INTRODUCTION TO DATA SCIENCE

FOOTBALL PLAYERS 2015-2024

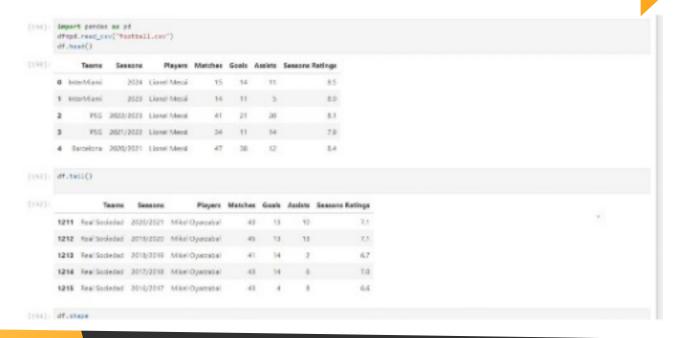
project overview

Title: Football Player Data Cleaning and Analysis (2015-2024

Objective: Clean and preprocess football player data to enable insightful analysis and visualization.



let's read the data head and tail values



memory usage of the dataset

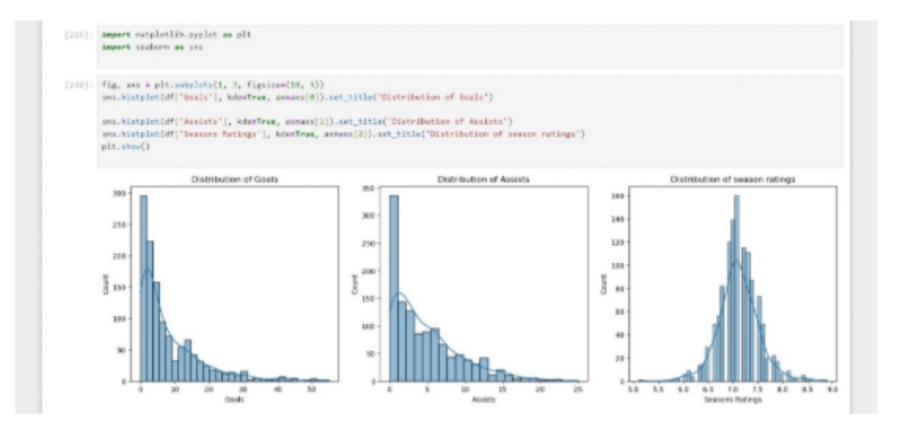
how to reduce memory size?

```
[220]: import pandas as pd
       dfspd.read_csv("football.csv",usecolssreq_cols)
       df.info(memory_usage="deep")
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 1216 entries, 0 to 1215
       Data columns (total 7 columns):
            Column
                            Non-Null Count Dtype
       ... .....
                            ...... .....
            Teams
                            1216 non-null
                                            object
            Seasons
                            1216 non-null
                                            object
            Players
                            1216 non-null
                                           object
            Hatches
                            1216 non-null
                                            int64
            Goals
                            1216 non-null
                                            int64
            Assists
                            1216 non-null
                                            int64
            Seasons Ratings 1216 non-null
                                           float64
       dtypes: float64(1), int64(3), object(3)
       memory usage: 249.2 KB
```

after reducing the memory size

```
[224]: df.info(memory_usage="deep")
       <class 'pandas.core.frame.DataFrame'>
       RangeIndex: 1216 entries, 0 to 1215
       Data columns (total 7 columns):
            Column
                            Non-Null Count Dtype
                            ...... .... .....
            -----
            Teams
                            1216 non-null
                                           object
           Seasons
                          1216 non-null
                                           object
                          1216 non-null
                                           object
        2 Players
                          1216 non-null
           Matches
                                           int32
                            1216 non-null
           Goals
                                           int32
            Assists
                            1216 non-null
                                           int32
            Seasons Ratings 1216 non-null
                                           float32
       dtypes: float32(1), int32(3), object(3)
       memory usage: 230.2 KB
```

histogram



accuracy and prediction

```
[31]: dfwdf.drop(columnss["Seasons"])
[ax]: X = df.drop(columns=('Seasons Hatings'))
      y = df["Seasons Ratings"]
[37]: from sklearn.model_selection import train_test_split
      X_train,X_test,y_train,y_test = train_test_split(X,y, random_state=42,test_size=8.2)
                                     Players Matches Goals Assists
       432
                     Seville
                                Jules Founde
       277
                     Chelses
                                 Ked Heverto
       721
                     Men City
                                Manuel Akandi
       991 Atletico Madrid
                                Thomas Fartey
       678
           Atletico Madrid Rodrigo De Paul
                    Holfsburg Victor Oxiohea
                     Tuventus.
                               Adries Rabiot
       1159
                     Brighton
                                  Levis Dunk
           Linares Deportivo
                                Fernám Lopez
       [972 rows x 5 columns],
       277
              7.1
              7.2
       991
              6.7
       678
              7.1
       1844
             5.8
```

```
[283]: y_predict=model.predict(X_train)
[283]: model.score(X_train,y_train)*100
[283]: 92.51897108808892
```

accuracy is 92%

prediction

M 1 N U U I - U II WWW -

```
[68]: print("predicted values:\n",y:predict)
      print("actual values: \n", y_test)
      predicted values:
       [7.17400006 7.07899992 7.16299986 6.82599987 7.1159999 6.85000011
       6.67299992 7.87799992 7.37200007 6.77000006 6.77499991 7.01399994
       7,18299985 7,22100008 7,27000005 6,89900012 6,81800007 7,0949999
       7.37000001 7.26900013 6.93800007 7.02299999 6.74199994 7.14816655
       7,18299988 7,48799987 7,43899997 7,29488813 6,88799987 7,22499997
       7.85399987 7.61999988 7.45399998 7.85899998 6.69899993 7.41288888
       7.1040999 7.26400005 7.44099994 6.73099988 6.465
       6.48799997 6.84600015 7.28400001 7.70699988 7.30300007 6.86200005
       6,91399999 6,91700008 7,35700009 7,12900002 6,89700015 7,25300013
       7.47699999 7.83799998 6.897
                                      7.07699994 7.35100013 7.89800005
       7.18199994 6.99599999 6.93580006 7.3338001 7.11899997 7.81580009
       6.99000006 7.14299988 7.18800012 7.44499996 7.07799993 6.72799992
       7.12199986 7.10599994 6.45399987 7.05100008 6.988
       7.22699985 7.20000007 7.822
                                     7.04299999 6.87500012 6.97500004
       7.12599988 6.83399994 7.16699998 7.21599989 7.01699994 6.99200006
       6.63599996 7.87699996 7.05699993 7.38300007 7.09199991 7.44499999
       7.68699998 6.94188813 7.26488881 6.91688885 6.97788882 6.91888813
       7.01800008 6.92500008 7.28100007 6.72799992 6.94399995 7.2150001
       6.59699995 6.86675007 7.19100012 7.289
                                                7.318 6.80199986
       7.16099986 7.95400025 8.46199987 7.14599995 7.12199996 7.17700011
       7.88299994 7.088800085 7.77900024 6.59199992 7.94680001 7.13799988
       7.32200006 7.22199992 6.89300008 6.92300007 7.26300012 6.88500011
       7.22699985 6.72799991 6.7059999 7.1509999 7.2560001 6.98200015
       8.21399975 7.30200001 6.75600012 8.10100029 7.69600006 7.13800001
       6.86600012 7.68100012 7.25700015 7.19199983 7.28400012 6.5800001
       6.99900004 7.20000013 7.50599994 6.99823339 7.15399986 6.97699995
       6.80800002 7.14199995 7.44400009 6.73199996 7.27499995 7.11499992
       7,46900001 6,93600005 7,35800001 7,02499998 7,45999993 6,94300001
                 7.19799988 7.10299994 6.96300006 6.69099995 7.02099998
       8.20400014 6.86900009 7.46100001 7.00900003 7.09999987 6.75099993
       7.09399992 7.37400009 7.26700013 6.43299995 6.91200011 7.35000001
       7.57200012 7.05599996 6.91700001 6.87200006 7.00700001 7.69600008
       7.13299989 6.98500005 7.889
                                     6,75699998 7,05100001 6,90800006
       6.58800008 7.20300014 7.26100012 6.92300006 7.50899987 7.02233333
       7.02499998 7.15700011 6.55999999 6.22899994 7.34300014 7.87700007
       7.27400012 6.305
                          7.30800014 6.91600006 7.45200004 7.20199986
       6.9100001 7.22200006 8.14599998 7.28400012 7.26899988 7.02899984
       6.6250001 7.04599996 7.06249998 7.20599988 6.93800005 7.02099999
       7.15899992 7.68599989 7.09500001 6.93800005 6.2210001 6.83900015
       6.41100014 6.75999988 7.16000012 6.68199985 6.79999988 7.21599999
```

7 Instance 7 oranges 7 teconose 7 talances 6 sensons 7 teconose

```
7.09499994 6.80400006 7.38900004 7.13499994 7.25899987 7.07800002
5.92699993 6.85849989 7.12699992 7.16599989 7.49499995 7.29100011
7.48800002 7.07500004 6.88300013 7.31100004 7.22399987 7.29100007
6.54300006 7.62699986 7.6890001 7.64199999 8.11899992 6.78700012
6.87100014 7.33900004 7.12299989 6.63099999 7.07199997 7.31500006
7.46400001 6.87600012 7.07199996 6.91899992 7.04299996 7.17799984
6.86700006 7.093
                     7,51599995 6,91400008 7,07199993 7,392
6.73200011 6.76399991 6.94500002 6.28099994 7.38599999 6.96900002
7.05899993 7.32200012 6.84100011 6.75299988 6.56100005 7.20000012
7.09499993 7.10399996 7.04000007 7.09299986 7.27700012 6.66899997
7.43199994 7.12499985 7.06700006 6.62199997 6.58199999 6.92400015
7.22799991 6.73399995 6.79199985 7.45299995 6.76799994 7.87899991
6.71200001 7.40500001 6.85500011 7.06800014 6.90400008 7.26500009
7.18800014 6.52100006 7.47100006 6.99299997 7.59999997 7.24800011
7.21700013 7.67700006 7.31699997 6.99399999 7.38900002 7.09199992
7.63199997 6.59500002 7.78800004 7.01999999 7.12599991 7.05600002
6.96200004 6.67599993 7.503
                               7.25300014 7.443
6.99899992 7.87900007 6.97900007 6.76899984 7.34500012 7.30900013
          6.95499998 7.30000005 7.24400011 6.65199999 7.07899993
6,54400004 6,62
                     7.00900005 6.65799999 7.27100014 7.24500014
7.25888887 7.89799994 7.15899989 6.83188811 7.15299986 7.46188883
6.90400008 7.42600008 7.36600001 7.24000008 6.49999988 7.04000001
6.96300001 7.41399999 6.89400011 7.05399993 7.74200013 7.24800011
7,58499993 6,64299992 7,38
                               7,27300008 6,99500003 6,89500016
6.95899993 7.009
                    6,67499995 7,14546653 7,18499989 6,85999987
7.8740001 6.53500006 6.78700014 7.62699992 7.06799992 7.18099989
6.94000008 6.82500014 7.41500001 6.47100014 7.10499991 7.35600005
7.22599989 7.32400005 6.31
                                7,17999993 7,87399993 7,14699994
7.69100014 6.87300009 7.16399985 6.68399988 6.39599995 6.81000006]
actual values:
541
       6.7
259
       7.5
43
       7.5
1005
       7.1
584
       7.0
420
       6.8
243
       7.5
59
       6.9
1115
      6.7
63
       6.6
Name: Seasons Ratings, Length: 244, dtype: float32
```

[70]:

from sklearn.metrics import mean squared error

time of the dataset

	impor	National import pandes as pd df-pd.read_csv("footbell.csv") df											
		imes: total: time: 12.1 ms											
[384]:		Teams	Seasons	Players	Matches	Goals	Assists	Seasons Ratings					
	0	InterMiami	2024	Lionel Messi	15	14	11	8.5					
	1	InterMiami	2023	Lionel Messi	14	11	5	8.0					
	2	PSG	2022/2023	Lionel Messi	41	21	20	8.1					
	3	PSG	2021/2022	Lionel Messi	34	11	14	7.9					
	.4	Barcelona	2020/2021	Lionel Messi	47	36	12	8.4					
	***			-		-		-					
	1211	Real Sociedad	2020/2021	Mikel Oyarzabal	43	13	10	7.1					
	1212	Real Sociedad	2019/2020	Mikel Oyarzabal	45	13	13	7.1					
	1213	Real Sociedad	2018/2019	Mikel Oyarzabal	41	14	2	6.7					
	1214	Real Sociedad	2017/2018	Mikel Oyarzabal	43	14	6	7.0					
	1215	Real Sociedad	2016/2017	Mikel Oyarzabal	43	4	8	6.6					

after reducing time

```
[88]: %%time
   import pandas as pd
   df=pd.read_csv("football.csv",usecols=req_cols,iterator=True,chunksize=90)
   df

CPU times: total: 0 ns
   Wall time: 5.56 ms
```

outliers



THANK YOU

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ds project.pdf

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