Introduction

This project goal is to analysis to dataset. How is the distrubution of the features. Such as player market values or player ages etc. Firstly, we will make a visualization.

Step 0 - Load Data

Reading data and checking initial features. Also, I will import some libraries that are necessary.

In [1]:
```python
#some useful library and necessary things
import pandas as pd
import numpy as np


from scipy.stats import pearsonr

import matplotlib.pyplot as plt
import seaborn as sns

from IPython.display import display
```

In [2]:
```python
#Read data from .csv file

f_players = pd.read_csv("train.csv")

display(f_players.head())
print(f"Total number of rows: {f_players.shape[0]}\nTotal number of columns: {f_players.shape[1]}")
```

	Unnamed: 0	ID	Name	Age	Photo	Nationality	Flag	Overall	Potential
0	0	158023	L. Messi	31	https://cdn.sofifa.org/players/4/19/158023.png	Argentina	https://cdn.sofifa.org/flags/52.png	94	94
1	1	20801	Cristiano Ronaldo	33	https://cdn.sofifa.org/players/4/19/20801.png	Portugal	https://cdn.sofifa.org/flags/38.png	94	94
2	2	190871	Neymar Jr	26	https://cdn.sofifa.org/players/4/19/190871.png	Brazil	https://cdn.sofifa.org/flags/54.png	92	93
3	3	193080	De Gea	27	https://cdn.sofifa.org/players/4/19/193080.png	Spain	https://cdn.sofifa.org/flags/45.png	91	93
4	4	192985	K. De Bruyne	27	https://cdn.sofifa.org/players/4/19/192985.png	Belgium	https://cdn.sofifa.org/flags/7.png	91	92

5 rows × 89 columns

```
Total number of rows: 18207
Total number of columns: 89
```

Our dataset has a 89 features and 18207 examples.

In [3]:
```python
f_players.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18207 entries, 0 to 18206
Data columns (total 89 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Unnamed: 0                18207 non-null  int64
 1   ID                        18207 non-null  int64
 2   Name                      18207 non-null  object
 3   Age                       18207 non-null  int64
 4   Photo                     18207 non-null  object
 5   Nationality               18207 non-null  object
 6   Flag                      18207 non-null  object
 7   Overall                   18207 non-null  int64
 8   Potential                 18207 non-null  int64
 9   Club                      17966 non-null  object
 10  Club Logo                 18207 non-null  object
 11  Value                     18207 non-null  object
 12  Wage                      18207 non-null  object
 13  Special                   18207 non-null  int64
 14  Preferred Foot            18159 non-null  object
 15  International Reputation  18159 non-null  float64
 16  Weak Foot                 18159 non-null  float64
 17  Skill Moves               18159 non-null  float64
 18  Work Rate                 18159 non-null  object
 19  Body Type                 18159 non-null  object
 20  Real Face                 18159 non-null  object
 21  Position                  18147 non-null  object
 22  Jersey Number             18147 non-null  float64
 23  Joined                    16654 non-null  object
 24  Loaned From               1264 non-null   object
 25  Contract Valid Until      17918 non-null  object
 26  Height                    18159 non-null  object
 27  Weight                    18159 non-null  object
 28  LS                        16122 non-null  object
 29  ST                        16122 non-null  object
 30  RS                        16122 non-null  object
 31  LW                        16122 non-null  object
 32  LF                        16122 non-null  object
 33  CF                        16122 non-null  object
 34  RF                        16122 non-null  object
 35  RW                        16122 non-null  object
 36  LAM                       16122 non-null  object
 37  CAM                       16122 non-null  object
 38  RAM                       16122 non-null  object
 39  LM                        16122 non-null  object
 40  LCM                       16122 non-null  object
 41  CM                        16122 non-null  object
 42  RCM                       16122 non-null  object
 43  RM                        16122 non-null  object
 44  LWB                       16122 non-null  object
 45  LDM                       16122 non-null  object
 46  CDM                       16122 non-null  object
 47  RDM                       16122 non-null  object
 48  RWB                       16122 non-null  object
 49  LB                        16122 non-null  object
 50  LCB                       16122 non-null  object
 51  CB                        16122 non-null  object
 52  RCB                       16122 non-null  object
 53  RB                        16122 non-null  object
 54  Crossing                  18159 non-null  float64
 55  Finishing                 18159 non-null  float64
 56  HeadingAccuracy           18159 non-null  float64
 57  ShortPassing              18159 non-null  float64
 58  Volleys                   18159 non-null  float64
 59  Dribbling                 18159 non-null  float64
 60  Curve                     18159 non-null  float64
 61  FKAccuracy                18159 non-null  float64
 62  LongPassing               18159 non-null  float64
 63  BallControl               18159 non-null  float64
 64  Acceleration              18159 non-null  float64
 65  SprintSpeed               18159 non-null  float64
 66  Agility                   18159 non-null  float64
 67  Reactions                 18159 non-null  float64
 68  Balance                   18159 non-null  float64
 69  ShotPower                 18159 non-null  float64
 70  Jumping                   18159 non-null  float64
 71  Stamina                   18159 non-null  float64
 72  Strength                  18159 non-null  float64
 73  LongShots                 18159 non-null  float64
 74  Aggression                18159 non-null  float64
 75  Interceptions             18159 non-null  float64
 76  Positioning               18159 non-null  float64
 77  Vision                    18159 non-null  float64
 78  Penalties                 18159 non-null  float64
 79  Composure                 18159 non-null  float64
 80  Marking                   18159 non-null  float64
 81  StandingTackle            18159 non-null  float64
 82  SlidingTackle             18159 non-null  float64
 83  GKDiving                  18159 non-null  float64
 84  GKHandling                18159 non-null  float64
 85  GKKicking                 18159 non-null  float64
 86  GKPositioning             18159 non-null  float64
 87  GKReflexes                18159 non-null  float64
 88  Release Clause            16643 non-null  object
dtypes: float64(38), int64(6), object(45)
memory usage: 12.4+ MB
```

As you can see the above, in our dataset have 89 features and these are different type. Such as 38 variables are float, 6 variables are integer and 45 variables object. In the next step, we need convert float to integer.

In [4]:
```python
# fp is our new data set.
#drop_columns = [ 'Unnamed: 0', 'ID','Name', 'Photo', 'Flag','Club Logo','Real Face','Joined','Loaned From','Re
#fp = f_players.copy()
#fp.drop(drop_columns, axis =1 , inplace = True)
#display(fp.head())
#print(f"Total number of rows: {fp.shape[0]}\nTotal number of columns: {fp.shape[1]}")
```

In [5]:
```python
f_players.columns.values
```

Out[5]:
```
array(['Unnamed: 0', 'ID', 'Name', 'Age', 'Photo', 'Nationality', 'Flag',
       'Overall', 'Potential', 'Club', 'Club Logo', 'Value', 'Wage',
       'Special', 'Preferred Foot', 'International Reputation',
       'Weak Foot', 'Skill Moves', 'Work Rate', 'Body Type', 'Real Face',
       'Position', 'Jersey Number', 'Joined', 'Loaned From',
       'Contract Valid Until', 'Height', 'Weight', 'LS', 'ST', 'RS', 'LW',
       'LF', 'CF', 'RF', 'RW', 'LAM', 'CAM', 'RAM', 'LM', 'LCM', 'CM',
       'RCM', 'RM', 'LWB', 'LDM', 'CDM', 'RDM', 'RWB', 'LB', 'LCB', 'CB',
       'RCB', 'RB', 'Crossing', 'Finishing', 'HeadingAccuracy',
       'ShortPassing', 'Volleys', 'Dribbling', 'Curve', 'FKAccuracy',
       'LongPassing', 'BallControl', 'Acceleration', 'SprintSpeed',
       'Agility', 'Reactions', 'Balance', 'ShotPower', 'Jumping',
       'Stamina', 'Strength', 'LongShots', 'Aggression', 'Interceptions',
       'Positioning', 'Vision', 'Penalties', 'Composure', 'Marking',
       'StandingTackle', 'SlidingTackle', 'GKDiving', 'GKHandling',
       'GKKicking', 'GKPositioning', 'GKReflexes', 'Release Clause'],
      dtype=object)
```

Step 0.1 Missing Data

One of the most important things is checking the dataset before analyzing it. In this step, I will check the missing data, and if we have that clarify where is it.

In [6]:
```python
total = f_players.isnull().sum().sort_values(ascending=False)
percent= f_players.isnull().sum()/f_players.isnull().count()*100
percent_2 = (round(percent, 1))
missing_data = pd.concat([total, percent_2], axis=1, keys=['Total', '%'])
missing_data.head(60)
```

Out[6]:

	Total	%
Loaned From	16943	93.1
LWB	2085	11.5
LM	2085	11.5
CB	2085	11.5
LCB	2085	11.5
LB	2085	11.5
RWB	2085	11.5
RDM	2085	11.5
CDM	2085	11.5
LDM	2085	11.5
RM	2085	11.5
RCM	2085	11.5
CM	2085	11.5
LCM	2085	11.5
RAM	2085	11.5
RB	2085	11.5
CAM	2085	11.5
LAM	2085	11.5
RW	2085	11.5
RF	2085	11.5
CF	2085	11.5
LF	2085	11.5
LW	2085	11.5
RS	2085	11.5
ST	2085	11.5
LS	2085	11.5
RCB	2085	11.5
Release Clause	1564	8.6
Joined	1553	8.5
Contract Valid Until	289	1.6
Club	241	1.3
Position	60	0.3
Jersey Number	60	0.3
Marking	48	0.3
StandingTackle	48	0.3
SlidingTackle	48	0.3
Dribbling	48	0.3
GKHandling	48	0.3
GKKicking	48	0.3
Weight	48	0.3
Height	48	0.3
Curve	48	0.3
GKPositioning	48	0.3
Penalties	48	0.3
Real Face	48	0.3
Body Type	48	0.3
Work Rate	48	0.3
Skill Moves	48	0.3
Weak Foot	48	0.3
International Reputation	48	0.3
Preferred Foot	48	0.3
Composure	48	0.3
GKDiving	48	0.3
Vision	48	0.3
Agility	48	0.3
Volleys	48	0.3
ShortPassing	48	0.3
HeadingAccuracy	48	0.3
Finishing	48	0.3
Positioning	48	0.3

In [7]:
```python
"""Club has 241 missing values and GKKicking 48 values, and RCB,
CAM some specific positions have 2085 missing values but they are goalkeeper
and this is make sense. Be careful. We are dropping these missing datapoints"""

f_players = f_players.loc[f_players['Club'].notnull()].copy()
f_players = f_players.loc[f_players['GKKicking'].notnull()].copy()
f_players.drop(['Loaned From'] ,axis =1 , inplace = True)
## And checking missing values again
total = f_players.isnull().sum().sort_values(ascending=False)
percent= f_players.isnull().sum()/f_players.isnull().count()*100
percent_2 = (round(percent, 1))
missing_data = pd.concat([total, percent_2], axis=1, keys=['Total', '%'])
missing_data.head(30)
```

Out[7]:

	Total	%
LWB	1992	11.1
RB	1992	11.1
CB	1992	11.1
LCB	1992	11.1
LB	1992	11.1
RWB	1992	11.1
RDM	1992	11.1
CDM	1992	11.1
LDM	1992	11.1
RM	1992	11.1
RCM	1992	11.1
CM	1992	11.1
LCM	1992	11.1
LM	1992	11.1
RAM	1992	11.1
CAM	1992	11.1
LAM	1992	11.1
RW	1992	11.1
RF	1992	11.1
CF	1992	11.1
LF	1992	11.1
LW	1992	11.1
RS	1992	11.1
ST	1992	11.1
LS	1992	11.1
RCB	1992	11.1
Release Clause	1275	7.1
Joined	1264	7.1
FKAccuracy	0	0.0
GKHandling	0	0.0

Our new dataset has 78 features. Value and Wage feature type of string, and they need to be as number. That's why I will convert them. I will write a function that is helpful for this one. Example: Kevin de Bruyne Value = €102M €102*1000000 and wage= €355K €355000

In [8]:
```python
def str2float(amount):
    """
    This function help to us for convert string to float.

    """

    if amount[-1] == 'M':
        return float (amount[1:-1])*1000000
    elif amount[-1] == 'K':
        return float (amount[1:-1])*1000
    else:
        return float(amount[1:])

f_players['Value_Float'] = f_players['Value'].apply(lambda x: str2float(x))
f_players['Wage_Float'] = f_players ['Wage'].apply(lambda x: str2float(x))

#Now we do not need string value and wage. We can drop them

#fp.drop(['Value','Wage'] ,axis =1 , inplace = True)
```

In [9]:
```python
print(f_players['Wage_Float'].dtypes)
```

```
float64
```

Step 1 Data Visualization

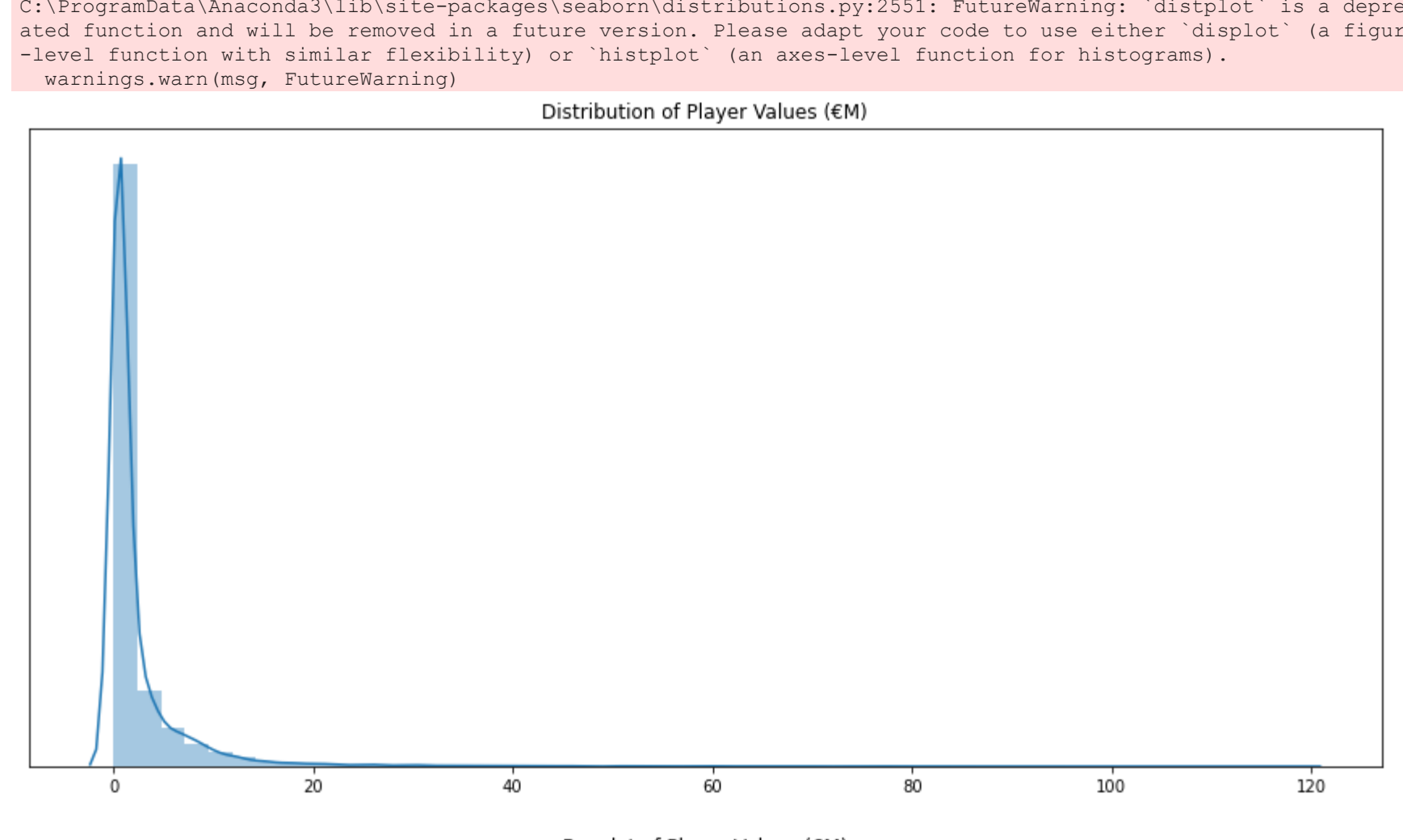
In this step, for features, we will plot a graph and understanding better our player distribution.

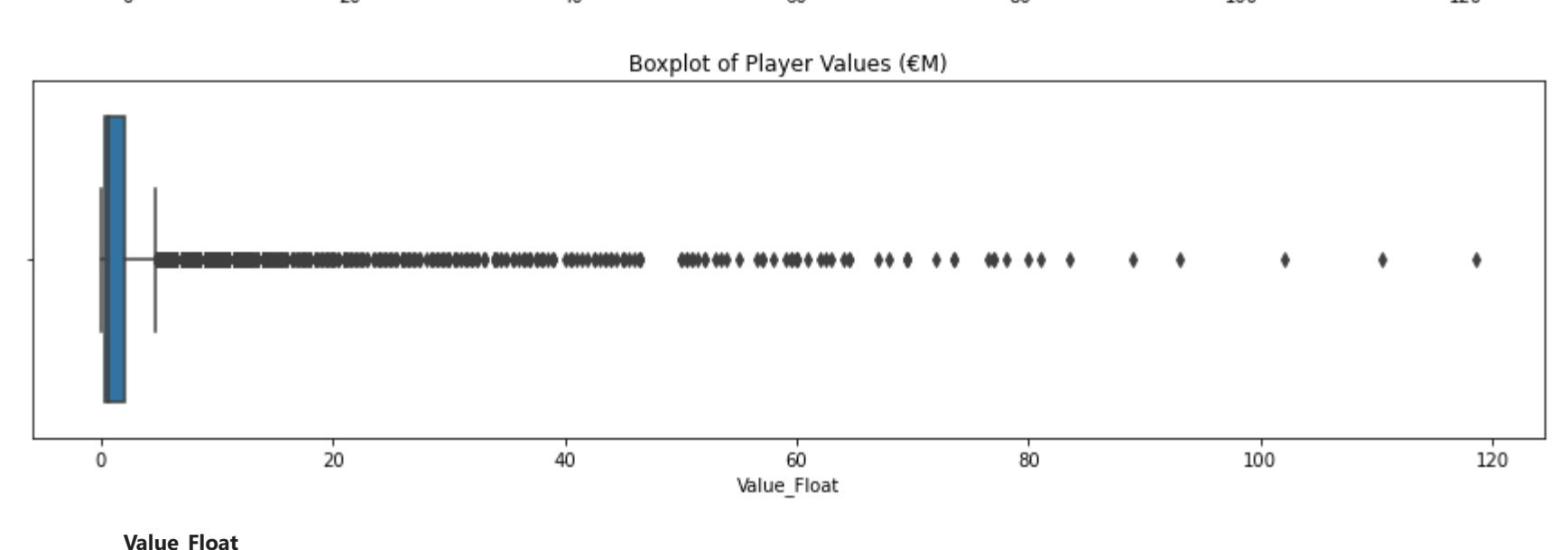
In [10]:
```python
def distribution_and_stats_plot(variable,Name):
    """For better understanding for players value distribution.I will draw a plot charts"""

    fig, ax = plt.subplots(nrows=2,figsize =(15,12),gridspec_kw={'height_ratios': [2,1]})
    sns.distplot(variable, ax = ax[0])
    ax[0].set(title = f"Distribution of {Name}",xlabel='',ylabel='')
    ax[0].set_yticks([])

    ax[1]=sns.boxplot(x=variable.columns[0],y=None,data=variable)
    ax[1].set_title(f"Boxplot of {Name}")
    plt.show()
    #sns.boxplot(x="distance", y="method", data=planets,  whis=[0, 100], width=.6, palette="vlag")



    display(variable.describe())
```

Step 1.1 Values

In [11]:
```python
distribution_and_stats_plot(f_players[["Value_Float"]]/1000000,'Player Values (\N{euro sign}M)')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



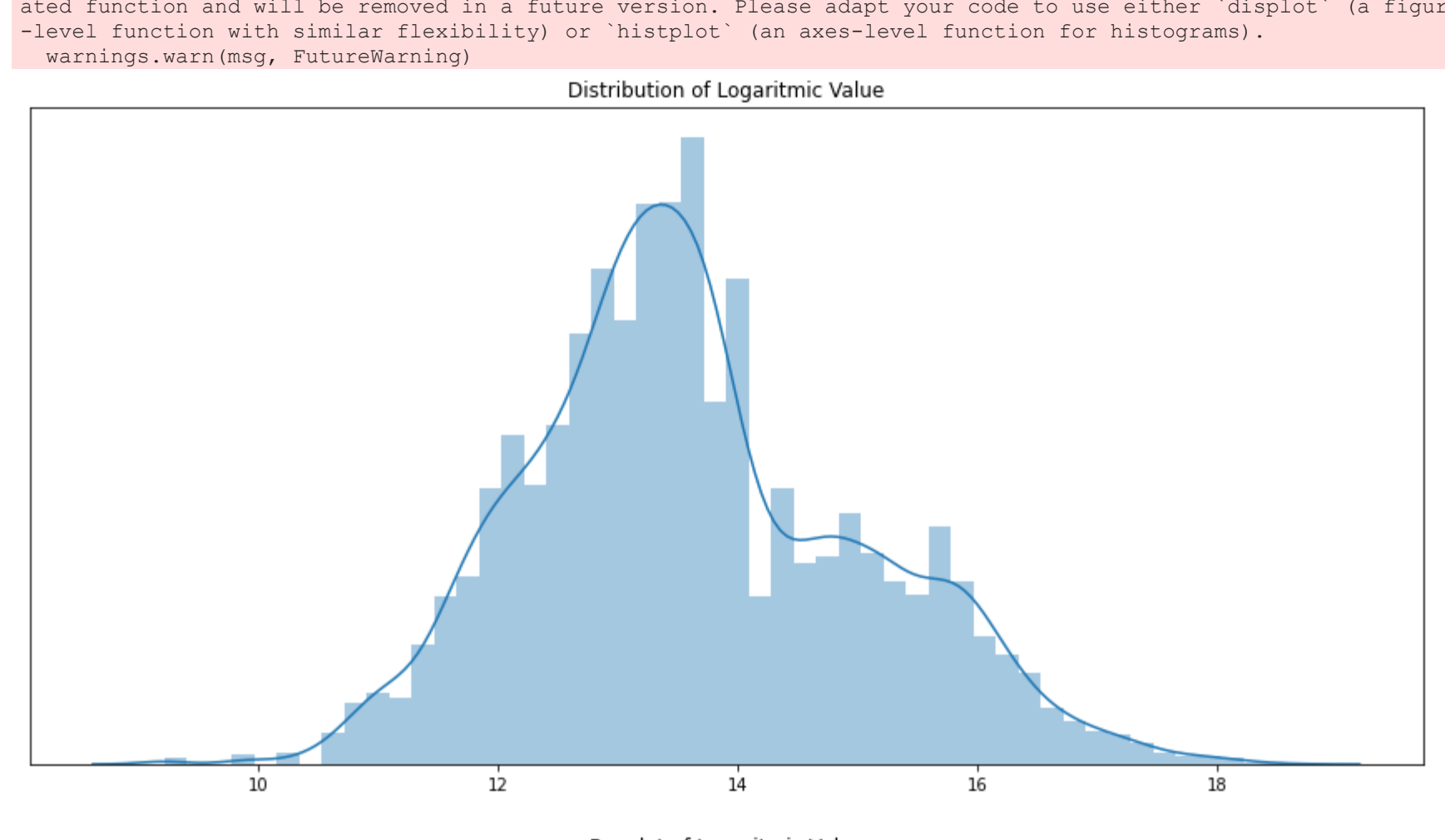


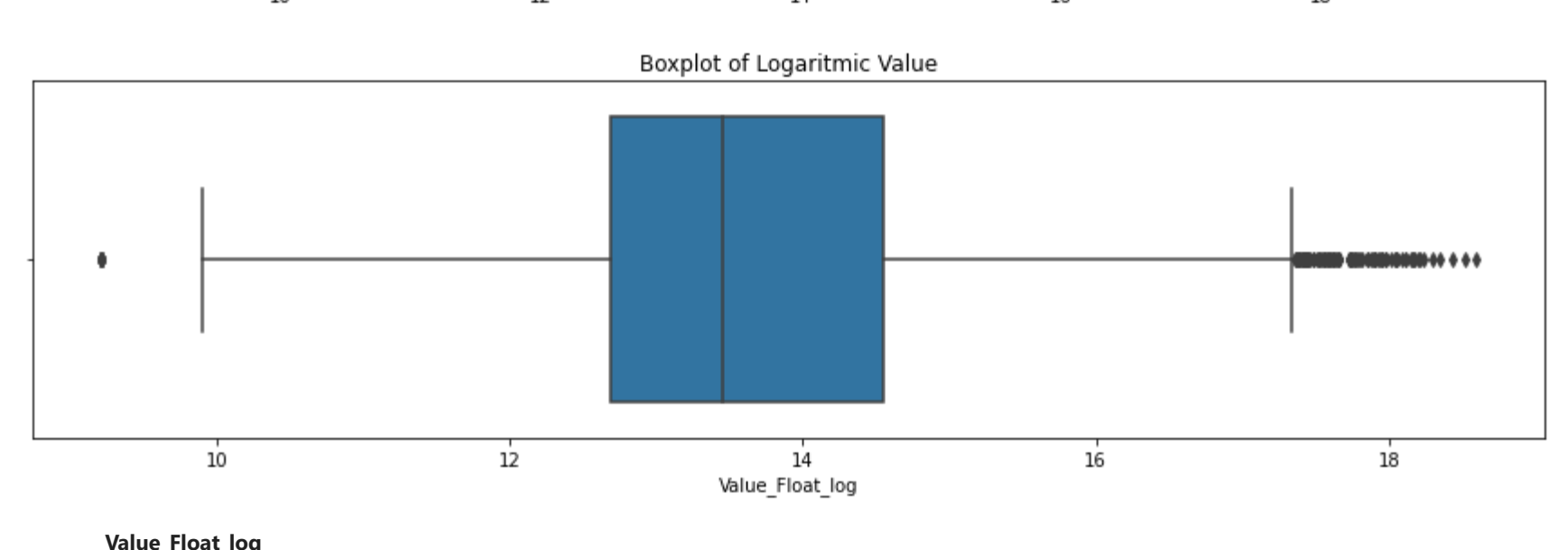
	Value_Float
count	17918.000000
mean	2.448629
std	5.631804
min	0.000000
25%	0.325000
50%	0.700000
75%	2.100000
max	118.500000

As you can see above, our players generally have low market value and for this reason, we can not see general the distribution of that. High prices players are almost not seeing on the chart. For that, we can use a logarithmic distribution chart, which shows us more clearly.

In [12]:
```python
# In my data set there are 11 values equal 0 that is why, I added plus 1 for every values for converting log
# After that I reaileze that 11 players old person and low overall rating. They do not any good affect on mode
# For this reason I deleted them and now my graphs is better than befor more clear and understandable.
#
#Convert to log

f_players["Value_Float_log"] = np.log(f_players["Value_Float"]+1)

#delete value_log=0
f_players =f_players[f_players["Value_Float_log"] !=0]

distribution_and_stats_plot(f_players[["Value_Float_log"]],'Logaritmic Value')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



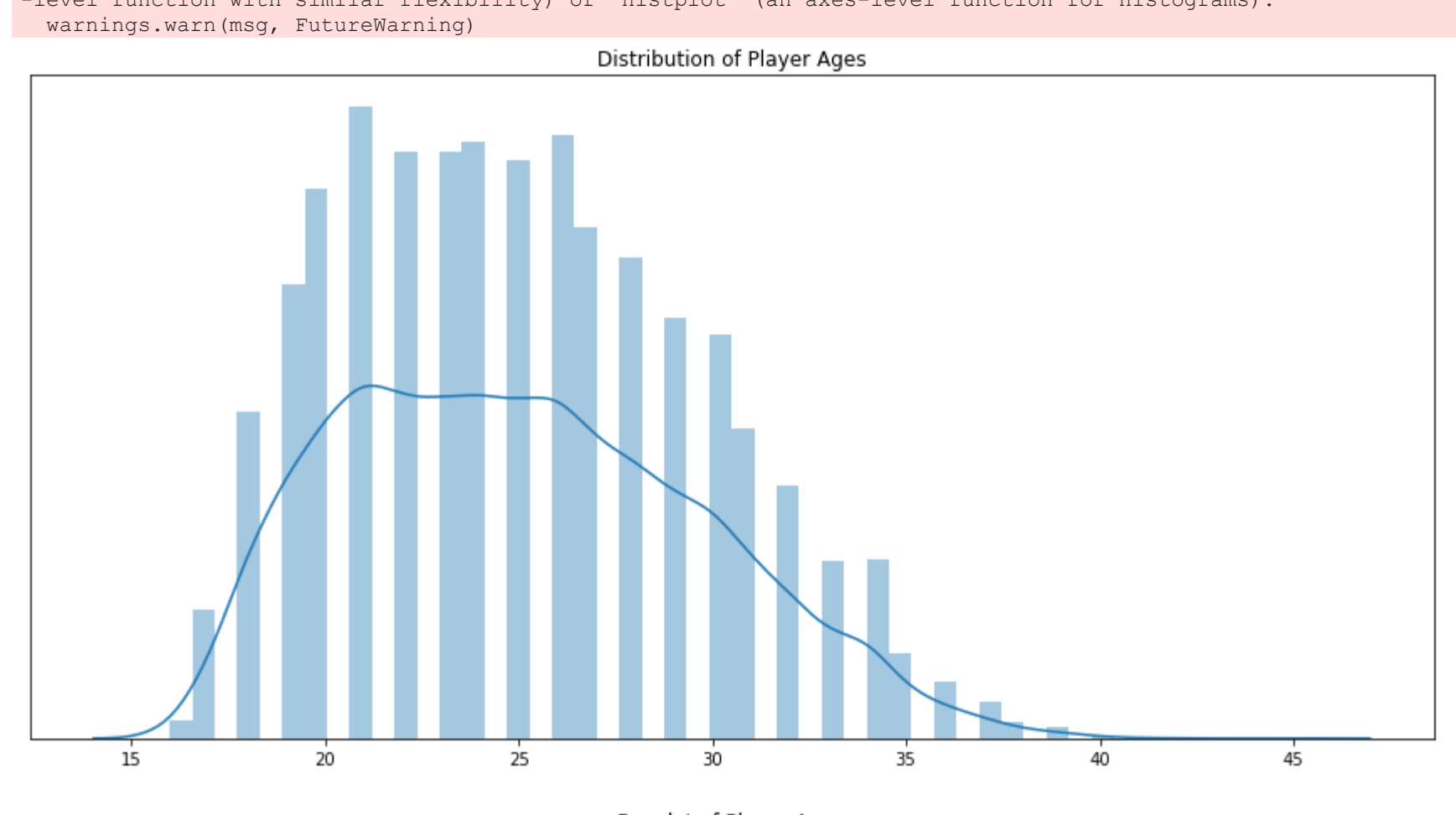


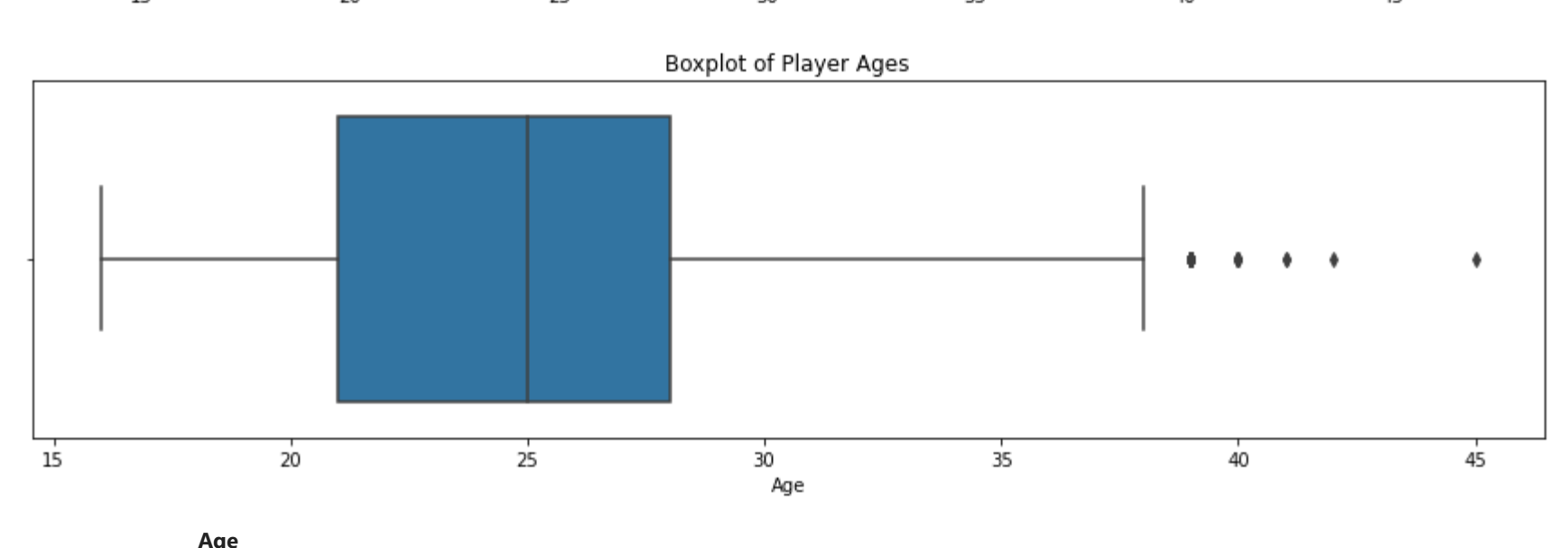
	Value_Float_log
count	17907.000000
mean	13.622829
std	1.407122
min	9.210440
25%	12.691584
50%	13.458837
75%	14.557448
max	18.590424

Step 1.2 Age

In [13]:
```python
distribution_and_stats_plot(f_players[["Age"]],'Player Ages')
```

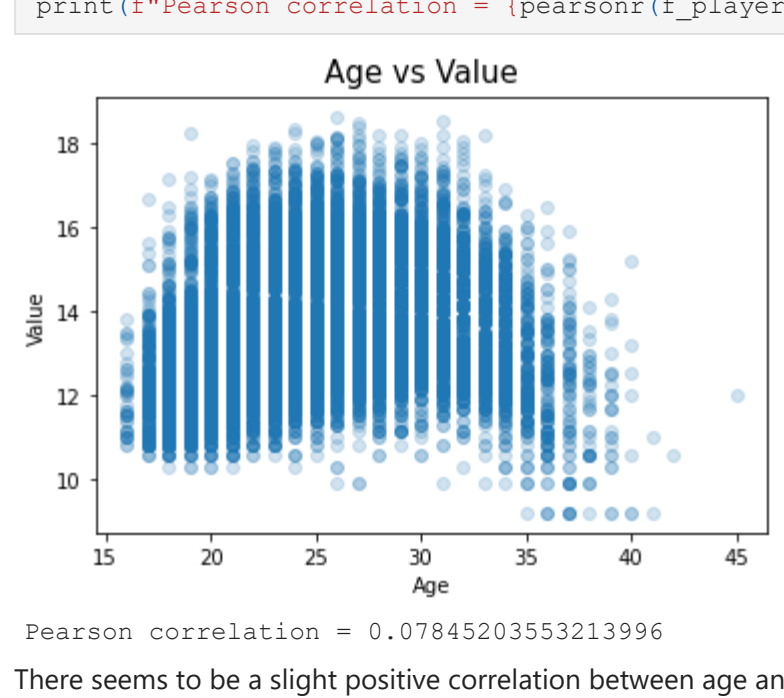
```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





	Age
count	17907.000000
mean	25.095605
std	4.660388
min	16.000000
25%	21.000000
50%	25.000000
75%	28.000000
max	45.000000

In [14]:
```python
from scipy.stats import pearsonr

plt.scatter(x=f_players["Age"],y=f_players["Value_Float_log"],alpha=0.2)
plt.suptitle("Age vs Value",fontsize=15,y=0.95)
plt.xlabel("Age")
plt.ylabel("Value")
plt.show()

print(f"Pearson correlation = {pearsonr(f_players['Value_Float'],f_players['Age'])[0]}")
```

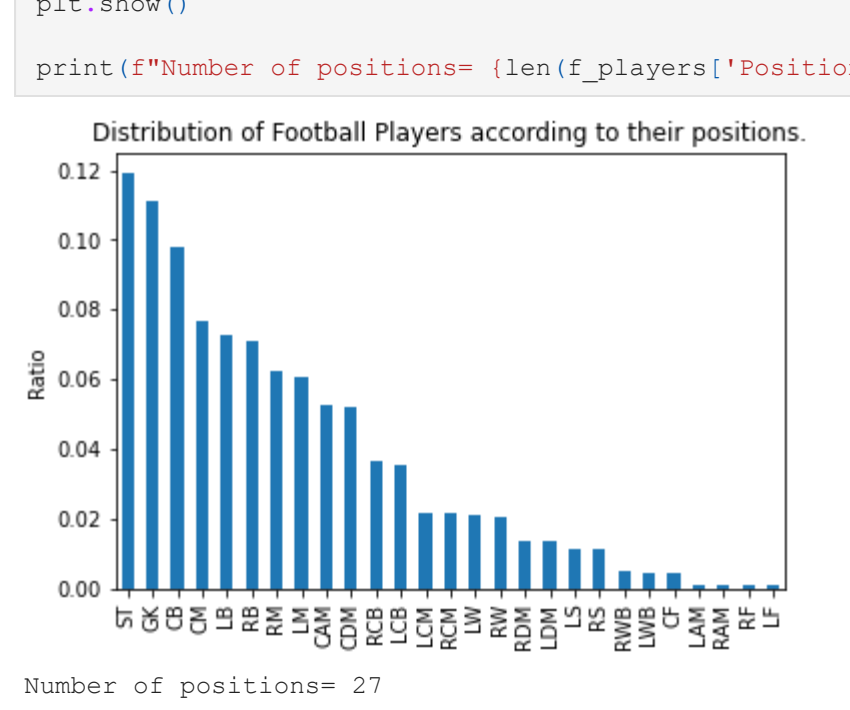



```
Pearson correlation = 0.07845203553213996
```

There seems to be a slight positive correlation between age and value (0.18) which suggests experience increases valuations, however, this is only up to a point. When the player age is approximately >35 then the values tend to decline. This makes sense as older players have fewer years left in their career so have less long term value for the club.

Step 1.3 Player Position

In [15]:
```python
f_players['Position'].value_counts(normalize= True).plot(kind='bar')
plt.title("Distribution of Football Players according to their positions.")
plt.ylabel("Ratio")
plt.show()

print(f"Number of positions= {len(f_players['Position'].unique())}")
```



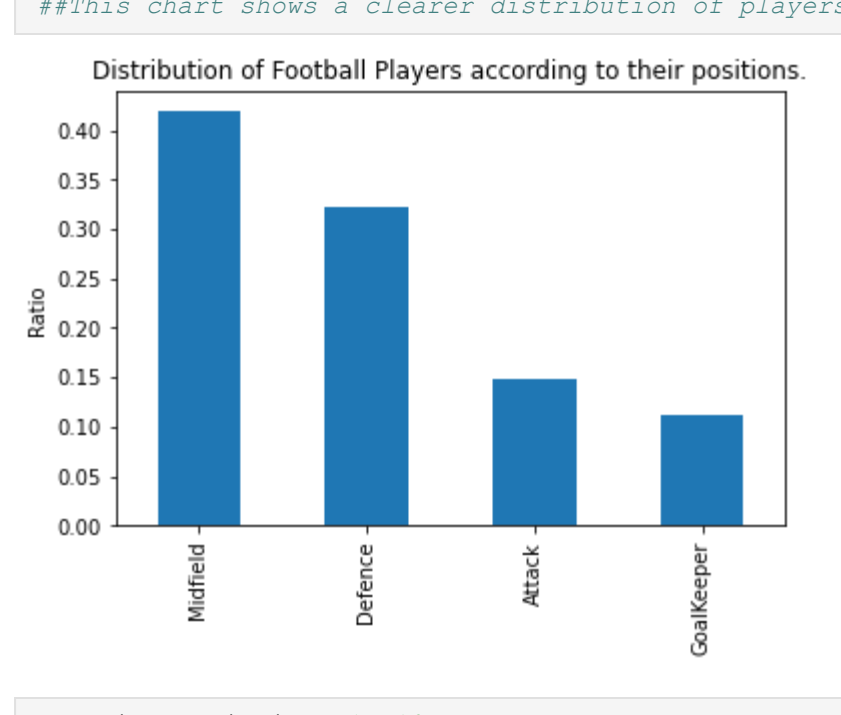

```
Number of positions= 27
```

As you can see from the above graphic, the most common positions are ST and GK.

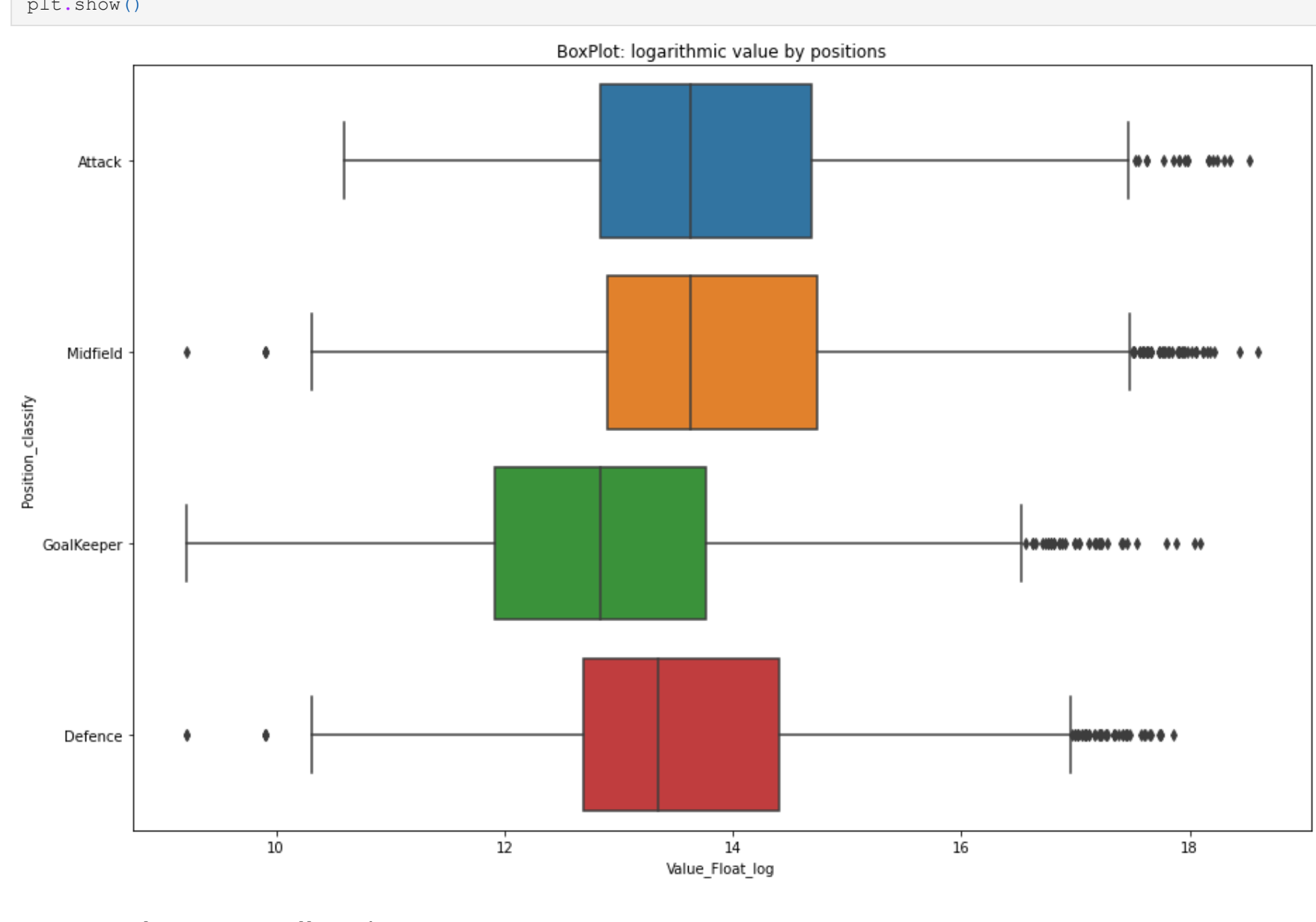
We have 27 unique positions. It's too much for analysis that's why we can classify these as, Attacker, midfielder, defender and goalkeeper. For that, I will create a new function.

In [16]:
```python
def classify_position(position):
    """This function help to you for classification football player position."""

    Position_dict= { 'Attack' : ['ST','LS','RS','CF','RF','LF'],
                    'Midfield': ['CM','RM','LM','CAM','CDM','LCM','RCM','LW',
                                 'RW','RDM','LDM','LAM','RAM'],
                     'Defence': ['CB','LB','RB','RCB','LCB','RWB','LWB'],
                   'GoalKeeper':['GK']}

    for group , position_list in Position_dict.items():

        if position in position_list:
            return group

    return np.nan
```

In [17]:
```python
f_players['Position_classify'] = f_players['Position'].apply(classify_position)
f_players['Position_classify'].value_counts(normalize= True).plot(kind='bar')
plt.title("Distribution of Football Players according to their positions.")
plt.ylabel("Ratio")
plt.show()

##This chart shows a clearer distribution of players' positions.
```



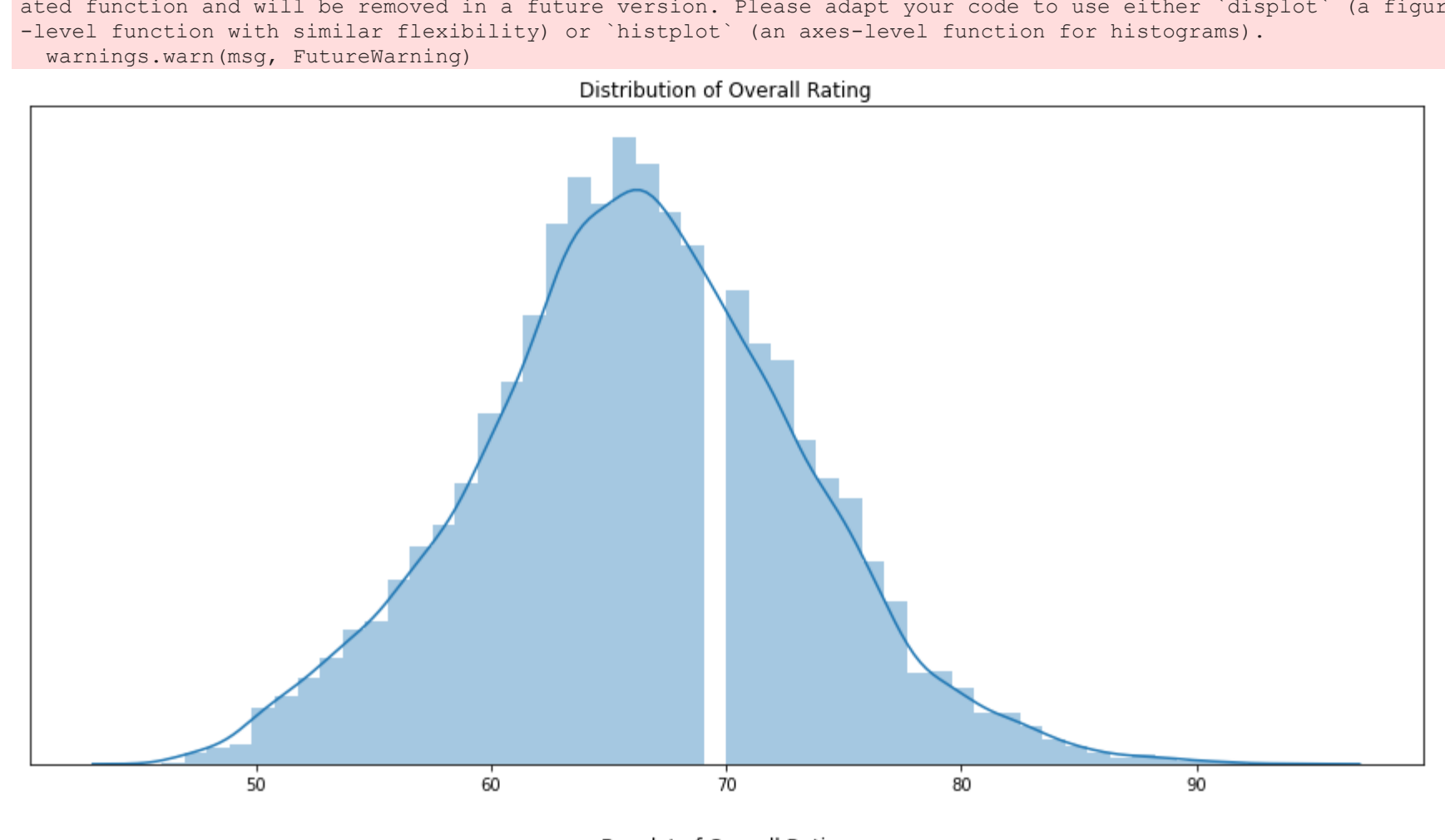
In [18]:
```python
plt.figure(figsize=(15,10))
sns.boxplot(x="Value_Float_log",y="Position_classify",data=f_players)
plt.title("BoxPlot: logarithmic value by positions")
plt.show()
```

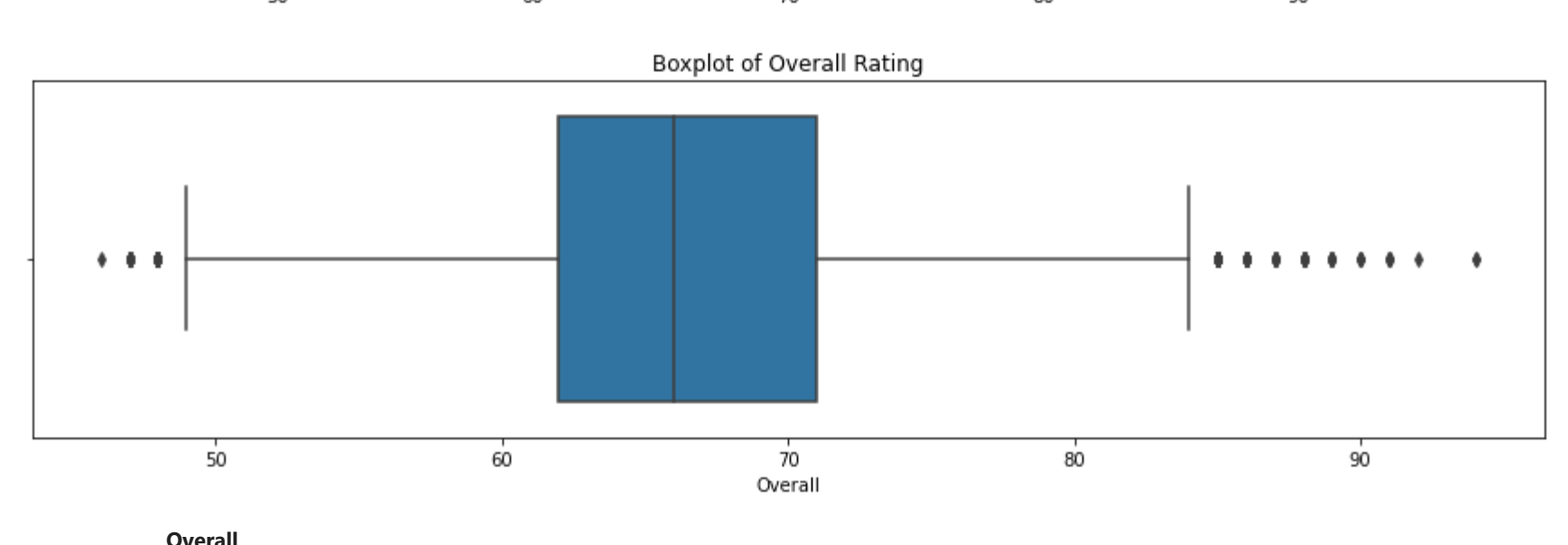


Step 1.4 Player Overall Rating

In [19]:
```python
distribution_and_stats_plot(f_players[["Overall"]],'Overall Rating')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

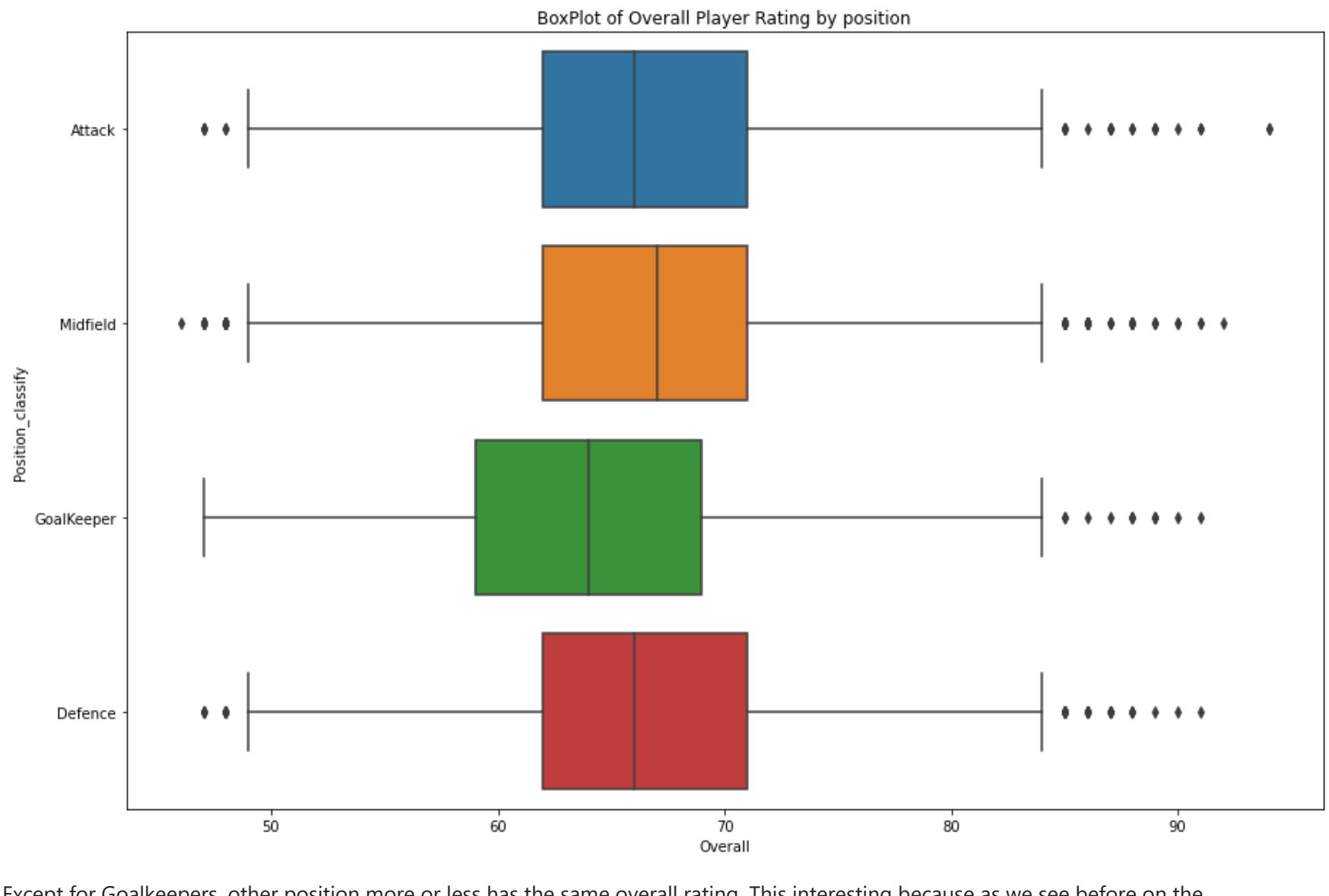




	Overall
count	17907.000000
mean	66.239571
std	6.926818
min	46.000000
25%	62.000000
50%	66.000000
75%	71.000000
max	94.000000

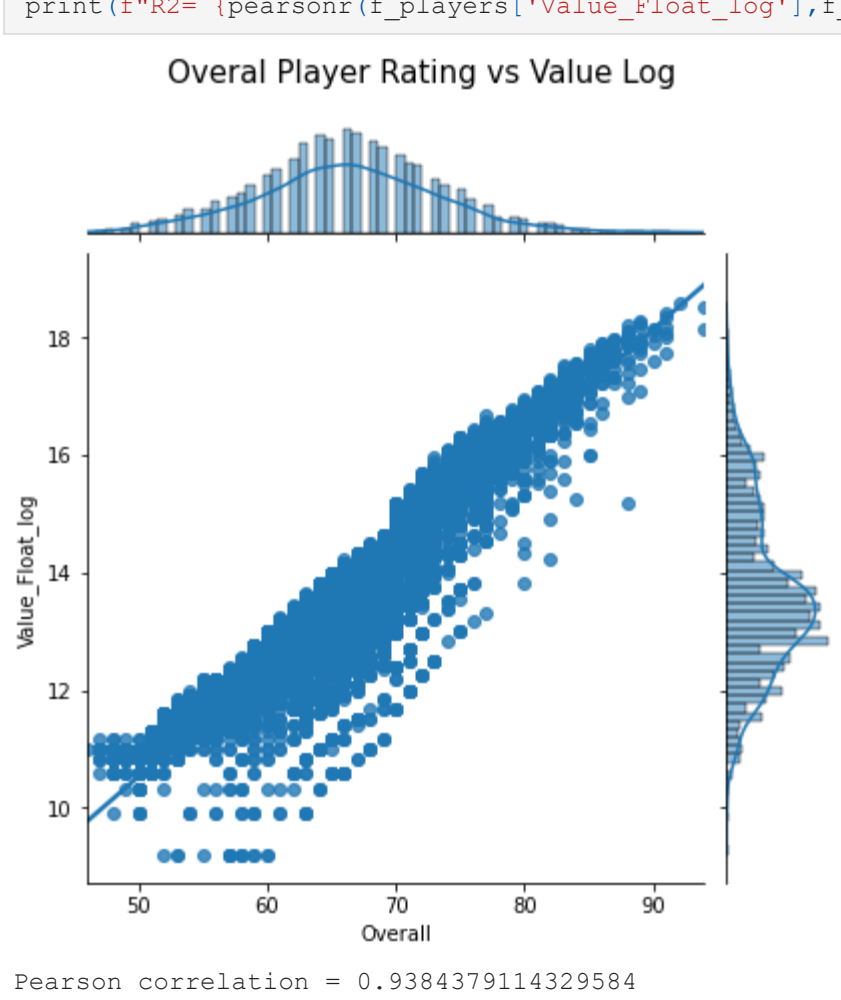
Overal rating is normally distributed with a average of 66, minimum 46 and maximum 94.

In [20]:
```python
plt.figure(figsize=(15,10))
sns.boxplot(x="Overall",y="Position_classify",data=f_players)
plt.title("BoxPlot of Overall Player Rating by position")
plt.show()
```



Except for Goalkeepers, other position more or less has the same overall rating. This interesting because as we see before on the logarithmic value by positions chart attackers and midfields market value higher than the others

In [21]:
```
sns.jointplot(x='Overall',y="Value_Float_log",data=f_players,kind='reg')
plt.suptitle("Overal Player Rating vs Value Log", fontsize=15,y=1.05)
plt.show()

print(f"Pearson correlation = {pearsonr(f_players['Value_Float_log'],f_players['Overall'])[0]}")
print(f"R2= {pearsonr(f_players['Value_Float_log'],f_players['Overall'])[0]**2}")
```



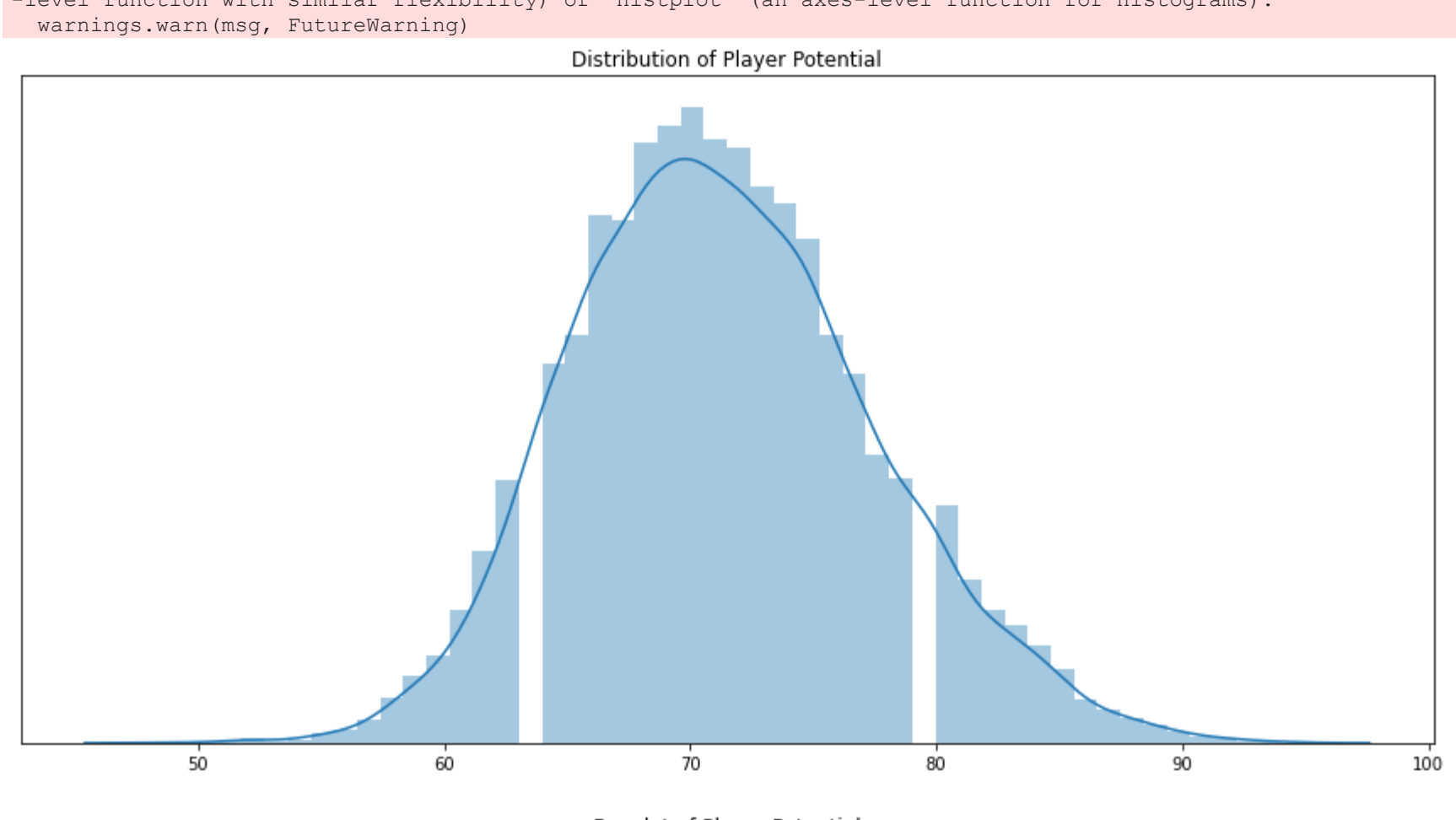

```
Pearson correlation = 0.9384379114329584
R2= 0.8806657136146531
```

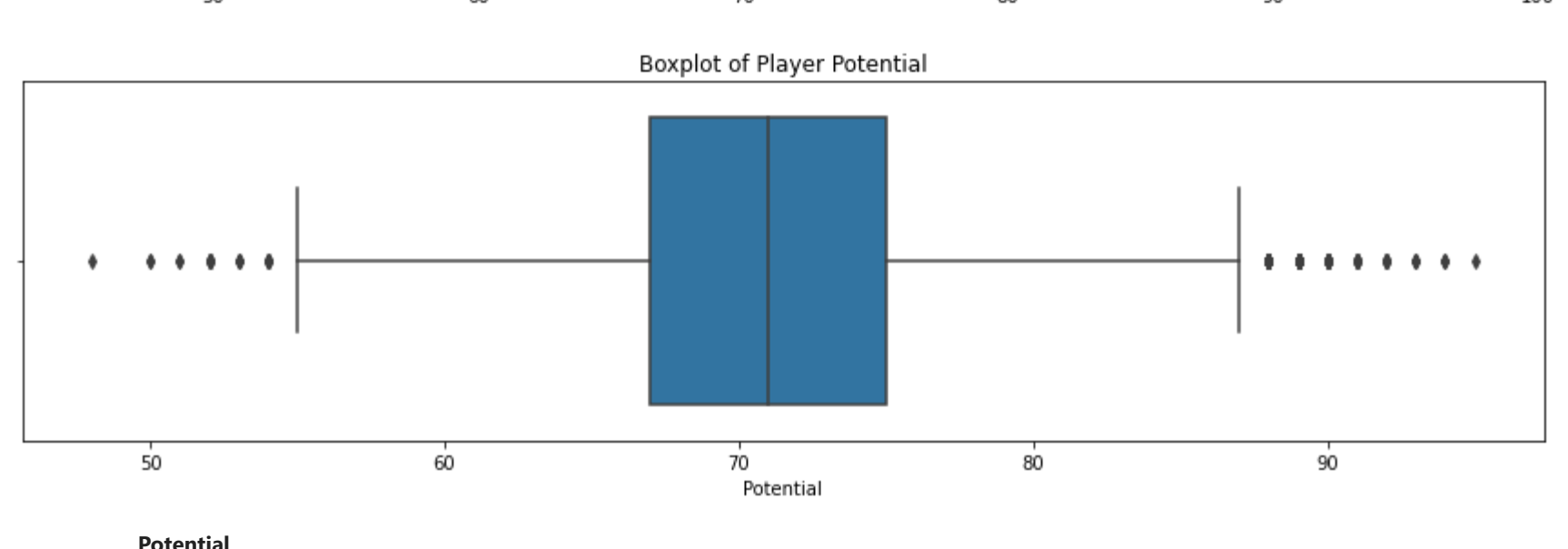
Overall rating is highly correlated with log value with an R2 of 0.89 and is likely to be the most predictive feature.

Step 1.5 Player Potential

In [22]:
```
distribution_and_stats_plot(f_players[["Potential"]],'Player Potential')
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `distplot` is a deprec
ated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure
-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



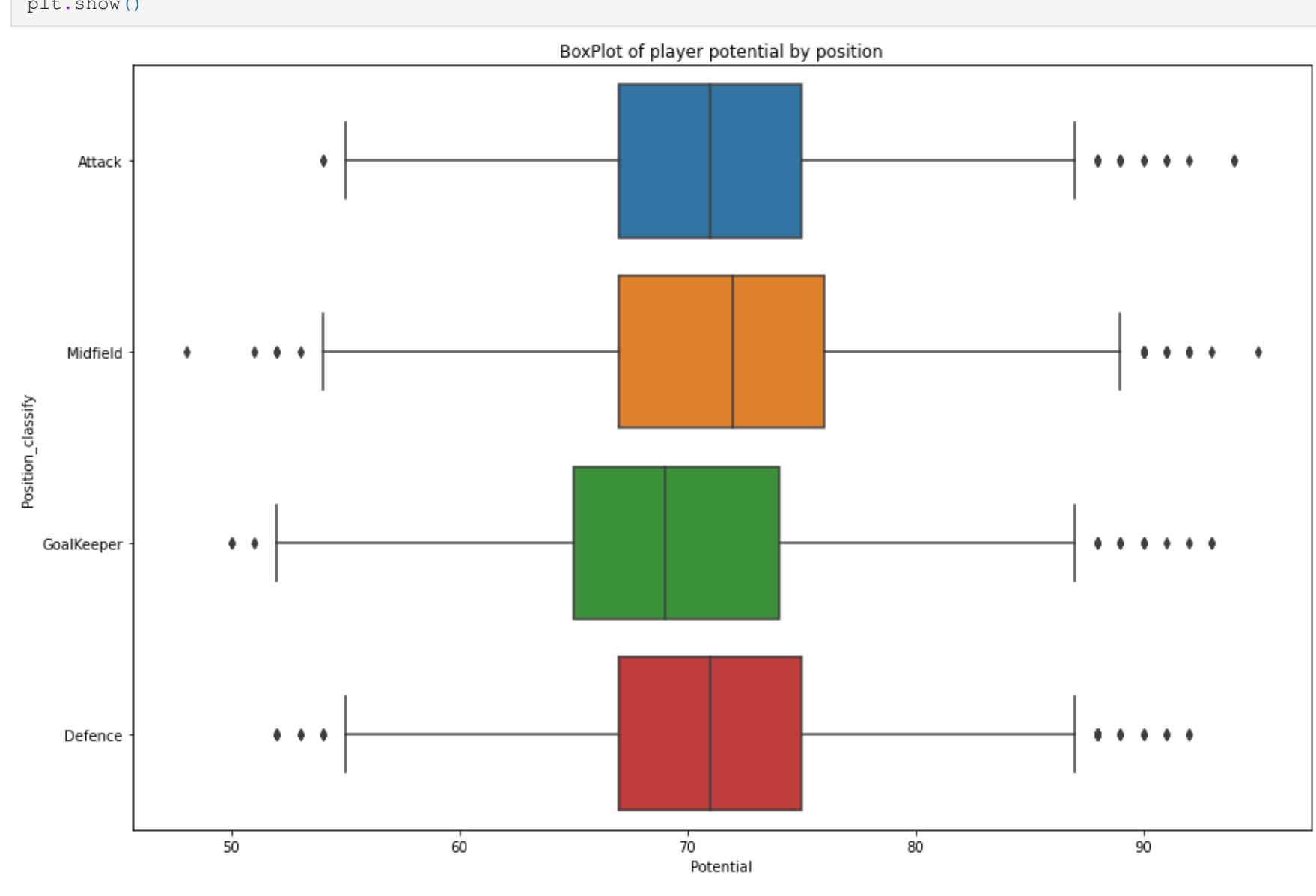


	Potential
count	17907.000000
mean	71.335232
std	6.137251
min	48.000000
25%	67.000000
50%	71.000000
75%	75.000000
max	95.000000

The chart is more or less normally distributed and with a mean of 71.32.

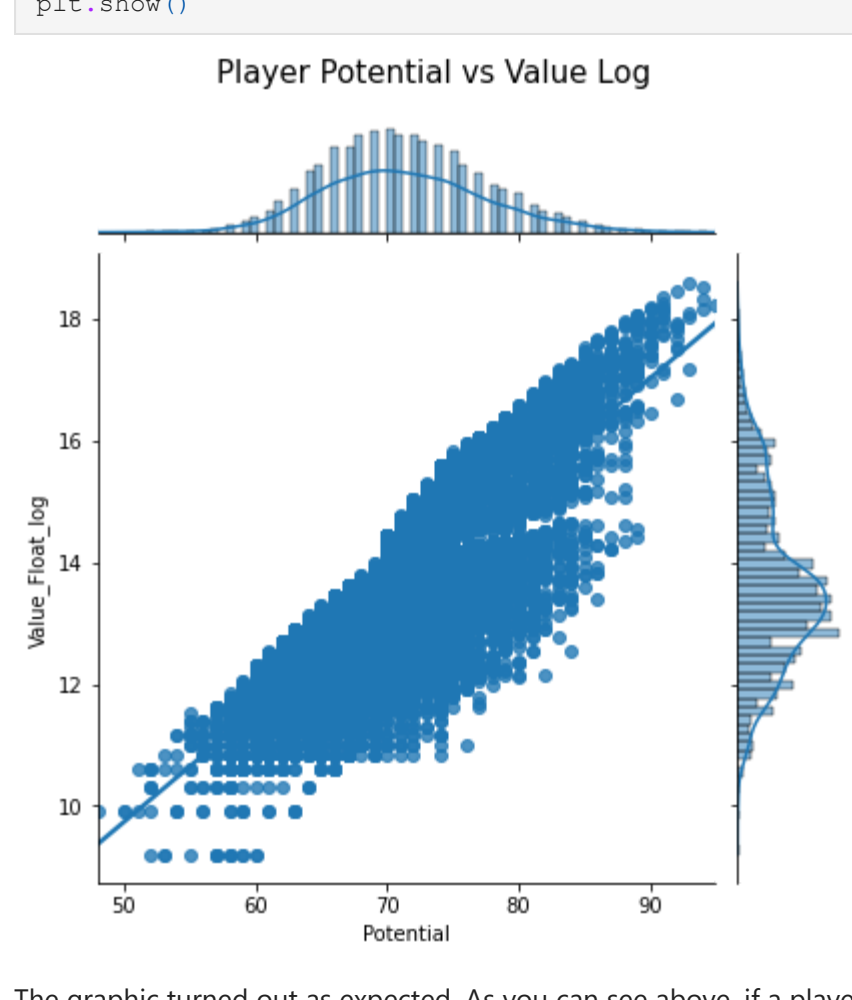
Also, we can examine in detail the player potential according to their positions.

In [23]:
```
plt.figure(figsize=(15,10))
sns.boxplot(x="Potential",y="Position_classify",data=f_players)
plt.title("BoxPlot of player potential by position")
plt.show()
```



The potential of the player does not seem much different for each position. Next step, we will look the relationship between player potential and player values.

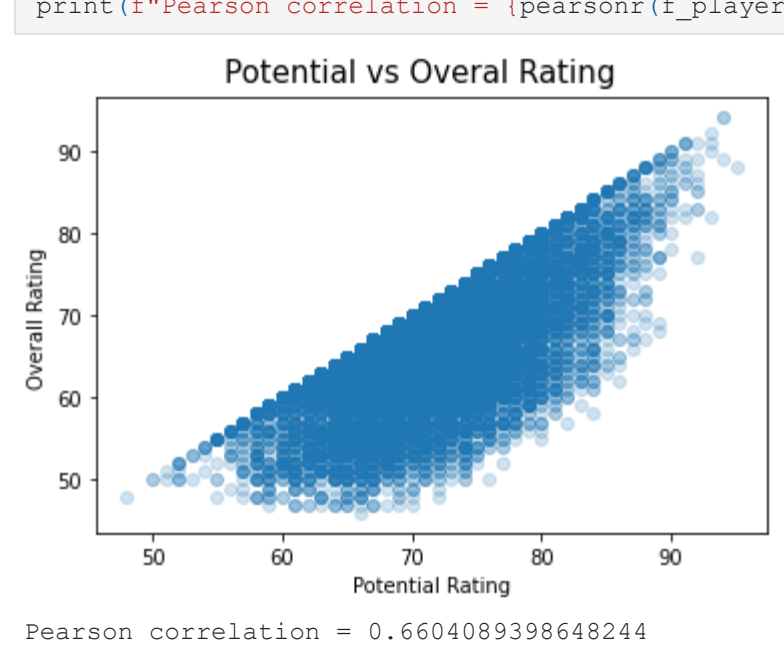
In [24]:
```
sns.jointplot(x='Potential',y="Value_Float_log",data=f_players,kind='reg')
plt.suptitle("Player Potential vs Value Log", fontsize=15,y=1.05)
plt.show()
```



The graphic turned out as expected. As you can see above, if a player has high potential it also has high market values. They are correlated.

This situation also expected between overall rating and potential. These are correlated. I will show them in the next step.

In [25]:
```
plt.scatter(x=f_players["Potential"],y=f_players["Overall"],alpha=0.2)
plt.suptitle("Potential vs Overal Rating",fontsize=15,y=0.95)
plt.xlabel("Potential Rating")
plt.ylabel("Overall Rating")
plt.show()

print(f"Pearson correlation = {pearsonr(f_players['Potential'],f_players['Overall'])[0]}")
```




```
Pearson correlation = 0.6604089398648244
```

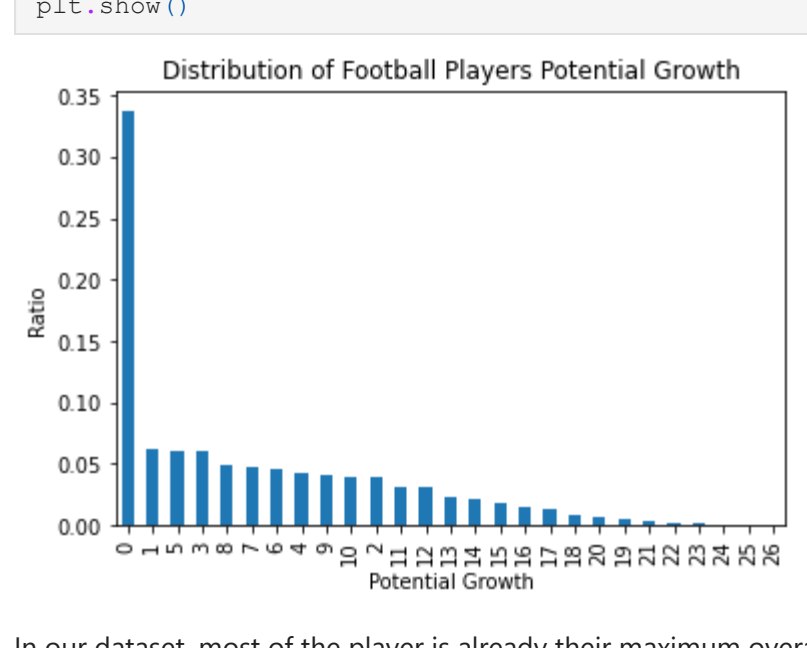
You can see in the above graphs, a potential rating is higher than the overall rating, which makes sense. But correlation is not enough the eliminate one feature, for this reason, I will keep both of them.

Next step, I will look difference between potential and overall rating. It can be a nice feature to show the effect of potential rating increase on market value.

Potential Growth vs Market Value

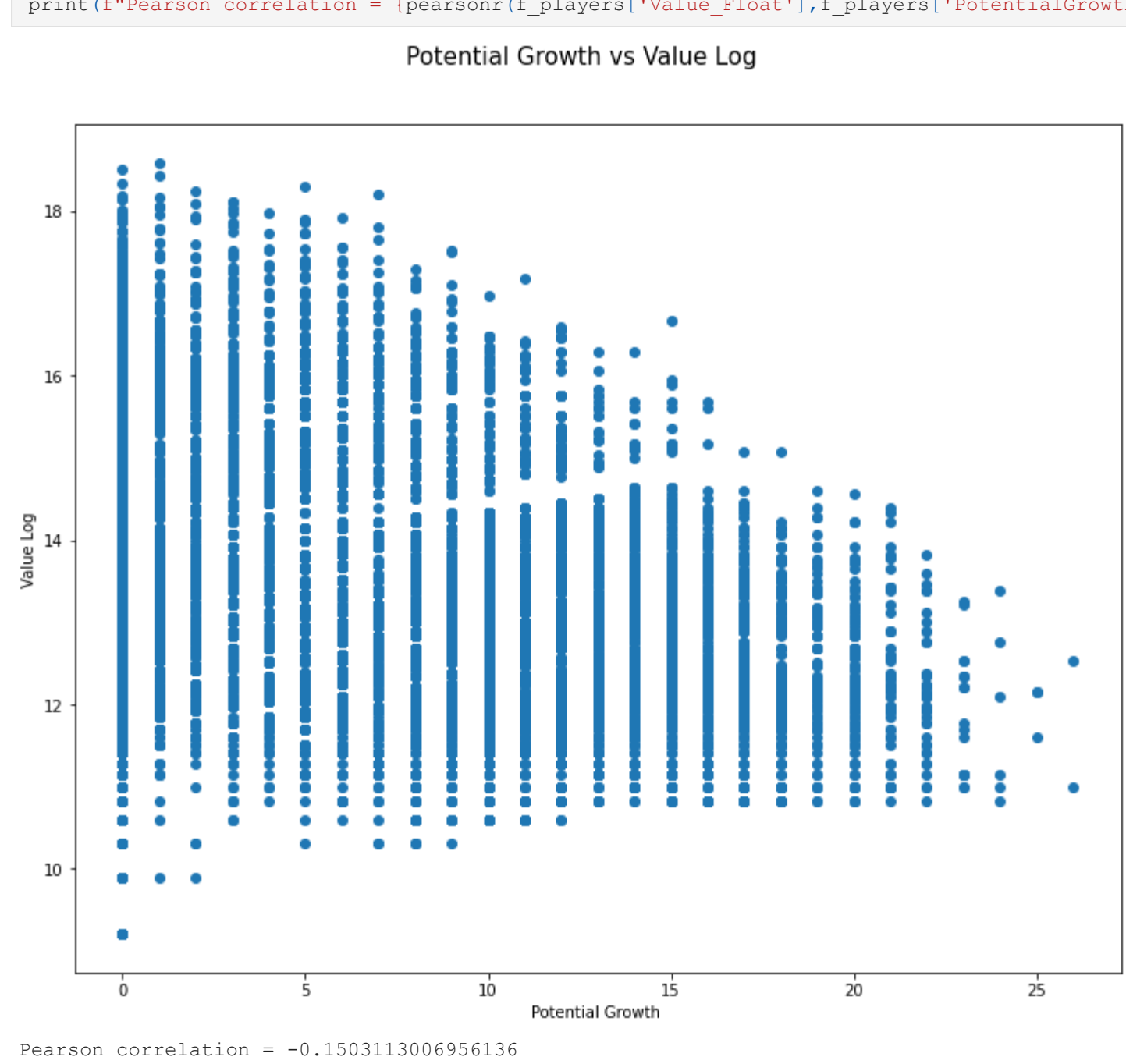
In this step, I will create a new feature as Potential Growth. For this new one, I will do this calculation. >> PotentialGrowth = Potential - Overall An I will just looking the how is the relationship between market values and potential growth.

In [26]:
```
# Potential Growth
from matplotlib.pyplot import figure
f_players['PotentialGrowth'] = f_players['Potential']-f_players['Overall']
f_players['PotentialGrowth'].value_counts(normalize= True).plot(kind='bar',)
plt.title("Distribution of Football Players Potential Growth")
plt.xlabel("Potential Growth")
plt.ylabel("Ratio")
plt.show()
```



In our dataset, most of the player is already their maximum overall rating.

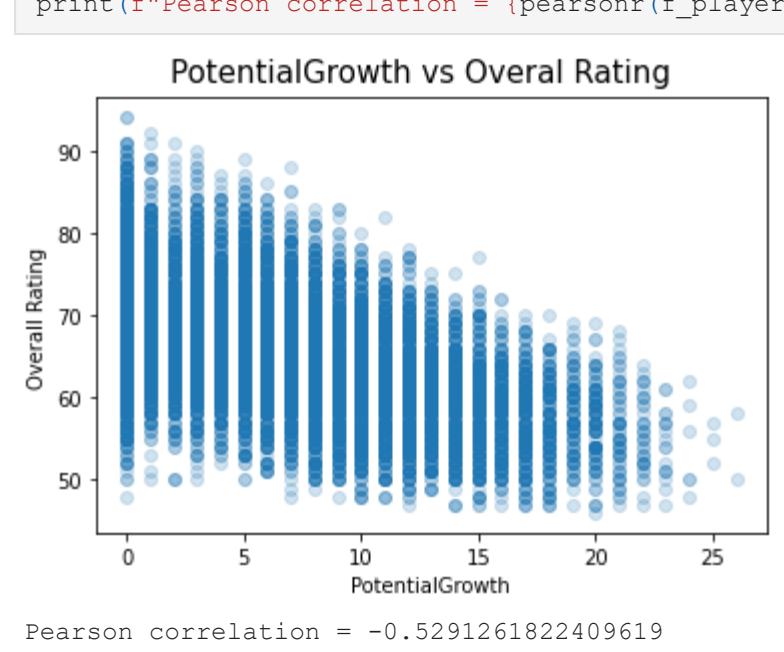
In [27]:
```
plt.figure(figsize=(12,10))
plt.scatter(x="PotentialGrowth",y="Value_Float_log",data=f_players)
plt.suptitle("Potential Growth vs Value Log",fontsize=15,y=0.95)
plt.xlabel("Potential Growth ")
plt.ylabel("Value Log")
plt.show()

print(f"Pearson correlation = {pearsonr(f_players['Value_Float'],f_players['PotentialGrowth'])[0]}")
```




```
Pearson correlation = -0.1503113006956136
```

As we expected, these two variables have an inverse relationship and the correlation value is proved this idea. If the maximum market values players potential growth is low. Because if you have low potential growth that's mean, you have a high overall rating for now(This is the general opinion, there may be some exceptions for that view.).

In [28]:
```
plt.scatter(x=f_players["PotentialGrowth"],y=f_players["Overall"],alpha=0.2)
plt.suptitle("PotentialGrowth vs Overal Rating",fontsize=15,y=0.95)
plt.xlabel("PotentialGrowth")
plt.ylabel("Overall Rating")
plt.show()

print(f"Pearson correlation = {pearsonr(f_players['PotentialGrowth'],f_players['Overall'])[0]}")
```




```
Pearson correlation = -0.5291261822409619
```

This graph shows better the relation between the overall rating and potential growth. If the potential growth increase, the overall rating is decreasing. Also, they have a negative correlation which makes sense.

Step 1.6 Best Player for each Position

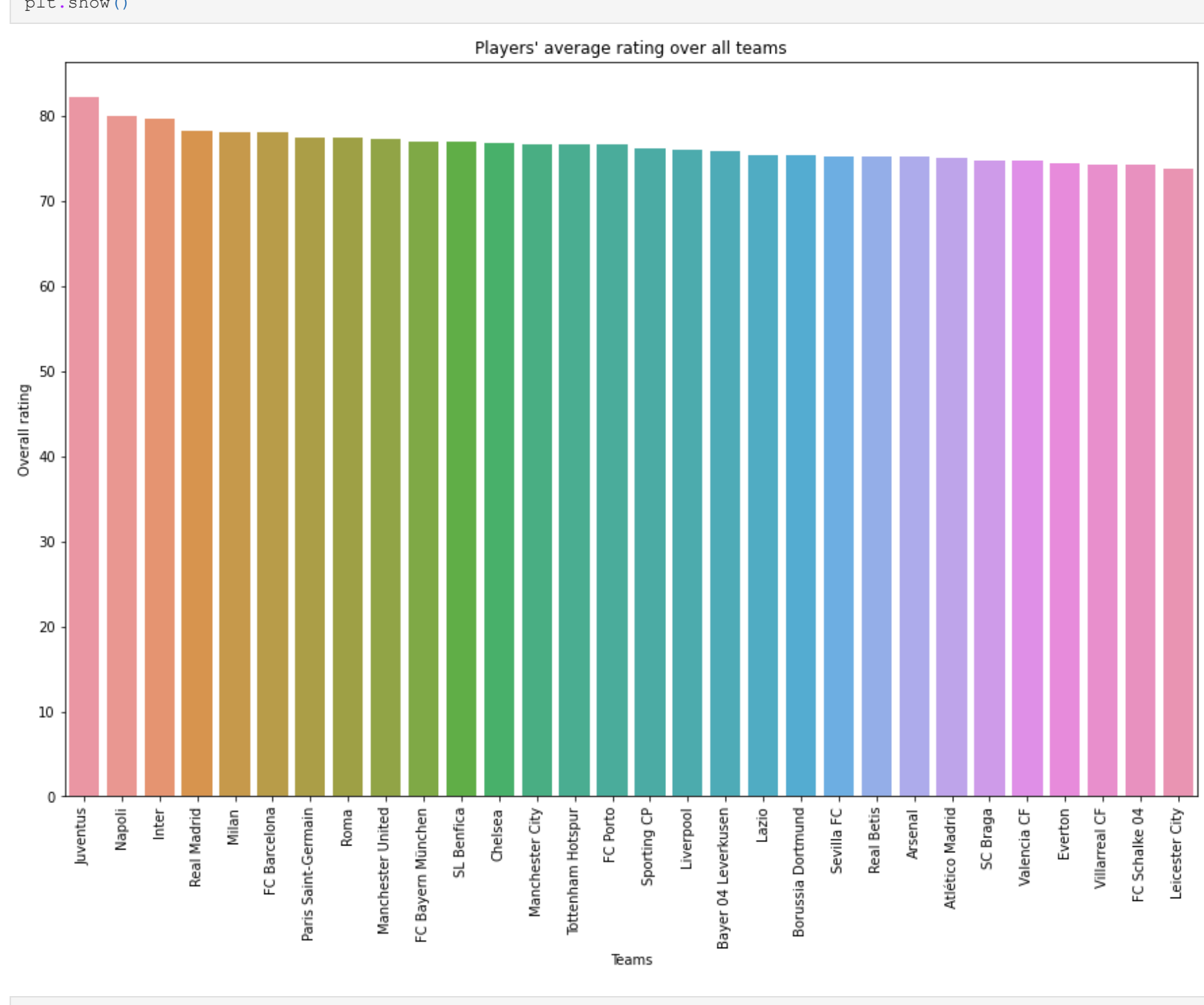
In [29]:
```
f_players.iloc[f_players.groupby(f_players['Position'])['Overall'].idxmax()].sort_values(by='Overall',
                    ascending=False).reset_index()[['Position', 'Name','Age','Club', 'Nationality', 'Overall',
                                                    'Position_classify','Wage','Value']].style.background_gradi
```

Out[29]:

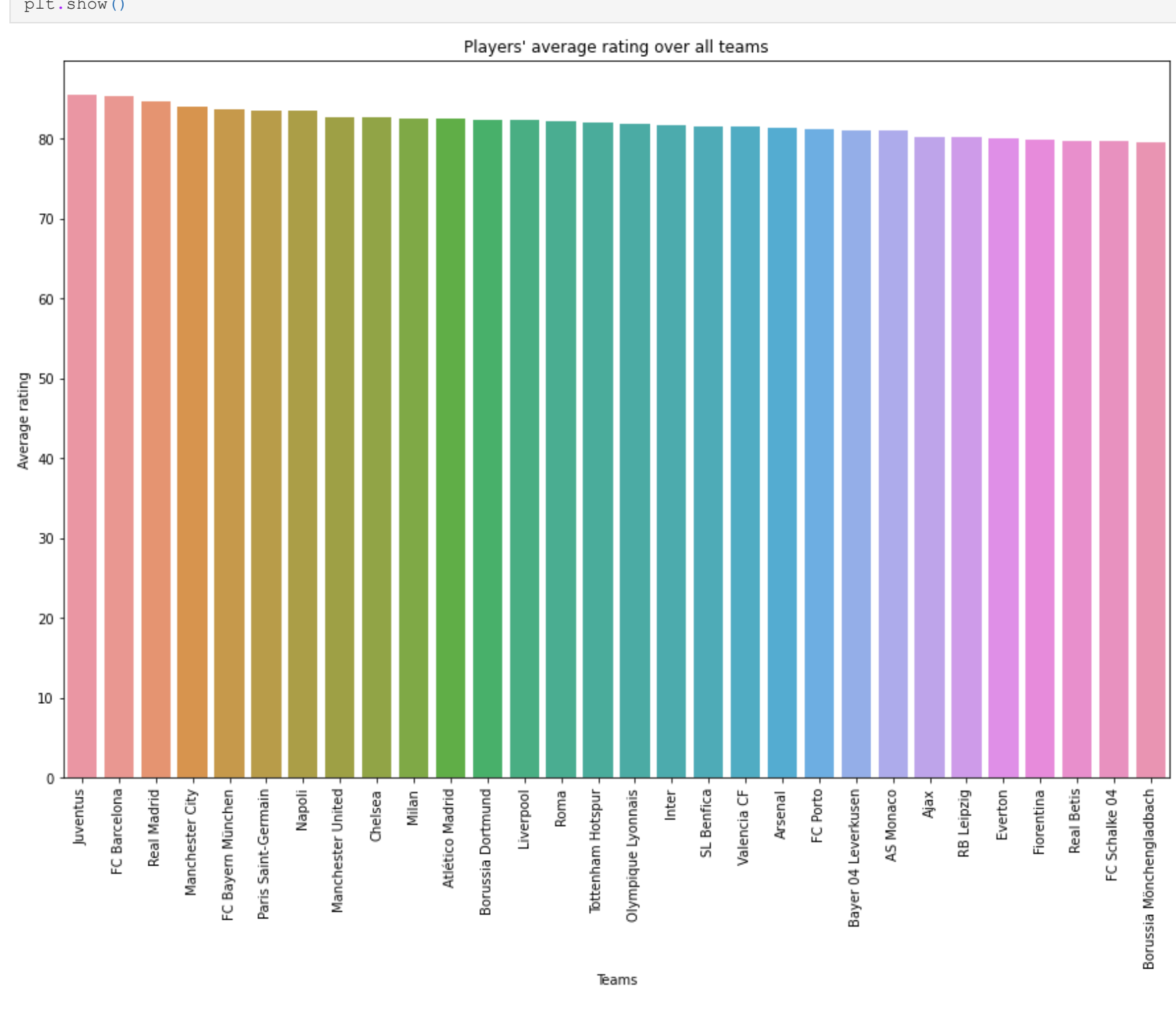
	Position	Name	Age	Club	Nationality	Overall	Position_classify	Wage	Value
0	ST	Cristiano Ronaldo	33	Juventus	Portugal	94	Attack	€405K	€77M
1	RF	L. Messi	31	FC Barcelona	Argentina	94	Attack	€565K	€110.5M
2	LW	Neymar Jr	26	Paris Saint-Germain	Brazil	92	Midfield	€290K	€118.5M
3	LF	E. Hazard	27	Chelsea	Belgium	91	Attack	€340K	€93M
4	RS	L. Suárez	31	FC Barcelona	Uruguay	91	Attack	€455K	€80M
5	RCM	K. De Bruyne	27	Manchester City	Belgium	91	Midfield	€355K	€102M
6	GK	De Gea	27	Manchester United	Spain	91	GoalKeeper	€260K	€72M
7	RCB	Sergio Ramos	32	Real Madrid	Spain	91	Defence	€380K	€51M
8	CB	D. Godín	32	Atlético Madrid	Uruguay	90	Defence	€125K	€44M
9	LCM	T. Kroos	28	Real Madrid	Germany	90	Midfield	€355K	€76.5M
10	CAM	A. Griezmann	27	Atlético Madrid	France	89	Midfield	€145K	€78M
11	LDM	N. Kanté	27	Chelsea	France	89	Midfield	€225K	€63M
12	LCB	G. Chiellini	33	Juventus	Italy	89	Defence	€215K	€27M
13	CDM	Sergio Busquets	29	FC Barcelona	Spain	89	Midfield	€315K	€51.5M
14	LS	E. Cavani	31	Paris Saint-Germain	Uruguay	89	Attack	€200K	€60M
15	LM	P. Aubameyang	29	Arsenal	Gabon	88	Midfield	€265K	€59M
16	LB	Marcelo	30	Real Madrid	Brazil	88	Defence	€285K	€43M
17	LAM	J. Rodríguez	26	FC Bayern München	Colombia	88	Midfield	€315K	€69.5M
18	RM	K. Mbappé	19	Paris Saint-Germain	France	88	Midfield	€100K	€81M
19	RDM	P. Pogba	25	Manchester United	France	87	Midfield	€210K	€64M
20	RB	Azpilicueta	28	Chelsea	Spain	86	Defence	€175K	€35M
21	CM	Thiago	27	FC Bayern München	Spain	86	Midfield	€130K	€45.5M
22	RW	Bernardo Silva	23	Manchester City	Portugal	86	Midfield	€180K	€59.5M
23	RAM	J. Cuadrado	30	Juventus	Colombia	84	Midfield	€150K	€29.5M
24	CF	Luis Alberto	25	Lazio	Spain	82	Attack	€67K	€28.5M
25	LWB	L. Digne	24	Everton	France	80	Defence	€79K	€16M
26	RWB	M. Ginter	24	Borussia Mönchengladbach	Germany	80	Defence	€28K	€15.5M

Step 1.7. Club Teams Overall

In [30]:
```
team_ret = f_players[['Club','Overall']].groupby('Club').mean().sort_values(by='Overall', ascending=False).head
fig, ax = plt.subplots(figsize=(15,10))
sns.barplot(x=team_ret.index, y=team_ret.Overall)
plt.xticks(rotation=90)
plt.xlabel('Teams')
plt.ylabel('Overall rating')
plt.title('Players\' average rating over all teams')
plt.show()
```

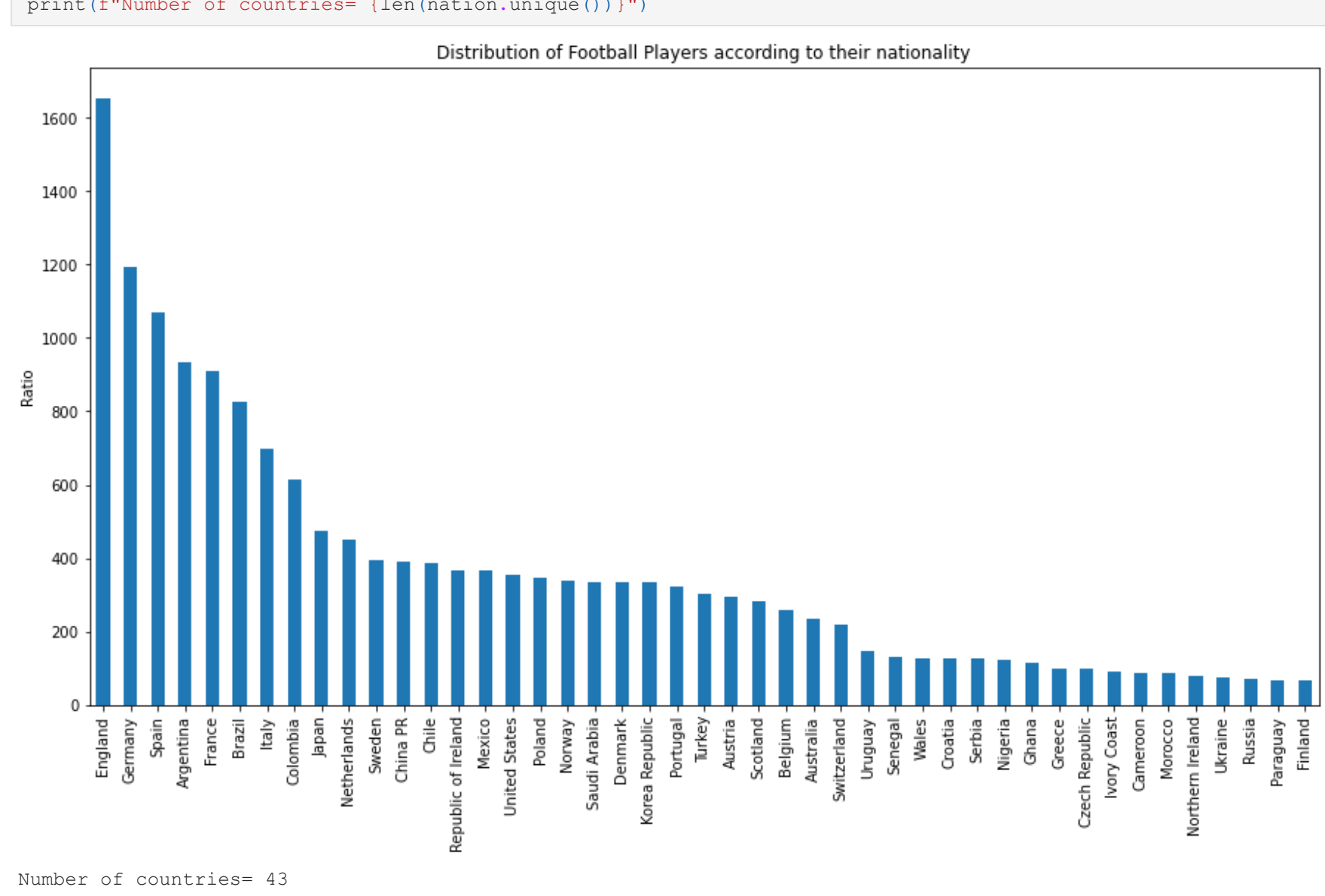


In [31]:
```
team_ret = f_players[['Club','Potential']].groupby('Club').mean().sort_values(by='Potential', ascending=False).
#country = df_nba[['country','full_name']].groupby('country').count().sort_values(by='full_name', ascending=Fa
fig, ax = plt.subplots(figsize=(15,10))
sns.barplot(x=team_ret.index, y=team_ret.Potential)
plt.xticks(rotation=90)
plt.xlabel('Teams')
plt.ylabel('Average rating')
plt.title('Players\' average rating over all teams')
plt.show()
```



Step 1.9 Nationality

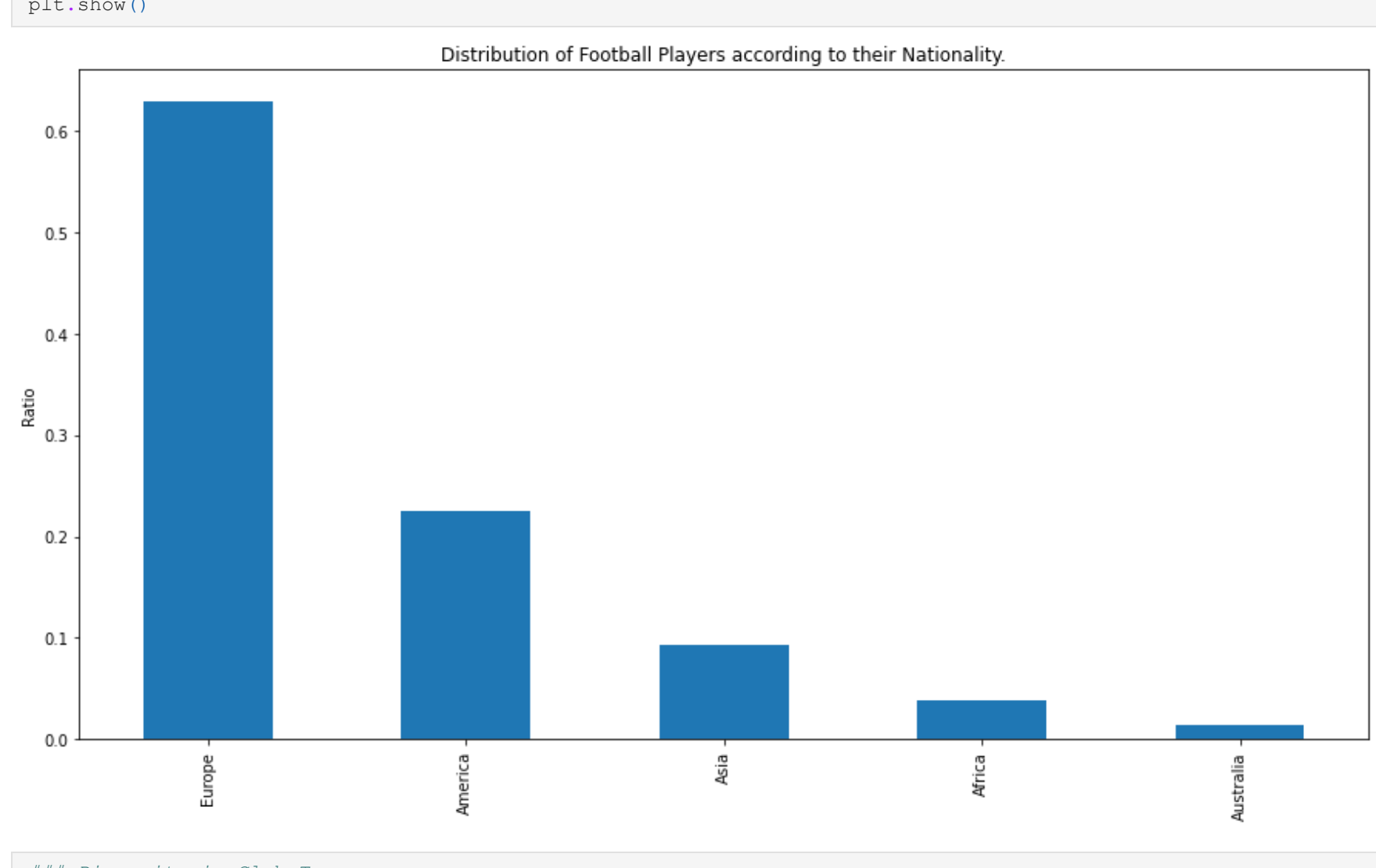
In [32]:
```
nation = f_players['Nationality'].value_counts().head(45)
from matplotlib.pyplot import figure
figure(figsize=(15,8))
nation.plot(kind='bar')
plt.title("Distribution of Football Players according to their nationality")
plt.ylabel("Ratio")
plt.show()
print(f"Number of countries= {len(nation.unique())}")
```



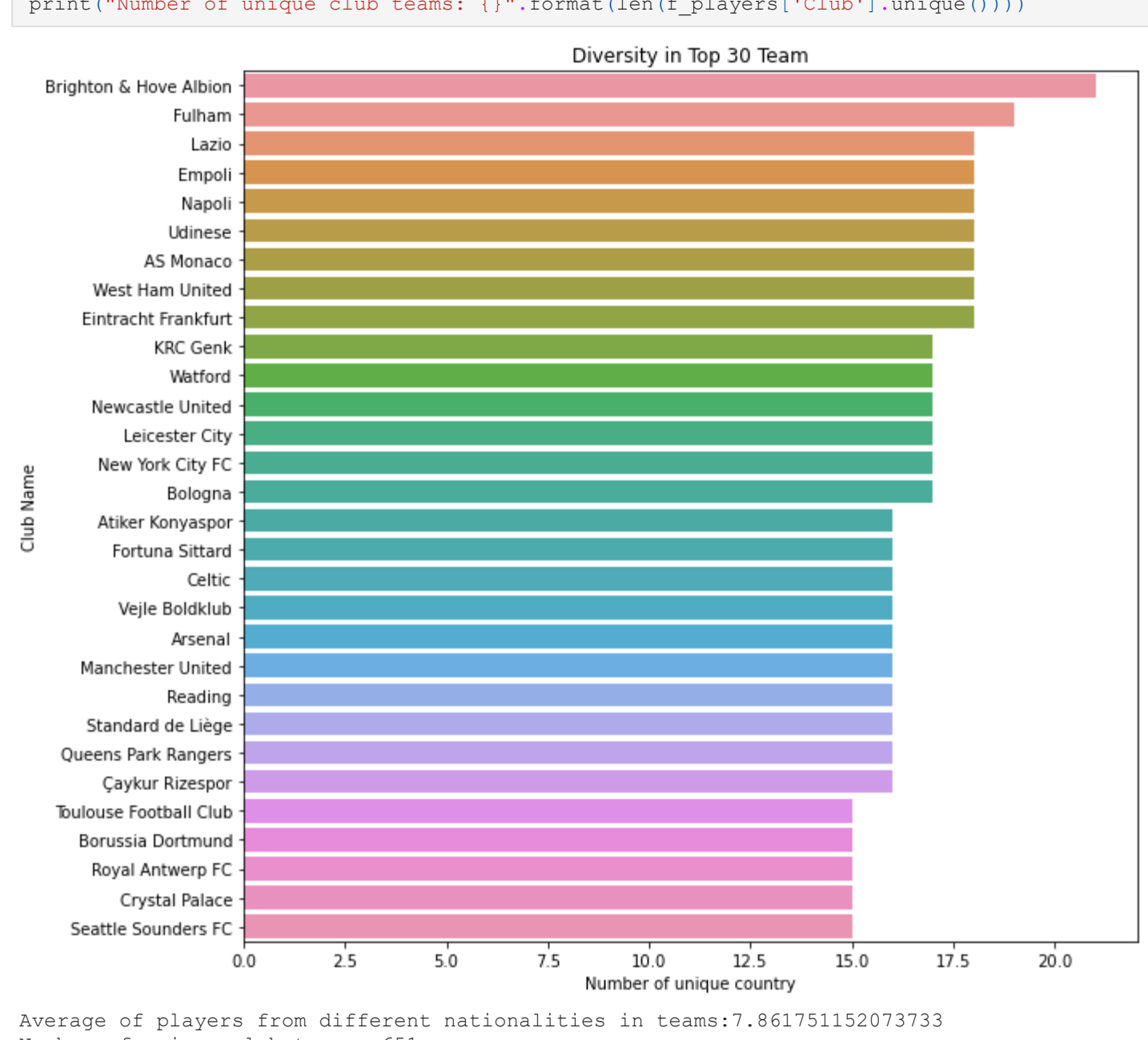

```
Number of countries= 43
```

In [33]:
```
def classify_position(nation):
    """This function help to you for classification football player nation."""

    Nation_dictionary= { 'Europe' : ['England','Germany','Spain','France','Italy','Netherlands','Sweden','Repub
                                     'Poland','Norway','Denmark','Portugal','Turkey','Austria','Scotland','Be
                                     'Switzerland','Wales','Serbia','Croatia','Greece','Czech Republic','Nort
                                     'Ukraine','Russia','Finland'],
                        'America': ['Argentina','Brazil','Colombia','Chile','Mexico','United States','Uruguay','Par
                         'Asia': ['Japan','China PR','Saudi Arabia','Korea Republic'],
                       'Australia':['Australia'],
                          'Africa':['Senegal','Nigeria','Ghana','Ivory Coast','Cameroon','Morocco']}

    for group , nation_list in Nation_dictionary.items():

        if nation in nation_list:
            return group

    return np.nan
```

In [34]:
```
f_players['Nation_classify'] = f_players['Nationality'].apply(classify_position)
figure(figsize=(15,8))
f_players['Nation_classify'].value_counts(normalize= True).plot(kind='bar')
plt.title("Distribution of Football Players according to their Nationality.")
plt.ylabel("Ratio")
plt.show()
```



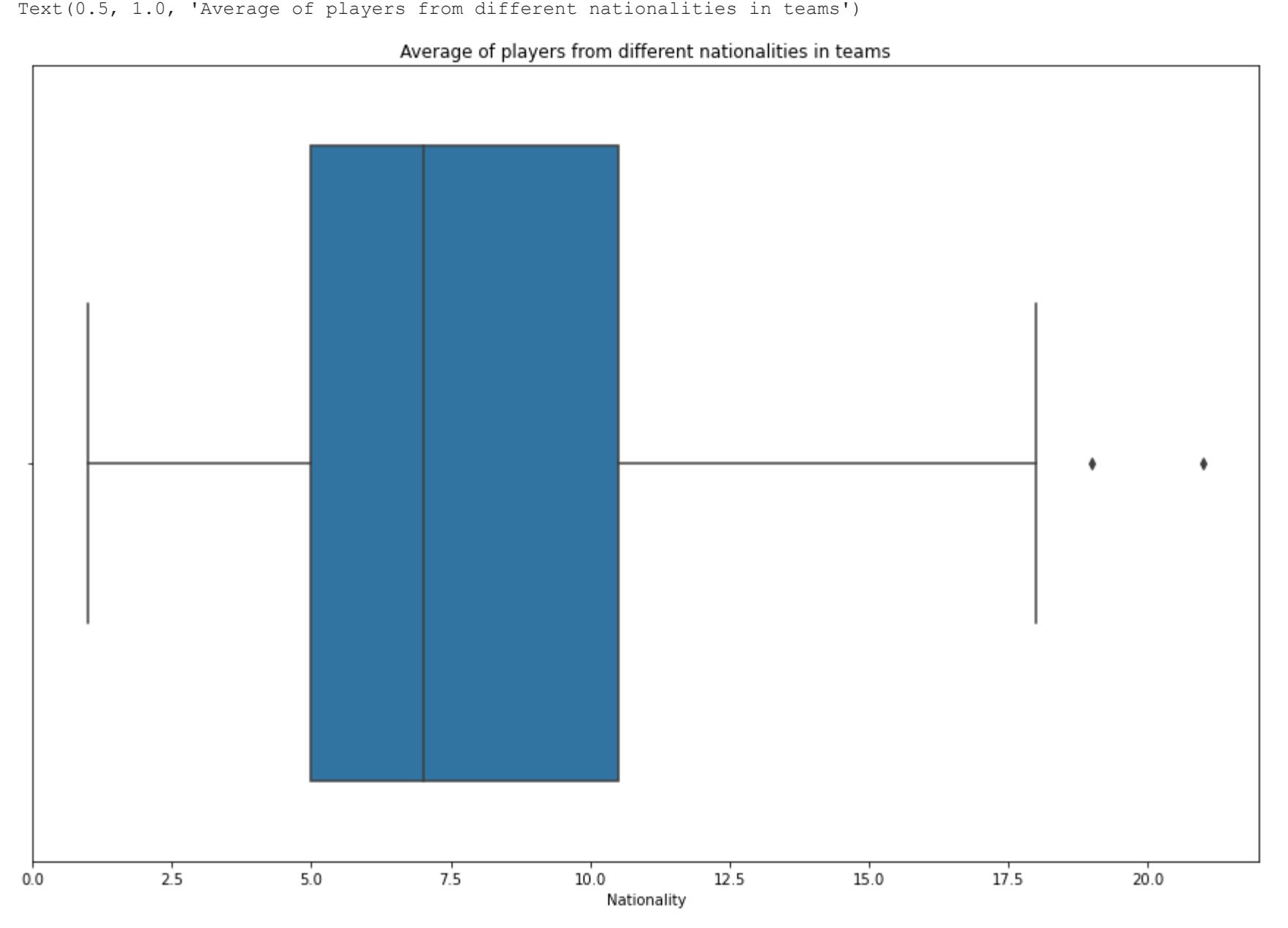
In [35]:
```
### Diversity in Club Teams
country_club = f_players.groupby(f_players['Club'])['Nationality'].nunique().sort_values(ascending = False)
country_nunique = country_club.head(30)
fig, ax = plt.subplots(figsize=(10,10))
sns.barplot(x=country_nunique.values, y=country_nunique.index)
plt.xticks()
plt.xlabel('Number of unique country')
plt.ylabel('Club Name')
plt.title('Diversity in Top 30 Team')
plt.show()
print("Average of players from different nationalities in teams:{}".format(np.mean(country_club)))
print("Number of unique club teams: {}".format(len(f_players['Club'].unique())))
```



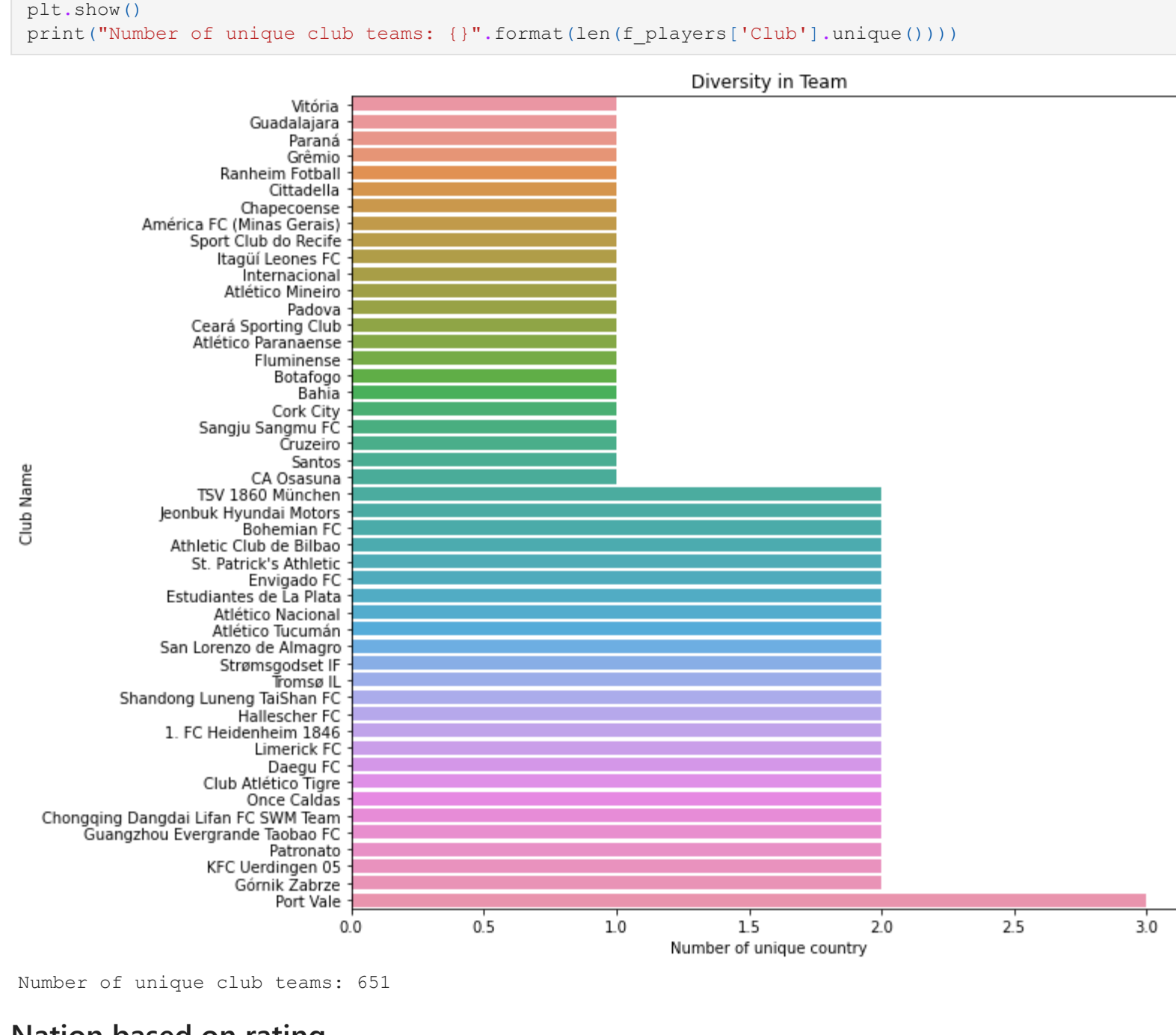

```
Average of players from different nationalities in teams:7.861751152073733
Number of unique club teams: 651
```

In [36]:
```
plt.figure(figsize=(15,10))
ax = sns.boxplot(x=country_club)
plt.title("Average of players from different nationalities in teams")
```

Out[36]: `Text(0.5, 1.0, 'Average of players from different nationalities in teams')`



In [37]:
```
country_nunique = f_players.groupby(f_players['Club'])['Nationality'].nunique().sort_values(ascending = True).h
fig, ax = plt.subplots(figsize=(10,10))
sns.barplot(x=country_nunique.values, y=country_nunique.index)
plt.xticks()
plt.xlabel('Number of unique country')
plt.ylabel('Club Name')
plt.title('Diversity in Team')
plt.show()
print("Number of unique club teams: {}".format(len(f_players['Club'].unique())))
```



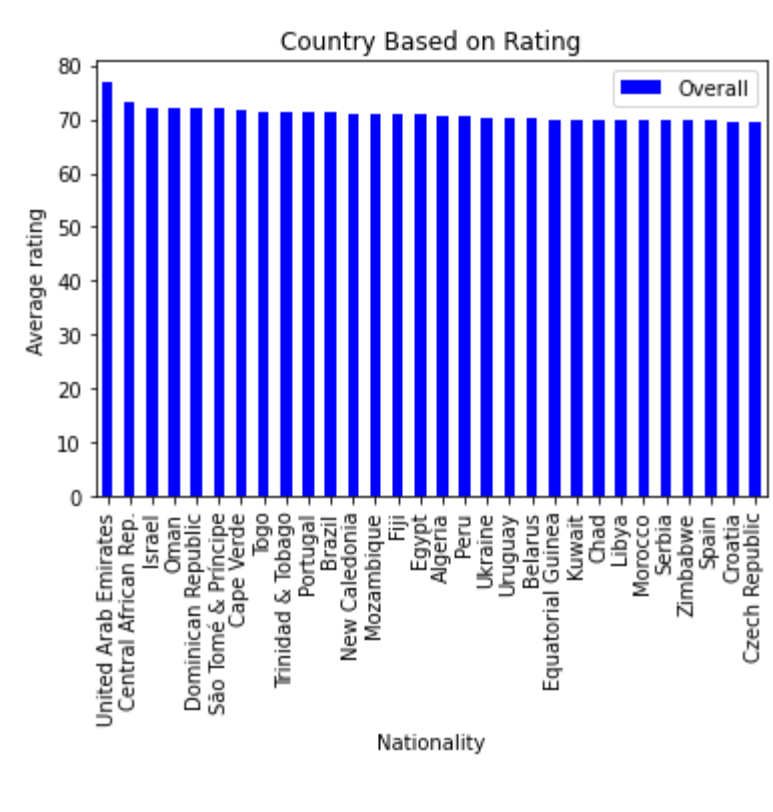

```
Number of unique club teams: 651
```

Nation based on rating

Sunuma koymayacağım

In [38]:
```
#plt.figure(figsize=(28,18))
Nation_overall = f_players[['Nationality','Overall']].groupby('Nationality').mean().sort_values(by='Overall', a
Nation_overall.head(30).plot(kind='bar', color='blue')
plt.xlabel('Nationality')
plt.ylabel('Average rating')
plt.title('Country Based on Rating')
```

Out[38]: `Text(0.5, 1.0, 'Country Based on Rating')`



Step 1.10 Wage

The ratio of total wage for all the players to the potential of each club and which clubs offer the least wage to players?

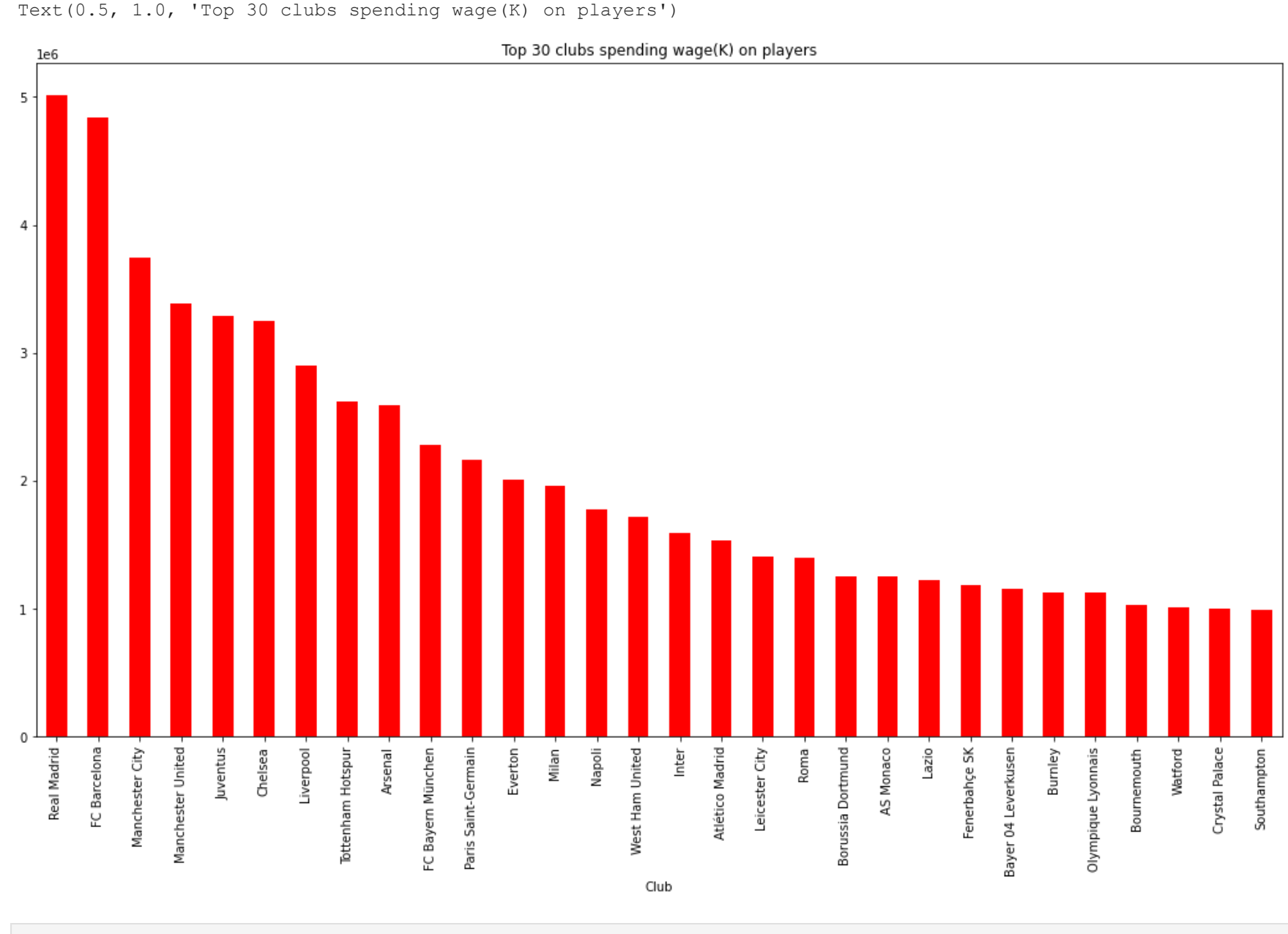
In [39]:
```
club_player = f_players.groupby('Club').sum()
# Number of clubs and average number of players in each club
print('Number of clubs is {}'.format(club_player.shape[0]))
print('Average number players in each club is {}'.format(round(club_player['Age'].mean()/f_players['Age'].mean
print('Total Average wage(K) potential ratio is {}'.
      format(round(club_player['Wage_Float'].sum()/(club_player['Potential'].sum()*1000), 2)))
##Wage ve Value çevirirken çarptığım için 1000'e böldük
```

```
Number of clubs is 651
Average number players in each club is 27.51
Total Average wage(K) potential ratio is 0.14
```

In [40]:
```
club_player['Wage/Potential'] = club_player['Wage_Float'] / club_player['Potential']
club_player['Player Number'] = club_player['Age']
club_player['Player Average Age'] = club_player['Age'] / club_player['Player Number']
```

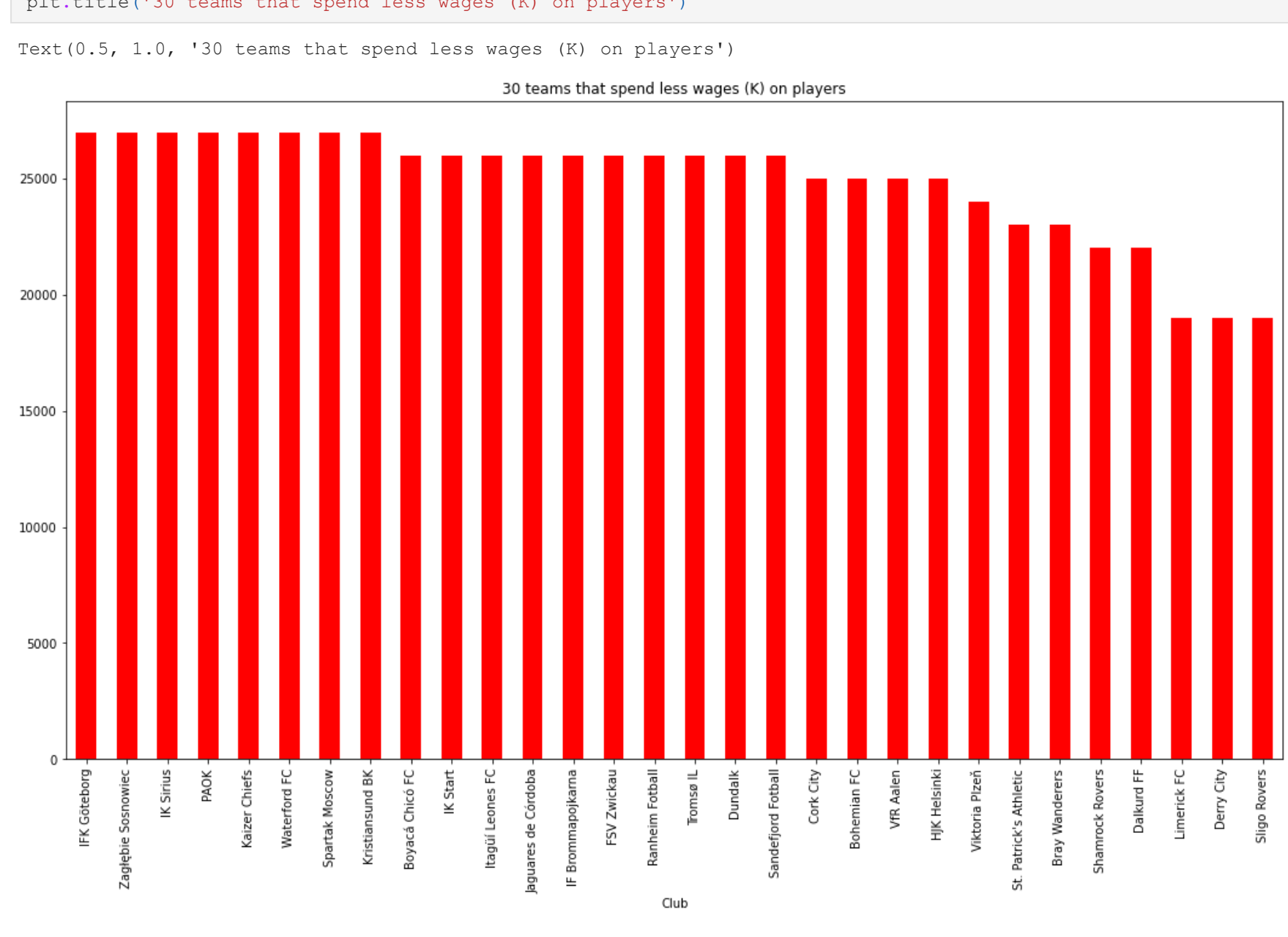
In [41]:
```
plt.figure(figsize=(18,10))
club_player.sort_values('Wage_Float', ascending=False, inplace=True)
club_player['Wage_Float'].head(30).plot(kind='bar', color='Red')
plt.title('Top 30 clubs spending wage(K) on players')
```

Out[41]: Text(0.5, 1.0, 'Top 30 clubs spending wage(K) on players')



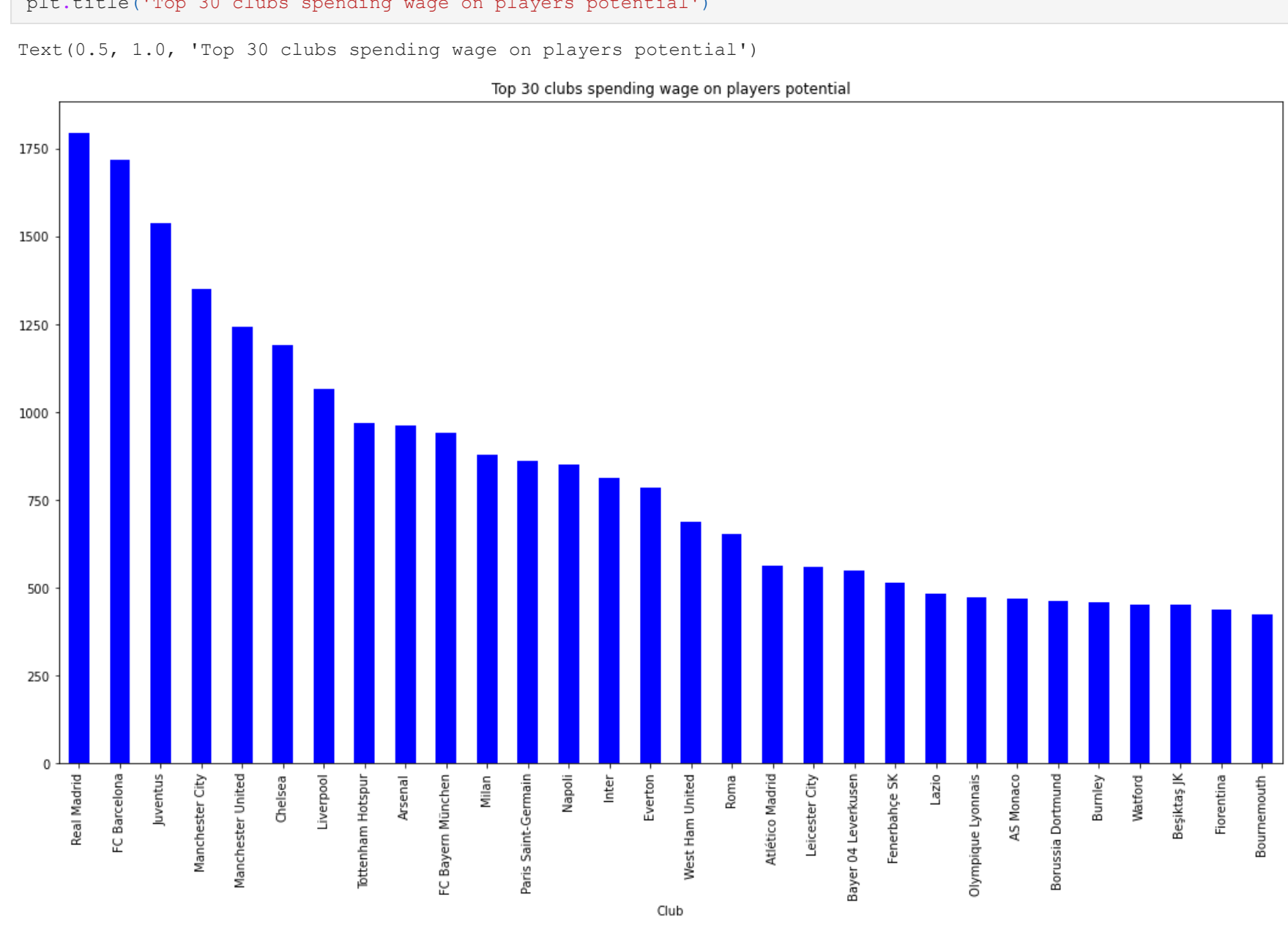
In [42]:
```
plt.figure(figsize=(18,10))
club_player.sort_values('Wage_Float', ascending=False, inplace=True)
club_player['Wage_Float'].tail(30).plot(kind='bar', color='Red')
plt.title('30 teams that spend less wages (K) on players')
```

Out[42]: Text(0.5, 1.0, '30 teams that spend less wages (K) on players')



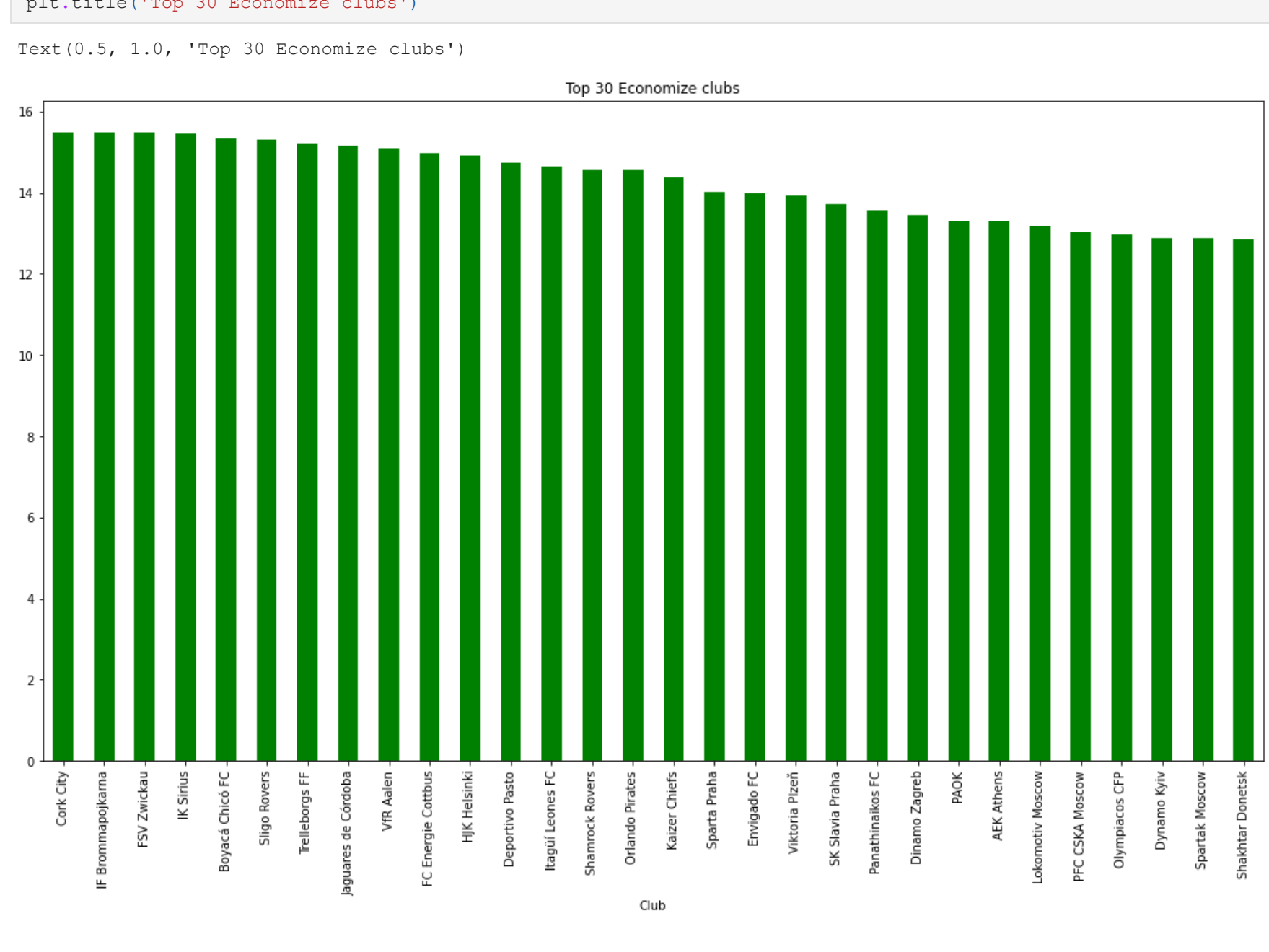
In [43]:
```
plt.figure(figsize=(18,10))
club_player.sort_values('Wage/Potential', ascending=False, inplace=True)
club_player['Wage/Potential'].head(30).plot(kind='bar', color='Blue')
plt.title('Top 30 clubs spending wage on players potential')
```

Out[43]: Text(0.5, 1.0, 'Top 30 clubs spending wage on players potential')



In [44]:
```
plt.figure(figsize=(18,10))
club_player['Wage/Potential'].tail(30).plot(kind='bar', color='Green')
plt.title('Top 30 Economize clubs')
```

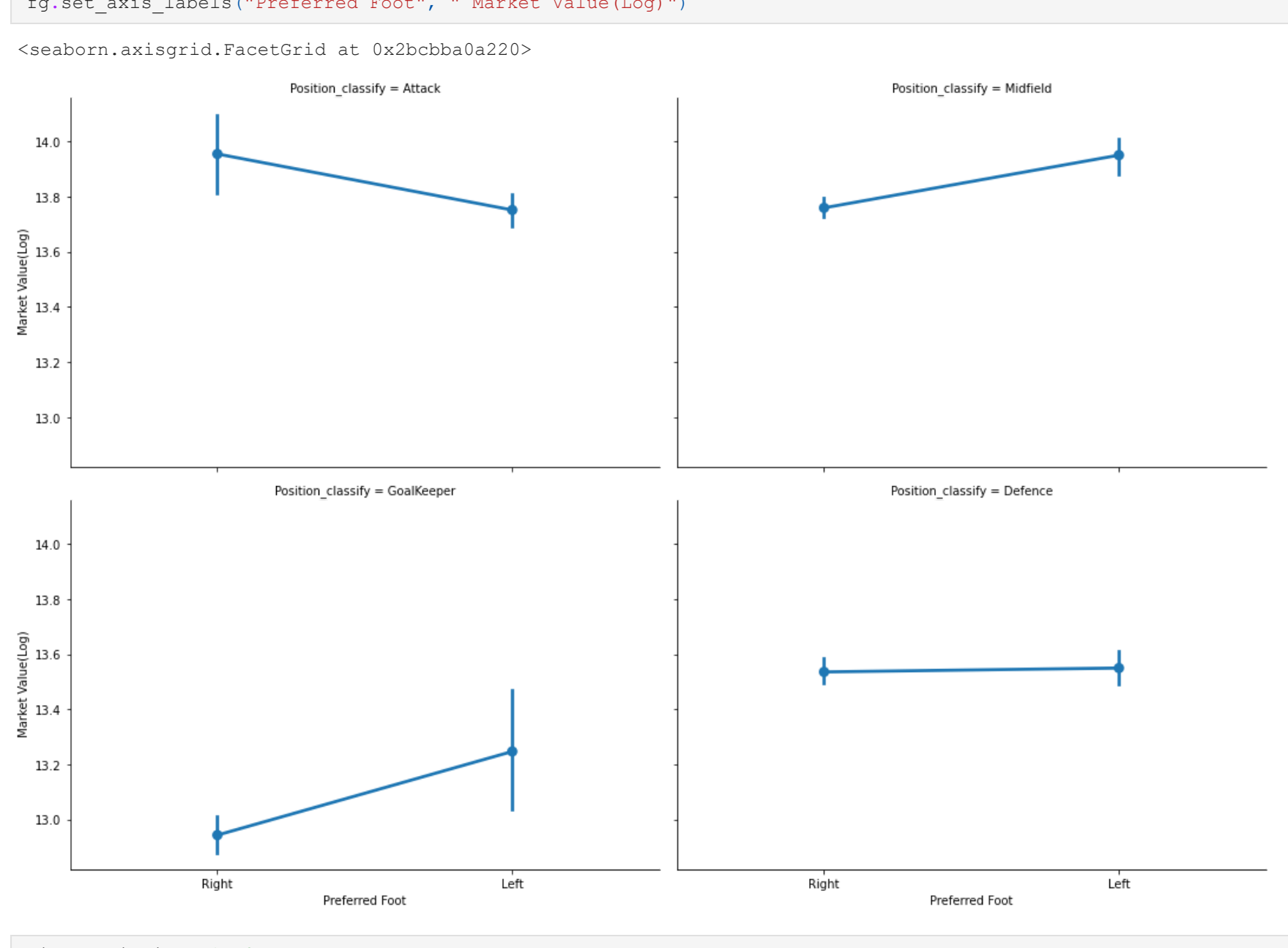
Out[44]: Text(0.5, 1.0, 'Top 30 Economize clubs')



Step 1.10 Preferred FOOT VS Market Value

In [45]:
```
fg = sns.FacetGrid(f_players,col='Position_classify',height=5,aspect=1.5,col_wrap=2)
fg.map(sns.pointplot,'Preferred Foot','Value_Float_log',palette= None, order= None, hue_order = None)
fg.add_legend()
fg.set_axis_labels("Preferred Foot", " Market Value(Log)")
```

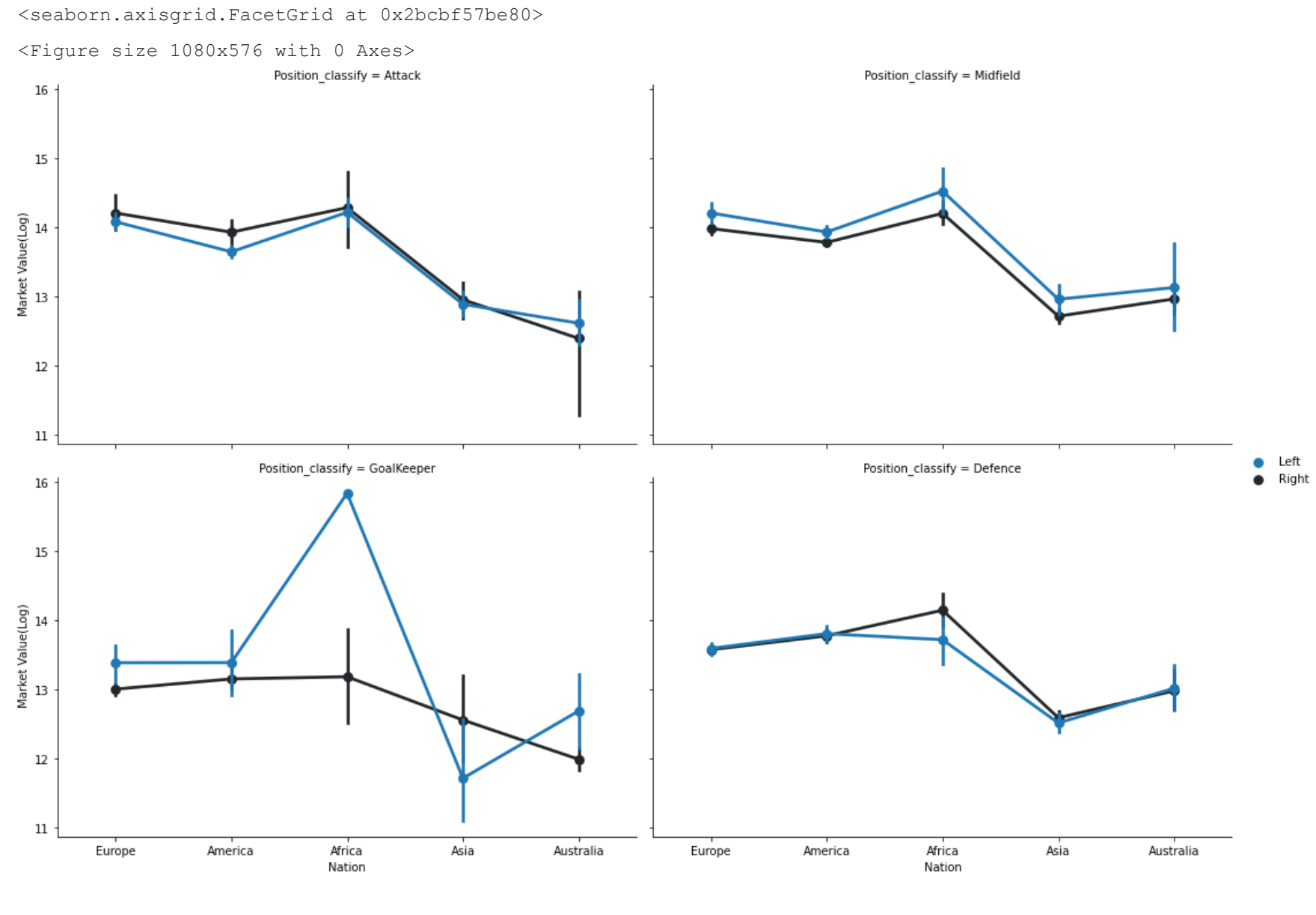
Out[45]: <seaborn.axisgrid.FacetGrid at 0x2bcbba0a220>



In [46]:
```
figure(figsize=(15,8))
fg = sns.FacetGrid(f_players,col='Position_classify',height=5,aspect=1.5,col_wrap=2)
fg.map(sns.pointplot,'Nation_classify','Value_Float_log','Preferred Foot',palette= None, order= None, hue_order
fg.add_legend()
fg.set_axis_labels("Nation", " Market Value(Log)")
```

Out[46]: <seaborn.axisgrid.FacetGrid at 0x2bcbf57be80>

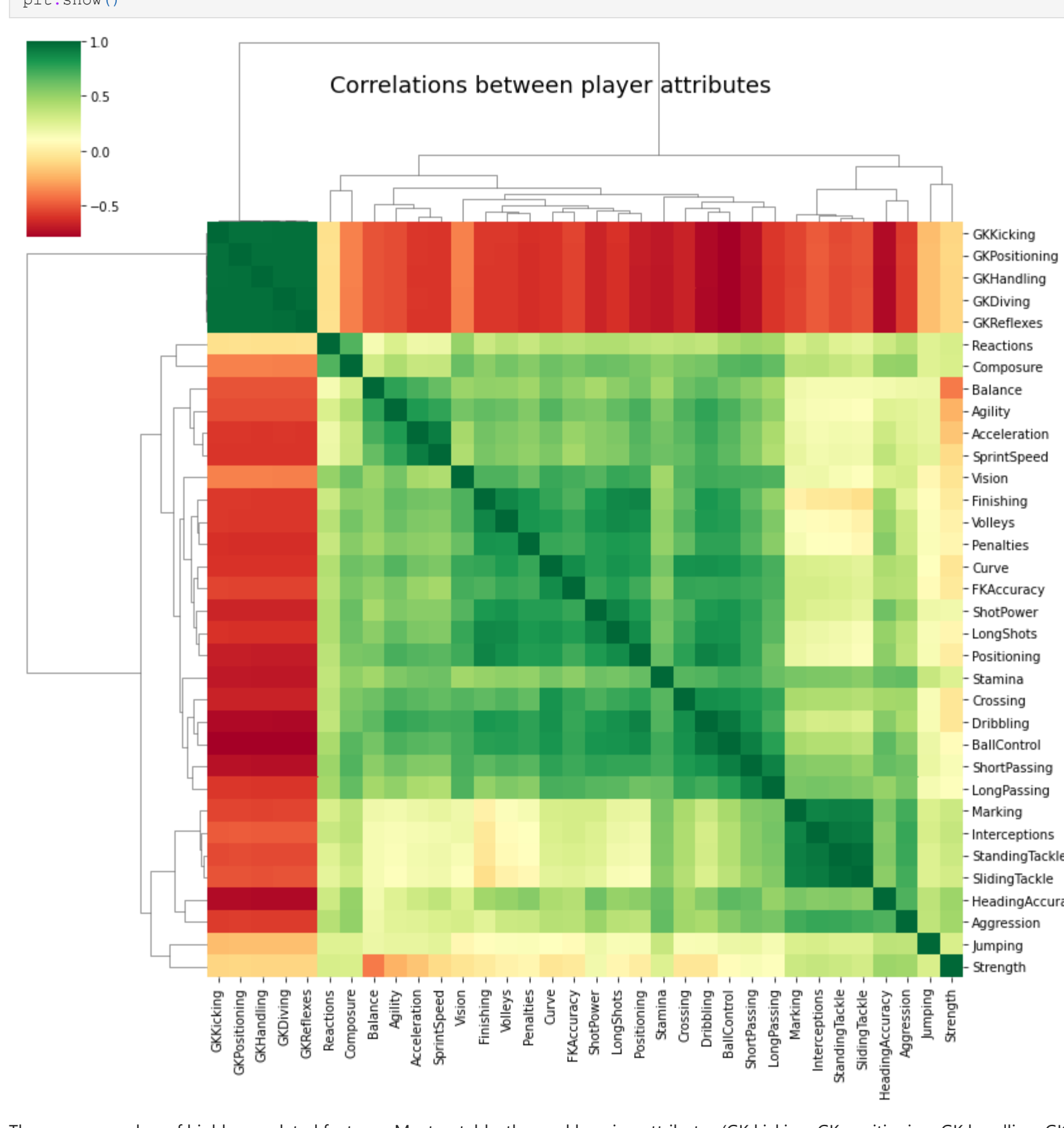
<Figure size 1080x576 with 0 Axes>



Step 1.11 Player attribute features

In [47]:
```
ATTRIBUTES =['Crossing', 'Finishing', 'HeadingAccuracy','ShortPassing', 'Volleys', 'Dribbling', 'Curve', 'FKAcc
             'LongPassing', 'BallControl', 'Acceleration', 'SprintSpeed', 'Agility','Reactions', 'Balance', 'Sh
             'Jumping','Stamina', 'Strength','LongShots', 'Aggression', 'Interceptions', 'Positioning', 'Vision
             'Composure', 'Marking', 'StandingTackle', 'SlidingTackle','GKDiving', 'GKHandling', 'GKKicking', '
             'GKReflexes',]
```

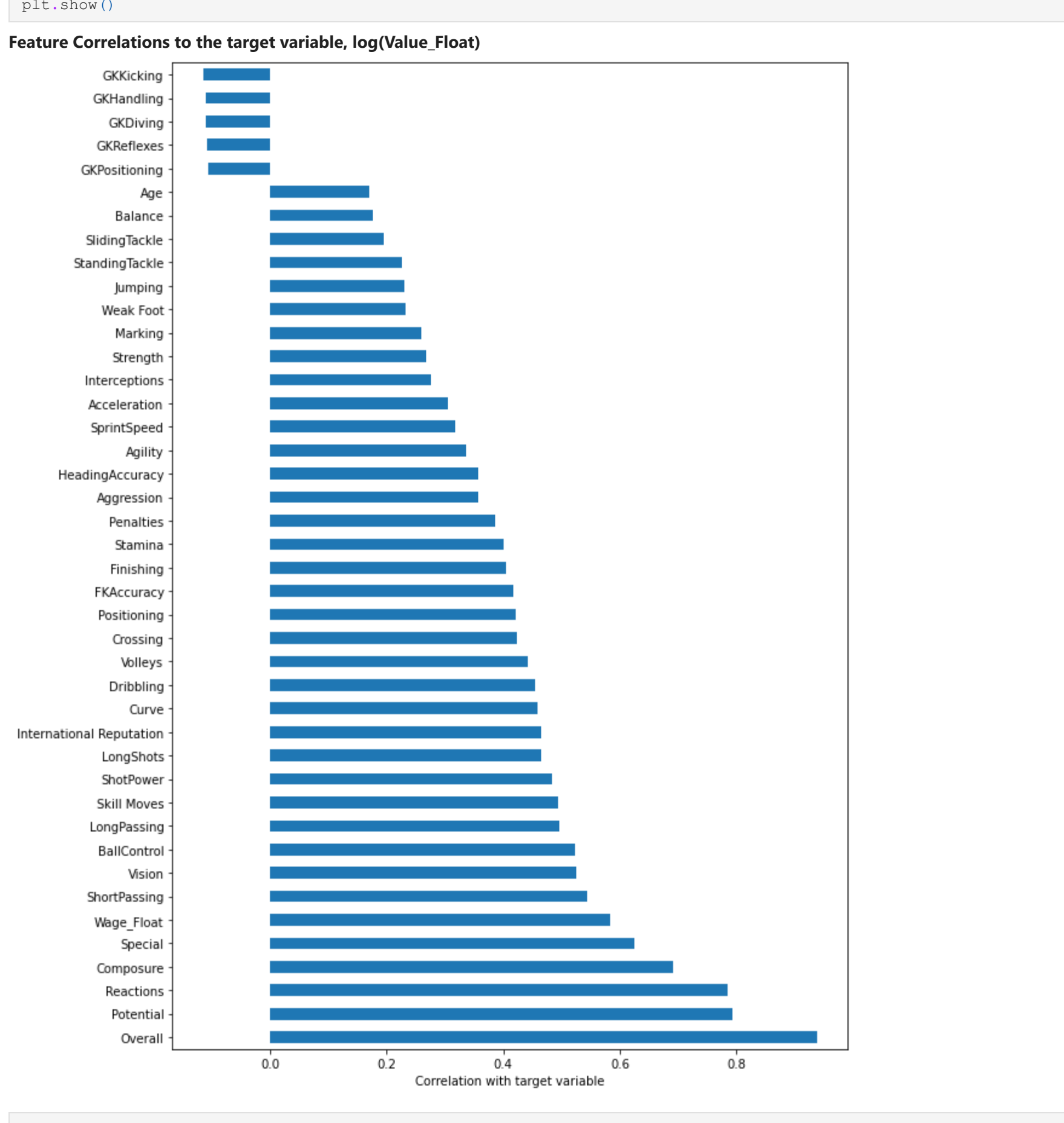
In [48]:
```
sns.clustermap(f_players[ATTRIBUTES].corr(),cmap='RdYlGn',figsize=(12,12))
plt.suptitle("Correlations between player attributes",fontsize=18,y=0.95)
plt.show()
```



There are a number of highly correlated features. Most notably, the goal keeping attributes (GK kicking, GK positioning, GK handling, GK diving and GK reflexes) are very correlated with each other and negatively correlated with the outfield attributes. Outfield attributes are generally all correlated with each other. Defending attributes (Marking, interceptions, standing tackle, sliding tackle etc) are very correlated with each other, however, the attacking attributes are not as strongly correlated. This shows that generally, goal keepers and defenders have a set of 'standard' skills whereas the attacking players have more specific skills sets (e.g. particularly good at volleying or crossing but not necessarily both.

In [49]:
```
f_players.drop(['PotentialGrowth','Jersey Number','ID','Unnamed: 0','Value_Float'] ,axis =1 , inplace = True)
from IPython.core.display import display, HTML
display(HTML("<b>Feature Correlations to the target variable, log(Value_Float)<b>"))
f_players.corr()["Value_Float_log"].sort_values(ascending=False).iloc[1:].plot(kind='barh',figsize=(10,15))
plt.xlabel("Correlation with target variable")
plt.show()
```

Feature Correlations to the target variable, log(Value_Float)



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