COGS 118A - Final Project

THE FIFA TRANSFERMARKET PREDICTION NOTEBOOK

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Abstract

Association Football (or soccer) is a worldwide sport played by over 250 million players in over 250 countries[1]. In fact, football is the world's sport, and the most popular across the globe in terms of fans as well. Football has a huge transfer market in which players are transferred across teams for up to hundreds of millions of euros. To put the amount of money that circulates in the global football market into perspective, squad values of top teams like Manchester United surpass billions of euros[2]. The market value of a player accounts for a huge role in how teams conduct their business in regards to transfers. Our goal is to help these clubs make the right investments in players they want to obtain, especially when spending huge amounts of money. More specifically, we want to accurately predict the market value of players so that clubs aren't overpaying, or underselling their valued players. Plenty of factors play a role in determining the market value of a player. The most important factors include age, performance for club and national team (measured in stats such as goals, assists, tackles etc.) for a player in that position, experience(measured by number of seasons in top leagues), marketing value (measured by social media presence), and injury vulnerability[2].

Background

The global football transfer market involves the circulation of billions of euros. Many top European clubs have spent hundreds of millions of dollars to bolster their respective teams. For example teams like Manchester United, Manchester City, and PSG have spent almost billions of euros to sign players to help their teams' success in their respective leagues and on the European stage[6]. There is no doubt that decisions involving huge sums of such money should be carefully analyzed so that clubs can maximize success in both the business side as well as the performance side of their respective clubs. Transfermarkt is an online platform for transfers, market values, rumors, and stats. The business model consists of, in addition to sports journalistic reporting, the profiles of the players and discussion forums on the performance and market values of individual soccer players, teams and leagues[4]. Frequently being discussed in sports science and sports economics literature over the past few years, the so-called "market values" („Marktwerte") have s to become the center of media attentioMultipleous studies have shown positive correlations between the predicted market values on Transfermarkt and the actual player income.'It's reportedly known that players who are in contract negotiations would sometimes refer to Transfermarkt values as baselines for their salary expectations[4]. The "market values" can also be used as a measure of marketability; a higher marketability helps a player secure partnerships through sponsorship contracts. The age and performance statistics on Transfermarkt are also particularly useful in that player observers can identify young players and predict the development opportunities[4].

The open forums of Transfermarkt allow users to discuss and predict individual players' market values and performance. Previous studies on collective intelligence[2] have used OLS regression models to evaluate the accuracy of predictions. It is shown that "forecasts of international soccer results based on the crowd's valuations are more accurate than those based on standard predictors."[3] This reveals a potential possibility that distributed intelligence is a contributing factor to the accuracy of predictions. We want to know if supervised machine learning algorithms, as another form of distributed intelligence, can make accurate predictions just as humans do. More particularly, we want to use machine learning models like OLS to predict market value of players across the football world.

Problem Statement

Given the considerable number of players in football across the globe, it can get tedious to know which players have potential and are worth investing in. Do they have high performance for a player in their position? Are they playing for a renowned club or in a renowned league? Is their behavior respectable and are they marketable? These are the kinds of questions top clubs use when considering paying the big bucks for players. The problem we are trying to tackle is predicting the market value of players (in euros) using stats that are important when investing in a player such as goals, assists, and marketability.

Data

The dataset[7] is composed of 7 different subsets, we will be using 4 of the datasets. Since each feature resides in different sets.

- `Appearances.csv`
  - Player ID, Game ID, Appearance ID, Competition ID, Player club ID, Assist, Minutes Played, Yellow cards, Red Cards
- `Clubs.csv`
  - Club ID, Name, Pretty_name, Domestic_competition_id, Total_market_value, Squad_size, Average_age, Foreigners_numbers, Foreigners_percentage, National_team_players, Stadium_name, Stadium_seats, Net_transfer_record, Coach_name, URL
- `Competitions.csv`
  - Competition_id, Name, type, country_id, country_name, domestic_league_code, confederation, URL.
- `Games.csv`

    - Game_id, Competition_code, Season, Round, Date, Home_club_id, Away_club_id, Home_club_goals, away_club_goals, Home_club_postions, Away_club_postion, Stadium, Attendance, Referee, URL
- `Leagues.csv`
    - League_id, name, Confederation
- `Player_valuations.csv`
    - Player_id, Date, Market_value
- `Players.csv`
    - Player_id, Last_season, Current_club_id, Name, Pretty_name, country_of_birth, Country_of_citizenship, Date_of_birth, Position, Sub_position, Foot, Height_in_cm, Market_value_in_gbp, Highest_market_value_in_gbp, URL
- *What an observation consists of*: We are trying to use the variables we assume to be the most important and independent from each other. We decided on
    - Club, Nationality, Minutes, Goals, Assist, Age, Conduct, Years Played, Position, Physicality.
- *What some critical variables are, how they are represented*: We want variables which have the highest co-variance with each other. The metric should handle most features as unique features.
- *Any special handling, transformations, cleaning, etc will be needed*: There will be club names, and probably inferences in our data. Such as Media Presence or Potential, these are metrics which can be objective to the person. How popular is the player that we are analyzing?

We are still going to be in search of more databases that might have different descriptive data that we might like to see how organizations search for talent. We can use what they might describe as their most sought out characteristics.

For simplicity we can also assume that all players have no contracts for their evaluation and are based solely on performance and the other variables mentioned.

In [ ]:
```
import sys
```

In [ ]:
```
import re
_r = re.escape
def _re_replace(s : str, to_replace : dict):
    for p, r in to_replace.items():
        s = re.compile(p).sub(r, s)
    return s
```

In [ ]:
```
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
%config InlineBackend.figure_formats = ['svg']
```

In [ ]:
```
!{sys.executable} -m pip install --quiet pandas
import pandas as pd
```

```
'c:\Users\DanDan' is not recognized as an internal or external command,
operable program or batch file.
```

In [ ]:

```
!{sys.executable} -m pip install --quiet seaborn
import seaborn as sns
```

```
'c:\Users\DanDan' is not recognized as an internal or external command,
operable program or batch file.
```

In [ ]:

```
# OLS using statsmodels
!{sys.executable} -m pip install --quiet statsmodels numpy
import statsmodels.api as sm
import numpy as np
```

```
'c:\Users\DanDan' is not recognized as an internal or external command,
operable program or batch file.
```

In [ ]:

```
!{sys.executable} -m pip install --quiet sklearn
!{sys.executable} -m pip install --quiet patsy
import sklearn as skl

import sklearn.linear_model

from sklearn.compose import ColumnTransformer
from sklearn.datasets import fetch_openml
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import Lasso
from sklearn.linear_model import ElasticNet
from sklearn.model_selection import KFold
import scipy.stats as stats
import patsy
```

```
'c:\Users\DanDan' is not recognized as an internal or external command,
operable program or batch file.
'c:\Users\DanDan' is not recognized as an internal or external command,
operable program or batch file.
```

In [ ]:

```
_data_ = {
    name: pd.read_csv(
        file,
        engine = 'c',
        low_memory = True,
        memory_map = False, # set `False` to load into memory
        **kwargs
    ) for name, file, kwargs in [
        ('appearances', 'data/appearances.csv', {
            'dtype': {
                'player_id': 'object',
                'game_id': 'object',
                'appearance_id': 'object',
                'competition_id': 'object',
```

```
                'player_club_id': 'object'
            }
        }),
        ('clubs', 'data/clubs.csv', {
            'dtype': {
                'club_id': 'object'
            }
        }),
        #('competitions', 'data/competitions.csv', {}),
        ('games', 'data/games.csv', {
            'dtype': {
                'game_id': 'object'
            }
        }),
        #('leagues', 'data/leagues.csv', {}),
        ('players', 'data/players.csv', {
            'parse_dates': ['date_of_birth'],
            'dtype': {
                'player_id': 'object',
                'country_of_birth': 'category',
                'country_of_citizenship': 'category',
                'position': 'category',
                'sub_position': 'category'
            }
        }),
        ('player_valuations', 'data/player_valuations.csv', {
            'parse_dates': ['date'],
            'dtype': {
                'player_id': 'object'
            }
        })
    ]
}
```

In [ ]:

```
data = {}
```

In [ ]:

```
# clubs
data['clubs'] = _data_['clubs'].copy()

data['clubs'] = data['clubs'][[
    'club_id',
    'pretty_name'
]]
data['clubs'].rename(
    columns = {'pretty_name': 'club_name'},
    inplace = True
)
data['clubs'].set_index('club_id', inplace = True)

data['clubs']
```

Out[ ]:

	club_name
club_id	
1032	Fc Reading

	club_name
club_id	
2323	Orduspor
1387	Acn Siena 1904
3592	Kryvbas Kryvyi Rig
1071	Wigan Athletic
...	...
1269	Pec Zwolle
200	Fc Utrecht
317	Fc Twente Enschede
3948	Royale Union Saint Gilloise
1304	Heracles Almelo

801 rows × 1 columns

In [ ]:

```
# games
data['games'] = _data_['games'].copy()

data['games'] = data['games'][[
    'season',
    'game_id'
]]
data['games'].set_index('game_id', inplace = True)

data['games']
```

Out[ ]:

	season
game_id	
2244388	2012
2219794	2011
2244389	2012
2271112	2012
2229332	2012
...	...
3646190	2021
3646188	2021
3655616	2021
3655629	2021
3646191	2021

56028 rows × 1 columns

In [ ]:

```
# appearances
data['appearances'] = _data_['appearances'].copy()

data['appearances'] = data['appearances'].loc[
    :, ~data['appearances'].columns.isin([
        'appearance_id',
        'competition_id'
    ])
]
data['appearances'].rename(
    columns = {'player_club_id': 'club_id'},
    inplace = True
)

data['appearances'] = (
    data['appearances']
        .merge(
            data['games'],
            on = 'game_id',
            copy = False
        ).drop(columns = 'game_id')
        .merge(
            data['clubs'],
            on = 'club_id',
            copy = False
        ).drop(columns = 'club_id')
)

data['appearances'] = (
    data['appearances']
        .groupby(['player_id', 'season'])
        .agg({
            **{
                c: 'sum' for c in [
                    'goals',
                    'assists',
                    'minutes_played',
                    'yellow_cards',
                    'red_cards'
                ]
            },
            'club_name': 'last'
        })
        .reset_index('season')
)

data['appearances']
```

Out[ ]:

	season	goals	assists	minutes_played	yellow_cards	red_cards	club_name
player_id							
10	2014	32	18	4578	12	0	Lazio Rom
10	2015	16	14	3428	6	0	Lazio Rom

	season	goals	assists	minutes_played	yellow_cards	red_cards	club_name
player_id							
100009	2014	0	0	5576	8	0	Kuban Krasnodar
100009	2015	2	2	4512	12	0	Kuban Krasnodar
100009	2016	0	0	1260	6	0	Anzhi Makhachkala
...	...	...	...	...	...	...	...
99923	2014	0	2	832	4	0	Cagliari Calcio
99924	2016	0	2	1824	6	0	Ca Osasuna
99977	2014	0	0	194	0	0	Rcd Mallorca
99977	2015	10	6	3046	2	0	Royal Excel Mouscron
99977	2019	0	0	716	0	0	Caykur Rizespor

54216 rows × 7 columns

In [ ]:

```
# player valuations
data['player_valuations'] = _data_['player_valuations'].copy()

data['player_valuations']['season'] = (
    pd.DatetimeIndex(data['player_valuations']['date']).year
)
data['player_valuations'].drop(columns = 'date', inplace = True)

data['player_valuations'] = (
    data['player_valuations']
        .groupby(['player_id', 'season'])
        .agg({'market_value': 'mean'})
        .reset_index('season')
)
data['player_valuations'].rename(
    columns = {'market_value_in_gbp': 'market_value'},
    inplace = True
)

data['player_valuations']
```

Out[ ]:

	season	market_value
player_id		
10	2004	6300000.0
10	2005	10800000.0
10	2006	22500000.0
10	2007	20700000.0
10	2008	18000000.0
...	...	...
99977	2018	990000.0

	season	market_value
player_id		
99977	2019	720000.0
99977	2020	562500.0
99977	2021	495000.0
99977	2022	540000.0

181182 rows × 2 columns

In [ ]:

```
# players
data['players'] = _data_['players'].copy()

data['players'] = data['players'].loc[
    :, ~data['players'].columns.isin([
        'last_season',
        'name',
        'current_club_id',
        'market_value_in_gbp',
        'highest_market_value_in_gbp',
        'country_of_birth',
        'url',
        'foot'
    ])
]
data['players'].rename(
    columns = {
        'pretty_name': 'name',
        'height_in_cm': 'height',
        'country_of_citizenship': 'nationality'
    },
    inplace = True
)

data['players']['sub_position'] = (
    data['players']['sub_position'].cat
        .rename_categories(
            lambda s: (
                _re_replace(s, {
                    fr'''^(.*){_r(' - ')}(.*)$''': r'\2'
                })
                .title()
            )
        )
)

data['players'].set_index('player_id', inplace = True)

data['players']
```

Out[ ]:

	name	nationality	date_of_birth	position	sub_position	height
player_id						
254016	Arthur Delalande	France	1992-05-18	Midfield	Central Midfield	186

player_id	name	nationality	date_of_birth	position	sub_position	height
51053	Daniel Davari	Iran	1988-01-06	Goalkeeper	Goalkeeper	192
31451	Torsten Oehrl	Germany	1986-01-07	Attack	Centre-Forward	192
44622	Vladimir Kisenkov	Russia	1981-10-08	Defender	Right-Back	182
30802	Oscar Diaz	Spain	1984-04-24	Attack	Centre-Forward	183
...	...	...	...	...	...	...
462285	Fabian De Keijzer	Netherlands	2000-05-10	Goalkeeper	Goalkeeper	193
368612	Merveille Bokadi	DR Congo	1996-05-21	Defender	Centre-Back	186
408574	Joey Veerman	Netherlands	1998-11-19	Midfield	Central Midfield	185
364245	Jordan Teze	Netherlands	1999-09-30	Defender	Centre-Back	183
575367	Richard Ledezma	United States	2000-09-06	Attack	Attacking Midfield	174

23682 rows × 6 columns

In [ ]:

```
# final dataset
data['all'] = data['players'].merge(
    data['player_valuations'].merge(
        data['appearances'],
        on = ['player_id', 'season'],
        copy = False
    ),
    on = 'player_id',
    copy = False
)

data['all']['age'] = (
    pd.to_datetime(data['all']['season'], format = '%Y', utc = True)
        - pd.to_datetime(data['all']['date_of_birth'], utc = True)
).astype('timedelta64[Y]')
data['all'].drop(columns = 'date_of_birth', inplace = True)

data['all'].dropna(axis = 'index', inplace = True)

data['all']
```

Out[ ]:

player_id	name	nationality	position	sub_position	height	season	market_value	goals	assists
9800	Artem Milevskyi	Ukraine	Attack	Centre-Forward	189	2020	90000.0	0	0
43084	Gaetano Berardi	Switzerland	Defender	Right-Back	179	2020	360000.0	0	0
230826	Gennaro Acampora	Italy	Midfield	Central Midfield	174	2020	360000.0	2	4

player_id	name	nationality	position	sub_position	height	season	market_value	goals	assists
198087	Matteo Ricci	Italy	Midfield	Defensive Midfield	176	2020	1530000.0	0	6
110689	Deniz Mehmet	Turkey	Goalkeeper	Goalkeeper	192	2020	68000.0	0	0
...	...	...	...	...	...	...	...	...	...
364245	Jordan Teze	Netherlands	Defender	Centre-Back	183	2019	420000.0	0	0
364245	Jordan Teze	Netherlands	Defender	Centre-Back	183	2020	1102500.0	0	2
364245	Jordan Teze	Netherlands	Defender	Centre-Back	183	2021	5400000.0	2	8
575367	Richard Ledezma	United States	Attack	Attacking Midfield	174	2020	658250.0	0	2
575367	Richard Ledezma	United States	Attack	Attacking Midfield	174	2021	765000.0	2	0

50781 rows × 14 columns

Evaluation

In [ ]:

```
data['all'][data['all'].isna().any(axis = 1)]
```

Out[ ]:

player_id	name	nationality	position	sub_position	height	season	market_value	goals	assists	minu

In [ ]:

```
data['all'].dtypes
```

Out[ ]:

```
name              object
nationality     category
position        category
sub_position    category
height             int64
season             int64
market_value     float64
goals              int64
assists            int64
minutes_played     int64
yellow_cards       int64
red_cards          int64
club_name         object
age              float64
dtype: object
```

In [ ]:

```
data['all'].describe()
```

Out[ ]:

	height	season	market_value	goals	assists	minutes_played	yellow_c
count	50781.000000	50781.000000	5.078100e+04	50781.000000	50781.000000	50781.000000	50781.00(
mean	180.794628	2017.380063	3.630890e+06	3.880546	2.949883	2805.795987	6.00
std	17.703409	2.318805	8.274637e+06	7.352176	4.793814	2103.361660	6.09
min	0.000000	2013.000000	9.000000e+03	0.000000	0.000000	2.000000	0.00(
25%	178.000000	2015.000000	3.600000e+05	0.000000	0.000000	884.000000	2.00(
50%	182.000000	2017.000000	9.000000e+05	0.000000	2.000000	2566.000000	4.00(
75%	187.000000	2019.000000	3.150000e+06	4.000000	4.000000	4410.000000	10.00(
max	206.000000	2021.000000	1.800000e+08	122.000000	62.000000	10122.000000	46.00(

In [ ]:

```
pd.DataFrame(data['all']['sub_position'].unique())
```

Out[ ]:

	0
0	Centre-Forward
1	Right-Back
2	Central Midfield
3	Defensive Midfield
4	Goalkeeper
5	Centre-Back
6	Attacking Midfield
7	Right Winger
8	Left Winger
9	Left-Back
10	Left Midfield
11	Midfield
12	Second Striker
13	Right Midfield
14	Attack
15	Defender

In [ ]:

```
data['all'][data['all']['name'] == 'Cristiano Ronaldo']
```

Out[ ]:

	name	nationality	position	sub_position	height	season	market_value	goals	assists	mi

player_id	name	nationality	position	sub_position	height	season	market_value	goals	assists	mi
player_id										
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2014	96000000.0	122	46	
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2015	105000000.0	102	30	
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2016	99000000.0	84	24	
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2017	90000000.0	88	16	
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2018	96000000.0	56	20	
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2019	74250000.0	70	14	
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2020	54000000.0	76	8	
8198	Cristiano Ronaldo	Portugal	Attack	Centre-Forward	187	2021	39000000.0	48	6	

One hot encoding

In [ ]:

```
# one hot encode categorical features
data['all_onehot'] = pd.get_dummies(data['all'], columns = [
    'position',
    'sub_position',
    'nationality',
    'club_name'
])

data['all_onehot']
```

Out[ ]:

	name	height	season	market_value	goals	assists	minutes_played	yellow_cards	red_ca
player_id									
9800	Artem Milevskyi	189	2020	90000.0	0	0	720	6	
43084	Gaetano Berardi	179	2020	360000.0	0	0	228	0	
230826	Gennaro Acampora	174	2020	360000.0	2	4	1248	4	
198087	Matteo Ricci	176	2020	1530000.0	0	6	4880	10	

	name	height	season	market_value	goals	assists	minutes_played	yellow_cards	red_ca
player_id									
110689	Deniz Mehmet	192	2020	68000.0	0	0	1080	0	
...	...	...	...	...	...	...	...	...	
364245	Jordan Teze	183	2019	420000.0	0	0	360	0	
364245	Jordan Teze	183	2020	1102500.0	0	2	7494	10	
364245	Jordan Teze	183	2021	5400000.0	2	8	5260	12	
575367	Richard Ledezma	174	2020	658250.0	0	2	234	2	
575367	Richard Ledezma	174	2021	765000.0	2	0	88	0	

50781 rows × 588 columns

In [ ]:

```
data['all_onehot'].dtypes
```

Out[ ]:

```
name                              object
height                             int64
season                             int64
market_value                     float64
goals                              int64
                                ...
club_name_Yeni Malatyaspor         uint8
club_name_Zenit St Petersburg      uint8
club_name_Zirka Kropyvnytskyi      uint8
club_name_Zorya Lugansk            uint8
club_name_Zska Moskau              uint8
Length: 588, dtype: object
```

In [ ]:

```
data['all_onehot'].describe()
```

Out[ ]:

	height	season	market_value	goals	assists	minutes_played	yellow_c
count	50781.000000	50781.000000	5.078100e+04	50781.000000	50781.000000	50781.000000	50781.00(
mean	180.794628	2017.380063	3.630890e+06	3.880546	2.949883	2805.795987	6.00'
std	17.703409	2.318805	8.274637e+06	7.352176	4.793814	2103.361660	6.09!
min	0.000000	2013.000000	9.000000e+03	0.000000	0.000000	2.000000	0.00(
25%	178.000000	2015.000000	3.600000e+05	0.000000	0.000000	884.000000	2.00(

	height	season	market_value	goals	assists	minutes_played	yellow_c
50%	182.000000	2017.000000	9.000000e+05	0.000000	2.000000	2566.000000	4.00(
75%	187.000000	2019.000000	3.150000e+06	4.000000	4.000000	4410.000000	10.00(
max	206.000000	2021.000000	1.800000e+08	122.000000	62.000000	10122.000000	46.00(

8 rows × 587 columns

In [ ]:

```
data['all_onehot'][data['all_onehot']['name'] == 'Lionel Messi']
```

Out[ ]:

	name	height	season	market_value	goals	assists	minutes_played	yellow_cards	red_cards
player_id									
28003	Lionel Messi	169	2014	108000000.0	116	62	10122	12	0
28003	Lionel Messi	169	2015	108000000.0	82	48	8458	10	0
28003	Lionel Messi	169	2016	108000000.0	108	40	8904	18	0
28003	Lionel Messi	169	2017	108000000.0	90	40	8936	14	0
28003	Lionel Messi	169	2018	156000000.0	102	44	8048	6	0
28003	Lionel Messi	169	2019	130500000.0	60	50	7262	14	0
28003	Lionel Messi	169	2020	95400000.0	78	30	8746	12	2
28003	Lionel Messi	169	2021	66000000.0	22	26	5384	2	0

8 rows × 588 columns

Exploratory Data Analysis

In [ ]:

```
data['all_eda'] = data['all'].copy()

data['all_eda']['log_market_value'] = np.log(data['all_eda']['market_value'])
```

In [ ]:

```
df_highest_market_value_players = data['all_eda'].nlargest(n = 1, columns = 'market_val
```

```
df_highest_market_value_players
```

Out[ ]:

player_id	name	nationality	position	sub_position	height	season	market_value	goals	assists	mi
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2019	180000000.0	48	24	

In [ ]:

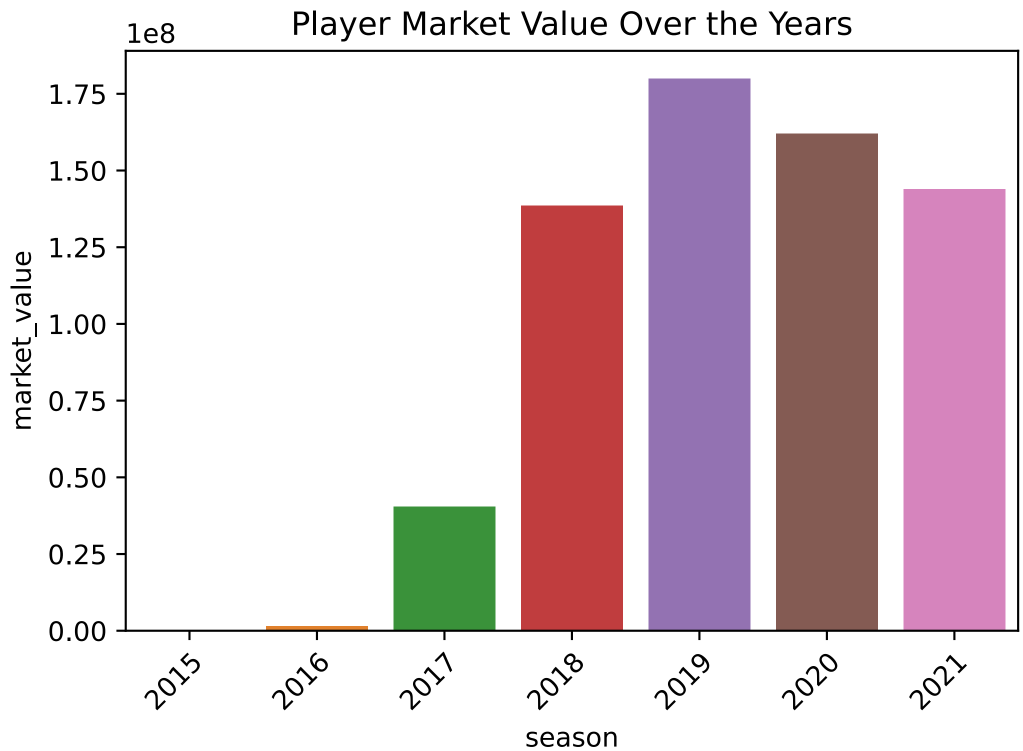
```
df_highest_market_value = data['all_eda'].loc[data['all_eda']['name'].isin(df_highest_m

df_highest_market_value
```

Out[ ]:

player_id	name	nationality	position	sub_position	height	season	market_value	goals	assists	mi
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2015	45000.0	2	4	
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2016	1518750.0	42	16	
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2017	40500000.0	34	20	
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2018	138600000.0	74	28	
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2019	180000000.0	48	24	
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2020	162000000.0	70	22	
342229	Kylian Mbappe	France	Attack	Centre-Forward	178	2021	144000000.0	62	50	

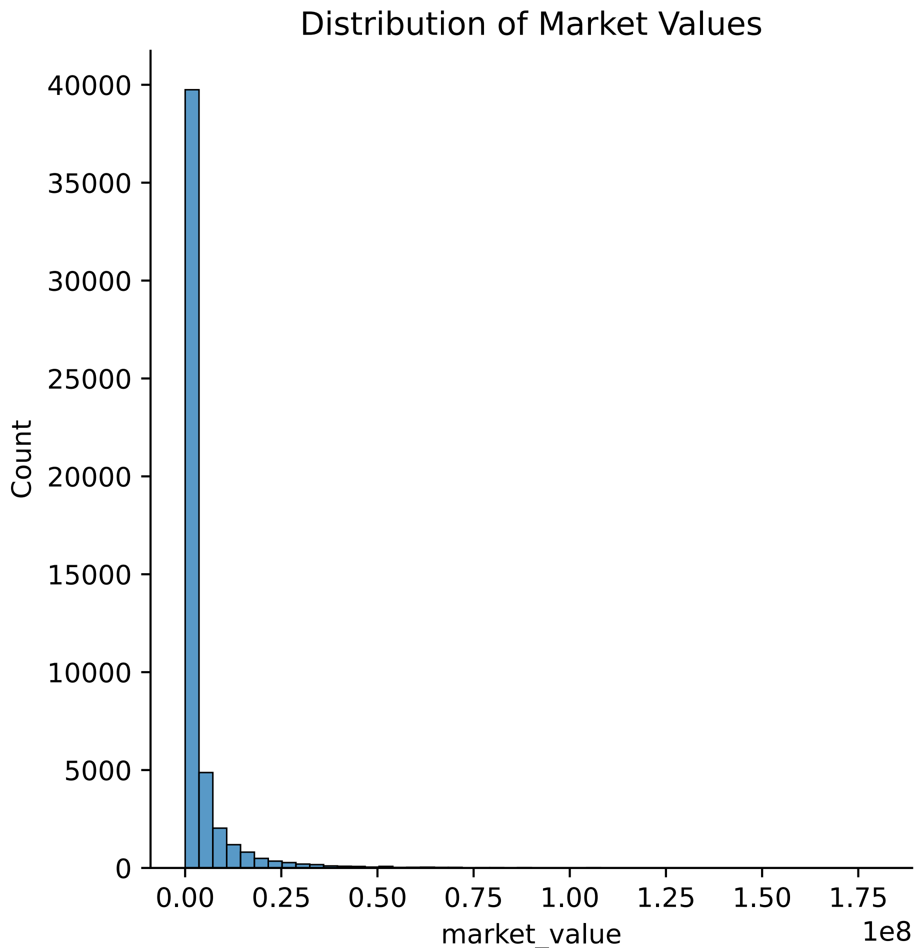
In [ ]:

```
_ = sns.barplot(
    data = df_highest_market_value,
    x = 'season', y = 'market_value'
).set(title = 'Player Market Value Over the Years')
plt.xticks(rotation = 45, ha = 'right', rotation_mode = 'anchor')

plt.show()
```



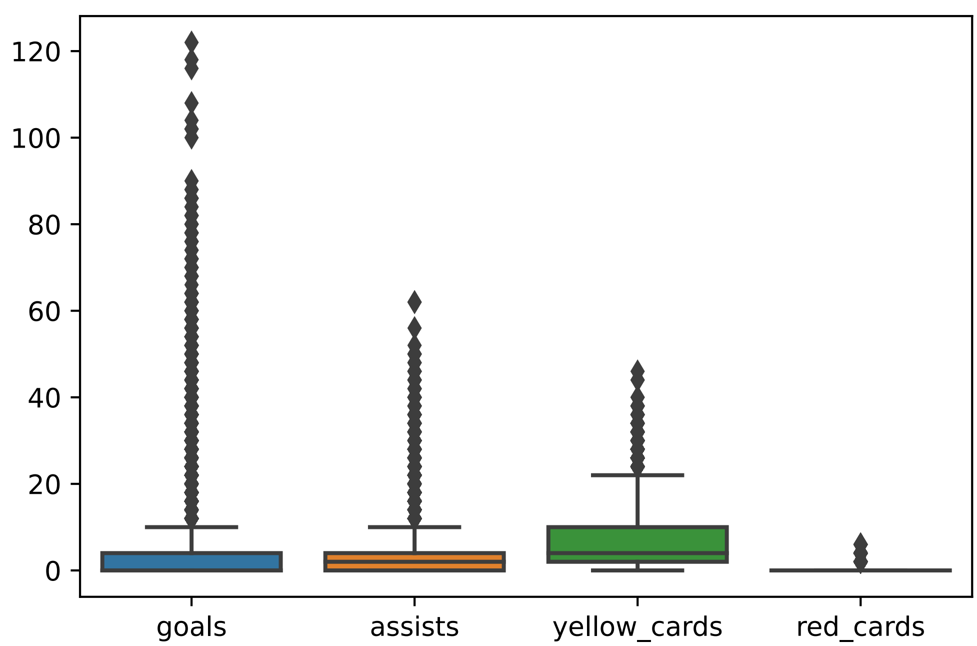
In [ ]:

```
_ = sns.displot(
    data = data['all_eda'].reset_index(),
    x = 'market_value',
    bins = 50
).set(title = 'Distribution of Market Values')

plt.show()
```



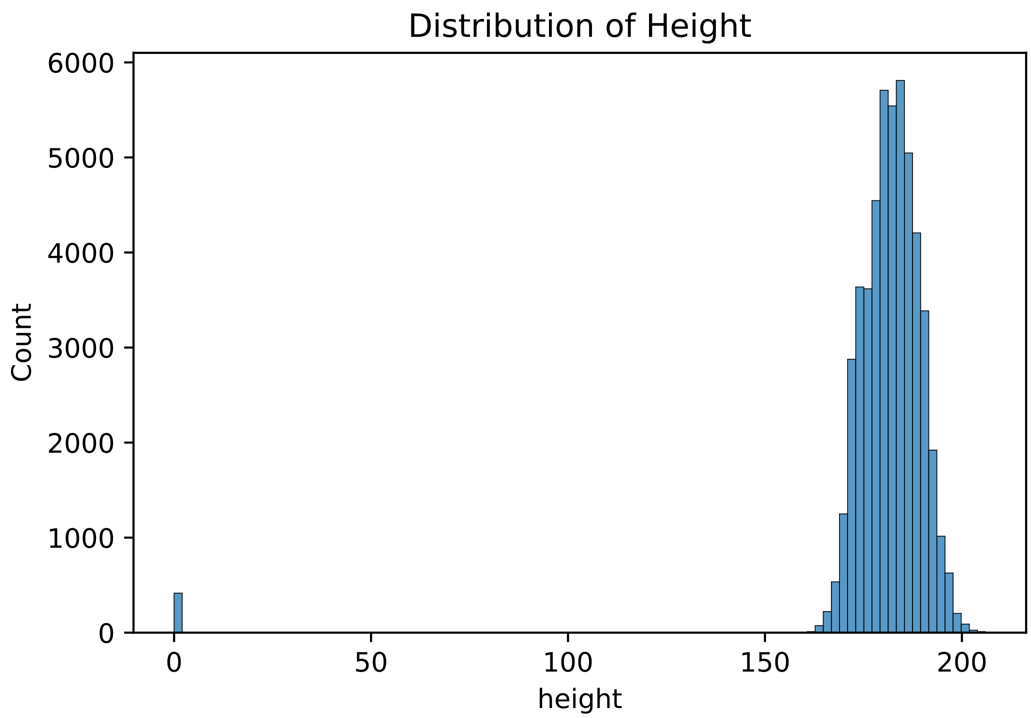
In [ ]:

```
_ = sns.boxplot(data = data['all_eda'][[
    'goals',
    'assists',
    'yellow_cards',
    'red_cards'
]]).set(title = '')
```



In [ ]:

```
_ = sns.histplot(
    data = data['all_eda'].reset_index(), x = 'height',
    bins = 100
).set(title = 'Distribution of Height')
```



Proposed Solution

Packages:

- `sklearn` (scikit-learn)
- `StatsModel`
- `Seaborn`
- Ordinary Least square regression: `statsmodels.api`

We believe that we can take the characteristics football clubs may regard to be the most important in the dataset and use those features to evaluate players. Those can be our core information in order to use regression analysis. If able to determine a certain cluster for the data set depending on the position and attributes. We can compare the players in the data set with the new data. We will be using OLS (Ordinary Least Squares).

We have to start with the most important step which is data cleaning and EDA analysis in order to get more accurate results, Matrix transformation with the numpy library. In order to increase covariance with variables, we can use dimension reduction techniques. Next we can normalize the data sets in order to not get skewed by one particular feature. Dealing with values missing or if we need to have numeric values for non-numeric data (i.e popularity, health, position).

Our comparison of errors will be coming from the Transfermrket.com website as it is updated everyday to evaluate different players. We can get the player's information to get a percent error or a total error for our evaluations. If we can, we will use the RMSE (Root mean square error) or Mean Absolute Values of our model prediction.

Evaluation Metrics

We will be using an OLS regression model and the evaluation techniques we are considering are RMSE and Euclidean distance. A possible evaluation metric we will use is RMSE or Mean Absolute Value of Errors. It is derived by calculating the difference between the estimated and actual value, square those results, then calculate the mean of those results. The formula for RMSE is

$$ \text{RMSE} = \sqrt{\frac{\sum_{i = 1}^{N}\left(\text{Predicted}_{i} - \text{Actual}_{i}\right)^{2}}{N}} $$

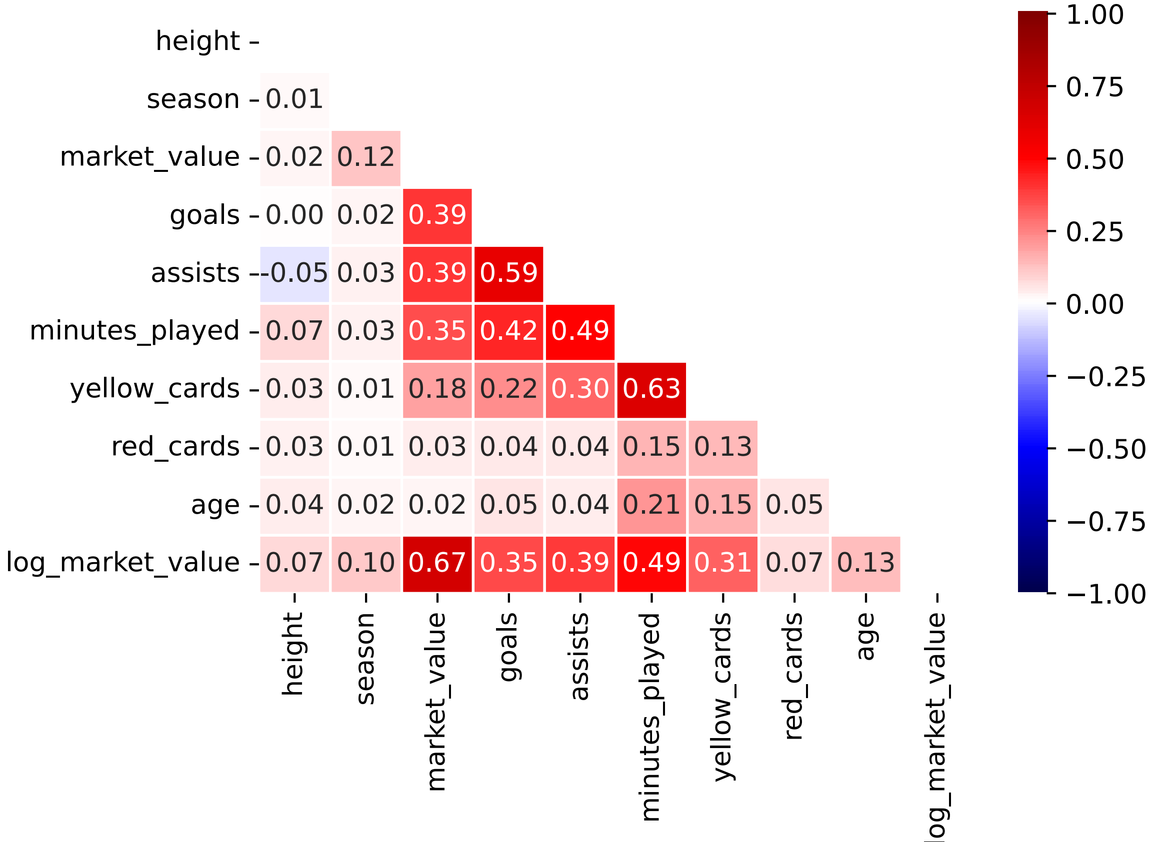
Results

Subsection 1

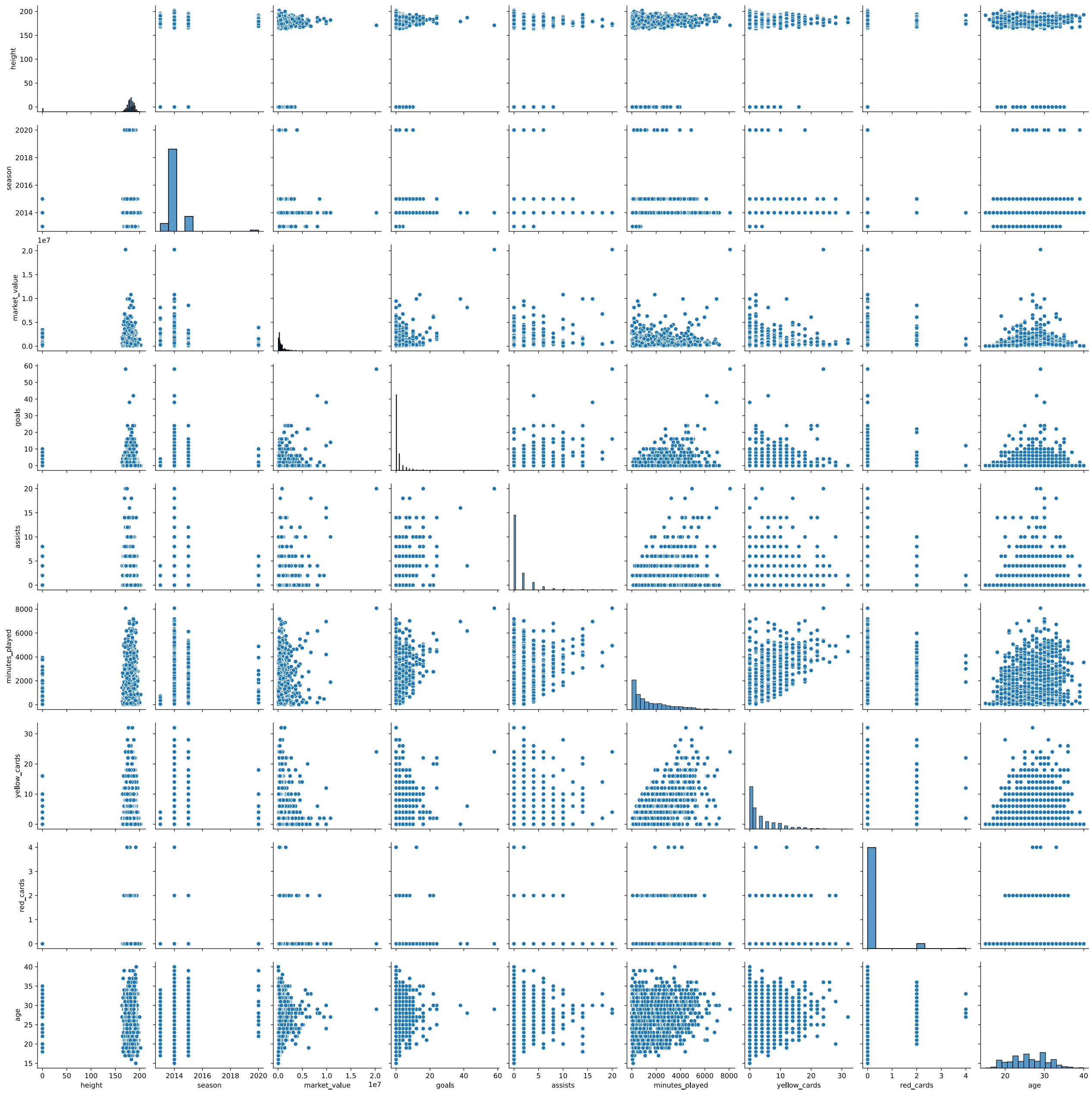
We wanted to start by analyzing which data variables are important and correlate with each other using a heat map. The heat map will allow us to determine which are important to keep and also the pair plot will show the correlation between the variables.

In [ ]:

```
corr = data['all_eda'].corr()
_ = sns.heatmap(corr,
    cmap = 'seismic',
    linewidth = 1, linecolor = 'white',
    vmax = 1, vmin = -1,
    mask = np.triu(np.ones_like(corr, dtype = bool)),
    annot = True,
    fmt = '0.2f'
)
```



In [ ]:
```
_ = sns.pairplot(data['all'][:1500].reset_index())
```



Subsection 2

After analyzing which variables we wanted to keep and how they relate to each other. Our first intial model would be a simple OLS which will only use numerical data. We want to see the difference in our model if its classifying only numerical data. Since we believe the categorical data present can be defined as subjective in the Soccer world.

In [ ]:

```
y, X = patsy.dmatrices('''
    market_value ~
        age + goals + assists + minutes_played
            + yellow_cards + red_cards
            + height + age
''', data=data['all_eda'], return_type="dataframe")
model = sm.OLS(y, X)
fit = model.fit()
pred = fit.predict(X)
fit.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	market_value	**R-squared:**	0.220
Model:	OLS	**Adj. R-squared:**	0.219
Method:	Least Squares	**F-statistic:**	2041.
Date:	Fri, 10 Jun 2022	**Prob (F-statistic):**	0.00
Time:	02:20:32	**Log-Likelihood:**	-8.7464e+05
No. Observations:	50781	**AIC:**	1.749e+06
Df Residuals:	50773	**BIC:**	1.749e+06
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.938e+05	3.77e+05	0.514	0.607	-5.45e+05	9.33e+05
age	-7.077e+04	7609.677	-9.300	0.000	-8.57e+04	-5.59e+04
goals	2.389e+05	5556.790	42.994	0.000	2.28e+05	2.5e+05
assists	3.135e+05	8922.514	35.136	0.000	2.96e+05	3.31e+05
minutes_played	826.8657	22.786	36.288	0.000	782.205	871.526
yellow_cards	-6.638e+04	6910.754	-9.606	0.000	-7.99e+04	-5.28e+04
red_cards	-7.781e+04	6.05e+04	-1.287	0.198	-1.96e+05	4.07e+04
height	7851.4099	1846.711	4.252	0.000	4231.837	1.15e+04

Omnibus:	53530.739	**Durbin-Watson:**	0.636
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	5620986.518
Skew:	5.193	**Prob(JB):**	0.00
Kurtosis:	53.485	**Cond. No.**	4.08e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.08e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [ ]:

```
print((y))
print((pred))

np.sqrt(mean_squared_error((y),(pred)))
```

```
           market_value
player_id
9800            90000.0
```

```
43084          360000.0
230826         360000.0
198087        1530000.0
110689          68000.0
...                 ...
364245         420000.0
364245        1102500.0
364245        5400000.0
575367         658250.0
575367         765000.0

[50781 rows x 1 columns]
player_id
9800     -5.312852e+05
43084    -4.060252e+05
230826    2.289005e+06
198087    5.058775e+06
110689    6.836034e+05
              ...
364245    5.837390e+05
364245    6.375011e+06
364245    6.683061e+06
575367    9.031230e+05
575367    6.952160e+05
Length: 50781, dtype: float64
```

Out[ ]:

```
7309873.947199644
```

Taking the Log of the market value was a way to incorportate a different way of showing an error metric. The log would keep the monotonocity of each variable

In [ ]:

```
data['all_eda']['log_market_value'] = np.log(data['all_eda']['market_value'])
y, X = patsy.dmatrices('''
    log_market_value ~
        age + goals + assists + minutes_played
            + yellow_cards + red_cards
            + height + age
''', data=data['all_eda'], return_type="dataframe")
model = sm.OLS(y, X)
fit = model.fit()
pred2 = fit.predict(X)
fit.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	log_market_value	**R-squared:**	0.282
Model:	OLS	**Adj. R-squared:**	0.282
Method:	Least Squares	**F-statistic:**	2851.
Date:	Fri, 10 Jun 2022	**Prob (F-statistic):**	0.00
Time:	02:20:40	**Log-Likelihood:**	-84685.
No. Observations:	50781	**AIC:**	1.694e+05
Df Residuals:	50773	**BIC:**	1.695e+05
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	11.7302	0.066	177.262	0.000	11.600	11.860
age	0.0156	0.001	11.664	0.000	0.013	0.018
goals	0.0231	0.001	23.713	0.000	0.021	0.025
assists	0.0473	0.002	30.198	0.000	0.044	0.050
minutes_played	0.0003	4e-06	63.609	0.000	0.000	0.000
yellow_cards	0.0007	0.001	0.560	0.576	-0.002	0.003
red_cards	0.0093	0.011	0.880	0.379	-0.011	0.030
height	0.0047	0.000	14.436	0.000	0.004	0.005

Omnibus:	836.100	**Durbin-Watson:**	0.853
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	794.667
Skew:	0.271	**Prob(JB):**	2.76e-173
Kurtosis:	2.716	**Cond. No.**	4.08e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 4.08e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [ ]:

```
print(np.exp(y))
print(np.exp(pred2))

np.sqrt(mean_squared_error((y),(pred2)))
```

```
           log_market_value
player_id
9800                90000.0
43084              360000.0
230826             360000.0
198087            1530000.0
110689              68000.0
...                     ...
364245             420000.0
364245            1102500.0
364245            5400000.0
575367             658250.0
575367             765000.0

[50781 rows x 1 columns]
player_id
9800      6.157680e+05
43084     4.928576e+05
230826    7.211031e+05
198087    1.931418e+06
110689    6.111676e+05
```

```
                 ...
364245    4.307993e+05
364245    2.970482e+06
364245    2.380843e+06
575367    4.402778e+05
575367    4.100153e+05
Length: 50781, dtype: float64
```

Out[ ]: 1.2823693684295892

Subsection 3

Since our dataset contains categorical values, we want to perform again OLS but by including those values so we can compare the accuracy between categorical and non-categorical OLS.

In [ ]:

```
y, X = patsy.dmatrices('''
    log_market_value ~
        age + goals + assists + minutes_played
            + yellow_cards + red_cards
            + height + age
            + C(nationality) + C(position) + C(sub_position) + C(club_name)
''', data=data['all_eda'], return_type="dataframe")
model = sm.OLS(y, X)
fit = model.fit()
pred3 = fit.predict(X)
fit.summary()
```

Out[ ]:

OLS Regression Results

Dep. Variable:	log_market_value	**R-squared:**	0.678
Model:	OLS	**Adj. R-squared:**	0.674
Method:	Least Squares	**F-statistic:**	185.8
Date:	Fri, 10 Jun 2022	**Prob (F-statistic):**	0.00
Time:	02:20:54	**Log-Likelihood:**	-64329.
No. Observations:	50781	**AIC:**	1.298e+05
Df Residuals:	50211	**BIC:**	1.348e+05
Df Model:	569		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	11.2022	0.559	20.054	0.000	10.107	12.297
C(nationality)[T.Albania]	0.0602	0.622	0.097	0.923	-1.159	1.280
C(nationality)[T.Algeria]	0.2460	0.621	0.396	0.692	-0.972	1.463
C(nationality)[T.Angola]	0.3028	0.625	0.485	0.628	-0.922	1.527
C(nationality)[T.Antigua and Barbuda]	0.2055	0.714	0.288	0.774	-1.194	1.606
C(nationality)[T.Argentina]	0.2909	0.620	0.470	0.639	-0.924	1.505
C(nationality)[T.Armenia]	-0.0123	0.626	-0.020	0.984	-1.238	1.214

C(nationality)[T.Aruba]	-0.0934	0.652	-0.143	0.886	-1.372	1.185
C(nationality)[T.Australia]	0.1484	0.622	0.239	0.811	-1.071	1.368
C(nationality)[T.Austria]	0.2672	0.621	0.430	0.667	-0.950	1.484
C(nationality)[T.Azerbaijan]	-0.1249	0.643	-0.194	0.846	-1.386	1.136
C(nationality)[T.Bahrain]	-2.496e-12	7.41e-13	-3.369	0.001	-3.95e-12	-1.04e-12
C(nationality)[T.Barbados]	-1.154e-12	3.12e-13	-3.696	0.000	-1.77e-12	-5.42e-13
C(nationality)[T.Belarus]	0.0540	0.625	0.086	0.931	-1.170	1.278
C(nationality)[T.Belgium]	0.1501	0.619	0.242	0.808	-1.064	1.364
C(nationality)[T.Benin]	-0.0736	0.633	-0.116	0.907	-1.315	1.168
C(nationality)[T.Bermuda]	0.8495	1.065	0.798	0.425	-1.238	2.937
C(nationality)[T.Bolivia]	0.2664	0.665	0.401	0.689	-1.037	1.570
C(nationality)[T.Bosnia-Herzegovina]	0.1182	0.621	0.190	0.849	-1.099	1.336
C(nationality)[T.Brazil]	0.2350	0.619	0.379	0.704	-0.979	1.449
C(nationality)[T.Bulgaria]	0.1903	0.626	0.304	0.761	-1.036	1.416
C(nationality)[T.Burkina Faso]	0.2280	0.625	0.365	0.715	-0.998	1.454
C(nationality)[T.Burundi]	0.3019	0.656	0.460	0.645	-0.984	1.588
C(nationality)[T.Cameroon]	0.2571	0.621	0.414	0.679	-0.959	1.474
C(nationality)[T.Canada]	-0.0476	0.626	-0.076	0.939	-1.275	1.180
C(nationality)[T.Cape Verde]	0.1084	0.623	0.174	0.862	-1.113	1.330
C(nationality)[T.Central African Republic]	0.4384	0.647	0.677	0.498	-0.831	1.707
C(nationality)[T.Chad]	0.1484	0.665	0.223	0.823	-1.155	1.451
C(nationality)[T.Chile]	0.2310	0.623	0.371	0.711	-0.991	1.453
C(nationality)[T.China]	-0.4184	0.656	-0.638	0.524	-1.704	0.867
C(nationality)[T.Chinese Taipei (Taiwan)]	-0.7057	0.761	-0.927	0.354	-2.198	0.786
C(nationality)[T.Colombia]	0.4487	0.621	0.723	0.470	-0.768	1.666
C(nationality)[T.Comoros]	0.3576	0.641	0.558	0.577	-0.898	1.613
C(nationality)[T.Congo]	0.1482	0.626	0.237	0.813	-1.080	1.376
C(nationality)[T.Costa Rica]	0.1354	0.627	0.216	0.829	-1.093	1.363
C(nationality)[T.Cote d'Ivoire]	0.3575	0.620	0.576	0.564	-0.858	1.573
C(nationality)[T.Croatia]	0.3805	0.620	0.614	0.539	-0.835	1.596
C(nationality)[T.Cuba]	-0.0300	1.067	-0.028	0.978	-2.121	2.061
C(nationality)[T.Curacao]	-0.0399	0.626	-0.064	0.949	-1.267	1.187
C(nationality)[T.Cyprus]	0.2628	0.636	0.413	0.680	-0.984	1.510
C(nationality)[T.Czech Republic]	0.2576	0.622	0.414	0.679	-0.961	1.476

C(nationality)[T.DR Congo]	0.3258	0.621	0.525	0.600	-0.892	1.543
C(nationality)[T.Denmark]	0.0836	0.620	0.135	0.893	-1.131	1.298
C(nationality)[T.Dominican Republic]	-0.0826	0.665	-0.124	0.901	-1.385	1.220
C(nationality)[T.Ecuador]	0.3800	0.627	0.606	0.545	-0.849	1.609
C(nationality)[T.Egypt]	0.1848	0.627	0.295	0.768	-1.044	1.413
C(nationality)[T.El Salvador]	-0.4594	0.714	-0.643	0.520	-1.859	0.940
C(nationality)[T.England]	-0.0313	0.619	-0.051	0.960	-1.246	1.183
C(nationality)[T.Equatorial Guinea]	0.2308	0.650	0.355	0.723	-1.044	1.506
C(nationality)[T.Eritrea]	0.6033	0.871	0.693	0.489	-1.104	2.311
C(nationality)[T.Estonia]	-0.0422	0.648	-0.065	0.948	-1.311	1.227
C(nationality)[T.Ethiopia]	-0.9194	1.065	-0.863	0.388	-3.007	1.168
C(nationality)[T.Faroe Islands]	-0.2503	0.646	-0.388	0.698	-1.516	1.015
C(nationality)[T.Finland]	-0.0104	0.623	-0.017	0.987	-1.232	1.212
C(nationality)[T.France]	0.2056	0.619	0.332	0.740	-1.008	1.419
C(nationality)[T.French Guiana]	-0.1264	0.654	-0.193	0.847	-1.409	1.156
C(nationality)[T.Gabon]	0.3401	0.627	0.542	0.588	-0.890	1.570
C(nationality)[T.Georgia]	0.3154	0.623	0.506	0.613	-0.905	1.536
C(nationality)[T.Germany]	0.0235	0.619	0.038	0.970	-1.190	1.237
C(nationality)[T.Ghana]	0.2310	0.620	0.372	0.710	-0.985	1.447
C(nationality)[T.Greece]	0.0206	0.620	0.033	0.973	-1.194	1.235
C(nationality)[T.Grenada]	-0.4473	0.731	-0.612	0.541	-1.881	0.986
C(nationality)[T.Guadeloupe]	0.3269	0.632	0.517	0.605	-0.912	1.566
C(nationality)[T.Guinea]	0.2698	0.623	0.433	0.665	-0.951	1.490
C(nationality)[T.Guinea-Bissau]	0.2250	0.624	0.360	0.719	-0.999	1.449
C(nationality)[T.Guyana]	0.3923	0.713	0.550	0.582	-1.006	1.790
C(nationality)[T.Haiti]	0.0332	0.635	0.052	0.958	-1.211	1.278
C(nationality)[T.Honduras]	0.2133	0.639	0.334	0.739	-1.040	1.466
C(nationality)[T.Hungary]	0.1680	0.626	0.269	0.788	-1.058	1.394
C(nationality)[T.Iceland]	0.2479	0.622	0.398	0.690	-0.972	1.468
C(nationality)[T.India]	-1.499e-15	5.55e-14	-0.027	0.978	-1.1e-13	1.07e-13
C(nationality)[T.Indonesia]	0.9166	1.066	0.860	0.390	-1.172	3.005
C(nationality)[T.Iran]	0.4381	0.626	0.700	0.484	-0.788	1.664
C(nationality)[T.Iraq]	0.3928	0.642	0.612	0.541	-0.866	1.651
C(nationality)[T.Ireland]	-0.2612	0.621	-0.420	0.674	-1.479	0.957

C(nationality)[T.Israel]	0.0568	0.625	0.091	0.928	-1.169	1.282
C(nationality)[T.Italy]	-0.0981	0.620	-0.158	0.874	-1.312	1.116
C(nationality)[T.Jamaica]	0.0501	0.628	0.080	0.936	-1.181	1.281
C(nationality)[T.Japan]	0.3757	0.622	0.604	0.546	-0.843	1.594
C(nationality)[T.Jordan]	0.6521	0.758	0.860	0.390	-0.833	2.137
C(nationality)[T.Kazakhstan]	0.3630	0.644	0.564	0.573	-0.898	1.624
C(nationality)[T.Kenya]	0.1721	0.651	0.264	0.791	-1.103	1.447
C(nationality)[T.Korea, North]	-0.4479	1.065	-0.421	0.674	-2.535	1.639
C(nationality)[T.Korea, South]	0.3091	0.627	0.493	0.622	-0.920	1.538
C(nationality)[T.Kosovo]	0.2812	0.625	0.450	0.653	-0.943	1.506
C(nationality)[T.Kyrgyzstan]	0.4378	0.879	0.498	0.619	-1.286	2.161
C(nationality)[T.Laos]	0.3448	0.798	0.432	0.666	-1.219	1.908
C(nationality)[T.Latvia]	0.2093	0.652	0.321	0.748	-1.069	1.488
C(nationality)[T.Lebanon]	-0.4018	0.871	-0.461	0.645	-2.110	1.306
C(nationality)[T.Liberia]	-0.0332	0.701	-0.047	0.962	-1.407	1.341
C(nationality)[T.Libya]	0.0042	0.678	0.006	0.995	-1.324	1.333
C(nationality)[T.Liechtenstein]	-0.0960	0.797	-0.120	0.904	-1.658	1.466
C(nationality)[T.Lithuania]	-0.0942	0.636	-0.148	0.882	-1.341	1.153
C(nationality)[T.Luxembourg]	-0.0390	0.633	-0.062	0.951	-1.279	1.201
C(nationality)[T.Madagascar]	-0.2638	0.641	-0.412	0.681	-1.519	0.992
C(nationality)[T.Malawi]	0.2219	1.067	0.208	0.835	-1.869	2.313
C(nationality)[T.Malaysia]	-0.1996	0.684	-0.292	0.770	-1.540	1.141
C(nationality)[T.Mali]	0.2290	0.621	0.369	0.712	-0.989	1.447
C(nationality)[T.Malta]	0.0768	0.692	0.111	0.912	-1.280	1.433
C(nationality)[T.Martinique]	0.1781	0.629	0.283	0.777	-1.055	1.411
C(nationality)[T.Mauritania]	-0.2871	0.639	-0.449	0.653	-1.540	0.966
C(nationality)[T.Mauritius]	0.5728	0.714	0.802	0.422	-0.827	1.972
C(nationality)[T.Mexico]	0.6341	0.624	1.016	0.310	-0.589	1.857
C(nationality)[T.Moldova]	0.0073	0.631	0.012	0.991	-1.230	1.245
C(nationality)[T.Monaco]	-1.826e-16	7.62e-15	-0.024	0.981	-1.51e-14	1.48e-14
C(nationality)[T.Montenegro]	0.1850	0.624	0.296	0.767	-1.038	1.408
C(nationality)[T.Montserrat]	-0.3983	0.756	-0.527	0.598	-1.880	1.083
C(nationality)[T.Morocco]	0.1512	0.620	0.244	0.807	-1.064	1.367
C(nationality)[T.Mozambique]	0.0046	0.636	0.007	0.994	-1.242	1.251

C(nationality)[T.Netherlands]	0.0999	0.619	0.161	0.872	-1.113	1.313
C(nationality)[T.Neukaledonien]	0.2978	0.684	0.435	0.663	-1.043	1.639
C(nationality)[T.New Zealand]	0.2391	0.636	0.376	0.707	-1.008	1.486
C(nationality)[T.Nicaragua]	0.1843	1.065	0.173	0.863	-1.903	2.272
C(nationality)[T.Niger]	0.1077	0.684	0.158	0.875	-1.232	1.448
C(nationality)[T.Nigeria]	0.1656	0.620	0.267	0.789	-1.050	1.381
C(nationality)[T.North Macedonia]	0.0101	0.626	0.016	0.987	-1.218	1.238
C(nationality)[T.Northern Ireland]	-0.2763	0.624	-0.443	0.658	-1.499	0.946
C(nationality)[T.Norway]	0.2931	0.621	0.472	0.637	-0.924	1.510
C(nationality)[T.Pakistan]	-0.3998	0.731	-0.547	0.585	-1.833	1.034
C(nationality)[T.Palästina]	-0.3134	0.872	-0.360	0.719	-2.022	1.395
C(nationality)[T.Panama]	-0.1520	0.668	-0.227	0.820	-1.461	1.157
C(nationality)[T.Papua New Guinea]	5.418e-15	1.55e-15	3.486	0.000	2.37e-15	8.46e-15
C(nationality)[T.Paraguay]	0.4580	0.626	0.732	0.464	-0.768	1.684
C(nationality)[T.Peru]	0.3182	0.628	0.507	0.612	-0.912	1.549
C(nationality)[T.Philippines]	0.2035	0.654	0.311	0.756	-1.079	1.486
C(nationality)[T.Poland]	0.2277	0.621	0.367	0.714	-0.989	1.444
C(nationality)[T.Portugal]	0.2841	0.619	0.459	0.646	-0.930	1.498
C(nationality)[T.Qatar]	0.0395	0.733	0.054	0.957	-1.396	1.475
C(nationality)[T.Romania]	0.4041	0.622	0.650	0.516	-0.815	1.623
C(nationality)[T.Russia]	-0.1947	0.620	-0.314	0.753	-1.409	1.020
C(nationality)[T.Rwanda]	-0.2077	0.665	-0.312	0.755	-1.511	1.095
C(nationality)[T.Saint-Martin]	-0.4565	0.875	-0.522	0.602	-2.171	1.258
C(nationality)[T.San Marino]	-2.831e-15	2.11e-15	-1.343	0.179	-6.96e-15	1.3e-15
C(nationality)[T.Sao Tome and Principe]	0.4593	0.701	0.655	0.512	-0.915	1.833
C(nationality)[T.Saudi Arabia]	-0.0294	0.730	-0.040	0.968	-1.461	1.402
C(nationality)[T.Scotland]	-0.0778	0.620	-0.126	0.900	-1.293	1.137
C(nationality)[T.Senegal]	0.3065	0.620	0.494	0.621	-0.909	1.522
C(nationality)[T.Serbia]	0.2868	0.620	0.463	0.644	-0.928	1.502
C(nationality)[T.Sierra Leone]	0.0421	0.636	0.066	0.947	-1.205	1.289
C(nationality)[T.Slovakia]	0.1242	0.622	0.200	0.842	-1.095	1.344
C(nationality)[T.Slovenia]	0.1211	0.622	0.195	0.845	-1.097	1.339
C(nationality)[T.Somalia]	-2.86e-15	3.04e-15	-0.940	0.347	-8.82e-15	3.1e-15

C(nationality)[T.South Africa]	0.3139	0.626	0.501	0.616	-0.913	1.541
C(nationality)[T.Spain]	0.0023	0.619	0.004	0.997	-1.212	1.216
C(nationality)[T.St. Kitts & Nevis]	-0.0150	1.066	-0.014	0.989	-2.104	2.074
C(nationality)[T.St. Lucia]	2.414e-15	2.42e-15	0.997	0.319	-2.33e-15	7.16e-15
C(nationality)[T.Suriname]	0.0841	0.624	0.135	0.893	-1.139	1.307
C(nationality)[T.Sweden]	0.2727	0.620	0.440	0.660	-0.942	1.488
C(nationality)[T.Switzerland]	0.2839	0.621	0.457	0.647	-0.933	1.501
C(nationality)[T.Syria]	0.1419	0.672	0.211	0.833	-1.176	1.459
C(nationality)[T.Tajikistan]	-0.2933	0.797	-0.368	0.713	-1.855	1.268
C(nationality)[T.Tanzania]	-0.0136	0.692	-0.020	0.984	-1.370	1.342
C(nationality)[T.Thailand]	0.2942	1.078	0.273	0.785	-1.819	2.407
C(nationality)[T.The Gambia]	0.1888	0.629	0.300	0.764	-1.043	1.421
C(nationality)[T.Togo]	0.0932	0.626	0.149	0.882	-1.133	1.320
C(nationality)[T.Trinidad and Tobago]	0.3490	0.647	0.539	0.590	-0.920	1.618
C(nationality)[T.Tunisia]	0.1465	0.623	0.235	0.814	-1.075	1.368
C(nationality)[T.Turkey]	-0.2210	0.619	-0.357	0.721	-1.435	0.993
C(nationality)[T.Turkmenistan]	-5.063e-15	2.11e-15	-2.402	0.016	-9.19e-15	-9.31e-16
C(nationality)[T.Uganda]	-0.0914	0.641	-0.143	0.887	-1.347	1.164
C(nationality)[T.Ukraine]	0.0723	0.620	0.117	0.907	-1.143	1.288
C(nationality)[T.United States]	0.1875	0.622	0.302	0.763	-1.031	1.406
C(nationality)[T.Uruguay]	0.3865	0.621	0.622	0.534	-0.830	1.603
C(nationality)[T.Uzbekistan]	0.3134	0.635	0.494	0.622	-0.931	1.558
C(nationality)[T.Venezuela]	0.2504	0.624	0.402	0.688	-0.972	1.473
C(nationality)[T.Vietnam]	-0.5549	0.871	-0.637	0.524	-2.261	1.152
C(nationality)[T.Wales]	0.1269	0.623	0.204	0.839	-1.094	1.348
C(nationality)[T.Zambia]	0.1927	0.638	0.302	0.763	-1.058	1.443
C(nationality)[T.Zimbabwe]	-0.0710	0.634	-0.112	0.911	-1.314	1.172
C(position)[T.Defender]	0.6875	0.235	2.920	0.003	0.226	1.149
C(position)[T.Goalkeeper]	0.5183	0.039	13.383	0.000	0.442	0.594
C(position)[T.Midfield]	1.1611	0.071	16.262	0.000	1.021	1.301
C(sub_position)[T.Centre-Back]	0.6228	0.252	2.476	0.013	0.130	1.116
C(sub_position)[T.Left-Back]	0.6176	0.252	2.453	0.014	0.124	1.111
C(sub_position)[T.Right-Back]	0.5614	0.252	2.230	0.026	0.068	1.055
C(sub_position)[T.Goalkeeper]	0.5183	0.039	13.383	0.000	0.442	0.594

C(sub_position)[T.Attack]	1.0701	0.203	5.278	0.000	0.673	1.468
C(sub_position)[T.Centre-Forward]	1.5247	0.077	19.900	0.000	1.375	1.675
C(sub_position)[T.Left Winger]	1.5525	0.077	20.135	0.000	1.401	1.704
C(sub_position)[T.Right Winger]	1.5496	0.077	20.101	0.000	1.398	1.701
C(sub_position)[T.Second Striker]	1.5782	0.084	18.801	0.000	1.414	1.743
C(sub_position)[T.Midfield]	0.1824	0.177	1.032	0.302	-0.164	0.529
C(sub_position)[T.Attacking Midfield]	1.5602	0.077	20.233	0.000	1.409	1.711
C(sub_position)[T.Central Midfield]	0.3128	0.040	7.764	0.000	0.234	0.392
C(sub_position)[T.Defensive Midfield]	0.2723	0.041	6.663	0.000	0.192	0.352
C(sub_position)[T.Left Midfield]	0.1962	0.050	3.949	0.000	0.099	0.294
C(sub_position)[T.Right Midfield]	0.1974	0.050	3.932	0.000	0.099	0.296
C(club_name)[T.1 Fc Nurnberg]	-0.4285	0.161	-2.662	0.008	-0.744	-0.113
C(club_name)[T.1 Fc Union Berlin]	-0.2373	0.115	-2.067	0.039	-0.462	-0.012
C(club_name)[T.1 Fsv Mainz 05]	0.1497	0.090	1.666	0.096	-0.026	0.326
C(club_name)[T.Aalborg Bk]	-1.5202	0.094	-16.256	0.000	-1.704	-1.337
C(club_name)[T.Aarhus Gf]	-1.5066	0.094	-16.033	0.000	-1.691	-1.322
C(club_name)[T.Aberdeen Fc]	-1.5220	0.096	-15.839	0.000	-1.710	-1.334
C(club_name)[T.Ac Florenz]	0.6641	0.093	7.123	0.000	0.481	0.847
C(club_name)[T.Ac Horsens]	-1.7477	0.100	-17.428	0.000	-1.944	-1.551
C(club_name)[T.Ac Mailand]	1.1354	0.090	12.574	0.000	0.958	1.312
C(club_name)[T.Academica Coimbra]	-1.3883	0.135	-10.269	0.000	-1.653	-1.123
C(club_name)[T.Acn Siena 1904]	-1.3453	0.360	-3.735	0.000	-2.051	-0.639
C(club_name)[T.Adana Demirspor]	-0.7301	0.193	-3.779	0.000	-1.109	-0.351
C(club_name)[T.Adanaspor]	-1.1867	0.183	-6.467	0.000	-1.546	-0.827
C(club_name)[T.Ado Den Haag]	-1.3793	0.096	-14.413	0.000	-1.567	-1.192
C(club_name)[T.Ae Larisa]	-1.6752	0.098	-17.015	0.000	-1.868	-1.482
C(club_name)[T.Aek Athen]	-0.8059	0.093	-8.673	0.000	-0.988	-0.624
C(club_name)[T.Ael Kalloni]	-1.7709	0.131	-13.532	0.000	-2.027	-1.514
C(club_name)[T.Afc Bournemouth]	0.5318	0.103	5.166	0.000	0.330	0.734
C(club_name)[T.Afc Sunderland]	0.4600	0.125	3.688	0.000	0.216	0.704
C(club_name)[T.Ajax Amsterdam]	0.3685	0.092	4.012	0.000	0.188	0.548
C(club_name)[T.Akhisarspor]	-0.7119	0.103	-6.928	0.000	-0.913	-0.510
C(club_name)[T.Akhmat Grozny]	-0.5841	0.094	-6.199	0.000	-0.769	-0.399
C(club_name)[T.Alanyaspor]	-0.6991	0.098	-7.128	0.000	-0.891	-0.507
C(club_name)[T.Altay Sk]	-1.5116	0.194	-7.811	0.000	-1.891	-1.132

C(club_name)[T.Amiens Sc]	-0.5277	0.118	-4.475	0.000	-0.759	-0.297
C(club_name)[T.Amkar Perm]	-1.1928	0.114	-10.462	0.000	-1.416	-0.969
C(club_name)[T.Ankaraspor]	-0.4271	0.114	-3.748	0.000	-0.650	-0.204
C(club_name)[T.Antalyaspor]	-0.7002	0.093	-7.535	0.000	-0.882	-0.518
C(club_name)[T.Anzhi Makhachkala]	-0.8939	0.100	-8.913	0.000	-1.090	-0.697
C(club_name)[T.Ao Platanias]	-1.6862	0.109	-15.442	0.000	-1.900	-1.472
C(club_name)[T.Ao Xanthi]	-1.6323	0.098	-16.597	0.000	-1.825	-1.440
C(club_name)[T.Aok Kerkyra]	-1.8263	0.116	-15.749	0.000	-2.054	-1.599
C(club_name)[T.Apo Levadiakos]	-1.7009	0.100	-16.991	0.000	-1.897	-1.505
C(club_name)[T.Apollon Smyrnis]	-1.7257	0.111	-15.484	0.000	-1.944	-1.507
C(club_name)[T.Aris Thessaloniki]	-1.2442	0.108	-11.527	0.000	-1.456	-1.033
C(club_name)[T.Arminia Bielefeld]	-0.1347	0.144	-0.932	0.351	-0.418	0.148
C(club_name)[T.Arsenal Kiew]	-1.7168	0.138	-12.428	0.000	-1.988	-1.446
C(club_name)[T.Arsenal Tula]	-0.8831	0.094	-9.391	0.000	-1.067	-0.699
C(club_name)[T.As Livorno]	-0.5794	0.615	-0.942	0.346	-1.785	0.626
C(club_name)[T.As Monaco]	0.7824	0.089	8.792	0.000	0.608	0.957
C(club_name)[T.As Nancy Lorraine]	-1.0211	0.183	-5.565	0.000	-1.381	-0.661
C(club_name)[T.As Rom]	1.1245	0.092	12.264	0.000	0.945	1.304
C(club_name)[T.As Saint Etienne]	0.0619	0.092	0.674	0.500	-0.118	0.242
C(club_name)[T.Asteras Tripolis]	-1.4699	0.090	-16.323	0.000	-1.646	-1.293
C(club_name)[T.Aston Villa]	1.0315	0.106	9.764	0.000	0.824	1.239
C(club_name)[T.Atalanta Bergamo]	0.3369	0.092	3.673	0.000	0.157	0.517
C(club_name)[T.Athletic Bilbao]	0.5051	0.095	5.317	0.000	0.319	0.691
C(club_name)[T.Atletico Madrid]	1.4860	0.094	15.869	0.000	1.302	1.670
C(club_name)[T.Atromitos Athen]	-1.3711	0.091	-15.050	0.000	-1.550	-1.193
C(club_name)[T.Az Alkmaar]	-0.6281	0.093	-6.719	0.000	-0.811	-0.445
C(club_name)[T.Balikesirspor]	-0.8294	0.178	-4.659	0.000	-1.178	-0.480
C(club_name)[T.Bayer 04 Leverkusen]	1.0471	0.093	11.212	0.000	0.864	1.230
C(club_name)[T.Beerschot V A]	-1.2645	0.143	-8.845	0.000	-1.545	-0.984
C(club_name)[T.Belenenses Sad]	-1.3589	0.092	-14.849	0.000	-1.538	-1.180
C(club_name)[T.Benevento Calcio]	-0.3037	0.126	-2.417	0.016	-0.550	-0.057
C(club_name)[T.Benfica Lissabon]	0.5891	0.092	6.387	0.000	0.408	0.770
C(club_name)[T.Besiktas Istanbul]	0.3465	0.092	3.771	0.000	0.166	0.527
C(club_name)[T.Boavista Porto Fc]	-1.4923	0.092	-16.277	0.000	-1.672	-1.313
C(club_name)[T.Borussia Dortmund]	1.1845	0.089	13.236	0.000	1.009	1.360

C(club_name)[T.Borussia Monchengladbach]	0.7316	0.093	7.864	0.000	0.549	0.914
C(club_name)[T.Brescia Calcio]	0.0096	0.144	0.067	0.947	-0.272	0.291
C(club_name)[T.Brighton Amp Hove Albion]	0.8232	0.103	8.003	0.000	0.622	1.025
C(club_name)[T.Brondby If]	-1.0584	0.092	-11.511	0.000	-1.239	-0.878
C(club_name)[T.Bursaspor]	-0.3958	0.102	-3.889	0.000	-0.595	-0.196
C(club_name)[T.Buyuksehir Belediye Erzurumspor]	-1.4850	0.142	-10.456	0.000	-1.763	-1.207
C(club_name)[T.Ca Osasuna]	-0.3354	0.107	-3.124	0.002	-0.546	-0.125
C(club_name)[T.Cagliari Calcio]	0.1359	0.096	1.415	0.157	-0.052	0.324
C(club_name)[T.Cardiff City]	0.1529	0.162	0.942	0.346	-0.165	0.471
C(club_name)[T.Carpi Fc 1909]	-0.3386	0.151	-2.247	0.025	-0.634	-0.043
C(club_name)[T.Catania Calcio]	-0.0172	0.504	-0.034	0.973	-1.005	0.971
C(club_name)[T.Caykur Rizespor]	-0.7259	0.097	-7.512	0.000	-0.915	-0.537
C(club_name)[T.Cd Feirense]	-1.7222	0.113	-15.204	0.000	-1.944	-1.500
C(club_name)[T.Cd Leganes]	-0.1021	0.106	-0.965	0.335	-0.309	0.105
C(club_name)[T.Cd Nacional]	-1.3974	0.101	-13.842	0.000	-1.595	-1.200
C(club_name)[T.Cd Santa Clara]	-1.5681	0.104	-15.032	0.000	-1.773	-1.364
C(club_name)[T.Cd Tondela]	-1.5607	0.094	-16.571	0.000	-1.745	-1.376
C(club_name)[T.Celta Vigo]	0.3010	0.095	3.178	0.001	0.115	0.487
C(club_name)[T.Celtic Glasgow]	-0.2103	0.090	-2.332	0.020	-0.387	-0.034
C(club_name)[T.Cercle Brugge]	-1.0222	0.098	-10.459	0.000	-1.214	-0.831
C(club_name)[T.Cesena Fc]	-0.9259	0.162	-5.701	0.000	-1.244	-0.608
C(club_name)[T.Cf Uniao Madeira]	-1.9126	0.164	-11.645	0.000	-2.234	-1.591
C(club_name)[T.Chievo Verona]	-0.7447	0.106	-7.044	0.000	-0.952	-0.537
C(club_name)[T.Chornomorets Odessa]	-1.5272	0.102	-14.924	0.000	-1.728	-1.327
C(club_name)[T.Clermont Foot 63]	-0.5874	0.190	-3.088	0.002	-0.960	-0.215
C(club_name)[T.Crystal Palace]	0.8424	0.092	9.108	0.000	0.661	1.024
C(club_name)[T.Cs Maritimo]	-1.3668	0.093	-14.740	0.000	-1.549	-1.185
C(club_name)[T.De Graafschap Doetinchem]	-1.9424	0.140	-13.854	0.000	-2.217	-1.668
C(club_name)[T.Delfino Pescara 1936]	-0.5875	0.153	-3.840	0.000	-0.887	-0.288
C(club_name)[T.Denizlispor]	-1.3478	0.144	-9.341	0.000	-1.631	-1.065
C(club_name)[T.Deportivo Alaves]	-0.1007	0.096	-1.054	0.292	-0.288	0.087
C(club_name)[T.Deportivo La Coruna]	-0.1039	0.110	-0.948	0.343	-0.319	0.111
C(club_name)[T.Desna Chernigiv]	-1.4598	0.113	-12.935	0.000	-1.681	-1.239
C(club_name)[T.Desportivo Aves]	-1.6445	0.111	-14.765	0.000	-1.863	-1.426

C(club_name)[T.Dijon Fco]	-0.5194	0.104	-5.018	0.000	-0.722	-0.317
C(club_name)[T.Dinamo Moskau]	0.0411	0.097	0.423	0.672	-0.149	0.231
C(club_name)[T.Dnipro Dnipropetrovsk]	-0.4472	0.119	-3.762	0.000	-0.680	-0.214
C(club_name)[T.Dundee Fc]	-1.8224	0.105	-17.384	0.000	-2.028	-1.617
C(club_name)[T.Dundee United Fc]	-1.8480	0.114	-16.277	0.000	-2.071	-1.625
C(club_name)[T.Dynamo Kiew]	0.1928	0.094	2.043	0.041	0.008	0.378
C(club_name)[T.Ea Guingamp]	-0.6662	0.106	-6.307	0.000	-0.873	-0.459
C(club_name)[T.Eintracht Braunschweig]	-0.6400	0.615	-1.040	0.298	-1.846	0.566
C(club_name)[T.Eintracht Frankfurt]	0.1776	0.091	1.954	0.051	-0.001	0.356
C(club_name)[T.Enisey Krasnoyarsk]	-1.1658	0.147	-7.957	0.000	-1.453	-0.879
C(club_name)[T.Es Troyes Ac]	-0.8362	0.119	-7.036	0.000	-1.069	-0.603
C(club_name)[T.Esbjerg Fb]	-1.5751	0.097	-16.294	0.000	-1.765	-1.386
C(club_name)[T.Eskisehirspor]	-0.4748	0.136	-3.485	0.000	-0.742	-0.208
C(club_name)[T.Espanyol Barcelona]	0.0078	0.095	0.082	0.934	-0.178	0.194
C(club_name)[T.Fatih Karagumruk]	-0.9800	0.135	-7.266	0.000	-1.244	-0.716
C(club_name)[T.Fc Arouca]	-1.3753	0.107	-12.819	0.000	-1.586	-1.165
C(club_name)[T.Fc Arsenal]	1.6072	0.093	17.359	0.000	1.426	1.789
C(club_name)[T.Fc Augsburg]	0.0006	0.091	0.006	0.995	-0.179	0.180
C(club_name)[T.Fc Barcelona]	1.7170	0.093	18.490	0.000	1.535	1.899
C(club_name)[T.Fc Bayern Munchen]	1.5246	0.091	16.724	0.000	1.346	1.703
C(club_name)[T.Fc Bologna]	0.1517	0.092	1.645	0.100	-0.029	0.332
C(club_name)[T.Fc Brentford]	0.7550	0.171	4.428	0.000	0.421	1.089
C(club_name)[T.Fc Brugge]	0.0540	0.092	0.590	0.555	-0.125	0.233
C(club_name)[T.Fc Burnley]	0.5212	0.100	5.215	0.000	0.325	0.717
C(club_name)[T.Fc Cadiz]	-0.5253	0.137	-3.825	0.000	-0.795	-0.256
C(club_name)[T.Fc Chelsea]	1.8779	0.095	19.743	0.000	1.691	2.064
C(club_name)[T.Fc Cordoba]	-0.5106	0.175	-2.917	0.004	-0.854	-0.167
C(club_name)[T.Fc Crotone]	-0.7456	0.114	-6.525	0.000	-0.970	-0.522
C(club_name)[T.Fc Dordrecht]	-2.1142	0.176	-12.027	0.000	-2.459	-1.770
C(club_name)[T.Fc Elche]	-0.6117	0.124	-4.915	0.000	-0.856	-0.368
C(club_name)[T.Fc Emmen]	-1.6726	0.117	-14.262	0.000	-1.903	-1.443
C(club_name)[T.Fc Empoli]	-0.3508	0.104	-3.385	0.001	-0.554	-0.148
C(club_name)[T.Fc Everton]	1.3589	0.093	14.645	0.000	1.177	1.541
C(club_name)[T.Fc Famalicao]	-0.6373	0.116	-5.489	0.000	-0.865	-0.410
C(club_name)[T.Fc Fulham]	1.0195	0.128	7.986	0.000	0.769	1.270

C(club_name)[T.Fc Getafe]	0.1145	0.095	1.205	0.228	-0.072	0.301
C(club_name)[T.Fc Girona]	-0.3297	0.132	-2.498	0.012	-0.588	-0.071
C(club_name)[T.Fc Girondins Bordeaux]	0.0052	0.092	0.057	0.955	-0.175	0.186
C(club_name)[T.Fc Granada]	-0.1854	0.098	-1.888	0.059	-0.378	0.007
C(club_name)[T.Fc Groningen]	-1.0644	0.094	-11.290	0.000	-1.249	-0.880
C(club_name)[T.Fc Helsingor]	-2.1198	0.139	-15.220	0.000	-2.393	-1.847
C(club_name)[T.Fc Ingolstadt 04]	-0.6318	0.142	-4.444	0.000	-0.910	-0.353
C(club_name)[T.Fc Kopenhagen]	-0.6901	0.092	-7.513	0.000	-0.870	-0.510
C(club_name)[T.Fc Liverpool]	1.6921	0.093	18.207	0.000	1.510	1.874
C(club_name)[T.Fc Lorient]	-0.5483	0.104	-5.296	0.000	-0.751	-0.345
C(club_name)[T.Fc Malaga]	-0.0099	0.109	-0.090	0.928	-0.224	0.204
C(club_name)[T.Fc Metz]	-0.5922	0.099	-5.952	0.000	-0.787	-0.397
C(club_name)[T.Fc Middlesbrough]	0.5626	0.151	3.734	0.000	0.267	0.858
C(club_name)[T.Fc Midtjylland]	-1.1390	0.091	-12.547	0.000	-1.317	-0.961
C(club_name)[T.Fc Nantes]	-0.3154	0.093	-3.393	0.001	-0.498	-0.133
C(club_name)[T.Fc Nordsjaelland]	-1.4411	0.093	-15.547	0.000	-1.623	-1.259
C(club_name)[T.Fc Pacos De Ferreira]	-1.4240	0.094	-15.227	0.000	-1.607	-1.241
C(club_name)[T.Fc Paris Saint Germain]	1.5523	0.091	16.995	0.000	1.373	1.731
C(club_name)[T.Fc Penafiel]	-1.3852	0.173	-8.000	0.000	-1.725	-1.046
C(club_name)[T.Fc Porto]	0.6184	0.093	6.677	0.000	0.437	0.800
C(club_name)[T.Fc Reading]	0.0733	0.250	0.293	0.769	-0.416	0.563
C(club_name)[T.Fc Schalke 04]	0.7030	0.093	7.530	0.000	0.520	0.886
C(club_name)[T.Fc Sevilla]	0.7570	0.091	8.333	0.000	0.579	0.935
C(club_name)[T.Fc Southampton]	1.0955	0.096	11.432	0.000	0.908	1.283
C(club_name)[T.Fc Stade Rennes]	0.1215	0.093	1.308	0.191	-0.061	0.304
C(club_name)[T.Fc Toulouse]	-0.1991	0.099	-2.010	0.044	-0.393	-0.005
C(club_name)[T.Fc Turin]	0.2943	0.091	3.229	0.001	0.116	0.473
C(club_name)[T.Fc Twente Enschede]	-1.0740	0.096	-11.232	0.000	-1.261	-0.887
C(club_name)[T.Fc Utrecht]	-0.8458	0.091	-9.313	0.000	-1.024	-0.668
C(club_name)[T.Fc Valencia]	1.0982	0.094	11.682	0.000	0.914	1.283
C(club_name)[T.Fc Vestsjaelland]	-1.6439	0.156	-10.544	0.000	-1.950	-1.338
C(club_name)[T.Fc Villarreal]	0.5137	0.093	5.530	0.000	0.332	0.696
C(club_name)[T.Fc Vizela]	-1.6297	0.157	-10.386	0.000	-1.937	-1.322
C(club_name)[T.Fc Watford]	0.6911	0.095	7.244	0.000	0.504	0.878
C(club_name)[T.Fenerbahce Istanbul]	0.4205	0.091	4.625	0.000	0.242	0.599

C(club_name)[T.Feyenoord Rotterdam]	-0.0774	0.093	-0.832	0.406	-0.260	0.105
C(club_name)[T.Fk Khimki]	-0.8106	0.134	-6.053	0.000	-1.073	-0.548
C(club_name)[T.Fk Krasnodar]	0.1754	0.092	1.914	0.056	-0.004	0.355
C(club_name)[T.Fk Mariupol]	-1.4170	0.107	-13.245	0.000	-1.627	-1.207
C(club_name)[T.Fk Minaj]	-2.0720	0.161	-12.867	0.000	-2.388	-1.756
C(club_name)[T.Fk Nizhny Novgorod]	-0.8599	0.160	-5.376	0.000	-1.173	-0.546
C(club_name)[T.Fk Oleksandriya]	-1.4665	0.100	-14.663	0.000	-1.663	-1.270
C(club_name)[T.Fk Orenburg]	-0.9932	0.108	-9.218	0.000	-1.204	-0.782
C(club_name)[T.Fk Rostov]	-0.5281	0.091	-5.780	0.000	-0.707	-0.349
C(club_name)[T.Fk Sochi]	-0.4985	0.112	-4.448	0.000	-0.718	-0.279
C(club_name)[T.Fk Tosno]	-0.9606	0.142	-6.750	0.000	-1.240	-0.682
C(club_name)[T.Fk Ufa]	-0.9799	0.095	-10.312	0.000	-1.166	-0.794
C(club_name)[T.Fortuna Dusseldorf]	-0.0882	0.129	-0.684	0.494	-0.341	0.165
C(club_name)[T.Fortuna Sittard]	-1.4634	0.108	-13.527	0.000	-1.675	-1.251
C(club_name)[T.Frosinone Calcio]	-0.4184	0.132	-3.182	0.001	-0.676	-0.161
C(club_name)[T.Galatasaray Istanbul]	0.3332	0.092	3.606	0.000	0.152	0.514
C(club_name)[T.Gaziantep Fk]	-0.9243	0.120	-7.713	0.000	-1.159	-0.689
C(club_name)[T.Gaziantepspor]	-0.7521	0.119	-6.326	0.000	-0.985	-0.519
C(club_name)[T.Gd Chaves]	-1.2759	0.114	-11.205	0.000	-1.499	-1.053
C(club_name)[T.Gd Estoril Praia]	-1.2582	0.101	-12.488	0.000	-1.456	-1.061
C(club_name)[T.Genclerbirligi Ankara]	-0.8519	0.098	-8.669	0.000	-1.044	-0.659
C(club_name)[T.Genua Cfc]	0.1793	0.093	1.930	0.054	-0.003	0.361
C(club_name)[T.Gfc Ajaccio]	-1.5764	0.197	-7.990	0.000	-1.963	-1.190
C(club_name)[T.Gil Vicente Fc]	-1.4171	0.110	-12.899	0.000	-1.632	-1.202
C(club_name)[T.Giresunspor]	-0.6760	0.221	-3.058	0.002	-1.109	-0.243
C(club_name)[T.Glasgow Rangers]	-0.5688	0.097	-5.877	0.000	-0.759	-0.379
C(club_name)[T.Go Ahead Eagles Deventer]	-1.8404	0.131	-14.100	0.000	-2.096	-1.585
C(club_name)[T.Goverla Uzhgorod]	-1.5059	0.133	-11.328	0.000	-1.766	-1.245
C(club_name)[T.Goztepe]	-0.7922	0.103	-7.666	0.000	-0.995	-0.590
C(club_name)[T.Gs Ergotelis]	-1.4728	0.157	-9.365	0.000	-1.781	-1.165
C(club_name)[T.Hamburger Sv]	-0.0352	0.109	-0.323	0.747	-0.249	0.178
C(club_name)[T.Hamilton Academical Fc]	-2.1996	0.102	-21.488	0.000	-2.400	-1.999
C(club_name)[T.Hannover 96]	-0.1220	0.108	-1.134	0.257	-0.333	0.089
C(club_name)[T.Hatayspor]	-1.1647	0.149	-7.809	0.000	-1.457	-0.872
C(club_name)[T.Heart Of Midlothian Fc]	-1.3573	0.098	-13.846	0.000	-1.549	-1.165

C(club_name)[T.Hellas Verona]	-0.2078	0.096	-2.173	0.030	-0.395	-0.020
C(club_name)[T.Heracles Almelo]	-1.5233	0.093	-16.412	0.000	-1.705	-1.341
C(club_name)[T.Hertha Bsc]	0.3591	0.092	3.901	0.000	0.179	0.540
C(club_name)[T.Hibernian Fc]	-1.2933	0.106	-12.182	0.000	-1.501	-1.085
C(club_name)[T.Hobro Ik]	-1.9213	0.099	-19.329	0.000	-2.116	-1.726
C(club_name)[T.Huddersfield Town]	0.1015	0.132	0.769	0.442	-0.157	0.360
C(club_name)[T.Hull City]	0.5449	0.125	4.347	0.000	0.299	0.791
C(club_name)[T.Ingulets Petrove]	-1.8998	0.149	-12.711	0.000	-2.193	-1.607
C(club_name)[T.Inter Mailand]	1.1320	0.092	12.316	0.000	0.952	1.312
C(club_name)[T.Inverness Caledonian Thistle Fc]	-2.2548	0.139	-16.232	0.000	-2.527	-1.983
C(club_name)[T.Ionikos Nikeas]	-1.8971	0.190	-9.964	0.000	-2.270	-1.524
C(club_name)[T.Iraklis Thessaloniki]	-1.8644	0.132	-14.131	0.000	-2.123	-1.606
C(club_name)[T.Istanbul Basaksehir Fk]	-0.1475	0.092	-1.607	0.108	-0.327	0.032
C(club_name)[T.Juventus Turin]	1.5165	0.093	16.346	0.000	1.335	1.698
C(club_name)[T.Kaa Gent]	-0.3283	0.089	-3.673	0.000	-0.503	-0.153
C(club_name)[T.Kardemir Karabukspor]	-0.7373	0.117	-6.306	0.000	-0.966	-0.508
C(club_name)[T.Karpaty Lviv]	-1.4416	0.100	-14.371	0.000	-1.638	-1.245
C(club_name)[T.Kas Eupen]	-1.2221	0.094	-12.991	0.000	-1.406	-1.038
C(club_name)[T.Kasimpasa]	-0.6707	0.094	-7.168	0.000	-0.854	-0.487
C(club_name)[T.Kayseri Erciyesspor]	-0.5147	0.170	-3.020	0.003	-0.849	-0.181
C(club_name)[T.Kayserispor]	-0.8202	0.094	-8.680	0.000	-1.005	-0.635
C(club_name)[T.Kilmarnock Fc]	-1.8104	0.104	-17.431	0.000	-2.014	-1.607
C(club_name)[T.Kolos Kovalivka]	-1.7208	0.121	-14.214	0.000	-1.958	-1.484
C(club_name)[T.Konyaspor]	-0.8049	0.093	-8.666	0.000	-0.987	-0.623
C(club_name)[T.Krc Genk]	-0.2330	0.090	-2.583	0.010	-0.410	-0.056
C(club_name)[T.Krylya Sovetov Samara]	-0.5053	0.097	-5.217	0.000	-0.695	-0.315
C(club_name)[T.Ksc Lokeren]	-0.9655	0.098	-9.816	0.000	-1.158	-0.773
C(club_name)[T.Kuban Krasnodar]	-0.5086	0.149	-3.414	0.001	-0.801	-0.217
C(club_name)[T.Kv Kortrijk]	-0.9904	0.091	-10.844	0.000	-1.169	-0.811
C(club_name)[T.Kv Mechelen]	-0.9513	0.092	-10.310	0.000	-1.132	-0.770
C(club_name)[T.Kv Oostende]	-0.9321	0.090	-10.326	0.000	-1.109	-0.755
C(club_name)[T.Kvc Westerlo]	-1.3165	0.123	-10.676	0.000	-1.558	-1.075
C(club_name)[T.Lazio Rom]	0.5748	0.092	6.257	0.000	0.395	0.755
C(club_name)[T.Leeds United]	0.8682	0.133	6.546	0.000	0.608	1.128
C(club_name)[T.Leicester City]	0.9799	0.094	10.374	0.000	0.795	1.165

C(club_name)[T.Lierse Sk]	-1.0180	0.162	-6.280	0.000	-1.336	-0.700
C(club_name)[T.Livingston Fc]	-1.8763	0.110	-17.048	0.000	-2.092	-1.661
C(club_name)[T.Lokomotiv Moskau]	0.0954	0.094	1.019	0.308	-0.088	0.279
C(club_name)[T.Losc Lille]	0.3121	0.094	3.324	0.001	0.128	0.496
C(club_name)[T.Lyngby Bk]	-1.8061	0.103	-17.564	0.000	-2.008	-1.605
C(club_name)[T.Manchester City]	1.8927	0.095	20.005	0.000	1.707	2.078
C(club_name)[T.Manchester United]	1.7674	0.093	19.030	0.000	1.585	1.949
C(club_name)[T.Mersin Idmanyurdu]	-1.1230	0.140	-8.002	0.000	-1.398	-0.848
C(club_name)[T.Metalist 1925 Kharkiv]	-1.7694	0.173	-10.199	0.000	-2.109	-1.429
C(club_name)[T.Metalist Kharkiv]	-0.6346	0.129	-4.907	0.000	-0.888	-0.381
C(club_name)[T.Metalurg Donetsk]	-0.9515	0.191	-4.980	0.000	-1.326	-0.577
C(club_name)[T.Metalurg Zaporizhya Bis 2016]	-1.3840	0.139	-9.973	0.000	-1.656	-1.112
C(club_name)[T.Mke Ankaragucu]	-1.4019	0.110	-12.699	0.000	-1.618	-1.186
C(club_name)[T.Montpellier Hsc]	-0.4151	0.094	-4.431	0.000	-0.599	-0.231
C(club_name)[T.Mordovia Saransk]	-0.6939	0.146	-4.737	0.000	-0.981	-0.407
C(club_name)[T.Moreirense Fc]	-1.5195	0.091	-16.694	0.000	-1.698	-1.341
C(club_name)[T.Motherwell Fc]	-1.7634	0.100	-17.638	0.000	-1.959	-1.567
C(club_name)[T.Nac Breda]	-1.6113	0.118	-13.656	0.000	-1.843	-1.380
C(club_name)[T.Nec Nijmegen]	-1.4866	0.123	-12.132	0.000	-1.727	-1.246
C(club_name)[T.Newcastle United]	1.0884	0.095	11.426	0.000	0.902	1.275
C(club_name)[T.Niki Volou]	-1.6956	0.187	-9.060	0.000	-2.062	-1.329
C(club_name)[T.Nimes Olympique]	-0.2397	0.120	-1.991	0.047	-0.476	-0.004
C(club_name)[T.Nk Veres Rivne]	-1.5937	0.137	-11.661	0.000	-1.862	-1.326
C(club_name)[T.Norwich City]	0.6714	0.116	5.798	0.000	0.444	0.898
C(club_name)[T.Odense Boldklub]	-1.4570	0.095	-15.400	0.000	-1.642	-1.272
C(club_name)[T.Ofi Kreta]	-1.5216	0.102	-14.939	0.000	-1.721	-1.322
C(club_name)[T.Ogc Nizza]	0.3334	0.093	3.572	0.000	0.150	0.516
C(club_name)[T.Olimpik Donetsk]	-1.6456	0.098	-16.763	0.000	-1.838	-1.453
C(club_name)[T.Olympiakos Piraus]	-0.1644	0.090	-1.834	0.067	-0.340	0.011
C(club_name)[T.Olympique Lyon]	0.7555	0.093	8.161	0.000	0.574	0.937
C(club_name)[T.Olympique Marseille]	0.4870	0.093	5.262	0.000	0.306	0.668
C(club_name)[T.Oud Heverlee Leuven]	-1.1777	0.119	-9.869	0.000	-1.412	-0.944
C(club_name)[T.Palermo Fc]	-0.4999	0.115	-4.339	0.000	-0.726	-0.274
C(club_name)[T.Panathinaikos Athen]	-0.8554	0.089	-9.598	0.000	-1.030	-0.681
C(club_name)[T.Panetolikos Gfs]	-1.6353	0.092	-17.700	0.000	-1.816	-1.454

C(club_name)[T.Panionios Athen]	-1.6285	0.097	-16.719	0.000	-1.819	-1.438
C(club_name)[T.Panthrakikos Komotini]	-1.7697	0.132	-13.366	0.000	-2.029	-1.510
C(club_name)[T.Paok Thessaloniki]	-0.4713	0.090	-5.236	0.000	-0.648	-0.295
C(club_name)[T.Parma Calcio 1913]	0.0142	0.105	0.136	0.892	-0.192	0.220
C(club_name)[T.Partick Thistle Fc]	-1.9459	0.123	-15.815	0.000	-2.187	-1.705
C(club_name)[T.Pas Giannina]	-1.6537	0.097	-17.049	0.000	-1.844	-1.464
C(club_name)[T.Pas Lamia 1964]	-1.9142	0.099	-19.318	0.000	-2.108	-1.720
C(club_name)[T.Pec Zwolle]	-1.3495	0.093	-14.468	0.000	-1.532	-1.167
C(club_name)[T.Pfk Lviv]	-1.8235	0.116	-15.692	0.000	-2.051	-1.596
C(club_name)[T.Pfk Stal Kamyanske]	-1.5078	0.121	-12.496	0.000	-1.744	-1.271
C(club_name)[T.Pfk Tambov]	-1.2875	0.120	-10.716	0.000	-1.523	-1.052
C(club_name)[T.Portimonense Sc]	-1.3102	0.101	-12.930	0.000	-1.509	-1.112
C(club_name)[T.Psv Eindhoven]	0.2291	0.093	2.471	0.013	0.047	0.411
C(club_name)[T.Queens Park Rangers]	0.2684	0.184	1.462	0.144	-0.091	0.628
C(club_name)[T.Randers Fc]	-1.5948	0.094	-16.964	0.000	-1.779	-1.411
C(club_name)[T.Rasenballsport Leipzig]	1.0711	0.096	11.103	0.000	0.882	1.260
C(club_name)[T.Rayo Vallecano]	-0.3662	0.112	-3.279	0.001	-0.585	-0.147
C(club_name)[T.Rc Lens]	-0.5160	0.130	-3.965	0.000	-0.771	-0.261
C(club_name)[T.Rc Strassburg Alsace]	-0.1745	0.105	-1.667	0.095	-0.380	0.031
C(club_name)[T.Rcd Mallorca]	-0.2553	0.127	-2.006	0.045	-0.505	-0.006
C(club_name)[T.Real Betis Sevilla]	0.3661	0.094	3.880	0.000	0.181	0.551
C(club_name)[T.Real Madrid]	1.7153	0.092	18.640	0.000	1.535	1.896
C(club_name)[T.Real Saragossa]	-0.2053	0.393	-0.523	0.601	-0.975	0.565
C(club_name)[T.Real Sociedad San Sebastian]	0.6646	0.092	7.224	0.000	0.484	0.845
C(club_name)[T.Real Valladolid]	-0.1992	0.111	-1.791	0.073	-0.417	0.019
C(club_name)[T.Rfc Seraing]	-1.5597	0.165	-9.478	0.000	-1.882	-1.237
C(club_name)[T.Rio Ave Fc]	-1.1447	0.095	-11.991	0.000	-1.332	-0.958
C(club_name)[T.Rkc Waalwijk]	-1.7844	0.119	-15.036	0.000	-2.017	-1.552
C(club_name)[T.Roda Jc Kerkrade]	-1.6062	0.121	-13.251	0.000	-1.844	-1.369
C(club_name)[T.Ross County Fc]	-1.8293	0.100	-18.227	0.000	-2.026	-1.633
C(club_name)[T.Rotor Volgograd]	-0.9214	0.185	-4.984	0.000	-1.284	-0.559
C(club_name)[T.Royal Antwerpen Fc]	-0.6318	0.098	-6.446	0.000	-0.824	-0.440
C(club_name)[T.Royal Excel Mouscron]	-1.2765	0.091	-13.984	0.000	-1.455	-1.098
C(club_name)[T.Royale Union Saint Gilloise]	-0.8386	0.154	-5.435	0.000	-1.141	-0.536
C(club_name)[T.Rsc Anderlecht]	0.1837	0.088	2.086	0.037	0.011	0.356

C(club_name)[T.Rsc Charleroi]	-0.9001	0.091	-9.856	0.000	-1.079	-0.721
C(club_name)[T.Rubin Kazan]	-0.3546	0.096	-3.709	0.000	-0.542	-0.167
C(club_name)[T.Rukh Lviv]	-1.7859	0.143	-12.499	0.000	-2.066	-1.506
C(club_name)[T.Sampdoria Genua]	0.2594	0.093	2.789	0.005	0.077	0.442
C(club_name)[T.Sbv Excelsior Rotterdam]	-1.7153	0.107	-16.088	0.000	-1.924	-1.506
C(club_name)[T.Sc Bastia]	-1.0434	0.122	-8.548	0.000	-1.283	-0.804
C(club_name)[T.Sc Beira Mar]	-0.5714	0.867	-0.659	0.510	-2.271	1.128
C(club_name)[T.Sc Braga]	-0.2989	0.091	-3.282	0.001	-0.478	-0.120
C(club_name)[T.Sc Cambuur Leeuwarden]	-1.6969	0.126	-13.475	0.000	-1.944	-1.450
C(club_name)[T.Sc Farense]	-1.6438	0.178	-9.246	0.000	-1.992	-1.295
C(club_name)[T.Sc Freiburg]	0.0856	0.093	0.919	0.358	-0.097	0.268
C(club_name)[T.Sc Heerenveen]	-1.0551	0.096	-11.040	0.000	-1.242	-0.868
C(club_name)[T.Sc Olhanense]	-2.0547	0.870	-2.362	0.018	-3.759	-0.350
C(club_name)[T.Sc Paderborn 07]	-0.8829	0.143	-6.165	0.000	-1.164	-0.602
C(club_name)[T.Sco Angers]	-0.4928	0.094	-5.216	0.000	-0.678	-0.308
C(club_name)[T.Sd Eibar]	-0.3049	0.098	-3.105	0.002	-0.497	-0.112
C(club_name)[T.Sd Huesca]	-0.5592	0.133	-4.214	0.000	-0.819	-0.299
C(club_name)[T.Shakhtar Donetsk]	0.4848	0.093	5.214	0.000	0.303	0.667
C(club_name)[T.Sheffield United]	0.6197	0.139	4.467	0.000	0.348	0.892
C(club_name)[T.Silkeborg If]	-1.7335	0.100	-17.412	0.000	-1.929	-1.538
C(club_name)[T.Sivasspor]	-0.7092	0.097	-7.322	0.000	-0.899	-0.519
C(club_name)[T.Sk Dnipro 1]	-1.3228	0.121	-10.974	0.000	-1.559	-1.087
C(club_name)[T.Ska Khabarovsk]	-1.1513	0.135	-8.548	0.000	-1.415	-0.887
C(club_name)[T.Sm Caen]	-0.8034	0.110	-7.281	0.000	-1.020	-0.587
C(club_name)[T.Sonderjyske]	-1.7216	0.092	-18.650	0.000	-1.903	-1.541
C(club_name)[T.Spal]	-0.1259	0.108	-1.161	0.246	-0.339	0.087
C(club_name)[T.Sparta Rotterdam]	-1.4662	0.103	-14.212	0.000	-1.668	-1.264
C(club_name)[T.Spartak Moskau]	0.3307	0.096	3.435	0.001	0.142	0.519
C(club_name)[T.Spezia Calcio]	-0.2332	0.127	-1.833	0.067	-0.483	0.016
C(club_name)[T.Sporting Gijon]	-0.4350	0.136	-3.194	0.001	-0.702	-0.168
C(club_name)[T.Sporting Lissabon]	0.3628	0.090	4.042	0.000	0.187	0.539
C(club_name)[T.Spvgg Greuther Furth]	-0.5461	0.180	-3.041	0.002	-0.898	-0.194
C(club_name)[T.Ssc Neapel]	1.3826	0.093	14.811	0.000	1.200	1.566
C(club_name)[T.St Johnstone Fc]	-1.6149	0.100	-16.220	0.000	-1.810	-1.420
C(club_name)[T.St Mirren Fc]	-1.7823	0.112	-15.963	0.000	-2.001	-1.563

C(club_name)[T.Stade Brest 29]	-0.1555	0.124	-1.258	0.208	-0.398	0.087
C(club_name)[T.Stade Reims]	-0.1831	0.099	-1.856	0.063	-0.377	0.010
C(club_name)[T.Standard Luttich]	-0.2957	0.089	-3.327	0.001	-0.470	-0.122
C(club_name)[T.Stoke City]	0.6480	0.111	5.846	0.000	0.431	0.865
C(club_name)[T.Sv Darmstadt 98]	-0.8247	0.133	-6.198	0.000	-1.086	-0.564
C(club_name)[T.Sv Werder Bremen]	-0.0810	0.093	-0.871	0.384	-0.263	0.101
C(club_name)[T.Sv Zulte Waregem]	-0.9577	0.091	-10.493	0.000	-1.137	-0.779
C(club_name)[T.Swansea City]	0.4265	0.113	3.762	0.000	0.204	0.649
C(club_name)[T.Thonon Evian Grand Geneve Fc]	-0.7158	0.190	-3.770	0.000	-1.088	-0.344
C(club_name)[T.Tom Tomsk]	-1.2667	0.165	-7.669	0.000	-1.590	-0.943
C(club_name)[T.Torpedo Moskau]	-0.9719	0.182	-5.353	0.000	-1.328	-0.616
C(club_name)[T.Tottenham Hotspur]	1.6657	0.095	17.608	0.000	1.480	1.851
C(club_name)[T.Trabzonspor]	-0.1516	0.093	-1.634	0.102	-0.333	0.030
C(club_name)[T.Tsg 1899 Hoffenheim]	0.4987	0.092	5.446	0.000	0.319	0.678
C(club_name)[T.Ud Almeria]	-0.9034	0.194	-4.650	0.000	-1.284	-0.523
C(club_name)[T.Ud Las Palmas]	-0.5201	0.114	-4.581	0.000	-0.743	-0.298
C(club_name)[T.Ud Levante]	-0.1908	0.094	-2.027	0.043	-0.375	-0.006
C(club_name)[T.Udinese Calcio]	0.1533	0.093	1.652	0.099	-0.029	0.335
C(club_name)[T.Ural Ekaterinburg]	-0.9385	0.095	-9.919	0.000	-1.124	-0.753
C(club_name)[T.Us Lecce]	-0.3279	0.147	-2.232	0.026	-0.616	-0.040
C(club_name)[T.Us Salernitana 1919]	-0.3425	0.162	-2.117	0.034	-0.660	-0.025
C(club_name)[T.Us Sassuolo]	0.2407	0.092	2.612	0.009	0.060	0.421
C(club_name)[T.Vejle Boldklub]	-1.6151	0.113	-14.321	0.000	-1.836	-1.394
C(club_name)[T.Vendsyssel Ff]	-1.6472	0.135	-12.208	0.000	-1.912	-1.383
C(club_name)[T.Venezia Fc]	-0.2438	0.164	-1.490	0.136	-0.564	0.077
C(club_name)[T.Veria Nps]	-1.7127	0.119	-14.437	0.000	-1.945	-1.480
C(club_name)[T.Vfb Stuttgart]	0.2793	0.097	2.886	0.004	0.090	0.469
C(club_name)[T.Vfl Bochum]	-0.6721	0.174	-3.853	0.000	-1.014	-0.330
C(club_name)[T.Vfl Wolfsburg]	0.6672	0.092	7.222	0.000	0.486	0.848
C(club_name)[T.Viborg Ff]	-1.6879	0.109	-15.556	0.000	-1.901	-1.475
C(club_name)[T.Vitesse Arnheim]	-0.8675	0.094	-9.241	0.000	-1.052	-0.684
C(club_name)[T.Vitoria Guimaraes Sc]	-0.8025	0.091	-8.818	0.000	-0.981	-0.624
C(club_name)[T.Vitoria Setubal Fc]	-1.4773	0.098	-15.023	0.000	-1.670	-1.285
C(club_name)[T.Volga Nizhniy Novgorod]	-1.3473	0.617	-2.185	0.029	-2.556	-0.139
C(club_name)[T.Volos Nps]	-1.8088	0.124	-14.620	0.000	-2.051	-1.566

C(club_name)[T.Volyn Lutsk]	-1.5340	0.128	-12.000	0.000	-1.785	-1.283
C(club_name)[T.Vorskla Poltava]	-1.2073	0.097	-12.403	0.000	-1.398	-1.016
C(club_name)[T.Vv St Truiden]	-1.0456	0.092	-11.426	0.000	-1.225	-0.866
C(club_name)[T.Vvv Venlo]	-1.6141	0.109	-14.779	0.000	-1.828	-1.400
C(club_name)[T.Waasland Beveren]	-1.1518	0.092	-12.507	0.000	-1.332	-0.971
C(club_name)[T.West Bromwich Albion]	0.5443	0.107	5.077	0.000	0.334	0.754
C(club_name)[T.West Ham United]	1.0111	0.095	10.668	0.000	0.825	1.197
C(club_name)[T.Wigan Athletic]	-0.9346	0.369	-2.532	0.011	-1.658	-0.211
C(club_name)[T.Willem Ii Tilburg]	-1.3026	0.095	-13.759	0.000	-1.488	-1.117
C(club_name)[T.Wolverhampton Wanderers]	1.0977	0.110	9.976	0.000	0.882	1.313
C(club_name)[T.Yeni Malatyaspor]	-1.0827	0.103	-10.469	0.000	-1.285	-0.880
C(club_name)[T.Zenit St Petersburg]	0.6839	0.095	7.171	0.000	0.497	0.871
C(club_name)[T.Zirka Kropyvnytskyi]	-1.7463	0.129	-13.488	0.000	-2.000	-1.493
C(club_name)[T.Zorya Lugansk]	-1.1676	0.096	-12.134	0.000	-1.356	-0.979
C(club_name)[T.Zska Moskau]	0.3449	0.094	3.660	0.000	0.160	0.530
age	0.0201	0.001	20.931	0.000	0.018	0.022
goals	0.0080	0.001	10.457	0.000	0.007	0.009
assists	0.0151	0.001	13.086	0.000	0.013	0.017
minutes_played	0.0002	2.99e-06	68.984	0.000	0.000	0.000
yellow_cards	3.191e-05	0.001	0.035	0.972	-0.002	0.002
red_cards	0.0190	0.007	2.631	0.009	0.005	0.033
height	0.0027	0.000	11.838	0.000	0.002	0.003

Omnibus:	2497.905	**Durbin-Watson:**	1.351
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	3773.239
Skew:	-0.442	**Prob(JB):**	0.00
Kurtosis:	4.001	**Cond. No.**	1.57e+19

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.53e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [ ]:

```
print(np.exp(y))
print(np.exp(pred3))
```

```
np.sqrt(mean_squared_error((y),(pred3)))
```

```
            log_market_value
player_id
9800                 90000.0
43084               360000.0
230826              360000.0
198087             1530000.0
110689               68000.0
...                      ...
364245              420000.0
364245             1102500.0
364245             5400000.0
575367              658250.0
575367              765000.0

[50781 rows x 1 columns]
player_id
9800      1.742980e+05
43084     2.559757e+06
230826    8.474457e+05
198087    1.757640e+06
110689    9.412867e+04
              ...
364245    9.750404e+05
364245    4.477367e+06
364245    3.204029e+06
575367    1.339464e+06
575367    1.307280e+06
Length: 50781, dtype: float64
```

Out[ ]:

```
0.8588668100888358
```

In [ ]:

```
def diagnostic_plot(x, y):
    plt.figure(figsize=(20,5))

    rgr = LinearRegression()
    rgr.fit(x,y)
    pred = rgr.predict(x)

    plt.subplot(1, 3, 1)
    plt.scatter(pred,y,alpha=0.1)
    plt.plot(y, y, color='red',linewidth=1,)
    plt.title("Regression fit")
    plt.xlabel("Predicted y")
    plt.ylabel("y")

y = data['all_eda']['log_market_value']
X = data['all_eda'][[
    'goals',
    'assists',
    'minutes_played',
    'yellow_cards',
    'red_cards',
    'height',
    'age'
   # 'nationality',
   # 'position',
```

```
    # 'sub_position',
    # 'club_name'
]]
```

In [ ]:

```
sns.set(style='darkgrid')
diagnostic_plot(X, y)
```