Project: Investigate a soccer database by Michael Reda Adly Wassef

Table of Contents

Introduction

This soccer database comes from Kaggle. It contains data for soccer matches, players, and teams from several European countries from 2008 to 2016.

Questions to find answers for are:

- What teams improved the most over the time period?
- Which players had the most penalties?
- What team attributes lead to the most victories?
- What are the top teams that win at home?
- What are the top teams that win away ?
- Top scoring teams
- Which foot is more prefered by soccer players?
- Does playing at home contributes in winning?
- What teams improved the most over the time period?

In [1]:
```
import pandas as pd
% matplotlib inline

import numpy as np
```

Data Wrangling

General Properties

Merging the leagues dataframe with the countries using left joining on country_id

In [2]:
```
df_teams = pd.read_csv('data/Team.csv')
df_teams.head()
```

Out[2]:

	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 [3]:
```
df_teams_attr = pd.read_csv('data/Team_Attributes.csv')
df_teams_attr.head()
```

Out[3]:

	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

Merging the teams dataframe with the teams attributes using left joining on team_api_id

In [4]:
```
df_teams = pd.merge(left=df_teams, right=df_teams_attr, on='team_api_id', how=
'left',suffixes=('','_attr'))
df_teams.head()
```

Out[4]:

	id	team_api_id	team_fifa_api_id	team_long_name	team_short_name	id_attr	team_fifa_api_id
0	1	9987	673.0	KRC Genk	GEN	485.0	
1	1	9987	673.0	KRC Genk	GEN	486.0	
2	1	9987	673.0	KRC Genk	GEN	487.0	
3	1	9987	673.0	KRC Genk	GEN	488.0	
4	1	9987	673.0	KRC Genk	GEN	489.0	

5 rows × 29 columns

In [5]:
```
# removing duplicate columns which have "_attr" suffix
df_teams.drop(columns= ["id_attr","team_fifa_api_id_attr"], inplace=True)
df_teams.columns
```

Out[5]:
```
Index(['id', 'team_api_id', 'team_fifa_api_id', 'team_long_name',
       'team_short_name', 'date', 'buildUpPlaySpeed', 'buildUpPlaySpeedClas
s',
       'buildUpPlayDribbling', 'buildUpPlayDribblingClass',
       'buildUpPlayPassing', 'buildUpPlayPassingClass',
       'buildUpPlayPositioningClass', 'chanceCreationPassing',
       'chanceCreationPassingClass', 'chanceCreationCrossing',
       'chanceCreationCrossingClass', 'chanceCreationShooting',
       'chanceCreationShootingClass', 'chanceCreationPositioningClass',
       'defencePressure', 'defencePressureClass', 'defenceAggression',
       'defenceAggressionClass', 'defenceTeamWidth', 'defenceTeamWidthClass',
       'defenceDefenderLineClass'],
      dtype='object')
```

Checking for missing values

In [6]:
```
df_teams.isnull().sum()
```

Out[6]:
```
id                                0
team_api_id                       0
team_fifa_api_id                 11
team_long_name                    0
team_short_name                   0
date                             11
buildUpPlaySpeed                 11
buildUpPlaySpeedClass            11
buildUpPlayDribbling            980
buildUpPlayDribblingClass        11
buildUpPlayPassing               11
buildUpPlayPassingClass          11
buildUpPlayPositioningClass      11
chanceCreationPassing            11
chanceCreationPassingClass       11
chanceCreationCrossing           11
chanceCreationCrossingClass      11
chanceCreationShooting           11
chanceCreationShootingClass      11
chanceCreationPositioningClass   11
defencePressure                  11
defencePressureClass             11
defenceAggression                11
defenceAggressionClass           11
defenceTeamWidth                 11
defenceTeamWidthClass            11
defenceDefenderLineClass         11
dtype: int64
```

as you can see above, some columns have missing value. First, we will drop the rows in which the attribute are NaN. Then,we will replace the missing values in buildUpPlayDribbling column with the column's mean.

In [7]:
```
df_teams.dropna(axis='rows',subset=["team_fifa_api_id"], inplace=True)
df_teams.isnull().sum()
```

Out[7]:
```
id                                0
team_api_id                       0
team_fifa_api_id                  0
team_long_name                    0
team_short_name                   0
date                              0
buildUpPlaySpeed                  0
buildUpPlaySpeedClass             0
buildUpPlayDribbling            969
buildUpPlayDribblingClass         0
buildUpPlayPassing                0
buildUpPlayPassingClass           0
buildUpPlayPositioningClass       0
chanceCreationPassing             0
chanceCreationPassingClass        0
chanceCreationCrossing            0
chanceCreationCrossingClass       0
chanceCreationShooting            0
chanceCreationShootingClass       0
chanceCreationPositioningClass    0
defencePressure                   0
defencePressureClass              0
defenceAggression                 0
defenceAggressionClass            0
defenceTeamWidth                  0
defenceTeamWidthClass             0
defenceDefenderLineClass          0
dtype: int64
```

In [8]:
```
df_teams['buildUpPlayDribbling'].fillna(df_teams['buildUpPlayDribbling'].mean
(), inplace=True)
df_teams.isnull().any().any()
```

Out[8]:
```
False
```

In [9]:
```
df_players = pd.read_csv('data/Player.csv', parse_dates=True)
df_players.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 [10]:
```
df_players_attr = pd.read_csv('data/Player_Attributes.csv')
df_players_attr.head()
```

Out[10]:

	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

Merging the players dataframe with the players attributes using left joining on player_api_id

In [11]:
```
df_players = pd.merge(left=df_players, right=df_players_attr, on='player_api_id', how='left',suffixes=('','_attr'))
df_players.head()
```

Out[11]:

	id	player_api_id	player_name	player_fifa_api_id	birthday	height	weight	id_attr	player_fifa
0	1	505942	Aaron Appindangoye	218353	1992-02-29 00:00:00	182.88	187	1	
1	1	505942	Aaron Appindangoye	218353	1992-02-29 00:00:00	182.88	187	2	
2	1	505942	Aaron Appindangoye	218353	1992-02-29 00:00:00	182.88	187	3	
3	1	505942	Aaron Appindangoye	218353	1992-02-29 00:00:00	182.88	187	4	
4	1	505942	Aaron Appindangoye	218353	1992-02-29 00:00:00	182.88	187	5	

5 rows × 48 columns

In [12]:
```
# removing duplicate columns which have "_attr" suffix
df_players.drop(columns= ["id_attr","player_fifa_api_id_attr"], inplace=True)
df_players.columns
```

Out[12]:
```
Index(['id', 'player_api_id', 'player_name', 'player_fifa_api_id', 'birthda
y',
       'height', 'weight', 'date', 'overall_rating', 'potential',
       'preferred_foot', 'attacking_work_rate', 'defensive_work_rate',
       'crossing', 'finishing', 'heading_accuracy', 'short_passing', 'volley
s',
       'dribbling', 'curve', 'free_kick_accuracy', 'long_passing',
       'ball_control', 'acceleration', 'sprint_speed', 'agility', 'reaction
s',
       'balance', 'shot_power', 'jumping', 'stamina', 'strength', 'long_shot
s',
       'aggression', 'interceptions', 'positioning', 'vision', 'penalties',
       'marking', 'standing_tackle', 'sliding_tackle', 'gk_diving',
       'gk_handling', 'gk_kicking', 'gk_positioning', 'gk_reflexes'],
      dtype='object')
```

Checking for missing values

In [13]:
```
df_players.isna().sum()
```

Out[13]:
```
id                        0
player_api_id             0
player_name               0
player_fifa_api_id        0
birthday                  0
height                    0
weight                    0
date                      0
overall_rating          836
potential               836
preferred_foot          836
attacking_work_rate    3230
defensive_work_rate     836
crossing                836
finishing               836
heading_accuracy        836
short_passing           836
volleys                2713
dribbling               836
curve                  2713
free_kick_accuracy      836
long_passing            836
ball_control            836
acceleration            836
sprint_speed            836
agility                2713
reactions               836
balance                2713
shot_power              836
jumping                2713
stamina                 836
strength                836
long_shots              836
aggression              836
interceptions           836
positioning             836
vision                 2713
penalties               836
marking                 836
standing_tackle         836
sliding_tackle         2713
gk_diving               836
gk_handling             836
gk_kicking              836
gk_positioning          836
gk_reflexes             836
dtype: int64
```

as you can see above, some columns have missing value. We will replace the missing values with the column's mean.

In [14]:
```
df_players['attacking_work_rate'].fillna('medium',inplace=True) # assinging "m
edium" to attacking_work_rate missing values
df_players['defensive_work_rate'].fillna('medium',inplace=True) # assinging "m
edium" to defensive_work_rate missing values
df_players['preferred_foot'].fillna('unknown',inplace=True) # assinging "unkno
wn" to preferred_foot missing values
df_players.apply(lambda x: x.fillna(x.mean(), inplace=True) if x.isna().any().
any() else x)
df_players.isna().sum()
```

Out[14]:
```
id                     0
player_api_id          0
player_name            0
player_fifa_api_id     0
birthday               0
height                 0
weight                 0
date                   0
overall_rating         0
potential              0
preferred_foot         0
attacking_work_rate    0
defensive_work_rate    0
crossing               0
finishing              0
heading_accuracy       0
short_passing          0
volleys                0
dribbling              0
curve                  0
free_kick_accuracy     0
long_passing           0
ball_control           0
acceleration           0
sprint_speed           0
agility                0
reactions              0
balance                0
shot_power             0
jumping                0
stamina                0
strength               0
long_shots             0
aggression             0
interceptions          0
positioning            0
vision                 0
penalties              0
marking                0
standing_tackle        0
sliding_tackle         0
gk_diving              0
gk_handling            0
gk_kicking             0
gk_positioning         0
gk_reflexes            0
dtype: int64
```

In [15]:
```
df_matches = pd.read_csv("data/Match.csv", parse_dates=True)
df_matches.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 [16]:
```
df_matches.columns
```

Out[16]:
```
Index(['id', 'country_id', 'league_id', 'season', 'stage', 'date',
       'match_api_id', 'home_team_api_id', 'away_team_api_id',
       'home_team_goal',
       ...
       'SJA', 'VCH', 'VCD', 'VCA', 'GBH', 'GBD', 'GBA', 'BSH', 'BSD', 'BSA'],
      dtype='object', length=115)
```

In [17]:
```
#removing unneeded columns
df_matches.drop(df_matches.loc[:, 'home_player_X1':], axis = 1, inplace = True
,)
df_matches.columns
```

Out[17]:
```
Index(['id', 'country_id', 'league_id', 'season', 'stage', 'date',
       'match_api_id', 'home_team_api_id', 'away_team_api_id',
       'home_team_goal', 'away_team_goal'],
      dtype='object')
```

Checking for missing values

In [18]:
```
df_matches.isnull().sum()
```

Out[18]:
```
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
dtype: int64
```

as seen above, no missing data in matches dataframe

Data Cleaning (Replace this with more specific notes!)

checking for duplicates in dataframes

In [19]:
```
print(f"teams table has duplicates? {df_teams.duplicated().any()}")
print(f"players table has duplicates? {df_players.duplicated().any()}")
print(f"matches table has duplicates? {df_matches.duplicated().any()}")
```

```
teams table has duplicates? True
players table has duplicates? True
matches table has duplicates? False
```

removing duplicates in teams and players dataframes

In [20]:
```
df_teams.drop_duplicates(inplace=True)
df_players.drop_duplicates(inplace=True)
print(f"teams table has duplicates? {df_teams.duplicated().any()}")
print(f"players table has duplicates? {df_players.duplicated().any()}")
```

```
teams table has duplicates? False
players table has duplicates? False
```

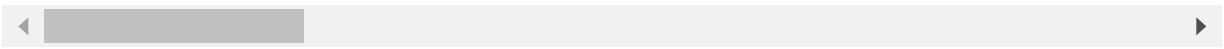
removing unnecessary redundant rows

In [21]:
```
df_teams.query('team_long_name=="FC Barcelona"')
```

Out[21]:

	id	team_api_id	team_fifa_api_id	team_long_name	team_short_name	date	buildU
1261	43042	8634	241.0	FC Barcelona	BAR	2010-02-22 00:00:00	
1262	43042	8634	241.0	FC Barcelona	BAR	2011-02-22 00:00:00	
1263	43042	8634	241.0	FC Barcelona	BAR	2012-02-22 00:00:00	
1264	43042	8634	241.0	FC Barcelona	BAR	2013-09-20 00:00:00	
1265	43042	8634	241.0	FC Barcelona	BAR	2014-09-19 00:00:00	
1266	43042	8634	241.0	FC Barcelona	BAR	2015-09-10 00:00:00	

6 rows × 27 columns



as you can see above, a single team has more than one entry. A team has one entry for each year, which is redundant to our research questions. Therefore, lets clean the data.

In [22]:
```
# saving a copy with dates for the 8th research question
df_teams_with_dates = df_teams.copy()
df_teams.drop_duplicates(subset='team_api_id', inplace=True)
df_teams.query('team_long_name=="FC Barcelona"')
```

Out[22]:

	id	team_api_id	team_fifa_api_id	team_long_name	team_short_name	date	buildU
1261	43042	8634	241.0	FC Barcelona	BAR	2010-02-22 00:00:00	

1 rows × 27 columns

doing the same for the players (removing unnecessary redundant rows)

In [23]:
```
df_players.query("player_name=='David Villa'").head()
```

Out[23]:

	id	player_api_id	player_name	player_fifa_api_id	birthday	height	weight	date	o
40699	2430	30909	David Villa	113422	1981-12-03 00:00:00	175.26	152	2016-05-19 00:00:00	
40700	2430	30909	David Villa	113422	1981-12-03 00:00:00	175.26	152	2016-01-21 00:00:00	
40701	2430	30909	David Villa	113422	1981-12-03 00:00:00	175.26	152	2015-10-02 00:00:00	
40702	2430	30909	David Villa	113422	1981-12-03 00:00:00	175.26	152	2015-08-14 00:00:00	
40703	2430	30909	David Villa	113422	1981-12-03 00:00:00	175.26	152	2015-04-10 00:00:00	

5 rows × 46 columns

In [24]:
```
df_players.drop_duplicates(subset='player_api_id', inplace=True)
df_players.query("player_name=='David Villa'")
```

Out[24]:

	id	player_api_id	player_name	player_fifa_api_id	birthday	height	weight	date	o
40699	2430	30909	David Villa	113422	1981-12-03 00:00:00	175.26	152	2016-05-19 00:00:00	

1 rows × 46 columns

Exploratory Data Analysis

Research Question 1: What are the top winning teams over the time period?

In [25]:
```
# selecting the winning side
df_home_winning_teams = df_matches.query("home_team_goal > away_team_goal")
df_away_winning_teams = df_matches.query("home_team_goal < away_team_goal")
```

In [26]:
```
# making a new column to hold the winning team
df_home_winning_teams = df_home_winning_teams[['home_team_api_id']].rename(col
umns={'home_team_api_id':'winning_team'})
df_away_winning_teams = df_away_winning_teams[['away_team_api_id']].rename(col
umns={'away_team_api_id':'winning_team'})
df_winning_teams = df_home_winning_teams.append(df_away_winning_teams) # combi
ning both dataframes
df_winning_teams.head()
```

Out[26]:

	winning_team
3	9991
8	10001
9	8342
21	9984
25	10001

In [27]:
```
 #counting the number of wins
df_count_of_wins = df_winning_teams.winning_team.value_counts().rename_axis('team_api_id').to_frame('counts')
 #counting the number of played games
df_count_of_plays = df_matches.home_team_api_id.value_counts() + df_matches.away_team_api_id.value_counts()
df_count_of_plays = df_count_of_plays.rename_axis('team_api_id').to_frame('counts') # sieres to DF
df_count_of_plays
```

Out[27]:

team_api_id	counts
1601	240
1773	90
1957	240
2033	150
2182	240
...	...
158085	98
177361	30
188163	34
208931	38
274581	60

299 rows × 1 columns

In [28]:
```
#calculating winning rate
df_win_rate = df_count_of_wins / df_count_of_plays
df_win_rate.rename(columns={"counts":"win_rate"}, inplace=True)
df_win_rate.head()
```

Out[28]:

team_api_id	win_rate
1601	0.383333
1773	0.244444
1957	0.362500
2033	0.213333
2182	0.516667

In [29]:
```
# getting top 10 teams
df_top_winning_teams = df_win_rate.nlargest(columns="win_rate", n=10)
df_top_winning_teams
```

Out[29]:

team_api_id	win_rate
8634	0.769737
8633	0.750000
9772	0.745968
9773	0.737903
9925	0.717105
8548	0.710526
9823	0.709559
8593	0.665441
8640	0.654412
8635	0.641509

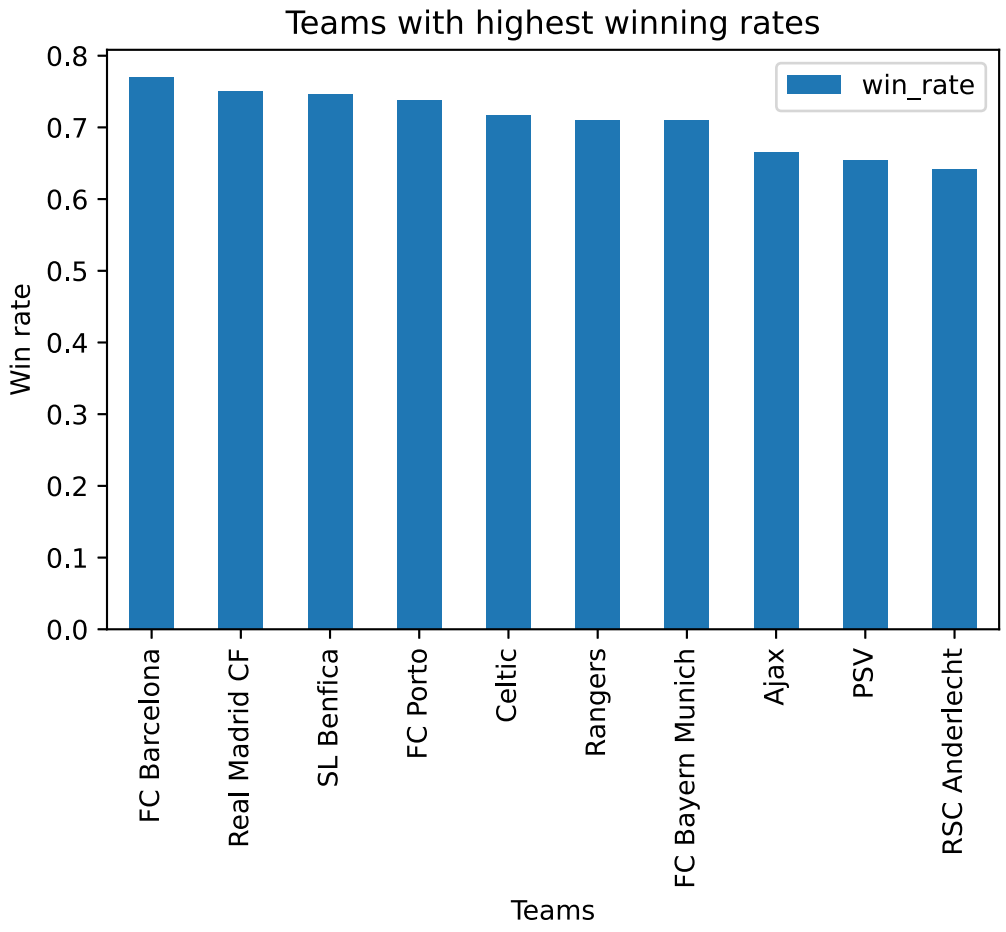
In [30]:
```
#mapping teams ids to the team names
df_top_winning_teams = pd.merge(left=df_top_winning_teams,right=df_teams,on="team_api_id", how="inner")
df_top_winning_teams[['team_long_name','win_rate']]
```

Out[30]:

	team_long_name	win_rate
0	FC Barcelona	0.769737
1	Real Madrid CF	0.750000
2	SL Benfica	0.745968
3	FC Porto	0.737903
4	Celtic	0.717105
5	Rangers	0.710526
6	FC Bayern Munich	0.709559
7	Ajax	0.665441
8	PSV	0.654412
9	RSC Anderlecht	0.641509

In [31]:
```
plt = df_top_winning_teams[['team_long_name','win_rate']].plot(kind="bar",titl
e="Teams with highest winning rates", x='team_long_name', y='win_rate')
plt.set_xlabel('Teams')
plt.set_ylabel('Win rate')
```

Out[31]: Text(0, 0.5, 'Win rate')



The top 10 teams that had the highest winning rates are shown in the above table and chart

Research Question 2: Which players had the most penalties?

In [32]:
```
df_players.nlargest(n=10, columns=['penalties'])[['player_name','penalties']]
```

Out[32]:

	player_name	penalties
149591	Rickie Lambert	96.0
40699	David Villa	92.0
113498	Mario Balotelli	92.0
122634	Michael Ballack	91.0
183672	Zlatan Ibrahimovic	91.0
37971	Dario Smoje	90.0
66178	Graham Alexander	90.0
100475	Leighton Baines	90.0
138694	Paolo Maldini	90.0
155157	Ruud van Nistelrooy	90.0

Research Question 3: What team attributes lead to the most victories?

In [33]:
```
features = ['win_rate','buildUpPlaySpeed', 'buildUpPlaySpeedClass', 'buildUpPl
ayDribblingClass',
       'buildUpPlayPassing', 'buildUpPlayPassingClass',
       'buildUpPlayPositioningClass', 'chanceCreationPassing',
       'chanceCreationPassingClass', 'chanceCreationCrossing',
       'chanceCreationCrossingClass', 'chanceCreationShooting',
       'chanceCreationShootingClass', 'chanceCreationPositioningClass',
       'defencePressure',
        'defencePressureClass', 'defenceAggression',
       'defenceAggressionClass', 'defenceTeamWidth', 'defenceTeamWidthClass',
       'defenceDefenderLineClass']

# getting teams that have winning rates above average
df_winning_teams_above_average = df_win_rate.query("win_rate > win_rate.mean
()")
df_winning_teams_above_average = pd.merge(left=df_winning_teams_above_average,
right=df_teams,on="team_api_id", how="left")
pd.plotting.scatter_matrix(frame= df_winning_teams_above_average.loc[:,feature
s], figsize=(20,20))
```

Out[33]:
```
array([[<AxesSubplot:xlabel='win_rate', ylabel='win_rate'>,
        <AxesSubplot:xlabel='buildUpPlaySpeed', ylabel='win_rate'>,
        <AxesSubplot:xlabel='buildUpPlayPassing', ylabel='win_rate'>,
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```
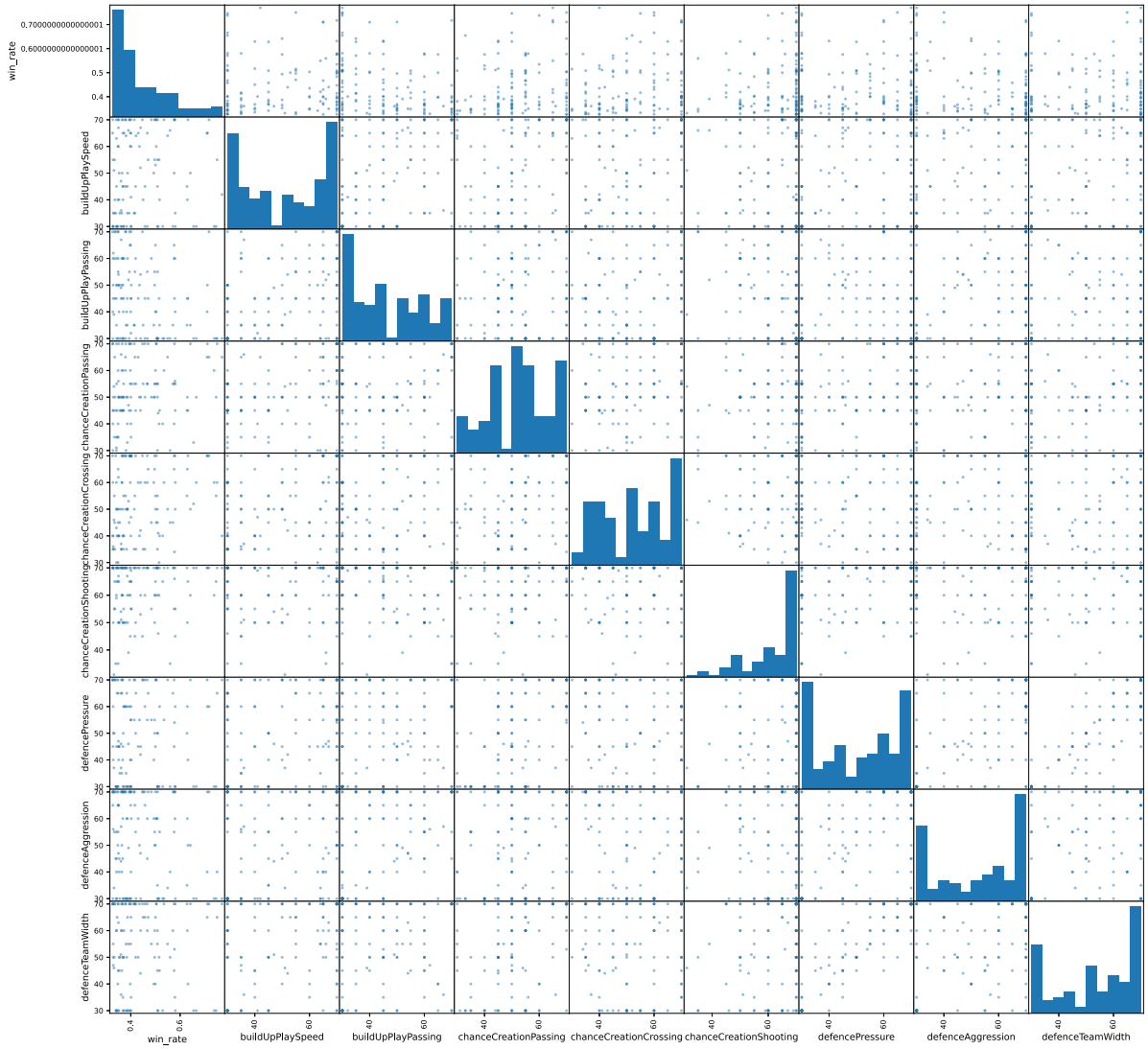



from the scatter matrix, one can see that as there is a direct proportional relation between the shooting chance creation and the winning rate of the team

Research Question 4: What are the top teams that win at home?

In [34]:
```
def get_win_rate_top_n_teams(query, team_of_interest, n=10):
    df_queried_teams = df_matches.query(query) #quering winning side
    # getting top teams based in winning rates
    df_top_winning_teams = calculate_win_rate(df_queried_teams,f'{team_of_interest}_team_api_id').nlargest(columns="win_rate", n=n)
    return map_team_ids(df_top_winning_teams)
```

In [35]:
```
def calculate_win_rate(df_teams, team_column_selector):
    #counting the number of wins
    df_count_of_wins = df_teams[team_column_selector].value_counts().rename_axis('team_api_id').to_frame('counts')
    #counting the number of played games
    df_count_of_plays = df_matches[team_column_selector].value_counts()
    df_count_of_plays = df_count_of_plays.rename_axis('team_api_id').to_frame('counts') # sieres to DF
    # calculating win rate
    df_win_rate = df_count_of_wins / df_count_of_plays
    df_win_rate.rename(columns={"counts":"win_rate"}, inplace=True)
    return df_win_rate
```

In [36]:
```
def map_team_ids(team_ids, df_teams = df_teams):
    return pd.merge(left=team_ids,right=df_teams,on="team_api_id", how="left")
```

In [37]:
```
df_top_home_winning_teams = get_win_rate_top_n_teams(query = "home_team_goal > away_team_goal", team_of_interest='home')
df_top_home_winning_teams[['team_long_name','win_rate']]
```

Out[37]:

	team_long_name	win_rate
0	FC Barcelona	0.861842
1	Real Madrid CF	0.848684
2	SL Benfica	0.822581
3	FC Porto	0.822581
4	FC Bayern Munich	0.801471
5	Celtic	0.789474
6	PSV	0.772059
7	Manchester United	0.763158
8	Ajax	0.757353
9	RSC Anderlecht	0.745283

The top 10 teams that had the highest winning rates at home are shown in the above table

Research Question 5: What are the top teams that win away from home?

In [38]:
```
df_top_away_winning_teams = get_win_rate_top_n_teams(query = "home_team_goal < away_team_goal", team_of_interest='away')
df_top_away_winning_teams[['team_long_name','win_rate']]
```

Out[38]:

	team_long_name	win_rate
0	Rangers	0.684211
1	FC Barcelona	0.677632
2	SL Benfica	0.669355
3	FC Porto	0.653226
4	Real Madrid CF	0.651316
5	Celtic	0.644737
6	FC Bayern Munich	0.617647
7	Ajax	0.573529
8	Juventus	0.560000
9	FC Basel	0.538462

The top 10 teams that had the highest winning rates away from home are shown in the above table

Research Question 5: Top scoring teams

In [39]:
```
#getting total home goals for each team
renamed_cols_home = {'home_team_goal':'goals'}
df_home_goals = df_matches[['home_team_api_id','home_team_goal']].groupby('home_team_api_id').sum().rename(columns=renamed_cols_home)
```

In [40]:
```
#getting total away goals for each team
renamed_cols_away = {'away_team_goal':'goals'}
df_away_goals = df_matches[['away_team_api_id','away_team_goal']].groupby('away_team_api_id').sum().rename(columns=renamed_cols_away)
```

In [41]:
```
#summing home and away goals for each team and then getting top 10 teams
df_goals = df_home_goals + df_away_goals
df_goals.rename_axis('team_api_id', inplace=True)
map_team_ids(df_goals.nlargest(n=10, columns='goals'))[['team_long_name','goals']]
```

Out[41]:

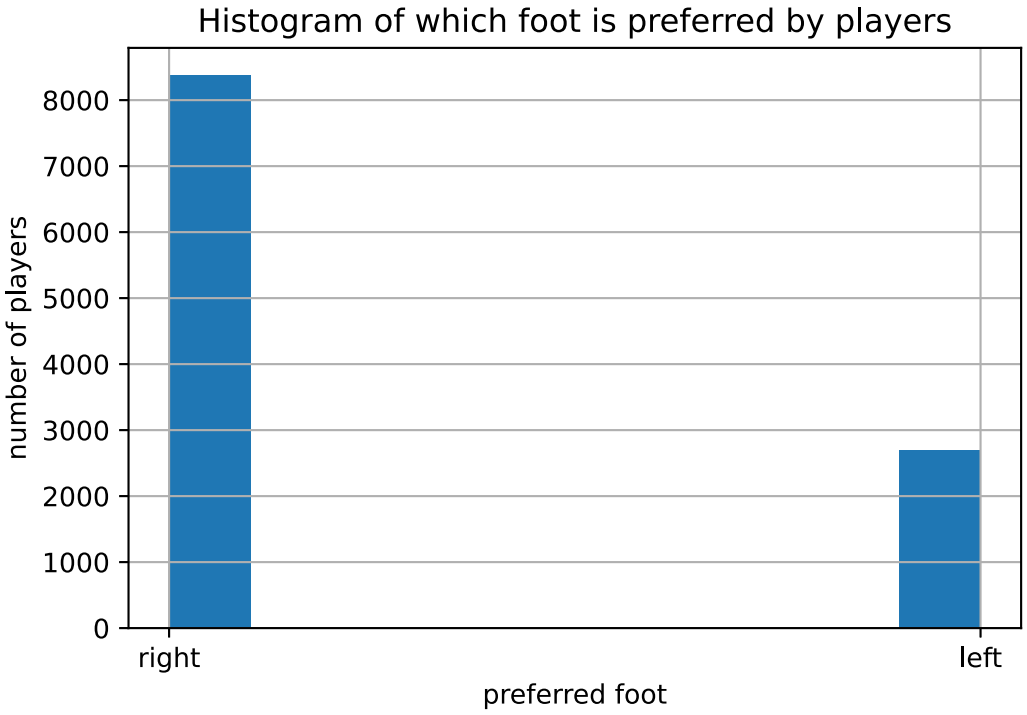
	team_long_name	goals
0	FC Barcelona	849
1	Real Madrid CF	843
2	Celtic	695
3	FC Bayern Munich	653
4	PSV	652
5	Ajax	647
6	FC Basel	619
7	Manchester City	606
8	Chelsea	583
9	Manchester United	582

The top 10 scoring teams are shown in the above table

Research Question 6: Which foot is more prefered by soccer players?

In [42]:
```
plt = df_players.preferred_foot.hist()
plt.set_xlabel('preferred foot')
plt.set_ylabel('number of players')
plt.set_title('Histogram of which foot is preferred by players')
```

Out[42]: Text(0.5, 1.0, 'Histogram of which foot is preferred by players')

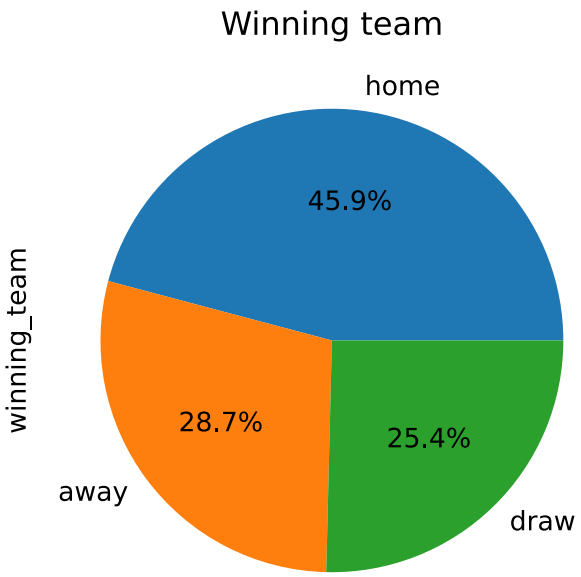


as shown above, most players prefer the right foot

Research Question 7: Does playing at home contributes in winning?

In [43]:
```
def who_win(match):
    if match['home_team_goal'] > match['away_team_goal']:
        return 'home'
    elif match['home_team_goal'] < match['away_team_goal']:
        return 'away'
    return 'draw'
df_matches['winning_team'] = df_matches.apply(who_win, axis=1)

plt = df_matches.winning_team.value_counts().plot.pie(autopct='%1.1f%%')
plt.set_title('Winning team')
```

Out[43]:
```
Text(0.5, 1.0, 'Winning team')
```



As seen in the above pie chart, teams that play at home tends to win with probablity about 45.9%. On the other hand, teams that plays away tends to win with probability of 28.7% only.

Research Question 7: What teams improved the most over the time period?

We will know the teams that improved the most through considering the difference in the following attributes over the time perioid: buildUpPlaySpeed, buildUpPlayDribbling, and buildUpPlayPassing

In [44]:
```
df_teams_improvments = df_teams_with_dates.sort_values(['team_api_id','date'],
ascending=True).groupby('team_api_id')[['buildUpPlaySpeed','buildUpPlayDribbli
ng','buildUpPlayPassing']].apply(lambda team: team.iloc[-1] - team.iloc[0])

df_teams_improvments.head()
```

Out[44]:

team_api_id	buildUpPlaySpeed	buildUpPlayDribbling	buildUpPlayPassing
1601	17.0	-0.607362	-2.0
1773	0.0	2.392638	0.0
1957	36.0	5.392638	-12.0
2033	0.0	13.392638	-15.0
2182	17.0	1.392638	5.0

In [45]:
```
# normalizing columns
df_teams_improvments_norm = df_teams_improvments.apply(lambda x: x/x.max())

df_teams_improvments_norm.head()
```

Out[45]:

team_api_id	buildUpPlaySpeed	buildUpPlayDribbling	buildUpPlayPassing
1601	0.354167	-0.021392	-0.054054
1773	0.000000	0.084270	0.000000
1957	0.750000	0.189931	-0.324324
2033	0.000000	0.471694	-0.405405
2182	0.354167	0.049049	0.135135

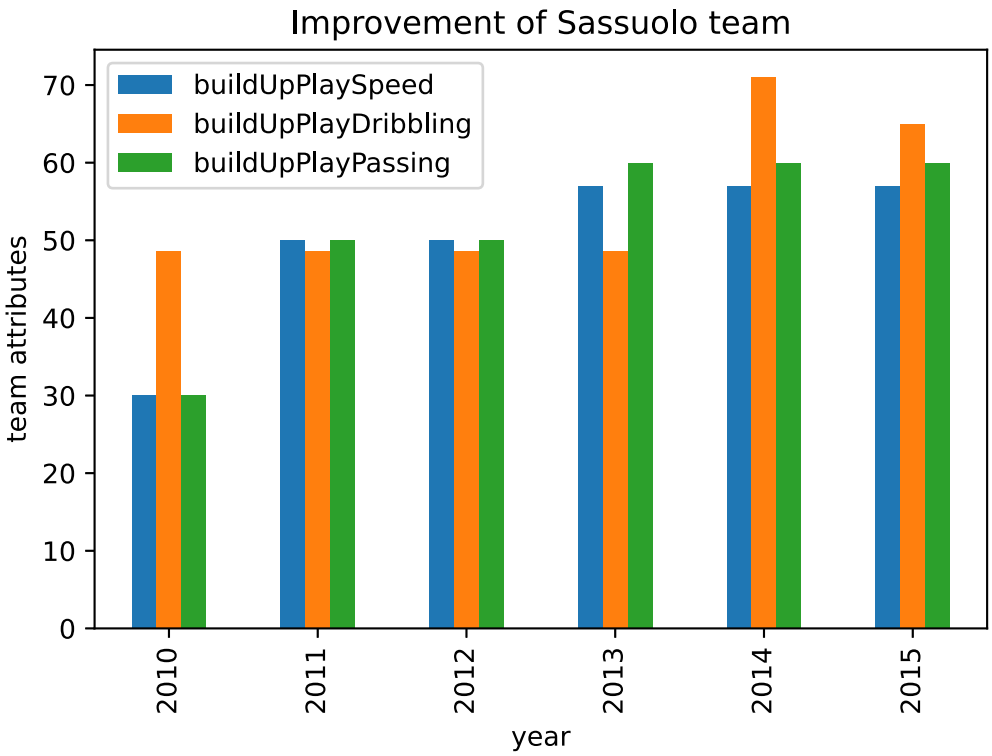
In [46]:
```
#taking means of improvements
df_teams_improvments_norm['mean'] = df_teams_improvments_norm.mean(axis = 1,sk
ipna=True)
df_top_improved_teams = map_team_ids(df_teams_improvments_norm.nlargest(5, 'me
an'))[['team_api_id','team_long_name','buildUpPlaySpeed_y','buildUpPlayDribbli
ng_y','buildUpPlayPassing_y','mean']]

df_top_improved_teams
```

Out[46]:

	team_api_id	team_long_name	buildUpPlaySpeed_y	buildUpPlayDribbling_y	buildUpPlayPassin
0	7943	Sassuolo	30.0	48.607362	
1	8537	Livorno	30.0	48.607362	
2	208931	Carpi	32.0	46.000000	
3	9768	Sporting CP	30.0	48.607362	
4	9772	SL Benfica	30.0	48.607362	

As shown in the above table, the top 5 improved teams over the period based on the mean improvments in buildUpPlaySpeed, buildUpPlayDribbling, buildUpPlayPassing

In [48]:
```
df_top_improved_teams_with_dates = df_teams_with_dates.loc[df_teams_with_dates
['team_api_id'].isin(df_top_improved_teams['team_api_id'])]

df_top_improved_teams_with_dates['date'] =pd.to_datetime(df_top_improved_teams
_with_dates['date']).dt.year

df_top_improved_teams_with_dates = df_top_improved_teams_with_dates.sort_value
s(['team_api_id','date'], ascending=True).groupby('team_api_id')[['date','team
_long_name','buildUpPlaySpeed','buildUpPlayDribbling','buildUpPlayPassing']]

for group_name, df_group in df_top_improved_teams_with_dates:
    plt = df_group[['date','team_long_name','buildUpPlaySpeed','buildUpPlayDri
bbling','buildUpPlayPassing']].plot(kind="bar", x='date')
    plt.set_xlabel('year')
    plt.set_ylabel('team attributes')
    team_name = df_teams[df_teams['team_api_id'] == group_name].team_long_name
    plt.set_title("Improvement of " + team_name.item() + " team")
```


Improvement of Sassuolo team
buildUpPlaySpeed
buildUpPlayDribbling
buildUpPlayPassing
team attributes
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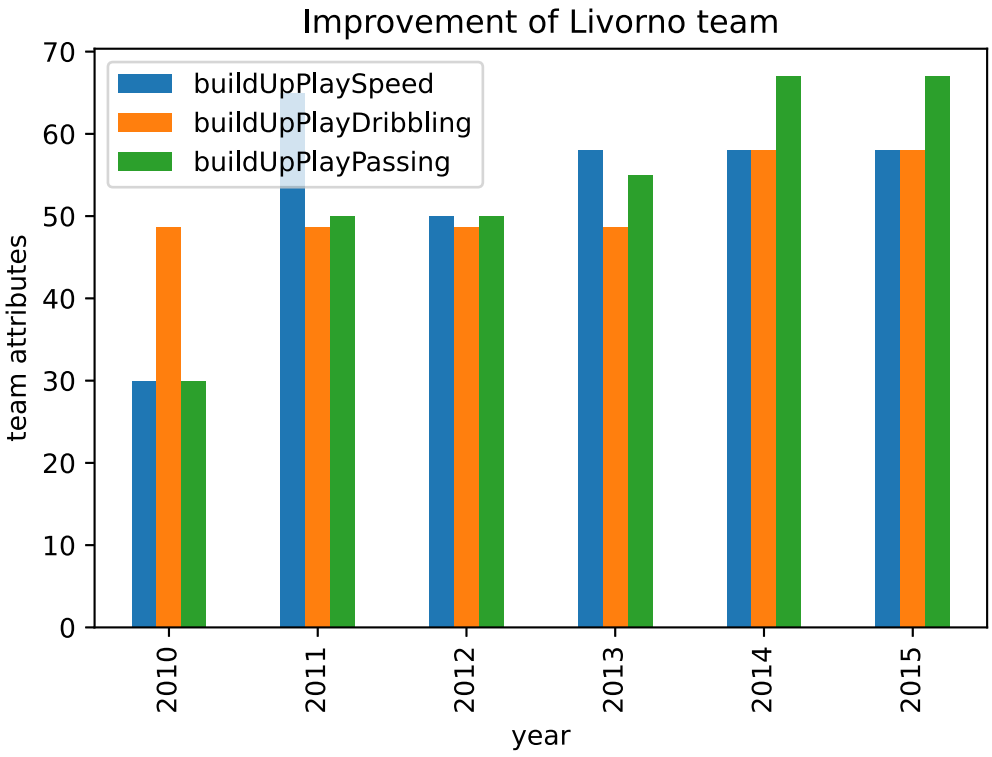
Improvement of Livorno team
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buildUpPlayDribbling
buildUpPlayPassing
team attributes
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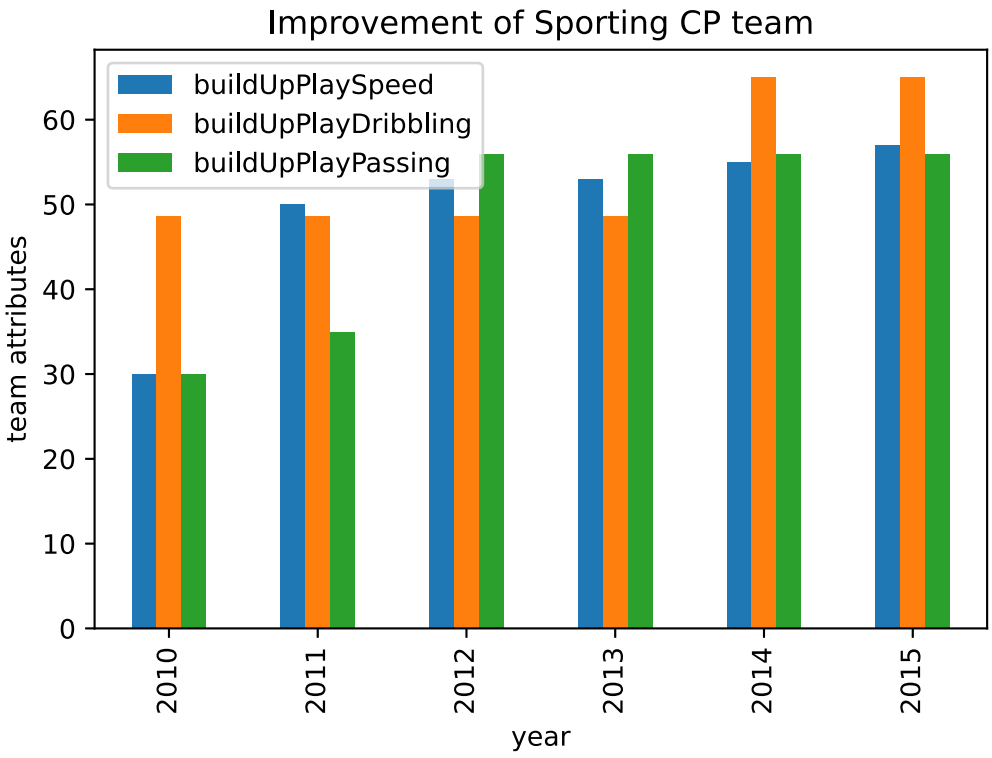
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buildUpPlayDribbling
buildUpPlayPassing
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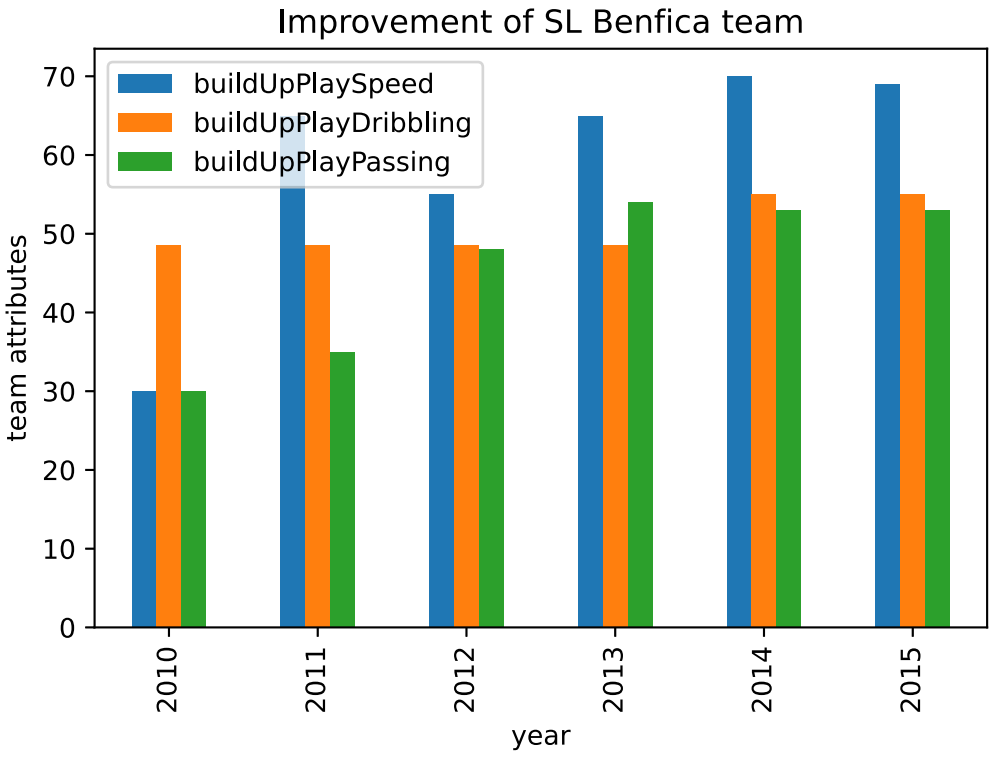
Improvement of SL Benfica team
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buildUpPlayDribbling
buildUpPlayPassing
team attributes
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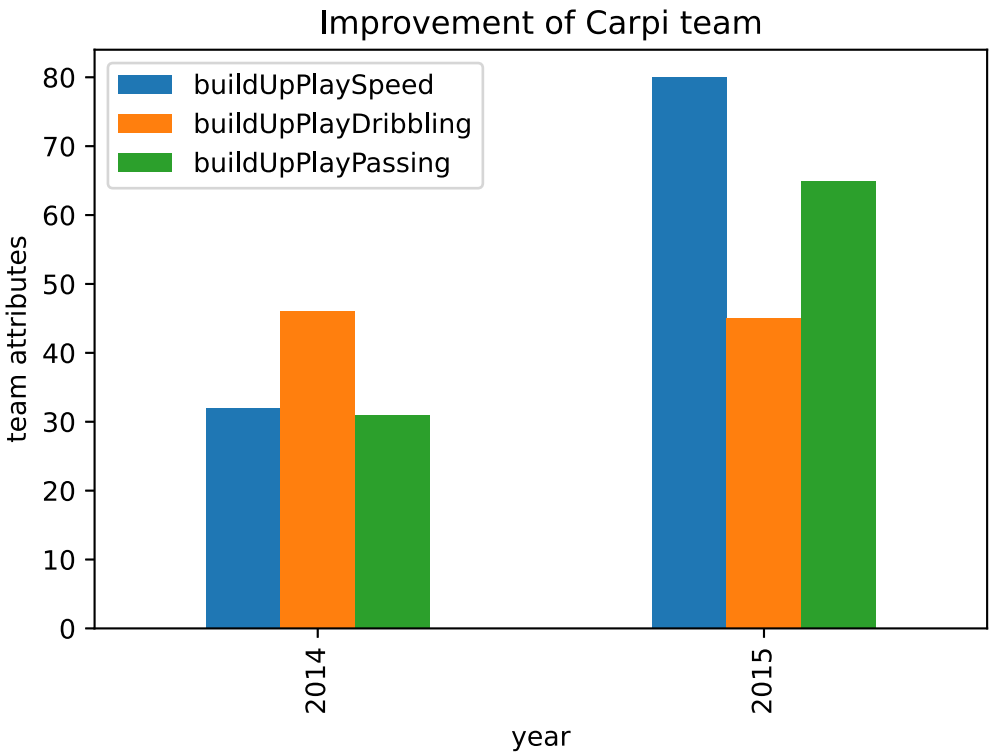

Conclusions

In this report, we analyzed a soccer databse in european leagues. First, we joined the tables as needed. Then, the data is wrangled. Afterthen, we started our data analysis to answer the mentioned research questions before. We Found that Barcelona and RealMadrid were on the top of the all time winning teams. Barcelona specially was top winning team at home and the second winning team away from their home. Moreover, Barcelona was the top scoring team with 849 goals followed by Real Madrid with 843, and then followed by far away by Celtic with 695 goals. We also found that shooting change creation is one of the team attributes that lead to having a better winning rate. Moreover, we found that playing at home increases the probablity of winning. After doing a 1D analysis on players showed that most of the players prefer to use their right foot. Finally, we got the top 5 improved teams based on buildUpPlaySpeed, buildUpPlayDribbling, buildUpPlayPassing.

Limitations

- More teams are needed to further verify our finding of which team attributes that lead to have a better winning rate.
- Not all the players have the preferred foot attribute.