EU-Soccer-Competition-Analysis

April 16, 2018

1 Project: European Soccer Database

1.1 Table of Contents

Introduction

> European Soccer match has a top level and may be the most exciting soccer match in the world. There are many European national teams qualifying for the World Cup every time. At the same time a lot of football players are playing for different teams in Europe. Though it is dramatic to watch a match, it is also enjoyable to analyze these teams and players.

Question 1: In 2015/2016 season, which league has the most mean goals? Which teams have the most mean scores respectivelyWhat about mean fumbles?

Question 2: What is the win rate for the best team that ranks first in England Premier League, Germany 1. Bundesliga, Italy Serie A and Spain LIGA BBVA in 2015/2016 season separately

Question 3: What is the difference between fastest team and the mean team attributes?

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

Data Wrangling > At the beginning, I convert the database.sqilte to csv files according to the table and we get nine files. Let's see them in details. I will skip over some simply files.

1.1.1 General Properties

```
In [2]: # Load your data and print out a few lines. Perform operations to inspect data
        #   types and look for instances of missing or possibly errant data.
        df_country = pd.read_csv('./data/Country.csv')
        df_country.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 [3]: df_league = pd.read_csv('./data/League.csv')
        df_league.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 [4]: df_player = pd.read_csv('./data/Player.csv')
        df_player.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 [5]: sum(df_player.duplicated())
```

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

There are 11060 players and no any duplicated or null elements. This data is clean.

```
In [6]: df_player_attributes = pd.read_csv('./data/Player_Attributes.csv')
        print(df_player_attributes.shape)
        print(sum(df_player_attributes.duplicated()))
        df_player_attributes.isnull().sum()
```

```
(183978, 42)
0
```

```
Out[6]: id                        0
        player_fifa_api_id        0
        player_api_id             0
        date                      0
        overall_rating          836
        potential               836
        preferred_foot          836
        attacking_work_rate    3230
        defensive_work_rate     836
        crossing                836
        finishing               836
        heading_accuracy        836
        short_passing           836
        volleys                2713
        dribbling               836
        curve                  2713
        free_kick_accuracy      836
        long_passing            836
        ball_control            836
        acceleration            836
        sprint_speed            836
        agility                2713
        reactions               836
        balance                2713
        shot_power              836
        jumping                2713
        stamina                 836
        strength                836
        long_shots              836
        aggression              836
        interceptions           836
        positioning             836
        vision                 2713
        penalties               836
        marking                 836
        standing_tackle         836
        sliding_tackle         2713
```

```
gk_diving               836
gk_handling             836
gk_kicking              836
gk_positioning          836
gk_reflexes             836
dtype: int64
```

The player attributes have 183978 rows and up to over 3000 null parts. We will remove the null parts. It has little effects on the whole data.

```
In [8]: df_team = pd.read_csv('./data/Team.csv')
        df_team.info()
        print(df_team.duplicated().sum())
        print(df_team.head(2))
```

```
<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
0
   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
```

```
In [14]: df_team_attributes = pd.read_csv('./data/Team_Attributes.csv')
         print(df_team_attributes.info())
         print(df_team_attributes.duplicated().sum())
         df_team_attributes.head()
```

```
<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
None
0
```

Out[14]:

```
   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
3   4                77         8485  2010-02-22 00:00:00                70
4   5                77         8485  2011-02-22 00:00:00                47

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

   buildUpPlayPassing buildUpPlayPassingClass           ...              \
0                  50                   Mixed           ...
1                  56                   Mixed           ...
2                  54                   Mixed           ...
3                  70                    Long           ...
4                  52                   Mixed           ...

  chanceCreationShooting  chanceCreationShootingClass  \
0                     55                       Normal
1                     64                       Normal
2                     64                       Normal
3                     70                         Lots
4                     52                       Normal
```

```
  chanceCreationPositioningClass  defencePressure defencePressureClass  \
0                      Organised               50               Medium
1                      Organised               47               Medium
2                      Organised               47               Medium
3                      Organised               60               Medium
4                      Organised               47               Medium

   defenceAggression defenceAggressionClass defenceTeamWidth  \
0                 55                  Press               45
1                 44                  Press               54
2                 44                  Press               54
3                 70                 Double               70
4                 47                  Press               52

   defenceTeamWidthClass defenceDefenderLineClass
0                 Normal                    Cover
1                 Normal                    Cover
2                 Normal                    Cover
3                   Wide                    Cover
4                 Normal                    Cover

[5 rows x 25 columns]
```

From the above data, we can see there are only less than 500 non-null buildUpPlayDribbling data in more than 1400 rows. Further more, when buildUpPlayDribbling is NaN, the buildUpPlayDribblingClass is Little. We can guess there may be some relations. Let's continue to see the Match file.

In [9]:
```
df_match = pd.read_csv('./data/Match.csv')
print(df_match.info())
df_match.head(2)
```

```
<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
None
```

Out[9]:
```
   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

   match_api_id  home_team_api_id  away_team_api_id  home_team_goal ...   SJA  \
0        492473              9987              9993               1 ...   4.0
1        492474             10000              9994               0 ...   3.8
```

```
    VCH   VCD   VCA   GBH   GBD   GBA   BSH   BSD  BSA
0  1.65  3.40  4.50  1.78  3.25  4.00  1.73  3.40  4.2
1  2.00  3.25  3.25  1.85  3.25  3.75  1.91  3.25  3.6

[2 rows x 115 columns]
```

We can see the details in it.

```
In [10]: df_match['season'].unique()
```

```
Out[10]: array(['2008/2009', '2009/2010', '2010/2011', '2011/2012', '2012/2013',
                '2013/2014', '2014/2015', '2015/2016'], dtype=object)
```

```
In [11]: df_match['league_id'].unique()
```

```
Out[11]: array([    1,  1729,  4769,  7809, 10257, 13274, 15722, 17642, 19694,
                21518, 24558])
```

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

```
Out[12]: 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 [13]:
```
sum(df_match['goal'].isnull())
```

Out[13]:
```
11762
```

There are more than 100 columns with over 25000 entries in Match data. And nearly half of the 'goal' attribute is null. We can do research on some key columns.

1.1.2 Data Cleaning (Replace this with more specific notes!)

In [7]:
```
# After discussing the structure of the data and any problems that need to be
#   cleaned, perform those cleaning steps in the second part of this section.

# First Let's drop the null values in player_attributes
df_player_attributes.dropna(inplace=True);
df_player_attributes.info();
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 180354 entries, 0 to 183977
Data columns (total 42 columns):
id                     180354 non-null int64
player_fifa_api_id     180354 non-null int64
player_api_id          180354 non-null int64
date                   180354 non-null object
overall_rating         180354 non-null float64
potential              180354 non-null float64
preferred_foot         180354 non-null object
attacking_work_rate    180354 non-null object
defensive_work_rate    180354 non-null object
crossing               180354 non-null float64
finishing              180354 non-null float64
heading_accuracy       180354 non-null float64
short_passing          180354 non-null float64
volleys                180354 non-null float64
dribbling              180354 non-null float64
curve                  180354 non-null float64
free_kick_accuracy     180354 non-null float64
long_passing           180354 non-null float64
ball_control           180354 non-null float64
acceleration           180354 non-null float64
sprint_speed           180354 non-null float64
agility                180354 non-null float64
reactions              180354 non-null float64
balance                180354 non-null float64
shot_power             180354 non-null float64
jumping                180354 non-null float64
stamina                180354 non-null float64
strength               180354 non-null float64
long_shots             180354 non-null float64
aggression             180354 non-null float64
interceptions          180354 non-null float64
positioning            180354 non-null float64
vision                 180354 non-null float64
penalties              180354 non-null float64
marking                180354 non-null float64
standing_tackle        180354 non-null float64
sliding_tackle         180354 non-null float64
gk_diving              180354 non-null float64
gk_handling            180354 non-null float64
gk_kicking             180354 non-null float64
gk_positioning         180354 non-null float64
gk_reflexes            180354 non-null float64
dtypes: float64(35), int64(3), object(4)
memory usage: 59.2+ MB
```

Now this data is OK. Let's check our guess on team_attribute. We have found some null values before.

```
In [15]: # see all the buildUpPlayDribblingClass values and what value is null
         print(df_team_attributes['buildUpPlayDribblingClass'].unique())
         df_team_attributes[df_team_attributes['buildUpPlayDribbling'].isnull()]['buildUpPlayD
```

```
['Little' 'Normal' 'Lots']
```

```
Out[15]: array(['Little'], dtype=object)
```

```
In [21]: # see the details
         df_team_attributes[df_team_attributes['buildUpPlayDribblingClass'] == 'Little']['build
```

```
Out[21]: array([nan, 32., 30., 29., 24., 31., 33., 28., 26., 27.])
```

```
In [17]: df_team_attributes[df_team_attributes['buildUpPlayDribblingClass'] == 'Normal']['build
```

```
Out[17]: array([48., 41., 64., 57., 53., 47., 40., 43., 46., 61., 49., 66., 51.,
               37., 45., 52., 50., 38., 55., 35., 63., 34., 39., 60., 44., 36.,
               56., 54., 59., 58., 42., 62., 65.])
```

```
In [18]: df_team_attributes[df_team_attributes['buildUpPlayDribblingClass'] == 'Lots']['buildUp
```

```
Out[18]: array([70., 69., 67., 77., 68., 71., 74.])
```

Now our guess is true. When buildUpPlayDribblingClass is Little, the buildUpPlayDribbling is NaN. We can consider use the mean value to take place of the NaN values.

```
In [22]: print(df_team_attributes.query('buildUpPlayDribblingClass == "Normal"')['buildUpPlayD
         mean_buildUpPlayDribbling = df_team_attributes.query('buildUpPlayDribblingClass == "Li
```

```
34.0
```

```
In [23]: # use the mean value to fill and check it
         df_team_attributes.fillna(mean_buildUpPlayDribbling, inplace=True)
         df_team_attributes['buildUpPlayDribbling'].isnull().sum()
```

```
Out[23]: 0
```

Exploratory Data Analysis

1.1.3 Question 1: In 2015/2016 season, which league has the most mean goals? Which teams have the most mean scores respectively What about mean fumbles?

In [24]:
```
# Use this, and more code cells, to explore your data. Don't forget to add
#   Markdown cells to document your observations and findings.

def get_league_data(df, league_id, season):
    """ get one league data by league_id and season from Match file
    """
    columns = ['id', 'league_id', 'season', 'match_api_id', 'home_team_api_id', 'away_
    df_match = df[(df['league_id'] == league_id) & (df['season'] == season)]
    return df_match.loc[:, columns]
```

In [564]:
```
def process_float(data):
    return float("{0:.2f}".format(data))
```

In [562]:
```
# get total goals in a league
def get_league_mean_goals(df):
    matches = float(len(df.index))
    total_scores = df['home_team_goal'].sum() + df['away_team_goal'].sum()
    return process_float(total_scores / matches)
```

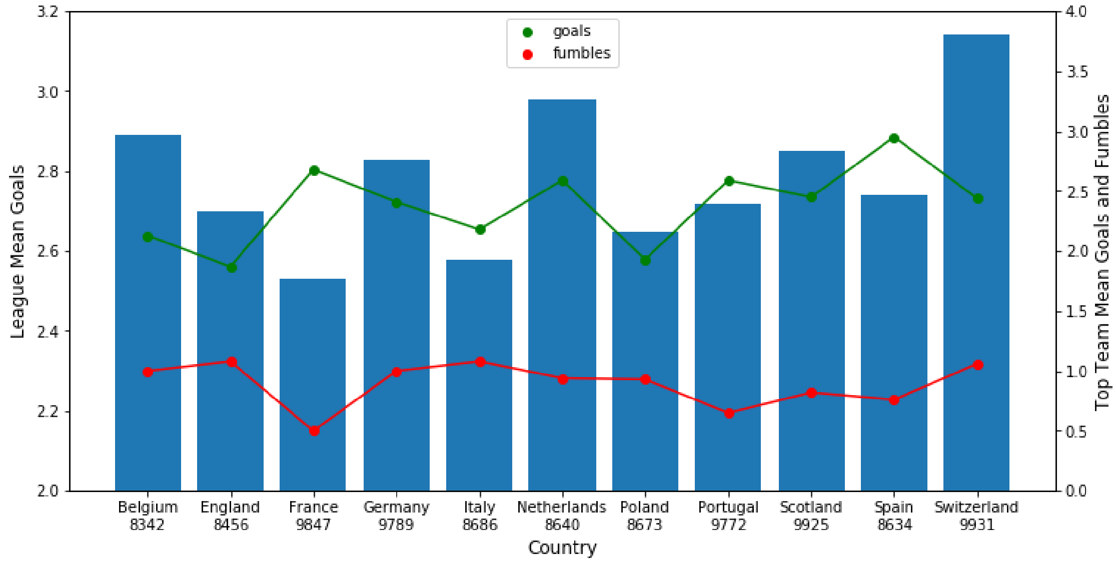
In [560]:
```
def get_team_mean_goals(df):
    """find the most mean goals and the team. Assume they have the same number of ma
    """
    # For the team_goals, the key is team_id, the value is three-element list.
    # In the list, the first element is goals, the second element is fumbles, the th
    team_goals = {}
    for row in df.itertuples():
        home_team = row[5]
        away_team = row[6]
        home_team_goal = row[7]
        away_team_goal = row[8]

        if team_goals.get(home_team) is None:
            team_goals[home_team] = [0] * 3
            team_goals[home_team][0] = home_team_goal
            team_goals[home_team][1] = away_team_goal
            team_goals[home_team][2] = 1
        else:
            team_goals[home_team][0] += home_team_goal
            team_goals[home_team][1] += away_team_goal
            team_goals[home_team][2] += 1

        if team_goals.get(away_team) is None:
            team_goals[away_team] = [0] * 3
            team_goals[away_team][0] = away_team_goal
            team_goals[away_team][1] += home_team_goal
            team_goals[away_team][2] = 1
```

```
                else:
                    team_goals[away_team][0] += away_team_goal
                    team_goals[away_team][1] += home_team_goal
                    team_goals[away_team][2] += 1
            team_goals = sorted(team_goals.items(), key=lambda d: d[1][0], reverse=True)
            max_goals_team = team_goals[0][0]
            goals = team_goals[0][1][0]
            fumbles = team_goals[0][1][1]
            matches = float(team_goals[0][1][2])
            max_mean_goals = process_float(goals / matches)
            mean_fumbles = process_float(fumbles / matches)
            return max_goals_team, max_mean_goals, mean_fumbles
```

In [29]:
```
def plot_goals_bar(league_list, league_goals_list, team_list, team_goals_list, team_fu
    fig = plt.figure(figsize=(12, 6))
    l = len(league_list)
    ind = np.arange(l)
    league_list = [league_list[i] + "\n" + str(team_list[i]) for i in range(l)]
    league = fig.add_subplot(111)
    team = league.twinx()

    league.set_ylim(2.0, 3.2)
    team.set_ylim(0, 4)
    league.set_xlabel('Country', fontsize=12)
    league.set_ylabel('League Mean Goals', fontsize=12)
    team.set_ylabel('Top Team Mean Goals and Fumbles', fontsize=12)
    league.bar(ind, league_goals_list)
    plt.xticks(ind, league_list)
    p1 = plt.plot(ind, team_goals_list, 'bo', ind, team_goals_list, 'k', color='g')
    p2 = plt.plot(ind, team_fumbles_list, 'bo', ind, team_fumbles_list, 'k', color='r

    plt.legend((p1[0], p2[0]), ('goals', "fumbles"), loc=9)
    plt.show()
```

In [563]:
```
# plot the league data in 2015/2016 season
league_id_list = list(df_league['id'])
season = '2015/2016'
league_country_list = []
league_mean_goals_list = []
team_list = []
team_goals_list = []
team_fumbles_list = []
for league_id in league_id_list:
    league = df_league[df_league['id'] == league_id]
    # mean_goals-country
    league_country = str(league['name']).split()[1]
    league_country_list.append(league_country)
```

```
        df_league_data = get_league_data(df_match, league_id, season)
        league_mean_goals = get_league_mean_goals(df_league_data)
        league_mean_goals_list.append(league_mean_goals)

        team, goals, fumbles = get_team_mean_goals(df_league_data)
        team_list.append(team)
        team_goals_list.append(goals)
        team_fumbles_list.append(fumbles)
    plot_goals_bar(league_country_list, league_mean_goals_list, team_list, team_goals_li
```



The xlabel is the league country and its best team id. The left yaxis is the the bar data and right yaxis is the line data.

1.1.4 Question 2: What is the win rate for the best team that ranks first in England Premier League, Germany 1. Bundesliga, Italy Serie A and Spain LIGA BBVA in 2015/2016 season separately

```
In [ ]: # Continue to explore the data to address your additional research
        #   questions. Add more headers as needed if you have more questions to
        #   investigate.
```

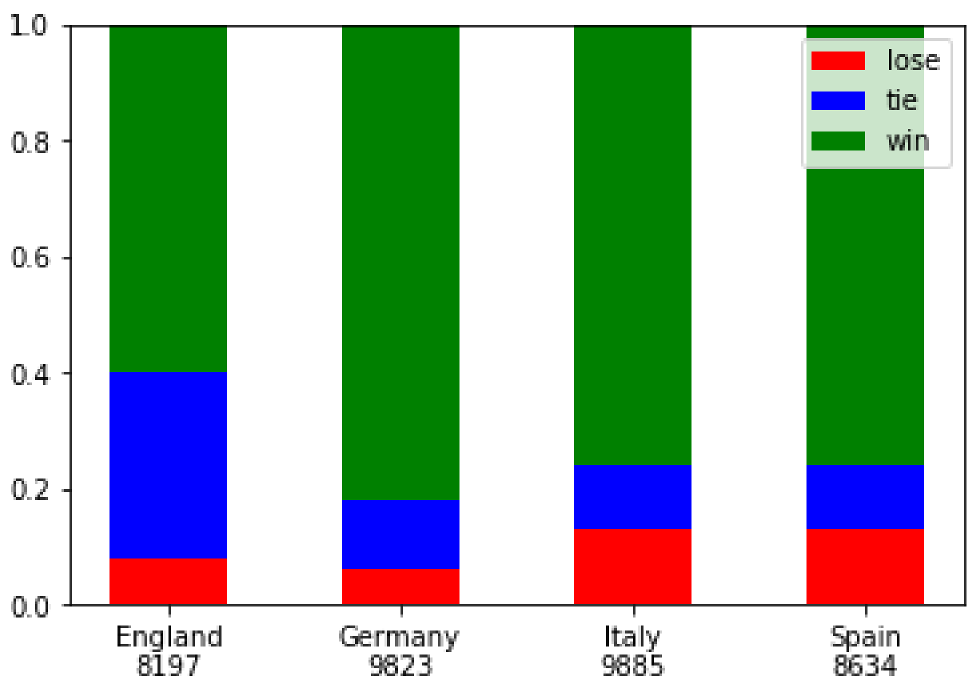
```
In [31]: # get points according to the rule three points for a win
         # https://en.wikipedia.org/wiki/Three_points_for_a_win
         def get_best_team_result(df):
             """ get team and win rate, tie rate, lose rate
             """
             team_points = {}
             for row in df.itertuples():
                 home_team = row[8]
```

```
            away_team = row[9]
            home_team_goal = row[10]
            away_team_goal = row[11]
            result = home_team_goal - away_team_goal

            # this four-element list means numbers of win, tie, lose and total points
            if team_points.get(home_team) is None:
                home_team_result = [0] * 4
                team_points[home_team] = home_team_result
            if team_points.get(away_team) is None:
                away_team_result = [0] * 4
                team_points[away_team] = away_team_result

            # home win
            if result > 0:
                team_points[home_team][0] += 1
                team_points[away_team][2] += 1
            # tie
            elif result == 0:
                team_points[home_team][1] += 1
                team_points[away_team][1] += 1
            # away win
            else:
                team_points[away_team][0] += 1
                team_points[home_team][2] += 1

        for team in team_points.keys():
            team_points[team][3] = 3 * team_points[team][0] + team_points[team][1]

        team_points = sorted(team_points.items(), key=lambda d: d[1][3], reverse=True)
        matches = team_points[0][1][0] + team_points[0][1][1] + team_points[0][1][2]
        # win rate, tie rate, lose rate
        win_rate = get_percentage(team_points[0][1][0] / matches)
        tie_rate = get_percentage(team_points[0][1][1] / matches)
        lose_rate = get_percentage(team_points[0][1][2] / matches)
        return {team_points[0][0]: [win_rate, tie_rate, lose_rate]}
```

```
In [32]: def plot_team_line(team_list, win_list, tie_list, lose_list):
        # fig = plt.figure(figsize=(12, 6))
        ind = np.arange(len(team_list))
        win_list = np.array(win_list)
        tie_list = np.array(tie_list)
        lose_list = np.array(lose_list)
        p1 = plt.bar(ind, lose_list, width=0.5, color='r')
        p2 = plt.bar(ind, tie_list, width=0.5, bottom=lose_list, color='b')
        p3 = plt.bar(ind, win_list, width=0.5, bottom=tie_list+lose_list, color='g')
        plt.ylim([0, 1])
        plt.legend((p1[0], p2[0], p3[0]), ('lose', 'tie', 'win'), loc=1)
```

```
        plt.xticks(ind, team_list)
        plt.show()
```

```
In [34]: # England, Germany, Italy, Spain League
         df_team_attribute = pd.read_csv('./data/Team_Attributes.csv')
         leagues_list = {1729: 'England', 7809: 'Germany', 10257: 'Italy', 21518: 'Spain'}
         best_teams = []
         team_list = []
         win_list = []
         tie_list = []
         lose_list = []
         for league_id in leagues_list.keys():
             df_league_match = df_match[(df_match['season'] == season) & (df_match['league_id']
             best_team = get_best_team_result(df_league_match)
             key = leagues_list[league_id] + "\n" + str(list(best_team.keys())[0])
             team_list.append(key)
             value = list(best_team.values())
             win_list.append(value[0][0])
             tie_list.append(value[0][1])
             lose_list.append(value[0][2])
         plot_team_line(team_list, win_list, tie_list, lose_list)
```

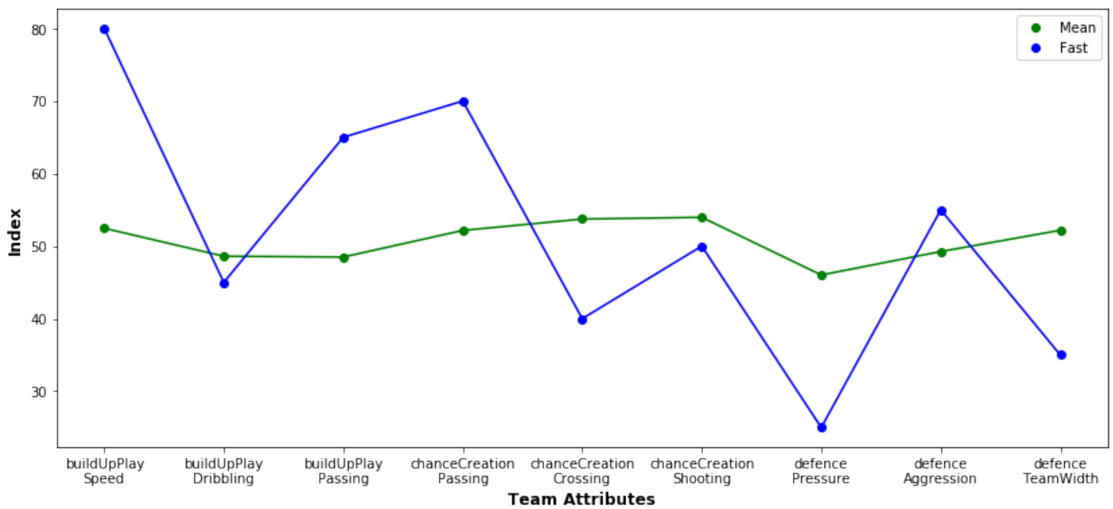


1.1.5 Question 3: What is the difference between fastest team and the mean team attributes?

```
In [35]: def plot_team_attributes(mean_team_attribute, fastest_team_attribute):
             ind = np.arange(len(mean_team_attribute))
```

```
    plt.figure(figsize=(14, 6))
    p1 = plt.plot(ind, mean_team_attribute, 'bo', ind, mean_team_attribute, 'k', colo
    p2 = plt.plot(ind, fastest_team_attribute, 'bo', ind, fastest_team_attribute, 'k'
    plt.legend((p1[0], p2[0]), ('Mean', 'Fast'))
    plt.xticks(ind, new_labels)
    plt.xlabel('Team Attributes', fontsize=12, weight='bold')
    plt.ylabel('Index', fontsize=12, weight='bold')
    plt.show()
```

```
In [36]: new_labels = ['buildUpPlay\nSpeed', 'buildUpPlay\nDribbling', 'buildUpPlay\nPassing',
                       'chanceCreation\nPassing', 'chanceCreation\nCrossing', 'chanceCreation\n
                       'defence\nPressure', 'defence\nAggression', 'defence\nTeamWidth']
         df_team_attribute = df_team_attribute.iloc[:, np.r_[4, 6, 8, 11, 13, 15, 18, 20, 22]]
         df_team_attribute.columns = new_labels
         mean_team_attributes = df_team_attribute.mean()
         fastest_team_mean_attributes = df_team_attribute[
             df_team_attribute['buildUpPlay\nSpeed'] == df_team_attribute['buildUpPlay\nSpeed']
         plot_team_attributes(mean_team_attributes, fastest_team_mean_attributes)
```



Conclusions

In all the leagues, Switzerland has the most mean goals. There are more three goals per match. For all their most-goals teams, Spain team 8634 has the highest mean goals, also nearly three goals per match. The France team 9847 followed it, but has the lowest fumbles, about 0.5, which indicates it has a good balance between attacking and defending.

For England, Germany, Italy, Spain four Leagues, Germany team 9823 has highest win rate over 80% and lowest lose rate in 2015/2016 season. England team 8197 has lowest win rate and highest tie rate. It is a little conservative in these four teams.

For the buildUpPlaySpeed fastest team, compared with mean team attributes, it has much higher passing no matter buildUpPlayPass or chanceCreationPassing, and lower chanceCreation in crossing and shooting, and much lower defencePressure.