

-----IMPORT LIBRARIES-----

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import warnings
warnings.filterwarnings('ignore')
```

-----IMPORT MODULES-----

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import
accuracy_score, classification_report, confusion_matrix, r2_score
from sklearn.metrics import mean_squared_error
```

LOAD THE DATASET

```
data=pd.read_csv(r"C:\Users\Admin\Downloads\EPL_20_21.csv")
data.head()
```

	Name	Club	Nationality	Position	Age	Matches	Starts
Mins \							
0	Mason Mount	Chelsea	ENG	MF,FW	21	36	32
2890							
1	Edouard Mendy	Chelsea	SEN	GK	28	31	31
2745							
2	Timo Werner	Chelsea	GER	FW	24	35	29
2602							
3	Ben Chilwell	Chelsea	ENG	DF	23	27	27
2286							
4	Reece James	Chelsea	ENG	DF	20	32	25
2373							
	Goals	Assists	Passes_Attempted	Perc_Passes_Completed			
	Penalty_Goals	\					

0	6	5	1881	82.300
1				
1	0	0	1007	84.600
0				
2	6	8	826	77.200
0				
3	3	5	1806	78.600
0				
4	1	2	1987	85.000
0				

	Penalty_Attempted	xG	xA	Yellow_Cards	Red_Cards
0	1	0.210	0.240	2	0
1	0	0.000	0.000	2	0
2	0	0.410	0.210	2	0
3	0	0.100	0.110	3	0
4	0	0.060	0.120	3	0

```
data.shape
```

```
(532, 18)
```

```
data.describe()
```

	Age	Matches	Starts	Mins	Goals	Assists
Passes_Attempted \						
count	532.000	532.000	532.000	532.000	532.000	532.000
mean	25.500	19.536	15.714	1411.444	1.853	1.288
std	4.319	11.840	11.921	1043.172	3.338	2.095
min	16.000	1.000	0.000	1.000	0.000	0.000
25%	22.000	9.000	4.000	426.000	0.000	0.000
50%	26.000	21.000	15.000	1345.000	1.000	0.000
75%	29.000	30.000	27.000	2303.500	2.000	2.000
max	38.000	38.000	38.000	3420.000	23.000	14.000

	Perc_Passes_Completed	Penalty_Goals	Penalty_Attempted	xG
\				
count	532.000	532.000	532.000	532.000
mean	77.824	0.192	0.235	0.113
std	13.012	0.851	0.976	0.148

min	-1.000	0.000	0.000	0.000
25%	73.500	0.000	0.000	0.010
50%	79.200	0.000	0.000	0.060
75%	84.625	0.000	0.000	0.150
max	100.000	9.000	10.000	1.160

	xA	Yellow_Cards	Red_Cards
count	532.000	532.000	532.000
mean	0.073	2.115	0.090
std	0.090	2.269	0.293
min	0.000	0.000	0.000
25%	0.000	0.000	0.000
50%	0.050	2.000	0.000
75%	0.110	3.000	0.000
max	0.900	12.000	2.000

```
pd.set_option('display.float_format', lambda x: '%.3f' %x)
data.describe().transpose()
```

	count	mean	std	min	25%
Age	532.000	25.500	4.319	16.000	22.000
Matches	532.000	19.536	11.840	1.000	9.000
Starts	532.000	15.714	11.921	0.000	4.000
Mins	532.000	1411.444	1043.172	1.000	426.000
Goals	532.000	1.853	3.338	0.000	0.000
Assists	532.000	1.288	2.095	0.000	0.000
Passes_Attempted	532.000	717.750	631.373	0.000	171.500
Perc_Passes_Completed	532.000	77.824	13.012	-1.000	73.500
Penalty_Goals	532.000	0.192	0.851	0.000	0.000
Penalty_Attempted	532.000	0.235	0.976	0.000	0.000
xG	532.000	0.113	0.148	0.000	0.010
xA	532.000	0.073	0.090	0.000	0.000

Yellow_Cards	532.000	2.115	2.269	0.000	0.000
2.000					
Red_Cards	532.000	0.090	0.293	0.000	0.000
0.000					

	75%	max
Age	29.000	38.000
Matches	30.000	38.000
Starts	27.000	38.000
Mins	2303.500	3420.000
Goals	2.000	23.000
Assists	2.000	14.000
Passes_Attempted	1129.500	3214.000
Perc_Passes_Completed	84.625	100.000
Penalty_Goals	0.000	9.000
Penalty_Attempted	0.000	10.000
xG	0.150	1.160
xA	0.110	0.900
Yellow_Cards	3.000	12.000
Red_Cards	0.000	2.000

```
data.duplicated().sum()
```

```
0
```

```
data.isnull().sum()
```

Name	0
Club	0
Nationality	0
Position	0
Age	0
Matches	0
Starts	0
Mins	0
Goals	0
Assists	0
Passes_Attempted	0
Perc_Passes_Completed	0
Penalty_Goals	0
Penalty_Attempted	0
xG	0
xA	0
Yellow_Cards	0
Red_Cards	0
dtype: int64	

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 532 entries, 0 to 531
```

Data columns (total 18 columns):

#	Column	Non-Null Count	Dtype
0	Name	532 non-null	object
1	Club	532 non-null	object
2	Nationality	532 non-null	object
3	Position	532 non-null	object
4	Age	532 non-null	int64
5	Matches	532 non-null	int64
6	Starts	532 non-null	int64
7	Mins	532 non-null	int64
8	Goals	532 non-null	int64
9	Assists	532 non-null	int64
10	Passes_Attempted	532 non-null	int64
11	Perc_Passes_Completed	532 non-null	float64
12	Penalty_Goals	532 non-null	int64
13	Penalty_Attempted	532 non-null	int64
14	xG	532 non-null	float64
15	xA	532 non-null	float64
16	Yellow_Cards	532 non-null	int64
17	Red_Cards	532 non-null	int64

dtypes: float64(3), int64(11), object(4)

memory usage: 74.9+ KB

data.duplicated().sum()

0

data.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 532 entries, 0 to 531

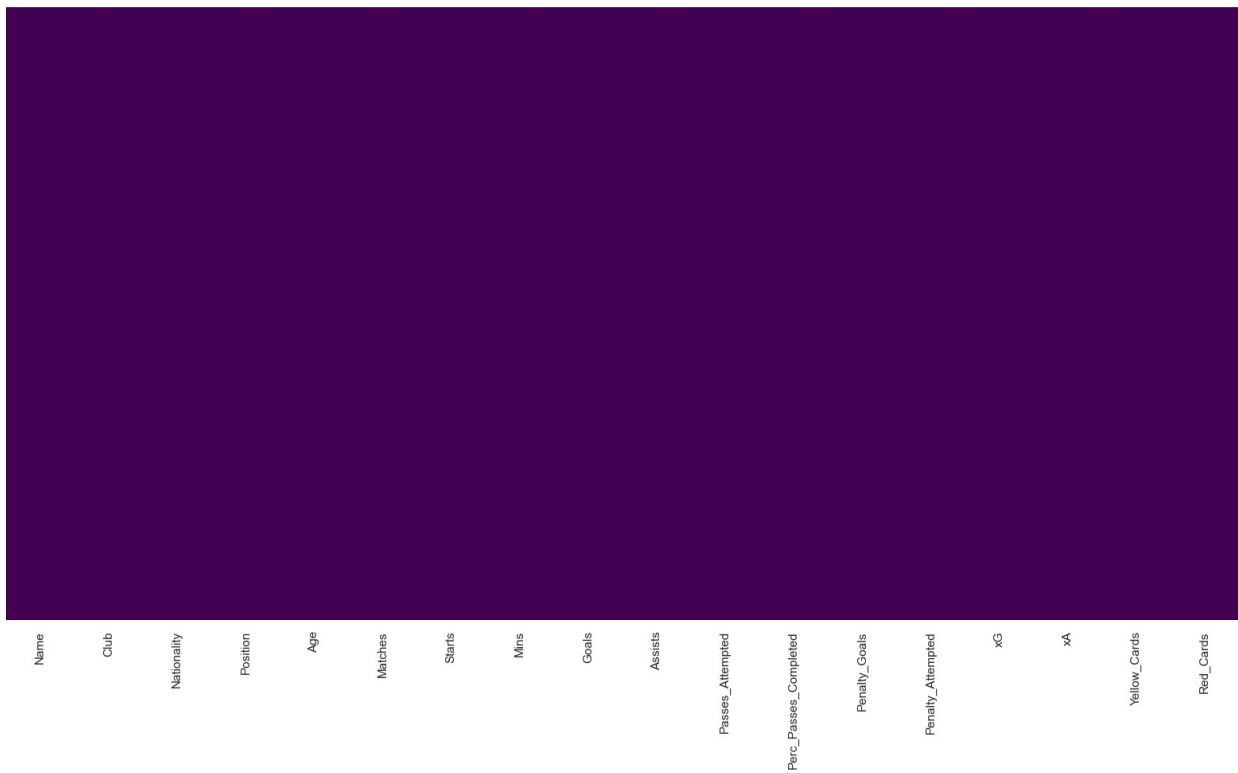
Data columns (total 18 columns):

#	Column	Non-Null Count	Dtype
0	Name	532 non-null	object
1	Club	532 non-null	object
2	Nationality	532 non-null	object
3	Position	532 non-null	object
4	Age	532 non-null	int64
5	Matches	532 non-null	int64
6	Starts	532 non-null	int64
7	Mins	532 non-null	int64
8	Goals	532 non-null	int64
9	Assists	532 non-null	int64
10	Passes_Attempted	532 non-null	int64
11	Perc_Passes_Completed	532 non-null	float64
12	Penalty_Goals	532 non-null	int64
13	Penalty_Attempted	532 non-null	int64
14	xG	532 non-null	float64

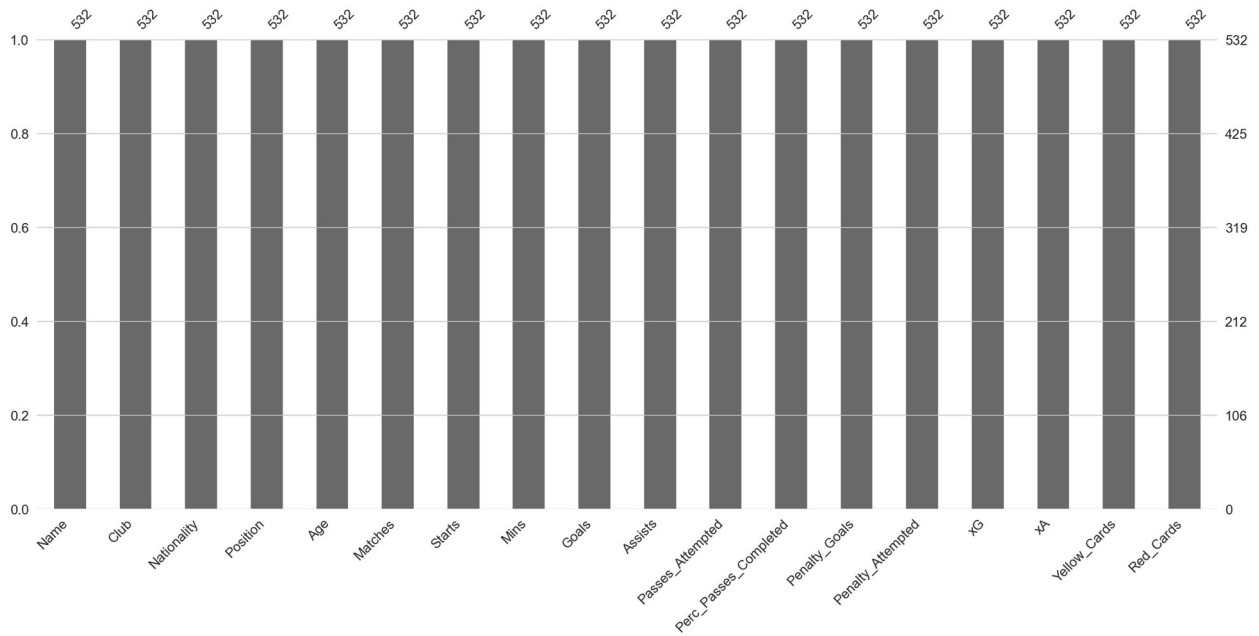
```
15  xA                    532 non-null    float64
16  Yellow_Cards          532 non-null    int64
17  Red_Cards              532 non-null    int64
dtypes: float64(3), int64(11), object(4)
memory usage: 74.9+ KB
```

Data Visualization

```
sns.heatmap(data.isnull(),yticklabels=False,cbar=False,cmap='viridis')
plt.show()
```



```
msno.bar(data)
<AxesSubplot:>
```



```
data.corr()
```

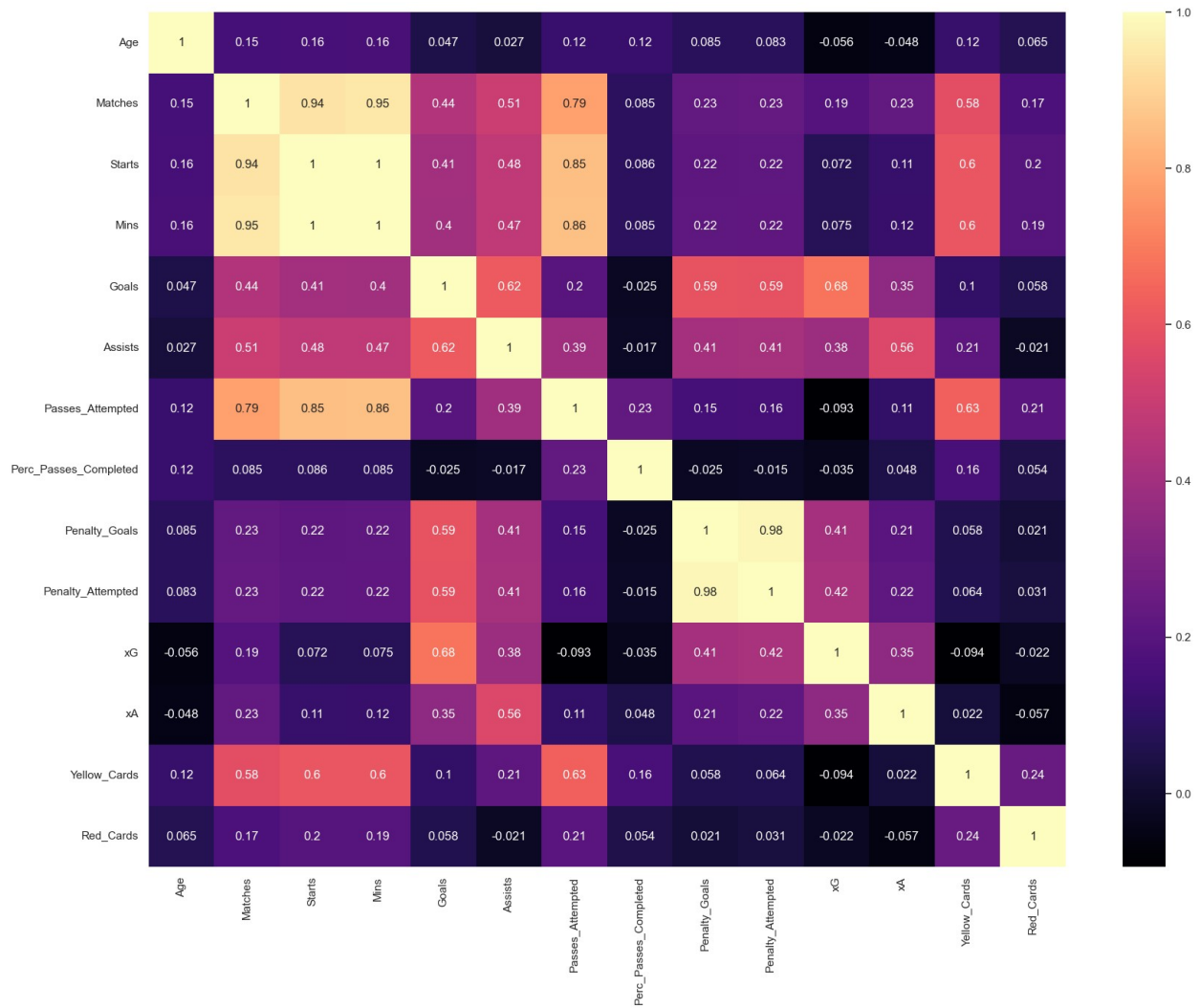
	Age	Matches	Starts	Mins	Goals	Assists	\
Age	1.000	0.150	0.156	0.159	0.047	0.027	
Matches	0.150	1.000	0.938	0.947	0.442	0.508	
Starts	0.156	0.938	1.000	0.997	0.405	0.478	
Mins	0.159	0.947	0.997	1.000	0.400	0.475	
Goals	0.047	0.442	0.405	0.400	1.000	0.618	
Assists	0.027	0.508	0.478	0.475	0.618	1.000	
Passes_Attempted	0.120	0.785	0.853	0.856	0.202	0.394	
Perc_Passes_Completed	0.123	0.085	0.086	0.085	-0.025	-0.017	
Penalty_Goals	0.085	0.228	0.217	0.219	0.595	0.408	
Penalty_Attempted	0.083	0.234	0.221	0.224	0.590	0.412	
xG	-0.056	0.192	0.072	0.075	0.682	0.383	
xA	-0.048	0.228	0.113	0.118	0.348	0.559	
Yellow_Cards	0.115	0.578	0.603	0.605	0.104	0.214	
Red_Cards	0.065	0.168	0.195	0.193	0.058	-0.021	

	Passes_Attempted	Perc_Passes_Completed
Penalty_Goals \		
Age	0.120	0.123
0.085		
Matches	0.785	0.085
0.228		
Starts	0.853	0.086
0.217		
Mins	0.856	0.085
0.219		
Goals	0.202	-0.025
0.595		

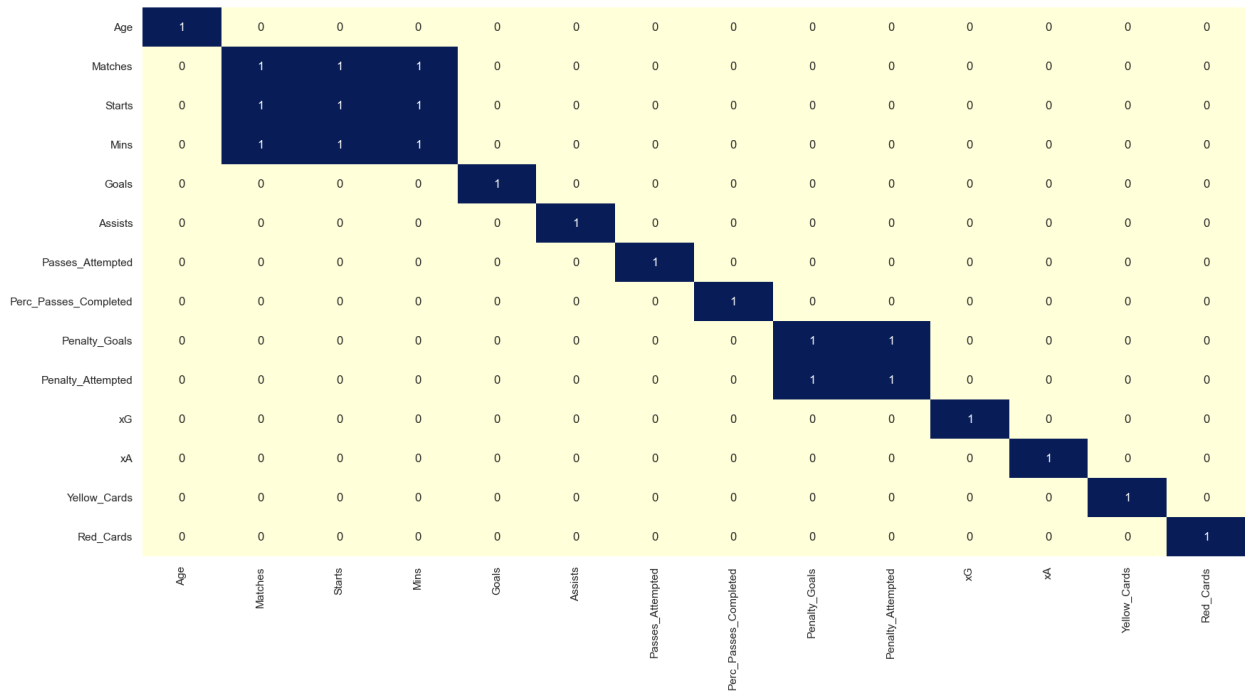
Assists	0.394			-0.017
0.408				
Passes_Attempted	1.000			0.228
0.150				
Perc_Passes_Completed	0.228			1.000
-0.025				
Penalty_Goals	0.150			-0.025
1.000				
Penalty_Attempted	0.157			-0.015
0.982				
xG	-0.093			-0.035
0.407				
xA	0.105			0.048
0.205				
Yellow_Cards	0.635			0.162
0.058				
Red_Cards	0.208			0.054
0.021				
	Penalty_Attempted	xG	xA	
Yellow_Cards \				
Age	0.083	-0.056	-0.048	0.115
Matches	0.234	0.192	0.228	0.578
Starts	0.221	0.072	0.113	0.603
Mins	0.224	0.075	0.118	0.605
Goals	0.590	0.682	0.348	0.104
Assists	0.412	0.383	0.559	0.214
Passes_Attempted	0.157	-0.093	0.105	0.635
Perc_Passes_Completed	-0.015	-0.035	0.048	0.162
Penalty_Goals	0.982	0.407	0.205	0.058
Penalty_Attempted	1.000	0.420	0.219	0.064
xG	0.420	1.000	0.347	-0.094
xA	0.219	0.347	1.000	0.022
Yellow_Cards	0.064	-0.094	0.022	1.000
Red_Cards	0.031	-0.022	-0.057	0.245
	Red_Cards			

Age	0.065
Matches	0.168
Starts	0.195
Mins	0.193
Goals	0.058
Assists	-0.021
Passes_Attempted	0.208
Perc_Passes_Completed	0.054
Penalty_Goals	0.021
Penalty_Attempted	0.031
xG	-0.022
xA	-0.057
Yellow_Cards	0.245
Red_Cards	1.000

```
plt.figure(figsize=(20,15))
corr = data.corr()
sns.heatmap(data.corr(), cmap="magma", annot=True)
plt.show()
```



```
sns.heatmap(data.corr() > 0.9, annot=True, cbar=False, cmap="YlGnBu")
plt.show()
```

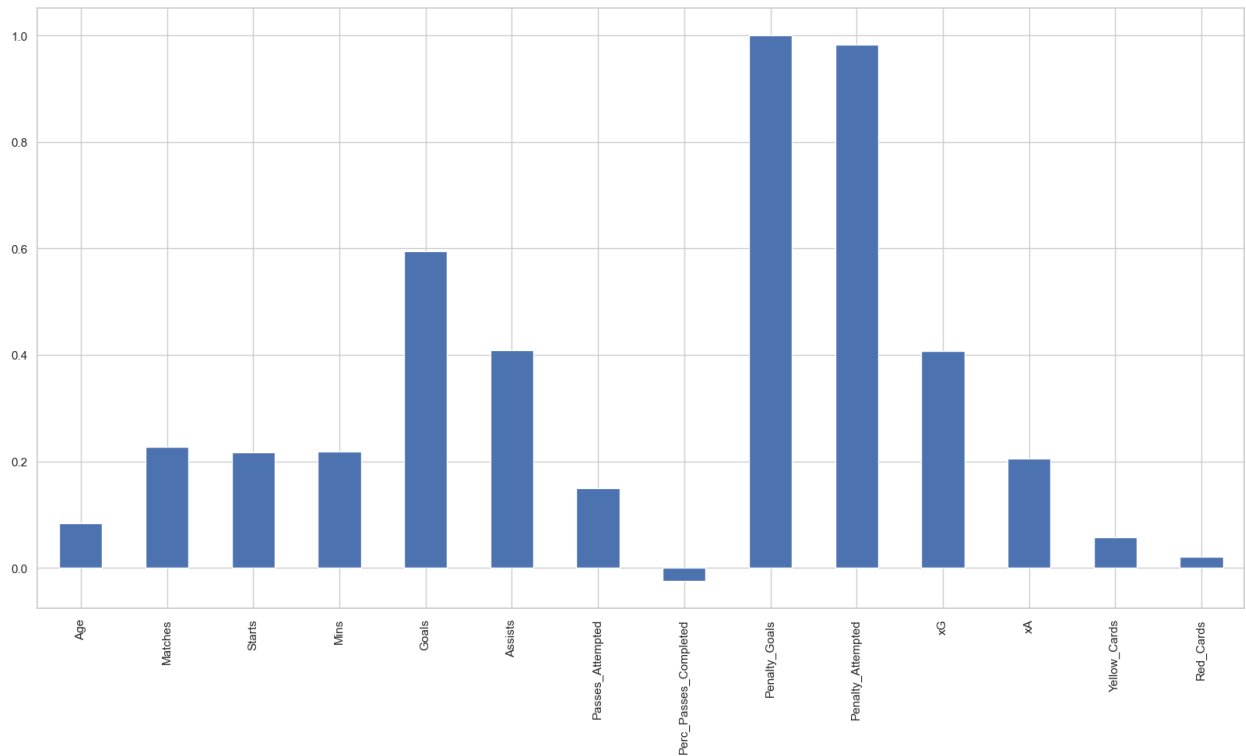


```
data.corr()['Goals']
```

```
Age          0.047
Matches      0.442
Starts       0.405
Mins         0.400
Goals        1.000
Assists      0.618
Passes_Attempted 0.202
Perc_Passes_Completed -0.025
Penalty_Goals 0.595
Penalty_Attempted 0.590
xG           0.682
xA           0.348
Yellow_Cards 0.104
Red_Cards    0.058
Name: Goals, dtype: float64
```

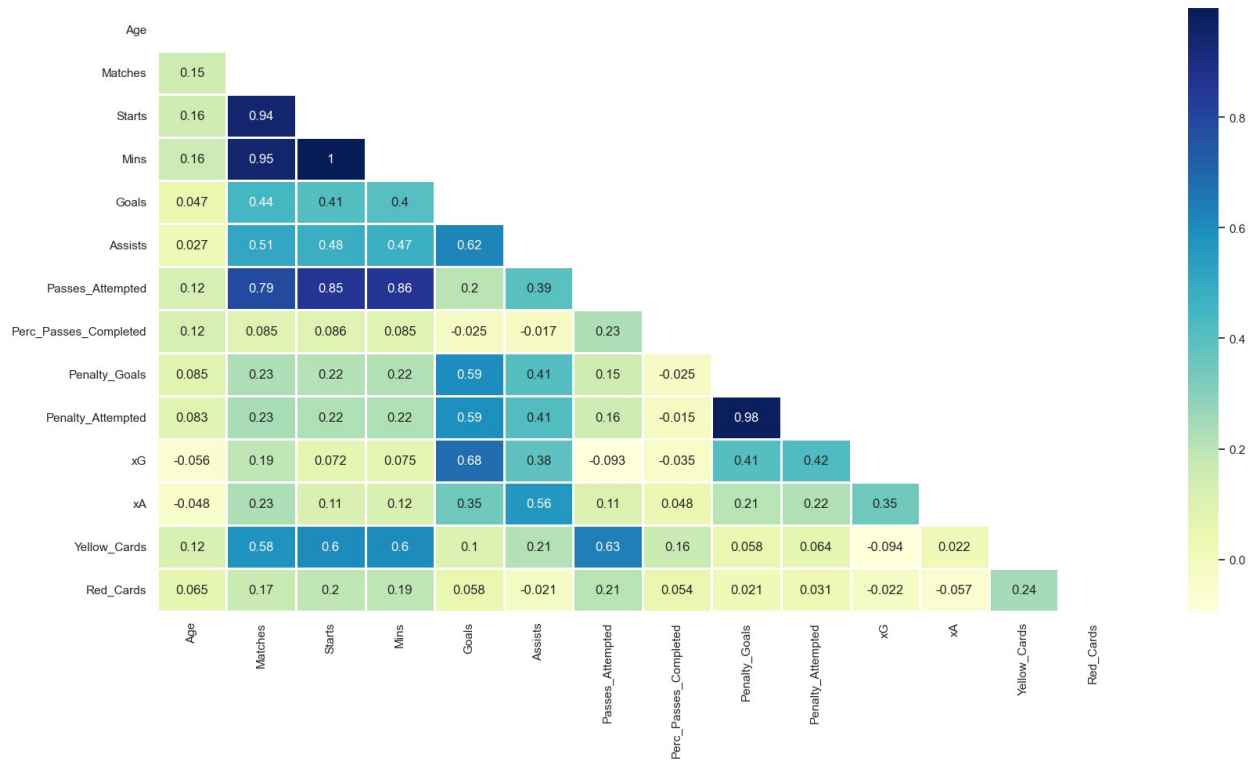
```
data.corr()['Penalty_Goals'].plot(kind='bar')
```

```
<AxesSubplot:>
```



```
plt.figure(figsize=(20,10))
corr = data.corr()
mask=np.triu(np.ones_like(corr,dtype=bool))

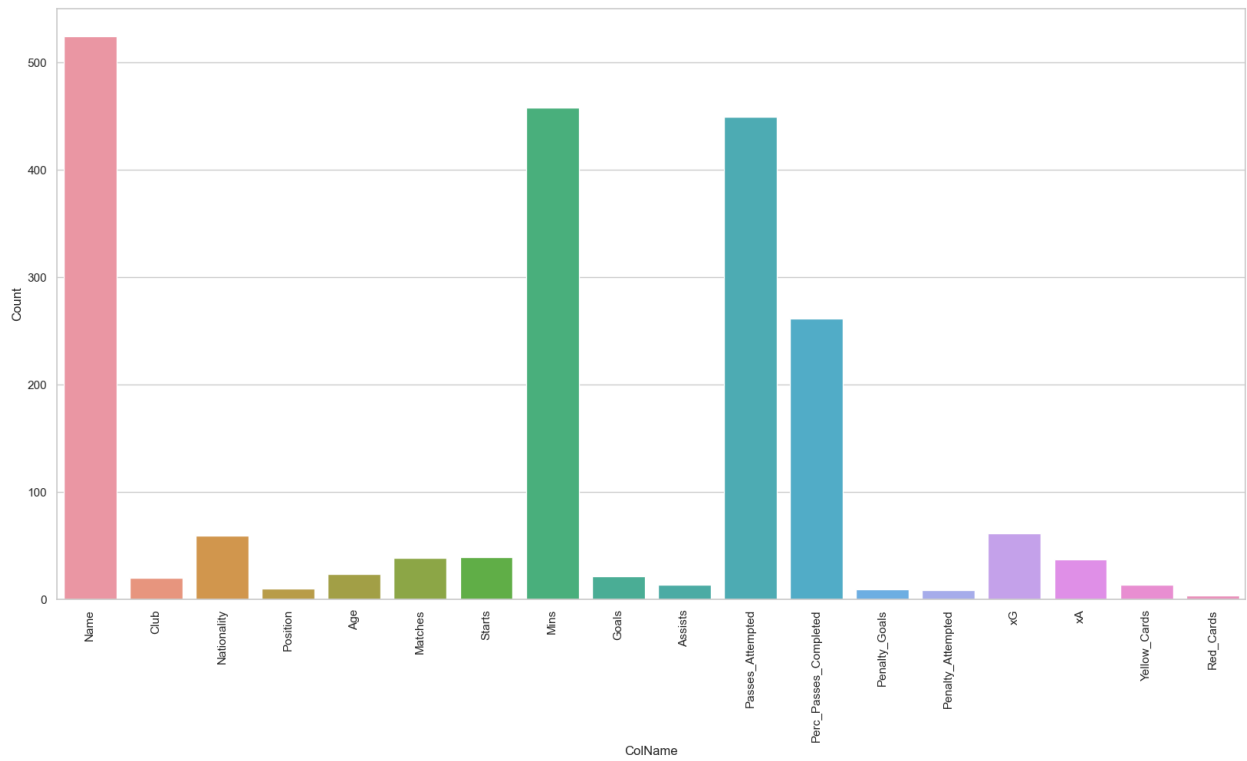
sns.heatmap(data=corr, mask=mask,
cmap="YlGnBu",annot=True,linewidth=2)
plt.show()
```



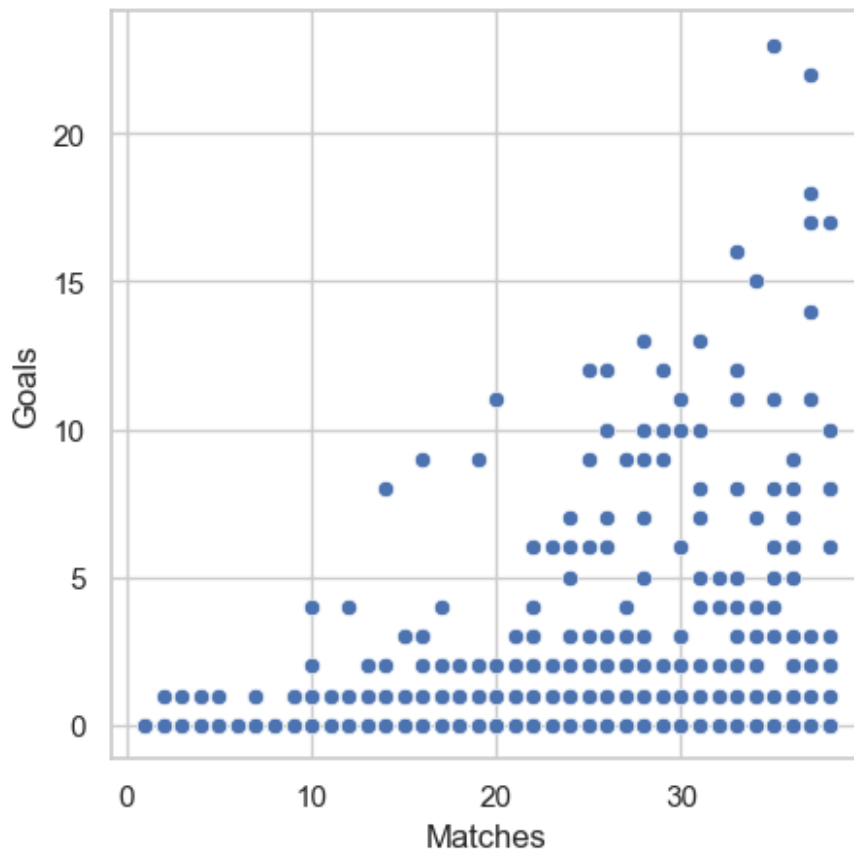
```

unique=data.nunique().to_frame()
unique.columns=['Count']
unique.index.names=['ColName']
unique=unique.reset_index()
sns.set(style='whitegrid',color_codes=True)
sns.barplot(x='ColName', y = 'Count', data = unique)
plt.xticks(rotation=90)
plt.show()

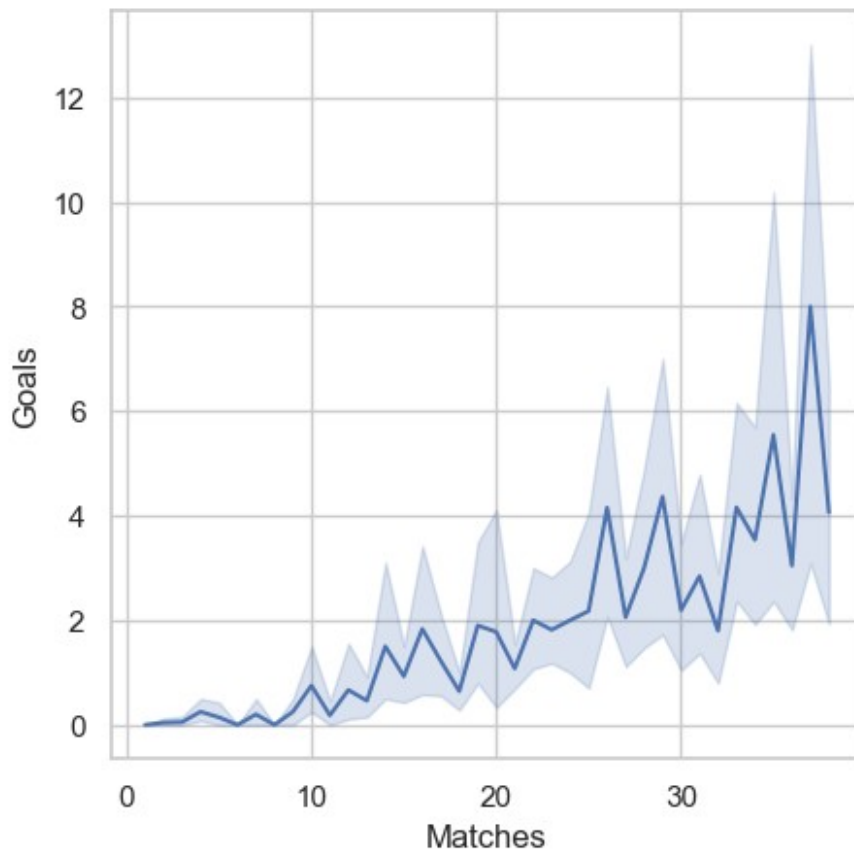
```



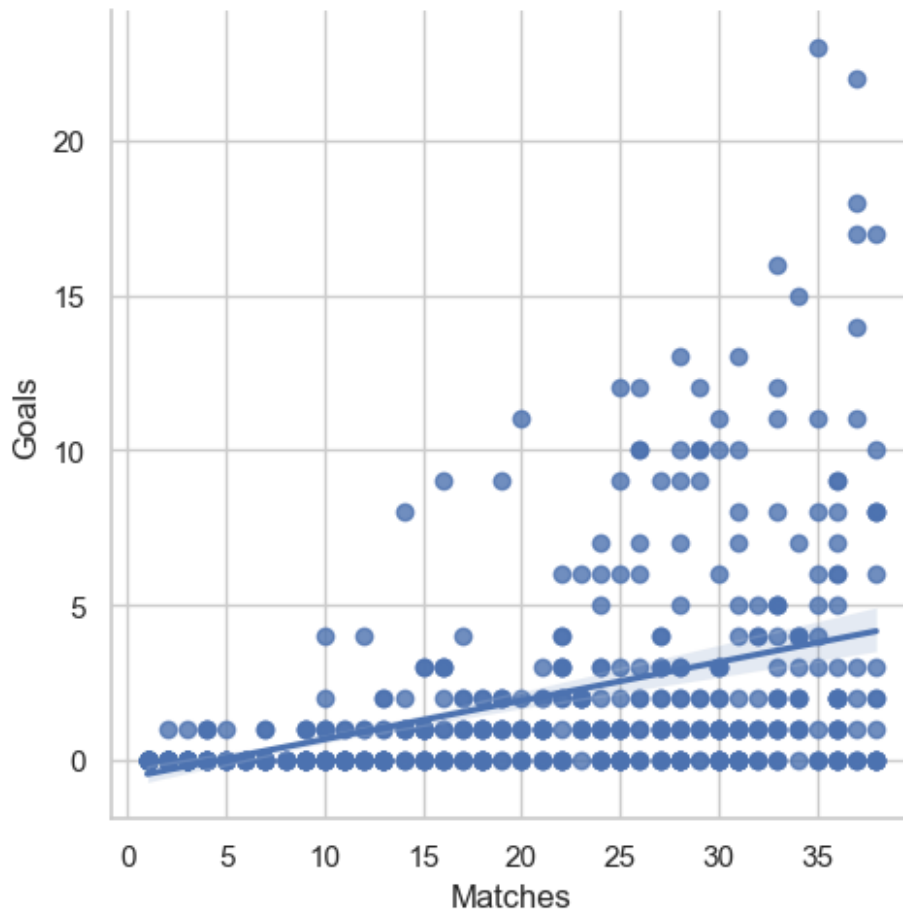
```
plt.figure(figsize=(5,5))
sns.scatterplot(x=data['Matches'],y=data['Goals'])
plt.show()
```



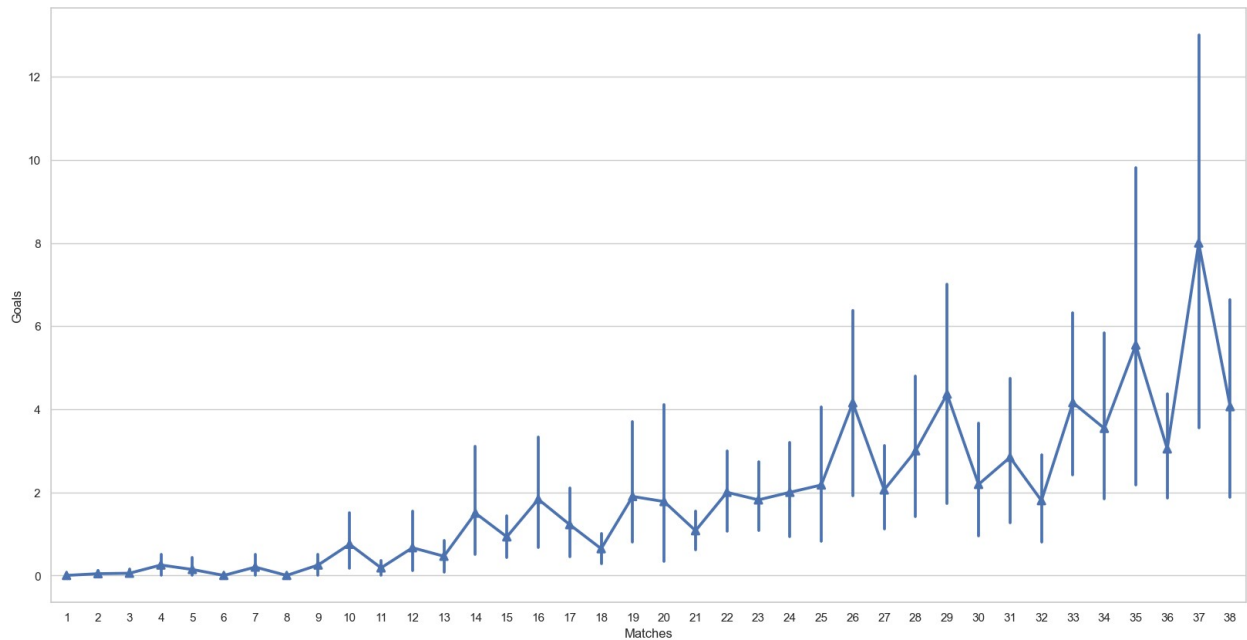
```
plt.figure(figsize=(5,5))
sns.lineplot(x=data['Matches'],y=data['Goals'])
plt.show()
```



```
sns.lmplot(x='Matches', y='Goals', data=data)  
<seaborn.axisgrid.FacetGrid at 0x2494e2e4e50>
```

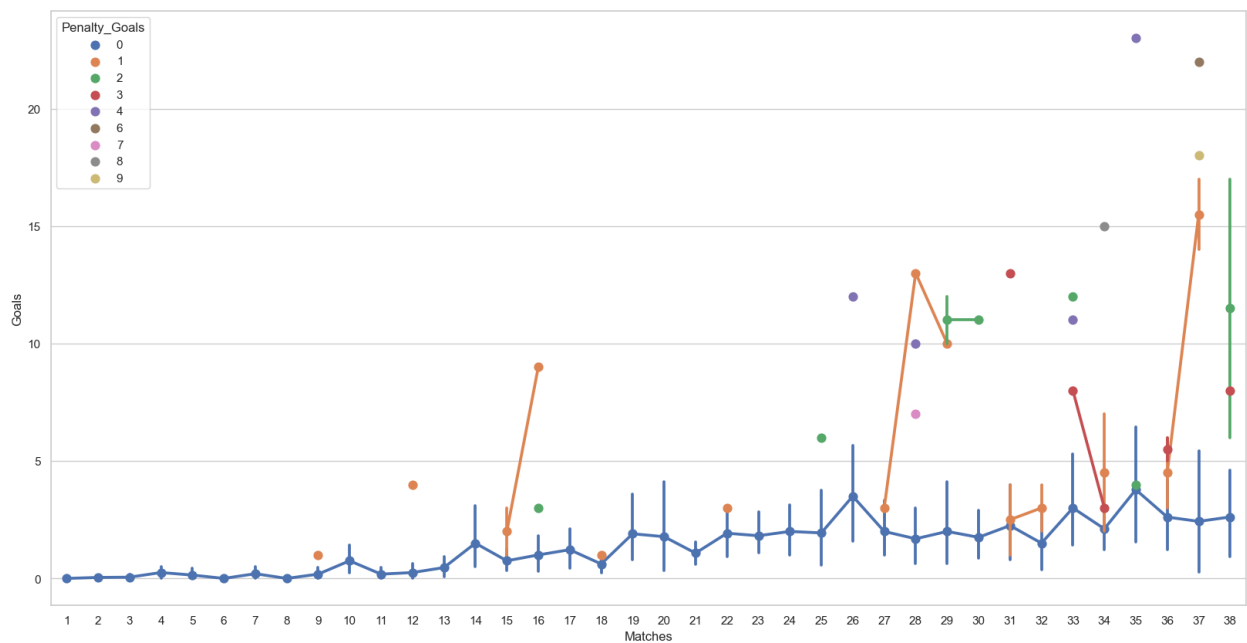



```
plt.figure(figsize=(20,10))  
#sns.factorplot(x='Matches',y='Goals',data=data)  
sns.pointplot(x='Matches',y='Goals',markers='^',data=data)  
plt.show()
```



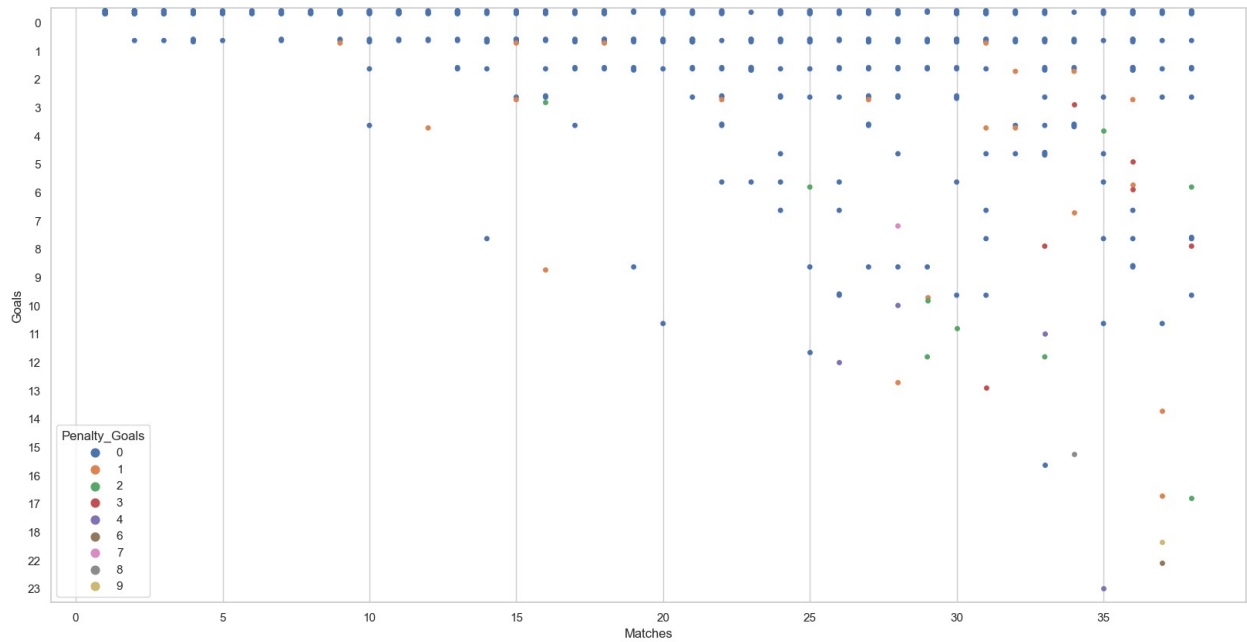
```
plt.figure(figsize=(20,10))

sns.pointplot(x='Matches',y='Goals',hue='Penalty_Goals',data=data)
plt.show()
```

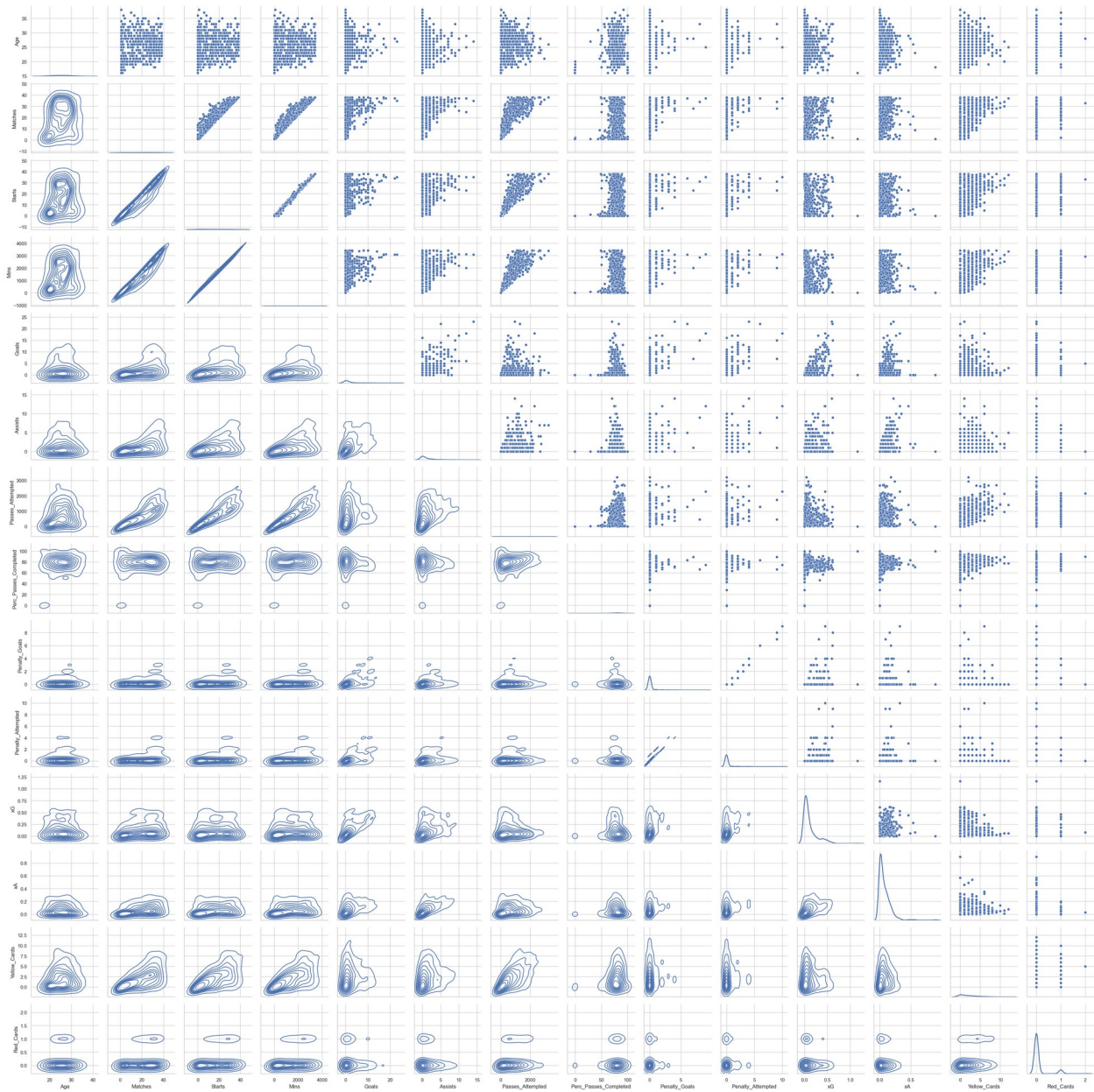


```
plt.figure(figsize=(20,10))

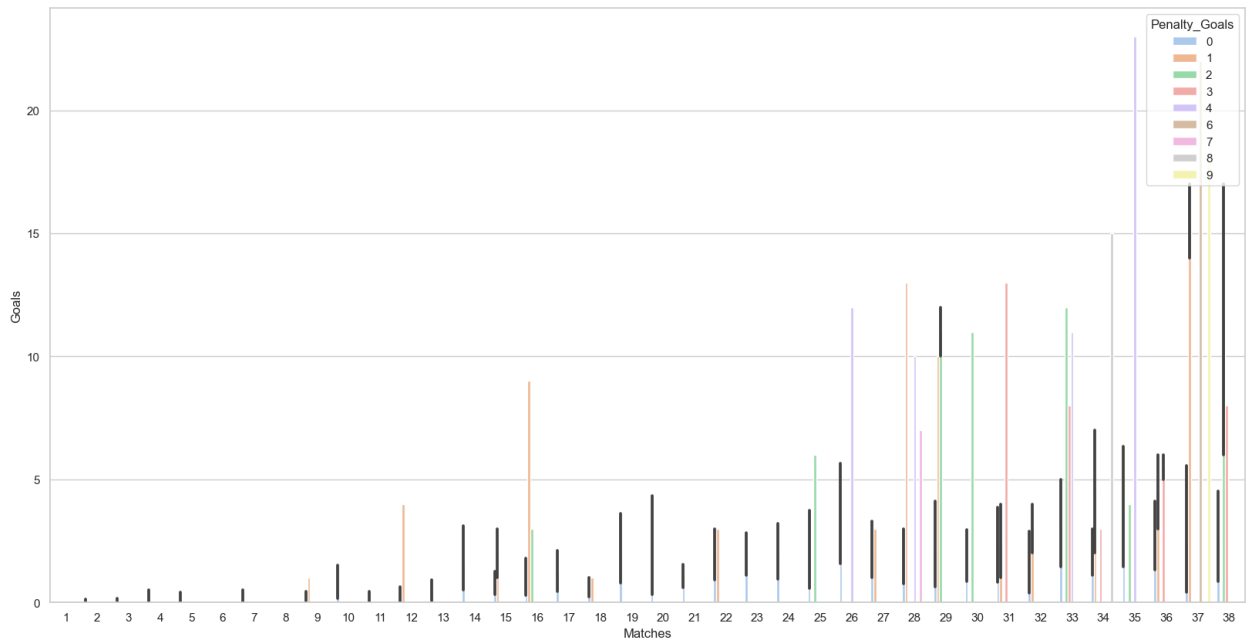
sns.swarmplot(x='Matches',y='Goals',hue='Penalty_Goals',orient='h',data=data,dodge=True)
plt.show()
```



```
graph=sns.PairGrid(data)
graph=graph.map_upper(sns.scatterplot)
graph=graph.map_lower(sns.kdeplot)
graph=graph.map_diag(sns.kdeplot, lw=2)
plt.show()
#kernel distribution estimation plot
```



```
plt.figure(figsize=(20,10))
sns.barplot(x='Matches',y='Goals',hue='Penalty_Goals',palette='pastel',
,data=data)
plt.show()
```



```
data['MinsPerMatch']=(data['Mins']/data['Matches']).astype(int)
data['GoalsPerMatch']=(data['Goals']/data['Matches']).astype(float)
data.head()
```

ColName	Name	Club	Nationality	Position	Age	Matches
Starts \						
0	Mason Mount	Chelsea	ENG	MF,FW	21	36
32						
1	Edouard Mendy	Chelsea	SEN	GK	28	31
31						
2	Timo Werner	Chelsea	GER	FW	24	35
29						
3	Ben Chilwell	Chelsea	ENG	DF	23	27
27						
4	Reece James	Chelsea	ENG	DF	20	32
25						

ColName	Mins	Goals	Assists	Passes_Attempted	Perc_Passes_Completed
\					
0	2890	6	5	1881	82.300
1	2745	0	0	1007	84.600
2	2602	6	8	826	77.200
3	2286	3	5	1806	78.600
4	2373	1	2	1987	85.000

ColName	Penalty_Goals	Penalty_Attempted	xG	xA	Yellow_Cards	\
0	1	1	0.210	0.240	2	
1	0	0	0.000	0.000	2	
2	0	0	0.410	0.210	2	
3	0	0	0.100	0.110	3	
4	0	0	0.060	0.120	3	

ColName	Red_Cards	MinsPerMatch	GoalsPerMatch
0	0	80	0.167
1	0	88	0.000
2	0	74	0.171
3	0	84	0.111
4	0	74	0.031

#total Goals

TotalGoals=data['Goals'].sum()

TotalGoals

986

#Penalty Goals

Total_PenaltyGoals=data['Penalty_Goals'].sum()

Total_PenaltyGoals

102

#Penalty Attempts

Total_PenaltyAttempts=data['Penalty_Attempted'].sum()

Total_PenaltyAttempts

125

#Pie chart for penalty missed and scored

plt.figure(figsize=(7,7))

Penalty_not_scored=data['Penalty_Attempted'].sum()- Total_PenaltyGoals

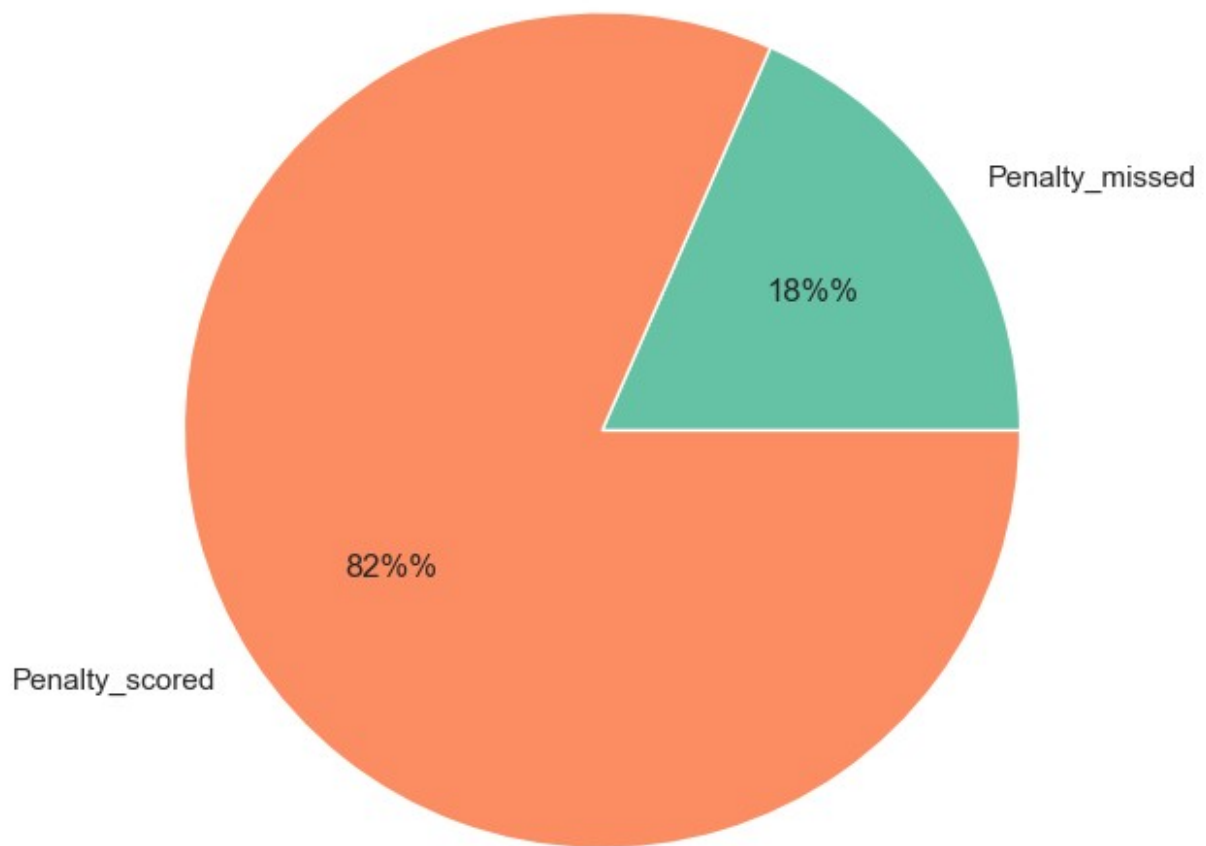
d=[Penalty_not_scored,Total_PenaltyGoals]

labels=['Penalty_missed','Penalty_scored']

color=sns.color_palette('Set2')

plt.pie(d,labels=labels,colors=color,autopct='%1.0f%%')

plt.show()



#Unique Positions

```
data['Position'].unique()
array(['MF,FW', 'GK', 'FW', 'DF', 'MF', 'FW,MF', 'FW,DF', 'DF,MF',
      'MF,DF', 'DF,FW'], dtype=object)
```

#Total Forward Players

```
data[data['Position']=='FW']
```

ColName	Name	Club	Nationality	Position
Age \				
2	Timo Werner	Chelsea	GER	FW
24				
16	Tammy Abraham	Chelsea	ENG	FW
22				
19	Olivier Giroud	Chelsea	FRA	FW

33					
23	Ruben Loftus-Cheek	Chelsea	ENG	FW	
24					
30	Raheem Sterling	Manchester City	ENG	FW	
25					
..
.					
516	Oliver Burke	Sheffield United	SCO	FW	
23					
518	Oliver McBurnie	Sheffield United	SCO	FW	
24					
519	Rhian Brewster	Sheffield United	ENG	FW	
20					
523	Billy Sharp	Sheffield United	ENG	FW	
34					
526	Daniel Jebbison	Sheffield United	ENG	FW	
17					

ColName	Matches	Starts	Mins	Goals	Assists	Passes_Attempted	\
2	35	29	2602	6	8	826	
16	22	12	1040	6	1	218	
19	17	8	748	4	0	217	
23	1	1	60	0	0	16	
30	31	28	2536	10	7	1127	
..	
516	25	14	1269	1	1	262	
518	23	12	1324	1	0	426	
519	27	12	1128	0	0	225	
523	16	7	735	3	0	123	
526	4	3	284	1	0	34	

ColName	Perc_Passes_Completed	Penalty_Goals	Penalty_Attempted	xG
xA \				
2	77.200	0	0	0.410
0.210				
16	68.300	0	0	0.560
0.070				
19	74.200	0	0	0.580
0.090				
23	68.800	0	0	0.000
0.000				
30	85.400	0	1	0.430
0.170				
..
...				
516	70.600	0	0	0.170
0.130				
518	62.900	0	0	0.210
0.070				

519	69.300	0	0 0.140
0.130			
523	69.900	2	2 0.330
0.070			
526	70.600	0	0 0.500
0.010			

ColName	Yellow_Cards	Red_Cards	MinsPerMatch	GoalsPerMatch
2	2	0	74	0.171
16	0	0	47	0.273
19	1	0	44	0.235
23	0	0	60	0.000
30	4	0	81	0.323
..
516	2	0	50	0.040
518	2	0	57	0.043
519	1	0	41	0.000
523	1	0	45	0.188
526	0	0	71	0.250

[81 rows x 20 columns]

#Total Goal Keepers

data[data['Position']=='GK']

ColName	Name	Club	Nationality
Position \			
1	Edouard Mendy	Chelsea	SEN
GK			
20	Kepa Arrizabalaga	Chelsea	ESP
GK			
22	Willy Caballero	Chelsea	ARG
GK			
27	Ederson	Manchester City	BRA
GK			
48	Scott Carson	Manchester City	ENG
GK			
49	Zack Steffen	Manchester City	USA
GK			
58	David de Gea	Manchester United	ESP
GK			
64	Dean Henderson	Manchester United	ENG
GK			
84	Alisson	Liverpool FC	BRA
GK			
101	Adrián	Liverpool FC	ESP
GK			
106	Caoimhín Kelleher	Liverpool FC	IRL
GK			

108	Kasper Schmeichel	Leicester City	DEN
GK			
137	Łukasz Fabiański	West Ham United	POL
GK			
155	Darren Randolph	West Ham United	IRL
GK			
160	Hugo Lloris	Tottenham Hotspur	FRA
GK			
183	Bernd Leno	Arsenal	GER
GK			
206	Mathew Ryan	Arsenal	AUS
GK			
211	Rúnar Alex Rúnarsson	Arsenal	ISL
GK			
215	Illan Meslier	Leeds United	FRA
GK			
230	Kiko Casilla	Leeds United	ESP
GK			
238	Jordan Pickford	Everton	ENG
GK			
251	Robin Olsen	Everton	SWE
GK			
259	João Virgínia	Everton	POR
GK			
264	Emiliano Martínez	Aston Villa	ARG
GK			
290	Karl Darlow	Newcastle United	ENG
GK			
306	Martin Dúbravka	Newcastle United	SVK
GK			
315	Rui Patrício	Wolverhampton Wanderers	POR
GK			
338	John Ruddy	Wolverhampton Wanderers	ENG
GK			
342	Vicente Guaita	Crystal Palace	ESP
GK			
364	Jack Butland	Crystal Palace	ENG
GK			
369	Alex McCarthy	Southampton	ENG
GK			
383	Fraser Forster	Southampton	ENG
GK			
402	Robert Sánchez	Brighton	ESP
GK			
409	Mathew Ryan	Brighton	AUS
GK			
426	Nick Pope	Burnley	ENG
GK			
439	Bailey Peacock-Farrell	Burnley	NIR

GK								
444		Will Norris				Burnley		ENG
GK								
447		Alphonse Areola				Fulham		FRA
GK								
470		Marek Rodák				Fulham		SVK
GK								
475		Sam Johnstone				West Bromwich Albion		ENG
GK								
500		David Button				West Bromwich Albion		ENG
GK								
505		Aaron Ramsdale				Sheffield United		ENG
GK								
ColName \	Age	Matches	Starts	Mins	Goals	Assists	Passes_Attempted	
1	28	31	31	2745	0	0	1007	
20	25	7	6	585	0	0	243	
22	38	1	1	90	0	0	26	
27	26	36	36	3240	0	1	1090	
48	34	1	1	90	0	0	16	
49	25	1	1	90	0	0	28	
58	29	26	26	2295	0	0	594	
64	23	13	12	1125	0	0	314	
84	27	33	33	2970	1	0	1137	
101	33	3	3	270	0	0	99	
106	21	2	2	180	0	0	62	
108	33	38	38	3420	0	0	1218	
137	35	35	35	3150	0	0	1002	
155	33	3	3	270	0	0	66	
160	33	38	38	3420	0	0	1067	
183	28	35	35	3131	0	0	1156	
206	28	3	3	270	0	0	67	
211	25	1	0	16	0	0	11	

215	20	35	35	3150	0	0	1348
230	33	3	3	270	0	0	94
238	26	31	31	2742	0	0	1152
251	30	7	7	630	0	0	199
259	20	1	0	48	0	0	17
264	27	38	38	3420	0	0	1295
290	29	25	25	2250	0	0	726
306	31	13	13	1170	0	0	427
315	32	37	37	3329	0	0	801
338	33	2	1	91	0	0	24
342	33	37	37	3330	0	0	1080
364	27	1	1	90	0	0	21
369	30	30	30	2700	0	0	1069
383	32	8	8	720	0	0	274
402	22	27	27	2430	0	0	1095
409	28	11	11	990	0	0	399
426	28	32	32	2880	0	0	979
439	23	4	4	360	0	0	113
444	26	2	2	180	0	0	56
447	27	36	36	3240	0	0	1001
470	23	2	2	180	0	0	46
475	27	37	37	3330	0	1	1282
500	31	1	1	90	0	0	37
505	22	38	38	3420	0	0	1141
ColName	Perc_Passes_Completed			Penalty_Goals	Penalty_Attempted		xG
xA	\						

1	84.600	0	0 0.000
0.000			
20	81.500	0	0 0.000
0.000			
22	92.300	0	0 0.000
0.000			
27	83.100	0	0 0.000
0.010			
48	93.800	0	0 0.000
0.000			
49	82.100	0	0 0.000
0.000			
58	77.100	0	0 0.000
0.000			
64	75.200	0	0 0.000
0.000			
84	85.200	0	0 0.000
0.000			
101	76.800	0	0 0.000
0.000			
106	82.300	0	0 0.000
0.000			
108	72.700	0	0 0.000
0.000			
137	60.500	0	0 0.000
0.000			
155	54.500	0	0 0.000
0.000			
160	71.500	0	0 0.000
0.000			
183	79.800	0	0 0.000
0.000			
206	92.500	0	0 0.000
0.000			
211	63.600	0	0 0.000
0.000			
215	80.900	0	0 0.000
0.000			
230	87.200	0	0 0.000
0.000			
238	66.100	0	0 0.000
0.000			
251	71.400	0	0 0.000
0.000			
259	52.900	0	0 0.000
0.000			
264	65.600	0	0 0.000
0.010			
290	50.100	0	0 0.000

0.000				
306	72.600	0	0	0.000
0.000				
315	66.700	0	0	0.000
0.000				
338	79.200	0	0	0.000
0.000				
342	55.400	0	0	0.000
0.000				
364	28.600	0	0	0.000
0.000				
369	64.300	0	0	0.000
0.000				
383	56.200	0	0	0.000
0.000				
402	71.600	0	0	0.000
0.000				
409	78.700	0	0	0.000
0.000				
426	50.700	0	0	0.000
0.010				
439	51.300	0	0	0.000
0.000				
444	48.200	0	0	0.000
0.040				
447	73.600	0	0	0.000
0.000				
470	80.400	0	0	0.000
0.000				
475	49.900	0	0	0.000
0.010				
500	43.200	0	0	0.000
0.000				
505	49.100	0	0	0.000
0.000				

ColName	Yellow_Cards	Red_Cards	MinsPerMatch	GoalsPerMatch
1	2	0	88	0.000
20	1	0	83	0.000
22	0	0	90	0.000
27	3	0	90	0.000
48	0	0	90	0.000
49	0	0	90	0.000
58	0	0	88	0.000
64	3	0	86	0.000
84	1	0	90	0.030
101	0	0	90	0.000
106	0	0	90	0.000
108	0	0	90	0.000

137	2	0	90	0.000
155	0	0	90	0.000
160	0	0	90	0.000
183	0	1	89	0.000
206	0	0	90	0.000
211	0	0	16	0.000
215	0	0	90	0.000
230	0	0	90	0.000
238	1	0	88	0.000
251	1	0	90	0.000
259	0	0	48	0.000
264	1	0	90	0.000
290	3	0	90	0.000
306	0	0	90	0.000
315	1	0	89	0.000
338	0	0	45	0.000
342	2	0	90	0.000
364	0	0	90	0.000
369	2	0	90	0.000
383	0	0	90	0.000
402	2	0	90	0.000
409	1	0	90	0.000
426	1	0	90	0.000
439	0	0	90	0.000
444	0	0	90	0.000
447	2	0	90	0.000
470	0	0	90	0.000
475	1	0	90	0.000
500	0	0	90	0.000
505	1	0	90	0.000

#Players from Different Nation

```
np.size((data['Nationality'].unique()))
```

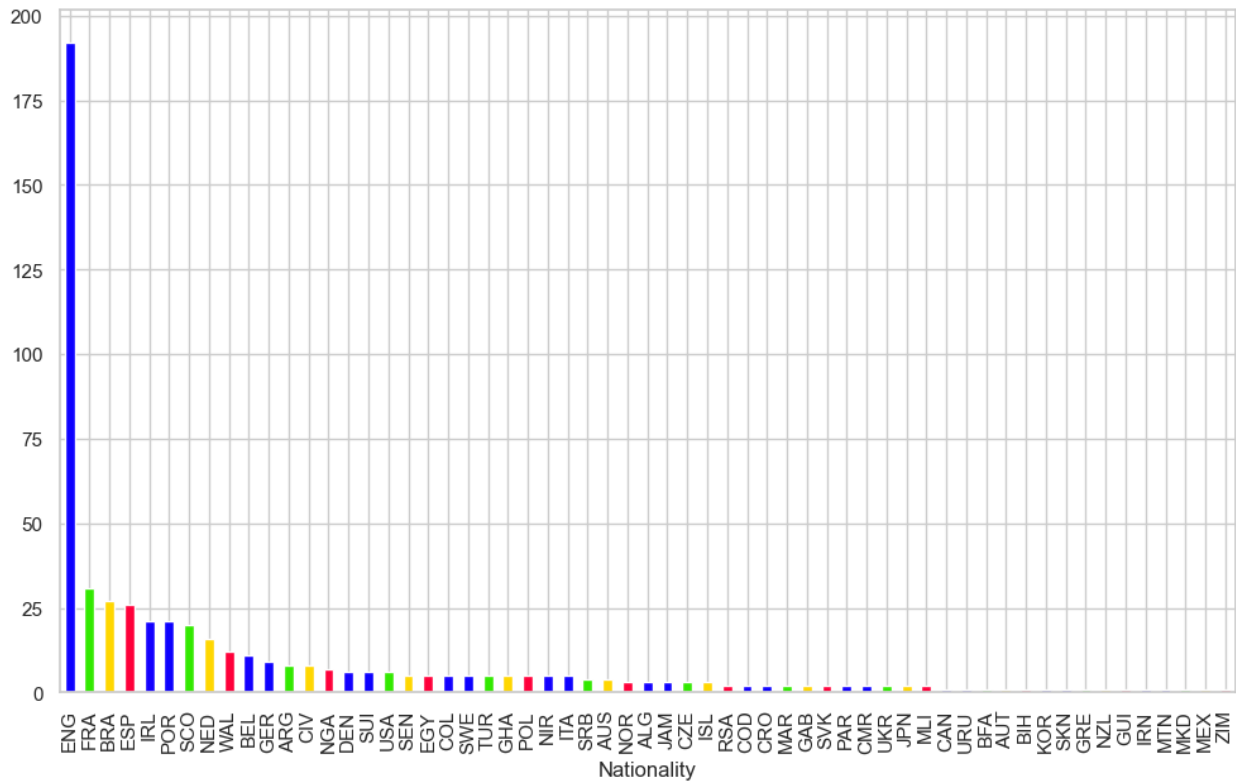
59

#Most players came from which countries

```
Nationality=data.groupby('Nationality').size().sort_values(ascending=False)
```

```
Nationality.plot(kind='bar',figsize=(12,7),color=sns.color_palette('prism',5))
```

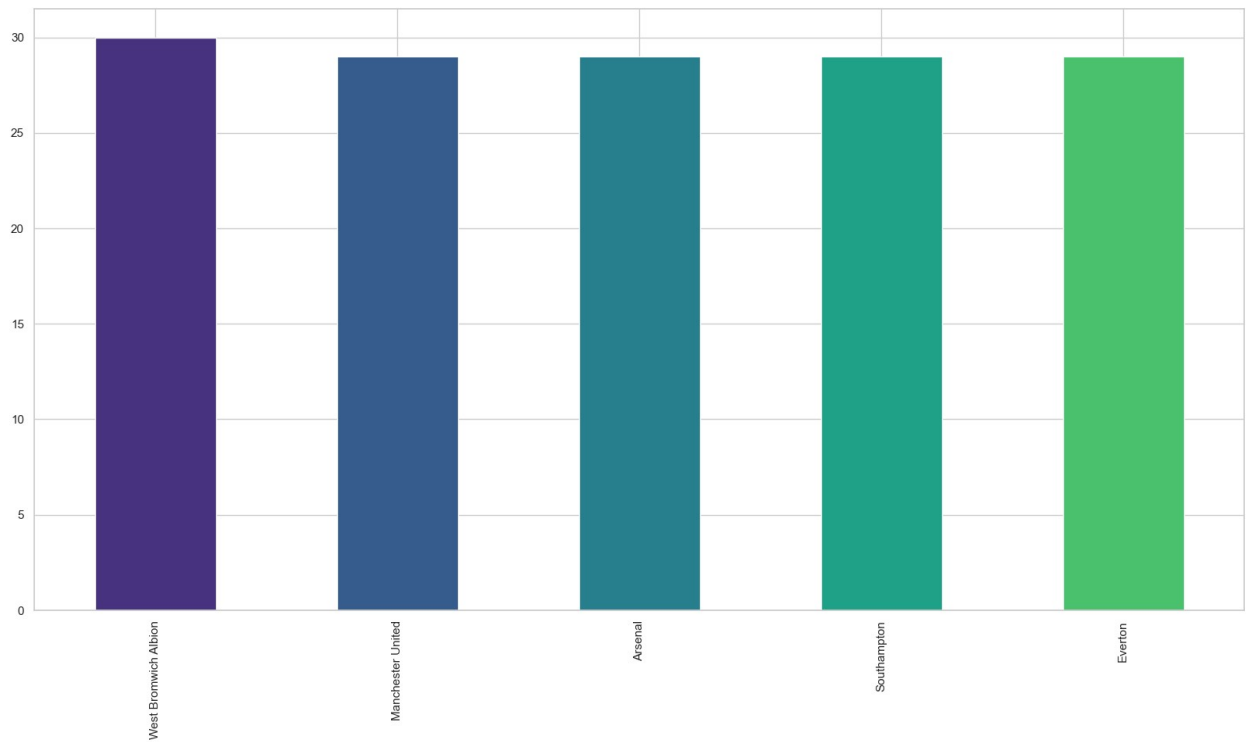
```
<AxesSubplot:xlabel='Nationality'>
```



```
#Clubs with maximum players in their squad
data['Club'].value_counts().nlargest(5).plot(kind='bar',color=sns.col
r_palette('viridis'))

#nlargest=head=top5

<AxesSubplot:>
```

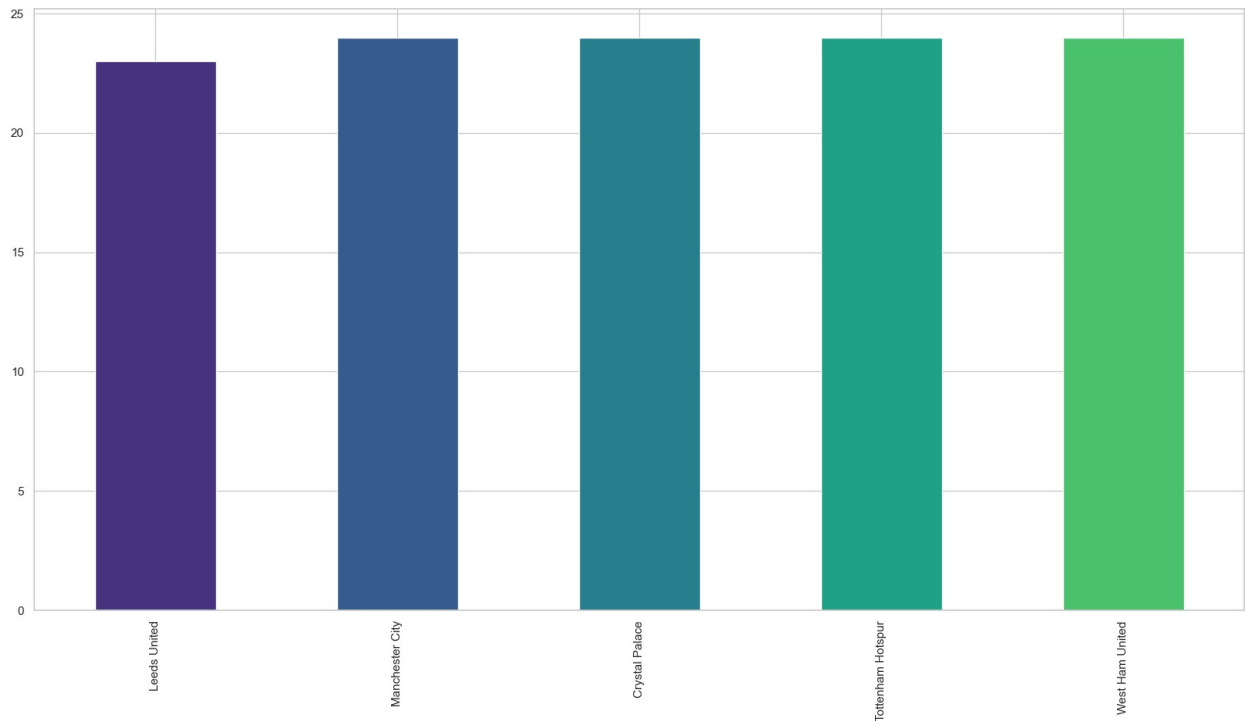



```
#club with least player in their squad
```

```
data['Club'].value_counts().nsmallest(5).plot(kind='bar',color=sns.col  
or_palette('viridis'))
```

```
#nsmallest=tail=last5
```

```
<AxesSubplot:>
```



#players based on age group

```
under20=data[data['Age']<=20]
```

```
age20_25=data[(data["Age"] > 20) & (data["Age"] <= 25)]
```

```
age25_30=data[(data["Age"] > 25) & (data["Age"] <= 30)]
```

```
above30=data[(data["Age"] > 30)]
```

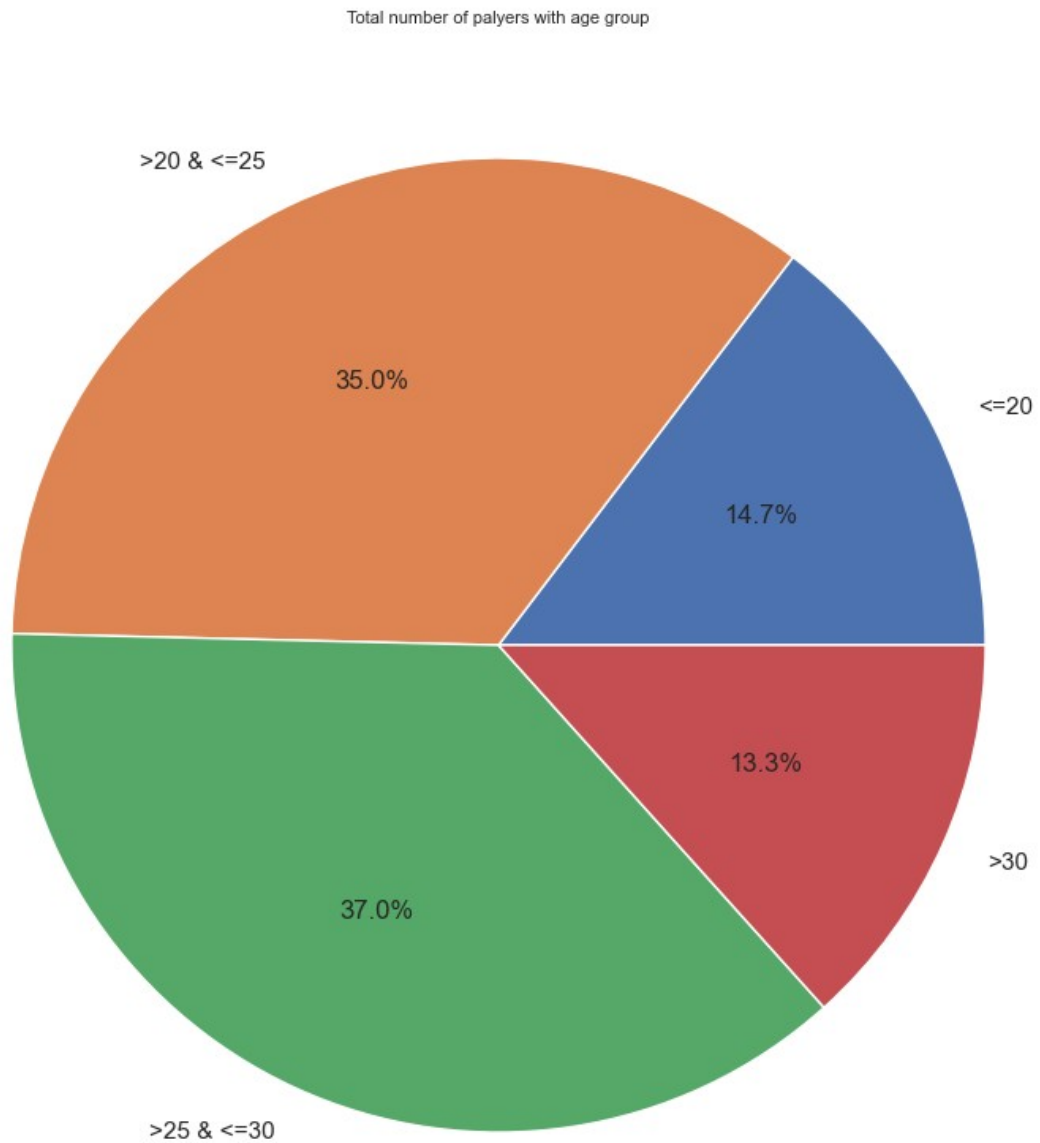
```
x=np.array([under20['Name'].count(),age20_25['Name'].count(),age25_30['Name'].count(),above30['Name'].count()])
```

```
labels=['<=20','>20 & <=25','>25 & <=30', '>30']
```

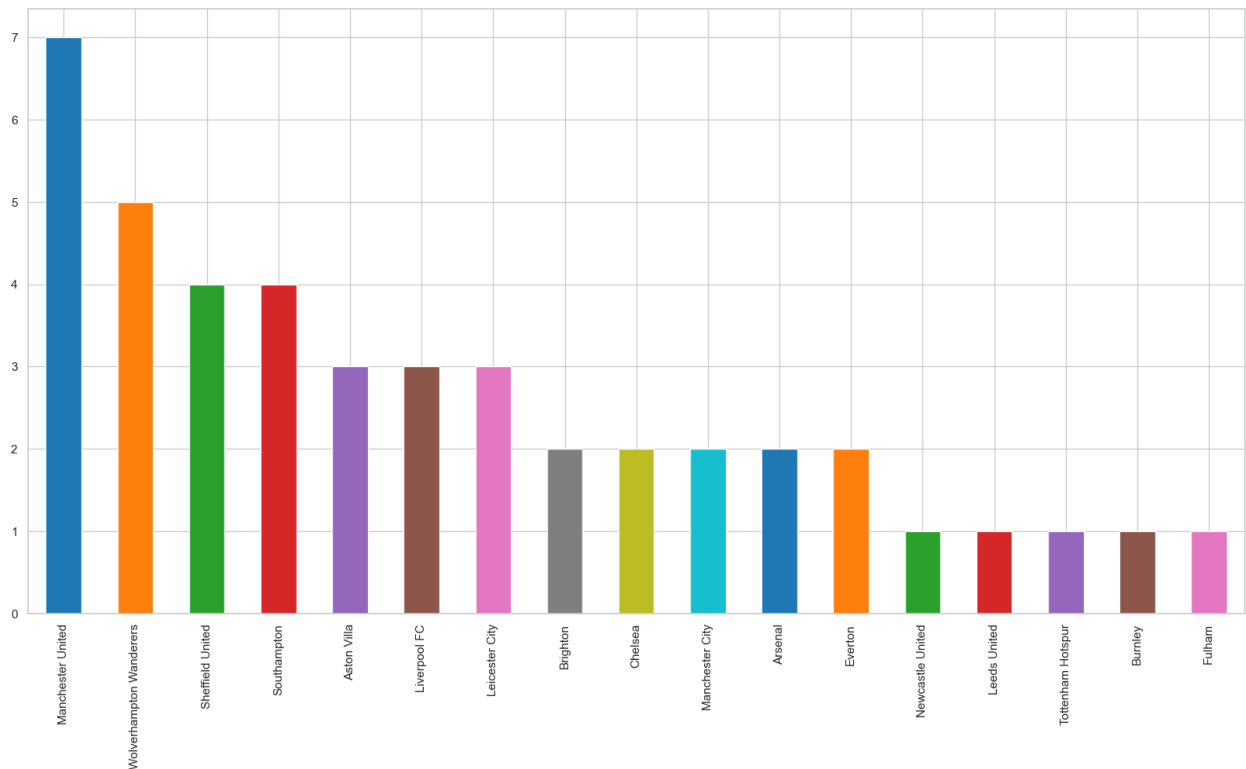
```
plt.title('Total number of palyers with age group', fontsize=8)
```

```
plt.pie(x,labels=labels,autopct='%.1f%%')
```

```
plt.show()
```



```
#Total under20 players in each club  
Players_under20=data[data['Age'] < 20]  
Players_under20['Club'].value_counts().plot(kind='bar',color=sns.color_palette('tab10'))  
<AxesSubplot:>
```



Under 20 players in manchester city

Players_under20[Players_under20['Club']=='Manchester City']

ColName	Name	Club	Nationality	Position	Age
Matches \					
47	Eric García	Manchester City	ESP	DF	19
6					
50	Liam Delap	Manchester City	ENG	FW	17
1					

ColName	Starts	Mins	Goals	Assists	Passes_Attempted \
47	3	383	0	0	344
50	0	40	0	0	7

ColName	Perc_Passes_Completed	Penalty_Goals	Penalty_Attempted	xG
xA \				
47	93.600	0	0	0.030
0.020				
50	71.400	0	0	0.060
0.000				

ColName	Yellow_Cards	Red_Cards	MinsPerMatch	GoalsPerMatch
47	0	0	63	0.000
50	0	0	40	0.000

Players_under20[Players_under20['Club']=='Chelsea']

ColName	Name	Club	Nationality	Position	Age
Matches \					
18	Callum Hudson-Odoi	Chelsea	ENG	FW,DF	19
23					
21	Billy Gilmour	Chelsea	SCO	MF	19
5					

ColName	Starts	Mins	Goals	Assists	Passes_Attempted	\
18	10	1059	2	3	659	
21	3	261	0	0	215	

ColName	Perc_Passes_Completed	Penalty_Goals	Penalty_Attempted	xG
xA \				
18	82.200	0	0	0.120
0.260				
21	89.300	0	0	0.010
0.040				

ColName	Yellow_Cards	Red_Cards	MinsPerMatch	GoalsPerMatch
18	0	0	46	0.087
21	0	0	52	0.000

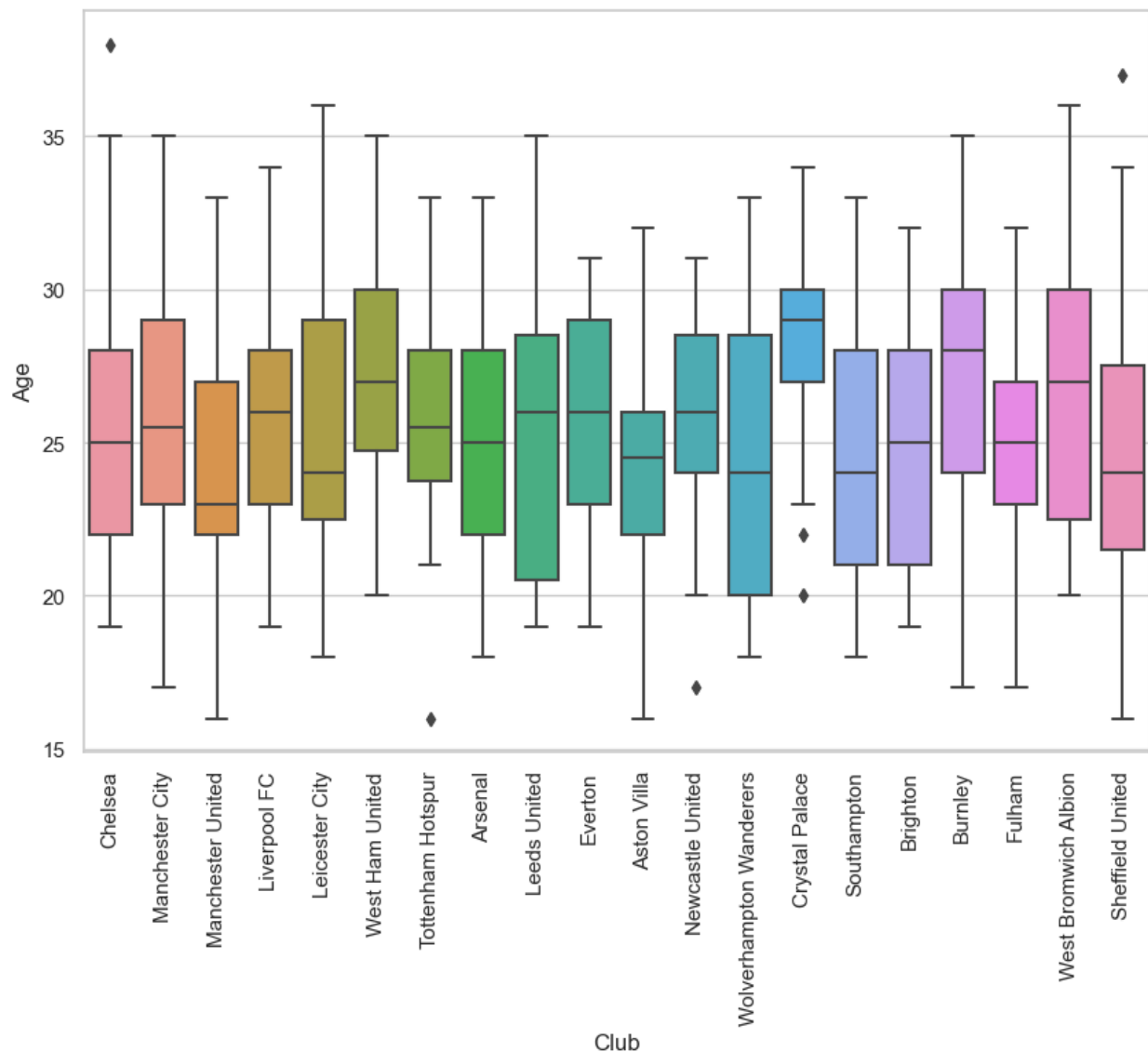
#average age of players in each club

```
plt.figure(figsize=(10,7))
sns.boxplot(x='Club', y='Age', data=data)
plt.xticks(rotation=90)
```

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14,
        15, 16,
```

```
        17, 18, 19]),
[Text(0, 0, 'Chelsea'),
 Text(1, 0, 'Manchester City'),
 Text(2, 0, 'Manchester United'),
 Text(3, 0, 'Liverpool FC'),
 Text(4, 0, 'Leicester City'),
 Text(5, 0, 'West Ham United'),
 Text(6, 0, 'Tottenham Hotspur'),
 Text(7, 0, 'Arsenal'),
 Text(8, 0, 'Leeds United'),
 Text(9, 0, 'Everton'),
 Text(10, 0, 'Aston Villa'),
 Text(11, 0, 'Newcastle United'),
 Text(12, 0, 'Wolverhampton Wanderers'),
 Text(13, 0, 'Crystal Palace'),
 Text(14, 0, 'Southampton'),
 Text(15, 0, 'Brighton'),
 Text(16, 0, 'Burnley'),
 Text(17, 0, 'Fulham'),
```

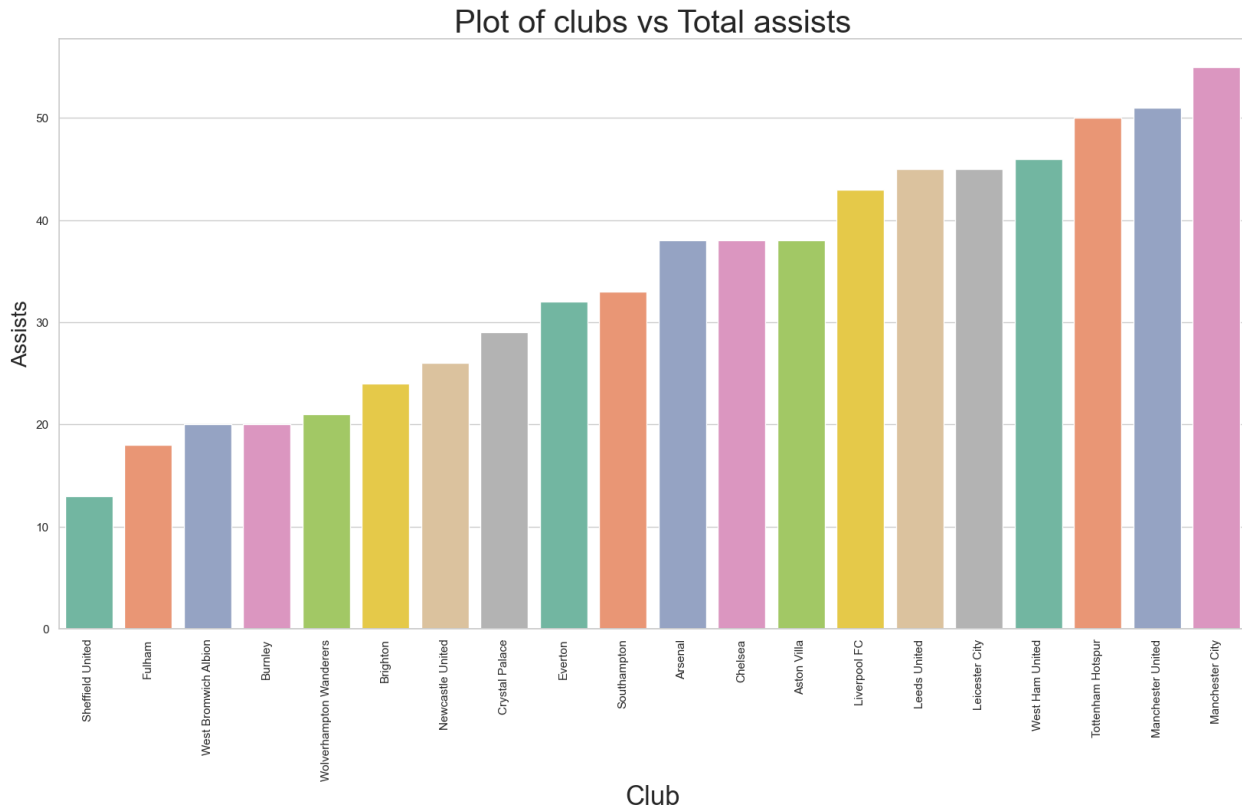
```
Text(18, 0, 'West Bromwich Albion'),
Text(19, 0, 'Sheffield United'))]
```



```
#total assesment from each club
```

```
assists_by_club=pd.DataFrame(data.groupby('Club',as_index=False)
['Assists'].sum())
sns.set_theme(style='whitegrid',color_codes=True)
ax=sns.barplot(x='Club',y='Assists',data=assists_by_club.sort_values(b
y='Assists'),palette='Set2')
ax.set_xlabel('Club',fontsize=25)
ax.set_ylabel('Assists',fontsize=20)
plt.xticks(rotation=90)
```

```
plt.rcParams['figure.figsize']=(20,10)
plt.title('Plot of clubs vs Total assists', fontsize=30)
Text(0.5, 1.0, 'Plot of clubs vs Total assists')
```



```
#Top 10 assists
assists=data[['Name','Club','Assists','Matches']].nlargest(n=10,column
s='Assists')
assists
```

ColName	Name	Club	Assists	Matches
162	Harry Kane	Tottenham Hotspur	14	35
34	Kevin De Bruyne	Manchester City	12	25
51	Bruno Fernandes	Manchester United	12	37
161	Son Heung-min	Tottenham Hotspur	10	37
273	Jack Grealish	Aston Villa	10	26
54	Marcus Rashford	Manchester United	9	37
110	Jamie Vardy	Leicester City	9	34
220	Raphael Dias Belloli	Leeds United	9	30
2	Timo Werner	Chelsea	8	35
136	Aaron Cresswell	West Ham United	8	36

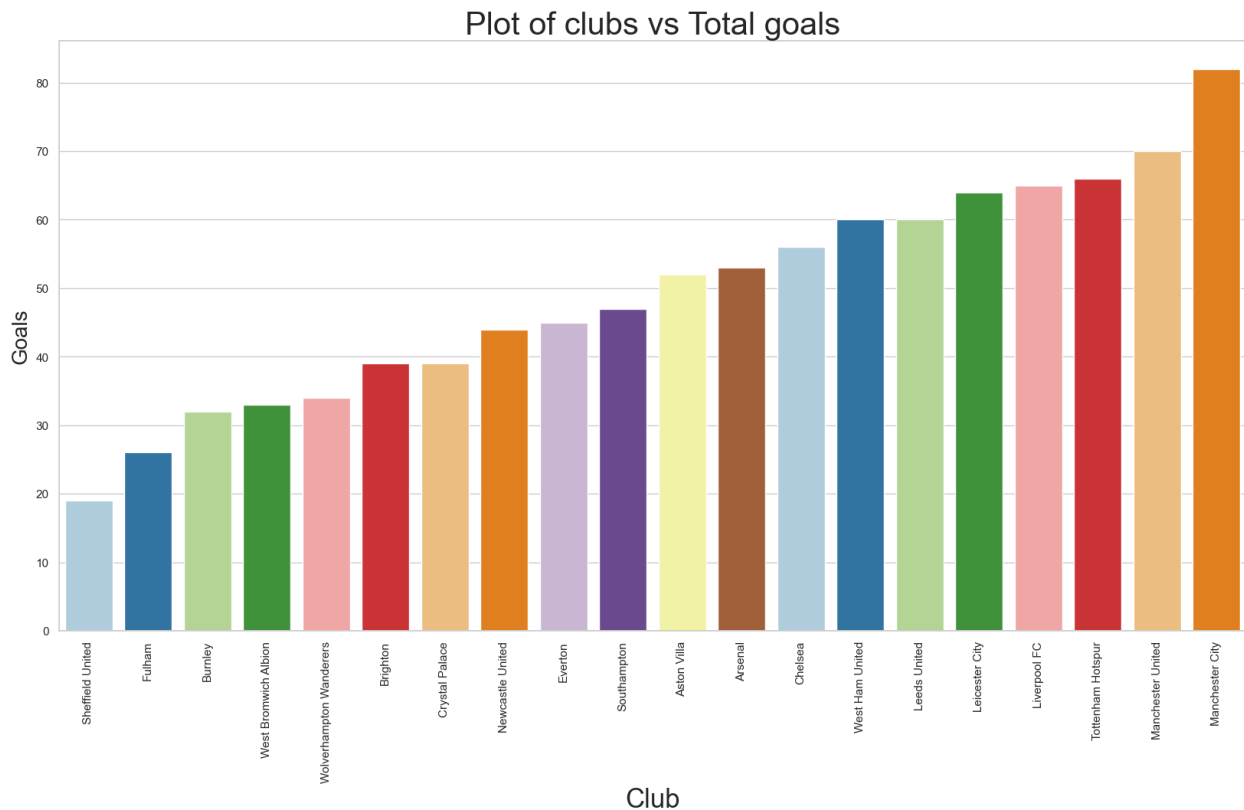
```
goals_by_club=pd.DataFrame(data.groupby('Club',as_index=False)
['Goals'].sum())
sns.set_theme(style='whitegrid',color_codes=True)
```

```

ax=sns.barplot(x='Club',y='Goals',data=goals_by_club.sort_values(by='Goals'),palette='Paired')
ax.set_xlabel('Club',fontsize=25)
ax.set_ylabel('Goals',fontsize=20)
plt.xticks(rotation=90)
plt.rcParams['figure.figsize']=(20,10)
plt.title('Plot of clubs vs Total goals', fontsize=30)

Text(0.5, 1.0, 'Plot of clubs vs Total goals')

```



#top 10 goals by player

```

goals=data[['Name','Club','Goals','Matches']].nlargest(n=10,columns='Goals')
goals

```

ColName	Name	Club	Goals	Matches
162	Harry Kane	Tottenham Hotspur	23	35
81	Mohamed Salah	Liverpool FC	22	37
51	Bruno Fernandes	Manchester United	18	37
161	Son Heung-min	Tottenham Hotspur	17	37
214	Patrick Bamford	Leeds United	17	38
237	Dominic Calvert-Lewin	Everton	16	33
110	Jamie Vardy	Leicester City	15	34
267	Ollie Watkins	Aston Villa	14	37

33	İlkay Gündoğan	Manchester City	13	28
191	Alexandre Lacazette	Arsenal	13	31

#top 10 goals per match

```
goals_per_match=data[['Name','GoalsPerMatch','Matches','Goals']].nlargest(n=10,columns='GoalsPerMatch')
goals_per_match
```

ColName	Name	GoalsPerMatch	Matches	Goals
162	Harry Kane	0.657	35	23
81	Mohamed Salah	0.595	37	22
307	Joe Willock	0.571	14	8
145	Jesse Lingard	0.562	16	9
175	Gareth Bale	0.550	20	11
74	Anthony Elanga	0.500	2	1
51	Bruno Fernandes	0.486	37	18
237	Dominic Calvert-Lewin	0.485	33	16
120	Kelechi Iheanacho	0.480	25	12
92	Diogo Jota	0.474	19	9

Dependent and independent features

```
X = data[['Matches']]
y = data['Goals']
```

Splitting the dataset into training and testing

```
from sklearn.model_selection import train_test_split

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=1)

from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
X_train=ss.fit_transform(X_train) # xtrain = training input samples
X_test=ss.transform(X_test) # xtest - testing input samples
```

Model Development and Model Training

```
from sklearn.ensemble import RandomForestClassifier

clfr=RandomForestClassifier(n_estimators=10,criterion='entropy',random_state=0)

clfr.fit(X_train,y_train)

RandomForestClassifier(criterion='entropy', n_estimators=10,
random_state=0)

from sklearn.ensemble import RandomForestClassifier

clfr1=RandomForestClassifier(n_estimators=10,criterion='gini',random_state=0)

clfr1.fit(X_train,y_train)

RandomForestClassifier(n_estimators=10, random_state=0)
```

Model Prediction

```
from sklearn.metrics import
confusion_matrix,classification_report,accuracy_score

ypre=clfr.predict(X_test)# entropy ypre calculation
ypre1=clfr1.predict(X_test)# gini ypre calculation

#entropy ypre calculation

data = pd.DataFrame({'Actual': y_test, 'Predicted': ypre})
data.head()
```

	Actual	Predicted
110	15	1
244	0	1
430	0	2
438	0	0
233	0	0

```
# gini ypre calculation

data = pd.DataFrame({'Actual': y_test, 'Predicted': ypre1})
data.head()
```

	Actual	Predicted
110	15	1

244	0	1
430	0	2
438	0	0
233	0	0

```
print('entropy Accuracy Score:')
accuracy_score(y_test,ypre)*100
```

entropy Accuracy Score:

44.85981308411215

```
print('gini Accuracy Score:')
accuracy_score(y_test,ypre1)*100
```

gini Accuracy Score:

44.85981308411215

```
print('entropy - confusion matrix\n-----\n')
print(confusion_matrix(y_test,ypre))
print('gini - confusion matrix\n-----\n')
print(confusion_matrix(y_test,ypre1))
```

entropy - confusion matrix

```
[[41  7  1  0  0  0  0  0  0  0  0  0  0  0]
 [17  7  2  0  0  0  0  0  0  0  0  0  0  0]
 [ 7  2  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 4  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 2  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 3  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  0  1  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 0  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  0  0  0  0  0  0  0  0  0  0  0  0  0]]
```

gini - confusion matrix

```
[[41  7  1  0  0  0  0  0  0  0  0  0  0  0]
 [17  7  2  0  0  0  0  0  0  0  0  0  0  0]
 [ 7  2  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 4  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 1  1  0  0  0  0  0  0  0  0  0  0  0  0]
 [ 2  1  0  0  0  0  0  0  0  0  0  0  0  0]]
```

```
[ 1  1  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0  1  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 1  1  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 3  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0  0  1  0  0  0  0  0  0  0  0  0  0  0  0]
[ 1  0  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0  1  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 0  1  0  0  0  0  0  0  0  0  0  0  0  0  0]
[ 1  0  0  0  0  0  0  0  0  0  0  0  0  0  0]]
```

```
print('entropy result\n-----')
print(classification_report(y_test,ypre))
print('gini index result\n-----')
print(classification_report(y_test,ypre1))
```

entropy result

	precision	recall	f1-score	support
0	0.52	0.84	0.64	49
1	0.29	0.27	0.28	26
2	0.00	0.00	0.00	9
3	0.00	0.00	0.00	5
4	0.00	0.00	0.00	2
5	0.00	0.00	0.00	3
6	0.00	0.00	0.00	2
7	0.00	0.00	0.00	1
8	0.00	0.00	0.00	2
9	0.00	0.00	0.00	3
10	0.00	0.00	0.00	1
14	0.00	0.00	0.00	1
15	0.00	0.00	0.00	1
16	0.00	0.00	0.00	1
17	0.00	0.00	0.00	1
accuracy			0.45	107
macro avg	0.05	0.07	0.06	107
weighted avg	0.31	0.45	0.36	107

gini index result

	precision	recall	f1-score	support
0	0.52	0.84	0.64	49
1	0.29	0.27	0.28	26
2	0.00	0.00	0.00	9
3	0.00	0.00	0.00	5
4	0.00	0.00	0.00	2
5	0.00	0.00	0.00	3
6	0.00	0.00	0.00	2

7	0.00	0.00	0.00	1
8	0.00	0.00	0.00	2
9	0.00	0.00	0.00	3
10	0.00	0.00	0.00	1
14	0.00	0.00	0.00	1
15	0.00	0.00	0.00	1
16	0.00	0.00	0.00	1
17	0.00	0.00	0.00	1
accuracy			0.45	107
macro avg	0.05	0.07	0.06	107
weighted avg	0.31	0.45	0.36	107
plt.scatter(X_train,y_train)				
plt.plot(X_train,clfr.predict(X_train))				
[<matplotlib.lines.Line2D at 0x2493b22ec70>]				

