Project: Investigate the 'Soccer Database' Dataset

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Introduction

Key notes:

"This soccer database comes from Kaggle and is well suited for data analysis and machine learning. It contains data for soccer matches, players, and teams from several European countries from 2008 to 2016. This dataset is quite extensive, and stored in a SQLite database".

Questions to explore:

- 1. What are the top 10 home team in terms of integral over time?
- 2. What are the top 10 away team in terms of integral over time?
- 3. What is the top 10 team points over time or in another term which 10 teams improved the most over the time period?
- 4. Best performance of home team in terms of win ratio by Season?
- 5. Best performance of away team in terms of win ratio by Season?
- 6. What is the disstribution of goal difference of home team and away team, respectively?
- 7. What team attributes lead to the most home_team victories?
- 8. Which players had the most penalties?
- 9. What is the relationship of vision and free_kick_accuracy?
- 10. What is the relationship of sprint_speed and acceleration?

Code used to generate CSV file for match in Mysql

with t1 as (select c.name country_name, l.name league_name, m.id match_id, m.date, m.season, m.stage, m.home_team_goal, m.away_team_goal, t1.defencepressure, t1.defencepressureclass, t1.defenceaggression, t1.defenceaggressionclass, t1.defenceteamwidth, t1.defenceteamwidthclass, t.team_short_name home_team_abbr, t.team_long_name home_team

```
from
country c
join league l
on c.id = l.country_id
join match m
on l.id = m.league_id
join team t
on m.home_team_api_id = t.team_api_id
join team_attributes t1
on t.team_api_id = t1.team_api_id
order by m.date desc),
```

t2 as (select m.id match_id, t.team_short_name away_team_abbr, t.team_long_name away_team from match m join team t on m.away_team_api_id = t.team_api_id)

select t1.*, t2.away_team_abbr, t2.away_team from t1 join t2 on t1.match_id = t2.match_id

In [1]:

```
# Set up import statements for all of the packages that are planed to use
# Include a 'magic word' so that visualizations are plotted
# call on dataframe to display the first 5 rows

import pandas as pd
import numpy as np
import datetime
from statistics import mode
% matplotlib inline
import matplotlib.pyplot as plt
%config InlineBackend.figure_format = 'retina'
import seaborn as sns
sns.set_style('darkgrid')
df = pd.read_csv('European Soccer Database.csv')
```

Data Wrangling

> **Key notes**: In this section of the report, the following work will be done: load the data; check for cleanliness; trim and clean dataset for analysis.

General Properties

In [2]:

```
# Load data and print out a few lines

df.head()
```

Out[2]:

	country_name	league_name	match_id	date	season	stage	home_team_goa
0	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
2	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
3	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
4	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0

In [3]:

```
# return a tuple of the dimensions of the dataframe

df.shape
```

Out[3]:

```
(142093, 18)
```

In [4]:

```
# print the column labels in the dataframe

for i, v in enumerate(df.columns):
    print(i, v)
```

```
0 country_name
1 league_name
2 match_id
3 date
4 season
5 stage
6 home_team_goal
7 away_team_goal
8 defencepressure
9 defencepressureclass
10 defenceaggression
11 defenceaggressionclass
12 defenceteamwidth
13 defenceteamwidthclass
14 home_team_abbr
15 home_team
16 t2.away_team_abbr
17 t2.away_team
```

In [5]:

```
# check for duplicates in the data

sum(df.duplicated())
```

Out[5]:

```
26746
```

In [6]:

```
#  check if any value is NaN in DataFrame and in how many columns

df.isnull().any().any(), sum(df.isnull().any())
```

Out[6]:

```
(False, 0)
```

In [7]:

```
# displays a concise summary of the dataframe
# including the number of non-null values in each column

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 142093 entries, 0 to 142092
Data columns (total 18 columns):
country_name              142093 non-null object
league_name               142093 non-null object
match_id                  142093 non-null int64
date                      142093 non-null object
season                    142093 non-null object
stage                     142093 non-null int64
home_team_goal            142093 non-null int64
away_team_goal            142093 non-null int64
defencepressure           142093 non-null int64
defencepressureclass      142093 non-null object
defenceaggression         142093 non-null int64
defenceaggressionclass    142093 non-null object
defenceteamwidth          142093 non-null int64
defenceteamwidthclass     142093 non-null object
home_team_abbr            142093 non-null object
home_team                 142093 non-null object
t2.away_team_abbr         142093 non-null object
t2.away_team              142093 non-null object
dtypes: int64(7), object(11)
memory usage: 19.5+ MB
```

In [8]:

```
# Generates descriptive statistics, excluding NaN values

df.describe()
```

Out[8]:

	match_id	stage	home_team_goal	away_team_goal	defencepres
count	142093.000000	142093.000000	142093.000000	142093.000000	142093.0000
mean	12766.872647	18.336554	1.573969	1.138079	46.550935
std	7488.593456	10.451842	1.308752	1.129731	10.321911
min	1.000000	1.000000	0.000000	0.000000	23.000000
25%	6283.000000	9.000000	1.000000	0.000000	39.000000
50%	12364.000000	18.000000	1.000000	1.000000	46.000000
75%	19391.000000	27.000000	2.000000	2.000000	53.000000
max	25979.000000	38.000000	10.000000	9.000000	72.000000

Data Cleaning

In [9]:

```
# drop duplicates
# confirm correction

df.drop_duplicates(inplace=True)
sum(df.duplicated())
```

Out[9]:

0

In [10]:

```
# Change column name into lower case for the convenience of analysis
# Confirm changes

df.rename(columns = lambda x: x.lower(), inplace = True)
df.head()
```

Out[10]:

	country_name	league_name	match_id	date	season	stage	home_team_goa
0	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
5	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
6	Switzerland	Switzerland Super League	25947	2016-05-25 00:00:00	2015/2016	36	2
7	Switzerland	Switzerland Super League	25947	2016-05-25 00:00:00	2015/2016	36	2

In [11]:

```
# Change some column name to avoid confusion
# Confirm changes

df.rename(columns = {'defencepressure': 'defence_pressure', 'defencepressureclas
s': 'defence_pressure_class',\
                     'defenceaggression': 'defence_aggression','defenceaggressio
nclass': \
                     'defence_aggression_class', 'defenceteamwidth': 'defencetea
m_width', \
                     'defenceteamwidthclass': 'defenceteam_width_class', 't2.awa
y_team_abbr':\
                     'away_team_abbr', 't2.away_team': 'away_team'}, inplace = T
rue)
df.head()
```

Out[11]:

	country_name	league_name	match_id	date	season	stage	home_team_goa
0	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
5	Switzerland	Switzerland Super League	25945	2016-05-25 00:00:00	2015/2016	36	0
6	Switzerland	Switzerland Super League	25947	2016-05-25 00:00:00	2015/2016	36	2
7	Switzerland	Switzerland Super League	25947	2016-05-25 00:00:00	2015/2016	36	2

In [12]:

```
# Fix datetime format
# Confirm changes

df.date = df.date.apply(pd.to_datetime, errors='coerce')
df.head()
```

Out[12]:

	country_name	league_name	match_id	date	season	stage	home_team_goal
0	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
5	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
6	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2
7	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2

In [13]:

```
# Add goals difference for home_team
# Confirm changes

home_diff = df.home_team_goal - df.away_team_goal
df['home_diff'] = home_diff
df.head()
```

Out[13]:

	country_name	league_name	match_id	date	season	stage	home_team_goal
0	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
5	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
6	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2
7	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2

In [14]:

```
# Add wins, draws, losses data for home team
# Confirm changes

home_wdl = []

for g in df.home_diff.tolist():
    if g > 0:
        home_wdl.append('w')
    elif g == 0:
        home_wdl.append('d')
    else:
        home_wdl.append('l')

df['home_wdl'] = np.array(home_wdl)

df.head()
```

Out[14]:

	country_name	league_name	match_id	date	season	stage	home_team_goal
0	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
5	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
6	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2
7	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2

In [15]:

```
# Add goals difference for away team
# Confirm changes

away_diff = df.away_team_goal - df.home_team_goal
df['away_diff'] = away_diff
df.head()
```

Out[15]:

	country_name	league_name	match_id	date	season	stage	home_team_goal
0	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
5	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
6	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2
7	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2

5 rows × 21 columns

In [16]:

```
# Add wins, draws, losses data for away team
# Confirm changes

away_wdl = []

for g in df.away_diff.tolist():
    if g > 0:
        away_wdl.append('w')
    elif g == 0:
        away_wdl.append('d')
    else:
        away_wdl.append('l')

df['away_wdl'] = np.array(away_wdl)

df.head()
```

Out[16]:

	country_name	league_name	match_id	date	season	stage	home_team_goal
0	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
1	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
5	Switzerland	Switzerland Super League	25945	2016-05-25	2015/2016	36	0
6	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2
7	Switzerland	Switzerland Super League	25947	2016-05-25	2015/2016	36	2

5 rows × 22 columns

In [17]:

```
# add score for home team, win = 3, draw = 1, lose = 0

home_score = []

for wdl in df.home_wdl:
    if wdl == 'w':
        home_score.append(3)
    elif wdl == 'd':
        home_score.append(1)
    else:
        home_score.append(0)

df['home_score'] = np.array(home_score)
```

In [18]:

```
# add score for away team, win = 3, draw = 1, lose = 0

away_score = []

for wdl in df.away_wdl:
    if wdl == 'w':
        away_score.append(3)
    elif wdl == 'd':
        away_score.append(1)
    else:
        away_score.append(0)

df['away_score'] = np.array(away_score)
```

In [19]:

```
# add win, draw and lose for home team, win = 1, draw = 0, lose = 0

home_win = []

for wdl in df.home_wdl:
    if wdl == 'w':
        home_win.append(1)
    elif wdl == 'd':
        home_win.append(0)
    else:
        home_win.append(0)

df['home_win'] = np.array(home_win)
```

In [20]:

```
# add win, draw and lose for home team, draw = 0, lose = 0

away_win = []

for wdl in df.away_wdl:
    if wdl == 'w':
        away_win.append(1)
    elif wdl == 'd':
        away_win.append(0)
    else:
        away_win.append(0)

df['away_win'] = np.array(away_win)
```

In [21]:

```
# return a tuple of the dimensions of the dataframe

df.shape
```

Out[21]:

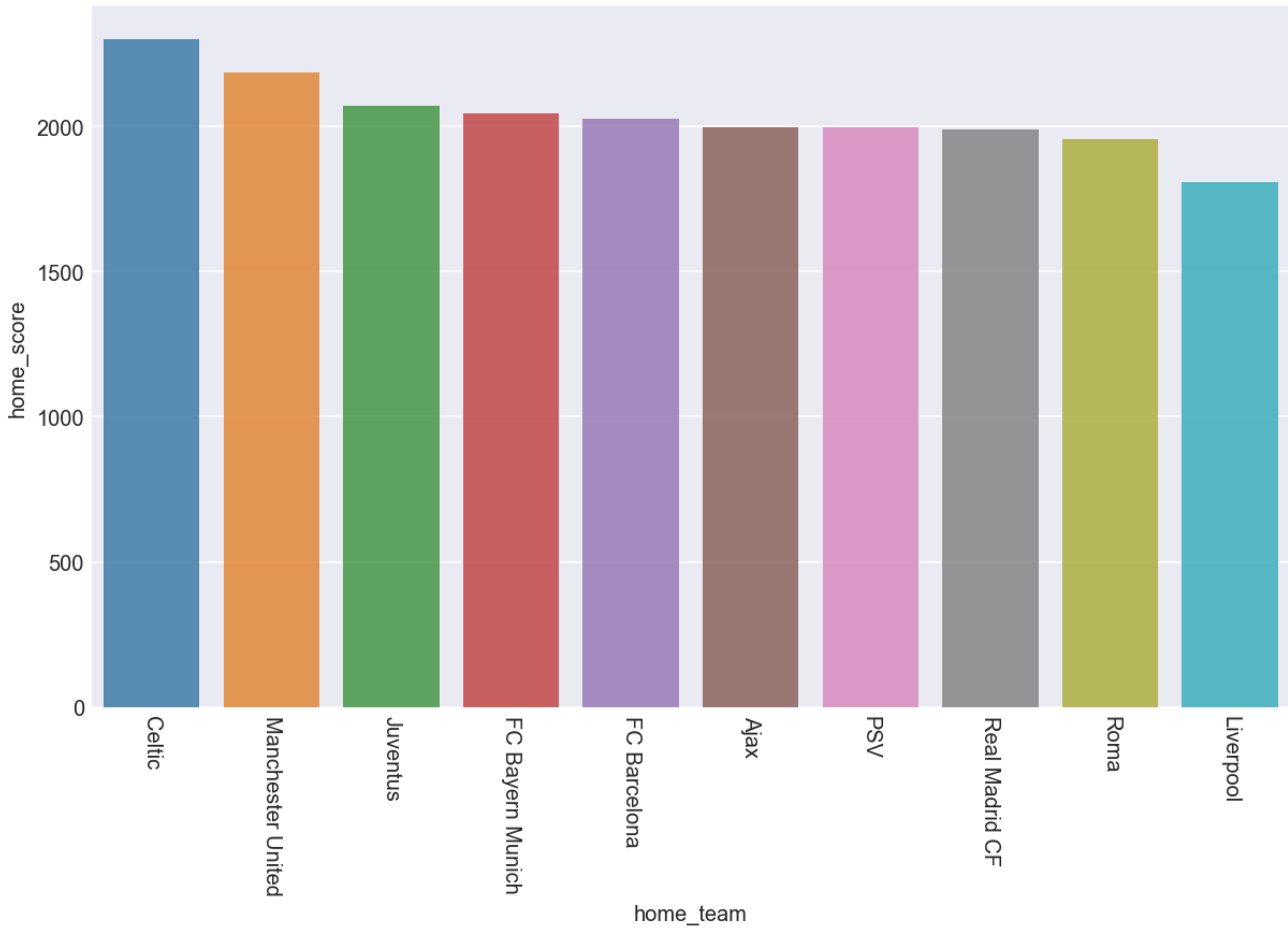
```
(115347, 26)
```

Exploratory Data Analysis

Research Question 1: What are the top 10 home team in terms of integral over time?

In [22]:

```
# Groupby of home team and home team integral

home_team_score = df.groupby(['home_team'])['home_score'].sum()

# Find the top 10

home_team_score_10 = home_team_score.nlargest(n = 10)

# Plot

plt.subplots(figsize=(10,6))

plt.xticks(rotation=-90)

sns.barplot(home_team_score_10.index, home_team_score_10, alpha=0.8);
```

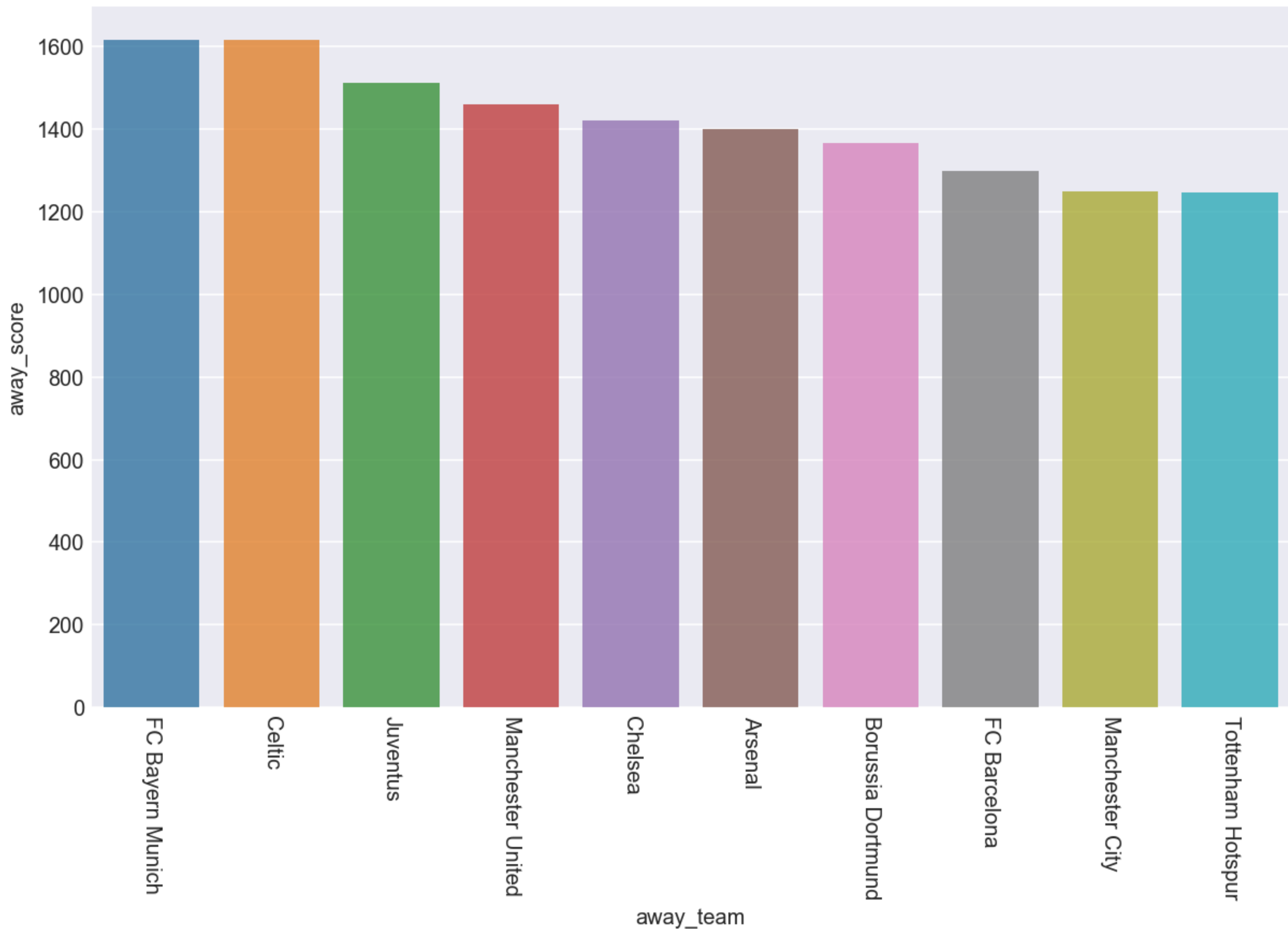


According to histogram above is the top 10 home team in terms of integral, with Celtic be the best over time.

Research Question 2: What are the top 10 away team in terms of integral over time?

In [23]:

```
# Groupby of home team and home team accumulated score

away_team_score = df.groupby(['away_team'])['away_score'].sum()

# Find the top 10

away_team_score_10 = away_team_score.nlargest(n = 10)

# Plot

plt.subplots(figsize=(10,6))

plt.xticks(rotation=-90)

sns.barplot(away_team_score_10.index, away_team_score_10, alpha=0.8);
```



According to histogram above is the top 10 away team in terms of integral, with FC Bayern Munich be the best over time.

Research Question 3: What is the top 10 team points over time or in another term which 10 teams improved the most over the time period?

In [24]:

```
home_team_score.index
```

Out[24]:

```
Index(['1. FC Kaiserslautern', '1. FC Köln', '1. FC Nürnberg',
       '1. FSV Mainz 05', 'AC Ajaccio', 'AC Arles-Avignon', 'AC Bell
inzona',
       'ADO Den Haag', 'AJ Auxerre', 'AS Monaco',
       ...
       'Widzew Łódź', 'Wigan Athletic', 'Willem II', 'Wisła Kraków',
       'Wolverhampton Wanderers', 'Xerez Club Deportivo', 'Zagłębie
Lubin',
       'Zawisza Bydgoszcz', 'Évian Thonon Gaillard FC', 'Śląsk Wrocł
aw'],
      dtype='object', name='home_team', length=285)
```

In [25]:

```
away_team_score.index
```

Out[25]:

```
Index(['1. FC Kaiserslautern', '1. FC Köln', '1. FC Nürnberg',
       '1. FSV Mainz 05', 'AC Ajaccio', 'AC Arles-Avignon', 'AC Bell
inzona',
       'ADO Den Haag', 'AJ Auxerre', 'AS Monaco',
       ...
       'Widzew Łódź', 'Wigan Athletic', 'Willem II', 'Wisła Kraków',
       'Wolverhampton Wanderers', 'Xerez Club Deportivo', 'Zagłębie
Lubin',
       'Zawisza Bydgoszcz', 'Évian Thonon Gaillard FC', 'Śląsk Wrocł
aw'],
      dtype='object', name='away_team', length=296)
```

In [26]:

```
# Check index difference
# away_team_score.index - home_team_score.index

ind_diff = away_team_score.index.difference(home_team_score.index)
diff = pd.Series(index = ind_diff)
```

In [27]:

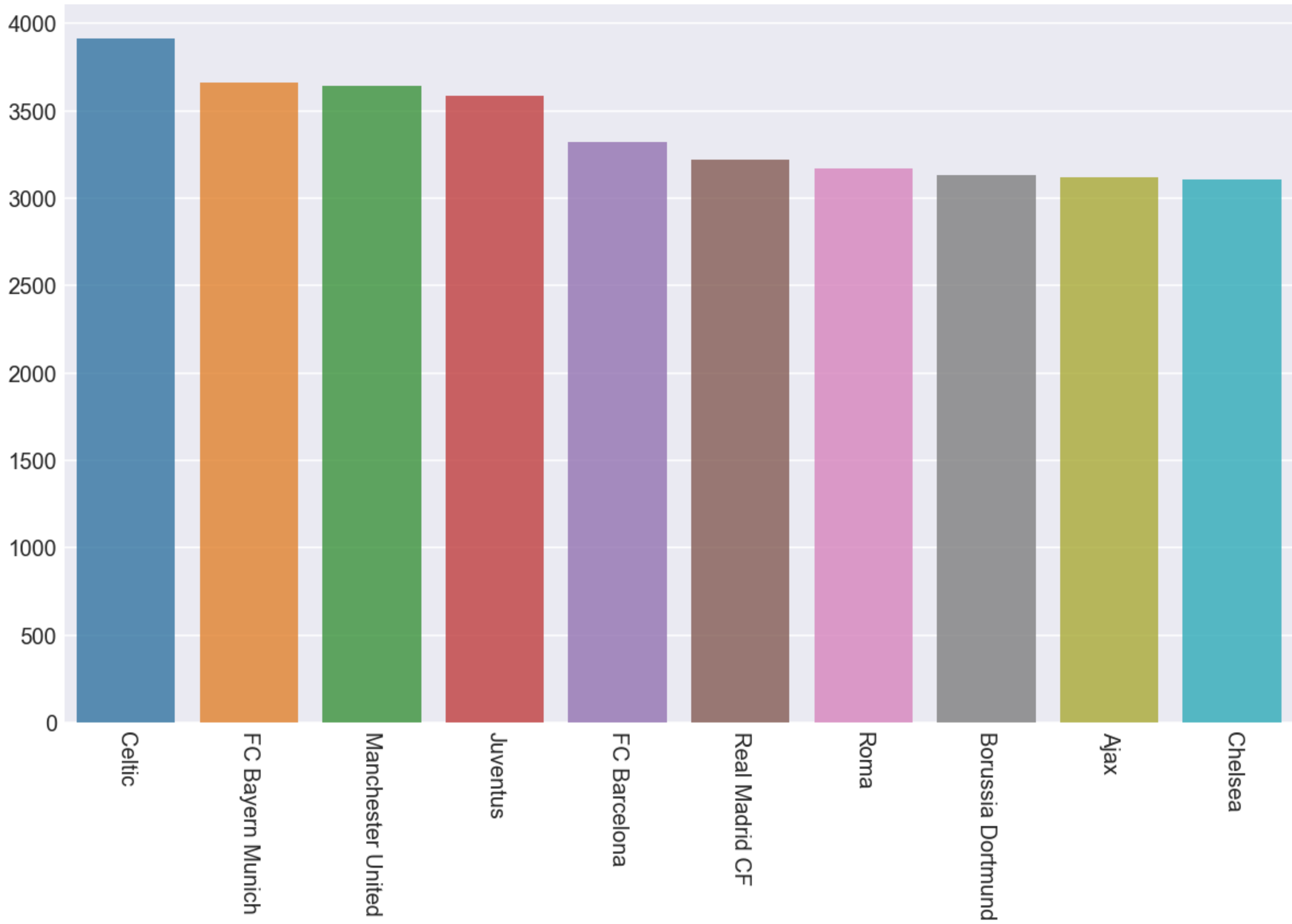
```
#home_team_score.fillna(0, inplace=True)

home_team_score.append(diff).head()
```

Out[27]:

```
1. FC Kaiserslautern     210.0
1. FC Köln               635.0
1. FC Nürnberg           666.0
1. FSV Mainz 05         1164.0
AC Ajaccio               201.0
dtype: float64
```

In [28]:

```
# total score

team_total_score =    away_team_score + home_team_score

# Find the top 10

team_total_score_10 = team_total_score.nlargest(n = 10)

# Plot

plt.subplots(figsize=(10,6))

plt.xticks(rotation=-90)

sns.barplot(team_total_score_10.index, team_total_score_10, alpha=0.8);
```



In [29]:

```
# matchscore2 = pd.ExcelWriter('matchscore2.xlsx', engine='xlsxwriter')
# away_team_score.to_excel(matchscore2,'Sheet1')
# home_team_score.to_excel(matchscore2,'Sheet2')
# team_total_score.to_excel(matchscore2,'Sheet3')
# matchscore2.save()
```

Research Question 4: Best performance of home team in terms of win ratio by Season?

In [30]:

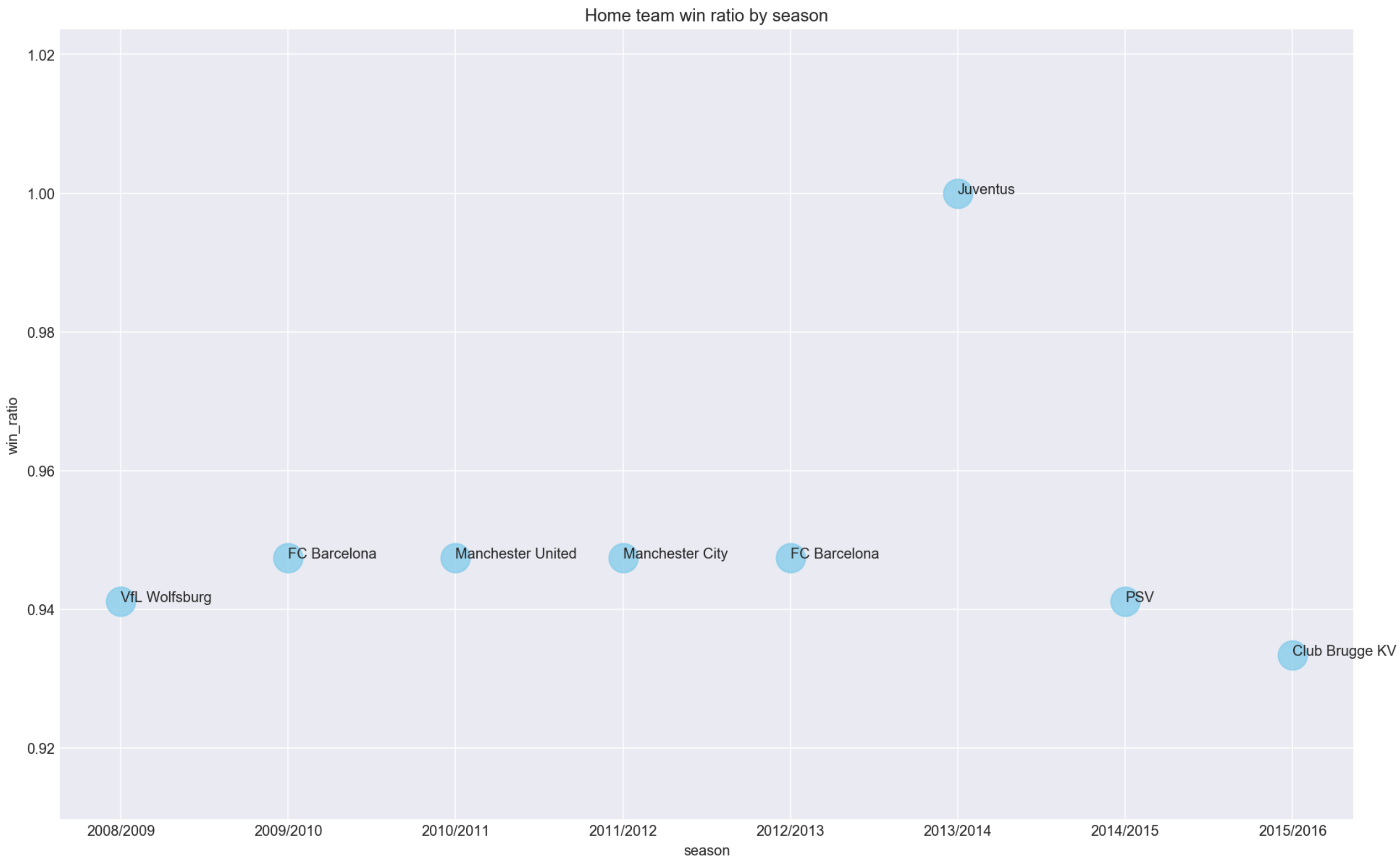
```
# Convert w,d,l into numbers as 1, 0, 0

df1 = df.copy()

df1['home_wdl'].replace(['w'], 1, inplace = True)
df1['home_wdl'].replace(['l', 'd'], 0, inplace = True)

# Calculate win ratio home team

home_win_ratio = df1.groupby(['season', 'home_team'])['home_wdl'].sum()\
/df1.groupby(['season', 'home_team'])['home_wdl'].count()
```

In [31]:

```
# Creating a new dataframe and fill respective coulumns with season, home_team,
win_ratio accordingly

home_win_ratio.index.levels[0]
topteam1 = pd.DataFrame(columns=['season','home_team','win_ratio'])
season1=[]
home_team1=[]
win_ratio1=[]

for ind in home_win_ratio.index.levels[0]:
    for i in range(0,1):
        season1.append(ind)
        home_team1.append(home_win_ratio.loc[ind].sort_values(ascending=False).i
ndex[i])
        win_ratio1.append(home_win_ratio.loc[ind].sort_values(ascending=False).v
alues[i])

topteam1['season'] = season1
topteam1['home_team'] = home_team1
topteam1['win_ratio'] = win_ratio1
```

In [32]:

```
plt.figure(figsize=(16,10))
p1=sns.regplot(data=topteam1, x="season", y="win_ratio", fit_reg=False, marker="
o", color="skyblue", scatter_kws={'s':400})



plt.title('Home team win ratio by season')
# Set x-axis label
plt.xlabel('season')
# Set y-axis label
plt.ylabel('win_ratio')

def label_point(x, y, val, ax):
    a = pd.concat({'x': x, 'y': y, 'val': val}, axis=1)
    for i, point in a.iterrows():
        ax.text(point['x'], point['y'], str(point['val']))


label_point(topteam1.season, topteam1.win_ratio,topteam1.home_team, plt.gca())
```



Research Question 5: Best performance of away team in terms of win ratio by Season?

In [33]:

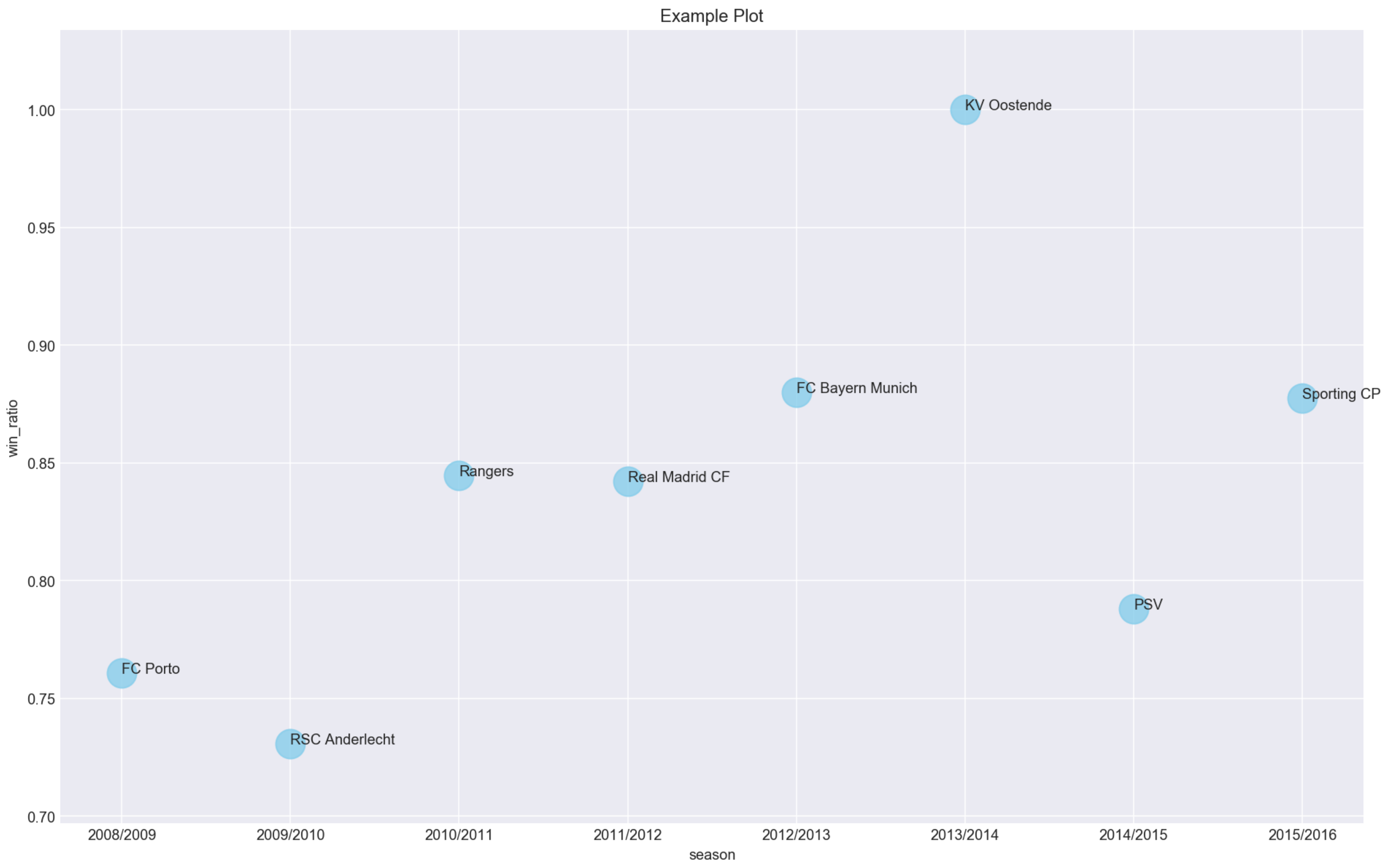
```
# Same steps as for home team




df1['away_wdl'].replace(['w'], 1, inplace = True)
df1['away_wdl'].replace(['l', 'd'], 0, inplace = True)

# Calculate win ratio home team

away_win_ratio = df1.groupby(['season', 'away_team'])['away_wdl'].sum()\
/df1.groupby(['season', 'away_team'])['away_wdl'].count()
```

In [34]:

```
# Creating a new dataframe and fill respective coulumns with season, home_team,
win_ratio accordingly

away_win_ratio.index.levels[0]
away_topteam1 = pd.DataFrame(columns=['season','home_team','win_ratio'])
away_season1=[]
away_team1=[]
away_win_ratio1=[]

for ind in away_win_ratio.index.levels[0]:
    for i in range(0,1):
        away_season1.append(ind)
        away_team1.append(away_win_ratio.loc[ind].sort_values(ascending=False).i
ndex[i])
        away_win_ratio1.append(away_win_ratio.loc[ind].sort_values(ascending=Fal
se).values[i])

away_topteam1['season'] = away_season1
away_topteam1['away_team'] = away_team1
away_topteam1['win_ratio'] = away_win_ratio1
```

In [35]:

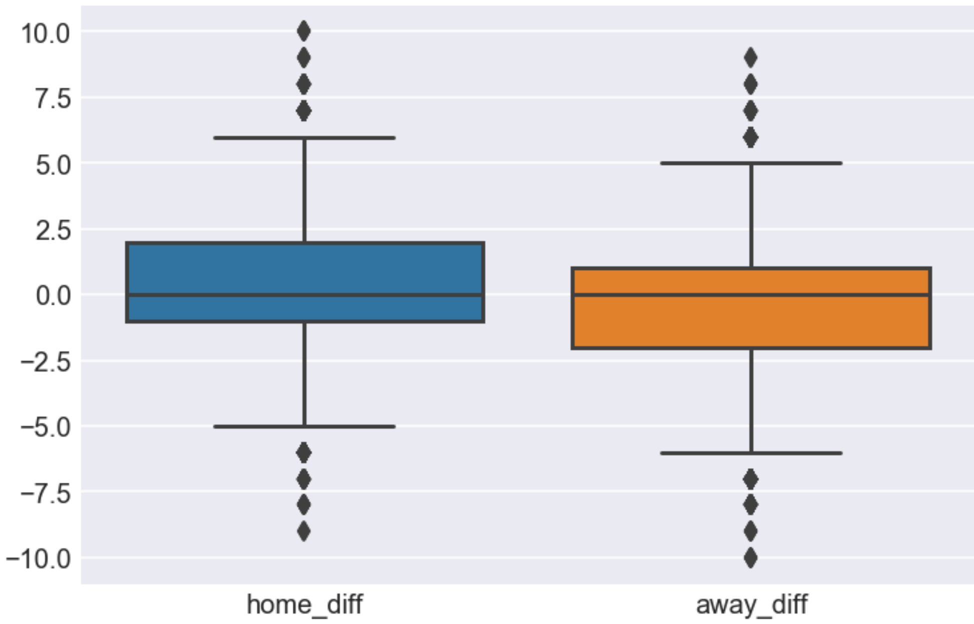
```
plt.figure(figsize=(16,10))
p1=sns.regplot(data=away_topteam1, x="season", y="win_ratio", fit_reg=False, mar
ker="o", color="skyblue", scatter_kws={'s':400})



plt.title('Example Plot')
# Set x-axis label
plt.xlabel('season')
# Set y-axis label
plt.ylabel('win_ratio')

def label_point1(x, y, val, ax):
    b = pd.concat({'x': x, 'y': y, 'val': val}, axis=1)
    for i, point in b.iterrows():
        ax.text(point['x'], point['y'], str(point['val']))


label_point1(away_topteam1.season, away_topteam1.win_ratio,away_topteam1.away_te
am, plt.gca())
```



Research Question 6: What is the disstribution of goal difference of home team and away team, respectively?

In [36]:

```
# boxplot

sns.boxplot(data=df.loc[:,'home_diff':'away_diff']);
```



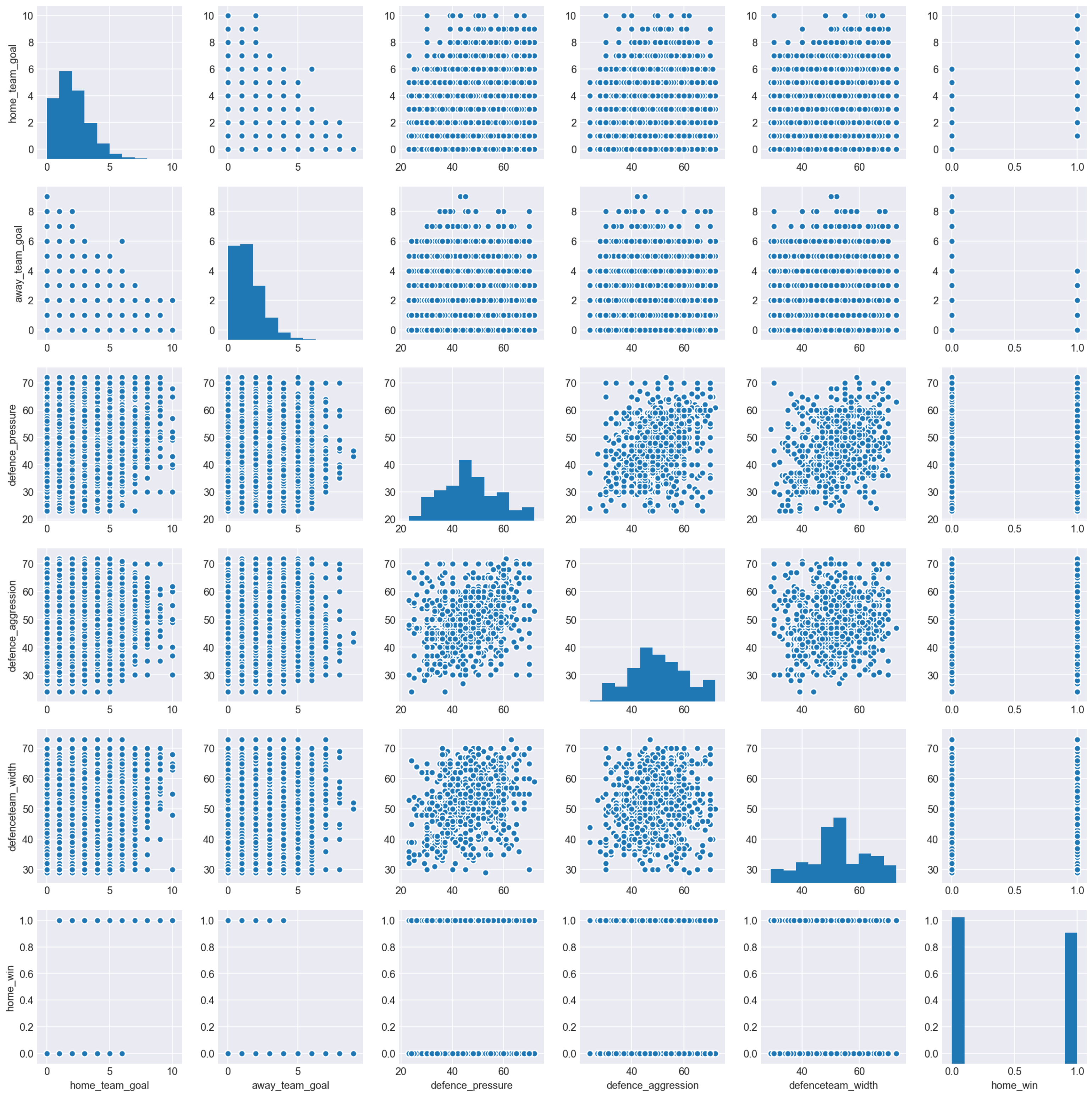
Research Question 7: What team attributes lead to the most home_team victories?

In [37]:

```
df_vct = df.copy()

df_vct.drop(df_vct.columns[np.r_[0:6, 9, 11, 13, 14:24, 25]], axis=1, inplace = True)
```

In [38]:

```
sns.pairplot(df_vct);
```



> According to the result, home team goal number and away team goal number are positively and negatively correlated with home_team victories, respectively.

Code used to generte CSV file for player in Mysql

select player_id, p.player_name, p.birthday, p.height, p.weight, pa.*

```
from player p join player_attributes pa
ON
p.player_api_id = pa.player_api_id
```

Data Wrangling

> **Key notes**: In this section of the report, the following work will be done: load the data; check for cleanliness; trim and clean dataset for analysis.

General Properties

In [39]:

```
# Load data and print out a few lines

df2 = pd.read_csv('European Soccer Database_Player.csv')

df2.head()
```

Out[39]:

	player_id	player_name	birthday	height	weight	id	player_fifa_api_id	player_api_i
0	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	1	218353	505942
1	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	2	218353	505942
2	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	3	218353	505942
3	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	4	218353	505942
4	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	5	218353	505942

5 rows × 47 columns

In [40]:

```
# return a tuple of the dimensions of the dataframe

df2.shape
```

Out[40]:

```
(183978, 47)
```

In [41]:

```
# print the column labels in the dataframe

for i, v in enumerate(df2.columns):
    print(i, v)
```

```
0 player_id
1 player_name
2 birthday
3 height
4 weight
5 id
6 player_fifa_api_id
7 player_api_id
8 date
9 overall_rating
10 potential
11 preferred_foot
12 attacking_work_rate
13 defensive_work_rate
14 crossing
15 finishing
16 heading_accuracy
17 short_passing
18 volleys
19 dribbling
20 curve
21 free_kick_accuracy
22 long_passing
23 ball_control
24 acceleration
25 sprint_speed
26 agility
27 reactions
28 balance
29 shot_power
30 jumping
31 stamina
32 strength
33 long_shots
34 aggression
35 interceptions
36 positioning
37 vision
38 penalties
39 marking
40 standing_tackle
41 sliding_tackle
42 gk_diving
43 gk_handling
44 gk_kicking
45 gk_positioning
46 gk_reflexes
```

In [42]:

```
# return the datatypes of the columns

df2.dtypes
```

Out[42]:

```
player_id                int64
player_name             object
birthday                object
height                 float64
weight                   int64
id                       int64
player_fifa_api_id       int64
player_api_id            int64
date                    object
overall_rating         float64
potential              float64
preferred_foot          object
attacking_work_rate     object
defensive_work_rate     object
crossing               float64
finishing              float64
heading_accuracy       float64
short_passing          float64
volleys                float64
dribbling              float64
curve                  float64
free_kick_accuracy     float64
long_passing           float64
ball_control           float64
acceleration           float64
sprint_speed           float64
agility                float64
reactions              float64
balance                float64
shot_power             float64
jumping                float64
stamina                float64
strength               float64
long_shots             float64
aggression             float64
interceptions          float64
positioning            float64
vision                 float64
penalties              float64
marking                float64
standing_tackle        float64
sliding_tackle         float64
gk_diving              float64
gk_handling            float64
gk_kicking             float64
gk_positioning         float64
gk_reflexes            float64
dtype: object
```

In [43]:

```
# check for duplicates in the data

sum(df2.duplicated())
```

Out[43]:

```
0
```

In [44]:

```
#  check if any value is NaN in DataFrame and in how many columns

df2.isnull().any().any(), sum(df2.isnull().any())
```

Out[44]:

```
(True, 38)
```

In [45]:

```
# displays a concise summary of the dataframe
# including the number of non-null values in each column

df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183978 entries, 0 to 183977
Data columns (total 47 columns):
player_id              183978 non-null int64
player_name            183978 non-null object
birthday               183978 non-null object
height                 183978 non-null float64
weight                 183978 non-null int64
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(36), int64(5), object(6)
memory usage: 66.0+ MB
```

In [46]:

```
# Generates descriptive statistics, excluding NaN values

df2.describe()
```

Out[46]:

	player_id	height	weight	id	player_fifa_api_id
count	183978.000000	183978.000000	183978.000000	183978.00000	183978.000000
mean	5520.197785	181.878872	168.776245	91989.50000	165671.524291
std	3191.425870	6.394818	15.088920	53110.01825	53851.094769
min	1.000000	157.480000	117.000000	1.00000	2.000000
25%	2754.000000	177.800000	159.000000	45995.25000	155798.000000
50%	5532.000000	182.880000	168.000000	91989.50000	183488.000000
75%	8256.000000	185.420000	179.000000	137983.75000	199848.000000
max	11075.000000	208.280000	243.000000	183978.00000	234141.000000

8 rows × 41 columns

Data Cleaning

In [47]:

```
# Drop useless columns

df2.drop(['date', 'player_fifa_api_id', 'player_api_id'], axis=1, inplace = True
)

# Confirm changes

df2.head()
```

Out[47]:

	player_id	player_name	birthday	height	weight	id	overall_rating	potential	prefe
0	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	1	67.0	71.0	right
1	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	2	67.0	71.0	right
2	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	3	62.0	66.0	right
3	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	4	61.0	65.0	right
4	1	Aaron Appindangoye	1992-02-29 00:00:00	182.88	187	5	61.0	65.0	right

5 rows × 44 columns

In [48]:

```
# Convert string into datatime format in df2

df2.birthday = pd.to_datetime(df2['birthday'], errors='coerce')
```

In [49]:

```
# Check which columns contain NaN values

df2.isnull().any()
```

Out[49]:

```
player_id              False
player_name            False
birthday               False
height                 False
weight                 False
id                     False
overall_rating          True
potential               True
preferred_foot          True
attacking_work_rate     True
defensive_work_rate     True
crossing                True
finishing               True
heading_accuracy        True
short_passing           True
volleys                 True
dribbling               True
curve                   True
free_kick_accuracy      True
long_passing            True
ball_control            True
acceleration            True
sprint_speed            True
agility                 True
reactions               True
balance                 True
shot_power              True
jumping                 True
stamina                 True
strength                True
long_shots              True
aggression              True
interceptions           True
positioning             True
vision                  True
penalties               True
marking                 True
standing_tackle         True
sliding_tackle          True
gk_diving               True
gk_handling             True
gk_kicking              True
gk_positioning          True
gk_reflexes             True
dtype: bool
```

In [50]:

```
# Fill numerical type of NaN values with mean

col = df2.iloc[:, np.r_[6, 7, 11:44]].columns

for c in col:
    c_mean = df2[c].mean()
    df2[c].fillna(c_mean, inplace = True)
```

In [51]:

```
# Replace the all string type of NaN in df with 'No Record'

df2.fillna('No record', inplace = True)

# Confirm changes

df2.isnull().any().any()
```

Out[51]:

```
False
```

Exploratory Data Analysis

Research Question 8: Which players had the most penalties?

In [52]:

```
# Find the index of player who had the most penalties

df2.penalties.idxmax()
```

Out[52]:

```
149591
```

In [53]:

```
# Print out the complete info

df2.iloc[149591]
```

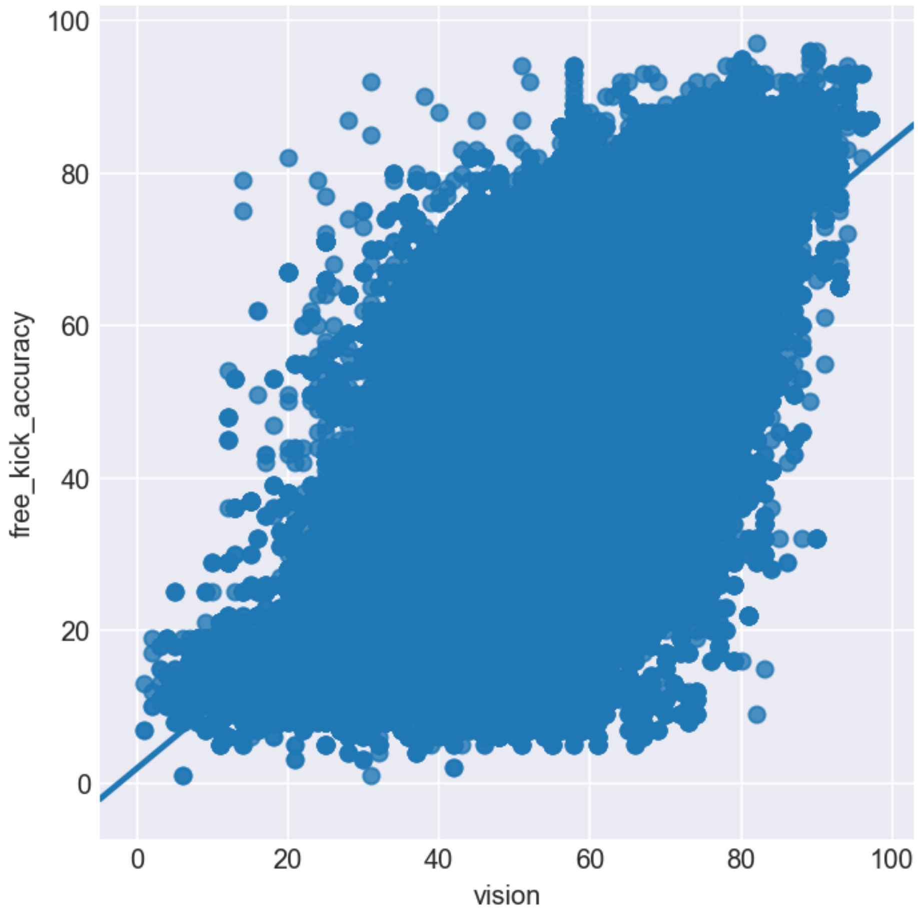
```
Out[53]:

player_id                                 8981
player_name                     Rickie Lambert
birthday                   1982-02-16 00:00:00
height                                  187.96
weight                                     170
id                                      149592
overall_rating                              75
potential                                   75
preferred_foot                           right
attacking_work_rate                       high
defensive_work_rate                     medium
crossing                                    67
finishing                                   81
heading_accuracy                            84
short_passing                               66
volleys                                     72
dribbling                                   65
curve                                       77
free_kick_accuracy                          84
long_passing                                72
ball_control                                75
acceleration                                48
sprint_speed                                46
agility                                     57
reactions                                   76
balance                                     59
shot_power                                  85
jumping                                     71
stamina                                     65
strength                                    85
long_shots                                  74
aggression                                  76
interceptions                               32
positioning                                 79
vision                                      77
penalties                                   96
marking                                     30
standing_tackle                             26
sliding_tackle                              19
gk_diving                                   13
gk_handling                                 15
gk_kicking                                   7
gk_positioning                              16
gk_reflexes                                 11
Name: 149591, dtype: object
```

Player 'Rickie Lambert' had the most penalties over time.

Research Question 9: What is the relationship of vision and free_kick_accuracy?

In [54]:

```
sns.lmplot(x='vision', y='free_kick_accuracy', data=df2);
```

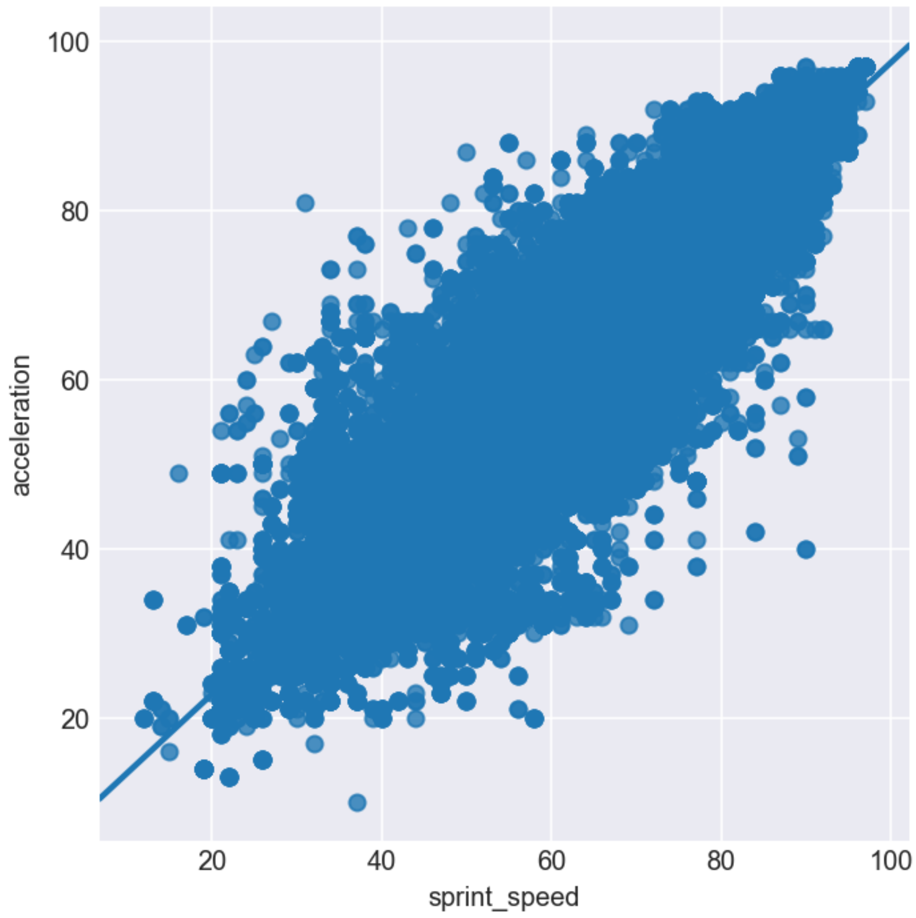


> The relationship of vision and free_kick_accuracy is positively correlated, The estimated linear regression is shown as the blue line, the estimates varies in the light blue shade with 95% confident level.

Research Question 10: What is the relationship of sprint_speed and acceleration?

In [55]:

```
sns.lmplot(x='sprint_speed', y='acceleration', data=df2);
```



The relationship of sprint_speed and acceleration is positively correlated, The estimated linear regression is shown as the blue line, the estimates varies in the light blue shade with 95% confident level.

Conclusions

In current study, a good amount of profound analysis has been carried out. Prior to each step, deailed instructions was given and interpretions was also provided afterwards. The two dataset included 115347 and 183978 pieces of european soccer match information ranging from 2008 to 2016, respectively. Based on such substantial data, the analysis would be more reliable as opposed to small scale analysis.

The limitations of current study were original data from website hadn't been organized well, as many tables were connected via foreign to foreign key relation. More important, there was no key paired for match and player information. As such, profound analysis was inadmissible, such as player attributes's impact on match.

In [56]:

```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_the_Soccer_Database_Dataset_2018
0108.ipynb'])
```

Out[56]:

0