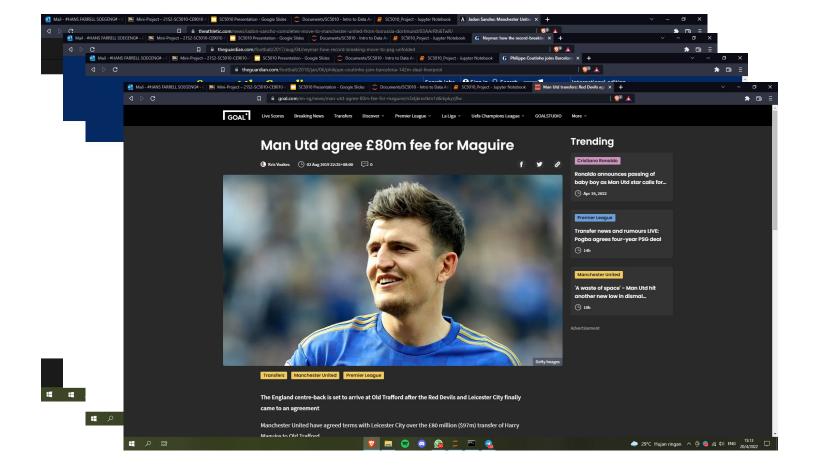
Predicting the Football Market

Team 6

Hans Farrell Soegeng Rivaldo Billy Sebastian Nicholas Chin Wei Lun

Problem Motivation



The Football Transfer Market

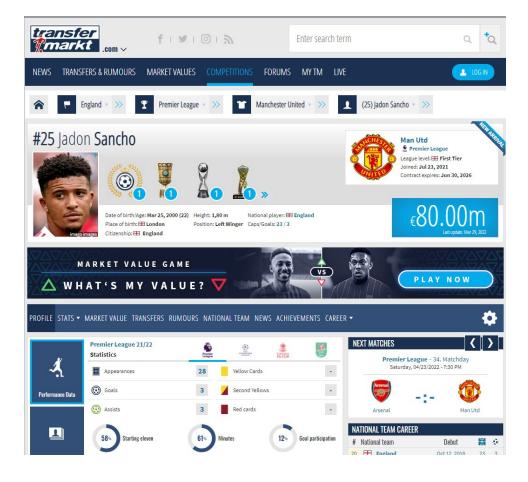
- Clubs buy or sell players every transfer window to strengthen their squad or get money from sales.
- Transfers happen for a fee agreed between the clubs
- This fee is determined by how much the transferred player is worth for the buying club.
- But how do clubs value a player?

Market Value Estimate

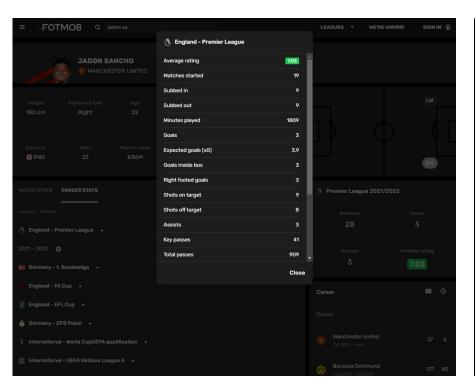
Several websites have tried to estimate players based on their market value to clubs.

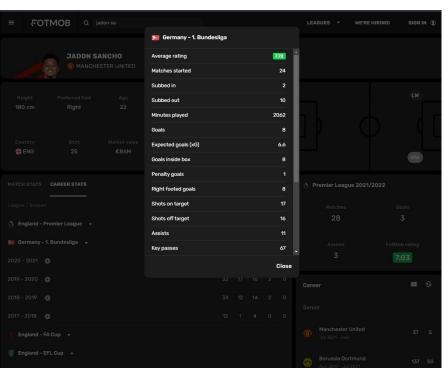
They use the wisdom the community to evaluate these players

But, is there a way we can objectively find a player's value?



Statistics!





Statistics of Jadon Sancho for 2021/22 Premier League and 2020/21 Bundesliga seasons

Objective

Statistics provide us a concrete and objective way to rate a football player.

The idea is then to create a machine learning model to predict a player's market value based on their statistics of their past seasons

Data Preparation

Data Collection

- Extract the statistics of every attacking player in the top 5 leagues for the past 2 seasons (2020/21 & 2021/22) obtained from FotMob.com and their respective estimated market values into an excel file through web scraping
- Used BeautifulSoup to parse the website's html into a readable format

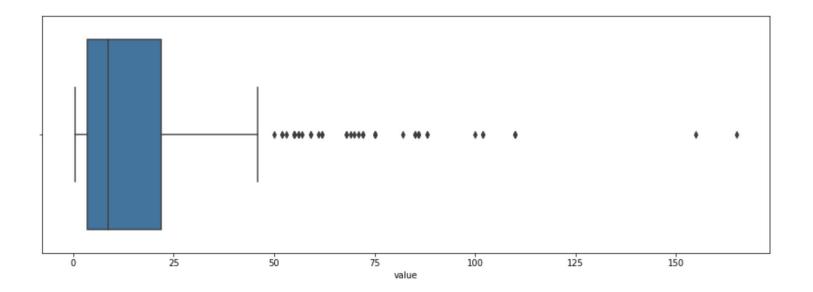
In [16]:	df											
Out[16]:		name	height	age	value	preferred_foot	average_rating_2021	matches_started_2021	subbed_in_2021	subbed_out_2021	minutes_played_2021	sl
	0	Roberto Soriano	181	31	8.50	Both	6.97	26.0	1.0	10.0	2121	***
	1	Musa Barrow	183	23	22.00	Right	6.94	19.0	6.0	16.0	1592	
	2	Nicola Sansone	175	30	3.20	Right	6.42	6.0	16.0	5.0	768	
	3	Ricardo Orsolini	183	25	11.00	Left	6.99	17.0	5.0	13.0	1367	
	4	Emanuel Vignato	175	21	4.20	Right	6.43	3.0	19.0	3.0	557	***
			1000	***	X-ex	***		***	nes	***	***	***
	565	Amadou Traore	175	20	0.65	Right	5.68	NaN	1.0	NaN	19	***
	566	M'baye Niang	184	27	5.00	Right	5.99	1.0	15.0	1.0	342	200
	567	Hwang Ui-Jo	184	29	5.50	Both	6.67	23.0	1.0	15.0	1946	***
	568	Sekou Mara	183	19	2.20	Right	6.18	5.0	13.0	5.0	551	***
	569	Jimmy Briand	180	36	1.20	Right	6.67	1.0	11.0	1.0	180	***

Objective : Predict value (in millions of euros) for every 570 players.

Data Cleaning

- Filled null values with 0 as Fotmob does not list statistics of players with value 0
- Remove players with average rating of 0

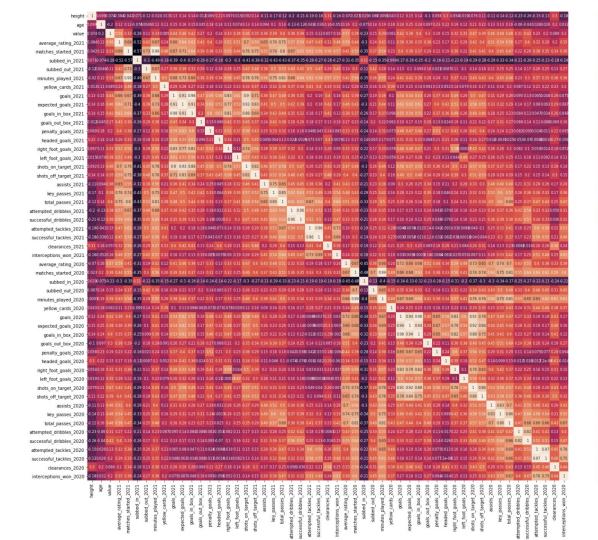
Exploratory Data Analysis



- Consider players with value greater than 100 million euros as outliers
- Removed these players from the dataset

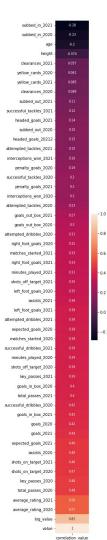
```
In [53]: plt.figure(figsize=(15, 5))
          sb.boxplot(x="preferred_foot", y="value", data=df)
Out[53]: <AxesSubplot:xlabel='preferred_foot', ylabel='value'>
                             Both
                                                           Right
                                                                                         Left
                                                                       preferred foot
          There does not appear to be a strong relationship between preferred_foot and value so we choose not to include this variable.
In [54]: df = df.drop(columns = ['preferred_foot'])
```

Compare the market value across different preferred foot categories



- Some variables are highly correlated with each other, such as attempted_tackles_2020 and successful_tackles_2020 with a correlation of 0.97, goals_2021 and goals_in_box_2021 with a correlation of 0.98
- The variables subbed_in_2020 and subbed_in_2021 are least correlated with other variables

Compare the correlation coefficient of market value with all the numerical predictor variables

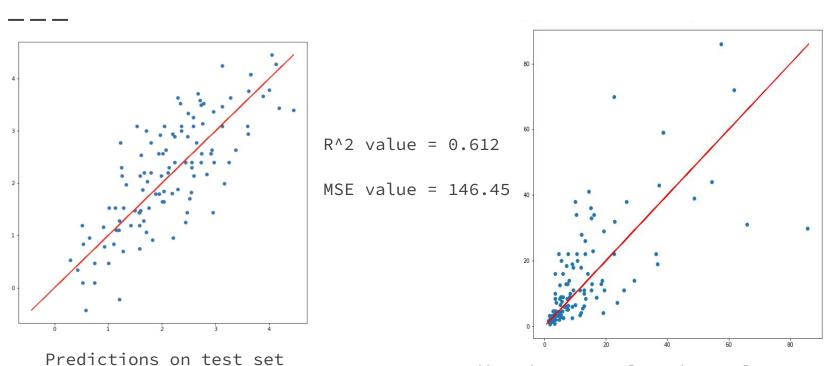


Machine Learning

Machine Learning Models

- Used regression models to predict value
- Tried 5 different models
 - Linear Regression
 - Linear Regression (with higher order terms)
 - Ridge Regression
 - Lasso Regression
 - Random Forest Regression
- Performed log transformation on value to ensure only positive values are predicted
- Used 80% training and 20% test sets
- Comparing the models in terms of R squared and mean squared error

Linear Regression



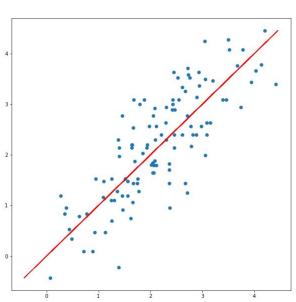
Predicted vs actual market value on test set

Linear Regression (with higher order terms)

- Limitation of this linear regression model is that it assumes the response variable has a linear relationship against every predictor variable
- Try to improve this model by adding higher order terms for predictor variables having correlation coefficient with absolute value higher than 0.5, which are average_rating_2020 and average_rating_2021
- Add the second order term of age, as even though its correlation coefficient is less than 0.5, age may have a complex relationship with market value

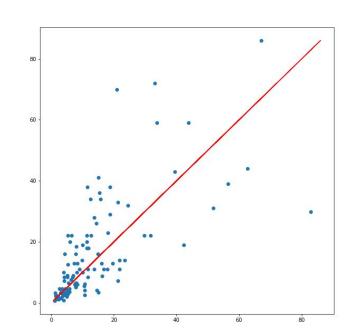
Linear Regression (with higher order terms)





 R^2 value = 0.643

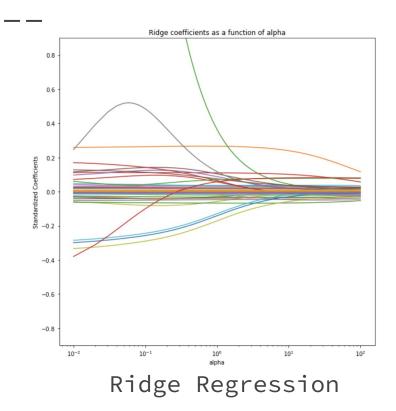
MSE value = 144.95



Predictions on test set

Predicted vs actual market value on test set

Ridge and Lasso Regression



Lasso coefficients as a function of alpha 0.20 0.15 0.10 0.00 -0.05 10^{-2} 10^{-1} 10° 10¹ 10² alpha

Lasso Regression

Model Comparison

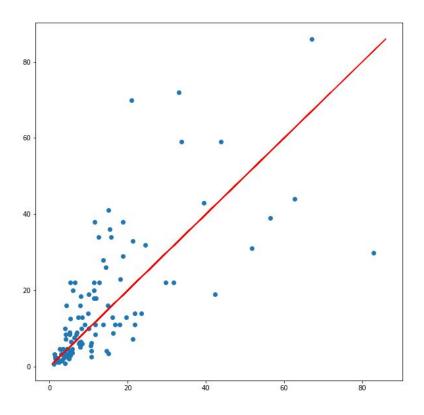
Model Comparison				
Model	R2 Score	MSE		
Linear Regression	0.6124299824151251	146.45024016416988		
Linear Regression (higher order terms)	0.6431267219862531	144.95331830442498		
Ridge Regression	0.6448971342819805	134.5894783980847		
Lasso Regression	0.640337661964369	123.10347326169641		
Random Forest Regression	0.6063040966499413	147.7985546636136		

- Based on R2 score, Ridge Regression appears to be the best performing model
- Based on MSE, Lasso Regression appears to be the best performing model
- Since the MSE of Lasso Regression is significantly less as compared to the other models, we select it as the best performing model.

Conclusion

From the regression models, we notice that our predicted market value gets more inaccurate as the value increases

Insert lasso graph plot here



Market Value Factors

- On-pitch performance
- Age (development potential and future prospects)
- Reputation/prestige
- Marketing value
- Number & reputation of interested clubs
- Experience
- Injury susceptibility
- General demand and 'trends' of the market

Future Ideas

If we could somehow quantify the off-pitch element of a football player in terms of the commercial value he brings to a club, it could be an important variable in predicting market value

E.g, total followers on his social medias, engagements on media networks, sponsorship deals values, etc