Udacity - Data Science NanoDegree

Investigate a Dataset

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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

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.

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)
```

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)
```

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.

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
```

Merge Data

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 on the date a
nd team name
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	date	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUpP
296	9817	1795.0	Watford	WAT	2011-02-22 00:00:00	64	Balanced	
994	8569	110744.0	GKS Bełchatów	BEL	2013-09-20 00:00:00	52	Balanced	
1157	8597	82.0	Kilmarnock	KIL	2015-09-10 00:00:00	50	Balanced	

In [9]:

```
print(teams.shape)
print(team_attributes.shape)
print(teamsDF.shape)
```

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

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]:

Out[10]:

	id	Country	country_id	League
0	1	Belgium	1	Belgium Jupiler League
3	7809	Germany	7809	Germany 1. Bundesliga
2	4769	France	4769	France Ligue 1

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	league_id	season	stage	date	match_api_id	home_team_api_id	away_team_a
4658	1729	England	1729	England Premier League	4659	1729	2015/2016	34	2016-04-17 00:00:00	1989040	9825	
3113	1729	England	1729	England Premier League	3114	1729	2011/2012	31	2012-04-01 00:00:00	1025836	10261	
7514	4769	France	4769	France Ligue 1	7515	4769	2015/2016	17	2015-12-04 00:00:00	1989944	9831	

In [ ]:

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=True)
# 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
_x',
                        '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_name_y':'Away Team'})
leaguesFinal.sample(3)
```

Out[14]:

	Country	League	season	date	match_api_id	Home Team	Away Team	home_team_goal	away_team_goal
9920	Germany	Germany 1. Bundesliga	2014/2015	2014-09-28 00:00:00	1732766	Hamburger SV	Eintracht Frankfurt	1	2
23176	Spain	Spain LIGA BBVA	2012/2013	2013-01-28 00:00:00	1260007	Sevilla FC	Granada CF	3	0
19272	Portugal	Portugal Liga ZON Sagres	2014/2015	2015-04-18 00:00:00	1750729	CF Os Belenenses	SL Benfica	0	2

In [15]:

```
# functions to decide the winner and loser of each match and append the df with that feature

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=1)
```

In [16]:

```
leaguesFinal.shape
```

Out[16]:

```
(25979, 11)
```

In [17]:

```
leaguesFinal.sample(3)
```

Out[17]:

	Country	League	season	date	match_api_id	Home Team	Away Team	home_team_goal	away_team_goal	win	
1386	Belgium	Belgium Jupiler League	2014/2015	2015-02-07 00:00:00	1718011	KAA Gent	KVC Westerlo	4	0	KAA Gent	W
15760	Poland	Poland Ekstraklasa	2008/2009	2008-11-12 00:00:00	506540	Polonia Bytom	Lech Poznań	1	1	DRAW	
19731	Scotland	Scotland Premier League	2008/2009	2008-11-22 00:00:00	490067	Motherwell	Hibernian	1	4	Hibernian	Mot

Feature Engineering

Feature Engineering

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 with df2
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
559	France Ligue 1	LOSC Lille	2015/2016	15	8
421	England Premier League	Cardiff City	2013/2014	7	22
1240	Netherlands Eredivisie	Roda JC Kerkrade	2008/2009	7	18
1930	Spain LIGA BBVA	Villarreal CF	2010/2011	18	12
776	Germany 1. Bundesliga	VfL Wolfsburg	2008/2009	21	7

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'})
```

```
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 = True)
teamRecords.shape
```

Out[19]:

```
(1453, 6)
```

In [20]:

```
teamRecords.sample(3)
```

Out[20]:

	League	Team	Seasons	Wins	Losses	Goals
734	Italy Serie A	Carpi	2015/2016	9	18	37
633	Italy Serie A	Juventus	2008/2009	21	6	69
382	France Ligue 1	Valenciennes FC	2011/2012	12	19	40

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, inplace = True)
# 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	Goals
League	**Seasons**				
Belgium Jupiler League	**2008/2009**	RSC Anderlecht	24	5	75
	2009/2010	RSC Anderlecht	22	3	62
	2010/2011	KRC Genk	19	4	64
	2011/2012	RSC Anderlecht	20	3	61
	2012/2013	RSC Anderlecht	20	3	69
	2014/2015	Club Brugge KV	17	3	69
	2015/2016	Club Brugge KV	21	8	64
England Premier League	**2008/2009**	Manchester United	28	4	68
	2009/2010	Chelsea	27	6	103
	2010/2011	Manchester United	23	4	78
	2011/2012	Manchester City	28	5	93
	2012/2013	Manchester United	28	5	86
	2013/2014	Manchester City	27	6	102
	2014/2015	Chelsea	26	3	73
	2015/2016	Leicester City	23	3	68
France Ligue 1	**2008/2009**	Girondins de Bordeaux	24	6	64

League	Seasons	Team	Wins	Losses	Goals
	2009/2010	Olympique de Marseille	23	6	69
	2010/2011	LOSC Lille	21	4	68
	2011/2012	Montpellier Hérault SC	25	6	68
	2012/2013	Paris Saint-Germain	25	5	69
	2013/2014	Paris Saint-Germain	27	3	84
	2014/2015	Paris Saint-Germain	24	3	83
	2015/2016	Paris Saint-Germain	30	2	102
Germany 1. Bundesliga	**2008/2009**	VfL Wolfsburg	21	7	80
	2009/2010	FC Bayern Munich	20	4	72
	2010/2011	Borussia Dortmund	23	5	67
	2011/2012	Borussia Dortmund	25	3	80
	2012/2013	FC Bayern Munich	29	1	98
	2013/2014	FC Bayern Munich	29	2	94
	2014/2015	FC Bayern Munich	25	5	80
	2015/2016	FC Bayern Munich	28	2	80
Italy Serie A	**2008/2009**	Inter	25	4	70
	2009/2010	Inter	24	4	75
	2010/2011	Milan	24	4	65
	2011/2012	Milan	23	6	72
	2012/2013	Juventus	27	5	71
	2013/2014	Juventus	33	2	80
	2014/2015	Juventus	26	3	72
	2015/2016	Juventus	29	5	75
Netherlands Eredivisie	**2008/2009**	AZ	25	4	66
	2009/2010	Ajax	27	3	106
	2010/2011	Ajax	22	5	72
	2011/2012	Ajax	23	4	93
	2012/2013	Ajax	22	2	83
	2013/2014	Ajax	20	3	69
	2014/2015	PSV	29	4	92
	2015/2016	PSV	26	2	88
Poland Ekstraklasa	**2008/2009**	Wisła Kraków	19	4	53
	2009/2010	Lech Poznań	19	3	51
	2010/2011	Wisła Kraków	17	8	44
	2011/2012	Śląsk Wrocław	17	8	47
	2012/2013	Legia Warszawa	20	3	59
	2013/2014	Legia Warszawa	20	7	60
	2014/2015	Legia Warszawa	17	8	57
	2015/2016	Legia Warszawa	17	4	58
Portugal Liga ZON Sagres	**2008/2009**	FC Porto	21	2	61
	2009/2010	SL Benfica	24	2	78
	2010/2011	SL Benfica	20	7	61
	2011/2012	FC Porto	23	1	69
	2012/2013	SL Benfica	24	1	77
	2013/2014	SL Benfica	23	2	58
	2014/2015	SL Benfica	27	3	86
	2015/2016	SL Benfica	29	4	88
Scotland Premier League	**2008/2009**	Rangers	26	4	77
	2009/2010	Rangers	26	3	82
	2010/2011	Rangers	30	5	88

League	Seasons	Team	Wins	Losses	Goals
	2011/2012	Celtic	30	5	84
	2012/2013	Celtic	24	7	92
	2013/2014	Celtic	31	1	102
	2014/2015	Celtic	29	4	84
	2015/2016	Celtic	26	4	93
Spain LIGA BBVA	2008/2009	FC Barcelona	27	5	105
	2009/2010	FC Barcelona	31	1	98
	2010/2011	FC Barcelona	30	2	95
	2011/2012	Real Madrid CF	32	2	121
	2012/2013	FC Barcelona	32	2	115
	2013/2014	Atlético Madrid	28	4	77
	2014/2015	FC Barcelona	30	4	110
	2015/2016	FC Barcelona	29	5	112
Switzerland Super League	2008/2009	FC Zürich	24	5	80
	2009/2010	BSC Young Boys	25	9	78
	2010/2011	FC Basel	21	5	76
	2011/2012	FC Basel	22	4	78
	2012/2013	FC Basel	21	6	61
	2013/2014	FC Basel	19	2	70
	2014/2015	FC Basel	24	6	84
	2015/2016	FC Basel	26	5	88

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, inplace = True)
# 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]:

League	Seasons	Team	Wins	Losses	Goals
Belgium Jupiler League	2008/2009	RAEC Mons	3	21	31
	2009/2010	Sporting Lokeren	5	20	22
	2010/2011	Sporting Charleroi	4	19	20
	2011/2012	KVC Westerlo	5	20	29
	2012/2013	KSV Cercle Brugge	3	22	30
	2014/2015	Waasland-Beveren	7	18	30
	2015/2016	Sint-Truidense VV	8	16	28
England Premier League	2008/2009	West Bromwich Albion	8	22	36
	2009/2010	Burnley	8	24	42
	2010/2011	Wolverhampton Wanderers	11	20	46
	2011/2012	Blackburn Rovers	8	23	48
	2012/2013	Reading	6	22	43
	2013/2014	Fulham	9	24	40
	2014/2015	Queens Park Rangers	8	24	42

League	Seasons	Team	Wins	Losses	Goals
	2014/2015	Queens Park Rangers	8	24	42
	2015/2016	Aston Villa	3	27	27
France Ligue 1	2008/2009	Le Havre AC	7	26	30
	2009/2010	Grenoble Foot 38	5	25	31
	2010/2011	AC Arles-Avignon	3	24	21
	2011/2012	Dijon FCO	9	20	38
	2012/2013	Stade Brestois 29	8	25	32
	2013/2014	Valenciennes FC	7	23	37
	2014/2015	Évian Thonon Gaillard FC	11	23	41
	2015/2016	ES Troyes AC	3	26	28
Germany 1. Bundesliga	2008/2009	Karlsruher SC	8	21	30
	2009/2010	Hertha BSC Berlin	5	20	34
	2010/2011	FC St. Pauli	8	21	35
	2011/2012	1. FC Köln	8	20	39
	2012/2013	SpVgg Greuther Fürth	4	21	26
	2013/2014	Hamburger SV	7	21	51
	2014/2015	Hamburger SV	9	17	25
	2015/2016	Hannover 96	7	23	31
Italy Serie A	2008/2009	Torino	8	20	37
	2009/2010	Livorno	7	23	27
	2010/2011	Bari	5	24	27
	2011/2012	Cesena	4	22	24
	2012/2013	Pescara	6	28	27
	2013/2014	Livorno	6	25	39
	2014/2015	Parma	6	24	33
	2015/2016	Frosinone	8	23	35
Netherlands Eredivisie	2008/2009	ADO Den Haag	8	18	41
	2009/2010	RKC Waalwijk	5	29	30
	2010/2011	VVV-Venlo	6	25	34
	2011/2012	Excelsior	4	23	28
	2012/2013	Willem II	5	21	33
	2013/2014	Roda JC Kerkrade	7	19	44
	2014/2015	FC Dordrecht	4	22	24
	2015/2016	SC Cambuur	3	22	33
Poland Ekstraklasa	2008/2009	Lechia Gdańsk	9	16	30
	2009/2010	Odra Wodzisław	7	17	27
	2010/2011	Cracovia	8	17	37
	2011/2012	Widzew Łódź	5	16	23
	2012/2013	Pogoń Szczecin	10	15	29
	2013/2014	Zagłębie Lubin	7	15	31
	2014/2015	Zawisza Bydgoszcz	8	17	32
	2015/2016	Jagiellonia Białystok	10	15	37
Portugal Liga ZON Sagres	2008/2009	Vitória Setúbal	7	18	21
	2009/2010	Leixões SC	5	19	25
	2010/2011	Naval 1° de Maio	5	17	26
	2011/2012	União de Leiria, SAD	5	21	25
	2012/2013	Vitória Setúbal	7	18	30
	2013/2014	FC Paços de Ferreira	6	18	28
	2014/2015	FC Penafiel	5	22	29
	2015/2016	CS Marítimo	10	19	45
Scotland Premier League	2008/2009	Hamilton Academical FC	12	21	30

League	Seasons	Team	Wins	Losses	Goals
	2009/2010	Kilmarnock	8	21	29
	2010/2011	Aberdeen	11	22	39
	2011/2012	Dunfermline Athletic	5	23	40
	2012/2013	Dundee FC	7	22	28
	2013/2014	Kilmarnock	11	21	45
	2014/2015	St. Mirren	9	26	30
	2015/2016	Dundee United	8	23	45
Spain LIGA BBVA	**2008/2009**	Real Sporting de Gijón	14	23	47
	2009/2010	CD Tenerife	9	20	40
	2010/2011	Real Sociedad	14	21	49
	2011/2012	Rayo Vallecano	13	21	53
	2012/2013	Real Zaragoza	9	22	37
	2013/2014	Real Betis Balompié	6	25	36
	2014/2015	Córdoba CF	3	24	22
	2015/2016	Levante UD	8	22	37
Switzerland Super League	**2008/2009**	FC Vaduz	5	24	28
	2009/2010	AC Bellinzona	7	25	42
	2010/2011	FC St. Gallen	8	21	34
	2011/2012	Grasshopper Club Zürich	7	22	32
	2012/2013	Servette FC	6	22	32
	2013/2014	FC Lausanne-Sports	7	26	38
	2014/2015	FC Vaduz	7	19	28
	2015/2016	FC St. Gallen	10	18	41

Team Attributes Catagories

In [23]:

```
teamsDF.sample(3)
```

Out[23]:

	team_api_id	team_fifa_api_id	team_long_name	team_short_name	date	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUpPl
479	8550	68.0	FC Metz	MET	2010-02-22 00:00:00	50	Balanced	
845	8674	1915.0	FC Groningen	GRO	2015-09-10 00:00:00	55	Balanced	
575	9788	23.0	Borussia Mönchengladbach	GLA	2013-09-20 00:00:00	76	Fast	

In [24]:

```
# left the 'date' column as an object to easily slice off the 00:00:00 from the feature
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_football_season
        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
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't care about
losing edge features / data
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'], how = 'left')
leagueLosers_attributes = leagueLosers_season.merge(df, on = ['Seasons', 'Team'], how = 'left')
# get rid of unneeded features for the radar charts
leagueWinners_attributes.drop(['team_api_id', 'team_fifa_api_id', 'team_short_name', 'date'], axis
=1, inplace=True)
leagueLosers_attributes.drop(['team_api_id', 'team_fifa_api_id', 'team_short_name', 'date'], axis=
1, inplace=True)
leagueWinners_attributes.sample(3)
```

Out[24]:

	Seasons	Team	Wins	Losses	Goals	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUpPlayDribbling	buildUpPlayDribblingCl
79	2008/2009	FC Zürich	24	5	80	NaN	NaN	NaN	N
37	2014/2015	Juventus	26	3	72	26.0	Slow	47.0	Nor
27	2012/2013	FC Bayern Munich	29	1	98	NaN	NaN	NaN	N

In [25]:

```
# create a function that compares the winning team attributes vs losing team attributes in
# three major categories: Build Up, Offense, and Defense

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

# 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)

# 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']].res
et_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)

# create the function for viewing
```

```
# 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()
```

Visualization and Analysis

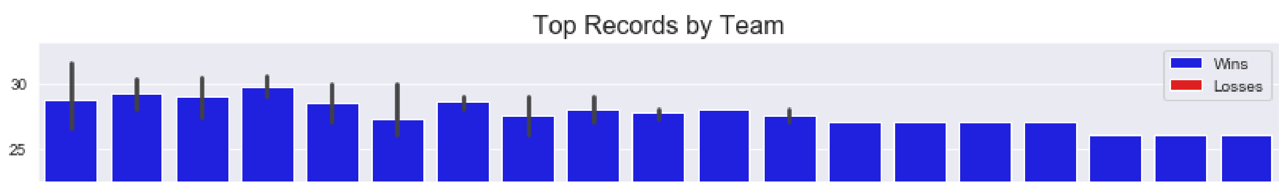
In [26]:

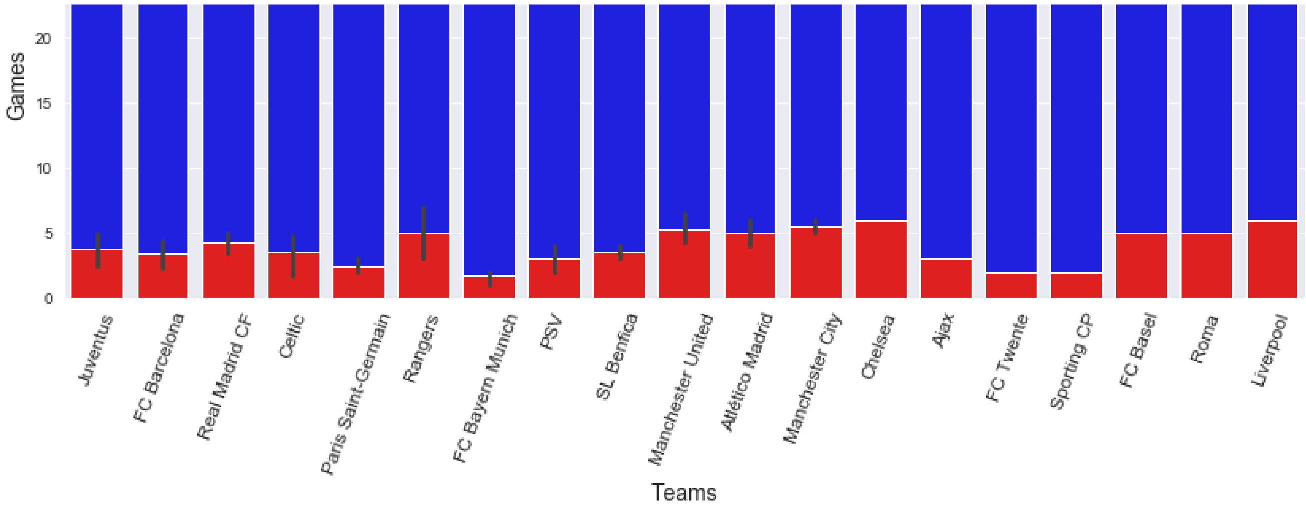
```
goals_per_year = []
seasons = leaguesFinal['season'].unique()

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

df = pd.DataFrame([goals_per_year]).transpose()
df['Season'] = ['2008/2009', '2009/2010', '2010/2011', '2011/2012', '2012/2013', '2013/2014', '2014
/2015', '2015/2016']
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 [27]:

```
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()
```

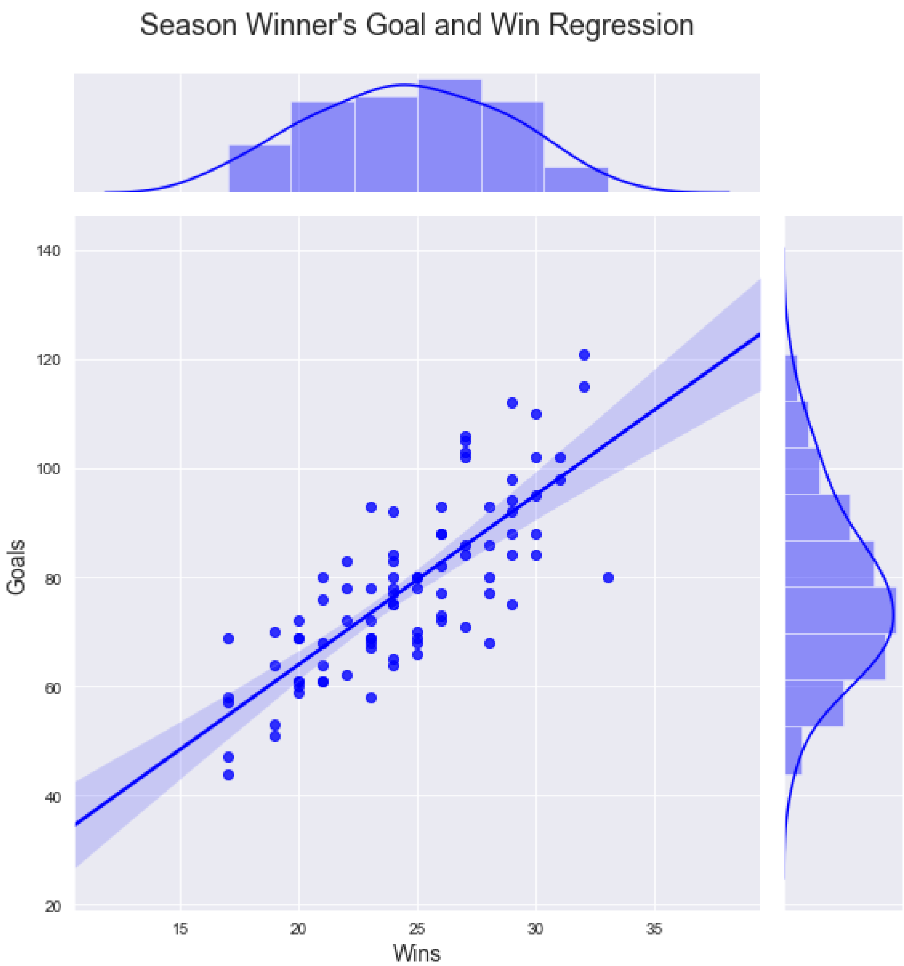




It's no surprise the teams at the very top of their league have a supurb win to loss ration. This would also be that teams best year if the team had more than one winning season.

In [28]:

```
sns.jointplot(leagueWinners_season['Wins'], leagueWinners_season['Goals'], kind = 'reg', color =
'b', height = 8)
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 [29]:

```
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 = 16)
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.

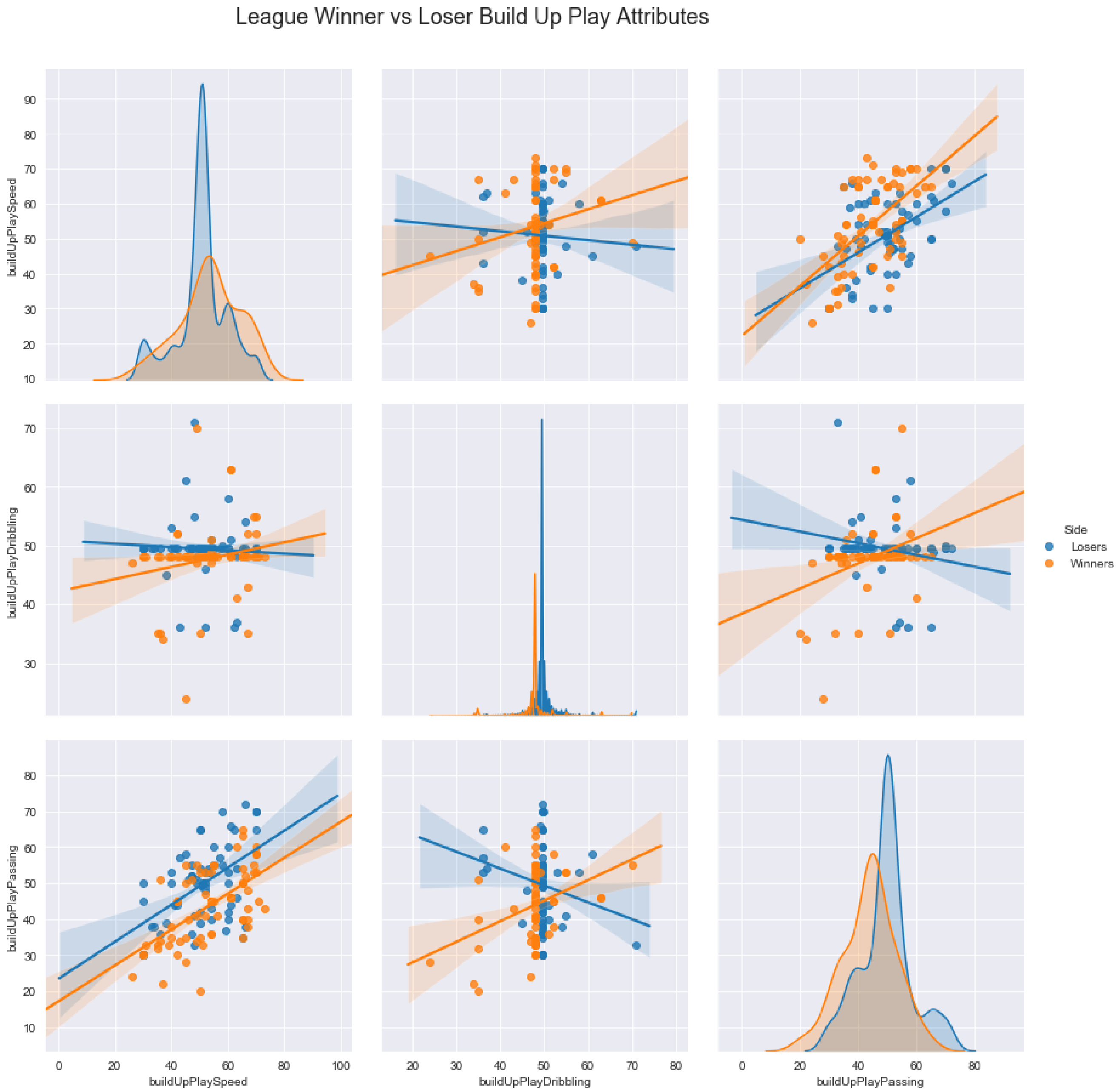
In [30]:

```
# create a function that compares the winning team attributes vs losing team attributes in
# three major categories: Build Up, Offense, and Defense

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

# 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)

# 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
```

```
# 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']].res
et_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)

# 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 [31]:

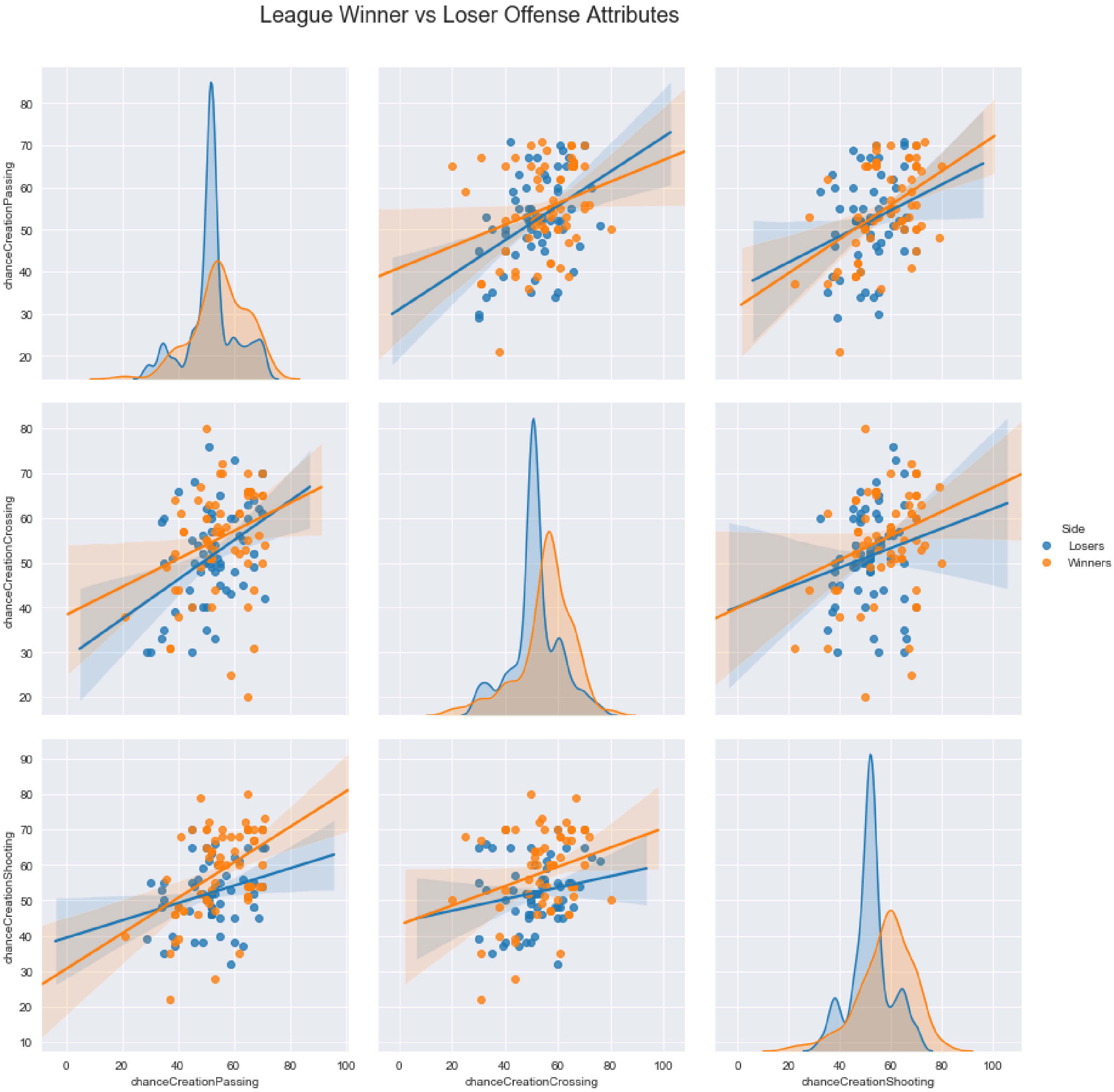
```
pair_plot(df1, title1)
```



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 [32]:

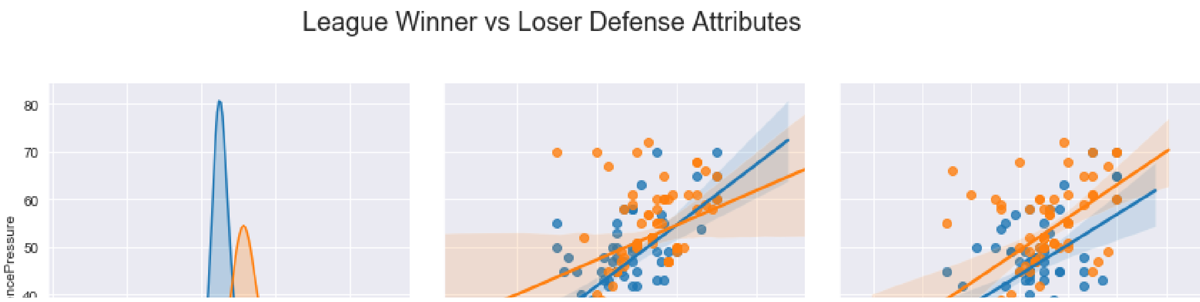
```
pair_plot(df2, title2)
```

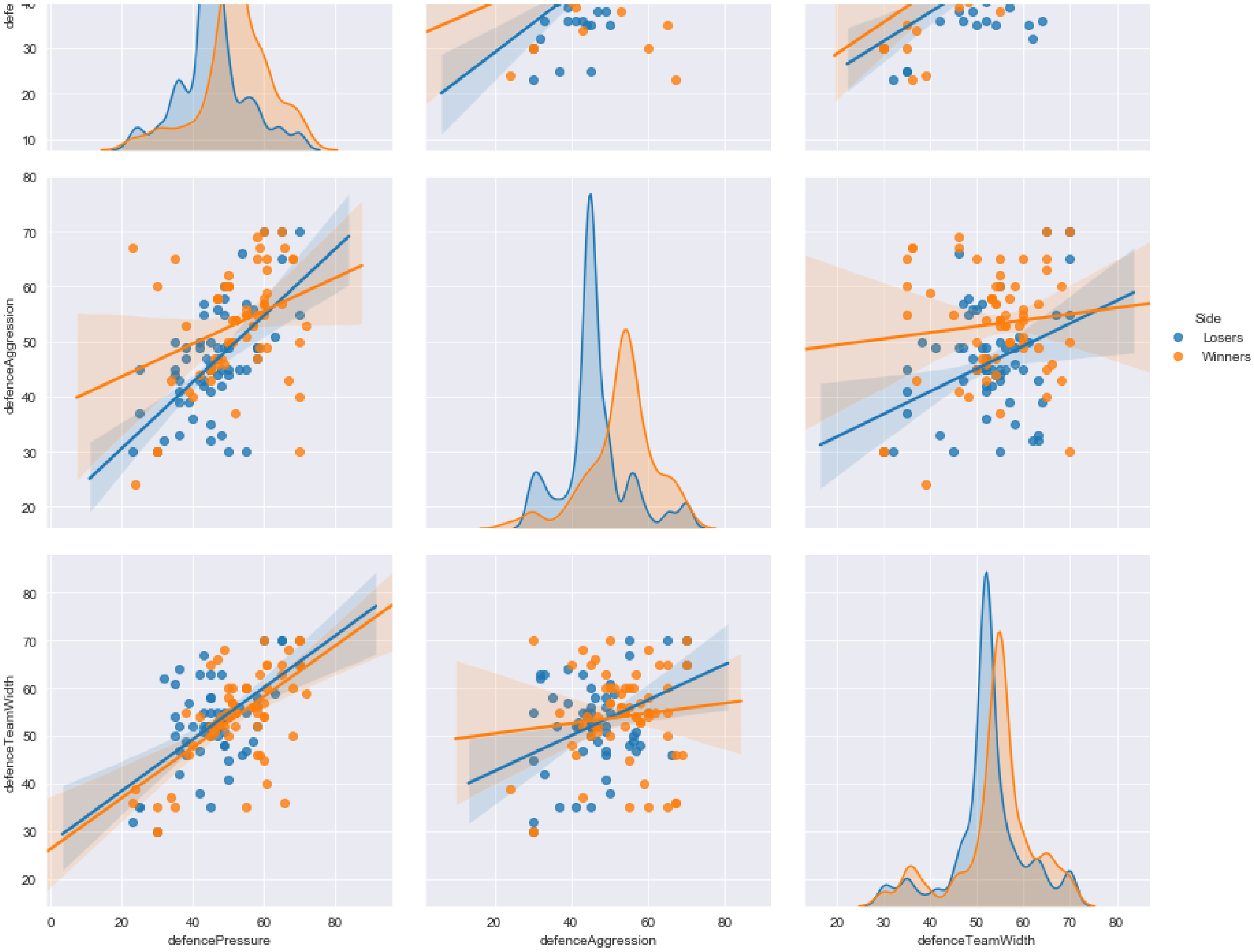


Offensively this comparison was interesting because the losing teams had a more positive correlation in categories like Passing vs Crossing, although the winning teams still maintained a higher average across all teams. This seems to be a consistent trend, the winning team is on average higher than the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

In [33]:

```
pair_plot(df3, title3)
```





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).

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.