Predicting Footballers Market Values

Using 2008 - 2017 data from transfermarkt.co.uk

Christopher Williams
Capstone
GA DSI
Austin
Feb 2019

Contents

Data Science Problem

In this project the problem I'm seeking to understand is how well annual statistics predict the estimated market values of professional footballers in the top 5 European leagues.

Using players annual data to see how applicable machine learning prediction models are on market values.

Data: comes from transfermarket.co.uk which has crowd sourced market values for players in the top flight of European football over the last 10 years. Think Penelope and wisdom of the crowds!

The Data

Getting it

Data Challenges

Most sites focus on the just high level stats like: shots, goals, assists, cards, minutes-played, and games played.

Lack of one site with all the stats desired for true merits of each different position.

Complex Process to unify all the stats needed to build a truly complete dataset at scale that could be used to predict market values of players in defensive positions along with forwards & midfielders.

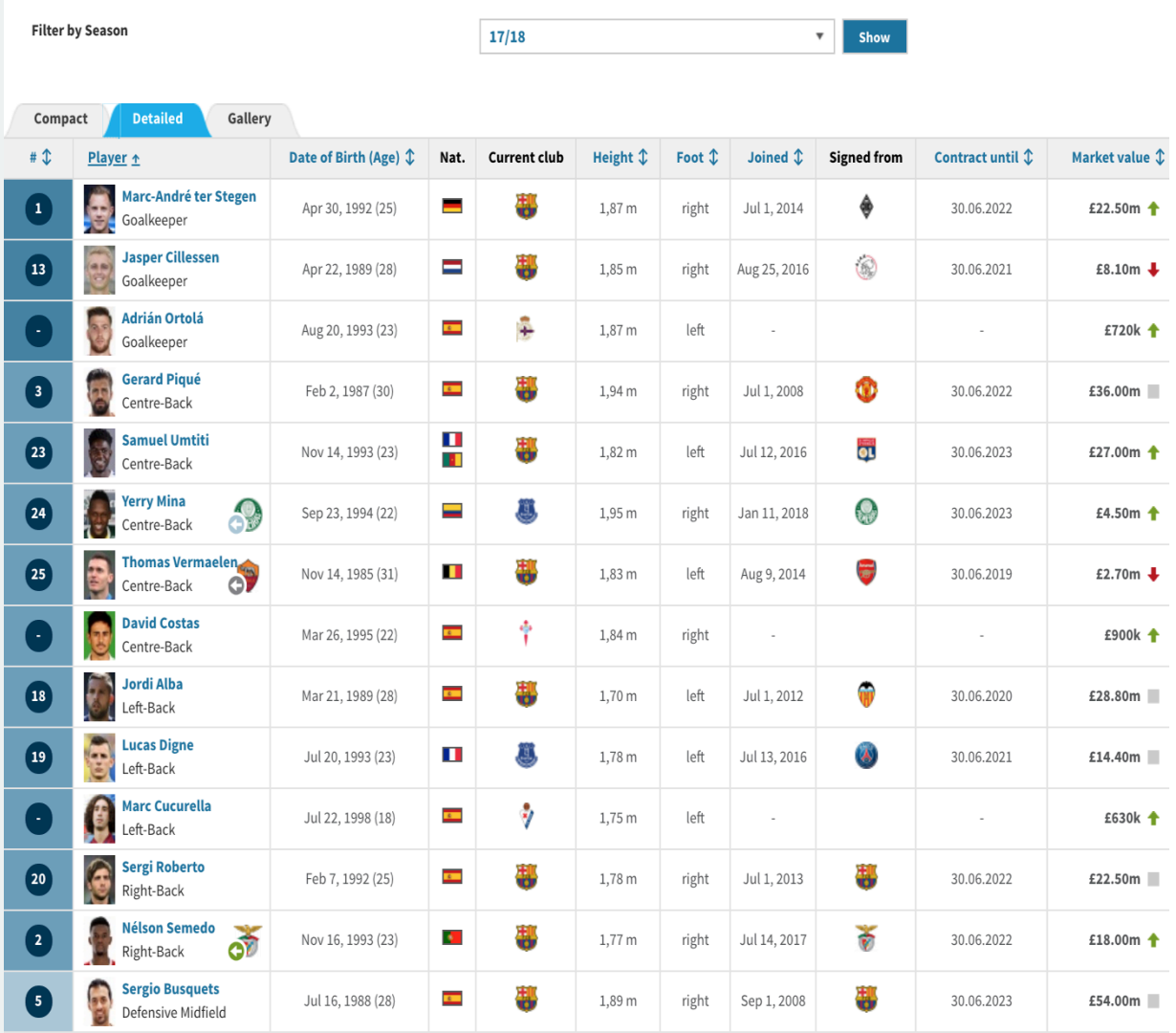
Data Collection

Market Values

2008 - 2017

DOB
Nationality
Height
Foot
Joined
Signed From
Transfer Fee
Contract Until
Market Value

Source: transfermarkt.co.uk



Filter by Season: 17/18 — Show

Compact | Detailed | Gallery

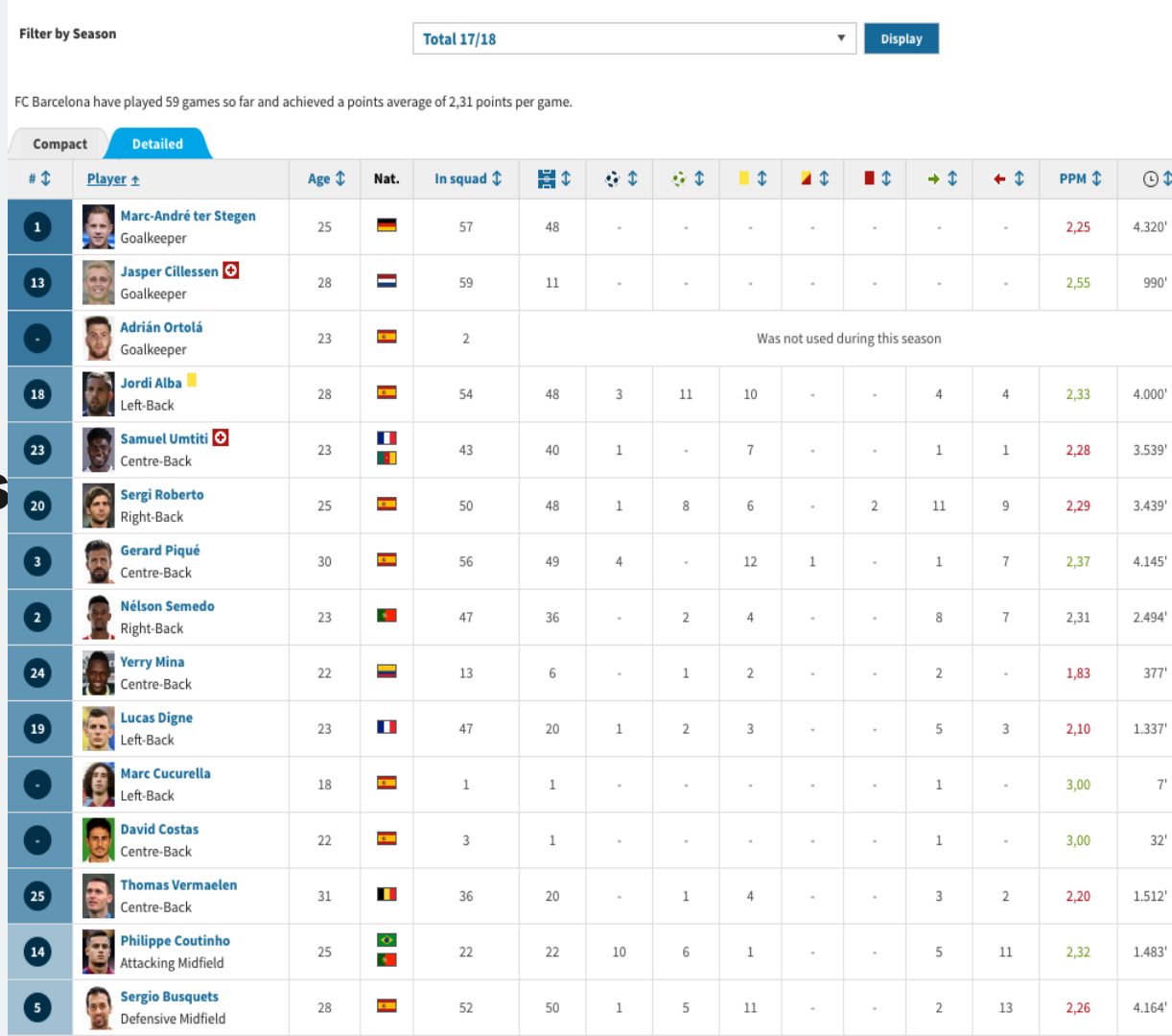
#	Player	Date of Birth (Age)	Nat.	Current club	Height	Foot	Joined	Signed from	Contract until	Market value
1	Marc-André ter Stegen Goalkeeper	Apr 30, 1992 (25)			1,87 m	right	Jul 1, 2014		30.06.2022	£22.50m
13	Jasper Cillessen Goalkeeper	Apr 22, 1989 (28)			1,85 m	right	Aug 25, 2016		30.06.2021	£8.10m
-	Adrián Ortolá Goalkeeper	Aug 20, 1993 (23)			1,87 m	left	-		-	£720k
3	Gerard Piqué Centre-Back	Feb 2, 1987 (30)			1,94 m	right	Jul 1, 2008		30.06.2022	£36.00m
23	Samuel Umtiti Centre-Back	Nov 14, 1993 (23)			1,82 m	left	Jul 12, 2016		30.06.2023	£27.00m
24	Yerry Mina Centre-Back	Sep 23, 1994 (22)			1,95 m	right	Jan 11, 2018		30.06.2023	£4.50m
25	Thomas Vermaelen Centre-Back	Nov 14, 1985 (31)			1,83 m	left	Aug 9, 2014		30.06.2019	£2.70m
-	David Costas Centre-Back	Mar 26, 1995 (22)			1,84 m	right	-		-	£900k
18	Jordi Alba Left-Back	Mar 21, 1989 (28)			1,70 m	left	Jul 1, 2012		30.06.2020	£28.80m
19	Lucas Digne Left-Back	Jul 20, 1993 (23)			1,78 m	left	Jul 13, 2016		30.06.2021	£14.40m
-	Marc Cucurella Left-Back	Jul 22, 1998 (18)			1,75 m	left	-		-	£630k
20	Sergi Roberto Right-Back	Feb 7, 1992 (25)			1,78 m	right	Jul 1, 2013		30.06.2022	£22.50m
2	Nélson Semedo Right-Back	Nov 16, 1993 (23)			1,77 m	right	Jul 14, 2017		30.06.2022	£18.00m
5	Sergio Busquets Defensive Midfield	Jul 16, 1988 (28)			1,89 m	right	Sep 1, 2008		30.06.2023	£54.00m

Data Collection

Player's Yearly Stats

2008 - 2017

In-squad
Appearances
Goals
Assists
Yellow Cards
Second Yellows
Red Cards
Substituted On
Substituted Off
PPM
Time Played



Filter by Season: Total 17/18 — Display

FC Barcelona have played 59 games so far and achieved a points average of 2,31 points per game.

Compact | Detailed

#	Player	Age	Nat.	In squad									PPM	
1	Marc-André ter Stegen Goalkeeper	25		57	48	-	-	-	-	-	-	-	2,25	4.320'
13	Jasper Cillessen Goalkeeper	28		59	11	-	-	-	-	-	-	-	2,55	990'
-	Adrián Ortolá Goalkeeper	23		2	Was not used during this season									
18	Jordi Alba Left-Back	28		54	48	3	11	10	-	-	4	4	2,33	4.000'
23	Samuel Umtiti Centre-Back	23		43	40	1	-	7	-	-	1	1	2,28	3.539'
20	Sergi Roberto Right-Back	25		50	48	1	8	6	-	2	11	9	2,29	3.439'
3	Gerard Piqué Centre-Back	30		56	49	4	-	12	1	-	1	7	2,37	4.145'
2	Nélson Semedo Right-Back	23		47	36	-	2	4	-	-	8	7	2,31	2.494'
24	Yerry Mina Centre-Back	22		13	6	-	1	2	-	-	2	-	1,83	377'
19	Lucas Digne Left-Back	23		47	20	1	2	3	-	-	5	3	2,10	1.337'
-	Marc Cucurella Left-Back	18		1	1	-	-	-	-	-	1	-	3,00	7'
-	David Costas Centre-Back	22		3	1	-	-	-	-	-	1	-	3,00	32'
25	Thomas Vermaelen Centre-Back	31		36	20	-	1	4	-	-	3	2	2,20	1.512'
14	Philippe Coutinho Attacking Midfield	25		22	22	10	6	1	-	-	5	11	2,32	1.483'
5	Sergio Busquets Defensive Midfield	28		52	50	1	5	11	-	-	2	13	2,26	4.164'

Kylian **Mbappé vs** Dani **Alves**

Sergio Aguero, hat trick
Man City 6, Chelsea 0. Feb 10
£67.5m market value 2018

Sergio **Agüero vs** Lionel **Messi**

The Data

Seeing it

Data Assumptions.
How to deal with it.

How to deal with defenders & goalies compared to midfielders & forwards who score more goals, have more assist?

Min number of appearances?
Min number of time played?

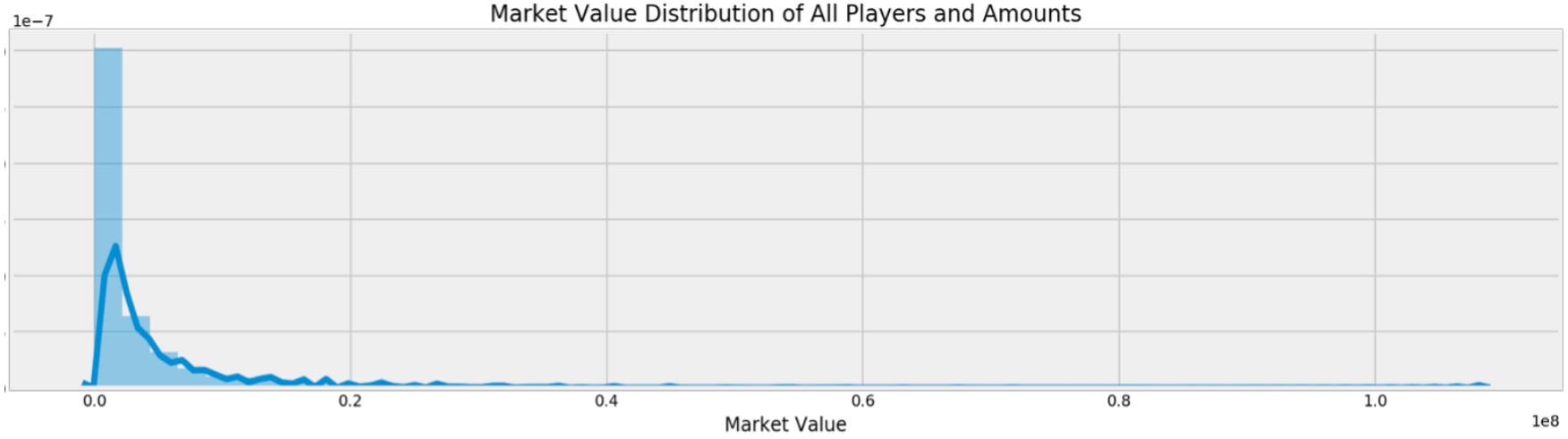
Facts about the data

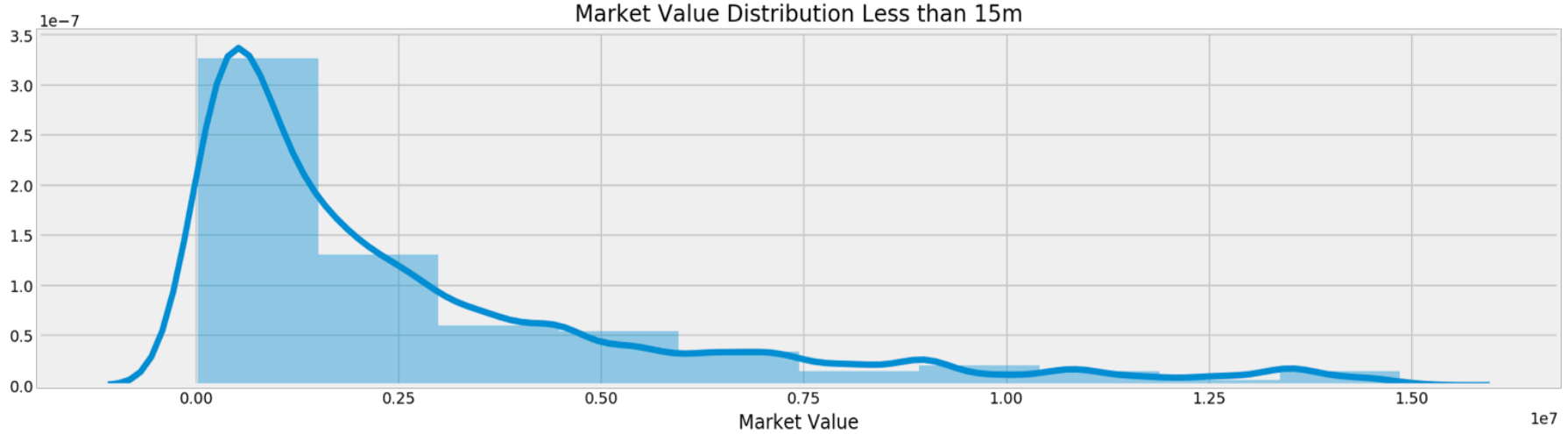
Top 5 European Leagues

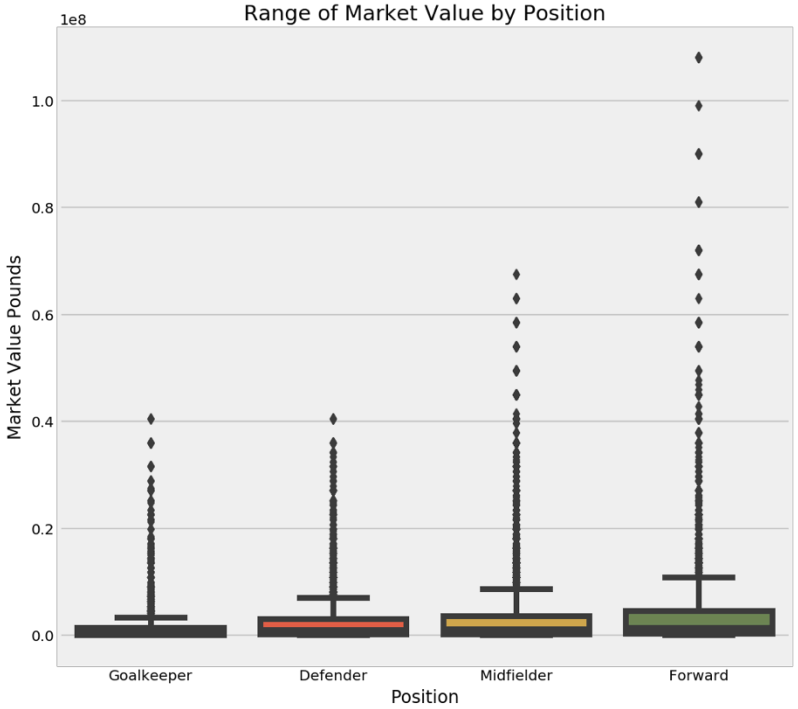
- Spanish La Liga
- French Ligue 1
- English Premier League
- Italian Serie A
- German Bundesliga (only 18 teams)

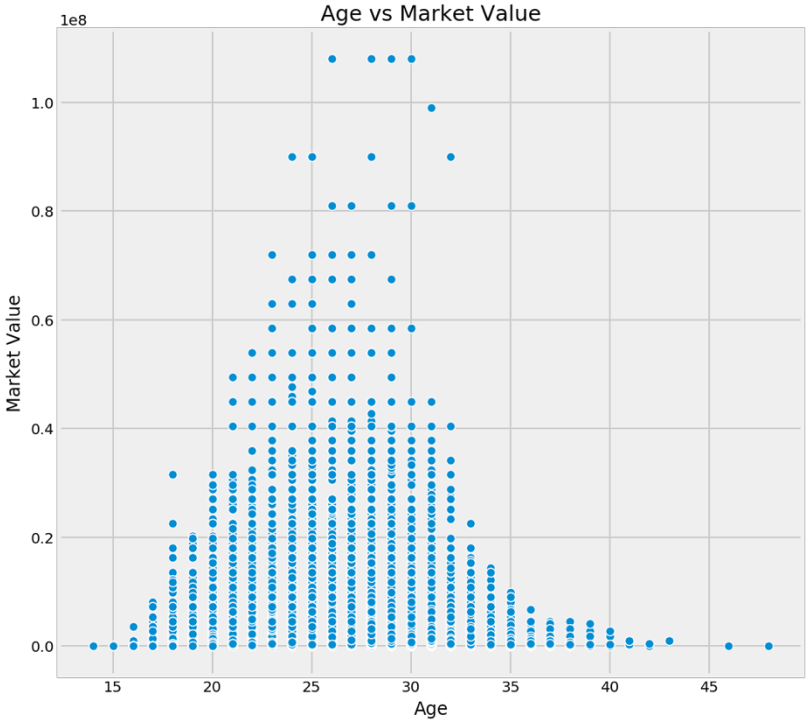
30504 observations over 2008-2017

- Dropped to 24,632
- Average Market Value of 3,257,152
- Median Market Value of 900,000
- 10584 unique players
- 1.85 average goals per season per player
- 17.3 average appearances
- 24 years old on average

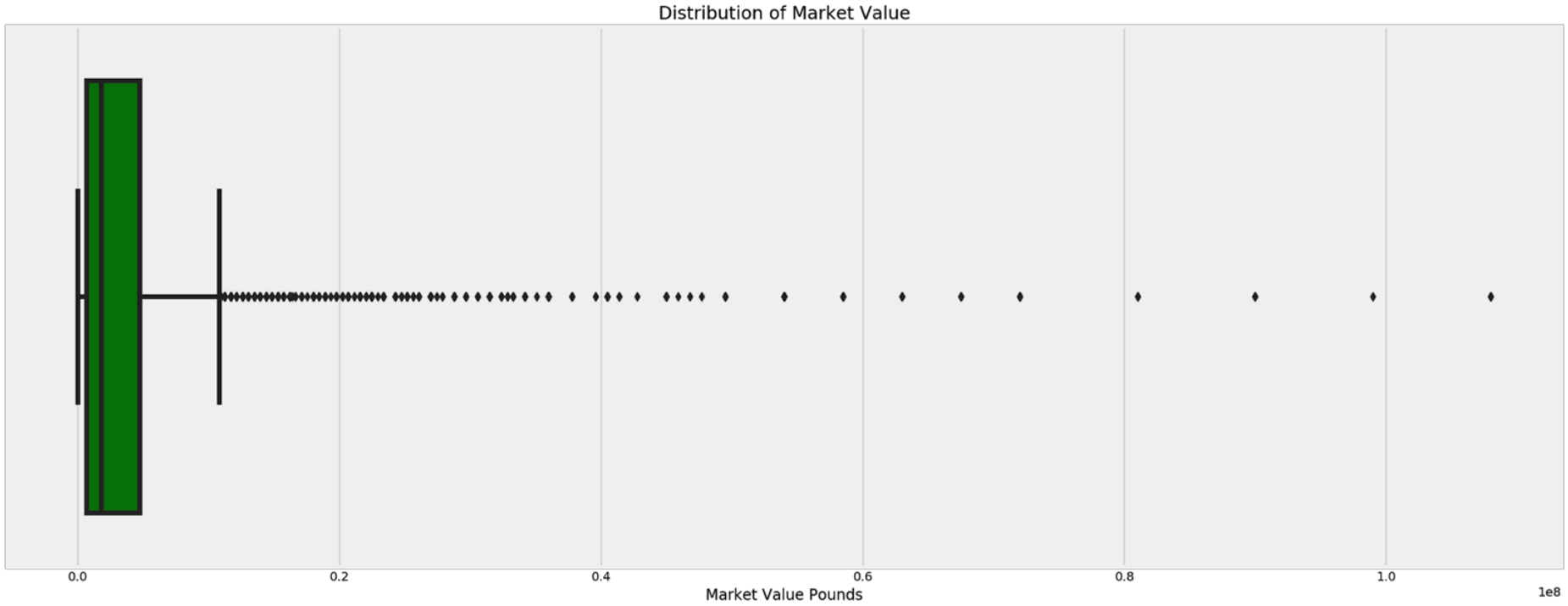

Market Value Distribution of All Players and Amounts
1e−7
0.0
0.2
0.4
0.6
0.8
1.0
Market Value
1e8


Market Value Distribution Less than 15m
1e−7
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
Market Value
1e7

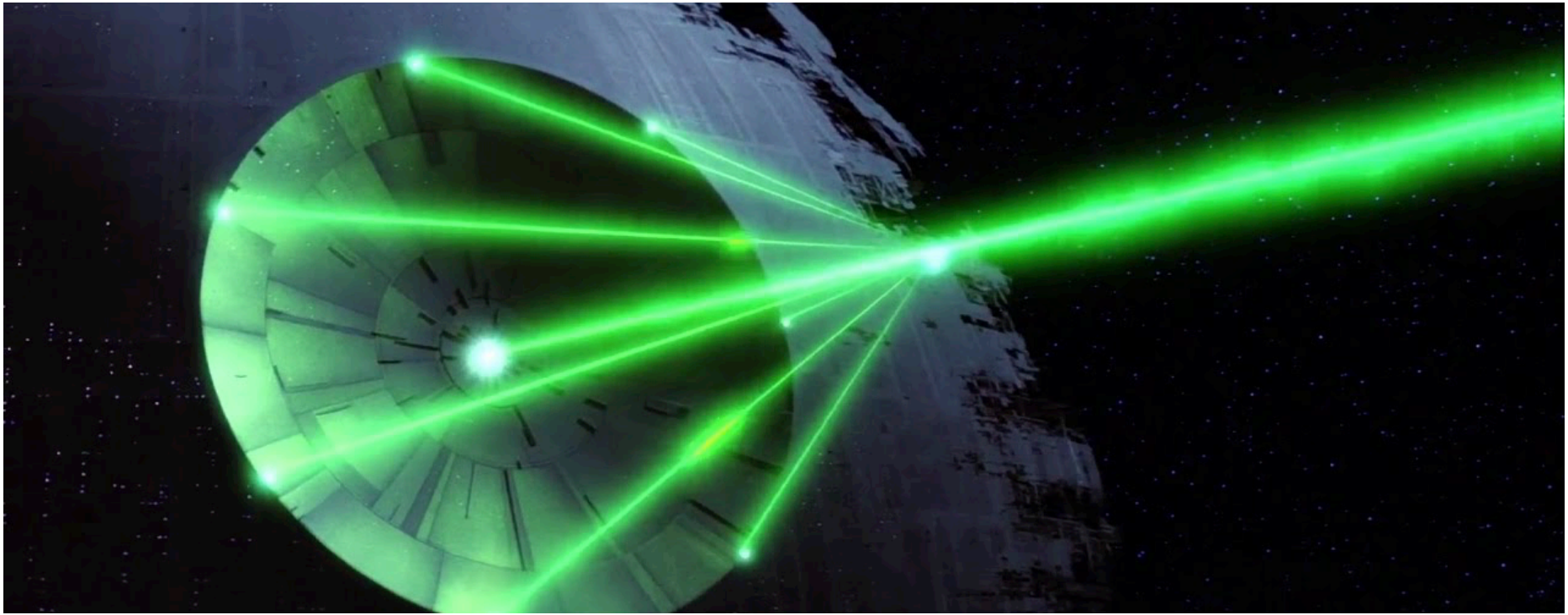




Position and Age vs Market Value

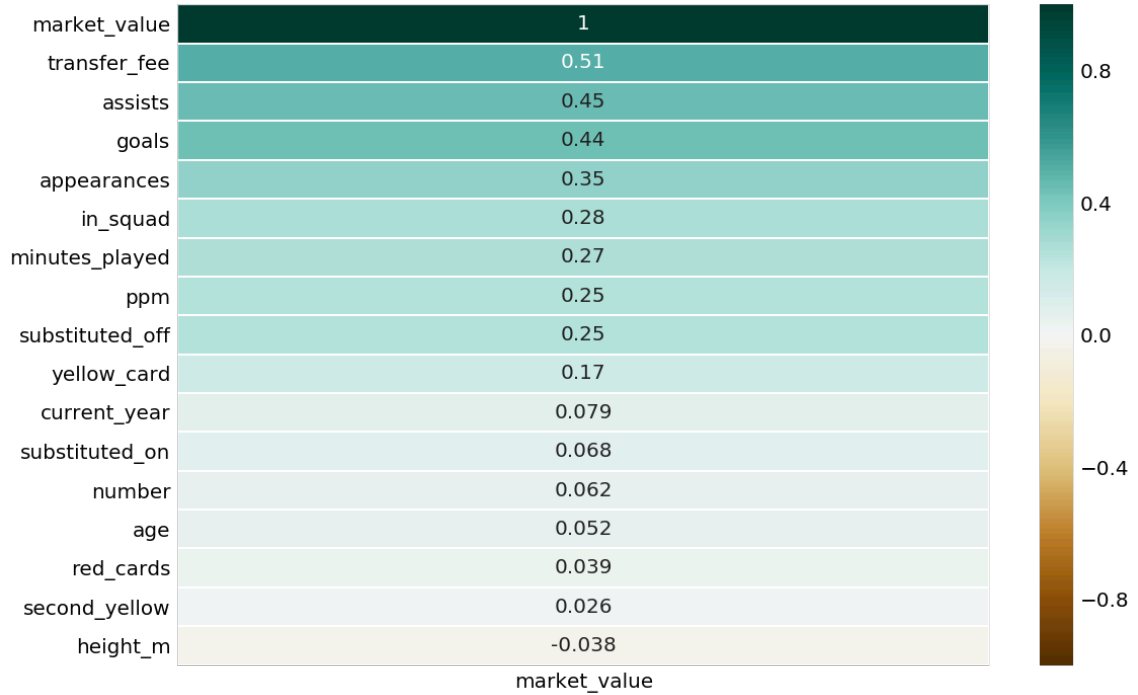


Distribution of Market Values



Distribution of Market Values

Correlation with market value



Modeling

Doing it

Dani Alves
Paris Saint-Germain
£ 6m market value 2018
£ 9m market value 2016
£ 20m market value 2009

Regression Models

- LinearRegression
- Ridge
- RidgeCV
- Lasso
- LassoCV
- ElasticNet
- ElasticNetCV
- DecisionTreeRegressor
- BaggingRegressor
- KNeighborsRegressor
- RandomForestRegressor
- AdaBoostRegressor
- SVR

Targets

Main Target is Market Value

- Primary objective for this project
- 21,859 observations

Transfer Fee

- Not primary objective for this project
- Limited Observations 4030

Classification of players by general position

- Forward
- Midfielder
- Defender
- Goalkeeper

Features

Categorical Features

- 98 clubs
- Position
- Foot
    - Right
    - Left
    - Both

Hard Features:

- Age
- Market -Value (not included when target)
- Transfer-Fee (not included when target)
- In-Squad (included on bench)
- Appearances (games played)
- Goals
- Assists
- Yellow Cards
- Second Yellow Cards
- Red Cards
- Substituted On
- Substituted Off
- PPM
- Minutes Played

Regression Models

Can we use the stats to predict the market value of a player?

Let’s do it with just the raw numerical stats and then the dummied categorical ones.

How do we slice the data?

What happens when we feed it to the machine?

Regression Model Function

```python
def run_and_plot_regression_model(model):
    X_train, X_test, y_train, y_test = train_test_split(Xr, y, random_state=42)
    ss = StandardScaler()
    X_train_sc = ss.fit_transform(X_train)

    name = str(model).split('(')[0] + ' model'
    model.fit(X_train_sc, y_train)

    train_predictions = model.predict(X_train_sc)
    train_residuals = y_train - train_predictions

    X_test_sc = ss.transform(X_test)
    predictions = model.predict(X_test_sc)
    residuals = y_test - predictions

    if r2_score(y_test, predictions) > .50:
        print(f"{name} R2 Score: {round(r2_score(y_test, predictions), 3)}")
        print(f"{name} MSE: {round(mean_squared_error(y_test, predictions), 3)}")
        print(f"{name} RMSE Train: {round(sqrt(mean_squared_error(train_predictions, y_train)), 3)}")
        print(f"{name} RMSE Test: {round(sqrt(mean_squared_error(y_test, predictions)), 3)}")

    if r2_score(y_test, predictions) > .50:
        fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(10, 5))

        ax1.scatter(predictions, residuals, s=30, c='b', marker='+', zorder=10, alpha=.5)
        ax1.set_title(f"{name} Residual Plot")
        ax1.set_ylabel("Residuals")
        ax1.set_xlabel("Predictions")

        ax2.scatter(predictions, y_test, s=30, c='g', marker='+', zorder=10, alpha=.5)  ##changed
        ax2.set_title(f"{name} True vs Predicted")
        ax2.set_ylabel("True Values")
        ax2.set_xlabel("Predictions")


    else:
        pass
```

Regression Model For Loop example

3.3 Run and Plot Regression Models with Market Value as Target

3.3.1 Target Market Value, Leave in Transfer-Fee

```
Xr = df_dummied[features_including_transfer_fee]
y = df_dummied[target].iloc[:,0]


for mod in [LinearRegression(),
            Ridge(),
            RidgeCV(),
            Lasso(),
            LassoCV(),
            ElasticNet(),
            ElasticNetCV(),
            DecisionTreeRegressor(max_depth=5, random_state=42),
            BaggingRegressor(),
            KNeighborsRegressor(),
            RandomForestRegressor(),
            AdaBoostRegressor(),
            SVR()]:
    run_and_plot_regression_model(mod)
    print(" ")
```

Classification Models

Can we use the stats to determine which position a player is?

Use all numerical stats and include market value and transfer value.

Model Results

Cristiano Ronaldo
Market value 100m

Purely Statistics

Without dummying data - taking into account solely the 14 numerical annual statistics:

- Transfer Fee - Included and not in some various as correlation was high at 51%
- Age
- Height - meters
- In-Squad
- Appearances
- Goals
- Assists
- Yellow Cards, Second Yellows and Red Cards
- Substituted On & Off
- PPM
- Minutes Played

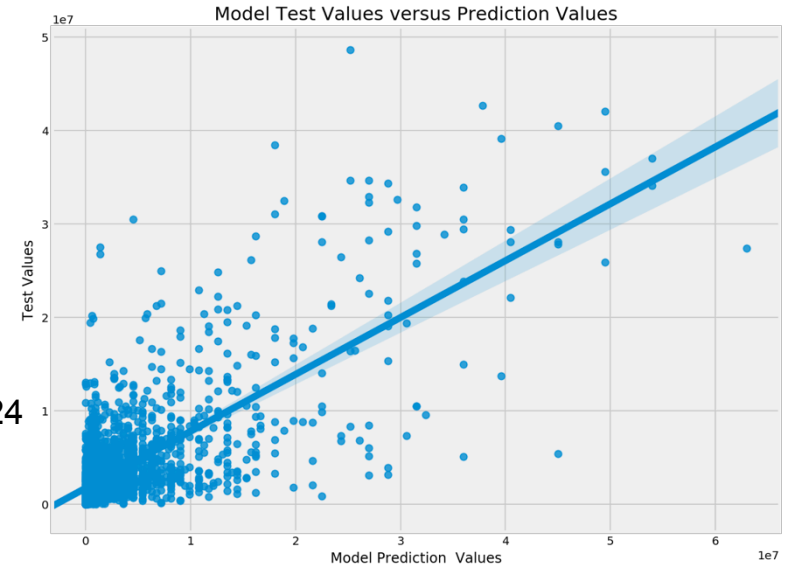
Regression Model Performance No Categorical

Without dummying data

Only numerical statistics, no categorical data.

Model for forwards (including transfer fee) :

LinearRegression model R2 Score: 0.585
LinearRegression model MSE: 42,765,455,460,624
LinearRegression model RMSE Train: 6,819,546
LinearRegression model RMSE Test: 6,539,530



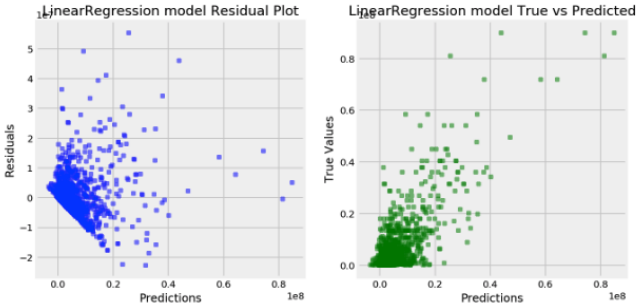
Regression Model Performance No Categorical

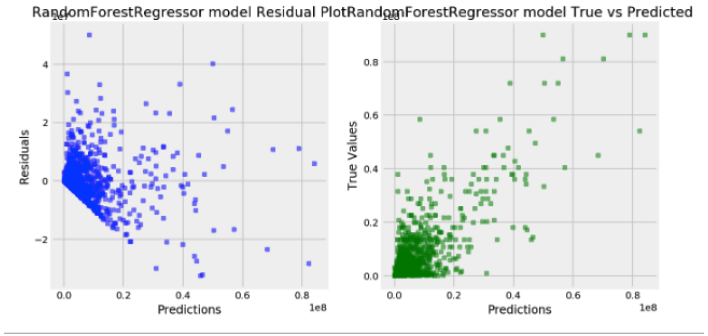
Performance of players with more than 540 minutes played ~ 6 games.

16183 observations with 28 features - no dummies

LinearRegression model R2 Score: 0.585
LinearRegression model MSE: 42765455460624.98
LinearRegression model RMSE Train: 6819546.765
LinearRegression model RMSE Test: 6539530.217

RandomForestRegressor model R2 Score: 0.607
RandomForestRegressor model MSE: 40548077649726.484
RandomForestRegressor model RMSE Train: 2792440.133
RandomForestRegressor model RMSE Test: 6367737.247





Dummying Features

With dummying data - taking into account categorical data:

- Foot
  - right, left, both
- Team
  - 98 different ones
- Position
  - 4 major
- Total Features - 120

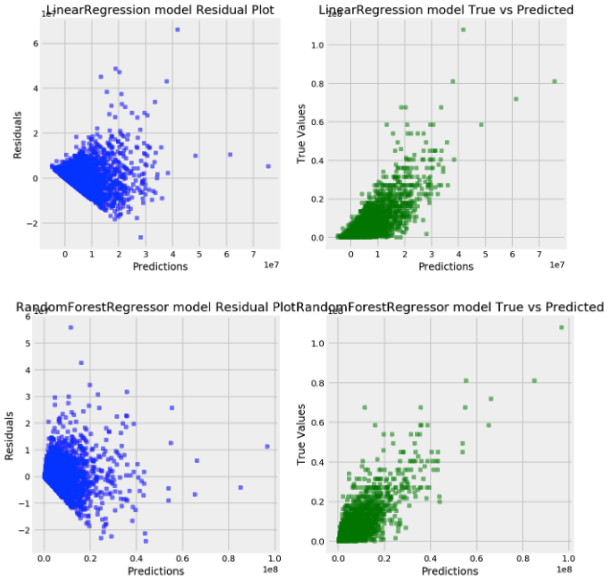
Model Performance with Categorical

Best Performance was on players with more than 540 minutes played ~ 6 games.

16183 observations with 130 features - dummied included

LinearRegression model R2 Score: 0.621
LinearRegression model MSE: 23950821762912.28
LinearRegression model RMSE Train: 4860018.106
LinearRegression model RMSE Test: 4893957.679

RandomForestRegressor model R2 Score: 0.675
RandomForestRegressor model MSE: 20523282524001.484
RandomForestRegressor model RMSE Train: 2036772.958
RandomForestRegressor model RMSE Test: 4530262.964



Classification Model Performance

Support Vector Classification
SVC model Training Accuracy Score: 0.755
SVC model Testing Accuracy Score: 0.74

DecisionTreeClassifier model Training Accuracy Score: 1.0
DecisionTreeClassifier model Testing Accuracy Score: 0.628

	y_test	predictions	diff	players_position_y_test
0	1.0	2.0	-1.0	Forward
1	1.0	1.0	0.0	Forward
2	3.0	3.0	0.0	Defender
3	4.0	4.0	0.0	Goalkeeper
4	4.0	4.0	0.0	Goalkeeper
5	3.0	3.0	0.0	Defender
6	3.0	3.0	0.0	Defender
7	3.0	3.0	0.0	Defender
8	2.0	1.0	1.0	Midfielder
9	2.0	2.0	0.0	Midfielder

Conclusions

Gather more stats

Get stats that demonstrate strengths of defenders, midfielders and goalkeepers

Dealing with Outliers

Leave them in if you have enough data that supports their value

Much of Futbol is Not Tracked

There is opportunity to find more golden players like Kylian Mbappé, can you use data to do it?