Data Preprocessing Task

Import Packages

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder,MinMaxScaler
from sklearn.model_selection import train_test_split
import os
```

Read the Dataset provided (Dataset 1)

- For my own dataset I have used a Air pollution measurement dataset.
- Each rows contain the hourly measurement recording of the 5 pollutants (NO, NO2, NOX, PM10, and PM2.5).
- The data was collected in a location in Londan for the entirety of year 2017.

In [2]:
```
DATA_PATH=os.path.join(os.getcwd(),"LaqnData.csv")
data_1=pd.read_csv(DATA_PATH)
```

In [3]:
```
data_1.head() ##preview the dataset using head function
```

Out[3]:

	Site	Species	ReadingDateTime	Value	Units	Provisional or Ratified
0	HI0	CO	01/01/2018 00:00	NaN	mg m-3	P
1	HI0	CO	01/01/2018 00:15	NaN	mg m-3	P
2	HI0	CO	01/01/2018 00:30	NaN	mg m-3	P
3	HI0	CO	01/01/2018 00:45	NaN	mg m-3	P
4	HI0	CO	01/01/2018 01:00	NaN	mg m-3	P

In [4]:
```
print("shape of dataset ----> ",data_1.shape)
print("Number of examples -----> ",data_1.shape[0])
print("Number of columns -----> ",data_1.shape[1])
```

```
shape of dataset ---->  (175200, 6)
Number of examples ----->  175200
Number of columns ----->  6
```

Quick check of the statistics of the dataset using pandas api

As you could see using the describe function it gives us the basic statistics out of it

In [5]:
```
data_1.describe()
```

Out[5]:

	Value
count	131724.000000
mean	48.050503
std	54.252123
min	0.000000
25%	12.500000
50%	33.200000
75%	64.200000
max	643.900020

Info function gives us the information about how many null data we have out of total entries and along with the datatype

In [6]:
```
data_1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175200 entries, 0 to 175199
Data columns (total 6 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   Site                      175200 non-null  object
 1   Species                   175200 non-null  object
 2   ReadingDateTime           175200 non-null  object
 3   Value                     131724 non-null  float64
 4   Units                     175200 non-null  object
 5   Provisional or Ratified   175200 non-null  object
dtypes: float64(1), object(5)
memory usage: 8.0+ MB
```

1. Remove Duplicates value

In [7]:
```
# shape before removing duplicates
```

In [8]:
```
data_1.shape
```

Out[8]:
```
(175200, 6)
```

In [9]:
```
data_1 = data_1.drop_duplicates()
```

In [10]:
```
data_1.shape
```

Out[10]:
```
(175200, 6)
```

- So we conclude that there is no duplicates.

2. Remove unwanted columns

- drop function allows to drop any column which is unncessary and using inplace="True", does not show the column in the dataframe when we see the dataframe back again
- In this case we dont want datetime when it was recorded and the site as it contains single value doesnot provide any insight.

In [11]:
```python
data_1.drop(columns=['ReadingDateTime', 'Site'], axis=1, inplace=True)
```

3. Checking the null values

In [12]:
```python
data_1.isna().sum()
```

Out[12]:
```
Species                       0
Value                     43476
Units                         0
Provisional or Ratified       0
dtype: int64
```

In [13]:
```python
##from the above info function, we can see that Value column has 131724 floa
## even from the above dataframe view we saw Value column has NaN value
## so we need to remove those rows or impute with some impute techniques
## here we would be imputing with mean of the value.


print('rows present before handling nan :', data_1.shape[0])
data_1['Value'] = data_1['Value'].fillna(data_1['Value'].mean())
print('rows present after handling nan :', data_1.shape[0])
```

```
rows present before handling nan : 175200
rows present after handling nan : 175200
```

4. Encoding of the categorical variable

In [14]:
```python
data_1['Provisional or Ratified'].value_counts()
```

Out[14]:
```
Provisional or Ratified
R    140160
P     35040
Name: count, dtype: int64
```

binary encoding :

- As there are only two value, we will use binary encoding and replace the value with 0 and 1.

In [15]:
```
data_1['Provisional or Ratified'] = data_1['Provisional or Ratified'].replac
```

In [16]:
```
data_1.head()
```

Out[16]:

	Species	Value	Units	Provisional or Ratified
0	CO	48.050503	mg m-3	0
1	CO	48.050503	mg m-3	0
2	CO	48.050503	mg m-3	0
3	CO	48.050503	mg m-3	0
4	CO	48.050503	mg m-3	0

In [17]:
```
data_1['Species'].value_counts()
```

Out[17]:
```
Species
CO      35040
NO      35040
NO2     35040
NOX     35040
O3      35040
Name: count, dtype: int64
```

One-hot enconding:

- As there are multiple value in Species. We will apply one-hot encoding as there is no sequence here.

In [18]:
```
data_1 = pd.get_dummies(data_1, columns=['Species'], dtype=int)
```

In [19]:
```
data_1.head()
```

Out[19]:

	Value	Units	Provisional or Ratified	Species_CO	Species_NO	Species_NO2	Species_NOX	Sp
0	48.050503	mg m-3	0	1	0	0	0	
1	48.050503	mg m-3	0	1	0	0	0	
2	48.050503	mg m-3	0	1	0	0	0	
3	48.050503	mg m-3	0	1	0	0	0	
4	48.050503	mg m-3	0	1	0	0	0	

In [20]:
```
data_1['Units'].value_counts()
```

Out[20]:
```
Units
ug m-3           105120
mg m-3            35040
ug m-3 as NO2     35040
Name: count, dtype: int64
```

Again we impliment the same for the Units column

In [21]:
```
data_1 = pd.get_dummies(data_1, columns=['Units'], dtype=int)
```

In [22]:
```
data_1.head()
```

Out[22]:

	Value	Provisional or Ratified	Species_CO	Species_NO	Species_NO2	Species_NOX	Species_(
0	48.050503	0	1	0	0	0	
1	48.050503	0	1	0	0	0	
2	48.050503	0	1	0	0	0	
3	48.050503	0	1	0	0	0	
4	48.050503	0	1	0	0	0	

5. Split the dataset

In [23]:
```
data_train, data_test = train_test_split(data_1, test_size=0.25)
```

show the dataset size after spliting the dataset

In [24]:
```
print(data_train.shape)
print(data_test.shape)
```

```
(131400, 10)
(43800, 10)
```

Mean and standard deviation result for numerical columns

- As there is a single column that is numerical we will only calculate the mean and standard deviation for the same column

In [25]:
```
Numeric_columns = ['Value']
for col in Numeric_columns:
  print("Column name : ",col)
  print('Training set mean:', data_train[col].mean())
  print('Testing set mean:', data_test[col].mean())
  print('Training set std:', data_train[col].std())
  print('Testing set std:', data_test[col].std())
```

```
Column name :  Value
Training set mean: 48.0201911489353
Testing set mean: 48.141436815864544
Training set std: 46.884353690008936
Testing set std: 47.510488663962995
```

Conclusion

- We can see that the training datasets mean and standard deviation is slightly less than the test set.

Read the Dataset provided (Dataset 2)

In [26]:
```
DATA_PATH_SalaryPrediction=os.path.join(os.getcwd(),"SalaryPrediction.csv")
data_SalaryPrediction=pd.read_csv(DATA_PATH_SalaryPrediction)
```

In [27]:
```
data_SalaryPrediction.head() ##preview the dataset using head function
```

Out[27]:

	Wage	Age	Club	League	Nation	Position	Apps	Caps
0	46,427,000	23.0	PSG	Ligue 1 Uber Eats	FRA	Forward	190	57
1	42,125,000	30.0	PSG	Ligue 1 Uber Eats	BRA	Midfilder	324	119
2	34,821,000	35.0	PSG	Ligue 1 Uber Eats	ARG	Forward	585	162
3	19,959,000	31.0	R. Madrid	La Liga	BEL	Forward	443	120
4	19,500,000	NaN	Man UFC	Premier League	ESP	Goalkeeper	480	45

In [28]:
```
data_SalaryPrediction.columns ## columns present in the traffic dataset
```

Out[28]:
```
Index(['Wage', 'Age', 'Club', 'League', 'Nation', 'Position', 'Apps', 'Cap
s'], dtype='object')
```

In [29]:
```
print("shape of dataset ----> ",data_SalaryPrediction.shape)
print("Number of examples -----> ",data_SalaryPrediction.shape[0])
print("Number of columns -----> ",data_SalaryPrediction.shape[1])
```

```
shape of dataset ---->  (3907, 8)
Number of examples ----->  3907
Number of columns ----->  8
```

Below we would be following same basic techniques to get the statistics as we did in the above

In [30]:
```
data_SalaryPrediction.describe()
```

Out[30]:

	Age	Apps	Caps
count	3833.000000	3907.000000	3907.000000
mean	24.060788	140.057077	8.926542
std	4.933452	131.694425	20.518234
min	18.000000	0.000000	0.000000
25%	20.000000	15.000000	0.000000
50%	23.000000	115.000000	0.000000
75%	28.000000	224.500000	6.000000
max	41.000000	715.000000	180.000000

In [31]:
```
data_SalaryPrediction.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3907 entries, 0 to 3906
Data columns (total 8 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Wage      3907 non-null   object 
 1   Age       3833 non-null   float64
 2   Club      3907 non-null   object 
 3   League    3907 non-null   object 
 4   Nation    3907 non-null   object 
 5   Position  3907 non-null   object 
 6   Apps      3907 non-null   int64  
 7   Caps      3907 non-null   int64  
dtypes: float64(1), int64(2), object(5)
memory usage: 244.3+ KB
```

1. Remove Duplicates value

In [32]:
```
# shape before removing duplicates
```

In [33]:
```
data_SalaryPrediction.shape
```

Out[33]:
```
(3907, 8)
```

In [34]:
```
data_SalaryPrediction = data_SalaryPrediction.drop_duplicates()
```

In [35]:
```
data_SalaryPrediction.shape
```

Out[35]:
```
(3842, 8)
```

- There were some duplicated value which we removed.

2. Remove unwanted columns

- In this dataset, all are important columns. So we will keep all columns for now.

In [36]:
```
#data_1.drop(columns=[], axis=1, inplace=True)
```

3. Checking the null values

In [37]:
```
data_SalaryPrediction.isna().sum()
```

Out[37]:
```
Wage         0
Age         74
Club         0
League       0
Nation       0
Position     0
Apps         0
Caps         0
dtype: int64
```

In [ ]:
```

```

In [38]:
```
##from the above info function, we can see that Value column has 131724 floa
## even from the above dataframe view we saw Value column has NaN value
## so we need to remove those rows or impute with some impute techniques
## here we would be imputing with mean of the value.


print('rows present before handling nan :', data_SalaryPrediction.shape[0])
data_SalaryPrediction['Age'] = data_SalaryPrediction['Age'].fillna(int(data_
print('rows present after handling nan :', data_SalaryPrediction.shape[0])
```

```
rows present before handling nan : 3842
rows present after handling nan : 3842
```

4. Transformation of the data

In [39]:
```
data_SalaryPrediction.head()
```

Out[39]:

	Wage	Age	Club	League	Nation	Position	Apps	Caps
0	46,427,000	23.0	PSG	Ligue 1 Uber Eats	FRA	Forward	190	57
1	42,125,000	30.0	PSG	Ligue 1 Uber Eats	BRA	Midfilder	324	119
2	34,821,000	35.0	PSG	Ligue 1 Uber Eats	ARG	Forward	585	162
3	19,959,000	31.0	R. Madrid	La Liga	BEL	Forward	443	120
4	19,500,000	24.0	Man UFC	Premier League	ESP	Goalkeeper	480	45

- We see that Wage column should be numerical but it is object datatype. So we will remove comma and make it to numerical.

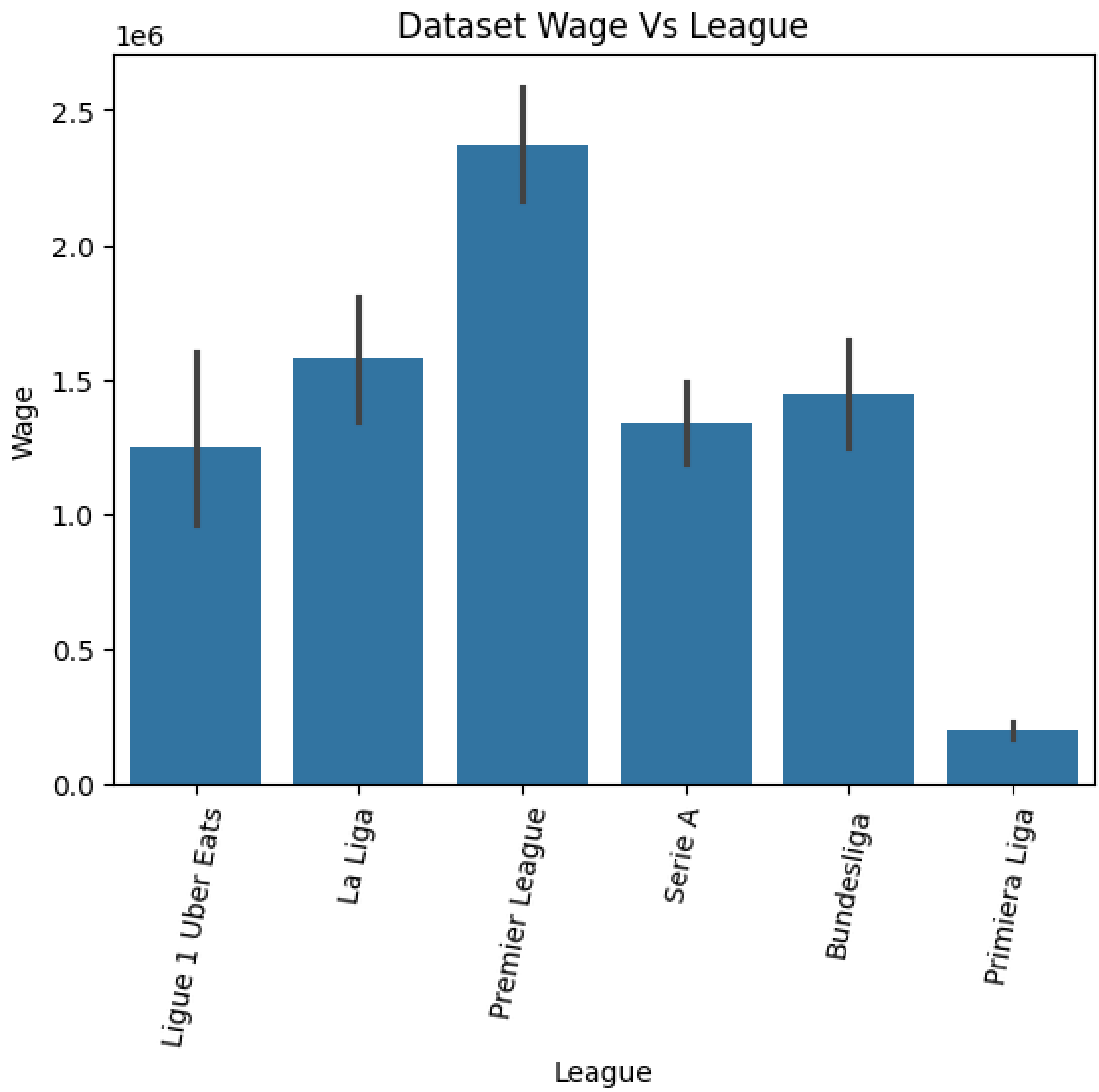
In [40]:
```
data_SalaryPrediction['Wage'] = data_SalaryPrediction['Wage'].str.replace(",
```

scatter plot wage v/s age

In [41]:
```
sns.scatterplot(data=data_SalaryPrediction,  x='Age', y='Wage',hue="Wage")
plt.title('Dataset Wage Vs Age')
plt.show()
```

Bar plot wage v/s league

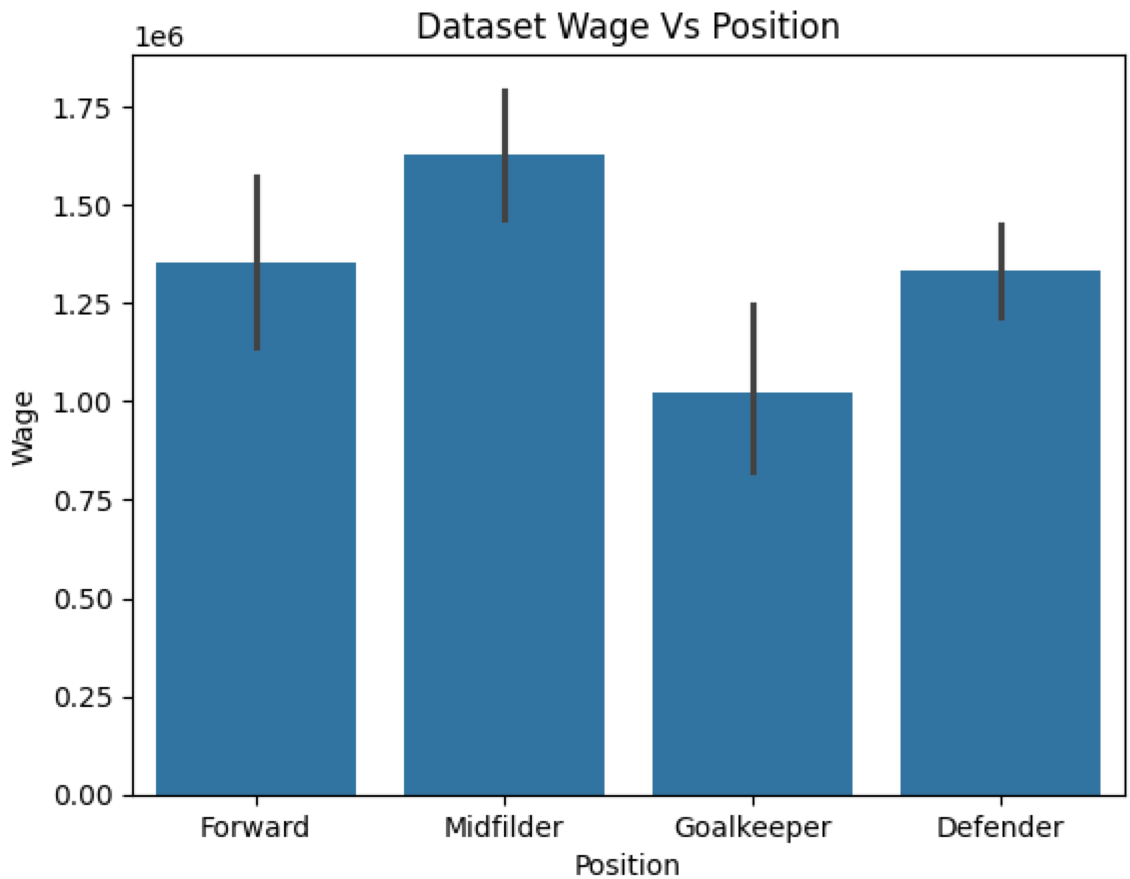
In [42]:
```
sns.barplot(data=data_SalaryPrediction, x="League", y="Wage")
plt.title('Dataset Wage Vs League')
plt.xticks(rotation=80)
plt.show()
```



Bar plot wage v/s age

In [43]:
```
## bar plot wage v/s age

sns.barplot(data=data_SalaryPrediction, x="Position", y="Wage")
plt.title('Dataset Wage Vs Position')
plt.show()
```



5. Encoding of the categorical variable

In [44]:
```
data_SalaryPrediction.head()
```

Out[44]:

	Wage	Age	Club	League	Nation	Position	Apps	Caps
0	46427000	23.0	PSG	Ligue 1 Uber Eats	FRA	Forward	190	57
1	42125000	30.0	PSG	Ligue 1 Uber Eats	BRA	Midfilder	324	119
2	34821000	35.0	PSG	Ligue 1 Uber Eats	ARG	Forward	585	162
3	19959000	31.0	R. Madrid	La Liga	BEL	Forward	443	120
4	19500000	24.0	Man UFC	Premier League	ESP	Goalkeeper	480	45

In [45]:
```
data_SalaryPrediction['Club'].value_counts()
```

Out[45]:
```
Club
MRT             64
BRG             60
VIZ             55
Chelsea         52
Leicester       51
                ..
OL              21
FC Lorient      21
LOSC            21
PSG             20
Clermont        18
Name: count, Length: 116, dtype: int64
```

In [46]:
```
data_SalaryPrediction['Nation'].value_counts()
```

Out[46]:
```
Nation
ESP    431
POR    419
ENG    396
FRA    351
GER    283
      ...
BDI      1
MSR      1
UZB      1
SUR      1
SIN      1
Name: count, Length: 114, dtype: int64
```

Label Encoding

In [47]:
```
import pandas as pd
from sklearn.preprocessing import LabelEncoder

# Assuming data_SalaryPrediction is your DataFrame
# Creating an instance of LabelEncoder
label_encoder = LabelEncoder()

# Fit and transform the 'Club' column
data_SalaryPrediction['Club'] = label_encoder.fit_transform(data_SalaryPredi
```

In [48]:
```
label_encoder = LabelEncoder()

# Fit and transform the 'Club' column
data_SalaryPrediction['Nation'] = label_encoder.fit_transform(data_SalaryPre
```

One-hot enconding:

- As there are multiple value but limited in League,Position. We will apply one-hot encoding as there is no sequence here.

In [49]:
```
data_SalaryPrediction['League'].value_counts()
```

Out[49]:
```
League
Premier League       861
Primiera Liga        736
Serie A              669
La Liga              573
Bundesliga           542
Ligue 1 Uber Eats    461
Name: count, dtype: int64
```

In [50]:
```
data_SalaryPrediction['Position'].value_counts()
```

Out[50]:
```
Position
Defender      1452
Midfilder     1140
Forward        821
Goalkeeper     429
Name: count, dtype: int64
```

In [51]:
```
data_SalaryPrediction = pd.get_dummies(data_SalaryPrediction, columns=['Leag
```

In [52]:
```
data_SalaryPrediction.head()
```

Out[52]:

	Wage	Age	Club	Nation	Apps	Caps	League_Bundesliga	League_La Liga	League_Ligu 1 Uber Eat
0	46427000	23.0	73	40	190	57	0	0	
1	42125000	30.0	73	13	324	119	0	0	
2	34821000	35.0	73	3	585	162	0	0	
3	19959000	31.0	76	8	443	120	0	1	
4	19500000	24.0	64	37	480	45	0	0	

5. Normalising of the data

In [53]:
```
data_SalaryPrediction.head()
```

Out[53]:

	Wage	Age	Club	Nation	Apps	Caps	League_Bundesliga	League_La Liga	League_Ligu 1 Uber Eat
0	46427000	23.0	73	40	190	57	0	0	
1	42125000	30.0	73	13	324	119	0	0	
2	34821000	35.0	73	3	585	162	0	0	
3	19959000	31.0	76	8	443	120	0	1	
4	19500000	24.0	64	37	480	45	0	0	

In [54]:
```
numerical_columns = ['Age'      ,'Apps' ,'Caps' ]
```

In [55]:
```
from sklearn.preprocessing import MinMaxScaler
min_maxscaler = MinMaxScaler()
```

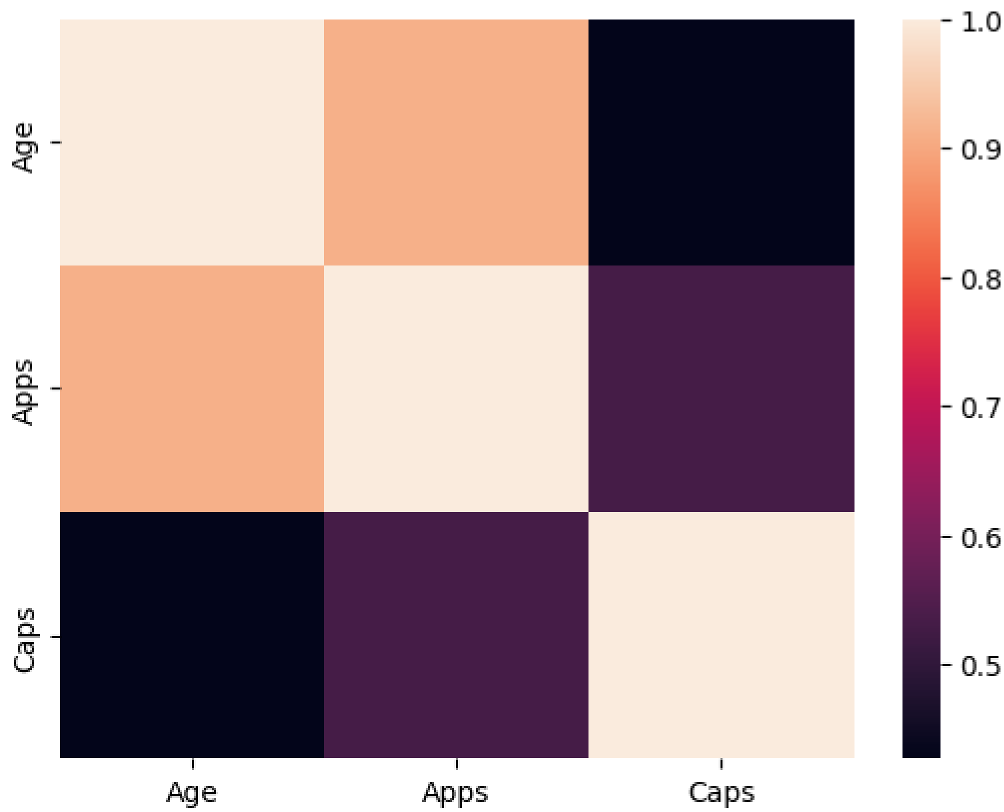
In [56]:
```
data_SalaryPrediction[numerical_columns] =  min_maxscaler.fit_transform(data
```

6.correlation matrix

to find the correlation between each columns

In [57]:
```
## correlation matrix
data_SalaryPrediction_corr=data_SalaryPrediction[numerical_columns].corr()
sns.heatmap(data_SalaryPrediction_corr)
```

Out[57]:
```
<Axes: >
```



7. Split the dataset

In [58]:
```
data_x = data_SalaryPrediction.drop(['Wage'], axis = 1)
data_y = data_SalaryPrediction['Wage']
data_x_train, data_x_test, data_y_train, data_y_test = train_test_split(data
```

show the dataset size after spliting the dataset

In [59]:
```
print(data_x_train.shape, data_y_train.shape)
print(data_x_test.shape,data_y_test.shape)
```

```
(2881, 15) (2881,)
(961, 15) (961,)
```

Mean and standard deviation result

In [60]:
```
for col in numerical_columns:
  print(col)
  print('\tTraining set mean:', data_x_train[col].mean())
  print('\tTesting set mean:', data_x_test[col].mean())
  print('\tTraining set std:', data_x_train[col].std())
  print('\tTesting set std:', data_x_test[col].std())
```

```
Age
        Training set mean: 0.26517060803163156
        Testing set mean: 0.2757091797493553
        Training set std: 0.20886794459407704
        Testing set std: 0.21938420733236186
Apps
        Training set mean: 0.1973285305461633
        Testing set mean: 0.20479977878521063
        Training set std: 0.18220882835729854
        Testing set std: 0.18907767274145107
Caps
        Training set mean: 0.04928458482779899
        Testing set mean: 0.053867499132847725
        Training set std: 0.11206559670877406
        Testing set std: 0.12250378917178928
```

Conclusion

By this practise, we got to know that data preprocessing is one of crucial steps before putting the data before training. the dataset which we recieve are usually quite noisy, so they required proper preprocessing techniques, such that the model doesn't learn the unwanted information.Putting a lot of time is essential, as cleaning makes the data more readable and model friendly, which ultimately helps us in achiving our goals