חלק א' - חקירת מערך נתונים

```
In [1]: #Import libraries:
    import pandas as pd # pandas is a package we will use to work with data tables
    import matplotlib.pyplot as plt # matplotlib is a package for plotting data
    import matplotlib.style as style
    style.use('tableau-colorblind10')
    import seaborn as sns # seaborn is also a package for plotting data, built on top
    sns.set_palette("viridis")
    import numpy as np # numpy is a package for working with numerical data
In [2]: #Reading the 'HW1_data.csv' file:
    df_soccer = pd.read_csv('HW1_data.csv')
```

## question 1:

```
In [3]: #1
        df_soccer.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 684 entries, 0 to 683
        Data columns (total 11 columns):
         # Column Non-Null Count Dtype
        --- ----- -----
           league 684 non-null object
         0
                     684 non-null int64
         1 year
         2 position 684 non-null int64
            team 684 non-null object
         4 matches 684 non-null int64
         5 wins 684 non-null int64
6 draws 684 non-null int64
7 loses 684 non-null int64
8 scored 684 non-null int64
         9 conceded 681 non-null float64
                     684 non-null
                                      int64
        dtypes: float64(1), int64(8), object(2)
        memory usage: 58.9+ KB
```

We can see according to the "info()" of the data frame that there are 684 entries.

# question 2:

```
In [4]: #2

df_soccer.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 684 entries, 0 to 683
Data columns (total 11 columns):
    Column
           Non-Null Count Dtype
   ----
             -----
---
   league
0
             684 non-null object
   year
           684 non-null int64
1
2 position 684 non-null int64
            684 non-null object
   team
                           int64
   matches 684 non-null
   wins 684 non-null int64 draws 684 non-null int64
6
            684 non-null int64
7
   loses
   scored 684 non-null int64
9
    conceded 681 non-null float64
                           int64
10 pts
            684 non-null
dtypes: float64(1), int64(8), object(2)
memory usage: 58.9+ KB
```

We can see according to the "info()" of the data frame that there are two fields of type "object", so we can be asure that they are categorical. About the other columns, we can see according to the data frame table that the other fields are continuous, so thay are numerical. To sum up:

The fields that are categorical are:

- 1. league
- 2. team

The fields that are numerical are:

- 1. year
- 2. position
- 3. matches
- 4. wins
- 5. draws
- 6. loses
- 7. scored
- 8. conceded
- 9. pts

## question 3:

```
In [5]: #3

print('Number of unique values at "league" field:', len(df_soccer.league.unique())
print()
print('Number of unique values at "team" field:', len(df_soccer.team.unique()))

Number of unique values at "league" field: 6

Number of unique values at "team" field: 168
```

# question 4:

```
In [6]: #4

for i in df_soccer.columns:
    if df_soccer.isna().sum()[i] != 0:
        print('The field', i, 'have', df_soccer.isna().sum()[i], 'missing values.'
```

The field conceded have 3 missing values.

## question 5:

```
In [7]: #5
        print('Number of different teams over the years of:')
        min_league = ''
        temp = 0
        flag = True
        for diff_league in df_soccer.league.unique():
             if flag:
                temp = len(df_soccer[df_soccer.league == diff_league].team.unique())
                flag = False
             print(diff_league + ':',len(df_soccer[df_soccer.league == diff_league].team.un
             if len(df_soccer[df_soccer.league == diff_league].team.unique()) < temp:</pre>
             temp = len(df_soccer[df_soccer.league == diff_league].team.unique())
              min league = diff league
        print()
        print("The league that has the least number of teams over the years is:", min_league
        #display(df_soccer[df_soccer.league == 'Bundesliga'].team.unique())
        Number of different teams over the years of:
        La_liga: 30
        EPL: 30
        Bundesliga: 24
        Serie A: 30
        Ligue 1: 29
        RFPL: 25
```

The league that has the least number of teams over the years is: Bundesliga

# question 6:

AC Milan

	year	avg_goals
357	2014	1.473684
374	2015	1.289474
393	2016	1.500000
413	2017	1.473684
432	2018	1.447368
453	2019	1.657895

### Alaves

	year	avg_goals
48	2016	1.078947
73	2017	1.052632
89	2018	1.026316
115	2019	0.894737

### Almeria

	year	avg_goals
18	2014	0.921053

### Amiens

	year	avg_goals
540	2017	0.973684
563	2018	0.815789
586	2019	1.107143

#### Amkar

	year	avg_goals
598	2014	0.833333
614	2015	0.733333
629	2016	0.833333
648	2017	0.666667

### Angers

	year	avg_goals
496	2015	1.052632
519	2016	1.052632
541	2017	1.105263
560	2018	1.157895
577	2019	1.000000

Anzhi Makhachkala

	year	avg_goals
616	2015	0.933333
630	2016	0.800000
649	2017	1.033333
666	2018	0.433333

### Arsenal

	year	avg_goals
122	2014	1.868421
141	2015	1.710526
164	2016	2.026316
185	2017	1.947368
204	2018	1.921053
227	2019	1.473684

### Arsenal Tula

	year	avg_goals
603	2014	0.666667
634	2016	0.600000
642	2017	1.166667
657	2018	1.333333
676	2019	1.233333

#### Aston Villa

	year	avg_goals
135	2014	0.815789
159	2015	0.710526
236	2019	1.078947

#### Atalanta

	year	avg_goals
364	2014	1.000000
379	2015	1.078947
391	2016	1.631579
414	2017	1.500000
430	2018	2.026316
451	2019	2.578947

### Athletic Club

	year	avg_goals
6	2014	1.105263
24	2015	1.526316
46	2016	1.394737
75	2017	1.078947
87	2018	1.078947
110	2019	1.078947

### Atletico Madrid

	year	avg_goals
2	2014	1.763158
22	2015	1.657895
42	2016	1.842105
61	2017	1.526316
81	2018	1.447368
103	2019	1.342105

### Augsburg

	year	avg_goals
244	2014	1.264706
271	2015	1.235294
288	2016	1.029412
305	2017	1.264706
326	2018	1.500000
343	2019	1.323529

#### Barcelona

	year	avg_goals
0	2014	2.894737
20	2015	2.947368
41	2016	3.052632
60	2017	2.605263
80	2018	2.368421
101	2019	2.263158

Bayer Leverkusen

	year	avg_goals
243	2014	1.823529
260	2015	1.647059
287	2016	1.558824
296	2017	1.705882
315	2018	2.029412
334	2019	1.794118

### Bayern Munich

	year	avg_goals
240	2014	2.352941
258	2015	2.352941
276	2016	2.617647
294	2017	2.705882
312	2018	2.588235
330	2019	2.941176

#### Benevento

	year	avg_goals
427	2017	0.868421

### Bologna

	year	avg_goals
381	2015	0.868421
402	2016	1.052632
422	2017	1.052632
437	2018	1.263158
458	2019	1.378378

#### Bordeaux

	year	avg_goals
473	2014	1.236842
497	2015	1.315789
513	2016	1.394737
533	2017	1.394737
561	2018	0.894737
580	2019	1.428571

Borussia Dortmund

	year	avg_goals
246	2014	1.382353
259	2015	2.411765
278	2016	2.117647
298	2017	1.882353
313	2018	2.382353
331	2019	2.470588

### Borussia M.Gladbach

	year	avg_goals
242	2014	1.558824
261	2015	1.970588
284	2016	1.323529
302	2017	1.382353
316	2018	1.617647
333	2019	1.941176

#### Bournemouth

	year	avg_goals
155	2015	1.184211
167	2016	1.447368
190	2017	1.184211
213	2018	1.473684
238	2019	1.052632

### Brescia

	year	avg_goals
466	2019	0.921053

#### Brest

	year	avg_goals
582	2019	1.214286

### Brighton

	year	avg_goals
194	2017	0.894737
216	2018	0.921053
234	2019	1.026316

### Burnley

	year	avg_goals
138	2014	0.736842
176	2016	1.026316
186	2017	0.947368
214	2018	1.184211
228	2019	1.131579

#### CSKA Moscow

	year	avg_goals
589	2014	2.233333
604	2015	1.700000
621	2016	1.566667
637	2017	1.633333
655	2018	1.533333
671	2019	1.433333

#### Caen

	year	avg_goals
480	2014	1.421053
494	2015	1.026316
523	2016	0.947368
543	2017	0.710526
566	2018	0.763158

## Cagliari

	year	avg_goals
365	2014	1.263158
399	2016	1.447368
423	2017	0.868421
442	2018	0.947368
460	2019	1.368421

### Cardiff

	year	avg_goals
217	2018	0.894737

### Carpi

	year	avg_goals
385	2015	0.973684

### Celta Vigo

	year	avg_goals
7	2014	1.236842
25	2015	1.342105
52	2016	1.394737
70	2017	1.552632
95	2018	1.394737
116	2019	0.973684

#### Cesena

	year	avg_goals
367	2014	0.947368

#### Chelsea

	year	avg_goals
120	2014	1.921053
149	2015	1.552632
160	2016	2.236842
184	2017	1.631579
202	2018	1.657895
223	2019	1.815789

### Chievo

	year	avg_goals
361	2014	0.736842
376	2015	1.131579
401	2016	1.131579
421	2017	0.947368
447	2018	0.657895

### Cordoba

	year	avg_goals
19	2014	0.578947

#### Crotone

	year	avg_goals
404	2016	0.894737
425	2017	1.052632

### Crystal Palace

	year	avg_goals
129	2014	1.236842
154	2015	1.026316
173	2016	1.315789
189	2017	1.184211
211	2018	1.342105
233	2019	0.815789

### Darmstadt

	year	avg_goals
269	2015	1.117647
293	2016	0.823529

### Deportivo La Coruna

	year	avg_goals
15	2014	0.921053
34	2015	1.184211
55	2016	1.131579
77	2017	1.000000

### Dijon

	year	avg_goals
524	2016	1.210526
538	2017	1.447368
565	2018	0.815789
583	2019	0.964286

### Dinamo Moscow

	year	avg_goals
591	2014	1.766667
618	2015	0.833333
643	2017	0.966667
663	2018	0.933333
673	2019	0.900000

Eibar

	year	avg_goals
17	2014	0.894737
33	2015	1.289474
49	2016	1.473684
68	2017	1.157895
91	2018	1.210526
113	2019	1.026316
Eint	racht	Frankfur
Eint	year	Frankfur avg_goals
249		
	year	avg_goals
249	<b>year</b> 2014	avg_goals 1.647059
249 273	<b>year</b> 2014 2015	avg_goals 1.647059 1.000000
249 273 286	year 2014 2015 2016	avg_goals 1.647059 1.000000 1.058824

### Elche

	year	avg_goals
12	2014	0.921053

### Empoli

	year	avg_goals
362	2014	1.210526
378	2015	1.052632
405	2016	0.763158
445	2018	1.342105

### Espanyol

	year	avg_goals
10	2014	1.236842
32	2015	1.052632
47	2016	1.289474
71	2017	0.947368
86	2018	1.263158
119	2019	0.710526

Everton

	year	avg_goals
131	2014	1.263158
151	2015	1.552632
166	2016	1.631579
187	2017	1.157895
207	2018	1.421053
231	2019	1.157895

#### Evian Thonon Gaillard

	year	avg_goals
485	2014	1.078947

### FC Cologne

	year	avg_goals
250	2014	1.000000
266	2015	1.117647
281	2016	1.500000
311	2017	1.029412
344	2019	1.500000

### FC Krasnodar

	year	avg_goals
590	2014	1.733333
607	2015	1.800000
623	2016	1.333333
639	2017	1.533333
654	2018	1.833333
670	2019	1.633333

### FC Orenburg

	year	avg_goals
632	2016	0.833333
658	2018	1.300000
683	2019	0.933333

FC Rostov

	year	avg_goals
601	2014	0.900000
605	2015	1.366667
624	2016	1.200000
646	2017	0.900000
660	2018	0.833333
672	2019	1.500000

### FC Tambov

	year	avg_goals
682	2019	1.233333

### FC Ufa

	year	avg_goals
599	2014	0.866667
615	2015	0.833333
626	2016	0.733333
641	2017	1.133333
665	2018	0.800000
675	2019	0.733333

### FC Yenisey Krasnoyarsk

	year	avg_goals
667	2018	0.8

#### FK Akhmat

	year	avg_goals
596	2014	1.000000
610	2015	1.166667
625	2016	1.266667
644	2017	1.000000
659	2018	0.933333
680	2019	0.900000

Fiorentina

	year	avg_goals
351	2014	1.605263
372	2015	1.578947
395	2016	1.657895
415	2017	1.421053
441	2018	1.236842
457	2019	1.297297

#### Fortuna Duesseldorf

	year	avg_goals
321	2018	1.441176
346	2019	1.058824

### Freiburg

	year	avg_goals
256	2014	1.058824
282	2016	1.235294
308	2017	0.941176
324	2018	1.352941
337	2019	1.411765

### Frosinone

	year	avg_goals
386	2015	0.921053
446	2018	0.763158

### Fulham

	year	avg_goals
218	2018	0.894737

### GFC Ajaccio

	year	avg_goals
506	2015	0.973684

#### Genoa

	year	avg_goals
353	2014	1.631579
377	2015	1.184211
403	2016	1.000000
419	2017	0.868421
444	2018	1.026316
464	2019	1.189189

### Getafe

	year	avg_goals
13	2014	0.868421
38	2015	0.973684
67	2017	1.105263
85	2018	1.263158
107	2019	1.131579

#### Girona

	year	avg_goals
69	2017	1.315789
97	2018	0.973684

#### Granada

	year	avg_goals
16	2014	0.763158
36	2015	1.210526
59	2016	0.789474
106	2019	1.368421

### Guingamp

	year	avg_goals
477	2014	1.078947
503	2015	1.236842
517	2016	1.210526
539	2017	1.263158
567	2018	0.736842

### Hamburger SV

	year	avg_goals
254	2014	0.735294
267	2015	1.176471
289	2016	0.970588
310	2017	0.852941

### Hannover 96

	year	avg_goals
252	2014	1.176471
275	2015	0.911765
306	2017	1.294118
328	2018	0.911765

Hertha Berlin

	year	avg_goals
255	2014	1.058824
264	2015	1.235294
280	2016	1.264706
303	2017	1.264706
322	2018	1.441176
339	2019	1.411765

### Hoffenheim

	year	avg_goals
247	2014	1.441176
272	2015	1.147059
279	2016	1.882353
297	2017	1.941176
320	2018	2.058824
335	2019	1.558824

### Huddersfield

	year	avg_goals
195	2017	0.736842
219	2018	0.578947

### Hull

	year	avg_goals
137	2014	0.868421
177	2016	0.973684

### Ingolstadt

	year	avg_goals
268	2015	0.970588
292	2016	1.058824

### Inter

	year	avg_goals
355	2014	1.552632
371	2015	1.315789
394	2016	1.894737
411	2017	1.736842
431	2018	1.500000
449	2019	2.131579

Juventus

	year	avg_goals
348	2014	1.894737
368	2015	1.973684
388	2016	2.026316
408	2017	2.263158
428	2018	1.842105
448	2019	2.000000

### Krylya Sovetov Samara

	year	avg_goals
612	2015	0.633333
633	2016	1.033333
664	2018	0.833333
681	2019	1.100000

### Kuban Krasnodar

	year	avg_goals
597	2014	1.066667
617	2015	1.133333

### Las Palmas

	year	avg_goals
31	2015	1.184211
53	2016	1.394737
78	2017	0.631579

### Lazio

	year	avg_goals
350	2014	1.868421
375	2015	1.368421
392	2016	1.947368
412	2017	2.342105
435	2018	1.473684
450	2019	2.078947

#### Lecce

	year	avg_goals
465	2019	1.324324

### Leganes

	year	avg_goals
56	2016	0.947368
76	2017	0.894737
92	2018	0.973684
117	2019	0.789474

### Leicester

	year	avg_goals
133	2014	1.210526
140	2015	1.789474
172	2016	1.263158
188	2017	1.473684
209	2018	1.342105
224	2019	1.763158

### Lens

	year	avg_goals
487	2014	0.842105

#### Levante

	year	avg_goals
14	2014	0.894737
39	2015	0.973684
74	2017	1.157895
93	2018	1.552632
111	2019	1.236842

#### Lille

	year	avg_goals
474	2014	1.131579
492	2015	1.026316
518	2016	1.052632
542	2017	1.078947
549	2018	1.789474
571	2019	1.250000

Liverpool

	year	avg_goals
125	2014	1.368421
147	2015	1.657895
163	2016	2.052632
183	2017	2.210526
201	2018	2.342105
220	2019	2.236842
Loko	motiv	Moscow
Loko		Moscow avg_goals
Loko		_
	year	avg_goals
594	<b>year</b> 2014	avg_goals 1.033333

### Lorient

**653** 2018

**669** 2019

	year	avg_goals
483	2014	1.157895
502	2015	1.236842
525	2016	1.157895

1.500000

1.366667

### Lyon

	year	avg_goals
469	2014	1.894737
489	2015	1.763158
511	2016	2.105263
530	2017	2.289474
550	2018	1.842105
576	2019	1.500000

### Mainz 05

	year	avg_goals
251	2014	1.323529
263	2015	1.352941
290	2016	1.294118
307	2017	1.117647
323	2018	1.352941
342	2019	1.294118

### Malaga

	year	avg_goals
8	2014	1.105263
27	2015	1.000000
50	2016	1.289474
79	2017	0.631579

#### Mallorca

	year	avg_goals
118	2019	1.052632

### Manchester City

	year	avg_goals
121	2014	2.184211
144	2015	1.868421
162	2016	2.105263
180	2017	2.789474
200	2018	2.500000
221	2019	2.684211

### Manchester United

	year	avg_goals
123	2014	1.631579
143	2015	1.289474
165	2016	1.421053
181	2017	1.789474
205	2018	1.710526
222	2019	1.736842

### Marseille

	year	avg_goals
471	2014	2.000000
501	2015	1.263158
512	2016	1.500000
531	2017	2.105263
552	2018	1.578947
569	2019	1.464286

Metz

	year	avg_goals
486	2014	0.815789
521	2016	1.026316
547	2017	0.894737
581	2019	0.964286

### Middlesbrough

	year	avg_goals
178	2016	0.710526

#### Monaco

	year	avg_goals
470	2014	1.342105
490	2015	1.500000
508	2016	2.815789
529	2017	2.236842
564	2018	1.000000
575	2019	1.571429

### Montpellier

	year	avg_goals
475	2014	1.210526
499	2015	1.289474
522	2016	1.263158
537	2017	0.947368
553	2018	1.394737
574	2019	1.250000

### Mordovya

	year	avg_goals
595	2014	0.733333
619	2015	1.000000

#### Nancy

	year	avg_goals
526	2016	0.763158

### Nantes

	year	avg_goals
481	2014	0.763158
500	2015	0.868421
514	2016	1.052632
536	2017	0.947368
559	2018	1.263158
579	2019	1.000000

### Napoli

	year	avg_goals
352	2014	1.842105
369	2015	2.105263
390	2016	2.473684
409	2017	2.026316
429	2018	1.947368
454	2019	1.605263

### Newcastle United

	year	avg_goals
134	2014	1.052632
157	2015	1.157895
191	2017	1.026316
212	2018	1.105263
232	2019	1.000000

### Nice

	year	avg_goals
478	2014	1.157895
491	2015	1.526316
510	2016	1.657895
535	2017	1.394737
554	2018	0.789474
572	2019	1.464286

### Nimes

	year	avg_goals
556	2018	1.500000
585	2019	1.035714

### Norwich

	year	avg_goals
158	2015	1.026316
239	2019	0.684211

### Nuernberg

	year	avg_goals
329	2018	0.764706

#### 0sasuna

	year	avg_goals
58	2016	1.052632
109	2019	1.210526

### PFC Sochi

	year	avg_goals
679	2019	1.333333

#### Paderborn

	year	avg_goals
257	2014	0.911765
347	2019	1.088235

### Palermo

	year	avg_goals
358	2014	1.394737
383	2015	1.000000
406	2016	0.868421

### Paris Saint Germain

	year	avg_goals
468	2014	2.184211
488	2015	2.684211
509	2016	2.184211
528	2017	2.842105
548	2018	2.763158
568	2019	2.777778

#### Parma

	year	avg_goals
366	2014	0.868421

Parma Calcio 1913

	year	avg_goals
443	2018	1.078947
459	2019	1.405405

#### Pescara

	year	avg_goals
407	2016	0.921053

### Queens Park Rangers

	year	avg_goals
139	2014	1.105263

### RasenBallsport Leipzig

	year	avg_goals
277	2016	1.941176
299	2017	1.676471
314	2018	1.852941
332	2019	2.382353

### Rayo Vallecano

	year	avg_goals
9	2014	1.210526
37	2015	1.368421
99	2018	1.078947

### Real Betis

	year	avg_goals
29	2015	0.894737
54	2016	1.078947
65	2017	1.578947
90	2018	1.157895
114	2019	1.263158

#### Real Madrid

	year	avg_goals
1	2014	3.105263
21	2015	2.894737
40	2016	2.789474
62	2017	2.473684
82	2018	1.657895
100	2019	1.842105

Real Sociedad

	year	avg_goals
11	2014	1.157895
28	2015	1.184211
45	2016	1.552632
72	2017	1.736842
88	2018	1.184211
105	2019	1.473684

### Real Valladolid

	year	avg_goals
96	2018	0.842105
112	2019	0.842105

### Reims

	year	avg_goals
482	2014	1.236842
505	2015	1.157895
555	2018	1.026316
573	2019	0.928571

#### Rennes

	year	avg_goals
476	2014	0.921053
495	2015	1.368421
515	2016	0.947368
532	2017	1.315789
557	2018	1.447368
570	2019	1.357143

#### Roma

	year	avg_goals
349	2014	1.421053
370	2015	2.184211
389	2016	2.368421
410	2017	1.605263
433	2018	1.736842
452	2019	2.026316

Rubin Kazan

	year	avg_goals
592	2014	1.300000
613	2015	1.100000
628	2016	1.000000
645	2017	1.066667
662	2018	0.800000
677	2019	0.600000

### SC Bastia

	year	avg_goals
479	2014	0.973684
498	2015	0.947368
527	2016	0.763158

#### SD Huesca

	year	avg_goals
98	2018	1.131579

#### SKA-Khabarovsk

	yeai	avg_goals
651	2017	0.533333

### SPAL 2013

	year	avg_goals
424	2017	1.026316
440	2018	1.157895
467	2019	0.702703

### Saint-Etienne

	year	avg_goals
472	2014	1.342105
493	2015	1.105263
516	2016	1.078947
534	2017	1.236842
551	2018	1.552632
584	2019	1.035714

### Sampdoria

	year	avg_goals
354	2014	1.263158
382	2015	1.263158
398	2016	1.289474
416	2017	1.473684
436	2018	1.578947
461	2019	1.263158

### Sassuolo

	year	avg_goals
359	2014	1.289474
373	2015	1.289474
397	2016	1.578947
418	2017	0.763158
438	2018	1.394737
455	2019	1.864865

### Schalke 04

	year	avg_goals
245	2014	1.235294
262	2015	1.500000
285	2016	1.323529
295	2017	1.558824
325	2018	1.088235
341	2019	1.117647

#### Sevilla

	year	avg_goals
4	2014	1.868421
26	2015	1.342105
43	2016	1.815789
66	2017	1.289474
84	2018	1.631579
102	2019	1.421053

### Sheffield United

	year	avg_goals
229	2019	1.026316

### ${\tt Southampton}$

	year	avg_goals
126	2014	1.421053
145	2015	1.552632
168	2016	1.078947
196	2017	0.973684
215	2018	1.184211
230	2019	1.342105

### Spartak Moscow

	year	avg_goals
593	2014	1.400000
608	2015	1.600000
620	2016	1.533333
638	2017	1.700000
656	2018	1.200000
674	2019	1.166667

### Sporting Gijon

	year	avg_goals
35	2015	1.052632
57	2016	1.105263

### Stoke

	year	avg_goals
128	2014	1.263158
148	2015	1.078947
171	2016	1.078947
197	2017	0.921053

### Strasbourg

	year	avg_goals
544	2017	1.157895
558	2018	1.526316
578	2019	1.185185

#### Sunderland

	year	avg_goals
136	2014	0.815789
156	2015	1.263158
179	2016	0.763158

Swansea

	year	avg_goals
127	2014	1.210526
150	2015	1.105263
174	2016	1.184211
198	2017	0.736842

Tom Tomsk

	year	avg_goals
635	2016	0.566667

#### Torino

	year	avg_goals
356	2014	1.263158
380	2015	1.368421
396	2016	1.868421
417	2017	1.421053
434	2018	1.368421
463	2019	1.216216

### Torpedo Moscow

	year	avg_goals
602	2014	0.933333

#### Tosno

	year	avg_goals
650	2017	0.766667

#### Tottenham

	year	avg_goals
124	2014	1.526316
142	2015	1.815789
161	2016	2.263158
182	2017	1.947368
203	2018	1.763158
225	2019	1.605263

Toulouse

	year	avg_goals
484	2014	1.131579
504	2015	1.184211
520	2016	0.973684
545	2017	1.000000
562	2018	0.921053
587	2019	0.785714

### Troyes

	year	avg_goals
507	2015	0.736842
546	2017	0.842105

### Udinese

	year	avg_goals
363	2014	1.131579
384	2015	0.921053
400	2016	1.236842
420	2017	1.263158
439	2018	1.026316
462	2019	0.972973

### Union Berlin

	year	avg_goals
340	2019	1.205882

### Ural

	year	avg_goals
600	2014	1.033333
611	2015	1.300000
631	2016	0.800000
647	2017	1.033333
661	2018	1.100000
678	2019	1.200000

Valencia

	year	avg_goals
3	2014	1.842105
30	2015	1.210526
51	2016	1.473684
63	2017	1.710526
83	2018	1.342105
108	2019	1.210526

#### Verona

	year	avg_goals
360	2014	1.289474
387	2015	0.894737
426	2017	0.789474
456	2019	1.270270

### VfB Stuttgart

	year	avg_goals
253	2014	1.235294
274	2015	1.470588
300	2017	1.058824
327	2018	0.941176

### Villarreal

	year	avg_goals
5	2014	1.263158
23	2015	1.157895
44	2016	1.473684
64	2017	1.500000
94	2018	1.289474
104	2019	1.657895

#### Watford

	year	avg_goals
152	2015	1.052632
175	2016	1.052632
193	2017	1.157895
210	2018	1.368421
237	2019	0.947368

Werder Bremen

	year	avg_goals
248	2014	1.470588
270	2015	1.470588
283	2016	1.794118
304	2017	1.088235
319	2018	1.705882
345	2019	1.235294

#### West Bromwich Albion

	year	avg_goals
132	2014	1.000000
153	2015	0.894737
170	2016	1.131579
199	2017	0.815789

### West Ham

	year	avg_goals
130	2014	1.157895
146	2015	1.710526
169	2016	1.236842
192	2017	1.263158
208	2018	1.368421
235	2019	1.289474

### Wolfsburg

	year	avg_goals
241	2014	2.117647
265	2015	1.382353
291	2016	1.000000
309	2017	1.058824
317	2018	1.823529
336	2019	1.411765

### Wolverhampton Wanderers

	year	avg_goals
206	2018	1.236842
226	2019	1.342105

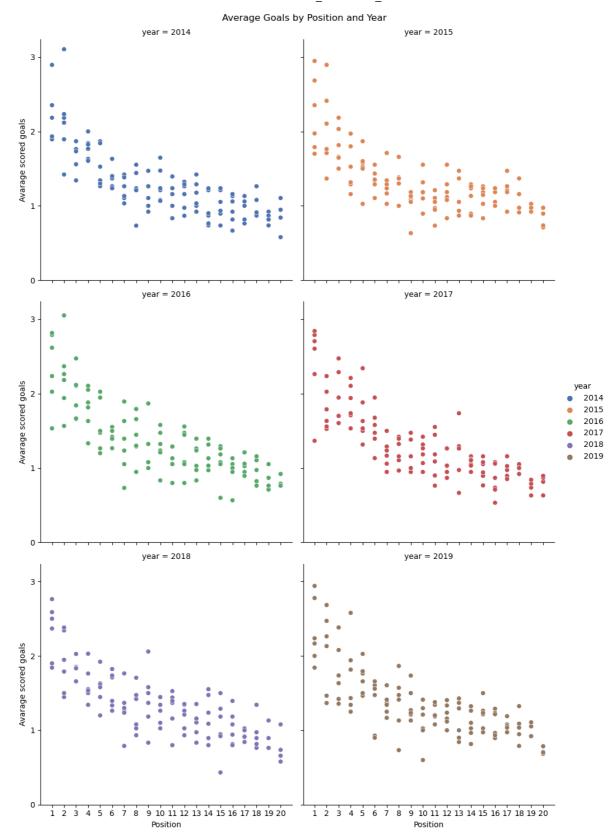
Zenit St. Petersburg

	year	avg_goals
588	2014	1.933333
606	2015	2.033333
622	2016	1.666667
640	2017	1.533333
652	2018	1.900000
668	2019	2.166667

```
In [9]: #checking the correlation
print(df_soccer.position.corr(df_soccer.avg_goals))
```

#### -0.7587818572237601

```
In [10]: #Prints a scatterplot graph of the corilation between the avarage scored goals of @
plot = sns.relplot(data=df_soccer, x="position", y="avg_goals", kind="scatter", hum
plt.yticks(range(int(min(df_soccer["avg_goals"])), int(max(df_soccer["avg_goals"]+))
plt.xticks(range(int(min(df_soccer["position"])), int(max(df_soccer["position"]+1)))
plot.set_axis_labels("Position", "Avarage scored goals")
plot.fig.suptitle("Average Goals by Position and Year")
plt.subplots_adjust(top=0.95)
```



The corilation we have got(-0.7587) tells us that there is a liniar corilation(-1<-0.7587<0), and even a strong corilation according to the high value of corilation pirson.

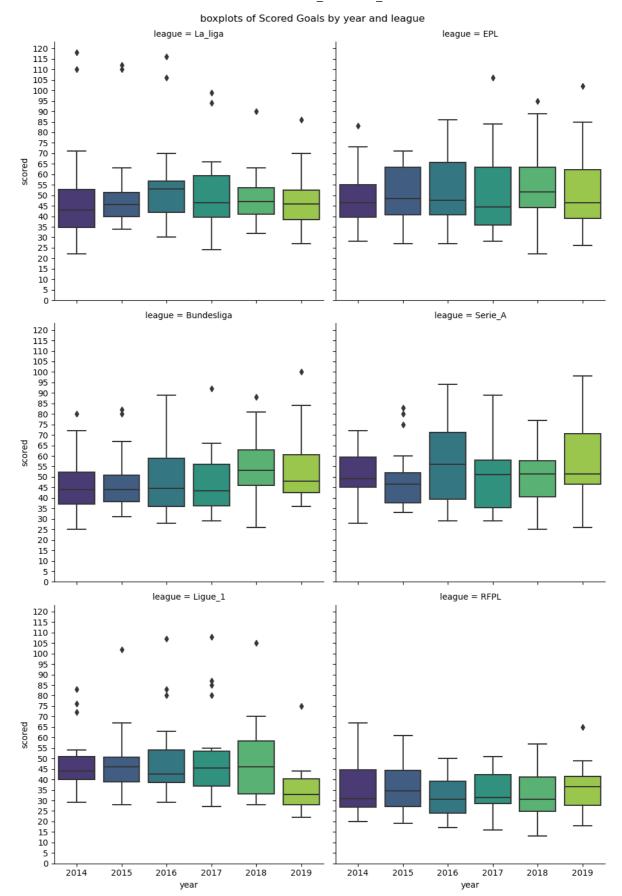
# question 7:

```
In [11]: #7

#Creates a groupby object of 'league' and 'year', and calculate the median value of
gb_median = df_soccer.groupby(['league', 'year']).median()['scored']
```

```
#Prints the groupby object we have created.
print(gb_median)
league
            year
Bundesliga
            2014
                    44.0
            2015
                    44.0
            2016
                    44.5
            2017
                    43.5
            2018
                    53.0
            2019
                    48.0
EPL
            2014
                    46.5
            2015
                    48.5
            2016
                    47.5
            2017
                    44.5
            2018
                   51.5
            2019
                   46.5
La_liga
            2014
                    43.0
            2015
                    45.5
            2016
                    53.0
            2017
                    46.5
            2018
                   47.0
            2019
                    46.0
Ligue_1
            2014
                    44.0
            2015
                    46.0
            2016
                    42.5
            2017
                    45.5
            2018
                   46.0
            2019
                   33.0
RFPL
            2014
                    31.0
            2015
                    34.5
            2016
                    30.5
            2017
                    31.5
            2018
                    30.5
            2019
                   36.5
                   49.0
Serie A
            2014
                    46.5
            2015
            2016
                    56.0
            2017
                    51.0
                    51.5
            2018
            2019
                    51.5
Name: scored, dtype: float64
C:\Users\liorb\AppData\Local\Temp\ipykernel 18768\2117126896.py:4: FutureWarning:
The default value of numeric_only in DataFrameGroupBy.median is deprecated. In a f
uture version, numeric_only will default to False. Either specify numeric_only or
select only columns which should be valid for the function.
 gb_median = df_soccer.groupby(['league', 'year']).median()['scored']
#Prints boxplots of the data above.
plot = sns.catplot( data = df_soccer, x="year", y="scored", kind="box" ,col = "leag")
plt.yticks(range(min(df_soccer["scored"]) - 13, max(df_soccer["scored"]+5), 5))
plot.fig.suptitle("boxplots of Scored Goals by year and league")
```

```
In [12]:
         plt.subplots_adjust(top=0.95)
```



We have found that the league that has the highest difference between the medians over the years is "ligue\_1" (difference of 13 goals scored (46 is the highest at year 2018 and 33 is the lowest at year 2019).

# question 8:

```
In [13]:
         #Method for calculate the sum of pts each team got at each year.
         def calculatePts(row):
              sumOfPts = row.wins*3 + row.draws*1
              return sumOfPts
         #Adds new columne to the data frame that store the sum of pts each team got at each
         df_soccer['our_pts'] = df_soccer.apply(calculatePts, axis='columns')
         #Method for compare our values of pts to the values that given to us.
         def comparePts(row):
             if row.pts == row.our_pts:
                  return True
             else:
                  return None
         #Adds new columne to the data frame that store boolian value - "True" if our values
         df_soccer['compare_pts'] = df_soccer.apply(comparePts, axis='columns')
         display(df_soccer[['year', 'team', 'matches', 'wins', 'draws', 'loses', 'pts', 'ou
         df_soccer.info()
         print()
         #we can use the `count()` method to count the number of non-NA values of 'compare_!
         print("the number of non-NA values of 'compare pts' column is: " + str(df soccer.co
         print()
         print("We will Find information about the mistake:")
         display(df_soccer[df_soccer['compare_pts'].isna() == True])
         #the mistake happens to be in league is "Serie_A", year 2017, the team "Crotone".
         print('According to that the "Serie_A" league have 38 matches per year according to
         print('and yaer can got is 38*3=116(if the team won all the games at that year), the
         print('so the origin of the mistake is the given "pts" column')
```

	year	team	matches	wins	draws	loses	pts	our_pts	compare_pts
0	2014	Barcelona	38	30	4	4	94	94	True
1	2014	Real Madrid	38	30	2	6	92	92	True
2	2014	Atletico Madrid	38	23	9	6	78	78	True
3	2014	Valencia	38	22	11	5	77	77	True
4	2014	Sevilla	38	23	7	8	76	76	True
•••									
679	2019	PFC Sochi	30	8	9	13	33	33	True
680	2019	FK Akhmat	30	7	10	13	31	31	True
681	2019	Krylya Sovetov Samara	30	8	7	15	31	31	True
682	2019	FC Tambov	30	9	4	17	31	31	True
683	2019	FC Orenburg	30	7	6	17	27	27	True

684 rows × 9 columns

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 684 entries, 0 to 683
Data columns (total 14 columns):
# Column
               Non-Null Count Dtype
---
               -----
0
   league
              684 non-null object
              684 non-null int64
1
   year
   position 684 non-null int64
              684 non-null
                            object
3
   team
                            int64
  matches
              684 non-null
4
   wins
              684 non-null int64
   draws
              684 non-null int64
6
   loses
              684 non-null int64
7
8 scored 684 non-null int64
9 conceded 681 non-null float64
                            int64
10 pts
              684 non-null
               684 non-null
                             float64
11 avg_goals
                           int64
12 our_pts
              684 non-null
13 compare_pts 683 non-null
                             object
dtypes: float64(2), int64(9), object(3)
memory usage: 74.9+ KB
```

the number of non-NA values of 'compare\_pts' column is: 683 of total 684 entries.

We will Find information about the mistake:

	league	year	position	team	matches	wins	draws	loses	scored	conceded	pts	avg_
425	Serie_A	2017	18	Crotone	38	9	8	21	40	66.0	180	1.05

According to that the "Serie\_A" league have 38 matches per year according to the i nformation we got, and the max number that a team at that league and yaer can got is 38\*3=116(if the team won all the games at that year), the give never set is not possible.

## question 9:

```
In [14]: #9
         #Method for compare the values of conceded goals to the values of scored goals.
         def isFailure(row):
             if row.conceded != None:
                     if row.conceded > row.scored:
                         return True
                     else:
                         return None
         #Adds new columne to the data frame that store boolian value - "True" if a team is
         df_soccer['is_failure'] = df_soccer.apply(isFailure, axis='columns')
         #Gets an array that store the different leagues in the data frame.
         arrOfLeagues = df_soccer.league.unique()
         listCountFailure = []
         #find the number of "failed teams" for over the years of each league and append to
         for i in arrOfLeagues:
             filt = (df soccer['league'] == i) & (df soccer['is failure'] == True)
             val = df_soccer.loc[filt].count()['is_failure']
             leagueAndVal = i + " " + str(val)
             listCountFailure.append(leagueAndVal)
         display(listCountFailure)
```

```
['La_liga 75',
  'EPL 71',
  'Bundesliga 63',
  'Serie_A 63',
  'Ligue_1 69',
  'RFPL 52']
```

According to the results we got, the league with the most "failed teams" for over the years is "La\_liga" league.