Soccer-Database-Kaggle

May 3, 2019

In [1]:
```
#You're gonna like this notebook if you want to brush up on SQL,get some tricks or want
#You're gonna love this notebook if you like football.

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sqlite3
%matplotlib inline


#The two research questions that I'll be concentrating on are:
# 1. How does Age of players correlate with Stamina, Reactions, Agility, Sprint Speed &
# 2. This is more Complex. I would like to find out which league is more unpredictable a
# EPL, Bundesliga, La Liga, Serie A and Ligue 1(Who watches anything else anyway?).
# For this I assign an Unpredictability score to every League. The steps to find this sc
#    a) Form league standings from match scores. [3 points to a team that wins, 0 for th
#    b) Find out the Top 5 teams and the Bottom 5 of each league in each season.
#    c) Find out the results of the matches between the Top 5 and the Bottom 5 in that p
#    d) If any of the bottom 5 teams beat any of the Top 5 teams at their own home groun
#       If they draw a match in their home ground give them 0.5 point.
#       If they manage to beat a Top 5 team away give them 1.25 points.
#       If they manage a draw with a Top 5 team away give them 0.75 points.
#       Add up all the scores for a season for each league and this is the Unpredictabil
```

In [2]:
```
#connect connect connect let python meet SQL

connection = sqlite3.connect('database.sqlite')

#Every SQLite database has an SQLITE_MASTER table(read-only) that defines the schema for
tables = pd.read_sql("""SELECT *
                        FROM sqlite_master
                        WHERE type='table';""",connection)
```

In [3]:
```
#deal witht the biggest baddest table first and life is easier thereafter
#Do not be afraid of SELECT *... try it out... its harmless.....

#Q: Why do you never ask SQL people to help you move your furniture?
```

```python
#A: They sometimes drop the tables

match = pd.read_sql("""SELECT *
                        FROM Match;
                        """, connection)

print(match.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25979 entries, 0 to 25978
Columns: 115 entries, id to BSA
dtypes: float64(96), int64(9), object(10)
memory usage: 22.8+ MB
None
```

In [4]:
```python
#they have an inbuilt for everything!!!!
match.isnull().sum(axis=0)
```

Out[4]:
```
id                     0
country_id             0
league_id              0
season                 0
stage                  0
date                   0
match_api_id           0
home_team_api_id       0
away_team_api_id       0
home_team_goal         0
away_team_goal         0
home_player_X1      1821
home_player_X2      1821
home_player_X3      1832
home_player_X4      1832
home_player_X5      1832
home_player_X6      1832
home_player_X7      1832
home_player_X8      1832
home_player_X9      1832
home_player_X10     1832
home_player_X11     1832
away_player_X1      1832
away_player_X2      1832
away_player_X3      1832
away_player_X4      1832
away_player_X5      1832
away_player_X6      1832
away_player_X7      1832
```

```
away_player_X8       1832
                      ...
B365H                3387
B365D                3387
B365A                3387
BWH                  3404
BWD                  3404
BWA                  3404
IWH                  3459
IWD                  3459
IWA                  3459
LBH                  3423
LBD                  3423
LBA                  3423
PSH                 14811
PSD                 14811
PSA                 14811
WHH                  3408
WHD                  3408
WHA                  3408
SJH                  8882
SJD                  8882
SJA                  8882
VCH                  3411
VCD                  3411
VCA                  3411
GBH                 11817
GBD                 11817
GBA                 11817
BSH                 11818
BSD                 11818
BSA                 11818
Length: 115, dtype: int64
```

In [5]:
```
#drop 'em dead if they be NaN
match_imp = match.dropna(axis='columns')
print(match_imp.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25979 entries, 0 to 25978
Data columns (total 11 columns):
id                    25979 non-null int64
country_id            25979 non-null int64
league_id             25979 non-null int64
season                25979 non-null object
stage                 25979 non-null int64
date                  25979 non-null object
match_api_id          25979 non-null int64
```

```
home_team_api_id    25979 non-null int64
away_team_api_id    25979 non-null int64
home_team_goal      25979 non-null int64
away_team_goal      25979 non-null int64
dtypes: int64(9), object(2)
memory usage: 2.2+ MB
None
```

```
In [6]: match_imp.duplicated().sum()
```

```
Out[6]: 0
```

```
In [7]: #merge Match Information with league information
        match_league = pd.read_sql("""SELECT m.country_id,lg.name,m.season,m.stage,m.date,m.matc
                                      FROM match m
                                      JOIN league lg
                                      ON m.league_id = lg.id""",connection)
        match_league.to_sql("match_league", connection, if_exists="replace")
        print(match_league.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25979 entries, 0 to 25978
Data columns (total 10 columns):
country_id          25979 non-null int64
name                25979 non-null object
season              25979 non-null object
stage               25979 non-null int64
date                25979 non-null object
match_api_id        25979 non-null int64
home_team_api_id    25979 non-null int64
away_team_api_id    25979 non-null int64
home_team_goal      25979 non-null int64
away_team_goal      25979 non-null int64
dtypes: int64(7), object(3)
memory usage: 2.0+ MB
None
```

```
In [8]: #All this work to create standings tables
        match_league['date'] = pd.to_datetime(match_league['date'])
        match_league['winner'] = np.where(match_league['home_team_goal']> match_league['away_tea
        match_league['winner'] = np.where(match_league['home_team_goal'] == match_league['away_t
        match_league['draw1'] = np.where(match_league['home_team_goal'] == match_league['away_te
        match_league['draw2'] = np.where(match_league['home_team_goal'] == match_league['away_te

        match_league.to_sql("match_league", connection, if_exists="replace")
        match_league.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25979 entries, 0 to 25978
Data columns (total 13 columns):
country_id          25979 non-null int64
name                25979 non-null object
season              25979 non-null object
stage               25979 non-null int64
date                25979 non-null datetime64[ns]
match_api_id        25979 non-null int64
home_team_api_id    25979 non-null int64
away_team_api_id    25979 non-null int64
home_team_goal      25979 non-null int64
away_team_goal      25979 non-null int64
winner              25979 non-null int64
draw1               25979 non-null int64
draw2               25979 non-null int64
dtypes: datetime64[ns](1), int64(10), object(2)
memory usage: 2.6+ MB
```

In [9]:
```
#check out your work of art
query = pd.read_sql("""SELECT *
                       FROM match_league
                       ;""",connection)
query.head()
```

Out[9]:
```
   index  country_id                   name     season  stage  \
0      0           1  Belgium Jupiler League  2008/2009      1
1      1           1  Belgium Jupiler League  2008/2009      1
2      2           1  Belgium Jupiler League  2008/2009      1
3      3           1  Belgium Jupiler League  2008/2009      1
4      4           1  Belgium Jupiler League  2008/2009      1

                 date  match_api_id  home_team_api_id  away_team_api_id  \
0 2008-08-17 00:00:00        492473              9987              9993
1 2008-08-16 00:00:00        492474             10000              9994
2 2008-08-16 00:00:00        492475              9984              8635
3 2008-08-17 00:00:00        492476              9991              9998
4 2008-08-16 00:00:00        492477              7947              9985

   home_team_goal  away_team_goal  winner   draw1   draw2
0               1               1  999999    9987    9993
1               0               0  999999   10000    9994
2               0               3    8635  999999  999999
3               5               0    9991  999999  999999
4               1               3    9985  999999  999999
```

In [10]:
```
#All ze stats of da Teams
home_draw = pd.read_sql("""SELECT name,season,draw1,count(draw1) AS dh
```

```
                                        FROM match_league
                                        WHERE draw1 != 999999
                                        GROUP BY 1,2,3;""",connection)
        away_draw = pd.read_sql("""SELECT name,season,draw2,count(draw2) AS da
                                        FROM match_league m1
                                        WHERE draw2 != 999999
                                        GROUP BY 1,2,3;""",connection)
        winner_t = pd.read_sql("""SELECT name,season,winner,count(winner) AS w
                                        FROM match_league m1
                                        WHERE winner != 999999
                                        GROUP BY 1,2,3;""",connection)
        home_draw.to_sql("home_draw", connection, if_exists="replace")
        away_draw.to_sql("away_draw", connection, if_exists="replace")
        winner_t.to_sql("winner_t", connection, if_exists="replace")
```

```
In [11]: #Statz of da players
        attribute = pd.read_sql("""SELECT pa.date,pl.birthday,pl.player_api_id,pl.player_name,p
                                FROM player pl
                                JOIN player_Attributes pa
                                ON pl.player_api_id = pa.player_api_id;""",connection)
        attribute['date'] = pd.to_datetime(attribute['date'])
        attribute['birthday'] = pd.to_datetime(attribute['birthday'])

        attribute.to_sql("attribute_imp",connection,if_exists="replace")
        attribute.info()
```

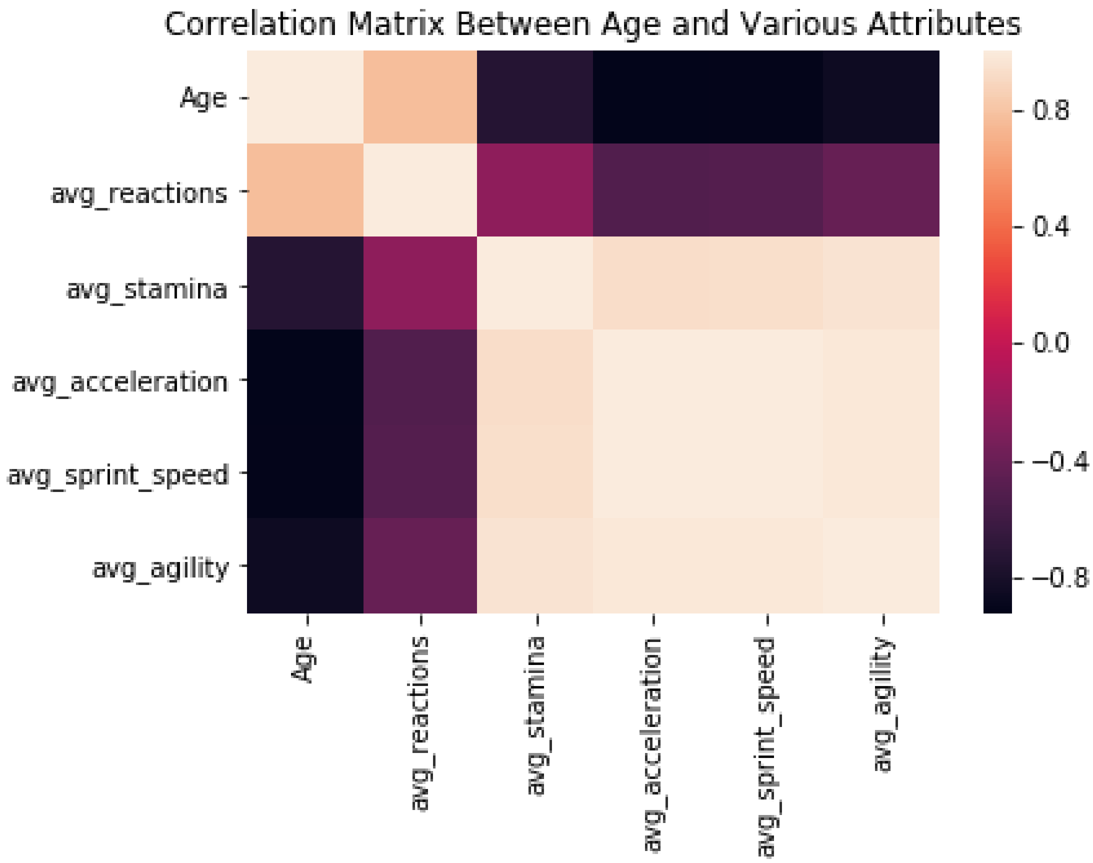
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183978 entries, 0 to 183977
Data columns (total 10 columns):
date                183978 non-null datetime64[ns]
birthday            183978 non-null datetime64[ns]
player_api_id       183978 non-null int64
player_name         183978 non-null object
acceleration        183142 non-null float64
sprint_speed        183142 non-null float64
stamina             183142 non-null float64
agility             181265 non-null float64
reactions           183142 non-null float64
preferred_foot      183142 non-null object
dtypes: datetime64[ns](2), float64(5), int64(1), object(2)
memory usage: 14.0+ MB
```

```
In [12]: #Preparation of data is half the job
        #Keeping most recent record of each player
        attribute.drop_duplicates(subset=['player_api_id',],keep="first",inplace=True)
        attribute.dropna(inplace=True)
        attribute.to_sql("attribute_imp",connection,if_exists="replace")
```

In [13]:
```
#Calculate the age of player

def num_years(start,curr):
    return(int((curr-start).days / 365.25))

query = pd.read_sql("""SELECT * FROM attribute_imp;""",connection)
query['date'] = pd.to_datetime(query['date'])
query['birthday'] = pd.to_datetime(query['birthday'])
#query['age'] = (query['date'].dt.year)-(query['birthday'].dt.year)
query['age'] = query.apply(lambda x: num_years(x['birthday'], x['date']), axis = 1)

query.to_sql("attribute_imp",connection,if_exists="replace")
```

In [14]:
```
import seaborn as sns
query1 = pd.read_sql("""  SELECT age AS Age,AVG(reactions) AS avg_reactions,AVG(stamina
                         ,AVG(acceleration) AS avg_acceleration,AVG(sprint_speed) AS a
                         ,AVG(agility) AS avg_agility
                         FROM attribute_imp
                         GROUP BY 1
                         ORDER BY 1""",connection)
corr = query1.corr()
ax = sns.heatmap(corr,
            xticklabels=corr.columns.values,
            yticklabels=corr.columns.values,)
ax.set_title("Correlation Matrix Between Age and Various Attributes")
```

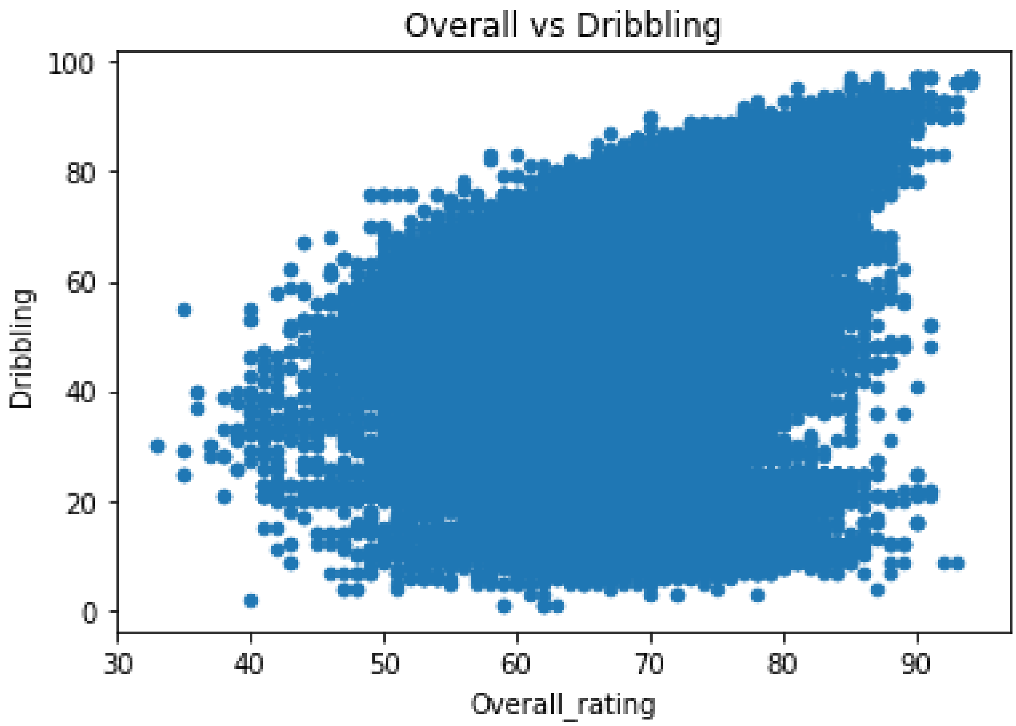
Out[14]: Text(0.5,1,'Correlation Matrix Between Age and Various Attributes')

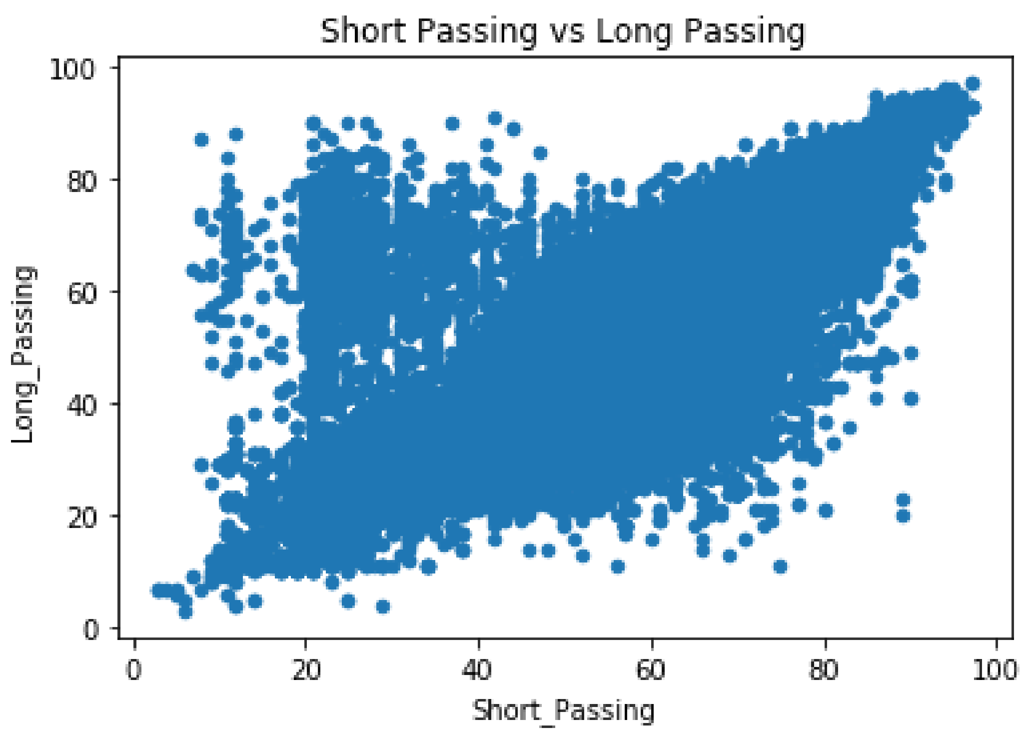


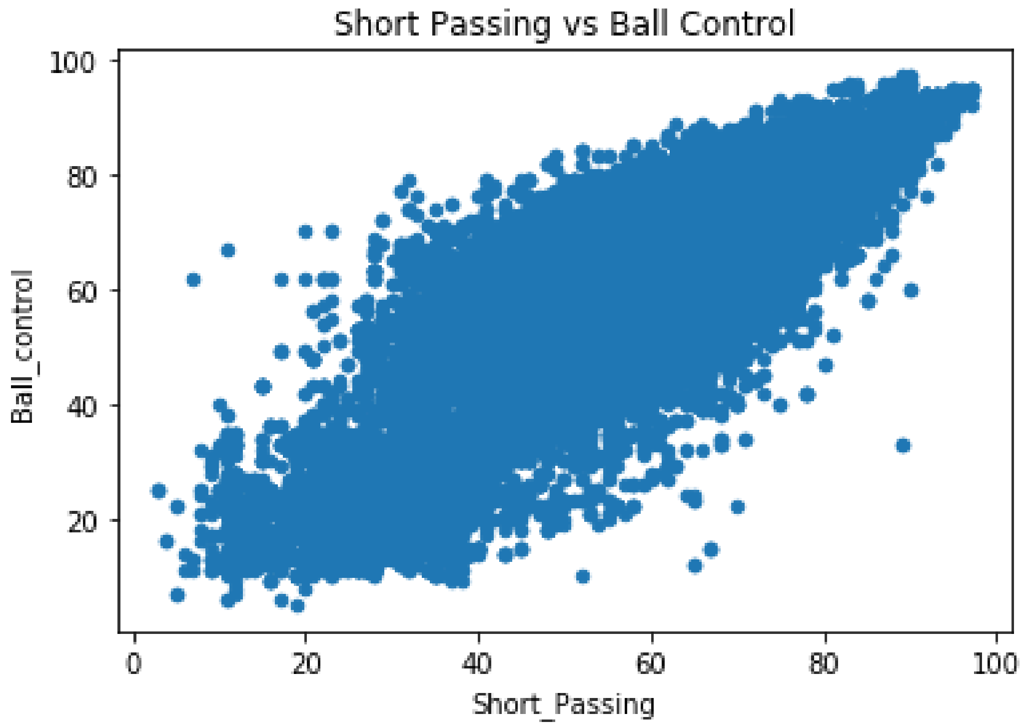
This Correlation matrix helps us find out how different attributes are linked to each other. We can clearly see that Age has a strong negative correlation with average acceleration,average agility, average stamina and average sprint speed of the players whereas age shows a weak positive correlation with the average reactions of the players.

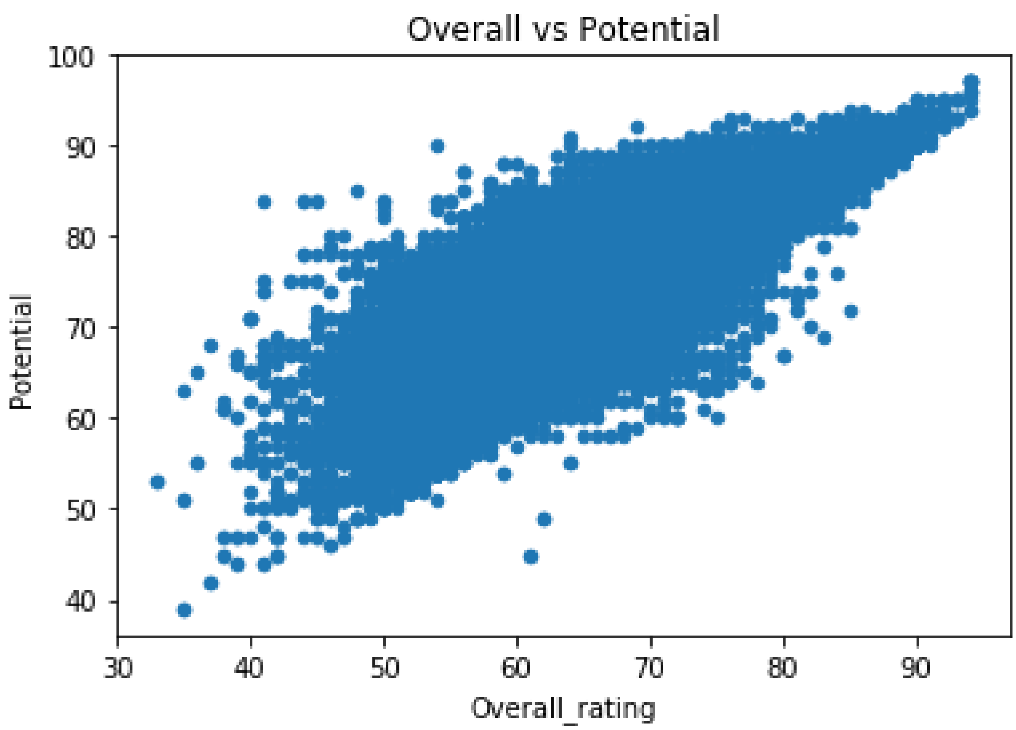
```
In [15]: qu = pd.read_sql("""  SELECT overall_rating AS Overall_rating,potential AS Potential, d
                                 short_passing as Short_Passing, long_passing AS Long_Passing, b
                                 FROM Player_Attributes
                                 ORDER BY 1""",connection)


         ax = qu.plot(x="Overall_rating",y="Dribbling",kind="scatter")
         ax.set_title("Overall vs Dribbling")

         ax = qu.plot(x="Short_Passing",y="Long_Passing",kind="scatter")
         ax.set_title("Short Passing vs Long Passing")

         ax = qu.plot(x="Short_Passing",y="Ball_control",kind="scatter")
         ax.set_title("Short Passing vs Ball Control")

         ax = qu.plot(x="Overall_rating",y="Potential",kind="scatter")
         ax.set_title("Overall vs Potential")
```

```
Out[15]: Text(0.5,1,'Overall vs Potential')
```






Short Passing vs Ball Control
100
80
60
40
20
Ball_control
0
20
40
60
80
100
Short_Passing


Overall vs Potential
100
90
80
70
60
50
40
Potential
30
40
50
60
70
80
90
Overall_rating

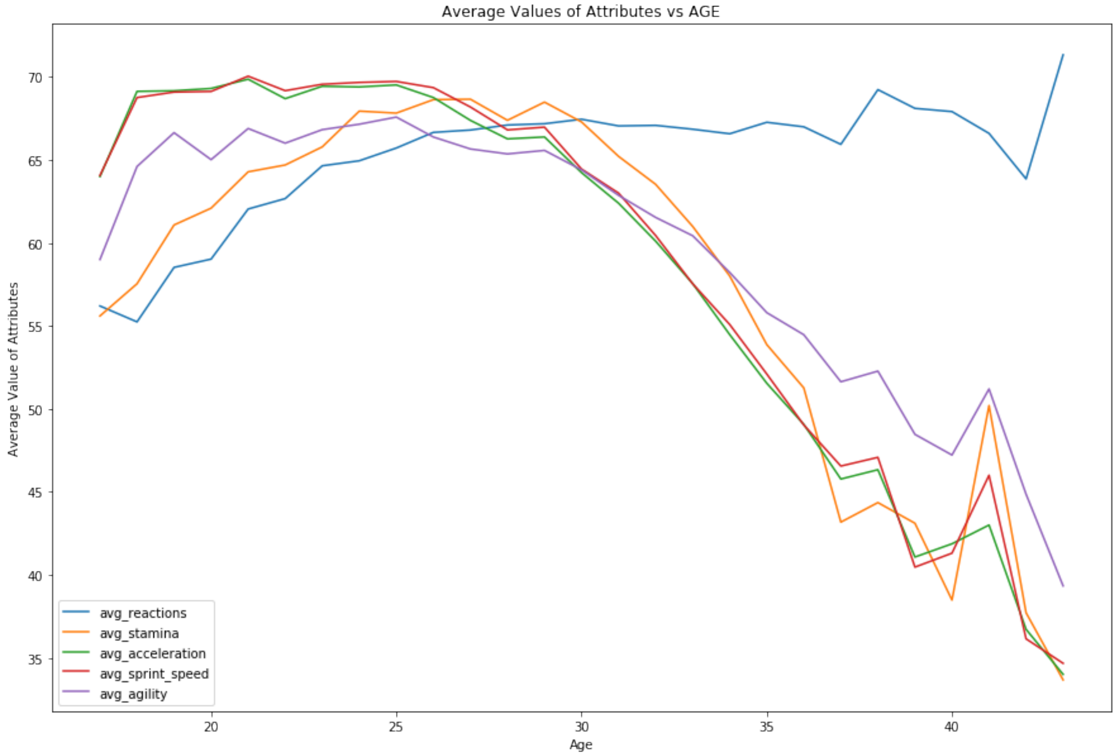
In this section I have displayed various scatter plots between attributes that I thought might have links with each other. In terms of prediction analysis later we might infer that ball control and short passing form a good fit.

Players with higher overall ratings are not always the players who can dribble well and this is true as several high rated players are defenders and goalkeepers whose strong suit is not dribbling.

Surprisingly there are a lot of players who despite having high Long Passing scores have low Short Passing scores and this is a very interesting point

```
In [16]: #This is where we plot
         query1 = pd.read_sql("""  SELECT age AS Age,AVG(reactions) AS avg_reactions,AVG(stamina
                                   ,AVG(acceleration) AS avg_acceleration,AVG(sprint_speed) AS a
                                   ,AVG(agility) AS avg_agility
                                   FROM attribute_imp
                                   GROUP BY 1
                                   ORDER BY 1""",connection)
         ax = query1.plot(x="Age", y=["avg_reactions", "avg_stamina", "avg_acceleration","avg_sp

         ax.set_ylabel("Average Value of Attributes")
         ax.set_title("Average Values of Attributes vs AGE")
         print("Correlation of Reactions with Age: ",query1['Age'].corr(query1['avg_reactions'])
         print("Correlation of Stamina with Age: ",query1['Age'].corr(query1['avg_stamina']))
         print("Correlation of Acceleration with Age: ",query1['Age'].corr(query1['avg_accelerat
         print("Correlation of Sprint Speed with Age: ",query1['Age'].corr(query1['avg_sprint_sp
         print("Correlation of Agility with Age: ",query1['Age'].corr(query1['avg_agility']))
```

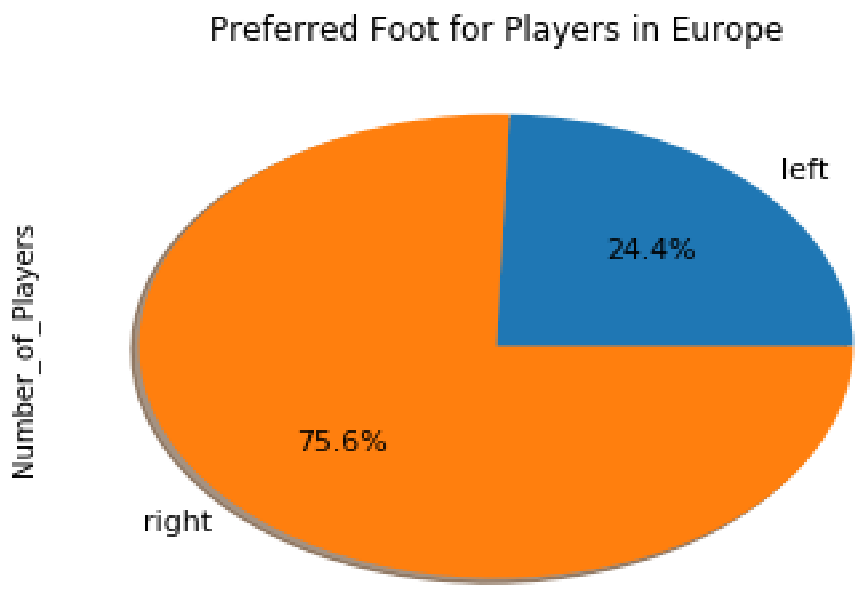
```
Correlation of Reactions with Age:  0.7675305570880387
Correlation of Stamina with Age:  -0.7260835589278937
Correlation of Acceleration with Age:  -0.9199811468752116
Correlation of Sprint Speed with Age:  -0.9104739545625228
Correlation of Agility with Age:  -0.849583392075151
```




```
In [17]: query = pd.read_sql("""SELECT preferred_foot AS Preferred_Foot,COUNT(*) as Number_of_Pl
                                  FROM attribute_imp
                                  GROUP BY 1""",connection)



         ax = query.plot(kind="pie",y='Number_of_Players', autopct='%1.1f%%',
          startangle=0, shadow=True, labels=query['Preferred_Foot'], legend = False, fontsize=11


         ax.set_title("Preferred Foot for Players in Europe")
         query
```

Out[17]:

	Preferred_Foot	Number_of_Players
0	left	2583
1	right	7999




```
In [18]: #Forming league Tables
         query = pd.read_sql("""SELECT hd.name,hd.season,hd.draw1 AS Team_id,hd.dh+ad.da+3*wi.w
                                FROM home_draw hd
                                JOIN away_draw ad
                                ON hd.name = ad.name AND hd.season=ad.season AND hd.draw1=ad.dra
                                JOIN winner_t wi
                                ON hd.name = wi.name AND hd.season=wi.season AND hd.draw1 = wi.w
                                WHERE hd.name LIKE "England Premier League" OR hd.name LIKE "Fra
                                hd.name LIKE "Germany 1. Bundesliga" OR hd.name LIKE "Italy Seri
                                hd.name LIKE "Spain LIGA BBVA"
                                ORDER BY 1,2,4 DESC;""",connection)
         query.to_sql("league_tables",connection,if_exists="replace")
```

```
In [19]: #To find Top 5 and Bottom 5 of each league in each season
         query = pd.read_sql("""SELECT * FROM league_tables;""",connection)
         lar = (query.groupby(['name','season'],group_keys=False)).apply(lambda x: x.nlargest(5,
         sma=(query.groupby(['name','season'],group_keys=False)).apply(lambda x: x.nsmallest(5,'
```

```
In [20]: #To find Top 5 and Bottom 5 of each league in each season
         ### SQL APPROACH USING SQLITE syntax(due to Pandas adhering to that) i.e. solve this SE

         #query = pd.read_sql("""SELECT *
         #                        FROM test t1
         #                        WHERE
         #                            (SELECT count(*)
         #                              FROM test t2
```

```
#                               WHERE t2.name = t1.name and t2.season = t1.season and t2.
#                         ORDER BY name, season, points desc""")
```

In [21]:
```
#Evaluating head-to-head scores to find the Unpredictability of each league
query = pd.read_sql("""SELECT * FROM league_tables;""",connection)
lar = (query.groupby(['name','season'],group_keys=False)).apply(lambda x: x.nlargest(5,

sma=(query.groupby(['name','season'],group_keys=False)).apply(lambda x: x.nsmallest(5,'

query1 = pd.read_sql("""SELECT * FROM match_league
                        WHERE name IN ("France Ligue 1","England Premier League","Spain
                        ORDER BY name,date;""",connection)
l=0

c=[0]*40
ss = []
for k in range(0,200,5):
    for i in range(k,k+5):
        for j in range(k,k+5):
            sid = sma.iloc[i,3] #Team_id of one of the Bottom 5
            lid = lar.iloc[j,3] #Team_id of one of the Top 5
            s=sma.iloc[i,2]     #Season for which we are evaluating
            ss.append(s)
            #When bottom 5 teams plays the Top 5 teams at their home
            a = query1.loc[query1.home_team_api_id == sid] #Filtering by home team
            b = a.loc[(query1.away_team_api_id == lid)]    #Filtering by away team
            d = b.loc[(query1.season == s)]                #Filtering by season

            if((not d.empty)):
                if((d.iloc[0,11]==sid)):
                    c[l] = c[l] + 1
                elif((d.iloc[0,11]==999999)):
                    c[l] = c[l] + 0.5

            #When bottom 5 teams plays the Top 5 teams away
            a = query1.loc[query1.home_team_api_id == lid]
            b = a.loc[(query1.away_team_api_id == sid)]
            d = b.loc[(query1.season == s)]
            if((not d.empty)):
                if((d.iloc[0,11]==sid)):
                    c[l] = c[l] + 1.25
                elif((d.iloc[0,11]==999999)):
                    c[l] = c[l] + 0.5


    l=l+1
```

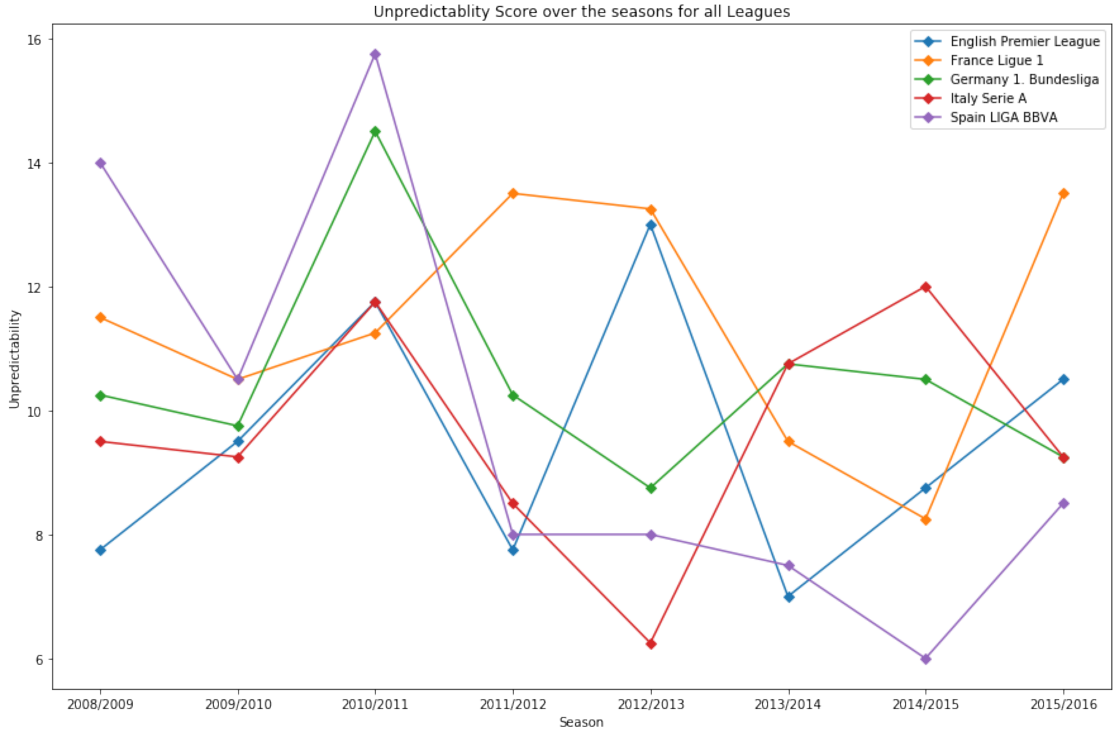
In [22]:
```
from collections import OrderedDict
a=list(OrderedDict.fromkeys(ss))
```

```python
df = {'English Premier League':pd.Series(data=c[0:8],index=a),
      'France Ligue 1':pd.Series(data=c[8:16],index=a),
      'Germany 1. Bundesliga':pd.Series(data=c[16:24],index=a),
      'Italy Serie A':pd.Series(data=c[24:32],index=a),
      'Spain LIGA BBVA':pd.Series(data=c[32:40],index=a)}
df=pd.DataFrame(df)
ax = df.plot(figsize=(15,10),marker='D')
ax.set_xlabel("Season")
ax.set_ylabel("Unpredictability")
ax.set_title("Unpredictablity Score over the seasons for all Leagues")
x= [0, 1, 2, 3, 4, 5, 6, 7]
labels =['2008/2009','2009/2010','2010/2011','2011/2012','2012/2013','2013/2014','2014/
plt.xticks(x,labels)
plt.subplots_adjust(bottom=0.15)
print("Average Unpredictability: \n",df.mean(axis=0))
df
```

```
Average Unpredictability:
 English Premier League     9.50000
France Ligue 1            11.40625
Germany 1. Bundesliga     10.50000
Italy Serie A              9.65625
Spain LIGA BBVA            9.78125
dtype: float64
```

Out[22]:

	English Premier League	France Ligue 1	Germany 1. Bundesliga	Italy Serie A	Spain LIGA BBVA
2008/2009	7.75	11.50	10.25	9.50	14.00
2009/2010	9.50	10.50	9.75	9.25	10.50
2010/2011	11.75	11.25	14.50	11.75	15.75
2011/2012	7.75	13.50	10.25	8.50	8.00
2012/2013	13.00	13.25	8.75	6.25	8.00
2013/2014	7.00	9.50	10.75	10.75	7.50
2014/2015	8.75	8.25	10.50	12.00	6.00
2015/2016	10.50	13.50	9.25	9.25	8.50

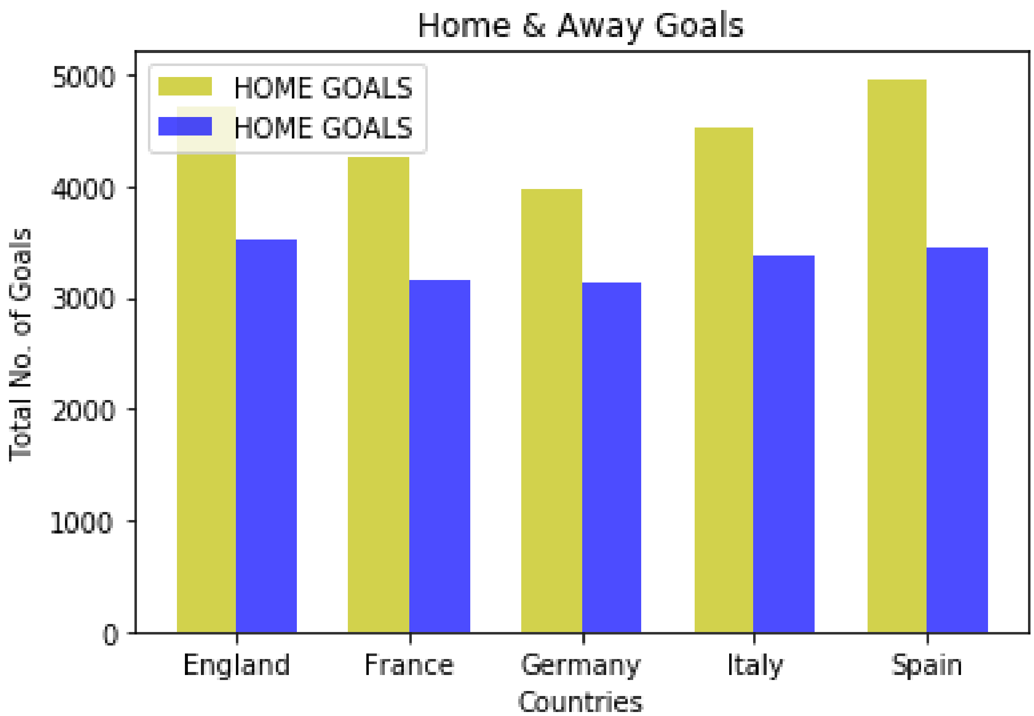



```
In [23]: query = pd.read_sql("""SELECT name,SUM(home_team_goal) as HOME,SUM(away_team_goal) AS A
                              FROM match_league
                              WHERE name IN ("France Ligue 1","England Premier League","Spain
                              GROUP BY 1""",connection)

         ind = np.arange(5)
         width = 0.35

         hm = plt.bar(ind, query['HOME'],width,color='y',alpha=0.7,label='HOME GOALS')
         aw = plt.bar(ind+width, query['AWAY'],width,color='b',alpha=0.7,label='HOME GOALS')
         plt.ylabel('Total No. of Goals')
         plt.xlabel('Countries')
         plt.title('Home & Away Goals')
         locations = ind+width / 2
         labels = ["England","France","Germany","Italy","Spain"]
         plt.xticks(locations,labels)
         plt.legend()
         query
```

Out[23]:

	name	HOME	AWAY
0	England Premier League	4715	3525
1	France Ligue 1	4265	3162
2	Germany 1. Bundesliga	3982	3121

```
3          Italy Serie A  4528  3367
4         Spain LIGA BBVA  4959  3453
```

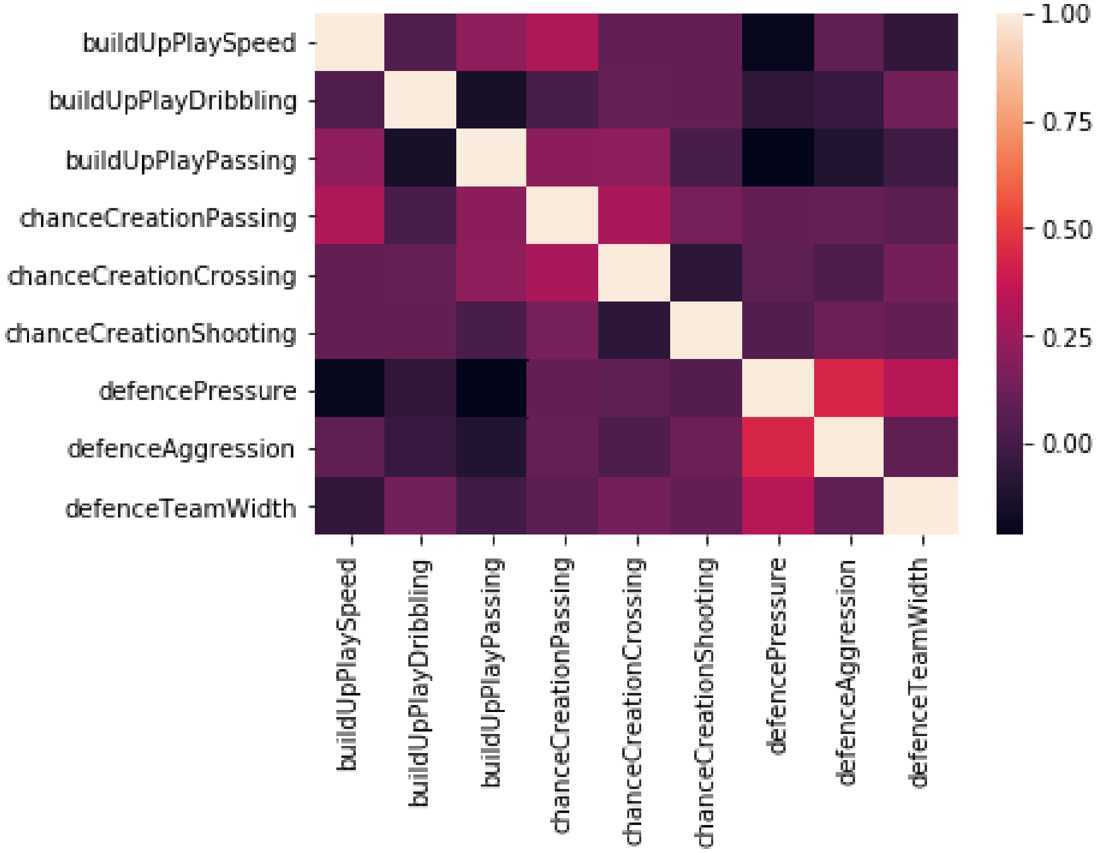



```
In [24]: query = pd.read_sql("""SELECT player_api_id
                                FROM player_attributes
                                WHERE (long_passing>85) and (short_passing<15)""",connection)
         query
```

```
Out[24]:    player_api_id
         0          24494
         1          27697
```

```
In [25]: import seaborn as sns
         query1 = pd.read_sql(""" SELECT * FROM Team_Attributes;""",connection)
         query1.drop_duplicates(subset=['team_api_id',],keep="last",inplace=True)
         query1.dropna(inplace=True)

         query1.drop(['id','team_api_id','team_fifa_api_id'],axis=1,inplace=True)
         corr = query1.corr()
         ax = sns.heatmap(corr,
                     xticklabels=corr.columns.values,
                     yticklabels=corr.columns.values,)
         corr
```

Out[25]:
```
                          buildUpPlaySpeed  buildUpPlayDribbling  \
buildUpPlaySpeed                  1.000000              0.041926
buildUpPlayDribbling              0.041926              1.000000
buildUpPlayPassing                0.224527             -0.135027
chanceCreationPassing             0.308168              0.021167
chanceCreationCrossing            0.094170              0.101190
chanceCreationShooting            0.095448              0.099434
defencePressure                  -0.190411             -0.057030
defenceAggression                 0.089650             -0.036704
defenceTeamWidth                 -0.054177              0.144537

                          buildUpPlayPassing  chanceCreationPassing  \
buildUpPlaySpeed                    0.224527               0.308168
buildUpPlayDribbling               -0.135027               0.021167
buildUpPlayPassing                  1.000000               0.214923
chanceCreationPassing               0.214923               1.000000
chanceCreationCrossing              0.220470               0.297821
chanceCreationShooting              0.021519               0.153480
defencePressure                    -0.213262               0.097371
defenceAggression                  -0.102824               0.103659
defenceTeamWidth                   -0.005014               0.072126

                          chanceCreationCrossing  chanceCreationShooting  \
buildUpPlaySpeed                        0.094170                0.095448
buildUpPlayDribbling                    0.101190                0.099434
buildUpPlayPassing                      0.220470                0.021519
chanceCreationPassing                   0.297821                0.153480
chanceCreationCrossing                  1.000000               -0.067472
chanceCreationShooting                 -0.067472                1.000000
defencePressure                         0.082154                0.051954
defenceAggression                       0.037898                0.122866
defenceTeamWidth                        0.149792                0.095715

                          defencePressure  defenceAggression  defenceTeamWidth
buildUpPlaySpeed                -0.190411           0.089650         -0.054177
buildUpPlayDribbling            -0.057030          -0.036704          0.144537
buildUpPlayPassing              -0.213262          -0.102824         -0.005014
chanceCreationPassing            0.097371           0.103659          0.072126
chanceCreationCrossing           0.082154           0.037898          0.149792
chanceCreationShooting           0.051954           0.122866          0.095715
defencePressure                  1.000000           0.436227          0.334042
defenceAggression                0.436227           1.000000          0.086278
defenceTeamWidth                 0.334042           0.086278          1.000000
```

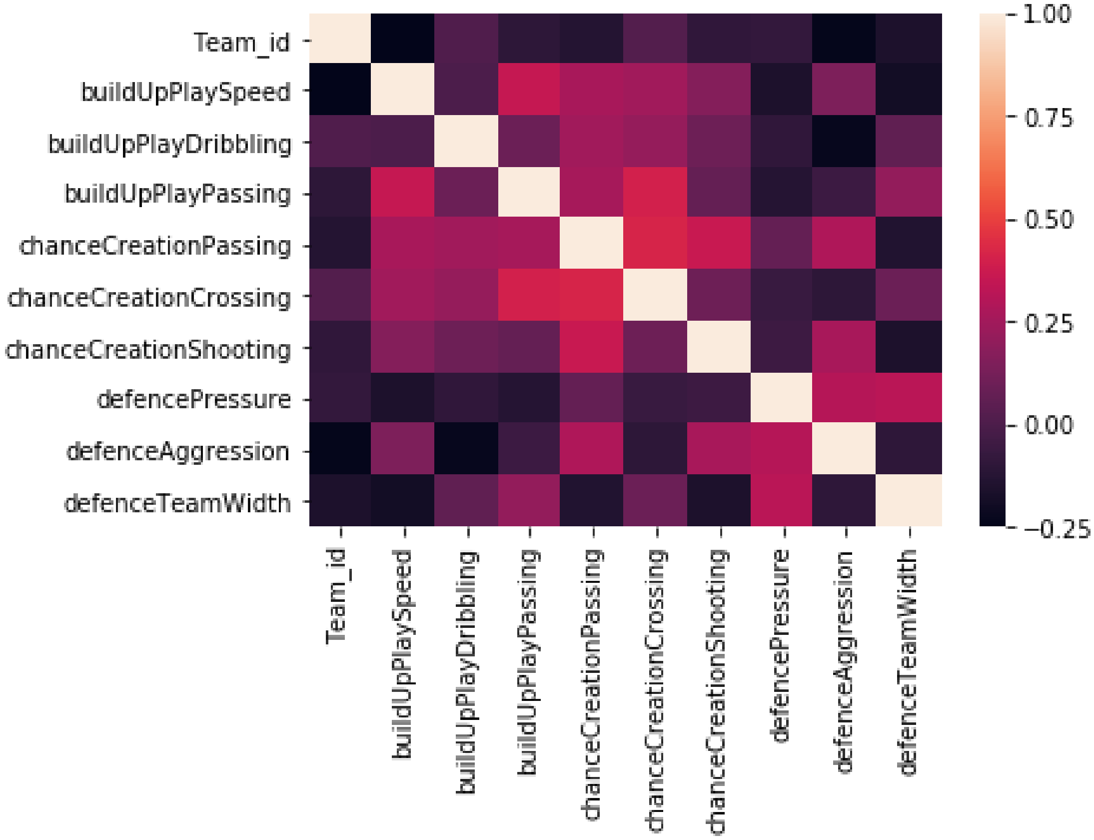



```
In [26]: query = pd.read_sql("""SELECT * FROM league_tables;""",connection)
         lar = (query.groupby(['name','season'],group_keys=False)).apply(lambda x: x.nlargest(5,
         sma=(query.groupby(['name','season'],group_keys=False)).apply(lambda x: x.nsmallest(5,'

         lar.to_sql("top_teams",connection,if_exists="replace")
         sma.to_sql("bottom_teams",connection,if_exists="replace")
```

```
In [27]: query = pd.read_sql("""SELECT tp.Team_id,ta.buildUpPlaySpeed, ta.buildUpPlayDribbling,t
                                     ta.chanceCreationCrossing, ta.chanceCreationShooting, ta.

                                 FROM top_teams tp
                                 JOIN Team_Attributes ta
                                 ON tp.Team_id = ta.team_api_id;""",connection)
         query.dropna(inplace=True)
         query.drop_duplicates(subset=['Team_id',],keep="last",inplace=True)
         corr = query.corr()
         ax = sns.heatmap(corr,
                     xticklabels=corr.columns.values,
                     yticklabels=corr.columns.values,)
         corr
```

Out[27]:

```
                        Team_id  buildUpPlaySpeed  buildUpPlayDribbling  \
Team_id                1.000000         -0.250212              0.009046
buildUpPlaySpeed      -0.250212          1.000000              0.000256
buildUpPlayDribbling   0.009046          0.000256              1.000000
buildUpPlayPassing    -0.103029          0.356335              0.095492
chanceCreationPassing -0.132435          0.271060              0.250461
chanceCreationCrossing 0.020501          0.248865              0.217277
chanceCreationShooting -0.093685         0.165148              0.100975
defencePressure       -0.082604         -0.154096             -0.089749
defenceAggression     -0.235655          0.149654             -0.229192
defenceTeamWidth      -0.156068         -0.186901              0.058084

                        buildUpPlayPassing  chanceCreationPassing  \
Team_id                          -0.103029              -0.132435
buildUpPlaySpeed                  0.356335               0.271060
buildUpPlayDribbling              0.095492               0.250461
buildUpPlayPassing                1.000000               0.266928
chanceCreationPassing             0.266928               1.000000
chanceCreationCrossing            0.402928               0.418667
chanceCreationShooting            0.074793               0.366746
defencePressure                  -0.124527               0.076841
defenceAggression                -0.052160               0.289263
defenceTeamWidth                  0.211757              -0.142000

                        chanceCreationCrossing  chanceCreationShooting  \
Team_id                               0.020501               -0.093685
buildUpPlaySpeed                      0.248865                0.165148
buildUpPlayDribbling                  0.217277                0.100975
buildUpPlayPassing                    0.402928                0.074793
chanceCreationPassing                 0.418667                0.366746
chanceCreationCrossing                1.000000                0.096994
chanceCreationShooting                0.096994                1.000000
defencePressure                      -0.062433               -0.046234
defenceAggression                    -0.102750                0.270918
defenceTeamWidth                      0.092390               -0.154875

                        defencePressure  defenceAggression  defenceTeamWidth
Team_id                       -0.082604          -0.235655         -0.156068
buildUpPlaySpeed              -0.154096           0.149654         -0.186901
buildUpPlayDribbling          -0.089749          -0.229192          0.058084
buildUpPlayPassing            -0.124527          -0.052160          0.211757
chanceCreationPassing          0.076841           0.289263         -0.142000
chanceCreationCrossing        -0.062433          -0.102750          0.092390
chanceCreationShooting        -0.046234           0.270918         -0.154875
defencePressure                1.000000           0.310743          0.322512
defenceAggression              0.310743           1.000000         -0.095188
defenceTeamWidth               0.322512          -0.095188          1.000000
```




```
In [28]: query = pd.read_sql("""SELECT tp.Team_id,ta.buildUpPlaySpeed, ta.buildUpPlayDribbling,t
                                    ta.chanceCreationCrossing, ta.chanceCreationShooting, ta.

                                FROM bottom_teams tp
                                JOIN Team_Attributes ta
                                ON tp.Team_id = ta.team_api_id;""",connection)
         query.dropna(inplace=True)
         query.drop_duplicates(subset=['Team_id',],keep="last",inplace=True)
         corr = query.corr()
         ax = sns.heatmap(corr,
                     xticklabels=corr.columns.values,
                     yticklabels=corr.columns.values,)
         corr
```

Out[28]:

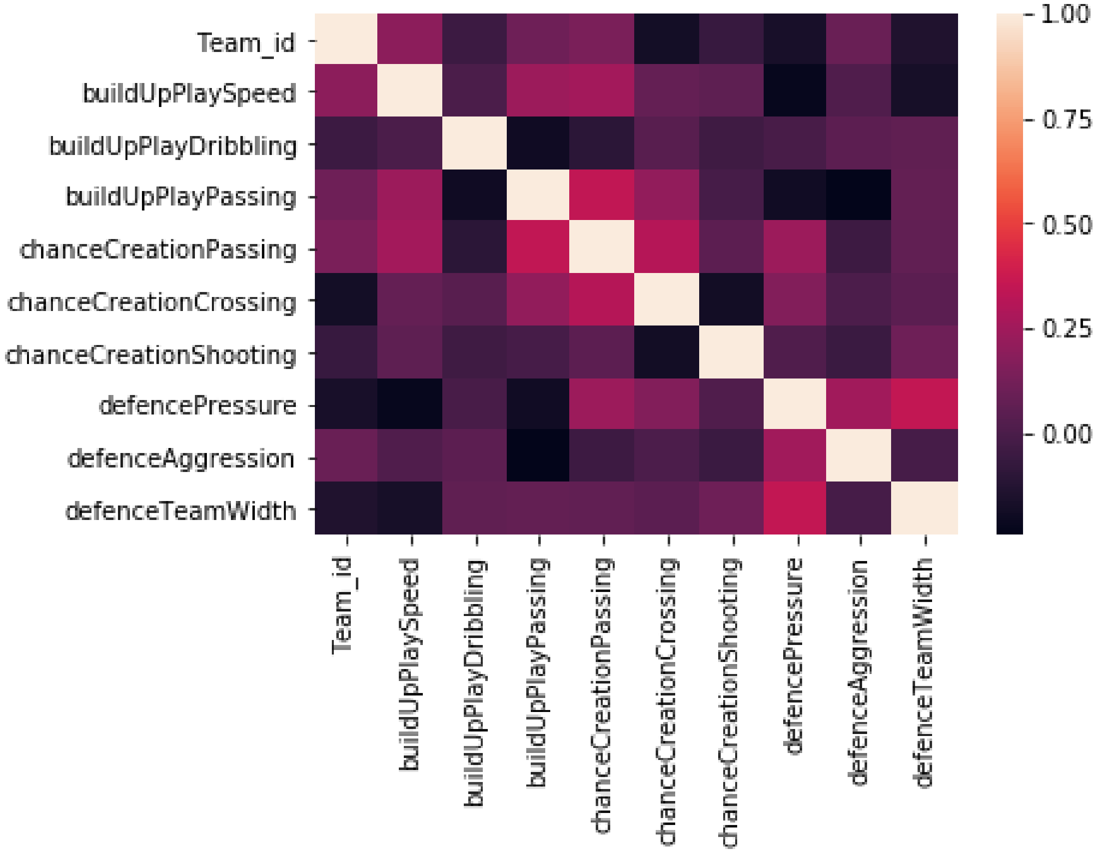
	Team_id	buildUpPlaySpeed	buildUpPlayDribbling \
Team_id	1.000000	0.198624	-0.047098
buildUpPlaySpeed	0.198624	1.000000	0.003092
buildUpPlayDribbling	-0.047098	0.003092	1.000000
buildUpPlayPassing	0.110351	0.241157	-0.189952
chanceCreationPassing	0.141142	0.258670	-0.100440

chanceCreationCrossing	-0.177328	0.079392	0.041266
chanceCreationShooting	-0.060931	0.060156	-0.036427
defencePressure	-0.163041	-0.218705	-0.007714
defenceAggression	0.094610	0.017667	0.054012
defenceTeamWidth	-0.137373	-0.169604	0.067166

	buildUpPlayPassing	chanceCreationPassing	\
Team_id	0.110351	0.141142	
buildUpPlaySpeed	0.241157	0.258670	
buildUpPlayDribbling	-0.189952	-0.100440	
buildUpPlayPassing	1.000000	0.348211	
chanceCreationPassing	0.348211	1.000000	
chanceCreationCrossing	0.213442	0.311002	
chanceCreationShooting	-0.014544	0.053611	
defencePressure	-0.187025	0.241265	
defenceAggression	-0.242950	-0.040432	
defenceTeamWidth	0.074978	0.070156	

	chanceCreationCrossing	chanceCreationShooting	\
Team_id	-0.177328	-0.060931	
buildUpPlaySpeed	0.079392	0.060156	
buildUpPlayDribbling	0.041266	-0.036427	
buildUpPlayPassing	0.213442	-0.014544	
chanceCreationPassing	0.311002	0.053611	
chanceCreationCrossing	1.000000	-0.179887	
chanceCreationShooting	-0.179887	1.000000	
defencePressure	0.167048	0.016190	
defenceAggression	0.006809	-0.049673	
defenceTeamWidth	0.048797	0.109003	

	defencePressure	defenceAggression	defenceTeamWidth
Team_id	-0.163041	0.094610	-0.137373
buildUpPlaySpeed	-0.218705	0.017667	-0.169604
buildUpPlayDribbling	-0.007714	0.054012	0.067166
buildUpPlayPassing	-0.187025	-0.242950	0.074978
chanceCreationPassing	0.241265	-0.040432	0.070156
chanceCreationCrossing	0.167048	0.006809	0.048797
chanceCreationShooting	0.016190	-0.049673	0.109003
defencePressure	1.000000	0.256296	0.349493
defenceAggression	0.256296	1.000000	-0.009973
defenceTeamWidth	0.349493	-0.009973	1.000000


Team_id
buildUpPlaySpeed
buildUpPlayDribbling
buildUpPlayPassing
chanceCreationPassing
chanceCreationCrossing
chanceCreationShooting
defencePressure
defenceAggression
defenceTeamWidth
1.00
0.75
0.50
0.25
0.00

```
In [ ]:
```