Investigate_a_Dataset

June 15, 2022

1 Project: Investigate a Dataset - [European Football Database]

1.1 Table of Contents

1.1.1 Dataset Description

I will be performing an analysis on the European Football dataset gotten from Kaggle, this data set contains match information about 25979 games, players, and teams from several European countries from 2008 to 2016.

1.1.2 Some of the questions that will be answered through the analysis of this dataset include:

What is the most likely occurence in a game between(Home win, away win or draw)?

What teams have had the most wins over the time period?

What is the average goal scored per game in the european leagues?

Which teams conceeded the most goals within the period ?

Which of the top five european leagues is the most competitive?

In [1]:
```
# Use this cell to set up import statements for all of the packages that you
#   plan to use.

# Remember to include a 'magic word' so that your visualizations are plotted
#   inline with the notebook. See this page for more:
#   http://ipython.readthedocs.io/en/stable/interactive/magics.html


import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
%matplotlib inline
```

Data Wrangling

In this section of the report, I will be making observations about the dataset by performing operations to view available files, note features present in each file, inspect data types and look for instances of missing and duplicate data.

```
In [5]: # Get file names from directory
        import os
        def fn():
            file_list=os.listdir(r"Database_Soccer/")
            print (file_list)
        fn()
```

```
['Match.csv', 'Player_Attributes.csv', 'Country.csv', 'Team_Attributes.csv', 'sqlite_sequence.cs
```

```
In [ ]: # Upgrade pandas to use dataframe.explode() function.
        !pip install --upgrade pandas==0.25.2
```

```
In [2]: # Access the various dataframes
        match_df = pd.read_csv('Database_Soccer/Match.csv')
        player_df = pd.read_csv('Database_Soccer/Player.csv')
        player_att_df = pd.read_csv('Database_Soccer/Player_Attributes.csv')
        country_df = pd.read_csv('Database_Soccer/Country.csv')
        team_df = pd.read_csv('Database_Soccer/Team.csv')
        team_att_df = pd.read_csv('Database_Soccer/Team_Attributes.csv')
        seq_df = pd.read_csv('Database_Soccer/sqlite_sequence.csv')
        league_df = pd.read_csv('Database_Soccer/League.csv')
```

Match

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

```
Out[7]: (25979, 115)
```

```
In [8]: match_df.head(3)
```

```
Out[8]:    id  country_id  league_id     season  stage                 date  \
        0   1           1          1  2008/2009      1  2008-08-17 00:00:00
        1   2           1          1  2008/2009      1  2008-08-16 00:00:00
        2   3           1          1  2008/2009      1  2008-08-16 00:00:00

           match_api_id  home_team_api_id  away_team_api_id  home_team_goal  ...   \
        0        492473              9987              9993               1  ...
        1        492474             10000              9994               0  ...
        2        492475              9984              8635               0  ...

           SJA   VCH   VCD   VCA   GBH   GBD   GBA   BSH   BSD   BSA
        0  4.0  1.65  3.40  4.50  1.78  3.25  4.00  1.73  3.40  4.20
        1  3.8  2.00  3.25  3.25  1.85  3.25  3.75  1.91  3.25  3.60
        2  2.5  2.35  3.25  2.65  2.50  3.20  2.50  2.30  3.20  2.75

        [3 rows x 115 columns]
```

```
In [9]: # Check data types
        match_df.dtypes
```

```
Out[9]: id                   int64
        country_id           int64
        league_id            int64
        season              object
        stage                int64
        date                object
        match_api_id         int64
        home_team_api_id     int64
        away_team_api_id     int64
        home_team_goal       int64
        away_team_goal       int64
        home_player_X1     float64
        home_player_X2     float64
        home_player_X3     float64
        home_player_X4     float64
        home_player_X5     float64
        home_player_X6     float64
        home_player_X7     float64
        home_player_X8     float64
        home_player_X9     float64
        home_player_X10    float64
        home_player_X11    float64
        away_player_X1     float64
        away_player_X2     float64
        away_player_X3     float64
        away_player_X4     float64
        away_player_X5     float64
        away_player_X6     float64
        away_player_X7     float64
        away_player_X8     float64
                             ...
        B365H              float64
        B365D              float64
        B365A              float64
        BWH                float64
        BWD                float64
        BWA                float64
        IWH                float64
        IWD                float64
        IWA                float64
        LBH                float64
        LBD                float64
        LBA                float64
        PSH                float64
        PSD                float64
```

```
PSA                 float64
WHH                 float64
WHD                 float64
WHA                 float64
SJH                 float64
SJD                 float64
SJA                 float64
VCH                 float64
VCD                 float64
VCA                 float64
GBH                 float64
GBD                 float64
GBA                 float64
BSH                 float64
BSD                 float64
BSA                 float64
Length: 115, dtype: object
```

```
In [10]: #View available columns in the match dataframe
         cols = match_df.columns
         print(*cols)
```

```
id country_id league_id season stage date match_api_id home_team_api_id away_team_api_id home_te
```

```
In [4]: # check for null rows
        match_df.isnull().sum()
```

```
Out[4]: id                     0
        country_id             0
        league_id              0
        season                 0
        stage                  0
        date                   0
        match_api_id           0
        home_team_api_id       0
        away_team_api_id       0
        home_team_goal         0
        away_team_goal         0
        home_player_X1      1821
        home_player_X2      1821
        home_player_X3      1832
        home_player_X4      1832
        home_player_X5      1832
        home_player_X6      1832
        home_player_X7      1832
        home_player_X8      1832
        home_player_X9      1832
        home_player_X10     1832
```

```
home_player_X11      1832
away_player_X1       1832
away_player_X2       1832
away_player_X3       1832
away_player_X4       1832
away_player_X5       1832
away_player_X6       1832
away_player_X7       1832
away_player_X8       1832
                     ...
B365H                3387
B365D                3387
B365A                3387
BWH                  3404
BWD                  3404
BWA                  3404
IWH                  3459
IWD                  3459
IWA                  3459
LBH                  3423
LBD                  3423
LBA                  3423
PSH                 14811
PSD                 14811
PSA                 14811
WHH                  3408
WHD                  3408
WHA                  3408
SJH                  8882
SJD                  8882
SJA                  8882
VCH                  3411
VCD                  3411
VCA                  3411
GBH                 11817
GBD                 11817
GBA                 11817
BSH                 11818
BSD                 11818
BSA                 11818
Length: 115, dtype: int64
```

In [12]:
```
def perc_miss(df):
    '''Return sorted dataframe showing percentage of missing values in given data'''
    percent_missing = df.isnull().sum() * 100 / len(df)
    missing_value_df = pd.DataFrame({'column_name': df.columns,
                                     'percent_missing': percent_missing})
```

```
        missing_value_df.sort_values('percent_missing',ascending= False, inplace=True)

        return missing_value_df
```

In [13]:
```
# Percentage of missing rows in match data
perc_miss(match_df)
```

Out[13]:

	column_name	percent_missing
PSD	PSD	57.011432
PSA	PSA	57.011432
PSH	PSH	57.011432
BSA	BSA	45.490589
BSH	BSH	45.490589
BSD	BSD	45.490589
GBA	GBA	45.486739
GBD	GBD	45.486739
GBH	GBH	45.486739
shotoff	shotoff	45.275030
goal	goal	45.275030
shoton	shoton	45.275030
possession	possession	45.275030
corner	corner	45.275030
cross	cross	45.275030
card	card	45.275030
foulcommit	foulcommit	45.275030
SJH	SJH	34.189153
SJD	SJD	34.189153
SJA	SJA	34.189153
IWD	IWD	13.314600
IWA	IWA	13.314600
IWH	IWH	13.314600
LBH	LBH	13.176027
LBD	LBD	13.176027
LBA	LBA	13.176027
VCA	VCA	13.129836
VCD	VCD	13.129836
VCH	VCH	13.129836
WHA	WHA	13.118288
...	...	...
home_player_10	home_player_10	5.527541
away_player_8	away_player_8	5.161862
away_player_5	away_player_5	5.138766
away_player_9	away_player_9	5.111821
home_player_6	home_player_6	5.100273
home_player_4	home_player_4	5.092575
away_player_4	away_player_4	5.084876
home_player_5	home_player_5	5.065630
home_player_2	home_player_2	5.061781

```
away_player_6        away_player_6         5.054082
home_player_8        home_player_8         5.038685
away_player_3        away_player_3         4.977097
home_player_3        home_player_3         4.930906
away_player_2        away_player_2         4.919358
home_player_9        home_player_9         4.900112
away_player_7        away_player_7         4.753840
away_player_1        away_player_1         4.749990
home_player_7        home_player_7         4.723046
home_player_1        home_player_1         4.711498
match_api_id          match_api_id         0.000000
league_id                league_id         0.000000
season                     season         0.000000
stage                       stage         0.000000
date                         date         0.000000
home_team_goal      home_team_goal         0.000000
home_team_api_id  home_team_api_id         0.000000
away_team_api_id  away_team_api_id         0.000000
away_team_goal      away_team_goal         0.000000
country_id              country_id         0.000000
id                             id          0.000000

[115 rows x 2 columns]
```

```
In [14]: # count of duplicate
         match_df.duplicated().sum()
```

```
Out[14]: 0
```

```
In [15]: # count of match weeks
         match_df['stage'].unique()
```

```
Out[15]: array([ 1, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19,  2, 20, 21, 22, 23, 24,
                25, 26, 27, 28, 29,  3, 30, 31, 32, 33, 34,  4,  5,  6,  7,  8,  9,
                35, 36, 37, 38])
```

Players

```
In [16]: # view first rows
         player_df.head()
```

```
Out[16]:    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 [17]: # dataframe info
         player_df.info()
```

```
<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
```

```
In [18]: # count of duplicates
         player_df.duplicated().sum()
```

```
Out[18]: 0
```

Player Attributes

```
In [19]: # view first rows
         player_att_df.head(3)
```

```
Out[19]:    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

            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

               ...       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

            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 rows x 42 columns]
```

```
In [20]: # view dataframe info
         player_att_df.info()
```

```
<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
```

```
In [21]: # count duplicate rows
         player_att_df.duplicated().sum()
```

```
Out[21]: 0
```

Country

```
In [22]: # view first rows
         country_df.head(3)
```

```
Out[22]:      id     name
         0     1  Belgium
         1  1729  England
         2  4769   France
```

```
In [23]: # view dataframe info
         country_df.info()
```

```
<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
```

```
In [24]: # count duplicate rows
         country_df.duplicated().sum()
```

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

Team attributes

```
In [25]: # view first rows
         team_att_df.head(3)
```

```
Out[25]:    id  team_fifa_api_id  team_api_id                 date  buildUpPlaySpeed  \
         0   1               434         9930  2010-02-22 00:00:00                60
         1   2               434         9930  2014-09-19 00:00:00                52
```

```
2   3               434         9930  2015-09-10 00:00:00                47

  buildUpPlaySpeedClass  buildUpPlayDribbling buildUpPlayDribblingClass  \
0              Balanced                   NaN                    Little
1              Balanced                  48.0                    Normal
2              Balanced                  41.0                    Normal

   buildUpPlayPassing buildUpPlayPassingClass           ...             \
0                  50                   Mixed           ...
1                  56                   Mixed           ...
2                  54                   Mixed           ...

  chanceCreationShooting  chanceCreationShootingClass  \
0                     55                       Normal
1                     64                       Normal
2                     64                       Normal

  chanceCreationPositioningClass  defencePressure defencePressureClass  \
0                      Organised               50               Medium
1                      Organised               47               Medium
2                      Organised               47               Medium

   defenceAggression defenceAggressionClass defenceTeamWidth  \
0                 55                  Press              45
1                 44                  Press              54
2                 44                  Press              54

   defenceTeamWidthClass defenceDefenderLineClass
0                 Normal                    Cover
1                 Normal                    Cover
2                 Normal                    Cover

[3 rows x 25 columns]
```

In [26]:
```
# view info
team_att_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458 entries, 0 to 1457
Data columns (total 25 columns):
id                            1458 non-null int64
team_fifa_api_id              1458 non-null int64
team_api_id                   1458 non-null int64
date                          1458 non-null object
buildUpPlaySpeed              1458 non-null int64
buildUpPlaySpeedClass         1458 non-null object
buildUpPlayDribbling          489 non-null float64
buildUpPlayDribblingClass     1458 non-null object
```

```
buildUpPlayPassing                1458 non-null int64
buildUpPlayPassingClass           1458 non-null object
buildUpPlayPositioningClass       1458 non-null object
chanceCreationPassing             1458 non-null int64
chanceCreationPassingClass        1458 non-null object
chanceCreationCrossing            1458 non-null int64
chanceCreationCrossingClass       1458 non-null object
chanceCreationShooting            1458 non-null int64
chanceCreationShootingClass       1458 non-null object
chanceCreationPositioningClass    1458 non-null object
defencePressure                   1458 non-null int64
defencePressureClass              1458 non-null object
defenceAggression                 1458 non-null int64
defenceAggressionClass            1458 non-null object
defenceTeamWidth                  1458 non-null int64
defenceTeamWidthClass             1458 non-null object
defenceDefenderLineClass          1458 non-null object
dtypes: float64(1), int64(11), object(13)
memory usage: 284.8+ KB
```

```
In [27]: # count rows
         team_att_df.duplicated().sum()
```

```
Out[27]: 0
```

Team

```
In [28]: # view first rows
         team_df.head(3)
```

```
Out[28]:    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
```

```
In [29]: # view data info
         team_df.info()
```

```
<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
```

League

```
In [30]: # First 3 rows
         league_df.head(3)
```

```
Out[30]:      id  country_id                     name
         0     1           1  Belgium Jupiler League
         1  1729        1729  England Premier League
         2  4769        4769          France Ligue 1
```

```
In [31]: # show data info
         league_df.info()
```

```
<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
```

```
In [32]: # count duplicates
         league_df.duplicated().sum()
```

```
Out[32]: 0
```

1.1.3 Data Cleaning

I am going only keep the necessary columns and dataframes required to answer the questions posed earlier on, the columns containing key match information will be kept and then joined with other data on related keys to create a single combined dataframe

```
In [33]: # Filter match data and keep columns relevant to questions posed
         match_df = match_df.filter(items=['id','country_id','league_id', 'season', 'stage', 'da
```

```
In [34]: # Create result column that contains three possible values home_win, away_win or draw

         # create a list of our conditions
         conditions = [
             (match_df['home_team_goal'] > match_df['away_team_goal']),
             (match_df['home_team_goal'] < match_df['away_team_goal']),
             (match_df['home_team_goal'] == match_df['away_team_goal']),
             ]

         # create a list of the values we want to assign for each condition
         values = ['home_win', 'away_win', 'draw']
```

```
# create a new column and use np.select to assign values to it using our lists as argun
match_df['result'] = np.select(conditions, values)

# display updated DataFrame
match_df.head()
```

Out[34]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_api_id	home_team_goal	away_team_goal	result
0	1	1	1	2008/2009	1	2008-08-17 00:00:00	492473	9987	9993	1	1	draw
1	2	1	1	2008/2009	1	2008-08-16 00:00:00	492474	10000	9994	0	0	draw
2	3	1	1	2008/2009	1	2008-08-16 00:00:00	492475	9984	8635	0	3	away_win
3	4	1	1	2008/2009	1	2008-08-17 00:00:00	492476	9991	9998	5	0	home_win
4	5	1	1	2008/2009	1	2008-08-16 00:00:00	492477	7947	9985	1	3	away_win

```
In [35]: # combine datasets to get country, league, club names

# combine match and team
df_combined = match_df.merge(team_df, left_on='home_team_api_id', right_on='team_api_id
df_combined =df_combined.filter(items = ['id','country_id','league_id','season','stage'
df_combined = df_combined.merge(team_df, left_on='away_team_api_id', right_on='team_api
df_combined = df_combined.filter(items = ['id','country_id','league_id','season','stage
df_combined.head(3)
```

Out[35]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team	away_team	home_team_goal	away_team_goal	result
0	2	1	1	2008/2009	1	2008-08-17 00:00:00	492473	KRC Genk	Beerschot AC	1	1	draw
1	4	1	1	2008/2009	1	2008-08-16 00:00:00	492474	SV Zulte-Waregem	Sporting Lokeren	0	0	draw
2	6	1	1	2008/2009	1	2008-08-16 00:00:00	492475	KSV Cercle Brugge	RSC Anderlecht	0	3	away_win

```
1               0      draw
2               3  away_win
```

In [36]:
```
# combine with league info
df_combined = df_combined.merge(league_df, left_on='league_id', right_on='id', how='lef
df_combined.head(3)
```

Out[36]:
```
   id_left  country_id_left  league_id     season  stage                 date  \
0        2                1          1  2008/2009      1  2008-08-17 00:00:00
1        4                1          1  2008/2009      1  2008-08-16 00:00:00
2        6                1          1  2008/2009      1  2008-08-16 00:00:00

   match_api_id          home_team         away_team  home_team_goal  \
0        492473           KRC Genk      Beerschot AC               1
1        492474   SV Zulte-Waregem  Sporting Lokeren               0
2        492475  KSV Cercle Brugge    RSC Anderlecht               0

   away_team_goal    result  id_right  country_id_right  \
0               1      draw         1                 1
1               0      draw         1                 1
2               3  away_win         1                 1

                   league
0  Belgium Jupiler League
1  Belgium Jupiler League
2  Belgium Jupiler League
```

In [37]:
```
#combine with country

df_combined = df_combined.merge(country_df, left_on='country_id_left', right_on='id', h
df_combined = df_combined.filter(items = ['country','league','season','stage','date','m
df_combined.head(3)
```

Out[37]:
```
   country                  league     season  stage                 date  \
0  Belgium  Belgium Jupiler League  2008/2009      1  2008-08-17 00:00:00
1  Belgium  Belgium Jupiler League  2008/2009      1  2008-08-16 00:00:00
2  Belgium  Belgium Jupiler League  2008/2009      1  2008-08-16 00:00:00

   match_api_id          home_team         away_team  home_team_goal  \
0        492473           KRC Genk      Beerschot AC               1
1        492474   SV Zulte-Waregem  Sporting Lokeren               0
2        492475  KSV Cercle Brugge    RSC Anderlecht               0

   away_team_goal    result
0               1      draw
1               0      draw
2               3  away_win
```

In [38]:
```
# Get points home and away
#for home points if result is equals to draw then 1, if result is equal to home win the
```

```
#for away points  if result is equals to draw then 1, if result is equal to away win th

# create a list of our conditions
conditions = [
    (df_combined['result'] == 'draw'),
    (df_combined['result'] == 'home_win'),
    (df_combined['result'] == 'away_win')
    ]

conditions_away = [
    (df_combined['result'] == 'draw'),
    (df_combined['result'] == 'home_win'),
    (df_combined['result'] == 'away_win')
    ]

# create a list of the values we want to assign for each condition
values = [1, 3, 0]
values_2 = [1,0,3]

# create a new column and use np.select to assign values to it using our lists as argum
df_combined['home_points'] = np.select(conditions, values)
df_combined['away_points'] = np.select(conditions_away, values_2)

# display updated DataFrame
df_combined.head()
```

Out[38]:

	country	league	season	stage	date	match_api_id	home_team	away_team	home_team_goal	away_team_goal	result	home_points	away_points
0	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-17 00:00:00	492473	KRC Genk	Beerschot AC	1	1	draw	1	1
1	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-16 00:00:00	492474	SV Zulte-Waregem	Sporting Lokeren	0	0	draw	1	1
2	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-16 00:00:00	492475	KSV Cercle Brugge	RSC Anderlecht	0	3	away_win	0	3
3	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-17 00:00:00	492476	KAA Gent	RAEC Mons	5	0	home_win	3	0
4	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-16 00:00:00	492477	FCV Dender EH	Standard de Liège	1	3	away_win	0	3

```
In [39]: def make_table(league,season):
             '''Function that returns league table for a season
```

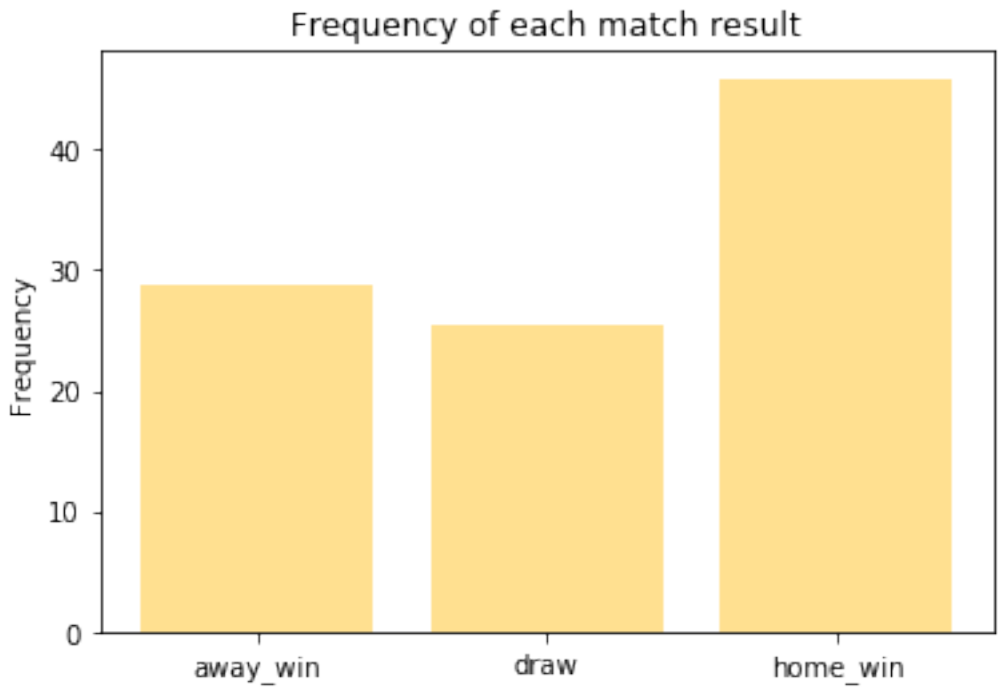
```
    Input string - league(name of league in ""),season(season in "")
    Output  df- league table with club, points, gf, ga, gd
    '''
    # Group by league and season
    league_year = df_combined.query('league == @league & season == @season')
    # Get team's home points
    home_points = league_year.groupby('home_team')['home_points'].sum().reset_index()
    home_points = pd.DataFrame(data= home_points)
    # Get team's away points
    away_points = league_year.groupby('away_team')['away_points'].sum().reset_index()
    away_points = pd.DataFrame(data= away_points)
    # Get total points
    points = home_points.merge(away_points, left_on='home_team', right_on='away_team',
    points['points'] = points['home_points'] + points['away_points']
    points = points.filter(['team_points','points'])

    # get goals scored
    home_goals = league_year.groupby('home_team')['home_team_goal'].sum().reset_index()
    home_goals =  pd.DataFrame(data= home_goals)

    away_goals = league_year.groupby('away_team')['away_team_goal'].sum().reset_index()
    away_goals =  pd.DataFrame(data= away_goals)
    # Get total goals
    goals_for = home_goals.merge(away_goals, left_on='home_team', right_on='away_team',
    goals_for['gf'] = goals_for['home_team_goal'] + goals_for['away_team_goal']
    goals_for = goals_for.filter(['team_gf','gf'])

    # get goals conceeded home and away
    conceed_home = league_year.groupby('home_team')['away_team_goal'].sum().reset_index
    conceed_home =  pd.DataFrame(data= conceed_home)

    conceed_away = league_year.groupby('away_team')['home_team_goal'].sum().reset_index
    conceed_away =  pd.DataFrame(data= conceed_away)

    # join conceeded goals dfs
    goals_against = conceed_home.merge(conceed_away, left_on='home_team', right_on='awa
    # get total conceeded
    goals_against['ga'] = goals_against['away_team_goal'] + goals_against['home_team_go
    goals_against = goals_against.filter(['team_ga','ga'])

    # join all goals and get goal difference
    goals = goals_against.merge(goals_for, left_on='team_ga', right_on='team_gf', how='
    goals['gd'] = goals['gf'] - goals['ga']

    # Combine all and get the table
    table = points.merge(goals, left_on='team_points', right_on='team_ga', how='left').
    table = table.filter(['club','points','gf','ga','gd']).reset_index(drop=True)
    # Make index start at one
```

```
        table.index = table.index + 1

        return table
```

Exploratory Data Analysis

1.1.4 What is the most likely occurence in a game between(Home win, away win or draw) ?

```
In [40]: # Use this, and more code cells, to explore your data. Don't forget to add
         #   Markdown cells to document your observations and findings.
         game_results = df_combined['result'].value_counts()* 100 / len(df_combined)
         game_results = game_results.rename_axis('Match outcome').reset_index()
         game_results = pd.DataFrame(data= game_results)
         game_results

Out[40]:   Match outcome     result
         0      home_win  45.871666
         1      away_win  28.738597
         2          draw  25.389738

In [41]: plt.bar(x = game_results['Match outcome'],
                 # using the data from the game results
                 height = game_results['result'],
                 # aligned in the center
                 align='center',
                 # with color
                 color='#FFC222',
                 # alpha 0.5
                 alpha=0.5)
         plt.title('Frequency of each match result')
         plt.ylabel('Frequency')
         plt.show()
```



The most frequent occurence is a home win 45.87% , followed by an away win 28.7, and finally the least frequent is a draw with 25.39%

1.1.5 What teams have had the most wins over the time period?

```
In [42]: # Get home and away wins for clubs
         home_res = df_combined.filter(items=['home_team','result'])
         home_res = home_res.query('result == "home_win"')
         home_res = home_res.groupby('home_team').count().rename_axis('home_team').rename(column
         home_res=pd.DataFrame(data= home_res)


         away_res = df_combined.filter(items=['away_team','result'])
         away_res = away_res.query('result == "away_win"')
         away_res = away_res.groupby('away_team').count().rename_axis('away_team').rename(column
         away_res=pd.DataFrame(data= away_res)



         club_res = home_res.merge(away_res, left_on='home_team', right_on='away_team', how='lef
         club_res= club_res.filter(items =['team','home_wins','away_wins'])
         club_res['wins'] = club_res['home_wins'] + club_res['away_wins']
         club_res.sort_values('wins',ascending= False, inplace=True)

In [43]: # View top ten clubs by wins
         club_res.head(10)
```

Out[43]:

	team	home_wins	away_wins	wins
75	FC Barcelona	131	103	234
211	Real Madrid CF	129	99	228
49	Celtic	120	98	218
77	FC Bayern Munich	109	84	193
162	Manchester United	116	76	192
133	Juventus	105	84	189
232	SL Benfica	102	83	185
89	FC Porto	102	81	183
15	Ajax	103	78	181
76	FC Basel	103	77	180

Fc Barcelona of Spain had the most wins during the period with **234** wins, closely followed by their league rivals **Real Madrid** with **228** wins

1.1.6 What is the average goal scored per game in the european leagues?

In [44]:
```
# View available leagues
league_df['name']
```

Out[44]:
```
0       Belgium Jupiler League
1       England Premier League
2               France Ligue 1
3        Germany 1. Bundesliga
4               Italy Serie A
5       Netherlands Eredivisie
6           Poland Ekstraklasa
7     Portugal Liga ZON Sagres
8      Scotland Premier League
9             Spain LIGA BBVA
10    Switzerland Super League
Name: name, dtype: object
```

In [45]:
```
# Avg goals scored per game
avg_goals= df_combined.filter(items = ['league','home_team_goal','away_team_goal'])
avg_goals['goals'] = avg_goals['home_team_goal'] + avg_goals['away_team_goal']
avg_goals = avg_goals.groupby('league')['goals'].mean().rename_axis('league').reset_ind
games = df_combined.groupby('league')['match_api_id'].count().rename_axis('league').res

avg_goals = pd.DataFrame(data= avg_goals)

games = df_combined.groupby('league')['match_api_id'].count().rename_axis('league').res

combined = avg_goals.merge(games, left_on='league', right_on='league', how='left').rena

combined.sort_values('goals',ascending= False, inplace=True)
combined.head(10)
```

Out[45]:

	League	goals	games
5	Netherlands Eredivisie	3.080882	2448

```
10  Switzerland Super League  2.929677   1422
3      Germany 1. Bundesliga  2.901552   2448
0     Belgium Jupiler League  2.801505   1728
9           Spain LIGA BBVA   2.767105   3040
1     England Premier League  2.710526   3040
8    Scotland Premier League  2.633772   1824
4              Italy Serie A  2.616838   3017
7   Portugal Liga ZON Sagres  2.534600   2052
2             France Ligue 1  2.443092   3040
```

The Eredivisie has the highest number of goals per game with 3.08 goals on average over 2448 games, followed by the Switzerland Super League with 2.9 goals on average in 1422 games

1.1.7 Which teams conceeded the most goals over the period?

In [46]:
```
df_combined.head(3)
```

Out[46]:

	country	league	season	stage	date	match_api_id	home_team	away_team	home_team_goal	away_team_goal	result	home_points	away_points
0	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-17 00:00:00	492473	KRC Genk	Beerschot AC	1	1	draw	1	1
1	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-16 00:00:00	492474	SV Zulte-Waregem	Sporting Lokeren	0	0	draw	1	1
2	Belgium	Belgium Jupiler League	2008/2009	1	2008-08-16 00:00:00	492475	KSV Cercle Brugge	RSC Anderlecht	0	3	away_win	0	3

In [47]:
```
# Get goals conceeded at home and away
conceeded_at_home = df_combined.groupby('home_team')['away_team_goal'].sum().rename_axi
conceeded_at_home = pd.DataFrame(data= conceeded_at_home)

conceeded_at_away= df_combined.groupby('away_team')['home_team_goal'].sum().rename_axis
conceeded_at_away = pd.DataFrame(data= conceeded_at_away)
```

In [48]:
```
# combine goals conceeded at home and way to get goals against

goals_against = conceeded_at_home.merge(conceeded_at_away, left_on='home_team', right_o


goals_against['ga'] = goals_against['away_team_goal'] + goals_against['home_team_goal']


goals_against.sort_values('ga',ascending= False, inplace=True)
```

```
goals_against = goals_against.filter(items =['team','ga'])
```

```
In [49]: # View top 10 goals against
         goals_against.head(10)
```

Out[49]:

	team	ga
235	SV Werder Bremen	471
7	ADO Den Haag	468
122	Hannover 96	465
125	Heracles Almelo	463
20	Aston Villa	462
144	Kilmarnock	457
112	Getafe CF	457
229	SC Heerenveen	455
167	Motherwell	446
256	Sunderland	441

SV Werder Bremen(Bundesliga) Conceeded 471 goals over the period followed by ADO Den Haag(Eredivisie)

1.1.8 which of the top 5 european leagues is the most competitive?

Top five selected based on uefa country coefficient source

```
In [50]: def difference_btw(pos_1,pos_2,league, season):
             '''Returns Points Difference between two positions in the league table
             input: pos_1(int) - The position of the first team
                  pos_2(int) - The position of the second team
                  league - The league of the teams e.g "France Ligue 1"
                  season -  the season e.g "2011/2012"

             output: diff - point difference between teams
             '''
             vals = [season]
             table = make_table(league,season)
             diff = table['points'].loc[pos_1] - table['points'].loc[pos_2]
             vals.append(diff)
             return vals


         def seasons_diff(pos_1,pos_2,league):
             ''' Returns dataframe containing point difference between league positions

             input: pos_1(int) - The position of the first team
                  pos_2(int) - The position of the second team
                  league - The league of the teams e.g "France Ligue 1"

             output: df showing point difference by season
```

```
    '''
    season = ["2008/2009", "2009/2010", "2010/2011", "2011/2012", "2012/2013",
       "2013/2014", "2014/2015", "2015/2016"]
    col2_name = 'Points between {} and {}'.format(pos_1,pos_2)
    diff_seasons = []
    for year in season:
        items = difference_btw(pos_1,pos_2,league,year)
        diff_seasons.append(items)

    df = pd.DataFrame(diff_seasons, columns =['Season', col2_name])
    return df
```

```
In [51]: #plot bar chart

         def plot_bar(df,league):
             ''' return bar plot
             input df - dataframe
                   league (string) - e.g 'French Ligue 1'

             '''
             lt = df.plot.barh()
             #title
             lt.set(title = league)

             # on x axis
             lt.set_xlabel('Points', color = 'black', fontsize = '15')

             #figure size(width, height)
             lt.figure.set_size_inches(12, 9)
             lt.legend(loc = 7)
             plt.grid()
             #ploting the graph
             return plt.show()
```

French Ligue 1

```
In [52]: # Get differences btw 1st & 2nd ,then that of 1st and 4th
         france_12 = seasons_diff(1,2,"France Ligue 1")
         france_14 = seasons_diff(1,4,"France Ligue 1")
         france_diff  = france_14.merge(france_12, left_on='Season', right_on='Season', how='lef
         france_diff
```

```
Out[52]:            Points between 1 and 4  Points between 1 and 2
         Seasons
         2008/2009                      16                       3
         2009/2010                       8                       6
         2010/2011                      16                       8
         2011/2012                      18                       3
```

2012/2013	19	12
2013/2014	20	9
2014/2015	14	8
2015/2016	33	31

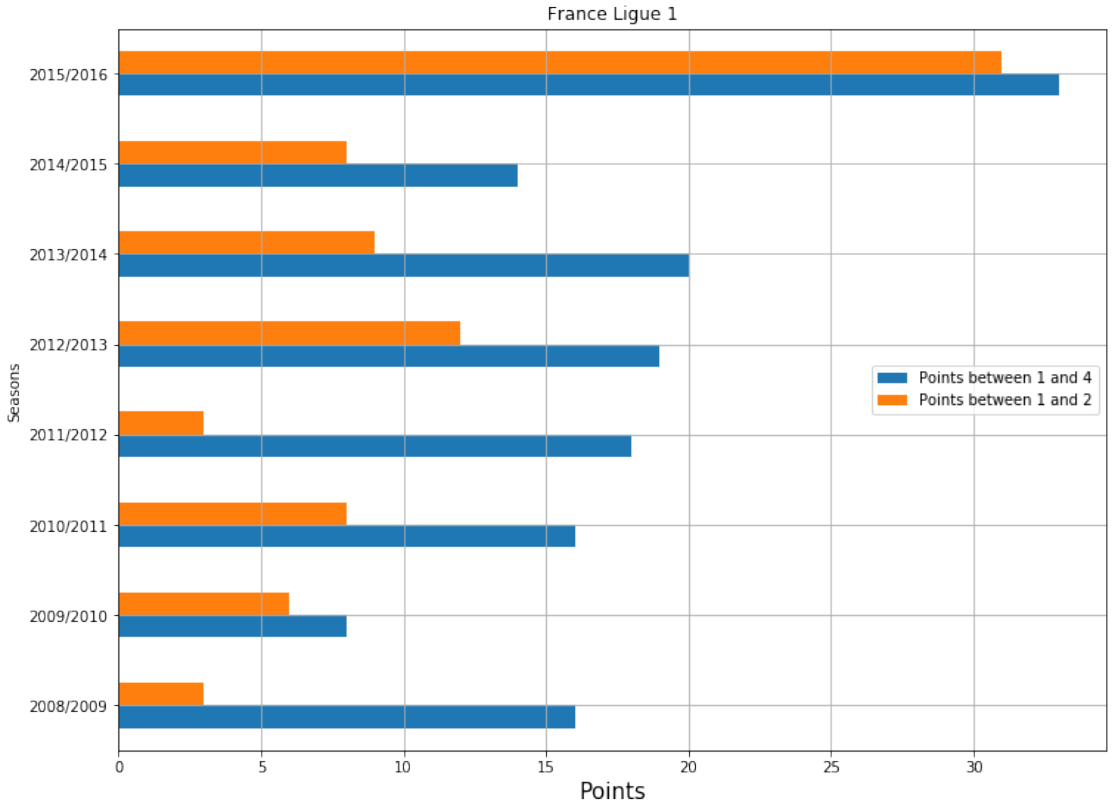
```
In [53]: # mean difference between top 2 from 2008 - 2015 season
         france_diff['Points between 1 and 2'].mean()
```

```
Out[53]: 10.0
```

```
In [54]: # mean difference between 1st and fourth from 2008 - 2015 season
         france_diff['Points between 1 and 4'].mean()
```

```
Out[54]: 18.0
```

```
In [55]: plot_bar(france_diff,'France Ligue 1')
```



The french league winner on average leads with 10 points on average, even though Psg won the league with 31 points in 2015/2016, the winner also gaps the 4th place with on average 18 points

England Premier League

```
In [56]: # Get differences btw 1st & 2nd ,then that of 1st and 4th
         england_12 = seasons_diff(1,2,"England Premier League")
```

```
england_14 = seasons_diff(1,4,"England Premier League")
england_diff  = england_14.merge(england_12, left_on='Season', right_on='Season', how='
england_diff
```

Out[56]:

Seasons	Points between 1 and 4	Points between 1 and 2
2008/2009	18	4
2009/2010	16	1
2010/2011	12	9
2011/2012	20	0
2012/2013	16	11
2013/2014	7	2
2014/2015	17	8
2015/2016	15	10

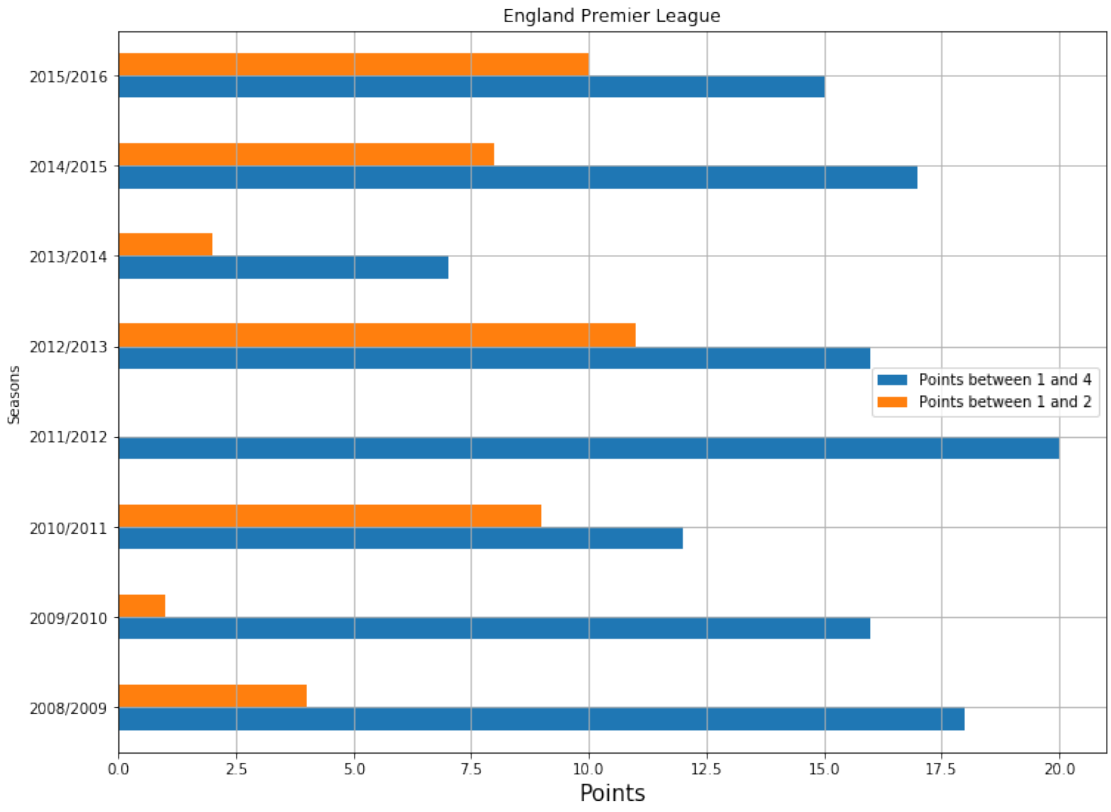
```
In [57]: # mean difference between 1st and second from 2008 - 2015 season
         england_diff['Points between 1 and 2'].mean()
```

Out[57]: 5.625

```
In [58]: # mean difference between 1st and fourth from 2008 - 2015 season
         england_diff['Points between 1 and 4'].mean()
```

Out[58]: 15.125

```
In [59]: plot_bar(england_diff,'England Premier League')
```



England's champion on average leads with 5.6 points and gaps the the 4th place with 15 points on average, though in the 2011/12 season was decided by goal difference between the red and blue half of manchester

Germany, Bundesliga

```
In [60]: # Get differences btw 1st & 2nd ,then that of 1st and 4th
         german_12 = seasons_diff(1,2,"Germany 1. Bundesliga")
         german_14 = seasons_diff(1,4,"Germany 1. Bundesliga")
         german_diff  = german_14.merge(german_12, left_on='Season', right_on='Season', how='lef
         german_diff
```

Out[60]:

Seasons	Points between 1 and 4	Points between 1 and 2
2008/2009	6	2
2009/2010	11	5
2010/2011	15	7
2011/2012	21	8
2012/2013	36	25
2013/2014	29	19
2014/2015	18	10
2015/2016	33	10

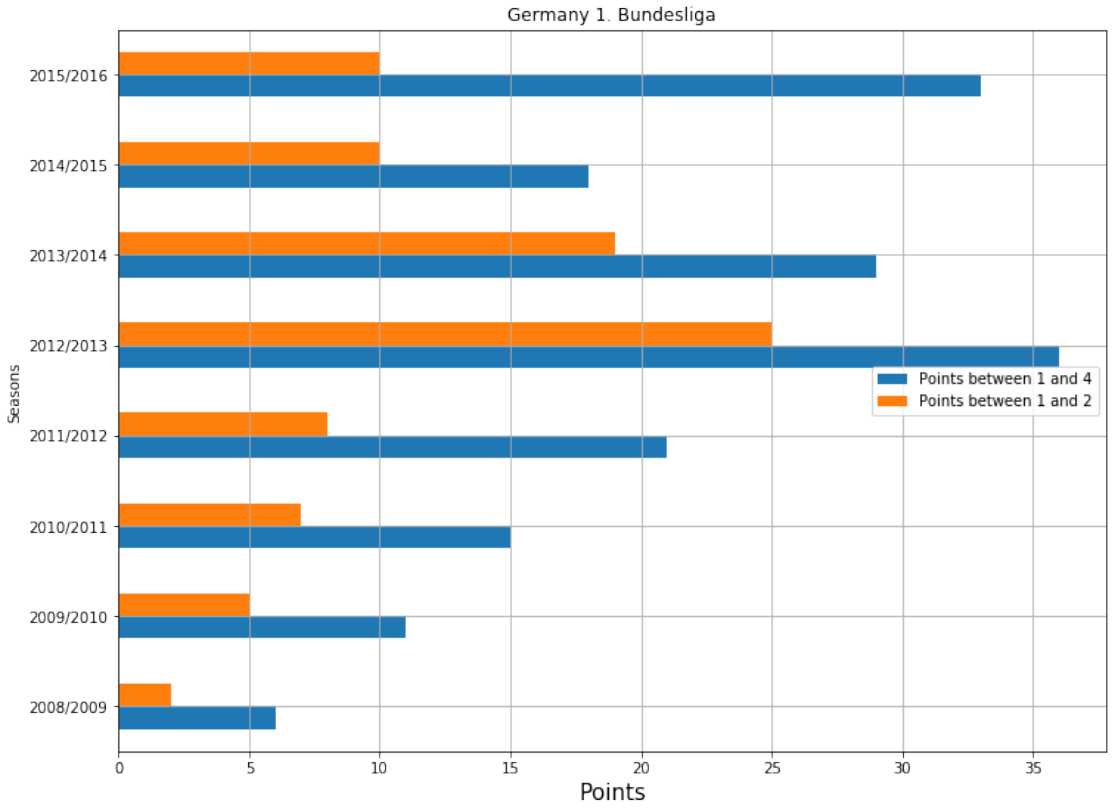
```
In [61]: # mean difference between 1st and second from 2008 - 2015 season
         german_diff['Points between 1 and 2'].mean()
```

```
Out[61]: 10.75
```

```
In [62]: # mean difference between 1st and second from 2008 - 2015 season
         german_diff['Points between 1 and 4'].mean()
```

```
Out[62]: 21.125
```

```
In [63]: plot_bar(german_diff,'Germany 1. Bundesliga')
```



Bundesliga has on average a 10.8 difference between the top 2 and a 21 points difference between the eventual winner and the 4th position, the 2012/2013 season saw a 36 points difference between the first and fourth place

Italy Serie A

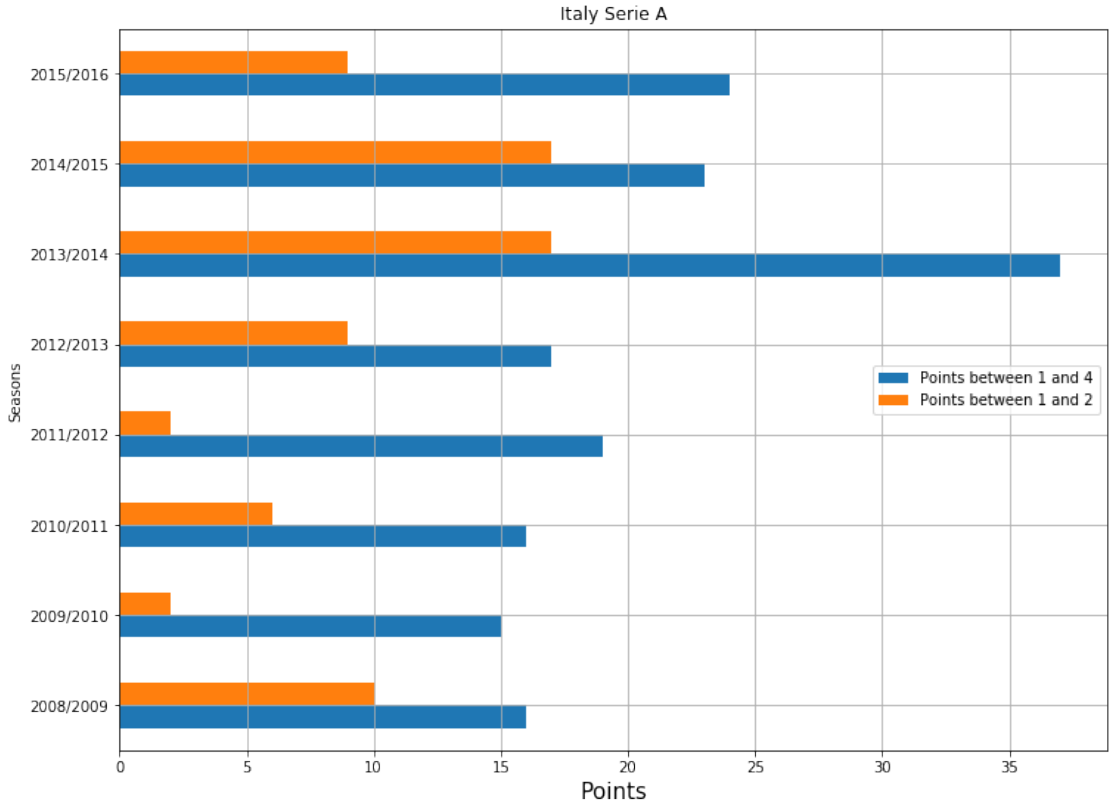
```
In [64]: # Get differences btw 1st & 2nd ,then that of 1st and 4th
         italy_12 = seasons_diff(1,2,"Italy Serie A")
         italy_14 = seasons_diff(1,4,"Italy Serie A")
         italy_diff  = italy_14.merge(italy_12, left_on='Season', right_on='Season', how='left')
         italy_diff
```

Out[64]:

Seasons	Points between 1 and 4	Points between 1 and 2
2008/2009	16	10
2009/2010	15	2
2010/2011	16	6
2011/2012	19	2
2012/2013	17	9
2013/2014	37	17
2014/2015	23	17
2015/2016	24	9

```
In [65]: # mean difference between 1st and 2nd from 2008 - 2015 season
         italy_diff['Points between 1 and 2'].mean()
```

```
Out[65]: 9.0

In [66]: # mean difference between 1st and 4th from 2008 - 2015 season
         italy_diff['Points between 1 and 4'].mean()

Out[66]: 20.875

In [67]: plot_bar(italy_diff,'Italy Serie A')
```



In the Italian Serie A, the winner takes the trophy having a 9 points lead on the second place on average and a 20.8 points lead over th fouth place on average, There was a 37 point gap in the 2013/2014 season between the eventual winners and 4th place

Spain LIGA BBVA

```
In [68]: # Get differences btw 1st & 2nd ,then that of 1st and 4th
         spain_12 = seasons_diff(1,2,"Spain LIGA BBVA")
         spain_14 = seasons_diff(1,4,"Spain LIGA BBVA")
         spain_diff  = spain_14.merge(spain_12, left_on='Season', right_on='Season', how='left')
         spain_diff

Out[68]:            Points between 1 and 4  Points between 1 and 2
         Seasons
         2008/2009                      20                       9
```

2009/2010	36	3
2010/2011	34	4
2011/2012	42	9
2012/2013	34	15
2013/2014	20	3
2014/2015	17	2
2015/2016	27	1

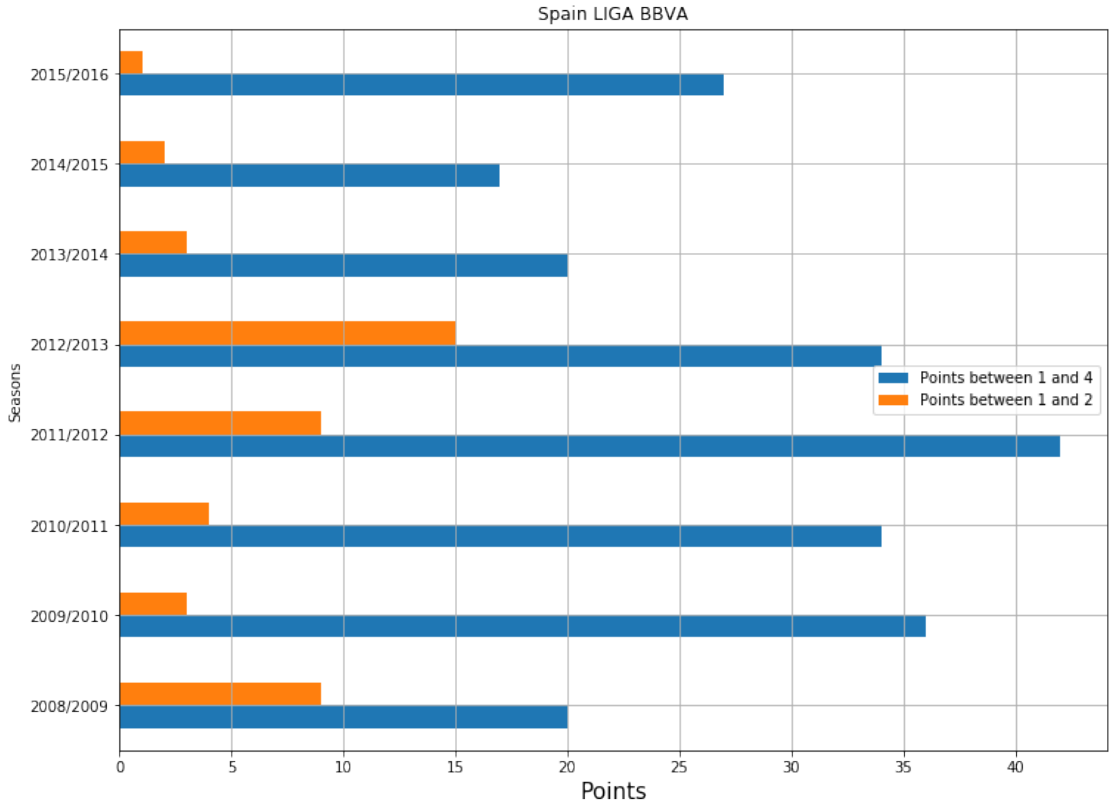
```
In [69]: # mean difference between 1st and 2nd from 2008 - 2015 season
         spain_diff['Points between 1 and 2'].mean()
```

```
Out[69]: 5.75
```

```
In [70]: # mean difference between 1st and 4th from 2008 - 2015 season
         spain_diff['Points between 1 and 4'].mean()
```

```
Out[70]: 28.75
```

```
In [71]: plot_bar(spain_diff,'Spain LIGA BBVA')
```



For Spain its usually tight between the top two teams with a 5.75 points difference on average, same can't be said about the 4th place , with the leader taking a 28.75 points gap over the 4th place, the 2011/2012 saw 42 points difference between 1st and 4th place, recording the highest difference in a season across the top five european leagues in the period

Different champoins in the last 8 years

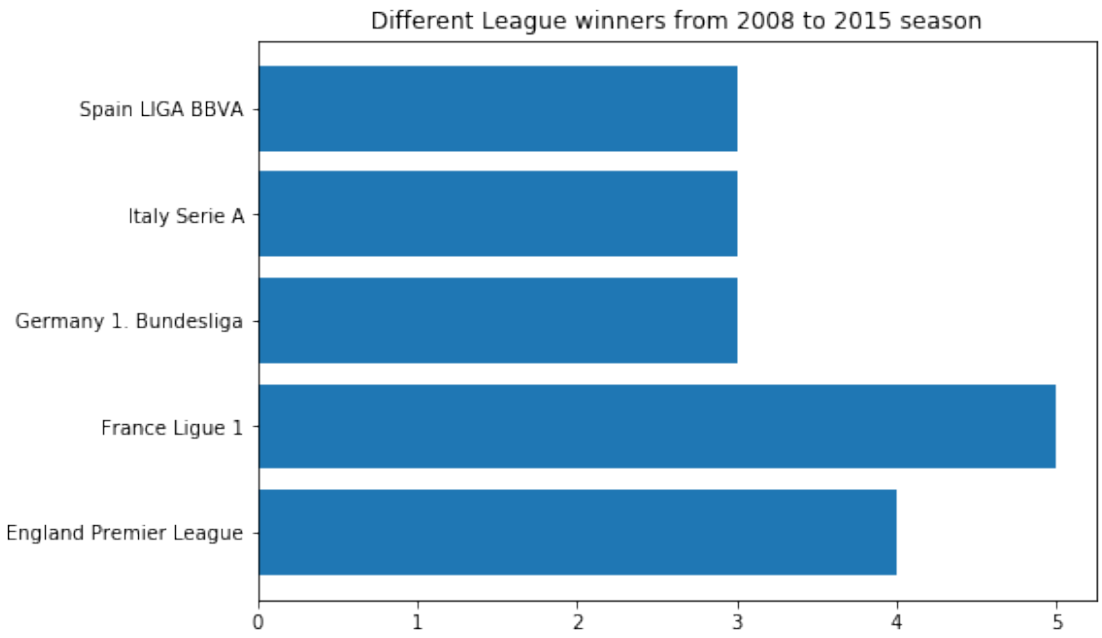
```
In [72]: def diff_winners(league,season):
             '''league(string)- name of league
                 season(string)- list containing seasons
                 returns df containig number of different winners for given seasons
             '''
             winners = []
             for year in seasons:
                 # make table
                 df = make_table(league,year)
                 # Get first place club
                 champion = df['club'].loc[1]
                 # Add to list
                 winners.append(champion)

             # Number of unique winners
             winners_count = len(set(winners))
             # Make dataframe
             d = {'League': [league], 'Number of Different winners': [winners_count]}
             df = pd.DataFrame(data=d)
             return df
         # List of seasons
         seasons =['2008/2009', '2009/2010', '2010/2011', '2011/2012', '2012/2013','2013/2014',


         def diff_top4(league,season):
             '''league(string)- name of league
                 season(string)- list containing seasons
                 returns df containig number of different top 4 teams for given seasons
             '''
             top_4 = []
             for year in seasons:
                 # make table
                 df = make_table(league,year)
                 # Get and append top 4 club
                 top_4.append(df['club'].loc[1])
                 top_4.append(df['club'].loc[2])
                 top_4.append(df['club'].loc[3])
                 top_4.append(df['club'].loc[4])


             #Number of unique top 4 members
             top_4_count = len(set(top_4))
             # Make dataframe
             d = {'League': [league], 'Number of Different top 4': [top_4_count]}
             df = pd.DataFrame(data=d)
             return df
         # List of seasons
         seasons =['2008/2009', '2009/2010', '2010/2011', '2011/2012', '2012/2013','2013/2014',
```

```
In [73]: germany = diff_winners('Germany 1. Bundesliga',seasons)
         england = diff_winners('England Premier League',seasons)
         spain = diff_winners('Spain LIGA BBVA',seasons)
         france = diff_winners('France Ligue 1',seasons)
         italy = diff_winners('Italy Serie A',seasons)
         diff_champs = pd.concat([germany,england,spain,france,italy], ignore_index=True)
         diff_champs
```

Out[73]:

	League	Number of Different winners
0	Germany 1. Bundesliga	3
1	England Premier League	4
2	Spain LIGA BBVA	3
3	France Ligue 1	5
4	Italy Serie A	3

```
In [74]: fig = plt.figure()
         ax = fig.add_axes([0,0,1,1])
         ax.barh(diff_champs['League'],diff_champs['Number of Different winners'])
         ax.set(title = 'Different League winners from 2008 to 2015 season')
         plt.show()
```



The French league has had five different winners during the period followed by the English premier league with four.

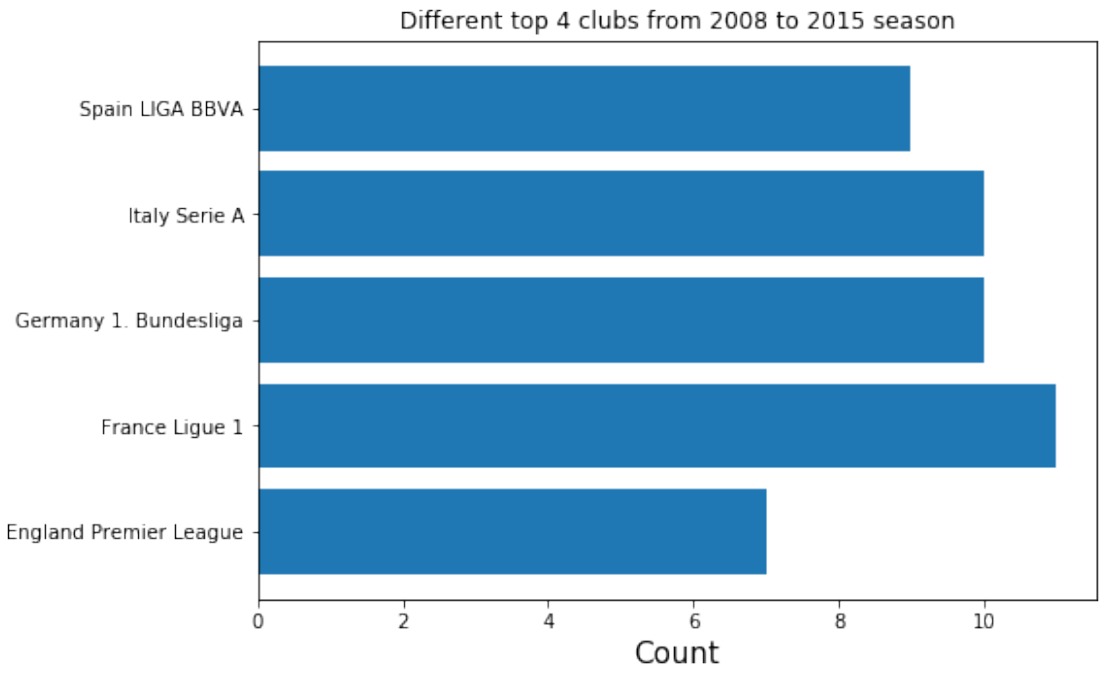
```
In [75]: germany = diff_top4('Germany 1. Bundesliga',seasons)
         england = diff_top4('England Premier League',seasons)
         spain = diff_top4('Spain LIGA BBVA',seasons)
```

```
france = diff_top4('France Ligue 1',seasons)
italy = diff_top4('Italy Serie A',seasons)
diff_top4 = pd.concat([germany,england,spain,france,italy], ignore_index=True)
diff_top4
```

Out[75]:

	League	Number of Different top 4
0	Germany 1. Bundesliga	10
1	England Premier League	7
2	Spain LIGA BBVA	9
3	France Ligue 1	11
4	Italy Serie A	10

In [76]:
```
fig = plt.figure()
ax = fig.add_axes([0,0,1,1])
ax.barh(diff_top4['League'],diff_top4['Number of Different top 4'])
#title
ax.set(title = 'Different top 4 clubs from 2008 to 2015 season')
# on x axis
ax.set_xlabel('Count', color = 'black', fontsize = '15')
plt.show()
```



The French Ligue 1 had eleven different in it's top four positions from 2008 to 2015, while the Bundesliga and Serie A had ten each, the English premier league had 7 different clubs alluding to the big 6 clubs who normally dominate the league in the past decade

Conclusions

Conclusions

At the end of this interesting data analysis. I discovered some unexpected facts about the football teams and leagues. Here are some of the insights I ganered:

Between a Home win, draw and an away win, the most frequent occurence in this dataset is a home win 45.87% , followed by an away win 28.7, and finally the least frequent is a draw with 25.39%

Fc Barcelona of Spain had the most wins during the period with 234 wins, closely followed by their la liga rivals Real Madrid with 228 wins

The Eredivisie has the highest number of goals per game with 3.08 goals on average over 2448 games, followed by the Switzerland Super League with 2.9 goals on average in 1422 games

SV Werder Bremen(Bundesliga) Conceeded 471 goals over the period followed by ADO Den Haag(Eredivisie) who conceeded 468 goals in the period

The English Premier league and The French ligue 1 seems to be the most competitive of the top five european league, with 4 and 5 different winners respectively between 2008 and 2015, ligue 1 also had 11 different teams making the top 4 places, while the Epl has a 5.6 point gap on average between the top two teams, with the 2011/12 season decided by goal difference between the red and blue half of Manchester.

Limitations:

This analysis was done considering the points, league winners and top 4 teams to decide which league was the most competitive, however other metrics could have been used

The matches dataset only contains values from the 2008 to 2015 season, an updated data will be needed for a more current analysis

```
In [77]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[77]: 0
```

```
In [ ]:
```

```
In [ ]:
```