Investigating a Dataset - European Soccer Database

September 3, 2018

1 Udacity - Data Science NanoDegree

1.1 Investigate a Dataset

1.1.1 Submission By: 55thSwiss

We'll be analyzing the soccer data set [1], mostly because it could be used for predictive ML and it's sports related, both of which interest me. All analysis and computation have been done in this notebook.

[1] https://www.kaggle.com/hugomathien/soccer

1.2 Intro

One of the most enjoyable parts about watching sports is watching a team win. This usually has to do with the fact that winning teams score more, but in this analysis I'm going to take a look at what makes a winning team, statistically, different than a losing team beyond just the goals.

We're going to manipulate the data into two basic categories, data about individual teams and data about how these teams did against one another, then we can compare what the make-up of these teams are that played one another.

1.3 Import Dependencies

```
In [1]: %matplotlib inline
        import pandas as pd
        import numpy as np
        import matplotlib as mpl
        import matplotlib.pyplot as plt
        import matplotlib.pylab as pylab
        import matplotlib.ticker as ticker
        import seaborn as sns
        from math import pi
        import sqlite3
        import datetime
        import warnings
        warnings.filterwarnings("ignore")
        pd.set_option('display.max_columns', None)
        pd.set_option('display.max_rows', None)
```

1.4 Import Data

```
In [2]: with sqlite3.connect('database.sqlite') as con:
            countries = pd.read_sql_query("SELECT * from Country", con)
            matches = pd.read_sql_query("SELECT * from Match", con)
            leagues = pd.read_sql_query("SELECT * from League", con)
            teams = pd.read_sql_query("SELECT * from Team", con)
            player = pd.read_sql_query("SELECT * from Player",con)
            player_attributes = pd.read_sql_query("SELECT * from Player_Attributes",con)
            sequence = pd.read_sql_query("SELECT * from sqlite_sequence",con)
            team_attributes = pd.read_sql_query("SELECT * from Team_Attributes",con)
```

1.5 Quick Look

Since we're interested in what makes a winning team different than a losing one, a large portion of this data is not going to be utilized, namely the 'player' and 'player_attributes' data sets. Normally I wouldn't want to disregard such a large accumulation of data but for the sake of not making this about discrepancies, anomalies, or general focus on the correlation between one data set and another it will be assumed the accumulation of individual player attributes into a single 'team' is therefore represented in the 'team_attributes' data set.

```
In [3]: teams.nunique()

Out[3]: id                  299
        team_api_id         299
        team_fifa_api_id    285
        team_long_name      296
        team_short_name     259
        dtype: int64

In [4]: team_attributes.nunique()

Out[4]: id                                1458
        team_fifa_api_id                   285
        team_api_id                        288
        date                                 6
        buildUpPlaySpeed                    57
        buildUpPlaySpeedClass                3
        buildUpPlayDribbling                49
        buildUpPlayDribblingClass            3
        buildUpPlayPassing                  58
        buildUpPlayPassingClass              3
        buildUpPlayPositioningClass          2
        chanceCreationPassing               50
        chanceCreationPassingClass           3
        chanceCreationCrossing              56
        chanceCreationCrossingClass          3
        chanceCreationShooting              57
        chanceCreationShootingClass          3
```

```
chanceCreationPositioningClass       2
defencePressure                     48
defencePressureClass                 3
defenceAggression                   47
defenceAggressionClass               3
defenceTeamWidth                    43
defenceTeamWidthClass                3
defenceDefenderLineClass             2
dtype: int64
```

```
In [5]: countries.nunique()
```

```
Out[5]: id      11
        name    11
        dtype: int64
```

```
In [6]: leagues.nunique()
```

```
Out[6]: id            11
        country_id    11
        name          11
        dtype: int64
```

```
In [7]: matches[['country_id',
                 'league_id',
                 'season',
                 'date',
                 'match_api_id',
                 'home_team_api_id',
                 'away_team_api_id']].nunique()
```

```
Out[7]: country_id             11
        league_id              11
        season                  8
        date                 1694
        match_api_id        25979
        home_team_api_id      299
        away_team_api_id      299
        dtype: int64
```

1.6 Merge Data

1.6.1 Team and Attributes

```
In [8]: # combine the df's on already existing features
        teamsDF = teams.merge(team_attributes, on=['team_api_id', 'team_fifa_api_id'])
        # get rid of some creationed columns from the merge
        teamsDF.drop(['id_x', 'id_y'], axis=1, inplace=True)
        # We only want one entry per team per year, so we need to eliminate duplicates based o
        teamsDF.drop_duplicates(subset=['date', 'team_long_name'], inplace = True)
        teamsDF.sample(3)
```

```
Out[8]:      team_api_id  team_fifa_api_id            team_long_name team_short_name  \
     508         8178              32.0       Bayer 04 Leverkusen             LEV
     992         8569          110744.0              GKS Bełchatów             BEL
     573         9788              23.0  Borussia Mönchengladbach             GLA

                    date  buildUpPlaySpeed buildUpPlaySpeedClass  \
     508  2014-09-19 00:00:00                69                  Fast
     992  2011-02-22 00:00:00                47              Balanced
     573  2011-02-22 00:00:00                63              Balanced

          buildUpPlayDribbling buildUpPlayDribblingClass  buildUpPlayPassing  \
     508                  30.0                    Little                  55
     992                   NaN                    Little                  27
     573                   NaN                    Little                  46

         buildUpPlayPassingClass buildUpPlayPositioningClass  \
     508                   Mixed                   Organised
     992                   Short                   Organised
     573                   Mixed                   Organised

          chanceCreationPassing chanceCreationPassingClass  chanceCreationCrossing  \
     508                     52                     Normal                      55
     992                     45                     Normal                      51
     573                     60                     Normal                      51

         chanceCreationCrossingClass  chanceCreationShooting  \
     508                      Normal                      39
     992                      Normal                      54
     573                      Normal                      61

         chanceCreationShootingClass chanceCreationPositioningClass  \
     508                      Normal                      Organised
     992                      Normal                      Organised
     573                      Normal                      Organised

          defencePressure defencePressureClass  defenceAggression  \
     508               50               Medium                 46
     992               48               Medium                 60
     573               49               Medium                 58

         defenceAggressionClass  defenceTeamWidth defenceTeamWidthClass  \
     508                  Press                54                Normal
     992                  Press                37                Normal
     573                  Press                49                Normal

         defenceDefenderLineClass
     508                    Cover
     992                    Cover
```

```
        573                    Cover
```

```
In [9]: print(teams.shape)
        print(team_attributes.shape)
        print(teamsDF.shape)
```

```
(299, 5)
(1458, 25)
(1450, 26)
```

1.6.2 Country, League, and Match

```
In [10]: # get the initial merge
         leaguesDF = countries.merge(leagues, on=['id'])
         # rename
         leaguesDF = leaguesDF.rename(columns={'name_x':'Country', 'name_y':'League'})
         leaguesDF.sample(3)
```

```
Out[10]:        id      Country  country_id                     League
         3    7809      Germany        7809     Germany 1. Bundesliga
         10  24558  Switzerland       24558  Switzerland Super League
         9   21518        Spain       21518           Spain LIGA BBVA
```

```
In [11]: # now import that 'matches' data set
         leaguesDF = leaguesDF.merge(matches, on = ['country_id'])
         leaguesDF.sample(3)
```

```
Out[11]:         id_x      Country  country_id                   League   id_y  \
         14122  13274  Netherlands       13274  Netherlands Eredivisie  14123
         9191    7809      Germany        7809   Germany 1. Bundesliga   9192
         12719  10257        Italy       10257          Italy Serie A  12720

                league_id     season  stage                 date  match_api_id  \
         14122      13274  2010/2011     33  2011-05-01 00:00:00        836688
         9191        7809  2012/2013     25  2013-03-10 00:00:00       1239690
         12719      10257  2014/2015     28  2015-03-22 00:00:00       1786286

                home_team_api_id  away_team_api_id  home_team_goal  away_team_goal  \
         14122              9839             10235               3               2
         9191              10269              9790               0               1
         12719              9882              8636               1               0

                home_player_X1  home_player_X2  home_player_X3  home_player_X4  \
         14122             1.0             2.0             4.0             6.0
         9191              1.0             2.0             4.0             6.0
         12719             1.0             2.0             4.0             6.0

                home_player_X5  home_player_X6  home_player_X7  home_player_X8  \
```

```
14122            8.0            3.0            5.0            7.0
9191             8.0            5.0            2.0            8.0
12719            8.0            3.0            5.0            7.0

       home_player_X9  home_player_X10  home_player_X11  away_player_X1  \
14122             3.0              5.0              7.0             1.0
9191              4.0              6.0              6.0             1.0
12719             3.0              5.0              7.0             1.0

       away_player_X2  away_player_X3  away_player_X4  away_player_X5  \
14122             2.0             4.0             6.0             8.0
9191              2.0             4.0             6.0             8.0
12719             2.0             4.0             6.0             8.0

       away_player_X6  away_player_X7  away_player_X8  away_player_X9  \
14122             3.0             5.0             7.0             3.0
9191              4.0             6.0             2.0             8.0
12719             3.0             5.0             7.0             5.0

       away_player_X10  away_player_X11  home_player_Y1  home_player_Y2  \
14122              5.0              7.0             1.0             3.0
9191               4.0              6.0             1.0             3.0
12719              4.0              6.0             1.0             3.0

       home_player_Y3  home_player_Y4  home_player_Y5  home_player_Y6  \
14122             3.0             3.0             3.0             7.0
9191              3.0             3.0             3.0             6.0
12719             3.0             3.0             3.0             7.0

       home_player_Y7  home_player_Y8  home_player_Y9  home_player_Y10  \
14122             7.0             7.0            10.0             10.0
9191              7.0             7.0             9.0              9.0
12719             7.0             7.0            10.0             10.0

       home_player_Y11  away_player_Y1  away_player_Y2  away_player_Y3  \
14122             10.0             1.0             3.0             3.0
9191              11.0             1.0             3.0             3.0
12719             10.0             1.0             3.0             3.0

       away_player_Y4  away_player_Y5  away_player_Y6  away_player_Y7  \
14122             3.0             3.0             7.0             7.0
9191              3.0             3.0             6.0             6.0
12719             3.0             3.0             6.0             6.0

       away_player_Y8  away_player_Y9  away_player_Y10  away_player_Y11  \
14122             7.0            10.0             10.0             10.0
9191              8.0             8.0             10.0             10.0
12719             6.0             8.0             10.0             10.0
```

```
       home_player_1  home_player_2  home_player_3  home_player_4  \
14122        36013.0        26016.0        45888.0        72665.0
9191         94841.0       276738.0        36146.0        29471.0
12719        41671.0        25587.0        18823.0       362195.0

       home_player_5  home_player_6  home_player_7  home_player_8  \
14122        26674.0        20720.0            NaN       158278.0
9191         38842.0        26782.0        27324.0       215170.0
12719       163918.0       213366.0        27702.0       181995.0

       home_player_9  home_player_10  home_player_11  away_player_1  \
14122       232103.0        193410.0         45960.0       112107.0
9191         27234.0         58351.0         36084.0        27424.0
12719            NaN         33639.0        196484.0        42422.0

       away_player_2  away_player_3  away_player_4  away_player_5  \
14122       186847.0       188555.0        41462.0       212511.0
9191        141113.0       184821.0        27461.0        30987.0
12719       130155.0        25526.0        30865.0       197352.0

       away_player_6  away_player_7  away_player_8  away_player_9  \
14122        45466.0       108038.0       109638.0       209014.0
9191        141699.0        52243.0        40108.0        33338.0
12719       206508.0        49970.0        41199.0       176300.0

       away_player_10  away_player_11  \
14122        189237.0         36391.0
9191          30840.0         79982.0
12719        282770.0         32118.0

                                                    goal  \
14122                                               None
9191   <goal><value><comment>n</comment><stats><goals...
12719  <goal><value><comment>n</comment><stats><goals...

                                                  shoton  \
14122                                               None
9191                                         <shoton />
12719  <shoton><value><stats><blocked>1</blocked></st...

                                                 shotoff  \
14122                                               None
9191                                        <shotoff />
12719  <shotoff><value><stats><shotoff>1</shotoff></s...

                                              foulcommit  \
14122                                               None
```

```
9191                                         <foulcommit />
12719  <foulcommit><value><stats><foulscommitted>1</f...

                                                   card  \
14122                                              None
9191   <card><value><comment>y</comment><stats><ycard...
12719  <card><value><comment>y</comment><stats><ycard...

                                                  cross  \
14122                                              None
9191                                          <cross />
12719  <cross><value><stats><crosses>1</crosses></sta...

                                                 corner  \
14122                                              None
9191                                         <corner />
12719  <corner><value><stats><corners>1</corners></st...

                                             possession  B365H  B365D  B365A  \
14122                                              None   4.75   4.00   1.67
9191                                     <possession />   2.25   3.40   3.10
12719  <possession><value><comment>30</comment><event...   2.63   3.25   2.75

        BWH  BWD   BWA  IWH  IWD   IWA   LBH  LBD   LBA   PSH   PSD   PSA  \
14122  4.33  4.0  1.62  4.6  4.0  1.50  3.75  3.5  1.73   NaN   NaN   NaN
9191   2.35  3.4  2.90  2.4  3.3  2.75  2.25  3.4  3.10  2.43  3.51  3.09
12719  2.70  3.0  2.70  2.6  3.1  2.70  2.75  3.2  2.62  2.72  3.30  2.86

        WHH  WHD   WHA   SJH  SJD   SJA   VCH   VCD   VCA   GBH   GBD   GBA  \
14122  4.33  4.0  1.65  5.00  4.0  1.62  4.75  4.00  1.67  4.20  3.75  1.67
9191   2.50  3.1  2.90  2.25  3.4  3.00  2.38  3.50  3.10  2.35  3.40  2.90
12719  2.70  3.1  2.70   NaN  NaN   NaN  2.80  3.12  2.90   NaN   NaN   NaN

        BSH  BSD   BSA
14122  5.00  3.6  1.57
9191   2.25  3.4  3.00
12719   NaN  NaN   NaN
```

In [12]:
```
a, b, c, d = countries.shape, leagues.shape, matches.shape, leaguesDF.shape
print(a)
print(b)
print(c)
print(d)
```

```
(11, 2)
(11, 3)
(25979, 115)
(25979, 118)
```

In [13]:
```
# capture only two columns
temp = teamsDF[['team_api_id', 'team_long_name']]
# rename the column to match other df for key
temp = temp.rename(columns={'team_api_id':'home_team_api_id'})
# make sure there's no duplicates
temp.drop_duplicates(subset=['home_team_api_id', 'team_long_name'], inplace = True)
# merge them together on 'home_team_api_id'
leaguesDF = leaguesDF.merge(temp, on=['home_team_api_id'], how='left')
# rename again for away columns
temp = temp.rename(columns={'home_team_api_id':'away_team_api_id'})
# merge again
leaguesDF = leaguesDF.merge(temp, on=['away_team_api_id'], how='left')
# drop some useless features
leaguesDF.drop(['id_x', 'id_y', 'country_id', 'league_id', 'stage'], axis=1, inplace='
# create a copy of 'leagueDF' to simplify the information even more
leaguesFinal = leaguesDF
leaguesFinal = leaguesFinal[['Country', 'League', 'season', 'date', 'match_api_id', '
                        'team_long_name_y', 'home_team_goal', 'away_team_goal']]
```

In [14]:
```
# rename for clarity
leaguesFinal = leaguesFinal.rename(columns={'team_long_name_x':'Home Team', 'team_long
leaguesFinal.sample(3)
```

Out[14]:
```
      Country               League     season                 date  \
17177  Poland  Poland Ekstraklasa  2014/2015  2014-10-05 00:00:00
10926   Italy        Italy Serie A  2009/2010  2010-05-02 00:00:00
23055   Spain     Spain LIGA BBVA  2012/2013  2012-11-04 00:00:00

       match_api_id                  Home Team       Away Team  \
17177       1722172              Piast Gliwice  Legia Warszawa
10926        705237                   Atalanta         Bologna
23055       1260150  RC Deportivo de La Coruña    RCD Mallorca

       home_team_goal  away_team_goal
17177               3               1
10926               1               1
23055               1               0
```

In [15]:
```
# functions to decide the winner and loser of each match and append the df with that

def win(leaguesFinal):
    if leaguesFinal['home_team_goal'] > leaguesFinal['away_team_goal']:
        return leaguesFinal['Home Team']
    elif leaguesFinal['away_team_goal'] > leaguesFinal['home_team_goal']:
        return leaguesFinal['Away Team']
    elif leaguesFinal['home_team_goal'] == leaguesFinal['away_team_goal']:
        return "DRAW"
```

```
def loss(leaguesFinal):
    if leaguesFinal['home_team_goal'] < leaguesFinal['away_team_goal']:
        return leaguesFinal['Home Team']
    elif leaguesFinal['away_team_goal'] < leaguesFinal['home_team_goal']:
        return leaguesFinal['Away Team']

leaguesFinal["win"] = leaguesFinal.apply(lambda leaguesFinal:win(leaguesFinal),axis=1)
leaguesFinal["loss"] = leaguesFinal.apply(lambda leaguesFinal:loss(leaguesFinal),axis=
```

In [16]:
```
leaguesFinal.shape
```

Out[16]:
```
(25979, 11)
```

In [17]:
```
leaguesFinal.sample(3)
```

Out[17]:
```
      Country                  League     season                 date  \
1638  Belgium  Belgium Jupiler League  2015/2016  2016-02-14 00:00:00
8363  Germany   Germany 1. Bundesliga  2009/2010  2010-05-08 00:00:00
802   Belgium  Belgium Jupiler League  2011/2012  2011-11-19 00:00:00

      match_api_id        Home Team          Away Team  home_team_goal  \
1638       1980030     KVC Westerlo  Standard de Liège               2
8363        674582  1. FSV Mainz 05       FC Schalke 04               0
802        1032802      KV Mechelen   SV Zulte-Waregem               1

      away_team_goal           win               loss
1638               0  KVC Westerlo  Standard de Liège
8363               0          DRAW               None
802                1          DRAW               None
```

1.7 Feature Engineering

1.7.1 Team Record (Wins / Losses) DataFrame

Draws are being diregarded in this analysis because they do not help to determine what makes a winning team different than a losing team.

In [18]:
```
# get indices
seasons = leaguesFinal['season'].unique()
teams = teamsDF['team_long_name'].unique()
# create an empty list
df = []

# first separate by season
for i in seasons:
    season = leaguesFinal['season'] == i
    season = leaguesFinal[season]
    # then count the games won and games lost
    for j in teams:
```

```
            team_season_wins = season['win'] == j
            team_season_win_record = team_season_wins[team_season_wins].count()
            team_season_loss = season['loss'] == j
            team_season_loss_record = team_season_loss[team_season_loss].count()
            df.append((j, i, team_season_win_record, team_season_loss_record))
    # create the new df and feature names
    df = pd.DataFrame(df, columns=('Team', 'Seasons', 'Wins', 'Losses'))
    # rename the team column to use as a key
    df = df.rename(columns={'Team':'Home Team'})
    # take just the information we want to merge ('League') plus a key column for merging
    df2 = leaguesFinal[['Home Team', 'League']]
    # clean it up, we only want one team name per league, there are no dates associated w
    df2.drop_duplicates(subset = ['Home Team'],inplace = True)
    # the merge
    df = df.merge(df2, on = 'Home Team')
    # change the feature name back
    df = df.rename(columns={'Home Team':'Team'})
    # create an identifiable df name
    teamRecords = df[['League', 'Team', 'Seasons', 'Wins', 'Losses']]
    # drop some outlier rows with odd data,
    # seemed to consistantly contain '0' for either win or loss
    teamRecords = teamRecords[teamRecords.Wins != 0]
    teamRecords = teamRecords[teamRecords.Losses != 0]
    teamRecords.sample(5)
```

Out[18]:

	League	Team	Seasons	Wins	Losses
1087	Italy Serie A	Sampdoria	2015/2016	10	18
1551	Poland Ekstraklasa	Zagbie Lubin	2015/2016	12	9
2224	Switzerland Super League	FC Vaduz	2008/2009	5	24
1512	Poland Ekstraklasa	Jagiellonia Biaystok	2008/2009	9	14
2197	Switzerland Super League	FC Basel	2013/2014	19	2

1.7.2 Team Goals by Season

In [19]:
```
# create another list
df = []
# group by 'home' or 'away' and season and sum the goal column
home_goals = leaguesFinal.groupby(('Home Team', 'season'))['home_team_goal'].sum()
away_goals = leaguesFinal.groupby(('Away Team', 'season'))['away_team_goal'].sum()
# lose the win and loss title for 'Team' to merge
a = home_goals.rename_axis(['Team','season'])
b = away_goals.rename_axis(['Team','season'])
# fill any NaN values with 0 goals
df = (a.add(b, fill_value=0)).reset_index(name='Goals')
df = df.rename(columns={'season':'Seasons'})
# the merge
teamRecords = teamRecords.merge(df, on = ['Team', 'Seasons'], how = 'left')
# organize for consistancy
```

```
teamRecords.sort_values(['League', 'Team', 'Seasons'], ascending = True, inplace = Tru
teamRecords.shape
```

Out[19]: (1453, 6)

In [20]:
```
teamRecords.sample(3)
```

Out[20]:
```
                          League                    Team    Seasons  Wins  \
396              France Ligue 1  Montpellier Hérault SC  2009/2010    20
81         Belgium Jupiler League           KVC Westerlo  2008/2009    15
1052  Portugal Liga ZON Sagres    Académica de Coimbra  2015/2016     5

      Losses  Goals
396        9     50
81        12     42
1052      19     32
```

1.7.3 League Winners

create a df of the team with the best record from each 'League' for each 'Seasons'

In [21]:
```
# create the df to work with
leagueWinners_season = teamRecords
# organize for what matters
leagueWinners_season.sort_values(['League', 'Seasons', 'Wins'], ascending = False, inp
# we don't care about the bottom of the barrel teams, they won't be a league winner
leagueWinners_season = leagueWinners_season[leagueWinners_season.Wins > 10]
# grab the first row in each combination of 'League' and 'Season'
leagueWinners_season = leagueWinners_season.groupby(['League', 'Seasons']).first()
# display winning teams of each league by season
leagueWinners_season.head(leagueWinners_season['Team'].count())
```

Out[21]:
```
                                                     Team  Wins  Losses  \
League                  Seasons
Belgium Jupiler League  2008/2009      RSC Anderlecht    24       5
                        2009/2010      RSC Anderlecht    22       3
                        2010/2011           KRC Genk    19       4
                        2011/2012      RSC Anderlecht    20       3
                        2012/2013      RSC Anderlecht    20       3
                        2014/2015      Club Brugge KV    17       3
                        2015/2016      Club Brugge KV    21       8
England Premier League  2008/2009   Manchester United    28       4
                        2009/2010             Chelsea    27       6
                        2010/2011   Manchester United    23       4
                        2011/2012     Manchester City    28       5
                        2012/2013   Manchester United    28       5
                        2013/2014     Manchester City    27       6
                        2014/2015             Chelsea    26       3
                        2015/2016      Leicester City    23       3
```

France Ligue 1	2008/2009	Girondins de Bordeaux	24	6
	2009/2010	Olympique de Marseille	23	6
	2010/2011	LOSC Lille	21	4
	2011/2012	Montpellier Hérault SC	25	6
	2012/2013	Paris Saint-Germain	25	5
	2013/2014	Paris Saint-Germain	27	3
	2014/2015	Paris Saint-Germain	24	3
	2015/2016	Paris Saint-Germain	30	2
Germany 1. Bundesliga	2008/2009	VfL Wolfsburg	21	7
	2009/2010	FC Bayern Munich	20	4
	2010/2011	Borussia Dortmund	23	5
	2011/2012	Borussia Dortmund	25	3
	2012/2013	FC Bayern Munich	29	1
	2013/2014	FC Bayern Munich	29	2
	2014/2015	FC Bayern Munich	25	5
	2015/2016	FC Bayern Munich	28	2
Italy Serie A	2008/2009	Inter	25	4
	2009/2010	Inter	24	4
	2010/2011	Milan	24	4
	2011/2012	Milan	23	6
	2012/2013	Juventus	27	5
	2013/2014	Juventus	33	2
	2014/2015	Juventus	26	3
	2015/2016	Juventus	29	5
Netherlands Eredivisie	2008/2009	AZ	25	4
	2009/2010	Ajax	27	3
	2010/2011	Ajax	22	5
	2011/2012	Ajax	23	4
	2012/2013	Ajax	22	2
	2013/2014	Ajax	20	3
	2014/2015	PSV	29	4
	2015/2016	PSV	26	2
Poland Ekstraklasa	2008/2009	Wisa Kraków	19	4
	2009/2010	Lech Pozna	19	3
	2010/2011	Wisa Kraków	17	8
	2011/2012	lsk Wrocaw	17	8
	2012/2013	Legia Warszawa	20	3
	2013/2014	Legia Warszawa	20	7
	2014/2015	Legia Warszawa	17	8
	2015/2016	Legia Warszawa	17	4
Portugal Liga ZON Sagres	2008/2009	FC Porto	21	2
	2009/2010	SL Benfica	24	2
	2010/2011	SL Benfica	20	7
	2011/2012	FC Porto	23	1
	2012/2013	SL Benfica	24	1
	2013/2014	SL Benfica	23	2
	2014/2015	SL Benfica	27	3
	2015/2016	SL Benfica	29	4

Scotland Premier League	2008/2009	Rangers	26	4
	2009/2010	Rangers	26	3
	2010/2011	Rangers	30	5
	2011/2012	Celtic	30	5
	2012/2013	Celtic	24	7
	2013/2014	Celtic	31	1
	2014/2015	Celtic	29	4
	2015/2016	Celtic	26	4
Spain LIGA BBVA	2008/2009	FC Barcelona	27	5
	2009/2010	FC Barcelona	31	1
	2010/2011	FC Barcelona	30	2
	2011/2012	Real Madrid CF	32	2
	2012/2013	FC Barcelona	32	2
	2013/2014	Atlético Madrid	28	4
	2014/2015	FC Barcelona	30	4
	2015/2016	FC Barcelona	29	5
Switzerland Super League	2008/2009	FC Zürich	24	5
	2009/2010	BSC Young Boys	25	9
	2010/2011	FC Basel	21	5
	2011/2012	FC Basel	22	4
	2012/2013	FC Basel	21	6
	2013/2014	FC Basel	19	2
	2014/2015	FC Basel	24	6
	2015/2016	FC Basel	26	5

		Goals
League	Seasons	
Belgium Jupiler League	2008/2009	75
	2009/2010	62
	2010/2011	64
	2011/2012	61
	2012/2013	69
	2014/2015	69
	2015/2016	64
England Premier League	2008/2009	68
	2009/2010	103
	2010/2011	78
	2011/2012	93
	2012/2013	86
	2013/2014	102
	2014/2015	73
	2015/2016	68
France Ligue 1	2008/2009	64
	2009/2010	69
	2010/2011	68
	2011/2012	68
	2012/2013	69
	2013/2014	84

	2014/2015	83
	2015/2016	102
Germany 1. Bundesliga	2008/2009	80
	2009/2010	72
	2010/2011	67
	2011/2012	80
	2012/2013	98
	2013/2014	94
	2014/2015	80
	2015/2016	80
Italy Serie A	2008/2009	70
	2009/2010	75
	2010/2011	65
	2011/2012	72
	2012/2013	71
	2013/2014	80
	2014/2015	72
	2015/2016	75
Netherlands Eredivisie	2008/2009	66
	2009/2010	106
	2010/2011	72
	2011/2012	93
	2012/2013	83
	2013/2014	69
	2014/2015	92
	2015/2016	88
Poland Ekstraklasa	2008/2009	53
	2009/2010	51
	2010/2011	44
	2011/2012	47
	2012/2013	59
	2013/2014	60
	2014/2015	57
	2015/2016	58
Portugal Liga ZON Sagres	2008/2009	61
	2009/2010	78
	2010/2011	61
	2011/2012	69
	2012/2013	77
	2013/2014	58
	2014/2015	86
	2015/2016	88
Scotland Premier League	2008/2009	77
	2009/2010	82
	2010/2011	88
	2011/2012	84
	2012/2013	92
	2013/2014	102

```
                              2014/2015     84
                              2015/2016     93
Spain LIGA BBVA               2008/2009    105
                              2009/2010     98
                              2010/2011     95
                              2011/2012    121
                              2012/2013    115
                              2013/2014     77
                              2014/2015    110
                              2015/2016    112
Switzerland Super League      2008/2009     80
                              2009/2010     78
                              2010/2011     76
                              2011/2012     78
                              2012/2013     61
                              2013/2014     70
                              2014/2015     84
                              2015/2016     88
```

1.7.4 League Losers

In [22]:
```
# create the df to work with
leagueLosers_season = teamRecords
# organize for what matters
leagueLosers_season.sort_values(['League', 'Seasons', 'Losses'], ascending = False, i
# we don't care about the bottom of the barrel teams, they won't be a league losers
leagueLosers_season = leagueLosers_season[leagueLosers_season.Losses > 10]
# grab the first row in each combination of 'League' and 'Season'
leagueLosers_season = leagueLosers_season.groupby(['League', 'Seasons']).first()
# display losing teams of each league by season
leagueLosers_season.head(leagueLosers_season['Team'].count())
```

Out[22]:
```
                                                         Team  Wins  Losses  \
League                   Seasons
Belgium Jupiler League   2008/2009                  RAEC Mons     3      21
                         2009/2010           Sporting Lokeren     5      20
                         2010/2011         Sporting Charleroi     4      19
                         2011/2012               KVC Westerlo     5      20
                         2012/2013          KSV Cercle Brugge     3      22
                         2014/2015           Waasland-Beveren     7      18
                         2015/2016           Sint-Truidense VV     8      16
England Premier League   2008/2009        West Bromwich Albion     8      22
                         2009/2010                    Burnley     8      24
                         2010/2011     Wolverhampton Wanderers    11      20
                         2011/2012           Blackburn Rovers     8      23
                         2012/2013                    Reading     6      22
                         2013/2014                     Fulham     9      24
                         2014/2015         Queens Park Rangers     8      24
```

	2015/2016	Aston Villa	3	27
France Ligue 1	2008/2009	Le Havre AC	7	26
	2009/2010	Grenoble Foot 38	5	25
	2010/2011	AC Arles-Avignon	3	24
	2011/2012	Dijon FCO	9	20
	2012/2013	Stade Brestois 29	8	25
	2013/2014	Valenciennes FC	7	23
	2014/2015	Évian Thonon Gaillard FC	11	23
	2015/2016	ES Troyes AC	3	26
Germany 1. Bundesliga	2008/2009	Karlsruher SC	8	21
	2009/2010	Hertha BSC Berlin	5	20
	2010/2011	FC St. Pauli	8	21
	2011/2012	1. FC Köln	8	20
	2012/2013	SpVgg Greuther Fürth	4	21
	2013/2014	Hamburger SV	7	21
	2014/2015	Hamburger SV	9	17
	2015/2016	Hannover 96	7	23
Italy Serie A	2008/2009	Torino	8	20
	2009/2010	Livorno	7	23
	2010/2011	Bari	5	24
	2011/2012	Cesena	4	22
	2012/2013	Pescara	6	28
	2013/2014	Livorno	6	25
	2014/2015	Parma	6	24
	2015/2016	Frosinone	8	23
Netherlands Eredivisie	2008/2009	ADO Den Haag	8	18
	2009/2010	RKC Waalwijk	5	29
	2010/2011	VVV-Venlo	6	25
	2011/2012	Excelsior	4	23
	2012/2013	Willem II	5	21
	2013/2014	Roda JC Kerkrade	7	19
	2014/2015	FC Dordrecht	4	22
	2015/2016	SC Cambuur	3	22
Poland Ekstraklasa	2008/2009	Lechia Gdask	9	16
	2009/2010	Odra Wodzisaw	7	17
	2010/2011	Cracovia	8	17
	2011/2012	Widzew ód	5	16
	2012/2013	Pogo Szczecin	10	15
	2013/2014	Zagbie Lubin	7	15
	2014/2015	Zawisza Bydgoszcz	8	17
	2015/2016	Jagiellonia Biaystok	10	15
Portugal Liga ZON Sagres	2008/2009	Vitória Setúbal	7	18
	2009/2010	Leixões SC	5	19
	2010/2011	Naval 1ř de Maio	5	17
	2011/2012	União de Leiria, SAD	5	21
	2012/2013	Vitória Setúbal	7	18
	2013/2014	FC Paços de Ferreira	6	18
	2014/2015	FC Penafiel	5	22

	2015/2016	CS Marítimo	10	19
Scotland Premier League	2008/2009	Hamilton Academical FC	12	21
	2009/2010	Kilmarnock	8	21
	2010/2011	Aberdeen	11	22
	2011/2012	Dunfermline Athletic	5	23
	2012/2013	Dundee FC	7	22
	2013/2014	Kilmarnock	11	21
	2014/2015	St. Mirren	9	26
	2015/2016	Dundee United	8	23
Spain LIGA BBVA	2008/2009	Real Sporting de Gijón	14	23
	2009/2010	CD Tenerife	9	20
	2010/2011	Real Sociedad	14	21
	2011/2012	Rayo Vallecano	13	21
	2012/2013	Real Zaragoza	9	22
	2013/2014	Real Betis Balompié	6	25
	2014/2015	Córdoba CF	3	24
	2015/2016	Levante UD	8	22
Switzerland Super League	2008/2009	FC Vaduz	5	24
	2009/2010	AC Bellinzona	7	25
	2010/2011	FC St. Gallen	8	21
	2011/2012	Grasshopper Club Zürich	7	22
	2012/2013	Servette FC	6	22
	2013/2014	FC Lausanne-Sports	7	26
	2014/2015	FC Vaduz	7	19
	2015/2016	FC St. Gallen	10	18

		Goals
League	Seasons	
Belgium Jupiler League	2008/2009	31
	2009/2010	22
	2010/2011	20
	2011/2012	29
	2012/2013	30
	2014/2015	30
	2015/2016	28
England Premier League	2008/2009	36
	2009/2010	42
	2010/2011	46
	2011/2012	48
	2012/2013	43
	2013/2014	40
	2014/2015	42
	2015/2016	27
France Ligue 1	2008/2009	30
	2009/2010	31
	2010/2011	21
	2011/2012	38
	2012/2013	32

	2013/2014	37
	2014/2015	41
	2015/2016	28
Germany 1. Bundesliga	2008/2009	30
	2009/2010	34
	2010/2011	35
	2011/2012	39
	2012/2013	26
	2013/2014	51
	2014/2015	25
	2015/2016	31
Italy Serie A	2008/2009	37
	2009/2010	27
	2010/2011	27
	2011/2012	24
	2012/2013	27
	2013/2014	39
	2014/2015	33
	2015/2016	35
Netherlands Eredivisie	2008/2009	41
	2009/2010	30
	2010/2011	34
	2011/2012	28
	2012/2013	33
	2013/2014	44
	2014/2015	24
	2015/2016	33
Poland Ekstraklasa	2008/2009	30
	2009/2010	27
	2010/2011	37
	2011/2012	23
	2012/2013	29
	2013/2014	31
	2014/2015	32
	2015/2016	37
Portugal Liga ZON Sagres	2008/2009	21
	2009/2010	25
	2010/2011	26
	2011/2012	25
	2012/2013	30
	2013/2014	28
	2014/2015	29
	2015/2016	45
Scotland Premier League	2008/2009	30
	2009/2010	29
	2010/2011	39
	2011/2012	40
	2012/2013	28

```
                            2013/2014     45
                            2014/2015     30
                            2015/2016     45
Spain LIGA BBVA             2008/2009     47
                            2009/2010     40
                            2010/2011     49
                            2011/2012     53
                            2012/2013     37
                            2013/2014     36
                            2014/2015     22
                            2015/2016     37
Switzerland Super League    2008/2009     28
                            2009/2010     42
                            2010/2011     34
                            2011/2012     32
                            2012/2013     32
                            2013/2014     38
                            2014/2015     28
                            2015/2016     41
```

1.7.5 Team Attributes Catagories

```
In [23]: teamsDF.sample(3)
```

```
Out[23]:      team_api_id  team_fifa_api_id team_long_name team_short_name  \
         200         9879             144.0         Fulham             FUL
         189        10194            1806.0     Stoke City             STK
         986         2182             873.0    Lech Pozna             POZ

                        date  buildUpPlaySpeed buildUpPlaySpeedClass  \
         200  2011-02-22 00:00:00                50              Balanced
         189  2012-02-22 00:00:00                75                  Fast
         986  2011-02-22 00:00:00                64              Balanced

              buildUpPlayDribbling buildUpPlayDribblingClass  buildUpPlayPassing  \
         200                   NaN                    Little                  55
         189                   NaN                    Little                  75
         986                   NaN                    Little                  57

             buildUpPlayPassingClass buildUpPlayPositioningClass  \
         200                   Mixed                   Organised
         189                    Long                   Organised
         986                   Mixed                   Organised

              chanceCreationPassing chanceCreationPassingClass  chanceCreationCrossing  \
         200                     45                     Normal                      55
         189                     40                     Normal                      72
         986                     68                      Risky                      48
```

```
    chanceCreationCrossingClass  chanceCreationShooting  \
200                      Normal                      40
189                        Lots                      55
986                      Normal                      70

    chanceCreationShootingClass chanceCreationPositioningClass  \
200                      Normal                      Organised
189                      Normal                      Organised
986                        Lots                      Organised

     defencePressure defencePressureClass  defenceAggression  \
200               45               Medium                 35
189               50               Medium                 58
986               59               Medium                 37

    defenceAggressionClass  defenceTeamWidth defenceTeamWidthClass  \
200                  Press                50                Normal
189                  Press                45                Normal
986                  Press                48                Normal

    defenceDefenderLineClass
200                    Cover
189                    Cover
986                    Cover
```

In [24]:
```python
# left the 'date' column as an object to easily slice off the 00:00:00 from the featu
teamsDF['date'] = teamsDF['date'].map(lambda x: x.rstrip(' 00:'))
# sort for testing
teamsDF.sort_values(['team_long_name', 'date'], inplace = True)
# manipulation df
df = teamsDF
# empty list
lst = []

for d in df['date']:
    # create variables from the year, month, and day in 'date' feature
    datee = datetime.datetime.strptime(d, '%Y-%m-%d')
    # assigment
    currentYear = datee.year
    # decide what season it is
    if datee.month < 7: # https://en.m.wikipedia.org/wiki/Domestic_association_footba
        season = str(currentYear - 1) + '/' + str(currentYear)
    else:
        season = str(currentYear) + '/' + str(currentYear + 1)
    # compile the list with a reference to the original df(d) for merging
    lst.append((d, season))
# create the second df for merging
```

```python
df2 = pd.DataFrame(lst, columns = ['date', 'Seasons'])
# merge on original 'date' feature
df = df.merge(df2, on = 'date')
# merged df was huge, creating dulipcates
# this manipulation df was made only to merge with 'leagueWinners_season', so we don'
df.drop_duplicates(subset = ['date', 'team_long_name', 'Seasons'],inplace = True)
# checking
df.sort_values(['team_long_name', 'date'], inplace = True)
# format feature name for merge
df = df.rename(columns = {'team_long_name' : 'Team'})
# create final df with 'leagueWinners' and all their attributes
leagueWinners_attributes = leagueWinners_season.merge(df, on = ['Seasons', 'Team'], ho
leagueLosers_attributes = leagueLosers_season.merge(df, on = ['Seasons', 'Team'], how
# get rid of unneeded features for the radar charts
leagueWinners_attributes.drop(['team_api_id', 'team_fifa_api_id', 'team_short_name',
leagueLosers_attributes.drop(['team_api_id', 'team_fifa_api_id', 'team_short_name', '
leagueWinners_attributes.sample(3)
```

Out[24]:

```
      Seasons                Team  Wins  Losses  Goals  buildUpPlaySpeed  \
57  2010/2011           SL Benfica    20       7     61              65.0
26  2011/2012    Borussia Dortmund    25       3     80              71.0
19  2012/2013  Paris Saint-Germain    25       5     69               NaN

   buildUpPlaySpeedClass  buildUpPlayDribbling buildUpPlayDribblingClass  \
57              Balanced                   NaN                    Little
26                  Fast                   NaN                    Little
19                   NaN                   NaN                       NaN

    buildUpPlayPassing buildUpPlayPassingClass buildUpPlayPositioningClass  \
57                35.0                   Mixed                   Free Form
26                45.0                   Mixed                   Organised
19                 NaN                     NaN                         NaN

    chanceCreationPassing chanceCreationPassingClass  chanceCreationCrossing  \
57                   65.0                     Normal                    55.0
26                   67.0                      Risky                    44.0
19                    NaN                        NaN                     NaN

   chanceCreationCrossingClass  chanceCreationShooting  \
57                      Normal                    51.0
26                      Normal                    70.0
19                         NaN                     NaN

   chanceCreationShootingClass chanceCreationPositioningClass  \
57                      Normal                      Organised
26                        Lots                      Free Form
19                         NaN                            NaN
```

```
   defencePressure defencePressureClass  defenceAggression  \
57            55.0               Medium               56.0
26            58.0               Medium               69.0
19             NaN                  NaN                NaN

  defenceAggressionClass  defenceTeamWidth defenceTeamWidthClass  \
57                 Press              60.0                Normal
26                Double              46.0                Normal
19                   NaN               NaN                   NaN

  defenceDefenderLineClass
57                    Cover
26                    Cover
19                      NaN
```

2 create a function that compares the winning team attributes vs losing team attributes in

3 three major categories: Build Up, Offense, and Defense

4 list features that'll be compared

means = ['buildUpPlaySpeed', 'buildUpPlayDribbling', 'buildUpPlayPassing', 'chanceCreationPassing', 'chanceCreationCrossing', 'chanceCreationShooting', 'defencePressure', 'defenceAggression', 'defenceTeamWidth']

5 fill the NaN values with the median. Had the best results compared with mean and mode

for m in means: leagueLosers_attributes[m].fillna((leagueLosers_attributes[m].median()), inplace=True) leagueWinners_attributes[m].fillna((leagueWinners_attributes[m].median()), inplace=True)

6 create a distinguishing feature for the 'hue'

leagueWinners_attributes['Side'] = 'Winners' leagueLosers_attributes['Side'] = 'Losers' # learned this simple new way to concat haha frames = [leagueLosers_attributes, leagueWinners_attributes] df = pd.concat(frames) # separate the three frames df1 = df[['buildUpPlaySpeed', 'buildUpPlayDribbling', 'buildUpPlayPassing', 'Side']].reset_index() title1 = 'League Winner vs Loser Build Up Play Attributes' df1.drop(['index'], axis=1, inplace=True) df2 = df[['chanceCreationPassing', 'chanceCreationCrossing', 'chanceCreationShooting', 'Side']].reset_index() title2 = 'League Winner vs Loser Offense Attributes' df2.drop(['index'], axis=1, inplace=True) df3 = df[['defencePressure', 'defenceAggression', 'defenceTeamWidth', 'Side']].reset_index() title3 = 'League Winner vs Loser Defense Attributes' df3.drop(['index'], axis=1, inplace=True)

7 create the function for viewing

def pair_plot(df, title): # plot chart sns.pairplot(df, kind = 'scatter', hue = 'Side') plt.title(title, y = 3.4, x = -1.31, fontsize = 18) plt.show()

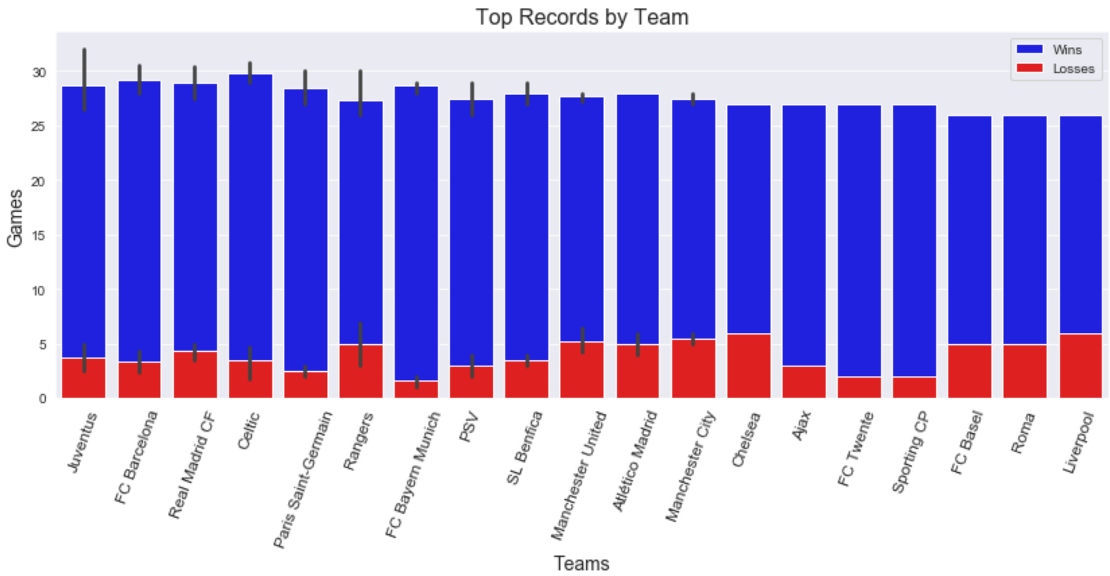
7.1 Visualization and Analysis

```
In [25]: goals_per_year = []
         seasons = leaguesFinal['season'].unique()

         for i in range(0,8):
             mask = leaguesFinal['season'] == seasons[i]
             goals = leaguesFinal[mask]['home_team_goal'].sum() + leaguesFinal[mask]['away_tean
             goals_per_year.append(goals)

         df = pd.DataFrame([goals_per_year]).transpose()
         df['Season'] = ['2008/2009', '2009/2010', '2010/2011', '2011/2012', '2012/2013', '201
         df = df.rename(columns = {0 : 'Goals'})

         #
         sns.set_style("darkgrid")
         plt.figure(figsize=(16, 4))
         plt.plot(df['Season'], df['Goals'], color = 'royalblue')
         plt.ylabel('Goals', fontsize = 14)
         plt.xlabel('Season', fontsize = 14)
         plt.title('Goals Scored in All Leagues by Year', fontsize = 16)
         mpl.rcParams['agg.path.chunksize'] = 10000
```

Besides the 2013/2014 season, European soccer has seen a gradual increase in scoring every year. I'm unaware of historical rule changes and things like that which could contribute to this besides the overall offensive talent of a team increasing, but this is very similar to most other sports where the scoring has been rising consistently.

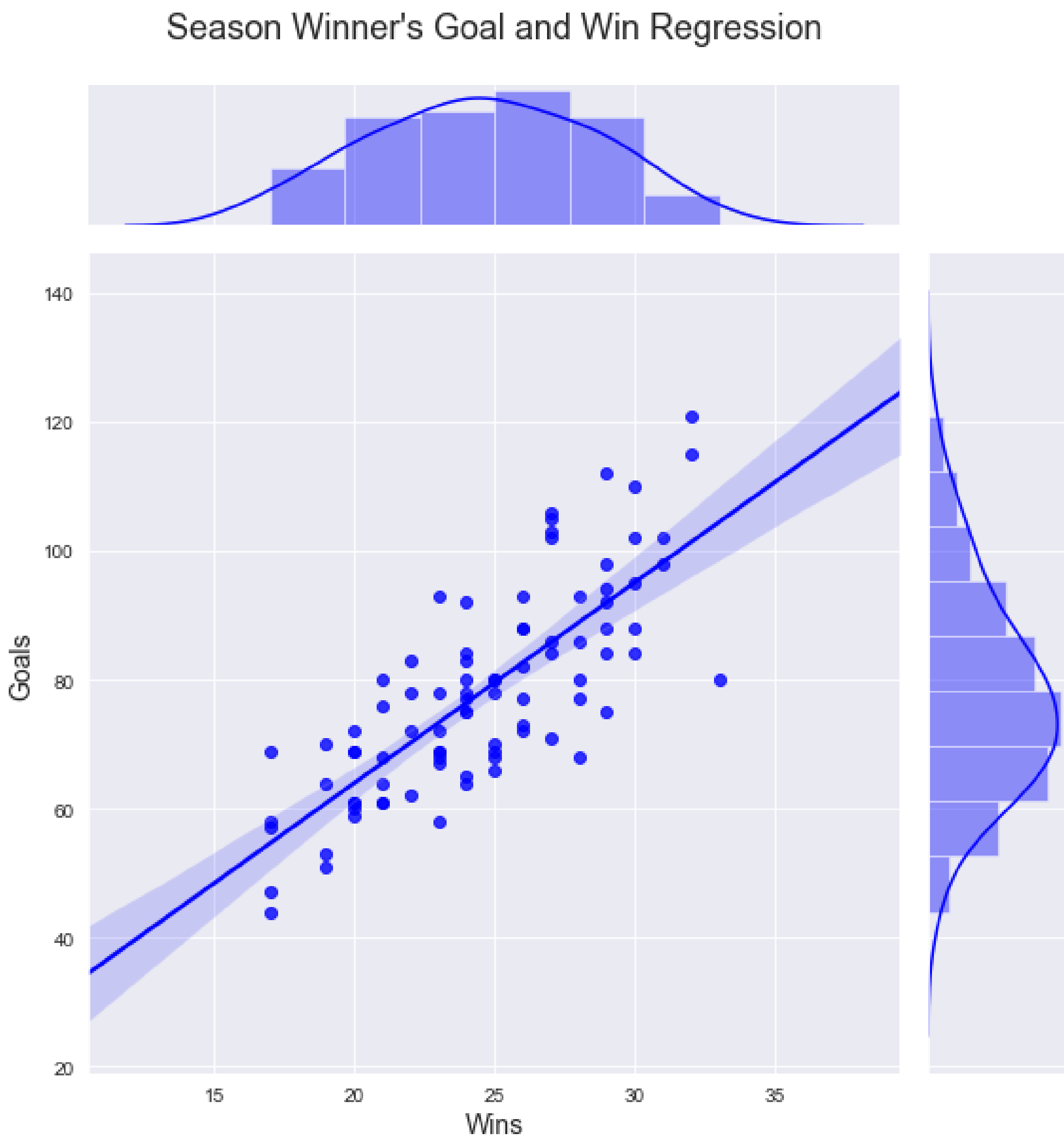
```
In [26]: d = teamRecords.sort_values(by = 'Wins', ascending=False)
         plt.figure(figsize=(14,5))
         sns.barplot('Team', 'Wins', data = d[:50], color = 'b', label = 'Wins')
```

```
sns.barplot('Team', 'Losses', data = d[:50], color = 'r', label = 'Losses')
plt.xticks(rotation = 70, fontsize = 12)
plt.xlabel('Teams', fontsize = 14)
plt.ylabel('Games', fontsize = 14)
plt.legend(loc="best")
plt.title('Top Records by Team', fontsize = 16)
plt.show()
```



It's no surprise the teams at the very top of their league have a supurb win to loss ration. This would also be that teams best year if the team had more than one winning season.

```
In [27]: sns.jointplot(leagueWinners_season['Wins'], leagueWinners_season['Goals'], kind = 'reg
         plt.title('Season Winner\'s Goal and Win Regression', y = 1.25, fontsize = 18)
         plt.xlabel('Wins', fontsize=14)
         plt.ylabel('Goals', fontsize=14)
         plt.show()
```



We can see the extremely positive correlation between goals and wins for the best teams in each league. The regression line is nearly a 45 degree angle.

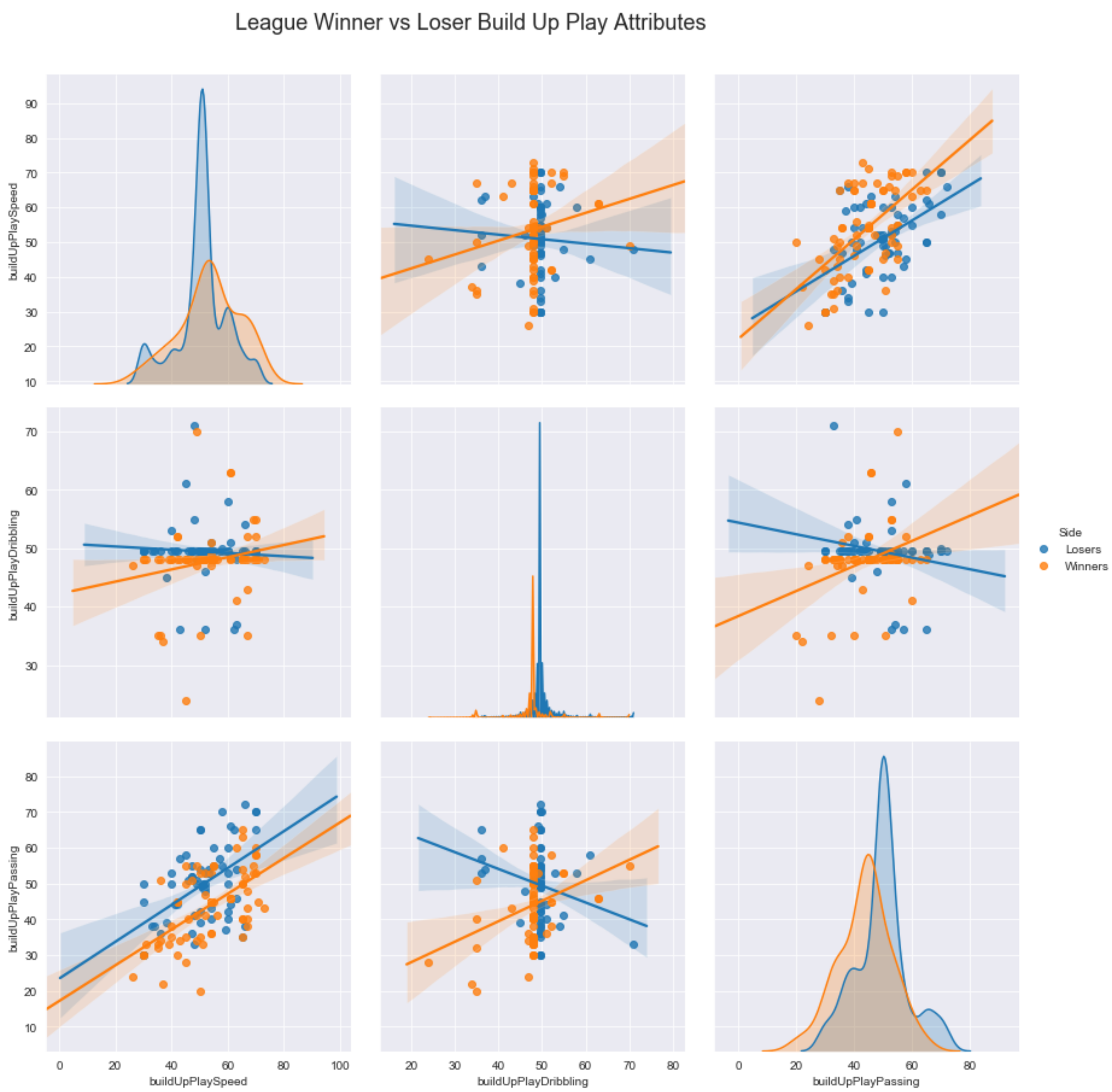
```
In [28]: leagueWinners_season['Side'] = 'Winners'
         leagueLosers_season['Side'] = 'Losers'
         scatter = leagueWinners_season.merge(leagueLosers_season, how = 'outer')
         scatter = scatter[['Wins', 'Goals', 'Side']]
         plt.figure(figsize=(10,10))
         plt.title('Goals to Win Ratio for Highest Winning vs Highest Losing Teams', fontsize =
         plt.xlabel('Wins', fontsize=14)
         plt.ylabel('Goals', fontsize=14)
         ax = sns.scatterplot(x = 'Wins', y = 'Goals', hue = 'Side', data = scatter)
```

This is the bigger picture of the last figure which now contains the closing team's goal to win ration. We can imagine with the short gap between the two clusters that the main body of all the teams in the middle would fall here with leading and trailing data points over lapping with these two clusters. The literal complete disconnect between the two clusters shows how closely related scoring and winning is.

```
In [29]: # create a function that compares the winning team attributes vs losing team attribut
         # three major categories: Build Up, Offense, and Defense

         # list features that'll be compared
         means = ['buildUpPlaySpeed', 'buildUpPlayDribbling', 'buildUpPlayPassing',
                  'chanceCreationPassing', 'chanceCreationCrossing', 'chanceCreationSho
                  'defencePressure', 'defenceAggression', 'defenceTeamWidth']
```

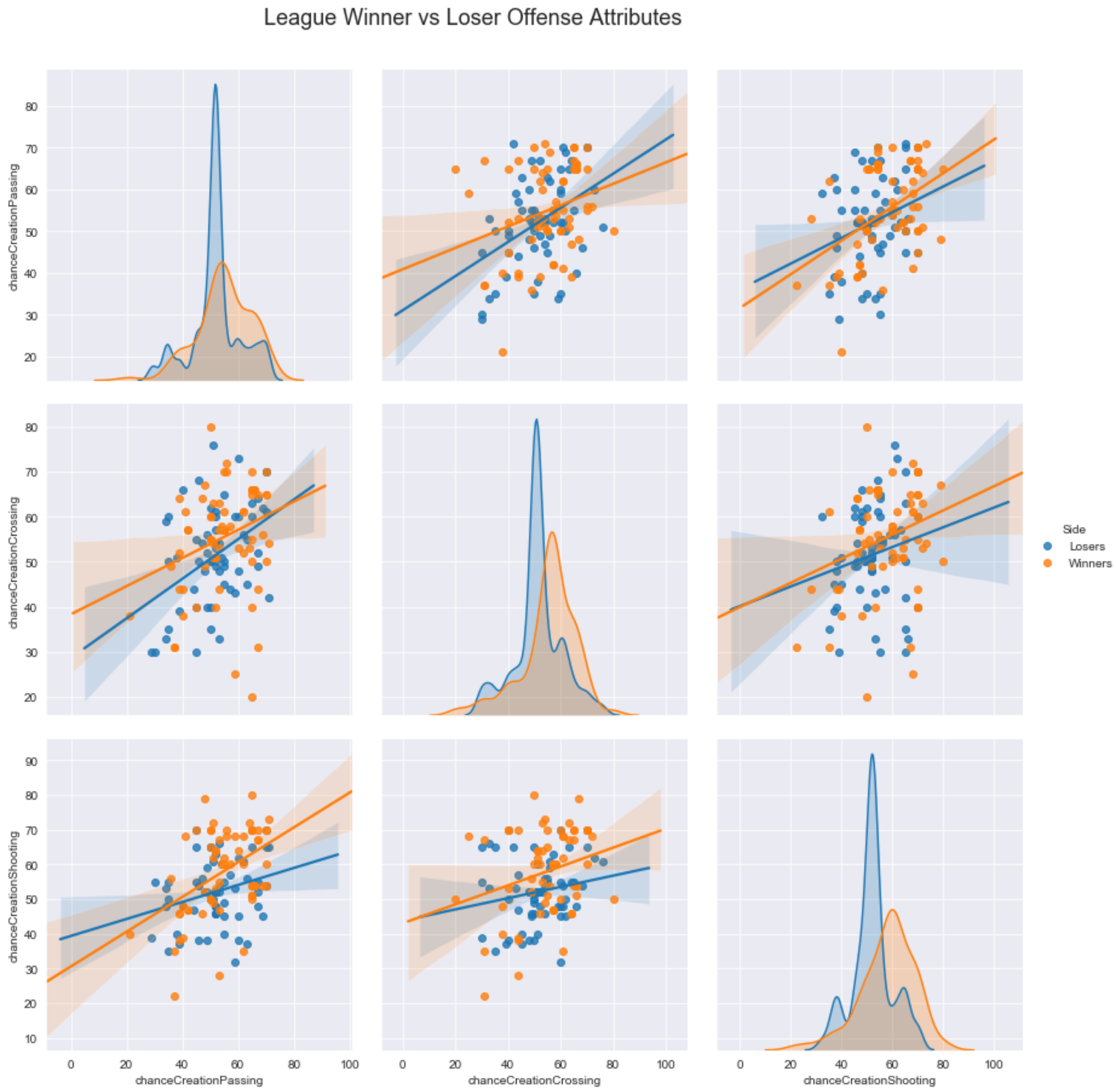
```
# fill the NaN values with the median. Had the best results compared with mean and mo
for m in means:
    leagueLosers_attributes[m].fillna((leagueLosers_attributes[m].median()), inplace=T
    leagueWinners_attributes[m].fillna((leagueWinners_attributes[m].median()), inplace

# create a distinguishing feature for the 'hue'
leagueWinners_attributes['Side'] = 'Winners'
leagueLosers_attributes['Side'] = 'Losers'
# learned this simple new way to concat haha
frames = [leagueLosers_attributes, leagueWinners_attributes]
df = pd.concat(frames)
# separate the three frames
df1 = df[['buildUpPlaySpeed', 'buildUpPlayDribbling', 'buildUpPlayPassing', 'Side']].r
title1 = 'League Winner vs Loser Build Up Play Attributes'
df1.drop(['index'], axis=1, inplace=True)
df2 = df[['chanceCreationPassing', 'chanceCreationCrossing', 'chanceCreationShooting'
title2 = 'League Winner vs Loser Offense Attributes'
df2.drop(['index'], axis=1, inplace=True)
df3 = df[['defencePressure', 'defenceAggression', 'defenceTeamWidth', 'Side']].reset_i
title3 = 'League Winner vs Loser Defense Attributes'
df3.drop(['index'], axis=1, inplace=True)

# create the function for viewing
def pair_plot(df, title):
    # plot chart
    sns.pairplot(df, kind = 'reg', hue = 'Side', height = 4)
    plt.title(title, y = 2.2, x = -0.8, fontsize = 18)
    plt.show()
```

In [30]:
```
pair_plot(df1, title1)
```



There is only a single combination of categories (Speed and Passing) which both the winning and losing teams have a positive correlation, although the winning team is still stronger. Including that frame, the winning team has positive correlations with every single combination of Build Up statistic.

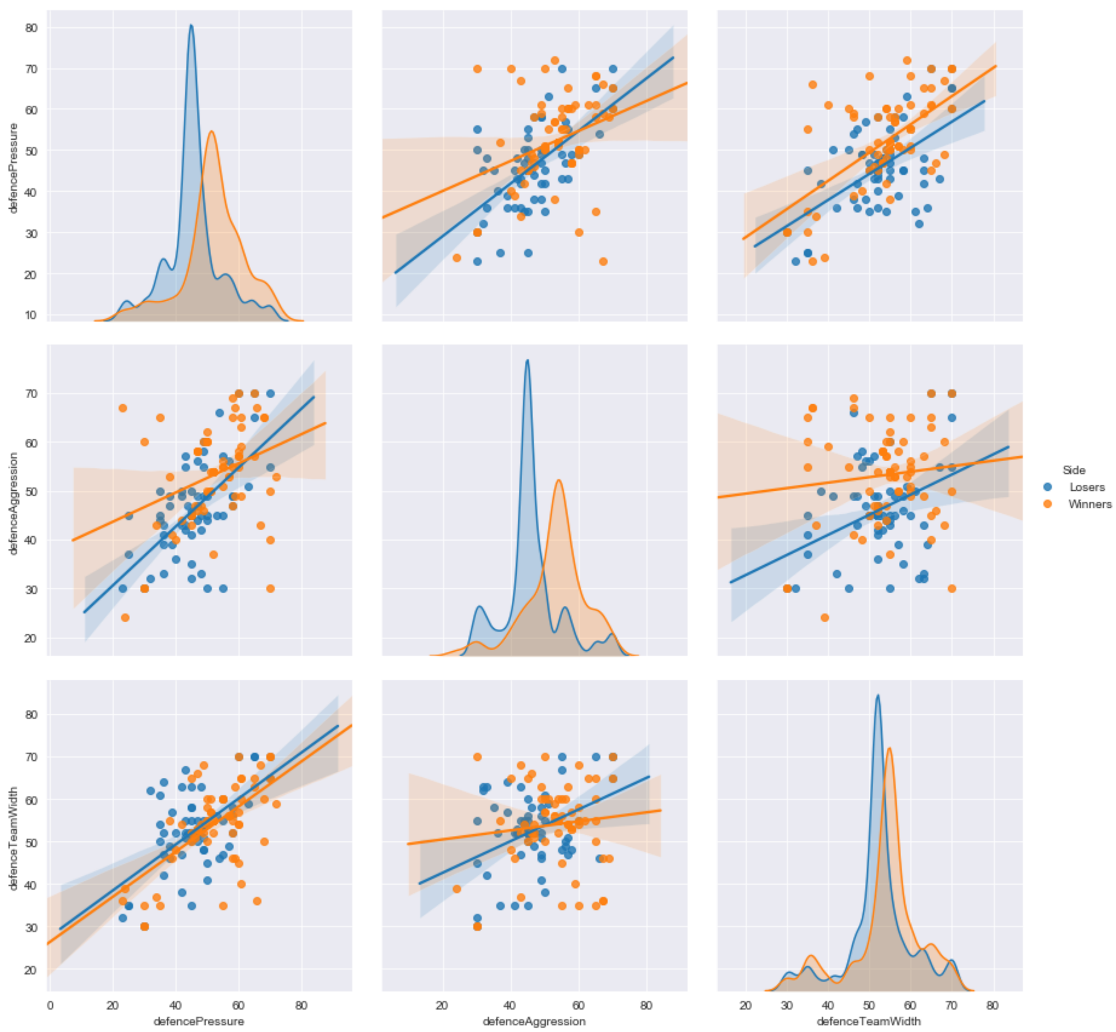
```
In [31]: pair_plot(df2, title2)
```



Offensively this comparison was interesting because the losing teams had a more positive correlation in categories like Passing vs Crossing, although the winning teams still maintained a higher average across all teams. This seems to be a consistent trend, the winning team is on average higher than the losing teams, regardless of correlation.

```
In [32]: pair_plot(df3, title3)
```

League Winner vs Loser Defense Attributes



The most interesting stat in this frame for me is the 'Width'. I have no idea what this stat is mean to represent relative to a team's defensive rating but it has a direct correlation to the team's defensive pressure. The winning and losing distributions are nearly identical, and the correlation between defensive pressure and the width for both winning and losing teams are almost parallel. Interestingly similar, again like Offense the losing teams seem to have a tighter correlation between categories, but on average the winning teams have much higher statistics.

Lastly we can see in all three frames that there are a least a couple teams that are on par statistically with the best winning teams in almost every category, yet still managed to lose enough games to get grouped into the worst of the worst (thin high peaks on the losing distribution charts).

7.2 Conclusion

We can see that just going by face value wins and losses is not really enough to judge the difference between a first place team and a last place team. In many circumstances there's a lot of grey area, with losing teams ranking in indivudal categories right on par with a winning club, but it's the high overall average - across all categories - that elevates the winning teams.

One particular area which I believe leads to the inevitable higher goal scoring of the winning teams is the higher average and more positive correlation of Build Up Play Speed vs Build Up Play Dribbling and Build Up Play Speed vs Build Up Play Passing. In both comparisons the winning teams did significantly better. I think these stats translate into a much stronger transition game for the winning teams, meaning when they get the ball and are setting up and moving down field, they do this much more quickly and effectively than the other team, leading to more time in the offensive zone.