European Soccer

May 23, 2018

1 Project: European Soccer Analysis

1.1 Table of Contents

> ## Introduction

About this Dataset

- The ultimate European Soccer database for data analysis and machine learning

What you get

- +25,000 matches
- +10,000 players

- 11 European Countries with their lead championship
- Seasons 2008 to 2016
- Players and Teams' attributes* sourced from EA Sports' FIFA video game series, including the weekly updates
- Team line up with squad formation (X, Y coordinates)
- Betting odds from up to 10 providers
- Detailed match events (goal types, possession, corner, cross, fouls, cards etc...) for +10,000 matches

Exploring the data

- Q1. I'd like to know how much more is home teams likely to win over away teams.
- Q2. Which country scores more in average per game?
- Q3. If a team played more games then do they score more, or the other way around?
- Q4. Why some players have no games?
- Q5. Do Goalkeepers actually tend to be taller and bigger than other players?

```
In [1]: import pandas as pd
        import numpy as np
        import sqlite3 as sq
        import sqlalchemy
        import time
        import datetime
        import seaborn as sns
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
        %pylab inline
        pylab.rcParams['figure.figsize'] = (12.0, 10.0)
```

```
Populating the interactive namespace from numpy and matplotlib
```

```
In [2]: def call_table(table):
            """ 1) This is a query to get whole data from each tables.
                2) It returns a dataframe with data of all tables.
            """

            query = "select * from {}".format(table)

            return(pd.read_sql_query(query, con))
```

In [3]:
```
def check_null_value(df):
    """ 1) After checking missing values of dataframe, and then get rid of the columns
        2) Returning a new dataframe with only valid values.
    """

    cc = 0
    rr = 0
    cnt_df = len(df.columns)
    cnt_r_df = df.shape[0]

    print("There are {} rows in this dataset.\n".format(cnt_r_df))


    # cleaning null-columns
    clean_df = df.dropna(axis=1, how='any')

    cnt_cl_df = len(clean_df.columns)
    cc = cnt_df - cnt_cl_df
    if cc > 0:
        print("{} columns with null values have been removed.".format(cc))

    # cleaning null-rows
    clean_df = clean_df.drop_duplicates(keep='first')

    cnt_r_cl_df = clean_df.shape[0]
    rr =  cnt_r_df - cnt_r_cl_df
    if rr > 0:
        print("{} of duplicated rows.".format(rr))

    return clean_df
```

In [4]:
```
def check_null_value_by_row(df):
    """
    After checking missing values of called dataframe, and then deleting the null rows
    Returning a new dataframe with valid values.
    """

    rr = 0
    dr = 0
    cnt_r_df = df.shape[0]

    print("There are {} rows in this dataset.\n".format(cnt_r_df))


    # cleaning null-rows
    clean_df = df.dropna(axis=0, how='any')

    cnt_r_cln_df = clean_df.shape[0]
```

```
    rr = cnt_r_df - cnt_r_cln_df
    if rr > 0:
        print("{} rows with null values have been removed.".format(rr))

    # cleaning duplicated-rows
    clean_df1 = clean_df.drop_duplicates(keep='first')

    dr =  cnt_r_cln_df - clean_df1.shape[0]
    if dr > 0:
        print("{} of duplicated rows.".format(dr))

    return clean_df1
```

In [5]:
```
def api_to_name(api_df, name_df, key_col):
    """ 1) Merging two dataframes on the key column(key_col).
        2) The key column should have the same name in both dataframes when calling th
        3) name_df should have only two columns: name_df.columns = ['key_col','adding_
    """

    merged_df = pd.merge(left=api_df, right=name_df, on=key_col, how='left')
    merged_df[key_col] = merged_df[name_df.columns[-1]]

    return merged_df.iloc[:,:-1]
```

In [6]:
```
start_sec = time.time()

# Read sqlite query results into a pandas DataFrame
con = sq.connect("database.sqlite")
tables = pd.read_sql("""SELECT *
                        FROM sqlite_master
                        WHERE type='table';""", con)
sql = pd.read_sql_query("select * from sqlite_sequence", con)

# whole_df is a joined dataframe of all tables
whole_df = sql['name'].apply(call_table)

end_sec = time.time()
print("It took {} seconds for excuting queries!".format(np.round(end_sec - start_sec, 
```

```
It took 11.0 seconds for excuting queries!
```

In [7]:
```
# Dividing the dataframe(whole_df) into seven individual dataframes;
#  1) df_team
#  2) df_country
#  3) df_league
#  4) df_match
#  5) df_player
#  6) df_player_attributes
```

```
#  7) df_team_attributes

df_team = whole_df[0]
df_country = whole_df[1]
df_league = whole_df[2]
df_match = whole_df[3]
df_player = whole_df[4]
df_player_attributes = whole_df[5]
df_team_attributes = whole_df[6]
```

Data Wrangling

1.2 Dataframe: df_team

In [8]:
```
df_team.info()
print('\n')
df_team.head()
```

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

Out[8]:

	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 [9]:
```
# Filtering rows with Null-values on 'team_fifa_api_id'
# These teams with no team_fifa_api_id are still needed for merging dataframes for lat
df_no_fifa_api = df_team[df_team["team_fifa_api_id"].isnull()]
print(df_no_fifa_api)


# 'df_team_api_id' is a new dataframe with no Null-values
```

```python
df_team_api_id = df_team.dropna(axis=1)
print(df_team_api_id.info())


# change the datatype of "team_fifa_api_id" from float64 to int64
# df_team['team_fifa_api_id'] = df_team['team_fifa_api_id'].astype(int)
# print(df_team.info())
```

```
        id  team_api_id  team_fifa_api_id                team_long_name  \
8        9         7947               NaN                  FCV Dender EH
14      15         4049               NaN                         Tubize
170  26561         6601               NaN                    FC Volendam
204  34816       177361               NaN  Termalica Bruk-Bet Nieciecza
208  35286         7992               NaN                       Trofense
213  35291        10213               NaN                        Amadora
223  36248         9765               NaN                   Portimonense
225  36723         4064               NaN                       Feirense
232  38789         6367               NaN              Uniao da Madeira
233  38791       188163               NaN                        Tondela
298  51606         7896               NaN                         Lugano

    team_short_name
8               DEN
14              TUB
170             VOL
204             TBN
208             TRO
213             AMA
223             POR
225             FEI
232             MAD
233             TON
298             LUG
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 4 columns):
id                  299 non-null int64
team_api_id         299 non-null int64
team_long_name      299 non-null object
team_short_name     299 non-null object
dtypes: int64(2), object(2)
memory usage: 9.4+ KB
None
```

1.3 Dataframe: df_country

```
In [10]: df_country.info()
         print('\n')
         df_country.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 2 columns):
id      11 non-null int64
name    11 non-null object
dtypes: int64(1), object(1)
memory usage: 256.0+ bytes
```

```
Out[10]:       id     name
         0      1  Belgium
         1   1729  England
         2   4769   France
         3   7809  Germany
         4  10257    Italy
```

1.4 Dataframe: df_league

```
In [11]: df_league.info()
         print('\n')
         df_league.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 3 columns):
id            11 non-null int64
country_id    11 non-null int64
name          11 non-null object
dtypes: int64(2), object(1)
memory usage: 344.0+ bytes
```

```
Out[11]:       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 [12]:
```
# Joining dataframes of leagues + countries.

league_info = pd.merge(left=df_league, right=df_country, on='id', how='left')
league_info.rename(columns={"name_x":"league", "name_y":"country"}, inplace=True)
league_info
```

Out[12]:

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

1.5 Dataframe: df_match

European matches' Information from 2008/2009 to 2015/2016

In [13]:
```
df_match.info()
print('\n')
print(df_match.columns)
print('\n')
df_match.head()


# Checking all columns whether it has null values or not by calling func:check_null_v
df_match = check_null_value(df_match)
```

```
<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


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)
```

```
There are 25979 rows in this dataset.

104 columns with null values have been removed.
```

Exploratory Data Analysis

In [14]:
```
# Merging two dataframes of df_match and df_league
# Call the function: api_to_name(left df, right df, key_column)
df_match_new = api_to_name(df_match, df_league, "country_id")
df_match_new.rename(columns={'country_id':'league'}, inplace=True)


# Call the function: api_to_name(left df, right df, key_column)
# It is for matching 'home_team_api_id' with characters to recognize easily.
df_match_new.rename(columns={'home_team_api_id':'team_api_id'}, inplace=True)
df_match_new = api_to_name(df_match_new, df_team[["team_api_id","team_long_name"]], "
df_match_new.rename(columns={'team_api_id':'home_team'}, inplace=True)


# Call the function:api_to_name(left df, right df, key_column)
# It is for matching 'away_team_api_id' with characters to recognize easily.
df_match_new.rename(columns={'away_team_api_id':'team_api_id'}, inplace=True)
df_match_new = api_to_name(df_match_new, df_team[["team_api_id","team_long_name"]], "
df_match_new.rename(columns={'team_api_id':'away_team'}, inplace=True)


# Dropping some columns of the dataframe(df_match) those don't seem to be meaningful.
df_match_new.drop(['id_x','league_id','stage','match_api_id','id_y'], axis=1, inplace=
df_match_new.head()
```

Out[14]:
```
                   league     season                 date         home_team  \
0  Belgium Jupiler League  2008/2009  2008-08-17 00:00:00          KRC Genk
1  Belgium Jupiler League  2008/2009  2008-08-16 00:00:00  SV Zulte-Waregem
2  Belgium Jupiler League  2008/2009  2008-08-16 00:00:00 KSV Cercle Brugge
3  Belgium Jupiler League  2008/2009  2008-08-17 00:00:00          KAA Gent
4  Belgium Jupiler League  2008/2009  2008-08-16 00:00:00      FCV Dender EH

          away_team  home_team_goal  away_team_goal
0       Beerschot AC               1               1
1   Sporting Lokeren               0               0
2     RSC Anderlecht               0               3
3          RAEC Mons               5               0
4  Standard de Liège               1               3
```

> # < Research Question 1: Home Game Advantages>

Q. I want to analyze that whether there actually are home game advatages or not?

Q. How much is Home Winning Rate different depends on countries?

In [15]:
```
df_match_home = df_match_new.copy()

# Categorizing Won-or-Lost on the point of home team's side.
df_match_home['goal_dif'] = df_match_home['home_team_goal']-df_match_home['away_team_g
df_match_home['W/L_of_home'] = df_match_home['goal_dif'].apply(lambda x:'WIN' if x>0 e


# Grouping teams and add up all game results over the period.
df_match_home = df_match_home.groupby(['league','W/L_of_home']).count()
df_match_home = df_match_home[['home_team']]
df_match_home.rename(columns={'home_team':'counts'}, inplace=True)
df_match_home.head()
```

Out[15]:

league	W/L_of_home	counts
Belgium Jupiler League	LOST	493
	TIE	425
	WIN	810
England Premier League	LOST	867
	TIE	783

In [16]:
```
df_home_wining = df_match_home.unstack().reset_index()
df_home_wining
```

Out[16]:

	league	counts		
W/L_of_home		LOST	TIE	WIN
0	Belgium Jupiler League	493	425	810
1	England Premier League	867	783	1390
2	France Ligue 1	822	859	1359
3	Germany 1. Bundesliga	744	597	1107
4	Italy Serie A	814	796	1407
5	Netherlands Eredivisie	696	581	1171
6	Poland Ekstraklasa	525	525	870
7	Portugal Liga ZON Sagres	611	533	908
8	Scotland Premier League	617	447	760
9	Spain LIGA BBVA	851	704	1485
10	Switzerland Super League	426	346	650

In [17]:
```
# Computing winning rate for home games.
total_match = {('league',''):'Average', ('counts','LOST'):df_home_wining['counts'].sur
                ('counts','TIE'):df_home_wining['counts'].sum()[1],\
                ('counts','WIN'):df_home_wining['counts'].sum()[2]}
```

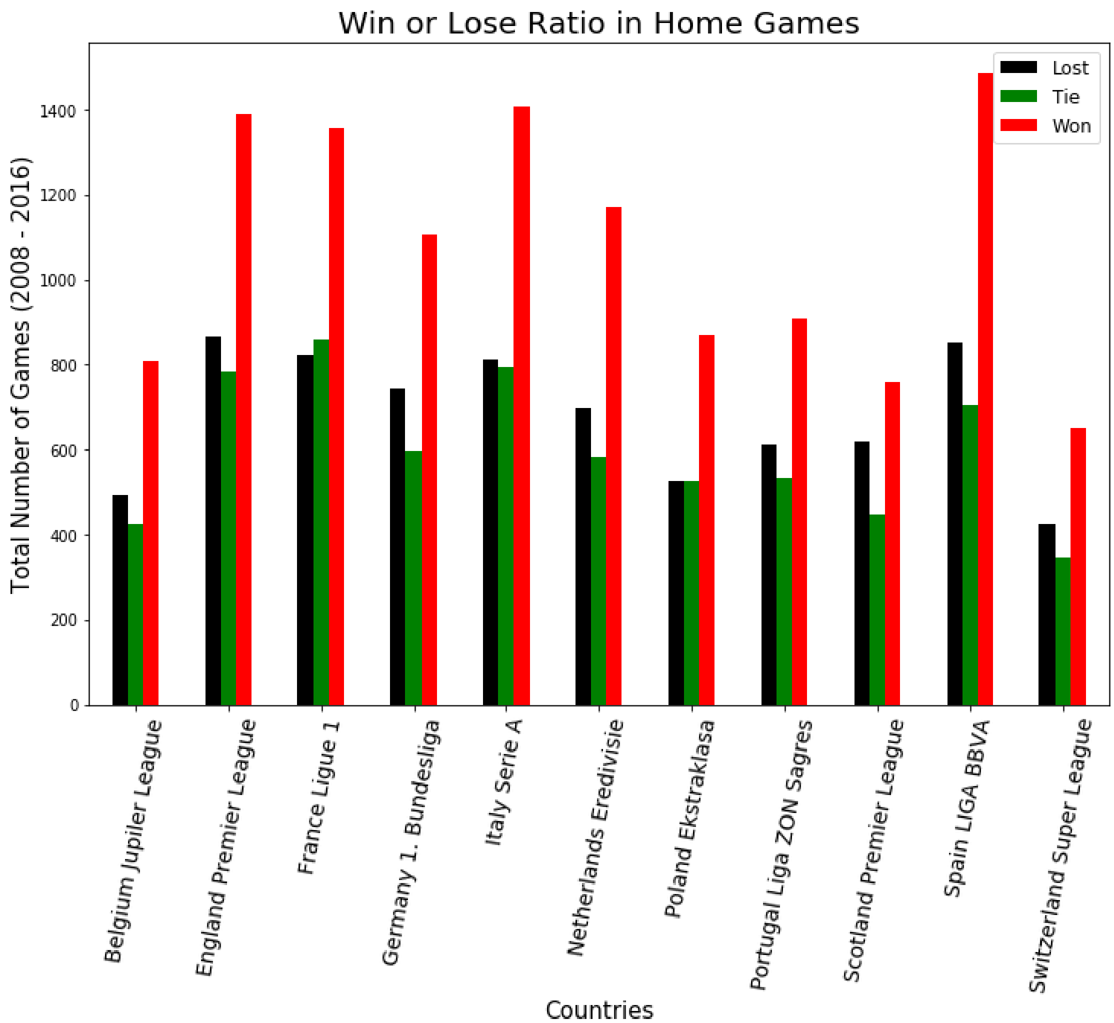
```
df_home_wining = df_home_wining.append(total_match, ignore_index=True)

home_win = df_home_wining['counts']['WIN']
home_tie = df_home_wining['counts']['TIE']
home_lost = df_home_wining['counts']['LOST']

df_home_wining['home_win_rate'] = home_win/(home_lost+home_tie+home_win)*100

result = df_home_wining.sort_values(['home_win_rate'], ascending=[0])
ranks = list(range(1, df_home_wining.shape[0]+1))
result['rank'] = ranks
result.set_index('rank', inplace=True)
result
```

Out[17]:

	league	counts			home_win_rate
W/L_of_home		LOST	TIE	WIN	
rank					
1	Spain LIGA BBVA	851	704	1485	48.848684
2	Netherlands Eredivisie	696	581	1171	47.834967
3	Belgium Jupiler League	493	425	810	46.875000
4	Italy Serie A	814	796	1407	46.635731
5	Average	7466	6596	11917	45.871666
6	England Premier League	867	783	1390	45.723684
7	Switzerland Super League	426	346	650	45.710267
8	Poland Ekstraklasa	525	525	870	45.312500
9	Germany 1. Bundesliga	744	597	1107	45.220588
10	France Ligue 1	822	859	1359	44.703947
11	Portugal Liga ZON Sagres	611	533	908	44.249513
12	Scotland Premier League	617	447	760	41.666667

In [18]:

```
colrs = ['Black','Green','Red']
df_match_home.unstack().plot(kind='bar', figsize=(12,8), color=colrs)
plt.title('Win or Lose Ratio in Home Games', size=20)
plt.ylabel('Total Number of Games (2008 - 2016)', size=15)
plt.xlabel('Countries', size=15)
plt.legend(('Lost','Tie','Won'), fontsize=12)
plt.xticks(rotation=80, fontsize=14)
plt.show();
```



> ## Observation #1:

1) Teams of some countries like Spain, Netherlands, Belgium, Italy have higher possibility to win when they play at home ground than average.

2) Teams of Scotland and Switzerland don't seem to be affected by home advantages much.

> # < Research Question 2: Ranks by Average Goal Scores >

Q. Analysis of Average Goals by Countries(Leagues) over the period from 2008 to 2016

```
In [19]: df_match_new.head()
```

```
Out[19]:                     league     season                 date           home_team  \
         0  Belgium Jupiler League  2008/2009  2008-08-17 00:00:00            KRC Genk
         1  Belgium Jupiler League  2008/2009  2008-08-16 00:00:00    SV Zulte-Waregem
         2  Belgium Jupiler League  2008/2009  2008-08-16 00:00:00   KSV Cercle Brugge
         3  Belgium Jupiler League  2008/2009  2008-08-17 00:00:00            KAA Gent
         4  Belgium Jupiler League  2008/2009  2008-08-16 00:00:00        FCV Dender EH

                    away_team  home_team_goal  away_team_goal
         0       Beerschot AC               1               1
         1   Sporting Lokeren               0               0
         2     RSC Anderlecht               0               3
         3          RAEC Mons               5               0
         4  Standard de Liège               1               3
```

```
In [20]: df_match_avg_goal = df_match_new.copy()

         df_match_avg_goal['total_goal'] = df_match_avg_goal['home_team_goal'] + df_match_avg_g

         df_match_avg_goal['date'] = pd.to_datetime(df_match_avg_goal['date'])
         df_match_avg_goal.set_index(pd.DatetimeIndex(df_match_avg_goal['date']), inplace=True)

         df_match_avg_goal = df_match_avg_goal.groupby(['league']).resample('2W').mean()
         df_match_avg_goal = df_match_avg_goal[['total_goal']]
         avg_goal_by_league = (df_match_avg_goal.unstack()).transpose()
         avg_goal_by_league.head()
```

```
Out[20]: league                 Belgium Jupiler League  England Premier League  \
                    date
         total_goal 2008-07-20                     NaN                     NaN
                    2008-08-03                     NaN                     NaN
                    2008-08-10                     NaN                     NaN
                    2008-08-17                    2.75                     3.2
                    2008-08-24                     NaN                     NaN

         league                 France Ligue 1  Germany 1. Bundesliga  Italy Serie A  \
                    date
         total_goal 2008-07-20             NaN                    NaN            NaN
                    2008-08-03             NaN                    NaN            NaN
                    2008-08-10            2.40                    NaN            NaN
                    2008-08-17             NaN               3.222222            NaN
                    2008-08-24            2.15                    NaN            NaN

         league                 Netherlands Eredivisie  Poland Ekstraklasa  \
                    date
         total_goal 2008-07-20                     NaN                 NaN
                    2008-08-03                     NaN                 NaN
                    2008-08-10                     NaN               2.000
                    2008-08-17                     NaN                 NaN
```

```
            2008-08-24                     NaN              2.375

league                Portugal Liga ZON Sagres  Scotland Premier League  \
            date
total_goal  2008-07-20                     NaN                      NaN
            2008-08-03                     NaN                      NaN
            2008-08-10                     NaN                 2.000000
            2008-08-17                     NaN                      NaN
            2008-08-24                    2.25                 2.153846

league                Spain LIGA BBVA  Switzerland Super League
            date
total_goal  2008-07-20            NaN                  3.250000
            2008-08-03            NaN                  2.066667
            2008-08-10            NaN                       NaN
            2008-08-17            NaN                  2.900000
            2008-08-24            NaN                       NaN
```

In [21]:
```python
avg_score = avg_goal_by_league.copy()
avg_score.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 410 entries, (total_goal, 2008-07-20 00:00:00) to (total_goal, 2016-05-29 00:00:00)
Data columns (total 11 columns):
Belgium Jupiler League      127 non-null float64
England Premier League      166 non-null float64
France Ligue 1              164 non-null float64
Germany 1. Bundesliga       151 non-null float64
Italy Serie A               157 non-null float64
Netherlands Eredivisie      155 non-null float64
Poland Ekstraklasa          139 non-null float64
Portugal Liga ZON Sagres    163 non-null float64
Scotland Premier League     170 non-null float64
Spain LIGA BBVA             162 non-null float64
Switzerland Super League    161 non-null float64
dtypes: float64(11)
memory usage: 39.7+ KB
```

In [22]:
```python
# Dropping weeks with Null_values for all teams didn't have any game.

avg_score = avg_score.dropna(axis=0, how='all')
avg_score.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 368 entries, (total_goal, 2008-07-20 00:00:00) to (total_goal, 2016-05-29 00:00:00
Data columns (total 11 columns):
Belgium Jupiler League      127 non-null float64
England Premier League      166 non-null float64
```

```
France Ligue 1              164 non-null float64
Germany 1. Bundesliga       151 non-null float64
Italy Serie A               157 non-null float64
Netherlands Eredivisie      155 non-null float64
Poland Ekstraklasa          139 non-null float64
Portugal Liga ZON Sagres    163 non-null float64
Scotland Premier League     170 non-null float64
Spain LIGA BBVA             162 non-null float64
Switzerland Super League    161 non-null float64
dtypes: float64(11)
memory usage: 36.0+ KB
```

> # Limitation:

1) NaN_values here mean that the team didn't have any game during the weeks.

2) Therefore, if we filled NaN_values with 0(zero value) then it affects the averages because it would count as the games with no-goal.

3) After dropping Null_values by individual columns, each column's statistic describe data is combined into a dataframe of whole countries.

In [23]:
```
# Dropping all Null-values for each team.
# And then merging all teams' statistics result to compare it each other.

# Create a new dataframe for getting describes from all countries without Null-values
desc_avg_goals = pd.DataFrame()

avg_Bel = avg_score[['Belgium Jupiler League']]
avg_Bel = avg_Bel.dropna()
desc_Bel = avg_Bel.describe()
desc_Bel.reset_index(inplace=True)
desc_avg_goals = desc_Bel.copy()

avg_Eng = avg_score[['England Premier League']]
avg_Eng = avg_Eng.dropna()
desc_Eng = avg_Eng.describe()
desc_Eng.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Eng, how='left', on='index')

avg_Fra = avg_score[['France Ligue 1']]
avg_Fra = avg_Fra.dropna()
desc_Fra = avg_Fra.describe()
desc_Fra.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Fra, how='left', on='index')
```

```python
avg_Ger = avg_score[['Germany 1. Bundesliga']]
avg_Ger = avg_Ger.dropna()
desc_Ger = avg_Ger.describe()
desc_Ger.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Ger, how='left', on='index')

avg_Ita = avg_score[['Italy Serie A']]
avg_Ita = avg_Ita.dropna()
desc_Ita = avg_Ita.describe()
desc_Ita.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Ita, how='left', on='index')

avg_Net = avg_score[['Netherlands Eredivisie']]
avg_Net = avg_Net.dropna()
desc_Net = avg_Net.describe()
desc_Net.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Net, how='left', on='index')

avg_Pol = avg_score[['Poland Ekstraklasa']]
avg_Pol = avg_Pol.dropna()
desc_Pol = avg_Pol.describe()
desc_Pol.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Pol, how='left', on='index')

avg_Por = avg_score[['Portugal Liga ZON Sagres']]
avg_Por = avg_Por.dropna()
desc_Por = avg_Por.describe()
desc_Por.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Por, how='left', on='index')

avg_Sco = avg_score[['Scotland Premier League']]
avg_Sco = avg_Sco.dropna()
desc_Sco = avg_Sco.describe()
desc_Sco.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Sco, how='left', on='index')

avg_Spa = avg_score[['Spain LIGA BBVA']]
avg_Spa = avg_Spa.dropna()
desc_Spa = avg_Spa.describe()
desc_Spa.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Spa, how='left', on='index')

avg_Swi = avg_score[['Switzerland Super League']]
avg_Swi = avg_Swi.dropna()
desc_Swi = avg_Swi.describe()
desc_Swi.reset_index(inplace=True)
desc_avg_goals = desc_avg_goals.merge(desc_Swi, how='left', on='index')
```

```
desc_avg_goals.set_index('index', inplace=True, drop=True)
desc_avg_goals
```

Out[23]:
```
league  Belgium Jupiler League  England Premier League  France Ligue 1  \
index
count               127.000000              166.000000      164.000000
mean                  2.805427                2.726599        2.448319
std                   0.461371                0.456915        0.377380
min                   1.000000                1.300000        1.526316
25%                   2.466063                2.444444        2.200000
50%                   2.857143                2.700000        2.400000
75%                   3.100962                3.051974        2.700000
max                   4.250000                4.000000        3.600000

league  Germany 1. Bundesliga  Italy Serie A  Netherlands Eredivisie  \
index
count              151.000000     157.000000              155.000000
mean                 2.907533       2.631104                3.085732
std                  0.400635       0.459860                0.521972
min                  2.000000       1.400000                1.444444
25%                  2.638889       2.347826                2.777778
50%                  2.888889       2.600000                3.074074
75%                  3.166667       2.850000                3.436508
max                  4.111111       4.200000                4.333333

league  Poland Ekstraklasa  Portugal Liga ZON Sagres  Scotland Premier League  \
index
count           139.000000                163.000000               170.000000
mean              2.424491                  2.498025                 2.648298
std               0.507040                  0.532362                 0.528882
min               1.000000                  0.000000                 1.250000
25%               2.117647                  2.216374                 2.333333
50%               2.437500                  2.500000                 2.666667
75%               2.812500                  2.800000                 3.000000
max               5.000000                  4.000000                 4.166667

league  Spain LIGA BBVA  Switzerland Super League
index
count        162.000000               161.000000
mean           2.751545                 2.911763
std            0.422853                 0.692768
min            0.888889                 1.333333
25%            2.537500                 2.400000
50%            2.750000                 2.900000
75%            3.000000                 3.400000
max            4.200000                 5.000000
```

In [24]:
```
# The ranking by average goals.
```

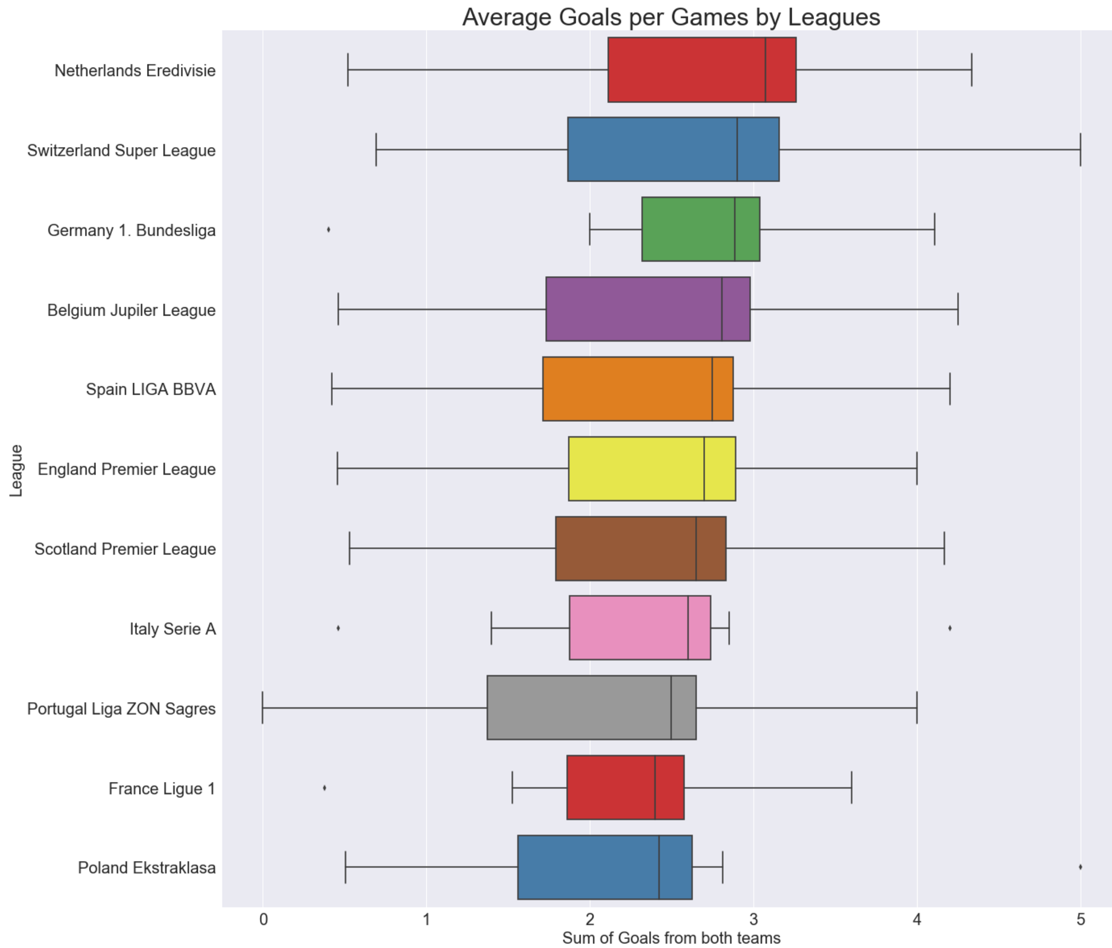
```
desc_avg_goals = desc_avg_goals.transpose()
desc_avg_goals= desc_avg_goals.sort_values(['mean'], ascending=[0])
desc_avg_goals = desc_avg_goals.reset_index()
desc_avg_goals['ranks'] = range(1, desc_avg_goals.shape[0]+1)
desc_avg_goals.set_index('ranks', inplace=True, drop=True)
desc_avg_goals.iloc[:,[0,2]]
```

Out[24]:

```
index                     league      mean
ranks
1        Netherlands Eredivisie  3.085732
2      Switzerland Super League  2.911763
3         Germany 1. Bundesliga  2.907533
4          Belgium Jupiler League  2.805427
5                Spain LIGA BBVA  2.751545
6          England Premier League  2.726599
7         Scotland Premier League  2.648298
8                  Italy Serie A  2.631104
9      Portugal Liga ZON Sagres  2.498025
10                France Ligue 1  2.448319
11            Poland Ekstraklasa  2.424491
```

In [25]:

```
desc_avg_goals = desc_avg_goals.transpose()

sns.set(rc={'figure.figsize':(20,20)})
sns.set(font_scale=2)
ax = sns.boxplot(data=desc_avg_goals[2:], orient='h', palette='Set1')
ax.set_title('Average Goals per Games by Leagues', size=30)
ax.set_yticklabels(desc_avg_goals.iloc[0])
ax.set_xlabel('Sum of Goals from both teams', size=20)
ax.set_ylabel('League', size=20);
```



> ## Observation #2:

1) Netherlands scores the highest goals in average at 3.086 over the period.

2) In the second place, Switzerland and Germany score almost the same around at 2.9.

3) On the other hand, Poland scores the lowest goals at 2.424 similar with France.

> # < Research Question 3: The More Games, The Better Scores?? >

Q. Are average scores and a number of games played related to each other?

1.6 Methodology

I summed up all games played per each year and then compared it with average scores.

In [26]:
```python
# Total number of games by leagues per season.
df_match_cnt = df_match_new.copy()

df_match_cnt['date'] = pd.to_datetime(df_match_cnt['date'])
df_match_cnt.set_index(pd.DatetimeIndex(df_match_cnt['date']), inplace=True)

df_match_cnt = df_match_cnt.groupby(['league']).resample('Y').count().iloc[:,[0]]
df_match_cnt.columns=['games_played']


# Average goal scores by leagues per season.
df_match_cnt1 = df_match_new.copy()

df_match_cnt1['date'] = pd.to_datetime(df_match_cnt1['date'])
df_match_cnt1.set_index(pd.DatetimeIndex(df_match_cnt1['date']), inplace=True)

df_match_cnt1 = df_match_cnt1.groupby(['league']).resample('Y').mean().iloc[:,[0]]
df_match_cnt1.columns=['goals']

# Joining two information into a dataframe, the number of games and average scores.
df_match_cnt1['games_played'] = df_match_cnt['games_played']
avg = df_match_cnt1.unstack().transpose().loc['goals']
games = df_match_cnt1.unstack().transpose().loc['games_played']
avg.head()
```

Out[26]:
```
league      Belgium Jupiler League  England Premier League  France Ligue 1  \
date
2008-12-31                1.712418                1.373737        1.257895
2009-12-31                1.521886                1.592593        1.358090
2010-12-31                1.627193                1.590909        1.335958
2011-12-31                1.573913                1.631300        1.442408
2012-12-31                1.719697                1.613811        1.476316

league      Germany 1. Bundesliga  Italy Serie A  Netherlands Eredivisie  \
date
2008-12-31               1.777778       1.550296                1.901961
2009-12-31               1.535948       1.485411                1.603226
2010-12-31               1.666667       1.498688                1.841772
2011-12-31               1.630719       1.469169                1.982877
2012-12-31               1.594771       1.552910                1.765079

league      Poland Ekstraklasa  Portugal Liga ZON Sagres  \
date
2008-12-31            1.352941                  1.145833
2009-12-31            1.300000                  1.320312
2010-12-31            1.379464                  1.429167
2011-12-31            1.359375                  1.362069
2012-12-31            1.263393                  1.476190
```

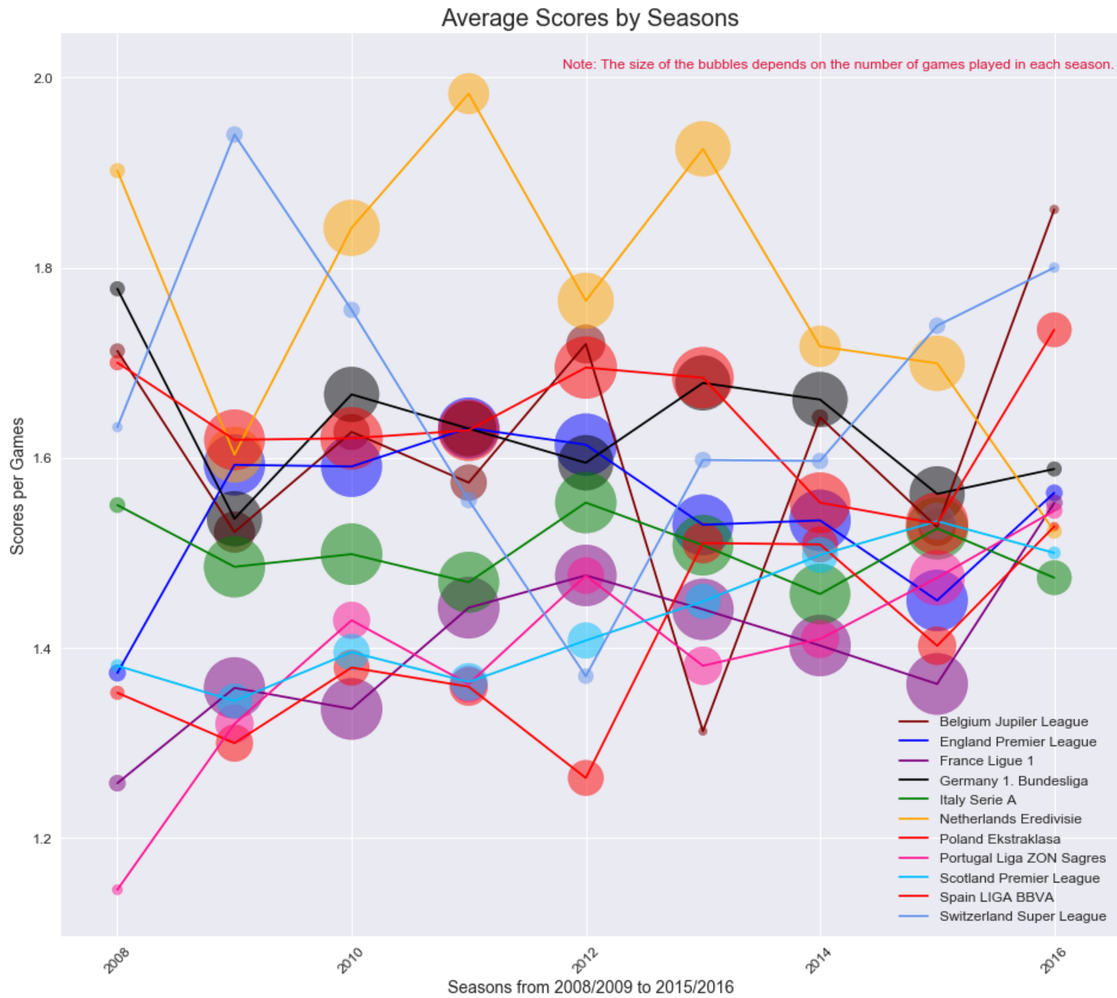
```
league      Scotland Premier League  Spain LIGA BBVA  Switzerland Super League
date
2008-12-31                 1.381356         1.700000                  1.632184
2009-12-31                 1.344340         1.618919                  1.939891
2010-12-31                 1.395652         1.620513                  1.755556
2011-12-31                 1.364372         1.628947                  1.555556
2012-12-31                 1.407895         1.694872                  1.370370
```

In [27]: games

```
Out[27]: league      Belgium Jupiler League  England Premier League  France Ligue 1  \
date
2008-12-31                   153.0                   198.0           190.0
2009-12-31                   297.0                   378.0           377.0
2010-12-31                   228.0                   374.0           381.0
2011-12-31                   230.0                   377.0           382.0
2012-12-31                   264.0                   391.0           380.0
2013-12-31                    64.0                   372.0           379.0
2014-12-31                   179.0                   380.0           380.0
2015-12-31                   241.0                   380.0           381.0
2016-12-31                    72.0                   190.0           190.0

league      Germany 1. Bundesliga  Italy Serie A  Netherlands Eredivisie  \
date
2008-12-31                  153.0          169.0                   153.0
2009-12-31                  306.0          377.0                   310.0
2010-12-31                  306.0          381.0                   316.0
2011-12-31                  306.0          373.0                   292.0
2012-12-31                  306.0          378.0                   315.0
2013-12-31                  305.0          370.0                   306.0
2014-12-31                  307.0          370.0                   297.0
2015-12-31                  306.0          388.0                   306.0
2016-12-31                  153.0          211.0                   153.0

league      Poland Ekstraklasa  Portugal Liga ZON Sagres  \
date
2008-12-31               136.0                      96.0
2009-12-31               240.0                     256.0
2010-12-31               224.0                     240.0
2011-12-31               256.0                     232.0
2012-12-31               224.0                     231.0
2013-12-31               288.0                     257.0
2014-12-31               224.0                     254.0
2015-12-31               256.0                     306.0
2016-12-31                72.0                     180.0

league      Scotland Premier League  Spain LIGA BBVA  Switzerland Super League
```

```
date
2008-12-31                    118.0          160.0                    87.0
2009-12-31                    212.0          370.0                   183.0
2010-12-31                    230.0          390.0                   180.0
2011-12-31                    247.0          380.0                   180.0
2012-12-31                    228.0          390.0                   162.0
2013-12-31                    216.0          380.0                   179.0
2014-12-31                    225.0          369.0                   181.0
2015-12-31                    240.0          390.0                   180.0
2016-12-31                    108.0          211.0                    90.0
```

In [28]:
```
colors = ['maroon','Blue','Purple','Black','Green','Orange','Red','deeppink','deepsky

ax = avg.plot(figsize=(16,14),color=colors)
ax.legend(markerscale=0.3, fontsize=12)

x = avg.index
for i in range(len(avg.columns)):
    ss = games.iloc[:,i]
    y = y = avg.iloc[:,i]
    c = colors[i]

    size = ss.apply(lambda x: 0.8*x if x<100 else(x if ((x<200) & (x>=100)) \
                                                    else (x*4 if ((x<300)&(x>=200)) else

    plt.scatter(x,y,s=size, alpha=0.5, color=c)

xticks(rotation=45, fontsize=12)
yticks(fontsize=12)
plt.grid(axis='both')
plt.xlabel('Seasons from 2008/2009 to 2015/2016', size=14)
plt.ylabel('Scores per Games', size=14)
plt.title('Average Scores by Seasons', size=20)
plt.text(41.8, 2.01, 'Note: The size of the bubbles depends on the number of games pla
         , fontsize=12, color='#DC143C')
plt.grid()

plt.show();
```



> ## Observation #3:

1) How many goals they're scoring doesn't look quite related to how many games they play.

2) The number of games seems pretty steady for each country.

3) Next Question? : Maybe teams or players' own abilities are affecting how many goals are scored, then what attributes are ?

1.7 Dataframe: df_player

In [29]:
```
df_player.info()
print('\n')
df_player.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11060 entries, 0 to 11059
Data columns (total 7 columns):
id                    11060 non-null int64
player_api_id         11060 non-null int64
player_name           11060 non-null object
player_fifa_api_id    11060 non-null int64
birthday              11060 non-null object
height                11060 non-null float64
weight                11060 non-null int64
dtypes: float64(1), int64(4), object(2)
memory usage: 604.9+ KB
```

Out[29]:
```
   id  player_api_id         player_name  player_fifa_api_id  \
0   1         505942  Aaron Appindangoye              218353
1   2         155782     Aaron Cresswell              189615
2   3         162549         Aaron Doran              186170
3   4          30572       Aaron Galindo              140161
4   5          23780        Aaron Hughes               17725

              birthday  height  weight
0  1992-02-29 00:00:00  182.88     187
1  1989-12-15 00:00:00  170.18     146
2  1991-05-13 00:00:00  170.18     163
3  1982-05-08 00:00:00  182.88     198
4  1979-11-08 00:00:00  182.88     154
```

In [30]:
```
df_player['birthdate'] = pd.to_datetime(df_player['birthday'])
now = pd.Timestamp(datetime.datetime.now())
df_player['age'] = (now - df_player['birthdate']).astype('<m8[Y]')
df_player.head()
```

Out[30]:
```
   id  player_api_id         player_name  player_fifa_api_id  \
0   1         505942  Aaron Appindangoye              218353
1   2         155782     Aaron Cresswell              189615
2   3         162549         Aaron Doran              186170
3   4          30572       Aaron Galindo              140161
4   5          23780        Aaron Hughes               17725

              birthday  height  weight  birthdate   age
0  1992-02-29 00:00:00  182.88     187 1992-02-29  26.0
1  1989-12-15 00:00:00  170.18     146 1989-12-15  28.0
2  1991-05-13 00:00:00  170.18     163 1991-05-13  27.0
3  1982-05-08 00:00:00  182.88     198 1982-05-08  36.0
4  1979-11-08 00:00:00  182.88     154 1979-11-08  38.0
```

1.8 Dataframe: df_player_attributes

Leauge and Country Mapping

```
In [31]: df_player_attributes = whole_df[5]
```

```
In [32]: df_player_attributes.info()
         print('\n')
         df_player_attributes.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183978 entries, 0 to 183977
Data columns (total 42 columns):
id                       183978 non-null int64
player_fifa_api_id       183978 non-null int64
player_api_id            183978 non-null int64
date                     183978 non-null object
overall_rating           183142 non-null float64
potential                183142 non-null float64
preferred_foot           183142 non-null object
attacking_work_rate      180748 non-null object
defensive_work_rate      183142 non-null object
crossing                 183142 non-null float64
finishing                183142 non-null float64
heading_accuracy         183142 non-null float64
short_passing            183142 non-null float64
volleys                  181265 non-null float64
dribbling                183142 non-null float64
curve                    181265 non-null float64
free_kick_accuracy       183142 non-null float64
long_passing             183142 non-null float64
ball_control             183142 non-null float64
acceleration             183142 non-null float64
sprint_speed             183142 non-null float64
agility                  181265 non-null float64
reactions                183142 non-null float64
balance                  181265 non-null float64
shot_power               183142 non-null float64
jumping                  181265 non-null float64
stamina                  183142 non-null float64
strength                 183142 non-null float64
long_shots               183142 non-null float64
aggression               183142 non-null float64
interceptions            183142 non-null float64
positioning              183142 non-null float64
vision                   181265 non-null float64
penalties                183142 non-null float64
marking                  183142 non-null float64
standing_tackle          183142 non-null float64
```

```
sliding_tackle         181265 non-null float64
gk_diving              183142 non-null float64
gk_handling            183142 non-null float64
gk_kicking             183142 non-null float64
gk_positioning         183142 non-null float64
gk_reflexes            183142 non-null float64
dtypes: float64(35), int64(3), object(4)
memory usage: 59.0+ MB
```

Out[32]:

```
   id  player_fifa_api_id  player_api_id                 date  overall_rating  \
0   1              218353         505942  2016-02-18 00:00:00            67.0
1   2              218353         505942  2015-11-19 00:00:00            67.0
2   3              218353         505942  2015-09-21 00:00:00            62.0
3   4              218353         505942  2015-03-20 00:00:00            61.0
4   5              218353         505942  2007-02-22 00:00:00            61.0

   potential preferred_foot attacking_work_rate defensive_work_rate  crossing  \
0       71.0          right              medium              medium      49.0
1       71.0          right              medium              medium      49.0
2       66.0          right              medium              medium      49.0
3       65.0          right              medium              medium      48.0
4       65.0          right              medium              medium      48.0

      ...       vision  penalties  marking  standing_tackle  sliding_tackle  \
0     ...         54.0       48.0     65.0             69.0            69.0
1     ...         54.0       48.0     65.0             69.0            69.0
2     ...         54.0       48.0     65.0             66.0            69.0
3     ...         53.0       47.0     62.0             63.0            66.0
4     ...         53.0       47.0     62.0             63.0            66.0

   gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes
0        6.0         11.0        10.0             8.0          8.0
1        6.0         11.0        10.0             8.0          8.0
2        6.0         11.0        10.0             8.0          8.0
3        5.0         10.0         9.0             7.0          7.0
4        5.0         10.0         9.0             7.0          7.0

[5 rows x 42 columns]
```

In [33]:

```
df_player_attributes.describe()
```

Out[33]:

```
                 id  player_fifa_api_id  player_api_id  overall_rating  \
count  183978.00000       183978.000000  183978.000000   183142.000000
mean    91989.50000       165671.524291  135900.617324       68.600015
std     53110.01825        53851.094769  136927.840510        7.041139
```

min	1.00000	2.000000	2625.000000	33.000000
25%	45995.25000	155798.000000	34763.000000	64.000000
50%	91989.50000	183488.000000	77741.000000	69.000000
75%	137983.75000	199848.000000	191080.000000	73.000000
max	183978.00000	234141.000000	750584.000000	94.000000

	potential	crossing	finishing	heading_accuracy \
count	183142.000000	183142.000000	183142.000000	183142.000000
mean	73.460353	55.086883	49.921078	57.266023
std	6.592271	17.242135	19.038705	16.488905
min	39.000000	1.000000	1.000000	1.000000
25%	69.000000	45.000000	34.000000	49.000000
50%	74.000000	59.000000	53.000000	60.000000
75%	78.000000	68.000000	65.000000	68.000000
max	97.000000	95.000000	97.000000	98.000000

	short_passing	volleys	...	vision \
count	183142.000000	181265.000000	...	181265.000000
mean	62.429672	49.468436	...	57.873550
std	14.194068	18.256618	...	15.144086
min	3.000000	1.000000	...	1.000000
25%	57.000000	35.000000	...	49.000000
50%	65.000000	52.000000	...	60.000000
75%	72.000000	64.000000	...	69.000000
max	97.000000	93.000000	...	97.000000

	penalties	marking	standing_tackle	sliding_tackle \
count	183142.000000	183142.000000	183142.000000	181265.000000
mean	55.003986	46.772242	50.351257	48.001462
std	15.546519	21.227667	21.483706	21.598778
min	2.000000	1.000000	1.000000	2.000000
25%	45.000000	25.000000	29.000000	25.000000
50%	57.000000	50.000000	56.000000	53.000000
75%	67.000000	66.000000	69.000000	67.000000
max	96.000000	96.000000	95.000000	95.000000

	gk_diving	gk_handling	gk_kicking	gk_positioning \
count	183142.000000	183142.000000	183142.000000	183142.000000
mean	14.704393	16.063612	20.998362	16.132154
std	16.865467	15.867382	21.452980	16.099175
min	1.000000	1.000000	1.000000	1.000000
25%	7.000000	8.000000	8.000000	8.000000
50%	10.000000	11.000000	12.000000	11.000000
75%	13.000000	15.000000	15.000000	15.000000
max	94.000000	93.000000	97.000000	96.000000

	gk_reflexes
count	183142.000000

```
mean        16.441439
std         17.198155
min          1.000000
25%          8.000000
50%         11.000000
75%         15.000000
max         96.000000

[8 rows x 38 columns]
```

In [34]:
```
# Total number of games each player's played

ttl_num_games = df_player_attributes.groupby('player_fifa_api_id').count()[['id']]
ttl_num_games.rename(columns={'id':'number_of_games'}, inplace=True)
ttl_num_games.head()
ttl_num_games.reset_index(inplace=True)
```

In [35]:
```
df_players = df_player_attributes.groupby('player_fifa_api_id').mean()
df_players.drop(['id','player_api_id'], axis=1, inplace=True, errors='ignore')
df_players.reset_index(inplace=True)
df_players.head()
```

Out[35]:
```
   player_fifa_api_id  overall_rating  potential   crossing  finishing  \
0                   2       70.600000  71.100000  74.100000  48.033333
1                   6       72.125000  76.250000  18.000000  18.000000
2                  11       67.352941  69.411765  63.588235  54.352941
3                  16       74.125000  76.562500  74.187500  73.937500
4                  27       76.500000  77.600000  80.933333  69.833333

   heading_accuracy  short_passing    volleys  dribbling      curve  \
0         62.800000      71.200000  56.566667  66.600000  67.733333
1         24.000000      28.750000   6.500000  17.000000   7.250000
2         60.882353      71.882353  64.470588  67.117647  69.058824
3         64.000000      68.750000  72.625000  76.125000  77.562500
4         49.833333      80.133333  76.833333  82.333333  83.333333

      ...         vision  penalties    marking  standing_tackle  \
0     ...      55.766667  59.766667  71.466667        74.000000
1     ...      42.000000  25.250000  24.750000        24.125000
2     ...      68.882353  68.117647  45.117647        49.588235
3     ...      59.875000  75.750000  27.062500        31.062500
4     ...      81.366667  67.700000  37.133333        36.200000

   sliding_tackle  gk_diving  gk_handling  gk_kicking  gk_positioning  \
0       72.833333  13.300000     7.633333   26.000000       11.766667
1       17.000000  71.750000    72.375000   71.000000       75.250000
2       58.941176   6.000000     7.058824   13.941176        7.470588
3       21.000000   9.250000    13.625000   24.250000       12.937500
```

```
4      29.333333   8.333333     7.666667   21.766667       16.033333

   gk_reflexes
0    13.466667
1    72.750000
2    11.882353
3    12.562500
4     8.333333

[5 rows x 36 columns]
```

In [36]:
```python
whole_info_players = pd.merge(left=df_players, right=ttl_num_games, on='player_fifa_a
whole_info_players.head()
```

Out[36]:
```
   player_fifa_api_id  overall_rating  potential   crossing  finishing  \
0                   2       70.600000  71.100000  74.100000  48.033333
1                   6       72.125000  76.250000  18.000000  18.000000
2                  11       67.352941  69.411765  63.588235  54.352941
3                  16       74.125000  76.562500  74.187500  73.937500
4                  27       76.500000  77.600000  80.933333  69.833333

   heading_accuracy  short_passing    volleys  dribbling      curve  \
0         62.800000      71.200000  56.566667  66.600000  67.733333
1         24.000000      28.750000   6.500000  17.000000   7.250000
2         60.882353      71.882353  64.470588  67.117647  69.058824
3         64.000000      68.750000  72.625000  76.125000  77.562500
4         49.833333      80.133333  76.833333  82.333333  83.333333

        ...         penalties    marking  standing_tackle  sliding_tackle  \
0       ...         59.766667  71.466667        74.000000       72.833333
1       ...         25.250000  24.750000        24.125000       17.000000
2       ...         68.117647  45.117647        49.588235       58.941176
3       ...         75.750000  27.062500        31.062500       21.000000
4       ...         67.700000  37.133333        36.200000       29.333333

   gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes  \
0  13.300000     7.633333   26.000000       11.766667    13.466667
1  71.750000    72.375000   71.000000       75.250000    72.750000
2   6.000000     7.058824   13.941176        7.470588    11.882353
3   9.250000    13.625000   24.250000       12.937500    12.562500
4   8.333333     7.666667   21.766667       16.033333     8.333333

   number_of_games
0               30
1                8
2               17
3               16
4               30
```

```
[5 rows x 37 columns]
```

```
In [37]: whole_info_players.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11062 entries, 0 to 11061
Data columns (total 37 columns):
player_fifa_api_id    11062 non-null int64
overall_rating        11060 non-null float64
potential             11060 non-null float64
crossing              11060 non-null float64
finishing             11060 non-null float64
heading_accuracy      11060 non-null float64
short_passing         11060 non-null float64
volleys               10582 non-null float64
dribbling             11060 non-null float64
curve                 10582 non-null float64
free_kick_accuracy    11060 non-null float64
long_passing          11060 non-null float64
ball_control          11060 non-null float64
acceleration          11060 non-null float64
sprint_speed          11060 non-null float64
agility               10582 non-null float64
reactions             11060 non-null float64
balance               10582 non-null float64
shot_power            11060 non-null float64
jumping               10582 non-null float64
stamina               11060 non-null float64
strength              11060 non-null float64
long_shots            11060 non-null float64
aggression            11060 non-null float64
interceptions         11060 non-null float64
positioning           11060 non-null float64
vision                10582 non-null float64
penalties             11060 non-null float64
marking               11060 non-null float64
standing_tackle       11060 non-null float64
sliding_tackle        10582 non-null float64
gk_diving             11060 non-null float64
gk_handling           11060 non-null float64
gk_kicking            11060 non-null float64
gk_positioning        11060 non-null float64
gk_reflexes           11060 non-null float64
number_of_games       11062 non-null int64
dtypes: float64(35), int64(2)
memory usage: 3.2 MB
```

In [38]:
```
whole_info_players = check_null_value_by_row(whole_info_players)
whole_info_players.head()
```

```
There are 11062 rows in this dataset.

480 rows with null values have been removed.
```

Out[38]:
```
   player_fifa_api_id  overall_rating  potential   crossing  finishing  \
0                   2       70.600000  71.100000  74.100000  48.033333
1                   6       72.125000  76.250000  18.000000  18.000000
2                  11       67.352941  69.411765  63.588235  54.352941
3                  16       74.125000  76.562500  74.187500  73.937500
4                  27       76.500000  77.600000  80.933333  69.833333

   heading_accuracy  short_passing    volleys  dribbling      curve  \
0         62.800000      71.200000  56.566667  66.600000  67.733333
1         24.000000      28.750000   6.500000  17.000000   7.250000
2         60.882353      71.882353  64.470588  67.117647  69.058824
3         64.000000      68.750000  72.625000  76.125000  77.562500
4         49.833333      80.133333  76.833333  82.333333  83.333333

        ...          penalties    marking  standing_tackle  sliding_tackle  \
0       ...          59.766667  71.466667        74.000000       72.833333
1       ...          25.250000  24.750000        24.125000       17.000000
2       ...          68.117647  45.117647        49.588235       58.941176
3       ...          75.750000  27.062500        31.062500       21.000000
4       ...          67.700000  37.133333        36.200000       29.333333

   gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes  \
0  13.300000     7.633333   26.000000       11.766667    13.466667
1  71.750000    72.375000   71.000000       75.250000    72.750000
2   6.000000     7.058824   13.941176        7.470588    11.882353
3   9.250000    13.625000   24.250000       12.937500    12.562500
4   8.333333     7.666667   21.766667       16.033333     8.333333

   number_of_games
0               30
1                8
2               17
3               16
4               30

[5 rows x 37 columns]
```

In [39]:
```
df_player.head()
```

Out[39]:
```
   id  player_api_id         player_name  player_fifa_api_id  \
0   1         505942  Aaron Appindangoye              218353
```

```
1   2          155782     Aaron Cresswell              189615
2   3          162549         Aaron Doran              186170
3   4           30572       Aaron Galindo              140161
4   5           23780        Aaron Hughes               17725

               birthday  height  weight  birthdate   age
0   1992-02-29 00:00:00  182.88     187 1992-02-29  26.0
1   1989-12-15 00:00:00  170.18     146 1989-12-15  28.0
2   1991-05-13 00:00:00  170.18     163 1991-05-13  27.0
3   1982-05-08 00:00:00  182.88     198 1982-05-08  36.0
4   1979-11-08 00:00:00  182.88     154 1979-11-08  38.0
```

In [40]: whole_info_players.head()

Out[40]:

```
   player_fifa_api_id  overall_rating  potential   crossing  finishing  \
0                   2       70.600000  71.100000  74.100000  48.033333
1                   6       72.125000  76.250000  18.000000  18.000000
2                  11       67.352941  69.411765  63.588235  54.352941
3                  16       74.125000  76.562500  74.187500  73.937500
4                  27       76.500000  77.600000  80.933333  69.833333

   heading_accuracy  short_passing    volleys  dribbling      curve  \
0         62.800000      71.200000  56.566667  66.600000  67.733333
1         24.000000      28.750000   6.500000  17.000000   7.250000
2         60.882353      71.882353  64.470588  67.117647  69.058824
3         64.000000      68.750000  72.625000  76.125000  77.562500
4         49.833333      80.133333  76.833333  82.333333  83.333333

        ...          penalties    marking  standing_tackle  sliding_tackle  \
0       ...          59.766667  71.466667        74.000000       72.833333
1       ...          25.250000  24.750000        24.125000       17.000000
2       ...          68.117647  45.117647        49.588235       58.941176
3       ...          75.750000  27.062500        31.062500       21.000000
4       ...          67.700000  37.133333        36.200000       29.333333

   gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes  \
0  13.300000     7.633333   26.000000       11.766667    13.466667
1  71.750000    72.375000   71.000000       75.250000    72.750000
2   6.000000     7.058824   13.941176        7.470588    11.882353
3   9.250000    13.625000   24.250000       12.937500    12.562500
4   8.333333     7.666667   21.766667       16.033333     8.333333

   number_of_games
0               30
1                8
2               17
3               16
4               30
```

```
[5 rows x 37 columns]
```

```
In [41]: # Merging two dataframes on 'player_fifa_api_id'.

         all_plr_info = pd.merge(left=df_player, right=whole_info_players, on='player_fifa_api_
         all_plr_info.head()
```

```
Out[41]:    id  player_api_id         player_name  player_fifa_api_id  \
         0   1         505942  Aaron Appindangoye              218353
         1   2         155782     Aaron Cresswell              189615
         2   3         162549         Aaron Doran              186170
         3   4          30572       Aaron Galindo              140161
         4   5          23780        Aaron Hughes               17725

                       birthday  height  weight  birthdate   age  overall_rating  \
         0  1992-02-29 00:00:00  182.88     187 1992-02-29  26.0       63.600000
         1  1989-12-15 00:00:00  170.18     146 1989-12-15  28.0       66.969697
         2  1991-05-13 00:00:00  170.18     163 1991-05-13  27.0       67.000000
         3  1982-05-08 00:00:00  182.88     198 1982-05-08  36.0       69.086957
         4  1979-11-08 00:00:00  182.88     154 1979-11-08  38.0       73.240000

                  ...         penalties    marking  standing_tackle  sliding_tackle  \
         0        ...         47.600000  63.800000        66.000000       67.800000
         1        ...         53.121212  69.393939        68.787879       71.515152
         2        ...         60.538462  22.038462        21.115385       21.346154
         3        ...         41.739130  70.608696        70.652174       68.043478
         4        ...         52.960000  77.600000        76.040000       74.600000

            gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes  \
         0   5.600000    10.600000    9.600000        7.600000     7.600000
         1  12.181818     8.666667   14.242424       10.363636    12.909091
         2  14.038462    11.807692   17.730769       10.115385    13.500000
         3  14.173913    11.173913   22.869565       11.173913    10.173913
         4   8.280000     8.320000   24.920000       12.840000    11.920000

            number_of_games
         0              5.0
         1             33.0
         2             26.0
         3             23.0
         4             25.0

         [5 rows x 45 columns]
```

```
In [42]: all_plr_info.describe()
```

```
Out[42]:                  id  player_api_id  player_fifa_api_id        height  \
         count  11060.000000   11060.000000        11060.000000  11060.000000
```

mean	5537.511392	156582.427215	165664.910488	181.867445
std	3197.692647	160713.700624	58649.928360	6.369201
min	1.000000	2625.000000	2.000000	157.480000
25%	2767.750000	35555.500000	151889.500000	177.800000
50%	5536.500000	96619.500000	184671.000000	182.880000
75%	8306.250000	212470.500000	203883.250000	185.420000
max	11075.000000	750584.000000	234141.000000	208.280000

	weight	age	overall_rating	potential	crossing \
count	11060.000000	11060.000000	10582.000000	10582.000000	10582.000000
mean	168.380289	30.822514	66.883061	72.124918	52.924873
std	14.990217	5.457384	6.173601	5.733254	16.208089
min	117.000000	19.000000	43.750000	51.000000	6.000000
25%	159.000000	27.000000	62.901190	68.040210	43.521739
50%	168.000000	30.000000	66.777778	72.060662	56.508621
75%	179.000000	35.000000	70.954891	76.000000	64.800000
max	243.000000	51.000000	92.192308	95.230769	89.357143

	finishing	...	penalties	marking \
count	10582.000000	...	10582.000000	10582.000000
mean	47.873222	...	53.389938	46.116013
std	18.158532	...	13.832901	20.050622
min	5.000000	...	9.000000	5.000000
25%	32.407143	...	44.466667	25.000000
50%	50.000000	...	54.711310	49.892857
75%	63.134531	...	63.618132	64.129076
max	92.230769	...	89.565217	89.666667

	standing_tackle	sliding_tackle	gk_diving	gk_handling \
count	10582.000000	10582.000000	10582.000000	10582.000000
mean	49.375659	47.131852	14.958130	16.331939
std	20.369817	20.590028	16.797796	15.476486
min	6.000000	5.000000	1.833333	2.000000
25%	28.900000	25.439236	7.824169	9.313322
50%	55.154705	52.200000	10.200000	12.234314
75%	67.000000	65.125000	13.000000	15.000000
max	90.200000	94.366667	89.863636	86.875000

	gk_kicking	gk_positioning	gk_reflexes	number_of_games
count	10582.000000	10582.000000	10582.000000	10582.000000
mean	21.530720	16.406330	16.718391	17.199301
std	16.293339	15.698238	16.795922	9.220732
min	3.260870	2.000000	2.000000	2.000000
25%	11.000000	9.312500	9.250000	9.000000
50%	15.422065	12.250000	12.222222	17.000000
75%	25.068391	15.000000	15.000000	24.000000
max	87.133333	91.625000	90.954545	96.000000

```
[8 rows x 42 columns]
```

```
In [43]: all_plr_info.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11060 entries, 0 to 11059
Data columns (total 45 columns):
id                     11060 non-null int64
player_api_id          11060 non-null int64
player_name            11060 non-null object
player_fifa_api_id     11060 non-null int64
birthday               11060 non-null object
height                 11060 non-null float64
weight                 11060 non-null int64
birthdate              11060 non-null datetime64[ns]
age                    11060 non-null float64
overall_rating         10582 non-null float64
potential              10582 non-null float64
crossing               10582 non-null float64
finishing              10582 non-null float64
heading_accuracy       10582 non-null float64
short_passing          10582 non-null float64
volleys                10582 non-null float64
dribbling              10582 non-null float64
curve                  10582 non-null float64
free_kick_accuracy     10582 non-null float64
long_passing           10582 non-null float64
ball_control           10582 non-null float64
acceleration           10582 non-null float64
sprint_speed           10582 non-null float64
agility                10582 non-null float64
reactions              10582 non-null float64
balance                10582 non-null float64
shot_power             10582 non-null float64
jumping                10582 non-null float64
stamina                10582 non-null float64
strength               10582 non-null float64
long_shots             10582 non-null float64
aggression             10582 non-null float64
interceptions          10582 non-null float64
positioning            10582 non-null float64
vision                 10582 non-null float64
penalties              10582 non-null float64
marking                10582 non-null float64
standing_tackle        10582 non-null float64
sliding_tackle         10582 non-null float64
gk_diving              10582 non-null float64
gk_handling            10582 non-null float64
```

```
gk_kicking            10582 non-null float64
gk_positioning        10582 non-null float64
gk_reflexes           10582 non-null float64
number_of_games       10582 non-null float64
dtypes: datetime64[ns](1), float64(38), int64(4), object(2)
memory usage: 3.9+ MB
```

> # < Research Question4: Inactive Players>

Q. Are players who didn't play any game different with the rest of other players?

1.9 Methodology

After extracting the information from the players with zero game and then compare with others.

In [44]:
```
# There are some players who didn't play any game over the period.
# So these players would be separated to another dataframe, called 'zero_plr'

zero_plr = all_plr_info[all_plr_info['overall_rating'].isnull()]
zero_plr = check_null_value(zero_plr)
zero_plr.info()
```

```
There are 478 rows in this dataset.

36 columns with null values have been removed.
<class 'pandas.core.frame.DataFrame'>
Int64Index: 478 entries, 25 to 11027
Data columns (total 9 columns):
id                    478 non-null int64
player_api_id         478 non-null int64
player_name           478 non-null object
player_fifa_api_id    478 non-null int64
birthday              478 non-null object
height                478 non-null float64
weight                478 non-null int64
birthdate             478 non-null datetime64[ns]
age                   478 non-null float64
dtypes: datetime64[ns](1), float64(2), int64(4), object(2)
memory usage: 37.3+ KB
```

In [45]:
```
zero_plr.describe()
```

Out[45]:
```
                 id  player_api_id  player_fifa_api_id      height  \
count    478.000000     478.000000          478.000000  478.000000
mean    5600.654812   48040.598326       103691.240586  181.381506
std     3254.804851   41541.741748        72152.254318    5.927388
min       26.000000    3263.000000          245.000000  165.100000
25%     2654.750000   26576.750000        18492.500000  177.800000
50%     5573.500000   34253.000000       136937.000000  180.340000
75%     8453.750000   42138.000000       169141.250000  185.420000
max    11043.000000  359194.000000       194951.000000  203.200000

           weight         age
count  478.000000  478.000000
mean   167.887029   38.010460
std     14.223132    4.769959
min    128.000000   27.000000
25%    159.000000   35.000000
50%    168.000000   38.000000
75%    176.000000   42.000000
max    212.000000   51.000000
```

In [46]:
```
all_plr_info = check_null_value_by_row(all_plr_info)
```

```
There are 11060 rows in this dataset.

478 rows with null values have been removed.
```

In [47]:
```
all_plr_info[['age']].describe()
```

Out[47]:
```
                age
count  10582.000000
mean      30.497826
std        5.259592
min       19.000000
25%       26.000000
50%       30.000000
75%       34.000000
max       49.000000
```

> ## Observation #4:

1) Average age is quite different between players in active & inactive.

2) 38 years old(inactive) vs 30 years old(active)

> ## < Research Question5: Physical Conditions Enhance Players' Abilities?>

Q. Are players who didn't play any game different with the rest of other players?

1.10 Methodology

After extracting the information from the players with zero game and then compare with others.

In [48]:
```
all_plr_info.head()
```

Out[48]:
```
   id  player_api_id         player_name  player_fifa_api_id  \
0   1         505942  Aaron Appindangoye              218353
1   2         155782     Aaron Cresswell              189615
2   3         162549         Aaron Doran              186170
3   4          30572       Aaron Galindo              140161
4   5          23780        Aaron Hughes               17725

              birthday  height  weight  birthdate   age  overall_rating  \
0  1992-02-29 00:00:00  182.88     187 1992-02-29  26.0       63.600000
1  1989-12-15 00:00:00  170.18     146 1989-12-15  28.0       66.969697
2  1991-05-13 00:00:00  170.18     163 1991-05-13  27.0       67.000000
3  1982-05-08 00:00:00  182.88     198 1982-05-08  36.0       69.086957
4  1979-11-08 00:00:00  182.88     154 1979-11-08  38.0       73.240000

        ...         penalties    marking  standing_tackle  sliding_tackle  \
0       ...         47.600000  63.800000        66.000000       67.800000
1       ...         53.121212  69.393939        68.787879       71.515152
2       ...         60.538462  22.038462        21.115385       21.346154
3       ...         41.739130  70.608696        70.652174       68.043478
4       ...         52.960000  77.600000        76.040000       74.600000

   gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes  \
0   5.600000    10.600000    9.600000        7.600000     7.600000
1  12.181818     8.666667   14.242424       10.363636    12.909091
2  14.038462    11.807692   17.730769       10.115385    13.500000
3  14.173913    11.173913   22.869565       11.173913    10.173913
4   8.280000     8.320000   24.920000       12.840000    11.920000

   number_of_games
0              5.0
1             33.0
2             26.0
3             23.0
4             25.0

[5 rows x 45 columns]
```

In [49]:
```
useful_info = all_plr_info.drop(['id','player_api_id','player_fifa_api_id','birthdate
useful_info.describe()
```

Out[49]:
```
             height       weight           age  overall_rating     potential  \
count  10582.000000  10582.00000  10582.000000    10582.000000  10582.000000
```

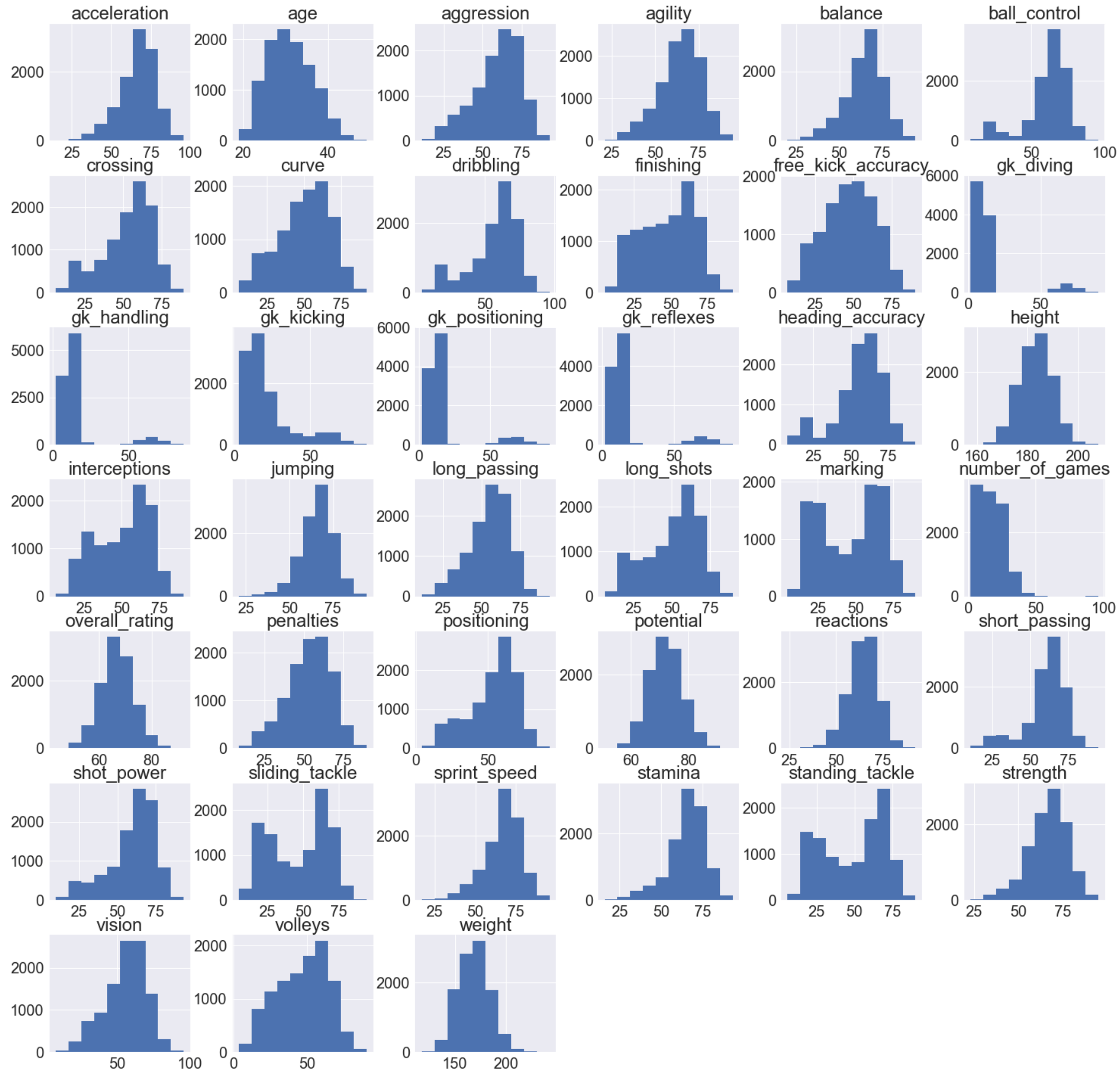
```
mean     181.889395    168.40257    30.497826       66.883061     72.124918
std        6.387826     15.02420     5.259592        6.173601      5.733254
min      157.480000    117.00000    19.000000       43.750000     51.000000
25%      177.800000    159.00000    26.000000       62.901190     68.040210
50%      182.880000    168.00000    30.000000       66.777778     72.060662
75%      185.420000    179.00000    34.000000       70.954891     76.000000
max      208.280000    243.00000    49.000000       92.192308     95.230769

           crossing    finishing  heading_accuracy  short_passing  \
count  10582.000000 10582.000000      10582.000000   10582.000000
mean      52.924873    47.873222         56.042183      60.447657
std       16.208089    18.158532         15.630905      13.479535
min        6.000000     5.000000          8.000000      10.571429
25%       43.521739    32.407143         49.149573      55.857143
50%       56.508621    50.000000         58.724747      63.000000
75%       64.800000    63.134531         66.714286      69.039615
max       89.357143    92.230769         93.111111      95.181818

            volleys       ...        penalties       marking  \
count  10582.000000       ...     10582.000000  10582.000000
mean      47.111253       ...        53.389938     46.116013
std       17.340928       ...        13.832901     20.050622
min        3.750000       ...         9.000000      5.000000
25%       33.250000       ...        44.466667     25.000000
50%       49.300000       ...        54.711310     49.892857
75%       60.740662       ...        63.618132     64.129076
max       90.789474       ...        89.565217     89.666667

       standing_tackle  sliding_tackle     gk_diving   gk_handling  \
count     10582.000000    10582.000000  10582.000000  10582.000000
mean         49.375659       47.131852     14.958130     16.331939
std          20.369817       20.590028     16.797796     15.476486
min           6.000000        5.000000      1.833333      2.000000
25%          28.900000       25.439236      7.824169      9.313322
50%          55.154705       52.200000     10.200000     12.234314
75%          67.000000       65.125000     13.000000     15.000000
max          90.200000       94.366667     89.863636     86.875000

         gk_kicking  gk_positioning   gk_reflexes  number_of_games
count  10582.000000    10582.000000  10582.000000     10582.000000
mean      21.530720       16.406330     16.718391        17.199301
std       16.293339       15.698238     16.795922         9.220732
min        3.260870        2.000000      2.000000         2.000000
25%       11.000000        9.312500      9.250000         9.000000
50%       15.422065       12.250000     12.222222        17.000000
75%       25.068391       15.000000     15.000000        24.000000
max       87.133333       91.625000     90.954545        96.000000
```

```
[8 rows x 39 columns]
```

In [50]:
```
# Reorganizing the columns order.
cols = useful_info.columns.tolist()
new_cols = cols[:4] + cols[-1:] + cols[4:-1]
useful_info = useful_info[new_cols]
useful_info.head()
```

Out[50]:
```
            player_name             birthday  height  weight  number_of_games  \
0  Aaron Appindangoye  1992-02-29 00:00:00  182.88     187              5.0
1     Aaron Cresswell  1989-12-15 00:00:00  170.18     146             33.0
2         Aaron Doran  1991-05-13 00:00:00  170.18     163             26.0
3       Aaron Galindo  1982-05-08 00:00:00  182.88     198             23.0
4        Aaron Hughes  1979-11-08 00:00:00  182.88     154             25.0

    age  overall_rating  potential   crossing  finishing     ...         \
0  26.0       63.600000  67.600000  48.600000  43.600000     ...
1  28.0       66.969697  74.484848  70.787879  49.454545     ...
2  27.0       67.000000  74.192308  68.115385  57.923077     ...
3  36.0       69.086957  70.782609  57.217391  26.260870     ...
4  38.0       73.240000  74.680000  45.080000  38.840000     ...

      vision  penalties    marking  standing_tackle  sliding_tackle  \
0  53.600000  47.600000  63.800000        66.000000       67.800000
1  57.454545  53.121212  69.393939        68.787879       71.515152
2  69.384615  60.538462  22.038462        21.115385       21.346154
3  53.782609  41.739130  70.608696        70.652174       68.043478
4  46.480000  52.960000  77.600000        76.040000       74.600000

   gk_diving  gk_handling  gk_kicking  gk_positioning  gk_reflexes
0   5.600000    10.600000    9.600000        7.600000     7.600000
1  12.181818     8.666667   14.242424       10.363636    12.909091
2  14.038462    11.807692   17.730769       10.115385    13.500000
3  14.173913    11.173913   22.869565       11.173913    10.173913
4   8.280000     8.320000   24.920000       12.840000    11.920000

[5 rows x 41 columns]
```

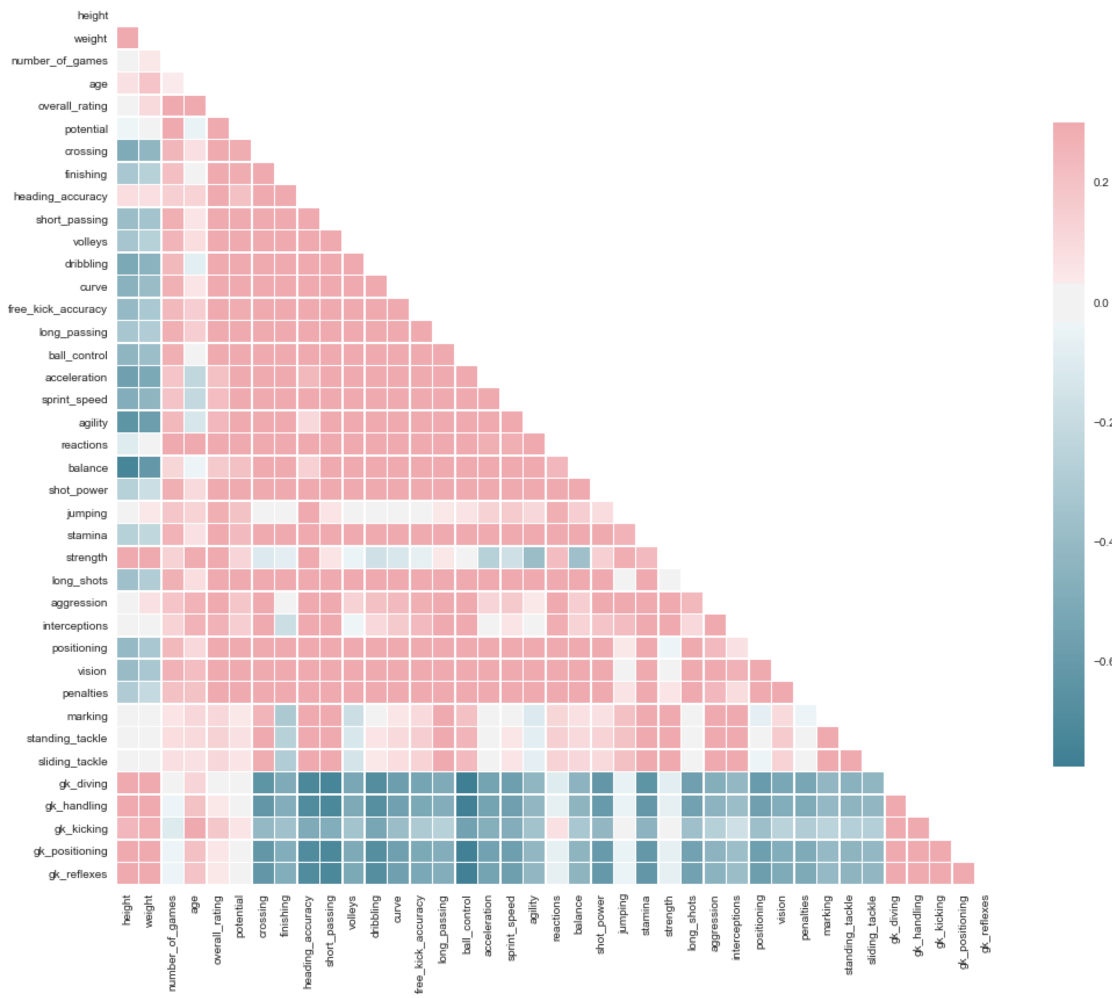
In [51]:
```
useful_info.hist(figsize=(25,25))
plt.show();
```




```
In [52]: sns.set(style="white")

         d = useful_info

         # Compute the correlation matrix
         corr = d.corr()

         # Generate a mask for the upper triangle
         mask = np.zeros_like(corr, dtype=np.bool)
         mask[np.triu_indices_from(mask)] = True

         # Set up the matplotlib figure
         f, ax = plt.subplots(figsize=(17, 17))
```

```python
# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .6})
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x1a14dce860>



> ## Observation #5:

1) Physical conditions like height and weight are important for goalkeepers.

2) The other players besides goalkeepers are rather better be short.

> ## Conclusions

Exploring the data

- Q1. I'd like to know how much more is home teams likely to win over away teams.
- **The possibility of winning for home teams is 46% in average. Home game appears to be a benefit to home teams.**
- Q2. Which country scores more in average per game?
- **Netherlands > Switzerland > Germany > Belgium > Spain > England > Scotland > Italy > Portugal > France > Poland**
- Q3. If a team played more games then do they score more, or the other way around?
- **The number of games played doesn't seem to be related to the scores they make in average.**
- Q4. Why some players have no games?
- **Inactive players are 8 years older than active ones in average.**
- Q5. Do Goalkeepers actually tend to be taller and bigger than other players?
- **Goalkeepers capabilities are hightly correlated to height and weight.**