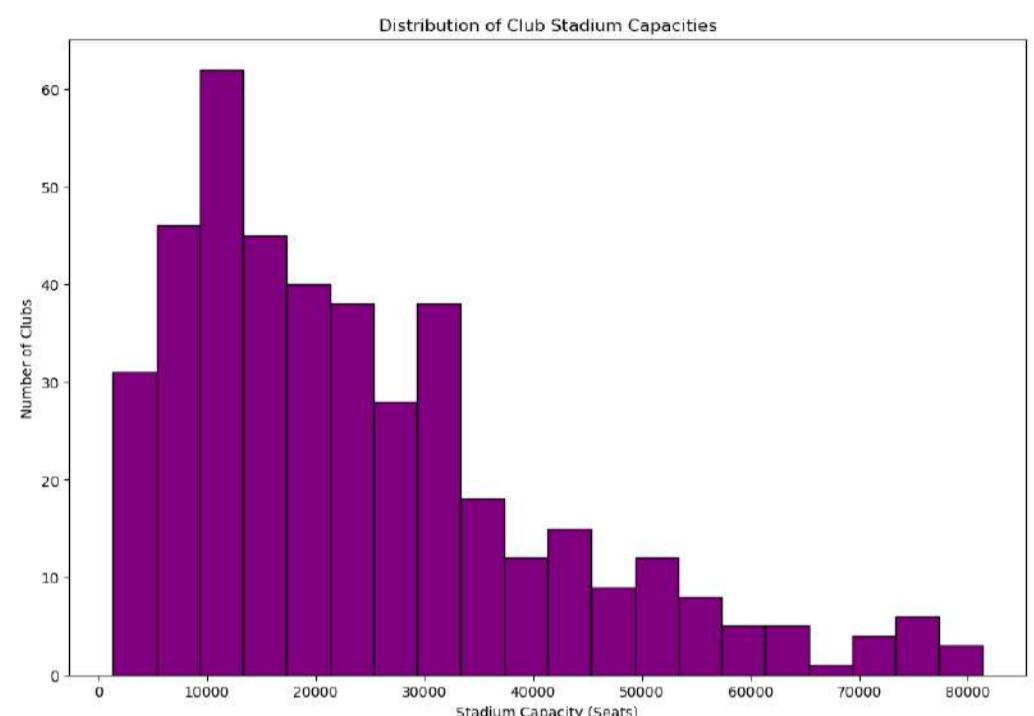
Visualizing Player Positions Distribution



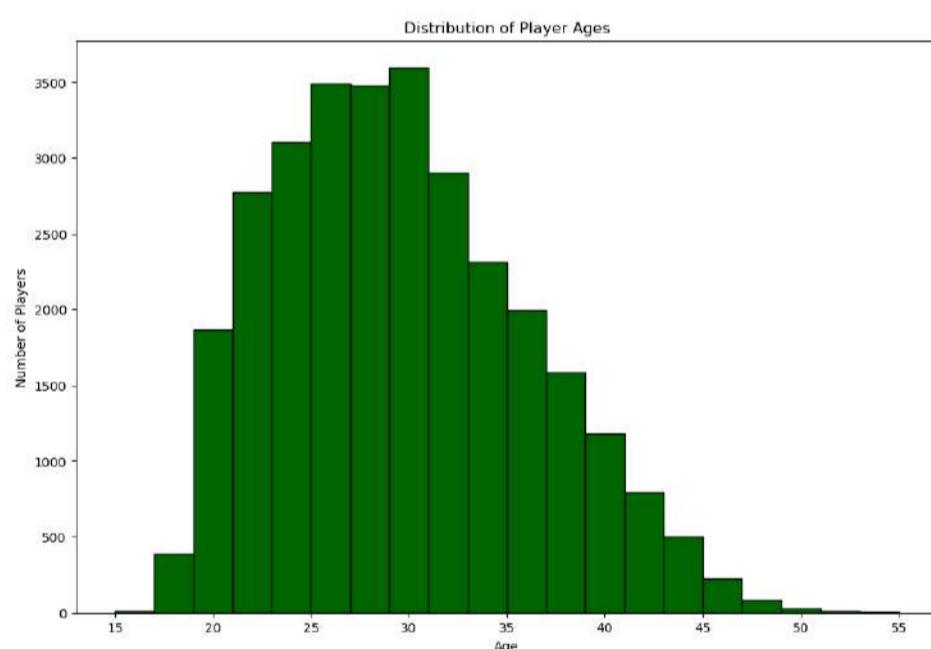
- Defenders are the majority! And some Players have "Missing" position. So in the modeling this issue should be care of.

- This two graphs have different distributions, because some players in the `players_df` are not located in the `clubs_df`!

Visualizing Club Stadium Capacity Distribution

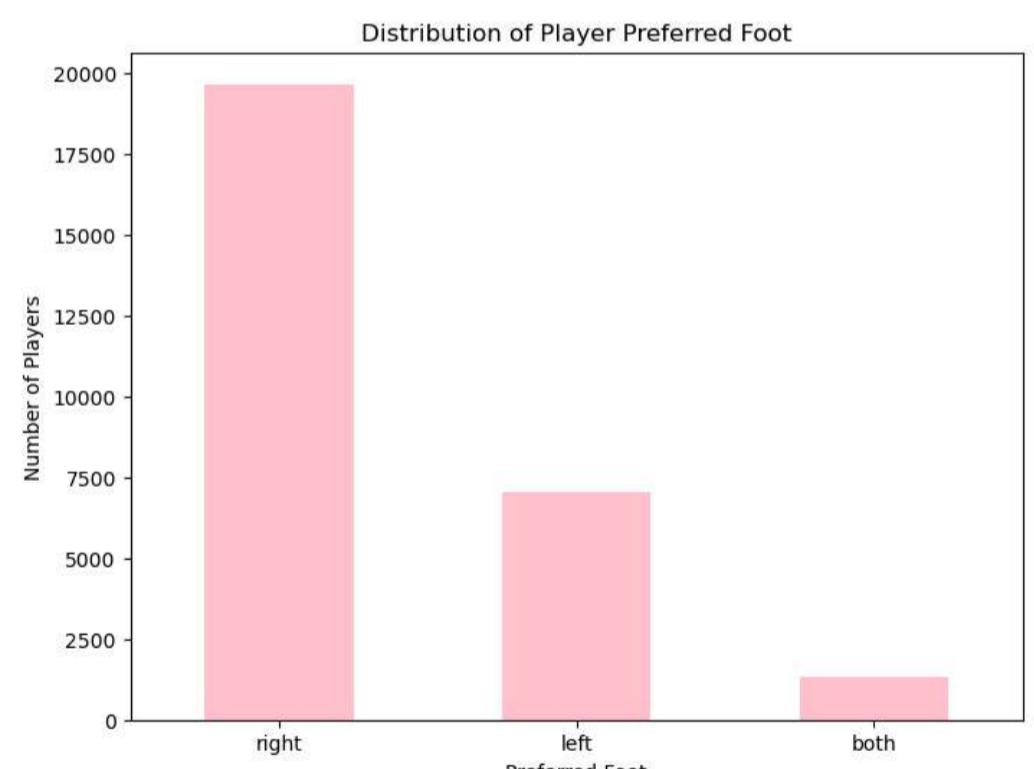


Visualizing Player Age Distribution

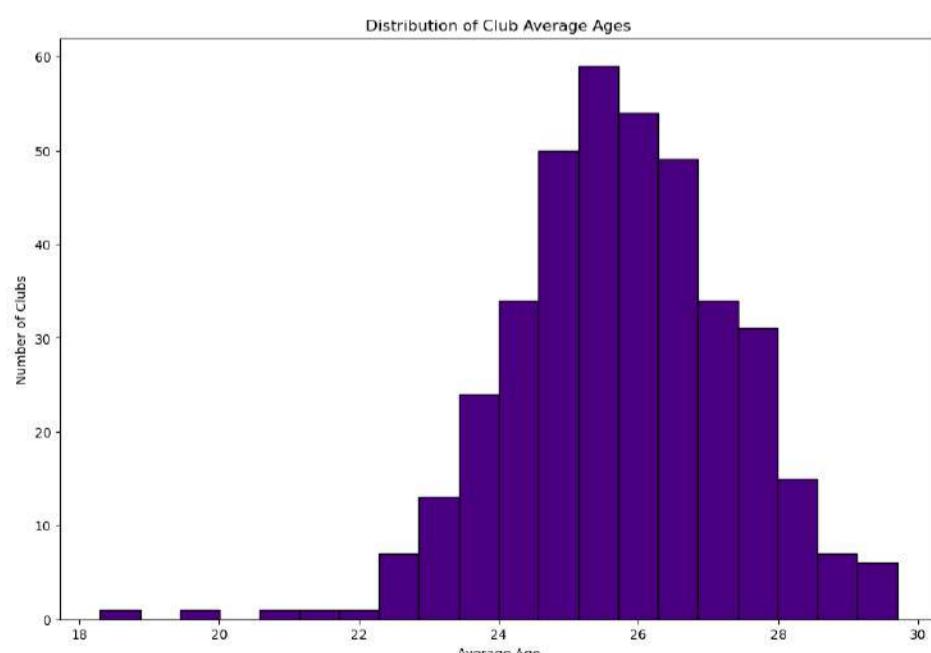


- As expected there are few stadium with high capacity like Camp Nou.

Visualization for Player Foot Distribution

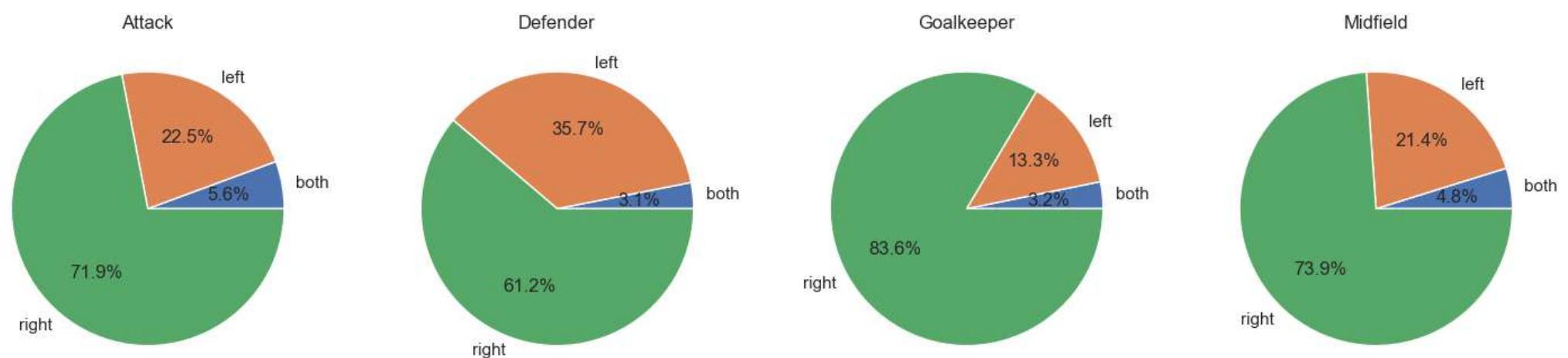


Visualizing Club Average Age Distribution



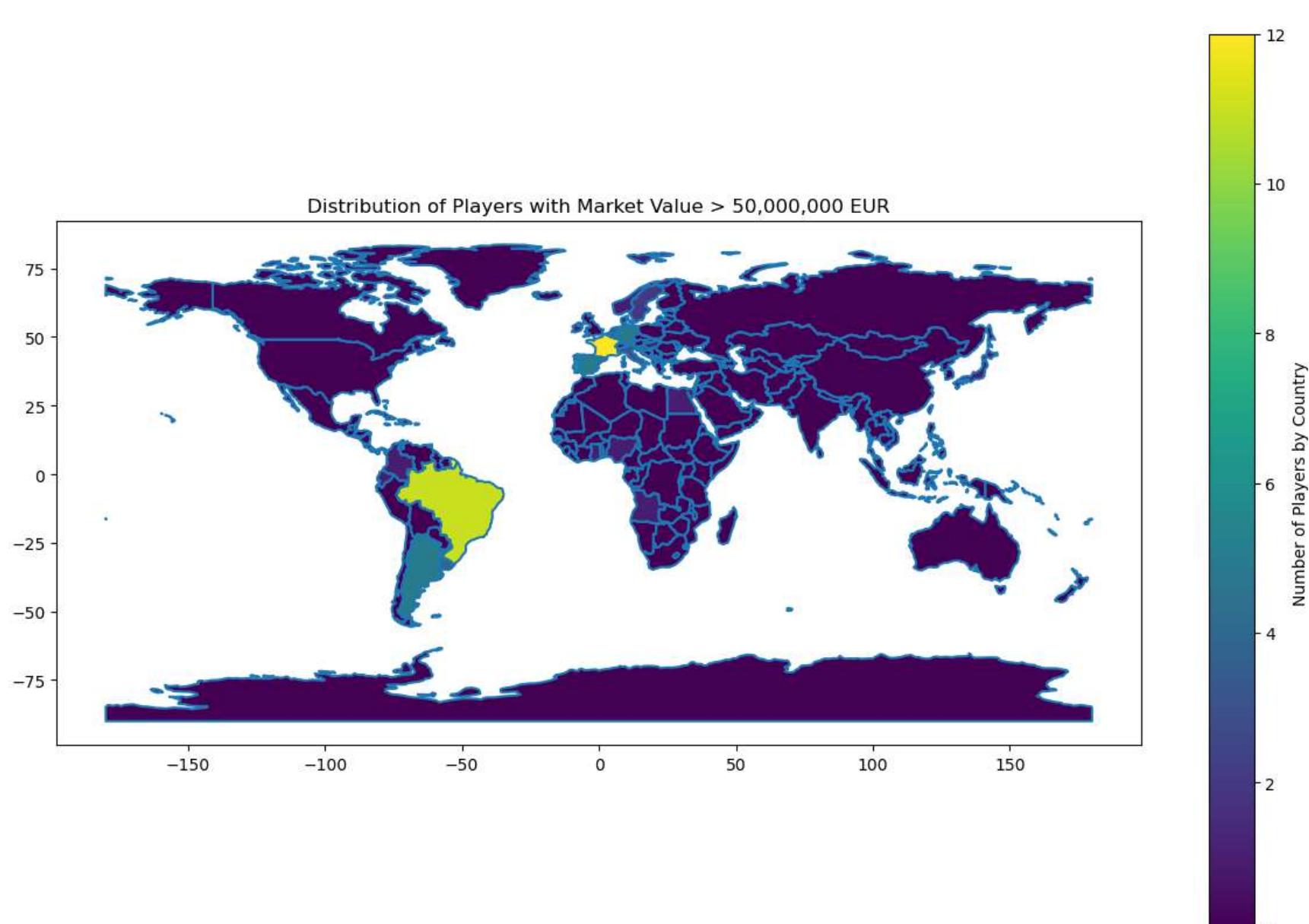
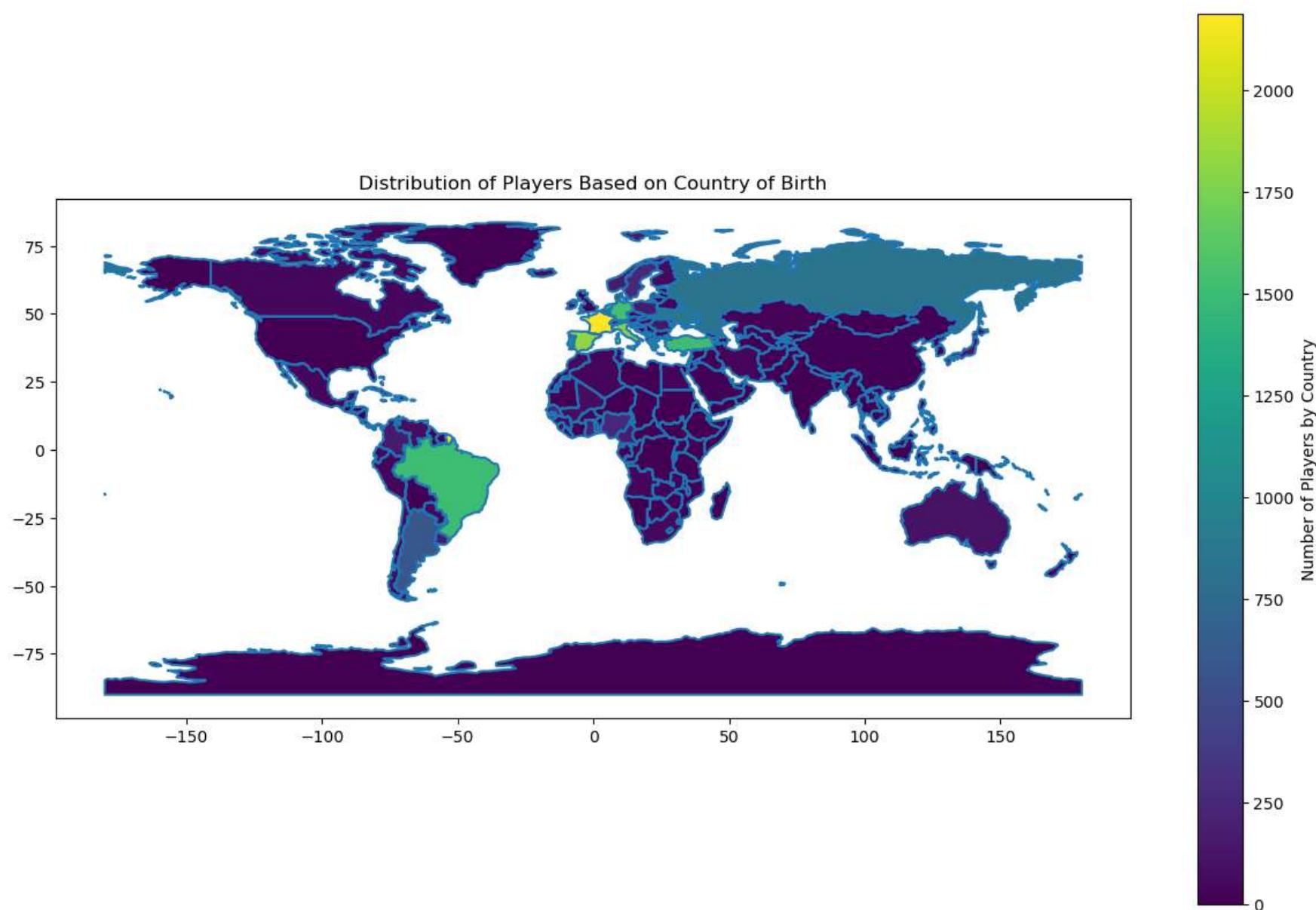
- Most players are right-footed and there is a Hypothesis that players with both feet are more valuable!

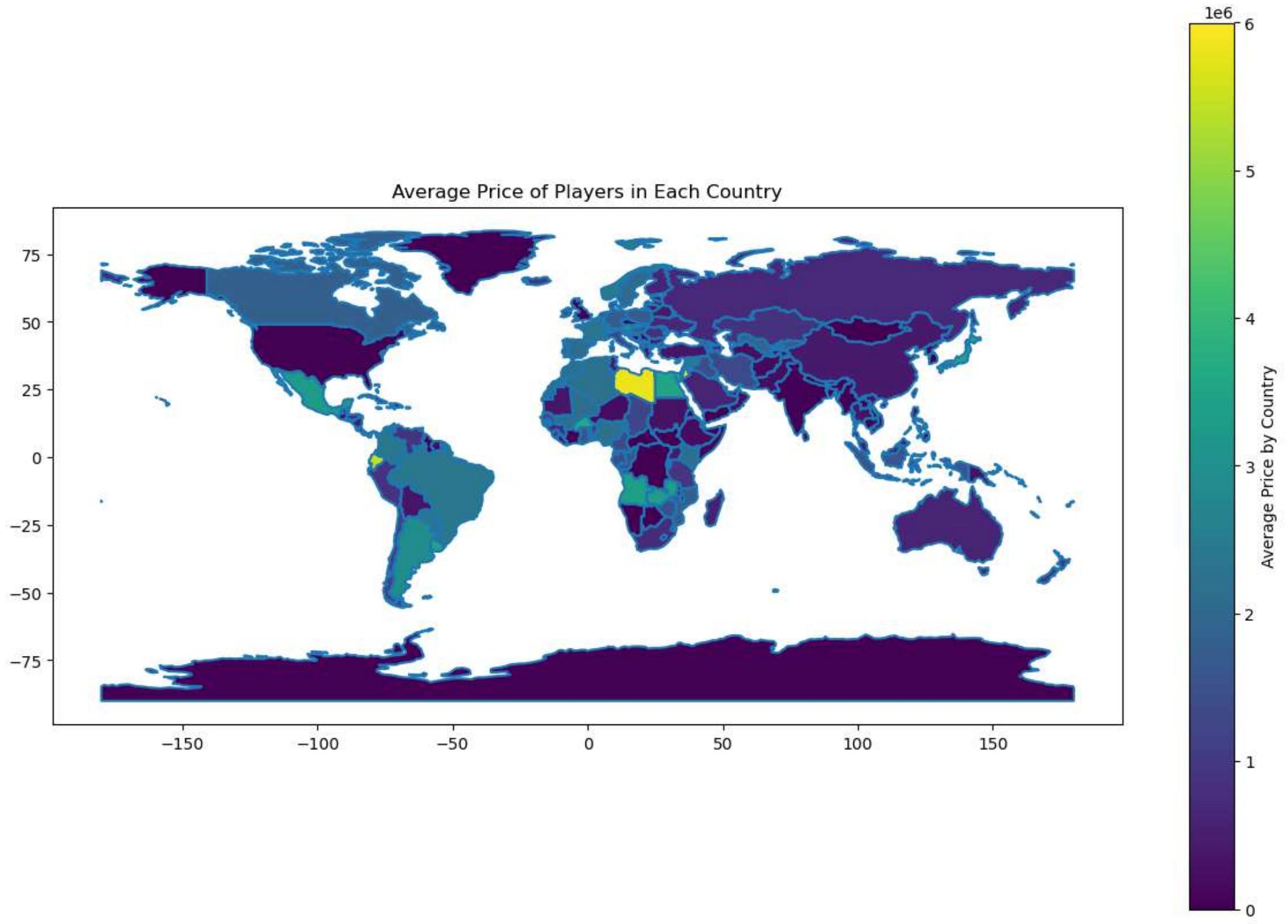
How frequent left footers are versus right footers across positions?



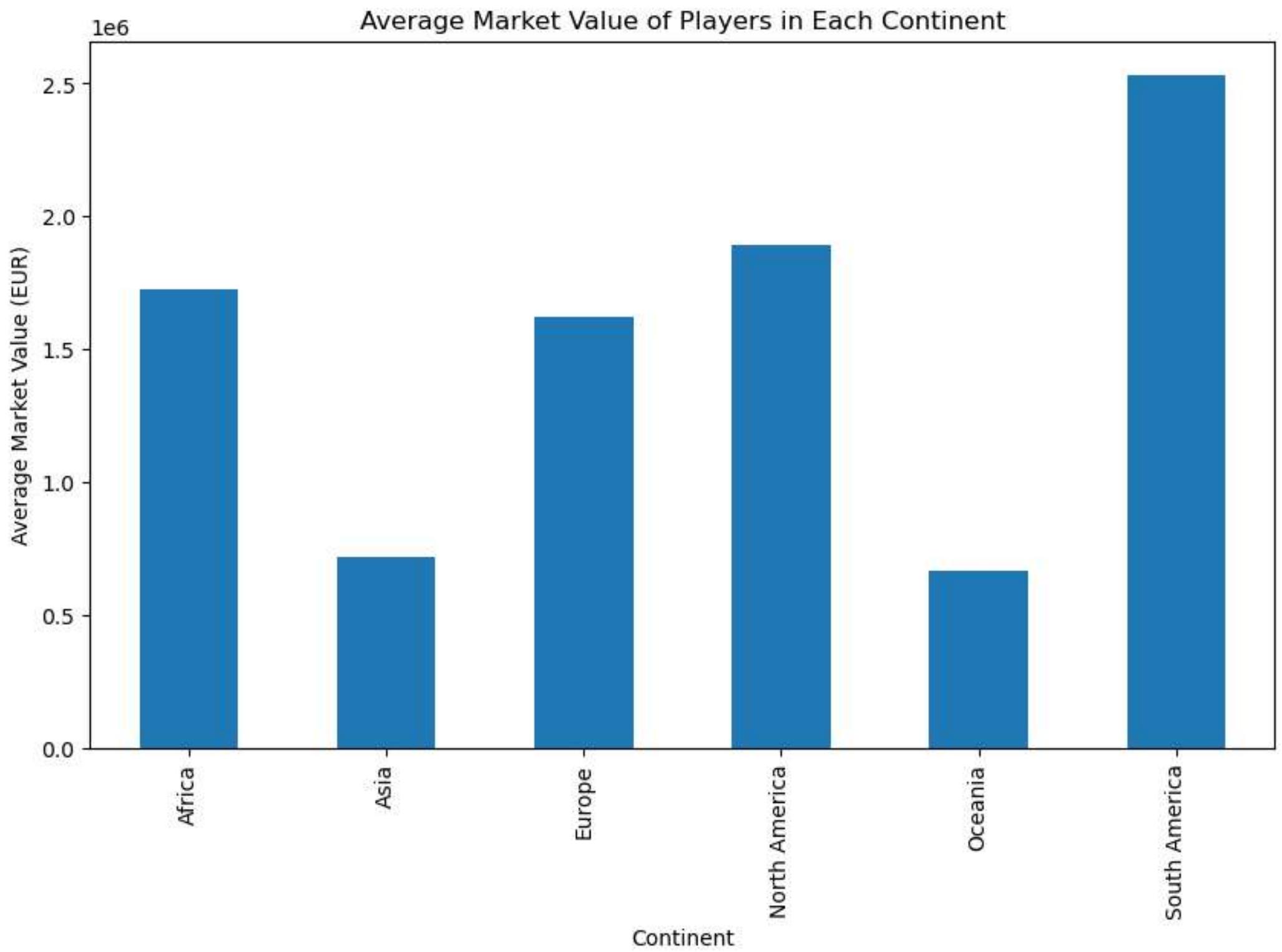
Below are the diagrams related to the map

- It shows that Europe and South America have more players
- Also, Europe and South America have a larger share of expensive players



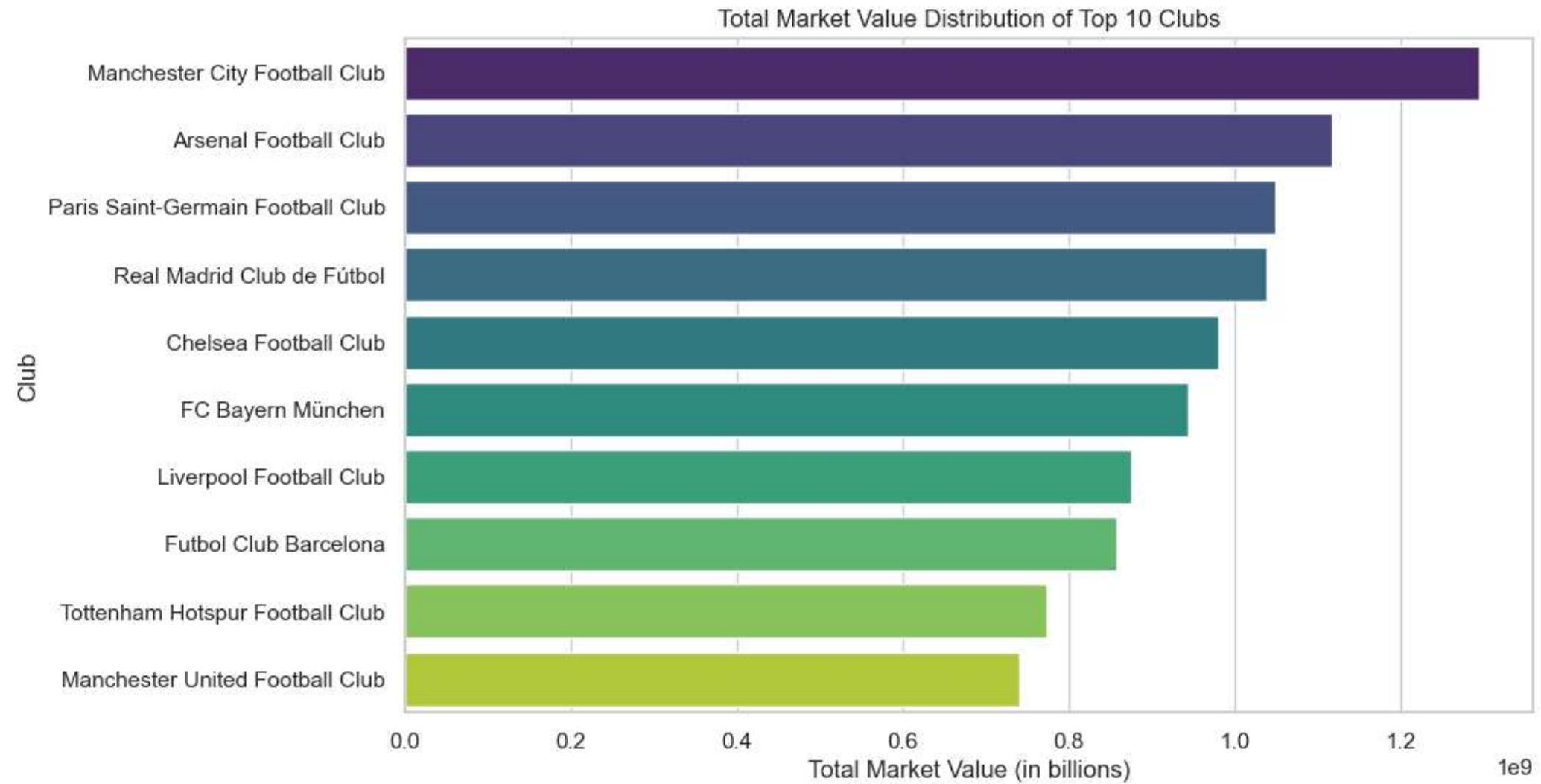


- Because South Africa has few registered players in the leagues, that is why the average of one of those countries "Libya" is high.



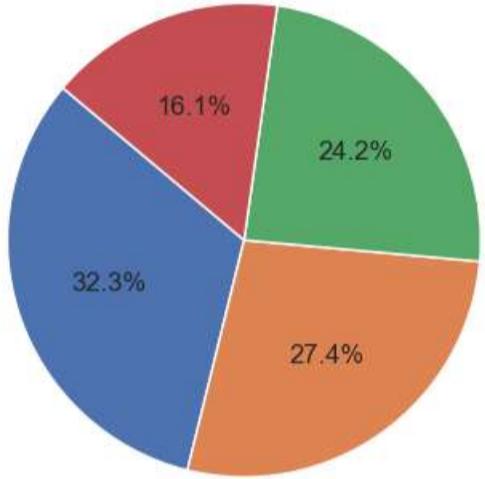
Club Compare

After looking at **clubs_df**, it can be understood that this data frame have null values for **total_market_value**. so based on **players_df** and the season = 2023, this column has been calculated.

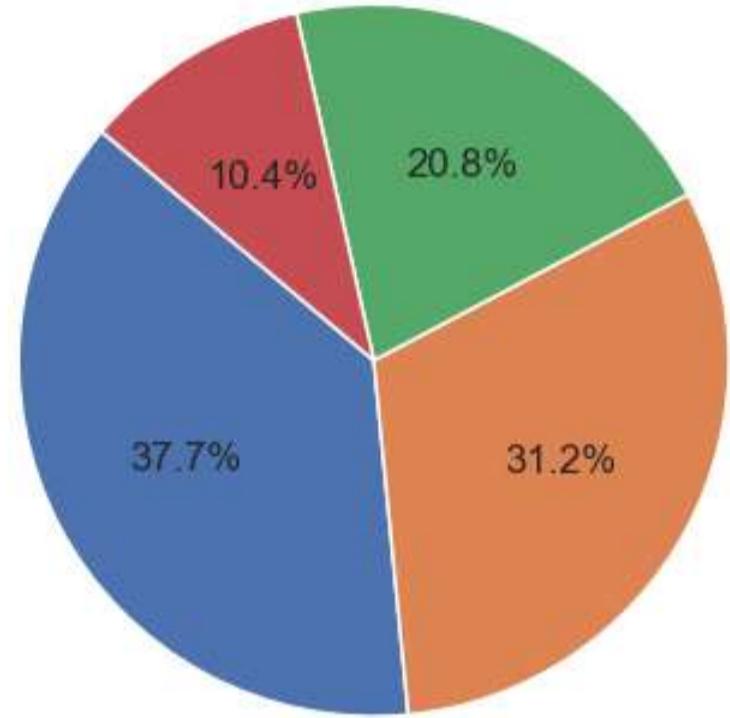


Pie chart showing the distribution of player positions in each club

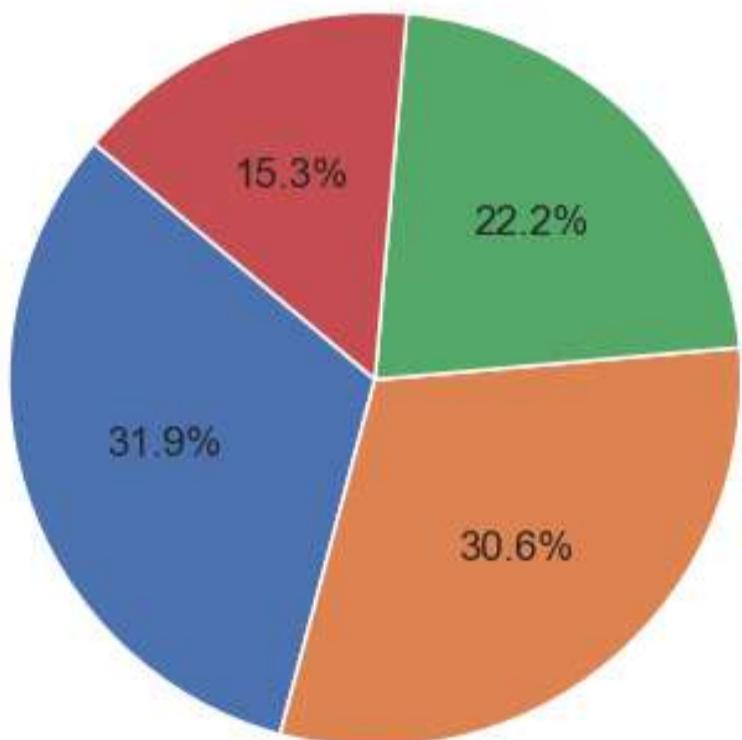
Player Position Distribution in Paris Saint-Germain Football Club



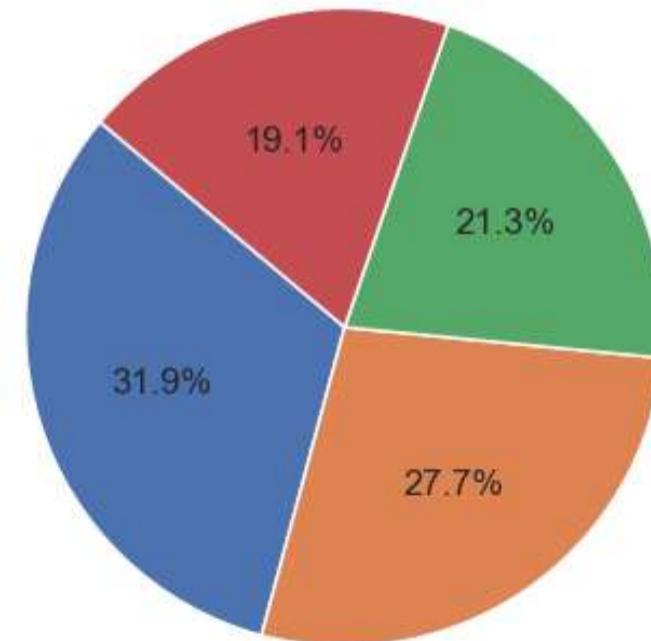
Player Position Distribution in Arsenal Football Club



Player Position Distribution in Chelsea Football Club



Player Position Distribution in Real Madrid Club de Fútbol



Iranian Players

Top 10 Iranian Players based on Highest Market Value:

		name	highest_market_value_in_eur	last_season
11441		Sardar Azmoun	25000000.0	2023
17245		Mehdi Taremi	20000000.0	2023
13154		Alireza Jahanbakhsh	18000000.0	2023
12803		Saman Ghoddos	5000000.0	2023
18145		Milad Mohammadi	5000000.0	2023
16911		Majid Hosseini	3500000.0	2023
25831		Mohammad Mohebi	1800000.0	2023
6550		Ehsan Haj safi	1500000.0	2023
14731		Saeid Ezatolahi	1500000.0	2023
14736		Ali Alipour	1500000.0	2023

2. Predict the price of players

In the next part, we will get information through data and by doing **EDA** and **FEATURE ENGINEERING**, we will test the machine learning **MODELS** for predicting the players' prices.

2.1 Data processing

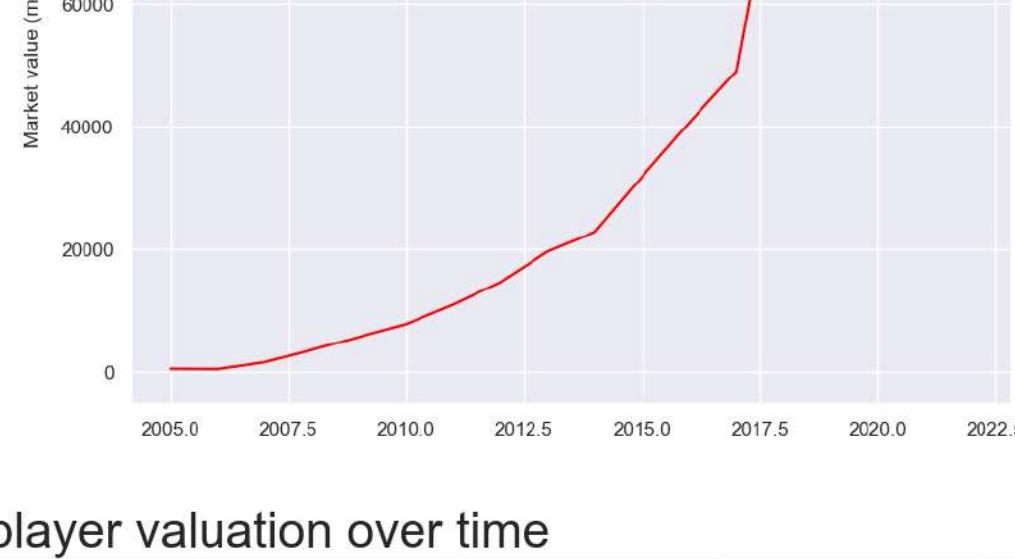
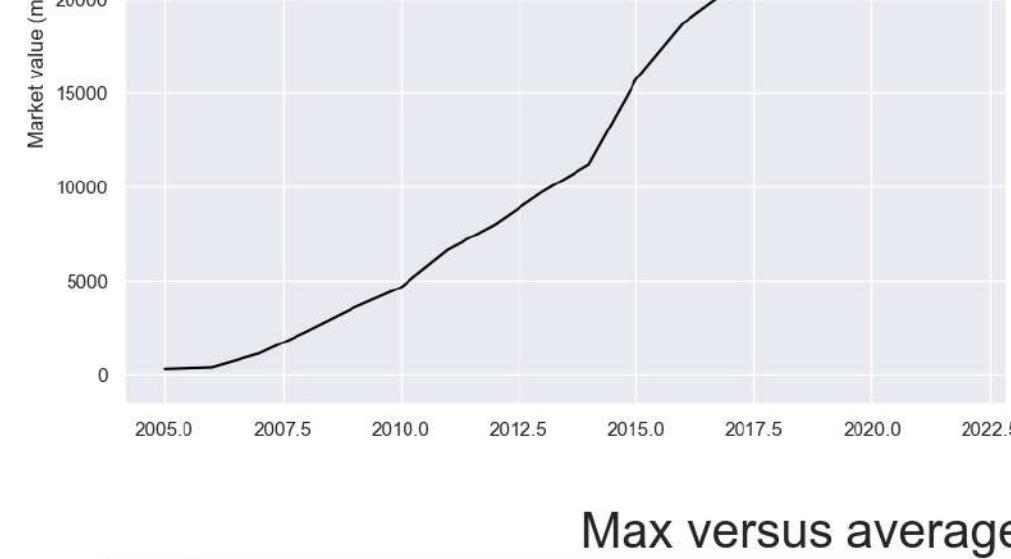
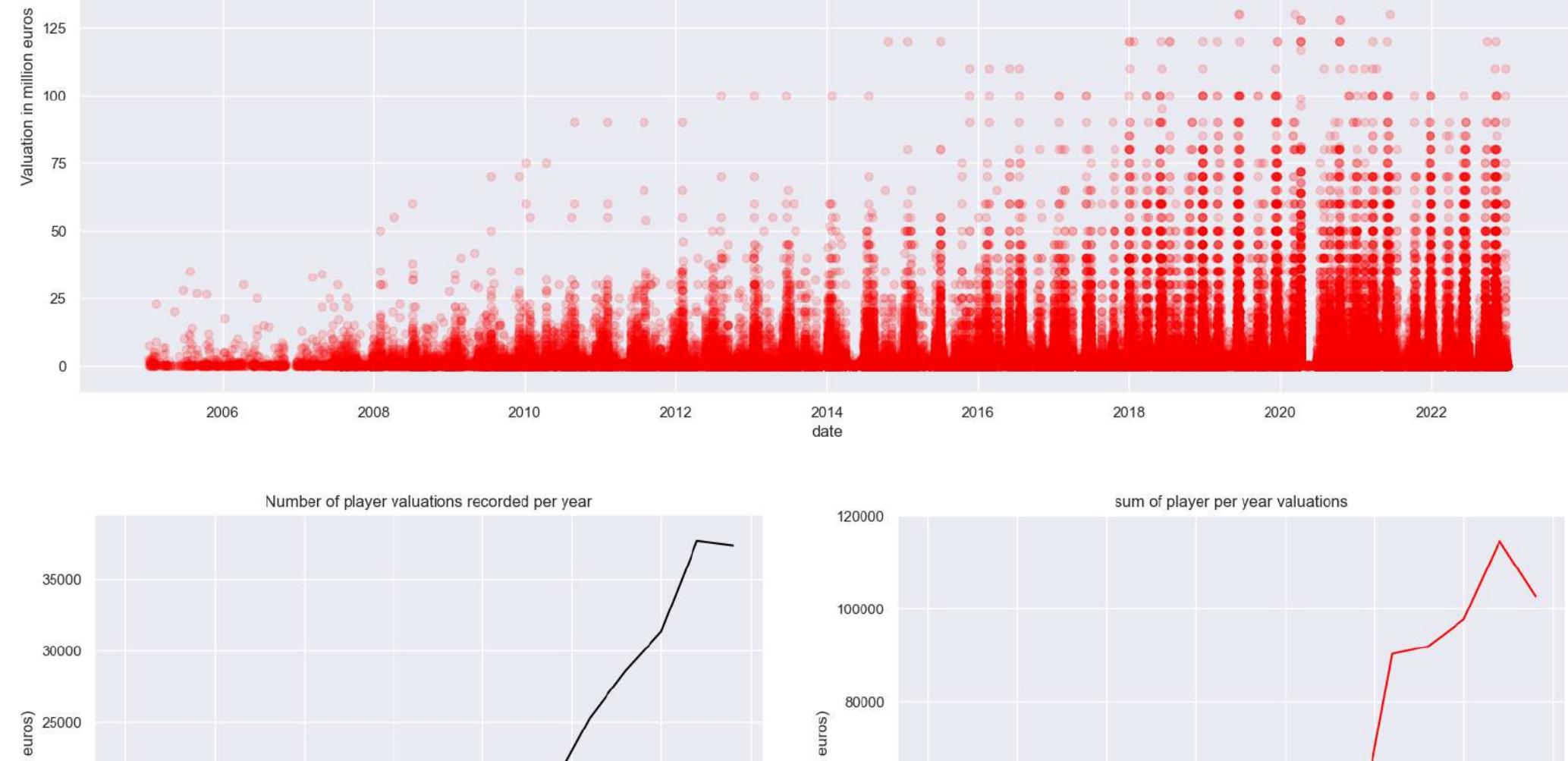
Before that, some Data processing on data set :

- Calculate the age of each player
- drop players with no date of birth
- Calculate the contract remaining of each player
- drop players with no date of birth
- add year to player valuations
- add year to player appearances
- add position to player valuations
- add position to appearances

Data processing completed.

2.2 Visualization

Player Valuation Data Visualization:



Observations on market value timeline data

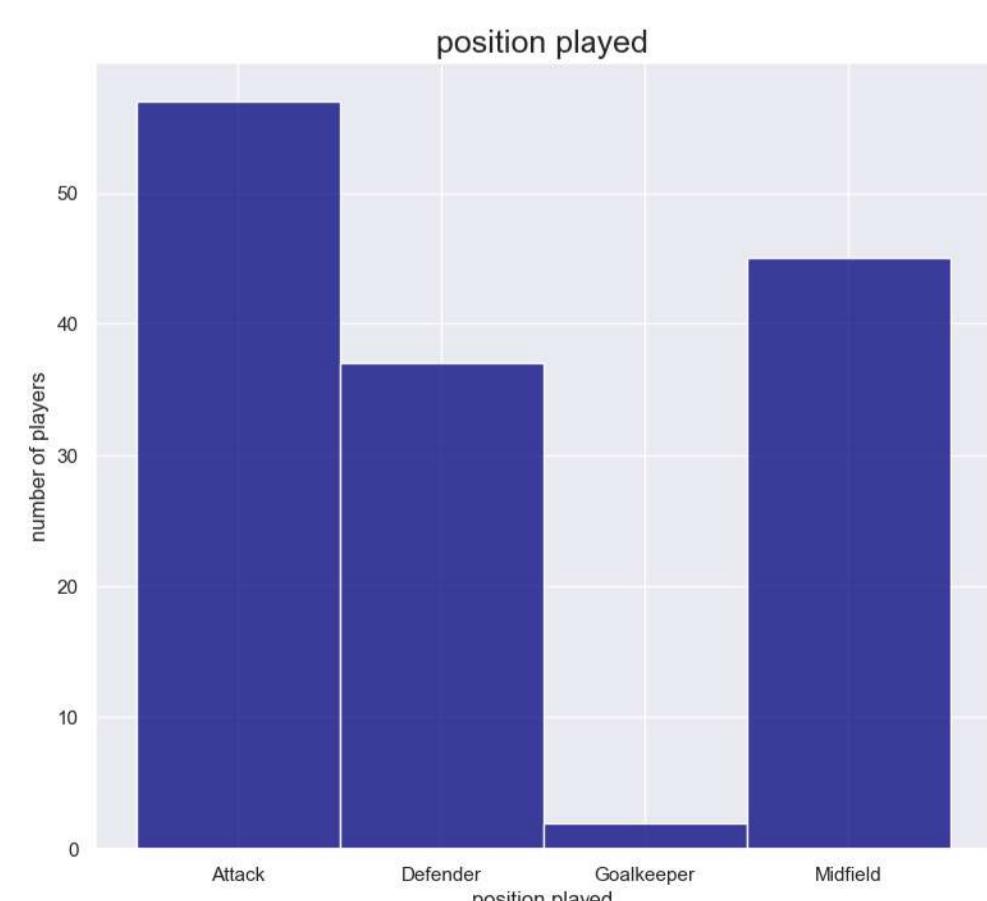
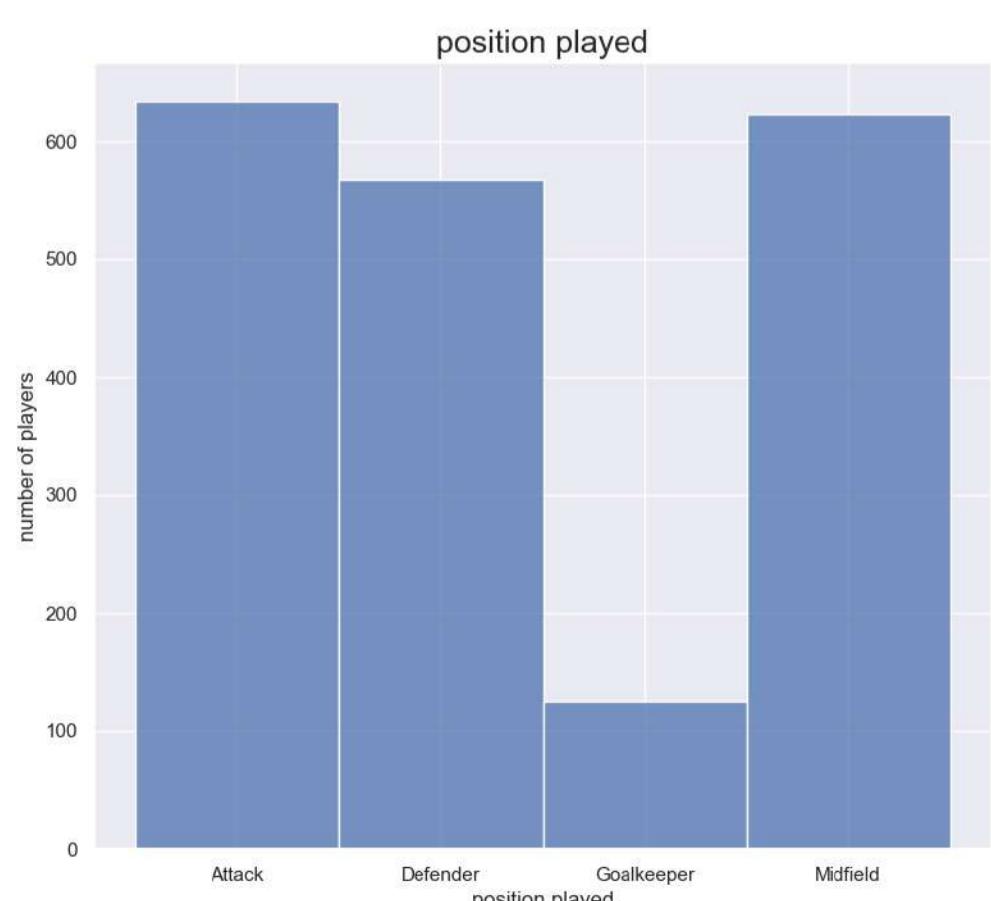
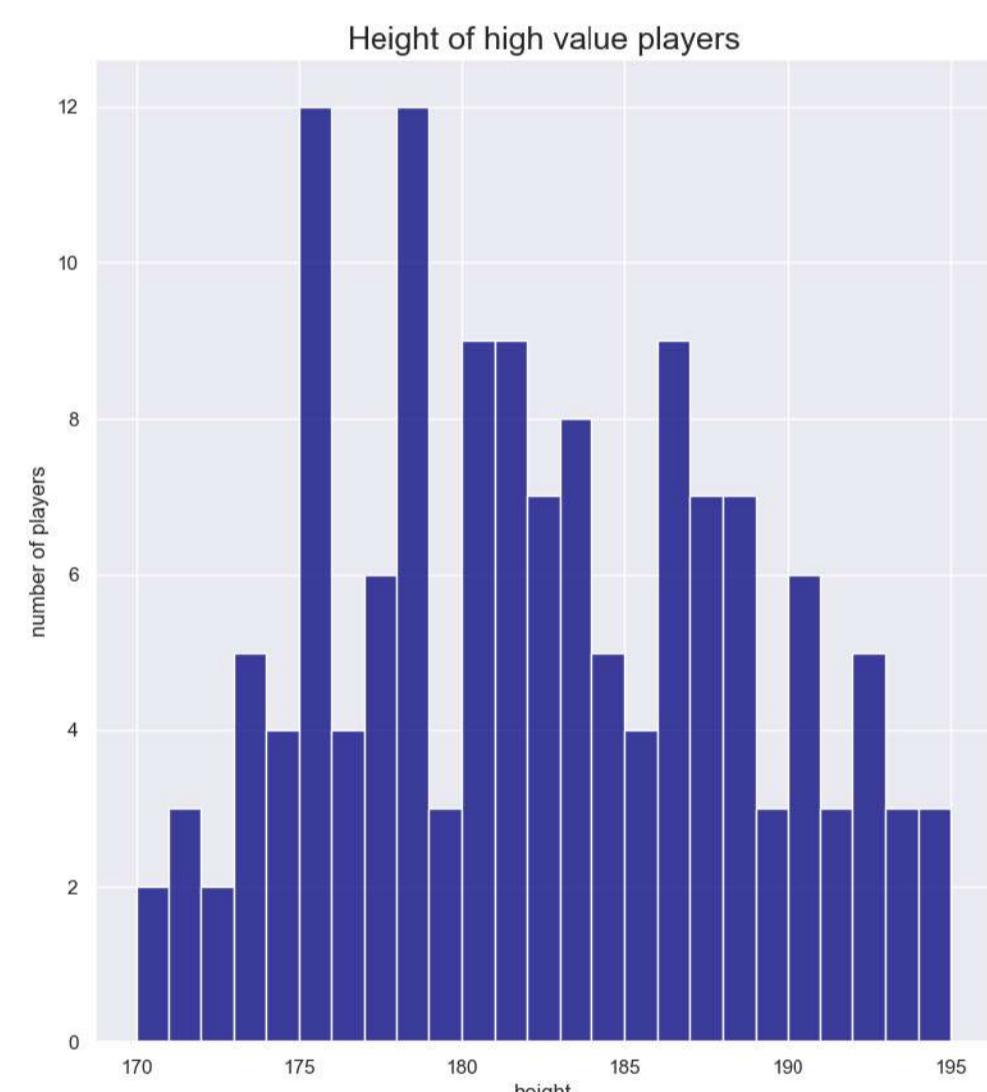
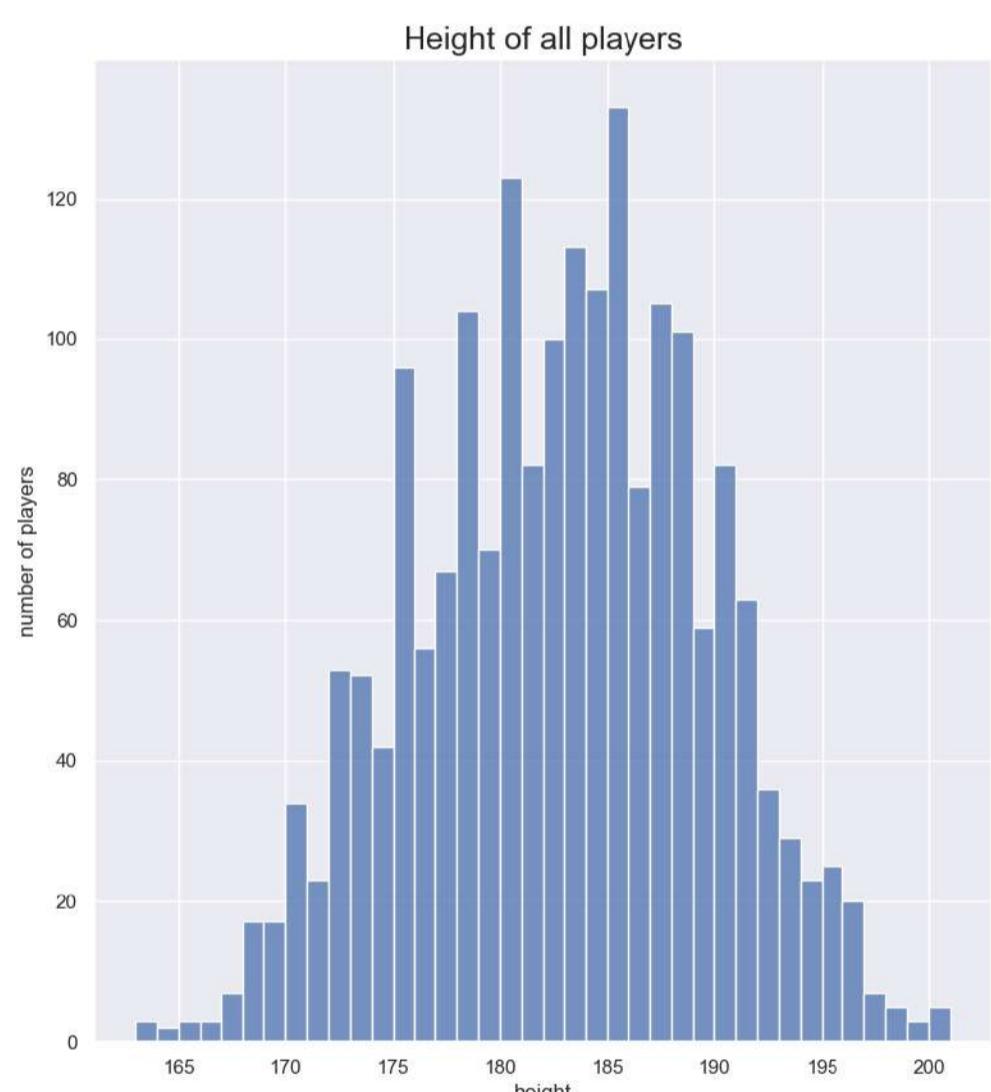
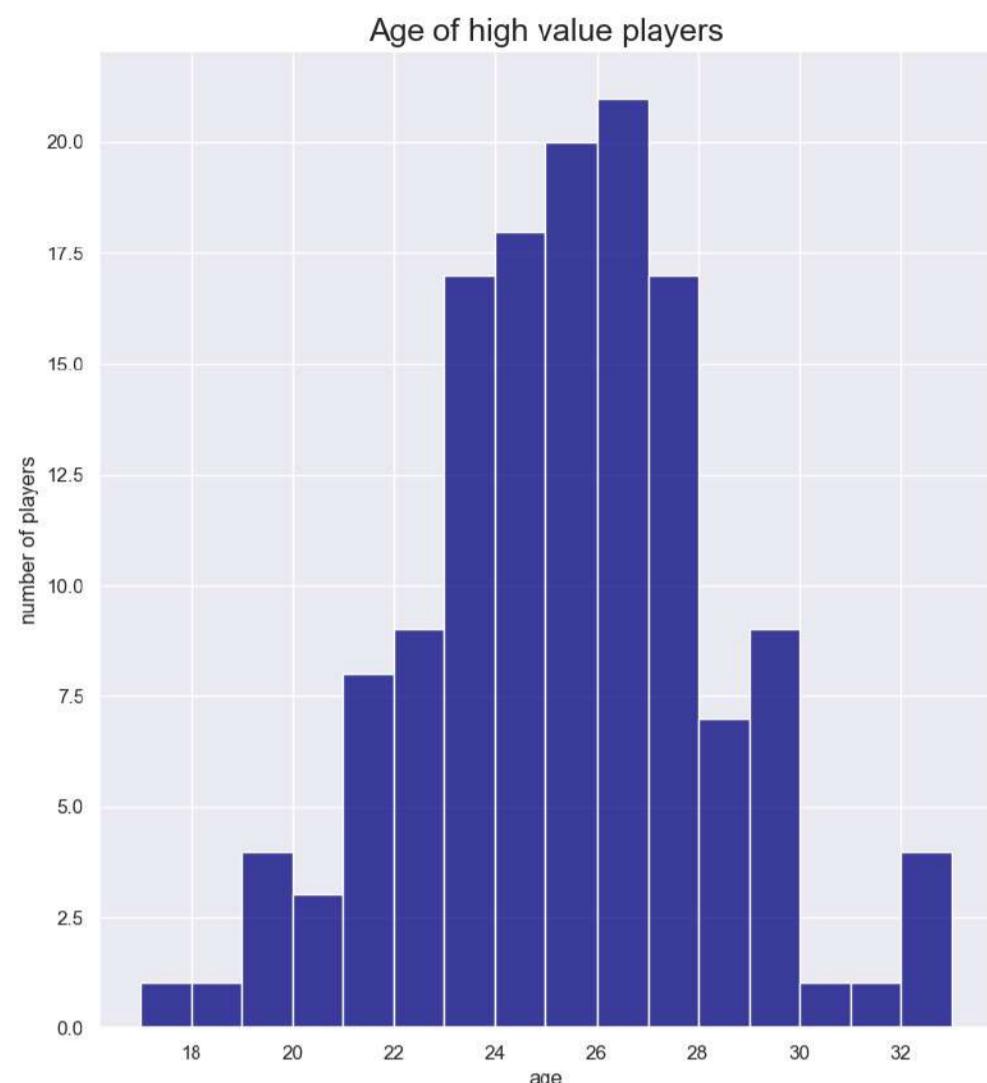
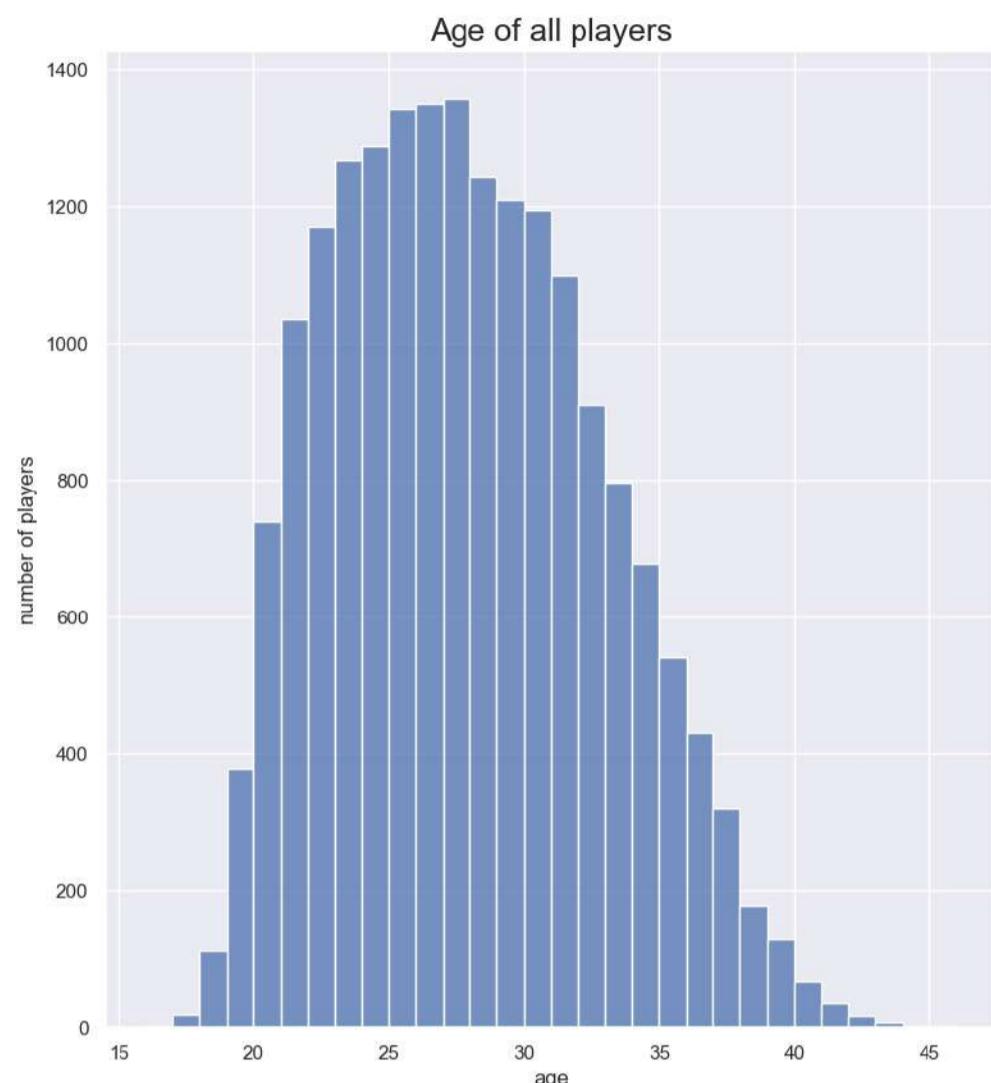
The scatter plot of player valuations over the period 2006 to 2022 shows that the value of players has generally risen over time. The plot shows that the vast majority of players are at the lower end of the scale below the 50 million euros mark.

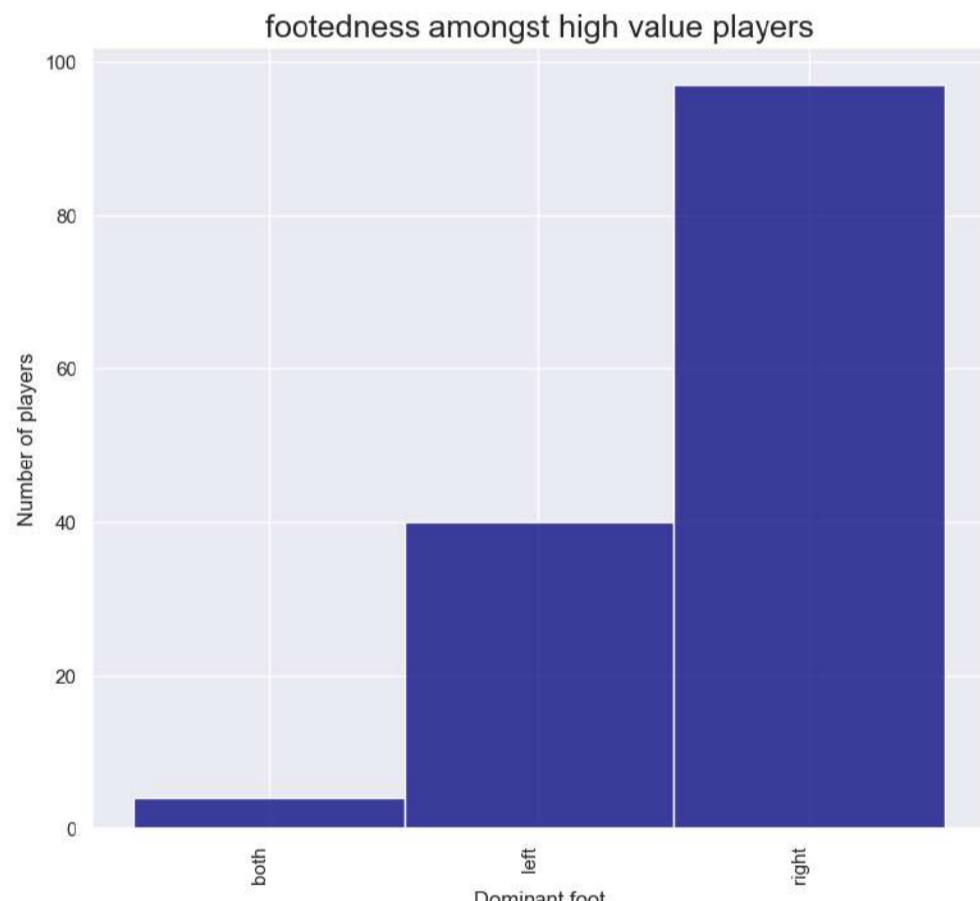
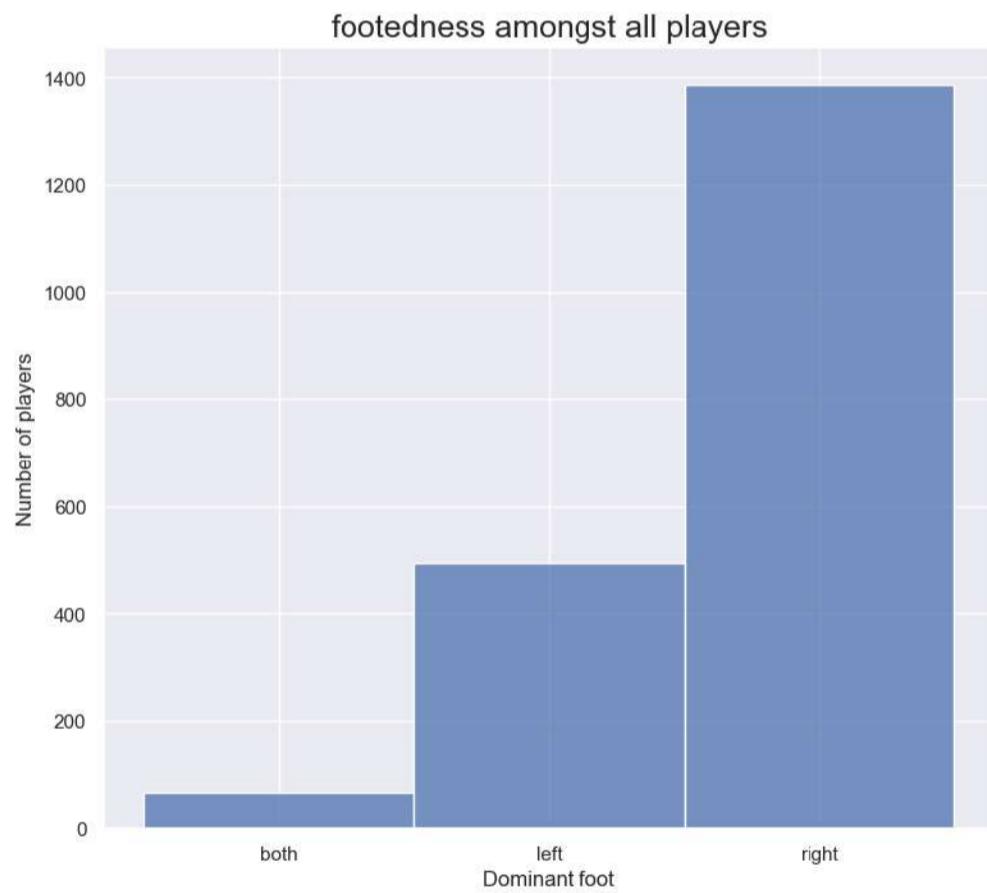
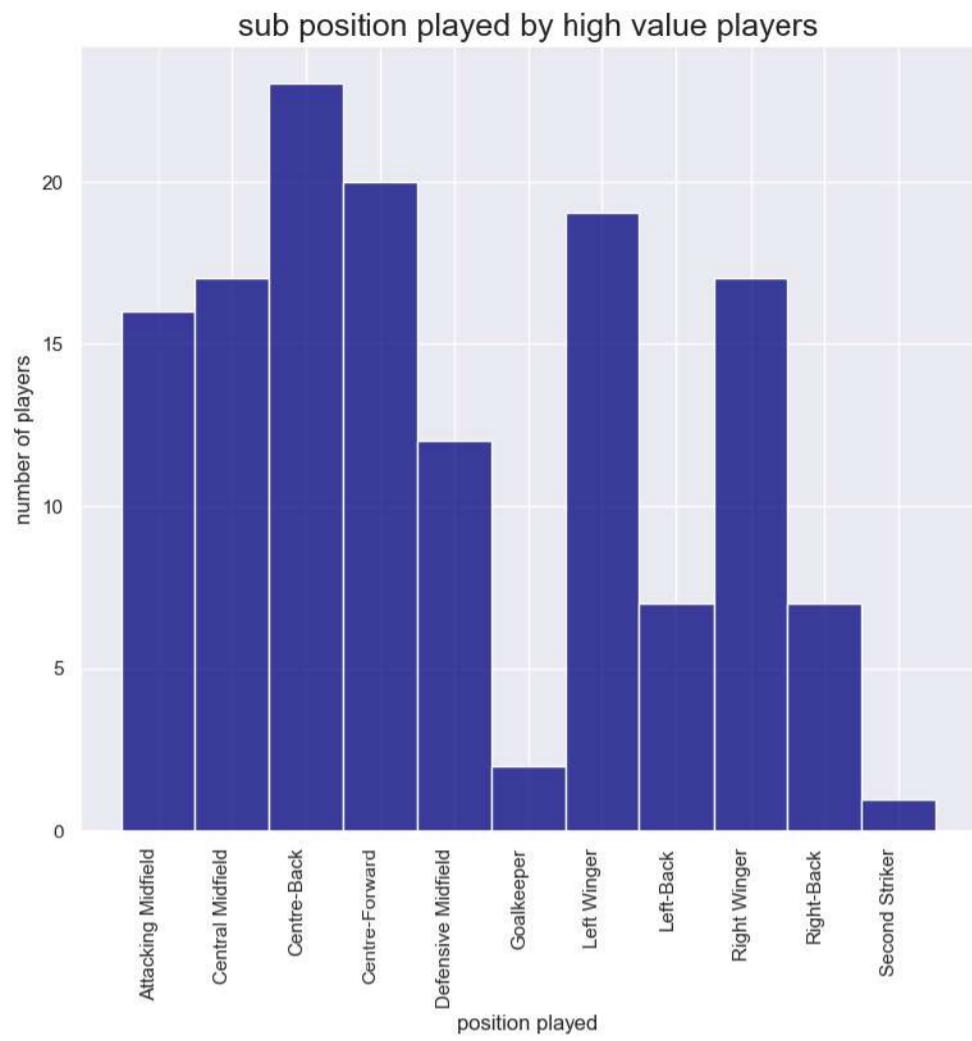
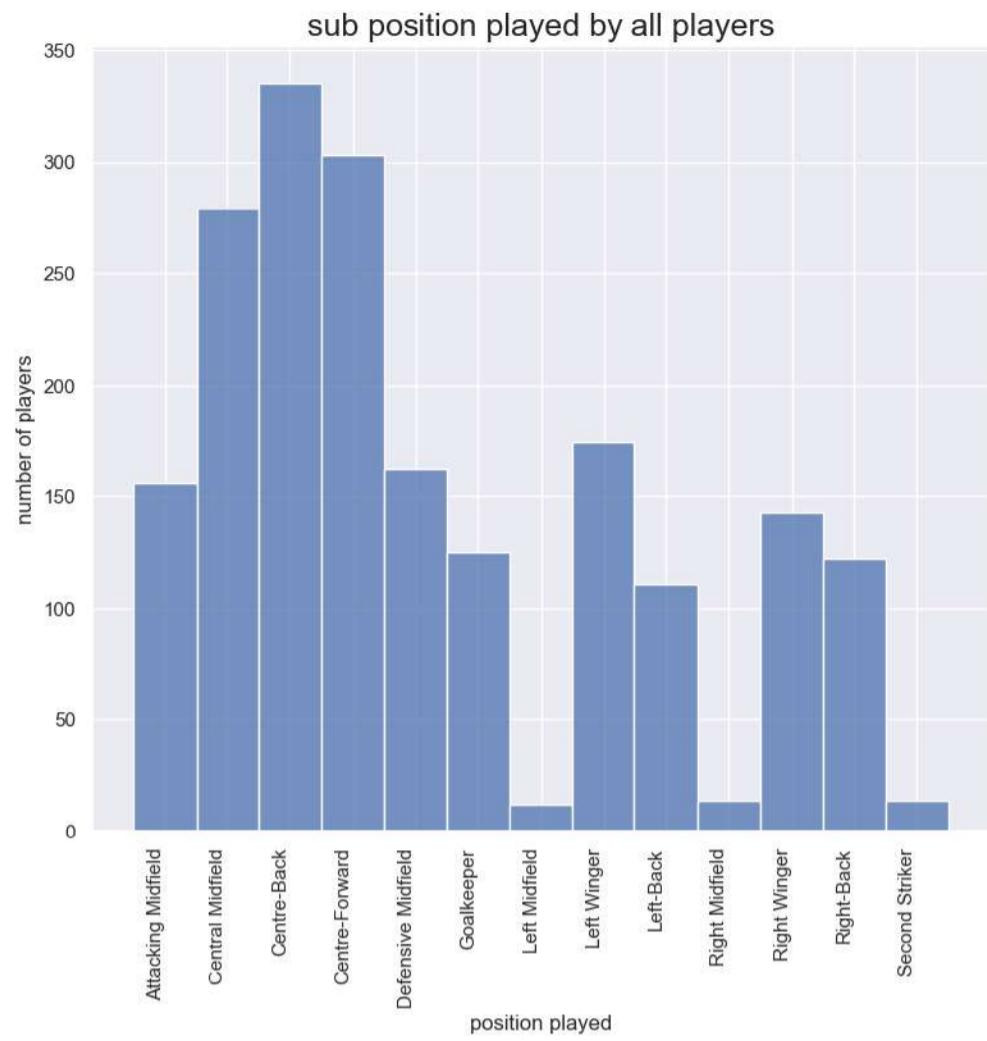
Separating player values in attack,midfield,defence and goal keeper positions shows attacking positions generally achieve the highest values while goal keepers command lower values.

There appears to be a shift around 2018 in where values at the higher end of the scale in most positions rose dramatically, this appears to have peaked and come down a little to 2022 rates.

Player Data Visualization

Exploratory data visualizations relating to players who's last season played was 2022 or 2023 with a market value of greater than 15 million euros.

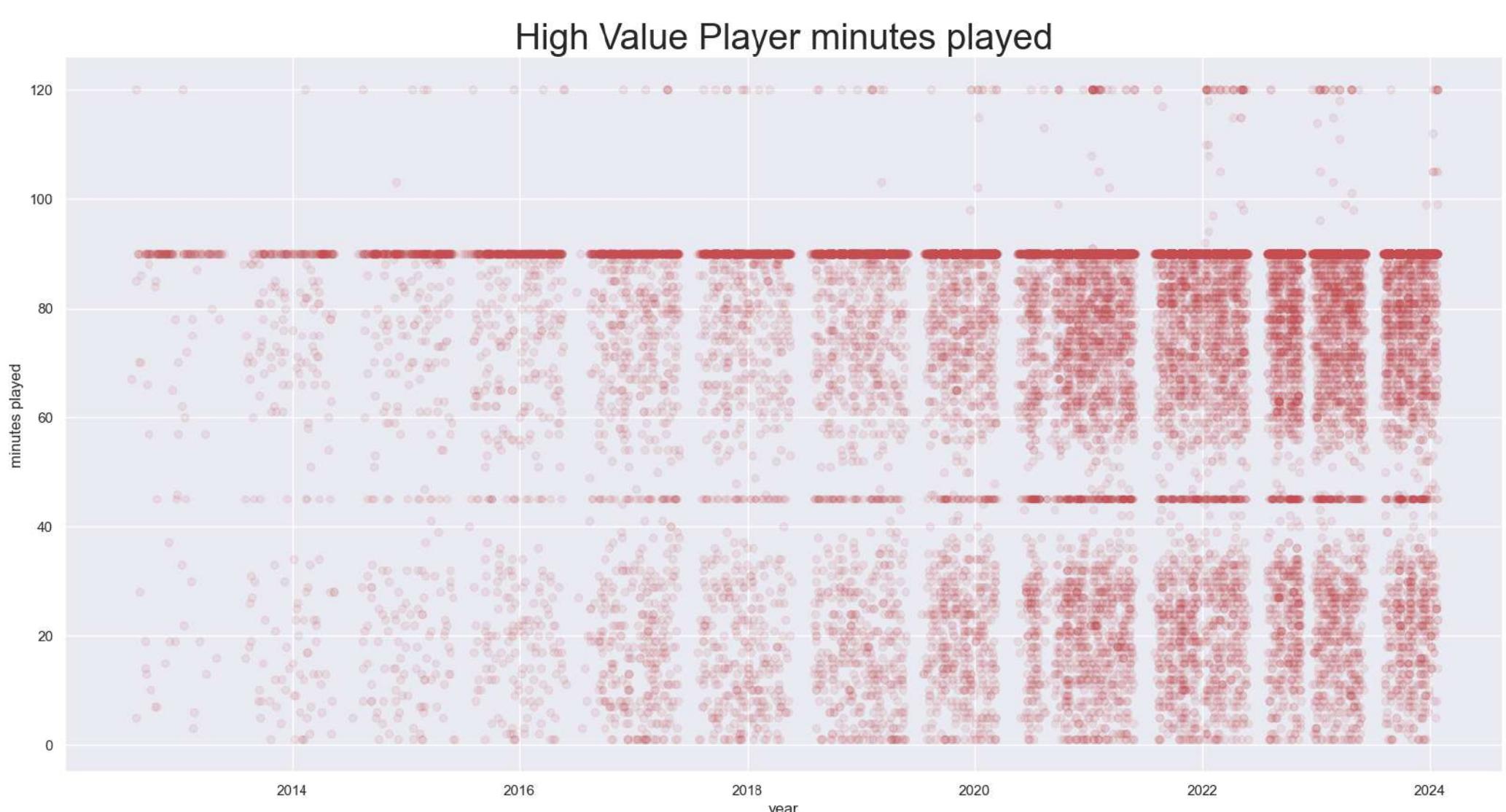
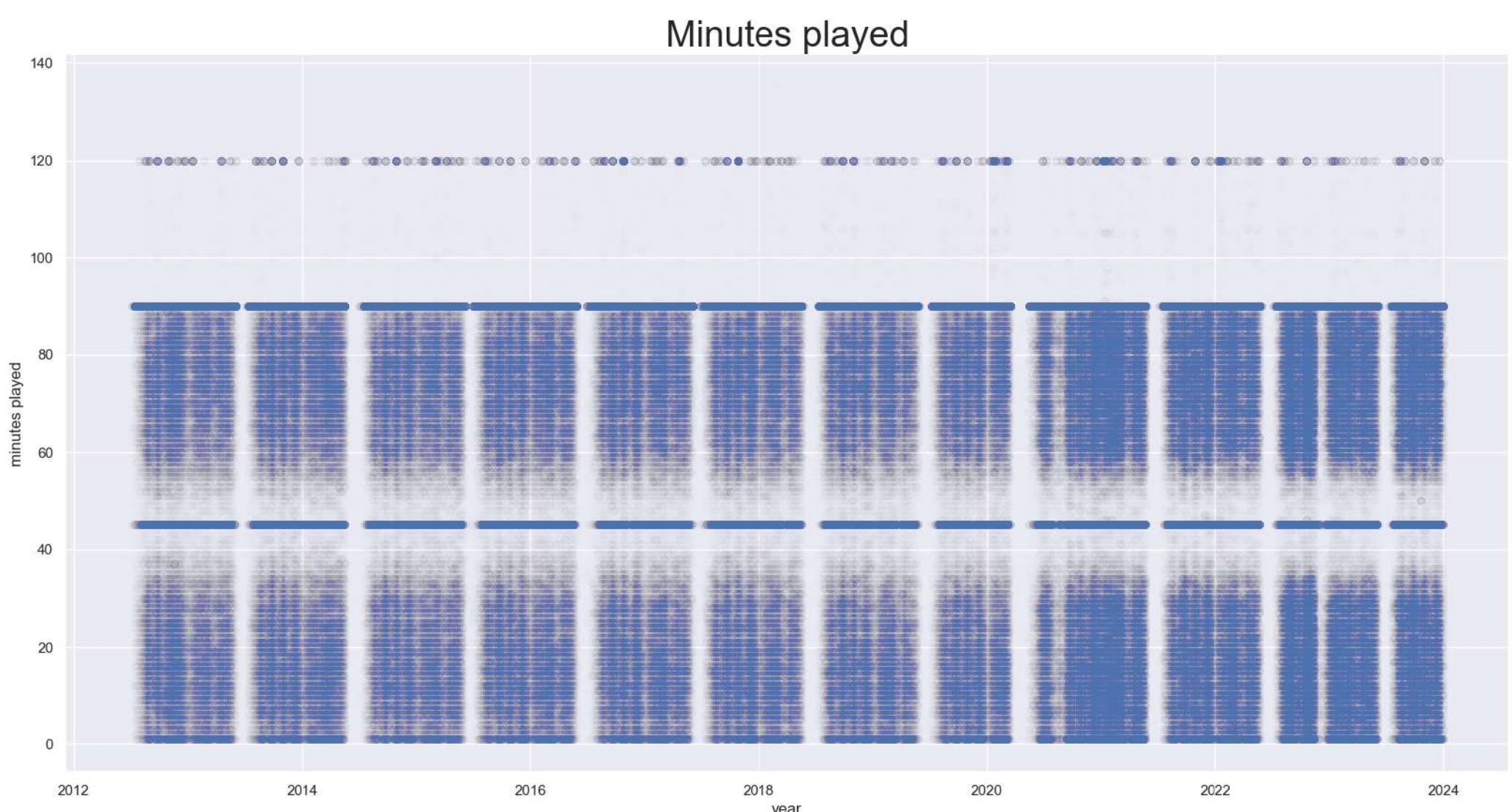
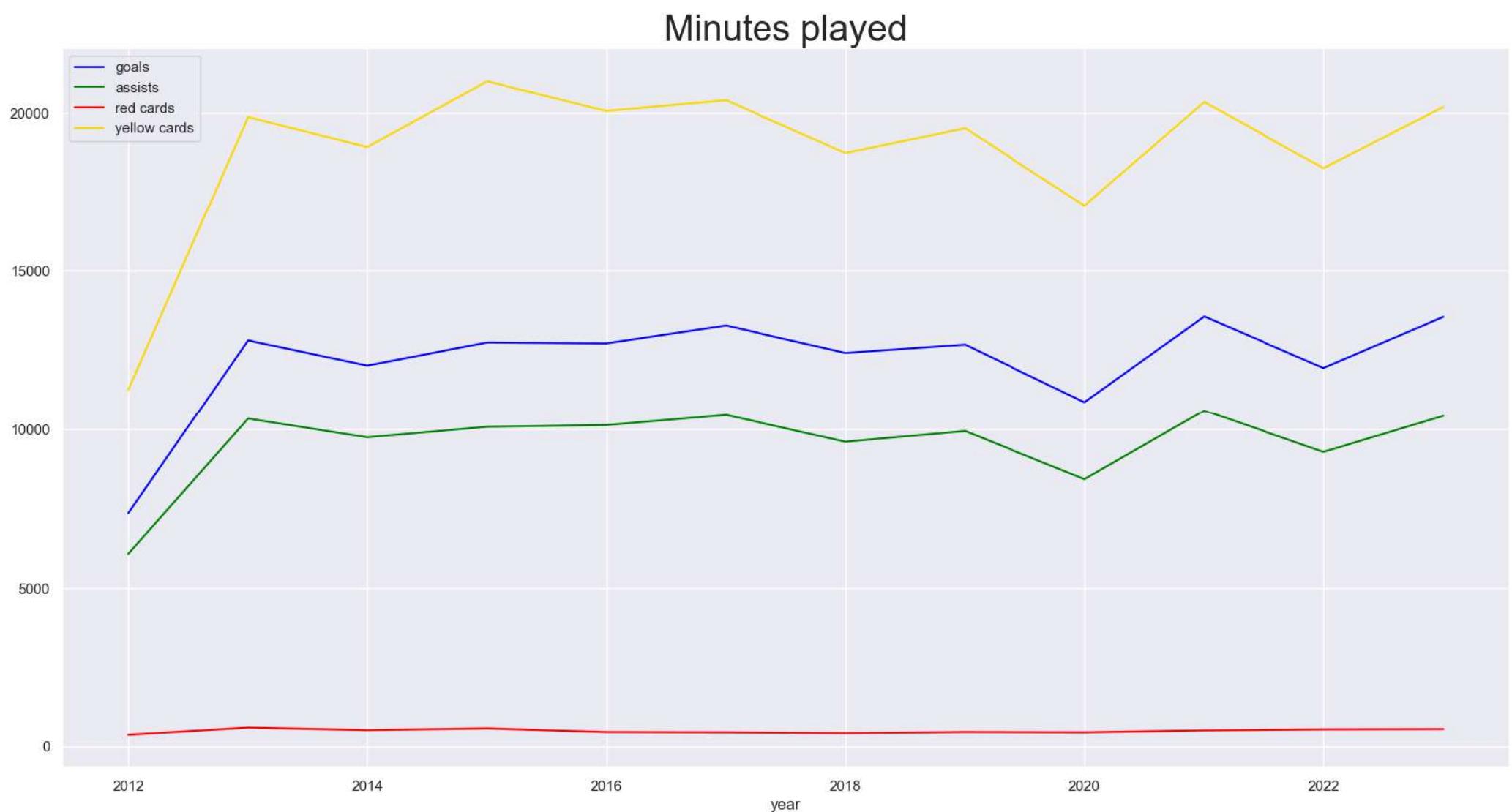




Observations on player data visualizations

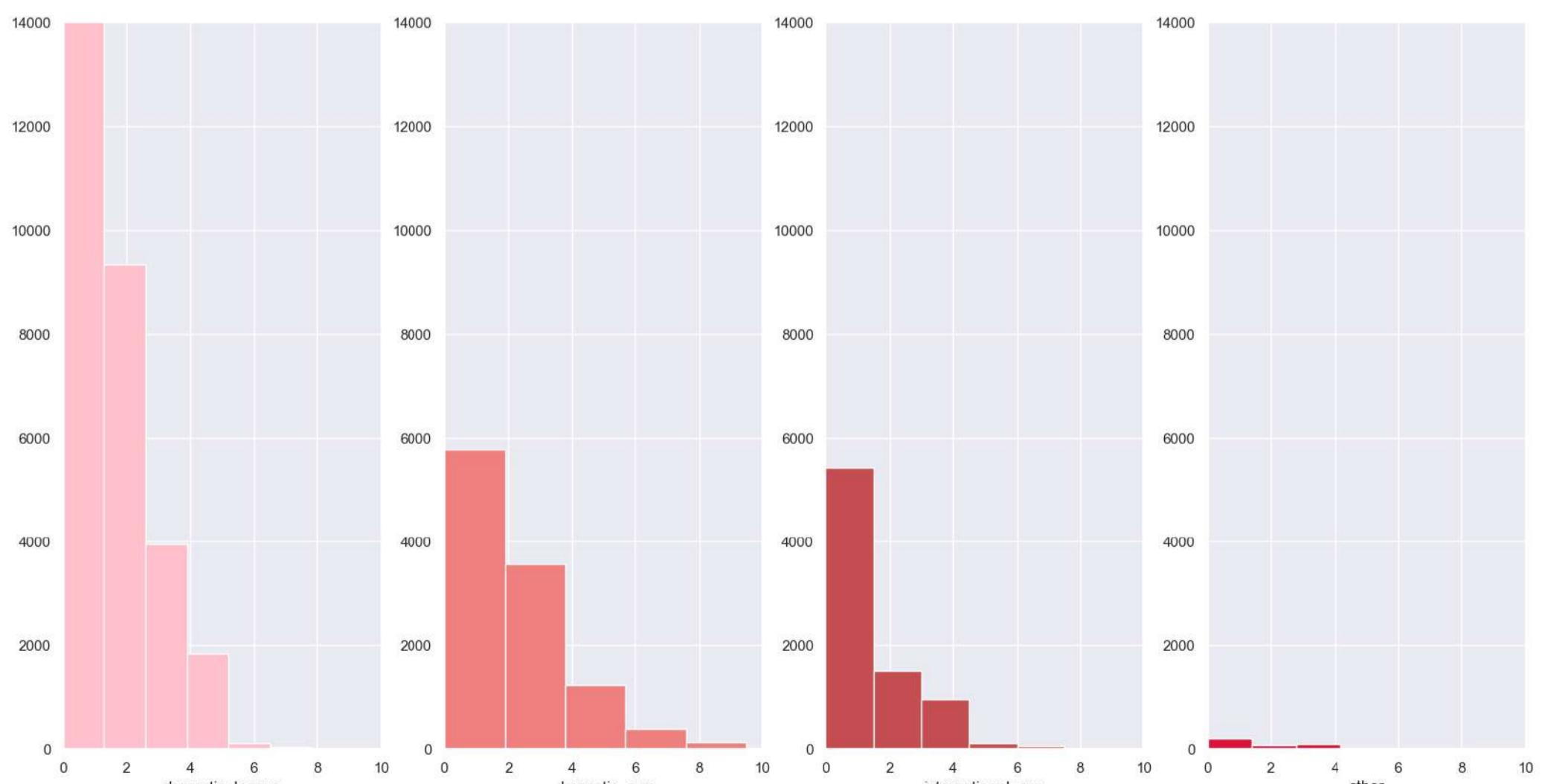
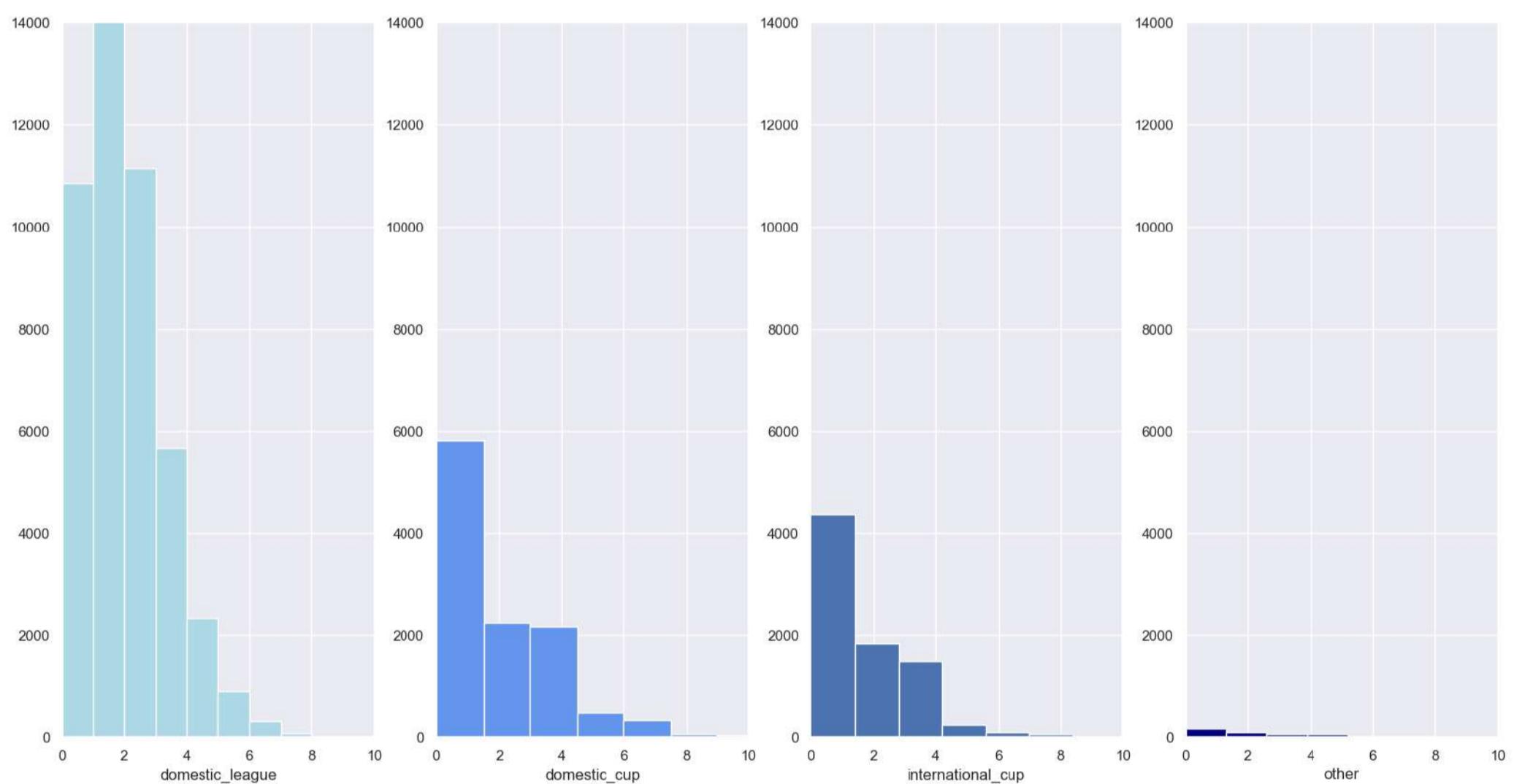
Generally the distributions of age is a skewed normal distribution and height is a normal distribution. Distributions amongst high value players appear to be reflective of values within the entire dataset.

Apearance Visualizations



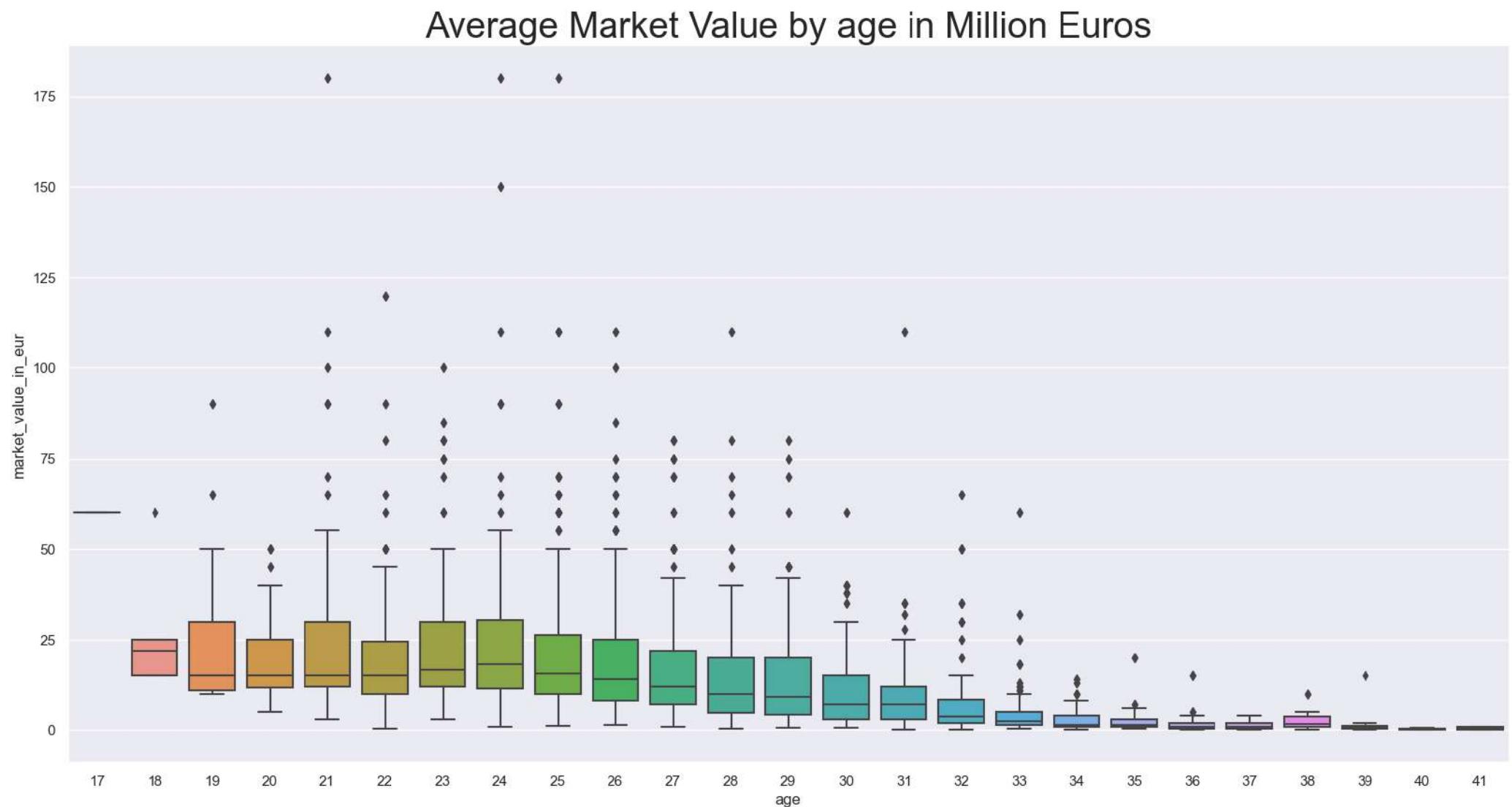
Game Visualizations

Annual home versus away goals



- As can be seen, usually the home teams score more goals. So hosting a match has an impact on the outcome of the game.

Data vizualisation of market value by age

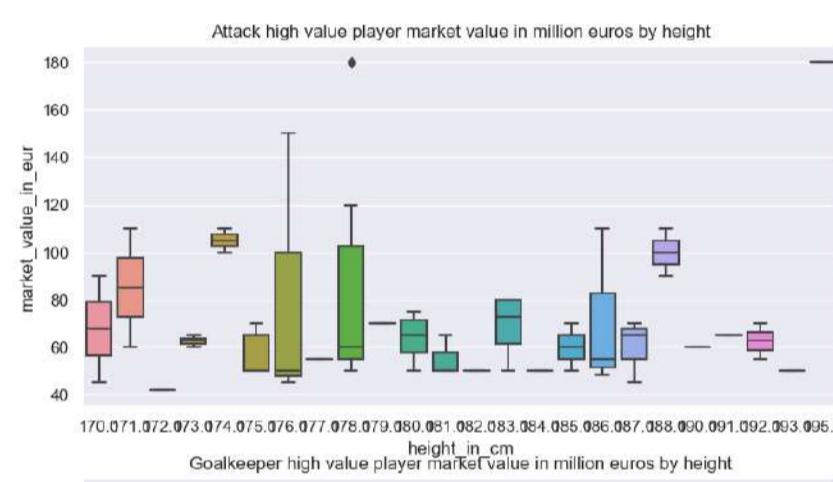
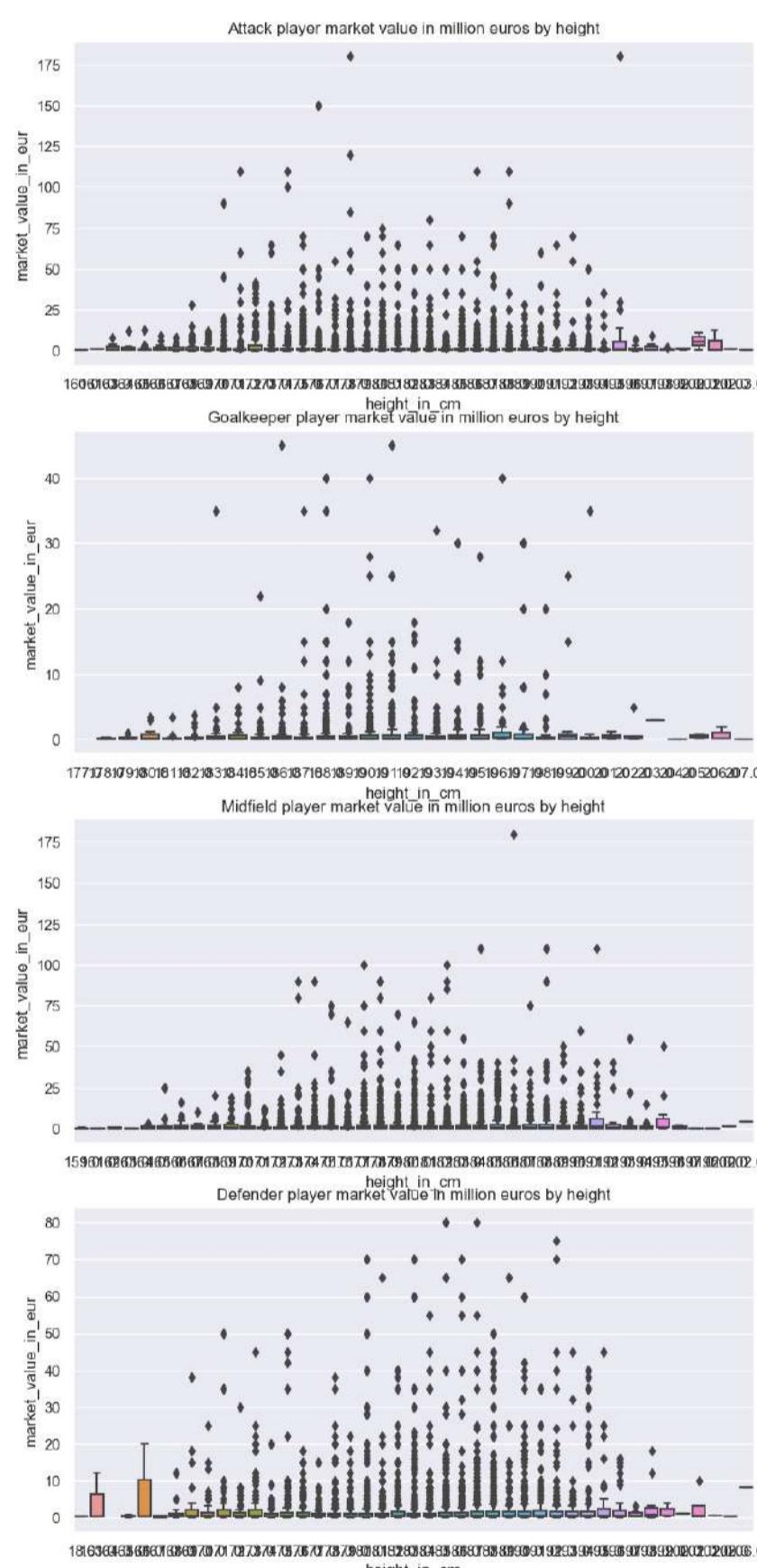
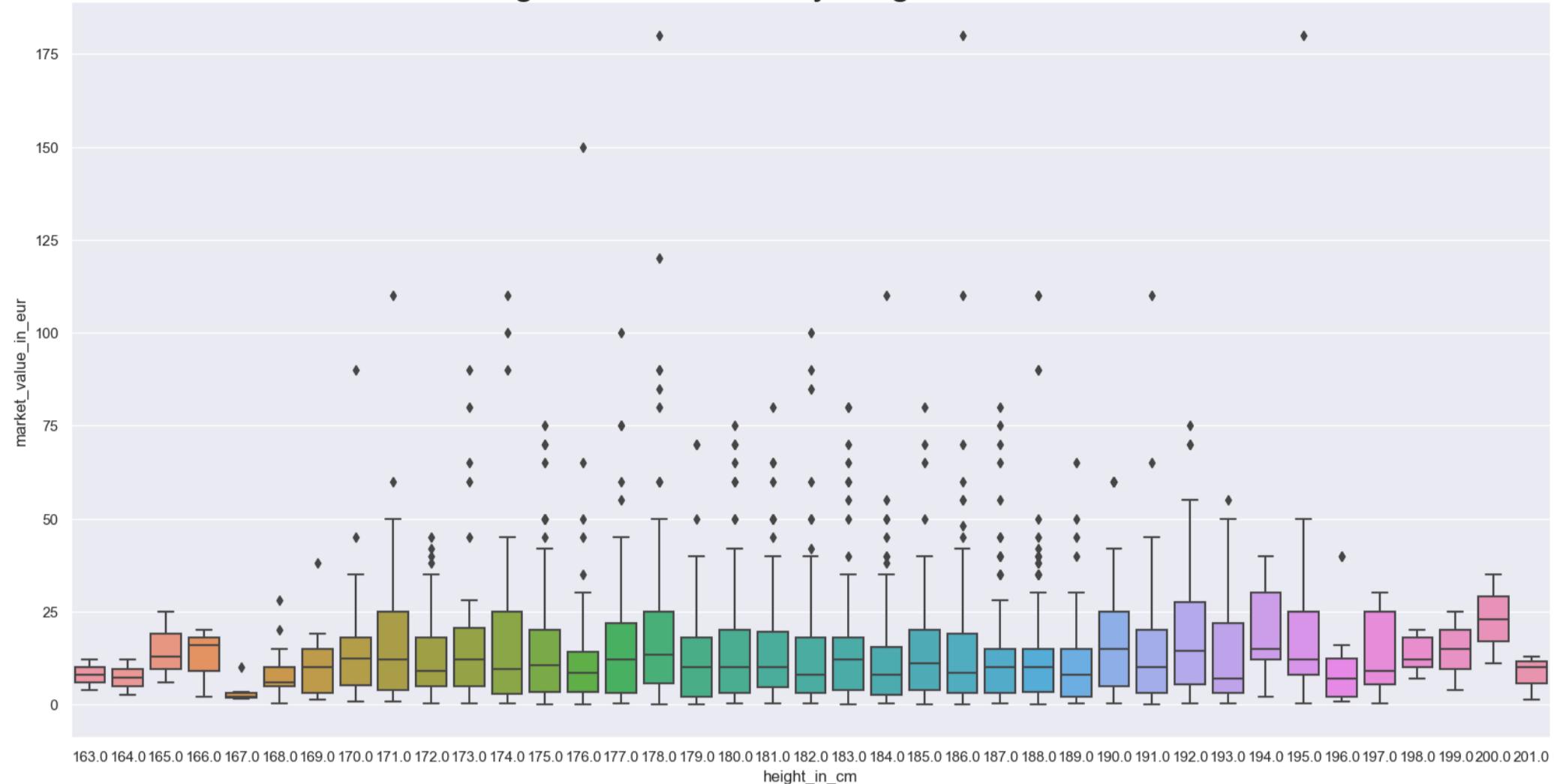


Observations on age

The age distribution of players is a skewed normal distribution starting at 17 years of age and going up 50 with an average age of 29. Players with a market value to over 400,000 euros form a normal distribution ranging from 19 to 32 years of age, with a significant number at age 25.

Data visualisation of market value by height

Average Market Value by height in Million Euros



Observations on height

The height distribution of players is a normal distribution ranging from 160cm to 200cm with an average age of 181cm. The average height for high value players is about 1cm taller than the general average.

There are relatively few high value goal keepers, but they are all tall ranging from 188 to 200cm.

There appears to be a normal like relationship between height and market value for each position when you look at all players, but does not appear to be any significant relationship between height and market value in the most valuable players.

Top players by Market Value

		name	market_value_in_eur	last_season
21474	Erling Haaland	180000000.0	2023	
25392	Jude Bellingham	180000000.0	2023	
18682	Kylian Mbappé	180000000.0	2023	
19862	Vinicius Junior	150000000.0	2023	
21891	Bukayo Saka	120000000.0	2023	
9419	Harry Kane	110000000.0	2023	
21158	Lautaro Martínez	110000000.0	2023	
21013	Victor Osimhen	110000000.0	2023	

		name	highest_market_value_in_eur	last_season
18682	Kylian Mbappé	200000000.0	2023	
5941	Neymar	180000000.0	2022	
21474	Erling Haaland	180000000.0	2023	
25392	Jude Bellingham	180000000.0	2023	
9496	Raheem Sterling	160000000.0	2023	
7171	Kevin De Bruyne	150000000.0	2023	
19862	Vinicius Junior	150000000.0	2023	

2.3 Collating All Player Data

Having look at each the data in each of the data files, going to pull all of the data together for each player, so that we can look at feature importance and start to model transfer values.

after filtering players with the last season of 2023, and dropping some columns, ([`'current_club_id'`, `'city_of_birth'`, `'date_of_birth'`, `'first_name'`, `'last_name'`, `'player_code'`, `'image_url'`, `'url'`]) **merged_players_df** have been created.

games_df and **appearances_df** have been merged together. and the result is the final data frame that we will run the machine learning models on it.

Select the top 10 players based on the sum of goals :

	player_name	goals
2004	Erling Haaland	51
3716	Kylian Mbappé	36
5608	Robert Lewandowski	33
1954	Enner Valencia	32
2565	Harry Kane	32
3486	Karim Benzema	31
4514	Mehdi Taremi	31
6621	Victor Osimhen	31
4696	Mohamed Salah	29
3763	Lautaro Martínez	28

After merging all data frames together the output is **merged_players_df**. it contains this columns:

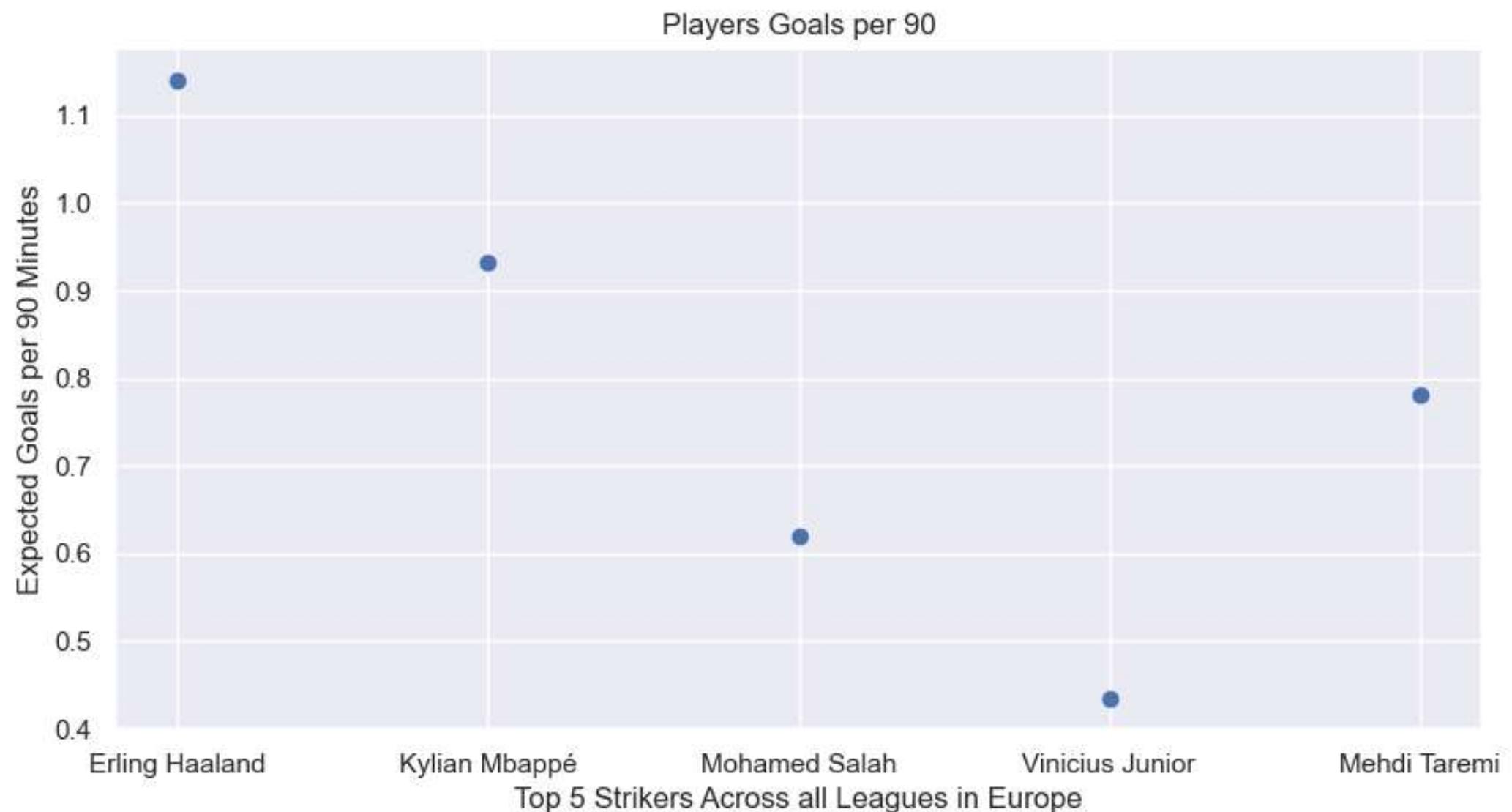
```
Index(['games_2022', 'minutes_played_2022', 'goals_2022', 'assists_2022', 'goals_against_2022',  
       'goals_for_2022', 'clean_sheet_2022', 'position', 'sub_position', 'last_season', 'foot', 'height_in_cm', 'age',  
       'country_of_birth', 'club_value', 'squad_size', 'current_club Domestic_competition_id',  
       'term_days_remaining', 'market_value_in_eur', 'highest_market_value_in_eur', 'yellow_cards_2022',  
       'red_cards_2022', 'direct_goal_contribution2022', 'goals_per_90', 'score_2022', 'price_last_year'],  
       dtype='object')
```

further feature engineering will be done on the data set to get ready for the models.

2.4 feature engineering

2.4.1 direct goal contribution , 2.4.2 goals per 90 min

These two features were made according to the previous features. based on total goals and assist for direct goal contribution, and minutes played and goals for creating goals per 90 min.



2.4.3 score_2022

this feature created based on this metrics:

Position	Minutes Played	Goals	Assists	Goals Against	Clean Sheet	Yellow Cards	Red Cards
GK	0.1	0	0	0	0.4	-0.1	-0.2
MD	0.2	0.3	0.3	0	0	-0.1	-0.2
DE	0.2	0	0	-0.6	0.3	-0.1	-0.2
AT	0.2	5	0.2	0	0	0	0

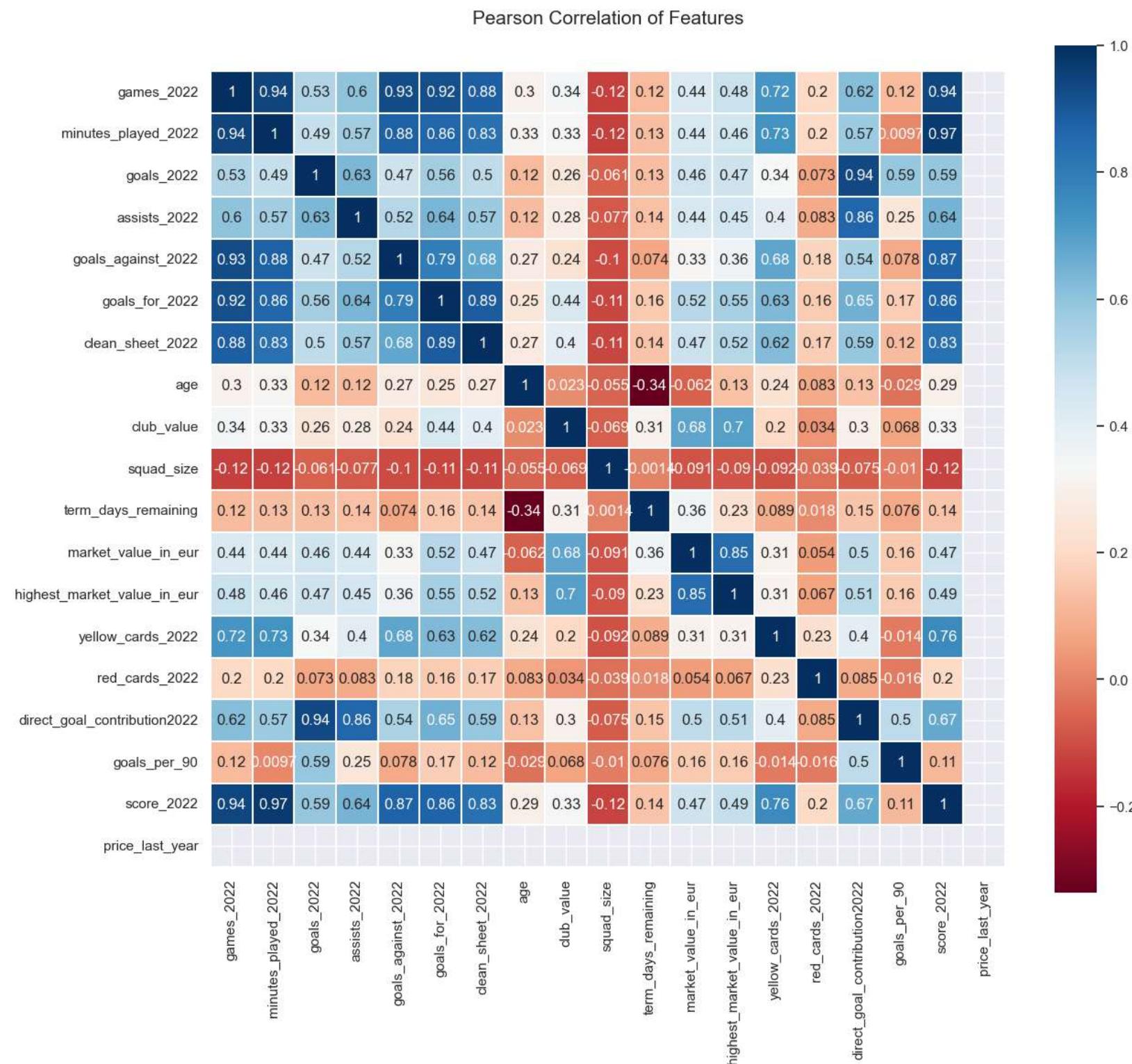
		name	position	score_2022
19862		Vinicius Junior	Attack	1071.0
21474		Erling Haaland	Attack	1061.6
9419		Harry Kane	Attack	1009.6
10048		Mohamed Salah	Attack	990.4
21158		Lautaro Martínez	Attack	965.8
3253		Robert Lewandowski	Attack	957.4
14313		Bruno Fernandes	Midfield	949.8
21719		Pedro Gonçalves	Attack	940.0
15238		Marcus Rashford	Attack	908.6
9909		Danilo	Defender	906.4
19742		Federico Valverde	Midfield	885.7

The correlation between 'score_2022' and 'market_value_in_eur' is: 0.47196412707964785

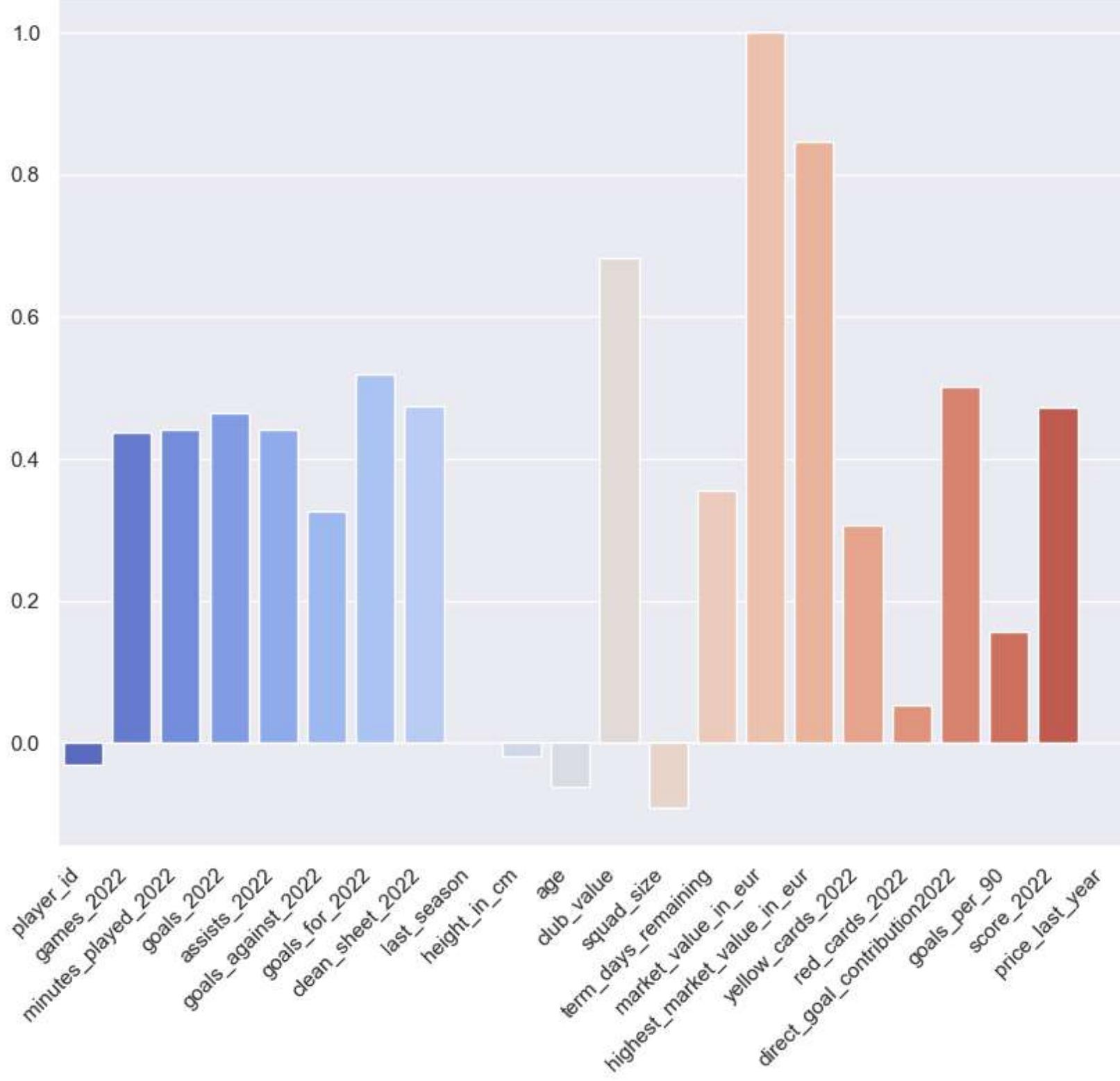
It shows that feature should be useful in model!

2.5 Statistical Test

Pearson Correlation of Features



Pearson Correlation with market_value_in_eur



These two plots show correlations between columns, first for **games_2022**, and the second one is for **market_value_in_eur**.

Hypothesis testing

1. test whether there is a significant difference in the 'market_value_in_eur' between players with different foot preferences (left and right foot)

F-statistic: 1.2185291313582847

P-value: 0.29573427267093705

Fail to reject the null hypothesis: There is no significant difference in market values between foot preference groups.

2. Analysis of Variance (ANOVA) test to investigate whether there is a significant difference in the average market values between players of different positions.

ANOVA Results:

F_onewayResult(statistic=19.506551702364632, pvalue=5.724310966553086e-16)

There is a significant difference in the average market values between players of different positions.

3. market values of players across different age groups

ANOVA Results for Age Groups:

F_onewayResult(statistic=36.884733657931115, pvalue=1.5666088444352123e-30)

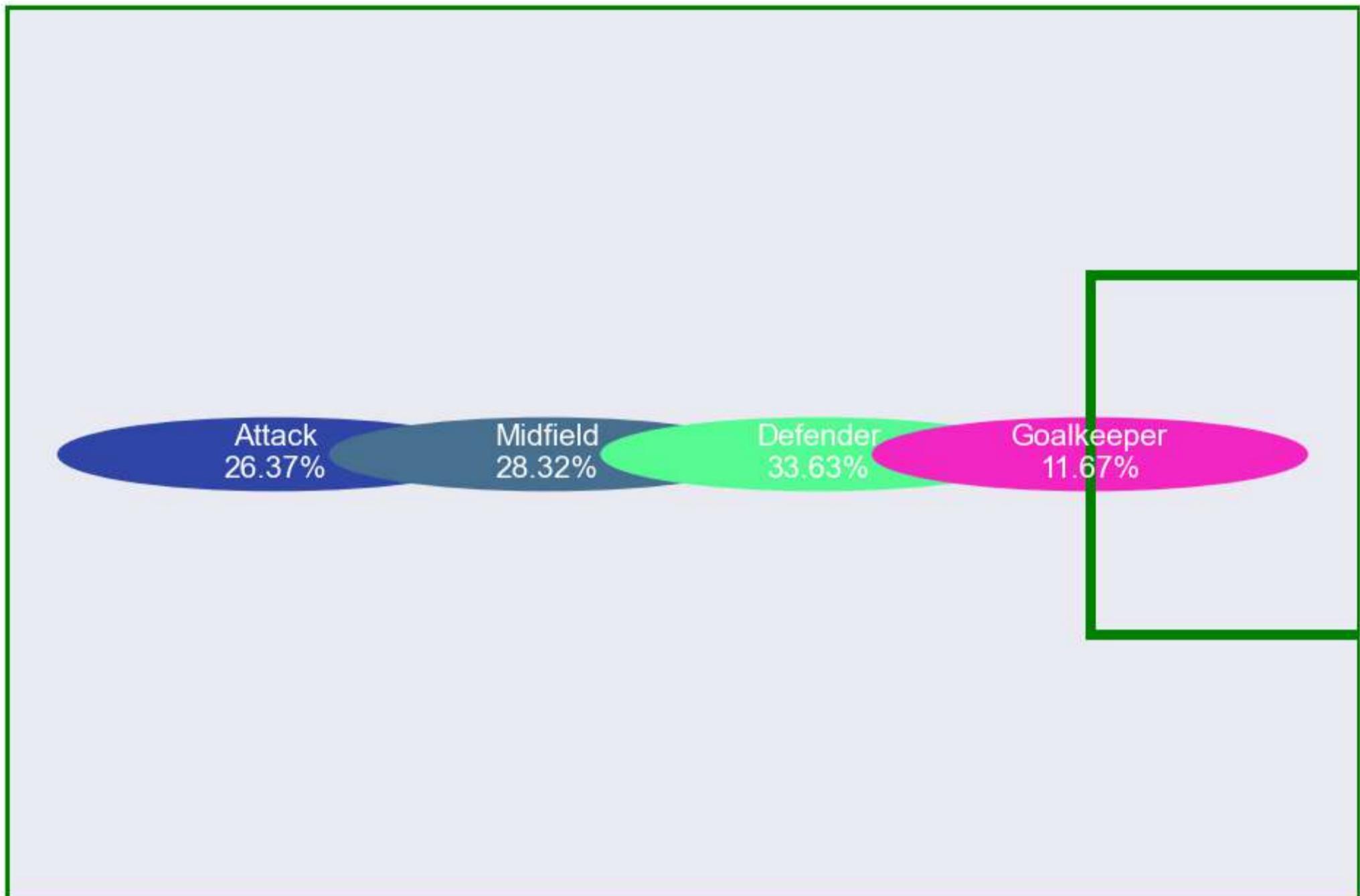
There is a significant difference in the market values of players across different age groups.

2.6 Handling missing values

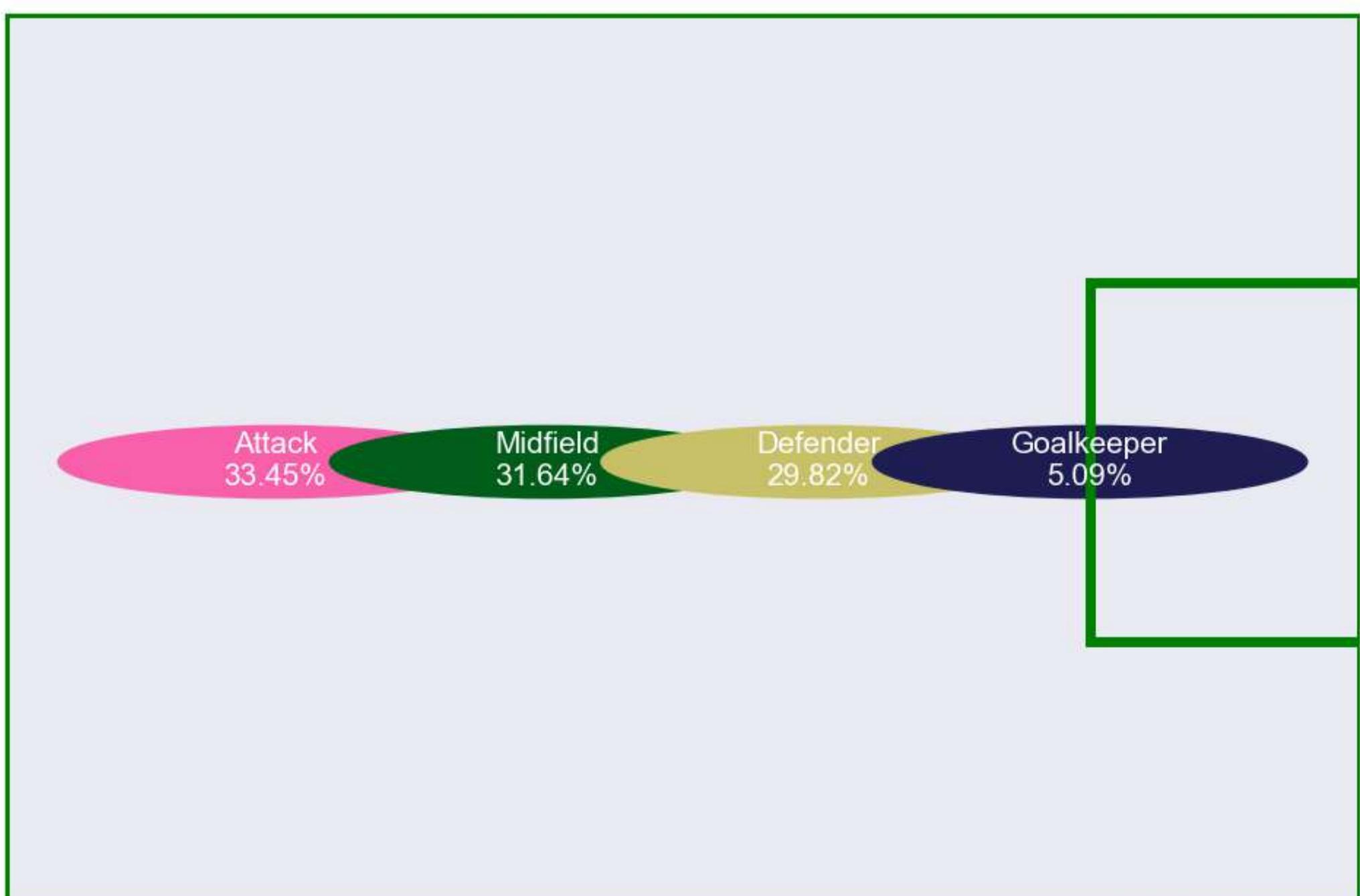
Handling missing values by imputing the mean for numerical columns and the mode (most common value) for categorical columns.

Distribution of players based on positions :

It is not without grace looking at this position distribution. it gives insightful idea of distribution of players in the football pitch.



Distribution of players with 30.000.000 and more market values:



2.7 Encoding Categorical Variables:

This columns are categorical. so we done a one hot-encoding, to use them in or model. because they are valuable columns!

```
['position','sub_position','foot','country_of_birth','current_club_domestic_competition_id']
```

Now after splitting data in **test_size=0.2**, we are ready to predict the market price of players!

2.8 Models

Model: Linear Regression R-squared Score: 0.7430768046370413

Model: Decision Tree R-squared Score: 0.686818655804631

Model: Random Forest R-squared Score: 0.8572988112124682

Model: Gradient Boosting R-squared Score: 0.8623650559226523

Model: Support Vector Machine R-squared Score: -0.1634947452556612

Observation on model

The negative R-squared score for the Support Vector Machine indicates that this model is not performing well on your data. It's possible that the SVM model may not be suitable for your regression task, or there might be an issue with the model's hyperparameters. Consider adjusting the parameters or trying different models to improve performance.

In contrast, both Random Forest and Gradient Boosting seem to be performing well, with high R-squared scores.

It's clear that the SVM model is not performing well, as indicated by the negative R-squared score and high error metrics. The other models (Linear Regression, Decision Tree, Random Forest, and Gradient Boosting) are providing better results, with Random Forest and Gradient Boosting showing particularly strong performance.

Model: Neural Network

- Neural Network Structure: A simple neural network architecture was employed with two hidden layers containing 100 and 50 neurons, respectively. The activation function used is the default rectified linear unit (ReLU).
- Training Parameters: The model was trained for a maximum of 500 iterations, and the random state was set to 42 for reproducibility.

Model: Neural Network

R-squared Score: 0.7373565166708334

A neural network regression model with two hidden layers (100, 50 neurons) achieved an R-squared score of 0.7374 on the test set. The model was trained for 500 iterations using standardized data.

Model: Neural Network (More Complex)

R-squared Score

The R-squared score for the more complex neural network regression model on the test set is approximately 0.7557.

The more complex neural network model demonstrates improved performance, as indicated by the higher R-squared score compared to the previous model. This suggests that increasing the model's complexity by adding more layers and neurons has contributed to better predictive capabilities.

Best hyperparameters for Random Forest and Gradient Boosting:

After performing **Grid Search** we found the best possible Models.

Best Hyperparameters for Random Forest:

```
{'max_depth': 10, 'min_samples_leaf': 2, 'min_samples_split': 2, 'n_estimators': 200}
```

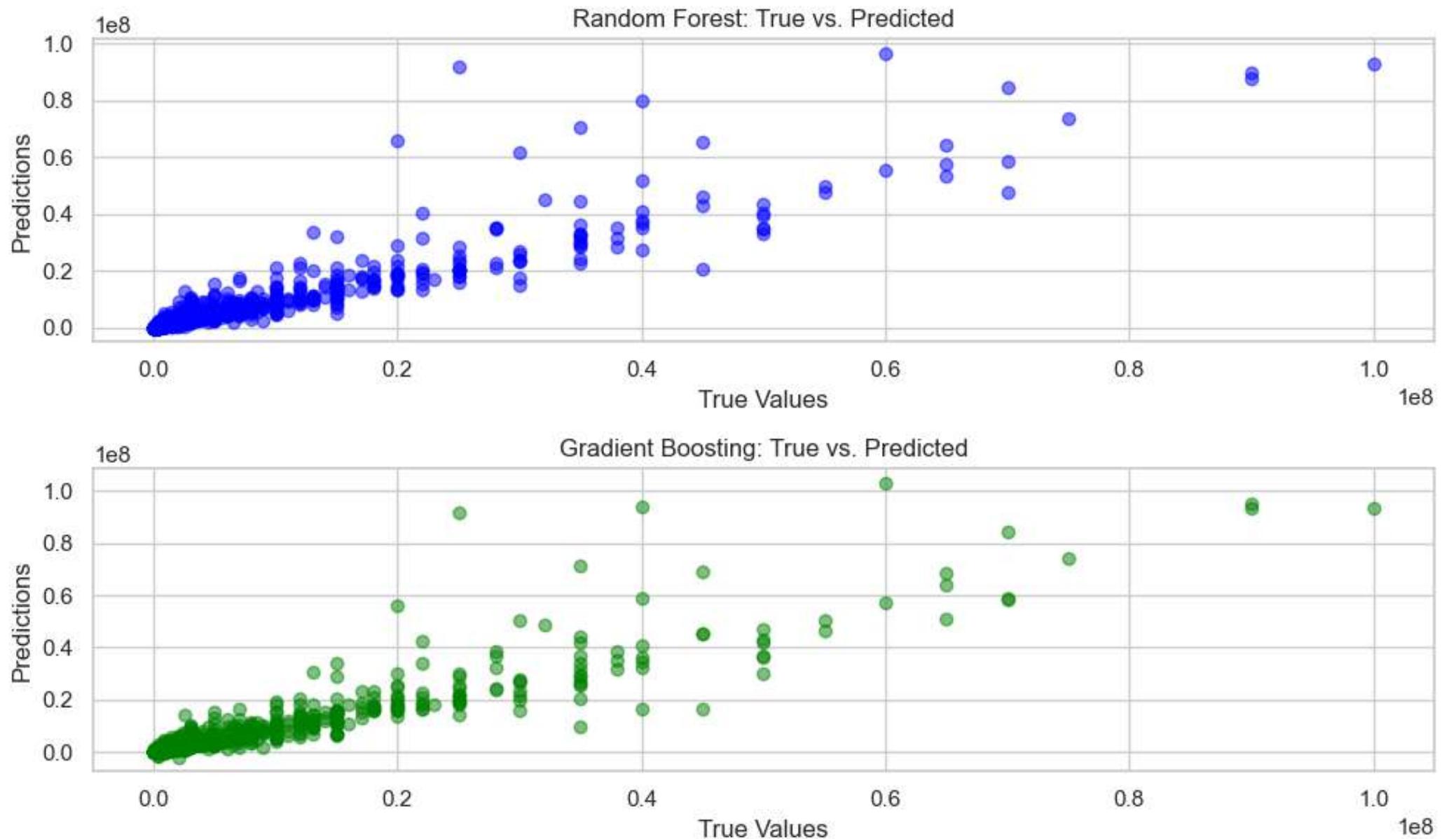
Best Hyperparameters for Gradient Boosting:

```
{'learning_rate': 0.1, 'max_depth': 5, 'min_samples_leaf': 1, 'min_samples_split': 10, 'n_estimators': 200}
```

Random Forest R-squared Score with Best Hyperparameters: 0.8787846261124929

Gradient Boosting R-squared Score with Best Hyperparameters: 0.8834115304962495

These results indicate that after hyperparameter tuning, both Random Forest and Gradient Boosting models have improved R-squared scores, suggesting better predictive performance.



Random Forest Metrics:

Mean Squared Error: 17583657502782.309

Mean Absolute Error: 1490477.8322360215

Gradient Boosting Metrics:

Mean Squared Error: 18959108041409.75

Mean Absolute Error: 1524660.2525385667

It looks like the Mean Squared Error (MSE) and Mean Absolute Error (MAE) for both Random Forest and Gradient Boosting models are quite large, indicating a significant level of error in the predictions. Large values for these metrics suggest that the models may not be performing optimally on the given data.

Conclusion

In general, a lot of work was done on the data. New features were made, statistical tests were done, many maps and plots were drawn, and finally, Machine learning models were used to predict players' prices!

Comparison of these models showed that **Random Forest** and **Gradient Boosting** performed well, Because of the tree nature! But in other metrics like **MES**, they were weak!

As a result, finding and estimating the price of players is a difficult task because it depends on several factors, one of the most important of which is sponsorship, because if a player has a good performance, but if he is in a weak league, the price is not high compared to the other players so that make mistake on the model. for example if we compare each leagues players together, the model would have a better result.

another reason that models have high MSE because prices have many distance between together. for example **Messi** have 180.000.000 price and the next player have 160.000.000 and they are in million scale! this is in much big scale. so validating models based on **MSE** is not a good metric to conclusion models result.