Project: Investigate a Dataset (Soccer Database)

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Introduction

> This soccer database comes from Kaggle and is well suited for data analysis and machine learning. It contains data for soccer matches, players, and teams from several European countries from 2008 to 2016. This dataset is quite extensive I investigate the Soccer dataset. Mainly, the dataset have 7 tables called 'Country', 'League', 'Match', 'Player', 'Player Attributes', 'Team' and 'Team Attributes'. the dataset contains useful data about 11 seasons between 2008 and 2016 in different leagues and a list of (players, teams) attributes Players and Teams' attributes* sourced from EA Sports' FIFA video game series. Detailed match events (goal types, possession, corner, cross, fouls, cards etc...) for +10,000 matches 16th Oct 2016: New table containing teams' attributes from FIFA ! Each record has its table connected with the other by identification numbers. the player's table describes players' names and their weight and height. player attributes describe their abilities and rating their potentials.

During the analysis of the dataset I wanna focus answer these questions:

- How many matches are there in each league in the 2016 season?
- Which League had the most matches end as draw in the 2016 season?
- Which League had the most Wins or not Draw in the 2016 season?
- Which team had lost the fewest matches in the 2016 season?
- Which League had the most goals in the 2016 season?
- Which teams had the most wins of matches in the 2016 season?
- What teams improved the most over the time period?
- Which players had the most penalties?
- What team attributes lead to the most victories?
- How many Players have overall rating more than 90?
- What are the attributes that contribute to the players' overall rating?

In [1]:
```
# import packages
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
% matplotlib inline
```

```
UsageError: Line magic function `%` not found.
```

Data Wrangling

Now we will gather and collect data from CSV files

In [2]:
```
# Load Data that I will investigate it
df_match = pd.read_csv('Match.csv')
df_player_attribute = pd.read_csv('Player_Attributes.csv')
df_team_attribute = pd.read_csv('Team_Attributes.csv')
df_team = pd.read_csv('Team.csv')
df_player = pd.read_csv('Player.csv')
df_country = pd.read_csv('Country.csv')
df_league = pd.read_csv('League.csv')
```

In [3]:
```
#Sample of Mactch Table
df_match.head()
```

Out[3]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_tea
0	1	1	1	2008/2009	1	2008-08-17 00:00:00	492473	9987	
1	2	1	1	2008/2009	1	2008-08-16 00:00:00	492474	10000	
2	3	1	1	2008/2009	1	2008-08-16 00:00:00	492475	9984	
3	4	1	1	2008/2009	1	2008-08-17 00:00:00	492476	9991	
4	5	1	1	2008/2009	1	2008-08-16 00:00:00	492477	7947	

5 rows × 115 columns

In [4]:
```
#Columns in the match table
df_match.columns
```

Out[4]:
```
Index(['id', 'country_id', 'league_id', 'season', 'stage', 'date',
       'match_api_id', 'home_team_api_id', 'away_team_api_id',
       'home_team_goal',
       ...
       'SJA', 'VCH', 'VCD', 'VCA', 'GBH', 'GBD', 'GBA', 'BSH', 'BSD', 'BSA'],
      dtype='object', length=115)
```

In [5]:
```
# Number of Rows, Columns
df_match.shape
```

Out[5]:
```
(25979, 115)
```

In [6]:
```
# information about Match table
```

```
df_match.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25979 entries, 0 to 25978
Columns: 115 entries, id to BSA
dtypes: float64(96), int64(9), object(10)
memory usage: 22.8+ MB
```

In [7]:
```
# Number of Duplicated Records in Match table
df_match.duplicated().sum()
```

Out[7]:
```
0
```

In [8]:
```
# Number of NULL values in Match table
df_match.isna().sum().sum()
```

Out[8]:
```
407395
```

In [9]:
```
df_match.describe()
```

Out[9]:

	id	country_id	league_id	stage	match_api_id	home_team_api_id	av
count	25979.000000	25979.000000	25979.000000	25979.000000	2.597900e+04	25979.000000	
mean	12990.000000	11738.630317	11738.630317	18.242773	1.195429e+06	9984.371993	
std	7499.635658	7553.936759	7553.936759	10.407354	4.946279e+05	14087.453758	
min	1.000000	1.000000	1.000000	1.000000	4.831290e+05	1601.000000	
25%	6495.500000	4769.000000	4769.000000	9.000000	7.684365e+05	8475.000000	
50%	12990.000000	10257.000000	10257.000000	18.000000	1.147511e+06	8697.000000	
75%	19484.500000	17642.000000	17642.000000	27.000000	1.709852e+06	9925.000000	
max	25979.000000	24558.000000	24558.000000	38.000000	2.216672e+06	274581.000000	

8 rows × 105 columns

Match Table:-

Contain 25979 Records & 115 Columns.
No duplicate records
Has a lot of missing values (407395) but all null values in columns I won't need in processes, So I'll drop it.

In [10]:
```
#Sample of Country Table
df_country
```

Out[10]:

	id	name
0	1	Belgium
1	1729	England
2	4769	France
3	7809	Germany
4	10257	Italy
5	13274	Netherlands

	id	name
6	15722	Poland
7	17642	Portugal
8	19694	Scotland
9	21518	Spain
10	24558	Switzerland

In [11]:
```
# Number of Rows, Columns
df_country.shape
```

Out[11]:
```
(11, 2)
```

In [12]:
```
# information about country table
df_country.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   id      11 non-null     int64 
 1   name    11 non-null     object
dtypes: int64(1), object(1)
memory usage: 304.0+ bytes
```

In [13]:
```
df_country.describe()
```

Out[13]:

	id
count	11.000000
mean	12452.090909
std	8215.308472
min	1.000000
25%	6289.000000
50%	13274.000000
75%	18668.000000
max	24558.000000

Country Table:-

Contain 11 Records & 2 Columns.
No duplicate records
No missing values.

In [14]:
```
#Sample of team Table
df_team.head()
```

Out[14]:

	id	team_api_id	team_fifa_api_id	team_long_name	team_short_name
0	1	9987	673.0	KRC Genk	GEN
1	2	9993	675.0	Beerschot AC	BAC

	id	team_api_id	team_fifa_api_id	team_long_name	team_short_name
2	3	10000	15005.0	SV Zulte-Waregem	ZUL
3	4	9994	2007.0	Sporting Lokeren	LOK
4	5	9984	1750.0	KSV Cercle Brugge	CEB

In [15]:
```
# Number of Rows, Columns
df_team.shape
```

Out[15]:
```
(299, 5)
```

In [16]:
```
# information about team table
df_team.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   id                299 non-null    int64 
 1   team_api_id       299 non-null    int64 
 2   team_fifa_api_id  288 non-null    float64
 3   team_long_name    299 non-null    object
 4   team_short_name   299 non-null    object
dtypes: float64(1), int64(2), object(2)
memory usage: 11.8+ KB
```

In [17]:
```
# Number of Duplicated Records team table
df_team.duplicated().sum()
```

Out[17]:
```
0
```

In [18]:
```
# Number of NULL values in each table in team table
df_team.isna().sum()
```

Out[18]:
```
id                  0
team_api_id         0
team_fifa_api_id    11
team_long_name      0
team_short_name     0
dtype: int64
```

In [19]:
```
# Number of NULL values in team table
df_team.isna().sum().sum()
```

Out[19]:
```
11
```

In [20]:
```
df_team.describe()
```

Out[20]:

	id	team_api_id	team_fifa_api_id
count	299.000000	299.000000	288.000000
mean	23735.301003	12340.521739	21534.305556
std	15167.914719	25940.411135	42456.439408
min	1.000000	1601.000000	1.000000
25%	9552.500000	8349.000000	178.750000
50%	22805.000000	8655.000000	673.500000

	id	team_api_id	team_fifa_api_id
75%	36250.500000	9886.500000	1910.750000
max	51606.000000	274581.000000	112513.000000

Team Table:-

Contain 299 Records & 5 Columns.
No duplicate records
Has missing values(11) but all null values in team_fifa_api_id column.

In [21]:
```
#Sample of team attribute Table
df_team_attribute.head()
```

Out[21]:

	id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUpPla
0	1	434	9930	2010-02-22 00:00:00	60	Balanced	
1	2	434	9930	2014-09-19 00:00:00	52	Balanced	
2	3	434	9930	2015-09-10 00:00:00	47	Balanced	
3	4	77	8485	2010-02-22 00:00:00	70	Fast	
4	5	77	8485	2011-02-22 00:00:00	47	Balanced	

5 rows × 25 columns

In [22]:
```
# Number of Rows, Columns
df_team_attribute.shape
```

Out[22]:
```
(1458, 25)
```

In [23]:
```
# information about team attribute table
df_team_attribute.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458 entries, 0 to 1457
Data columns (total 25 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              1458 non-null   int64
 1   team_fifa_api_id                1458 non-null   int64
 2   team_api_id                     1458 non-null   int64
 3   date                            1458 non-null   object
 4   buildUpPlaySpeed                1458 non-null   int64
 5   buildUpPlaySpeedClass           1458 non-null   object
 6   buildUpPlayDribbling            489 non-null    float64
 7   buildUpPlayDribblingClass       1458 non-null   object
 8   buildUpPlayPassing              1458 non-null   int64
 9   buildUpPlayPassingClass         1458 non-null   object
 10  buildUpPlayPositioningClass     1458 non-null   object
```

```
 11  chanceCreationPassing           1458 non-null   int64
 12  chanceCreationPassingClass      1458 non-null   object
 13  chanceCreationCrossing          1458 non-null   int64
 14  chanceCreationCrossingClass     1458 non-null   object
 15  chanceCreationShooting          1458 non-null   int64
 16  chanceCreationShootingClass     1458 non-null   object
 17  chanceCreationPositioningClass  1458 non-null   object
 18  defencePressure                 1458 non-null   int64
 19  defencePressureClass            1458 non-null   object
 20  defenceAggression               1458 non-null   int64
 21  defenceAggressionClass          1458 non-null   object
 22  defenceTeamWidth                1458 non-null   int64
 23  defenceTeamWidthClass           1458 non-null   object
 24  defenceDefenderLineClass        1458 non-null   object
dtypes: float64(1), int64(11), object(13)
memory usage: 284.9+ KB
```

In [24]:
```
# Number of Duplicated Records team attribute table
df_team_attribute.duplicated().sum()
```

Out[24]:
```
0
```

In [25]:
```
# Number of NULL values in each table in team attribute table
df_team_attribute.isna().sum()
```

Out[25]:
```
id                              0
team_fifa_api_id                0
team_api_id                     0
date                            0
buildUpPlaySpeed                0
buildUpPlaySpeedClass           0
buildUpPlayDribbling          969
buildUpPlayDribblingClass       0
buildUpPlayPassing              0
buildUpPlayPassingClass         0
buildUpPlayPositioningClass     0
chanceCreationPassing           0
chanceCreationPassingClass      0
chanceCreationCrossing          0
chanceCreationCrossingClass     0
chanceCreationShooting          0
chanceCreationShootingClass     0
chanceCreationPositioningClass  0
defencePressure                 0
defencePressureClass            0
defenceAggression               0
defenceAggressionClass          0
defenceTeamWidth                0
defenceTeamWidthClass           0
defenceDefenderLineClass        0
dtype: int64
```

In [26]:
```
# Number of NULL values in team attribute table
df_team_attribute.isna().sum().sum()
```

Out[26]:
```
969
```

In [27]:
```
df_team_attribute.describe()
```

Out[27]:

	id	team_fifa_api_id	team_api_id	buildUpPlaySpeed	buildUpPlayDribbling	buildU
count	1458.000000	1458.000000	1458.000000	1458.000000	489.000000	
mean	729.500000	17706.982167	9995.727023	52.462277	48.607362	
std	421.032659	39179.857739	13264.869900	11.545869	9.678290	

	id	team_fifa_api_id	team_api_id	buildUpPlaySpeed	buildUpPlayDribbling	buildU
min	1.000000	1.000000	1601.000000	20.000000	24.000000	
25%	365.250000	110.000000	8457.750000	45.000000	42.000000	
50%	729.500000	485.000000	8674.000000	52.000000	49.000000	
75%	1093.750000	1900.000000	9904.000000	62.000000	55.000000	
max	1458.000000	112513.000000	274581.000000	80.000000	77.000000	

Team Table:-

Contain 1458 Records & 25 Columns.
No duplicate records
Has a lot of missing values(969) but all null values in buildUpPlayDribbling colums, So I'll drop it.

In [28]:
```
#Sample of league Table
df_league
```

Out[28]:

	id	country_id	name
0	1	1	Belgium Jupiler League
1	1729	1729	England Premier League
2	4769	4769	France Ligue 1
3	7809	7809	Germany 1. Bundesliga
4	10257	10257	Italy Serie A
5	13274	13274	Netherlands Eredivisie
6	15722	15722	Poland Ekstraklasa
7	17642	17642	Portugal Liga ZON Sagres
8	19694	19694	Scotland Premier League
9	21518	21518	Spain LIGA BBVA
10	24558	24558	Switzerland Super League

In [29]:
```
# Number of Rows, Columns
df_league.shape
```

Out[29]:
```
(11, 3)
```

In [30]:
```
# information about league table
df_league.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          11 non-null     int64 
 1   country_id  11 non-null     int64 
 2   name        11 non-null     object
dtypes: int64(2), object(1)
memory usage: 392.0+ bytes
```

In [31]:
```
df_league.describe()
```

Out[31]:

	id	country_id
count	11.000000	11.000000
mean	12452.090909	12452.090909
std	8215.308472	8215.308472
min	1.000000	1.000000
25%	6289.000000	6289.000000
50%	13274.000000	13274.000000
75%	18668.000000	18668.000000
max	24558.000000	24558.000000

League Table:-

```
Contain 11 Records & 3 Columns.
No duplicate records
No missing values.
```

In [32]:
```
#Sample of player Table
df_player.head()
```

Out[32]:

	id	player_api_id	player_name	player_fifa_api_id	birthday	height	weight
0	1	505942	Aaron Appindangoye	218353	1992-02-29 00:00:00	182.88	187
1	2	155782	Aaron Cresswell	189615	1989-12-15 00:00:00	170.18	146
2	3	162549	Aaron Doran	186170	1991-05-13 00:00:00	170.18	163
3	4	30572	Aaron Galindo	140161	1982-05-08 00:00:00	182.88	198
4	5	23780	Aaron Hughes	17725	1979-11-08 00:00:00	182.88	154

In [33]:
```
# Number of Rows, Columns
df_player.shape
```

Out[33]:
```
(11060, 7)
```

In [34]:
```
# Number of Rows, Columns
df_player.duplicated().sum()
```

Out[34]:
```
0
```

In [35]:
```
# Number of NULL values in team table
df_player.isna().sum().sum()
```

Out[35]:
```
0
```

In [36]:
```
df_player.describe()
```

Out[36]:

	id	player_api_id	player_fifa_api_id	height	weight
count	11060.000000	11060.000000	11060.000000	11060.000000	11060.000000
mean	5537.511392	156582.427215	165664.910488	181.867445	168.380289

	id	player_api_id	player_fifa_api_id	height	weight
std	3197.692647	160713.700624	58649.928360	6.369201	14.990217
min	1.000000	2625.000000	2.000000	157.480000	117.000000
25%	2767.750000	35555.500000	151889.500000	177.800000	159.000000
50%	5536.500000	96619.500000	184671.000000	182.880000	168.000000
75%	8306.250000	212470.500000	203883.250000	185.420000	179.000000
max	11075.000000	750584.000000	234141.000000	208.280000	243.000000

Player Table:-

```
Contain 11060 Records & 7 Columns.
No duplicate records
Has missing values(11).
```

In [37]:
```
#Sample of player attribute Table
df_player_attribute.head()
```

Out[37]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attacking_v
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	

5 rows × 42 columns

In [38]:
```
# Number of Rows, Columns
df_player_attribute.shape
```

Out[38]:
```
(183978, 42)
```

In [39]:
```
# information about player attribute table
df_player_attribute.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183978 entries, 0 to 183977
Data columns (total 42 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   183978 non-null  int64
 1   player_fifa_api_id   183978 non-null  int64
 2   player_api_id        183978 non-null  int64
```

```
 3   date                 183978 non-null  object
 4   overall_rating       183142 non-null  float64
 5   potential            183142 non-null  float64
 6   preferred_foot       183142 non-null  object
 7   attacking_work_rate  180748 non-null  object
 8   defensive_work_rate  183142 non-null  object
 9   crossing             183142 non-null  float64
 10  finishing            183142 non-null  float64
 11  heading_accuracy     183142 non-null  float64
 12  short_passing        183142 non-null  float64
 13  volleys              181265 non-null  float64
 14  dribbling            183142 non-null  float64
 15  curve                181265 non-null  float64
 16  free_kick_accuracy   183142 non-null  float64
 17  long_passing         183142 non-null  float64
 18  ball_control         183142 non-null  float64
 19  acceleration         183142 non-null  float64
 20  sprint_speed         183142 non-null  float64
 21  agility              181265 non-null  float64
 22  reactions            183142 non-null  float64
 23  balance              181265 non-null  float64
 24  shot_power           183142 non-null  float64
 25  jumping              181265 non-null  float64
 26  stamina              183142 non-null  float64
 27  strength             183142 non-null  float64
 28  long_shots           183142 non-null  float64
 29  aggression           183142 non-null  float64
 30  interceptions        183142 non-null  float64
 31  positioning          183142 non-null  float64
 32  vision               181265 non-null  float64
 33  penalties            183142 non-null  float64
 34  marking              183142 non-null  float64
 35  standing_tackle      183142 non-null  float64
 36  sliding_tackle       181265 non-null  float64
 37  gk_diving            183142 non-null  float64
 38  gk_handling          183142 non-null  float64
 39  gk_kicking           183142 non-null  float64
 40  gk_positioning       183142 non-null  float64
 41  gk_reflexes          183142 non-null  float64
dtypes: float64(35), int64(3), object(4)
memory usage: 59.0+ MB
```

In [40]:
```
# Number of Duplicated Records player attribute table
df_player_attribute.duplicated().sum()
```

Out[40]:
```
0
```

In [41]:
```
# Number of NULL values in each columns in _player attribute table
df_player_attribute.isna().sum()
```

Out[41]:
```
id                       0
player_fifa_api_id       0
player_api_id            0
date                     0
overall_rating         836
potential              836
preferred_foot         836
attacking_work_rate   3230
defensive_work_rate    836
crossing               836
finishing              836
heading_accuracy       836
short_passing          836
volleys               2713
dribbling              836
curve                 2713
free_kick_accuracy     836
long_passing           836
```

```
ball_control            836
acceleration            836
sprint_speed            836
agility                2713
reactions               836
balance                2713
shot_power              836
jumping                2713
stamina                 836
strength                836
long_shots              836
aggression              836
interceptions           836
positioning             836
vision                 2713
penalties               836
marking                 836
standing_tackle         836
sliding_tackle         2713
gk_diving               836
gk_handling             836
gk_kicking              836
gk_positioning          836
gk_reflexes             836
dtype: int64
```

In [42]:
```
# Number of NULL values in player attribute table
df_player_attribute.isna().sum().sum()
```

Out[42]:
```
47301
```

In [43]:
```
df_player_attribute.describe()
```

Out[43]:

	id	player_fifa_api_id	player_api_id	overall_rating	potential	crossing
count	183978.00000	183978.000000	183978.000000	183142.000000	183142.000000	183142.000000
mean	91989.50000	165671.524291	135900.617324	68.600015	73.460353	55.086883
std	53110.01825	53851.094769	136927.840510	7.041139	6.592271	17.242135
min	1.00000	2.000000	2625.000000	33.000000	39.000000	1.000000
25%	45995.25000	155798.000000	34763.000000	64.000000	69.000000	45.000000
50%	91989.50000	183488.000000	77741.000000	69.000000	74.000000	59.000000
75%	137983.75000	199848.000000	191080.000000	73.000000	78.000000	68.000000
max	183978.00000	234141.000000	750584.000000	94.000000	97.000000	95.000000

8 rows × 38 columns

Player Attributes Table:-

```
Contain 183973 Records & 42 Columns.
No duplicate records
Has a lot of missing values(47301).
```

What I found:

+25,000 matches

+10,000 players

11 Countries with their lead championship

Seasons 2008 to 2016

Table	Records	Columns
League	11	3
Match	25979	115
Player	11060	7
Player_Attributes	183978	42
Team	299	5
Team_Attributes	1458	25

After realizing the DataSet We go through Clean it which handle data and remove the missed values

Data Cleaning (Matches Table)

In [44]:
```
# Select columns which we need in analysis
df_match=df_match.loc[:,:'away_team_goal']
```

In [45]:
```
#Convert Date to DateTime type to gain availability to dedicate a year of each date
df_match['date'] = pd.to_datetime(df_match['date'])
```

In [46]:
```
# Add new Columns to match table store years
df_match['season_year'] = df_match['date'].dt.year
#Print The maximum and minimum year in season year column
str(df_match['season_year'].min()) + " : " + str(df_match['season_year'].max())
```

Out[46]:
```
'2008 : 2016'
```

In [47]:
```
# rename column: name to country_name
df_country.rename(columns={'name' : 'country_name', }, inplace=True)

# join df_match with country table by inner join type .
df_match = df_match.merge(df_country, how='inner', left_on= "country_id", right_on =

# drop column id_y
df_match.drop(columns=['id_y'], inplace=True)
# rename column: id_x to id
df_match.rename(columns={'id_x' : 'id'}, inplace=True)
#Show sample
df_match.head()
```

Out[47]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_
0	1	1	1	2008/2009	1	2008-08-17	492473	9987	
1	2	1	1	2008/2009	1	2008-08-16	492474	10000	
2	3	1	1	2008/2009	1	2008-08-16	492475	9984	
3	4	1	1	2008/2009	1	2008-08-17	492476	9991	

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_
4	5	1	1	2008/2009	1	2008-08-16	492477	7947	

join df_match with team table by inner join type for home team

In [48]:
```
df_match = df_match.merge(df_team, how='inner', left_on='home_team_api_id', right_on
# rename column: team_long_name to home_team_name
df_match.rename(columns={'team_long_name': 'home_team_name','country_name_x'  : 'cou

# drop column home_team_api_id and team_api_id
df_match.drop(columns=['home_team_api_id', 'team_api_id', 'id_y'], axis=1, inplace=T
#Show sample
df_match.head()
```

Out[48]:

	id	country_id	league_id	season	stage	date	match_api_id	away_team_api_id	home_team_
0	1	1	1	2008/2009	1	2008-08-17	492473	9993	
1	29	1	1	2008/2009	12	2008-11-15	492583	9999	
2	47	1	1	2008/2009	14	2008-11-29	492651	9984	
3	65	1	1	2008/2009	16	2008-12-13	492713	9986	
4	94	1	1	2008/2009	19	2009-01-24	492805	9998	

join df_match with team table by left join type for away team

In [49]:
```
df_match = df_match.merge(df_team, how='left', left_on='away_team_api_id', right_on=
# rename column: team_long_name to away_team_name , id_x to id
df_match.rename(columns={'team_long_name': 'away_team_name', 'id_x' : 'id'}, inplace
# drop unnecessary columns
df_match.drop(columns=['team_api_id', 'away_team_api_id','team_fifa_api_id_x', 'team

#Show sample
df_match.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25979 entries, 0 to 25978
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 25979 non-null  int64
 1   country_id         25979 non-null  int64
 2   league_id          25979 non-null  int64
 3   season             25979 non-null  object
 4   stage              25979 non-null  int64
 5   date               25979 non-null  datetime64[ns]
 6   match_api_id       25979 non-null  int64
 7   home_team_goal     25979 non-null  int64
 8   away_team_goal     25979 non-null  int64
 9   season_year        25979 non-null  int64
 10  country_name       25979 non-null  object
 11  home_team_name     25979 non-null  object
 12  team_short_name_x  25979 non-null  object
 13  away_team_name     25979 non-null  object
```

```
dtypes: datetime64[ns](1), int64(8), object(5)
memory usage: 3.0+ MB
```

join df_match with league table by inner join type for away team

In [50]:
```
# rename the two columns 'name' and 'id'
df_league.rename(columns={'name': 'league_name', 'id': 'league_id'}, inplace=True)

# join df_match with league table by inner join type for away team
df_match = df_match.merge(df_league, how='inner', on='league_id')

# drop now country_id and league_id
df_match.drop(columns=["league_id","country_id_y" , "country_id_x"], inplace=True)

#Show sample
df_match.describe()
```

Out[50]:

	id	stage	match_api_id	home_team_goal	away_team_goal	season_year
count	25979.000000	25979.000000	2.597900e+04	25979.000000	25979.000000	25979.000000
mean	12990.000000	18.242773	1.195429e+06	1.544594	1.160938	2011.998653
std	7499.635658	10.407354	4.946279e+05	1.297158	1.142110	2.354741
min	1.000000	1.000000	4.831290e+05	0.000000	0.000000	2008.000000
25%	6495.500000	9.000000	7.684365e+05	1.000000	0.000000	2010.000000
50%	12990.000000	18.000000	1.147511e+06	1.000000	1.000000	2012.000000
75%	19484.500000	27.000000	1.709852e+06	2.000000	2.000000	2014.000000
max	25979.000000	38.000000	2.216672e+06	10.000000	9.000000	2016.000000

In [51]:
```
#Check Missed valuse befor start analysis
df_match.isna().sum().sum()
```

Out[51]:
```
0
```

Data Cleaning (Players)

join df_player with df_player_attribute table by inner join type to easy found pkayer name with attributes

In [52]:
```
df_player = df_player.merge(df_player_attribute, on=['player_api_id','player_fifa_ap
# rename column: id_x to id
df_player.rename(columns={'id_x' : 'id'}, inplace=True)
# drop column id_y,player_api_id, player_fifa_api_id
df_player.drop(columns=["id_y","player_api_id" , "player_fifa_api_id"], inplace=True
#Show sample
df_player.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 183766 entries, 0 to 183765
Data columns (total 44 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   183766 non-null  int64
 1   player_name          183766 non-null  object
 2   birthday             183766 non-null  object
 3   height               183766 non-null  float64
 4   weight               183766 non-null  int64
 5   date                 183766 non-null  object
 6   overall_rating       183016 non-null  float64
 7   potential            183016 non-null  float64
```

```
 8   preferred_foot       183016 non-null  object
 9   attacking_work_rate  180622 non-null  object
 10  defensive_work_rate  183016 non-null  object
 11  crossing             183016 non-null  float64
 12  finishing            183016 non-null  float64
 13  heading_accuracy     183016 non-null  float64
 14  short_passing        183016 non-null  float64
 15  volleys              181139 non-null  float64
 16  dribbling            183016 non-null  float64
 17  curve                181139 non-null  float64
 18  free_kick_accuracy   183016 non-null  float64
 19  long_passing         183016 non-null  float64
 20  ball_control         183016 non-null  float64
 21  acceleration         183016 non-null  float64
 22  sprint_speed         183016 non-null  float64
 23  agility              181139 non-null  float64
 24  reactions            183016 non-null  float64
 25  balance              181139 non-null  float64
 26  shot_power           183016 non-null  float64
 27  jumping              181139 non-null  float64
 28  stamina              183016 non-null  float64
 29  strength             183016 non-null  float64
 30  long_shots           183016 non-null  float64
 31  aggression           183016 non-null  float64
 32  interceptions        183016 non-null  float64
 33  positioning          183016 non-null  float64
 34  vision               181139 non-null  float64
 35  penalties            183016 non-null  float64
 36  marking              183016 non-null  float64
 37  standing_tackle      183016 non-null  float64
 38  sliding_tackle       181139 non-null  float64
 39  gk_diving            183016 non-null  float64
 40  gk_handling          183016 non-null  float64
 41  gk_kicking           183016 non-null  float64
 42  gk_positioning       183016 non-null  float64
 43  gk_reflexes          183016 non-null  float64
dtypes: float64(36), int64(2), object(6)
memory usage: 63.1+ MB
```

In [53]:
```
## Drop duplicated records
df_player.drop_duplicates(inplace = True)
## Drop records have missed value
df_player.dropna(inplace=True)
```

In [54]:
```
#Check Missed valuse befor start analysis
df_player.isna().sum().sum()
```

Out[54]: 0

Data Cleaning (Teams Table)

We Drop a buildUpPlayDribbling collum which has most missed values in team table

In [55]:
```
#Drop a collum which has most missed values
df_team_attribute.drop(columns=['buildUpPlayDribbling'], axis=1, inplace=True)
```

join df_team with df_team_attribute table by inner join type to easy merge name of name beside Their attributes

In [56]:
```
df_team = df_team.merge(df_team_attribute , on = ['team_api_id','team_fifa_api_id'],
# drop column id_y,team_api_id, team_fifa_api_id, team_short_name
df_team.drop(columns=["id_y","team_api_id" , "team_fifa_api_id","team_short_name"],
# rename column: id_x to id
df_team.rename(columns={'id_x': 'id'}, inplace=True)
```

```
#Show some information
df_player.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 180228 entries, 0 to 183765
Data columns (total 44 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   id                   180228 non-null  int64  
 1   player_name          180228 non-null  object 
 2   birthday             180228 non-null  object 
 3   height               180228 non-null  float64
 4   weight               180228 non-null  int64  
 5   date                 180228 non-null  object 
 6   overall_rating       180228 non-null  float64
 7   potential            180228 non-null  float64
 8   preferred_foot       180228 non-null  object 
 9   attacking_work_rate  180228 non-null  object 
 10  defensive_work_rate  180228 non-null  object 
 11  crossing             180228 non-null  float64
 12  finishing            180228 non-null  float64
 13  heading_accuracy     180228 non-null  float64
 14  short_passing        180228 non-null  float64
 15  volleys              180228 non-null  float64
 16  dribbling            180228 non-null  float64
 17  curve                180228 non-null  float64
 18  free_kick_accuracy   180228 non-null  float64
 19  long_passing         180228 non-null  float64
 20  ball_control         180228 non-null  float64
 21  acceleration         180228 non-null  float64
 22  sprint_speed         180228 non-null  float64
 23  agility              180228 non-null  float64
 24  reactions            180228 non-null  float64
 25  balance              180228 non-null  float64
 26  shot_power           180228 non-null  float64
 27  jumping              180228 non-null  float64
 28  stamina              180228 non-null  float64
 29  strength             180228 non-null  float64
 30  long_shots           180228 non-null  float64
 31  aggression           180228 non-null  float64
 32  interceptions        180228 non-null  float64
 33  positioning          180228 non-null  float64
 34  vision               180228 non-null  float64
 35  penalties            180228 non-null  float64
 36  marking              180228 non-null  float64
 37  standing_tackle      180228 non-null  float64
 38  sliding_tackle       180228 non-null  float64
 39  gk_diving            180228 non-null  float64
 40  gk_handling          180228 non-null  float64
 41  gk_kicking           180228 non-null  float64
 42  gk_positioning       180228 non-null  float64
 43  gk_reflexes          180228 non-null  float64
dtypes: float64(36), int64(2), object(6)
memory usage: 61.9+ MB
```

Add new Columns to team table store years

In [57]:
```
#convert date to datatime type to get year easily
df_team['date'] = pd.to_datetime(df_team['date'])
df_team['year'] = df_team['date'].dt.year
```

In [58]:
```
## Drop records have missed value
df_team.dropna(inplace=True)
## Drop duplicated records
df_team.drop_duplicates(inplace = True)
df_team.describe()
```

Out[58]:

	id	buildUpPlaySpeed	buildUpPlayPassing	chanceCreationPassing	chanceCreationC

	id	buildUpPlaySpeed	buildUpPlayPassing	chanceCreationPassing	chanceCreationC
count	1457.000000	1457.000000	1457.000000	1457.000000	1457
mean	22708.422787	52.463967	48.489362	52.166781	53
std	15008.544877	11.549653	10.899771	10.364195	11
min	1.000000	20.000000	20.000000	21.000000	20
25%	9548.000000	45.000000	40.000000	46.000000	47
50%	20525.000000	52.000000	50.000000	52.000000	53
75%	35294.000000	62.000000	55.000000	59.000000	62
max	50204.000000	80.000000	80.000000	80.000000	80

In [59]:
```
#Check Missed valuse befor start analysis
df_team.isna().sum().sum()
```

Out[59]:
```
0
```

Exploratory Data Analysis

How many matches are there in the 2016 season?

Now we will Discover How many matches are there in the 2016 season? To know Most result come from leagues have more matches for Winner or Goals That's make sense

In [60]:
```
# Create a new fuction which return name of winner team foorm every match
def win(df_match):
    """
    Input: DataFrame contain 4 Columns home_team_goal, away_team_goal, home_team_nam
    OutPut: New Column for winner teams
    """
    home_score = df_match[0] #home_team_goal
    away_score = df_match[1] #away_team_goal
    home_team_name = df_match[2] #home_team_name
    away_team_name = df_match[3] #away_team_name

    if home_score > away_score:
        return home_team_name
    elif home_score < away_score:
        return away_team_name
    else:
        return 'DRAW'

# Add new column which store winners team within Win Function
df_match['winner']  = df_match[['home_team_goal', 'away_team_goal', 'home_team_name'
```

In [61]:
```
# Filter matches that only played in the 2015/2016 season
match_2016 = df_match[df_match['season'] == '2015/2016']
```

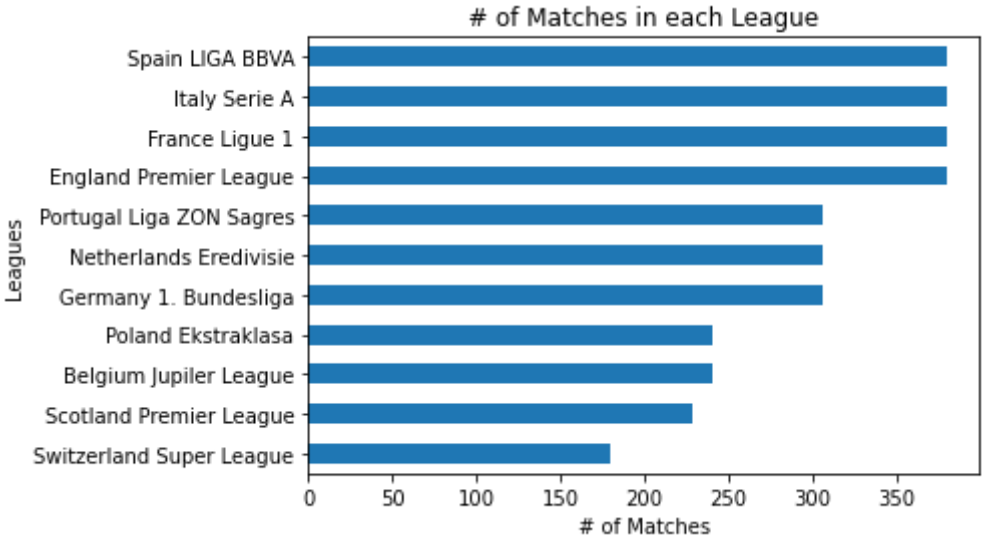
In [62]:
```
# Cuunt every match Played in each league in the 2015/2016 season
match_Played = match_2016.groupby('league_name')['home_team_name'].count().sort_valu
match_Played
```

Out[62]:
```
league_name
Switzerland Super League    180
```

```
Scotland Premier League     228
Belgium Jupiler League      240
Poland Ekstraklasa          240
Germany 1. Bundesliga       306
Netherlands Eredivisie      306
Portugal Liga ZON Sagres    306
England Premier League      380
France Ligue 1              380
Italy Serie A               380
Spain LIGA BBVA             380
Name: home_team_name, dtype: int64
```

In [63]:
```
# Figure the result
match_Played.plot(kind='barh', title='# of Matches in each League');
plt.xlabel('# of Matches')
plt.ylabel('Leagues')
```

Out[63]:
```
Text(0, 0.5, 'Leagues')
```



Which League had the most matches end as draw in the 2016 season?

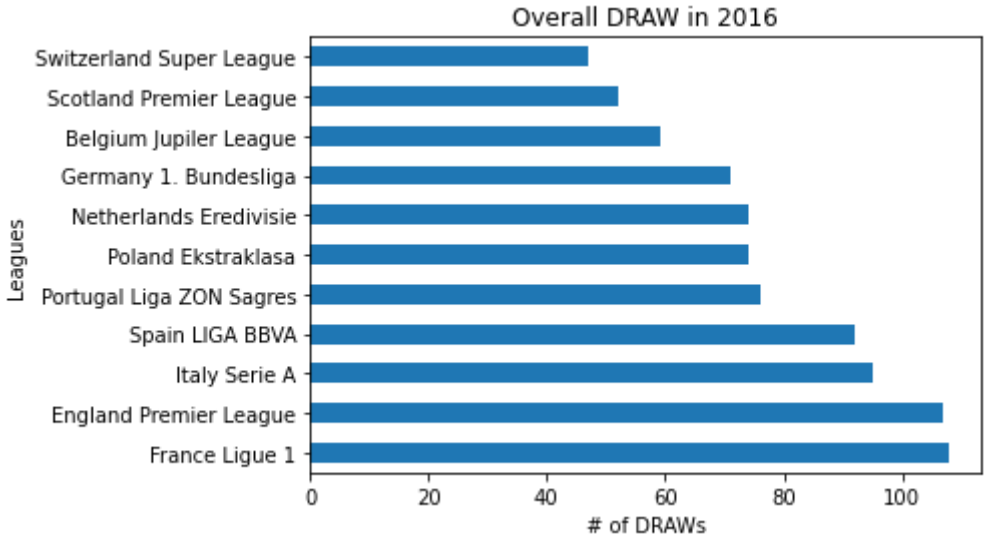
In this question, we will take an impression of the most defensive league

In [64]:
```
match_2016[['winner',"league_name"]].value_counts().loc["DRAW"]
```

Out[64]:
```
league_name
France Ligue 1              108
England Premier League      107
Italy Serie A                95
Spain LIGA BBVA              92
Portugal Liga ZON Sagres     76
Poland Ekstraklasa           74
Netherlands Eredivisie       74
Germany 1. Bundesliga        71
Belgium Jupiler League       59
Scotland Premier League      52
Switzerland Super League     47
dtype: int64
```

In [65]:
```
# Figure the result
match_2016[['winner',"league_name"]].value_counts().loc["DRAW"].plot(kind='barh', ti
plt.xlabel('# of DRAWs')
plt.ylabel('Leagues')
```

Out[65]:
```
Text(0, 0.5, 'Leagues')
```



In [66]:
```
match_2016[['winner',"league_name"]].value_counts().loc["DRAW"]
```

Out[66]:
```
league_name
France Ligue 1              108
England Premier League      107
Italy Serie A                95
Spain LIGA BBVA              92
Portugal Liga ZON Sagres     76
Poland Ekstraklasa           74
Netherlands Eredivisie       74
Germany 1. Bundesliga        71
Belgium Jupiler League       59
Scotland Premier League      52
Switzerland Super League     47
dtype: int64
```

Which team had the most Wins or not Draw in the 2016 season?

In this question, you get an impression of the most offensive league

In [67]:
```
wins16 = match_2016.groupby(["league_name"]).apply(lambda x: (x["winner"]!= 'DRAW').
wins16
```

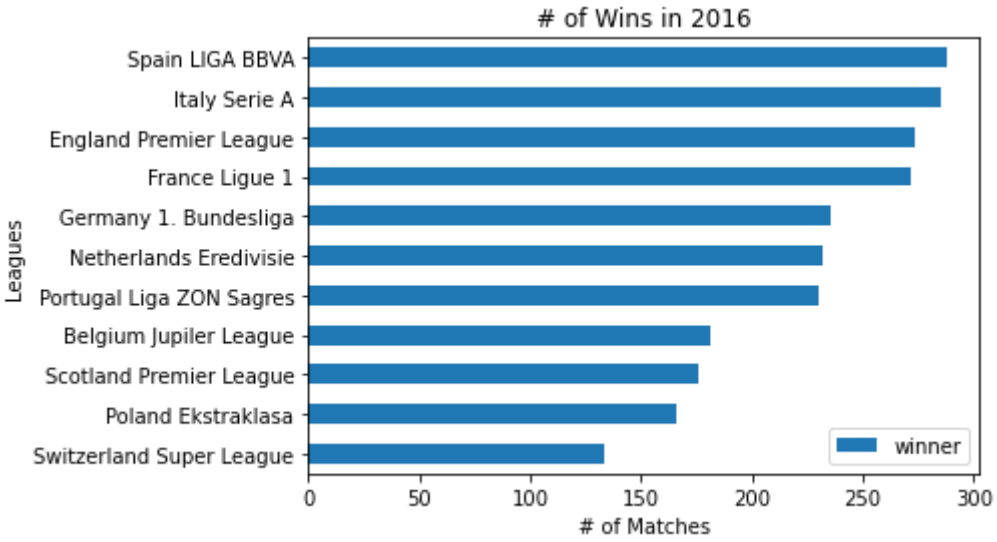
Out[67]:

	league_name	winner
10	Switzerland Super League	133
6	Poland Ekstraklasa	166
8	Scotland Premier League	176
0	Belgium Jupiler League	181
7	Portugal Liga ZON Sagres	230
5	Netherlands Eredivisie	232
3	Germany 1. Bundesliga	235
2	France Ligue 1	272
1	England Premier League	273
4	Italy Serie A	285
9	Spain LIGA BBVA	288

In [68]:
```
# Figure the result
```

```
wins16.plot(x= 'league_name' ,kind='barh', title='# of Wins in 2016')
plt.xlabel('# of Matches')
plt.ylabel('Leagues')
```

Out[68]: Text(0, 0.5, 'Leagues')



How many goals in each League are there in the 2016 season?

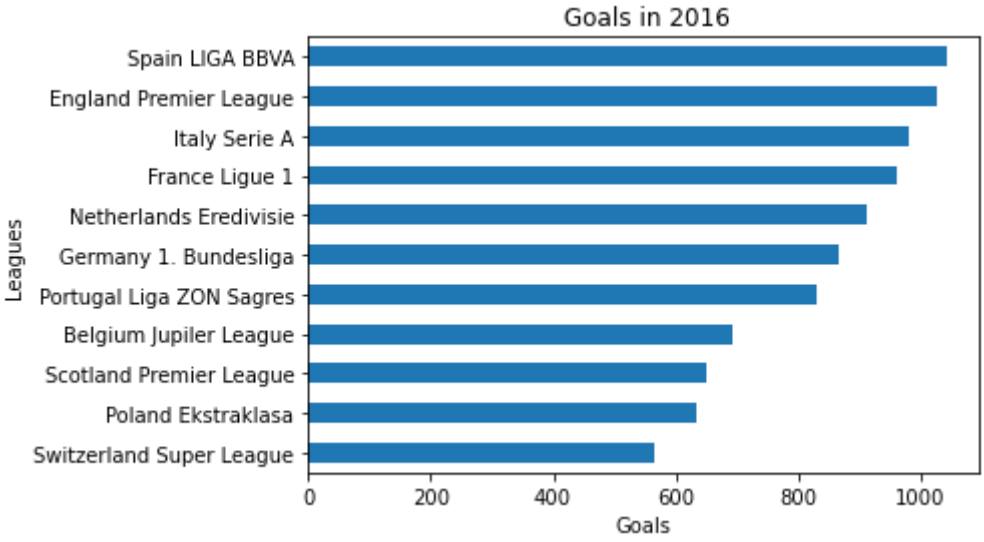
In this question, you get an impression of the league's most attacking tendency

In [69]:
```
goals_2016 = match_2016.groupby('league_name')['home_team_goal'].sum().sort_values(a
goals_2016.sort_values(ascending = True, inplace =True)
goals_2016
```

Out[69]:
```
league_name
Switzerland Super League     566
Poland Ekstraklasa           635
Scotland Premier League      650
Belgium Jupiler League       694
Portugal Liga ZON Sagres     831
Germany 1. Bundesliga        866
Netherlands Eredivisie       912
France Ligue 1               960
Italy Serie A                979
England Premier League      1026
Spain LIGA BBVA             1043
dtype: int64
```

In [70]:
```
# Figure the result
goals_2016.plot(kind='barh', title=' Goals in 2016')
plt.xlabel('Goals')
plt.ylabel('Leagues')
```

Out[70]: Text(0, 0.5, 'Leagues')



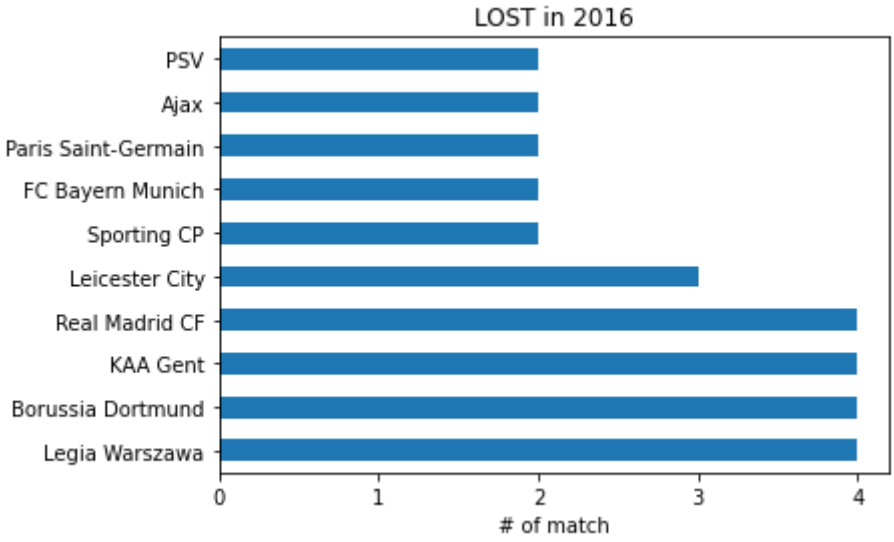
Which team had lost the fewest matches in the 2016 season?

This question gives us an impression that these teams has a great defense and Goalkeeper

In [71]:
```
# Add New Column f9r loser teams within lose function
def lose(df_match):
    '''
    Input: DataFrame contain 4 Columns home_team_goal, away_team_goal, home_team_nam
    OutPut: New Column f9r loser teams
    '''
    home_score = df_match[0] #home_team_goal
    away_score = df_match[1] #away_team_goal
    home_team_name = df_match[2] #home_team_name
    away_team_name = df_match[3] #away_team_name

    if home_score < away_score:
        return home_team_name
    elif home_score > away_score:
        return away_team_name
    else:
        return 'DRAW'

df_match['loser']  = df_match[['home_team_goal', 'away_team_goal', 'home_team_name',
```

In [72]:
```
# Figure the result
match_2016 = df_match[df_match['season'] == '2015/2016']

match_2016.loser.value_counts().tail(10).plot(kind='barh', title='LOST in 2016',xtic
plt.xlabel('# of match')
```

Out[72]:
```
Text(0.5, 0, '# of match')
```



Which teams had the most wins of matches in the 2016 season?

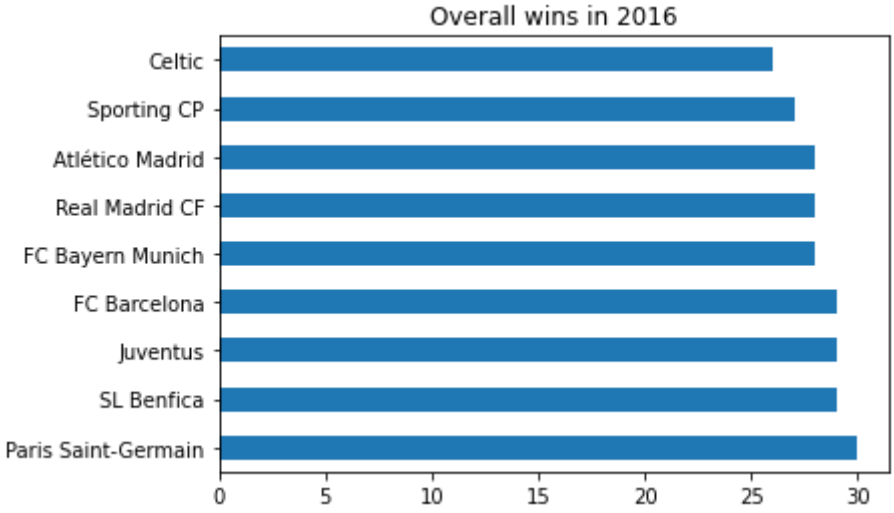
Now we will discover top teams had the most win maybe it's give us that this team did a wonderful season and gives us an impression that these teams has dangerous attack

In [73]:
```
wins_16 = match_2016.winner.value_counts().head(10).iloc[1:]
wins_16
```

Out[73]:
```
Paris Saint-Germain    30
SL Benfica             29
Juventus               29
FC Barcelona           29
FC Bayern Munich       28
Real Madrid CF         28
Atlético Madrid        28
Sporting CP            27
Celtic                 26
Name: winner, dtype: int64
```

In [74]:
```
# Figure the result
wins_16.plot(kind='barh', title='Overall wins in 2016')
```

Out[74]:
```
<AxesSubplot:title={'center':'Overall wins in 2016'}>
```



What teams improved the most over the time period?

Now in this question, I'll choose 2 diffrent years to cover a long period. So I have chosen 2010, and 2016 to compare the details of the teams. In order words, using these years we analyze

what teams improved the most.

Now we select the number of wins in 2010 and 2016 and take the difference then return process to calculate loses match for every team in 2010 and 2016

In [75]:
```
# Select wins games in 2010
W2010 = df_match[(df_match['season_year'] == 2010) & (df_match['winner'] != 'DRAW')]
# Select lose games in 2010
L2010 = df_match[(df_match['season_year'] == 2010) & (df_match['loser'] != 'DRAW')]
# count wins games in 2010
countW2010 = W2010['winner'].count()
# count lose games in 2010
countL2010 = L2010['loser'].count()
# Sustract between winner and loser in 2010
R2010 = W2010['winner'].value_counts()/countW2010 - L2010['loser'].value_counts()/co

# Select wins games in 2010
W2016 = df_match[(df_match['season_year'] == 2016) & (df_match['winner'] != 'DRAW')]
# Select lose games in 2010
L2016 = df_match[(df_match['season_year'] == 2016) & (df_match['loser'] != 'DRAW')]
# count wins games in 2010
countW2016 = W2016['winner'].count()
# count lose games in 2010
countL2016 = L2016['loser'].count()
# Sustract between winner and loser in 2010
R2016 = W2016['winner'].value_counts()/countW2010 - L2016['loser'].value_counts()/co
```

Then we take the average of total number of goals scored for each team in 2010 and 2016 and subtract them

In [76]:
```
# Select wins match in 2010
match_2010 = df_match[df_match['season_year'] == 2010]
# Select wins match in 2016
match_2016 = df_match[df_match['season_year'] == 2016]
#select average of away team goal in 2010
df_match_2010_away = match_2010.groupby(['away_team_name'])['away_team_goal'].mean()
#select average of home team goal in 2010
df_match_2010_home = match_2010.groupby(['home_team_name'])['home_team_goal'].mean()
#select average of away team goal in 2016
df_match_2016_away = match_2016.groupby(['away_team_name'])['away_team_goal'].mean()
#select average of home team goal in 2010
df_match_2016_home = match_2016.groupby(['home_team_name'])['home_team_goal'].mean()
#select average of all team goal in 2010
df_match_total_2010 = (df_match_2010_away + df_match_2010_home) / 2
#select average of all team goal in 2016
df_match_total_2016 = (df_match_2016_away + df_match_2016_home) / 2
```

select rate of change subtract average of all team goal in 2016 and 2010 then add result to subtract wins and loses

In [77]:
```
diff_match_2016_2010 = ((df_match_total_2016 - df_match_total_2010) + ( R2016 - R201
```

now we create a function to store color of improved team and not improved

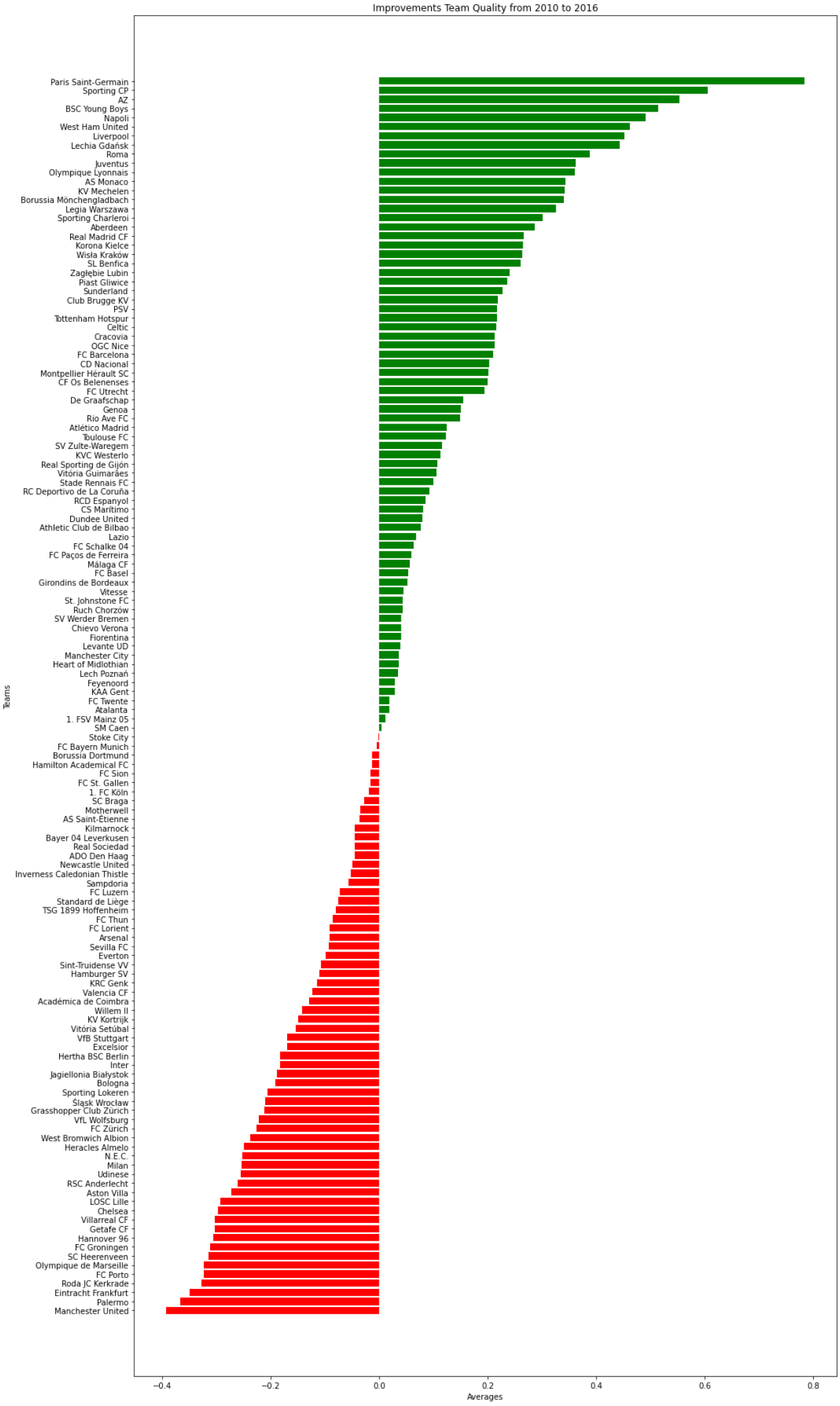
In [78]:
```
#set color list with green color for positive values and red color for negative valu
color = []
def coloring(df):
        '''
        input: DataFrame about rate of change match_2016_2010
        Output: New column store color of all teams
        '''
```

```
        if df < 0:
            return 'red' #red color for negative values
        else:
            return 'green'  #green color for positive values
#call function coloring and store the result in color list
color= diff_match_2016_2010.sort_values().apply(coloring)
```

Now will figure out using a color which red color for negative values and green color for positive values

In [79]:
```
diff_match_2016_2010.dropna(inplace=True)
print('Improved teams :' + str(diff_match_2016_2010[diff_match_2016_2010.sort_values

# sort the values
sorted_index = diff_match_2016_2010.sort_values().index

fig, ax = plt.subplots(figsize=(15, 25))

# plot a horizontal bar
plt.barh(range(0,len(sorted_index)), diff_match_2016_2010.sort_values(),color = colo

# Set the position of the y ticks
ax.set_yticks(range(0,len(sorted_index)))

# Set the position of the y ticks labels
ax.set_yticklabels(sorted_index)

# Set the y axis label
ax.set_ylabel('Teams')

# Set the chart's title
ax.set_title('Improvements Team Quality from 2010 to 2016')

# Set the y axis label
plt.xlabel("Averages")
#show Chart
plt.tight_layout();
```

```
Improved teams :72
```


Improvements Team Quality from 2010 to 2016
Paris Saint-Germain
Sporting CP
AZ
BSC Young Boys
Napoli
West Ham United
Liverpool
Lechia Gdańsk
Roma
Juventus
Olympique Lyonnais
AS Monaco
KV Mechelen
Borussia Mönchengladbach
Legia Warszawa
Sporting Charleroi
Aberdeen
Real Madrid CF
Korona Kielce
Wisła Kraków
SL Benfica
Zagłębie Lubin
Piast Gliwice
Sunderland
Club Brugge KV
PSV
Tottenham Hotspur
Celtic
Cracovia
OGC Nice
FC Barcelona
CD Nacional
Montpellier Hérault SC
CF Os Belenenses
FC Utrecht
De Graafschap
Genoa
Rio Ave FC
Atlético Madrid
Toulouse FC
SV Zulte-Waregem
KVC Westerlo
Real Sporting de Gijón
Vitória Guimarães
Stade Rennais FC
RC Deportivo de La Coruña
RCD Espanyol
CS Marítimo
Dundee United
Athletic Club de Bilbao
Lazio
FC Schalke 04
FC Paços de Ferreira
Málaga CF
FC Basel
Girondins de Bordeaux
Vitesse
St. Johnstone FC
Ruch Chorzów
SV Werder Bremen
Chievo Verona
Fiorentina
Levante UD
Manchester City
Heart of Midlothian
Lech Poznań
Feyenoord
KAA Gent
FC Twente
Atalanta
1. FSV Mainz 05
SM Caen
Stoke City
FC Bayern Munich
Borussia Dortmund
Hamilton Academical FC
FC Sion
FC St. Gallen
1. FC Köln
SC Braga
Motherwell
AS Saint-Étienne
Kilmarnock
Bayer 04 Leverkusen
Real Sociedad
ADO Den Haag
Newcastle United
Inverness Caledonian Thistle
Sampdoria
FC Luzern
Standard de Liège
TSG 1899 Hoffenheim
FC Thun
FC Lorient
Arsenal
Sevilla FC
Everton
Sint-Truidense VV
Hamburger SV
KRC Genk
Valencia CF
Académica de Coimbra
Willem II
KV Kortrijk
Vitória Setúbal
VfB Stuttgart
Excelsior
Hertha BSC Berlin
Inter
Jagiellonia Białystok
Bologna
Sporting Lokeren
Śląsk Wrocław
Grasshopper Club Zürich
VfL Wolfsburg
FC Zürich
West Bromwich Albion
Heracles Almelo
N.E.C.
Milan
Udinese
RSC Anderlecht
Aston Villa
LOSC Lille
Chelsea
Villarreal CF
Getafe CF
Hannover 96
FC Groningen
SC Heerenveen
Olympique de Marseille
FC Porto
Roda JC Kerkrade
Eintracht Frankfurt
Palermo
Manchester United
Teams
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
Averages

In [ ]:

Which players had the most penalties?

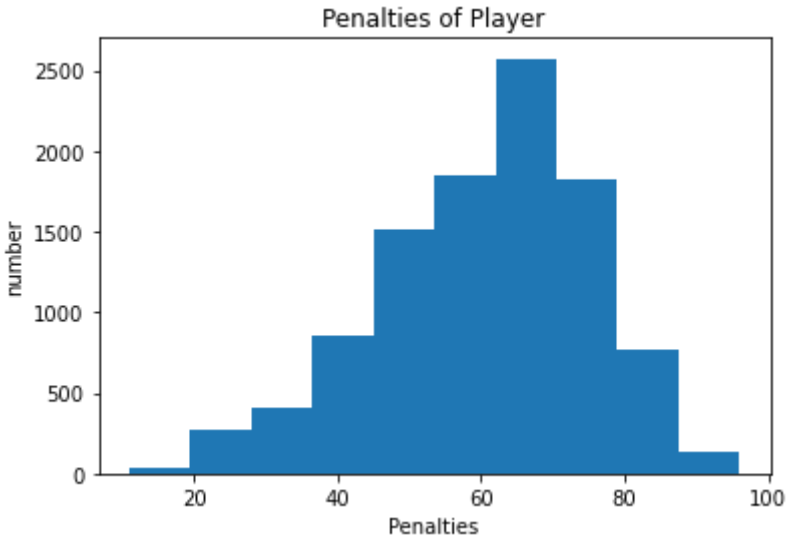
The data contains the order of penalty kicks for each player, so we will take the last date, which contains the largest glands of penalty kicks.

In [80]:
```
# Select top player name and their penalties in descending order
most_penalties = df_player.groupby(['player_name'])['penalties'].max().sort_values(a
most_penalties[:10]
```

Out[80]:
```
player_name
Rickie Lambert     96.0
Mario Balotelli    95.0
Xavi Hernandez     95.0
Andrea Pirlo       95.0
Paul Scholes       95.0
David Trezeguet    94.0
Cesc Fabregas      94.0
Adrian Mutu        94.0
Iker Casillas      94.0
Hernan Crespo      93.0
Name: penalties, dtype: float64
```

In [81]:
```
# Figure the result in Histogram
most_penalties.plot(kind='hist', title='Penalties of Player')
plt.xlabel('Penalties')
plt.ylabel('number')
```

Out[81]:
```
Text(0, 0.5, 'number')
```



What team attributes lead to the most victories?

Now we will discover which attributes lead to the most victories so we analyze data of the top 10 winner team

In [82]:
```
# Select a top team  that most winner in 2015/2016
top_teams = df_team[(df_team["team_long_name"].isin(wins_16.index)) & (df_team['year
```

In [83]:
```
# Show teams which have most wins in 2016
wins_16.index
```

Out[83]:
```
Index(['Paris Saint-Germain', 'SL Benfica', 'Juventus', 'FC Barcelona',
       'FC Bayern Munich', 'Real Madrid CF', 'Atlético Madrid', 'Sporting CP',
```

```
       'Celtic'],
      dtype='object')
```

I list all columns name store digital values

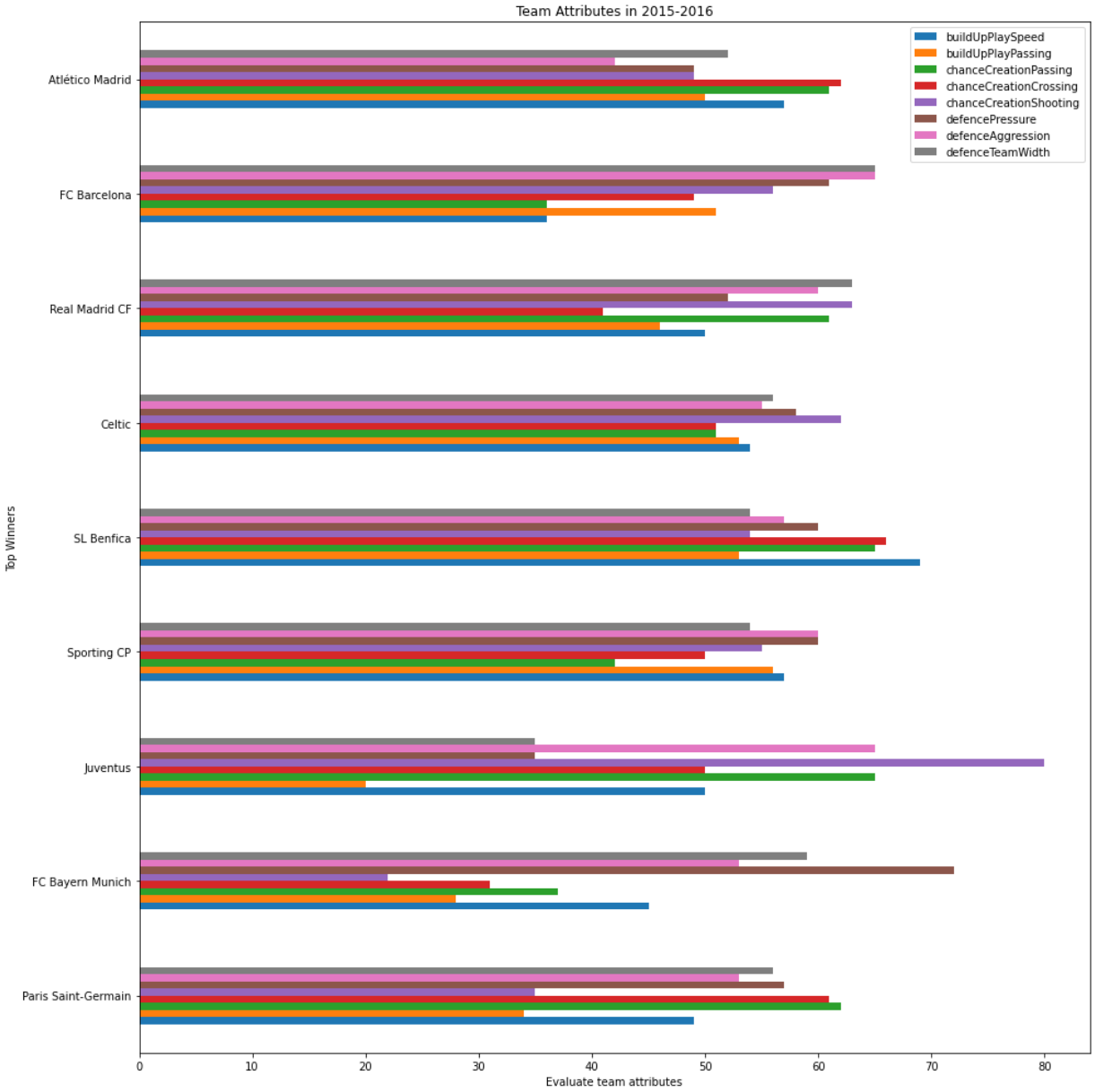
In [84]:
```
digital_attributes = ['team_long_name', 'buildUpPlaySpeed', 'buildUpPlayPassing','ch
```

In [85]:
```
#Sample of top_teams with only digital columns
top_teams[digital_attributes].head()
```

Out[85]:

	team_long_name	buildUpPlaySpeed	buildUpPlayPassing	chanceCreationPassing	chanceCreatic
370	Paris Saint-Germain	49	34	62	
497	FC Bayern Munich	45	28	37	
716	Juventus	50	20	65	
1052	Sporting CP	57	56	42	
1094	SL Benfica	69	53	65	

In [86]:
```
# Figure the result
fig, ax = plt.subplots(figsize=(14, 14))

# create a new bar char
ax = top_teams[digital_attributes].plot.barh(ax=ax);

ax.set_yticklabels(top_teams['team_long_name'])

# Set the y axis label
ax.set_ylabel('Top Winners')

# Set the chart's title
ax.set_title('Team Attributes in 2015-2016')

# Set the y axis label
plt.xlabel("Evaluate team attributes")

plt.tight_layout();
```

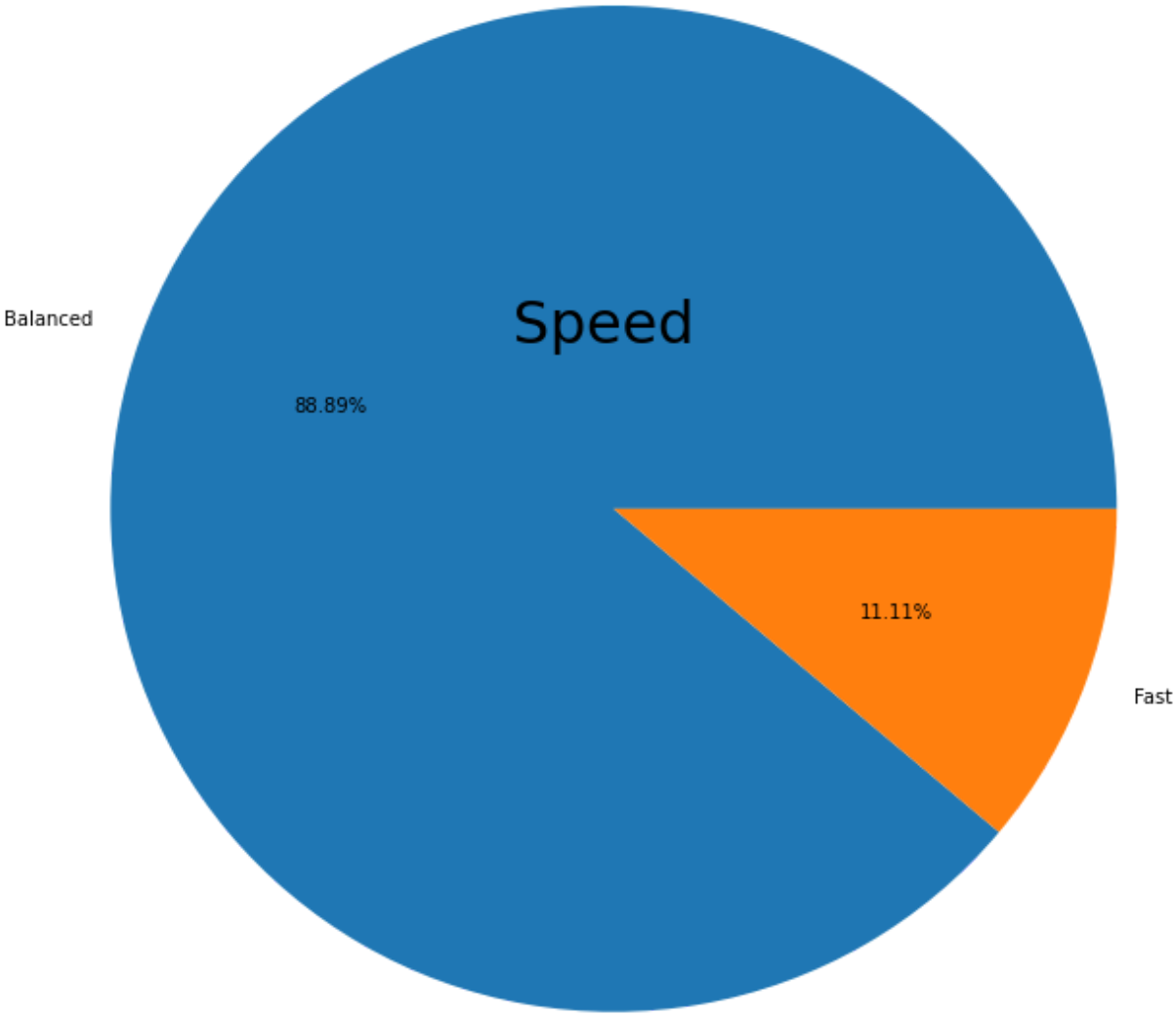


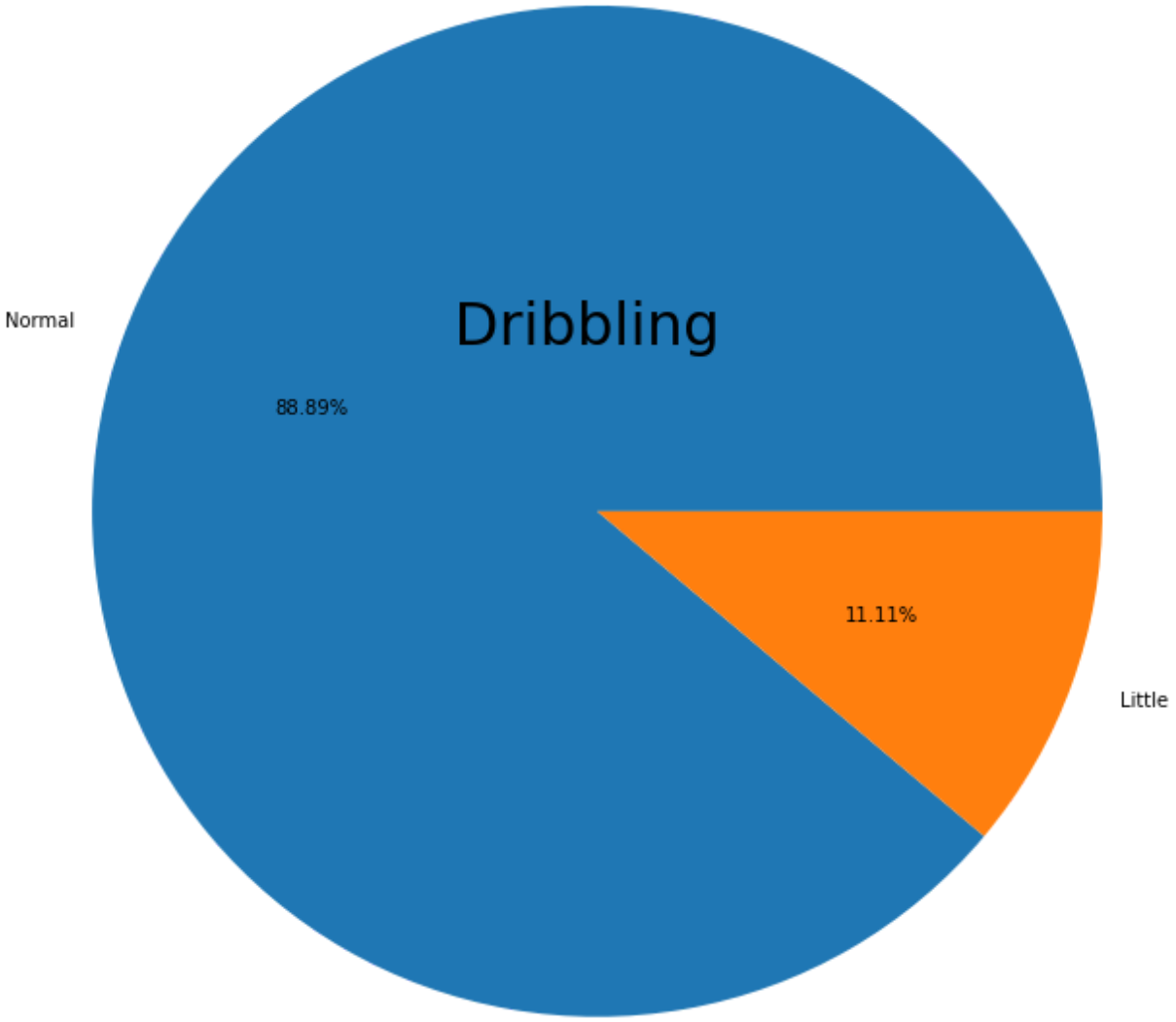
I list all columns name store descriptive values

In [87]:
```
descriptive_attributes = ['buildUpPlaySpeedClass','buildUpPlayDribblingClass','build
# assign only columns in descriptive_attributes
attr = top_teams[descriptive_attributes]
```

Now we will discover descriptive values in pie chart

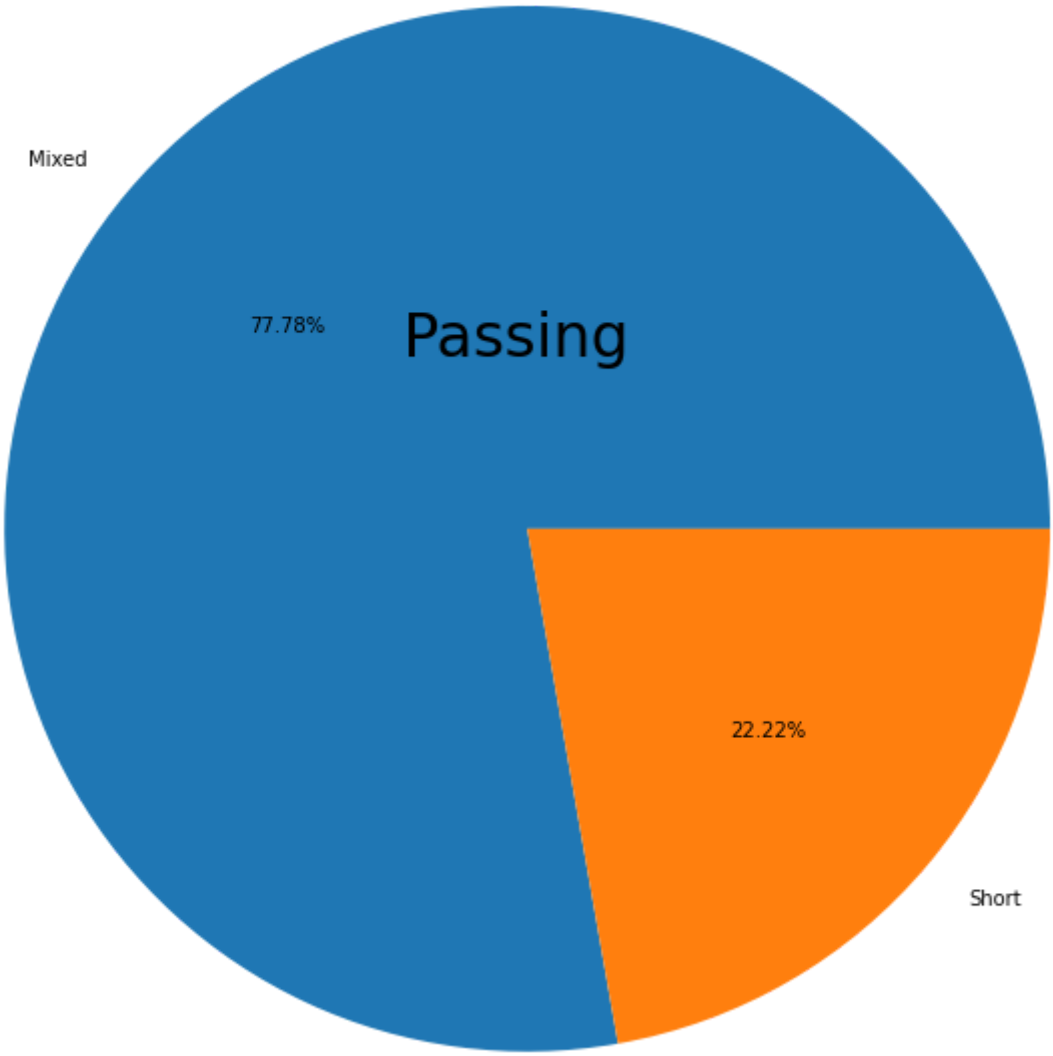
In [88]:
```
plt.figure(0)
# Create 1st chart here.
plt.pie(attr['buildUpPlaySpeedClass'].value_counts(), labels =  attr['buildUpPlaySpe
plt.figtext(.5,.8,'Speed',fontsize=30,ha='center')

plt.figure(1)
# Create 2nd chart here.
plt.pie(attr['buildUpPlayDribblingClass'].value_counts(), labels =  attr['buildUpPla
plt.figtext(.5,.8,'Dribbling',fontsize=30,ha='center')

plt.show() #show all figures
```

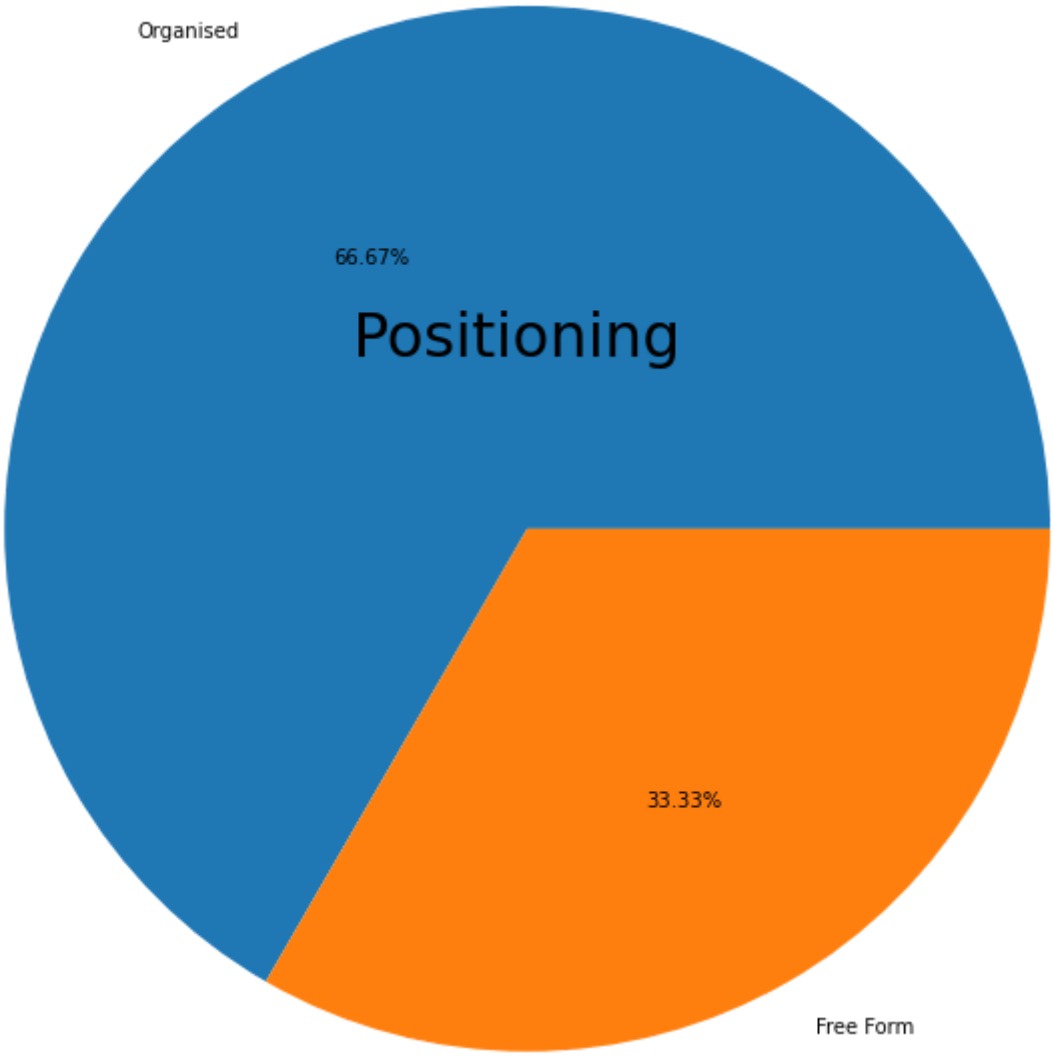

Speed
Balanced
88.89%
11.11%
Fast



In [89]:

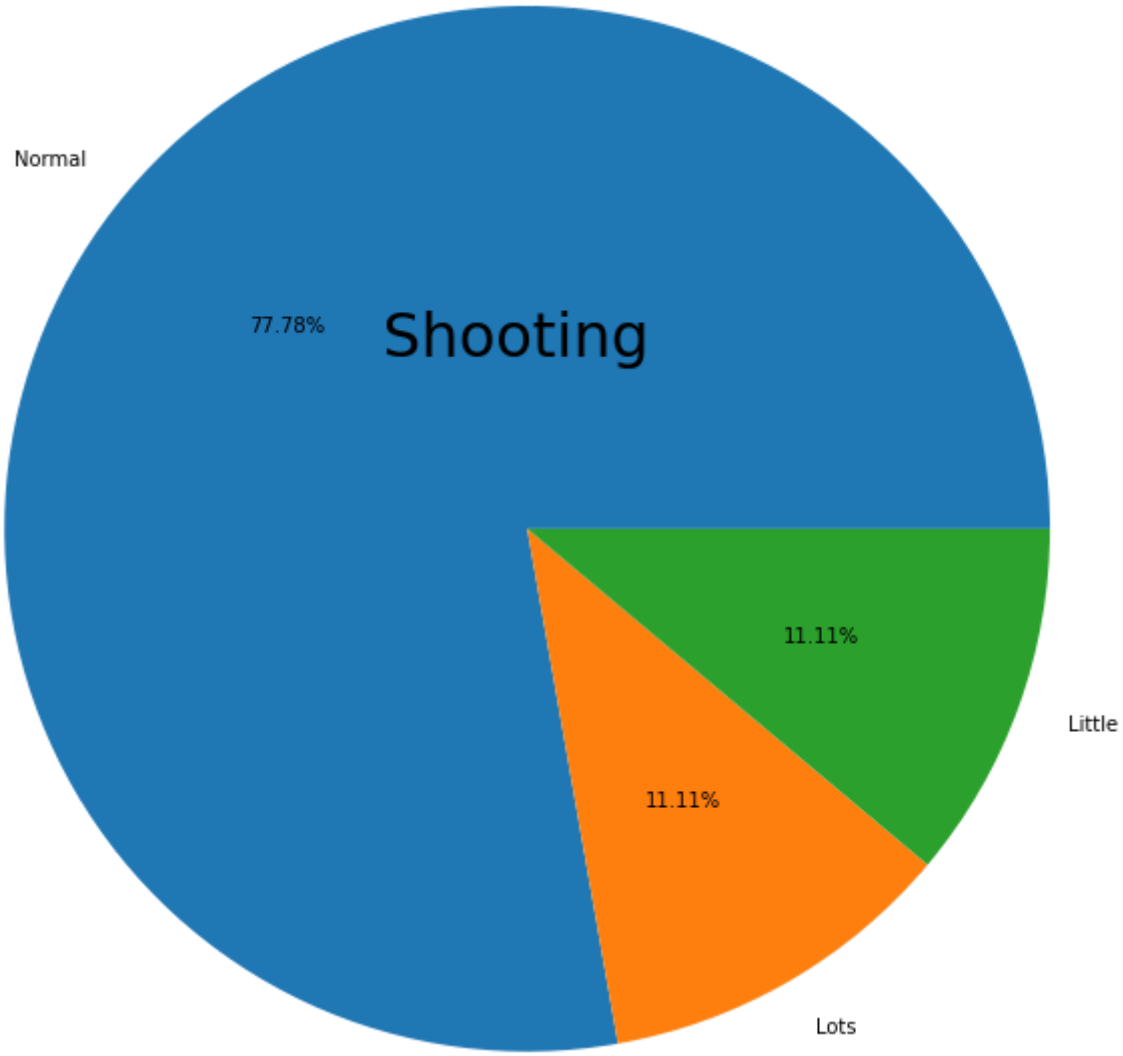
```
plt.figure(2)
# Create 3ird chart here.
plt.pie(attr['buildUpPlayPassingClass'].value_counts(), labels =  attr['buildUpPlayP
plt.figtext(.5,.8,'Passing',fontsize=30,ha='center')

plt.figure(3)
# Create 4th chart here.
plt.pie(attr['buildUpPlayPositioningClass'].value_counts(), labels =  attr['buildUpP
plt.figtext(.5,.8,'Positioning',fontsize=30,ha='center')


plt.show() #show all figures
```

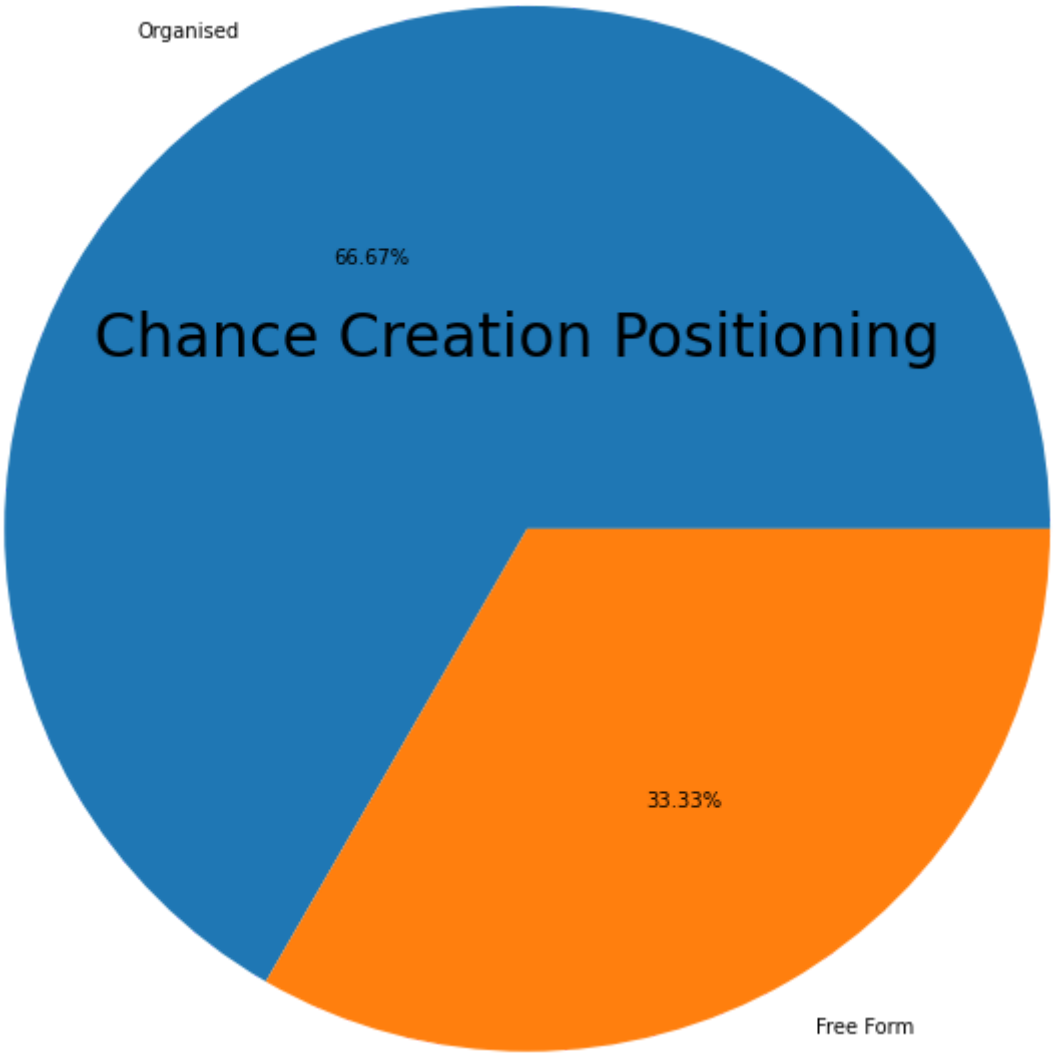

Passing
Mixed
77.78%
Short
22.22%



In [90]:

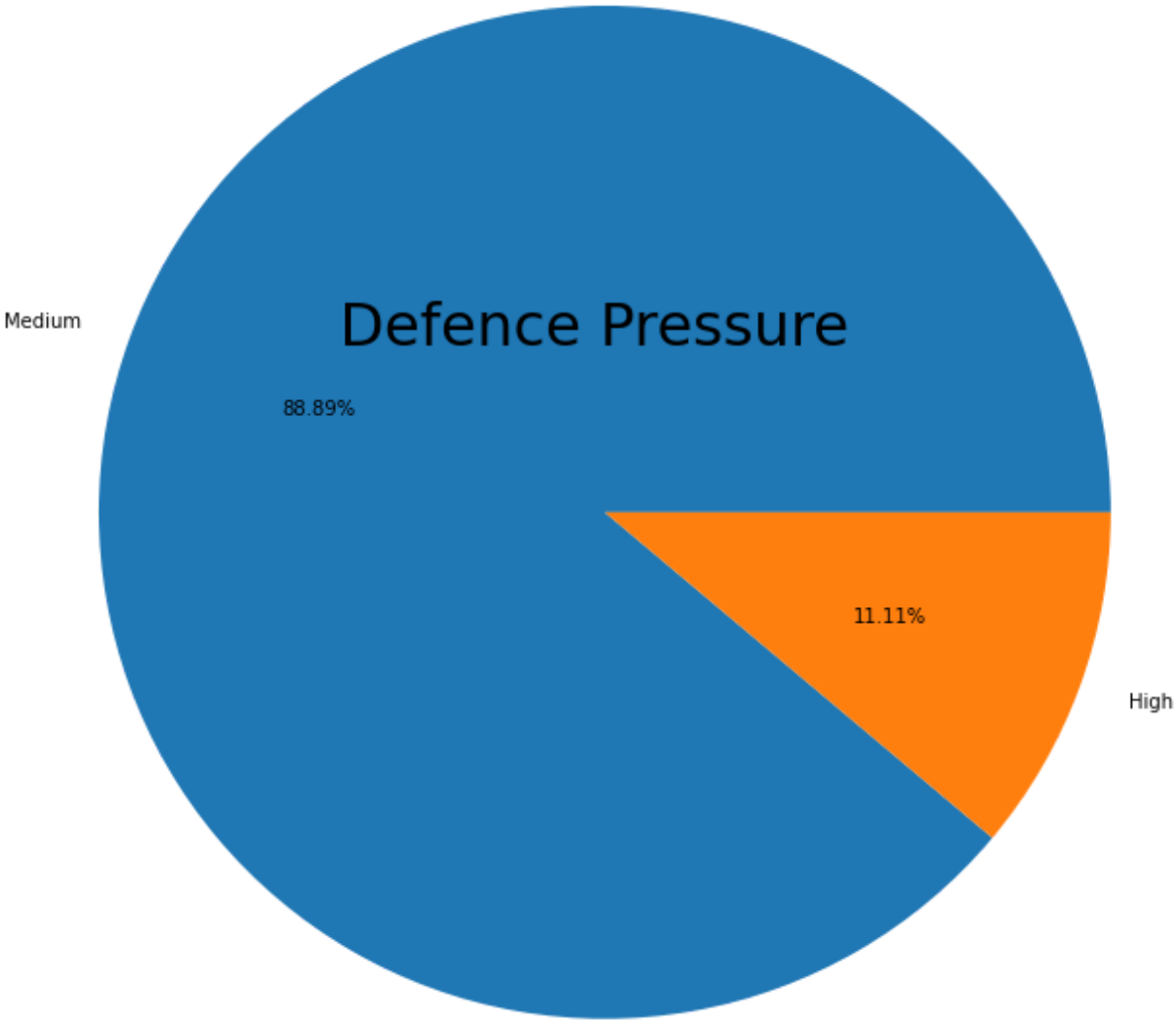
```
plt.figure(4)
# Create 5th chart here.
plt.pie(attr['chanceCreationShootingClass'].value_counts(), labels =  attr['chanceCr
plt.figtext(.5,.8,'Shooting',fontsize=30,ha='center')

plt.figure(5)
# Create 6th chart here.
plt.pie(attr['chanceCreationPositioningClass'].value_counts(), labels =  attr['chanc
plt.figtext(.5,.8,'Chance Creation Positioning',fontsize=30,ha='center')


plt.show() #show all figures
```

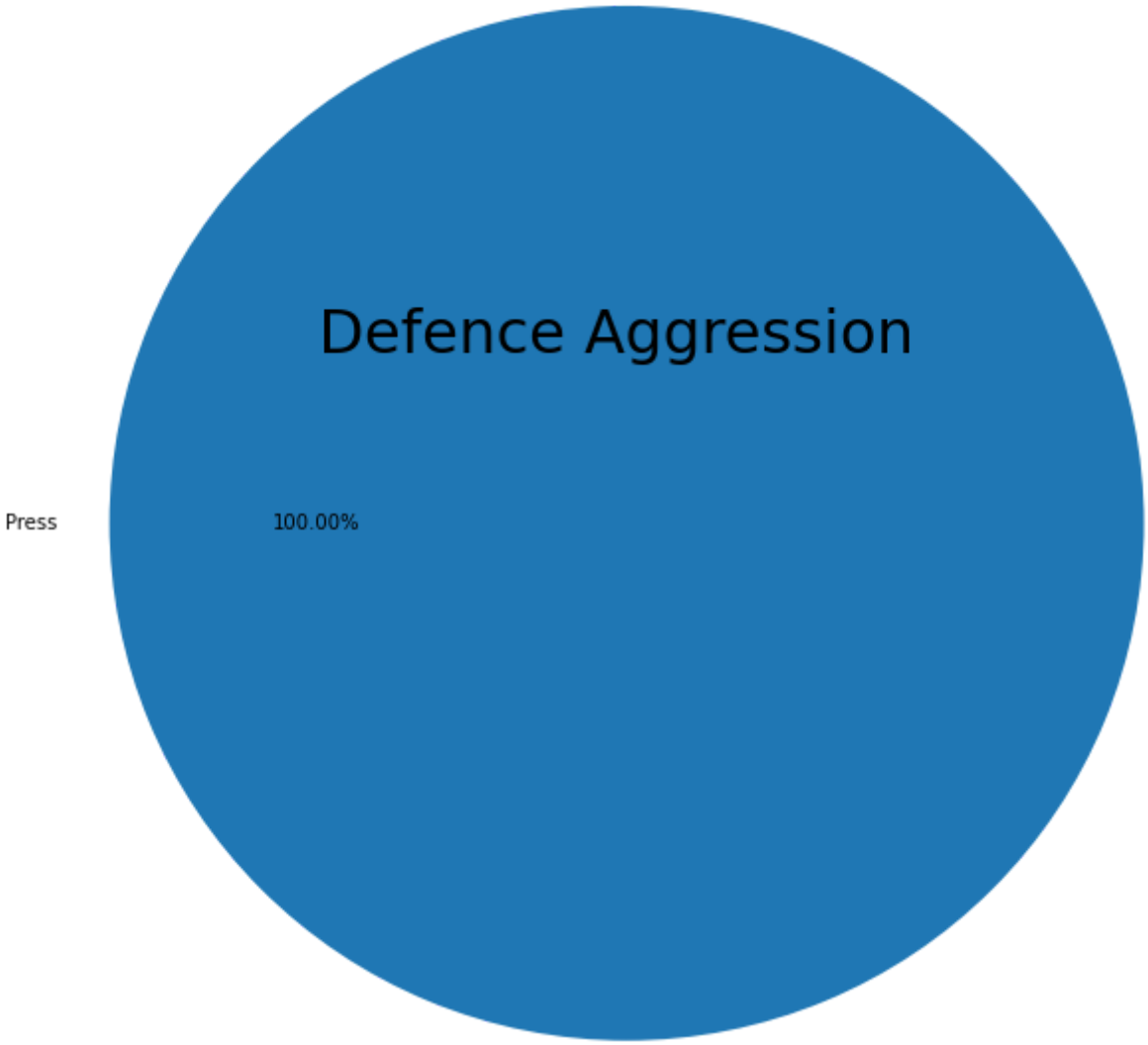

Shooting
Normal
77.78%
11.11%
Little
11.11%
Lots



In [91]:

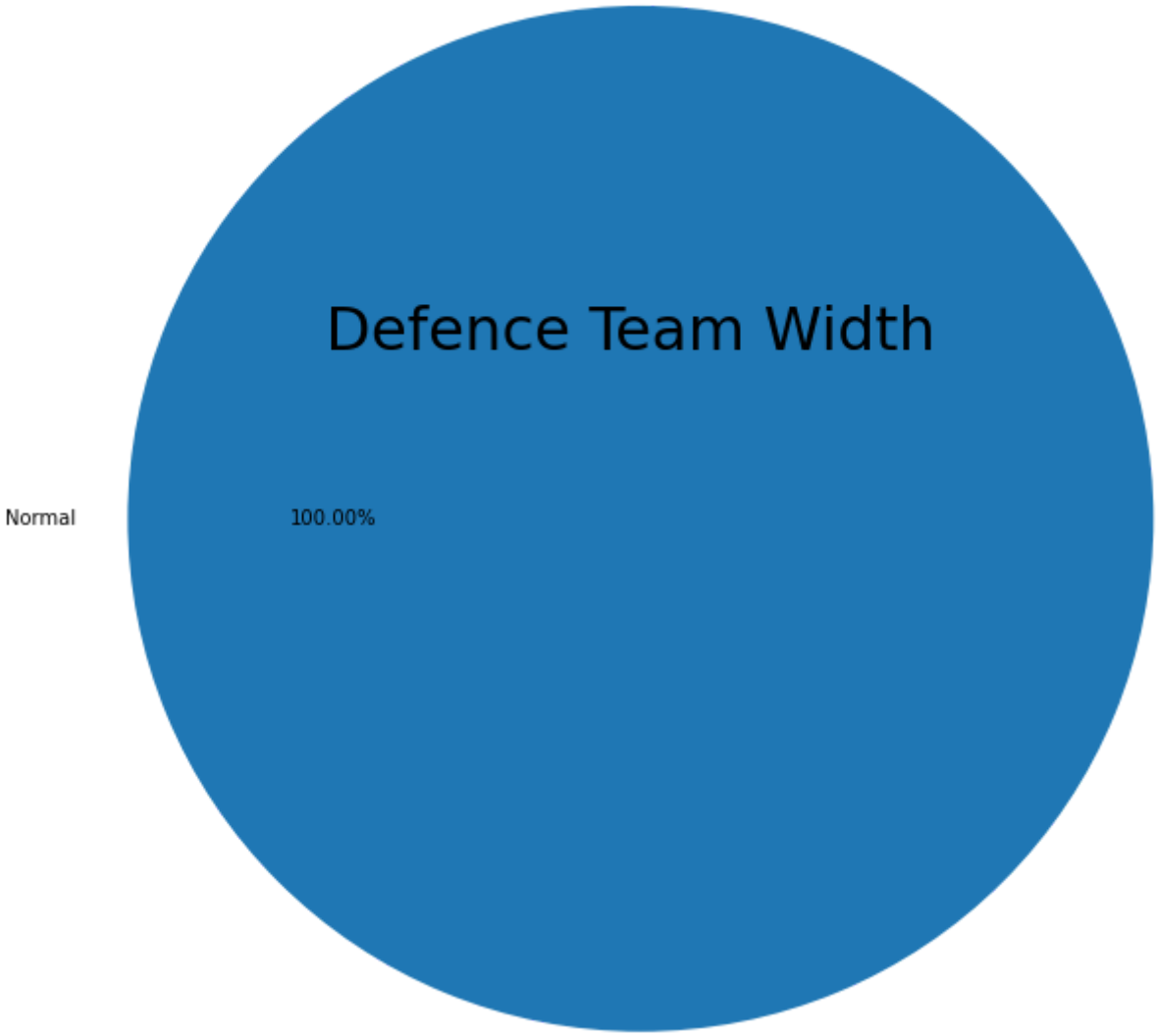
```
plt.figure(6)
# Create 7th chart here.
plt.pie(attr['defencePressureClass'].value_counts(), labels =  attr['defencePressure
plt.figtext(.5,.8,'Defence Pressure',fontsize=30,ha='center')

plt.figure(7)
# Create 8th chart here.
plt.pie(attr['defenceAggressionClass'].value_counts(), labels =  attr['defenceAggres
plt.figtext(.5,.8,'Defence Aggression',fontsize=30,ha='center')


plt.show() #show all figures
```

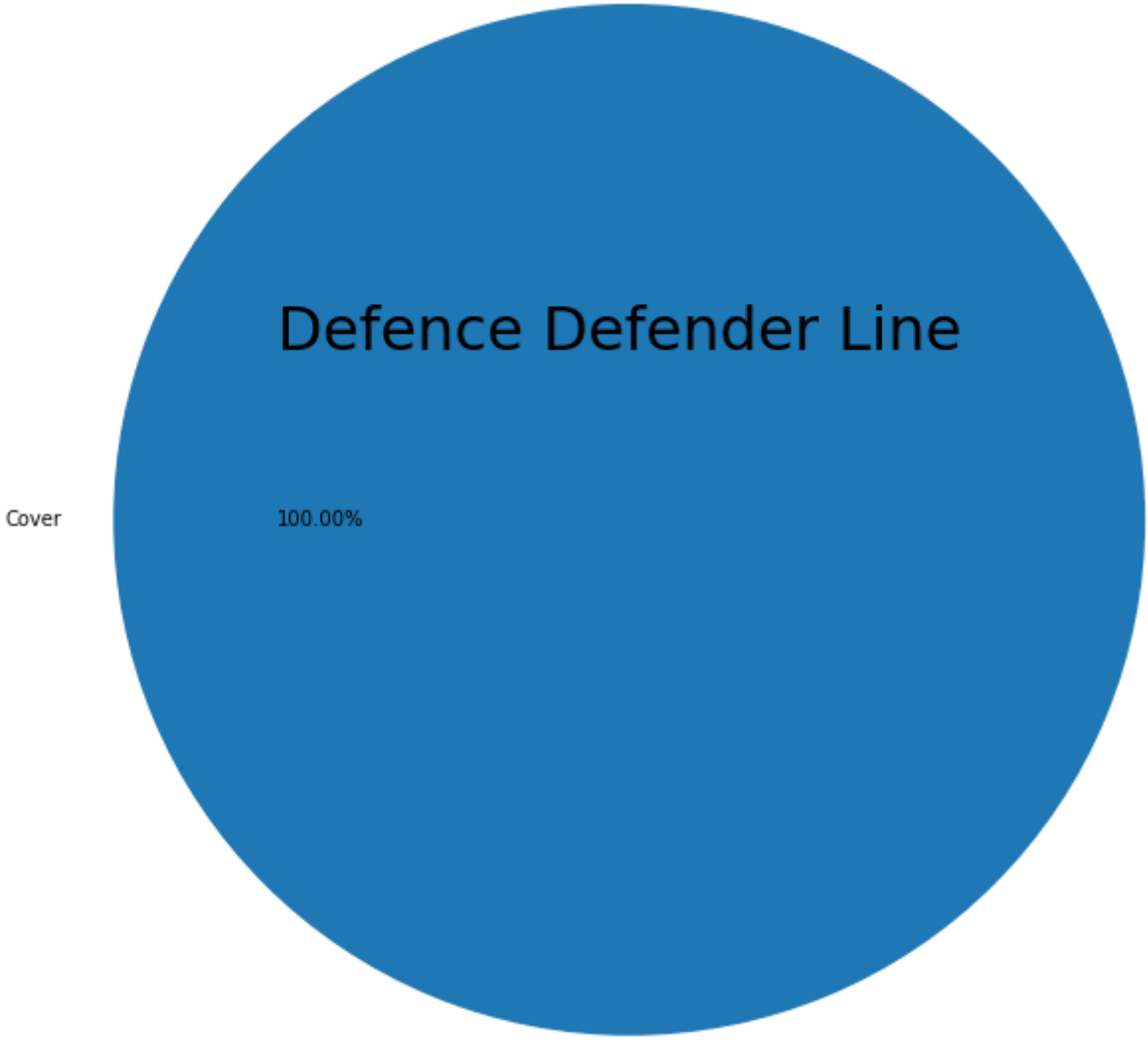

Defence Pressure
Medium
88.89%
11.11%
High



In [92]:

```
plt.figure(8)
# Create 9th chart here.
plt.pie(attr['defenceTeamWidthClass'].value_counts(), labels =  attr['defenceTeamWid
plt.figtext(.5,.8,'Defence Team Width',fontsize=30,ha='center')

plt.figure(9)
# Create 10th chart here.
plt.pie(attr['defenceDefenderLineClass'].value_counts(), labels =  attr['defenceDefe
plt.figtext(.5,.8,'Defence Defender Line',fontsize=30,ha='center')


plt.show() #show all figures
```


Defence Team Width
Normal
100.00%



How many Players have overall rating more than 90 ?

Now I'll discover How many Players have an overall rating of more than 90 in the dataset who is special players

In [93]:
```
# Select Maximum Rate
df_player['overall_rating'].max()
```

Out[93]: 94.0

In [94]:
```
# average of players' overall rating
average_rate = df_player['overall_rating'].mean()
average_rate
```

Out[94]: 68.63280955234481

Select players have above average rating Then Count it

In [95]:
```
above_rating = df_player[df_player['overall_rating'] > average_rate]
above_rating.player_name.nunique()
```

Out[95]: 6467

In [96]:
```
pd.DataFrame(above_rating.describe())
```

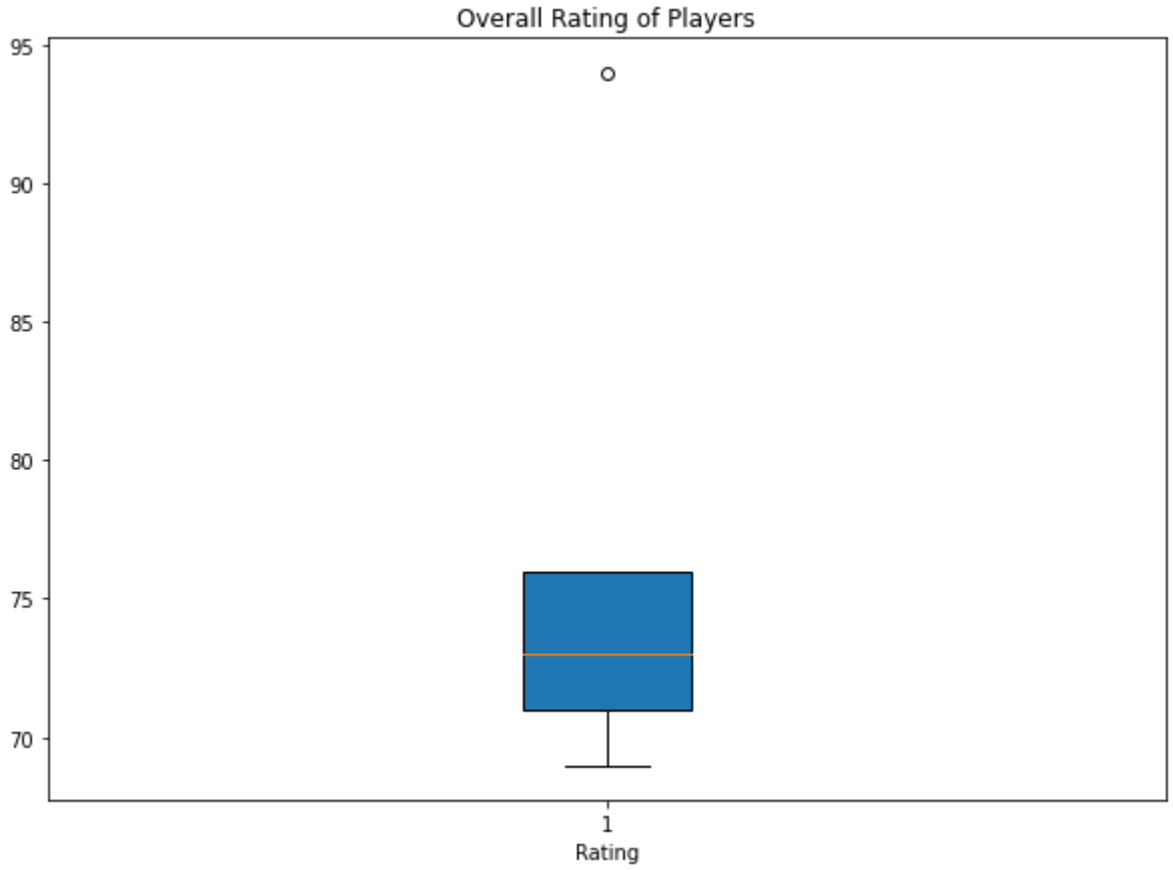
Out[96]:

	id	height	weight	overall_rating	potential	crossing	fin
count	92330.000000	92330.000000	92330.000000	92330.000000	92330.000000	92330.000000	92330.0

	id	height	weight	overall_rating	potential	crossing	fin
mean	5495.301581	181.792446	169.326297	74.063327	77.486483	60.008448	54.8
std	3197.477408	6.495631	15.240113	4.062179	4.885856	17.642107	19.5
min	2.000000	157.480000	117.000000	69.000000	59.000000	3.000000	1.0
25%	2741.000000	177.800000	159.000000	71.000000	74.000000	52.000000	40.0
50%	5457.000000	182.880000	170.000000	73.000000	77.000000	65.000000	60.0
75%	8229.000000	185.420000	179.000000	76.000000	81.000000	72.000000	70.0
max	11075.000000	203.200000	243.000000	94.000000	97.000000	95.000000	97.0

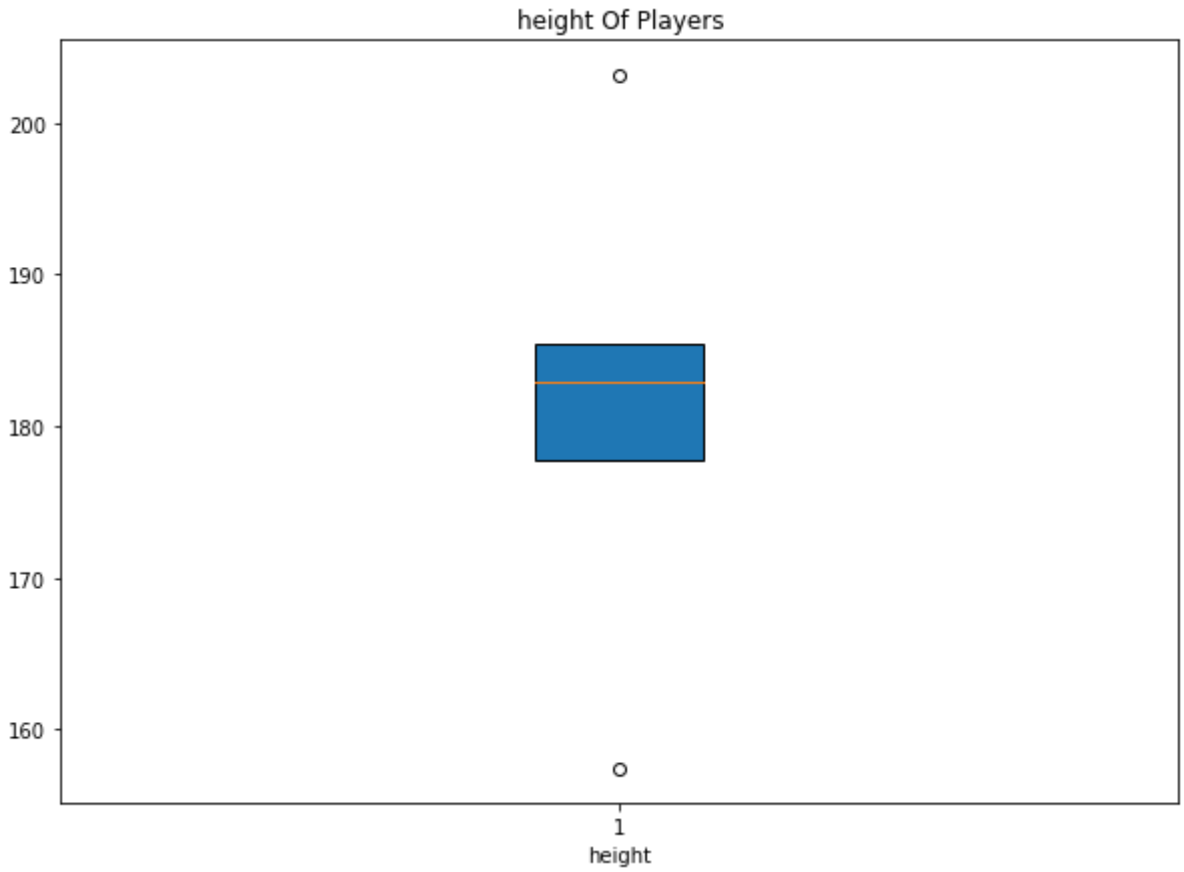
8 rows × 38 columns

In [97]:
```
# Filter data
data = above_rating.describe().loc['min':'max',"overall_rating"]
# initialitioze figure
fig = plt.figure(figsize =(10, 7))
# Creating plot
plt.boxplot(data,vert=True,patch_artist=True  )
#set title and lable
plt.title("Overall Rating of Players")
plt.xlabel('Rating')
# show plot
plt.show()
```

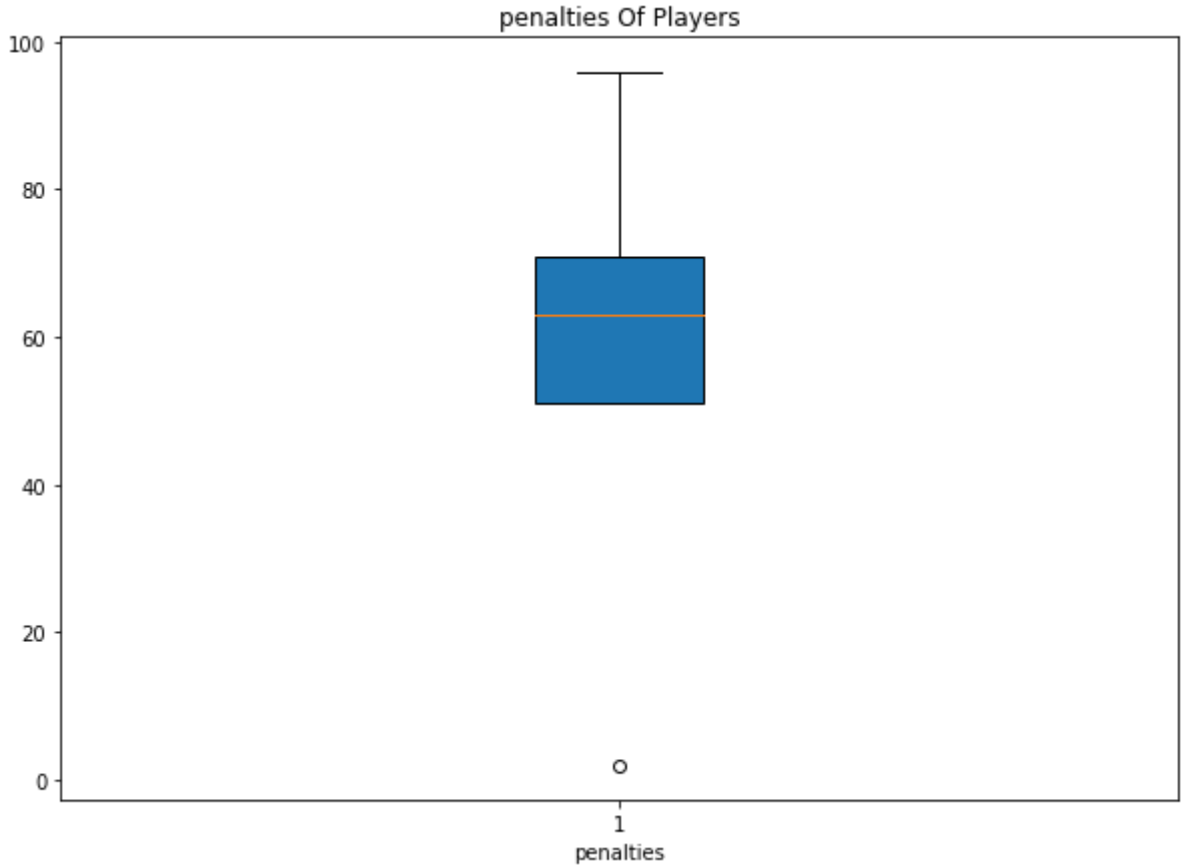


In [98]:
```
# Filter data
data = pd.DataFrame(above_rating.describe().loc['min':'max',"height"])
# initialitioze figure
fig = plt.figure(figsize =(10, 7))
# Creating plot
```

```
plt.boxplot(data,vert=True,patch_artist=True )
#set title and lable
plt.title("height Of Players")
plt.xlabel('height')
# show plot
plt.show()
```



In [99]:
```
# Filter data
data = above_rating.describe().loc['min':'max',"penalties"]
# initialitioze figure
fig = plt.figure(figsize =(10, 7))
# Creating plot
plt.boxplot(data,vert=True,patch_artist=True )
#set title and lable
plt.title("penalties Of Players")
plt.xlabel('penalties')
# show plot
plt.show()
```



Count players have overall rating more than 90

In [100…
```
df_player[(df_player['overall_rating'] > 90)].player_name.nunique()
```

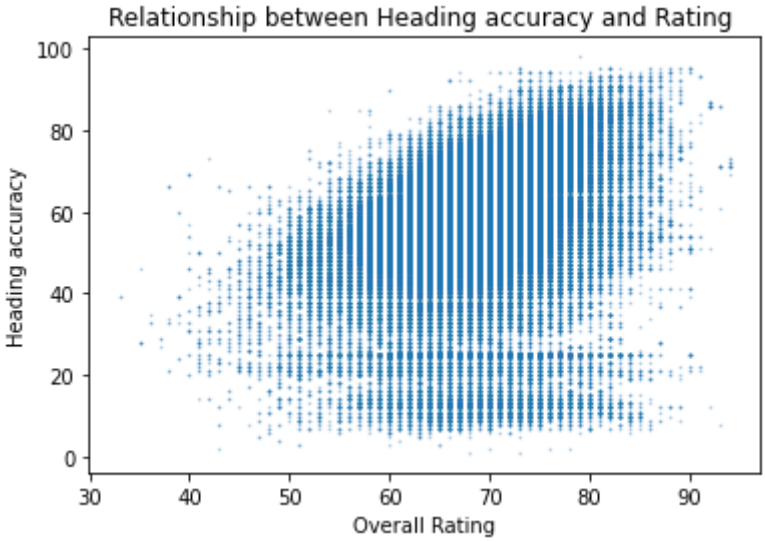
Out[100… 12

What are the attributes that contribute to the players' overall rating?

Now we will which attributes affect to Rating of the player which is good and which is Bad effection?

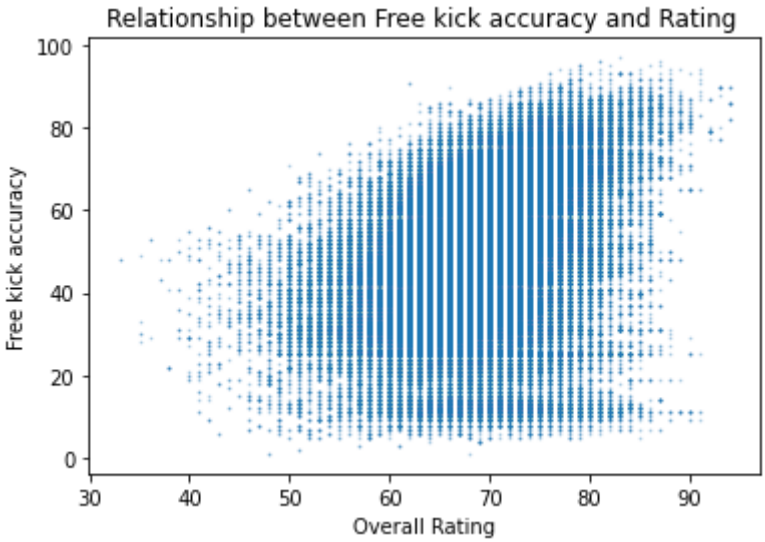
In [101…
```
#correlation between heading accuracy and rating
df_player.plot(x='overall_rating', y='heading_accuracy', kind='scatter', s=0.5, alph
plt.xlabel('Overall Rating')
plt.ylabel('Heading accuracy')
```

Out[101… Text(0, 0.5, 'Heading accuracy')



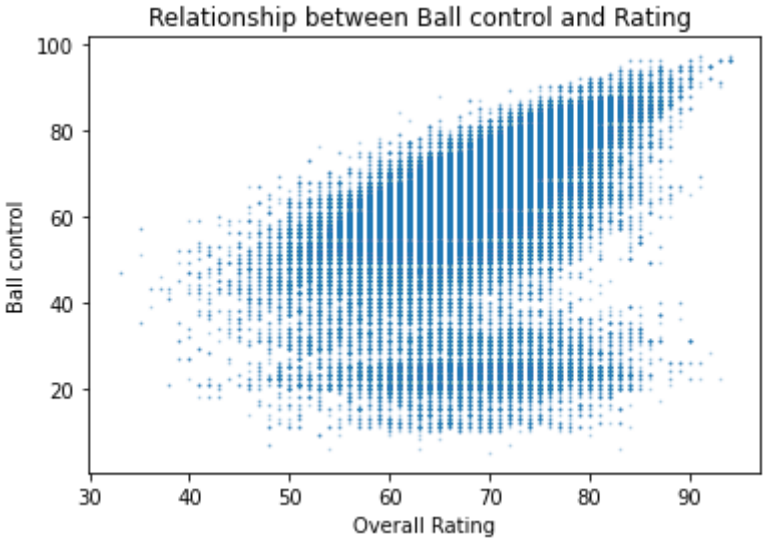
In [102…
```
#correlation between rating and free kick accuracy and rating
df_player.plot(x='overall_rating', y='free_kick_accuracy', kind='scatter', s=0.5, al
plt.xlabel('Overall Rating')
plt.ylabel('Free kick accuracy')
```

Out[102… `Text(0, 0.5, 'Free kick accuracy')`



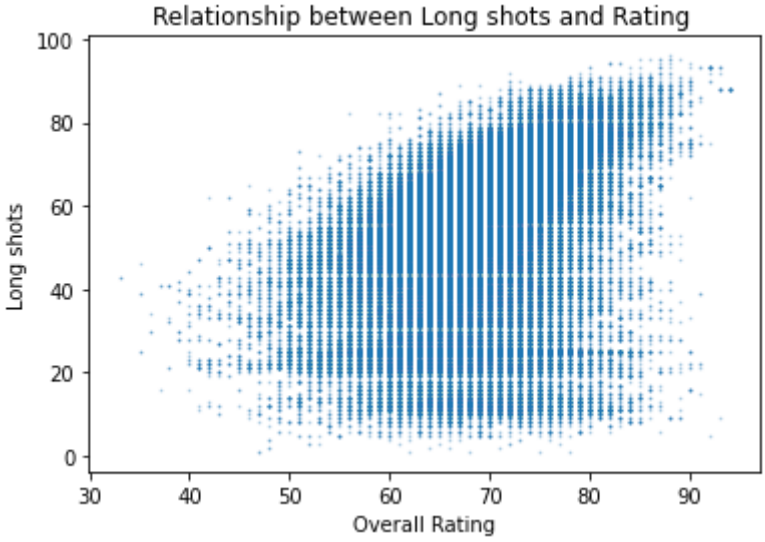
In [103…
```
#correlatio correlation between  ball control and rating
df_player.plot(x='overall_rating', y='ball_control', kind='scatter', s=0.5, alpha =
plt.xlabel('Overall Rating')
plt.ylabel('Ball control')
```

Out[103… `Text(0, 0.5, 'Ball control')`



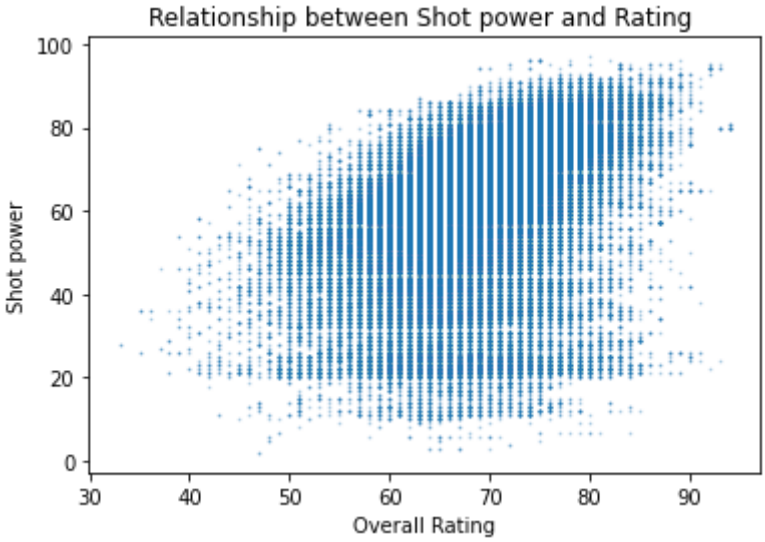
In [104…
```
#correlation between long shots and rating
df_player.plot(x='overall_rating', y='long_shots', kind='scatter', s=0.5, alpha = 0.
plt.xlabel('Overall Rating')
plt.ylabel('Long shots')
```

Out[104…
```
Text(0, 0.5, 'Long shots')
```



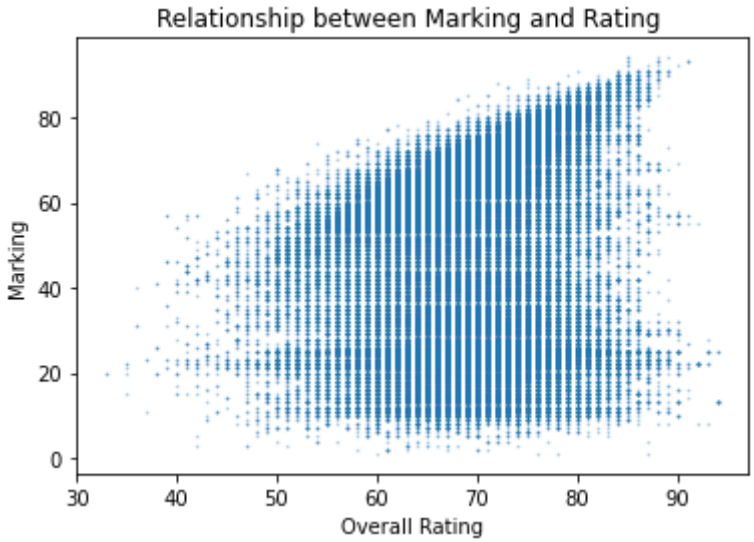
In [105…
```
#correlation between shot power and rating
df_player.plot(x='overall_rating', y='shot_power', kind='scatter', s=0.5, alpha = 0.
plt.xlabel('Overall Rating')
plt.ylabel('Shot power')
```

Out[105…
```
Text(0, 0.5, 'Shot power')
```



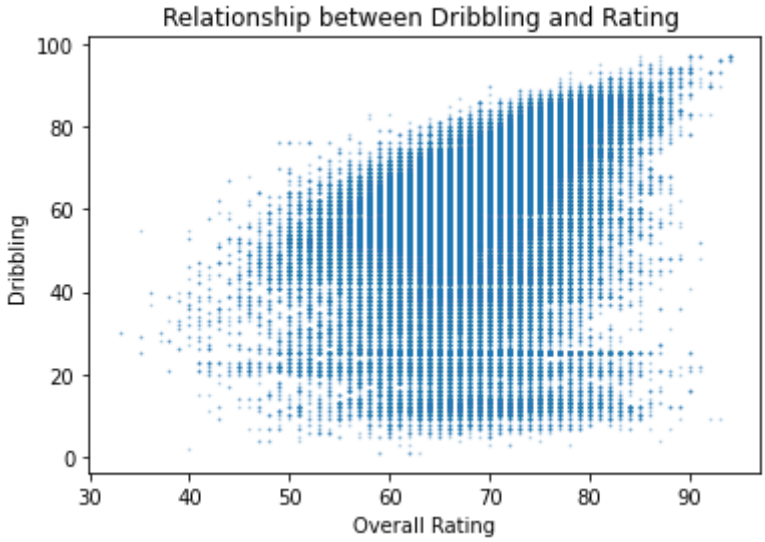
In [106…
```
#correlation between marking and rating
df_player.plot(x='overall_rating', y='marking', kind='scatter', s=0.5, alpha = 0.3,
plt.xlabel('Overall Rating')
plt.ylabel('Marking')
```

Out[106… Text(0, 0.5, 'Marking')



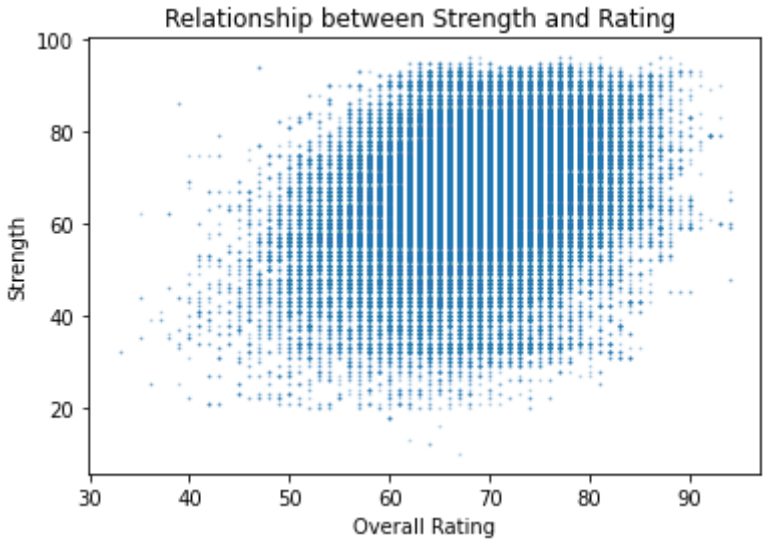
In [107…
```
#correlation between dribbling and rating
df_player.plot(x='overall_rating', y='dribbling', kind='scatter', s=0.5, alpha = 0.3
plt.xlabel('Overall Rating')
plt.ylabel('Dribbling')
```

Out[107… Text(0, 0.5, 'Dribbling')



In [108…
```
#correlation between strength and rating
df_player.plot(x='overall_rating', y='strength', kind='scatter', s=0.5, alpha = 0.3,
plt.xlabel('Overall Rating')
plt.ylabel('Strength')
```

Out[108… `Text(0, 0.5, 'Strength')`



Limitations

> I Noted that some players table are missing from the information of table (missed values).
>
> Noted that some Match table are missing from the information of table (missed values)
>
> The players' name are duplicated and incomplete so some results aren't accurated and I looking for the full names to disable matching result
>
> in the Player Attributes table, I found "the buildUpPlayDribbling" column has a huge missed value so If I dropped rows, I'll lose more players so I will remove the column until I fill missed values
>
> All Date in dataset come as string so I converted it to datetime

> Most of the Challenges in missed values and duplicated records

Conclusions

> I found that all leagues have not same number of matches in one season, So each league have diffrent number of teams England Premier League & France Ligue 1 & Italy Serie A & Spain LIGA BBVA have the most games: 380 Matches.
>
> The most league had Draw games is France Ligue 1 108 games than England Premier League 107 games.
>
> The most league had Win or lose games is Spain LIGA BBVA 288 games then Italy Serie A 285 games.
>
> the fewest team had losing matches in the 2016 season is Paris Saint-Germain which only lose 2 game.
>
> The league that had the most score a Goals in 2015/2016 season is England Premier League 1026 goals then Spain LIGA BBVA 1043 goals.
>
> The most team had won in 2015/16 is Paris Saint-Germain which win 30 game.
>
> From 2010 to 2016, the most improved teams by looking at the average Win times and goals are 'Paris Saint-Germain', 'Sporting CP', 'AZ', 'BSC Young Boys' and 'Napoli'.
>
> Rickie Lambert, Mario Balotelli, Xavi Hernandez, and Andrea Pirlo are the most penalty scorer in total.
>
> Most team attributes that lead the teams to win depend on the Change Creation Passing, defense pressure, Defense Aggression, build-up speed, and build dribbling column. Knowing that these results are according to the analysis of the top 10 winning teams
>
> The count of Players who have an overall rating of more than 90 is 12 players
>
> Most Top Player attributes depend on a balanced play speed, shot power, dribbling, strength.