Project: Investigate a Dataset - [European Soccer Database]

Table of Contents

Introduction

Dataset Description

> Data about soccer matches but they are usually scattered across different websites. A thorough data collection and processing has been done to make your life easier. it contain the following : +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

Question(s) for Analysis

> **Q1 : What's the season that have the most played matches?**
>
> **Q2 : What's the league that have the most scored goals ?**
>
> **Q3 : What top 5 teams scored most goals ?**
>
> **Q4 : What most fans choose to bet odds (Home Team ,Away Team,Draw) in all leagues ?**
>
> **Q5 : What's winning parcentage for Away Teams?**
>
> **Q6 : What's the most teams play speed type use ?**
>
> **Q7 : What's correlation of Slow play speed by years ?**

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

Data Wrangling

Load Data

In [2]:
```
cty = pd.read_csv('Database_Soccer\Country.csv')
leg = pd.read_csv('Database_Soccer\League.csv')
mth = pd.read_csv('Database_Soccer\Match.csv')
ply = pd.read_csv('Database_Soccer\Player.csv')
ply_att = pd.read_csv('Database_Soccer\Player_Attributes.csv')
sqs = pd.read_csv('Database_Soccer\sqlite_sequence.csv')
tm = pd.read_csv('Database_Soccer\Team.csv')
tm_att = pd.read_csv('Database_Soccer\Team_Attributes.csv')
```

Check Data

Check Country Database

In [3]:
```
cty.head()
```

Out[3]:

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

In [4]:
```
cty.info()
```

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

In [5]:
```
cty.duplicated().sum()
```

Out[5]:
```
0
```

Check League Database

In [6]:
```
leg.head()
```

Out[6]:

	id	country_id	name
0	1	1	Belgium Jupiler League
1	1729	1729	England Premier League
2	4769	4769	France Ligue 1

	id	country_id	name
3	7809	7809	Germany 1. Bundesliga
4	10257	10257	Italy Serie A

In [7]:
```
leg.info()
```

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

In [8]:
```
leg.duplicated().sum()
```

Out[8]:
```
0
```

Merge Country and League name

In [9]:
```
cty.rename(columns={'name':'country_name'},inplace=True)
leg.rename(columns={'name':'leauge_name'},inplace=True)
```

In [10]:
```
merge_country_league=pd.merge(cty,leg,on='id')
merge_country_league.drop(columns='id',inplace=True)
merge_country_league=merge_country_league[['country_id','country_name','leauge_name']]
merge_country_league=merge_country_league.rename(columns={'leauge_name':'league_name'})
merge_country_league
```

Out[10]:

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

Check Match Database

In [11]:
```
mth
```

Out[11]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_api_id
0	1	1	1	2008/2009	1	2008-08-17 00:00:00	492473	9987	9993
1	2	1	1	2008/2009	1	2008-08-16 00:00:00	492474	10000	9994
2	3	1	1	2008/2009	1	2008-08-16 00:00:00	492475	9984	8635
3	4	1	1	2008/2009	1	2008-08-17 00:00:00	492476	9991	9998
4	5	1	1	2008/2009	1	2008-08-16 00:00:00	492477	7947	9985
...	...	...	...	...	...	...	...	...	...
25974	25975	24558	24558	2015/2016	9	2015-09-22 00:00:00	1992091	10190	10191
25975	25976	24558	24558	2015/2016	9	2015-09-23 00:00:00	1992092	9824	10199
25976	25977	24558	24558	2015/2016	9	2015-09-23 00:00:00	1992093	9956	10179
25977	25978	24558	24558	2015/2016	9	2015-09-22 00:00:00	1992094	7896	10243
25978	25979	24558	24558	2015/2016	9	2015-09-23 00:00:00	1992095	10192	9931

25979 rows × 115 columns

In [12]:
```
mth.info()
```

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

In [13]:
```
mth.duplicated().sum()
```

Out[13]:
```
0
```

In [14]:
```
mth.isnull().sum()
```

Out[14]:
```
id                0
country_id        0
```

```
league_id         0
season            0
stage             0
                ...
GBD           11817
GBA           11817
BSH           11818
BSD           11818
BSA           11818
Length: 115, dtype: int64
```

In [15]:
```
mth.columns.to_list()
```

Out[15]:
```
['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',
 'home_player_X1',
 'home_player_X2',
 'home_player_X3',
 'home_player_X4',
 'home_player_X5',
 'home_player_X6',
 'home_player_X7',
 'home_player_X8',
 'home_player_X9',
 'home_player_X10',
 'home_player_X11',
 'away_player_X1',
 'away_player_X2',
 'away_player_X3',
 'away_player_X4',
 'away_player_X5',
 'away_player_X6',
 'away_player_X7',
 'away_player_X8',
 'away_player_X9',
 'away_player_X10',
 'away_player_X11',
 'home_player_Y1',
 'home_player_Y2',
 'home_player_Y3',
 'home_player_Y4',
 'home_player_Y5',
 'home_player_Y6',
 'home_player_Y7',
 'home_player_Y8',
 'home_player_Y9',
 'home_player_Y10',
 'home_player_Y11',
 'away_player_Y1',
 'away_player_Y2',
 'away_player_Y3',
 'away_player_Y4',
 'away_player_Y5',
 'away_player_Y6',
 'away_player_Y7',
 'away_player_Y8',
```

```
'away_player_Y9',
'away_player_Y10',
'away_player_Y11',
'home_player_1',
'home_player_2',
'home_player_3',
'home_player_4',
'home_player_5',
'home_player_6',
'home_player_7',
'home_player_8',
'home_player_9',
'home_player_10',
'home_player_11',
'away_player_1',
'away_player_2',
'away_player_3',
'away_player_4',
'away_player_5',
'away_player_6',
'away_player_7',
'away_player_8',
'away_player_9',
'away_player_10',
'away_player_11',
'goal',
'shoton',
'shotoff',
'foulcommit',
'card',
'cross',
'corner',
'possession',
'B365H',
'B365D',
'B365A',
'BWH',
'BWD',
'BWA',
'IWH',
'IWD',
'IWA',
'LBH',
'LBD',
'LBA',
'PSH',
'PSD',
'PSA',
'WHH',
'WHD',
'WHA',
'SJH',
'SJD',
'SJA',
'VCH',
'VCD',
'VCA',
'GBH',
'GBD',
'GBA',
'BSH',
'BSD',
'BSA']
```

> ***Clean Match Database***

No need for the following columns

Player Location on pitch

'home_player_X1', 'home_player_X2', 'home_player_X3', 'home_player_X4', 'home_player_X5', 'home_player_X6', 'home_player_X7', 'home_player_X8', 'home_player_X9', 'home_player_X10', 'home_player_X11', 'away_player_X1', 'away_player_X2', 'away_player_X3', 'away_player_X4', 'away_player_X5', 'away_player_X6', 'away_player_X7', 'away_player_X8', 'away_player_X9', 'away_player_X10', 'away_player_X11', 'home_player_Y1', 'home_player_Y2', 'home_player_Y3', 'home_player_Y4', 'home_player_Y5', 'home_player_Y6', 'home_player_Y7', 'home_player_Y8', 'home_player_Y9', 'home_player_Y10', 'home_player_Y11', 'away_player_Y1', 'away_player_Y2', 'away_player_Y3', 'away_player_Y4', 'away_player_Y5', 'away_player_Y6', 'away_player_Y7', 'away_player_Y8', 'away_player_Y9', 'away_player_Y10', 'away_player_Y11', 'home_player_1', 'home_player_2', 'home_player_3', 'home_player_4', 'home_player_5', 'home_player_6', 'home_player_7', 'home_player_8', 'home_player_9', 'home_player_10', 'home_player_11', 'away_player_1', 'away_player_2', 'away_player_3', 'away_player_4', 'away_player_5', 'away_player_6', 'away_player_7', 'away_player_8', 'away_player_9', 'away_player_10', 'away_player_11'

Match Status

'goal', 'shoton', 'shotoff', 'foulcommit', 'card', 'cross', 'corner', 'possession'

Bet odds for nine Companies

> I don't need for all , i choose the most comman bet company bet360

B365H = Bet365 home win odds

B365D = Bet365 draw odds

B365A = Bet365 away win odds

> for more explanation for the betting columns of the database: http://www.football-data.co.uk/notes.txt

'BWH', 'BWD', 'BWA', 'IWH', 'IWD', 'IWA', 'LBH', 'LBD', 'LBA', 'PSH', 'PSD', 'PSA', 'WHH', 'WHD', 'WHA', 'SJH', 'SJD', 'SJA', 'VCH', 'VCD', 'VCA', 'GBH', 'GBD', 'GBA', 'BSH', 'BSD', 'BSA'

In [16]:

```
mth.drop(columns=['home_player_X1',
 'home_player_X2',
 'home_player_X3',
 'home_player_X4',
 'home_player_X5',
 'home_player_X6',
 'home_player_X7',
 'home_player_X8',
 'home_player_X9',
 'home_player_X10',
 'home_player_X11',
 'away_player_X1',
 'away_player_X2',
 'away_player_X3',
 'away_player_X4',
 'away_player_X5',
 'away_player_X6',
 'away_player_X7',
 'away_player_X8',
 'away_player_X9',
 'away_player_X10',
```

```
'away_player_X11',
'home_player_Y1',
'home_player_Y2',
'home_player_Y3',
'home_player_Y4',
'home_player_Y5',
'home_player_Y6',
'home_player_Y7',
'home_player_Y8',
'home_player_Y9',
'home_player_Y10',
'home_player_Y11',
'away_player_Y1',
'away_player_Y2',
'away_player_Y3',
'away_player_Y4',
'away_player_Y5',
'away_player_Y6',
'away_player_Y7',
'away_player_Y8',
'away_player_Y9',
'away_player_Y10',
'away_player_Y11',
'home_player_1',
'home_player_2',
'home_player_3',
'home_player_4',
'home_player_5',
'home_player_6',
'home_player_7',
'home_player_8',
'home_player_9',
'home_player_10',
'home_player_11',
'away_player_1',
'away_player_2',
'away_player_3',
'away_player_4',
'away_player_5',
'away_player_6',
'away_player_7',
'away_player_8',
'away_player_9',
'away_player_10',
'away_player_11',
'goal',
'shoton',
'shotoff',
'foulcommit',
'card',
'cross',
'corner',
'possession',
'BWH',
'BWD',
'BWA',
'IWH',
'IWD',
'IWA',
'LBH',
'LBD',
'LBA',
'PSH',
'PSD',
'PSA',
'WHH',
```

```
'WHD',
'WHA',
'SJH',
'SJD',
'SJA',
'VCH',
'VCD',
'VCA',
'GBH',
'GBD',
'GBA',
'BSH',
'BSD',
'BSA'],inplace=True)
```

Merge match table with country and league name

In [17]:
```
merge_match_league=pd.merge(merge_country_league,mth,on='country_id')
merge_match_league.drop(columns=['country_id','date','id','match_api_id'],inplace=True)
merge_match_league
```

Out[17]:

	country_name	league_name	league_id	season	stage	home_team_api_id	away_team_api_id	home_team_
0	Belgium	Belgium Jupiler League	1	2008/2009	1	9987	9993	
1	Belgium	Belgium Jupiler League	1	2008/2009	1	10000	9994	
2	Belgium	Belgium Jupiler League	1	2008/2009	1	9984	8635	
3	Belgium	Belgium Jupiler League	1	2008/2009	1	9991	9998	
4	Belgium	Belgium Jupiler League	1	2008/2009	1	7947	9985	
...	...	...	...	...	...	...	...	
25974	Switzerland	Switzerland Super League	24558	2015/2016	9	10190	10191	
25975	Switzerland	Switzerland Super League	24558	2015/2016	9	9824	10199	
25976	Switzerland	Switzerland Super League	24558	2015/2016	9	9956	10179	
25977	Switzerland	Switzerland Super League	24558	2015/2016	9	7896	10243	
25978	Switzerland	Switzerland Super League	24558	2015/2016	9	10192	9931	

25979 rows × 12 columns

> ***Check Team Database***

In [18]:
```
tm.head()
```

Out[18]:

	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 [19]:
```
tm.info()
```

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

Merge Team Names with Match Table

In [20]:
```
tm.drop(columns=['id','team_short_name','team_fifa_api_id'],inplace=True)
```

In [21]:
```
tmhome=tm.rename(columns={'team_api_id':'home_team_api_id','team_long_name':'home_team_nar
tmway=tm.rename(columns={'team_api_id':'away_team_api_id','team_long_name':'away_team_name
```

In [22]:
```
merge_team_match=pd.merge(tmway,merge_match_league,on='away_team_api_id')
merge_team_match=pd.merge(tmhome,merge_team_match,on='home_team_api_id')
merge_team_match.drop(columns=['home_team_api_id','away_team_api_id'],inplace=True)
merge_team_match
```

Out[22]:

	home_team_name	away_team_name	country_name	league_name	league_id	season	stage	home_team_g
0	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2008/2009	1	
1	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2009/2010	5	
2	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2010/2011	1	
3	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2011/2012	1	
4	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2012/2013	11	

	home_team_name	away_team_name	country_name	league_name	league_id	season	stage	home_team_g
...	...	...	...	...	...	...	...	
25974	Lugano	FC Zürich	Switzerland	Switzerland Super League	24558	2015/2016	9	
25975	Lugano	FC St. Gallen	Switzerland	Switzerland Super League	24558	2015/2016	12	
25976	Lugano	FC St. Gallen	Switzerland	Switzerland Super League	24558	2015/2016	36	
25977	Lugano	FC Thun	Switzerland	Switzerland Super League	24558	2015/2016	2	
25978	Lugano	FC Thun	Switzerland	Switzerland Super League	24558	2015/2016	28	

25979 rows × 12 columns

Clean New Match database

In [23]:
```
merge_team_match.isnull().sum()
```

Out[23]:
```
home_team_name        0
away_team_name        0
country_name          0
league_name           0
league_id             0
season                0
stage                 0
home_team_goal        0
away_team_goal        0
B365H              3387
B365D              3387
B365A              3387
dtype: int64
```

In [24]:
```
merge_team_match.fillna(merge_team_match.mean(numeric_only=True),inplace=True)
merge_team_match
```

Out[24]:

	home_team_name	away_team_name	country_name	league_name	league_id	season	stage	home_team_g
0	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2008/2009	1	
1	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2009/2010	5	
2	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2010/2011	1	
3	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2011/2012	1	
4	KRC Genk	Beerschot AC	Belgium	Belgium Jupiler League	1	2012/2013	11	

	home_team_name	away_team_name	country_name	league_name	league_id	season	stage	home_team_g
...	...	...	...	...	...	...	...	
25974	Lugano	FC Zürich	Switzerland	Switzerland Super League	24558	2015/2016	9	
25975	Lugano	FC St. Gallen	Switzerland	Switzerland Super League	24558	2015/2016	12	
25976	Lugano	FC St. Gallen	Switzerland	Switzerland Super League	24558	2015/2016	36	
25977	Lugano	FC Thun	Switzerland	Switzerland Super League	24558	2015/2016	2	
25978	Lugano	FC Thun	Switzerland	Switzerland Super League	24558	2015/2016	28	

25979 rows × 12 columns

Get Match Result

In [25]:
```
def match_result(raw):
### Get Match result
    home_goals=raw['home_team_goal']
    away_goals=raw['away_team_goal']
    if home_goals > away_goals:
        return 'home_win'
    elif home_goals == away_goals:
        return 'draw'
    else :
        return 'away_win'
```

In [26]:
```
merge_team_match['match_result']=merge_team_match.apply(match_result,axis=1)
merge_team_match['match_result']
```

Out[26]:
```
0            draw
1            draw
2        home_win
3        home_win
4        home_win
           ...
25974        draw
25975    home_win
25976    home_win
25977    away_win
25978    home_win
Name: match_result, Length: 25979, dtype: object
```

> ***Check Teams attributes Database***

In [27]:
```
tm_att.head()
```

Out[27]:

	id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUpPlayDribbling	build
0	1	434	9930	2010-02-22 00:00:00	60	Balanced	NaN	

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

5 rows × 25 columns

In [28]:
```
tm_att.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458 entries, 0 to 1457
Data columns (total 25 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              1458 non-null   int64
 1   team_fifa_api_id                1458 non-null   int64
 2   team_api_id                     1458 non-null   int64
 3   date                            1458 non-null   object
 4   buildUpPlaySpeed                1458 non-null   int64
 5   buildUpPlaySpeedClass           1458 non-null   object
 6   buildUpPlayDribbling            489 non-null    float64
 7   buildUpPlayDribblingClass       1458 non-null   object
 8   buildUpPlayPassing              1458 non-null   int64
 9   buildUpPlayPassingClass         1458 non-null   object
 10  buildUpPlayPositioningClass     1458 non-null   object
 11  chanceCreationPassing           1458 non-null   int64
 12  chanceCreationPassingClass      1458 non-null   object
 13  chanceCreationCrossing          1458 non-null   int64
 14  chanceCreationCrossingClass     1458 non-null   object
 15  chanceCreationShooting          1458 non-null   int64
 16  chanceCreationShootingClass     1458 non-null   object
 17  chanceCreationPositioningClass  1458 non-null   object
 18  defencePressure                 1458 non-null   int64
 19  defencePressureClass            1458 non-null   object
 20  defenceAggression               1458 non-null   int64
 21  defenceAggressionClass          1458 non-null   object
 22  defenceTeamWidth                1458 non-null   int64
 23  defenceTeamWidthClass           1458 non-null   object
 24  defenceDefenderLineClass        1458 non-null   object
dtypes: float64(1), int64(11), object(13)
memory usage: 284.9+ KB
```

Clean Team attributes Data

In [29]:
```
tm_att.fillna(tm_att.mean(numeric_only=True),inplace=True)
tm_att.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458 entries, 0 to 1457
Data columns (total 25 columns):
 #   Column                          Non-Null Count  Dtype
```

```
---  ------                          --------------  -----
 0   id                              1458 non-null   int64
 1   team_fifa_api_id                1458 non-null   int64
 2   team_api_id                     1458 non-null   int64
 3   date                            1458 non-null   object
 4   buildUpPlaySpeed                1458 non-null   int64
 5   buildUpPlaySpeedClass           1458 non-null   object
 6   buildUpPlayDribbling            1458 non-null   float64
 7   buildUpPlayDribblingClass       1458 non-null   object
 8   buildUpPlayPassing              1458 non-null   int64
 9   buildUpPlayPassingClass         1458 non-null   object
 10  buildUpPlayPositioningClass     1458 non-null   object
 11  chanceCreationPassing           1458 non-null   int64
 12  chanceCreationPassingClass      1458 non-null   object
 13  chanceCreationCrossing          1458 non-null   int64
 14  chanceCreationCrossingClass     1458 non-null   object
 15  chanceCreationShooting          1458 non-null   int64
 16  chanceCreationShootingClass     1458 non-null   object
 17  chanceCreationPositioningClass  1458 non-null   object
 18  defencePressure                 1458 non-null   int64
 19  defencePressureClass            1458 non-null   object
 20  defenceAggression               1458 non-null   int64
 21  defenceAggressionClass          1458 non-null   object
 22  defenceTeamWidth                1458 non-null   int64
 23  defenceTeamWidthClass           1458 non-null   object
 24  defenceDefenderLineClass        1458 non-null   object
dtypes: float64(1), int64(11), object(13)
memory usage: 284.9+ KB
```

Merge Team names with thier attributes and cleaning data

In [30]:
```
tm_att=pd.merge(tm,tm_att)
tm_att.drop(columns=['team_api_id','id','team_fifa_api_id'],inplace=True)
```

In [31]:
```
tm_att_year = pd.DatetimeIndex(tm_att['date']).year
tm_att['year']=tm_att_year
tm_att.drop(columns=['date'],inplace=True)
```

In [32]:
```
tm_att.duplicated().sum()
```

Out[32]:
```
8
```

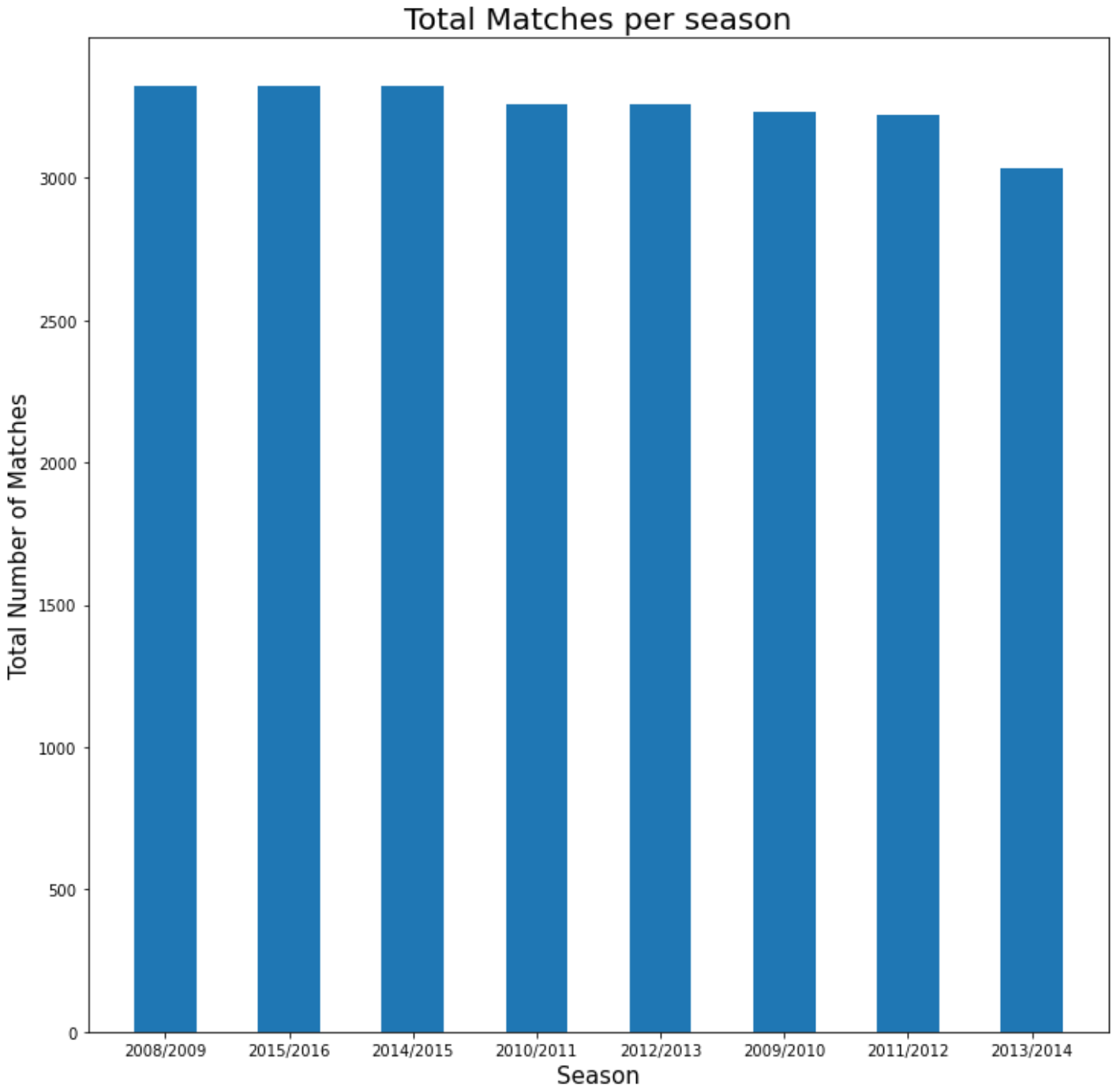
In [33]:
```
tm_att.drop_duplicates(inplace=True)
```

Exploratory Data Analysis

Question 1 : What's the season that have the most played matches?

In [34]:
```
season_matches= merge_team_match['season'].value_counts()
label= season_matches.keys()
sizes= season_matches[:]
width = 0.5
plt.subplots(figsize=(12,12))
plt.bar(label,sizes,width)
plt.title('Total Matches per season',fontsize=20)
plt.xlabel('Season',fontsize=15)
```

```
plt.ylabel('Total Number of Matches',fontsize=15)
plt.show()
```



In [35]:
```
season_matches
```

Out[35]:
```
2008/2009    3326
2015/2016    3326
2014/2015    3325
2010/2011    3260
2012/2013    3260
2009/2010    3230
2011/2012    3220
2013/2014    3032
Name: season, dtype: int64
```

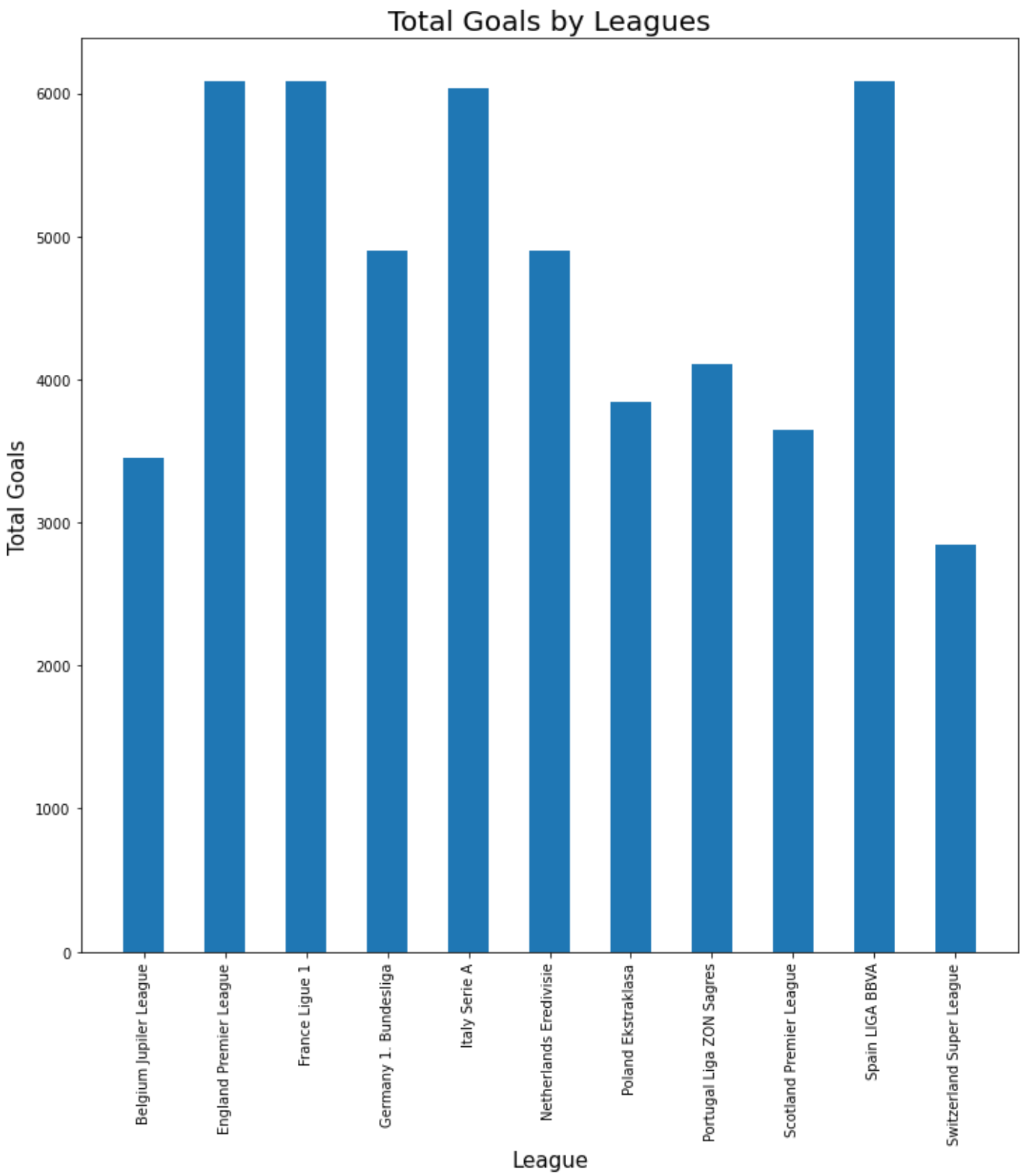
> From the database, I found that most seasons with the most played matches are seasons (2008/2009, 2015/2016) Among them, the total matches for each season decreased due to many reasons (cancellation of tournaments, political issues, ...etc)

Question 2 : What's the league that have the most scored goals ?

In [36]:
```
total_goals_league=merge_team_match.groupby('league_name')['home_team_goal'].count()+merge
total_goals_league
```

Out[36]:
```
league_name
Belgium Jupiler League      3456
England Premier League      6080
France Ligue 1              6080
Germany 1. Bundesliga       4896
Italy Serie A               6034
Netherlands Eredivisie      4896
Poland Ekstraklasa          3840
Portugal Liga ZON Sagres    4104
Scotland Premier League     3648
Spain LIGA BBVA             6080
Switzerland Super League    2844
dtype: int64
```

In [37]:
```
label= total_goals_league.keys()
sizes= total_goals_league[:]
width = 0.5
plt.subplots(figsize=(12,12))
plt.bar(label,sizes,width)
plt.title('Total Goals by Leagues',fontsize=20)
plt.xlabel('League',fontsize=15)
plt.xticks(rotation=90)
plt.ylabel('Total Goals',fontsize=15)
plt.show()
```



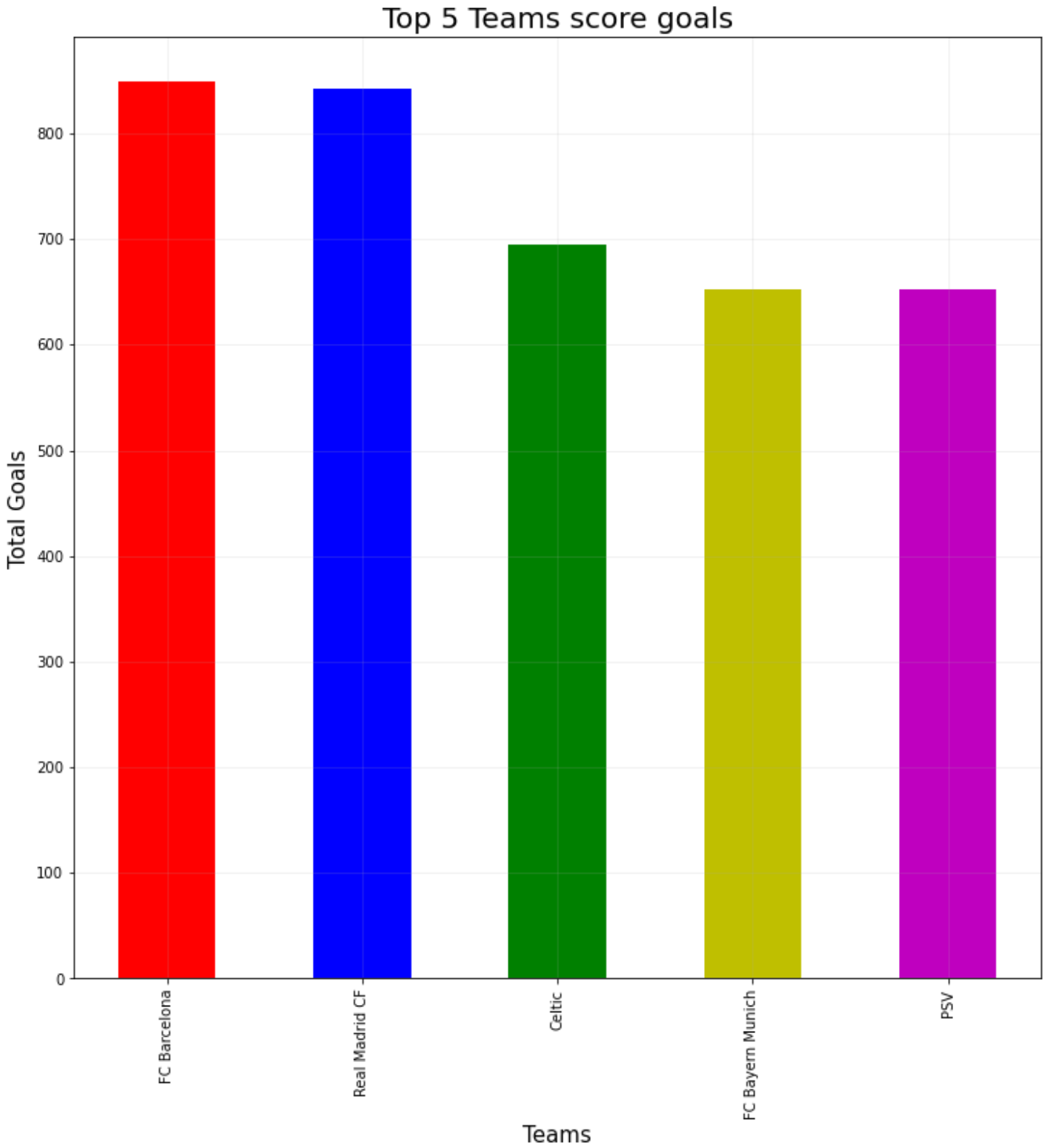
The leagues with the most goals are (Premier League, Ligue 1, Spain LIGA BBVA), and this positively affected the strength of those leagues

Question 3 : What top 5 teams scored most goals ?

In [38]:
```
total_team_goals=merge_team_match.groupby('home_team_name')['home_team_goal'].sum()+merge_
```

In [39]:
```
Top_5Goals = total_team_goals.nlargest(5)
label= Top_5Goals.keys()
sizes= Top_5Goals[:]
width = 0.5
```

```
plt.subplots(figsize=(12,12))
plt.bar(label,sizes,width,color=['r','b','g','y','m'])
plt.title('Top 5 Teams score goals',fontsize=20)
plt.xlabel('Teams',fontsize=15)
plt.xticks(rotation=90)
plt.ylabel('Total Goals',fontsize=15)
plt.grid(alpha=0.2)
plt.show()
```



In [40]:
```
Top_5Goals
```

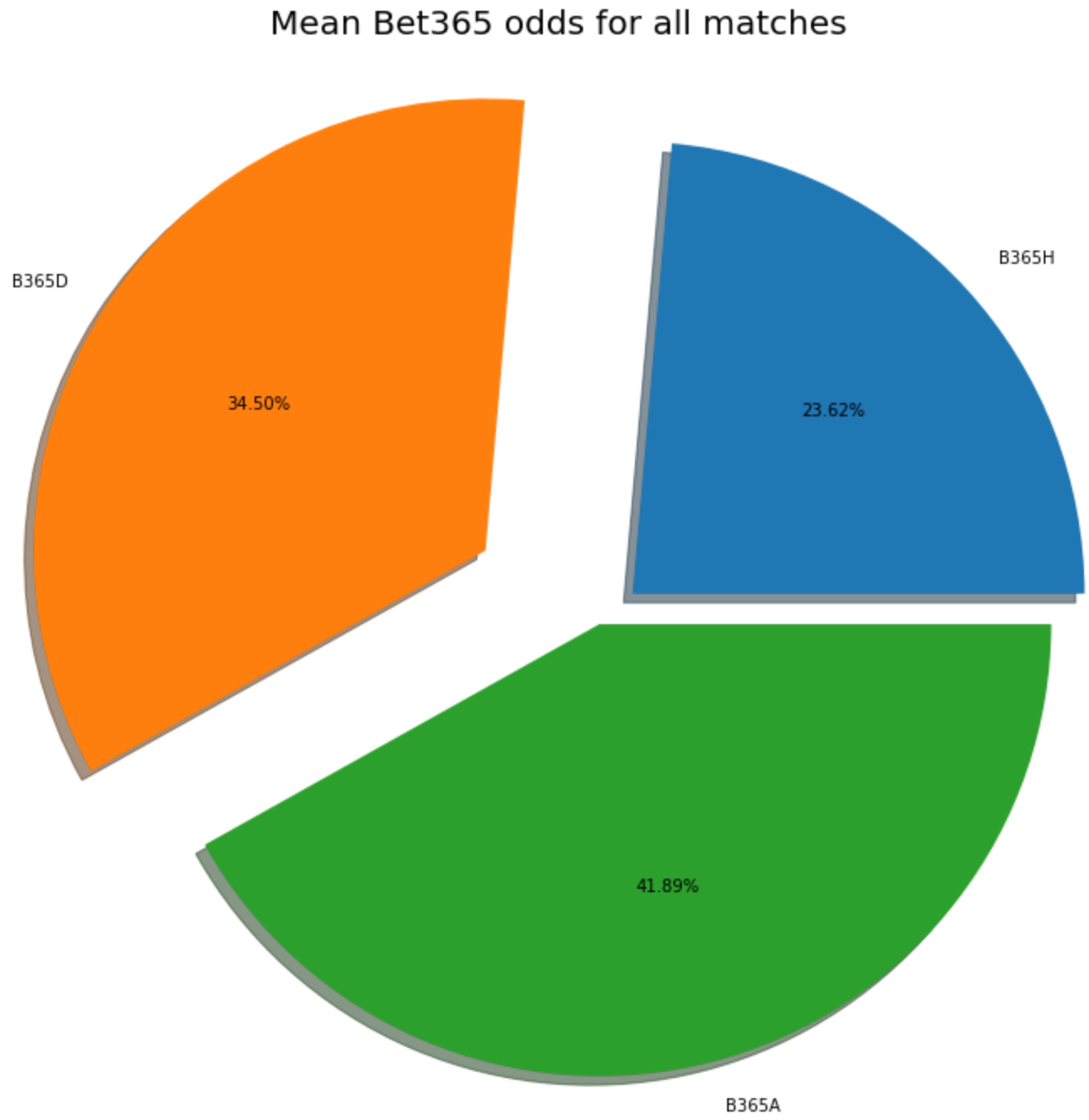
Out[40]:
```
home_team_name
FC Barcelona        849
Real Madrid CF      843
```

```
Celtic                695
FC Bayern Munich      653
PSV                   652
dtype: int64
```

Question 4 : What most fans choose to bet odds (Home Team ,Away Team,Draw) in all leagues ?

In [41]:

```
odds=merge_team_match.loc[:,'B365H':'B365A'].mean()
x= odds.keys()
y= odds[:]
explode = (0.1,0.3,0)
plt.subplots(figsize=(12,12))
plt.pie(y,labels=x,explode=explode,shadow=True,autopct='%.2f%%')
plt.title('Mean Bet365 odds for all matches',fontsize=20)
plt.axis('equal')
plt.show()
```



> Yes, of coarse. 360bets effected by the location of match and teams supporters , I found that Away

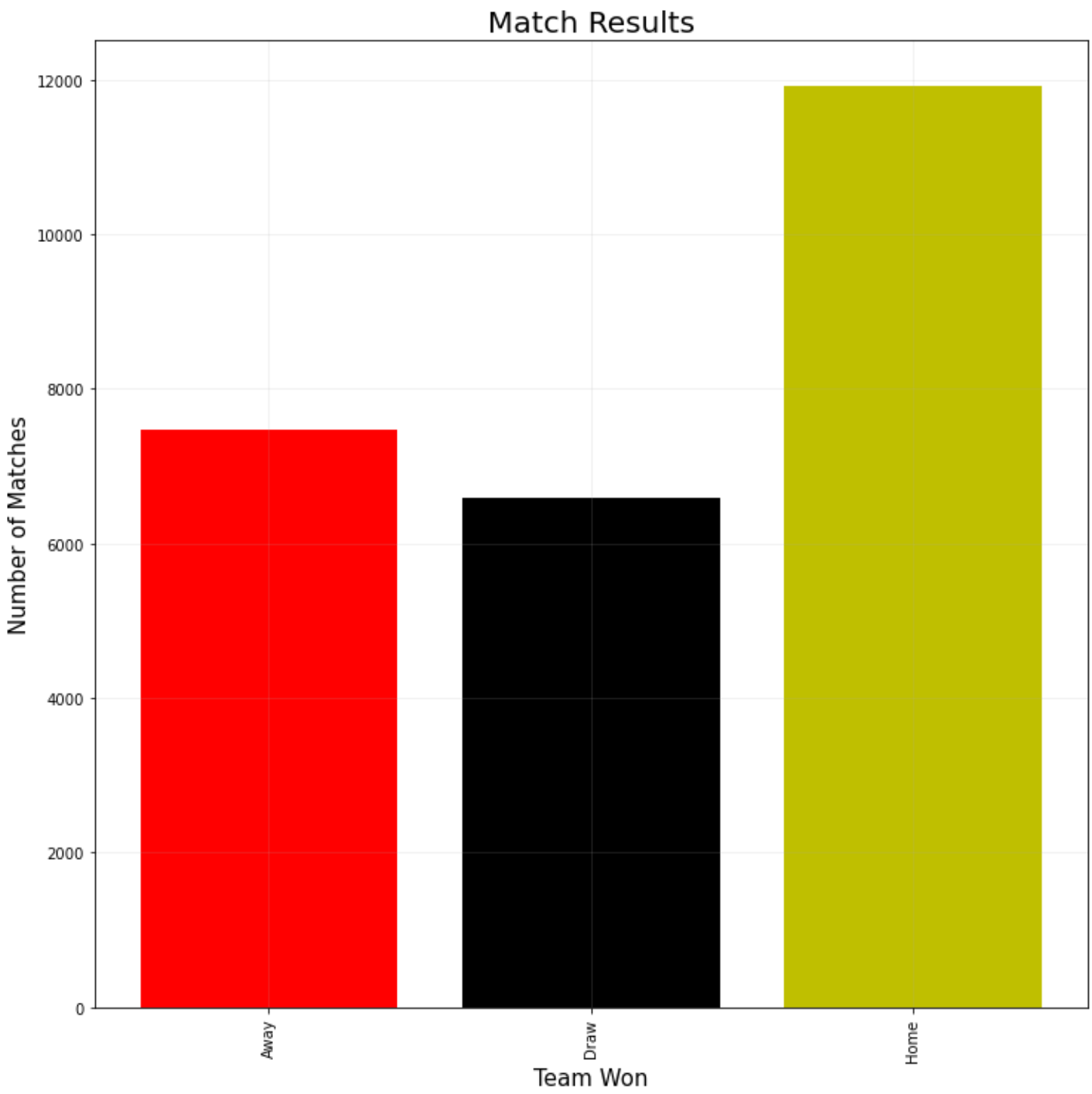
> teams supporters increased in bet odds by almost double bet odds rather than Home teams supporters.

> **Home teams are more Laky to score on their home rather than away**

Question 5 : What's winning parcentage for Away Teams?

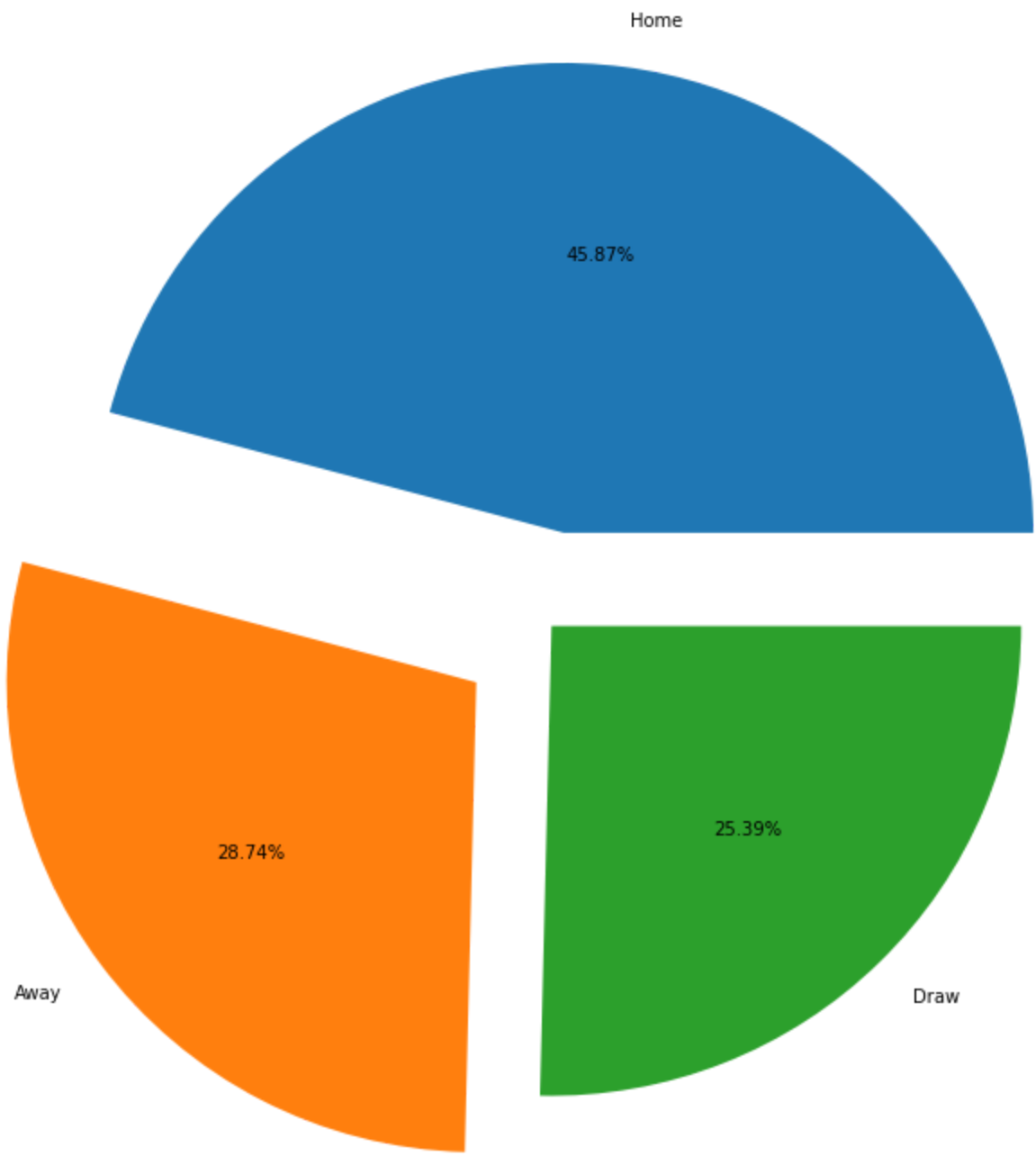
In [42]:

```
winning_effect=merge_team_match.groupby('match_result')['league_name'].count()
plt.subplots(figsize=(12,12));
plt.bar(winning_effect.keys(),winning_effect[:],color=['r','k','y']);
plt.title('Match Results',fontsize=20)
plt.xlabel('Team Won',fontsize=15)
values=['Away','Draw','Home']
plt.xticks(winning_effect.keys(),values,rotation=90)
plt.ylabel('Number of Matches',fontsize=15)
plt.grid(alpha=0.2)
plt.show()
```



In [43]:

```
total_count = merge_team_match.groupby('match_result')['league_name'].count().sum()
home_count = merge_team_match.query('match_result == "home_win"')['league_name'].count()
away_count = merge_team_match.query('match_result == "away_win"')['league_name'].count()
draw_count = merge_team_match.query('match_result == "draw"')['league_name'].count()
home_percentage=home_count/total_count *100
away_percentage=away_count/total_count *100
draw_percentage=draw_count/total_count *100
plt.subplots(figsize=(12,12));
plt.pie([home_percentage,away_percentage,draw_percentage],labels=['Home','Away','Draw'],ex
```

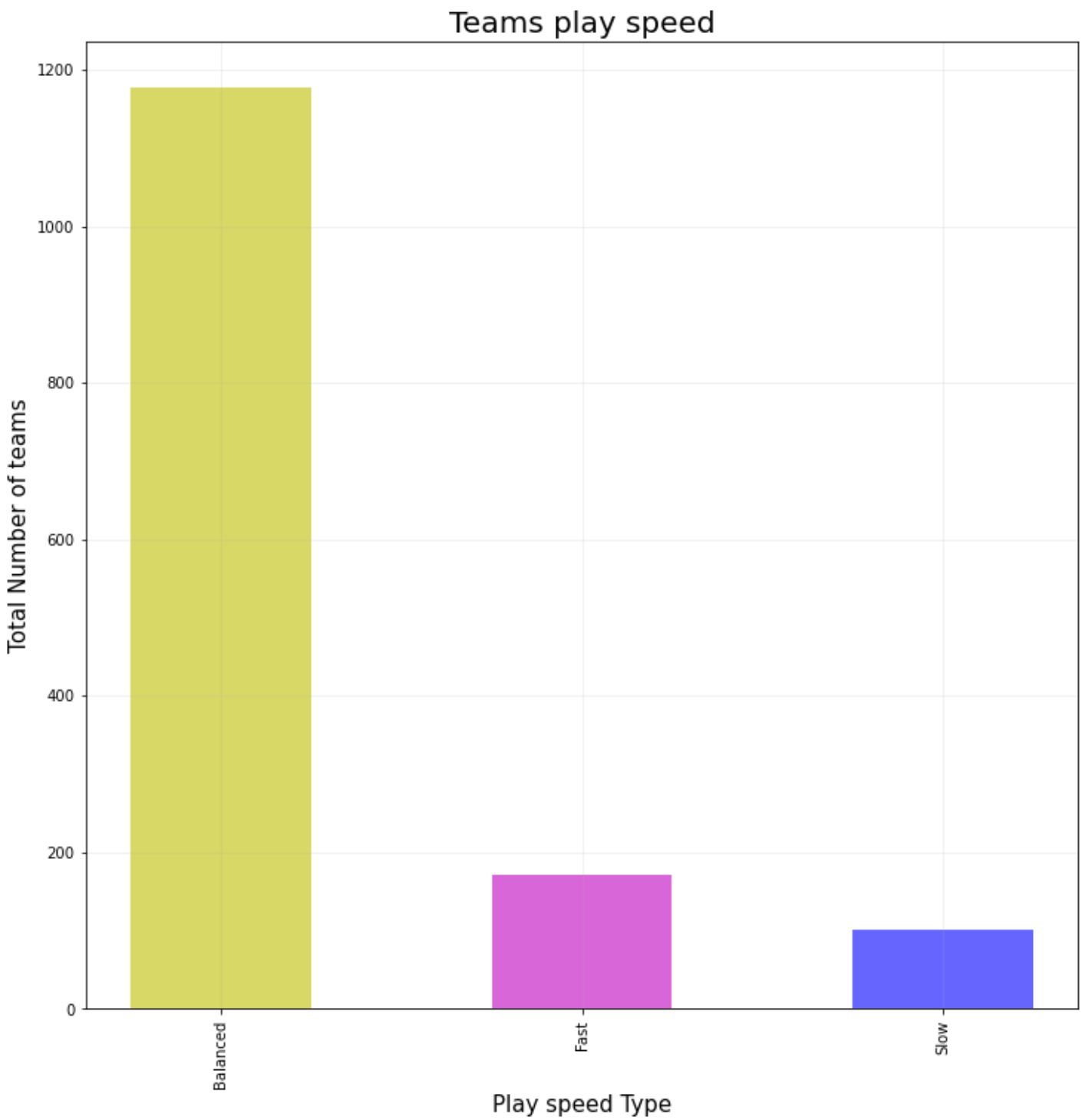


By Parcentage 45.87 % home team win , playing home had a big effect in winning match of course and i think this belong to their fans.

Question 6 : What's the most teams play speed type use ?

In [44]:

```
plyspeed=tm_att.groupby('buildUpPlaySpeedClass')['team_long_name'].count()
label = plyspeed.keys()
plt.subplots(figsize=(12,12));
plt.bar(label,plyspeed[:],width=0.5,alpha=0.6,color=['y','m','b']);
plt.title('Teams play speed',fontsize=20)
plt.xlabel('Play speed Type',fontsize=15)
plt.xticks(rotation=90)
plt.ylabel('Total Number of teams',fontsize=15)
plt.grid(alpha=0.2)
plt.show()
```



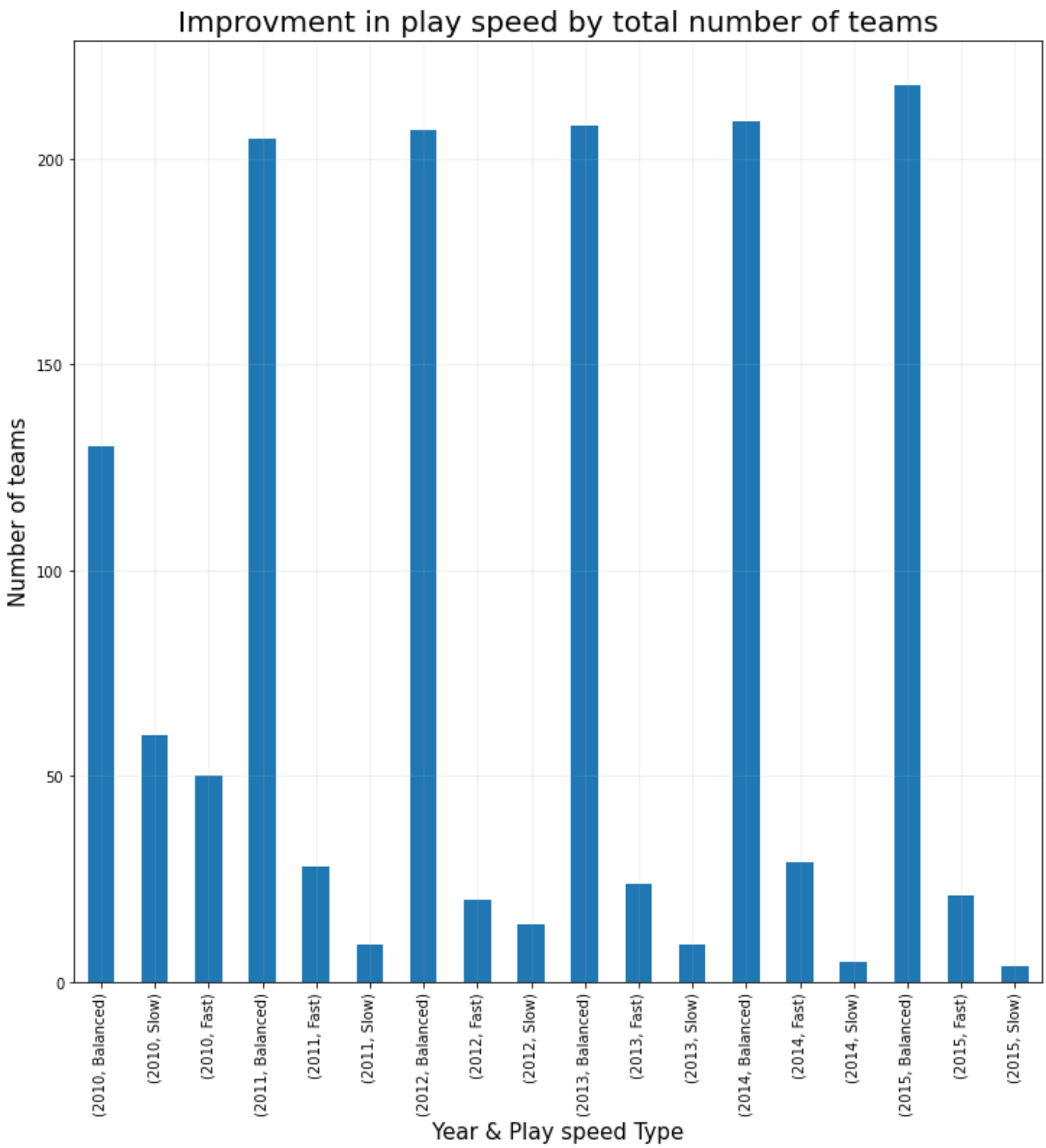
Question 7 : What's correlation of Slow play speed by years ?

In [45]:
```
speed_y=tm_att.loc[:,'buildUpPlaySpeedClass':'year']
speed_y.columns
```

Out[45]:
```
Index(['buildUpPlaySpeedClass', 'buildUpPlayDribbling',
       'buildUpPlayDribblingClass', 'buildUpPlayPassing',
       'buildUpPlayPassingClass', 'buildUpPlayPositioningClass',
       'chanceCreationPassing', 'chanceCreationPassingClass',
       'chanceCreationCrossing', 'chanceCreationCrossingClass',
       'chanceCreationShooting', 'chanceCreationShootingClass',
       'chanceCreationPositioningClass', 'defencePressure',
       'defencePressureClass', 'defenceAggression', 'defenceAggressionClass',
       'defenceTeamWidth', 'defenceTeamWidthClass', 'defenceDefenderLineClass',
       'year'],
      dtype='object')
```

In [46]:
```
speed_y.drop(columns=['buildUpPlayDribbling',
       'buildUpPlayDribblingClass', 'buildUpPlayPassing',
       'buildUpPlayPassingClass', 'buildUpPlayPositioningClass',
       'chanceCreationPassing', 'chanceCreationPassingClass',
       'chanceCreationCrossing', 'chanceCreationCrossingClass',
       'chanceCreationShooting', 'chanceCreationShootingClass',
       'chanceCreationPositioningClass', 'defencePressure',
       'defencePressureClass', 'defenceAggression', 'defenceAggressionClass',
       'defenceTeamWidth', 'defenceTeamWidthClass', 'defenceDefenderLineClass'],inplace=Tr
```

In [47]:
```
plt.subplots(figsize=(12,12));
speed_y.groupby('year')['buildUpPlaySpeedClass'].value_counts().plot(kind='bar',stacked=Tr
plt.title('Improvment in play speed by total number of teams',fontsize=20)
plt.ylabel('Number of teams',fontsize=15)
plt.xticks(rotation=90)
plt.xlabel('Year & Play speed Type',fontsize=15)
plt.grid(alpha=0.2)
plt.show()
```



Conclusions

Q1 : What's the season that have the most played matches?

> 2008/2009 , 2015/2016

Q2 : What's the league that have the most scored goals ?

> Premier League, Ligue 1, Spain LIGA BBVA

Q3 : What top 5 teams scored most goals ?

> FC Barcelona ---> 849 Goals
>
> Real Madrid CF ---> 843 Goals
>
> Celtic ---> 695 Goals
>
> FC Bayern Munich ---> 653 Goals
>
> PSV ---> 652 Goals

Q4 : What most fans choose to bet odds (Home Team ,Away Team,Draw) in all leagues ?

> Home Team

Q5 : What's winning parcentage for Away Teams?

> 28.74%

Q6 : What's the most teams play speed type use ?

> Balanced

Q7 : What's correlation of Slow play speed by years ?

> Negative correlation