Project: Soccer Database

Table of Contents

Introduction

In [67]:

```
# Use this cell to set up import statements for all of the packages that you
#   plan to use.

# Remember to include a 'magic word' so that your visualizations are plotted
#   inline with the notebook. See this page for more:
#   http://ipython.readthedocs.io/en/stable/interactive/magics.html
import pandas as pd
import pandasql as ps
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [68]:

```
df_country = pd.read_csv('Country.csv')
df_league = pd.read_csv('League.csv')
df_match = pd.read_csv('Match.csv')
df_player_att = pd.read_csv('Player_Attributes.csv')
df_player = pd.read_csv('Player.csv')
df_team_att = pd.read_csv('Team_Attributes.csv')
df_team = pd.read_csv('Team.csv')
```

Data Wrangling

General Properties

In [69]:

```
# Load your data and print out a few lines. Perform operations to inspect data
# types and look for instances of missing or possibly errant data.
# Viewing fist 5 raws of tables:
df_country.head()
```

Out[69]:

	id	name
0	1	Belgium
1	1729	England
2	4769	France
3	7809	Germany
4	10257	Italy

In [70]:

```
df_player.head()
```

Out[70]:

	id	player_api_id	player_name	player_fifa_api_id	birthday	height	weight
0	1	505942	Aaron Appindangoye	218353	1992-02-29 00:00:00	182.88	187
1	2	155782	Aaron Cresswell	189615	1989-12-15 00:00:00	170.18	146
2	3	162549	Aaron Doran	186170	1991-05-13 00:00:00	170.18	163
3	4	30572	Aaron Galindo	140161	1982-05-08 00:00:00	182.88	198
4	5	23780	Aaron Hughes	17725	1979-11-08 00:00:00	182.88	154

In [71]:

```
df_league.head()
```

Out[71]:

	id	country_id	name
0	1	1	Belgium Jupiler League
1	1729	1729	England Premier League
2	4769	4769	France Ligue 1
3	7809	7809	Germany 1. Bundesliga
4	10257	10257	Italy Serie A

In [72]:

```
df_match.head()
```

Out[72]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	awa
0	1	1	1	2008/2009	1	2008-08-17 00:00:00	492473	9987	
1	2	1	1	2008/2009	1	2008-08-16 00:00:00	492474	10000	
2	3	1	1	2008/2009	1	2008-08-16 00:00:00	492475	9984	
3	4	1	1	2008/2009	1	2008-08-17 00:00:00	492476	9991	
4	5	1	1	2008/2009	1	2008-08-16 00:00:00	492477	7947	

5 rows × 115 columns

In [73]:

```
df_player_att.head()
```

Out[73]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	preferred_foot	attackin
0	1	218353	505942	2016-02-18 00:00:00	67.0	71.0	right	
1	2	218353	505942	2015-11-19 00:00:00	67.0	71.0	right	
2	3	218353	505942	2015-09-21 00:00:00	62.0	66.0	right	
3	4	218353	505942	2015-03-20 00:00:00	61.0	65.0	right	
4	5	218353	505942	2007-02-22 00:00:00	61.0	65.0	right	

5 rows × 42 columns

In [74]:

```
df_team_att.head()
```

Out[74]:

	id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass	buildUp
0	1	434	9930	2010-02-22 00:00:00	60	Balanced	
1	2	434	9930	2014-09-19 00:00:00	52	Balanced	
2	3	434	9930	2015-09-10 00:00:00	47	Balanced	
3	4	77	8485	2010-02-22 00:00:00	70	Fast	
4	5	77	8485	2011-02-22 00:00:00	47	Balanced	

5 rows × 25 columns

In [75]:

```
df_team.head()
```

Out[75]:

	id	team_api_id	team_fifa_api_id	team_long_name	team_short_name
0	1	9987	673.0	KRC Genk	GEN
1	2	9993	675.0	Beerschot AC	BAC
2	3	10000	15005.0	SV Zulte-Waregem	ZUL
3	4	9994	2007.0	Sporting Lokeren	LOK
4	5	9984	1750.0	KSV Cercle Brugge	CEB

In [76]:

```
#getting some information about tables:
df_country.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   id      11 non-null     int64 
 1   name    11 non-null     object
dtypes: int64(1), object(1)
memory usage: 304.0+ bytes
```

In [77]:

```
df_league.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11 entries, 0 to 10
Data columns (total 3 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   id          11 non-null     int64 
 1   country_id  11 non-null     int64 
 2   name        11 non-null     object
dtypes: int64(2), object(1)
memory usage: 392.0+ bytes
```

In [78]:

```
df_player.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11060 entries, 0 to 11059
Data columns (total 7 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   id                  11060 non-null  int64  
 1   player_api_id       11060 non-null  int64  
 2   player_name         11060 non-null  object 
 3   player_fifa_api_id  11060 non-null  int64  
 4   birthday            11060 non-null  object 
 5   height              11060 non-null  float64
 6   weight              11060 non-null  int64  
dtypes: float64(1), int64(4), object(2)
memory usage: 605.0+ KB
```

In [79]:

```
df_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
```

In [80]:

```
df_player_att.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183978 entries, 0 to 183977
Data columns (total 42 columns):
 #   Column               Non-Null Count   Dtype  
---  ------               --------------   -----  
 0   id                   183978 non-null  int64  
 1   player_fifa_api_id   183978 non-null  int64  
 2   player_api_id        183978 non-null  int64  
 3   date                 183978 non-null  object 
 4   overall_rating       183142 non-null  float64
 5   potential            183142 non-null  float64
 6   preferred_foot       183142 non-null  object 
 7   attacking_work_rate  180748 non-null  object 
 8   defensive_work_rate  183142 non-null  object 
 9   crossing             183142 non-null  float64
 10  finishing            183142 non-null  float64
 11  heading_accuracy     183142 non-null  float64
 12  short_passing        183142 non-null  float64
 13  volleys              181265 non-null  float64
 14  dribbling            183142 non-null  float64
 15  curve                181265 non-null  float64
 16  free_kick_accuracy   183142 non-null  float64
 17  long_passing         183142 non-null  float64
 18  ball_control         183142 non-null  float64
 19  acceleration         183142 non-null  float64
 20  sprint_speed         183142 non-null  float64
 21  agility              181265 non-null  float64
 22  reactions            183142 non-null  float64
 23  balance              181265 non-null  float64
 24  shot_power           183142 non-null  float64
 25  jumping              181265 non-null  float64
 26  stamina              183142 non-null  float64
 27  strength             183142 non-null  float64
 28  long_shots           183142 non-null  float64
 29  aggression           183142 non-null  float64
 30  interceptions        183142 non-null  float64
 31  positioning          183142 non-null  float64
 32  vision               181265 non-null  float64
 33  penalties            183142 non-null  float64
 34  marking              183142 non-null  float64
 35  standing_tackle      183142 non-null  float64
 36  sliding_tackle       181265 non-null  float64
 37  gk_diving            183142 non-null  float64
 38  gk_handling          183142 non-null  float64
 39  gk_kicking           183142 non-null  float64
 40  gk_positioning       183142 non-null  float64
 41  gk_reflexes          183142 non-null  float64
dtypes: float64(35), int64(3), object(4)
memory usage: 59.0+ MB
```

In [81]:

```
df_team.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   id                299 non-null    int64  
 1   team_api_id       299 non-null    int64  
 2   team_fifa_api_id  288 non-null    float64
 3   team_long_name    299 non-null    object 
 4   team_short_name   299 non-null    object 
dtypes: float64(1), int64(2), object(2)
memory usage: 11.8+ KB
```

In [82]:

```
df_team_att.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458 entries, 0 to 1457
Data columns (total 25 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              1458 non-null   int64  
 1   team_fifa_api_id                1458 non-null   int64  
 2   team_api_id                     1458 non-null   int64  
 3   date                            1458 non-null   object 
 4   buildUpPlaySpeed                1458 non-null   int64  
 5   buildUpPlaySpeedClass           1458 non-null   object 
 6   buildUpPlayDribbling            489 non-null    float64
 7   buildUpPlayDribblingClass       1458 non-null   object 
 8   buildUpPlayPassing              1458 non-null   int64  
 9   buildUpPlayPassingClass         1458 non-null   object 
 10  buildUpPlayPositioningClass     1458 non-null   object 
 11  chanceCreationPassing           1458 non-null   int64  
 12  chanceCreationPassingClass      1458 non-null   object 
 13  chanceCreationCrossing          1458 non-null   int64  
 14  chanceCreationCrossingClass     1458 non-null   object 
 15  chanceCreationShooting          1458 non-null   int64  
 16  chanceCreationShootingClass     1458 non-null   object 
 17  chanceCreationPositioningClass  1458 non-null   object 
 18  defencePressure                 1458 non-null   int64  
 19  defencePressureClass            1458 non-null   object 
 20  defenceAggression               1458 non-null   int64  
 21  defenceAggressionClass          1458 non-null   object 
 22  defenceTeamWidth                1458 non-null   int64  
 23  defenceTeamWidthClass           1458 non-null   object 
 24  defenceDefenderLineClass        1458 non-null   object 
dtypes: float64(1), int64(11), object(13)
memory usage: 284.9+ KB
```

In [83]:

```
# Seems like match table is too big.
df_match.columns[df_match.isnull().any()]
```

Out[83]:

```
Index(['home_player_X1', 'home_player_X2', 'home_player_X3', 'home_pla
yer_X4',
       'home_player_X5', 'home_player_X6', 'home_player_X7', 'home_pla
yer_X8',
       'home_player_X9', 'home_player_X10',
       ...
       'SJA', 'VCH', 'VCD', 'VCA', 'GBH', 'GBD', 'GBA', 'BSH', 'BSD',
'BSA'],
      dtype='object', length=104)
```

In [84]:

```
df_team.columns[df_team.isnull().any()]
```

Out[84]:

```
Index(['team_fifa_api_id'], dtype='object')
```

In [85]:

```
df_player_att.columns[df_player_att.isnull().any()]
```

Out[85]:

```
Index(['overall_rating', 'potential', 'preferred_foot', 'attacking_wor
k_rate',
       'defensive_work_rate', 'crossing', 'finishing', 'heading_accura
cy',
       'short_passing', 'volleys', 'dribbling', 'curve', 'free_kick_ac
curacy',
       'long_passing', 'ball_control', 'acceleration', 'sprint_speed',
       'agility', 'reactions', 'balance', 'shot_power', 'jumping', 'st
amina',
       'strength', 'long_shots', 'aggression', 'interceptions', 'posit
ioning',
       'vision', 'penalties', 'marking', 'standing_tackle', 'sliding_t
ackle',
       'gk_diving', 'gk_handling', 'gk_kicking', 'gk_positioning',
       'gk_reflexes'],
      dtype='object')
```

In [86]:

```
df_team_att.columns[df_team_att.isnull().any()]
```

Out[86]:

```
Index(['buildUpPlayDribbling'], dtype='object')
```

There are four tables which have null values.

In [87]:

```
sum(df_match.duplicated())
```

Out[87]:

0

In [88]:

```
sum(df_country.duplicated())
```

Out[88]:

0

In [89]:

```
sum(df_league.duplicated())
```

Out[89]:

0

In [90]:

```
sum(df_player.duplicated())
```

Out[90]:

0

In [91]:

```
sum(df_player_att.duplicated())
```

Out[91]:

0

In [92]:

```
sum(df_team.duplicated())
```

Out[92]:

0

In [93]:

```
sum(df_team_att.duplicated())
```

Out[93]:

0

There is not any duplicate values.

In [94]:

```
df_player.birthday, df_match.date, df_player_att.date, df_team.team_fifa_api_id, df_
```

Out[94]:

```
(0        1992-02-29 00:00:00
 1        1989-12-15 00:00:00
 2        1991-05-13 00:00:00
 3        1982-05-08 00:00:00
 4        1979-11-08 00:00:00
                  ...
 11055    1979-04-03 00:00:00
 11056    1986-12-18 00:00:00
 11057    1979-04-29 00:00:00
 11058    1981-10-06 00:00:00
 11059    1982-06-05 00:00:00
 Name: birthday, Length: 11060, dtype: object,
 0        2008-08-17 00:00:00
 1        2008-08-16 00:00:00
 2        2008-08-16 00:00:00
 3        2008-08-17 00:00:00
 4        2008-08-16 00:00:00
                  ...
 25974    2015-09-22 00:00:00
 25975    2015-09-23 00:00:00
 25976    2015-09-23 00:00:00
 25977    2015-09-22 00:00:00
 25978    2015-09-23 00:00:00
 Name: date, Length: 25979, dtype: object,
 0         2016-02-18 00:00:00
 1         2015-11-19 00:00:00
 2         2015-09-21 00:00:00
 3         2015-03-20 00:00:00
 4         2007-02-22 00:00:00
                   ...
 183973    2009-08-30 00:00:00
 183974    2009-02-22 00:00:00
 183975    2008-08-30 00:00:00
 183976    2007-08-30 00:00:00
 183977    2007-02-22 00:00:00
 Name: date, Length: 183978, dtype: object,
 0        673.0
 1        675.0
 2      15005.0
 3       2007.0
 4       1750.0
          ...
 294      898.0
 295     1715.0
 296      324.0
 297     1862.0
 298        NaN
 Name: team_fifa_api_id, Length: 299, dtype: float64,
 0       2010-02-22 00:00:00
 1       2014-09-19 00:00:00
 2       2015-09-10 00:00:00
 3       2010-02-22 00:00:00
 4       2011-02-22 00:00:00
                 ...
 1453    2011-02-22 00:00:00
```

```
1454    2012-02-22 00:00:00
1455    2013-09-20 00:00:00
1456    2014-09-19 00:00:00
1457    2015-09-10 00:00:00
Name: date, Length: 1458, dtype: object)
```

These are wrong data types due to above info(). I will fix them.

Data Cleaning

In [95]:

```
#changing the dtype in matches
df_match['date'] = pd.to_datetime(df_match['date'])
df_match.shape
```

Out[95]:

```
(25979, 115)
```

In [96]:

```
#Create new dataframe only with necessary columns of match table:
df_match_score = df_match.iloc[:, :11]
df_match_score.head()
```

Out[96]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_te
0	1	1	1	2008/2009	1	2008-08-17	492473	9987	
1	2	1	1	2008/2009	1	2008-08-16	492474	10000	
2	3	1	1	2008/2009	1	2008-08-16	492475	9984	
3	4	1	1	2008/2009	1	2008-08-17	492476	9991	
4	5	1	1	2008/2009	1	2008-08-16	492477	7947	

In [97]:

```
#Filling, drop, dtype with player attributes table:
df_player_att['date'] = pd.to_datetime(df_player_att['date'])
```

In [98]:

```
df_player_att.drop(['preferred_foot', 'attacking_work_rate', 'defensive_work_rate'],
```

In [99]:

```
df_player_att.fillna(df_player_att.mean(), inplace = True)
```

In [100]:

```
df_player.birthday = pd.to_datetime(df_player.birthday)
df_player_att.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 183978 entries, 0 to 183977
Data columns (total 39 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   id                   183978 non-null  int64
 1   player_fifa_api_id   183978 non-null  int64
 2   player_api_id        183978 non-null  int64
 3   date                 183978 non-null  datetime64[ns]
 4   overall_rating       183978 non-null  float64
 5   potential            183978 non-null  float64
 6   crossing             183978 non-null  float64
 7   finishing            183978 non-null  float64
 8   heading_accuracy     183978 non-null  float64
 9   short_passing        183978 non-null  float64
 10  volleys              183978 non-null  float64
 11  dribbling            183978 non-null  float64
 12  curve                183978 non-null  float64
 13  free_kick_accuracy   183978 non-null  float64
 14  long_passing         183978 non-null  float64
 15  ball_control         183978 non-null  float64
 16  acceleration         183978 non-null  float64
 17  sprint_speed         183978 non-null  float64
 18  agility              183978 non-null  float64
 19  reactions            183978 non-null  float64
 20  balance              183978 non-null  float64
 21  shot_power           183978 non-null  float64
 22  jumping              183978 non-null  float64
 23  stamina              183978 non-null  float64
 24  strength             183978 non-null  float64
 25  long_shots           183978 non-null  float64
 26  aggression           183978 non-null  float64
 27  interceptions        183978 non-null  float64
 28  positioning          183978 non-null  float64
 29  vision               183978 non-null  float64
 30  penalties            183978 non-null  float64
 31  marking              183978 non-null  float64
 32  standing_tackle      183978 non-null  float64
 33  sliding_tackle       183978 non-null  float64
 34  gk_diving            183978 non-null  float64
 35  gk_handling          183978 non-null  float64
 36  gk_kicking           183978 non-null  float64
 37  gk_positioning       183978 non-null  float64
 38  gk_reflexes          183978 non-null  float64
dtypes: datetime64[ns](1), float64(35), int64(3)
memory usage: 54.7 MB
```

In [101]:

```
#Filling, drop, dtype with team attributes table
df_team.fillna(df_team.mean(), inplace = True)
```

In [102]:

```
df_team.team_fifa_api_id.astype(int)
df_team_att.date = pd.to_datetime(df_team_att.date)
df_team.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 299 entries, 0 to 298
Data columns (total 5 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   id                299 non-null    int64  
 1   team_api_id       299 non-null    int64  
 2   team_fifa_api_id  299 non-null    float64
 3   team_long_name    299 non-null    object 
 4   team_short_name   299 non-null    object 
dtypes: float64(1), int64(2), object(2)
memory usage: 11.8+ KB
```

In [103]:

```
df_team_att.fillna(df_team_att.mean(), inplace = True)
df_team_att.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1458 entries, 0 to 1457
Data columns (total 25 columns):
 #   Column                          Non-Null Count  Dtype         
---  ------                          --------------  -----         
 0   id                              1458 non-null   int64         
 1   team_fifa_api_id                1458 non-null   int64         
 2   team_api_id                     1458 non-null   int64         
 3   date                            1458 non-null   datetime64[ns]
 4   buildUpPlaySpeed                1458 non-null   int64         
 5   buildUpPlaySpeedClass           1458 non-null   object        
 6   buildUpPlayDribbling            1458 non-null   float64       
 7   buildUpPlayDribblingClass       1458 non-null   object        
 8   buildUpPlayPassing              1458 non-null   int64         
 9   buildUpPlayPassingClass         1458 non-null   object        
 10  buildUpPlayPositioningClass     1458 non-null   object        
 11  chanceCreationPassing           1458 non-null   int64         
 12  chanceCreationPassingClass      1458 non-null   object        
 13  chanceCreationCrossing          1458 non-null   int64         
 14  chanceCreationCrossingClass     1458 non-null   object        
 15  chanceCreationShooting          1458 non-null   int64         
 16  chanceCreationShootingClass     1458 non-null   object        
 17  chanceCreationPositioningClass  1458 non-null   object        
 18  defencePressure                 1458 non-null   int64         
 19  defencePressureClass            1458 non-null   object        
 20  defenceAggression               1458 non-null   int64         
 21  defenceAggressionClass          1458 non-null   object        
 22  defenceTeamWidth                1458 non-null   int64         
 23  defenceTeamWidthClass           1458 non-null   object        
 24  defenceDefenderLineClass        1458 non-null   object        
dtypes: datetime64[ns](1), float64(1), int64(11), object(12)
memory usage: 284.9+ KB
```

Exploratory Data Analysis

Exploratory Data Analysis

What teams improved the most over the time period?

In [104]:

```
# Creating new column winner which explains win or lost.
conditions = [(df_match_score['home_team_goal'] > df_match_score['away_team_goal']),
choices = [df_match_score['home_team_api_id'], df_match_score['away_team_api_id']]
df_match_score['winner'] = np.select(conditions, choices, default='draw')
df_match_score = df_match_score[df_match_score.winner != 'draw']
df_match_score.head()
```

Out[104]:

	id	country_id	league_id	season	stage	date	match_api_id	home_team_api_id	away_tea
2	3	1	1	2008/2009	1	2008-08-16	492475	9984	
3	4	1	1	2008/2009	1	2008-08-17	492476	9991	
4	5	1	1	2008/2009	1	2008-08-16	492477	7947	
7	8	1	1	2008/2009	1	2008-08-16	492480	4049	
8	9	1	1	2008/2009	1	2008-08-16	492481	10001	

In [105]:

```
#change the string to int
df_match_score['winner'] = df_match_score['winner'].astype(int)
df_match_score.winner
```

Out[105]:

```
2         8635
3         9991
4         9985
7         9996
8        10001
         ...
25973    10179
25974    10190
25975    10199
25976     9956
25978    10192
Name: winner, Length: 19383, dtype: int64
```

In [106]:

```
df_match_score['league_id'].value_counts()
```

Out[106]:

```
21518    2336
1729     2257
10257    2221
4769     2181
13274    1867
7809     1851
17642    1519
15722    1395
19694    1377
1        1303
24558    1076
Name: league_id, dtype: int64
```

In [107]:

```
#We do not these columns:
df_match_score.drop(['home_team_api_id', 'away_team_api_id', 'stage', 'match_api_id'
```

In [108]:

```
#Merging two tables on country_id column in order to know the name of league
result = pd.merge(df_match_score, df_league[['country_id', 'name']], on = 'country_i
```

In [109]:

```
#I am using pandasql in order to get three best leagues since SQL is kinda comfortab
def sql_name(country_id):
    return ps.sqldf('SELECT name FROM result WHERE country_id = ' + country_id)
sql_name('21518')
```

Out[109]:

	name
0	Spain LIGA BBVA
1	Spain LIGA BBVA
2	Spain LIGA BBVA
3	Spain LIGA BBVA
4	Spain LIGA BBVA
...	...
2331	Spain LIGA BBVA
2332	Spain LIGA BBVA
2333	Spain LIGA BBVA
2334	Spain LIGA BBVA
2335	Spain LIGA BBVA

2336 rows × 1 columns

In [110]:

```
sql_name('1729')
```

Out[110]:

	name
0	England Premier League
1	England Premier League
2	England Premier League
3	England Premier League
4	England Premier League
...	...
2252	England Premier League
2253	England Premier League
2254	England Premier League
2255	England Premier League
2256	England Premier League

2257 rows × 1 columns

In [111]:

```
sql_name('10257')
```

Out[111]:

	name
0	Italy Serie A
1	Italy Serie A
2	Italy Serie A
3	Italy Serie A
4	Italy Serie A
...	...
2216	Italy Serie A
2217	Italy Serie A
2218	Italy Serie A
2219	Italy Serie A
2220	Italy Serie A

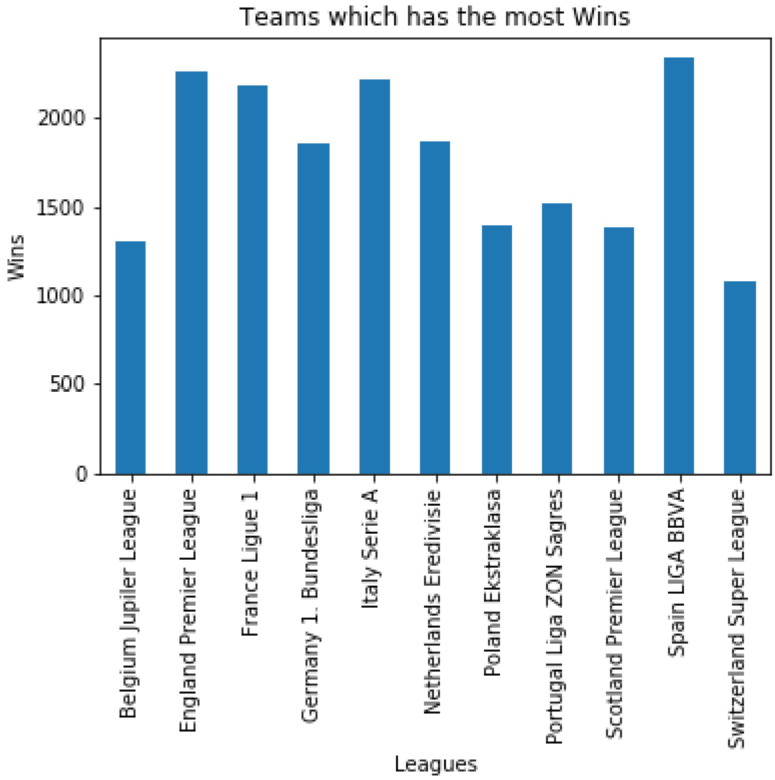
2221 rows × 1 columns

In [112]:

```
result.groupby('name')['winner'].count().plot(kind='bar', title='Teams which has the
plt.xlabel('Leagues')
plt.ylabel('Wins')
```

Out[112]:

```
Text(0, 0.5, 'Wins')
```



As you can see, Spain Liga BBVA's teams improved the most. Second place is for England Premier League's teams. Third place is for Italy Serie A's teams.

Which players had the most penalties?

In [113]:

```
#Merge df_player_att table and df_player:
result1 = pd.merge(df_player_att, df_player[['player_api_id', 'player_name']], on =
result1
```

Out[113]:

	id	player_fifa_api_id	player_api_id	date	overall_rating	potential	crossing	finish
0	1	218353	505942	2016-02-18	67.0	71.0	49.0	4
1	2	218353	505942	2015-11-19	67.0	71.0	49.0	4
2	3	218353	505942	2015-09-21	62.0	66.0	49.0	4
3	4	218353	505942	2015-03-20	61.0	65.0	48.0	4
4	5	218353	505942	2007-02-22	61.0	65.0	48.0	4
...	...	...	...	...	...	...	...	
183973	183974	102359	39902	2009-08-30	83.0	85.0	84.0	7
183974	183975	102359	39902	2009-02-22	78.0	80.0	74.0	7
183975	183976	102359	39902	2008-08-30	77.0	80.0	74.0	7
183976	183977	102359	39902	2007-08-30	78.0	81.0	74.0	6
183977	183978	102359	39902	2007-02-22	80.0	81.0	74.0	6

183978 rows × 40 columns

In [114]:

```
ps.sqldf('SELECT DISTINCT player_name, penalties FROM result1 ORDER BY penalties DES
```

Out[114]:

	player_name	penalties
0	Rickie Lambert	96.0
1	Andrea Pirlo	95.0
2	Mario Balotelli	95.0
3	Paul Scholes	95.0
4	Rickie Lambert	95.0
...	...	...
38167	Stefan Deloose	5.0
38168	Vincent Plante	5.0
38169	Vlada Avramov	5.0
38170	Jed Steer	3.0
38171	Kristoffer Nordfeldt	2.0

38172 rows × 2 columns

As you can see, Rickie Lambert had the most penalties with 96, Andrea Pirlo = 95, Mario Balotelli = 95 and so on.

What team attributes lead to the most victories?

In [115]:

```
#Looking for spain teams since they are the most powerful
def sql_all(team_api_id):
    return ps.sqldf('SELECT * FROM df_team_att WHERE  team_api_id = ' + team_api_id)
sql_all('8634')
```

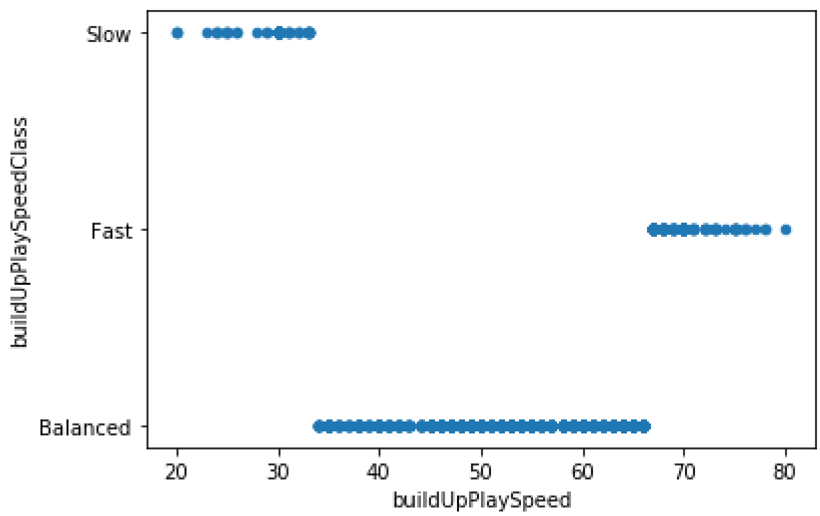
Out[115]:

	id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass
0	119	241	8634	2010-02-22 00:00:00.000000	42	Balanced
1	120	241	8634	2011-02-22 00:00:00.000000	43	Balanced
2	121	241	8634	2012-02-22 00:00:00.000000	24	Slow
3	122	241	8634	2013-09-20 00:00:00.000000	35	Balanced
4	123	241	8634	2014-09-19 00:00:00.000000	35	Balanced
5	124	241	8634	2015-09-10 00:00:00.000000	36	Balanced

6 rows × 25 columns

In [116]:

```
df_team_att.plot(x='buildUpPlaySpeed', y='buildUpPlaySpeedClass', kind='scatter');
```



This scatter plot clearly highlights that fast speed is important. However as you can see, balanced speed is also fine in order to win in match.

In [117]:

```
#Looking for england teams since they are powerful also:
sql_all('10260')
```

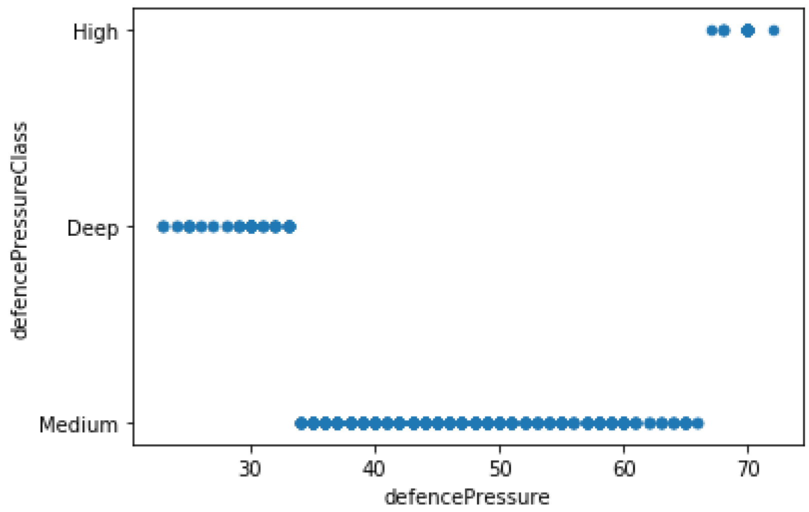
Out[117]:

	id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass
0	807	11	10260	2010-02-22 00:00:00.000000	70	Fast
1	808	11	10260	2011-02-22 00:00:00.000000	65	Balanced
2	809	11	10260	2012-02-22 00:00:00.000000	46	Balanced
3	810	11	10260	2013-09-20 00:00:00.000000	46	Balanced
4	811	11	10260	2014-09-19 00:00:00.000000	46	Balanced
5	812	11	10260	2015-09-10 00:00:00.000000	38	Balanced

6 rows × 25 columns

In [118]:

```
df_team_att.plot(x='defencePressure', y='defencePressureClass', kind='scatter');
```



Looks like defence pressure should be medium as there are lots mentions in medium.

In [119]:

```
#Looking for italy teams since they are powerful too:
sql_all('9885')
```

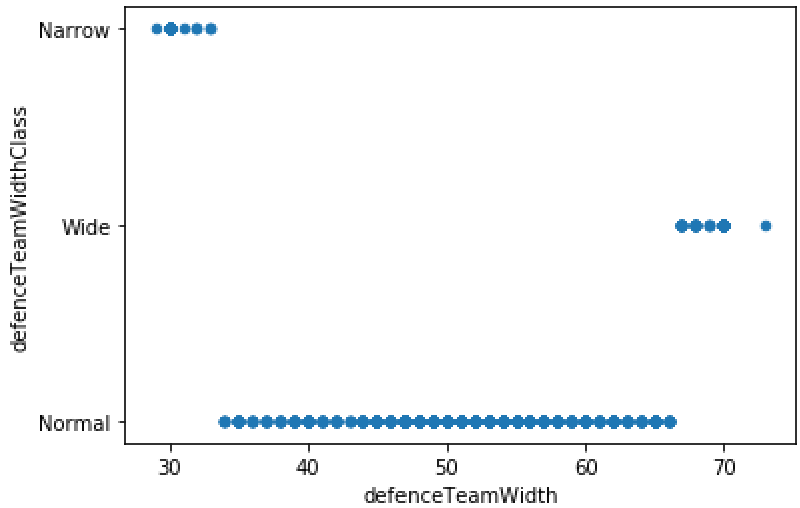
Out[119]:

	id	team_fifa_api_id	team_api_id	date	buildUpPlaySpeed	buildUpPlaySpeedClass
0	625	45	9885	2010-02-22 00:00:00.000000	45	Balanced
1	626	45	9885	2011-02-22 00:00:00.000000	65	Balanced
2	627	45	9885	2012-02-22 00:00:00.000000	50	Balanced
3	628	45	9885	2013-09-20 00:00:00.000000	39	Balanced
4	629	45	9885	2014-09-19 00:00:00.000000	26	Slow
5	630	45	9885	2015-09-10 00:00:00.000000	50	Balanced

6 rows × 25 columns

In [120]:

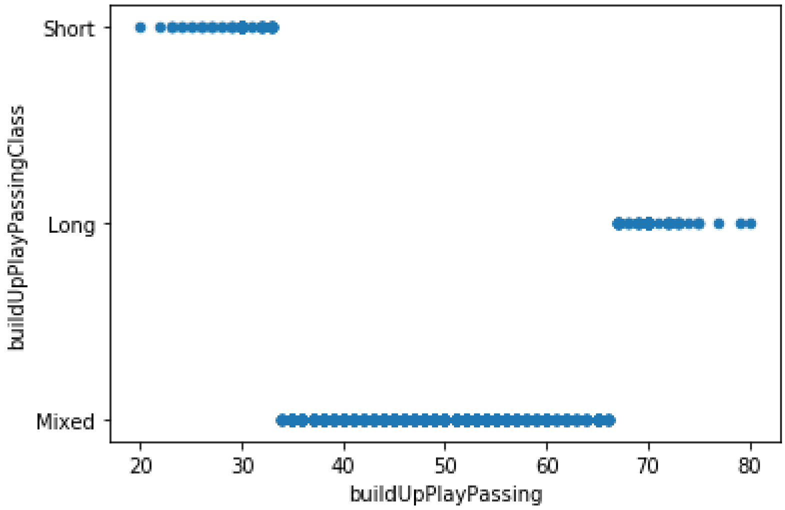
```
df_team_att.plot(x='defenceTeamWidth', y='defenceTeamWidthClass', kind='scatter');
```



Ok, it seems like normal team width is good for a team.

In [121]:

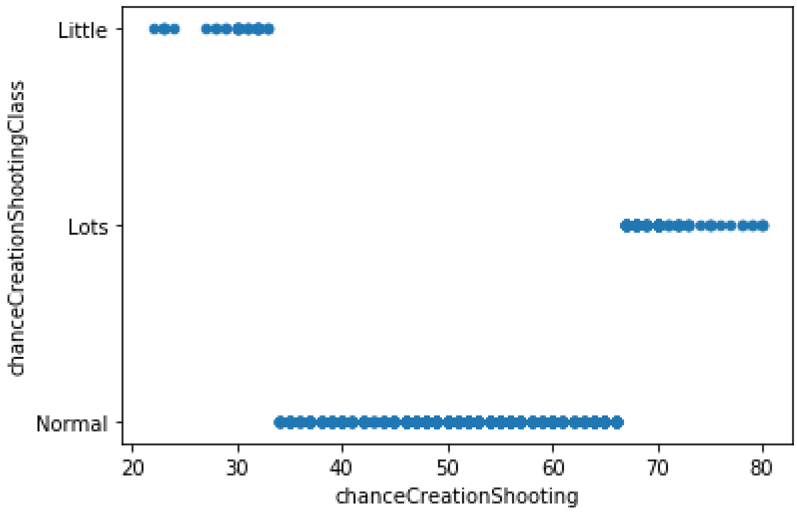
```
df_team_att.plot(x='buildUpPlayPassing', y='buildUpPlayPassingClass', kind='scatter'
```



Mixed passes are a good ones.

In [122]:

```
df_team_att.plot(x='chanceCreationShooting', y='chanceCreationShootingClass', kind='
```



Chances creation of shoots in a match should be normal but for better score it has to be a lot.

It seems to me that speed, passes are two of the attributes that proves the victory. Chances creation of shoots in a match are also one of the crucial ones.

Limitations and Challenges

I have viewed all the tables of this databse and realized that data is not clear. In fact, there are lots null values and one table has lots of columns which are very hard too read.

I have seen some players' names are not complete which mean they do not have any surnames or firstnames.

Meanwhile teams' names are also the same problem. That is why, I have used ids but not the names and this had challenged me a lot.

Conclusions

The best teams in Europe during 2008-2016 are Spain teams, England teams and Italy teams. The most powelful teams have won many games as my above codes said.

The most penalties are related to player Rickie Lambert with 96, Andrea Pirlo = 95, Mario Balotelli = 95 and so on. You can see the rest above.

Every successful team has fast speed and a lot of passes. Apart form this, Chances creation of shoots in a match are also important ones.

Refence:

https://www.w3schools.com/sql/sql_distinct.asp (https://www.w3schools.com/sql/sql_distinct.asp) https://www.shanelynn.ie/merge-join-dataframes-python-pandas-index-1/ (https://www.shanelynn.ie/merge-join-dataframes-python-pandas-index-1/) https://stackoverflow.com/questions/45865608/executing-an-sql-query-over-a-pandas-dataset (https://stackoverflow.com/questions/45865608/executing-an-sql-query-over-a-pandas-dataset) https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.value_counts.html) https://stackoverflow.com/questions/15891038/change-data-type-of-columns-in-pandas (https://stackoverflow.com/questions/15891038/change-data-type-of-columns-in-pandas) https://pandas.pydata.org/pandas-docs/stable/user_guide/merging.html (https://pandas.pydata.org/pandas-docs/stable/user_guide/merging.html) https://medium.com/jbennetcodes/how-to-rewrite-your-sql-queries-in-pandas-and-more-149d341fc53e (https://medium.com/jbennetcodes/how-to-rewrite-your-sql-queries-in-pandas-and-more-149d341fc53e) https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.astype.html (https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.astype.html) https://stackoverflow.com/questions/18689823/pandas-dataframe-replace-nan-values-with-average-of-columns (https://stackoverflow.com/questions/18689823/pandas-dataframe-replace-nan-values-with-average-of-columns) https://nces.ed.gov/nceskids/help/user_guide/graph/variables.asp (https://nces.ed.gov/nceskids/help/user_guide/graph/variables.asp)