

# PREDICTING MARKET VALUE OF A FOOTBALL PLAYER

### **GROUP MEMBERS**

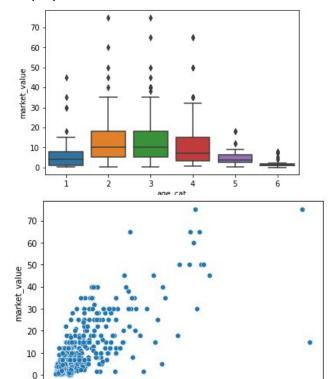
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### **PROBLEM DESCRIPTION:**

Predicting fair market value of football players with the help of features present in the dataset. Deploy the model as a RESTful Web Service.

### **EXPLORATORY DATA ANALYSIS (EDA):**

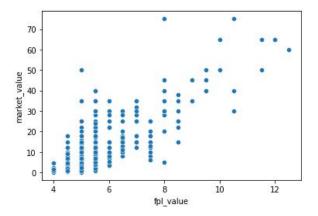
We used Seaborn library to explore the data with the help of graphs and analysed which features influenced the market value and were important in prediction of market value of the player and remove those features which were not influencing market value.



In the above graph we can see, players falling in the age category 2-4 are more popular and get a good price for themselves as compared to category 1, 5 and 6. The new players and the older players get less price as compared to other players. We do have a few outliers that get a higher price than others.

In this graph we can see that the players that have a higher number of the page views get a much better price as compared to other players with less number of views.

There are some outliers like some players with a huge number of page views have got a comparatively less price for themselves.



3000

4000

page\_views

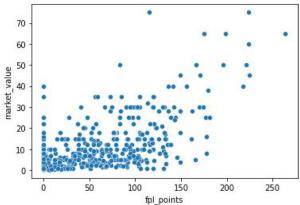
5000

6000

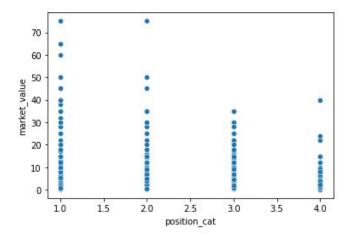
7000

8000

2000



In the above graphs, fpl\_value and fpl\_points have a high correlation with the market value. The higher the fpl value and fpl points the higher the price for the player.



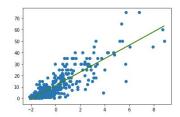
This graph shows that the players that come under position category 1 and 2 get a much better price as compared to the other categories.

We have taken age\_cat instead of age, position\_cat instead of position and region instead of nationality because these variables were highly correlated and also to reduce the dimensionality.

# **Models Tried:**

**Features Used**: age\_cat, page\_views, position\_cat, fpl\_value, fpl\_sel, fpl\_points, region, club\_id, big\_club, new\_signing.

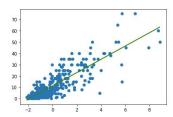
### 1. Linear Regression:



Mean squared error:

r2 score:

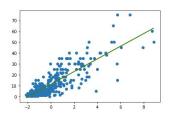
### 2. Lasso Regression



Mean\_squared\_error: 28.69

r2\_score: .8101

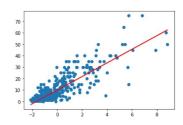
# 3. Ridge Regression:



Mean\_squared\_error: 28.36

r2\_score: .8102

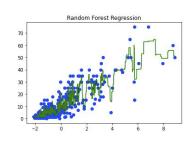
# 4. Support Vector Regression:



Mean\_squared\_error: 25.27

r2\_score: 0.8332

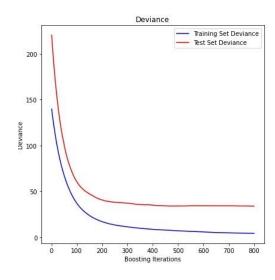
# 5. Random Forest:



Mean\_Squared\_error: 20.9

r2\_Score: 0.859

# 6. Gradient Boosted Regression:



Mean\_squared\_error: 34

r2\_score: 0.83

7. Nearest Neighbour Regression:

r2\_score: 0.71

8. Tree Regression:

Mean\_squared\_error: 79

r2\_score: 0.62

Random Forest is chosen because it has the highest r2\_score and least Mean\_squared\_error.

# **Restful web Service**

# Predict Price of a Football Player

5
Arsenal
LW V
$\bigcirc$ 1 $\bigcirc$ 2 $\bigcirc$ 3 $\bigcirc$ 4
010203040 nan
Chile ~
○ Yes ○ No
010203040506
○ Yes ○ No
010203040506
○ Yes ○ No