Project 2

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In [1]:

```
import numpy as np
import pandas as pd

# read in combined dataset into a dataframe
df = pd.read_csv("combined_data.csv")

df.head(5)
```

Out[1]:

	Unnamed: 0	Home Team	Away Team	Score	Half Time Score	Match Excitement	Home Team Rating	Away Team Rating	Home Team Possession %	A Po
0	0	MAN UTD	SWANSEA	1-2	0-1	5.9	5.6	7.6	60	
1	1	WEST BROM	SUNDERLAND	2-2	1-1	7.3	6.5	7.4	58	
2	2	LEICESTER CITY	EVERTON	2-2	1-2	7.0	6.5	6.3	37	
3	3	WEST HAM	TOTTENHAM	0-1	0-0	4.8	5.9	6.4	47	
4	4	QPR	HULL CITY	0-1	0-0	3.8	5.7	6.6	51	

5 rows × 42 columns

The first of our datasets provides various game data from each of the top 5 soccer leagues in the world: The Premier League, Ligue, The Budesliga, Seria, and La Liga. This dataset contains data from games from 2014-2020 and includes many different game statistics such as each team's rating, the match excitement, team posession percentages, shots on goal, etc. To get this dataset into a pandas dataframe, we first had to download the dataset from kaggle. After this, the data was downloaded into our local environment in the form of a .zip file with several different files within it. We then exported all of the individual .csv files from the original .zip file and loaded the combined .csv into our original dataframe.

In [2]:

```
# read in second dataset into a dataframe
df2 = pd.read_csv("Football_Data.csv")

df2.head(5)
```

Out[2]:

	League	Year	position	Team	matches	wins	draws	loses	scored	pts	xG	x
0	La_liga	2014	1	Barcelona	38	30	4	4	110	94	102.980152	28.444
1	La_liga	2014	2	Real Madrid	38	30	2	6	118	92	95.766243	42.607
2	La_liga	2014	3	Atletico Madrid	38	23	9	6	67	78	57.047670	29.069
3	La_liga	2014	4	Valencia	38	22	11	5	70	77	55.062500	39.392
4	La_liga	2014	5	Sevilla	38	23	7	8	71	76	69.526624	47.862

Rather than showing game-to-game statistics, our second dataset gives year totals for each team in the five biggest soccer leagues in the world. This dataset contains information such as total matches, total wins, total losses, points scored, foul statistics, and different shooting statistics. Unlike the first dataset, this dataset only contains information for 2014-2018 missing data from the 2019 and 2020 season which is contained in the first dataset. We hope that this will not be a problem moving forward; however, if it does prove to be a problem we may need to inpute the values for the missing years or drop 2019 and 2020 from the first dataset altogether.

Questions we hope to answer after data exploration:

- What individual match factors are most correlated with match wins?
- What season statisitics are most correlate total match wins?
- Do expected goals for/against provide a direct correlation to a team's finishing position that year?

2. Data Inspection

In [3]:
```
# data types of first dataset attributes
df.dtypes
```

Out[3]:
```
Unnamed: 0                        int64
Home Team                        object
Away Team                        object
Score                            object
Half Time Score                  object
Match Excitement                float64
Home Team Rating                float64
Away Team Rating                float64
Home Team Possession %            int64
Away Team Possession %            int64
Home Team Off Target Shots      float64
Home Team On Target Shots       float64
Home Team Total Shots           float64
Home Team Blocked Shots         float64
Home Team Corners               float64
Home Team Throw Ins             float64
Home Team Pass Success %        float64
Home Team Aerials Won           float64
Home Team Clearances            float64
Home Team Fouls                 float64
Home Team Yellow Cards          float64
Home Team Second Yellow Cards   float64
Home Team Red Cards             float64
Away Team Off Target Shots      float64
Away Team On Target Shots       float64
Away Team Total Shots           float64
Away Team Blocked Shots         float64
Away Team Corners               float64
Away Team Throw Ins             float64
Away Team Pass Success %        float64
Away Team Aerials Won           float64
Away Team Clearances            float64
Away Team Fouls                 float64
Away Team Yellow Cards          float64
Away Team Second Yellow Cards   float64
Away Team Red Cards             float64
Home Team Goals Scored            int64
Away Team Goals Scored            int64
Home Team Goals Conceeded         int64
Away Team Goals Conceeded         int64
year                              int64
league                           object
dtype: object
```

With the first dataset, nearly all the features are comprised of numerical data as many of them are totals for each statistical category throughout the game. Despite this, there are also several features that currently contain categorical data the obvious ones being the league and home/away team names. In addition, the final score and halftime score are also currently listed as strings and could be interpretted as categorical data or numerical data depending on the context. The string representation of the halftime and final scores are caused because the feature contains both the away and home team's goal total seperated by a hyphen. It may be beneficial to divide this feature into two features (home score and away score), but I believe that the total score representation also has merit because it shows the entire picture indicating the closeness of the game.

In [4]:
```
# data types of second dataset attributes
df2.dtypes
```

Out[4]:
```
League         object
Year            int64
position        int64
Team           object
matches         int64
wins            int64
draws           int64
loses           int64
scored          int64
pts             int64
xG            float64
xGA           float64
%LoseR        float64
%DrawR        float64
Shots         float64
Yellow        float64
Red           float64
Fouls         float64
S_OnTarget    float64
dtype: object
```

Similarly to our first dataset, the second dataset contains mostly numerical data representing totals in each listed statistical category accross an entire season. Also similarly to our first dataset, the exception to this rule is the league and team name features which are categorical variables and represented as strings.

In [5]:
```
print("The first dataset contains",df.size,"elements and",df.shape[0],"rows.")
```

```
The first dataset contains 506604 elements and 12062 rows.
```

In [6]:
```
print("The second dataset contains",df2.size,"elements and",df2.shape[0],"rows.")
```

```
The second dataset contains 9310 elements and 490 rows.
```

In [7]:
```
# check for null values
df.isnull().sum()
```

Out[7]:
```
Unnamed: 0                        0
Home Team                         0
Away Team                         0
Score                             0
Half Time Score                   0
Match Excitement                  0
Home Team Rating                  0
Away Team Rating                  0
Home Team Possession %            0
Away Team Possession %            0
Home Team Off Target Shots        0
Home Team On Target Shots         0
Home Team Total Shots             0
Home Team Blocked Shots           0
Home Team Corners                 0
Home Team Throw Ins               0
Home Team Pass Success %          0
Home Team Aerials Won             0
Home Team Clearances              0
Home Team Fouls                   0
Home Team Yellow Cards            0
Home Team Second Yellow Cards     0
Home Team Red Cards               0
Away Team Off Target Shots        0
Away Team On Target Shots         0
Away Team Total Shots             0
Away Team Blocked Shots           0
Away Team Corners                 0
Away Team Throw Ins               0
Away Team Pass Success %          0
Away Team Aerials Won             0
Away Team Clearances              0
Away Team Fouls                   0
Away Team Yellow Cards            0
Away Team Second Yellow Cards     0
Away Team Red Cards               0
Home Team Goals Scored            0
Away Team Goals Scored            0
Home Team Goals Conceeded         0
Away Team Goals Conceeded         0
year                              0
league                            0
dtype: int64
```

In [8]:
```
# check for null values
df2.isnull().sum()
```

Out[8]:
```
League        0
Year          0
position      0
Team          0
matches       0
wins          0
draws         0
loses         0
scored        0
pts           0
xG            0
xGA           0
%LoseR        6
%DrawR        6
Shots         6
Yellow        6
Red           6
Fouls         6
S_OnTarget    6
dtype: int64
```

In [136]:
```
# using this function, we can see that the "null" values are coming from the last
df_null = df2.isnull()
print (df_null)
```

```
11   False  False  False   False   False  False   False  False  False
12   False  False  False   False   False  False   False  False  False
13   False  False  False   False   False  False   False  False  False
14   False  False  False   False   False  False   False  False  False
15   False  False  False   False   False  False   False  False  False
16   False  False  False   False   False  False   False  False  False
17   False  False  False   False   False  False   False  False  False
18   False  False  False   False   False  False   False  False  False
19   False  False  False   False   False  False   False  False  False
20   False  False  False   False   False  False   False  False  False
21   False  False  False   False   False  False   False  False  False
22   False  False  False   False   False  False   False  False  False
23   False  False  False   False   False  False   False  False  False
24   False  False  False   False   False  False   False  False  False
25   False  False  False   False   False  False   False  False  False
26   False  False  False   False   False  False   False  False  False

27   False  False  False   False   False  False   False  False  False
28   False  False  False   False   False  False   False  False  False
29   False  False  False   False   False  False   False  False  False
```

In [137]:

```python
# this function shows the last rows where we are seeing missing data
df2.tail(6)
```

Out[137]:

	League	Year	position	Team	matches	wins	draws	loses	scored	pts	xG
484	Bundesliga	2014	11	FC Cologne	34	9	13	12	34	40	32.224092
485	Bundesliga	2015	9	FC Cologne	34	10	13	11	38	43	42.872219
486	Bundesliga	2016	6	FC Cologne	34	12	13	9	51	49	45.335524
487	Bundesliga	2017	18	FC Cologne	34	5	7	22	35	22	41.500611
488	Bundesliga	2018	10	Fortuna Duesseldorf	34	13	5	16	49	44	49.474933
489	Serie_A	2018	16	Parma Calcio 1913	38	10	11	17	41	41	41.098644

In [138]:

```python
# imputes missing %LoseR values
position = 484

while position < 490:
    tempMatches = df2.at[position,"matches"]
    tempDraws = df2.at[position,"draws"]
    newNumber = tempDraws/tempMatches
    df2.at[position,"%DrawR"] = newNumber
    position+=1
```

In [139]:

```python
# shows the newly inputed values
df2.tail(6)
```

Out[139]:

	League	Year	position	Team	matches	wins	draws	loses	scored	pts	xG
484	Bundesliga	2014	11	FC Cologne	34	9	13	12	34	40	32.224092
485	Bundesliga	2015	9	FC Cologne	34	10	13	11	38	43	42.872219
486	Bundesliga	2016	6	FC Cologne	34	12	13	9	51	49	45.335524
487	Bundesliga	2017	18	FC Cologne	34	5	7	22	35	22	41.500611
488	Bundesliga	2018	10	Fortuna Duesseldorf	34	13	5	16	49	44	49.474933
489	Serie_A	2018	16	Parma Calcio 1913	38	10	11	17	41	41	41.098644

From the isnull() functions above, we can see that our first dataset does not contain any missing or null values; however, our second dataset does have some missing values specifically within the last 6 rows and on the following features: %LoseR, %DrawR, Shots, Yellow, Red, Fouls, S_OnTarget. In the code sections following the isnull() function, I was able to impute the remaining values in both the %LoseR and %DrawR columns using the data on matches, loses, and draws in each respective row. This will help enhance the completeness of our final dataset and make our final model more accurate. The remaining missing values were not able to be simply imputed because there was no data on fouls or missed shots within each row.

3. Data Description

Let's start with the first dataset...

In [14]:
```
df.head(10)
```

Out[14]:

	Unnamed: 0	Home Team	Away Team	Score	Half Time Score	Match Excitement	Home Team Rating	Away Team Rating	Home Team Possession %
0	0	MAN UTD	SWANSEA	1-2	0-1	5.9	5.6	7.6	60
1	1	WEST BROM	SUNDERLAND	2-2	1-1	7.3	6.5	7.4	58
2	2	LEICESTER CITY	EVERTON	2-2	1-2	7.0	6.5	6.3	37
3	3	WEST HAM	TOTTENHAM	0-1	0-0	4.8	5.9	6.4	47
4	4	QPR	HULL CITY	0-1	0-0	3.8	5.7	6.6	51
5	5	STOKE	ASTON VILLA	0-1	0-0	2.8	6.5	7.0	63
6	6	ARSENAL	CRYSTAL PALACE	2-1	1-1	5.8	7.7	5.6	76
7	7	LIVERPOOL	SOUTHAMPTON	2-1	1-0	6.0	7.1	6.7	56
8	8	NEWCASTLE	MAN CITY	0-2	0-1	4.6	5.5	8.1	44
9	9	BURNLEY	CHELSEA	1-3	1-3	5.3	5.3	7.4	39

10 rows × 42 columns

In [11]:
```
# data types of first dataset attributes
df.dtypes
```

Out[11]:
```
Unnamed: 0                        int64
Home Team                        object
Away Team                        object
Score                            object
Half Time Score                  object
Match Excitement                float64
Home Team Rating                float64
Away Team Rating                float64
Home Team Possession %            int64
Away Team Possession %            int64
Home Team Off Target Shots      float64
Home Team On Target Shots       float64
Home Team Total Shots           float64
Home Team Blocked Shots         float64
Home Team Corners               float64
Home Team Throw Ins             float64
Home Team Pass Success %        float64
Home Team Aerials Won           float64
Home Team Clearances            float64
Home Team Fouls                 float64
Home Team Yellow Cards          float64
Home Team Second Yellow Cards   float64
Home Team Red Cards             float64
Away Team Off Target Shots      float64
Away Team On Target Shots       float64
Away Team Total Shots           float64
Away Team Blocked Shots         float64
Away Team Corners               float64
Away Team Throw Ins             float64
Away Team Pass Success %        float64
Away Team Aerials Won           float64
Away Team Clearances            float64
Away Team Fouls                 float64
Away Team Yellow Cards          float64
Away Team Second Yellow Cards   float64
Away Team Red Cards             float64
Home Team Goals Scored            int64
Away Team Goals Scored            int64
Home Team Goals Conceeded         int64
Away Team Goals Conceeded         int64
year                              int64
league                           object
dtype: object
```

Attribute Information

- Unnamed: 0 : index
- Home Team: club name of team playing at home
- Away Team: club name of team playing on the road
- Score: final score of the game
- Match excitement: excitement rating of the match
  - Not entirely sure how they derived this. I am assuming a combination between attendance, crowd noise, and TV views
- Home team rating: match rating of the home team

- Away team rating: match rating of the away team
    - Team Rating note: I am assuming this is a calculated value of how well a team performed in a match
- Home team possession %: percent of the match the home team had possession of the ball
- Away team possession %: percent of the match the away team had possession of the ball
- Home Team Off Target Shots: number of shots off target for the home team
- Home Team On Target Shots: number of shots on target for the home team
- Home Team Total Shots: total number of shots for the home team
- Home Team Blocked Shots: number of blocked shots by the home team
- Home Team Corners: number of corners for the home team
- Home Team Throw Ins: number of throw ins for the home team
- Home Team Pass Success %: percent of successful passes for the home team
- Home Team Aerials Won: number of balls won in the air by the home team
- Home Team Clearances: number of balls cleared by the home team
- Home Team Fouls: number of fouls committed by the home team
- Home Team Yellow Cards: number of yellow cards for the home team
- Home Team Second Yellow Cards: number of times a second yellow card is given to a player
- Home Team Red Cards: number of red cards for the home team
- Away Team Off Target Shots: number of shots off target for the away team
- Away Team On Target Shots: number of shots on target for the away team
- Away Team Total Shots: total number of shots for the away team
- Away Team Blocked Shots: number of blocked shots by the away team
- Away Team Corners: number of corners for the away team
- Away Team Throw Ins: number of throw ins for the away team
- Away Team Pass Success %: percent of successful passes for the away team
- Away Team Aerials Won: number of balls won in the air by the away team
- Away Team Clearances: number of balls cleared by the away team
- Away Team Fouls: number of fouls committed by the away team
- Away Team Yellow Cards: number of yellow cards for the away team
- Away Team Second Yellow Cards: number of times a second yellow card is given to a player
- Away Team Red Cards: number of red cards for the away team
- Home Team Goals Scored: number of goals scored by the home team
- Away Team Goals Scored: number of goals scored by the away team
- Home Team Goals Conceeded: number of goals conceded by the home team
- Away Team Goals Conceeded: number of goals conceded by the away team
- year: year
- league: soccer league

Categorical variables:

- Home team
- Away team
- Score
- League

In [16]:

```
# Let's look at these numerical variables
df.describe()
```

Out[16]:

ome Team Blocked Shots	...	Away Team Clearances	Away Team Fouls	Away Team Yellow Cards	Away Team Second Yellow Cards	Away Team Red Cards	Home Team Goals Scored	
62.000000	...	12062.000000	12062.000000	12062.000000	12062.000000	12062.000000	12062.000000	12
3.338501	...	22.792323	13.083154	2.162245	0.060852	0.057785	1.531172	
2.246498	...	10.141781	4.205046	1.365581	0.244216	0.243772	1.305178	
0.000000	...	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
2.000000	...	15.000000	10.000000	1.000000	0.000000	0.000000	1.000000	
3.000000	...	22.000000	13.000000	2.000000	0.000000	0.000000	1.000000	
5.000000	...	29.000000	16.000000	3.000000	0.000000	0.000000	2.000000	
19.000000	...	79.000000	32.000000	9.000000	2.000000	2.000000	10.000000	

Now let's look at the second data set...

In [19]:

```
df2.head(5)
```

Out[19]:

e	Year	position	Team	matches	wins	draws	loses	scored	pts	xG	xGA	%Los
a	2014	1	Barcelona	38	30	4	4	110	94	102.980152	28.444293	0.250
a	2014	2	Real Madrid	38	30	2	6	118	92	95.766243	42.607198	0.000
a	2014	3	Atletico Madrid	38	23	9	6	67	78	57.047670	29.069107	0.166
a	2014	4	Valencia	38	22	11	5	70	77	55.062500	39.392572	0.250
a	2014	5	Sevilla	38	23	7	8	71	76	69.526624	47.862742	0.166

In [18]:
```
df2.dtypes
```

Out[18]:
```
League          object
Year             int64
position         int64
Team            object
matches          int64
wins             int64
draws            int64
loses            int64
scored           int64
pts              int64
xG             float64
xGA            float64
%LoseR         float64
%DrawR         float64
Shots          float64
Yellow         float64
Red            float64
Fouls          float64
S_OnTarget     float64
dtype: object
```

Attribute Information

- League: league
- Year: year
- position: finishing position in that league for that year
- Team: club name
- matches: matches played
- wins: wins
- draws: draws/ties
- loses: loses
- scored: goals for
- pts: points, 3 for a win and 1 for a draw
- xG: expected goals for
- xGA: expected goals against
- %LoseR: % games lost
- %DrawR: % games drawn
- Shots: shots
- Yellow: yellow cards
- Red: red cards
- Fouls: fouls committed
- S_OnTarget: shots on target

In [20]:
```
df2.describe()
```

Out[20]:

	Year	position	matches	wins	draws	loses	scored	
count	490.000000	490.000000	490.000000	490.000000	490.000000	490.000000	490.000000	490.00
mean	2016.000000	10.316327	37.265306	13.965306	9.334694	13.965306	50.640816	51.23
std	1.415659	5.683537	1.550454	6.008925	2.957473	5.585259	17.409702	17.16
min	2014.000000	1.000000	34.000000	2.000000	2.000000	1.000000	22.000000	15.00
25%	2015.000000	5.000000	38.000000	10.000000	7.000000	10.000000	38.250000	39.00
50%	2016.000000	10.000000	38.000000	12.500000	9.000000	14.000000	47.000000	48.00
75%	2017.000000	15.000000	38.000000	17.000000	11.000000	18.000000	58.000000	61.00
max	2018.000000	20.000000	38.000000	32.000000	18.000000	29.000000	118.000000	100.00

4. Merge the Data

In [21]:
```
df.head(2)
```

Out[21]:

	Unnamed: 0	Home Team	Away Team	Score	Half Time Score	Match Excitement	Home Team Rating	Away Team Rating	Home Team Possession %	Away T Posses
0	0	MAN UTD	SWANSEA	1-2	0-1	5.9	5.6	7.6	60	
1	1	WEST BROM	SUNDERLAND	2-2	1-1	7.3	6.5	7.4	58	

2 rows × 42 columns

In [22]:
```
df2.head(2)
```

Out[22]:

	League	Year	position	Team	matches	wins	draws	loses	scored	pts	xG	›
0	La_liga	2014	1	Barcelona	38	30	4	4	110	94	102.980152	28.444
1	La_liga	2014	2	Real Madrid	38	30	2	6	118	92	95.766243	42.607

For our model, thinking of needing to build a model that predicts the number of goals scored for both the home and away team. To accomplish this, we are going to build two seperate models:

- 1) Predict home team score
- 2) Predict away team score

Following this process, our idea for merging is:

- 1) Copy 'df' into a home and away dataset
- 2) Copy 'df2' into two other datasets, called 'df2_<home/away>'

- 3) Rename the Team column to home or away team, respectively, of 'df2_<home/away>'
- 4) Change the values of Home/Away Team column to match with the syntax of the first dataset
    - example) Manchester United --> MAN UTD

In [38]:
```
teams = df['Home Team'].unique()
```

In [26]:
```
teams_df2 = df2['Team'].unique()
```

In [39]:
```
teams = np.sort(teams)
```

In [41]:
```
teams_df2 = np.sort(teams_df2)
```

In [44]:
```
teamsAcrossDatasets = {}
for t in teams_df2:
    temp = t
    t = t.upper()
    if t in teams:
        teamsAcrossDatasets[temp] = t
    else:
        teamsAcrossDatasets[temp] = "Need to find"
```

In [46]:
```
teamsAcrossDatasets
```

```
 'Freiburg': 'FREIBURG',
 'Frosinone': 'FROSINONE',
 'Fulham': 'FULHAM',
 'GFC Ajaccio': 'GFC AJACCIO',
 'Genoa': 'GENOA',
 'Getafe': 'GETAFE',
 'Girona': 'GIRONA',
 'Granada': 'GRANADA',
 'Guingamp': 'GUINGAMP',
 'Hamburger SV': 'Need to find',
 'Hannover 96': 'Need to find',
 'Hertha Berlin': 'Need to find',
 'Hoffenheim': 'HOFFENHEIM',
 'Huddersfield': 'HUDDERSFIELD',
 'Hull': 'Need to find',
 'Ingolstadt': 'INGOLSTADT',
 'Inter': 'INTER',
 'Juventus': 'JUVENTUS',
 'Las Palmas': 'LAS PALMAS',
```

In [50]:
```
teamsNeeded = [k for k,v in teamsAcrossDatasets.items() if v == 'Need to find']
```

In [52]:
```
# Imputed off of prior football knowledge and sources listed below
# For Evian Thonon Gaillard and THONON ÉVIAN: https://en.wikipedia.org/wiki/Thonor
# For HSV and Hamburger SV: https://www.hsv.de/en/homepage
# For Lens and RC LENS: https://en.wikipedia.org/wiki/RC_Lens
# For Reims and STADE DE REIMS: https://en.wikipedia.org/wiki/Stade_de_Reims

otherTeams = ['MILAN','ALAVÉS', 'ALMERÍA', 'ATHLETIC', 'LEVERKUSEN','BAYERN','DOR
              'CELTA', 'CÓRDOBA','DEPORTIVO','FRANKFURT','THONON ÉVIAN', '1. FC KÖ
              'HSV', 'HANNOVER', 'HERTHA', 'HULL CITY', 'LEGANÉS', 'LEICESTER CITY
             'MÁLAGA', 'MAN CITY','MAN UTD','FC METZ','NEWCASTLE','NÜRNBERG','PSG
             'VALLADOLID', 'STADE DE REIMS', 'STADE RENNAIS', 'HUESCA', 'SPAL','SA
             'GIJÓN','HELLAS','STUTTGART','W. BREMEN','WEST BROM','WOLVES']
```

In [57]:
```
for i, t in enumerate(teamsNeeded):
    teamsAcrossDatasets[t] = otherTeams[i]
```

In [58]:
```
teamsAcrossDatasets
```

```
 'Lille': 'LILLE',
 'Liverpool': 'LIVERPOOL',
 'Lorient': 'LORIENT',
 'Lyon': 'LYON',
 'Mainz 05': 'MAINZ',
 'Malaga': 'MÁLAGA',
 'Manchester City': 'MAN CITY',
 'Manchester United': 'MAN UTD',
 'Marseille': 'MARSEILLE',
 'Metz': 'FC METZ',
 'Middlesbrough': 'MIDDLESBROUGH',
 'Monaco': 'MONACO',
 'Montpellier': 'MONTPELLIER',
 'Nancy': 'NANCY',
 'Nantes': 'NANTES',
 'Napoli': 'NAPOLI',
 'Newcastle United': 'NEWCASTLE',
 'Nice': 'NICE',
 'Nimes': 'NIMES',
 'Norwich': 'NORWICH',
```

In [70]:
```
df.rename(columns = {'year':'Year'}, inplace = True)
df_home = df.copy()
df_away = df.copy()
```

In [63]:
```
def convert_to_common_team_name(team):
    return teamsAcrossDatasets[team]

def transformDF2(df2):
    df2_home = df2.copy()
    df2_away = df2.copy()
    df2_home['Team'] = df2_home['Team'].apply(convert_to_common_team_name)
    df2_away['Team'] = df2_away['Team'].apply(convert_to_common_team_name)
    df2_home.rename(columns = {'Team':'Home Team'}, inplace = True)
    df2_away.rename(columns = {'Team':'Away Team'}, inplace = True)
    return df2_home, df2_away
```

In [64]:
```
df2_home, df2_away = transformDF2(df2)
```

In [131]:
```
aggData = pd.merge(df2_home, df_home, on=['Year', 'Home Team'], how='inner')
aggData.head()
```

Out[131]:

	League	Year	position	Home Team	matches	wins	draws	loses	scored	pts	...	Away Team Clearances
0	La_liga	2014	1	BARCELONA	38	30	4	4	110	94	...	17.0
1	La_liga	2014	1	BARCELONA	38	30	4	4	110	94	...	19.0
2	La_liga	2014	1	BARCELONA	38	30	4	4	110	94	...	26.0
3	La_liga	2014	1	BARCELONA	38	30	4	4	110	94	...	35.0
4	La_liga	2014	1	BARCELONA	38	30	4	4	110	94	...	30.0

5 rows × 59 columns

In [84]:
```
len(aggData)
```

Out[84]:
```
8516
```

In [87]:
```
aggData.iloc[8510]
```

Out[87]:
```
League                            Serie_A
Year                                 2018
position                               16
Home Team                           PARMA
matches                                38
wins                                   10
draws                                  11
loses                                  17
scored                                 41
pts                                    41
xG                                41.0986
xGA                               64.9811
%LoseR                                NaN
%DrawR                                NaN
Shots                                 NaN
Yellow                                NaN
Red                                   NaN
Fouls                                 NaN
S_OnTarget                            NaN
Unnamed: 0                           8523
Away Team                           GENOA
Score                                 1-0
Half Time Score                       0-0
Match Excitement                      3.6
Home Team Rating                      6.8
Away Team Rating                      5.8
Home Team Possession %                 41
Away Team Possession %                 59
Home Team Off Target Shots              5
Home Team On Target Shots               3
Home Team Total Shots                   9
Home Team Blocked Shots                 1
Home Team Corners                       4
Home Team Throw Ins                    14
Home Team Pass Success %               76
Home Team Aerials Won                  16
Home Team Clearances                   24
Home Team Fouls                        12
Home Team Yellow Cards                  2
Home Team Second Yellow Cards           0
Home Team Red Cards                     0
Away Team Off Target Shots              9
Away Team On Target Shots               1
Away Team Total Shots                  13
Away Team Blocked Shots                 3
Away Team Corners                       5
Away Team Throw Ins                    32
Away Team Pass Success %               83
Away Team Aerials Won                  17
Away Team Clearances                    8
Away Team Fouls                        12
Away Team Yellow Cards                  1
Away Team Second Yellow Cards           0
Away Team Red Cards                     0
Home Team Goals Scored                  1
Away Team Goals Scored                  0
Home Team Goals Conceeded               0
Away Team Goals Conceeded               1
```

```
league                          italian
Name: 8510, dtype: object
```

In [83]:
```
aggData.iloc[1]
```

Out[83]:
```
League                             La_liga
Year                                  2014
position                                 1
Home Team                        BARCELONA
matches                                 38
wins                                    30
draws                                    4
loses                                    4
scored                                 110
pts                                     94
xG                                  102.98
xGA                                28.4443
%LoseR                                0.25
%DrawR                            0.714286
Shots                                  626
Yellow                                  66
Red                                      3
Fouls                                  369
S_OnTarget                             273
Unnamed: 0                            9423
Away Team                         ATHLETIC
Score                                  2-0
Half Time Score                        0-0
Match Excitement                       4.3
Home Team Rating                       7.7
Away Team Rating                       5.7
Home Team Possession %                  61
Away Team Possession %                  39
Home Team Off Target Shots               5
Home Team On Target Shots                8
Home Team Total Shots                   14
Home Team Blocked Shots                  1
Home Team Corners                        5
Home Team Throw Ins                     20
Home Team Pass Success %                84
Home Team Aerials Won                   12
Home Team Clearances                    11
Home Team Fouls                         12
Home Team Yellow Cards                   1
Home Team Second Yellow Cards            0
Home Team Red Cards                      0
Away Team Off Target Shots               1
Away Team On Target Shots                2
Away Team Total Shots                    3
Away Team Blocked Shots                  0
Away Team Corners                        1
Away Team Throw Ins                     22
Away Team Pass Success %                74
Away Team Aerials Won                   15
Away Team Clearances                    19
Away Team Fouls                         11
Away Team Yellow Cards                   1
Away Team Second Yellow Cards            0
Away Team Red Cards                      0
Home Team Goals Scored                   2
Away Team Goals Scored                   0
Home Team Goals Conceeded                0
Away Team Goals Conceeded                2
```

```
league                              spanish
Name: 1, dtype: object
```

The merge looks good!

From looking at this, columns can drop:

df: Goals conceded, Total Shots, Unnamed, league

5. Explore Bivariate Relationships

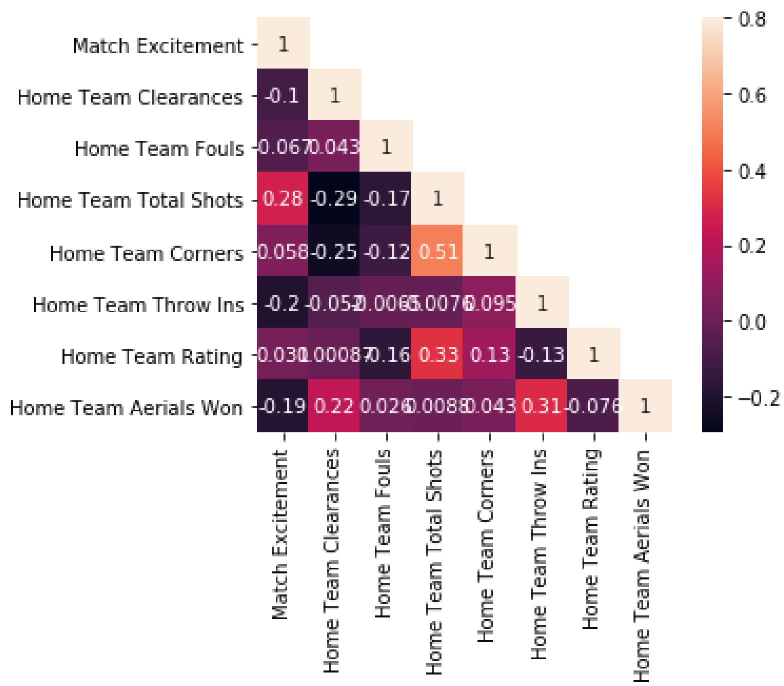
In [10]:

```
# Predict scores of 2019 and 2020
# Two models: one for home goals, one for away
# Eval on match winner, goal differential of match, accuracy of score
```

In [140]:

```
# correlation heat map giving correlation between single game statistics and overc
import seaborn as sn

corrMatt = aggData[["Match Excitement", "Home Team Clearances",
                    "Home Team Fouls", "Home Team Total Shots",
                    "Home Team Corners", "Home Team Throw Ins",
                    "Home Team Rating", "Home Team Aerials Won"]].corr()
mask = np.array(corrMatt)
mask[np.tril_indices_from(mask)] = False
sn.heatmap(corrMatt, mask=mask,
           vmax=.8, square=True,annot=True)
```

Out[140]: <matplotlib.axes._subplots.AxesSubplot at 0x154ea7ebe88>

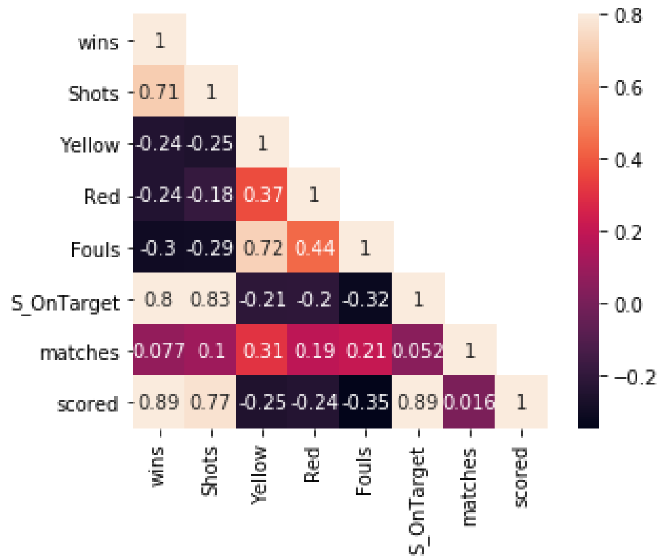


The above correlation heatmap finds the correlation between numerous different individual match statistics and the overall excitement rating. In creating this correlation map, we used all of the home team statistics because most of the fans at any given game will likely be favoring the home team and we believed that the home team statistics would be an overall better predictor of match excitement. Unsurprisingly, the statistics with the biggest positive correlation with match excitement was total shots with both clearances and total throw-ins exhibiting a slight negative correlation with match excitement. Another correlation that logically makes sense was that total corners was heavily correlated with total shots because most corners are generated through shots that the goalie blocks out of bounds.

In [141]:

```
# correlation heat map giving correlation between season statistics and total wins

corrMatt = aggData[["wins","Shots",
                    "Yellow","Red",
                    "Fouls","S_OnTarget",
                    "matches", "scored"]].corr()
mask = np.array(corrMatt)
mask[np.tril_indices_from(mask)] = False
sn.heatmap(corrMatt, mask=mask,
           vmax=.8, square=True,annot=True)
```

Out[141]: <matplotlib.axes._subplots.AxesSubplot at 0x154ec45bf48>



Based on the heatmap above, the number of goals scored by a team throughout the season seems to correlate most closely with the total number of wins by that team followed closely by the total number of shots taken. This makes sense as intuitively I would assume that goals and shots would create more of a difference in win percentage than other things such as yellow cards, red cards, or total fouls. I did find it interesting; however, that yellow cards, red cards, and total fouls did have a decently sized negative correlation with total wins indicating that these statistics did negatively impact total wins despite fouls being a critical and sometimes intentional part of the game.

In [142]:

```
# Get bottom teams
bottomTeams = aggData.where(aggData['position'] > 15)
bottomTeams = bottomTeams.dropna()
```

In [143]:

```
# Get top teams
topTeams = aggData.where(aggData['position'] <= 5)
topTeams = topTeams.dropna()
```

In [144]:

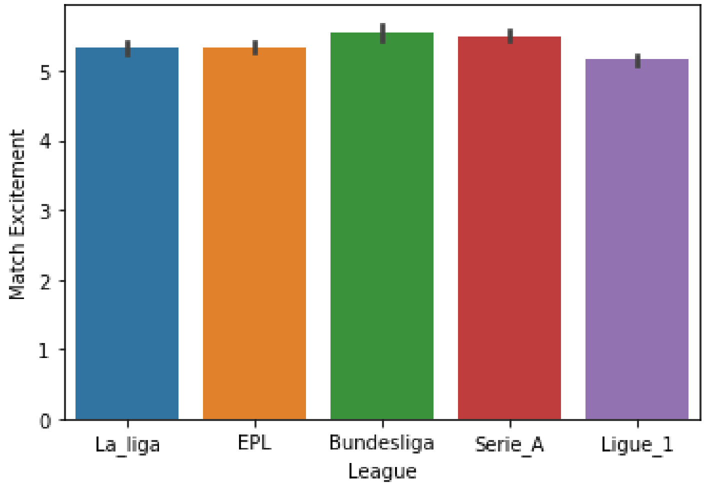
```
# displays avg of different season totals for teams in the top 15 vs bottom 5

print("Bottom 5 Team Averages:")
print("   Shots:",sum(bottomTeams["Shots"])/len(bottomTeams["Shots"]))
print("   Yellow Cards:",sum(bottomTeams["Yellow"])/len(bottomTeams["Yellow"]))
print("   Red Cards:",sum(bottomTeams["Red"])/len(bottomTeams["Red"]))
print("   Total Fouls:",sum(bottomTeams["Fouls"])/len(bottomTeams["Fouls"]))
print("   Shots on target:",sum(bottomTeams["S_OnTarget"])/len(bottomTeams["S_OnTa
print("   Total goals scored:",sum(bottomTeams["scored"])/len(bottomTeams["scored"

print("Top 5 Team Averages:")
print("   Shots:",sum(topTeams["Shots"])/len(topTeams["Shots"]))
print("   Yellow Cards:",sum(topTeams["Yellow"])/len(topTeams["Yellow"]))
print("   Red Cards:",sum(topTeams["Red"])/len(topTeams["Red"]))
print("   Total Fouls:",sum(topTeams["Fouls"])/len(topTeams["Fouls"]))
print("   Shots on target:",sum(topTeams["S_OnTarget"])/len(topTeams["S_OnTarget"]
print("   Total goals scored:",sum(topTeams["scored"])/len(topTeams["scored"]))
```

```
Bottom 5 Team Averages:
   Shots: 410.5486111111111
   Yellow Cards: 83.01636904761905
   Red Cards: 4.838293650793651
   Total Fouls: 510.35515873015873
   Shots on target: 133.7470238095238
   Total goals scored: 35.7281746031746
Top 5 Team Averages:
   Shots: 544.600464037123
   Yellow Cards: 70.32621809744779
   Red Cards: 3.266357308584687
   Total Fouls: 454.6324825986079
   Shots on target: 207.51647331786543
   Total goals scored: 73.25197215777263
```

The output of the code above shows the statistical averages of teams that are placed within the top 5 teams in a league in any given year versus the teams that are in the bottom 5. The results of this experiment are not very surprising with the teams at the top experiencing more shots and goals scored while getting called for less fouls than the teams in the bottom of the league.

In [145]:
```
# bar chart comparing average match excitment accross the 5 major leagues
sn.barplot(data=aggData,x='League',y='Match Excitement')
```

Out[145]: <matplotlib.axes._subplots.AxesSubplot at 0x154ec4ebdc8>



The output of the code above is a barchart representing the different average match excitment levels amongst the top 5 soccer leagues in the world. The line at the top of each bar serves to present the level of uncertainty around each estimation. As you can see, Ligue 1 (the French soccer league) appears to have the lowest average match excitement amongst the top 5 leagues. This isn't surprising as the French league is generally considered to be the least competitive and generally worst league amongst the top 5. However, what is surprising is that the English Premier League (EPL) which is considered to be the most competive league in the top 5 has a lower average excitement than both the Bundesliga (German soccer league) and Serie A (Italian soccer league) which are both generally considered to be less competitive. Overall, all of the averages are very similar meaning we can't take too much from these results; however, I do still think that comparing the leagues in this way is interesting. Additionally, I would like to know more about how the match excitement statistic was created and hopefully this can give us more insight into why we are seeing the differences amongst each league that are displayed above.

Ultimate model plan:

- Predict scores for 2019 and 2020 (target variables)
- Will attempt to use both past season statistics as well as past single-game statistics as our predictor variables
- Two models: one for home goals and one for away
- Eval on accuracy of score, goal differential, and match winner

6. References

[1] Football Data : Top 5 Leagues. https://www.kaggle.com/sanjeetsinghnaik/football-data-top-5-leagues (https://www.kaggle.com/sanjeetsinghnaik/football-data-top-5-leagues)

[2] Points Table: Top 5 Leagues. https://www.kaggle.com/thegreatcoder/points-table-of-5-leagues-in-football-20142018 (https://www.kaggle.com/thegreatcoder/points-table-of-5-leagues-in-football-20142018)

In [ ]:

```

```