Exploratory Analysis of European League Football Data

We have used two sets of data for our analysis.

The first dataset have been collected from http://www.datahub.io (http://www.datahub.io) (https://datahub.io/collections/football (https://datahub.io/collections/football))
EPL : https://datahub.io/sports-data/english-premier-league (https://datahub.io/sports-data/english-premier-league)
LaLiga : https://datahub.io/sports-data/spanish-la-liga (https://datahub.io/sports-data/spanish-la-liga)
Serie A : https://datahub.io/sports-data/italian-serie-a (https://datahub.io/sports-data/italian-serie-a)
Bundesliga : https://datahub.io/sports-data/german-bundesliga (https://datahub.io/sports-data/german-bundesliga)
Juventus : https://datahub.io/sports-data/french-ligue-1 (https://datahub.io/sports-data/french-ligue-1)
We have 5 zip files - one for each league
Each zip file unpacks into 9 CSV files (one for each season)
Each row in the CSV files corresponds to one league match

The second dataset is a collection of events during European football league matches.
The dataset has been collected from Kaggle (https://www.kaggle.com/secareanualin/football-events (https://www.kaggle.com/secareanualin/football-events))
Each row of the dataset corresponds to an event. Overall the dataset contains information about close to a million events
The dataset files can be downloaded from :

1. https://www.kaggle.com/secareanualin/football-events/downloads/events.csv/1 (https://www.kaggle.com/secareanualin/football-events/downloads/events.csv/1)
2. https://www.kaggle.com/secareanualin/football-events/downloads/ginf.csv/1 (https://www.kaggle.com/secareanualin/football-events/downloads/ginf.csv/1)

A dictionary file explaining the columns in the dataset is available at : https://www.kaggle.com/secareanualin/football-events/downloads/dictionary.txt/1 (https://www.kaggle.com/secareanualin/football-events/downloads/dictionary.txt/1)

The objective of this analysis is to :

1. Explore the various features in the data and observe the trend in movement of those features across leagues or across years
2. Identify the features influencing the outcome of a match
3. Build a predictive model and test it

Let's try loading one of the CSV files and examine it's meta-data

```
Out[6]: Index(['Date', 'HomeTeam', 'AwayTeam', 'FTHG', 'FTAG', 'FTR', 'HTHG', 'HTAG',
               'HTR', 'Referee', 'HS', 'AS', 'HST', 'AST', 'HF', 'AF', 'HC', 'AC',
               'HY', 'AY', 'HR', 'AR'],
              dtype='object')
```

We can rename the column headers to be more meaningful, like this :

```
Out[7]: Index(['Date', 'HomeTeam', 'AwayTeam', 'FullTime_HomeTeam_Goals',
               'FullTime_AwayTeam_Goals', 'FullTime_Result', 'HalfTime_HomeTeam_Goal
        s',
               'HalfTime_AwayTeam_Goals', 'HalfTime_Result', 'Referee',
               'HomeTeam_Shots', 'AwayTeam_Shots', 'HomeTeam_ShotsOnTarget',
               'AwayTeam_ShotsOnTarget', 'HomeTeam_FoulsCommitted',
               'AwayTeam_FoulsCommitted', 'HomeTeam_Corners', 'AwayTeam_Corners',
               'HomeTeam_YellowCards', 'AwayTeam_YellowCards', 'HomeTeam_RedCards',
               'AwayTeam_RedCards'],
              dtype='object')
```

We can change the default index and use date as index instead

Lets build a function to load data for all seasons and all leagues in a generic way

We'll start with EPL data first

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (120, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_
2018-08-10	Man United	Leicester	2	1	
2018-08-11	Bournemouth	Cardiff	2	0	
2018-08-11	Fulham	Crystal Palace	0	2	
2018-08-11	Huddersfield	Chelsea	0	3	
2018-08-11	Newcastle	Tottenham	1	2	

```
Loading 2017-2018 data from season-1718_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_
2017-08-11	Arsenal	Leicester	4	3	
2017-08-12	Brighton	Man City	0	2	
2017-08-12	Chelsea	Burnley	2	3	
2017-08-12	Crystal Palace	Huddersfield	0	3	
2017-08-12	Everton	Stoke	1	0	

```
Loading 2016-2017 data from season-1617_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_R
2016-08-13	Burnley	Swansea	0	1	
2016-08-13	Crystal Palace	West Brom	0	1	
2016-08-13	Everton	Tottenham	1	1	
2016-08-13	Hull	Leicester	2	1	
2016-08-13	Man City	Sunderland	2	1	

```
Loading 2015-2016 data from season-1516_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_
2015-08-08	Bournemouth	Aston Villa	0	1	
2015-08-08	Chelsea	Swansea	2	2	
2015-08-08	Everton	Watford	2	2	
2015-08-08	Leicester	Sunderland	4	2	
2015-08-08	Man United	Tottenham	1	0	

```
Loading 2014-2015 data from season-1415_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_R
2014-08-16	Arsenal	Crystal Palace	2	1	
2014-08-16	Leicester	Everton	2	2	
2014-08-16	Man United	Swansea	1	2	
2014-08-16	QPR	Hull	0	1	
2014-08-16	Stoke	Aston Villa	0	1	

```
Loading 2013-2014 data from season-1314_csv.csv
Data Shape : (380, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_R
Date					
2013-08-17	Arsenal	Aston Villa	1	3	
2013-08-17	Liverpool	Stoke	1	0	
2013-08-17	Norwich	Everton	2	2	
2013-08-17	Sunderland	Fulham	0	1	
2013-08-17	Swansea	Man United	1	4	

```
Loading 2012-2013 data from season-1213_csv.csv
Data Shape : (380, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_R
Date					
2012-08-18	Arsenal	Sunderland	0	0	
2012-08-18	Fulham	Norwich	5	0	
2012-08-18	Newcastle	Tottenham	2	1	
2012-08-18	QPR	Swansea	0	5	
2012-08-18	Reading	Stoke	1	1	

```
Loading 2011-2012 data from season-1112_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_R
2011-08-13	Blackburn	Wolves	1	2	
2011-08-13	Fulham	Aston Villa	0	0	
2011-08-13	Liverpool	Sunderland	1	1	
2011-08-13	Newcastle	Arsenal	0	0	
2011-08-13	QPR	Bolton	0	4	

```
Loading 2010-2011 data from season-1011_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_F
2010-08-14	Aston Villa	West Ham	3	0	
2010-08-14	Blackburn	Everton	1	0	
2010-08-14	Bolton	Fulham	0	0	
2010-08-14	Chelsea	West Brom	6	0	
2010-08-14	Sunderland	Birmingham	2	2	

So data has been loaded correctly. Next, lets concatenate all EPL data together. Except 2018-19 season, which is ongoing, all other datasets have 380 rows. So final dataset will have 8*380 + 120 i.e. 3160 rows

```
EPL data loaded fully - Shape:  (3160, 21)
```

Lets repeat the same process for other leagues

Let's try loading La Liga data next. First we'll try to load and examine one of the files

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (100, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
17/08/18	Betis	Levante	0	3	
17/08/18	Girona	Valladolid	0	0	
18/08/18	Barcelona	Alaves	3	0	
18/08/18	Celta	Espanol	1	1	
18/08/18	Villarreal	Sociedad	1	2	

So data has similar layout as EPL data. Lets load data for all the seasons

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (100, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
17/08/18	Betis	Levante	0	3	
17/08/18	Girona	Valladolid	0	0	
18/08/18	Barcelona	Alaves	3	0	
18/08/18	Celta	Espanol	1	1	
18/08/18	Villarreal	Sociedad	1	2	

```
Loading 2017-2018 data from season-1718_csv.csv
Data Shape : (380, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
18/08/17	Leganes	Alaves	1	0	
18/08/17	Valencia	Las Palmas	1	0	
19/08/17	Celta	Sociedad	2	3	
19/08/17	Girona	Ath Madrid	2	2	
19/08/17	Sevilla	Espanol	1	1	

```
Loading 2016-2017 data from season-1617_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
19/08/16	La Coruna	Eibar	2	1	
19/08/16	Malaga	Osasuna	1	1	
20/08/16	Barcelona	Betis	6	2	
20/08/16	Granada	Villarreal	1	1	
20/08/16	Sevilla	Espanol	6	4	

```
Loading 2015-2016 data from season-1516_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
21/08/15	Malaga	Sevilla	0	0	
22/08/15	Ath Madrid	Las Palmas	1	0	
22/08/15	Espanol	Getafe	1	0	
22/08/15	La Coruna	Sociedad	0	0	
22/08/15	Vallecano	Valencia	0	0	

```
Loading 2014-2015 data from season-1415_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
23/08/14	Almeria	Espanol	1	1	
23/08/14	Granada	La Coruna	2	1	
23/08/14	Malaga	Ath Bilbao	1	0	
23/08/14	Sevilla	Valencia	1	1	
24/08/14	Barcelona	Elche	3	0	

```
Loading 2013-2014 data from season-1314_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
17/08/13	Sociedad	Getafe	2	0	
17/08/13	Valencia	Malaga	1	0	
17/08/13	Valladolid	Ath Bilbao	1	2	
18/08/13	Barcelona	Levante	7	0	
18/08/13	Osasuna	Granada	1	2	

```
Loading 2012-2013 data from season-1213_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
18/08/12	Celta	Malaga	0	1	
18/08/12	Mallorca	Espanol	2	1	
18/08/12	Sevilla	Getafe	2	1	
19/08/12	Ath Bilbao	Betis	3	5	
19/08/12	Barcelona	Sociedad	5	1	

```
Loading 2011-2012 data from season-1112_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
27/08/11	Granada	Betis	0	1	
27/08/11	Sp Gijon	Sociedad	1	2	
27/08/11	Valencia	Santander	4	3	
28/08/11	Ath Bilbao	Vallecano	1	1	
28/08/11	Ath Madrid	Osasuna	0	0	

```
Loading 2010-2011 data from season-1011_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
28/08/10	Hercules	Ath Bilbao	0	1	
28/08/10	Levante	Sevilla	1	4	
28/08/10	Malaga	Valencia	1	3	
29/08/10	Espanol	Getafe	3	1	
29/08/10	La Coruna	Zaragoza	0	0	

```
La Liga data fully loaded - Shape:  (3140, 21)
```

Next we'll try to load Serie A data. To begin with, we'll try to load one of the files and see if the data layout meets our expectations

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (100, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
18/08/18	Chievo	Juventus	2	3	
18/08/18	Lazio	Napoli	1	2	
19/08/18	Bologna	Spal	0	1	
19/08/18	Empoli	Cagliari	2	0	
19/08/18	Parma	Udinese	2	2	

So data has similar layout as EPL or La Liga. Lets load data for all the 9 seasons

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (100, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
18/08/18	Chievo	Juventus	2	3	
18/08/18	Lazio	Napoli	1	2	
19/08/18	Bologna	Spal	0	1	
19/08/18	Empoli	Cagliari	2	0	
19/08/18	Parma	Udinese	2	2	

```
Loading 2017-2018 data from season-1718_csv.csv
Data Shape : (380, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
19/08/17	Juventus	Cagliari	3	0	
19/08/17	Verona	Napoli	1	3	
20/08/17	Atalanta	Roma	0	1	
20/08/17	Bologna	Torino	1	1	
20/08/17	Crotone	Milan	0	3	

```
Loading 2016-2017 data from season-1617_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
20/08/16	Juventus	Fiorentina	2	1	
20/08/16	Roma	Udinese	4	0	
21/08/16	Atalanta	Lazio	3	4	
21/08/16	Bologna	Crotone	1	0	
21/08/16	Chievo	Inter	2	0	

```
Loading 2015-2016 data from season-1516_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
22/08/15	Lazio	Bologna	2	1	
22/08/15	Verona	Roma	1	1	
23/08/15	Empoli	Chievo	1	3	
23/08/15	Fiorentina	Milan	2	0	
23/08/15	Frosinone	Torino	1	2	

```
Loading 2014-2015 data from season-1415_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
30/08/14	Chievo	Juventus	0	1	
30/08/14	Roma	Fiorentina	2	0	
31/08/14	Atalanta	Verona	0	0	
31/08/14	Cesena	Parma	1	0	
31/08/14	Genoa	Napoli	1	2	

```
Loading 2013-2014 data from season-1314_csv.csv
Data Shape : (380, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
24/08/13	Sampdoria	Juventus	0	1	
24/08/13	Verona	Milan	2	1	
25/08/13	Cagliari	Atalanta	2	1	
25/08/13	Inter	Genoa	2	0	
25/08/13	Lazio	Udinese	2	1	

```
Loading 2012-2013 data from season-1213_csv.csv
Data Shape : (380, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
25/08/12	Fiorentina	Udinese	2	1	
25/08/12	Juventus	Parma	2	0	
26/08/12	Atalanta	Lazio	0	1	
26/08/12	Chievo	Bologna	2	0	
26/08/12	Genoa	Cagliari	2	0	

```
Loading 2011-2012 data from season-1112_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
09/09/11	Milan	Lazio	2	2	
10/09/11	Cesena	Napoli	1	3	
11/09/11	Catania	Siena	0	0	
11/09/11	Chievo	Novara	2	2	
11/09/11	Fiorentina	Bologna	2	0	

```
Loading 2010-2011 data from season-1011_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
28/08/10	Roma	Cesena	0	0	
28/08/10	Udinese	Genoa	0	1	
29/08/10	Bari	Juventus	1	0	
29/08/10	Chievo	Catania	2	1	
29/08/10	Fiorentina	Napoli	1	1	

```
Serie A data loaded fully - shape : (3140, 21)
```

Next we'll try to load Bundesliga data. To begin with, we'll try to load one of the files and see if the data layout meets our expectations

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (81, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
24/08/18	Bayern Munich	Hoffenheim	3	1	
25/08/18	Fortuna Dusseldorf	Augsburg	1	2	
25/08/18	Freiburg	Ein Frankfurt	0	2	
25/08/18	Hertha	Nurnberg	1	0	
25/08/18	M'gladbach	Leverkusen	2	0	

So data has the same layout as we expected. Lets load data for all the 9 seasons

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (81, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
24/08/18	Bayern Munich	Hoffenheim	3	1	
25/08/18	Fortuna Dusseldorf	Augsburg	1	2	
25/08/18	Freiburg	Ein Frankfurt	0	2	
25/08/18	Hertha	Nurnberg	1	0	
25/08/18	M'gladbach	Leverkusen	2	0	

```
Loading 2017-2018 data from season-1718_csv.csv
Data Shape : (306, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
18/08/17	Bayern Munich	Leverkusen	3	1	
19/08/17	Hamburg	Augsburg	1	0	
19/08/17	Hertha	Stuttgart	2	0	
19/08/17	Hoffenheim	Werder Bremen	1	0	
19/08/17	Mainz	Hannover	0	1	

```
Loading 2016-2017 data from season-1617_csv.csv
Data Shape : (306, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
26/08/16	Bayern Munich	Werder Bremen	6	0	
27/08/16	Augsburg	Wolfsburg	0	2	
27/08/16	Dortmund	Mainz	2	1	
27/08/16	Ein Frankfurt	Schalke 04	1	0	
27/08/16	FC Koln	Darmstadt	2	0	

```
Loading 2015-2016 data from season-1516_csv.csv
Data Shape : (306, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
14/08/15	Bayern Munich	Hamburg	5	0	
15/08/15	Augsburg	Hertha	0	1	
15/08/15	Darmstadt	Hannover	2	2	
15/08/15	Dortmund	M'gladbach	4	0	
15/08/15	Leverkusen	Hoffenheim	2	1	

```
Loading 2014-2015 data from season-1415_csv.csv
Data Shape : (306, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
22/08/14	Bayern Munich	Wolfsburg	2	1	
23/08/14	Dortmund	Leverkusen	0	2	
23/08/14	Ein Frankfurt	Freiburg	1	0	
23/08/14	FC Koln	Hamburg	0	0	
23/08/14	Hannover	Schalke 04	2	1	

```
Loading 2013-2014 data from season-1314_csv.csv
Data Shape : (306, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTi
Date					
09/08/13	Bayern Munich	M'gladbach	3	1	
10/08/13	Augsburg	Dortmund	0	4	
10/08/13	Braunschweig	Werder Bremen	0	1	
10/08/13	Hannover	Wolfsburg	2	0	
10/08/13	Hertha	Ein Frankfurt	6	1	

```
Loading 2012-2013 data from season-1213_csv.csv
Data Shape : (306, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
24/08/12	Dortmund	Werder Bremen	2	1	
25/08/12	Augsburg	Fortuna Dusseldorf	0	2	
25/08/12	Ein Frankfurt	Leverkusen	2	1	
25/08/12	Freiburg	Mainz	1	1	
25/08/12	Greuther Furth	Bayern Munich	0	3	

```
Loading 2011-2012 data from season-1112_csv.csv
Data Shape : (306, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
05/08/11	Dortmund	Hamburg	3	1	
06/08/11	Augsburg	Freiburg	2	2	
06/08/11	FC Koln	Wolfsburg	0	3	
06/08/11	Hannover	Hoffenheim	2	1	
06/08/11	Hertha	Nurnberg	0	1	

```
Loading 2010-2011 data from season-1011_csv.csv
Data Shape : (306, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTi
20/08/10	Bayern Munich	Wolfsburg	2	1	
21/08/10	FC Koln	Kaiserslautern	1	3	
21/08/10	Freiburg	St Pauli	1	3	
21/08/10	Hamburg	Schalke 04	2	1	
21/08/10	Hannover	Ein Frankfurt	2	1	

```
Bundesliga data fully loaded - Shape : (2529, 21)
```

Next we'll try to load Ligue One data. To begin with, we'll try to load one of the files and see if the data layout meets our expectations

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (110, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
10/08/18	Marseille	Toulouse	4	0	
11/08/18	Angers	Nimes	3	4	
11/08/18	Lille	Rennes	3	1	
11/08/18	Montpellier	Dijon	1	2	
11/08/18	Nantes	Monaco	1	3	

So data shape is consistent with other league data. Let's proceed with loading data for all the 9 seasons

```
Loading 2018-2019 data from season-1819_csv.csv
Data Shape : (110, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
10/08/18	Marseille	Toulouse	4	0	
11/08/18	Angers	Nimes	3	4	
11/08/18	Lille	Rennes	3	1	
11/08/18	Montpellier	Dijon	1	2	
11/08/18	Nantes	Monaco	1	3	

```
Loading 2017-2018 data from season-1718_csv.csv
Data Shape : (380, 21)
```

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
Date					
04/08/17	Monaco	Toulouse	3	2	
05/08/17	Lyon	Strasbourg	4	0	
05/08/17	Metz	Guingamp	1	3	
05/08/17	Montpellier	Caen	1	0	
05/08/17	Paris SG	Amiens	2	0	

```
Loading 2016-2017 data from season-1617_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
12/08/16	Bastia	Paris SG	0	1	
12/08/16	Monaco	Guingamp	2	2	
13/08/16	Bordeaux	St Etienne	3	2	
13/08/16	Caen	Lorient	3	2	
13/08/16	Dijon	Nantes	0	1	

```
Loading 2015-2016 data from season-1516_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
07/08/15	Lille	Paris SG	0	1	
08/08/15	Bastia	Rennes	2	1	
08/08/15	Marseille	Caen	0	1	
08/08/15	Montpellier	Angers	0	2	
08/08/15	Nantes	Guingamp	1	0	

```
Loading 2014-2015 data from season-1415_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
08/08/14	Reims	Paris SG	2	2	
09/08/14	Bastia	Marseille	3	3	
09/08/14	Evian Thonon Gaillard	Caen	0	3	
09/08/14	Guingamp	St Etienne	0	2	
09/08/14	Lille	Metz	0	0	

```
Loading 2013-2014 data from season-1314_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
09/08/13	Montpellier	Paris SG	1	1	
10/08/13	Bordeaux	Monaco	0	2	
10/08/13	Evian Thonon Gaillard	Sochaux	1	1	
10/08/13	Lille	Lorient	1	0	
10/08/13	Lyon	Nice	4	0	

```
Loading 2012-2013 data from season-1213_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
10/08/12	Montpellier	Toulouse	1	1	
11/08/12	Evian Thonon Gaillard	Bordeaux	2	3	
11/08/12	Nancy	Brest	1	0	
11/08/12	Nice	Ajaccio	0	1	
11/08/12	Paris SG	Lorient	2	2	

```
Loading 2011-2012 data from season-1112_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTin
06/08/11	Ajaccio	Toulouse	0	2	
06/08/11	Brest	Evian Thonon Gaillard	2	2	
06/08/11	Caen	Valenciennes	1	0	
06/08/11	Marseille	Sochaux	2	2	
06/08/11	Montpellier	Auxerre	3	1	

```
Loading 2010-2011 data from season-1011_csv.csv
Data Shape : (380, 21)
```

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTin
07/08/10	Auxerre	Lorient	2	2	
07/08/10	Lens	Nancy	1	2	
07/08/10	Lyon	Monaco	0	0	
07/08/10	Marseille	Caen	1	2	
07/08/10	Nice	Valenciennes	0	0	

```
Ligue1 data loaded completely - Shape:  (3150, 21)
```

Lets append all the league data into a single dataframe

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_R
2010-08-14	Aston Villa	West Ham	3	0	
2010-08-14	Blackburn	Everton	1	0	

Sanitizing/Cleansing the data

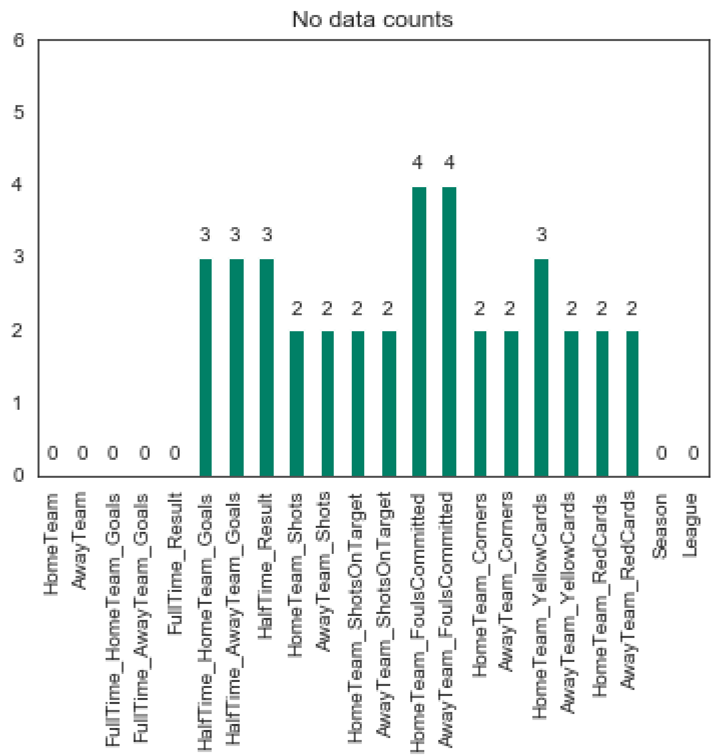
Lets check if the data has duplicate rows, if so, remove duplicates from the data

```
Good news !!! There are no duplicate rows in the data
```

So the data has no duplicate rows. Next we need to check if some of the columns have no values/junk values

```
Full Time Home-Team Goals (Unique Values) :  : [ 3  1  0  6  2  4  5  7  8  9
10]
Full Time Away-Team Goals (Unique Values) :  : [0 2 4 1 3 6 5 7 8 9]
Full Time Result (Unique Values) :  : ['H' 'D' 'A']
Half Time Home-Team Goals (Unique Values) :  : [ 2.  1.  0.  3.  4.  5.  6. n
an]
Half Time Away-Team Goals (Unique Values) :  : [ 0.  3.  2.  1.  4.  5. nan]
Half Time Result (Unique Values) :  : ['H' 'D' 'A' nan]
Home Team Shots (Unique Values) :  : [23.  7. 13. 18.  6. 22. 11. 26. 10. 14.
15. 17. 16. 20.  8. 12.  5.  9.
 27. 24. 19. 21.  1. 25. 32.  2.  3.  4. 28. 35. 30. 33. 31. 39. 29. 43.
 34. 37. 36. nan 38.]
Away Team Shots (Unique Values) :  : [12. 17. 10. 13. 11.  9. 14.  7.  3. 15.
  4. 16.  5.  6.  8.  2. 20. 19.
 24. 18. 21. 23. 25. 22. 26.  0. 30.  1. 27. 29. 28. 39. 35. nan 31.]
Home Team Shots on Target (Unique Values) :  : [11.  2.  9. 13. 18.  6.  7.
4. 10. 16.  5. 12.  8. 14.  3. 15. 17.  1.
  0. 19. 21. 20. 24. nan]
Away Team Shots on Target (Unique Values) :  : [ 2. 12.  7.  4.  6.  3.  1.
8.  9.  5. 10. 11.  0. 14. 13. 20. 16. 18.
 17. 19. 15. nan]
Home Team Fouls Committed (Unique Values) :  : [15. 19. 12. 10. 13.  8. 17.
9. 18. 16. 11.  7.  5.  6. 20. 14.  3. 21.
  4. 23.  2. 22. 24. 25. 31. 30. 29. 26. 27. 28. 33.  1. nan 32.]
Away Team Fouls Committed (Unique Values) :  : [15. 14. 13. 10. 16. 11.  5.
3.  4. 12. 18.  7.  6. 17.  8.  9. 21. 19.
  2. 20. 24.  1. 22. 23. 26. 27. 28. 25. 30. 29.  0. nan 32. 31.]
Home Team Corners (Unique Values) :  : [16.  1.  4.  3. 10.  6.  5.  9.  8.
0.  7. 14. 11.  2. 15. 12. 17. 13.
 19. 18. 20. 21. nan 22.]
Away Team Corners (Unique Values) :  : [ 7.  3.  8.  1.  6.  4.  5. 11.  2. 1
2.  0. 16. 10.  9. 14. 13. 15. 17.
 19. nan 18.]
Home Team Yellow Cards (Unique Values) :  : [ 1.  2.  3.  0.  7.  4.  5.  6.
8. nan]
Away Team Yellow Cards (Unique Values) :  : [ 2.  1.  3.  0.  4.  6.  5.  7.
8.  9. nan]
Home Team Red Cards (Unique Values) :  : [ 0.  1.  2.  3. nan]
Away Team Red Cards (Unique Values) :  : [ 0.  1.  2.  3. nan]
```

Clearly there are rows with missing data. Let's get a count of rows with missing information for each column



So we have a few rows with null values for certain columns

Lets try populating the null values now

We can assume that Half Time Results/Goals were in line with Full Time results/goals whenever Half Time data is empty So Half Time Goals = Full Time Goals/2

When data is missing we can assume that total no of shots/shots on target is same as the number of goals

Fouls committed, corners and red/yellow cards missing data can be populated based on average number of fouls committed/red or yellow cards in other matches involving these teams

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
23/09/12	Cagliari	Roma	0	3	
18/09/11	Lyon	Marseille	2	0	
17/12/11	Caen	Nancy	1	2	
16/04/17	Bastia	Lyon	0	3	

So, foul information is missing for the following matches :

1. Lyon vs Marseille
2. Caen vs Nancy
3. Bastia vs Lyon
4. Cagliary vs Roma
   We can use other matches involving these teams to populate the missing data

Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
23/09/12	Cagliari	Roma	0	3	
02/03/15	Roma	Juventus	1	1	
16/04/17	Bastia	Lyon	0	3	

Card information is missing for the following matches :

1. Cagliary vs Roma
2. Roma vs Juventus
3. Bastia vs Lyon

We can use other matches involving these teams to populate the missing data

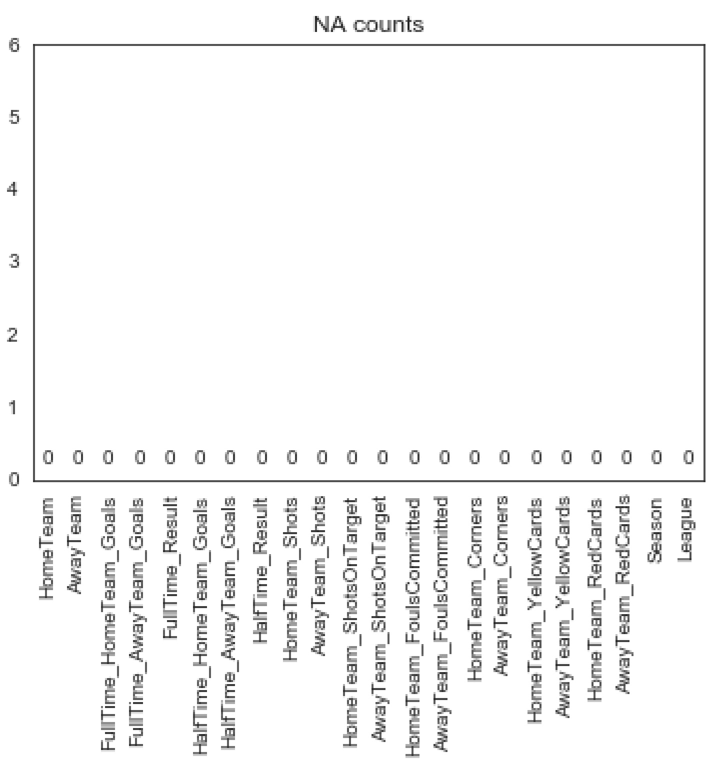
Date	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime
23/09/12	Cagliari	Roma	0	3	
16/04/17	Bastia	Lyon	0	3	

Corner information is missing for the following matches :

1. Cagliary vs Roma
2. Bastia vs Lyon

We can use other matches involving these teams to populate the missing data

Now there should not be any row/column with null values



As expected, there are no null values now. All the null values have been cleaned up

Feature Engineering

Now lets add the following extra columns :

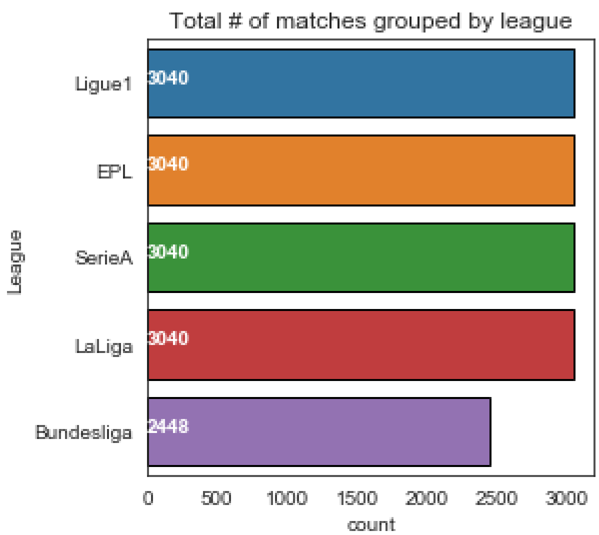
1. Winner : if FullTime_Result = 'H', then its Home Team. if FullTime_Result = 'A', then its Away Team. Else its null (implying draw)
2. Loser : if FullTime_Result = 'H', then its Home Team. if FullTime_Result = 'A', then its Away Team. Else its null (implying draw)
3. Total Cards (Home Team) : Home Team Yellow Cards + Home Team Red Cards
4. Total Cards (Away Team) : Away Team Yellow Cards + Away Team Red Cards
5. Percentage of Shots on Target (Home team): Home team shots on Target/Home team shots
6. Percentage of Shots on Target (Away team): Away team shots on Target/Away team shots
7. Home Team Goal saves = Away team shots on target - Full Time Away Team Goals
8. Away Team Goal saves = Home team shots on target - Full Time Home Team Goals
9. Total Goals = Full Time Home Team Goals + Full Time Away Team Goals
10. Total Cards = Total Cards (Home Team) + Total Cards(Away Team)

Let's look at the structure of our dataframe now

	HomeTeam	AwayTeam	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	FullTime_R
Date					
2010-08-14	Aston Villa	West Ham	3	0	
2010-08-14	Blackburn	Everton	1	0	

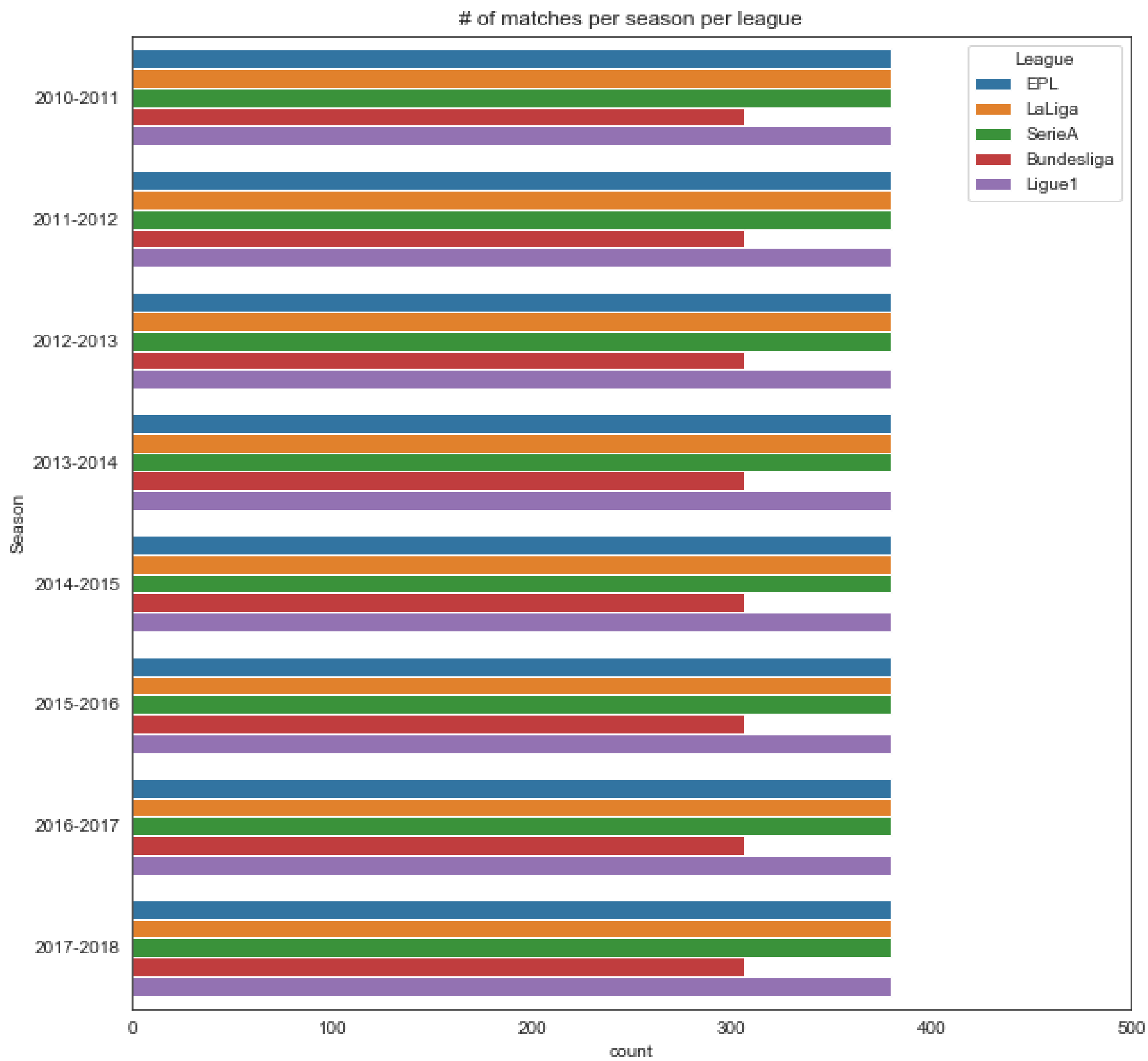
Lets have a look at the number of matches per season per league. If its not uniform, then we might need to adjust the aggregate data accordingly before comparing (We'll ignore the current season as not every league starts at the same time)

```
<Figure size 432x288 with 0 Axes>
```



Clearly Bundesliga has lesser number of matches as compared to other leagues. Lets see if number of matches per league varied across seasons

```
<Figure size 432x288 with 0 Axes>
```



So for a particular league, the number of matches per season has remained consistent over the years. So we can safely compare aggregate data for a league without adjusting (e.g total goals in EPL per season). However when we compare other league aggregate data with Bundesliga, the data might need some adjustment.

Bundesliga has 18 teams and 306 games (34 games for each team) per season whereas other leagues have 20 teams and 380 games a season (38 games for each team)
Hence when we compare data across leagues, aggregate data (such as total/count etc) for Bundesliga has to be scaled up accordingly in order to do a fair comparison

Feature Analysis

So finaly we have the following features for analysis

```
HomeTeam
AwayTeam
FullTime_HomeTeam_Goals
FullTime_AwayTeam_Goals
FullTime_Result
HalfTime_HomeTeam_Goals
HalfTime_AwayTeam_Goals
HalfTime_Result
HomeTeam_Shots
AwayTeam_Shots
HomeTeam_ShotsOnTarget
AwayTeam_ShotsOnTarget
HomeTeam_FoulsCommitted
AwayTeam_FoulsCommitted
HomeTeam_Corners
AwayTeam_Corners
HomeTeam_YellowCards
AwayTeam_YellowCards
HomeTeam_RedCards
AwayTeam_RedCards
Season
League
Winner
Loser
TotalGoals
HomeTeam_TotalCards
AwayTeam_TotalCards
TotalCards
HomeTeam_ShotsOnTarget_Percent
AwayTeam_ShotsOnTarget_Percent
HomeTeam_GoalSaves
AwayTeam_GoalSaves
```

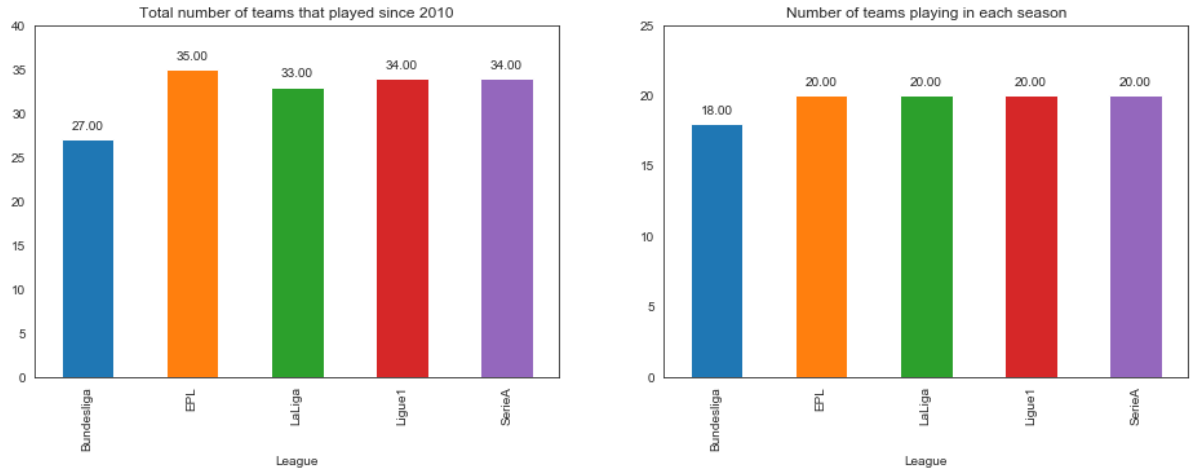
a) Home Team/Away Team : Contains the name of the home team/away team for a particular game

In every season, a team plays two games - one as home team another as away team. So the total number of unique values for HomeTeam and AwayTeam column should be identical

```
Home Team unique values # 163
Away Team unique values # 163
```

Let's look at the total number of teams per league as well as the average number of teams per season

```
<Figure size 432x288 with 0 Axes>
```

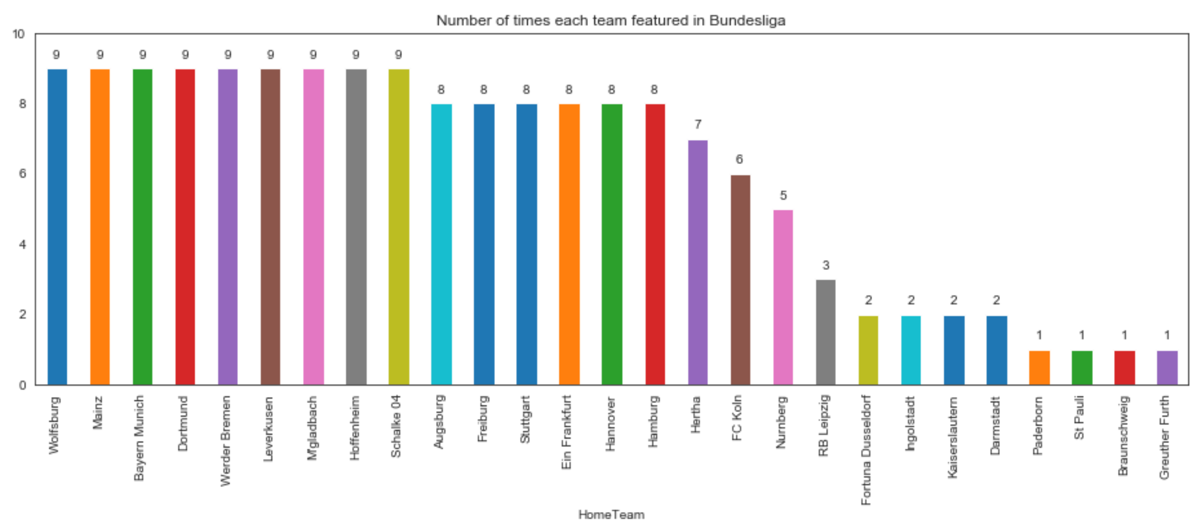


The difference between the two numbers indicates that there were occasions where teams were relegated to lower tier league or top teams from lower tier leagues were promoted

Let's look at the number of seasons each team featured in the league :

A. Bundesliga:

```
<Figure size 432x288 with 0 Axes>
```



The teams that have never been relegated from Bundesliga are :

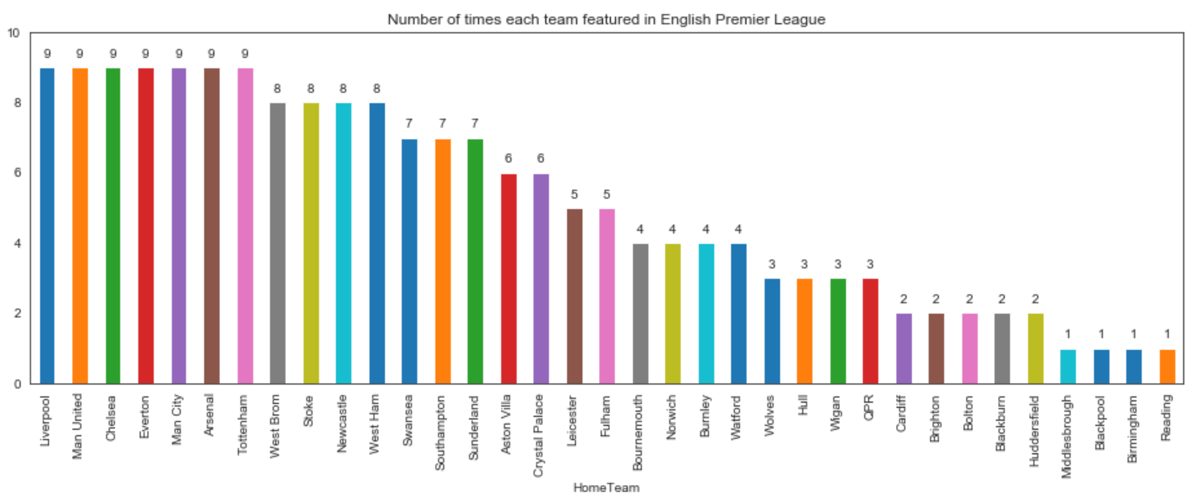
```
1. Wolfsburg
2. Mainz
3. Bayern Munich
4. Dortmund
5. Werder Bremen
6. Leverkusen
7. M'gladbach
8. Hoffenheim
9. Schalke04
```

Rest of the teams have been relegated at least once

9 out of 18 or 50 % of teams have remained consistent across last 9 seasons of Bundesliga

B. EPL

```
<Figure size 432x288 with 0 Axes>
```



Clearly the teams that have never been relegated from EPL are :

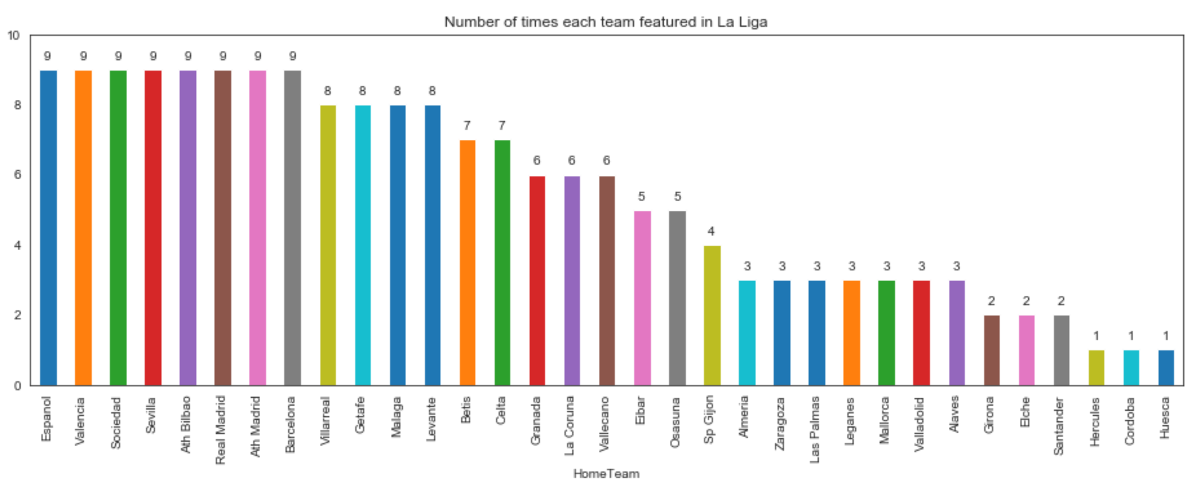
1. Liverpool
2. Man United
3. Chelsea
4. Everton
5. Man City
6. Arsenal
7. Tottenhum

Rest of the teams have been relegated at least once

7 out of 20 or 35 % of teams have remained consistent across last 9 seasons of EPL

C. La Liga

```
<Figure size 432x288 with 0 Axes>
```



Clearly the teams that have never been relegated from LaLiga are :

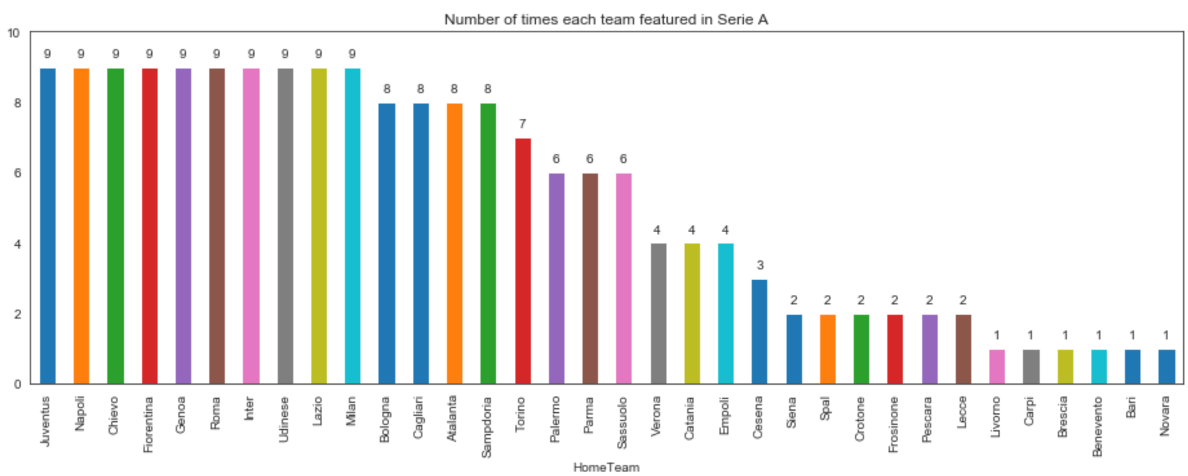
1. Espanol
2. Valencia
3. Sociedad
4. Sevilla
5. Ath Bilbao
6. Real Madrid
7. Ath Madrid
8. Barcelona

   Rest of the teams have been relegated at least once

8 out of 20 or 40 % of teams have remained consistent across last 9 seasons of La Liga

D. Serie A

```
<Figure size 432x288 with 0 Axes>
```



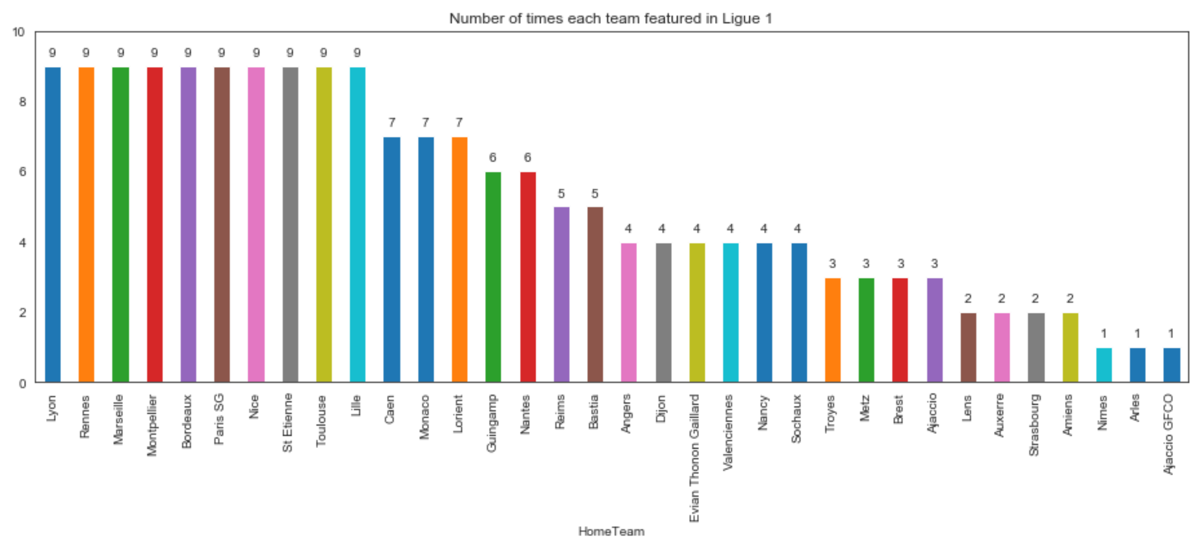
Clearly the teams that have never been relegated from Serie A are :

1. Juventus
2. Napoli
3. Chievo
4. Florentina
5. Genoa
6. Roma
7. Inter Milan
8. Udinese
9. Lazio
10. AC Milan

Rest of the teams have been relegated at least once
10 out of 20 or 50 % of teams have remained consistent across last 9 seasons of Serie A

E. Ligue 1

```
<Figure size 432x288 with 0 Axes>
```



Clearly the teams that have never been relegated from Ligue 1 are :

1. Lyon
2. Rennes
3. Marseille
4. Montpellier
5. Bordeaux
6. Paris SG
7. Nice
8. St Etienne
9. Toulouse
10. Lille

Rest of the teams have been relegated at least once
10 out of 20 or 50 % of teams have remained consistent across last 9 seasons of Serie A

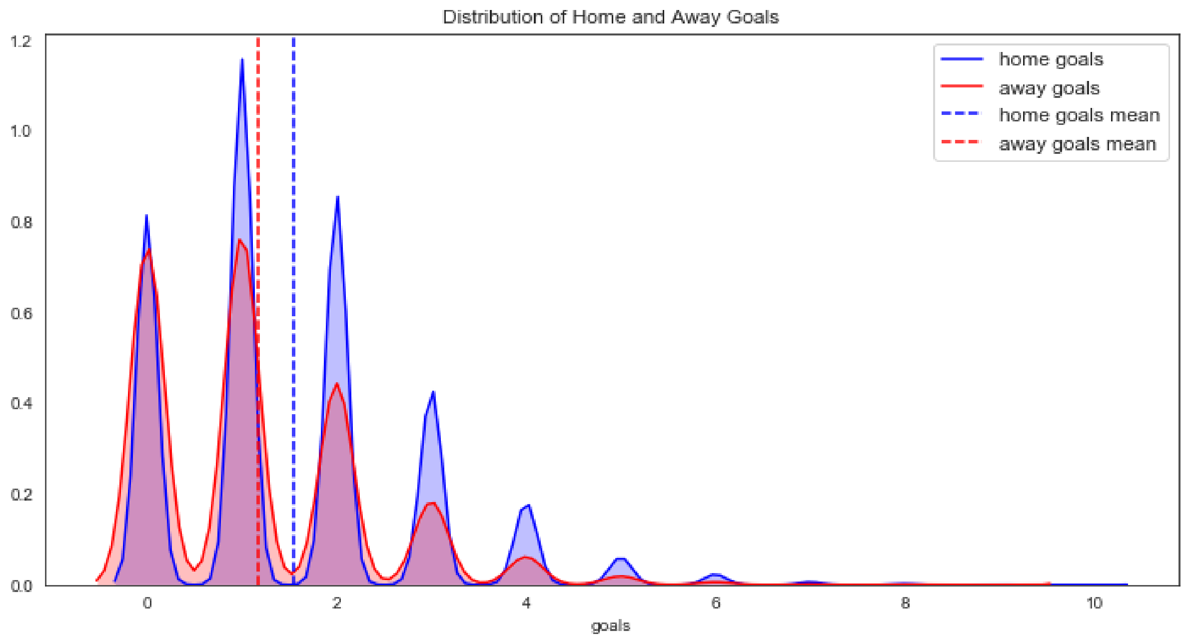
In terms of relegation, EPL has been the most volatile league over past 9 years. Only 35 % teams have been consistent. For other leagues, the percentage varies from 40 to 50 %

b. Full time Home/Away Team Goals/Total Goals : Indicates the number of goals scored by Home/Away team at the end of the match

Lets look at overall distribution of home and away goals first

```
C:\Users\ksaha\AppData\Local\Continuum\anaconda3\lib\site-packages\scipy\stat
s\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimension
al indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In th
e future this will be interpreted as an array index, `arr[np.array(seq)]`, wh
ich will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
<Figure size 432x288 with 0 Axes>
```

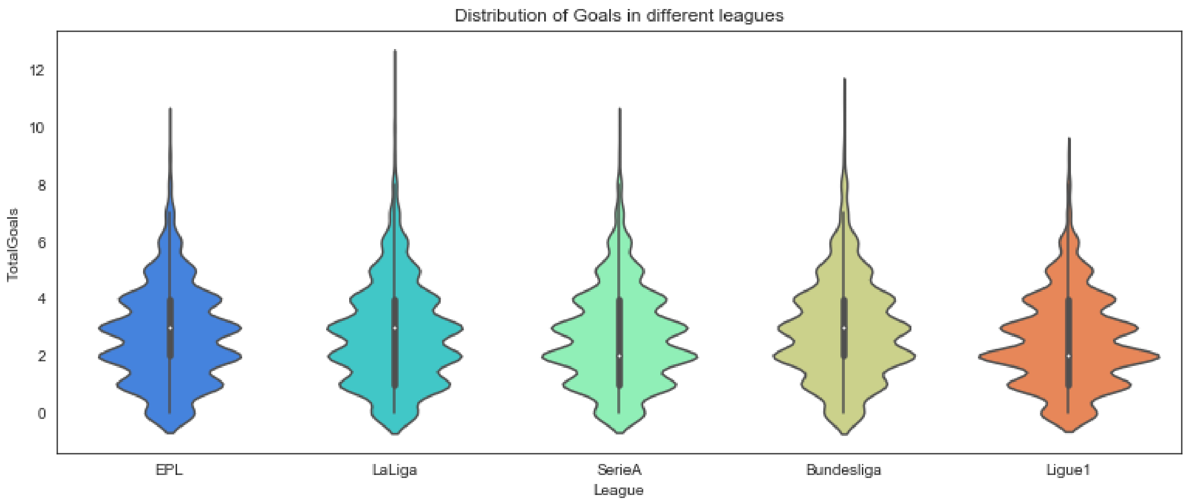


The mean value for home goals is higher than that of away goals. So there might be some home advantage.

Also lets take a look at how the distribution of total goals in a match varies across leagues

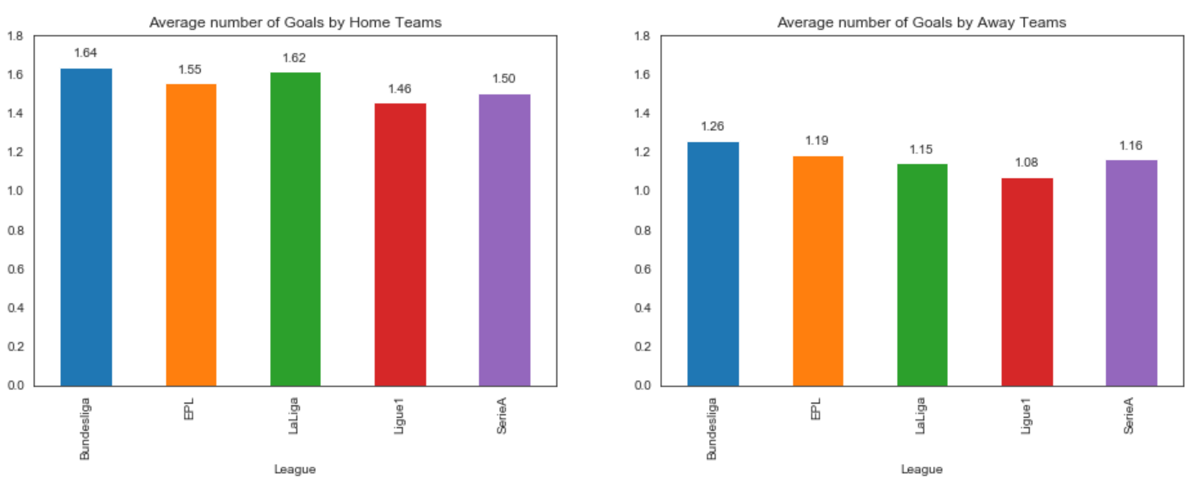
```
C:\Users\ksaha\AppData\Local\Continuum\anaconda3\lib\site-packages\scipy\stat
s\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimension
al indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In th
e future this will be interpreted as an array index, `arr[np.array(seq)]`, wh
ich will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
<Figure size 432x288 with 0 Axes>
```



Clearly for most of matches, the total number of goals varies between 1 and 4. It's quite rate to see more than 6 goals in a match in any league

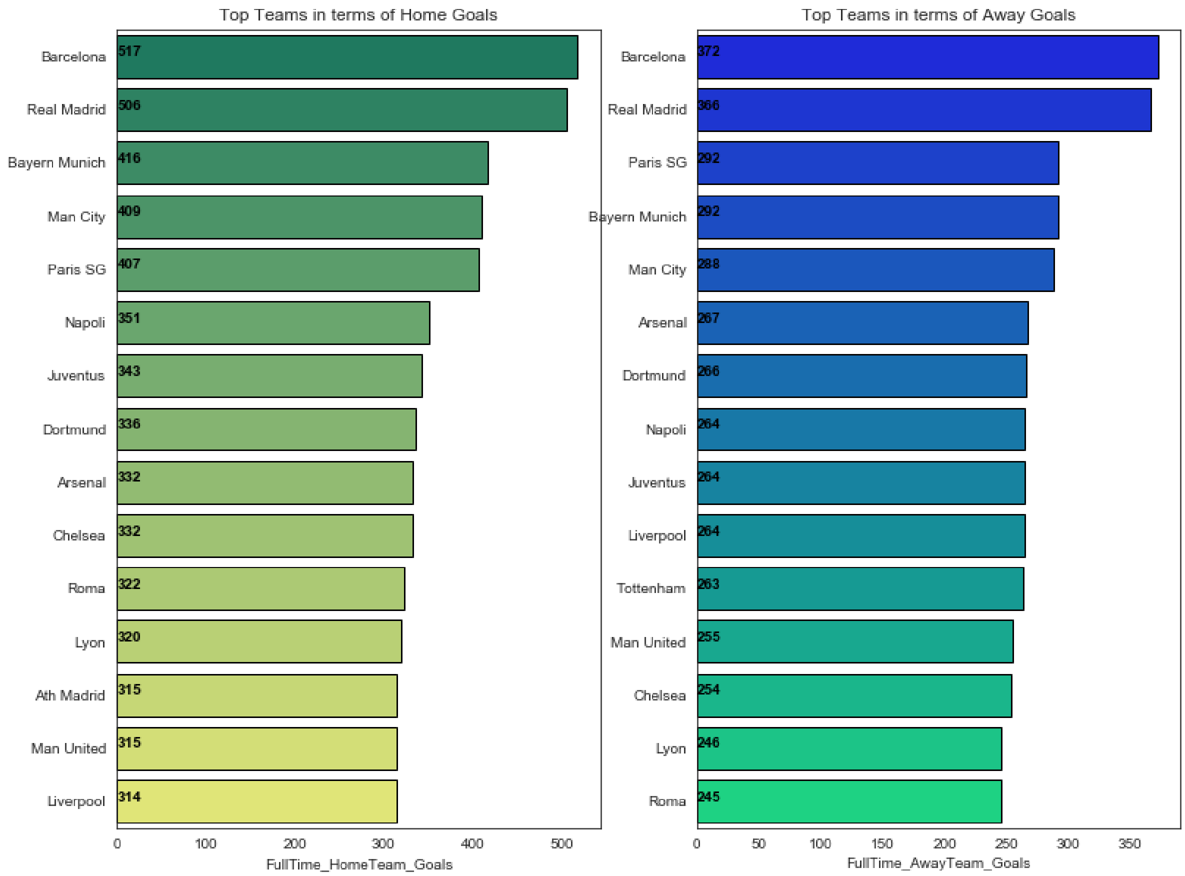
```
<Figure size 432x288 with 0 Axes>
```



Clearly in every league there's a significant home advantage

Lets look at the top teams in terms of number of home and away goals scored

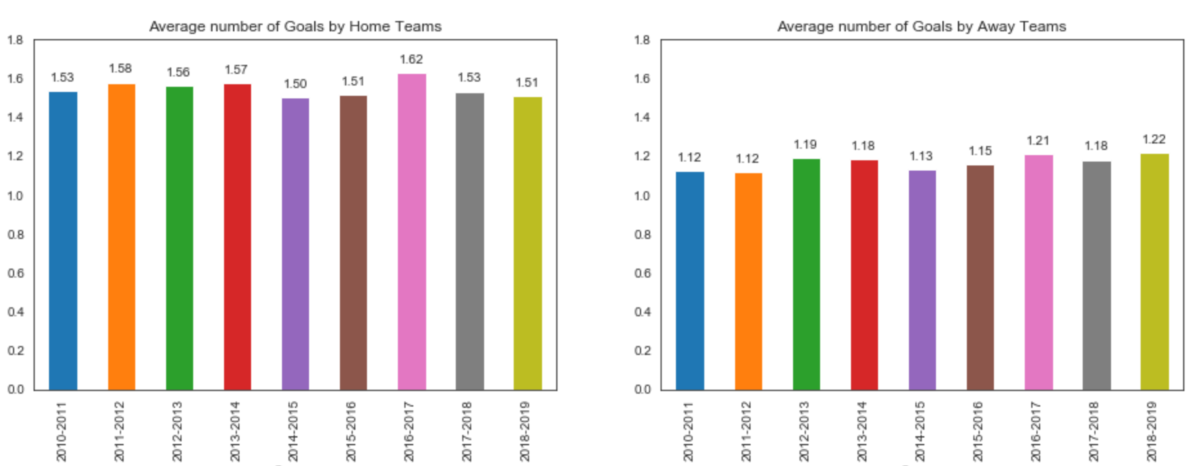
```
<Figure size 432x288 with 0 Axes>
```



These two lists have a lot of teams in common. This indicates that good teams usually do well at home as well as away (However they score better at home than at away).

Let's look at variation of goal data across last 9 seasons

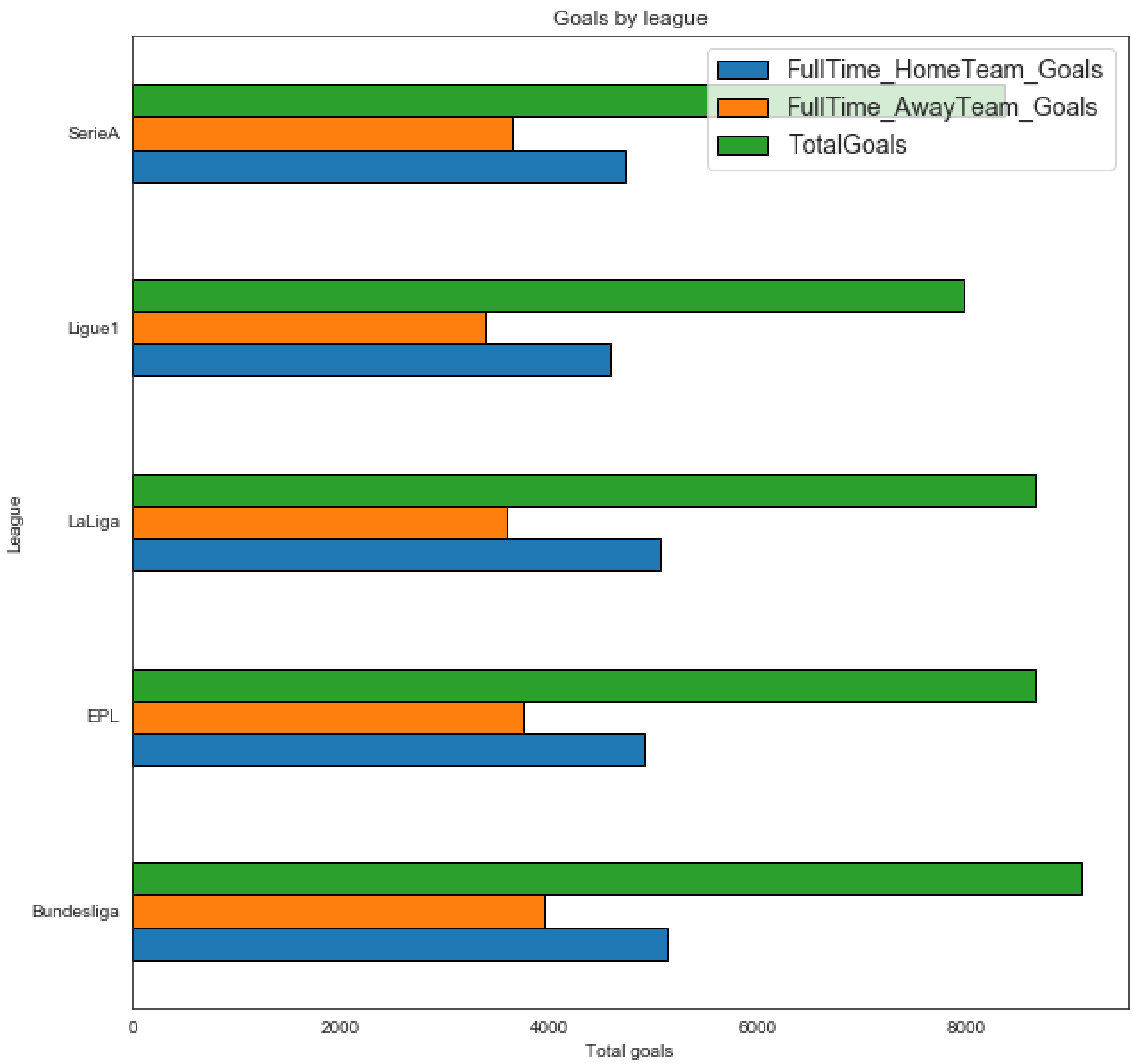
```
<Figure size 432x288 with 0 Axes>
```



In last 10 years, overall, away teams have improved (but only marginally) - from 1.12 goals per match to 1.22 goals per match

Lets look at the total number of goals as well. Let’s find out which league had the most goals. To make it a fair comparison we will adjust Bundesliga numbers (Bundesliga has 18 teams as opposed to 20 for other leagues)

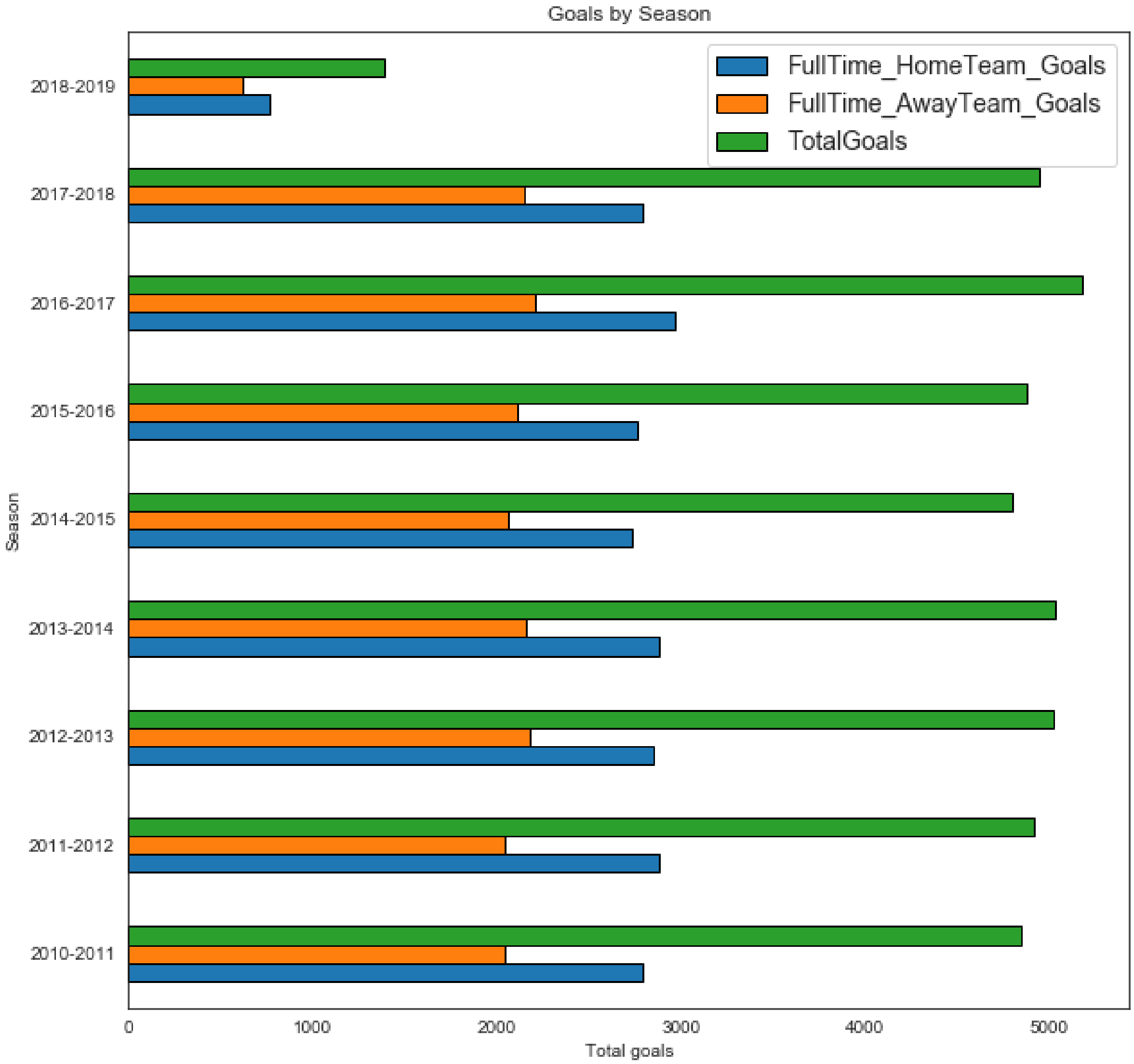
```
<Figure size 432x288 with 0 Axes>
```



Clearly Ligue One produces less goals as compared to other leagues. Post adjustment, Bundesliga produces more goals than anybody else.

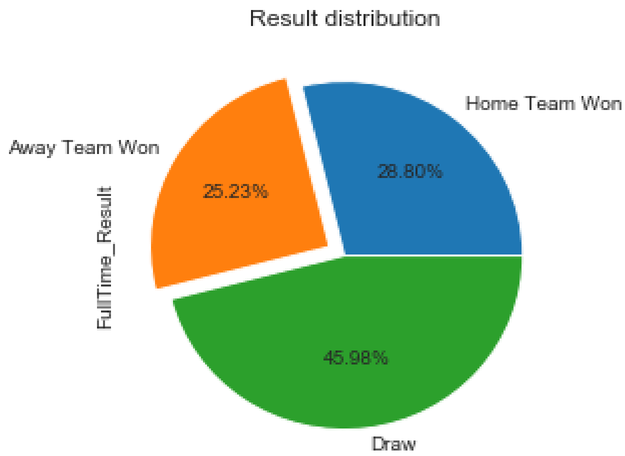
Lets look at the season-wise data as well.

```
<Figure size 432x288 with 0 Axes>
```



From 2010-11 to 2013-14, number of goals increased each season but stopped growing after 2013-14 season (except for a spike in 2016-17)

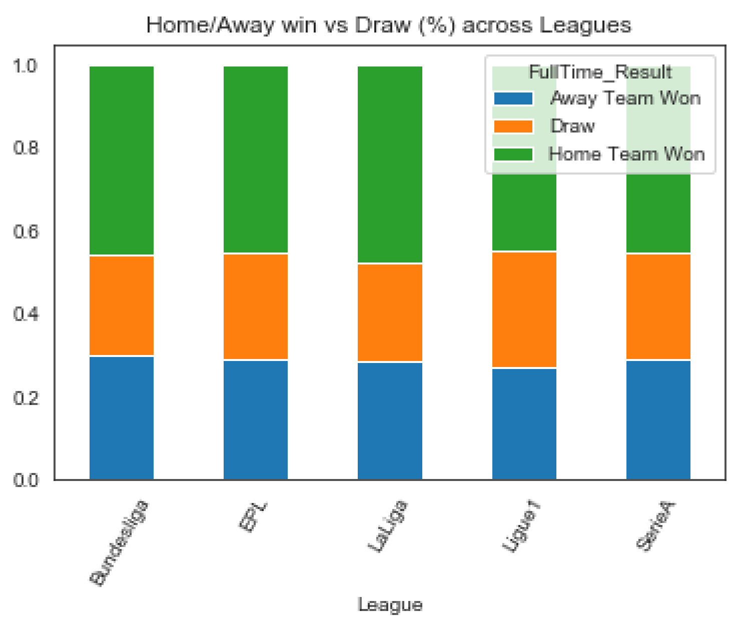
c. Full Time Result : Indicates whether Home or Away team won or if the match ended in a draw



Overall, home team wins nearly 46 % of matches

Lets look at distribution of match results in various league

```
<Figure size 432x288 with 0 Axes>
```



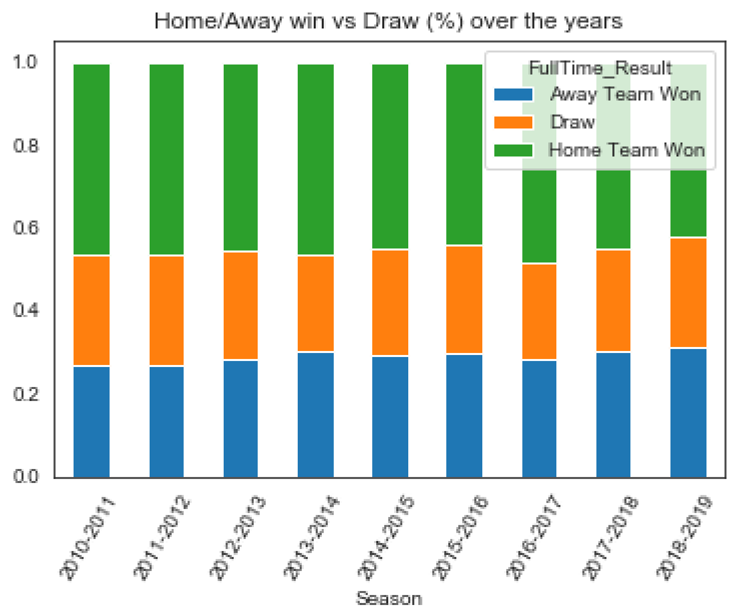
Home Team wins more than 40 % of matches in every league.

Home Advantage seems to be a bigger factor in La Liga as compared to other leagues

Ligue1 produces more draws than other leagues

Lets look at how the data changed over the years

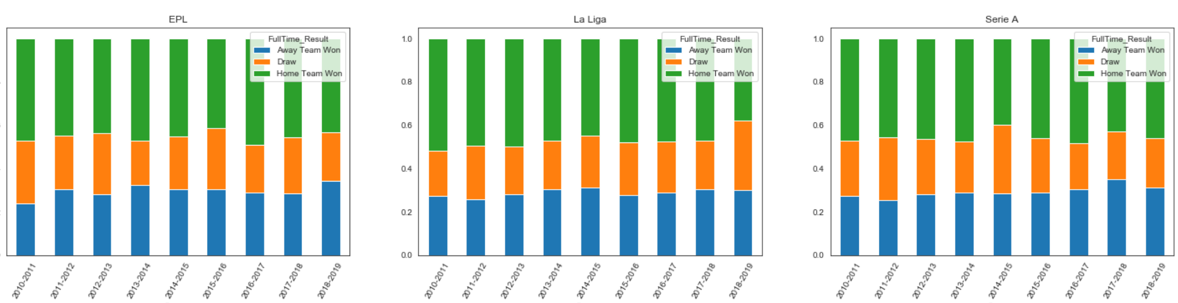
```
<Figure size 432x288 with 0 Axes>
```



There hasn't been any drastic change over the years - Home advantage has always been significant. Away performances have improved but only marginally

Lets look at how the data distribution varied from league-to-league over last 9 years

```
<Figure size 432x288 with 0 Axes>
```

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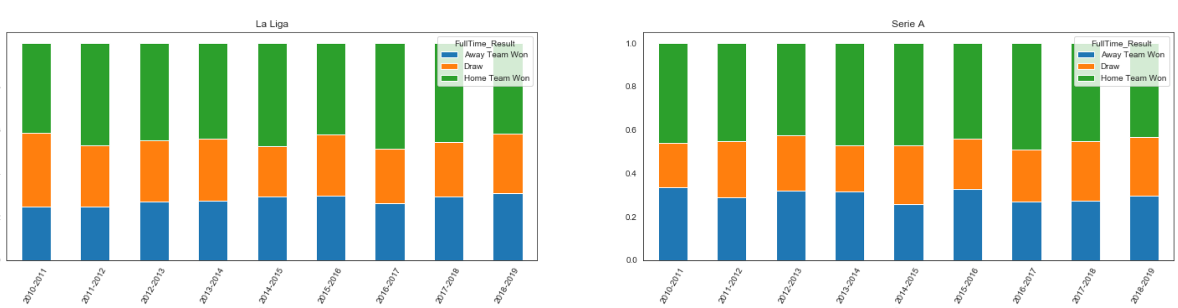

There is no league specific trend that emerged over the years. Home Advantage continues to be significant across leagues across seasons

d. Half Time Home/Away team goals : Indicates the number of Goals scored by Home/Away team at Half Time

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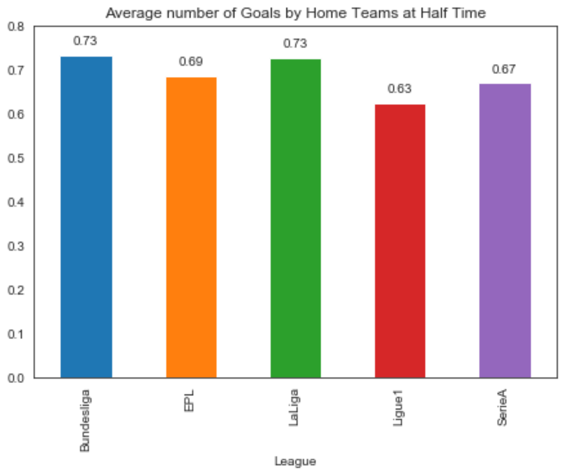

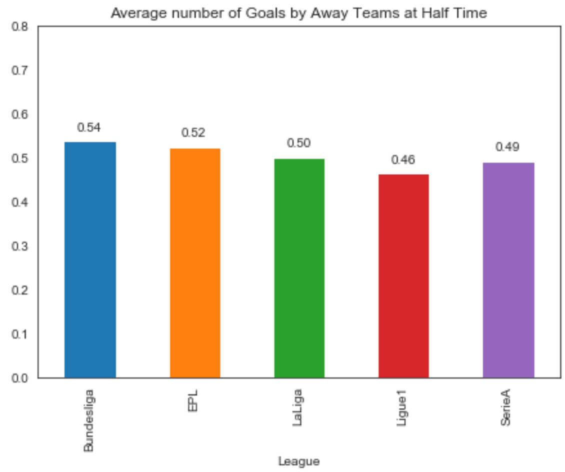

So Home Team typically dominates right from the beginning

If we look at the corresponding full time goal numbers :

Out[83]:

League	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	HalfTime_HomeTeam_Goals	H
Bundesliga	1.636220	1.260973	0.733887	
EPL	1.553165	1.186392	0.686392	
LaLiga	1.615287	1.145541	0.727707	
Ligue1	1.455556	1.075556	0.625079	
SerieA	1.504777	1.163057	0.671019	

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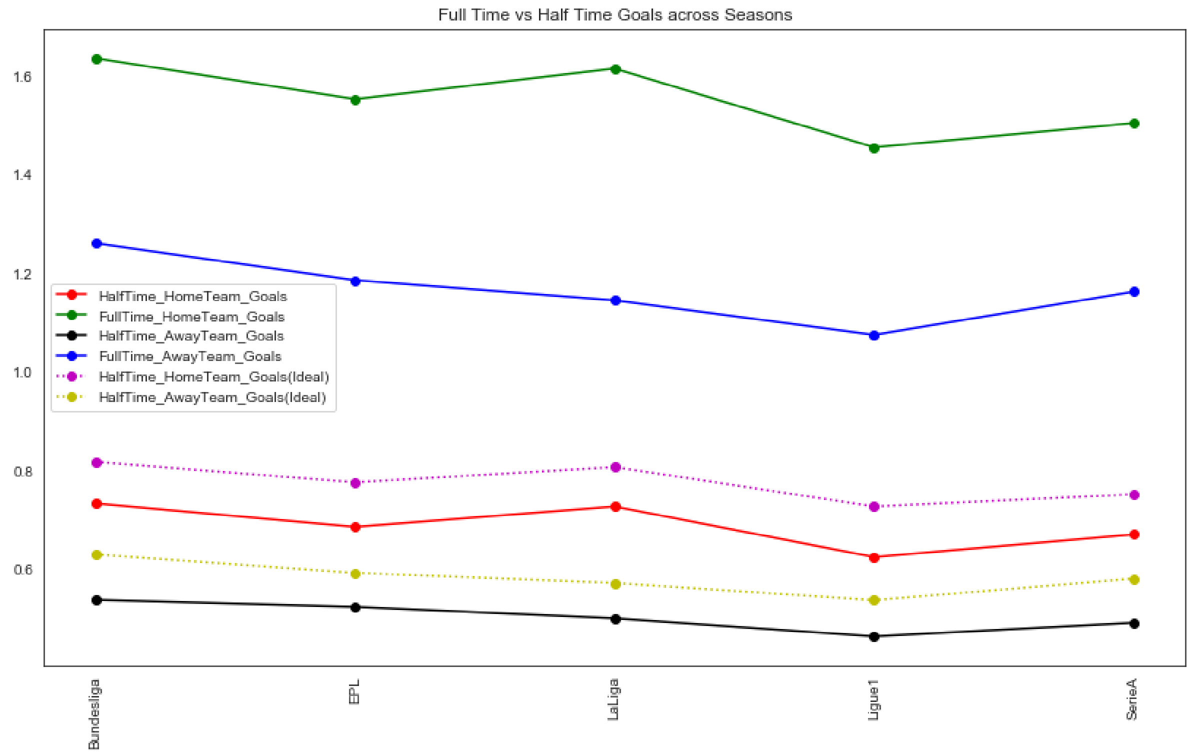

For Both Home and Away teams, Half Time goals is significantly less than full time goals/2

So both Home and Away teams are typically more aggressive and attack more during second half of the match

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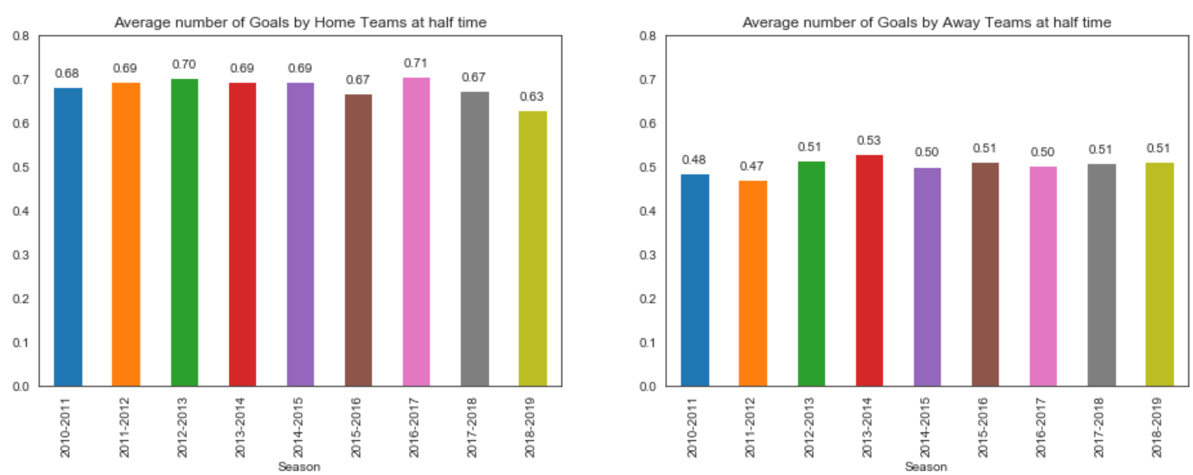

Data pattern remains almost uniform across years

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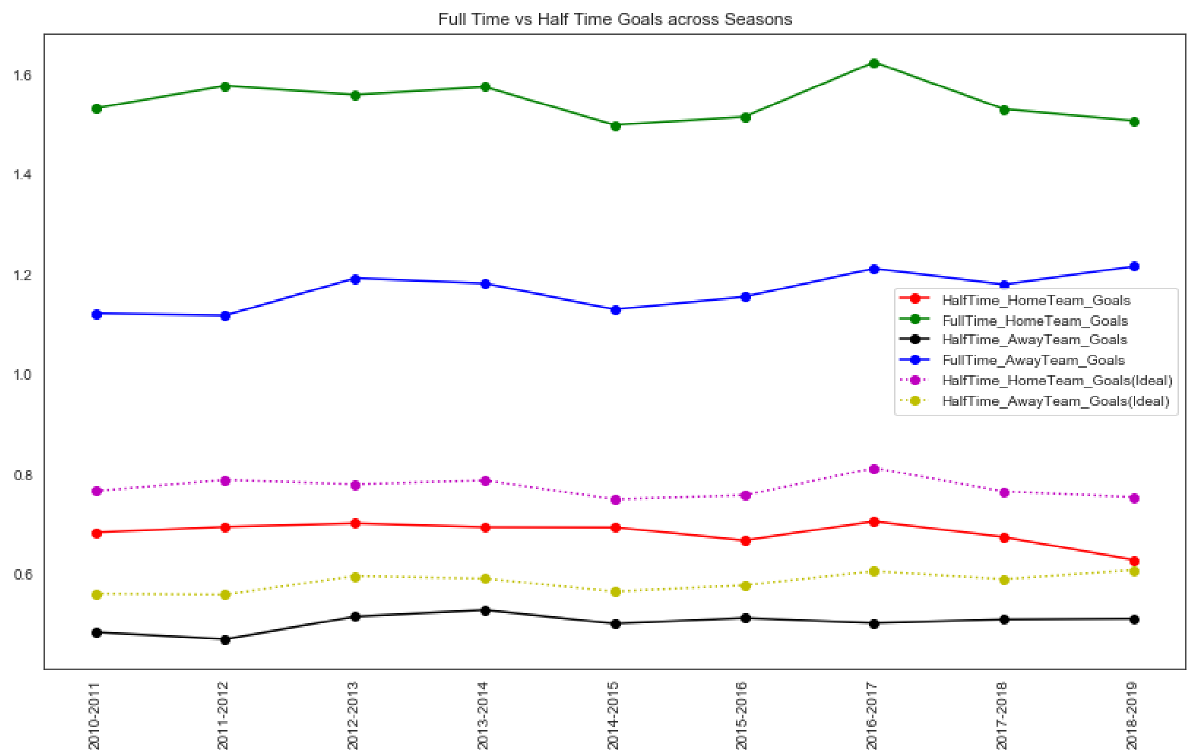
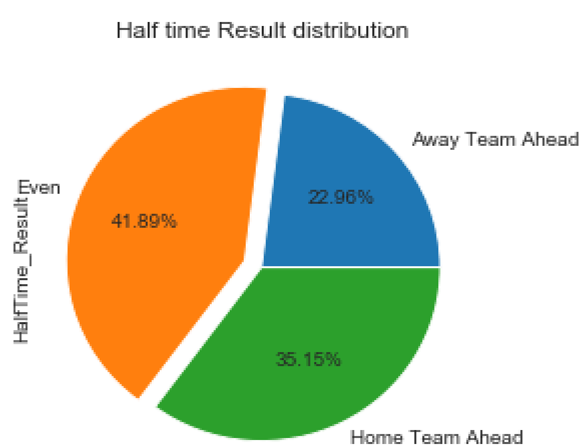


Over the years, both home and away teams have remained defensive during first half and more aggressive during second half

e. Half Time Result : Indicates whether Home or Away team was ahead at half time (or if both teams were tied at equal no of goals)

Lets look at overall distribution of data first



Home Team advantage falls but only by an insignificant margin. Let's look at how the data varied between different leagues

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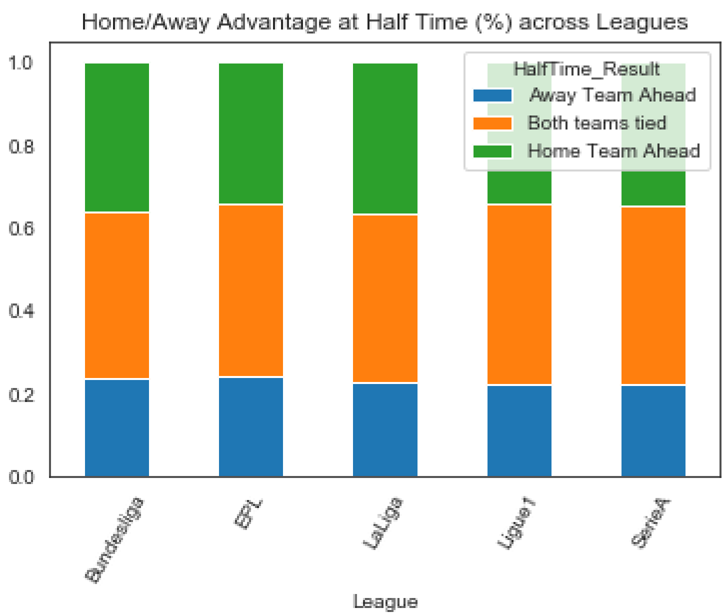

Home Team is ahead at half time in nearly 40 % of matches in every league. So home team dominates right from beginning

Lets look at the half time and full time data together

HalfTime_Result	A	D	H
League			
Bundesliga	0.237248	0.398577	0.364176
EPL	0.239557	0.417722	0.342722
LaLiga	0.228662	0.404777	0.366561
Ligue1	0.220952	0.438095	0.340952
SerieA	0.222930	0.431210	0.345860

FullTime_Result	A	D	H
League			
Bundesliga	0.298142	0.243575	0.458284
EPL	0.292405	0.253165	0.454430
LaLiga	0.287261	0.233439	0.479299
Ligue1	0.273016	0.276190	0.450794
SerieA	0.291083	0.253185	0.455732

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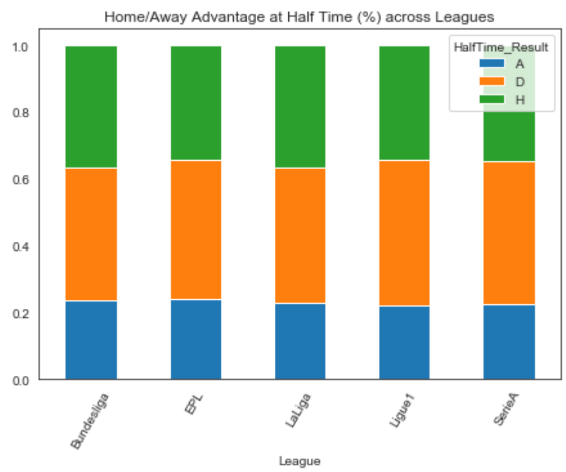

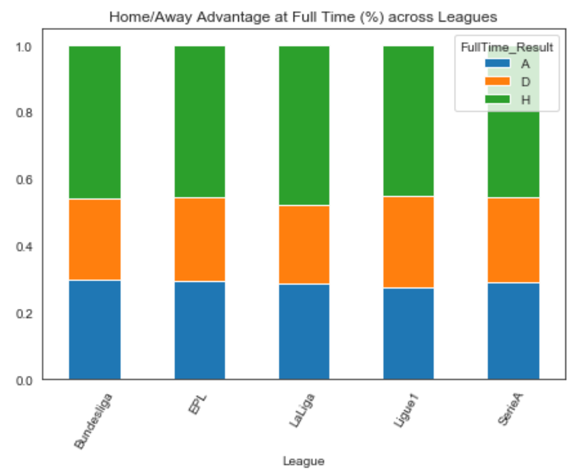

From the data the following points are clear :

1. Teams are more aggressive in second half and push for a result. Nearly 40 % of matches are tied at half time while only 23-26 % matches are tied at full time
2. Home Advantage is stronger in second half than in the first half

Lets look at how the data changed over the years

HalfTime_Result	A	D	H
Season			
2010-2011	0.224535	0.415663	0.359803
2011-2012	0.215772	0.427163	0.357065
2012-2013	0.223987	0.419496	0.356517
2013-2014	0.246988	0.403067	0.349945
2014-2015	0.216867	0.429901	0.353231
2015-2016	0.241512	0.422234	0.336254
2016-2017	0.225082	0.416210	0.358708
2017-2018	0.237130	0.416210	0.346659
2018-2019	0.246575	0.422701	0.330724

FullTime_Result	A	D	H
Season			
2010-2011	0.269989	0.262870	0.467141
2011-2012	0.268894	0.265608	0.465498
2012-2013	0.284775	0.259584	0.455641
2013-2014	0.300110	0.233297	0.466594
2014-2015	0.290800	0.259584	0.449617
2015-2016	0.297371	0.259036	0.443593
2016-2017	0.283133	0.230559	0.486309
2017-2018	0.301752	0.244797	0.453450
2018-2019	0.313112	0.262231	0.424658

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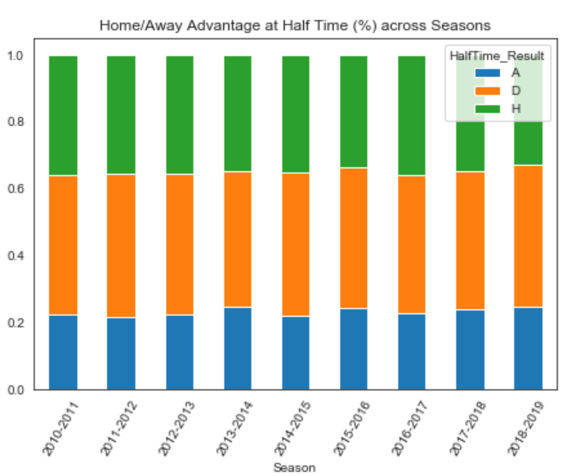

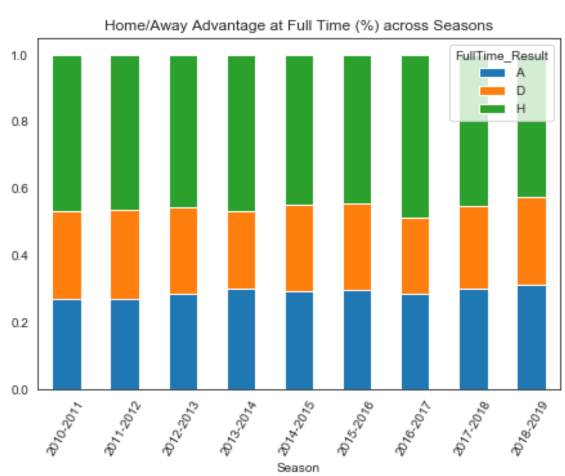

Lets calculate the correlation coefficient between half time and full time results

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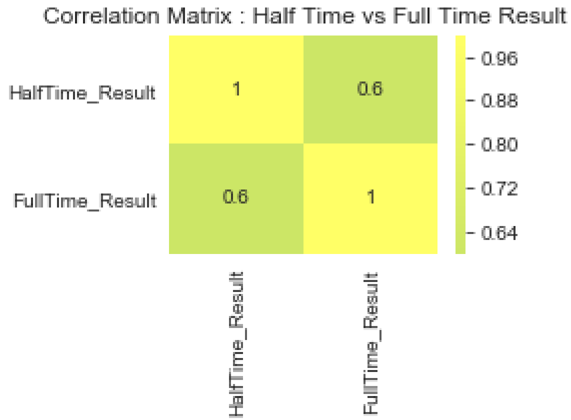

There is some coorelation between half time and full time results but not exactly a linear relationship

If we calculate correlation using Spearman approach instead of Pearson approach, we get similar numbers as well

```
0.5944584330392942

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s\stats.py:245: RuntimeWarning: The input array could not be properly checked
for nan values. nan values will be ignored.
  "values. nan values will be ignored.", RuntimeWarning)
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f. Home/Away Team Shots: This represents the number of shots at goal attempted by home or away team during a match

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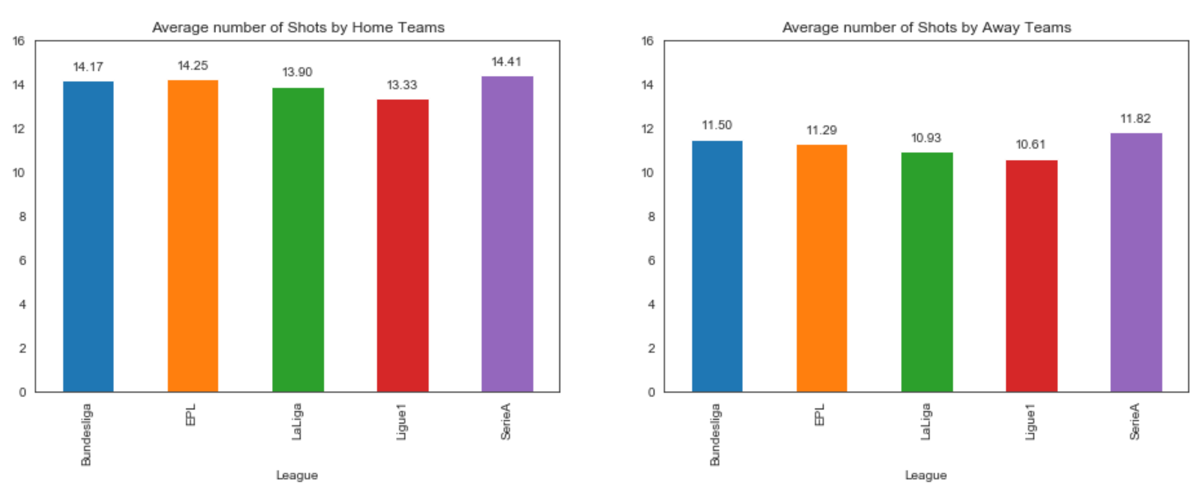

Home Teams are ahead here as well. Lets look at the trend over last 10 seasons

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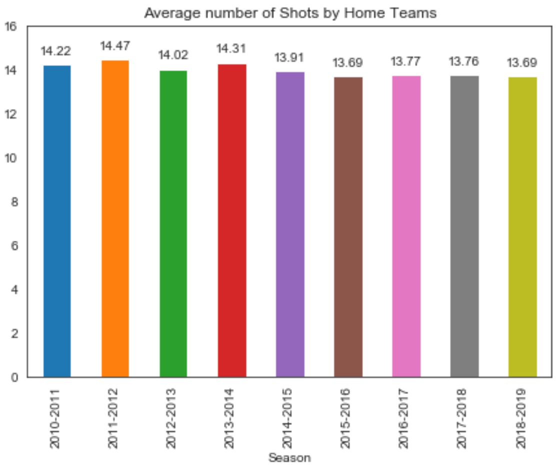

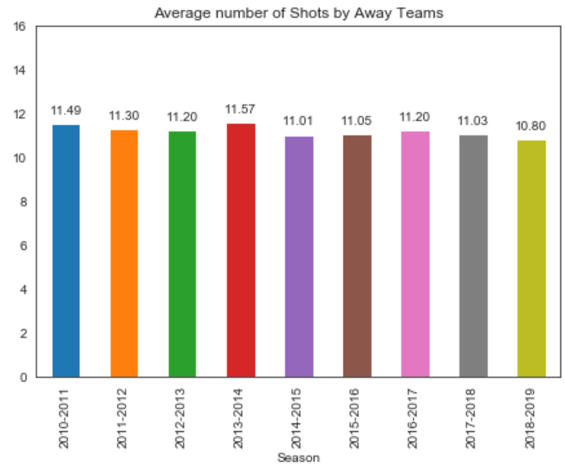

Lets look at the total number of shots as well. Total Number of shots = home team shots + away team shots

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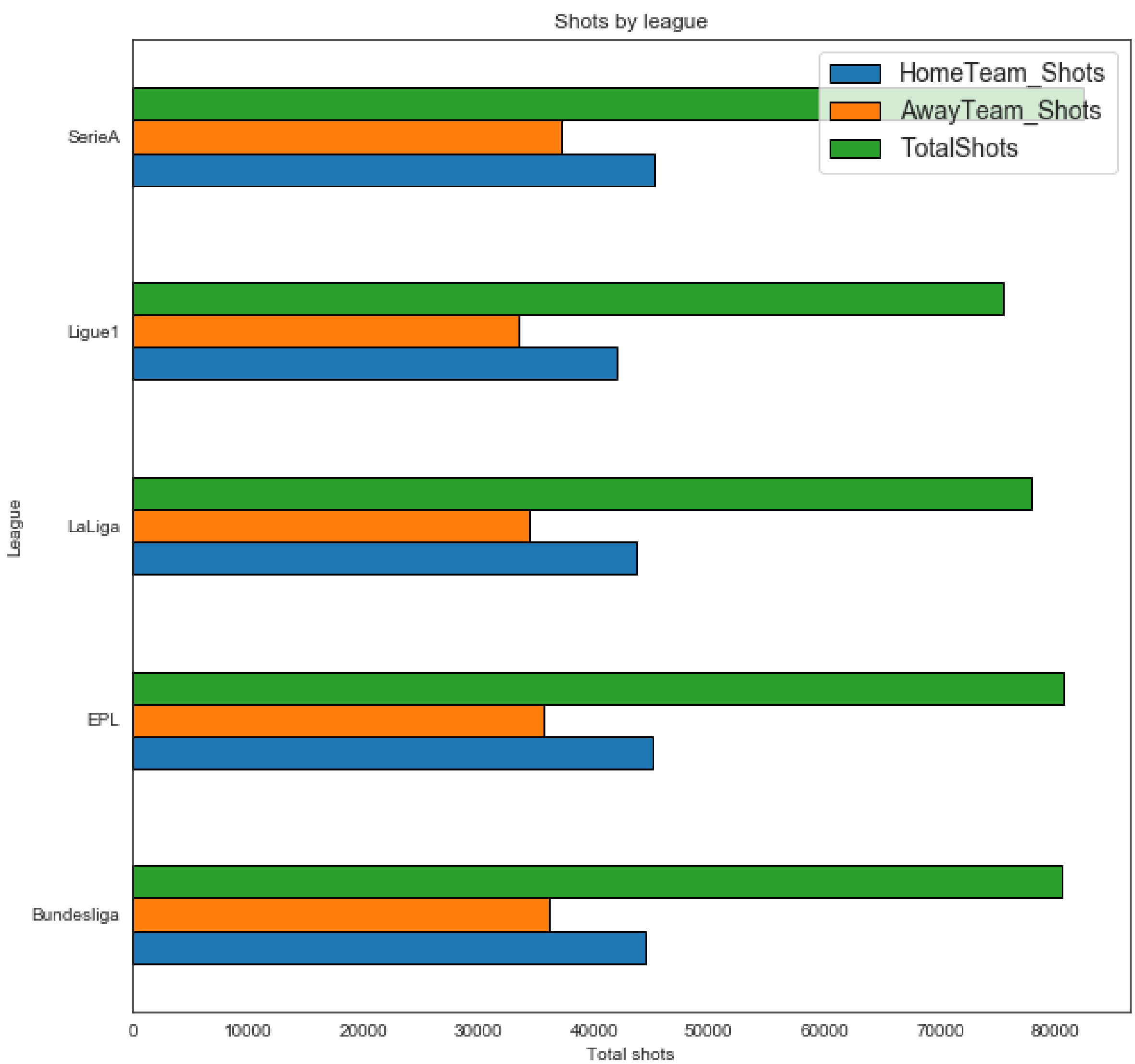

Serie A, Bundesliga (adjusted) and EPL has max number of shots at goal per season.

Interestingly, La Liga leads in number of goals per season but not at number of shots whereas it is other way round for Serie A

So, we can conclude that La Liga forwards are more accurate in general as compared to Serie A forwards

Now that we have both goal and shots data,. A good measure of accuracy will be number of attempts required to score a goal successfully we can take a look at accuracy

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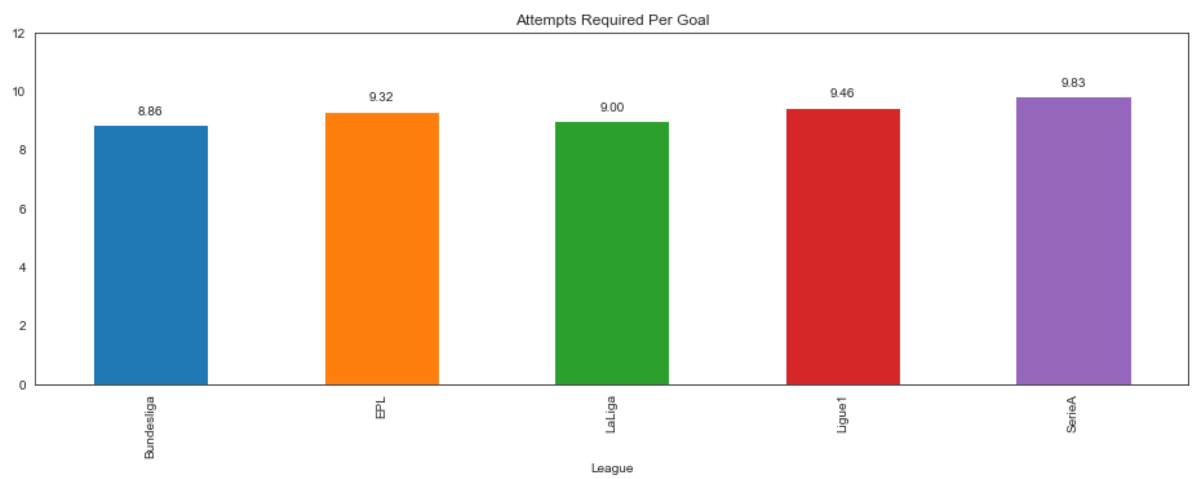

Forwards in Bundesliga and LaLiga are more accurate as compared to others. Forwards in SerieA are the least effective

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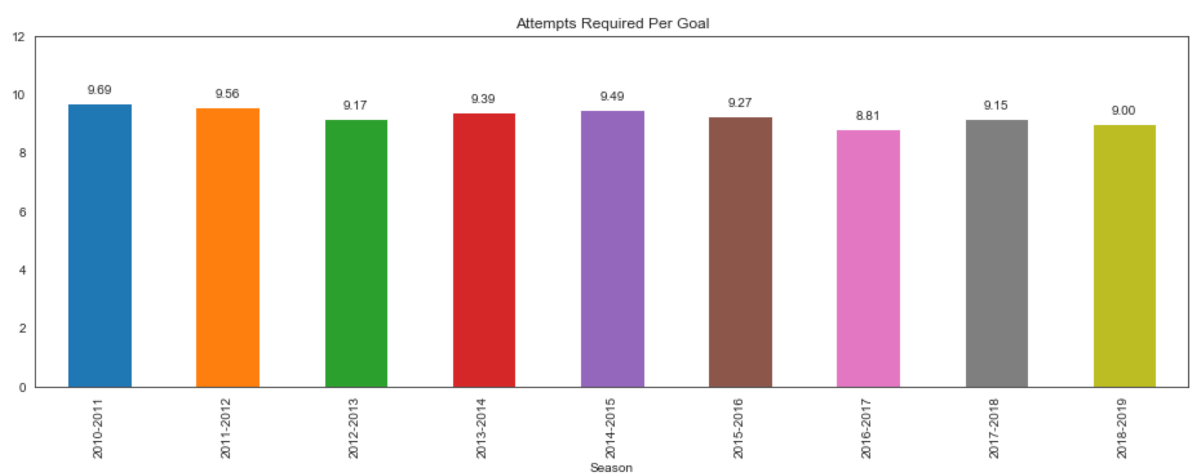

Over the years, forwards are getting more effective. But overall change is marginal

g. Home/Away team shots on target : This captures the number of shots on target (scored goals or hit the bar or saved by goal keeper)

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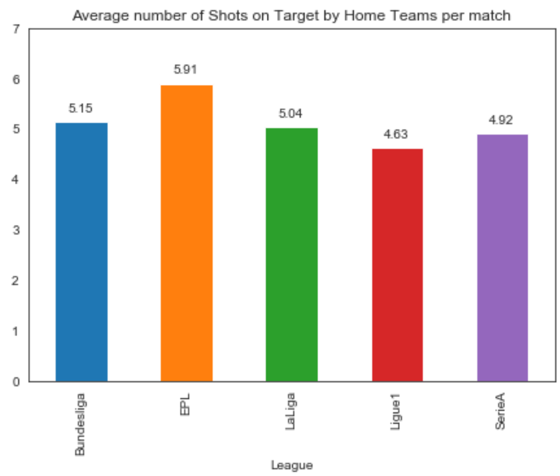

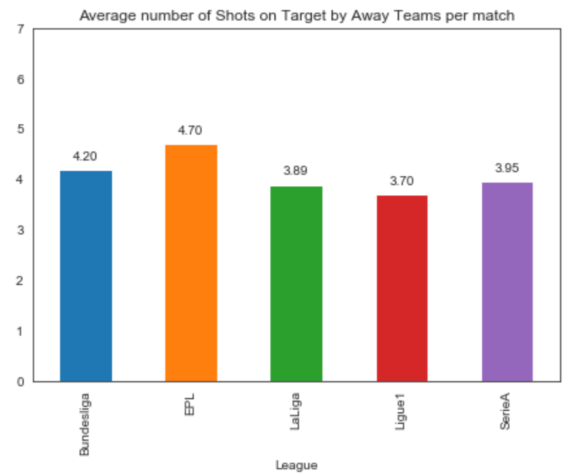

EPL has highest number of shots on target for both home and away team

Lets have a look at the Total number of shots on target as well. Total shots on target = Home team shots on target + Away team shots on target

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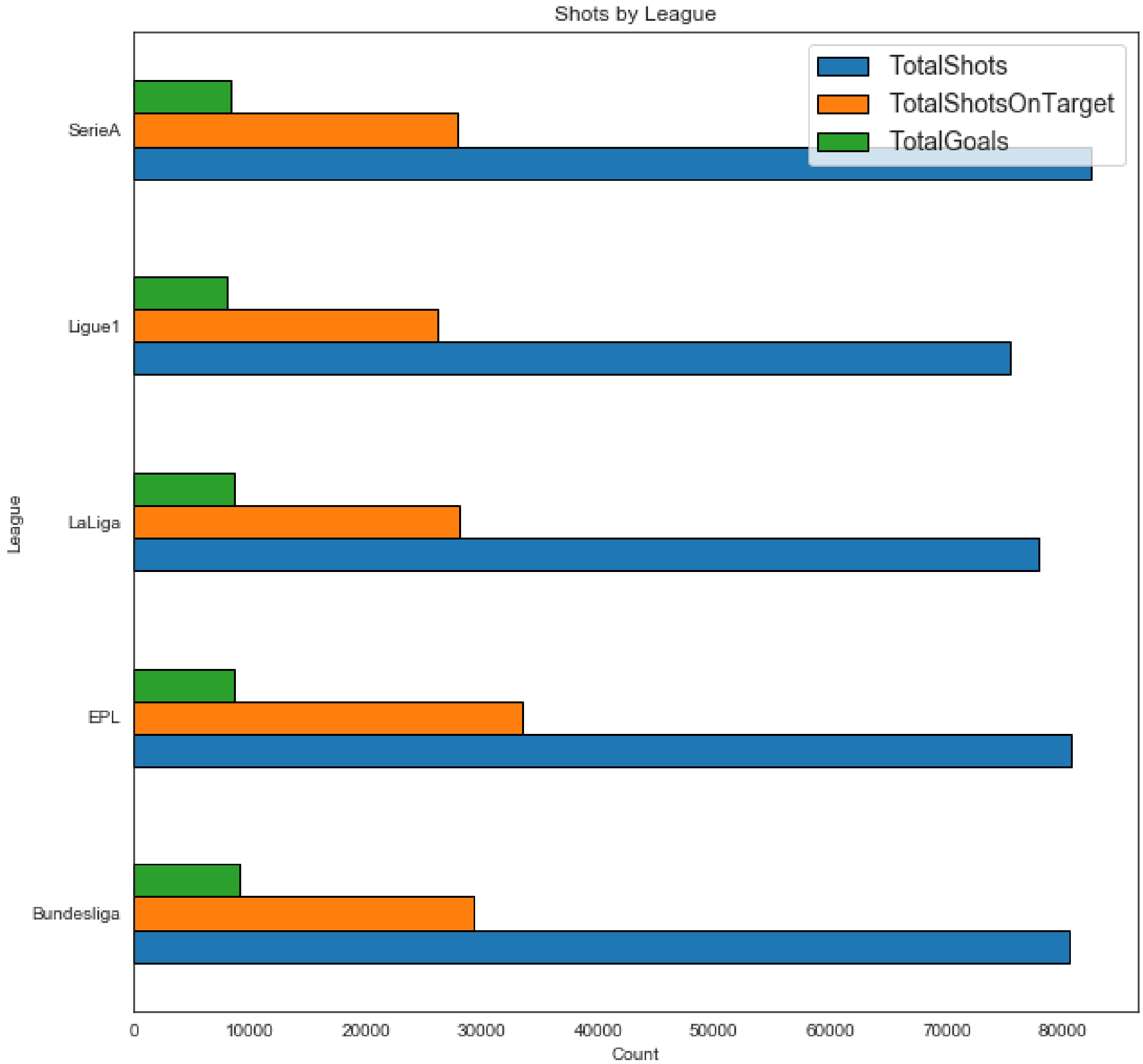

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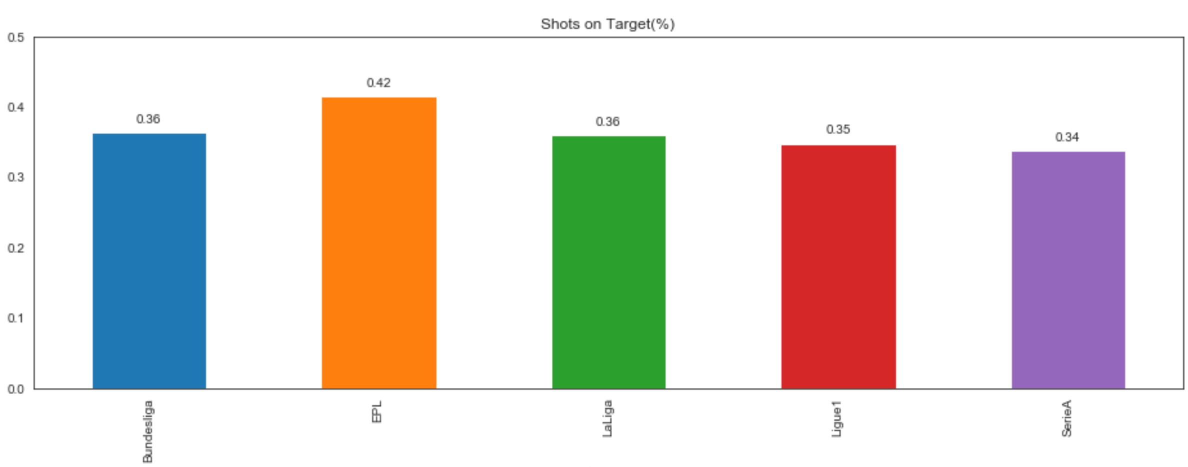

EPL forwards land the maximum proportion of shots on target

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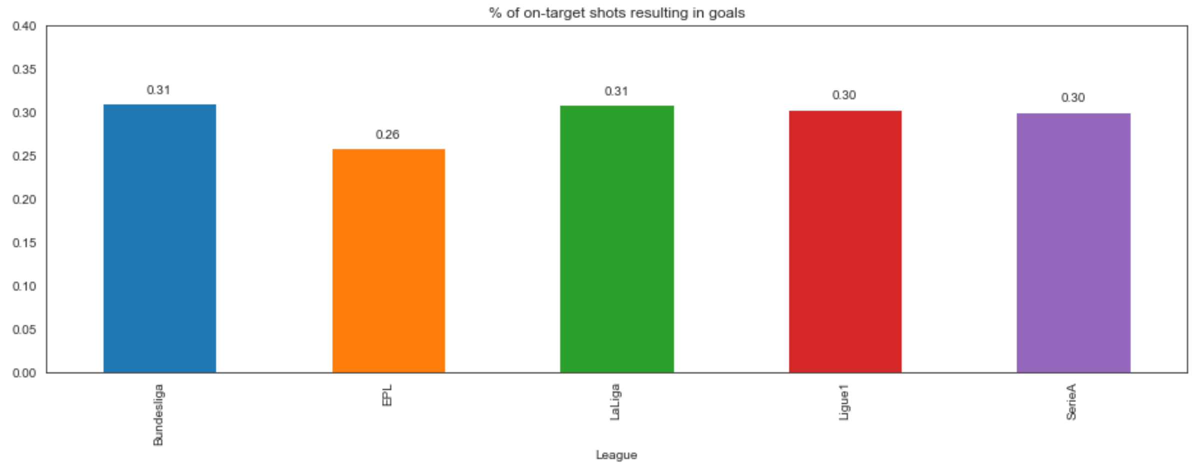

However, EPL ranks behind all other leagues in converting on target shots into goals

i. Home/Away team fouls committed : Number of fouls committed by Home or Away team in a game

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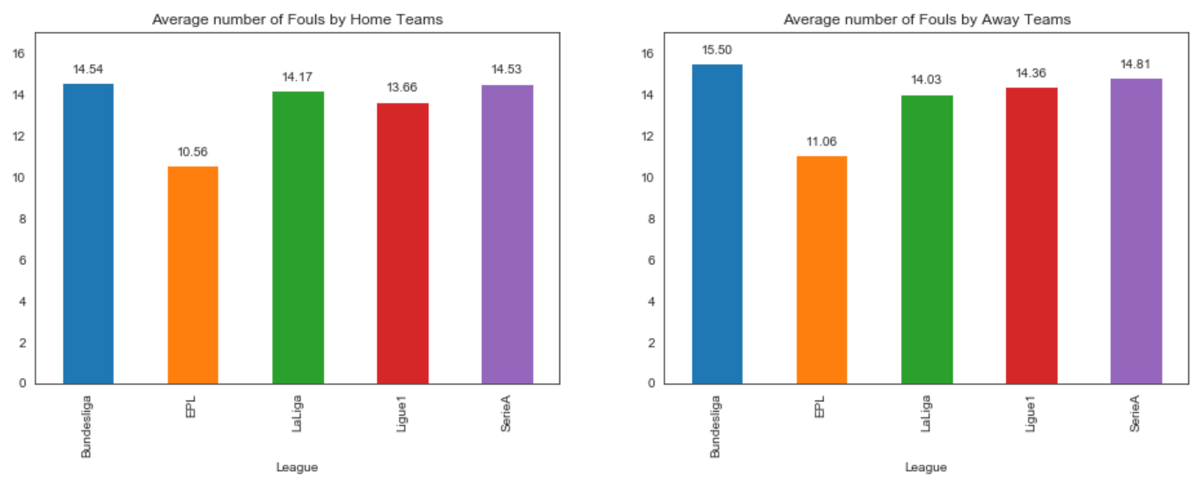

EPL clearly is the most disciplined league with least number of fouls by both Home and Away teams. Away Teams in Bundesliga commit the most number of fouls per match

Lets have a look at the Total number of fouls as well. Total number of fouls = sum of fouls committed by home and away team in a match

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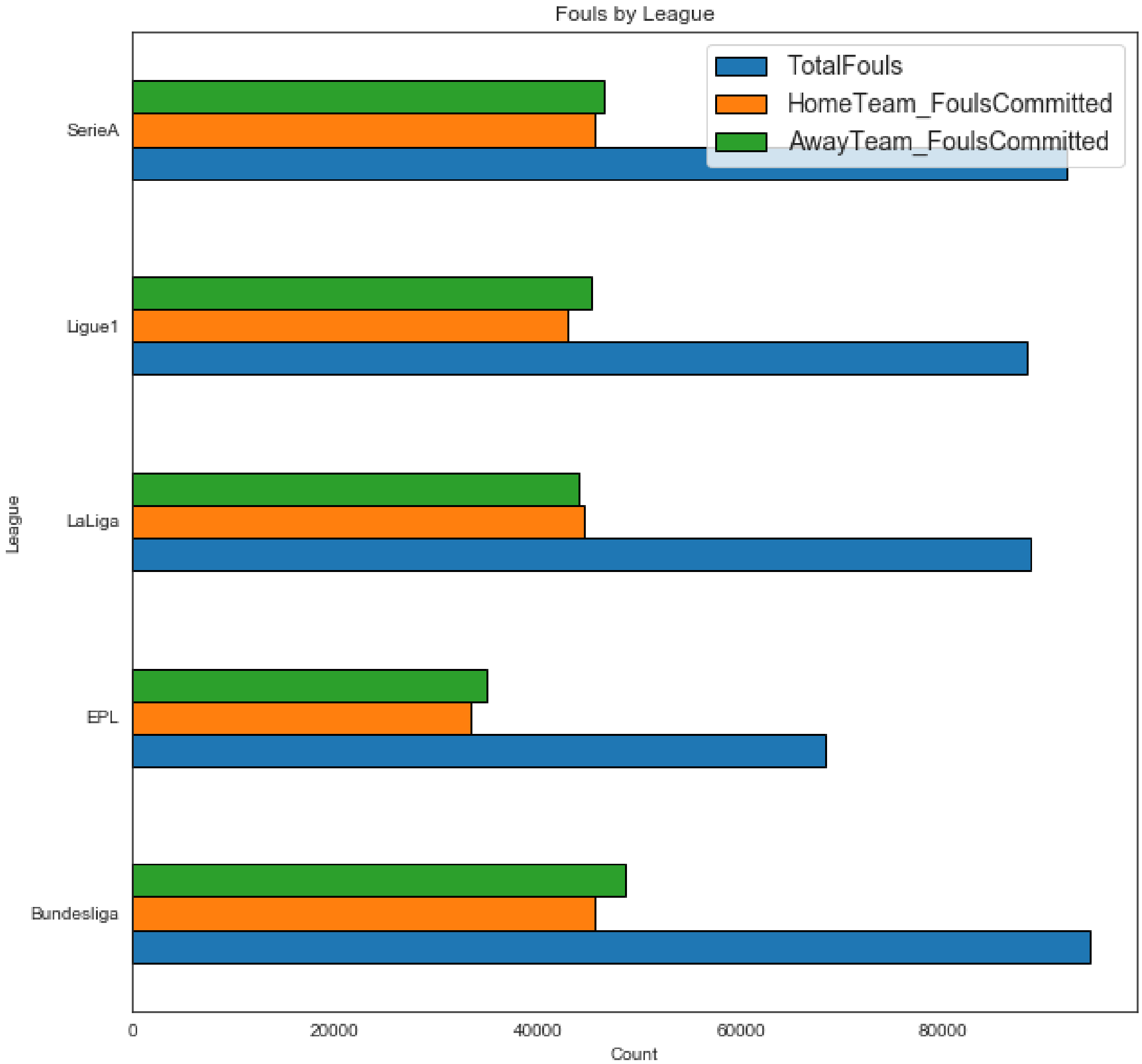

Clearly EPL has least number of fouls whereas Serie A and Bundesliga(adjusted) has very high number of fouls. Premier legaue is well known to have "fast paced" matches, which might explain the fewer number of fouls.

Lets look the seasonal trend in number of fouls

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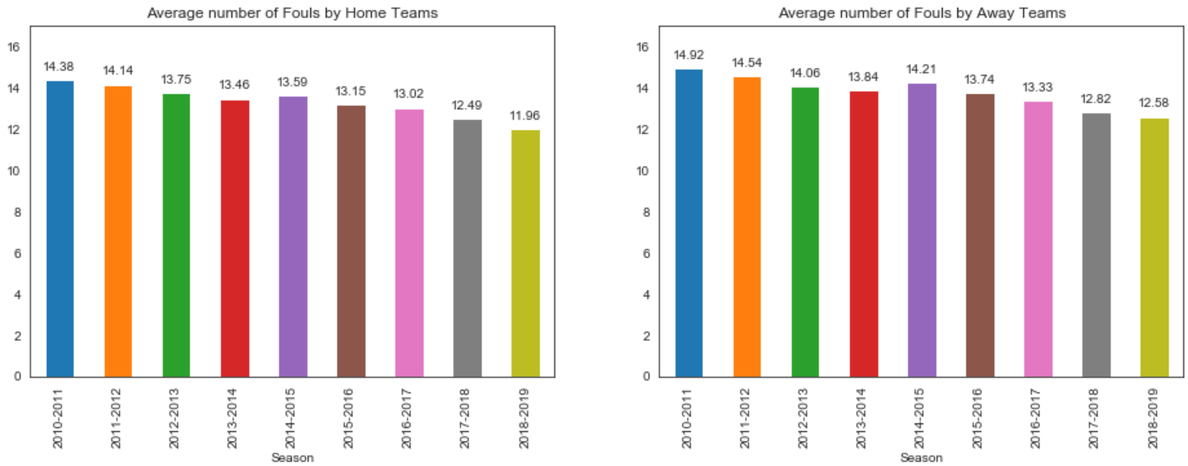

The number of fouls is on a steady decline over last 9 years

j. Home/Away Team Corners : Number of corner kicks awarded to home/away teams in every game

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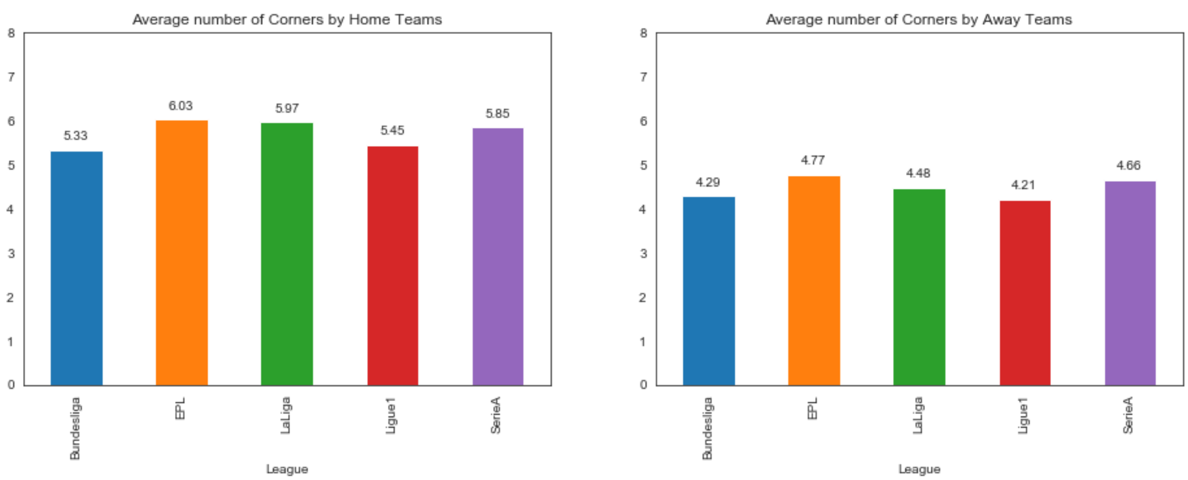

Interestingly, across all leagues, home team is awarded higher number of corner kicks compared to away team (Probably indicates that home team is usually more aggressive in approach)

Lets have a look at the Total number of corner kicks as well.

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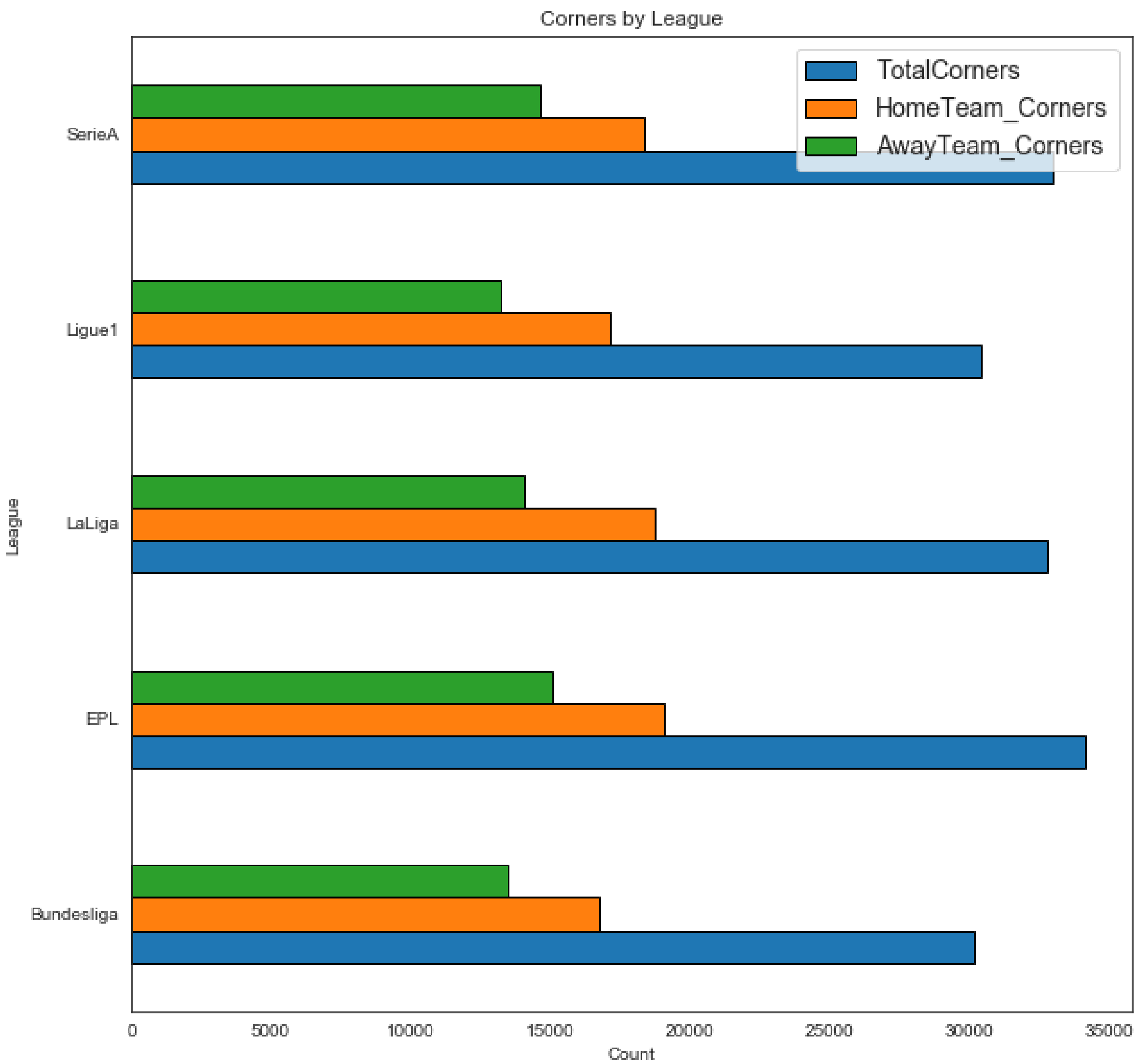

EPL has very high number of corner kicks. Ligue One produces the minimum number of corner kicks

Home/Away Team Red/Yellow cards : Number of red/yellow cards shown to players from home/away team in every match

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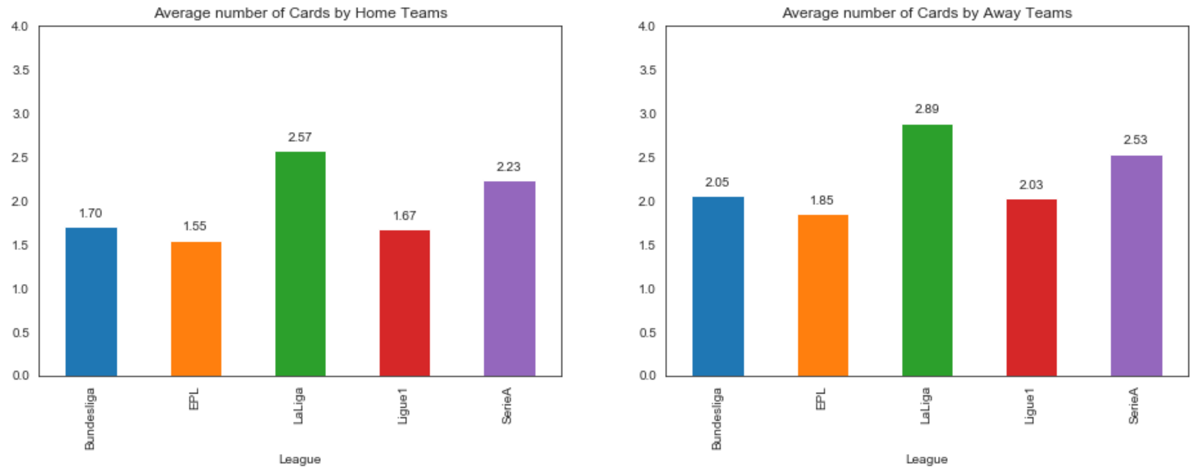

Clearly, La Liga witnesses the maximum number of cards while EPL sees the minimum number of cards. Away Teams face cards more often than Home Teans

Lets take a look at variation of red and yellow card data between leagues

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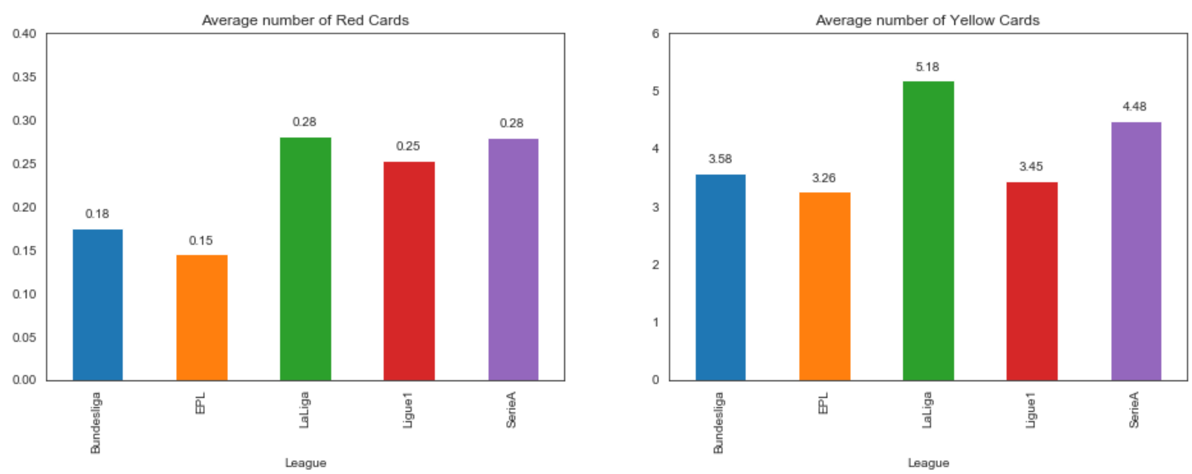

Red cards are quite rare in every league (extremely rare in EPL). La Liga and Serie A has highest number of red as well as yellow cards.

EPL witnesses least number of cards (in sync with our observation that it witnesses least number of fouls as well)

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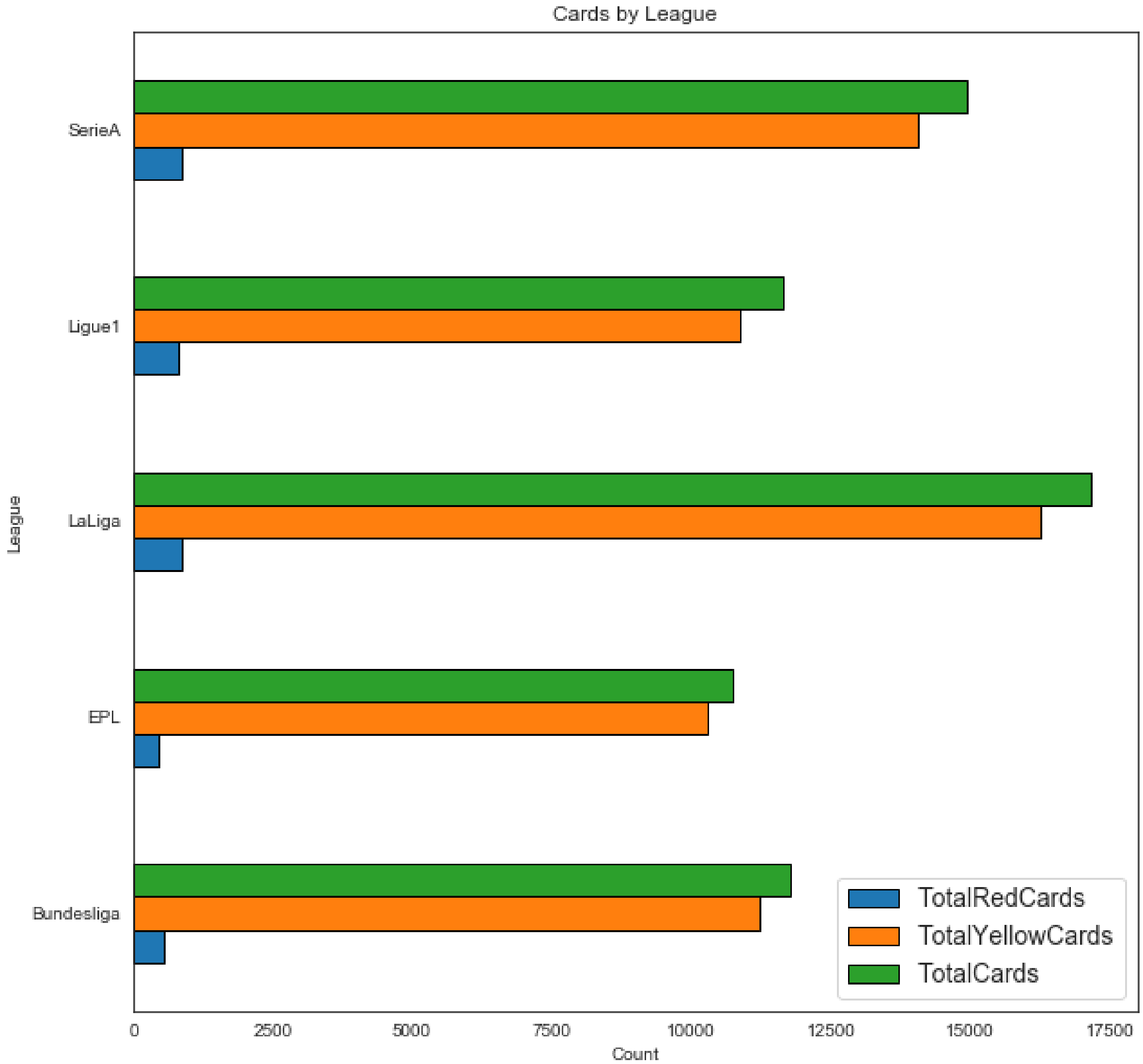

Is there a correlation between number of cards and number of fouls ?

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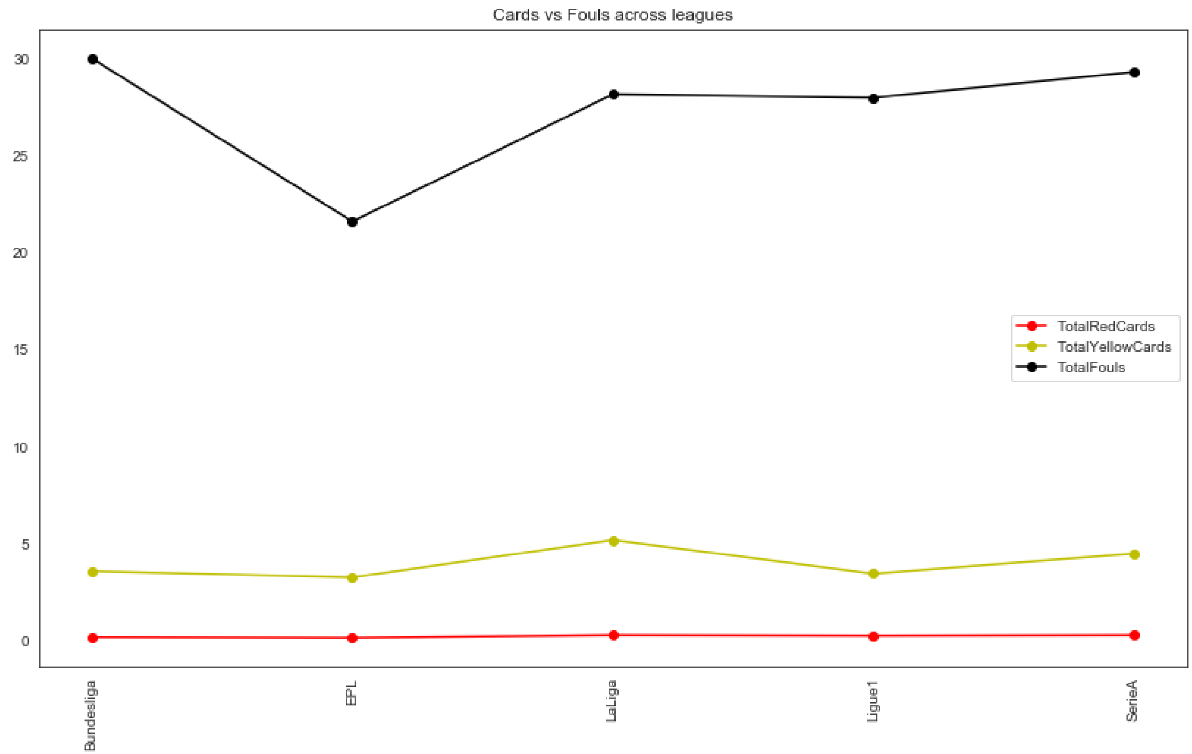

Except in EPL, there seems to be a linear correlation between number of cards and number of fouls

Lets look at how card data varied over the years

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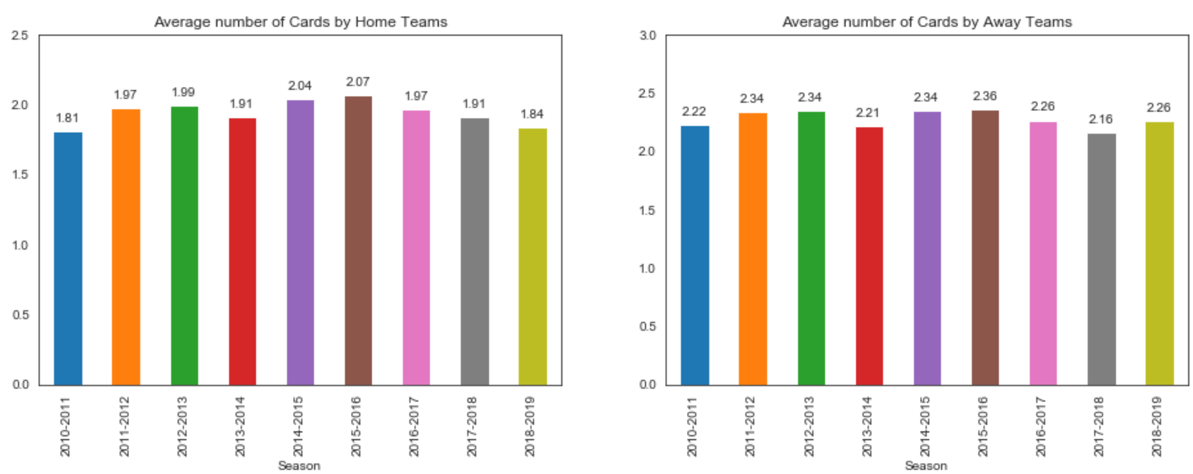

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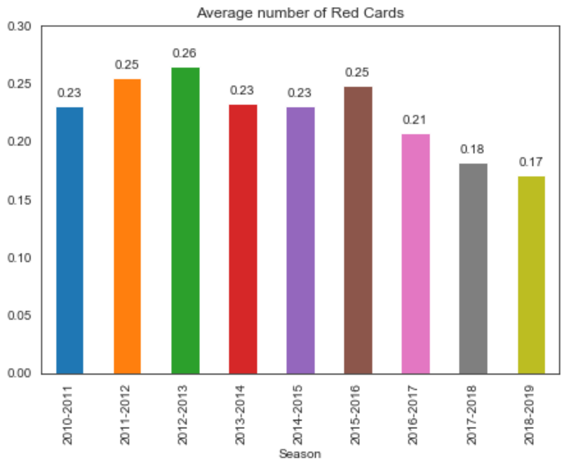

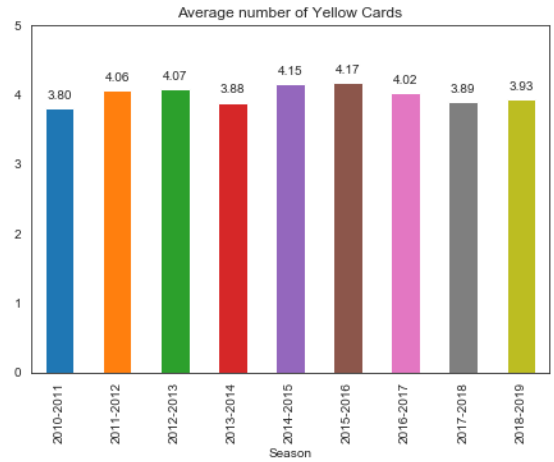

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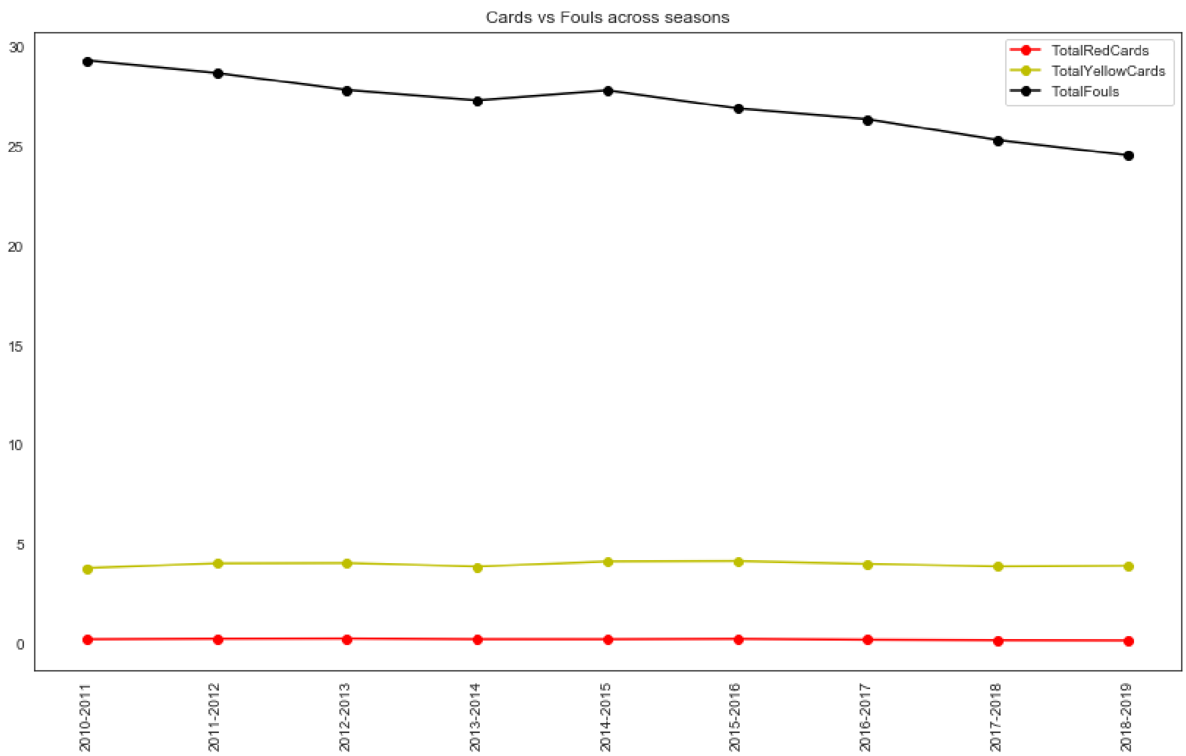

Clearly while the average number of fouls per game has come down significantly, the average number of cards havent changed much. This indicates that referees have become more strict over the years

Winner indicates the winning team

Lets look the most successful teams (teams with most number of wins in every league)

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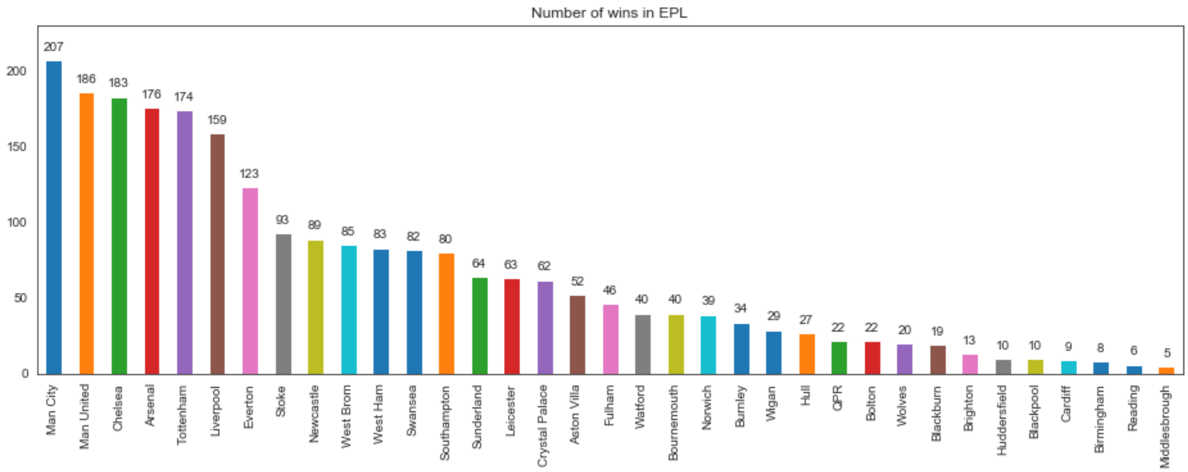

Interestingly, Manchester City (and not Manchester United) has been the most successful team in EPL since 2010 The top 5 EPL teams (in terms of number of wins) are :

1. Manchester City
2. Manchester United
3. Chelsea
4. Arsenal
5. Tottenhum Hotspur

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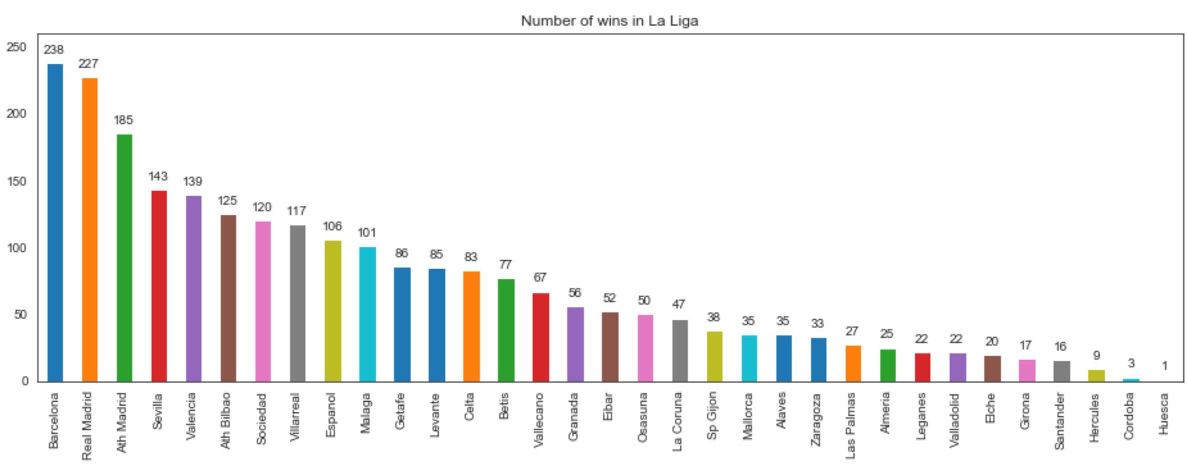

FC Barcelona has been the most successful team in La Liga over last 10 years. The top5 teams in La Liga have been

1. FC Barcelona
2. Real Madrid
3. Athletico Madrid
4. Sevilla
5. Valencia

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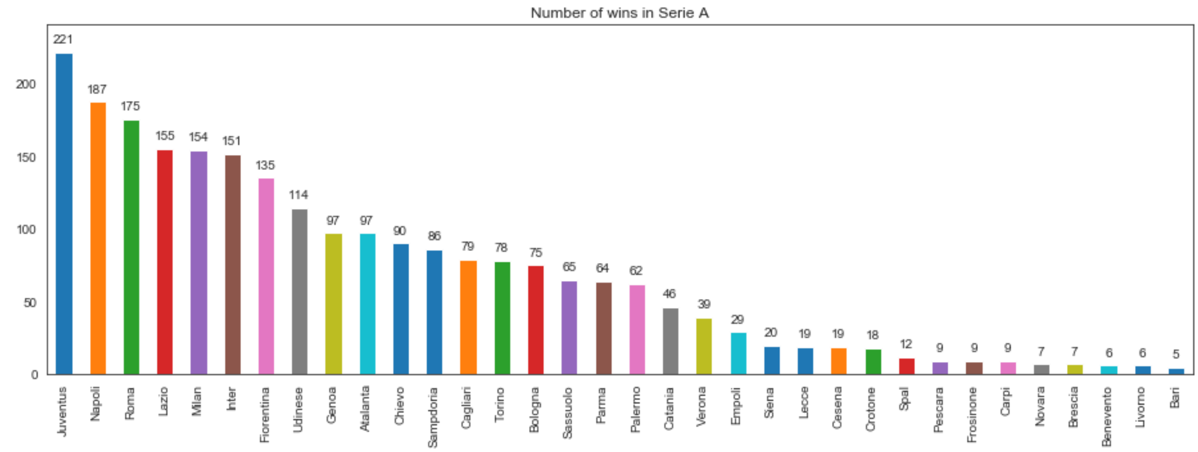

Juventus has been the most successful team in Serie A over last 10 years Interesting to see AC Milan and Inter Milan at no 5 and 6 - reflecting their current decline The top 5 teams in Serie A have been :

1. Juventus
2. Napoli
3. Roma
4. Lazio
5. AC Milan

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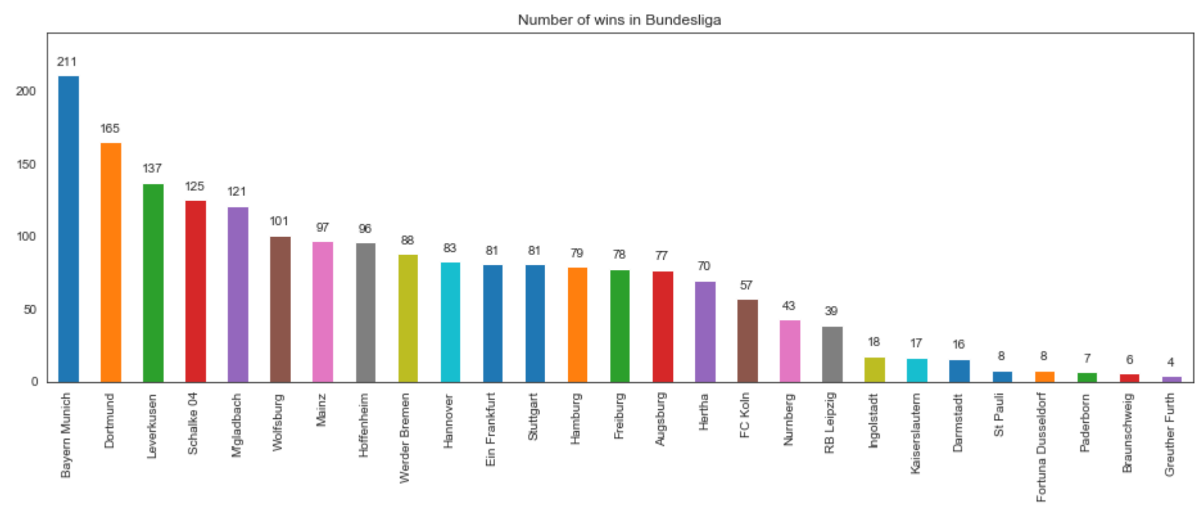

As expected Bayern Munich emerges as the top team in Bundesliga over last 10 years The top 5 teams are :

1. Bayern Munich
2. Borussia Dortmund
3. Bayer Leverkusen
4. Schalke04
5. Borussia Mönchengladbach

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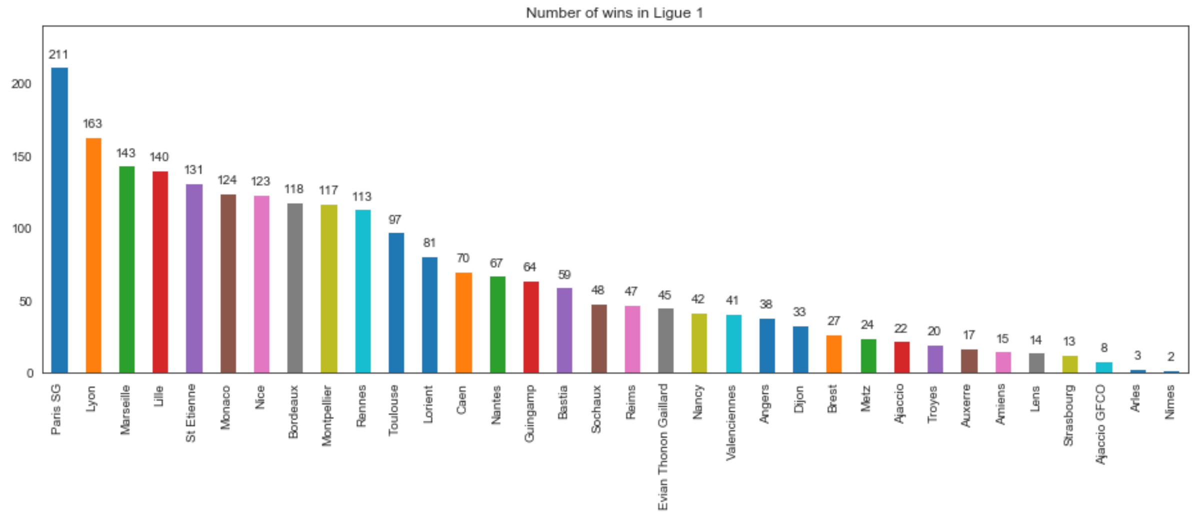

As expected, Paris Saint Germain emerges as the top team of Ligue 1 The top 5 teams in League 1 have been :

1. Paris Saint Germain
2. Lyon
3. Marseille
4. Lille
5. St Etienne

Overall, these are the top 15 and bottom 15 teams in terms of number of wins across all leagues

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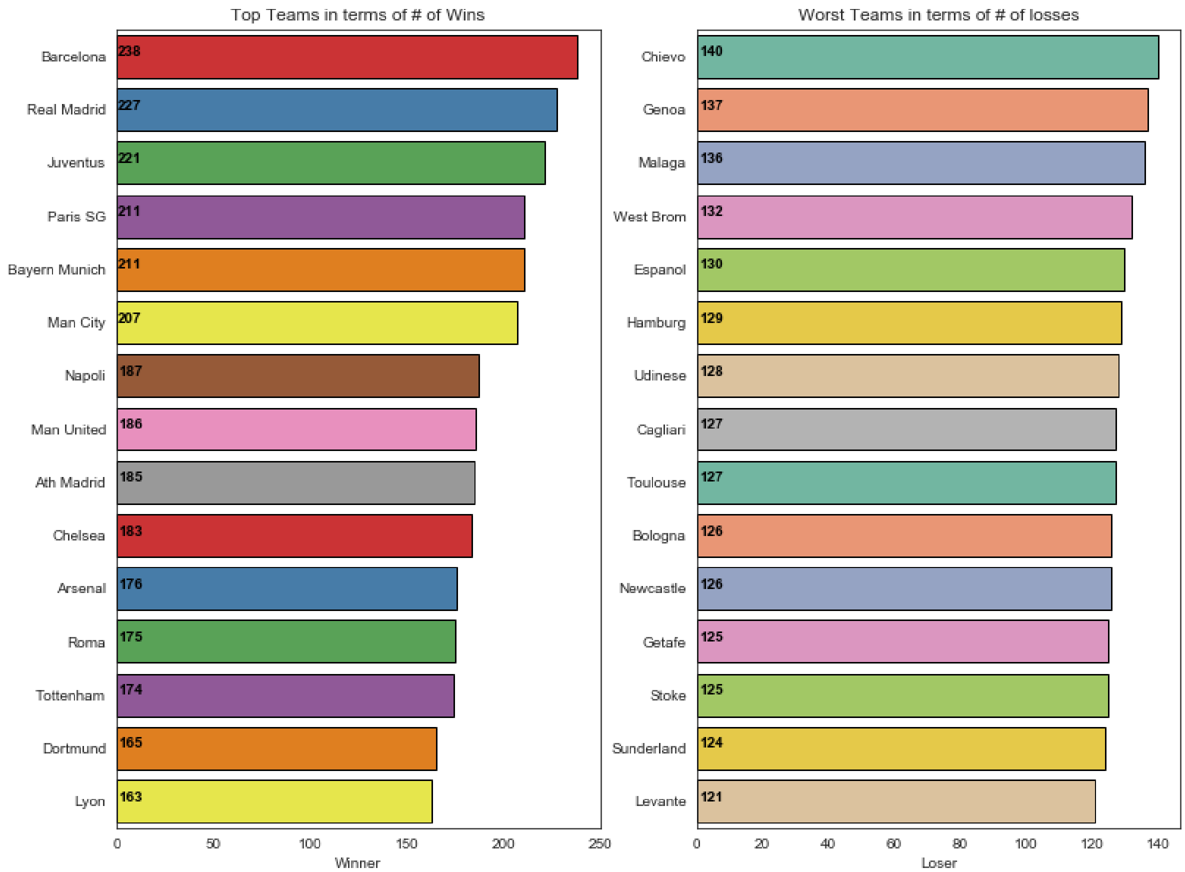

So the two La Liga giants - Barcelona and Real Madrid has won the maximum number of matches in last 9 seasons

But winning isnt everything - a draw (especially an away draw) is much more valuable than a loss

Let's implement a points system :
3 points for a win
1 point for a draw
0 point for a loss

Now lets have a look at top teams on the basis of points

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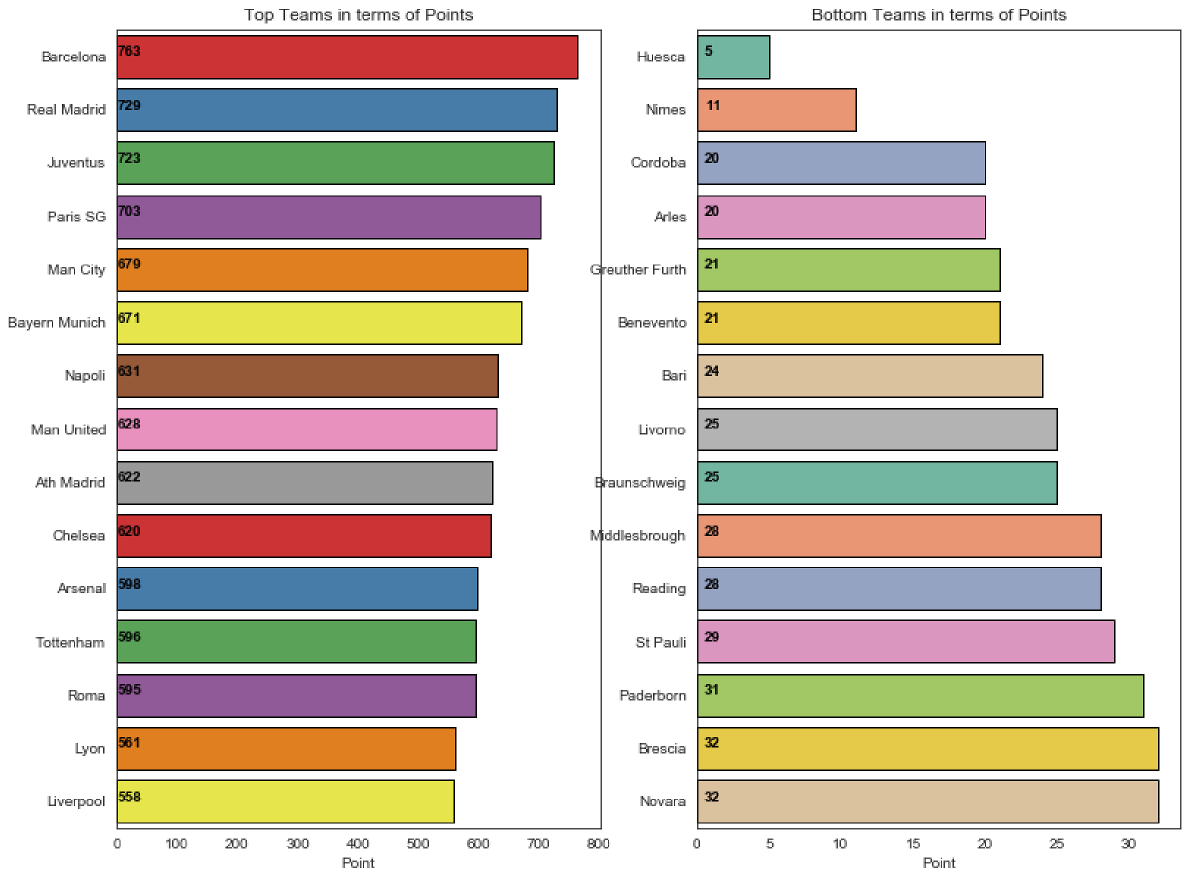

We still have FC Barcelona and Real Madrid at the top

Lets also look at the top performers in every league and season based on points. We'll exclude current ongoing season as it has incomplete data

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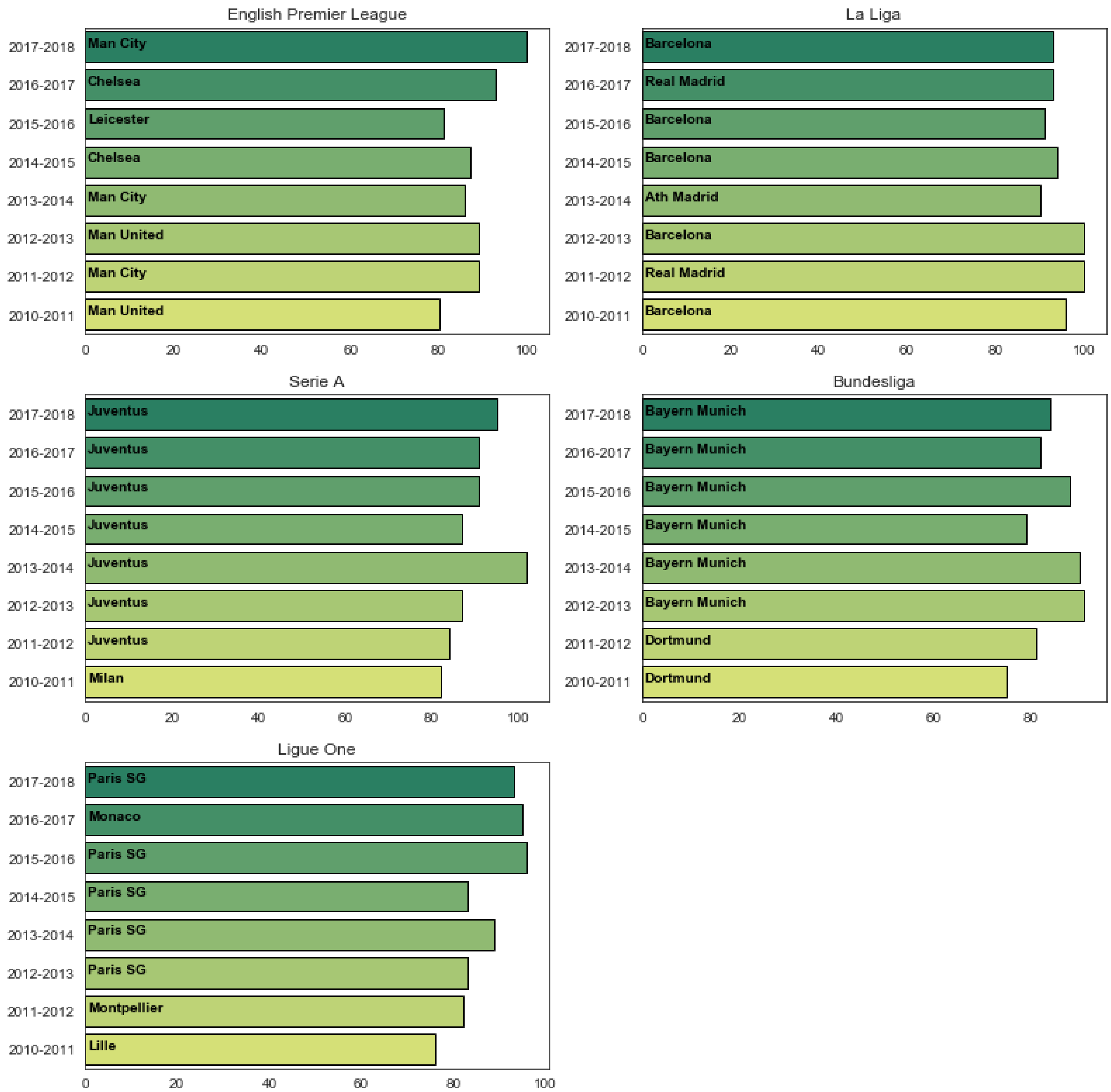

In most leagues its generally one or two clubs dominating the league. The only exception is EPL where we had 4 winners in last 8 years

Home/Away Goal Saves : The number of shots that were on target but didn't result in a goal (Not necessarily all of them are saved by GoalKeeper, some might be disqualified due to offside rule)

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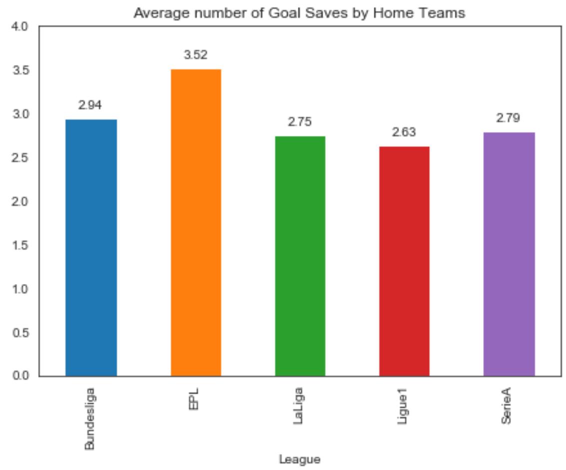

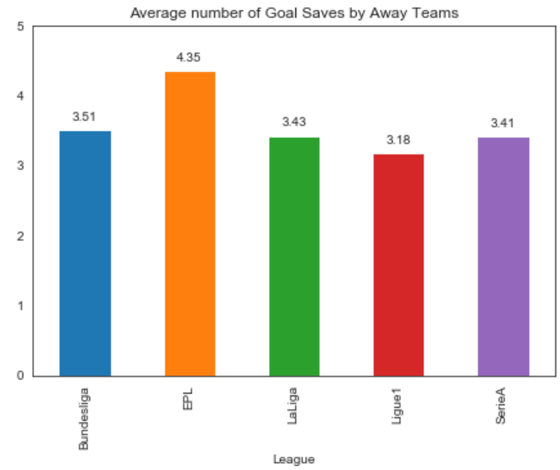

Interestingly Away teams save more goals than home team in almost every league. But that might also be because home teams usually are more effective with number of shots on target. EPL probably keeps goalkeepers busier than other leagues

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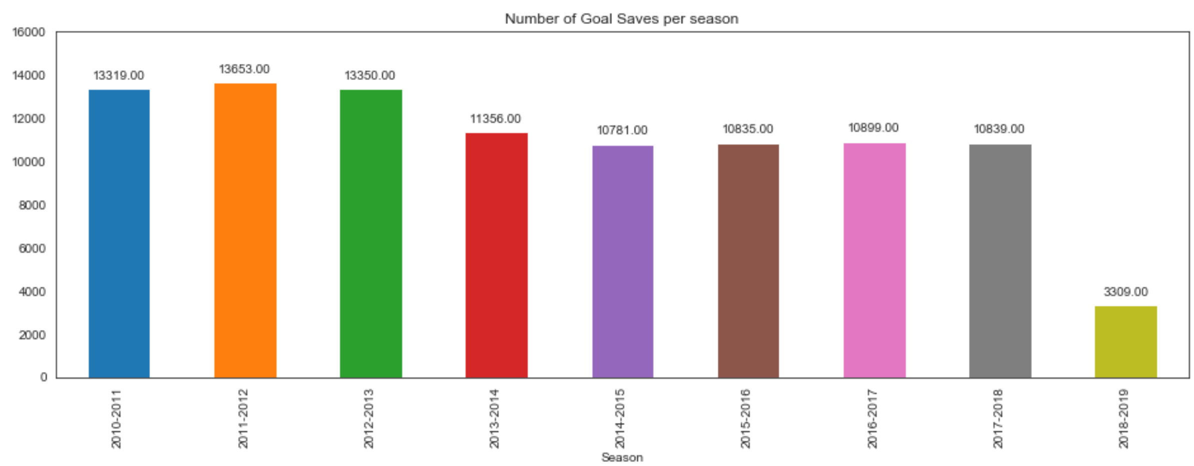

So from feature analysis we can conclude the following :

1. EPL is the most volatile league in terms of league qualification. Only 35 % of teams have been consistently present in last 10 years
2. There's a significant home advantage in every league. Away performance is improving in general but not at a very rapid pace
3. EPL and LaLiga produces more goals compared to other leagues
4. Both Home and Away teams produce more goals during second half
5. Forwards in La Liga and Bundesliga are the most effective. Forwards in Serie A are the least effective
6. EPL clearly is the most disciplined and least violent league with least number of fouls and cards. La Liga leads in number of red and yellow cards
7. Average number of fouls have fallen across all leagues over last 10 years. However average number of cards haven't
8. EPL forwards land maximum number of shots on target. However, EPL goalkeepers save maximum number of goals as well

Features and their impact on match outcome

For correlation analysis, lets convert the match results into numeric values

We also want to check if higher number of attempts have a correlation with wins (Is it important to be more aggressive ? or does it pay to be more accurate ?)

Lets create an extra feature called Winner_Shots. This will contain the number of attempts by the winning team

Similarly we can create a feature called Winner Accuracy. This will contain the propoprtion of shots by winning team that are on target

Similarly we can create a feature called Winner Goals

And also a feature called Winner Fouls

Lets have a look at the winner statistics, grouped by league

League	Winner_Goals	Winner_Shots	Winner_Fouls	Winner_Accuracy
Bundesliga	2.582399	15.264884	14.191544	41.749881
EPL	2.454735	15.518106	10.390669	46.191782
LaLiga	2.554817	14.653821	13.990698	42.320281
Ligue1	2.319014	13.857746	13.553345	41.146722
SerieA	2.395528	15.464011	14.132075	40.289794

```
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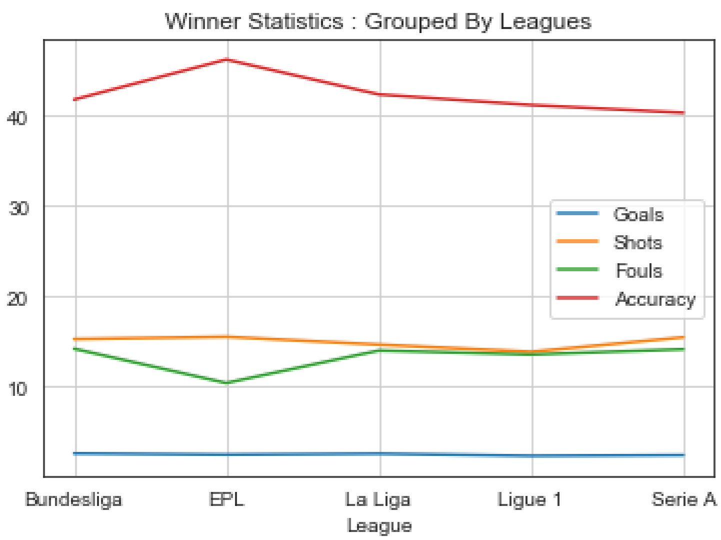

Because the goal data has lesser variation, its not very visible in this graph. Lets use a different scale just for the goal data

```
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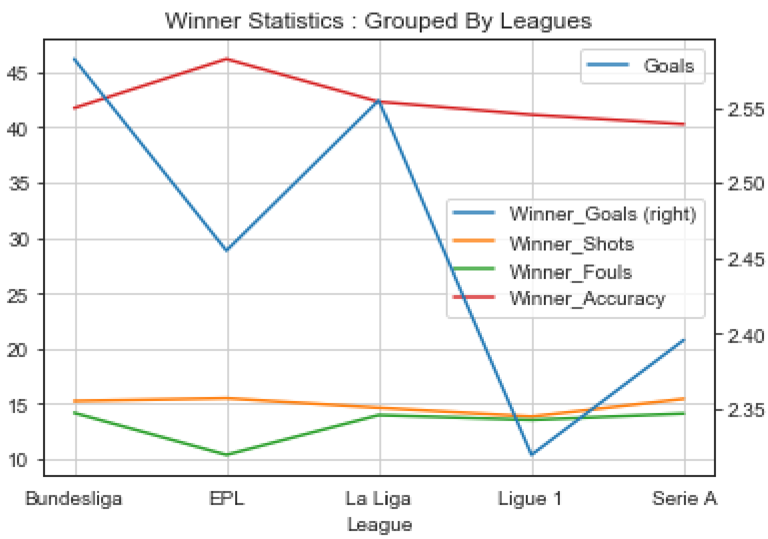

The number goals per game and shots per game of winner are steady which is 2.27 - 2.52 and 13.1 - 14.60 respectively. Bundesliga has the highest goal per game for winners. The EPL has the lowest number of fouls committed for winner. This may caused by higher tolerance of fouls in the EPL.

Now we would like to study the change for those 3 parameters for winners across different seasons.

Lets group each league data by seasons and look at the visual representation

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C:\Users\ksaha\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib
\figure.py:2299: UserWarning: This figure includes Axes that are not compatib
le with tight_layout, so results might be incorrect.
  warnings.warn("This figure includes Axes that are not compatible "
```
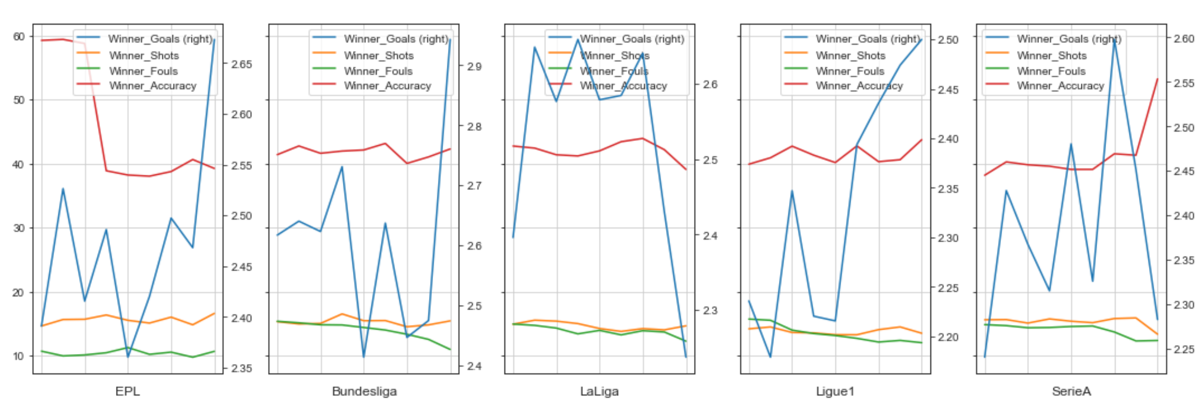



Again, goal is steady for each league and across all seasons.
However, the number of shots fluctuated a lot for every league. La liga has significant drop in the number of shot per game.
The most interesting feature is the fouls committed per game. Except EPL, all other 4 leagues has significant drop in the number of fouls committed per game over seasons.

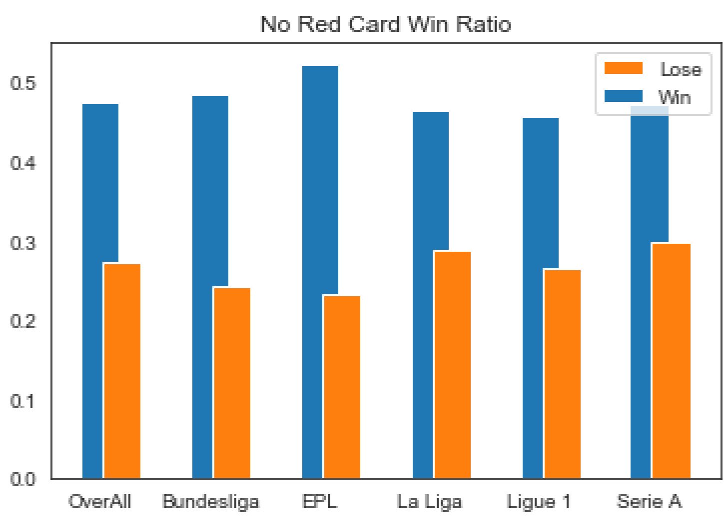
Next, we would like compare some of key features that can affect the game result by answering following questions:
1.What's the effect of red card on the win ratio?
2.What's the effect of number of shots on the win ratio?
3.What's the effect of number of fouls committed on the win ratio?
4.What's the effect of corners on the win ratio?

Let's start with the effect of red card

Calculate the win ratio of with and without red card group by league.

Out[160]:

League	RedResult	noRedResult	RedCardWinRatio	NoRedCardWinRatio
Bundesliga	104	208	0.242991	0.485981
EPL	103	232	0.232506	0.523702
LaLiga	236	382	0.287454	0.465286
Ligue1	197	339	0.265499	0.456873
SerieA	244	387	0.297561	0.471951

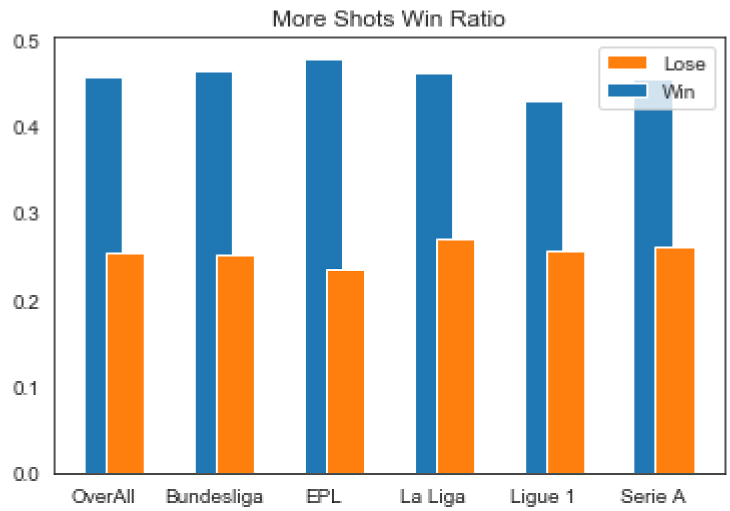


We can clearly see that the red card has huge impact on the win ratio, almost doubled the win ratio, especially in the EPL.

Then let's repeat the same procedure with the number of shots per game.

Out[165]:

	moreshots	lessshots	MoreshotsWinRatio	LessshotsWinRatio
League				
Bundesliga	1176	638	0.465006	0.252274
EPL	1512	742	0.478481	0.234810
LaLiga	1448	847	0.461146	0.269745
Ligue1	1354	804	0.429841	0.255238
SerieA	1430	818	0.455414	0.260510

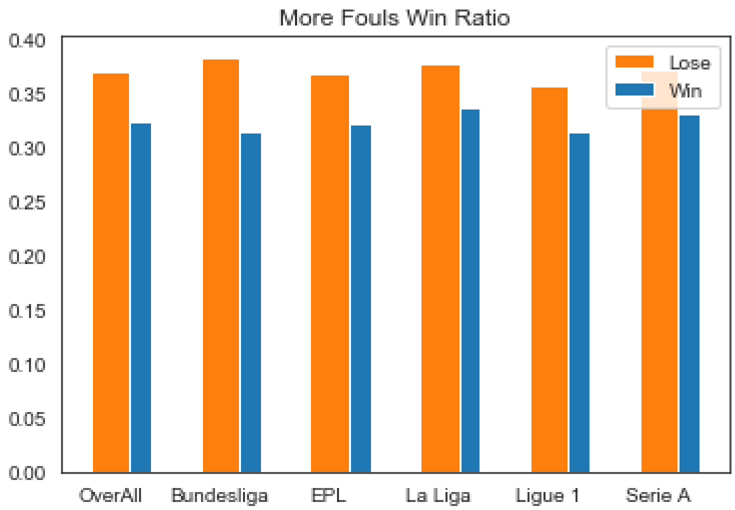


As we expect, the team with more shots tends to win the game.However, the effect is smaller than the effect of red card.

Repeat the procedure with numbers of fouls committed.

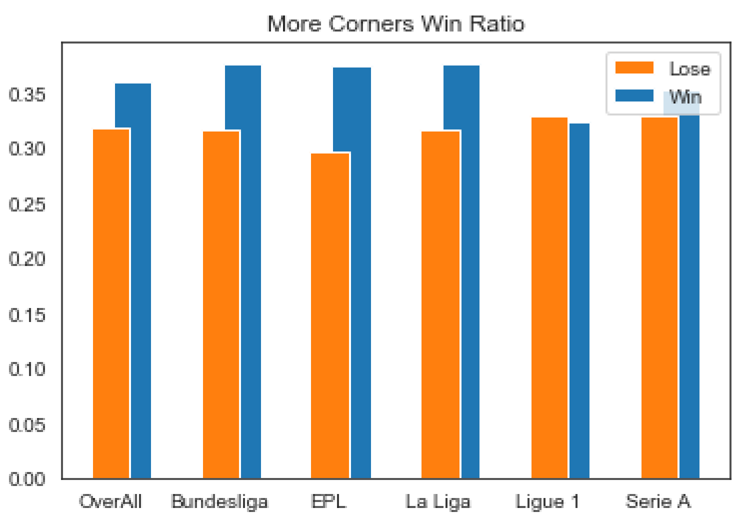
Out[170]:

League	moreFouls	lessFouls	MoreFoulsSTD	MoreFoulsWinRatio	LessFoulsWinRatio
Bundesliga	795	969	0.464350	0.314353	0.383155
EPL	1015	1160	0.467012	0.321203	0.367089
LaLiga	1059	1183	0.472850	0.337261	0.376752
Ligue1	991	1122	0.464431	0.314603	0.356190
SerieA	1037	1168	0.470380	0.330255	0.371975



The effect of fouls has small effect on the win ratio. However, the team committing more fouls tends to lose the game, This could be because of the fact that these teams have high pressure on defense.

Repeat the procedure with corners.



In general, more corners tend to result in wins. But this is not the case for Ligue 1.

What are the things that league winning teams tend to do differently ? Let's try to find an answer to this

We'll use the point metric to find the winning team

Out[178]:

	League	HomeTeam	Season	HomeTeam_Points	AwayTeam_Points
0	LaLiga	Almeria	2010-2011	19	11
1	Ligue1	Arles	2010-2011	12	8
2	EPL	Arsenal	2010-2011	37	31
3	EPL	Aston Villa	2010-2011	31	17
4	LaLiga	Ath Bilbao	2010-2011	37	21

Lets find total points for every team in every season

Out[181]:

			TotalPoints
League	**Season**	**HomeTeam**	
Bundesliga	**2010-2011**	**Bayern Munich**	65
		Dortmund	75
		Ein Frankfurt	34
		FC Koln	44
		Freiburg	44

Find the champion for each league for each season.

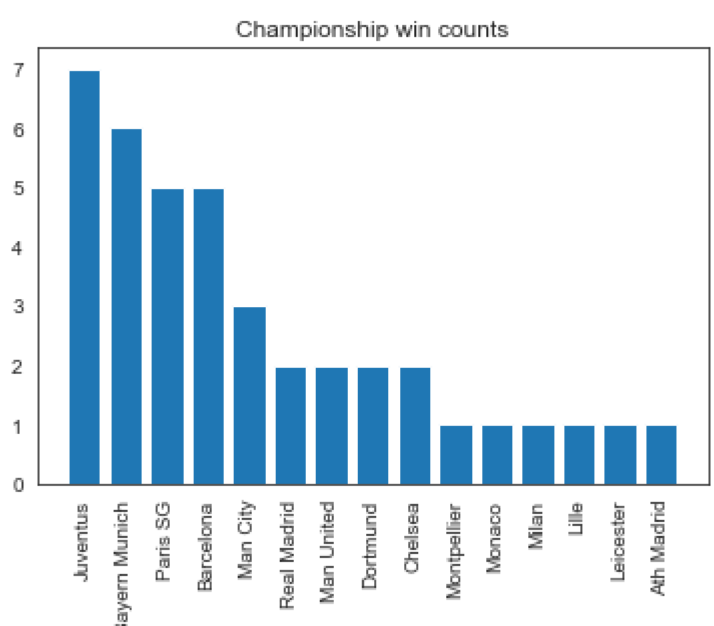
Out[182]:

	League	Season	Team
0	Bundesliga	2010-2011	Dortmund
1	EPL	2010-2011	Man United
2	LaLiga	2010-2011	Barcelona
3	Ligue1	2010-2011	Lille
4	SerieA	2010-2011	Milan
5	Bundesliga	2011-2012	Dortmund
6	EPL	2011-2012	Man City
7	LaLiga	2011-2012	Real Madrid
8	Ligue1	2011-2012	Montpellier
9	SerieA	2011-2012	Juventus
10	Bundesliga	2012-2013	Bayern Munich
11	EPL	2012-2013	Man United
12	LaLiga	2012-2013	Barcelona
13	Ligue1	2012-2013	Paris SG
14	SerieA	2012-2013	Juventus
15	Bundesliga	2013-2014	Bayern Munich
16	EPL	2013-2014	Man City
17	LaLiga	2013-2014	Ath Madrid
18	Ligue1	2013-2014	Paris SG
19	SerieA	2013-2014	Juventus
20	Bundesliga	2014-2015	Bayern Munich
21	EPL	2014-2015	Chelsea
22	LaLiga	2014-2015	Barcelona
23	Ligue1	2014-2015	Paris SG
24	SerieA	2014-2015	Juventus
25	Bundesliga	2015-2016	Bayern Munich
26	EPL	2015-2016	Leicester
27	LaLiga	2015-2016	Barcelona
28	Ligue1	2015-2016	Paris SG
29	SerieA	2015-2016	Juventus
30	Bundesliga	2016-2017	Bayern Munich
31	EPL	2016-2017	Chelsea
32	LaLiga	2016-2017	Real Madrid
33	Ligue1	2016-2017	Monaco
34	SerieA	2016-2017	Juventus

	League	Season	Team
35	Bundesliga	2017-2018	Bayern Munich
36	EPL	2017-2018	Man City
37	LaLiga	2017-2018	Barcelona
38	Ligue1	2017-2018	Paris SG
39	SerieA	2017-2018	Juventus
40	Bundesliga	2018-2019	Dortmund
41	EPL	2018-2019	Man City
42	LaLiga	2018-2019	Barcelona
43	Ligue1	2018-2019	Paris SG
44	SerieA	2018-2019	Juventus

Out[184]:

```
Team
Juventus          7
Bayern Munich     6
Paris SG          5
Barcelona         5
Man City          3
Real Madrid       2
Man United        2
Dortmund          2
Chelsea           2
Montpellier       1
Monaco            1
Milan             1
Lille             1
Leicester         1
Ath Madrid        1
Name: Season, dtype: int64
```



Find the key features of champion team and merge into one dataframe

Out[187]:

			FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	HalfT
Season	League	HomeTeam			
2010-2011	Bundesliga	Bayern Munich	48	13	
		Dortmund	35	8	
		Ein Frankfurt	13	24	
		FC Koln	30	21	
		Freiburg	24	24	
		Hamburg	29	24	
		Hannover	32	17	
		Hoffenheim	28	21	
		Kaiserslautern	25	19	
		Leverkusen	33	24	

Drop current season due to imcomplete data.

Out[195]:

	HomeTeam	League	Season	FullTime_HomeTeam_Goals	FullTime_AwayTeam_Goals	HalfTi
0	Dortmund	Bundesliga	2010-2011	38.888889	35.555556	
1	Man United	EPL	2010-2011	49.000000	29.000000	
2	Barcelona	LaLiga	2010-2011	46.000000	49.000000	
3	Lille	Ligue1	2010-2011	40.000000	28.000000	
4	Milan	SerieA	2010-2011	42.000000	23.000000	

Plot the total number of goals for each champion in different league.

Out[197]:
```
['2010-2011',
 '2011-2012',
 '2012-2013',
 '2013-2014',
 '2014-2015',
 '2015-2016',
 '2016-2017',
 '2017-2018',
 'League Average']
```

```
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```

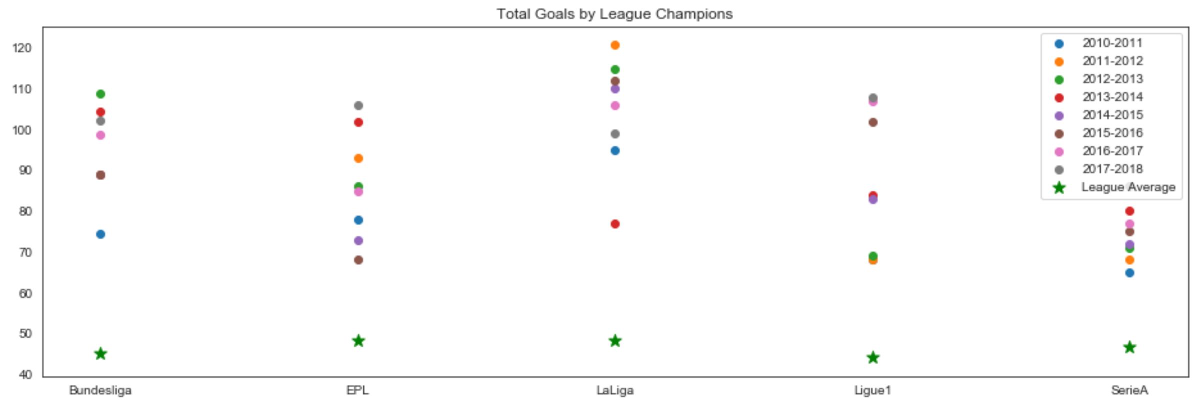

From the figure above, we can see that Laliga has the highest number of goals for champion except for one season. Serie A has the largest distribution on the total goals. The Bundesliga has the lowest number of goals since they has less games to play.

Out[199]:
```
League
Bundesliga     94.444444
EPL            86.375000
LaLiga        104.375000
Ligue1         86.125000
SerieA         74.250000
dtype: float64
```

Out[200]:
```
League
Bundesliga    45.228395
EPL           48.094444
LaLiga        48.161111
Ligue1        44.294444
SerieA        46.538889
dtype: float64
```

The total goal of champion team is way above the average goal of all teams.

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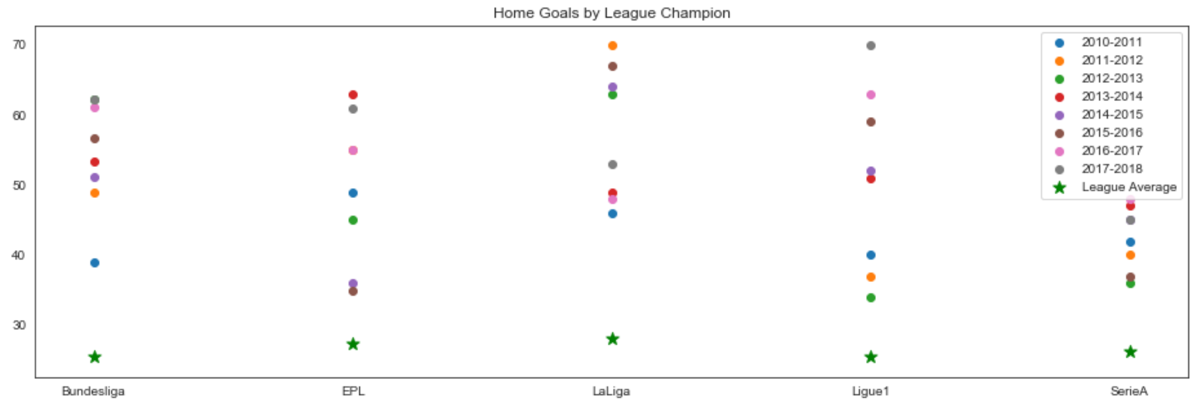
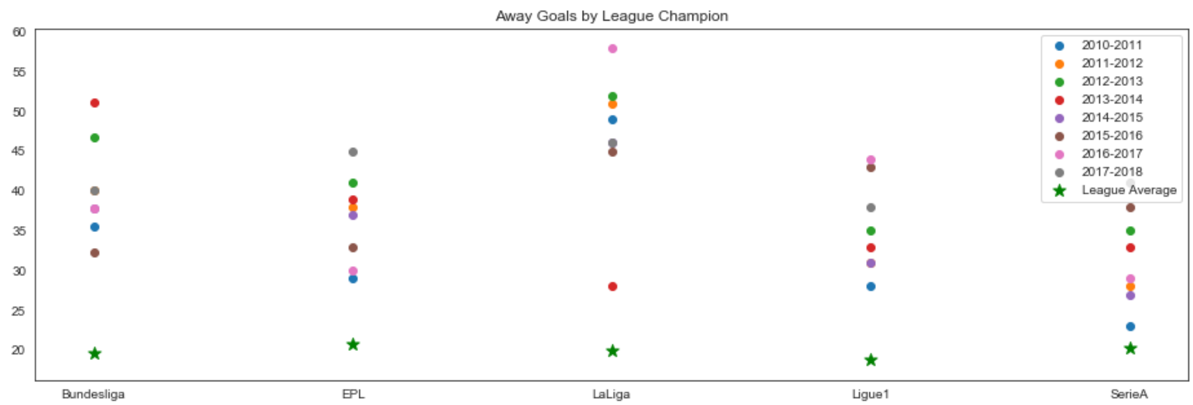


<Figure size 432x288 with 0 Axes>



Break down the goal by goals at home and away. The general trend is similar to the overall goal.

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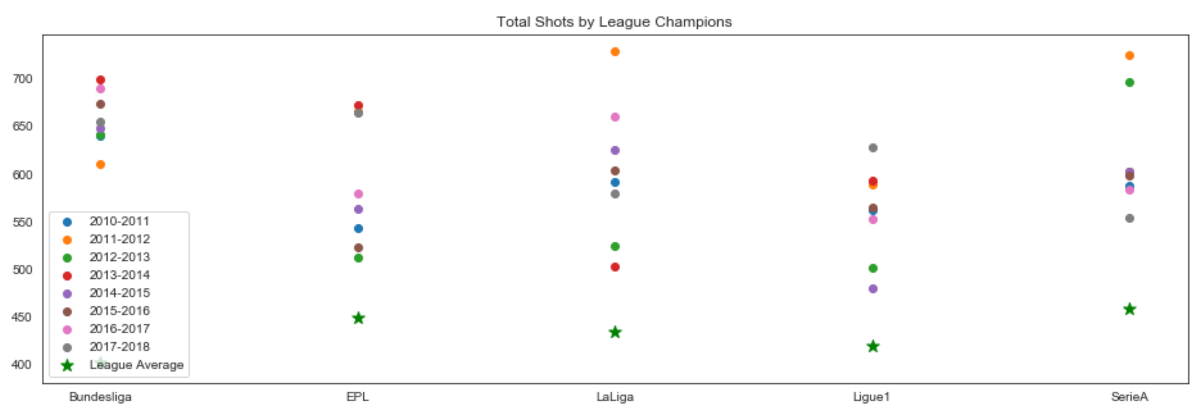

The trend is similar to the trend of goal except Serie A. The Serie A champion tend to attempt more. Maybe we should consider the goal per shot as a key feature to compare with leagues.

```
Out[204]: League
Bundesliga    657.500
EPL           590.500
LaLiga        602.250
Ligue1        558.750
SerieA        618.875
dtype: float64
```

```
Out[205]: League
Bundesliga    400.716049
EPL           448.405556
LaLiga        433.266667
Ligue1        418.961111
SerieA        457.516667
dtype: float64
```

Similar to the number of goal analysis, the total number of shots for champion's team is much higher than the league average.

```
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```

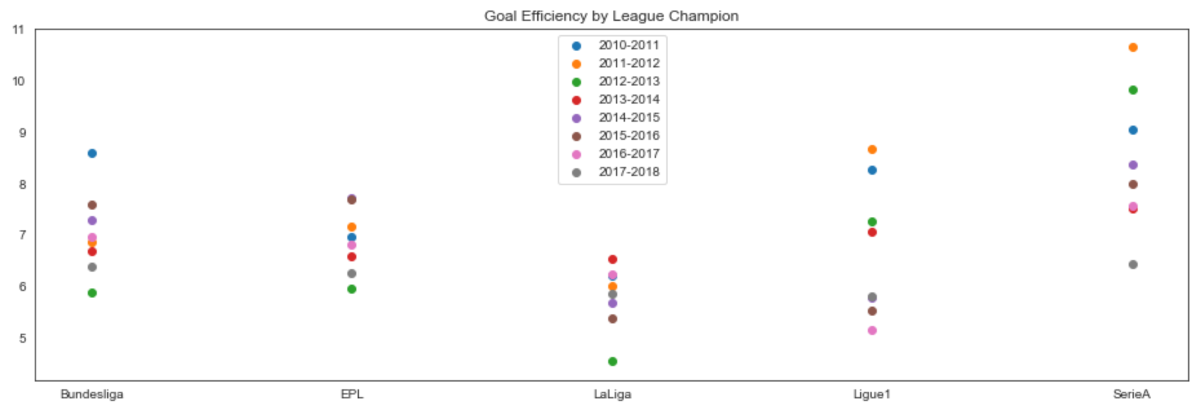

As we expected, Serie A has the lowest Goal coefficient

```
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```

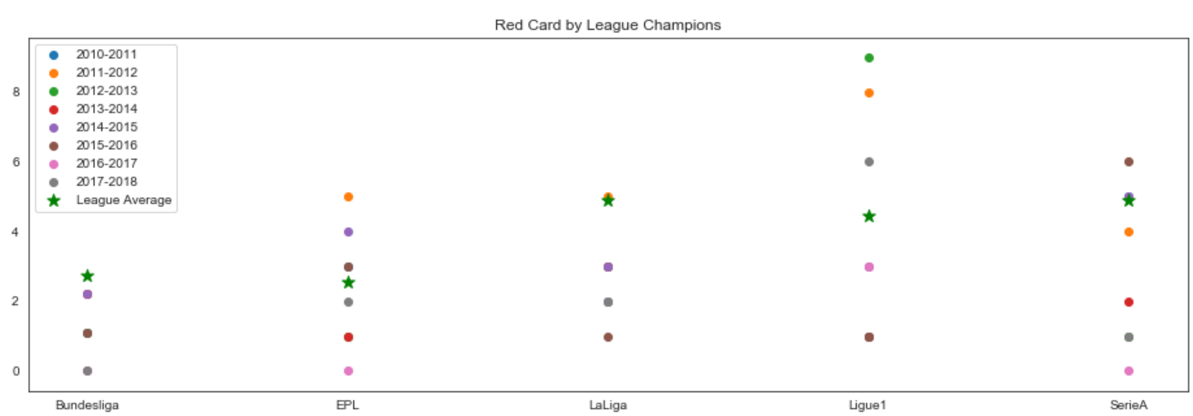

```
Out[209]: League
          Bundesliga    1.250
          EPL           2.375
          LaLiga        2.625
          Ligue1        4.000
          SerieA        3.000
          dtype: float64
```

```
Out[210]: League
          Bundesliga    2.734568
          EPL           2.550000
          LaLiga        4.911111
          Ligue1        4.430556
          SerieA        4.884259
          dtype: float64
```

The red card received by champion team is also lower than league average.

The number of red card by champions are low except Ligue 1.

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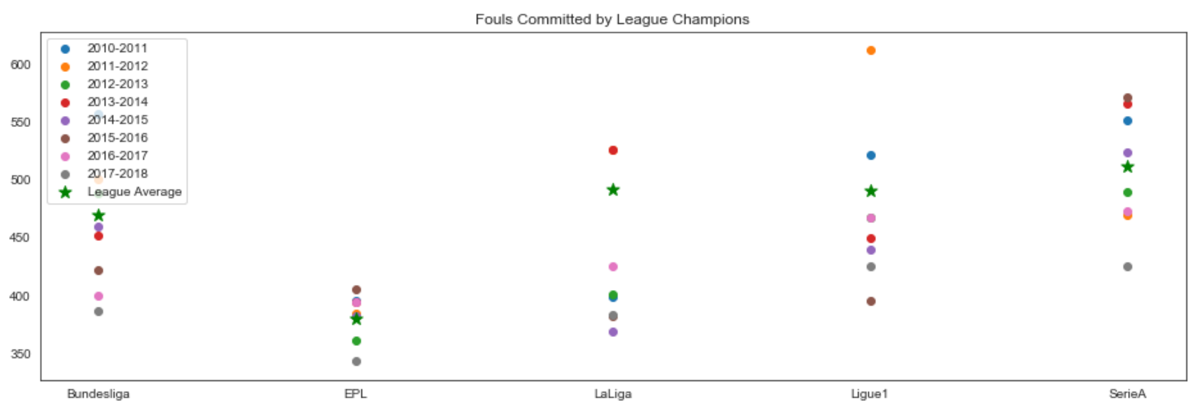
```



mean = Champs.groupby('League').mean() Allmean = ww.groupby('League').mean() mean['HomeTeam_FoulsCommitted']+mean['AwayTeam_FoulsCommitted']

```
Out[212]: League
          Bundesliga    469.067901
          EPL           379.655556
          LaLiga        491.800000
          Ligue1        490.271528
          SerieA        511.836111
          dtype: float64
```

Except Serie A, all other 4 league's champion's fouls committed is under average number of fouls committed by all teams.

Competitiveness of Leagues

Which European league is the most competitive ? Lets try to find an answer to this question

The gap between the top team and 20th team in a league may be too much (and also might be influenced by outliers). So we'll limit our analysis to top 10 teams of every league

```
C:\Users\ksaha\AppData\Local\Continuum\anaconda3\lib\site-packages\scipy\stat
s\stats.py:1713: FutureWarning: Using a non-tuple sequence for multidimension
al indexing is deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In th
e future this will be interpreted as an array index, `arr[np.array(seq)]`, wh
ich will result either in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

```
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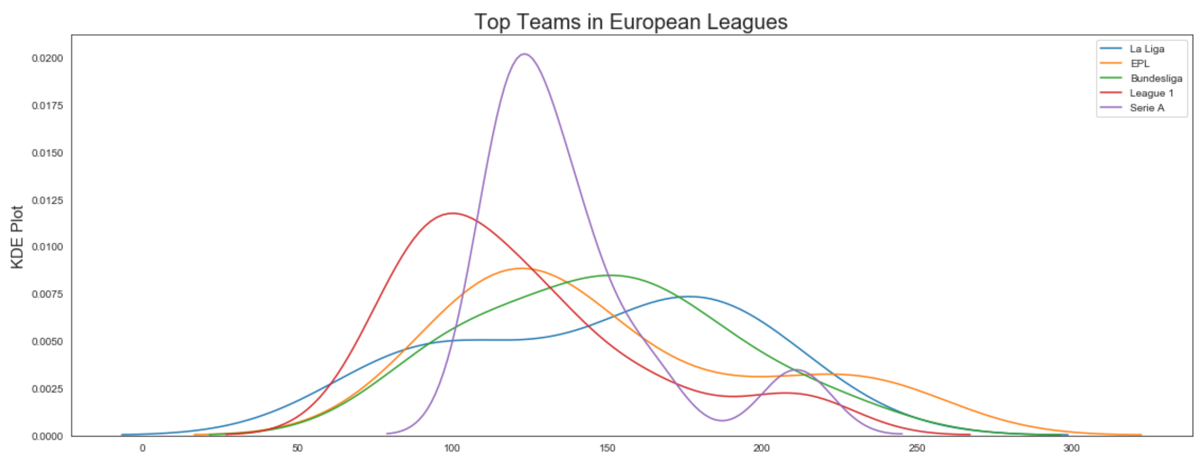


Leagues that are normally distributed are less competitive because the best and worst teams are equidistant from the mean

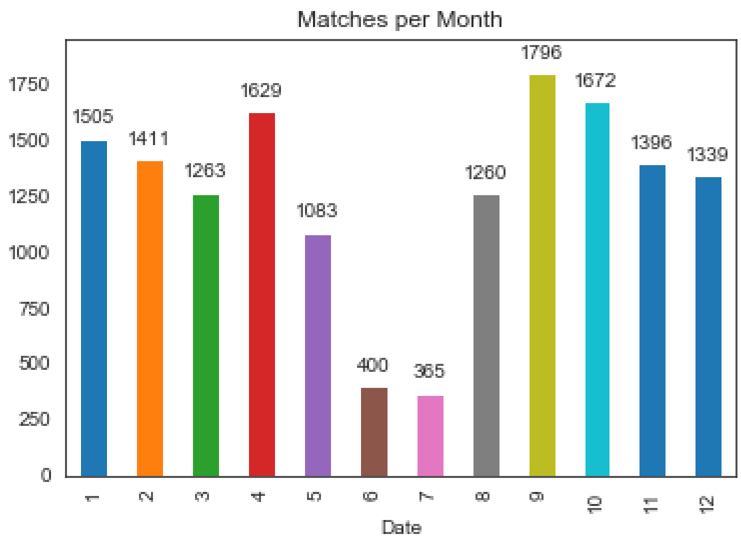
Left skewed distribution means only a few handful teams are close to the top whereas right skewed distribution means there's lot of competition at the top

From the plot it seems that La Liga and Bundesliga are the most competitive

Time Series Analysis

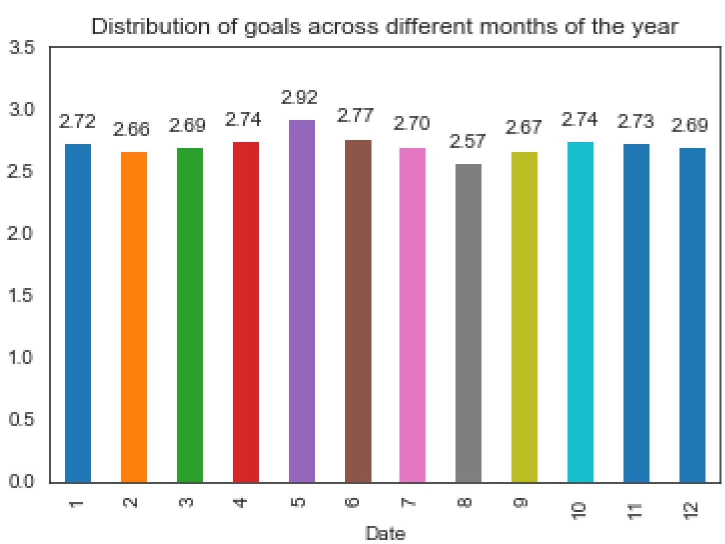
Lets convert the data into a time series first

During which months of the year are most games played ?



Very few matches are played during the months of June and July. Most of the matches are played during Fall (September-October)

Is there a seasonal trend in goal scoring rate ? Does goal scoring rate dip during winter months ?



Clearly there is no significant dip in goal scoring rate during Winter months. Most goals are scored in May/June, towards the end of the year

Predictive Analysis

Statistical studies on goal scoring pattern in football matches often suggest that goals in a football match follow Poisson distribution pattern. We'll continue with that assumption and use the the mean expected number of goals for a match to form a probability distribution and express the number of goals as a function of average rate of scoring goals

We'll use 2010-2011 to 2017-2018 data to train our model and 2018-2019 data to test our model

We'll create two distributions - one for home and other for away

First lets look at the data distribution of home and away goals

```
Full Time Home-Team Goals (Unique Values) :  : [ 3  1  0  6  2  4  5  7  8  9
10]
Full Time Away-Team Goals (Unique Values) :  : [0 2 4 1 3 6 5 7 8 9]
```

```
C:\Users\ksaha\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib
\axes\_axes.py:6571: UserWarning: The 'normed' kwarg is deprecated, and has b
een replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

```
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```

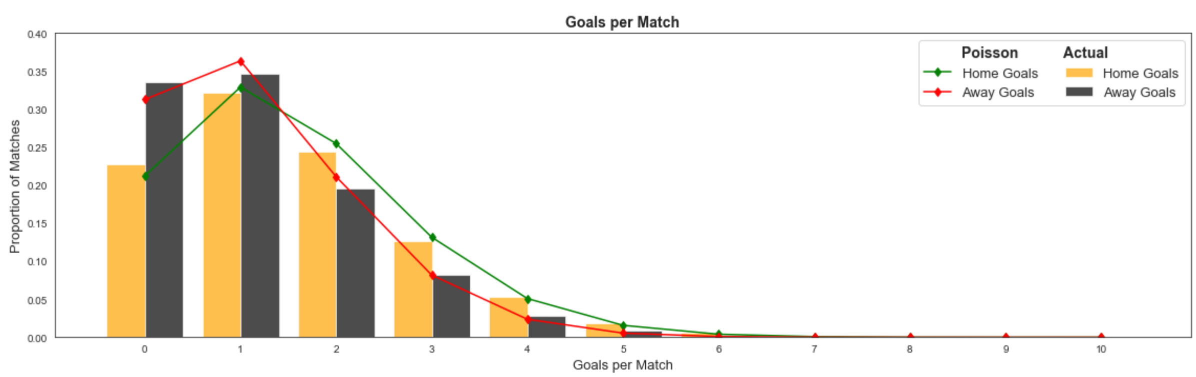

Now lets build a regression model based on Poisson distribution.
Our model formula will be :
Home/Away Goals = Opponent Team + Away/Home Goals

Since teams across leagues dont play each other (We dont have Champions league data), so we will build a separate model per league

Out[221]:

Generalized Linear Model Regression Results

Dep. Variable:	goals	**No. Observations:**	6080
Model:	GLM	**Df Residuals:**	6010
Model Family:	Poisson	**Df Model:**	69
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-8779.0
Date:	Fri, 07 Dec 2018	**Deviance:**	6823.0
Time:	15:23:42	**Pearson chi2:**	5.93e+03
No. Iterations:	5	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	0.2893	0.071	4.090	0.000	0.151	0.428
team[T.Aston Villa]	-0.6235	0.078	-7.962	0.000	-0.777	-0.470
team[T.Birmingham]	-0.7025	0.170	-4.129	0.000	-1.036	-0.369
team[T.Blackburn]	-0.4477	0.112	-4.005	0.000	-0.667	-0.229
team[T.Blackpool]	-0.2857	0.142	-2.016	0.044	-0.564	-0.008
team[T.Bolton]	-0.4078	0.110	-3.714	0.000	-0.623	-0.193
team[T.Bournemouth]	-0.3393	0.093	-3.637	0.000	-0.522	-0.156
team[T.Brighton]	-0.6946	0.177	-3.927	0.000	-1.041	-0.348
team[T.Burnley]	-0.6942	0.107	-6.471	0.000	-0.904	-0.484
team[T.Cardiff]	-0.7750	0.182	-4.263	0.000	-1.131	-0.419
team[T.Chelsea]	-0.0294	0.060	-0.494	0.621	-0.146	0.087
team[T.Crystal Palace]	-0.4800	0.080	-5.975	0.000	-0.637	-0.323
team[T.Everton]	-0.2836	0.064	-4.439	0.000	-0.409	-0.158
team[T.Fulham]	-0.4400	0.084	-5.209	0.000	-0.606	-0.274
team[T.Huddersfield]	-0.8850	0.194	-4.564	0.000	-1.265	-0.505
team[T.Hull]	-0.6475	0.105	-6.162	0.000	-0.853	-0.442
team[T.Leicester]	-0.2316	0.080	-2.900	0.004	-0.388	-0.075
team[T.Liverpool]	-0.0297	0.060	-0.498	0.618	-0.147	0.087
team[T.Man City]	0.1357	0.057	2.374	0.018	0.024	0.248
team[T.Man United]	-0.0477	0.060	-0.798	0.425	-0.165	0.069
team[T.Middlesbrough]	-0.9278	0.197	-4.706	0.000	-1.314	-0.541
team[T.Newcastle]	-0.4297	0.070	-6.167	0.000	-0.566	-0.293
team[T.Norwich]	-0.5749	0.090	-6.420	0.000	-0.750	-0.399
team[T.QPR]	-0.6141	0.102	-6.001	0.000	-0.815	-0.414
team[T.Reading]	-0.4968	0.158	-3.138	0.002	-0.807	-0.186
team[T.Southampton]	-0.3578	0.072	-4.975	0.000	-0.499	-0.217

team[T.Stoke]	-0.5547	0.069	-7.986	0.000	-0.691	-0.419
team[T.Sunderland]	-0.5745	0.073	-7.869	0.000	-0.718	-0.431
team[T.Swansea]	-0.4740	0.071	-6.684	0.000	-0.613	-0.335
team[T.Tottenham]	-0.0805	0.060	-1.333	0.182	-0.199	0.038
team[T.Watford]	-0.5008	0.099	-5.041	0.000	-0.696	-0.306
team[T.West Brom]	-0.5009	0.068	-7.327	0.000	-0.635	-0.367
team[T.West Ham]	-0.3907	0.069	-5.656	0.000	-0.526	-0.255
team[T.Wigan]	-0.5283	0.098	-5.402	0.000	-0.720	-0.337
team[T.Wolves]	-0.5315	0.116	-4.577	0.000	-0.759	-0.304
opponent[T.Aston Villa]	0.3613	0.075	4.806	0.000	0.214	0.509
opponent[T.Birmingham]	0.2793	0.143	1.958	0.050	-0.000	0.559
opponent[T.Blackburn]	0.4629	0.102	4.550	0.000	0.263	0.662
opponent[T.Blackpool]	0.5938	0.126	4.708	0.000	0.347	0.841
opponent[T.Bolton]	0.4351	0.103	4.232	0.000	0.234	0.637
opponent[T.Bournemouth]	0.4052	0.090	4.491	0.000	0.228	0.582
opponent[T.Brighton]	0.2087	0.147	1.421	0.155	-0.079	0.497
opponent[T.Burnley]	0.1150	0.099	1.161	0.246	-0.079	0.309
opponent[T.Cardiff]	0.5376	0.129	4.182	0.000	0.286	0.790
opponent[T.Chelsea]	-0.1151	0.079	-1.449	0.147	-0.271	0.041
opponent[T.Crystal Palace]	0.2116	0.082	2.579	0.010	0.051	0.372
opponent[T.Everton]	0.0782	0.075	1.037	0.300	-0.070	0.226
opponent[T.Fulham]	0.3293	0.085	3.883	0.000	0.163	0.495
opponent[T.Huddersfield]	0.2741	0.142	1.924	0.054	-0.005	0.553
opponent[T.Hull]	0.3467	0.092	3.776	0.000	0.167	0.527
opponent[T.Leicester]	0.2185	0.088	2.493	0.013	0.047	0.390
opponent[T.Liverpool]	0.0499	0.076	0.655	0.513	-0.099	0.199
opponent[T.Man City]	-0.1817	0.081	-2.240	0.025	-0.341	-0.023
opponent[T.Man United]	-0.1710	0.081	-2.122	0.034	-0.329	-0.013
opponent[T.Middlesbrough]	0.1884	0.148	1.273	0.203	-0.102	0.478
opponent[T.Newcastle]	0.3040	0.074	4.128	0.000	0.160	0.448
opponent[T.Norwich]	0.3760	0.083	4.513	0.000	0.213	0.539
opponent[T.QPR]	0.4257	0.090	4.754	0.000	0.250	0.601
opponent[T.Reading]	0.5248	0.129	4.059	0.000	0.271	0.778
opponent[T.Southampton]	0.0938	0.081	1.163	0.245	-0.064	0.252
opponent[T.Stoke]	0.1942	0.073	2.654	0.008	0.051	0.338
opponent[T.Sunderland]	0.2739	0.074	3.699	0.000	0.129	0.419
opponent[T.Swansea]	0.2348	0.075	3.139	0.002	0.088	0.381

opponent[T.Tottenham]	-0.0146	0.077	-0.189	0.850	-0.166	0.137
opponent[T.Watford]	0.3286	0.092	3.563	0.000	0.148	0.509
opponent[T.West Brom]	0.2495	0.072	3.450	0.001	0.108	0.391
opponent[T.West Ham]	0.2900	0.074	3.925	0.000	0.145	0.435
opponent[T.Wigan]	0.4122	0.090	4.573	0.000	0.236	0.589
opponent[T.Wolves]	0.5365	0.099	5.416	0.000	0.342	0.731
home	0.2724	0.022	12.312	0.000	0.229	0.316

Out[222]:

Generalized Linear Model Regression Results

Dep. Variable:	goals	**No. Observations:**	6080
Model:	GLM	**Df Residuals:**	6016
Model Family:	Poisson	**Df Model:**	63
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-8695.6
Date:	Fri, 07 Dec 2018	**Deviance:**	6710.9
Time:	15:23:42	**Pearson chi2:**	5.81e+03
No. Iterations:	5	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.2524	0.153	-1.647	0.100	-0.553	0.048
team[T.Almeria]	-0.0743	0.146	-0.510	0.610	-0.360	0.211
team[T.Ath Bilbao]	0.2167	0.122	1.779	0.075	-0.022	0.456
team[T.Ath Madrid]	0.4233	0.120	3.533	0.000	0.188	0.658
team[T.Barcelona]	0.9370	0.117	8.041	0.000	0.709	1.165
team[T.Betis]	0.1141	0.127	0.901	0.368	-0.134	0.362
team[T.Celta]	0.1826	0.126	1.453	0.146	-0.064	0.429
team[T.Cordoba]	-0.6250	0.241	-2.596	0.009	-1.097	-0.153
team[T.Eibar]	0.1128	0.134	0.844	0.398	-0.149	0.375
team[T.Elche]	-0.2459	0.167	-1.473	0.141	-0.573	0.081
team[T.Espanol]	0.0527	0.124	0.427	0.670	-0.190	0.295
team[T.Getafe]	-0.0362	0.127	-0.286	0.775	-0.284	0.212
team[T.Girona]	0.2321	0.180	1.290	0.197	-0.121	0.585
team[T.Granada]	-0.1658	0.131	-1.264	0.206	-0.423	0.091
team[T.Hercules]	-0.1318	0.201	-0.657	0.511	-0.525	0.262
team[T.La Coruna]	-0.0244	0.129	-0.190	0.850	-0.277	0.228
team[T.Las Palmas]	0.0137	0.143	0.095	0.924	-0.268	0.295
team[T.Leganes]	-0.1397	0.163	-0.855	0.392	-0.460	0.180
team[T.Levante]	-0.0133	0.126	-0.106	0.916	-0.261	0.234
team[T.Malaga]	0.0652	0.123	0.528	0.598	-0.177	0.307
team[T.Mallorca]	0.0124	0.143	0.086	0.931	-0.268	0.292
team[T.Osasuna]	-0.0568	0.133	-0.428	0.668	-0.317	0.203
team[T.Real Madrid]	0.9417	0.117	8.080	0.000	0.713	1.170
team[T.Santander]	-0.1777	0.164	-1.081	0.280	-0.500	0.144
team[T.Sevilla]	0.3670	0.120	3.047	0.002	0.131	0.603
team[T.Sociedad]	0.2905	0.121	2.397	0.017	0.053	0.528

team[T.Sp Gijon]	-0.0292	0.137	-0.214	0.831	-0.297	0.239
team[T.Valencia]	0.3643	0.120	3.025	0.002	0.128	0.600
team[T.Valladolid]	0.0434	0.155	0.280	0.779	-0.260	0.347
team[T.Vallecano]	0.1883	0.128	1.467	0.142	-0.063	0.440
team[T.Villarreal]	0.2064	0.123	1.674	0.094	-0.035	0.448
team[T.Zaragoza]	-0.0961	0.146	-0.658	0.511	-0.382	0.190
opponent[T.Almeria]	0.4077	0.125	3.252	0.001	0.162	0.653
opponent[T.Ath Bilbao]	0.0676	0.116	0.585	0.559	-0.159	0.294
opponent[T.Ath Madrid]	-0.3547	0.122	-2.918	0.004	-0.593	-0.116
opponent[T.Barcelona]	-0.3638	0.122	-2.971	0.003	-0.604	-0.124
opponent[T.Betis]	0.2854	0.116	2.454	0.014	0.057	0.513
opponent[T.Celta]	0.2081	0.117	1.774	0.076	-0.022	0.438
opponent[T.Cordoba]	0.3913	0.160	2.447	0.014	0.078	0.705
opponent[T.Eibar]	0.1653	0.124	1.332	0.183	-0.078	0.408
opponent[T.Elche]	0.1974	0.141	1.404	0.160	-0.078	0.473
opponent[T.Espanol]	0.1624	0.115	1.418	0.156	-0.062	0.387
opponent[T.Getafe]	0.1826	0.116	1.577	0.115	-0.044	0.409
opponent[T.Girona]	0.2396	0.167	1.438	0.150	-0.087	0.566
opponent[T.Granada]	0.3182	0.116	2.746	0.006	0.091	0.545
opponent[T.Hercules]	0.2860	0.166	1.723	0.085	-0.039	0.611
opponent[T.La Coruna]	0.3070	0.116	2.646	0.008	0.080	0.534
opponent[T.Las Palmas]	0.3642	0.126	2.901	0.004	0.118	0.610
opponent[T.Leganes]	0.1256	0.142	0.883	0.377	-0.153	0.404
opponent[T.Levante]	0.2116	0.115	1.833	0.067	-0.015	0.438
opponent[T.Malaga]	0.1275	0.115	1.110	0.267	-0.098	0.353
opponent[T.Mallorca]	0.2443	0.129	1.896	0.058	-0.008	0.497
opponent[T.Osasuna]	0.3126	0.118	2.641	0.008	0.081	0.545
opponent[T.Real Madrid]	-0.1293	0.119	-1.088	0.277	-0.362	0.104
opponent[T.Santander]	0.2678	0.139	1.929	0.054	-0.004	0.540
opponent[T.Sevilla]	0.1431	0.115	1.245	0.213	-0.082	0.368
opponent[T.Sociedad]	0.1787	0.115	1.561	0.119	-0.046	0.403
opponent[T.Sp Gijon]	0.2893	0.122	2.371	0.018	0.050	0.528
opponent[T.Valencia]	0.0472	0.116	0.407	0.684	-0.180	0.274
opponent[T.Valladolid]	0.2514	0.139	1.809	0.071	-0.021	0.524
opponent[T.Vallecano]	0.4594	0.117	3.940	0.000	0.231	0.688
opponent[T.Villarreal]	-0.0725	0.119	-0.609	0.543	-0.306	0.161
opponent[T.Zaragoza]	0.2514	0.129	1.955	0.051	-0.001	0.503

home	0.3498	0.022	15.807	0.000	0.306	0.393

Out[223]:

Generalized Linear Model Regression Results

Dep. Variable:	goals	**No. Observations:**	6080
Model:	GLM	**Df Residuals:**	6012
Model Family:	Poisson	**Df Model:**	67
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-8656.9
Date:	Fri, 07 Dec 2018	**Deviance:**	6684.9
Time:	15:23:42	**Pearson chi2:**	5.81e+03
No. Iterations:	5	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.0226	0.080	-0.282	0.778	-0.179	0.134
team[T.Bari]	-0.5114	0.201	-2.548	0.011	-0.905	-0.118
team[T.Benevento]	-0.3105	0.183	-1.696	0.090	-0.669	0.048
team[T.Bologna]	-0.1953	0.083	-2.345	0.019	-0.358	-0.032
team[T.Brescia]	-0.2847	0.181	-1.575	0.115	-0.639	0.070
team[T.Cagliari]	-0.0748	0.081	-0.925	0.355	-0.233	0.084
team[T.Carpi]	-0.2091	0.174	-1.202	0.229	-0.550	0.132
team[T.Catania]	-0.0559	0.095	-0.589	0.556	-0.242	0.130
team[T.Cesena]	-0.3172	0.116	-2.743	0.006	-0.544	-0.091
team[T.Chievo]	-0.2186	0.081	-2.705	0.007	-0.377	-0.060
team[T.Crotone]	-0.2121	0.129	-1.642	0.101	-0.465	0.041
team[T.Empoli]	-0.1741	0.109	-1.600	0.110	-0.387	0.039
team[T.Fiorentina]	0.2283	0.073	3.136	0.002	0.086	0.371
team[T.Frosinone]	-0.2451	0.178	-1.375	0.169	-0.595	0.104
team[T.Genoa]	-0.0352	0.077	-0.455	0.649	-0.187	0.116
team[T.Inter]	0.2905	0.072	4.041	0.000	0.150	0.431
team[T.Juventus]	0.4483	0.070	6.448	0.000	0.312	0.585
team[T.Lazio]	0.3145	0.072	4.395	0.000	0.174	0.455
team[T.Lecce]	-0.0401	0.122	-0.329	0.742	-0.279	0.199
team[T.Livorno]	-0.1300	0.170	-0.766	0.444	-0.463	0.203
team[T.Milan]	0.2655	0.072	3.679	0.000	0.124	0.407
team[T.Napoli]	0.4791	0.069	6.910	0.000	0.343	0.615
team[T.Novara]	-0.2427	0.178	-1.361	0.173	-0.592	0.107
team[T.Palermo]	-0.0063	0.083	-0.076	0.939	-0.169	0.156
team[T.Parma]	0.0122	0.087	0.141	0.888	-0.158	0.182
team[T.Pescara]	-0.3227	0.137	-2.355	0.019	-0.591	-0.054

team[T.Roma]	0.3999	0.070	5.686	0.000	0.262	0.538
team[T.Sampdoria]	0.0193	0.079	0.245	0.806	-0.135	0.174
team[T.Sassuolo]	0.0014	0.087	0.017	0.987	-0.169	0.171
team[T.Siena]	-0.1118	0.125	-0.897	0.370	-0.356	0.132
team[T.Spal]	-0.1687	0.170	-0.993	0.321	-0.502	0.164
team[T.Torino]	0.1826	0.079	2.324	0.020	0.029	0.337
team[T.Udinese]	0.0797	0.075	1.060	0.289	-0.068	0.227
team[T.Verona]	-0.0290	0.094	-0.308	0.758	-0.214	0.155
opponent[T.Bari]	0.1740	0.145	1.202	0.229	-0.110	0.458
opponent[T.Benevento]	0.5590	0.122	4.569	0.000	0.319	0.799
opponent[T.Bologna]	0.0729	0.076	0.958	0.338	-0.076	0.222
opponent[T.Brescia]	0.1072	0.149	0.718	0.473	-0.186	0.400
opponent[T.Cagliari]	0.2062	0.074	2.794	0.005	0.062	0.351
opponent[T.Carpi]	0.1696	0.144	1.182	0.237	-0.112	0.451
opponent[T.Catania]	0.1291	0.087	1.476	0.140	-0.042	0.301
opponent[T.Cesena]	0.2461	0.092	2.670	0.008	0.065	0.427
opponent[T.Chievo]	0.0341	0.074	0.459	0.646	-0.112	0.180
opponent[T.Crotone]	0.2587	0.105	2.456	0.014	0.052	0.465
opponent[T.Empoli]	0.1146	0.096	1.195	0.232	-0.073	0.302
opponent[T.Fiorentina]	-0.0258	0.076	-0.340	0.734	-0.174	0.123
opponent[T.Frosinone]	0.4560	0.127	3.580	0.000	0.206	0.706
opponent[T.Genoa]	0.0980	0.073	1.336	0.182	-0.046	0.242
opponent[T.Inter]	-0.0440	0.076	-0.577	0.564	-0.193	0.105
opponent[T.Juventus]	-0.5711	0.088	-6.469	0.000	-0.744	-0.398
opponent[T.Lazio]	-0.0041	0.075	-0.054	0.957	-0.152	0.144
opponent[T.Lecce]	0.2695	0.106	2.540	0.011	0.062	0.477
opponent[T.Livorno]	0.4579	0.127	3.618	0.000	0.210	0.706
opponent[T.Milan]	-0.1423	0.078	-1.824	0.068	-0.295	0.011
opponent[T.Napoli]	-0.1617	0.079	-2.054	0.040	-0.316	-0.007
opponent[T.Novara]	0.3172	0.136	2.335	0.020	0.051	0.584
opponent[T.Palermo]	0.2793	0.075	3.709	0.000	0.132	0.427
opponent[T.Parma]	0.1173	0.082	1.426	0.154	-0.044	0.278
opponent[T.Pescara]	0.5355	0.095	5.620	0.000	0.349	0.722
opponent[T.Roma]	-0.1332	0.078	-1.708	0.088	-0.286	0.020
opponent[T.Sampdoria]	0.1320	0.075	1.758	0.079	-0.015	0.279
opponent[T.Sassuolo]	0.1959	0.080	2.439	0.015	0.038	0.353
opponent[T.Siena]	0.0688	0.113	0.607	0.544	-0.153	0.291

opponent[T.Spal]	0.2110	0.141	1.491	0.136	-0.066	0.488
opponent[T.Torino]	0.1020	0.079	1.297	0.195	-0.052	0.256
opponent[T.Udinese]	0.0916	0.074	1.245	0.213	-0.053	0.236
opponent[T.Verona]	0.3553	0.082	4.353	0.000	0.195	0.515
home	0.2600	0.022	11.606	0.000	0.216	0.304

Out[224]:

Generalized Linear Model Regression Results

Dep. Variable:	goals	**No. Observations:**	4896
Model:	GLM	**Df Residuals:**	4842
Model Family:	Poisson	**Df Model:**	53
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-7244.0
Date:	Fri, 07 Dec 2018	**Deviance:**	5515.4
Time:	15:23:43	**Pearson chi2:**	4.78e+03
No. Iterations:	5	**Covariance Type:**	nonrobust

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-0.0023	0.083	-0.027	0.978	-0.165	0.160
team[T.Bayern Munich]	0.7428	0.071	10.457	0.000	0.604	0.882
team[T.Braunschweig]	-0.3079	0.195	-1.577	0.115	-0.691	0.075
team[T.Darmstadt]	-0.1688	0.137	-1.231	0.218	-0.437	0.100
team[T.Dortmund]	0.5704	0.073	7.802	0.000	0.427	0.714
team[T.Ein Frankfurt]	0.0413	0.084	0.493	0.622	-0.123	0.206
team[T.FC Koln]	0.0267	0.088	0.304	0.761	-0.145	0.199
team[T.Fortuna Dusseldorf]	-0.0237	0.171	-0.138	0.890	-0.359	0.312
team[T.Freiburg]	0.0202	0.084	0.239	0.811	-0.145	0.186
team[T.Greuther Furth]	-0.4266	0.205	-2.078	0.038	-0.829	-0.024
team[T.Hamburg]	-0.0519	0.083	-0.624	0.533	-0.215	0.111
team[T.Hannover]	0.1108	0.083	1.341	0.180	-0.051	0.273
team[T.Hertha]	0.0156	0.088	0.178	0.859	-0.157	0.188
team[T.Hoffenheim]	0.2867	0.077	3.711	0.000	0.135	0.438
team[T.Ingolstadt]	-0.1344	0.135	-0.998	0.318	-0.398	0.129
team[T.Kaiserslautern]	-0.1091	0.132	-0.824	0.410	-0.369	0.150
team[T.Leverkusen]	0.3797	0.076	5.017	0.000	0.231	0.528
team[T.M'gladbach]	0.2521	0.078	3.248	0.001	0.100	0.404
team[T.Mainz]	0.1348	0.080	1.693	0.090	-0.021	0.291
team[T.Nurnberg]	0.0053	0.099	0.053	0.957	-0.189	0.200
team[T.Paderborn]	-0.2436	0.189	-1.286	0.198	-0.615	0.128
team[T.RB Leipzig]	0.4444	0.108	4.100	0.000	0.232	0.657
team[T.Schalke 04]	0.2768	0.077	3.586	0.000	0.126	0.428
team[T.St Pauli]	-0.1310	0.179	-0.730	0.466	-0.483	0.221
team[T.Stuttgart]	0.1931	0.081	2.382	0.017	0.034	0.352
team[T.Werder Bremen]	0.2035	0.079	2.585	0.010	0.049	0.358

team[T.Wolfsburg]	0.1979	0.079	2.518	0.012	0.044	0.352
opponent[T.Bayern Munich]	-0.6688	0.091	-7.344	0.000	-0.847	-0.490
opponent[T.Braunschweig]	0.2096	0.140	1.495	0.135	-0.065	0.484
opponent[T.Darmstadt]	0.1757	0.108	1.630	0.103	-0.035	0.387
opponent[T.Dortmund]	-0.2519	0.080	-3.144	0.002	-0.409	-0.095
opponent[T.Ein Frankfurt]	0.0459	0.076	0.604	0.546	-0.103	0.195
opponent[T.FC Koln]	0.1289	0.077	1.666	0.096	-0.023	0.281
opponent[T.Fortuna Dusseldorf]	0.1755	0.143	1.224	0.221	-0.105	0.457
opponent[T.Freiburg]	0.1015	0.075	1.352	0.176	-0.046	0.249
opponent[T.Greuther Furth]	0.2114	0.140	1.507	0.132	-0.064	0.486
opponent[T.Hamburg]	0.1413	0.072	1.959	0.050	-3.38e-05	0.283
opponent[T.Hannover]	0.1289	0.075	1.725	0.084	-0.018	0.275
opponent[T.Hertha]	0.0271	0.079	0.341	0.733	-0.129	0.183
opponent[T.Hoffenheim]	0.1161	0.073	1.595	0.111	-0.027	0.259
opponent[T.Ingolstadt]	0.0186	0.114	0.162	0.871	-0.206	0.243
opponent[T.Kaiserslautern]	0.0790	0.112	0.707	0.480	-0.140	0.298
opponent[T.Leverkusen]	-0.0961	0.077	-1.254	0.210	-0.246	0.054
opponent[T.M'gladbach]	-0.0646	0.076	-0.852	0.394	-0.213	0.084
opponent[T.Mainz]	-0.0013	0.075	-0.018	0.986	-0.148	0.145
opponent[T.Nurnberg]	0.0927	0.088	1.056	0.291	-0.079	0.265
opponent[T.Paderborn]	0.2886	0.135	2.130	0.033	0.023	0.554
opponent[T.RB Leipzig]	-0.0427	0.118	-0.363	0.717	-0.273	0.188
opponent[T.Schalke 04]	-0.0943	0.076	-1.233	0.218	-0.244	0.056
opponent[T.St Pauli]	0.3391	0.133	2.549	0.011	0.078	0.600
opponent[T.Stuttgart]	0.1592	0.074	2.144	0.032	0.014	0.305
opponent[T.Werder Bremen]	0.2360	0.071	3.329	0.001	0.097	0.375
opponent[T.Wolfsburg]	0.0355	0.074	0.479	0.632	-0.110	0.181
home	0.2607	0.024	10.871	0.000	0.214	0.308

Out[225]:

Generalized Linear Model Regression Results

Dep. Variable:	goals	**No. Observations:**	6080
Model:	GLM	**Df Residuals:**	6014
Model Family:	Poisson	**Df Model:**	65
Link Function:	log	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-8475.4
Date:	Fri, 07 Dec 2018	**Deviance:**	6635.6
Time:	15:23:43	**Pearson chi2:**	5.80e+03
No. Iterations:	5	**Covariance Type:**	nonrobust

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
Intercept	0.1012	0.120	0.843	0.399	-0.134	0.337
team[T.Ajaccio GFCO]	-0.0280	0.189	-0.148	0.882	-0.399	0.343
team[T.Amiens]	-0.0695	0.189	-0.367	0.714	-0.441	0.302
team[T.Angers]	0.0434	0.130	0.333	0.739	-0.212	0.299
team[T.Arles]	-0.5932	0.237	-2.499	0.012	-1.058	-0.128
team[T.Auxerre]	0.1500	0.140	1.069	0.285	-0.125	0.425
team[T.Bastia]	0.0044	0.118	0.038	0.970	-0.226	0.235
team[T.Bordeaux]	0.2135	0.106	2.013	0.044	0.006	0.421
team[T.Brest]	-0.1777	0.137	-1.297	0.195	-0.446	0.091
team[T.Caen]	0.0377	0.113	0.333	0.739	-0.184	0.260
team[T.Dijon]	0.1851	0.126	1.468	0.142	-0.062	0.432
team[T.Evian Thonon Gaillard]	0.1469	0.119	1.232	0.218	-0.087	0.381
team[T.Guingamp]	0.1129	0.115	0.978	0.328	-0.113	0.339
team[T.Lens]	-0.1384	0.154	-0.901	0.368	-0.440	0.163
team[T.Lille]	0.2600	0.105	2.466	0.014	0.053	0.467
team[T.Lorient]	0.1709	0.109	1.575	0.115	-0.042	0.384
team[T.Lyon]	0.5581	0.102	5.449	0.000	0.357	0.759
team[T.Marseille]	0.3874	0.104	3.723	0.000	0.183	0.591
team[T.Metz]	-0.0957	0.135	-0.706	0.480	-0.361	0.170
team[T.Monaco]	0.5276	0.106	4.988	0.000	0.320	0.735
team[T.Montpellier]	0.1892	0.106	1.779	0.075	-0.019	0.398
team[T.Nancy]	-0.0548	0.124	-0.441	0.659	-0.298	0.189
team[T.Nantes]	-0.0904	0.120	-0.755	0.450	-0.325	0.144
team[T.Nice]	0.1865	0.106	1.753	0.080	-0.022	0.395
team[T.Paris SG]	0.7306	0.101	7.241	0.000	0.533	0.928
team[T.Reims]	0.0836	0.121	0.691	0.490	-0.153	0.321

team[T.Rennes]	0.1374	0.107	1.284	0.199	-0.072	0.347
team[T.Sochaux]	0.1364	0.120	1.142	0.254	-0.098	0.371
team[T.St Etienne]	0.2190	0.106	2.067	0.039	0.011	0.427
team[T.Strasbourg]	0.1314	0.178	0.739	0.460	-0.217	0.480
team[T.Toulouse]	0.0646	0.108	0.598	0.550	-0.147	0.276
team[T.Troyes]	-0.1113	0.136	-0.820	0.412	-0.377	0.155
team[T.Valenciennes]	0.0929	0.120	0.771	0.441	-0.143	0.329
opponent[T.Ajaccio GFCO]	-0.0616	0.151	-0.408	0.683	-0.357	0.234
opponent[T.Amiens]	-0.3833	0.172	-2.234	0.025	-0.720	-0.047
opponent[T.Angers]	-0.2837	0.113	-2.515	0.012	-0.505	-0.063
opponent[T.Arles]	0.1266	0.141	0.900	0.368	-0.149	0.402
opponent[T.Auxerre]	-0.2093	0.125	-1.671	0.095	-0.455	0.036
opponent[T.Bastia]	-0.1353	0.096	-1.412	0.158	-0.323	0.053
opponent[T.Bordeaux]	-0.3230	0.091	-3.543	0.000	-0.502	-0.144
opponent[T.Brest]	-0.2466	0.112	-2.209	0.027	-0.465	-0.028
opponent[T.Caen]	-0.0961	0.092	-1.044	0.296	-0.277	0.084
opponent[T.Dijon]	0.0590	0.103	0.571	0.568	-0.143	0.261
opponent[T.Evian Thonon Gaillard]	-0.0992	0.100	-0.992	0.321	-0.295	0.097
opponent[T.Guingamp]	-0.1500	0.096	-1.557	0.119	-0.339	0.039
opponent[T.Lens]	-0.0320	0.118	-0.272	0.786	-0.263	0.199
opponent[T.Lille]	-0.4033	0.093	-4.360	0.000	-0.585	-0.222
opponent[T.Lorient]	-0.0993	0.090	-1.107	0.268	-0.275	0.077
opponent[T.Lyon]	-0.3356	0.092	-3.658	0.000	-0.515	-0.156
opponent[T.Marseille]	-0.3835	0.092	-4.154	0.000	-0.564	-0.203
opponent[T.Metz]	0.1180	0.102	1.163	0.245	-0.081	0.317
opponent[T.Monaco]	-0.4764	0.100	-4.772	0.000	-0.672	-0.281
opponent[T.Montpellier]	-0.2852	0.091	-3.150	0.002	-0.463	-0.108
opponent[T.Nancy]	-0.1700	0.102	-1.674	0.094	-0.369	0.029
opponent[T.Nantes]	-0.3357	0.100	-3.356	0.001	-0.532	-0.140
opponent[T.Nice]	-0.2854	0.091	-3.151	0.002	-0.463	-0.108
opponent[T.Paris SG]	-0.6736	0.098	-6.853	0.000	-0.866	-0.481
opponent[T.Reims]	-0.1224	0.100	-1.219	0.223	-0.319	0.074
opponent[T.Rennes]	-0.2906	0.091	-3.207	0.001	-0.468	-0.113
opponent[T.Sochaux]	-0.0949	0.100	-0.949	0.343	-0.291	0.101
opponent[T.St Etienne]	-0.4274	0.093	-4.602	0.000	-0.609	-0.245
opponent[T.Strasbourg]	0.0925	0.143	0.645	0.519	-0.188	0.373
opponent[T.Toulouse]	-0.2433	0.090	-2.707	0.007	-0.419	-0.067

opponent[T.Troyes]	0.0986	0.102	0.966	0.334	-0.101	0.299
opponent[T.Valenciennes]	-0.1528	0.101	-1.509	0.131	-0.351	0.046
home	0.3028	0.023	13.118	0.000	0.258	0.348

Lets use the model to simulate matches

Manchester United vs Manchester City

```
Probability Man City Win (Man City Home) : 0.5213758840709862
Probability Man U win (Man City Home) : 0.237715360715005
Probability Draw (Man City Home) 0.2409069842947822

Probability Man U Win (Man U Home) : 0.394862588690056
Probability Man City win (Man U Home) : 0.3464427723828131
Probability Draw (Man U Home) 0.25869424116264067
```

Actual Results

1. At Etihad Stadium : [https://www.premierleague.com/match/ (https://www.premierleague.com/match/)](https://www.premierleague.com/match/) (Man City wins 3-1)
2. At Old Trafford : yet to be played this year

So our model correctly predicted a Man City win

Real Madrid vs Barcelona

```
Probability Madrid Win (Madrid) : 0.436996694620295l7
Probability Barcelona win (Madrid) : 0.3483928560868603
Probability Draw (Madrid) 0.21460109811900938

Probability Barcelona Win (Barcelona) : 0.6127844341417124
Probability Madrid win (Barcelona) : 0.20240895399328018
Probability Draw (Barcelona) 0.18475050565145482
```

Actual Results in 2018-2019 season :

1. Real Madrid vs Barcelona at Madrid : yet to be played this season
2. Real Madrid vs Barcelona at Barcelona : [https://www.bbc.com/sport/football/45995215 (https://www.bbc.com/sport/football/45995215)](https://www.bbc.com/sport/football/45995215) (Barcelona won 5-1)

Our model correctly predicted this one too

A game of football has much more scope for analysis than the commonly used statistics like number of goals, number of cards etc. To analyze the events and their impact and also the betting stats, lets look at a secondary dataset.

	id_odsp	id_event	sort_order	time	text	event_type	event_type2	side	event_team
0	UFot0hit/	UFot0hit1	1	2	Attempt missed. Mladen Petric (Hamburg) left f...	1	12.0	2	Hamburg SV
1	UFot0hit/	UFot0hit2	2	4	Corner, Borussia Dortmund. Conceded by Dennis...	2	NaN	1	Borussia Dortmund

Out[4]: (941009, 22)

So we have almost a million events in the dataset

We have one more file in the dataset. Lets look at it as well

	id_odsp	link_odsp	adv_stats	date	league	season	country	ht
0	UFot0hit/	/soccer/germany/bundesliga-2011-2012/dortmund-...	True	2011-08-05	D1	2012	germany	Borussia Dortmund
1	Aw5DflLH/	/soccer/germany/bundesliga-2011-2012/augsburg-...	True	2011-08-06	D1	2012	germany	FC Augsburg
2	bkjpaC6n/	/soccer/germany/bundesliga-2011-2012/werder-br...	True	2011-08-06	D1	2012	germany	Werder Bremen
3	CzPV312a/	/soccer/france/ligue-1-2011-2012/paris-sg-lori...	True	2011-08-06	F1	2012	france	Paris Saint-Germain
4	GUOdmtII/	/soccer/france/ligue-1-2011-2012/caen-valencie...	True	2011-08-06	F1	2012	france	Caen

	id_odsp	date	league	season	country	odd_h	odd_d	odd_a	fthg	ftag	prob_h	prob_
0	UFot0hit/	2011-08-05	D1	2012	germany	1.56	4.41	7.42	3	1	2.56	8.4
1	Aw5DflLH/	2011-08-06	D1	2012	germany	2.36	3.60	3.40	2	2	3.36	4.4
2	bkjpaC6n/	2011-08-06	D1	2012	germany	1.83	4.20	4.80	2	0	2.83	5.8
3	CzPV312a/	2011-08-06	F1	2012	france	1.55	4.50	9.40	0	1	2.55	10.4
4	GUOdmtII/	2011-08-06	F1	2012	france	2.50	3.40	3.45	1	0	3.50	4.4

This dataset uses cryptic names like D1, F1 etc for the leagues. Lets replace the values to have the same set of names that we used in the original match result dataset

Out[9]:

		id_odsp	date	league	season	country	odd_h	odd_d	odd_a	fthg	ftag	pr
league	**country**											
D1	**germany**	1690	526	1	6	1	358	240	500	10	8	
E0	**england**	2120	553	1	6	1	358	227	498	9	7	
F1	**france**	2107	594	1	6	1	347	224	507	7	9	
I1	**italy**	2106	541	1	6	1	361	268	516	8	8	
SP1	**spain**	2089	681	1	6	1	390	304	572	11	9	

So E0 means EPL, SP1 means La Liga, I1 means Serie A, F1 means Ligue1 and D1 means Bundesliga

Out[11]:

		id_odsp	date	league	season	country	odd_h	odd_d	odd_a	fthg	ftag
league	**country**										
Bundesliga	**germany**	1690	526	1	6	1	358	240	500	10	8
EPL	**england**	2120	553	1	6	1	358	227	498	9	7
LaLiga	**spain**	2089	681	1	6	1	390	304	572	11	9
Ligue1	**france**	2107	594	1	6	1	347	224	507	7	9
SerieA	**italy**	2106	541	1	6	1	361	268	516	8	8

Lets merge the two dataframes together

	id_odsp	id_event	sort_order	time	text	event_type	event_type2	side	event_team
0	UFot0hit/	UFot0hit1	1	2	Attempt missed. Mladen Petric (Hamburg) left f...	1	12.0	2	Hamburg SV
1	UFot0hit/	UFot0hit2	2	4	Corner, Borussia Dortmund. Conceded by Dennis...	2	NaN	1	Borussia Dortmund

The data has a lot of columns with cryptic numeric values. Lets use the dictionary file to replace the cryptic values with meaningful data instead

Lets look at the dataset once again now

	id_odsp	id_event	sort_order	time	text	event_type	event_type2	side	event_team
0	UFot0hit/	UFot0hit1	1	2	Attempt missed. Mladen Petric (Hamburg) left f...	Attempt	Key Pass	Away	Hamburg SV
1	UFot0hit/	UFot0hit2	2	4	Corner, Borussia Dortmund. Conceded by Dennis...	Corner	NaN	Home	Borussia Dortmund
2	UFot0hit/	UFot0hit3	3	4	Corner, Borussia Dortmund. Conceded by Heiko ...	Corner	NaN	Home	Borussia Dortmund
3	UFot0hit/	UFot0hit4	4	7	Foul by Sven Bender (Borussia Dortmund).	Foul	NaN	Home	Borussia Dortmund
4	UFot0hit/	UFot0hit5	5	7	Gokhan Tore (Hamburg) wins a free kick in the ...	Free kick won	NaN	Away	Hamburg SV

Now the event dataset is ready for analysis

Lets visualize the number of occurences for each type of event

```
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```

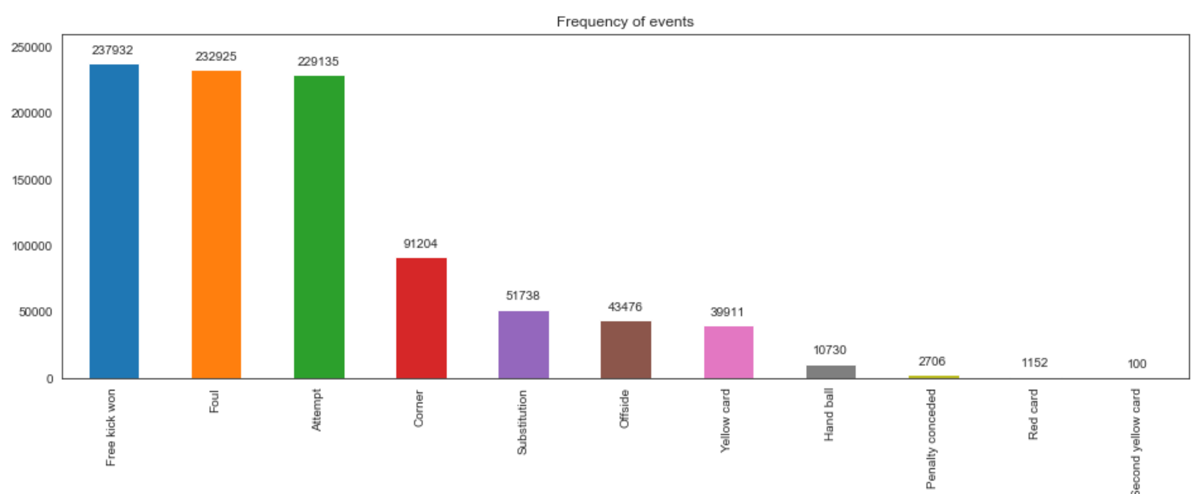

Overall, the most frequent events are :

1. Free kick won
2. Foul
3. Attempt

Lets look at a league wise view of the number of events

a) **English Premier League**

```
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```

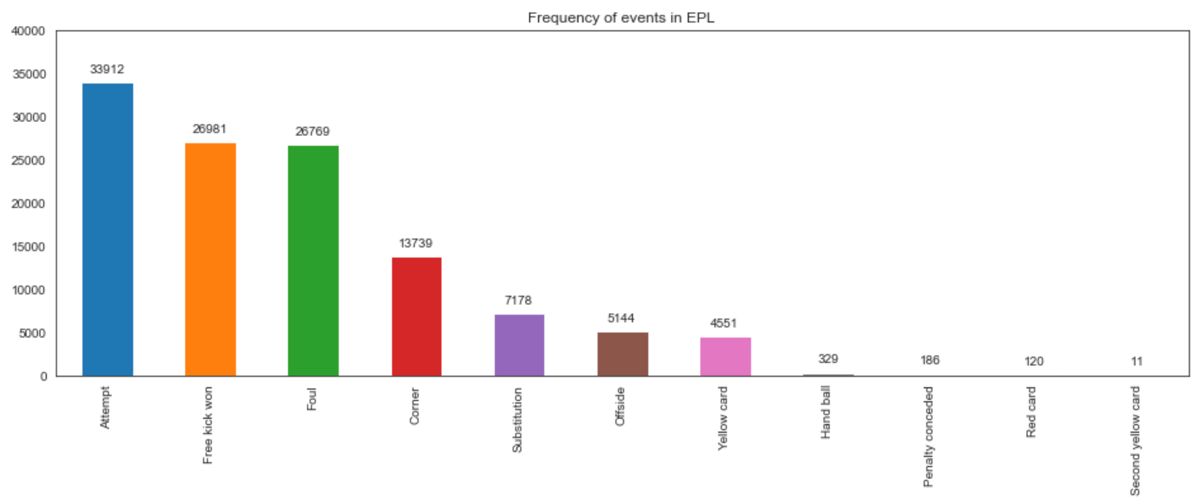

Foul moves from no 2 to no 3 position. This is consistent with our observation from the previous dataset that EPL has lesser number of fouls.

Attempt moves from no 3 to no 1 position. This is consistent with our observation from the other dataset that EPL has higher number of shots at goal as compared to other leagues

b) **La Liga**

```
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```

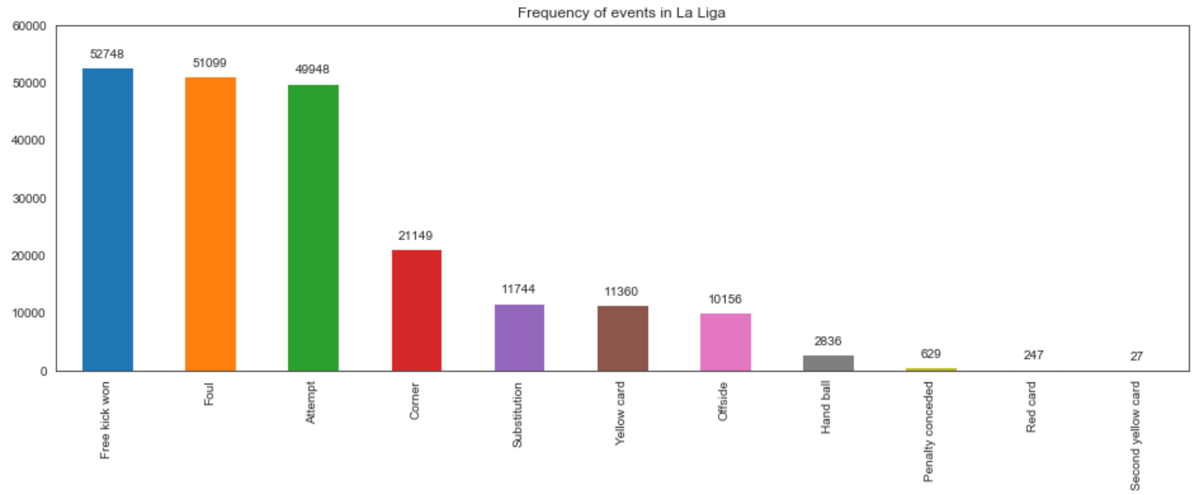

c) **Serie A**

```
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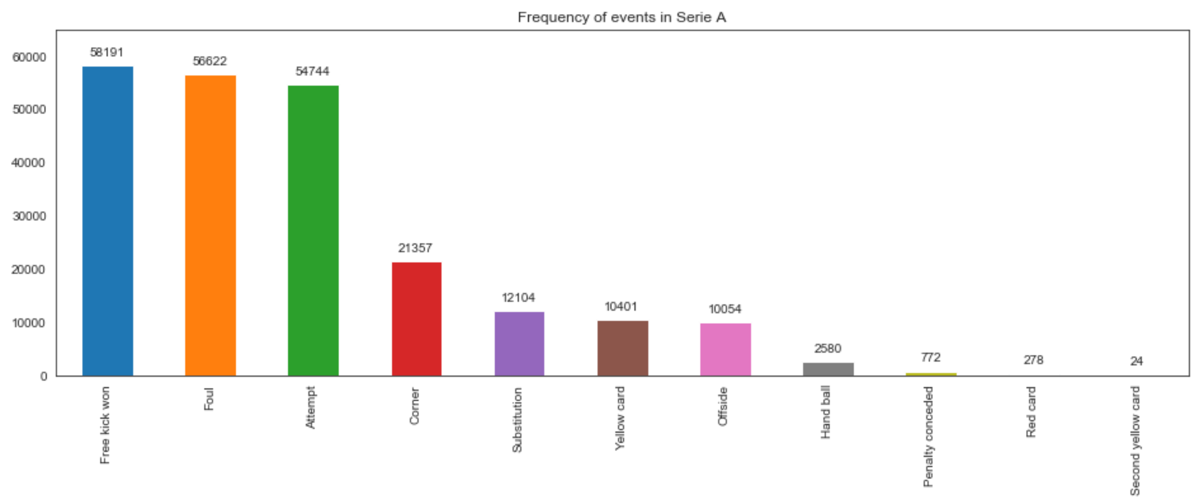

d) **Bundesliga**

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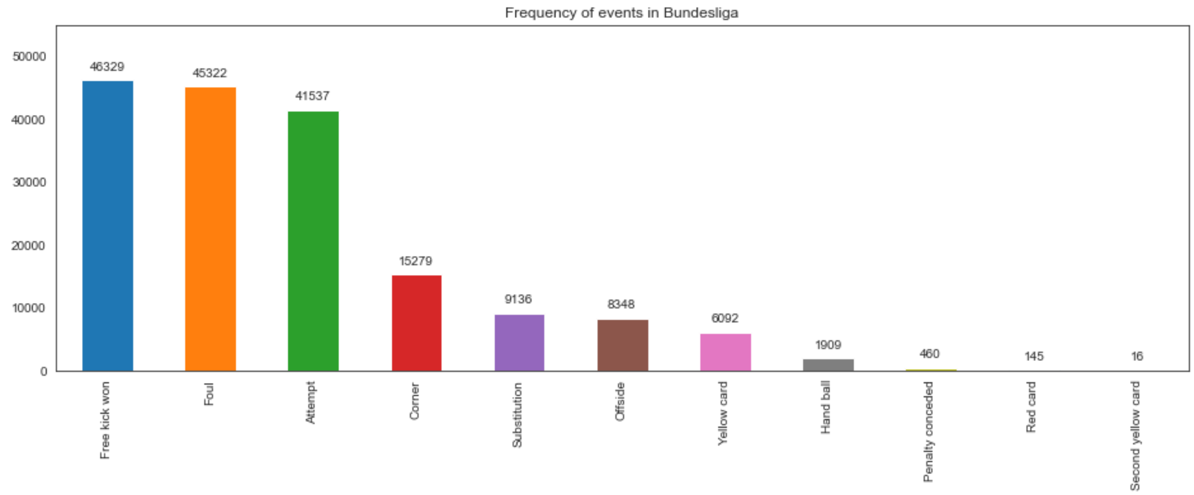
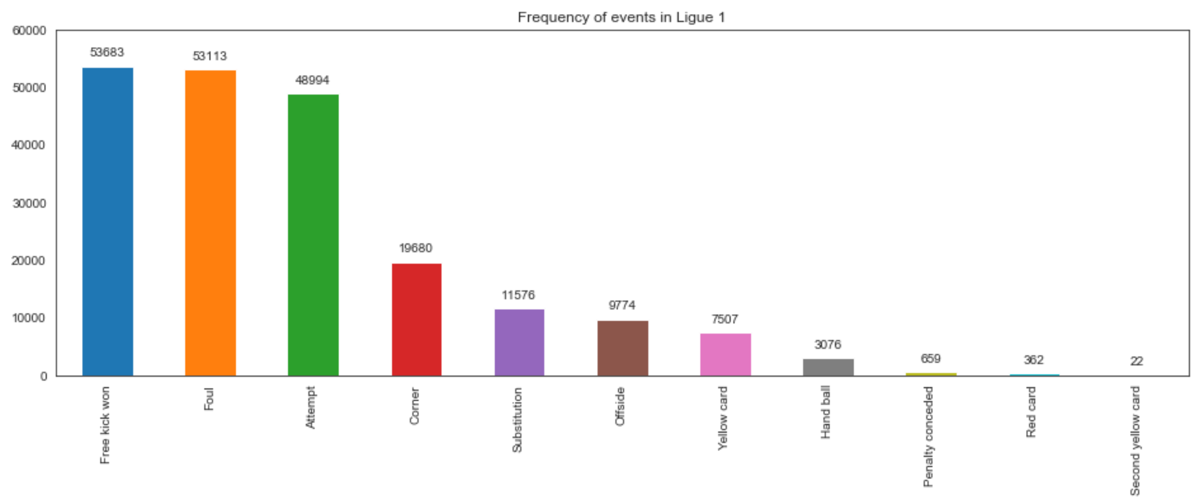


e) **Ligue One**

<Figure size 432x288 with 0 Axes>



So the top 3 events in every league are Free kick won, Fouls and Attempts. EPL witnesses almost half the number of Fouls as LaLiga even though both the leagues involve equal number of games per season

Where to shoot if you want to score a goal ?

Lets look at the shots that resulted in goals

```
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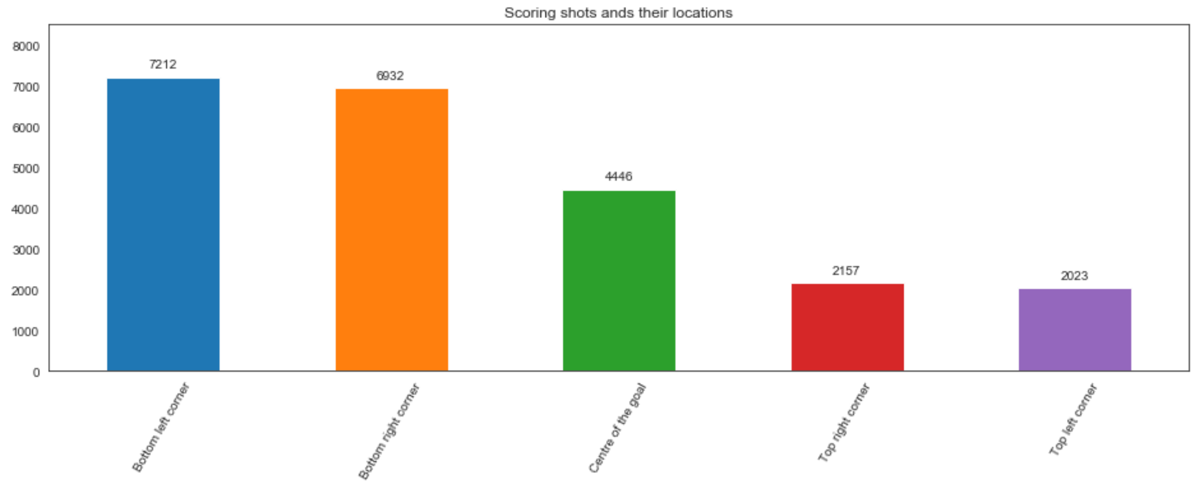
```



The data suggests that its more effective to shoot at the bottom than to shoot at the top or centre

Lets have a look at the missed attempts as well

```
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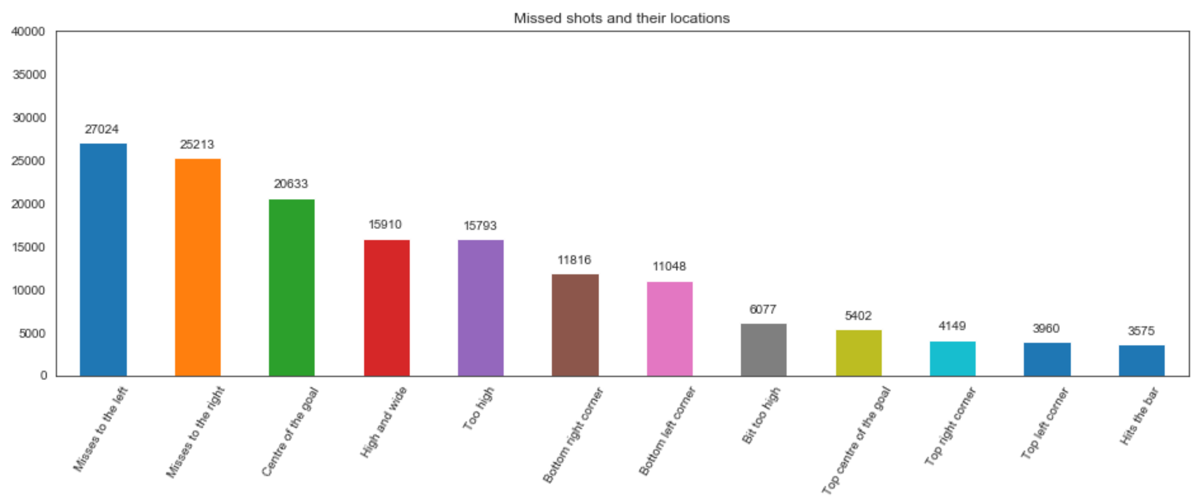
```



The number of saves in bottom left/right corner is quite low as opposed to centre of the box

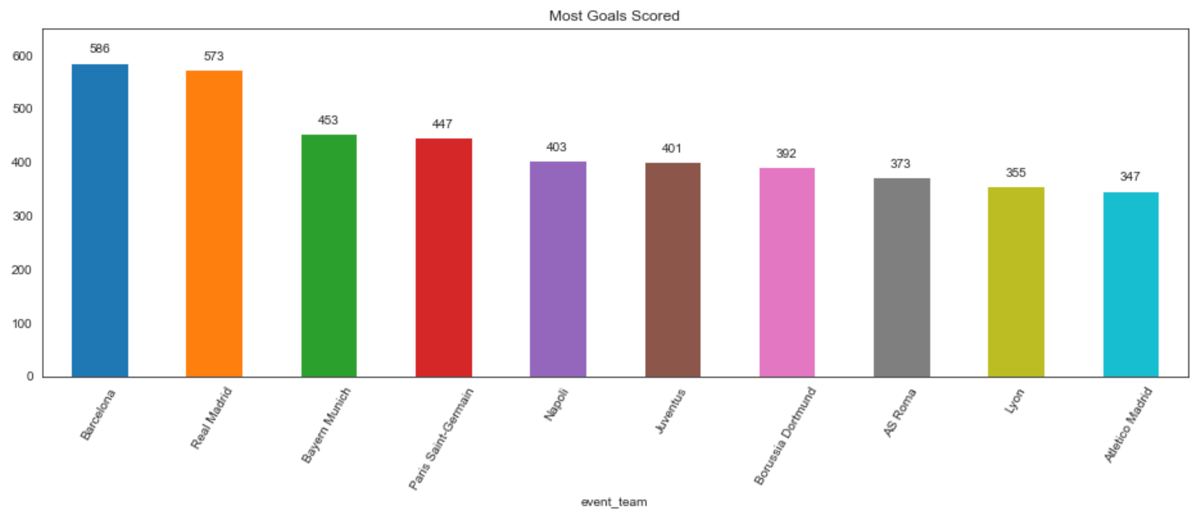
There are fewer saves at top left/right corner but the chances of missing are high (might hit the bar or may be too high)

So, we can conclude that bottom right or left corners are the best locations to aim at while trying to score a goal

Which teams and players are the most prolific scorers ?

Lets have a look at the most heavily scoring teams first

<Figure size 432x288 with 0 Axes>

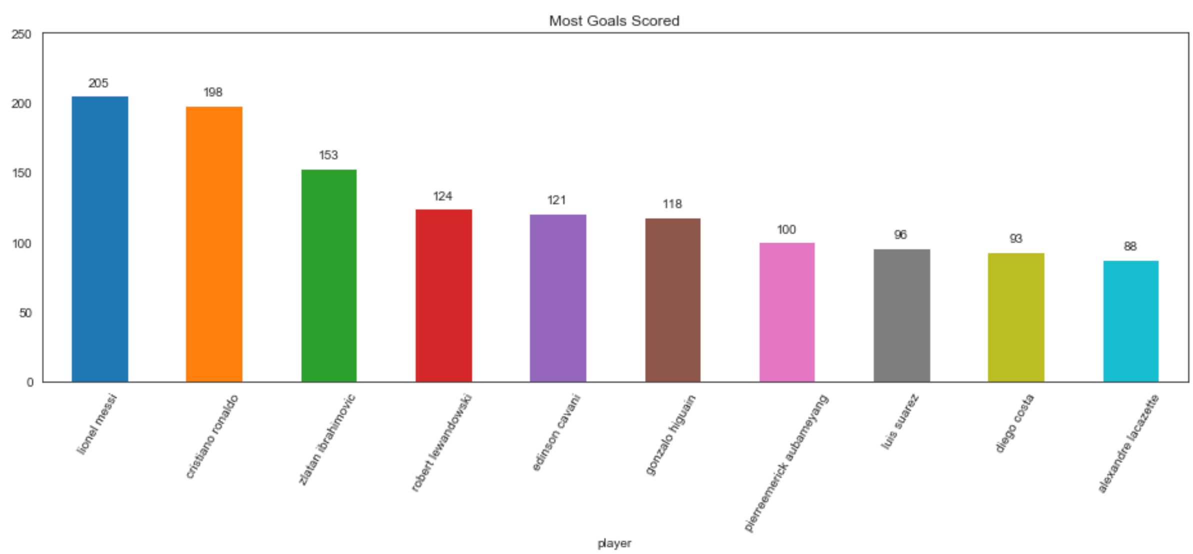


Barcelona and Real Madrid are at the top. This is also in line with our observation that La Liga witnesses high number of goals.

Interestingly none of the EPL teams make it to this list

Lets have a look at most prolific individual scorers now

<Figure size 432x288 with 0 Axes>



No surprises there in the top two names !!!

Zlatan Ibrahimovic is the only player to make it to this list after playing in three different leagues during this period

The players in the above chart might have high number of misses as well. Lets look at the players with maximum number of missed attempts

```
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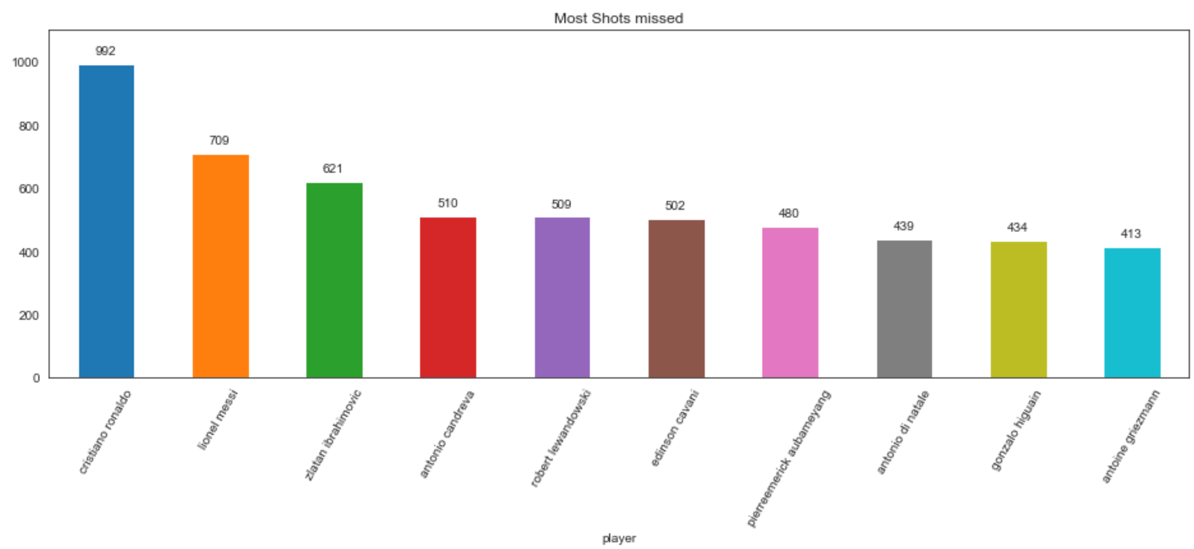

The top 3 are still Cristiano Ronaldo, Lionel Messi and Zlatan Ibrahimovic

Let's have a look at total number of Attempts as well

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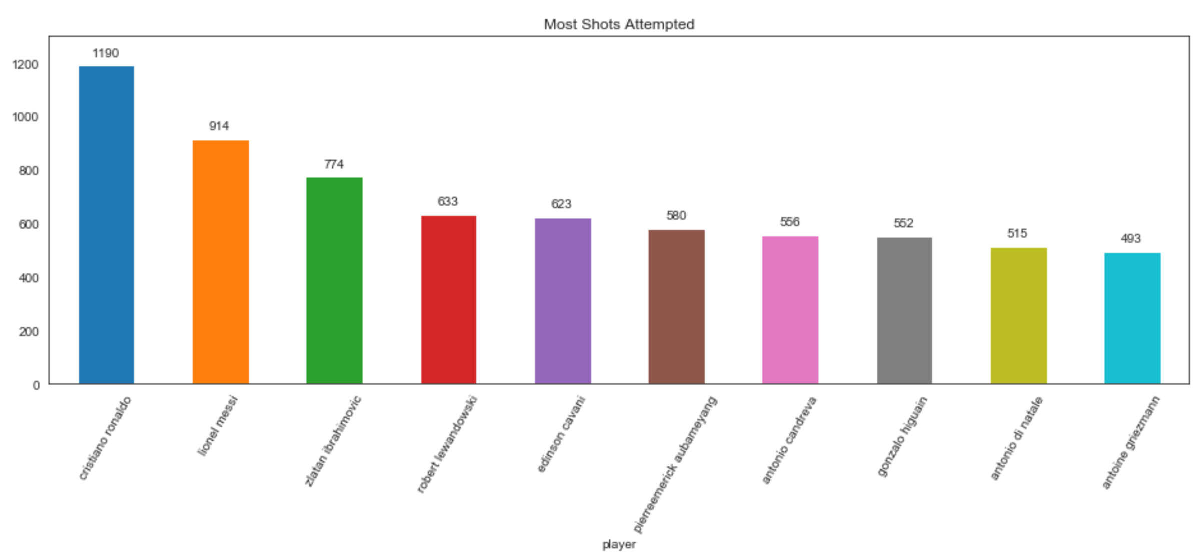

No wonder Christiano Ronaldo is considered as one of the greatest forwards of all time. He is almost 20 % ahead of Messi at second position

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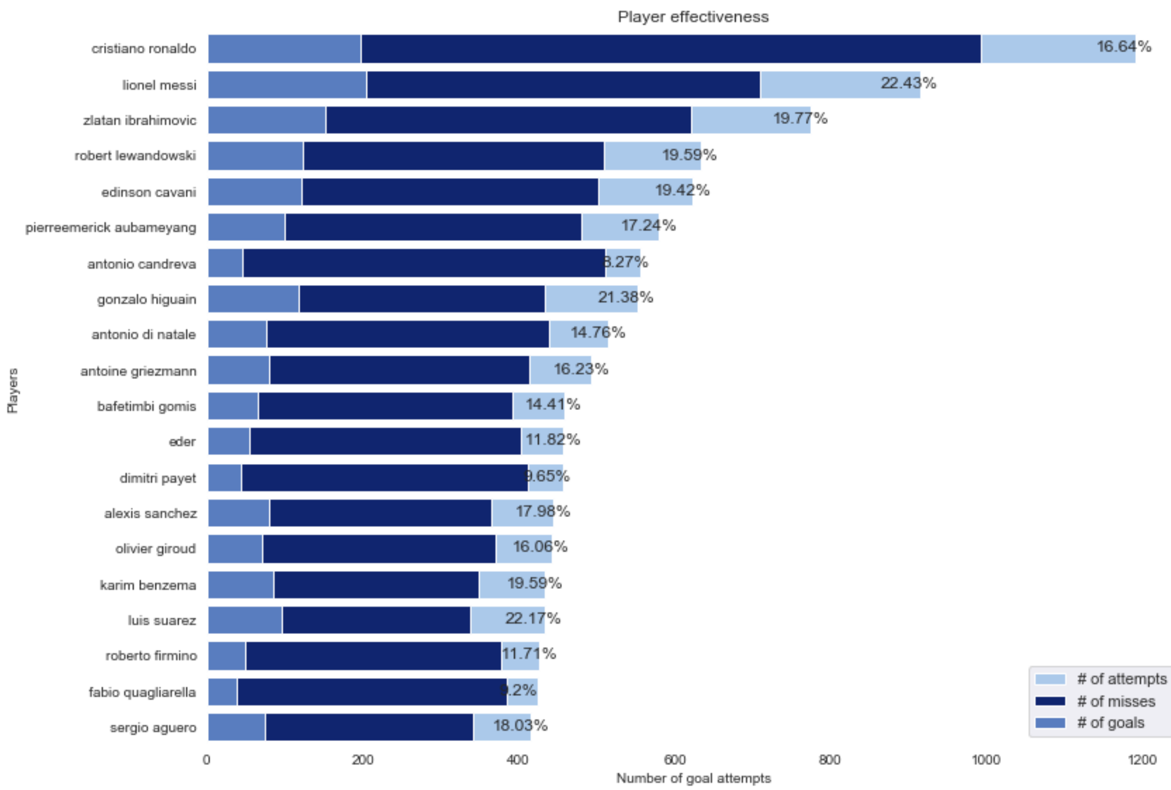

Clearly Christiano Ronaldo and Lionel Messi are considered among greatest off all times because they have been consistently creating chances.

Their teammates like Suarez and Higuain have better attempt-to-goal-conversion-rate but doesn't create half as many chances as Messi and Ronaldo

Which teams and players commit the maximum number of fouls ?

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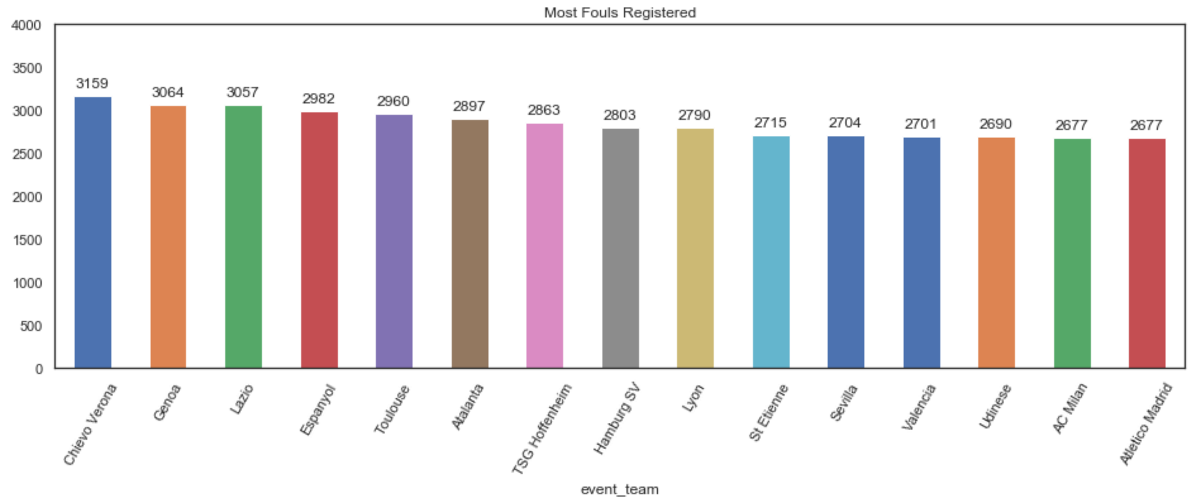

More fouls are being committed by lower ranked teams in the league. Lyon and Lazio are the only top tier teams with very high number of fouls

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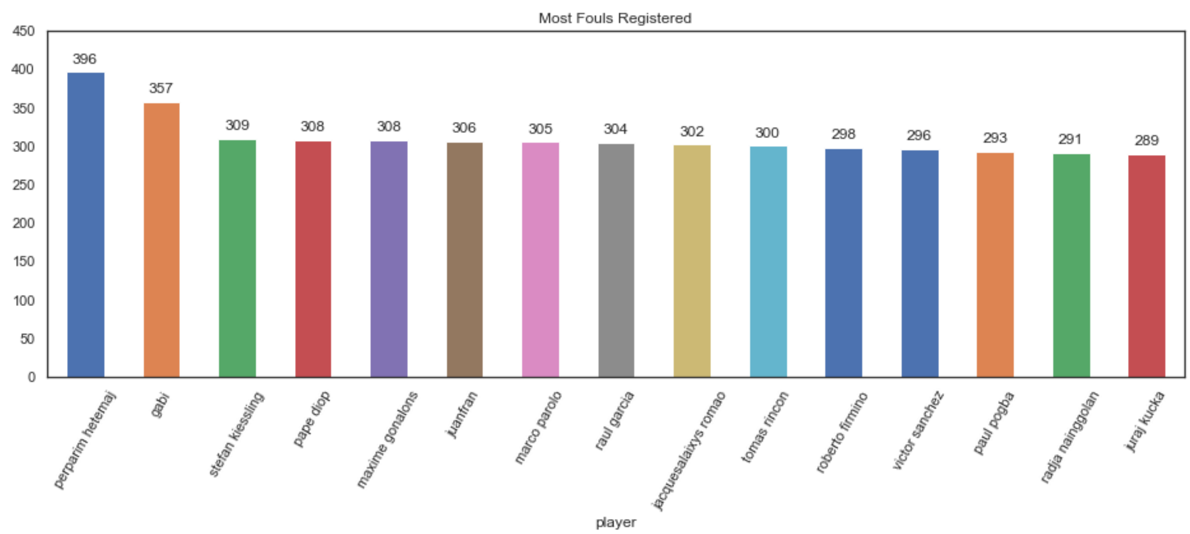

Surprising to not see Sergio Ramos among top 15

Lets look the card data as well, there should be some correlation between the two lists

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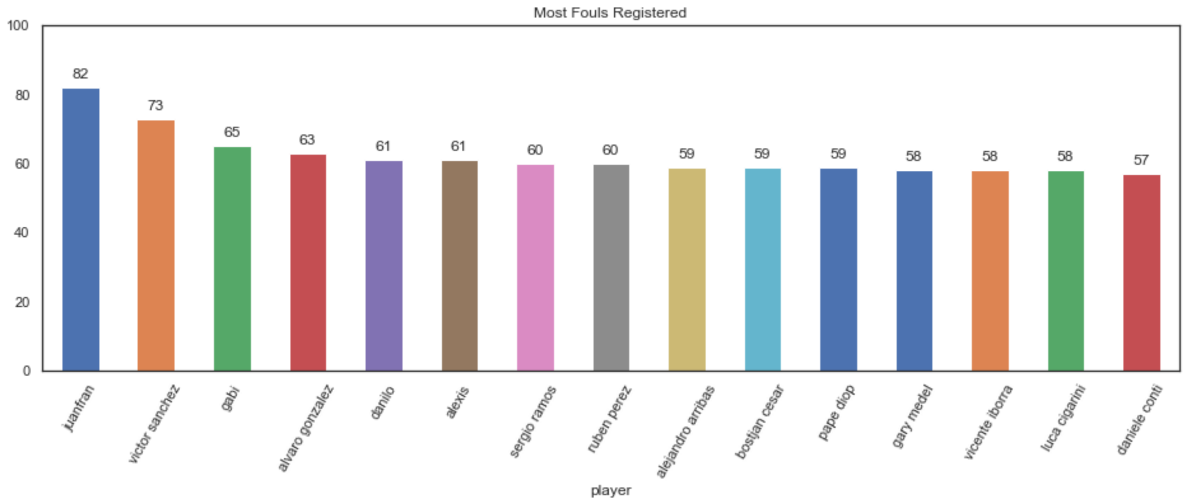

Gabi from Athletico Madrid is among the worst offenders - he features in top 3 in terms of both the number of fouls committed as well as the number of cards

Which teams and players concede the maximum number of corners ?

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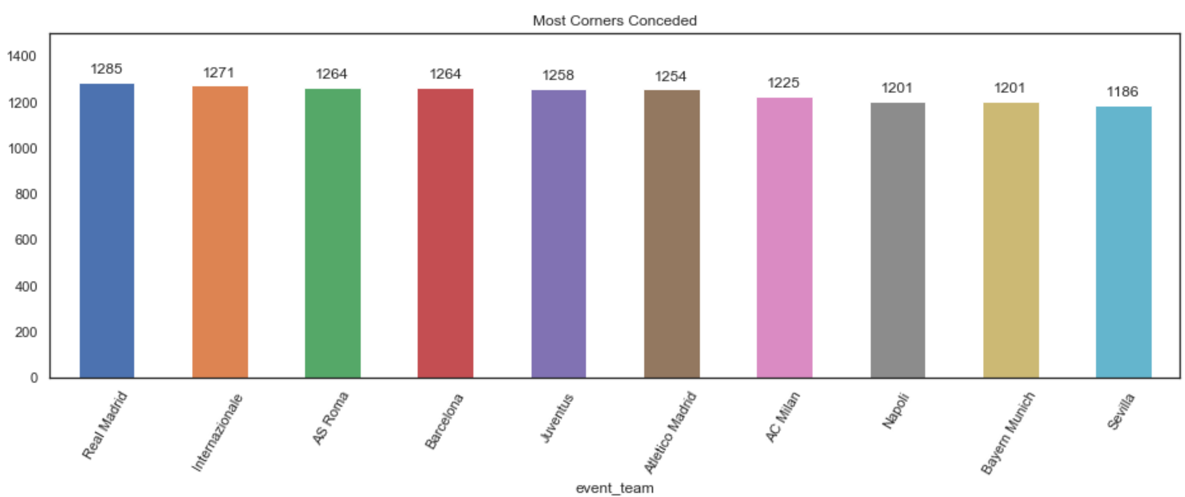

The top 10 list is dominated by La Liga (Real Madrid, Barcelona, Athletico Madrid, Sevilla) and Serie A (Internazionale, AS Roma, Juventus, AC Milan, Napoli)

So we can clearly conclude that teams in La Liga and Serie A concede more corners compared to other leagues

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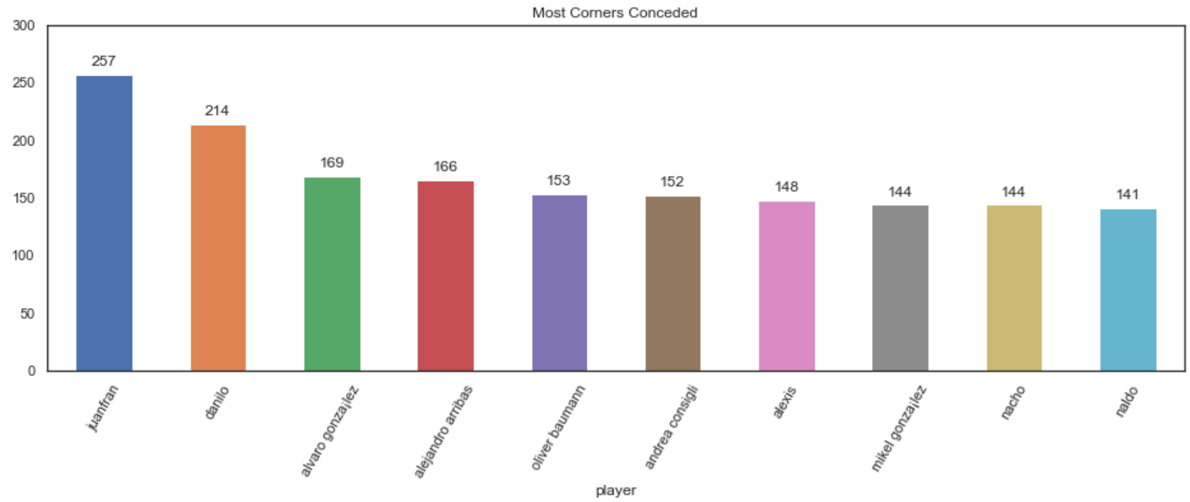

Which players contribute the most through assists ?

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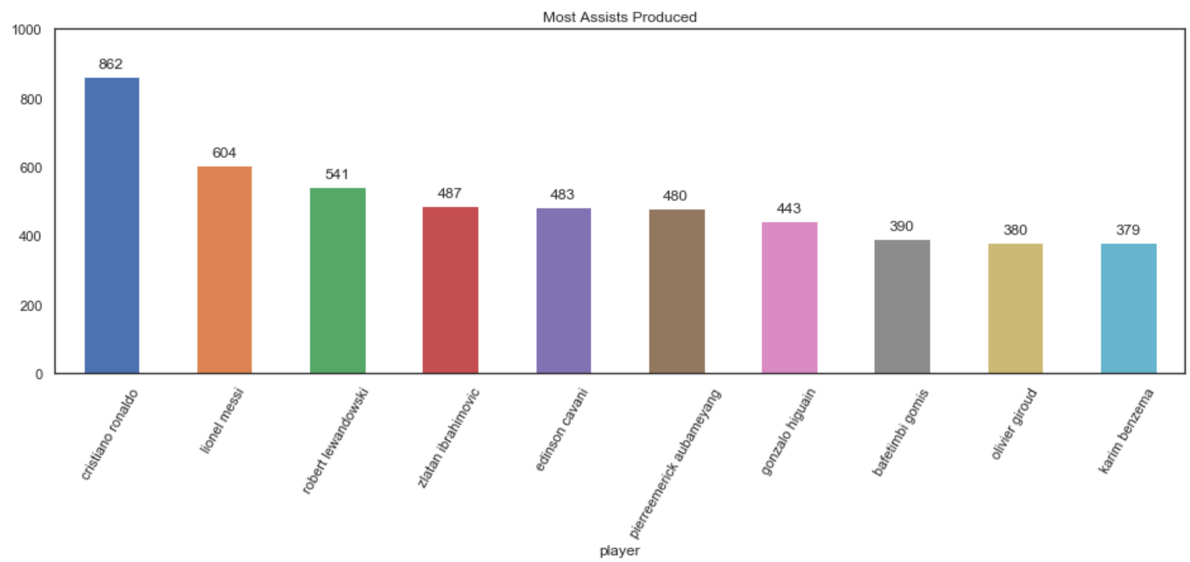

Again we have the two usual suspects at the top. Cristiano Ronaldo tops the number of assists as well (and is ahead of Messi at no 2 by 30 %)

Higuain and Benzema also appear in the top 10 list indicating that they played a significant role behind Christiano Ronaldo's success as a goalscorer

Messi vs Ronaldo - What does data indicate ?

Lets build a player comparator

	Goals	Misses	Attempts	Assists	Cards	Fouls	Offsides
lionel messi	205	709	914	604	17	68	89
cristiano ronaldo	198	992	1190	862	29	100	206
zlatan ibrahimovic	153	621	774	487	29	248	225
gonzalo higuain	118	434	552	443	21	155	190
luis suarez	96	337	433	322	22	113	161
karim benzema	85	349	434	379	4	91	137
gareth bale	50	251	301	234	9	61	52
harry kane	65	288	353	278	9	85	78
neymar	58	260	318	248	23	106	69

When are the most goals scored during a football match ?

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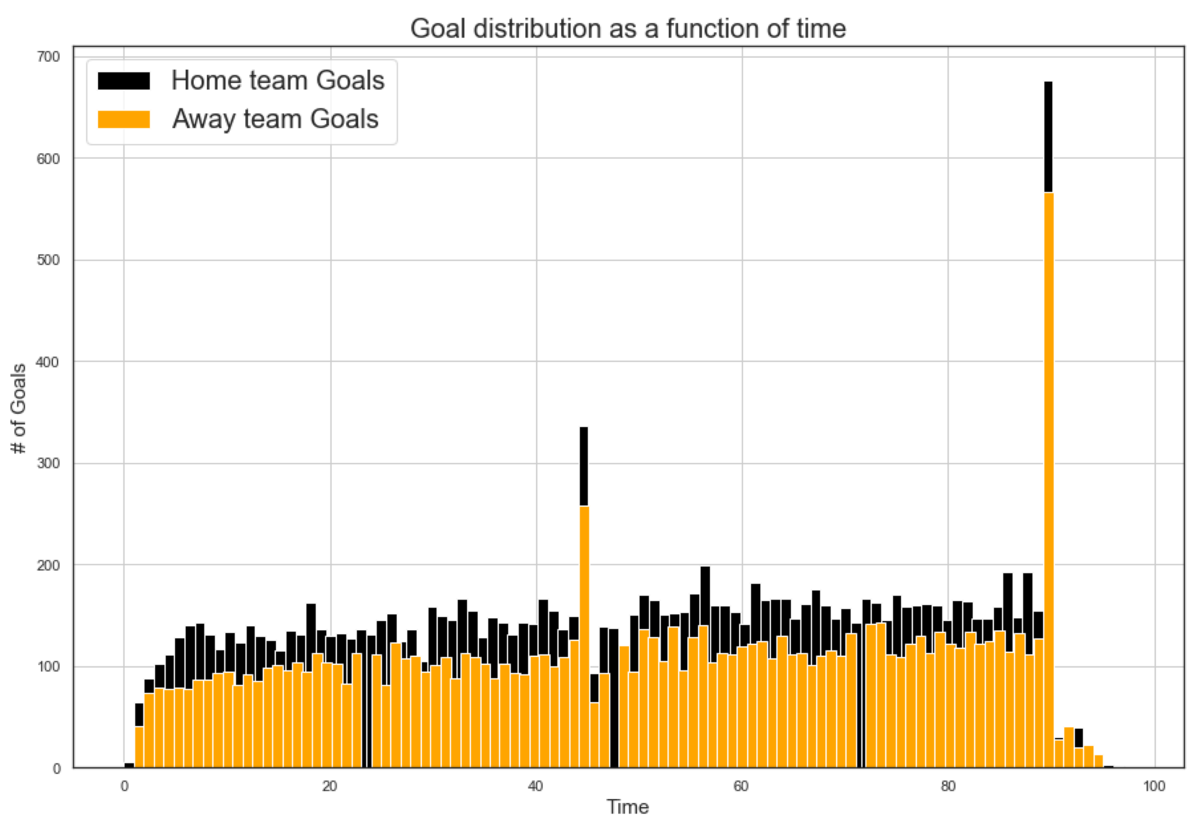

Interestingly there's a massive spike in number of goals just before half time and full time

When do the most substitutions occur ?

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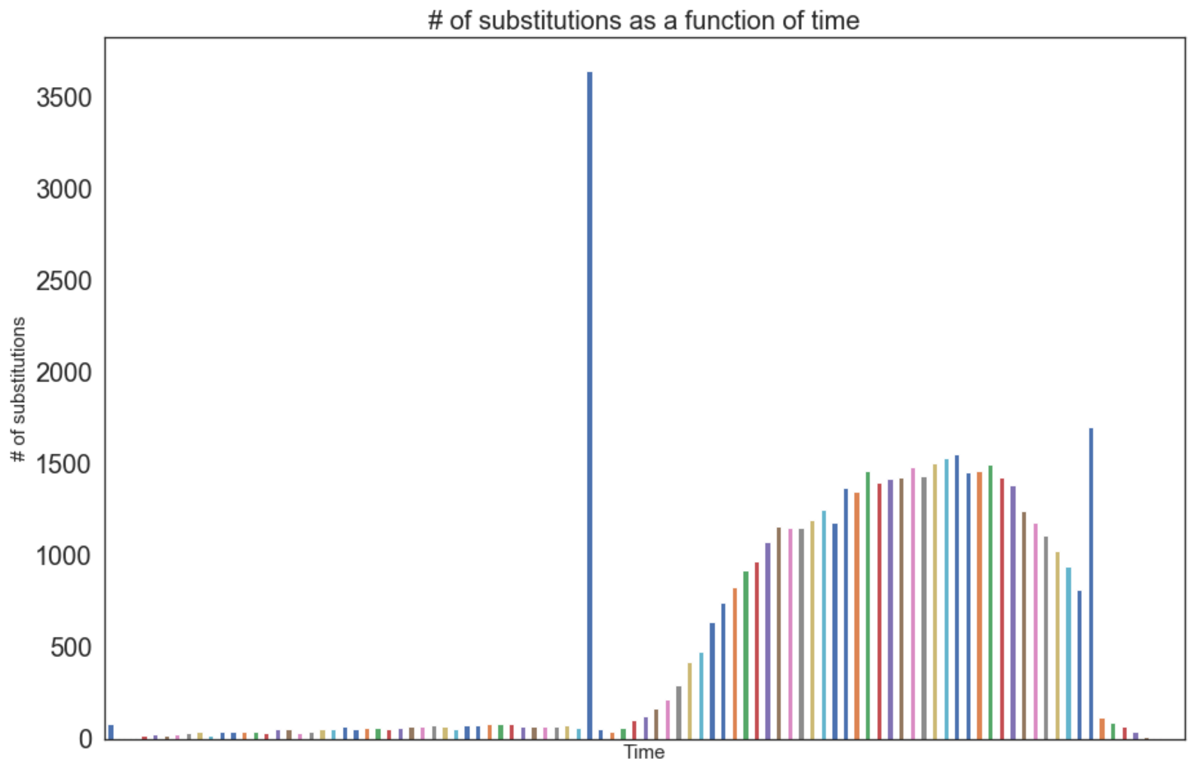

There's a massive spike in number of substitutions at around half time More substitutions happen during the second half of a match which makes logical sense

When are the most number of red/yellow cards shown during a football match ?

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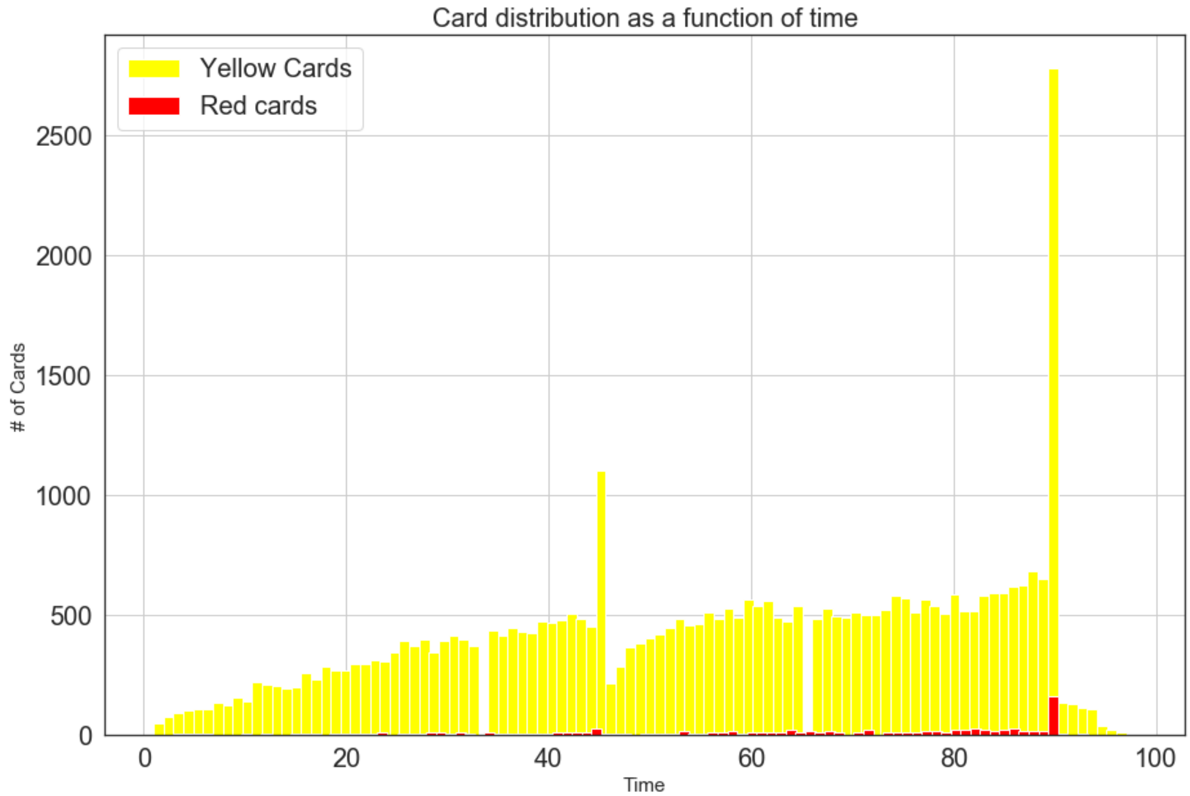

There's a spike in number of yellow cards just before half time and full time Most red cards are shown in last few minutes of a match (possibly when opponent is trailing by a goal and desperate to score and thus, the stakes are high))

Which players provide the most number of early breakthroughs ?

For our analysis we'll consider a goal scored in first 10 minutes of a match as an early breakthrough

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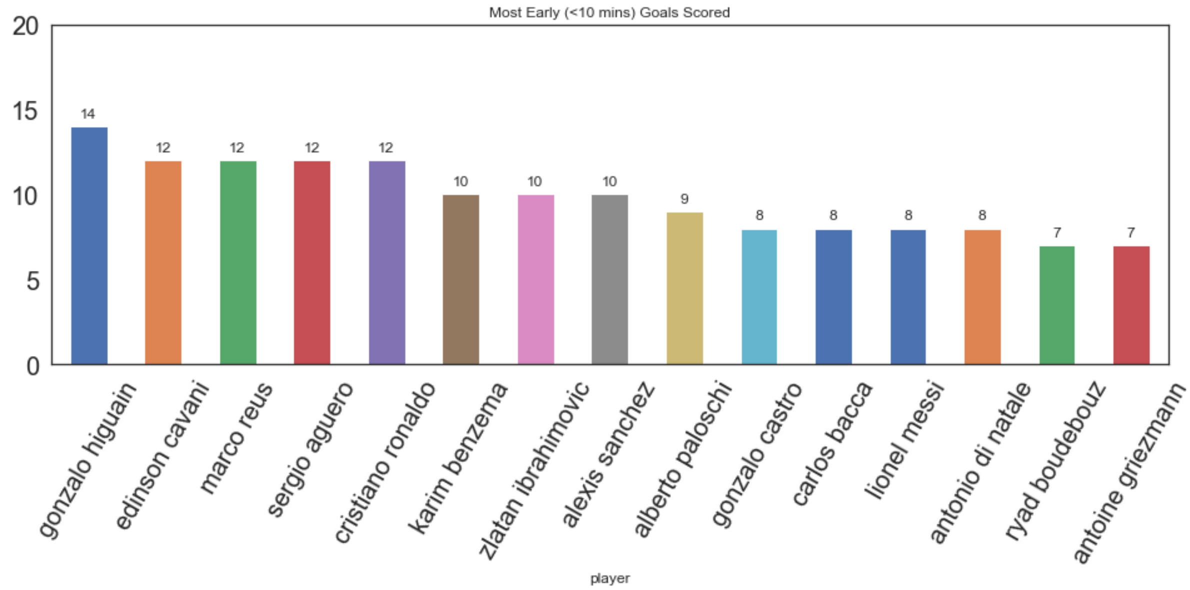

There are very few goals that are scored in first 10 minutes of a match. Real Madrid has 3 players in the top 5 list

Let's look the corresponding team data as well

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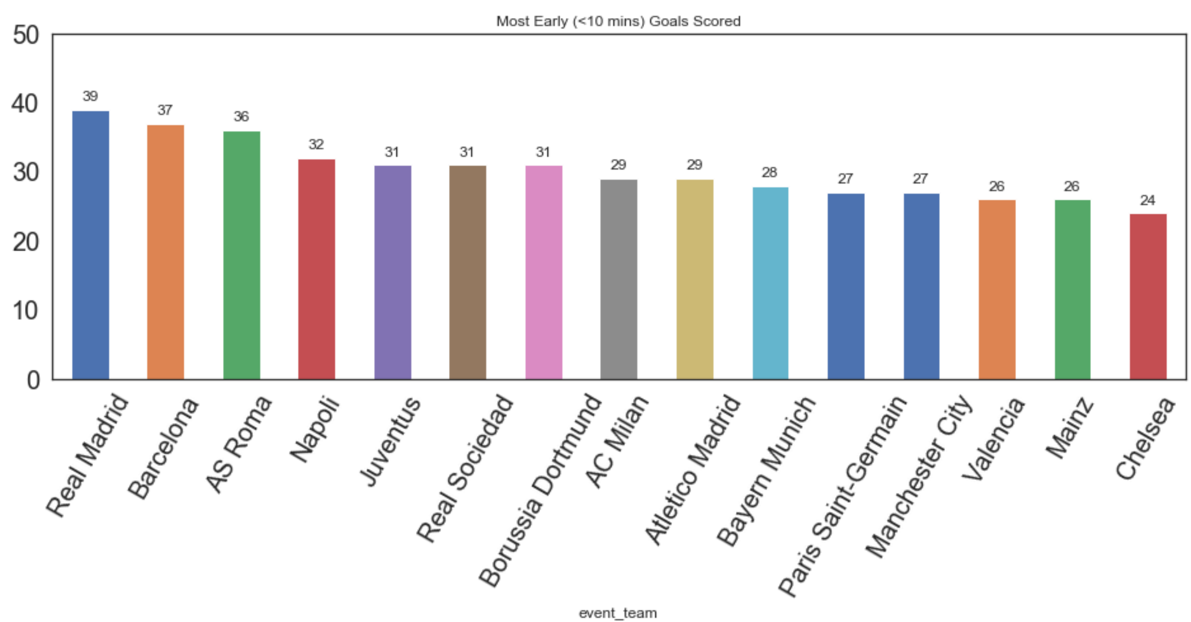

No surprises there. Real Madrid scores the maximum number of goals in first 10 minutes of a match

Which players tend to score the most during last few minutes ?

For this, we will only consider goals scored after 85 minutes

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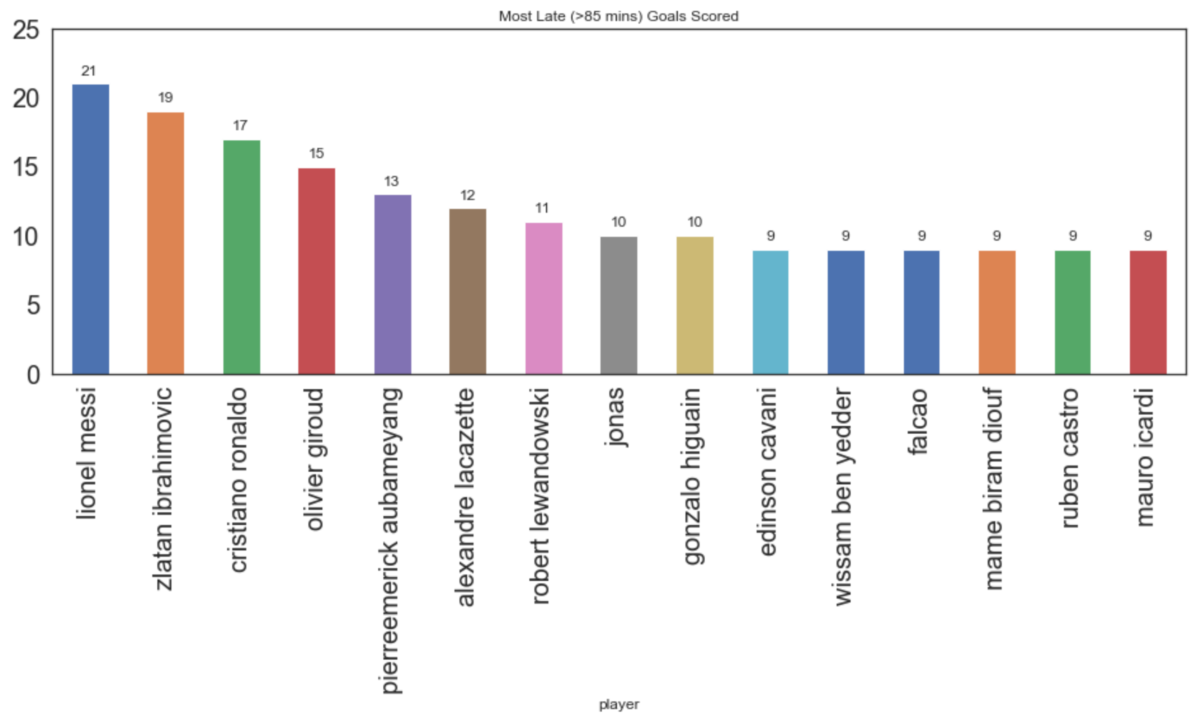

Again we have the same trio at top 3

Let's look at team level data as well

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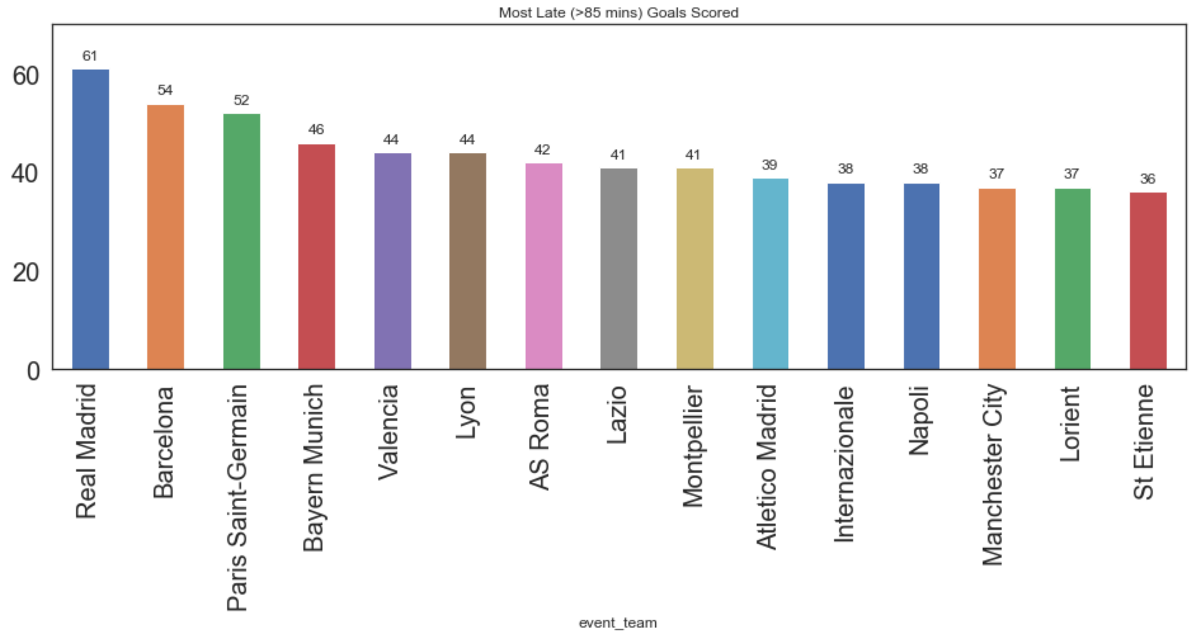

Just like early goals, Real Madrid leads in terms of number of late goals scored too

Whats the best league to bet if you are a rookie ?

Let's do a league-wise analysis

A. **EPL**

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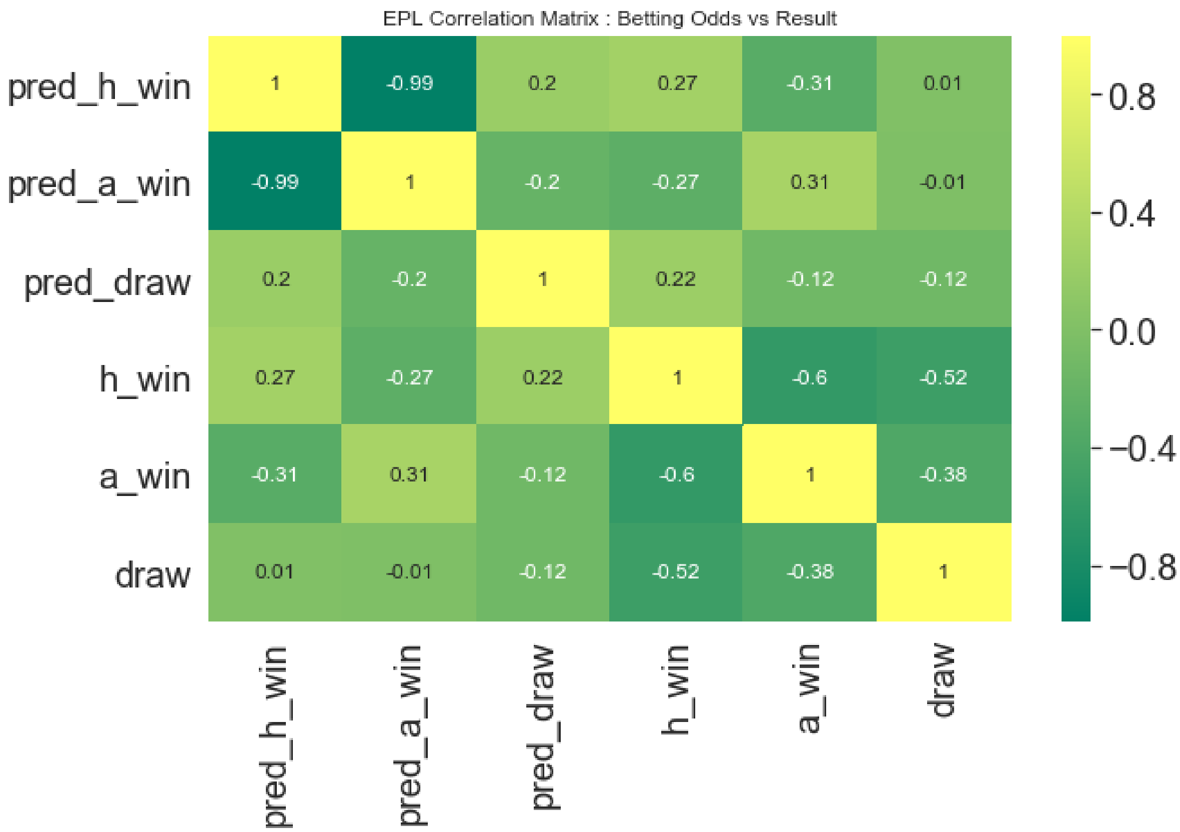

The betting odds have the following correlation with the actual results:
a) Home Team Win : 0.38
b) Away Team Win : 0.37
c) Draw : 0.14

b) **La Liga**

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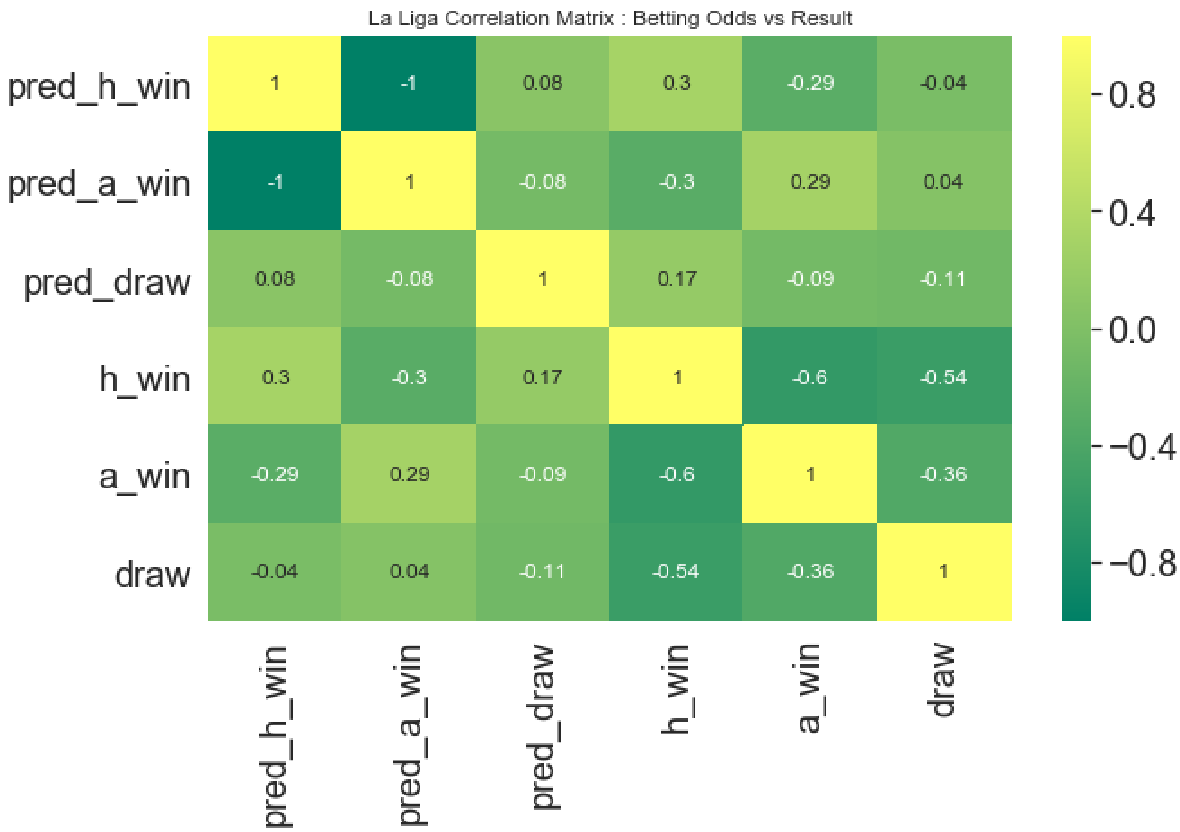

The betting odds have the following correlation with the actual results:

a) Home Team Win : 0.41

b) Away Team Win : 0.38

c) Draw : 0.16

c) **Serie A**

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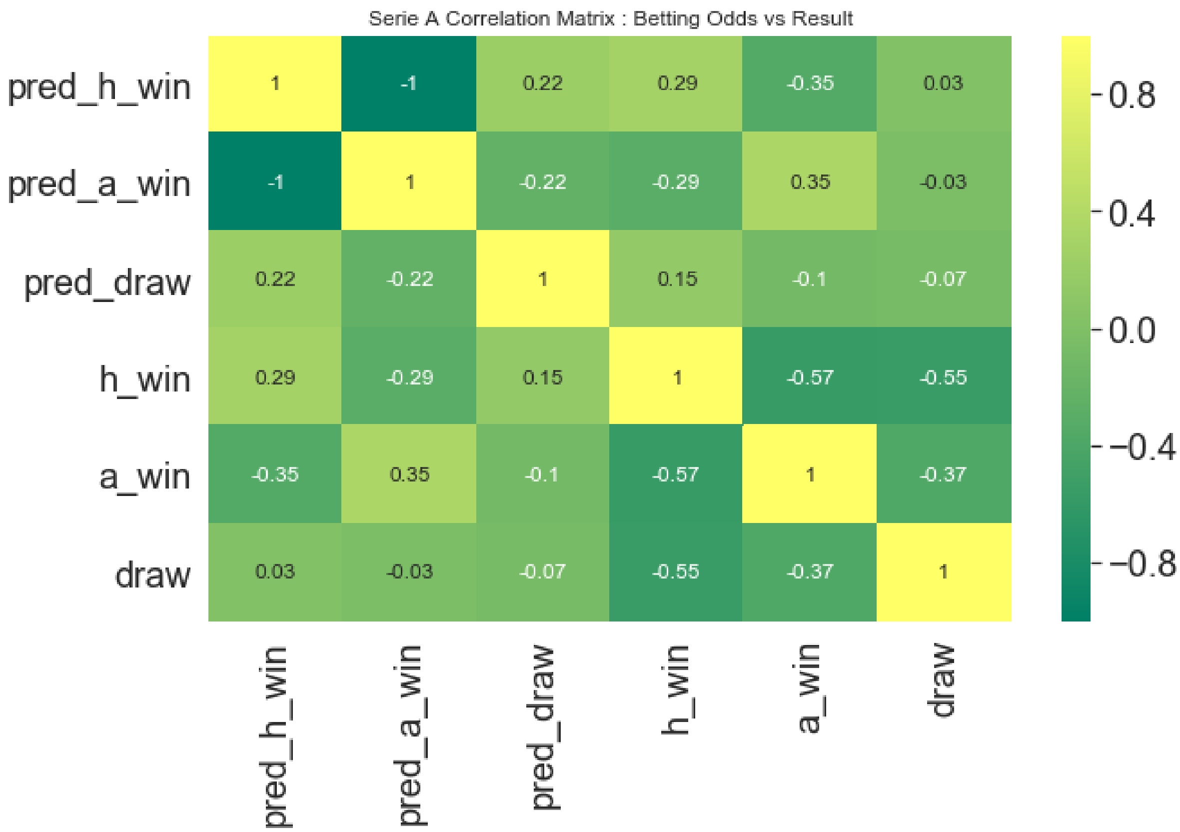

The betting odds have the following correlation with the actual results:
a) Home Team Win : 0.36
b) Away Team Win : 0.39
c) Draw : 0.1

d) **Bundesliga**

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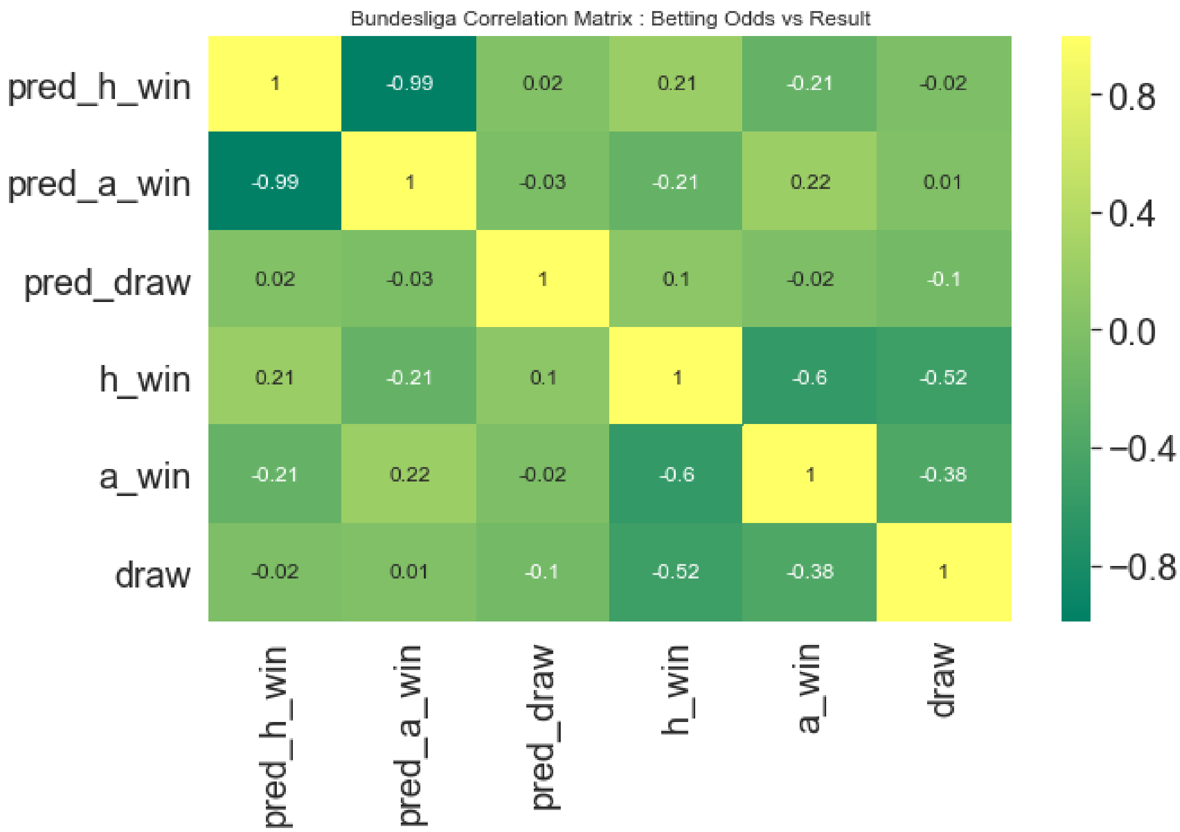

The betting odds have the following correlation with the actual results:
a) Home Team Win : 0.32
b) Away Team Win : 0.32
c) Draw : 0.13

e) **Ligue One**

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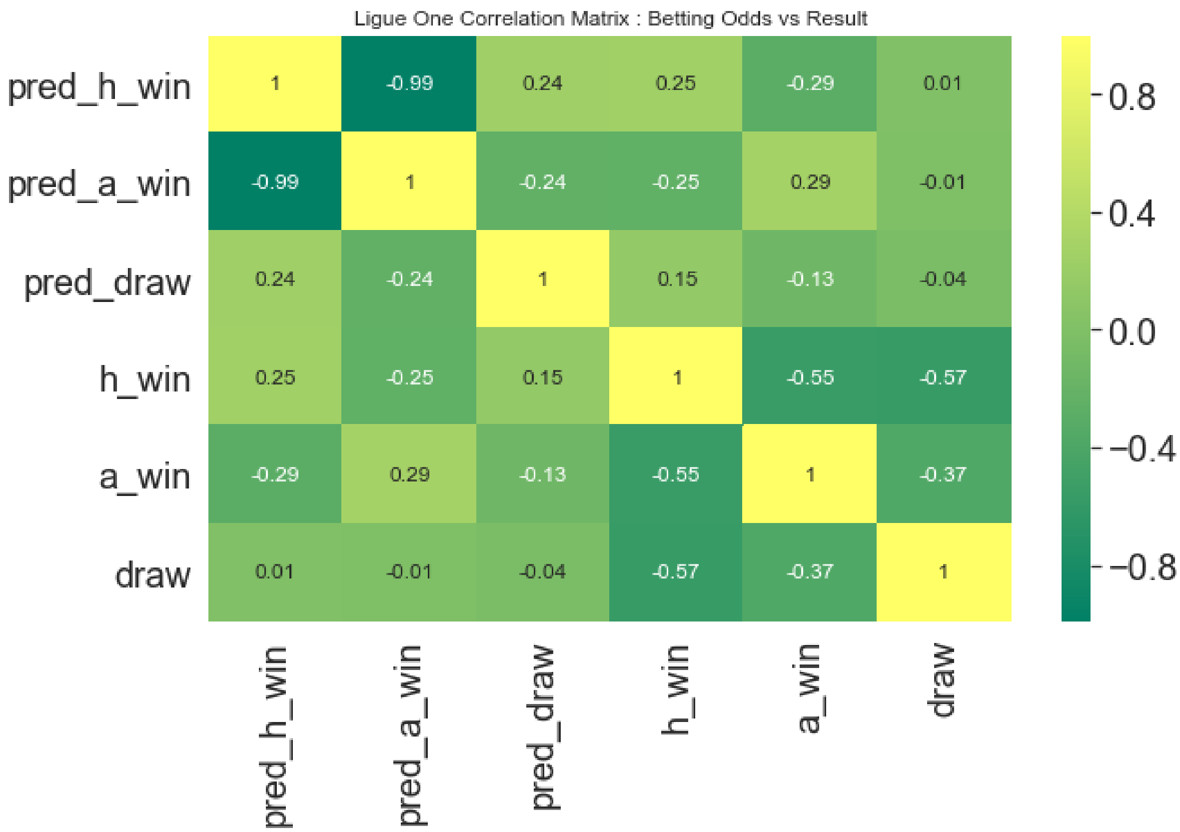

The betting odds have the following correlation with the actual results:
a) Home Team Win : 0.3
b) Away Team Win : 0.33
c) Draw : 0.1

In general, the bookie odds are not a very good indicator of actual results

The odds for draw are the worst

Moral of the story : Dont rely on betting odds if you aim to get rich through betting !!