Project: Investigating Soccer Database for Seasons 2008/2009 to 2015/2016

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Introduction

This soccer database comes from Kaggle. It contains data for soccer matches, players, and teams from 11 European countries from 2008 to 2016.\ There are 7 datasets: country, league, Match, Player, Player Attributes, Team, Team Attributes.\

Questions for Analysis:

- How many matches did each season and each league have?
- Who are the top 3 winning teams for home or away matches? Compare results?
- What does match results convey?
- Which Season had the highest number of winnings by home and away teams?
- Did Celtic team improve its performance throughout the 8 seasons?
- What teams improved the most over the time period?
- What team attributes lead to the most victories?
- Who is the oldest and the youngest players?
- How many players use either preferred right or left foot?
- Who made the most penalties?
- What are the attributes of the best players based on their average overall ratings?

In [1]:
```
# import the modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
# color set used for visualization.
plt.style.use('seaborn')
sns_colors = sns.color_palette("Set3", 12)
```

Data Wrangling

The data for the indicators were downloaded separately, therefore I had to first clean each dataset and then merge them together.

In [3]:
```
# Load your data and print out a few lines. Perform operations to inspect data.
# use shape and info()
df_country= pd.read_csv('Country.csv')
df_country.head()
```

Out[3]:

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

In [4]:
```
df_country.shape
```

Out[4]: (11, 2)

Country dataset has 11 entries representing 11 countries with their id number and name.

In [5]:
```
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
```

There are no null values, but will have to rename columns to "country_id" and "country_name" for consistency and it will be easy to merge with other datasets.

In [6]:
```
df_league= pd.read_csv('League.csv')
df_league.head()
```

Out[6]:

	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

In [7]:
```
df_league.shape
```

Out[7]: (11, 3)

There are 11 entries representing 11 leagues with their respective id number, league full name and country.

In [8]:
```
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
```

Fortunately, no null values, but will have to rename columns to "league_id", 'country_id' and "league_name" for consistency and later for merging. Although the values in both league id and country id are the same, I will not merge them.

In [9]:
```
df_match= pd.read_csv('Match.csv')
df_match.head()
```

Out[9]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_api_id	home_team_goal	...	SJA	VCH	V
0	1	1	1	2008/2009	1	2008-08-17 00:00:00	492473	9987	9993	1	...	4.00	1.65	
1	2	1	1	2008/2009	1	2008-08-16 00:00:00	492474	10000	9994	0	...	3.80	2.00	
2	3	1	1	2008/2009	1	2008-08-16 00:00:00	492475	9984	8635	0	...	2.50	2.35	
3	4	1	1	2008/2009	1	2008-08-17	492476	9991	9998	5	...	7.50	1.45	

						00:00:00									
4	5	1	1	2008/2009	1	2008-08-16 00:00:00	492477	7947	9985	1	...	1.73	4.50		

5 rows × 115 columns

In [10]:
```
df_match.shape
```

Out[10]:
```
(25979, 115)
```

Their are 25979 entries representing number of matches across all 11 leagues and 8 seasons from 2008/2009 till 2015/2016.

In [11]:
```
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 [12]:
```
df_match.isnull()
```

Out[12]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_api_id	home_team_goal	...	SJA	VC
0	False	False	False	False	False	False	False	False	False	False	...	False	Fals
1	False	False	False	False	False	False	False	False	False	False	...	False	Fals
2	False	False	False	False	False	False	False	False	False	False	...	False	Fals
3	False	False	False	False	False	False	False	False	False	False	...	False	Fals
4	False	False	False	False	False	False	False	False	False	False	...	False	Fals
...	...	...	...	...	...	...	...	...	...	...	...	...	
25974	False	False	False	False	False	False	False	False	False	False	...	True	Tru
25975	False	False	False	False	False	False	False	False	False	False	...	True	Tru
25976	False	False	False	False	False	False	False	False	False	False	...	True	Tru
25977	False	False	False	False	False	False	False	False	False	False	...	True	Tru
25978	False	False	False	False	False	False	False	False	False	False	...	True	Tru

25979 rows × 115 columns

In [13]:
```
df_match.isnull().sum()
```

Out[13]:
```
id                0
country_id        0
league_id         0
season            0
stage             0
                ...
GBD           11817
GBA           11817
BSH           11818
BSD           11818
BSA           11818
Length: 115, dtype: int64
```

Only the first 11 columns don't have any null values. there is no use for the other columns, since there is no clear explanation of what they are or entail. I will drop them.

In [14]:
```
df_teams= pd.read_csv('Team.csv')
df_teams.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
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]:
```
df_teams.count()
```

Out[15]:
```
id                  299
team_api_id         299
team_fifa_api_id    288
team_long_name      299
team_short_name     299
dtype: int64
```

In [16]:
```
df_teams.shape
```

Out[16]:
```
(299, 5)
```

In the team dataset, there are 299 entries representing 299 teams from 11 countries.

In [17]:
```
df_teams.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
```

Only 'team_fifa_api_id' column has null values. I will drop it, since `team_api_id` column is only common with match dataset.

In [18]:
```
df_teams_attri= pd.read_csv('Team_Attributes.csv')
df_teams_attri.head()
```

Out[18]:

	id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUpPlayDribbling	buildUpPlayDribblingClass	buildU
0	1	434	9930	2010-02-22 00:00:00	60	Balanced	NaN	Little	
1	2	434	9930	2014-09-19 00:00:00	52	Balanced	48.0	Normal	
2	3	434	9930	2015-09-10 00:00:00	47	Balanced	41.0	Normal	
3	4	77	8485	2010-02-22 00:00:00	70	Fast	NaN	Little	
4	5	77	8485	2011-02-22 00:00:00	47	Balanced	NaN	Little	

5 rows × 25 columns

In [19]:
```
df_teams_attri.shape
```

Out[19]:
```
(1458, 25)
```

In [20]:
```
df_teams_attri.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 the teams attributes dataset, there are 1458 entries, only `buildUpPlayDribbling` has null values, so it can be droped.\ `date` column needs to be changed to datetime.\

In [21]:
```
df_players= pd.read_csv('Player.csv')
df_players.head()
```

Out[21]:

	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 [22]:
```
df_players.shape
```

Out[22]:
```
(11060, 7)
```

In [23]:
```
df_players.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11060 entries, 0 to 11059
Data columns (total 7 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   id                  11060 non-null  int64
 1   player_api_id       11060 non-null  int64
 2   player_name         11060 non-null  object
 3   player_fifa_api_id  11060 non-null  int64
 4   birthday            11060 non-null  object
 5   height              11060 non-null  float64
 6   weight              11060 non-null  int64
dtypes: float64(1), int64(4), object(2)
```

```
memory usage: 605.0+ KB
```

11060 players and no null values.

In [24]:
```
df_players_attri= pd.read_csv('Player_Attributes.csv')
df_players_attri.head(7)
```

Out[24]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attacking_work_rate	defensive_work_rate	crossing	...
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	medium	medium	49.0	...
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	medium	medium	49.0	...
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	medium	medium	49.0	...
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	medium	medium	48.0	...
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	medium	medium	48.0	...
5	6	189615	155782	2016-04-21 00:00:00	74.0	76.0	left	high	medium	80.0	...
6	7	189615	155782	2016-04-07 00:00:00	74.0	76.0	left	high	medium	80.0	...

7 rows × 42 columns

In [25]:
```
df_players_attri.shape
```

Out[25]:
```
(183978, 42)
```

In [26]:
```
df_players_attri.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
```

With the exception of the first 4 columns, the rest have null values. I noticed that there is multiple entries for each single player in different dates form 2007 till 2016. This explains the 183978 entries.

General Properties Concluded:

11 countries\ 11 league champions\ 25979 matches\ 299 teams\ 21 team sttributes\ 11060 players\ 38 players attributes

Data Cleaning

Changes in `df_country`

In [27]:
```
# Rename columns in ```df_country``` for consistency.
df_country.rename(columns={'id':'country_id', 'name':'country_name'},inplace=True)
df_country
```

Out[27]:

	country_id	country_name
0	1	Belgium
1	1729	England
2	4769	France
3	7809	Germany
4	10257	Italy
5	13274	Netherlands
6	15722	Poland
7	17642	Portugal
8	19694	Scotland
9	21518	Spain
10	24558	Switzerland

In [28]:
```
# Drop country_id column and rename the rest of the columns in df_league.
df_league.rename(columns={'id':'league_id', 'name':'league_name'},inplace=True)
df_league.drop('country_id',axis= 1, inplace= True)
df_league
```

Out[28]:

	league_id	league_name
0	1	Belgium Jupiler League
1	1729	England Premier League
2	4769	France Ligue 1
3	7809	Germany 1. Bundesliga
4	10257	Italy Serie A
5	13274	Netherlands Eredivisie
6	15722	Poland Ekstraklasa
7	17642	Portugal Liga ZON Sagres
8	19694	Scotland Premier League

9	21518	Spain LIGA BBVA
10	24558	Switzerland Super League

Changes in `df_teams`

In [29]:
```
# Check for any duplicated team name
duplicated= df_teams[df_teams.duplicated('team_long_name')]
duplicated
```

Out[29]:

	id	team_api_id	team_fifa_api_id	team_long_name	team_short_name
24	2510	274581	111560.0	Royal Excel Mouscron	MOP
183	31445	8020	111429.0	Polonia Bytom	GOR
199	32409	8024	301.0	Widzew Łódź	WID

In [30]:
```
# Drop the duplicated names.
df_teams.drop([df_teams.index[24], df_teams.index[183], df_teams.index[199]], axis=0, inplace=True)
df_teams.count()
```

Out[30]:
```
id                  296
team_api_id         296
team_fifa_api_id    285
team_long_name      296
team_short_name     296
dtype: int64
```

In [31]:
```
# Drop unneeded columns.
df_teams.drop(['id', 'team_fifa_api_id', 'team_short_name'],axis= 1, inplace= True)
df_teams.head()
```

Out[31]:

	team_api_id	team_long_name
0	9987	KRC Genk
1	9993	Beerschot AC
2	10000	SV Zulte-Waregem
3	9994	Sporting Lokeren
4	9984	KSV Cercle Brugge

In [32]:
```
df_teams.rename(columns={'team_api_id':'team_id'},inplace=True)
```

In [33]:
```
# Save changes.
df_teams.to_csv('teams_clean.csv', index=False)
```

Changes in `df_teams_attri`

In [34]:
```
# Add team names column.
team_attribute= df_teams_attri.merge(df_teams, left_on='team_api_id', right_on='team_id', how='inner')

# Drop null values.
team_attribute.dropna(axis=1, inplace=True)
```

In [35]:
```
# Drop unnecessary columns
team_attribute.drop(['id','team_fifa_api_id', 'team_api_id'], axis=1, inplace=True)
```

In [36]:
```
# Rearrange columns.
team_attribute= team_attribute[['team_id','team_long_name','date', 'buildUpPlaySpeed', 'buildUpPlaySpeedClass',
       'buildUpPlayDribblingClass', 'buildUpPlayPassing',
       'buildUpPlayPassingClass', 'buildUpPlayPositioningClass',
       'chanceCreationPassing', 'chanceCreationPassingClass',
       'chanceCreationCrossing', 'chanceCreationCrossingClass',
```

```
       'chanceCreationShooting', 'chanceCreationShootingClass',
       'chanceCreationPositioningClass', 'defencePressure',
       'defencePressureClass', 'defenceAggression', 'defenceAggressionClass',
       'defenceTeamWidth', 'defenceTeamWidthClass', 'defenceDefenderLineClass']]
```

In [37]:
```
# Change date column to datetime.
team_attribute['date']= pd.to_datetime(team_attribute['date'])
```

In [38]:
```
#drop non nonnumeric columns and team id.
team_attribute.drop(['team_id','buildUpPlaySpeedClass','buildUpPlayPassingClass','buildUpPlayDribblingClass','bui
                     'chanceCreationPassingClass','chanceCreationCrossingClass','chanceCreationShootingClass',
                     'chanceCreationPositioningClass','defencePressureClass','defenceAggressionClass',
                    'defenceTeamWidthClass','defenceDefenderLineClass'],axis= 1, inplace= True)
```

In [39]:
```
# Save changes
team_attribute.to_csv('team_attribute_clean.csv', index=False)
```

Changes in `df_match`

In [40]:
```
# I am only interested in the first 11 columns and the reset is dropped
df_match.drop(df_match.loc[:, 'home_player_X1':'BSA'], axis=1, inplace=True)
```

In [41]:
```
# Add country_name from df_country by using merge() and create new dataframe match.
match= pd.merge(df_match, df_country, on='country_id', how='inner')
```

In [42]:
```
# Add league_name from df_league by using merge().
match= match.merge(df_league, on='league_id', how='inner')
```

In [43]:
```
# Add team names as home_team and away_team using merge with df_teams.
```

In [44]:
```
# Create and add home_team.
match= match.merge(df_teams, left_on='home_team_api_id', right_on='team_id',how='inner')
match.rename(columns={'team_long_name':'home_team'},inplace=True)
```

In [45]:
```
# Create and add away_team.
match= match.merge(df_teams, left_on='away_team_api_id', right_on='team_id',how='left')
match.rename(columns={'team_long_name':'away_team'},inplace=True)
```

In [46]:
```
match.head()
```

Out[46]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_api_id	home_team_goal	away_team_goal
0	1	1	1	2008/2009	1	2008-08-17 00:00:00	492473	9987	9993	1	1
1	29	1	1	2008/2009	12	2008-11-15 00:00:00	492583	9987	9999	1	1
2	47	1	1	2008/2009	14	2008-11-29 00:00:00	492651	9987	9984	3	2
3	65	1	1	2008/2009	16	2008-12-13 00:00:00	492713	9987	9986	1	0
4	94	1	1	2008/2009	19	2009-01-24 00:00:00	492805	9987	9998	2	0

In [47]:
```
# Drop unnecessary columns in match
match.drop(['id','country_id', 'league_id',
            'home_team_api_id','away_team_api_id',
            'team_id_x','team_id_y'], axis=1, inplace=True)
```

In [48]:
```
# Rearrange the remaining columns.
match= match[['country_name','league_name','season', 'stage', 'date', 'match_api_id',
              'home_team','away_team','home_team_goal','away_team_goal']]
```

In [49]:
```
match.head()
```

Out[49]:

	country_name	league_name	season	stage	date	match_api_id	home_team	away_team	home_team_goal	away_team_goal
0	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-17 00:00:00	492473	KRC Genk	Beerschot AC	1	1
1	Belgium	Belgium Jupiler League	2008/2009	12	2008-11-15 00:00:00	492583	KRC Genk	KSV Roeselare	1	1
2	Belgium	Belgium Jupiler League	2008/2009	14	2008-11-29 00:00:00	492651	KRC Genk	KSV Cercle Brugge	3	2
3	Belgium	Belgium Jupiler League	2008/2009	16	2008-12-13 00:00:00	492713	KRC Genk	Sporting Charleroi	1	0
4	Belgium	Belgium Jupiler League	2008/2009	19	2009-01-24 00:00:00	492805	KRC Genk	RAEC Mons	2	0

In [50]:
```
# Creat column for match result and add it to match dataframe.
def result(match):
    if match['home_team_goal'] > match['away_team_goal']:
        return match['home_team']
    elif match['home_team_goal'] < match['away_team_goal']:
        return match['away_team']
    elif match['home_team_goal'] == match['away_team_goal']:
        return 'Tie'

match['match_result']= match.apply(result, axis=1)
```

In [51]:
```
match.head()
```

Out[51]:

	country_name	league_name	season	stage	date	match_api_id	home_team	away_team	home_team_goal	away_team_goal	match_re
0	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-17 00:00:00	492473	KRC Genk	Beerschot AC	1	1	
1	Belgium	Belgium Jupiler League	2008/2009	12	2008-11-15 00:00:00	492583	KRC Genk	KSV Roeselare	1	1	
2	Belgium	Belgium Jupiler League	2008/2009	14	2008-11-29 00:00:00	492651	KRC Genk	KSV Cercle Brugge	3	2	KRC G
3	Belgium	Belgium Jupiler League	2008/2009	16	2008-12-13 00:00:00	492713	KRC Genk	Sporting Charleroi	1	0	KRC G
4	Belgium	Belgium Jupiler League	2008/2009	19	2009-01-24 00:00:00	492805	KRC Genk	RAEC Mons	2	0	KRC G

In [52]:
```
#check for null values.
match.isnull().sum()
```

Out[52]:
```
country_name        0
league_name         0
season              0
stage               0
date                0
match_api_id        0
home_team           0
away_team         187
home_team_goal      0
away_team_goal      0
match_result       38
dtype: int64
```

In [53]:
```
match.dropna(axis=0, inplace=True)
```

In [54]:
```
match.isnull().sum()
```

Out[54]:
```
country_name      0
league_name       0
season            0
```

```
stage            0
date             0
match_api_id     0
home_team        0
away_team        0
home_team_goal   0
away_team_goal   0
match_result     0
dtype: int64
```

In [55]:
```
#check for duplicates.
match.duplicated().sum()
```

Out[55]:
```
0
```

In [56]:
```
match.to_csv('match_clean.csv', index=False)
```

Changes in `df_players`

In [57]:
```
#Remove id and player_fifa_api_id.
df_players.drop(['id','player_fifa_api_id'], axis=1, inplace=True)
```

In [58]:
```
#Convert birthday column to datetime.
df_players['birthday']= pd.to_datetime(df_players['birthday'])
```

In [59]:
```
# Rename column player_api_id to player_id
df_players.rename(columns={'player_api_id':'player_id'},inplace=True)
```

In [60]:
```
df_players.head()
```

Out[60]:

	player_id	player_name	birthday	height	weight
0	505942	Aaron Appindangoye	1992-02-29	182.88	187
1	155782	Aaron Cresswell	1989-12-15	170.18	146
2	162549	Aaron Doran	1991-05-13	170.18	163
3	30572	Aaron Galindo	1982-05-08	182.88	198
4	23780	Aaron Hughes	1979-11-08	182.88	154

In [61]:
```
df_players.dtypes
```

Out[61]:
```
player_id              int64
player_name           object
birthday      datetime64[ns]
height               float64
weight                 int64
dtype: object
```

In [62]:
```
df_players.isnull().sum()
```

Out[62]:
```
player_id      0
player_name    0
birthday       0
height         0
weight         0
dtype: int64
```

In [63]:
```
df_players.duplicated().sum()
```

Out[63]:
```
0
```

Changes in `df_players_attri`

In [64]:
```
# Drop all null values.
df_players_attri.dropna(inplace=True)
```

In [65]:
```
# Drop id and player_fifa_api_id
df_players_attri.drop(['id','player_fifa_api_id'], axis=1, inplace=True)
```

In [66]:
```
# Rename column player_api_id to player_id
df_players_attri.rename(columns={'player_api_id':'player_id'},inplace=True)
```

In [67]:
```
#Convert date column to datetime.
df_players_attri['date']= pd.to_datetime(df_players_attri['date'])
```

In [68]:
```
# Merge df_players and df_players_attri
players= df_players_attri.merge(df_players, left_on='player_id', right_on='player_id',how='inner')
```

In [69]:
```
# Rearrange columns.
players= players[['player_id','player_name','birthday', 'height', 'weight','date','overall_rating','potential',
                  'preferred_foot','attacking_work_rate','defensive_work_rate','crossing','finishing','free_kick_
                 'long_passing','ball_control','acceleration','sprint_speed','agility','reactions','balance','sho
                 'jumping','stamina','strength','long_shots','aggression','interceptions','positioning','vision',
                  'marking','standing_tackle','sliding_tackle','gk_diving','gk_handling','gk_kicking','gk_positio
```

In [70]:
```
players.head()
```

Out[70]:

	player_id	player_name	birthday	height	weight	date	overall_rating	potential	preferred_foot	attacking_work_rate	...	vision	penalties	n
0	505942	Aaron Appindangoye	1992-02-29	182.88	187	2016-02-18	67.0	71.0	right	medium	...	54.0	48.0	
1	505942	Aaron Appindangoye	1992-02-29	182.88	187	2015-11-19	67.0	71.0	right	medium	...	54.0	48.0	
2	505942	Aaron Appindangoye	1992-02-29	182.88	187	2015-09-21	62.0	66.0	right	medium	...	54.0	48.0	
3	505942	Aaron Appindangoye	1992-02-29	182.88	187	2015-03-20	61.0	65.0	right	medium	...	53.0	47.0	
4	505942	Aaron Appindangoye	1992-02-29	182.88	187	2007-02-22	61.0	65.0	right	medium	...	53.0	47.0	

5 rows × 39 columns

In [71]:
```
# Save changes.
players.to_csv('players_clean.csv', index=False)
```

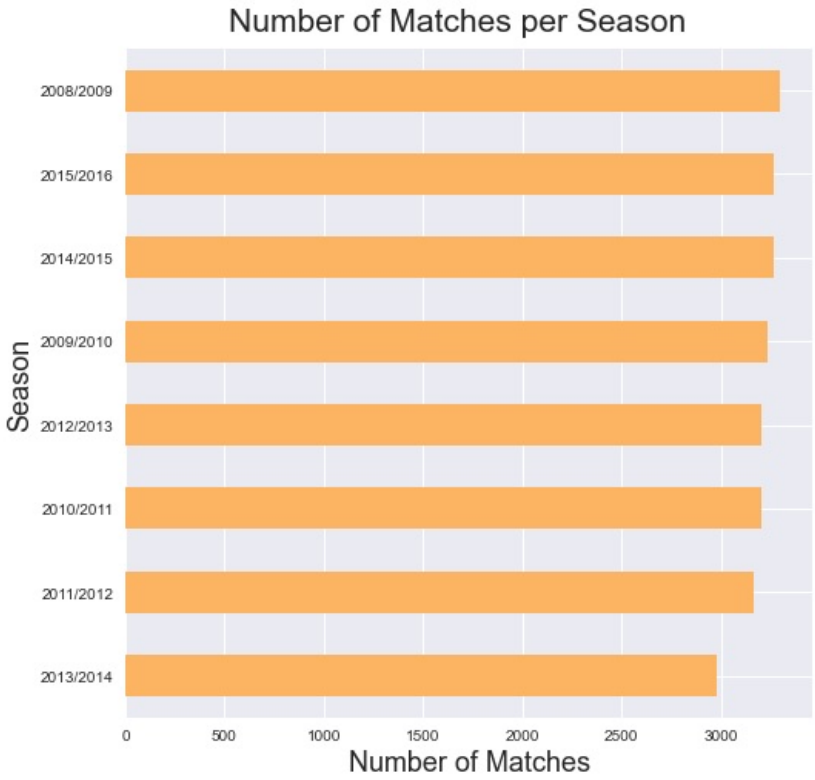
Exploratory Data Analysis

How many matches did each season have?

In [72]:
```
df=match['season'].value_counts().sort_values(ascending=True)
df
```

Out[72]:
```
2013/2014    2974
2011/2012    3162
2010/2011    3202
2012/2013    3202
2009/2010    3230
2014/2015    3265
2015/2016    3266
2008/2009    3296
Name: season, dtype: int64
```

In [73]:
```
#Plot results.
colors= sns_colors[5]
df.plot(kind='barh', color=colors, figsize=(8,8));
plt.figtext(.5,.9,'Number of Matches per Season', fontsize=21, ha='center');
plt.xlabel('Number of Matches', fontsize=18);
plt.ylabel('Season', fontsize=18);
```



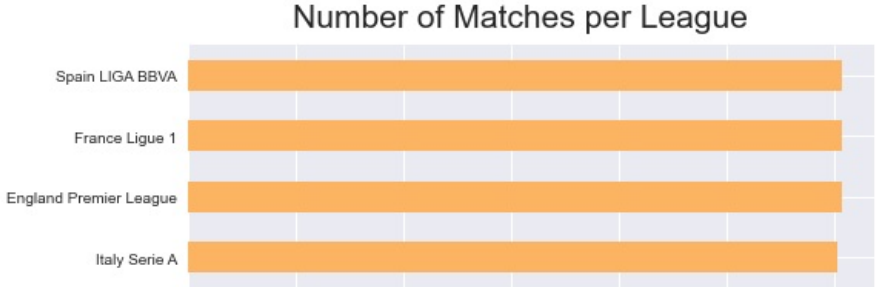
Throughout the 8 seasons, 2008/2009 had the most number of matches while 2013/2014 had the lowest number of matches.

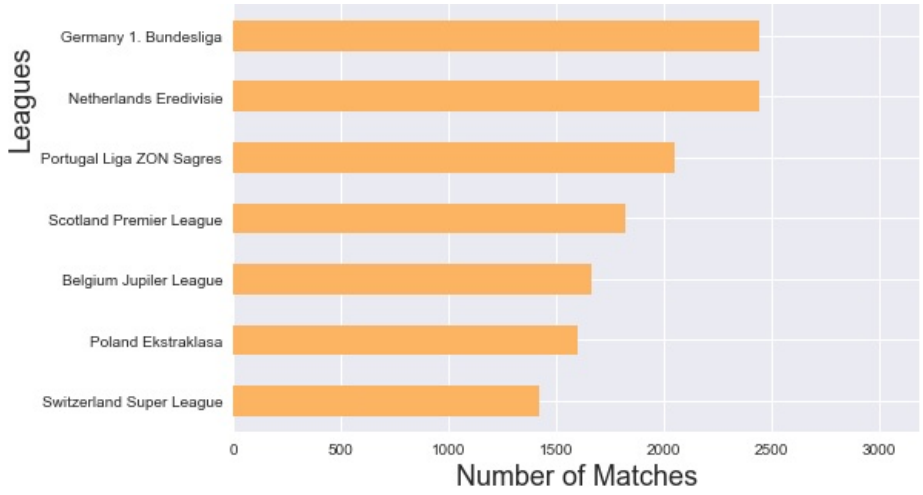
How many matches did each league have?

In [74]:
```
df1= match['league_name'].value_counts().sort_values(ascending=True)
df1
```

Out[74]:
```
Switzerland Super League    1422
Poland Ekstraklasa          1598
Belgium Jupiler League      1668
Scotland Premier League     1824
Portugal Liga ZON Sagres    2052
Netherlands Eredivisie      2448
Germany 1. Bundesliga       2448
Italy Serie A               3017
England Premier League      3040
France Ligue 1              3040
Spain LIGA BBVA             3040
Name: league_name, dtype: int64
```

In [75]:
```
#Plot results.
colors= sns_colors[5]
df1.plot(kind='barh', color=colors, figsize=(8,8))
plt.figtext(.5,.9,'Number of Matches per League', fontsize=21, ha='center');
plt.xlabel('Number of Matches', fontsize=18);
plt.ylabel('Leagues', fontsize=18);
```





England Premier League, Spain LIGA BBVA, France Ligue 1 have the highest number of matches throughout the 8 seasons.

Who are the top 3 winning teams for home or away matches? Compare results?

In [76]:
```
# Top 3 winning home teams.
win_home= match.query('home_team == match_result')
home= win_home['match_result'].value_counts().sort_values(ascending=False)[:3]
print(home)
```

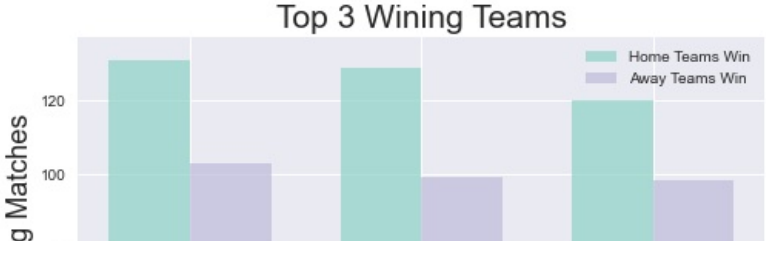
```
FC Barcelona      131
Real Madrid CF    129
Celtic            120
Name: match_result, dtype: int64
```

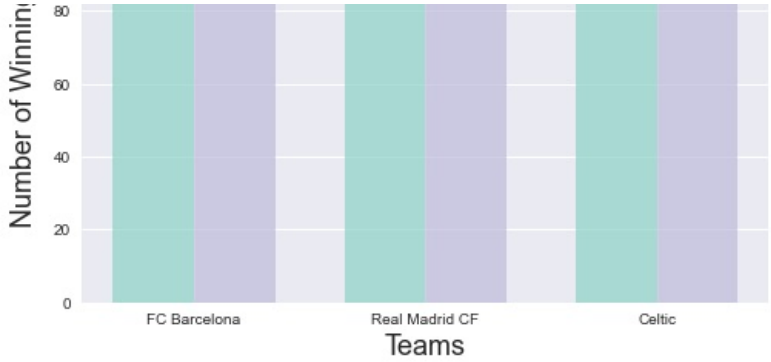
In [77]:
```
# Top 3 winning away teams.
win_away= match.query('away_team == match_result')
away= win_away['match_result'].value_counts().sort_values(ascending=False)[:3]
print(away)
```

```
FC Barcelona      103
Real Madrid CF     99
Celtic             98
Name: match_result, dtype: int64
```

`FC Barcelona` , `Real Madrid CF` ,and `Celtic` are top 3 winning teams both as a home team and away team with a difference in winning results.So, lets compare the results.

In [78]:
```
# Compare the results.
ind = np.arange(len(home))
width = 0.35
fig = plt.figure(figsize = (8, 6));

home_bars = plt.bar(ind, home, width, color=sns_colors[0], alpha=.7, label='Home Teams Win');
away_bars = plt.bar(ind+width, away, width, color=sns_colors[2], alpha=.7, label='Away Teams Win');

locations = ind + width / 2
labels = ['FC Barcelona', 'Real Madrid CF', 'Celtic']
plt.xticks(locations, labels);

plt.ylabel('Number of Winning Matches', fontsize=18);
plt.xlabel('Teams', fontsize=18);
plt.title('Top 3 Wining Teams', fontsize=21);

plt.legend();
```





Top teams who play in their homeland have more winnings than playing away from their homeland.

What does match results convey?

To answer this, we will have to calculate total wins by home teams and away teams, and also total number of ties. Then, we'll get their percentages and plot them for visual comparison.

In [79]:
```
# Total wins by home teams.
total_home_wins= win_home['match_result'].count()

# Total wins by away teams.
total_away_wins= win_away['match_result'].count()

# Total ties.
tie= match.query('match_result == "Tie"')
total_tie= tie['match_result'].count()

# Total matches
total_matches= match['match_result'].count()
```

In [80]:
```
# Percentage of home teams winnings.
home_proportion= (total_home_wins/total_matches)*100
home_proportion
```

Out[80]: 45.872563190998946

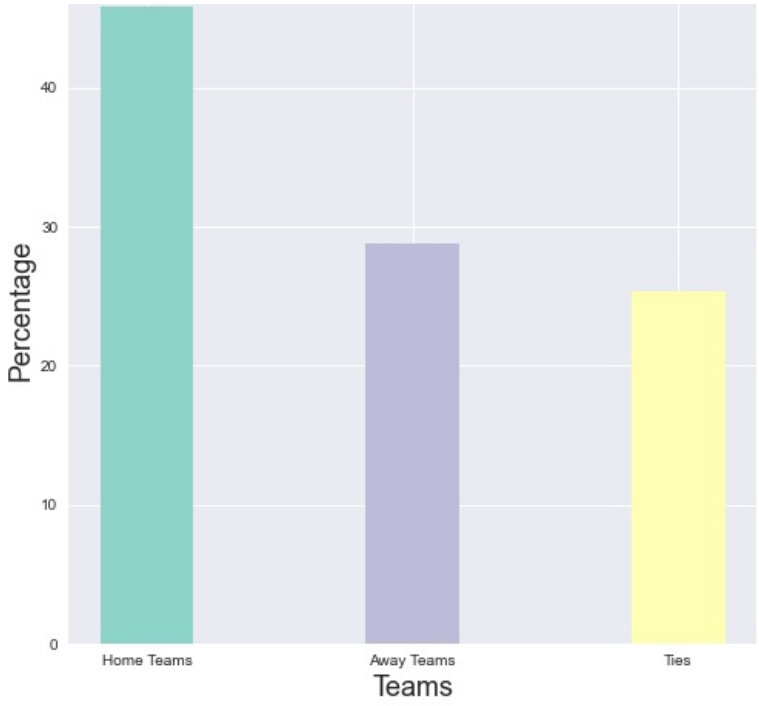
In [81]:
```
# Percentage of away teams winnings.
away_proportion= (total_away_wins/total_matches)*100
away_proportion
```

Out[81]: 28.800250029300305

In [82]:
```
# Percentage of total ties.
tie_proportion= (total_tie/total_matches)*100
tie_proportion
```

Out[82]: 25.327186779700746

In [83]:
```
# Plot results using bar chart.
data = {'Home Teams':home_proportion, 'Away Teams':away_proportion, 'Ties':tie_proportion}
keys = data.keys()
values = data.values()

fig = plt.figure(figsize = (8, 8));

plt.bar(keys, values, color =[sns_colors[0], sns_colors[2], sns_colors[1]],
        width = 0.35);

plt.xlabel("Teams", fontsize=18);
plt.ylabel("Percentage", fontsize=18);
plt.title("Percentage of Winnings", fontsize=21);
```



Home teams have 45.87% chance of winning a match compared to away teams of 28.74% chance.\ There are 25.38% chance for ties.

Which Season had the highest number of winnings by home and away teams?

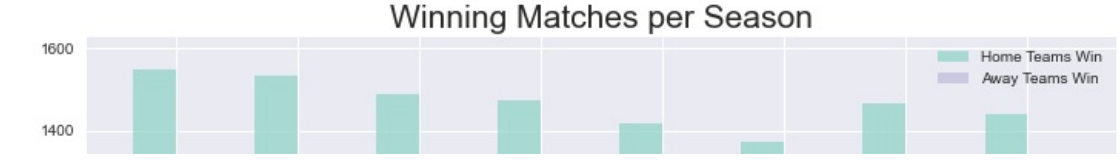
In [84]:
```
# The season with highest number of home teams winning
home_season = win_home.groupby(['season']).count()
print('The season with highest number of home teams winning:\n{}'.format(home_season['match_result'].nlargest(1))
```

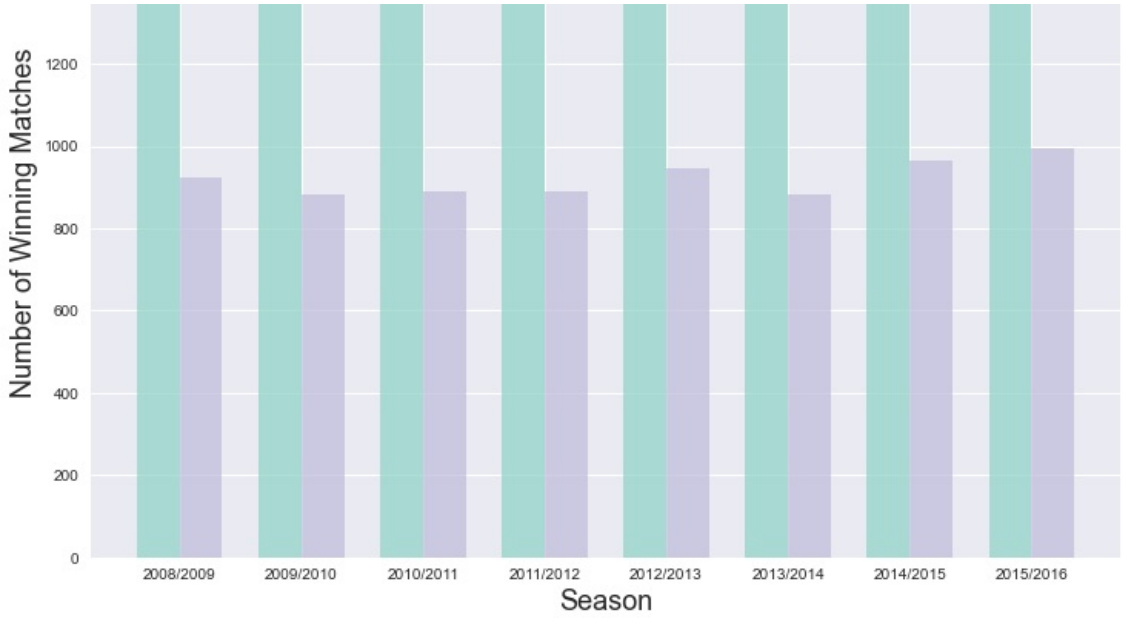
```
The season with highest number of home teams winning:
season
2008/2009    1550
Name: match_result, dtype: int64
```

In [85]:
```
# The season with highest number of away teams winning.
away_season = win_away.groupby(['season']).count()
print('The season with highest number of away teams winning:\n{}'.format(away_season['match_result'].nlargest(1))
```

```
The season with highest number of away teams winning:
season
2015/2016    994
Name: match_result, dtype: int64
```

In [86]:
```
# Plot the results.

ind = np.arange(len(away_season['match_result']))
width = 0.35
fig = plt.subplots(figsize =(12, 8))

home_bars = plt.bar(ind, home_season['match_result'], width, color=sns_colors[0], alpha=.7, label='Home Teams Wir
away_bars = plt.bar(ind+width, away_season['match_result'], width, color=sns_colors[2], alpha=.7, label='Away Tea

locations = ind + width / 2
labels = ['2008/2009', '2009/2010', '2010/2011','2011/2012','2012/2013','2013/2014','2014/2015','2015/2016']
plt.xticks(locations, labels);

plt.ylabel('Number of Winning Matches', fontsize=18);
plt.xlabel('Season', fontsize=18);
plt.title('Winning Matches per Season', fontsize=21);

plt.legend();
```

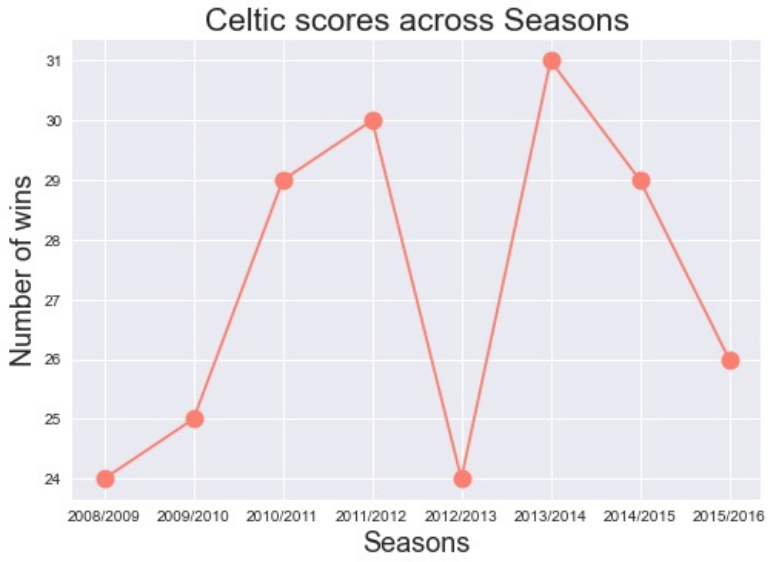




Did Celtic team improve its performance throughout the 8 seasons?

In [87]:
```
# Create a dataframe with match results end with Celtic winning.
df4= match.loc[match['match_result']== 'Celtic']
# Get number of winning matches per season for Celtic
df5= df4['season'].value_counts()
```

In [88]:
```
# Plot results
season= ['2008/2009','2009/2010','2010/2011','2011/2012','2012/2013','2013/2014','2014/2015','2015/2016']
heights = df5.reindex(season)
labels = season

plt.plot(labels, heights, color=sns_colors[3], marker='o', markerfacecolor=sns_colors[3], markersize=12);
plt.title('Celtic scores across Seasons', fontsize=21)
plt.xlabel('Seasons', fontsize=18);
plt.ylabel('Number of wins', fontsize=18);
```



Celtic team's performance fluctuated across the 8 seasons. They started with 24 wins in 2008/2009 and gradually increased till 2011/2012 achieving 30 wins. They had a fallout in 2012/2013 with 24 wins. In 2013/2014, they improved significantly achieveing 31 wins. Their performance started to drop gradually ending with 26 wins in 2015/2016.

What are the teams that improved the most over the time period?

To do this, I will have to calculate mean difference of total goal scores between two seasons which will be 2008/2009 and 2015/2016. First,I will have to get the mean of total goal scores seperately. Second, get their difference.

In [89]:
```
#2008/2009.
```

```
match_2008= match.query('season == "2008/2009"')
match_2008.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3296 entries, 0 to 25337
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   country_name    3296 non-null   object
 1   league_name     3296 non-null   object
 2   season          3296 non-null   object
 3   stage           3296 non-null   int64 
 4   date            3296 non-null   object
 5   match_api_id    3296 non-null   int64 
 6   home_team       3296 non-null   object
 7   away_team       3296 non-null   object
 8   home_team_goal  3296 non-null   int64 
 9   away_team_goal  3296 non-null   int64 
 10  match_result    3296 non-null   object
dtypes: int64(4), object(7)
memory usage: 309.0+ KB
```

In [90]:

```
# Calculate home teams mean goal scores.
home_2008= match_2008.groupby(['home_team'])['home_team_goal'].mean()
# Calculate away teams mean goal scores.
away_2008= match_2008.groupby(['away_team'])['away_team_goal'].mean()
# Add them to get the total goal scores for the whole season.
total_2008= (home_2008 + away_2008)/2
total_2008.head()
```

Out[90]:

```
home_team
1. FC Köln       1.029412
AC Bellinzona    1.222222
ADO Den Haag     1.205882
AJ Auxerre       0.921053
AS Monaco        1.078947
dtype: float64
```

In [91]:

```
#2015/2016.
match_2015= match.query('season == "2015/2016"')
match_2015.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3266 entries, 91 to 25783
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   country_name    3266 non-null   object
 1   league_name     3266 non-null   object
 2   season          3266 non-null   object
 3   stage           3266 non-null   int64 
 4   date            3266 non-null   object
 5   match_api_id    3266 non-null   int64 
 6   home_team       3266 non-null   object
 7   away_team       3266 non-null   object
 8   home_team_goal  3266 non-null   int64 
 9   away_team_goal  3266 non-null   int64 
 10  match_result    3266 non-null   object
dtypes: int64(4), object(7)
memory usage: 306.2+ KB
```

In [92]:

```
# Calculate home teams mean goal scores.
home_2015= match_2015.groupby(['home_team'])['home_team_goal'].mean()
# Calculate away teams mean goal scores.
away_2015= match_2015.groupby(['away_team'])['away_team_goal'].mean()
# Add them to get the total goal scores for the whole season.
total_2015= (home_2015 + away_2015)/2
total_2015.head()
```

Out[92]:

```
home_team
1. FC Köln          1.117647
1. FSV Mainz 05     1.352941
ADO Den Haag        1.411765
AS Monaco           1.500000
AS Saint-Étienne    1.105263
```

```
dtype: float64
```

In [93]:
```
# Get the difference between 2008 & 2015.
difference= total_2015 - total_2008
difference.head()
```

Out[93]:
```
home_team
1. FC Köln         0.088235
1. FSV Mainz 05         NaN
AC Bellinzona           NaN
ADO Den Haag       0.205882
AJ Auxerre              NaN
dtype: float64
```

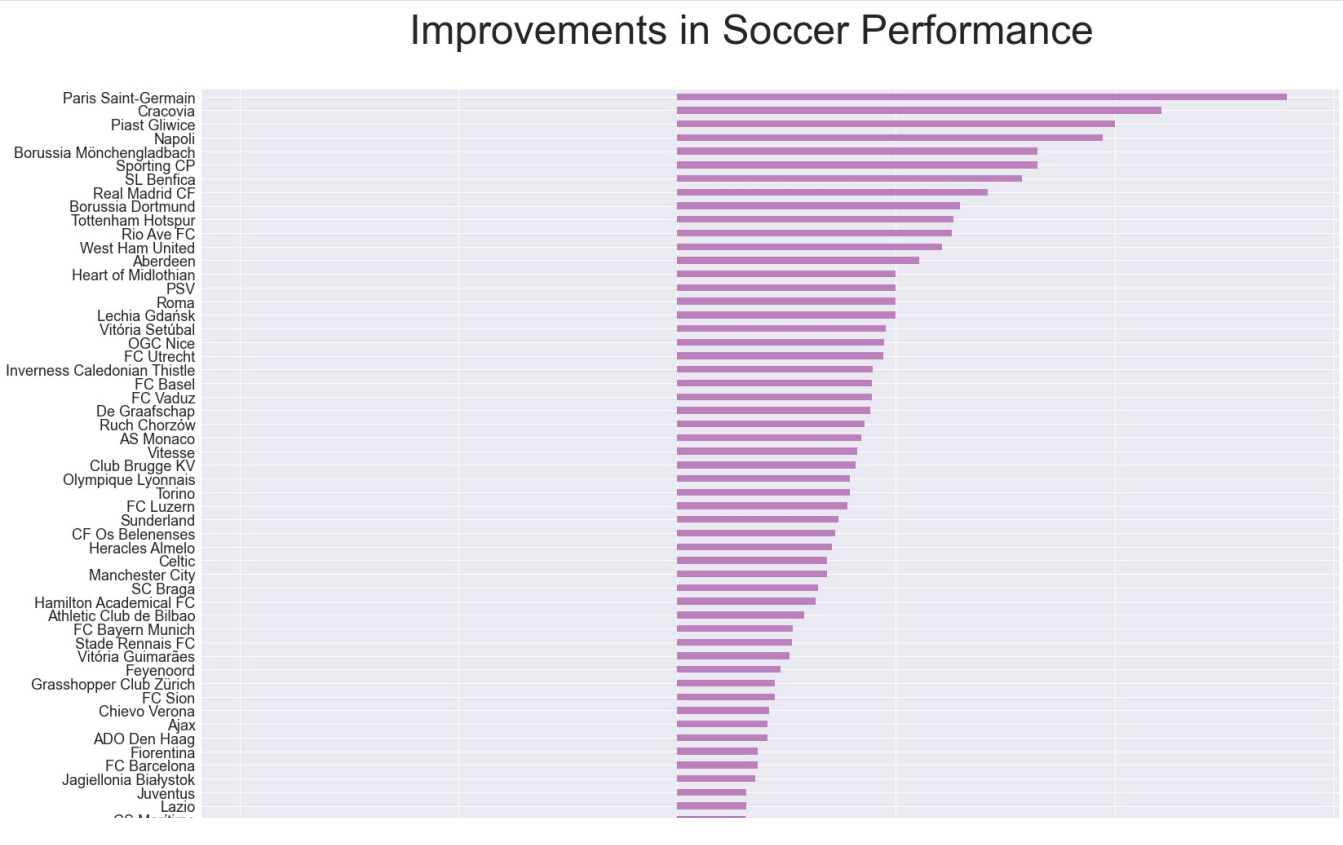
Since there is difference in number of matches between 2008/2009 and 2015/2016, there will be NaN values will conducting the necessary calculations. Thus, we will have to drop them.

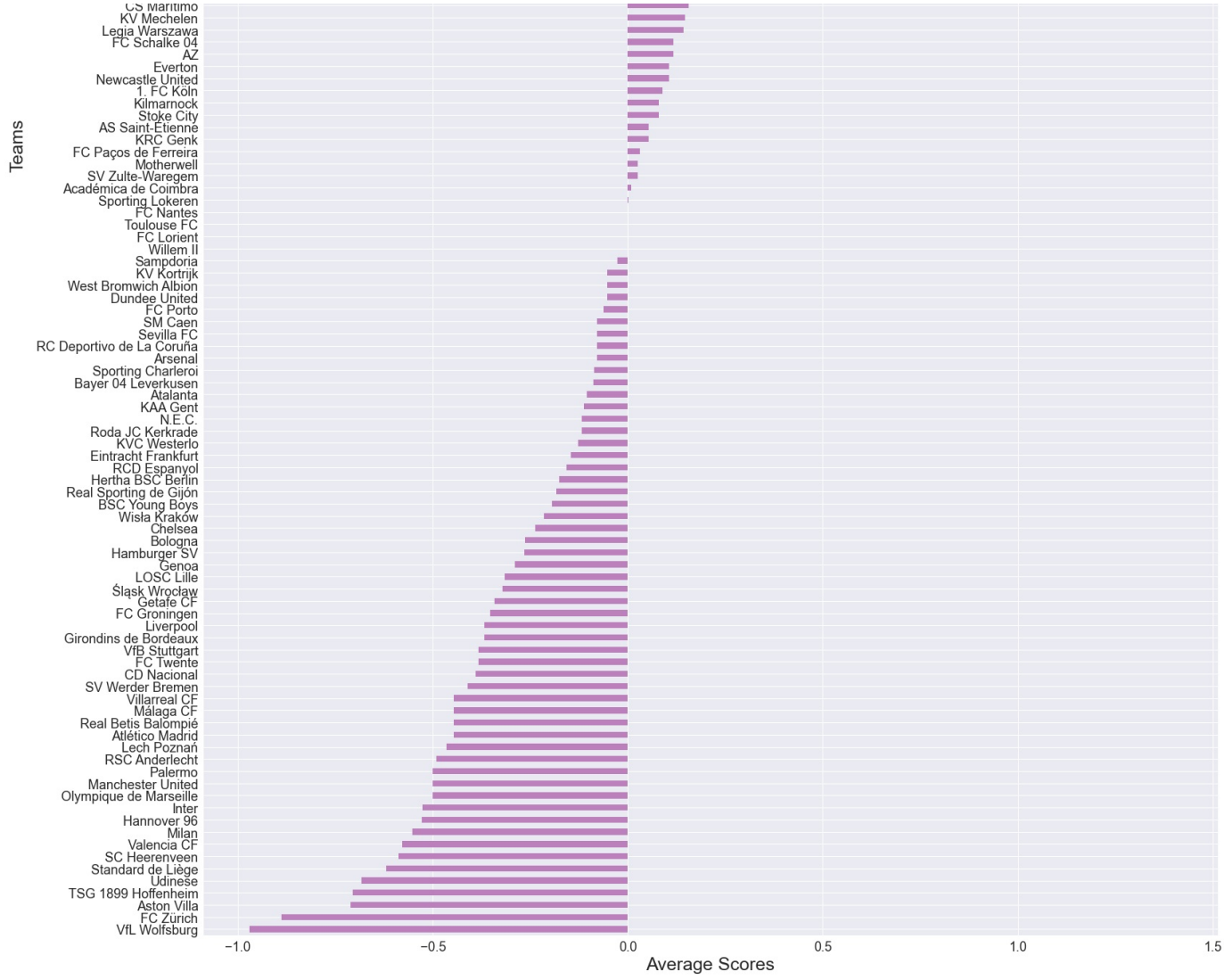
In [94]:
```
difference.dropna(inplace=True)
```

In [95]:
```
# Top 10 teams who achieved improvements throughout the 8 seasons
difference.sort_values(ascending=False)[:10]
```

Out[95]:
```
home_team
Paris Saint-Germain         1.394737
Cracovia                    1.107143
Piast Gliwice               1.000000
Napoli                      0.973684
Borussia Mönchengladbach    0.823529
Sporting CP                 0.823529
SL Benfica                  0.788235
Real Madrid CF              0.710526
Borussia Dortmund           0.647059
Tottenham Hotspur           0.631579
dtype: float64
```

In [96]:
```
# Plot results
colors= sns_colors[9]
difference.sort_values(ascending=True).plot(kind='barh',fontsize=18,color=colors, figsize=(25,40));
plt.figtext(.5,.9,'Improvements in Soccer Performance', fontsize=50, ha='center')
plt.xlabel('Average Scores', fontsize=25);
plt.ylabel('Teams', fontsize=25);
```





What team attributes lead to the most victories?

In [97]:
```
# top three teams throughout the 8 seasons.
top= match['match_result'].value_counts().sort_values(ascending=False)[1:4]
top
```

Out[97]:
```
FC Barcelona      234
Real Madrid CF    228
Celtic            218
Name: match_result, dtype: int64
```

In [98]:
```
team_attribute.describe()
```

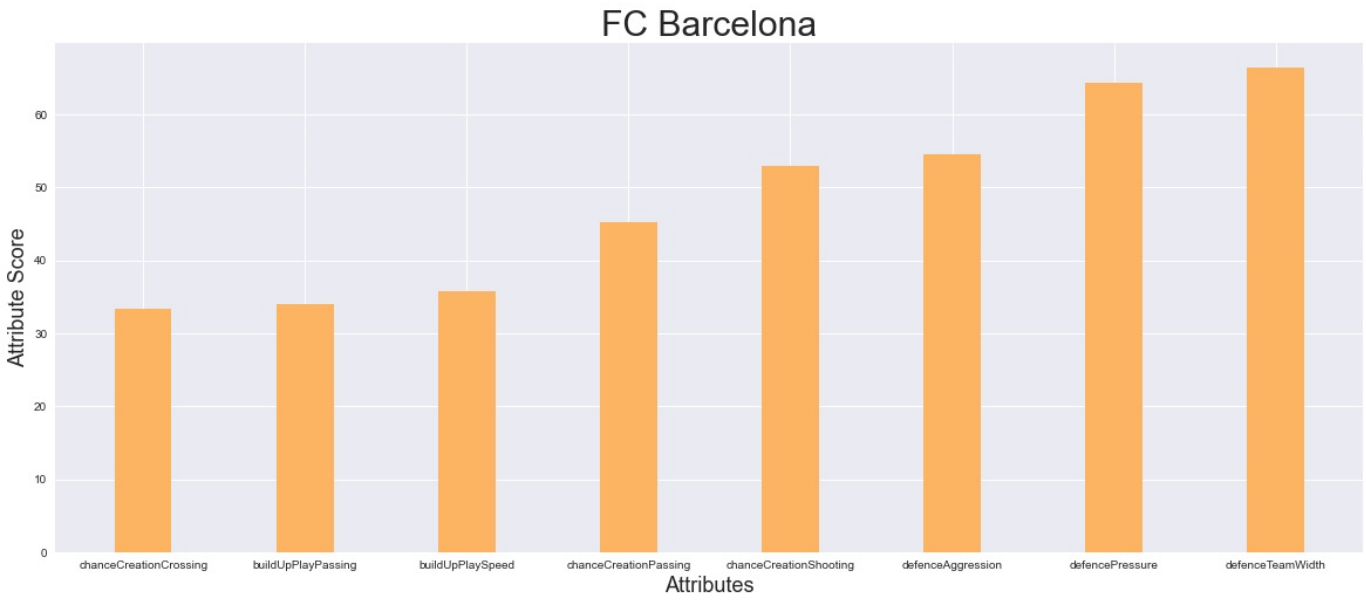
Out[98]:

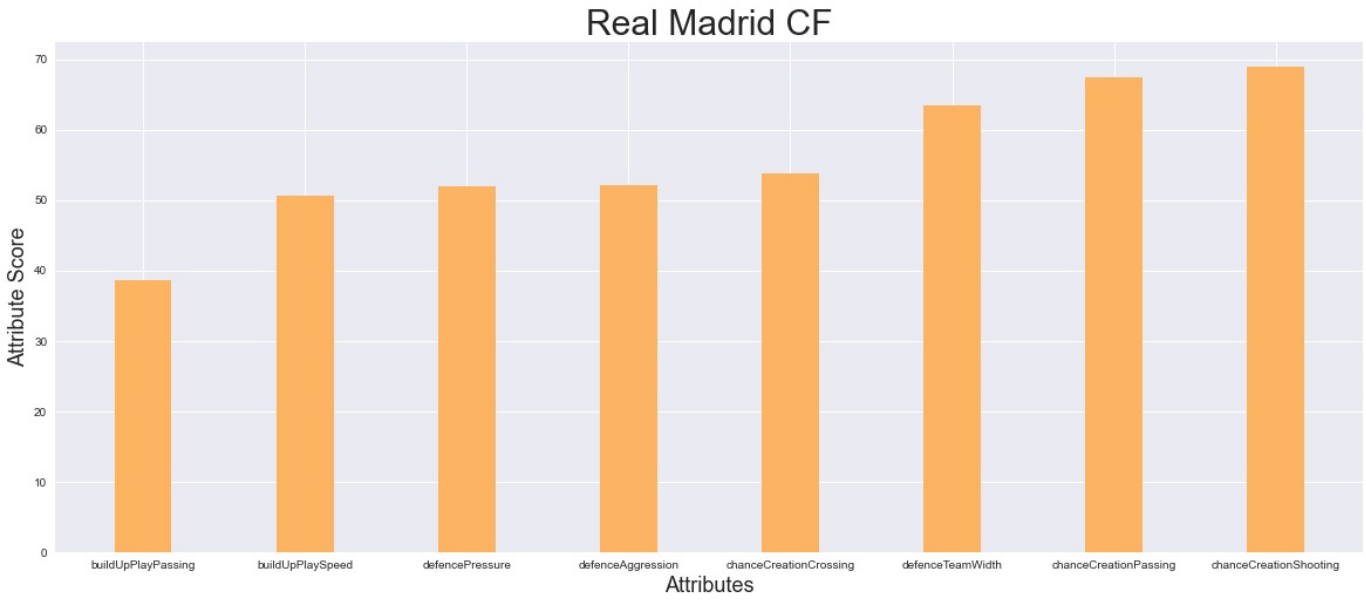
	buildUpPlaySpeed	buildUpPlayPassing	chanceCreationPassing	chanceCreationCrossing	chanceCreationShooting	defencePressure	defen
count	1451.000000	1451.000000	1451.000000	1451.000000	1451.000000	1451.000000	
mean	52.448656	48.456237	52.170227	53.732598	53.964163	46.035837	
std	11.537493	10.880225	10.354907	11.073742	10.343018	10.224249	
min	20.000000	20.000000	21.000000	20.000000	22.000000	23.000000	
25%	45.000000	40.000000	46.000000	47.000000	48.000000	39.000000	
50%	52.000000	50.000000	52.000000	53.000000	53.000000	45.000000	
75%	62.000000	55.000000	59.000000	62.000000	61.000000	51.000000	
max	80.000000	80.000000	80.000000	80.000000	80.000000	72.000000	

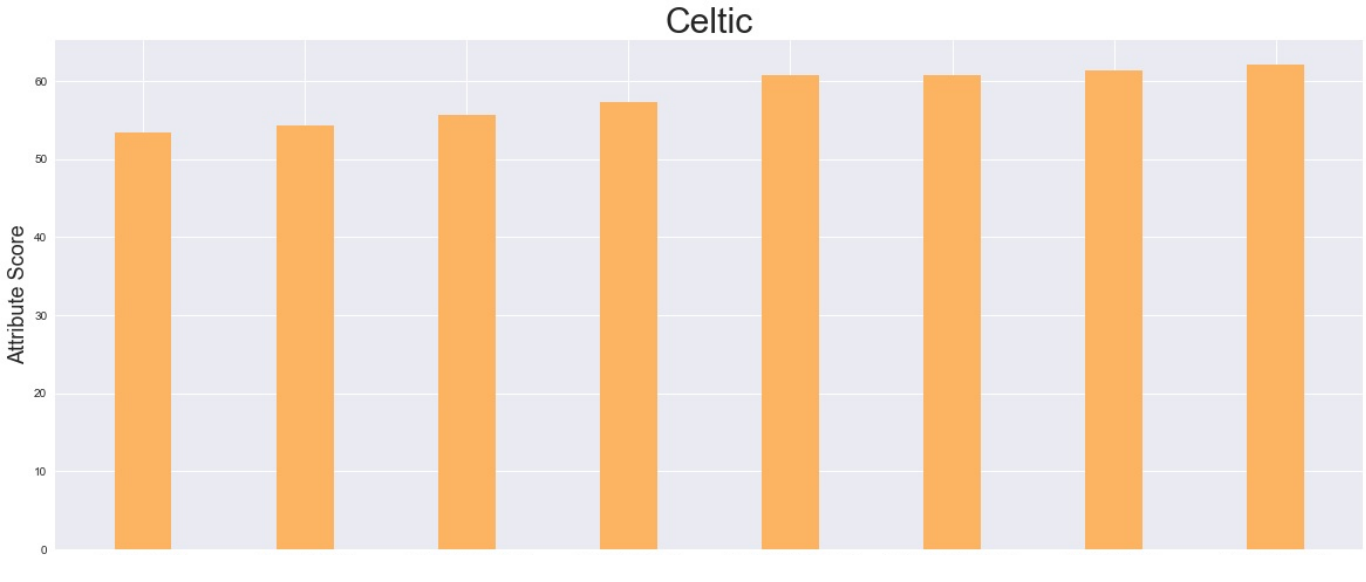
On a whole scale, there are total 1451 entries for each attribute. Overall mean scores is between 46 and 53.9. Maximum score recorded is 80 and minimum score recorded is 20 across all attributes.

In [99]:

```
# Using for loop, get mean values of team attributes for each top three teams.
list= top.to_dict().keys()
for team in list:
    x= team_attribute.loc[(team_attribute.team_long_name == team)]
    y= x.mean(numeric_only=True).sort_values().to_dict()

    keys = y.keys()
    values = y.values()

    fig = plt.figure(figsize=(20,8));

    plt.bar(keys, values, color =sns_colors[5] ,width = 0.35);
    plt.title(team, fontsize=30);
    plt.ylabel('Attribute Score', fontsize=18);
    plt.xlabel('Attributes', fontsize=18);
```

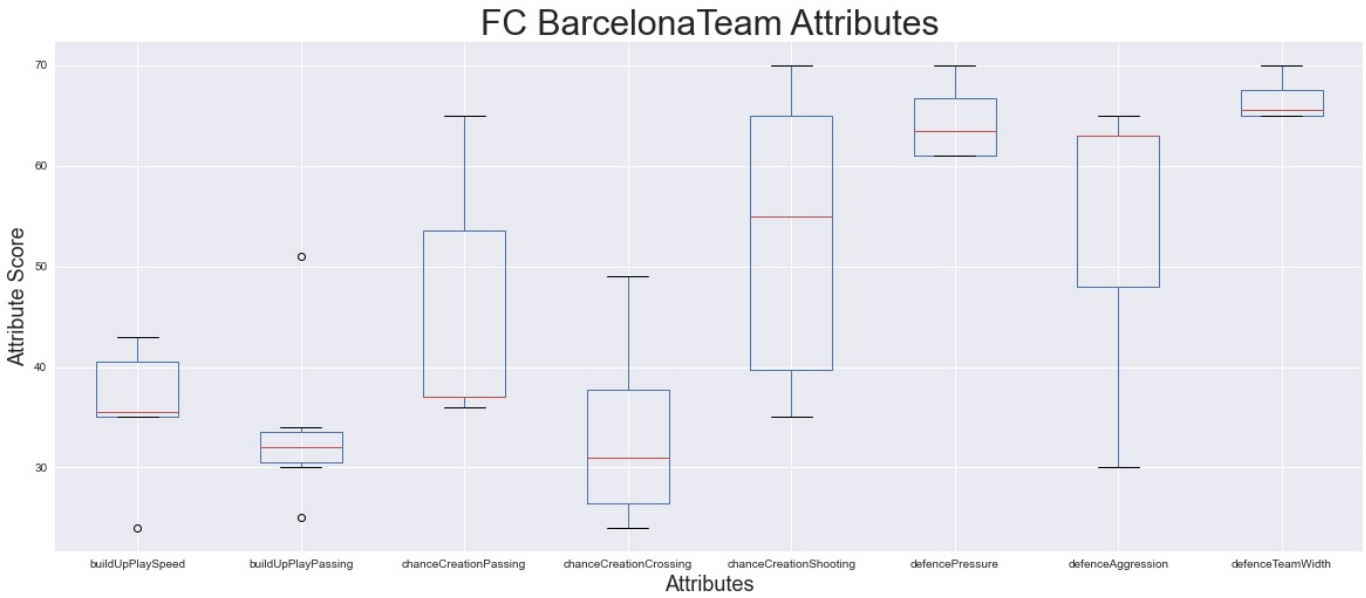


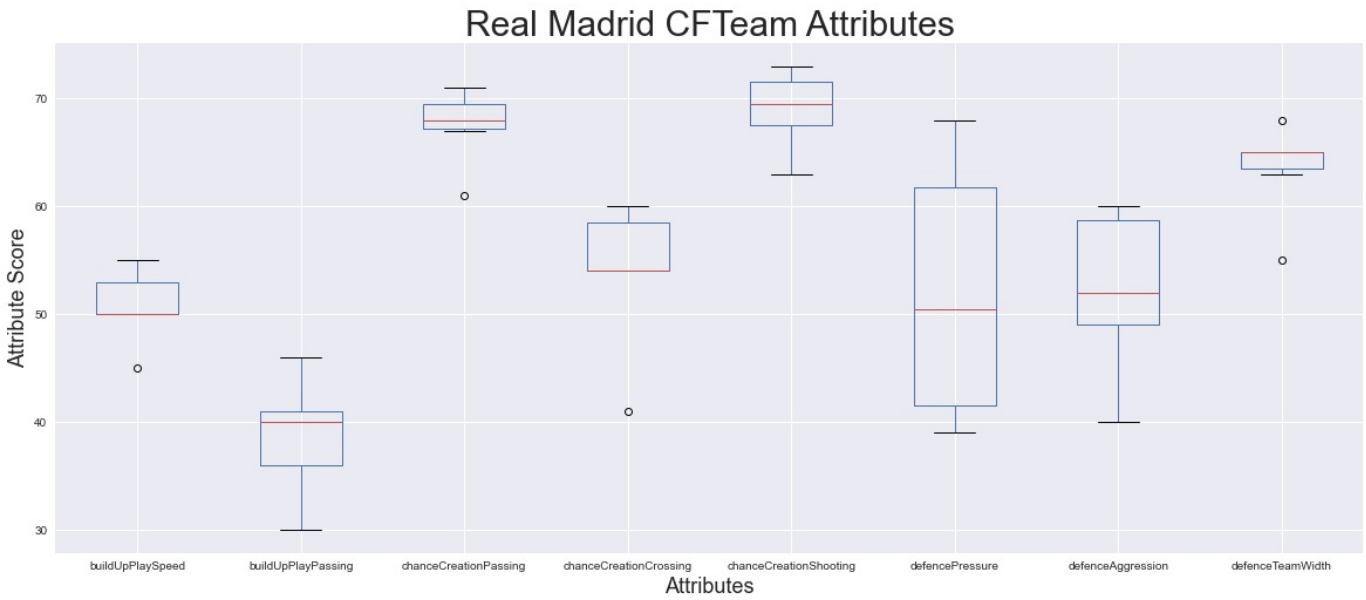


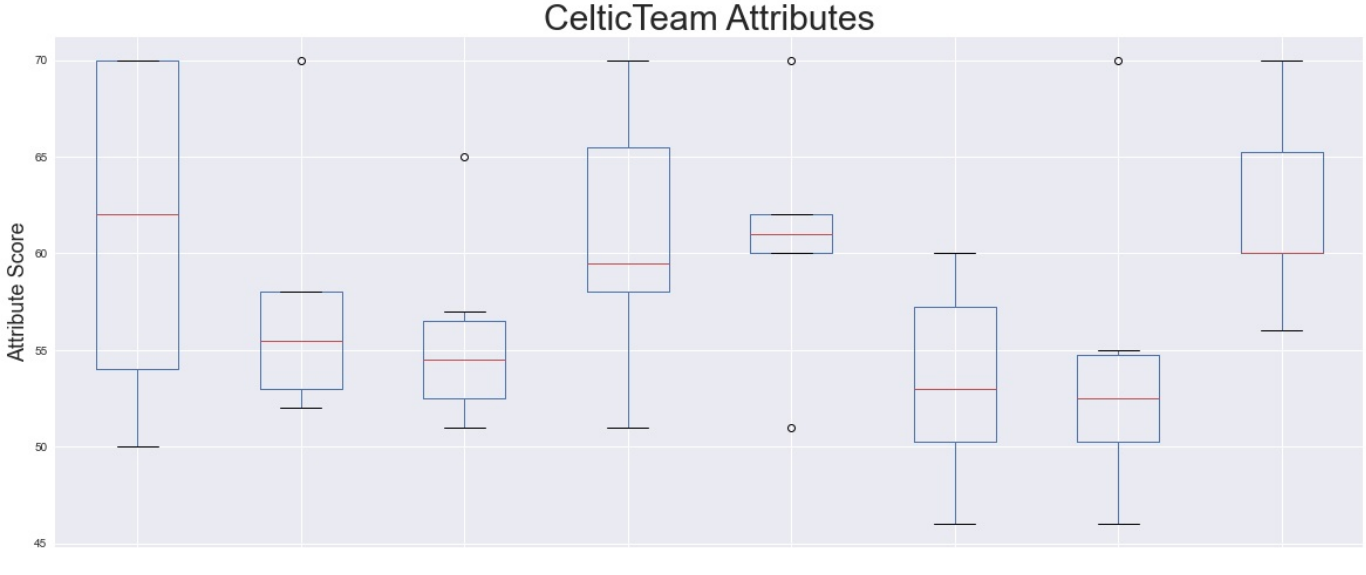


In [100…

```
# Use box plot to show the five-number summary for each attribute for each top team.
list= ['FC Barcelona','Real Madrid CF','Celtic']
for item in list:
    x= team_attribute.loc[(team_attribute.team_long_name == item)]
    x.groupby('team_long_name').plot(kind='box', figsize=(20,8));
    plt.title(item + 'Team Attributes', fontsize=30);
    plt.ylabel('Attribute Score', fontsize=18);
    plt.xlabel('Attributes', fontsize=18);
```







Who is the oldest and the youngest player?

In [101…
```
#Youngest player.
df_players['birthday'].max()
```

Out[101… `Timestamp('1999-04-24 00:00:00')`

In [102…
```
young_player= df_players.query('birthday == birthday.max()')
print('Youngest Player is:')
young_player
```

```
Youngest Player is:
```

Out[102…

	player_id	player_name	birthday	height	weight
5176	682552	Jonathan Leko	1999-04-24	182.88	141

In [103…
```
# Oldest player.
df_players['birthday'].min()
```

Out[103… `Timestamp('1967-01-23 00:00:00')`

In [104…
```
old_player= df_players.query('birthday == birthday.min()')
print('Oldest Player is:')
old_player
```

```
Oldest Player is:
```

Out[104…

	player_id	player_name	birthday	height	weight
289	39425	Alberto Fontana	1967-01-23	185.42	161

Who is the tallest players?

In [105…
```
df_players['height'].max()
```

Out[105… `208.28`

In [106…
```
tallest_player= df_players.query('height == height.max()')
print('Tallest Player is:')
tallest_player
```

```
Tallest Player is:
```

Out[106…

	player_id	player_name	birthday	height	weight
5901	148325	Kristof van Hout	1987-02-09	208.28	243

who has the highest and the lowest average of overall rating?

In [107…
```
# Highest average of overall rating.
highest_rating= players.groupby('player_name')
highest_rating.overall_rating.mean().sort_values(ascending=False)[:1]
```

Out[107… `player name`

```
Lionel Messi    92.192308
Name: overall_rating, dtype: float64
```

In [108…
```
# Lowest average of overall rating.
lowest_rating= players.groupby('player_name')
lowest_rating.overall_rating.mean().sort_values(ascending=False)[-1:]
```

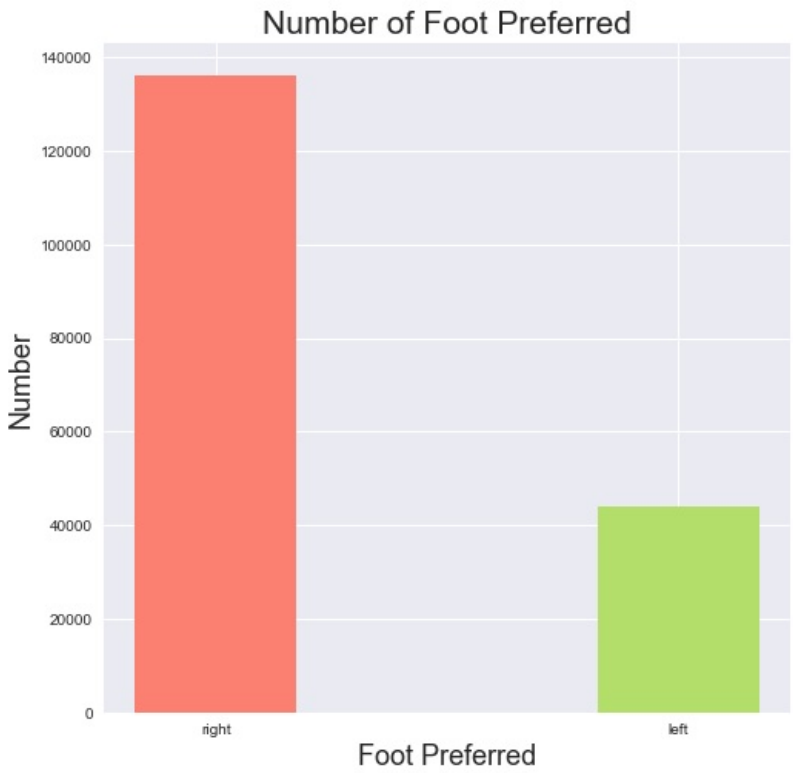
Out[108…
```
player_name
Gianluca D'Angelo    43.75
Name: overall_rating, dtype: float64
```

How many players use either preferred right or left foot?

In [109…
```
players['preferred_foot'].value_counts()
```

Out[109…
```
right    136247
left      44107
Name: preferred_foot, dtype: int64
```

In [110…
```
# Plot results using bar chart.
foot= players['preferred_foot'].value_counts().to_dict()
keys = foot.keys()
values = foot.values()

fig = plt.figure(figsize = (8, 8));

plt.bar(keys, values, color =[sns_colors[3], sns_colors[6]], width = 0.35);
plt.xlabel("Foot Preferred", fontsize=18);
plt.ylabel("Number", fontsize=18);
plt.title("Number of Foot Preferred", fontsize=21);
```



Who made the most penalties?

In [111…
```
# Use average.
penalty= players.groupby('player_name')
print('The player who made the most penalties:')
penalty.penalties.mean().sort_values(ascending=False)[:1]
```

```
The player who made the most penalties:
```

Out[111…
```
player_name
Mario Balotelli    89.565217
Name: penalties, dtype: float64
```

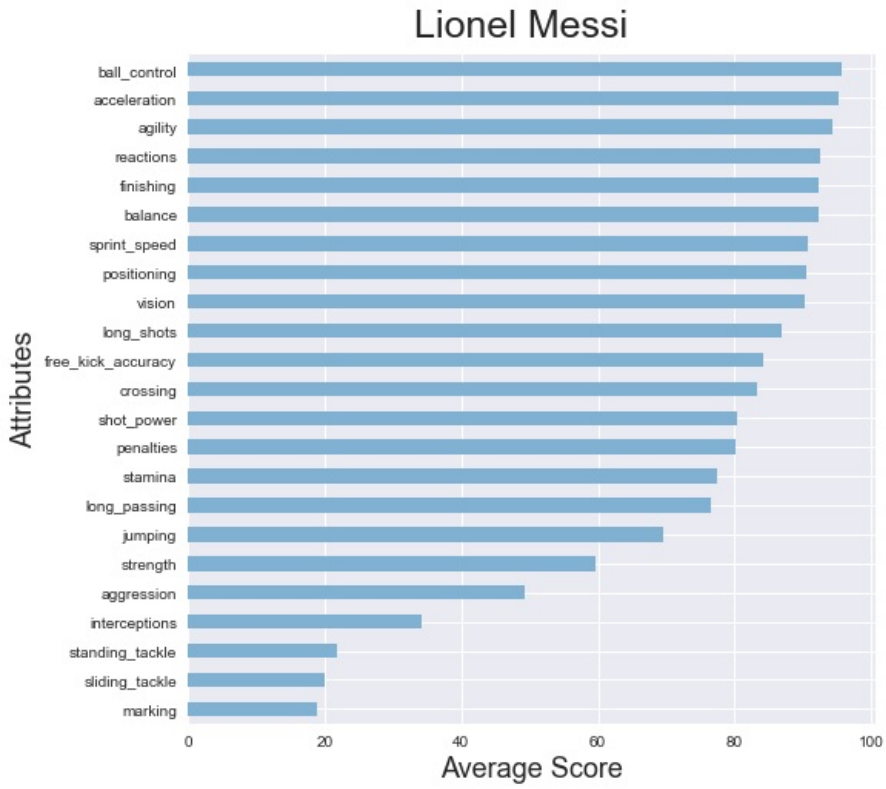
What are the attributes of the 5 best players based on their average overall ratings?

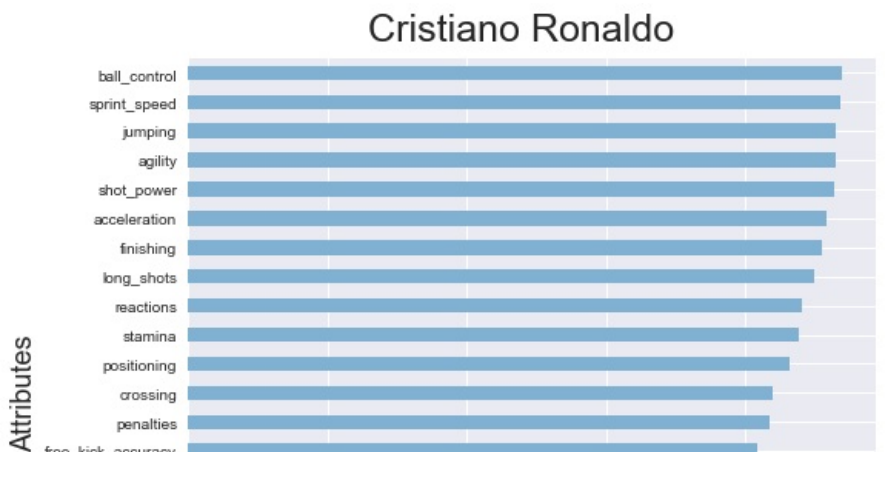
In [112…
```
best_players= players.groupby('player_name').overall_rating.mean().sort_values(ascending=False)[:5]
best_players.to_dict().keys()
```

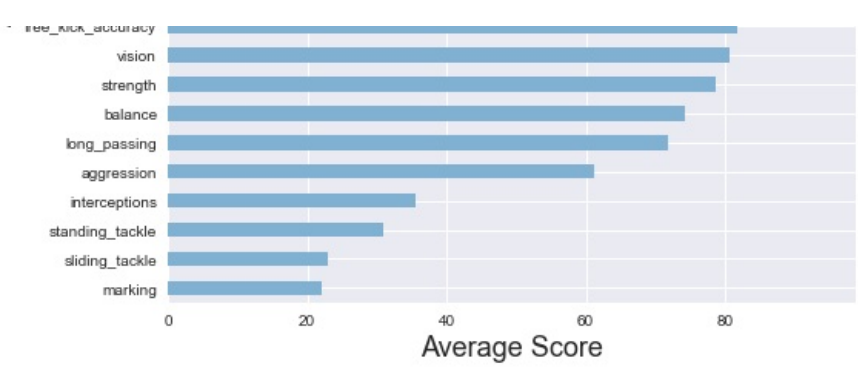
Out[112…
```
dict_keys(['Lionel Messi', 'Cristiano Ronaldo', 'Franck Ribery', 'Andres Iniesta', 'Zlatan Ibrahimovic'])
```

In [113…
```
# Drop few not needed columns.
players.drop(['player_id','birthday', 'height','overall_rating','potential', 'weight','gk_diving', 'gk_handling',
       'gk_kicking', 'gk_positioning', 'gk_reflexes'], axis=1, inplace=True)
```

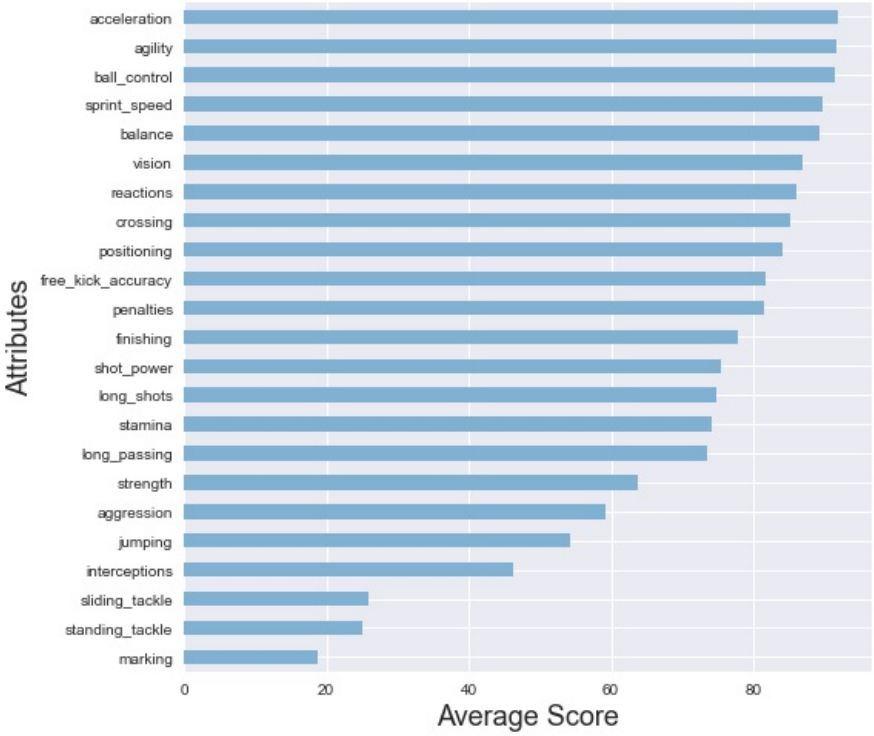
In [114…
```
# Using for loop, get mean values of player attributes for each 5 best players.
list= best_players.to_dict()
for player in list:
    x= players.loc[(players.player_name == player)]
    y= x.mean(numeric_only=True).sort_values()
    colors= sns_colors[4]
    y.plot(kind='barh', color=colors, figsize=(8,8));
    plt.figtext(.5,.9,player, fontsize=25, ha='center');
    plt.xlabel('Average Score', fontsize=18);
    plt.ylabel('Attributes', fontsize=18);
    plt.show();
```



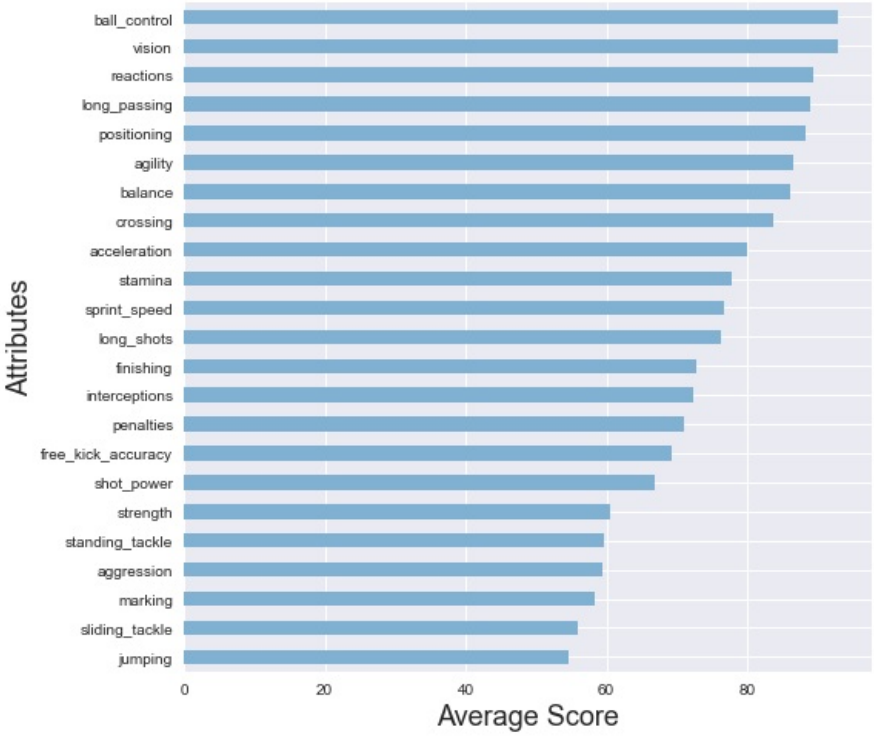




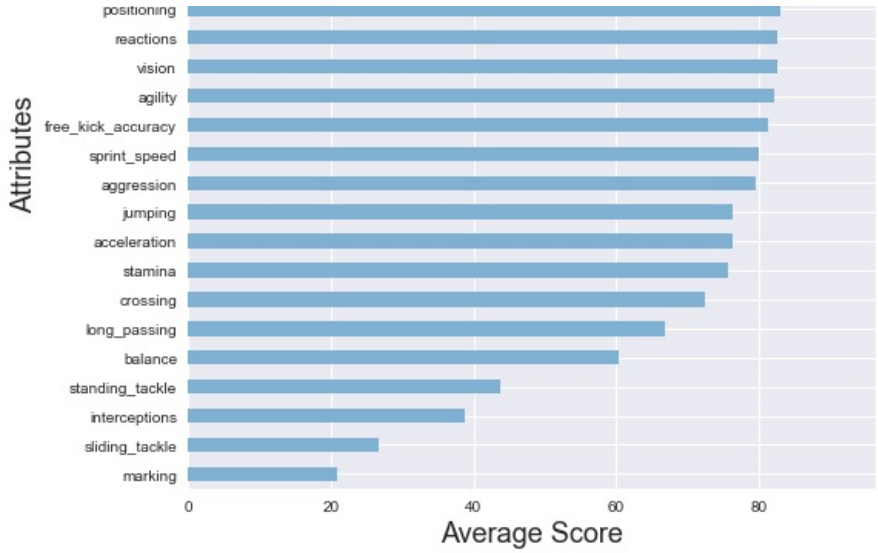
Franck Ribery



Andres Iniesta



Zlatan Ibrahimovic



Conclusions

From the soccer datasets provided, we can conclude the following:\

1. Season 2008/2009 had the highest number of matches.
2. England, France, and Spain with their respective leagues hosted the highest number of matches throughout the 8 seasons.
3. 'FC Barcelona','Real Madrid CF','Celtic' are the most victorious teams throughout the 8 seasons.
4. Teams who play on their homeland are more likely to win by 45.87%.
5. Paris Saint-German has made the highest performance progress throughout the 8 seasons.
6. Features that mostly lead teams to victory differs among diferent teams. But for the top three teams these are their highest attribute mean score:
    - FC Barcelona: defence pressure and defence team width.
    - Real Madrid CF: chance creation passing and chance creation shooting.
    - Celtic: build up play speed and defence team width.
7. Jonathan Leko is the youngest player, while Alberto Fontana is the oldest player.
8. Kristof van Hout is the tallest player.
9. Lionel Messi had the highest average overall rating, while Gianluca D'Angelo has the lowest average overall rating.
10. Number of players who prefere to use their right foot is greater than those who use their left foot.
11. Mario Balotelli made the most penalties on average.
12. Combined top attributes differs for each player.
    - Lionel Messi: ball control, acceleration, and agility.
    - Cristiano Ronaldo: ball control, sprint speed, and jumping.
    - Frank Ribery: acceleration, agility, and ball control.
    - Andres Iniesta: ball control, vision, and reactions.
    - Zlatan Ibrahimovic: shot power, ball control, and strength.

Limitation:

- There is no explanation for attributes in both teams and players.
- Duplicated team names with different id numbers.
- Duplicated players name but with different set of data. Also, in player_name column there were some players with only first name or surname.
- The player dataset doesn't include what team each player belonged to.

In [ ]: