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Assignment 5:

```
Take all the columns in mall_customers.csv

gender age annual income spending score

perform label encoding on gender

train your data
```

Data Preprocessing.

```
o       Import the Libraries.
o       Importing the dataset.
o       Checking for Null Values.
o       Data Visualization.
o       Outlier Detection
o       Splitting Dependent and Independent variables
o       Encoding
o       Feature Scaling.
o       Splitting Data into Train and Test.
```

1.import the necessary libraries"

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

2.import the dataset

In [2]:
```
df = pd.read_csv("mall_customers.csv")
df
```

Out[2]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

In [3]:
```
df.head()
```

Out[3]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

3.Handling null values

In [4]:
```
df.isnull().any()
```

Out[4]:
```
CustomerID                False
Genre                     False
Age                       False
Annual Income (k$)        False
Spending Score (1-100)    False
dtype: bool
```

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [6]:
```
df.describe()
```

Out[6]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Genre                   200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

In [10]:
```
corr = df.corr()
corr
```

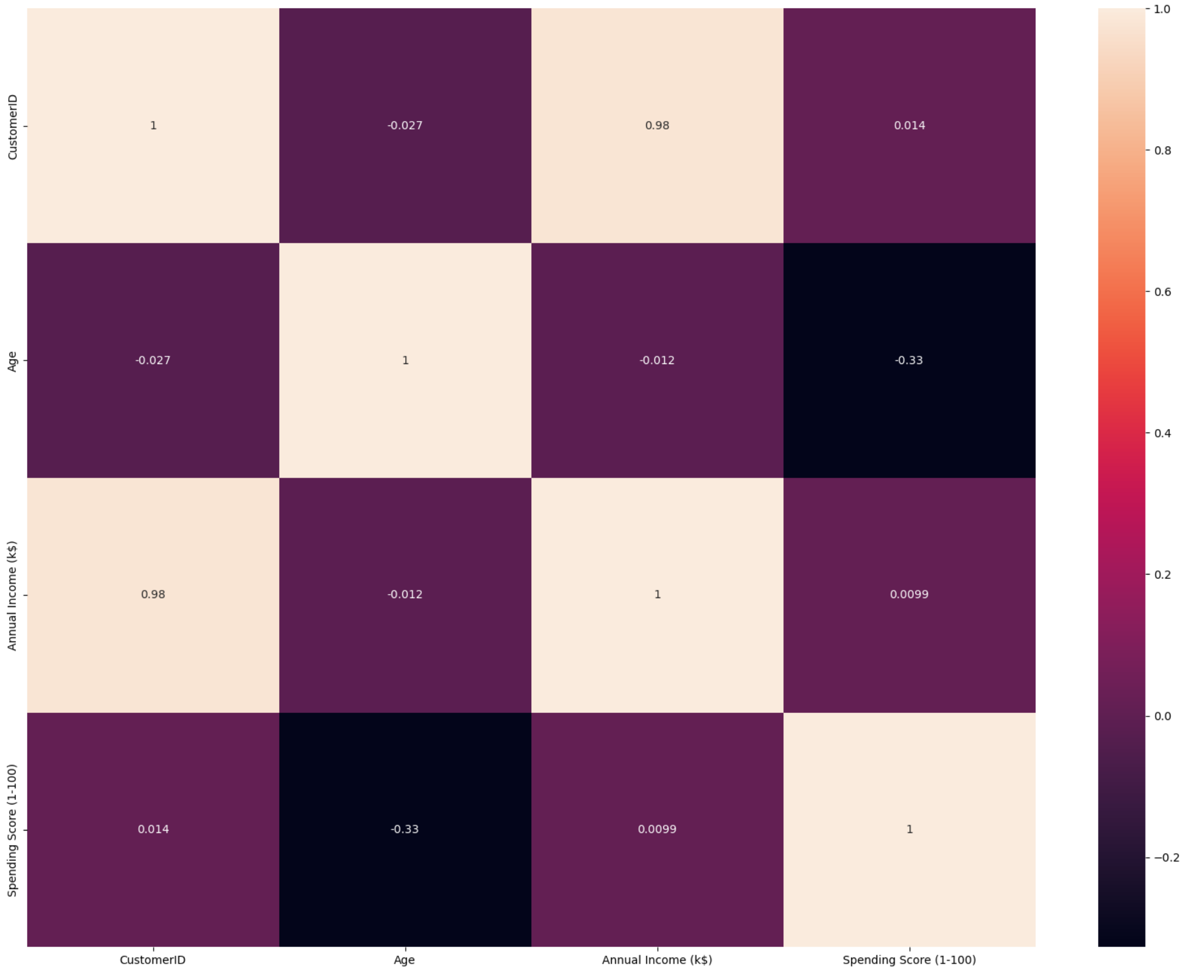
```
/var/folders/0g/xqmh0yz92jx_s8ljsv3x08wr0000gn/T/ipykernel_5542/243808
4875.py:1: FutureWarning: The default value of numeric_only in DataFra
me.corr is deprecated. In a future version, it will default to False.
Select only valid columns or specify the value of numeric_only to sile
nce this warning.
  corr = df.corr()
```

Out[10]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
CustomerID	1.000000	-0.026763	0.977548	0.013835
Age	-0.026763	1.000000	-0.012398	-0.327227
Annual Income (k$)	0.977548	-0.012398	1.000000	0.009903
Spending Score (1-100)	0.013835	-0.327227	0.009903	1.000000

In [11]:
```
plt.subplots(figsize=(20,15))
sns.heatmap(corr,annot=True)
```

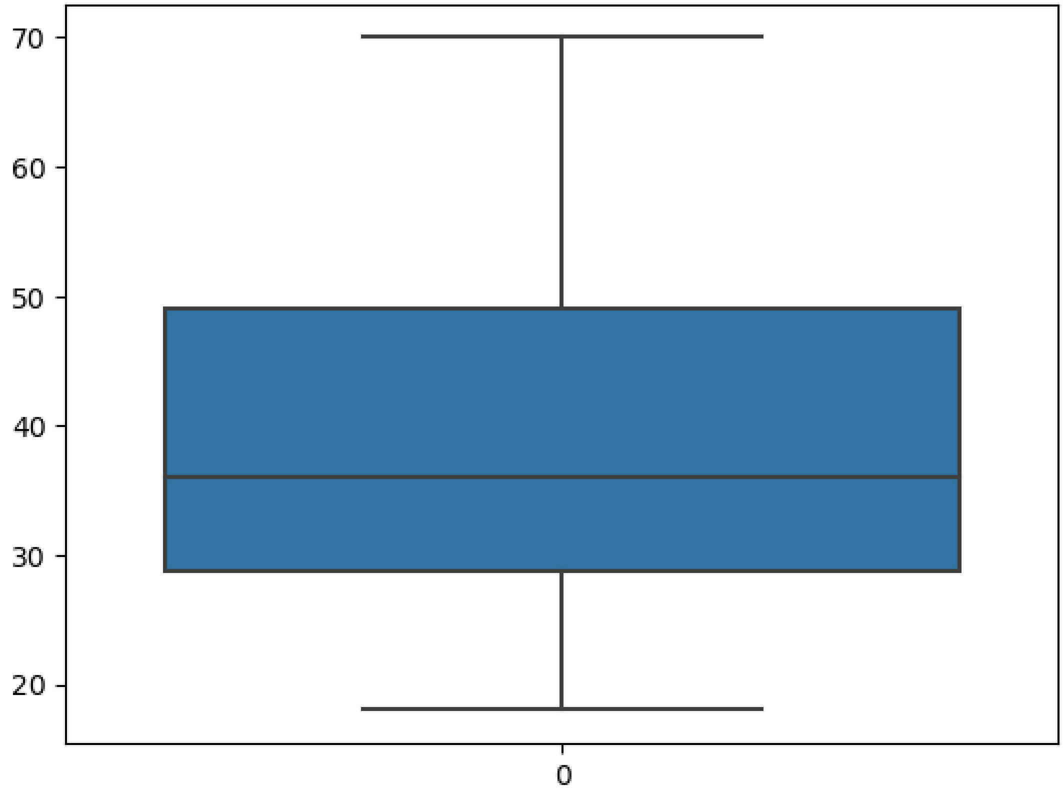
Out[11]: <Axes: >



4.Outlier detection

In [29]:
```
sns.boxplot(df.Age)
```

Out[29]: <Axes: >



5.Seperate Dependent and independent variables

In [30]:
```
df.head()
```

Out[30]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

In [53]:
```
#datset.iloc[rows,column]
x=df['Spending Score (1-100)'] # Dependent
y=df.drop(columns=["Spending Score (1-100)"],axis=1)  # Independent
```

In [54]:
```
x
```

Out[54]:
```
0      39
1      81
2       6
3      77
4      40
       ..
195    79
196    28
197    74
198    18
199    83
Name: Spending Score (1-100), Length: 200, dtype: int64
```

In [55]:
```
y
```

Out[55]:

	CustomerID	Genre	Age	Annual Income (k$)
0	1	Male	19	15
1	2	Male	21	15
2	3	Female	20	16
3	4	Female	23	16
4	5	Female	31	17
...	...	...	...	...
195	196	Female	35	120
196	197	Female	45	126
197	198	Male	32	126
198	199	Male	32	137
199	200	Male	30	137

200 rows × 4 columns

6.Encoding

perform label encoding on gender

We use label encoder on Genre

In [56]:
```
from sklearn.preprocessing import LabelEncoder
```

In [57]:
```
le=LabelEncoder()
```

In [63]:
```
y["Genre"]=le.fit_transform(y["Genre"])
```

In [64]:
```
y["Genre"]
```

Out[64]:
```
0      1
1      1
2      0
3      0
4      0
      ..
195    0
196    0
197    1
198    1
199    1
Name: Genre, Length: 200, dtype: int64
```

In [66]:
```
y["Genre"].value_counts()
```

Out[66]:
```
0    112
1     88
Name: Genre, dtype: int64
```

In [67]:
```
y["Genre"].nunique()
```

Out[67]:
```
2
```

In [68]:
```
y.head()
```

Out[68]:

	CustomerID	Genre	Age	Annual Income (k$)
0	1	1	19	15
1	2	1	21	15
2	3	0	20	16
3	4	0	23	16
4	5	0	31	17

In [76]:
```
x=pd.concat([x,y],axis=1)
x
```

Out[76]:

	Spending Score (1-100)	CustomerID	Genre	Age	Annual Income (k$)	CustomerID	Genre	Age	Annual Income (k$)
0	39	1	1	19	15	1	1	19	15
1	81	2	1	21	15	2	1	21	15
2	6	3	0	20	16	3	0	20	16
3	77	4	0	23	16	4	0	23	16
4	40	5	0	31	17	5	0	31	17
...	...	...	...	...	...	...	...	...	...
195	79	196	0	35	120	196	0	35	120
196	28	197	0	45	126	197	0	45	126
197	74	198	1	32	126	198	1	32	126
198	18	199	1	32	137	199	1	32	137
199	83	200	1	30	137	200	1	30	137

200 rows × 9 columns

7. Feature Scaling

In [77]:
```
from sklearn.preprocessing import MinMaxScaler
ms=MinMaxScaler()
```

In [78]:
```
x_Scaled=ms.fit_transform(x)
```

In [80]:
```
x_Scaled=pd.DataFrame(ms.fit_transform(x),columns=x.columns)
```

In [81]:
```
x_Scaled.head()
```

Out[81]:

	Spending Score (1-100)	CustomerID	Genre	Age	Annual Income (k$)	CustomerID	Genre	Age	Annual Income (k$)
0	0.387755	0.000000	1.0	0.019231	0.000000	0.000000	1.0	0.019231	0.000000
1	0.816327	0.005025	1.0	0.057692	0.000000	0.005025	1.0	0.057692	0.000000
2	0.051020	0.010050	0.0	0.038462	0.008197	0.010050	0.0	0.038462	0.008197
3	0.775510	0.015075	0.0	0.096154	0.008197	0.015075	0.0	0.096154	0.008197
4	0.397959	0.020101	0.0	0.250000	0.016393	0.020101	0.0	0.250000	0.016393

8. Train your data

In [82]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x_Scaled,y,test_size =0
```

In [83]:
```
print(x_train.shape,x_test.shape,y_train.shape,y_test.shape)
```

```
(160, 9) (40, 9) (160, 4) (40, 4)
```

In [ ]: