1.import libraries

```
# import library

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

2.Load the dataset

```
# load dataset
from google.colab import files
upload=files.upload()
```

```
<IPython.core.display.HTML object>
```

```
Saving Mall_Customers.xlsx to Mall_Customers (1).xlsx
```

```
customer=pd.read_excel("Mall_Customers.xlsx")
```

3.Univariate Analysis

```
df=pd.read_excel("Mall_Customers.xlsx")
```

```
#view first five rows of DataFrame
df.head()
```

```
   CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
0         1.0    Male  19.0                15.0
39.0
1         2.0    Male  21.0                15.0
81.0
2         3.0  Female  20.0                16.0
6.0
3         4.0  Female  23.0                16.0
77.0
4         5.0  Female  31.0                17.0
40.0
```

```
#calculate mean of 'Annual Income (K$)'
df["Annual Income (k$)"].mean()
```

```
60.56
```

```
#calculate median of 'Annual Income (K$)'
df["Annual Income (k$)"].median()
```

```
61.5
```

```
#calculate standard deviation of 'Annual Income (K$)'
df["Annual Income (k$)"].std()
```

```
26.264721165271244
```

```
#calculate mode of 'Annual Income (K$)'
df["Annual Income (k$)"].mode()
```

```
0    54.0
1    78.0
dtype: float64
```

```
#create frequency table for 'Annual Income (k$)'
df["Annual Income (k$)"].value_counts()
```

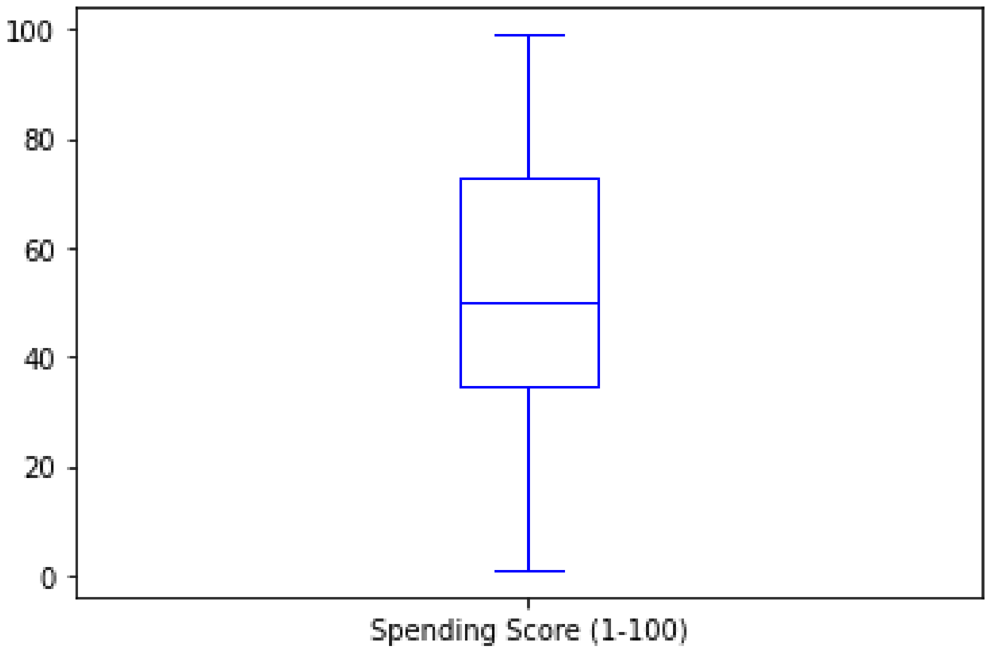
```
54.0     12
78.0     12
48.0      6
71.0      6
63.0      6
         ..
58.0      2
59.0      2
16.0      2
64.0      2
137.0     2
Name: Annual Income (k$), Length: 64, dtype: int64
```

```
#view last five rows of DataFrame
df.tail()
```

```
     CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
195       196.0  Female  35.0               120.0
79.0
196       197.0  Female  45.0               126.0
28.0
197       198.0    Male  32.0               126.0
74.0
198       199.0    Male  32.0               137.0
18.0
199       200.0    Male  30.0               137.0
83.0
```

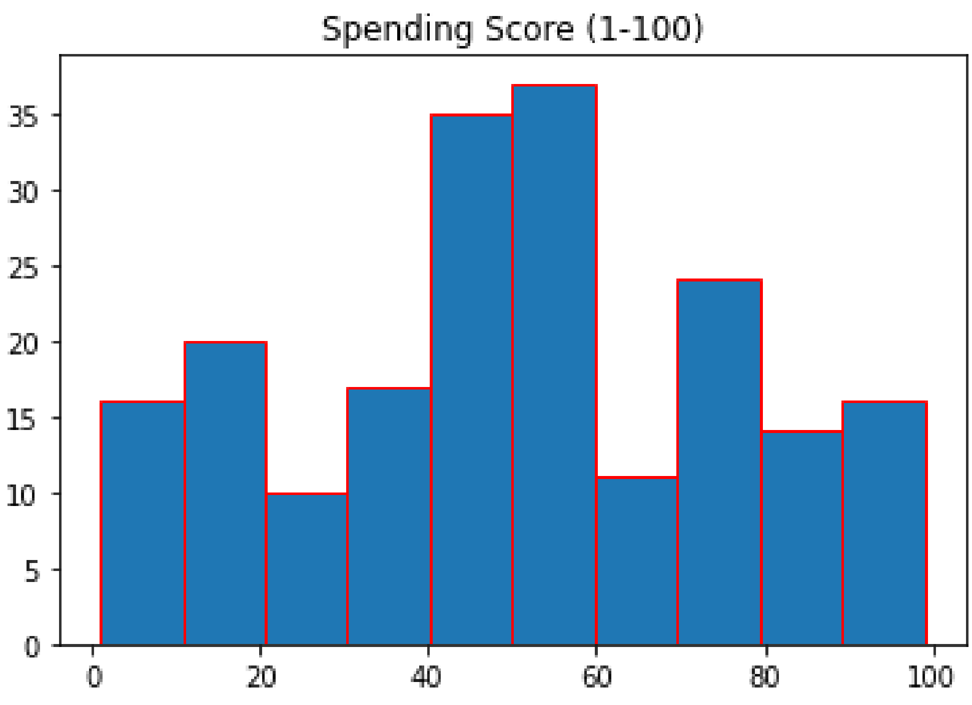
```
#create a boxplot for the 'Spending Score' variable
import matplotlib.pyplot as plt
customer.boxplot(column=['Spending Score (1-
100)'],grid=False,color='blue')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b924e850>
```



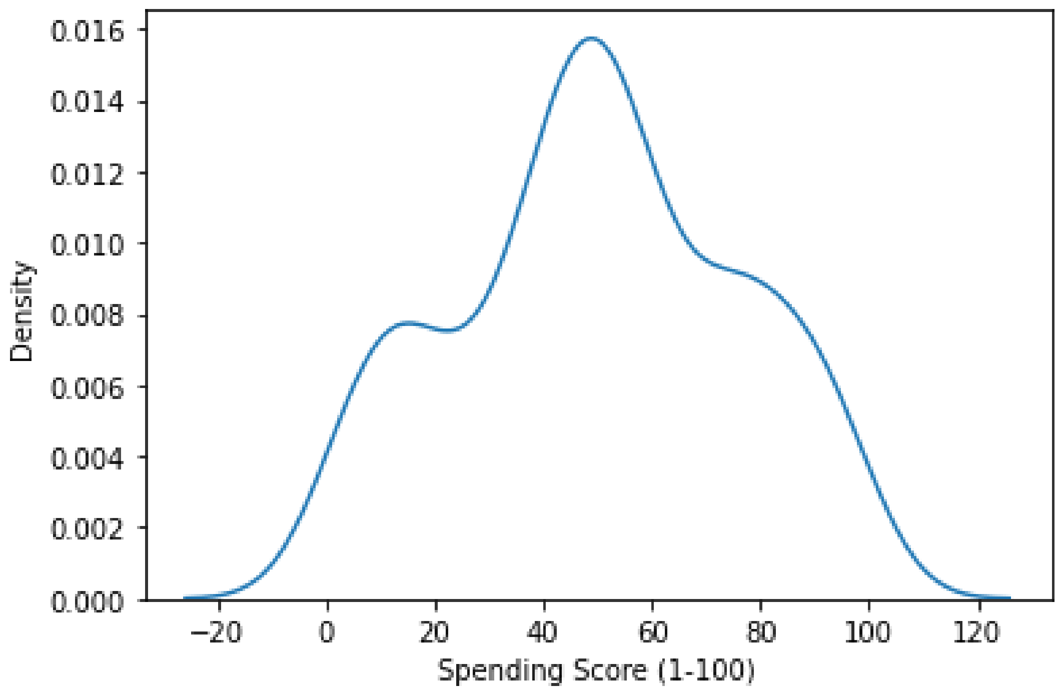

```
#to create histogram for the 'Spending Score' variable
customer.hist(column='Spending Score (1-
100)',grid=False,edgecolor='red')
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at
0x7fc3b982a490>]],
      dtype=object)
```



```python
#to create a density curve for the 'Spending Score' variable
sns.kdeplot(customer['Spending Score (1-100)'])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b9255f10>
```



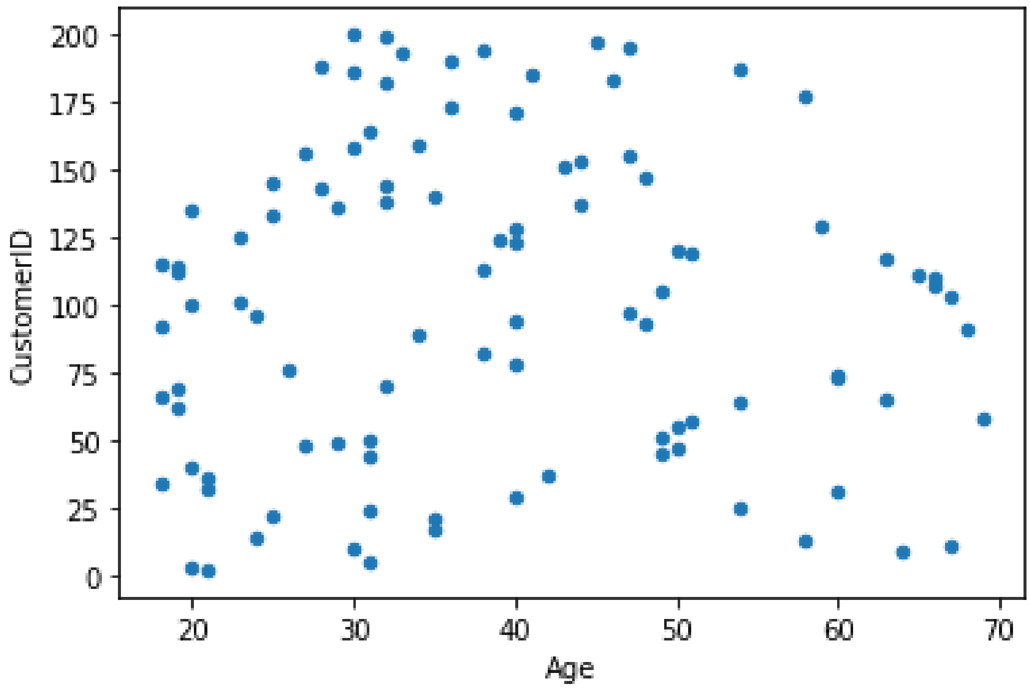

```python
#information of dataset
customer.info()
```

```
<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    float64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    float64
 3   Annual Income (k$)      200 non-null    float64
 4   Spending Score (1-100)  200 non-null    float64
dtypes: float64(4), object(1)
memory usage: 7.9+ KB
```

4.Bi-Variate Analysis

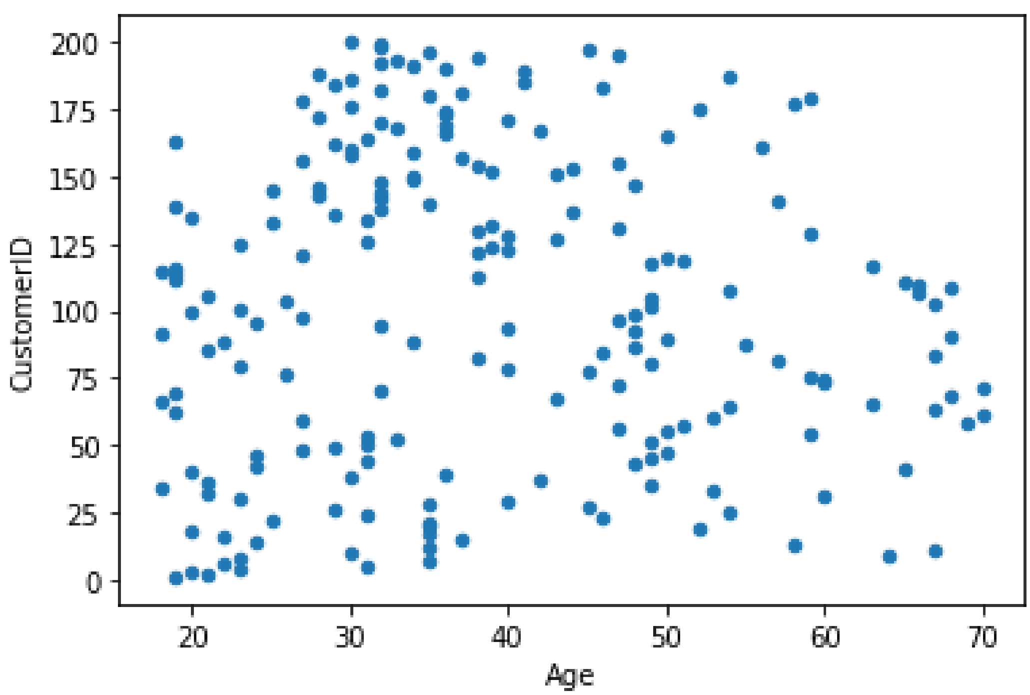
```python
#Scatter Plot
customer[customer['Spending Score (1-100)'] <
100].sample(100).plot.scatter(x='Age', y='CustomerID')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b8f1e4d0>
```



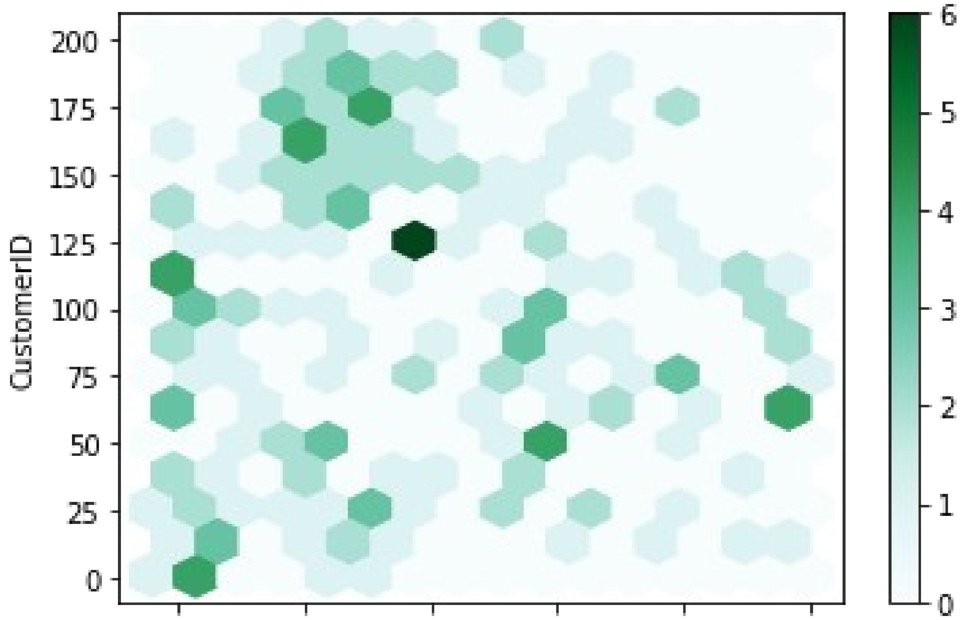

```
customer[customer['Spending Score (1-100)'] <
100].plot.scatter(x='Age', y='CustomerID')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b8eb2b10>
```



```
#Hex Plot
customer[customer['Spending Score (1-100)'] <
100].plot.hexbin(x='Age', y='CustomerID', gridsize=15)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b8dc0310>
```



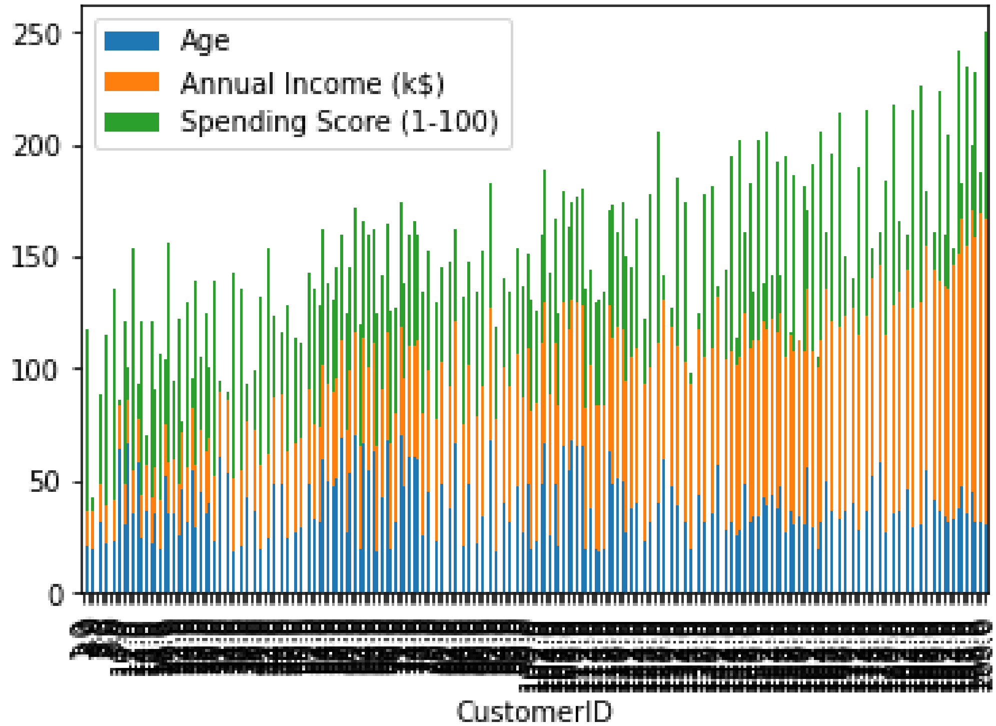

```
#stacked plot
customer_count=pd.read_excel("Mall_Customers.xlsx",index_col=0)
```

```
customer_count.head()
```

```
            Gender   Age  Annual Income (k$)  Spending Score (1-100)
CustomerID
1.0           Male  19.0                15.0                    39.0
2.0           Male  21.0                15.0                    81.0
3.0         Female  20.0                16.0                     6.0
4.0         Female  23.0                16.0                    77.0
5.0         Female  31.0                17.0                    40.0
```

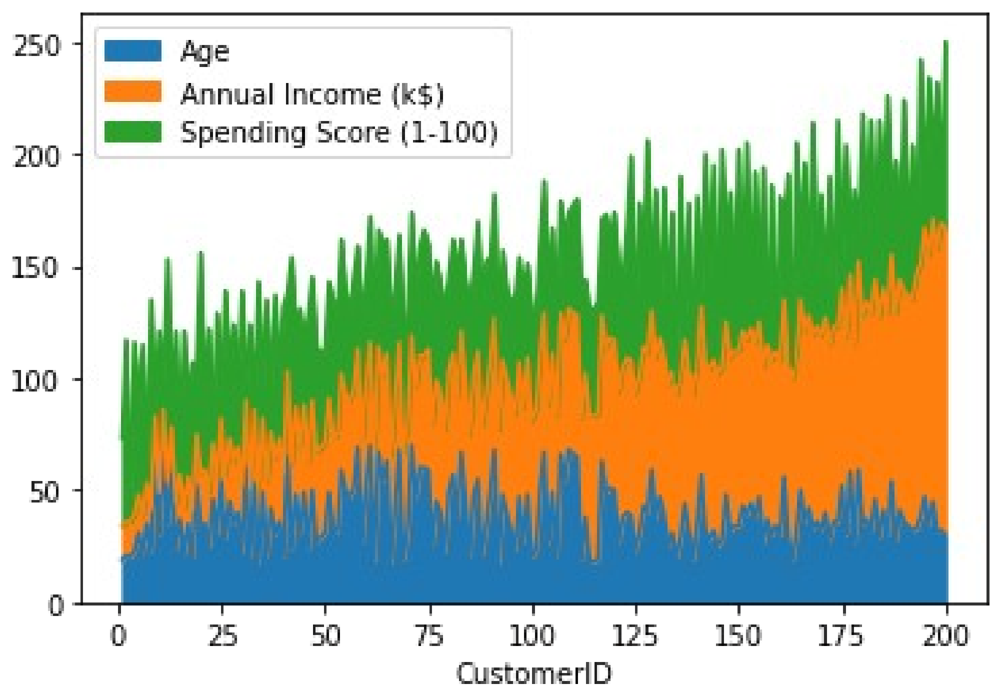
```
customer_count.plot.bar(stacked=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b8ead250>
```



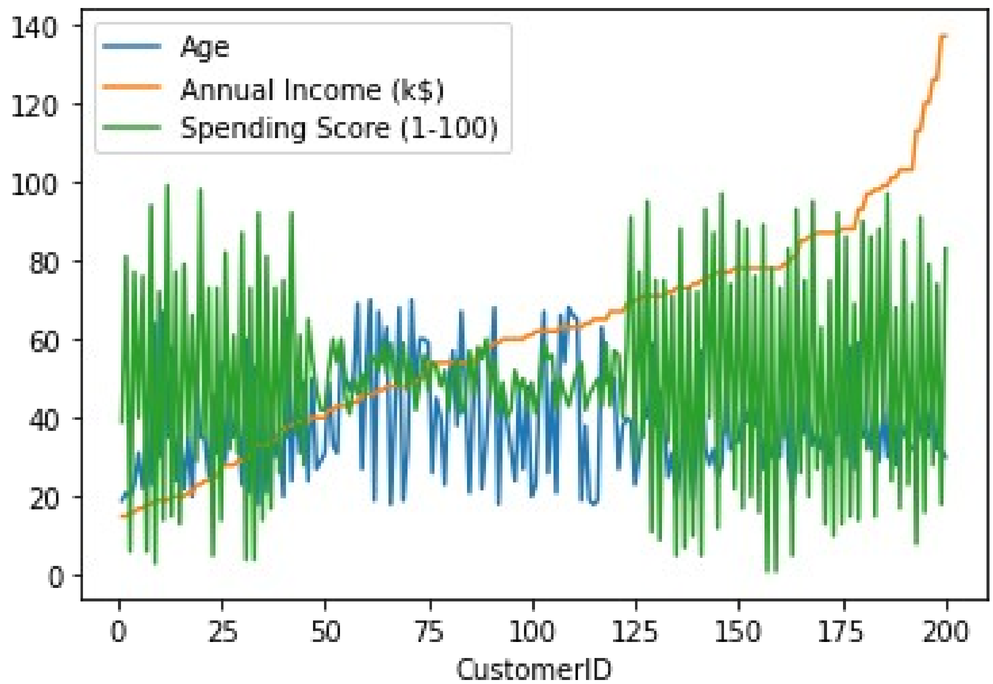

```
customer_count.plot.area()
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b832b8d0>



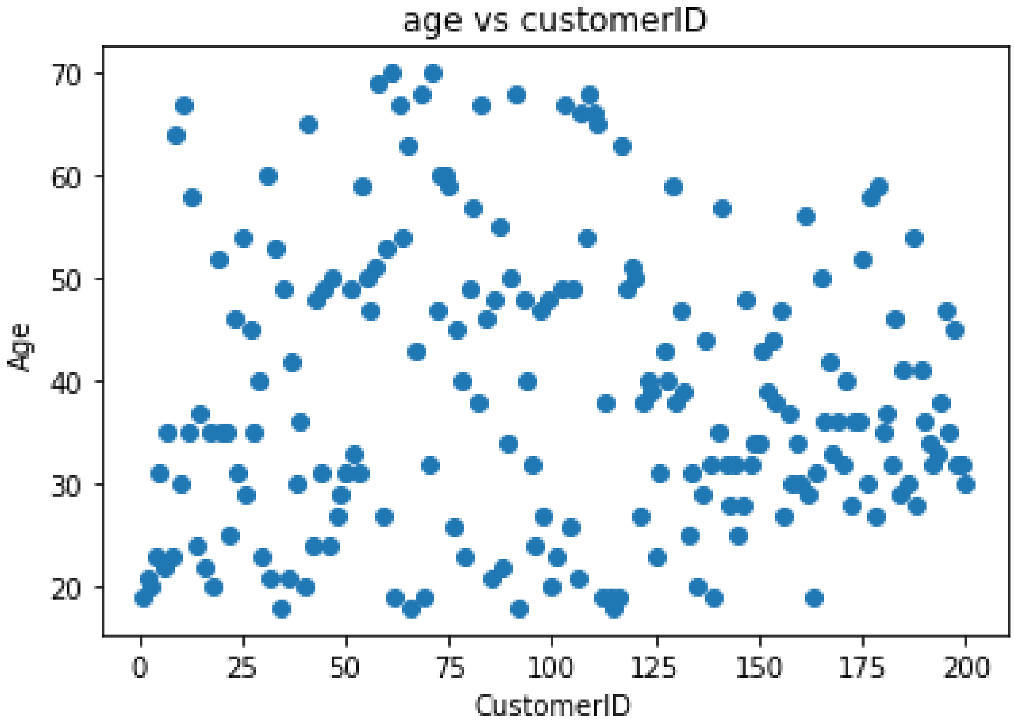
```
#Bivariate line chart
customer_count.plot.line()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3b8338290>
```




```
#create scatterplot of Annual Income vs Spending Score
plt.scatter(customer.CustomerID,customer.Age)
plt.title('age vs customerID')
plt.xlabel('CustomerID')
plt.ylabel('Age')
```

```
Text(0, 0.5, 'Age')
```




```
#create correlation matrix
customer.corr()

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

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

import statsmodels.api as sm

#define response variable
y=customer['CustomerID']

#define response variable
x=customer['Age']

#add constant to predictor variables
x=sm.add_constant(x)

/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/
tsatools.py:142: FutureWarning: In a future version of pandas all
arguments of concat except for the argument 'objs' will be keyword-
```

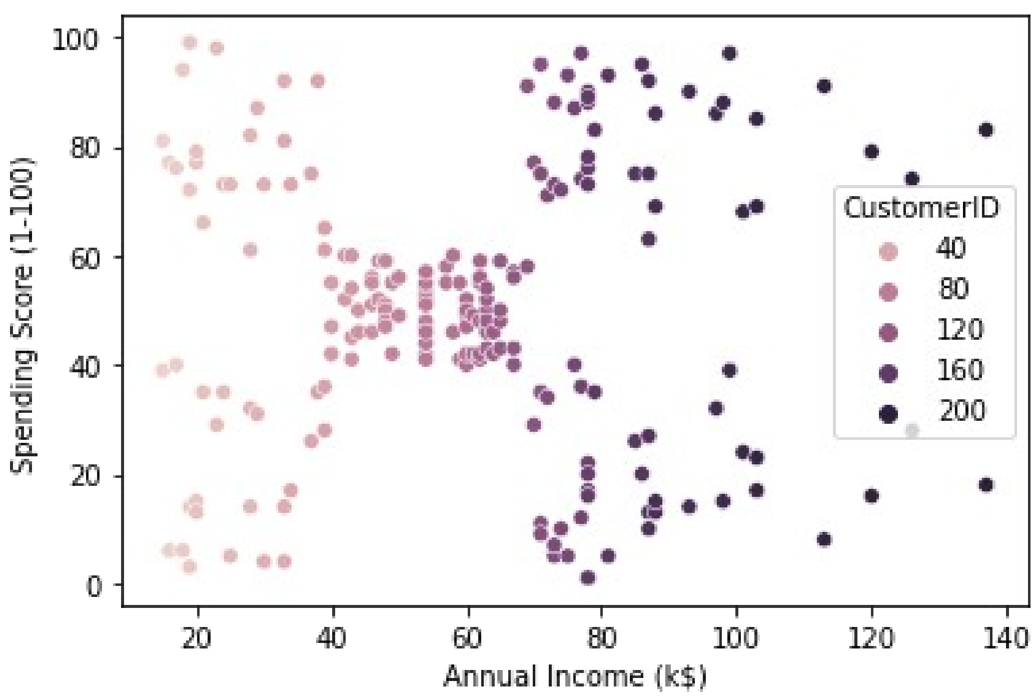
```
only
  x = pd.concat(x[::order], 1)

#fit linear regression model
model=sm.OLS(y,x).fit()

#view model summary
print(model.summary())
                            OLS Regression Results

======================================================================
========
Dep. Variable:             CustomerID   R-squared:
0.001
Model:                            OLS   Adj. R-squared:
-0.004
Method:                 Least Squares   F-statistic:
0.1419
Date:                Sat, 22 Oct 2022   Prob (F-statistic):
0.707
Time:                        14:53:57   Log-Likelihood:
-1094.9
No. Observations:                 200   AIC:
2194.
Df Residuals:                     198   BIC:
2200.
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
const        104.8081     12.149      8.627      0.000      80.850
128.766
Age           -0.1109      0.294     -0.377      0.707      -0.691
0.470
======================================================================
========
Omnibus:                       84.500   Durbin-Watson:
0.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
11.691
Skew:                          -0.014   Prob(JB):
0.00289
Kurtosis:                       1.816   Cond. No.
```

```
122.
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

5.Multi-Variate Analysis

```
sns.scatterplot(customer["Annual Income (k$)"],customer["Spending Score (1-100)"],hue=customer["CustomerID"])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning

<matplotlib.axes._subplots.AxesSubplot at 0x7fc3ac87c410>
```

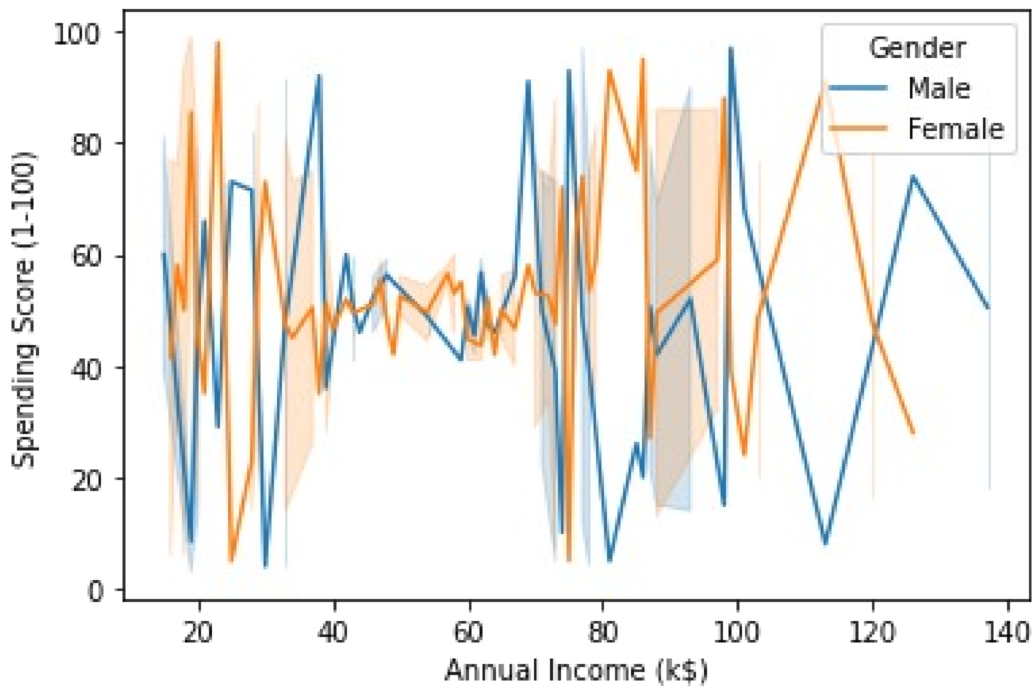



```
sns.lineplot(customer["Annual Income (k$)"],customer["Spending Score (1-100)"],hue=customer["Gender"])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in
```

```
an error or misinterpretation.
  FutureWarning
```

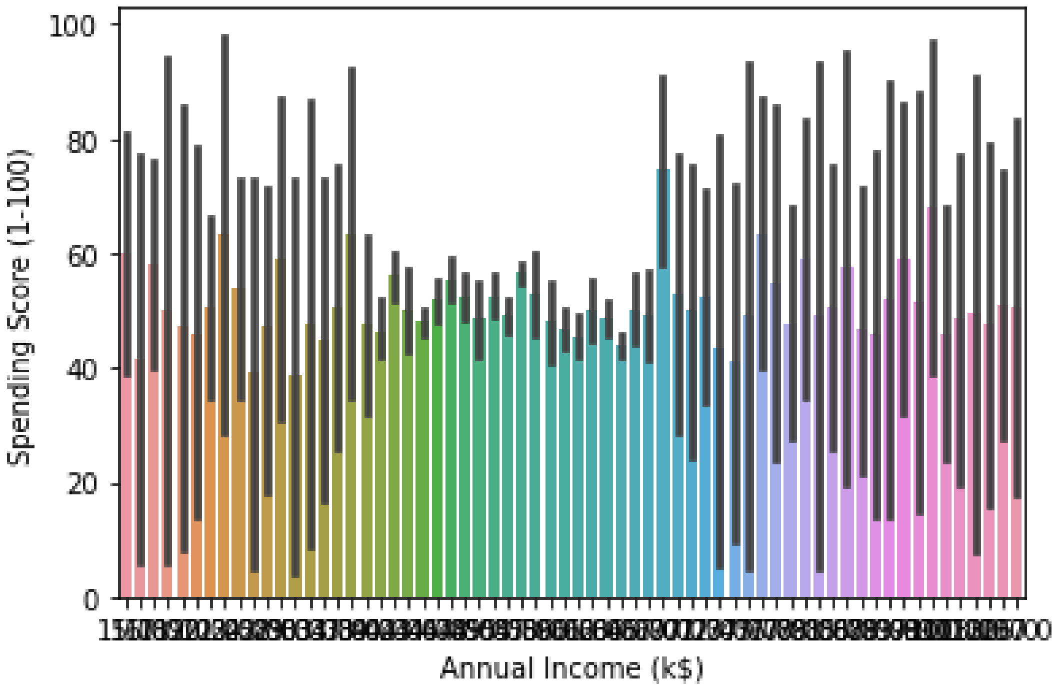
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3ac4aee90>
```




```
sns.barplot(customer["Annual Income (k$)"],customer["Spending Score
(1-100)"])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variables as keyword args: x, y.
From version 0.12, the only valid positional argument will be `data`,
and passing other arguments without an explicit keyword will result in
an error or misinterpretation.
  FutureWarning
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc3ac102f10>
```




```
customer.skew()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
FutureWarning: Dropping of nuisance columns in DataFrame reductions
(with 'numeric_only=None') is deprecated; in a future version this
will raise TypeError.  Select only valid columns before calling the
reduction.
  """Entry point for launching an IPython kernel.
```

```
CustomerID                0.000000
Age                       0.485569
Annual Income (k$)        0.321843
Spending Score (1-100)   -0.047220
dtype: float64
```

```
label=df.CustomerID.value_counts().index
count=df.CustomerID.value_counts().values
```

```
plt.pie(count,labels=label)
```

```
([<matplotlib.patches.Wedge at 0x7fc3a615b150>,
  <matplotlib.patches.Wedge at 0x7fc3a615b610>,
  <matplotlib.patches.Wedge at 0x7fc3a615bd50>,
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```

```
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```

```
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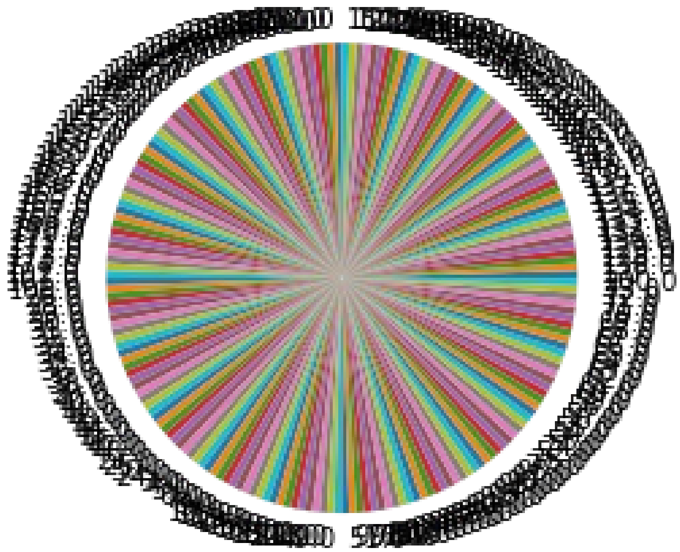

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```

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```
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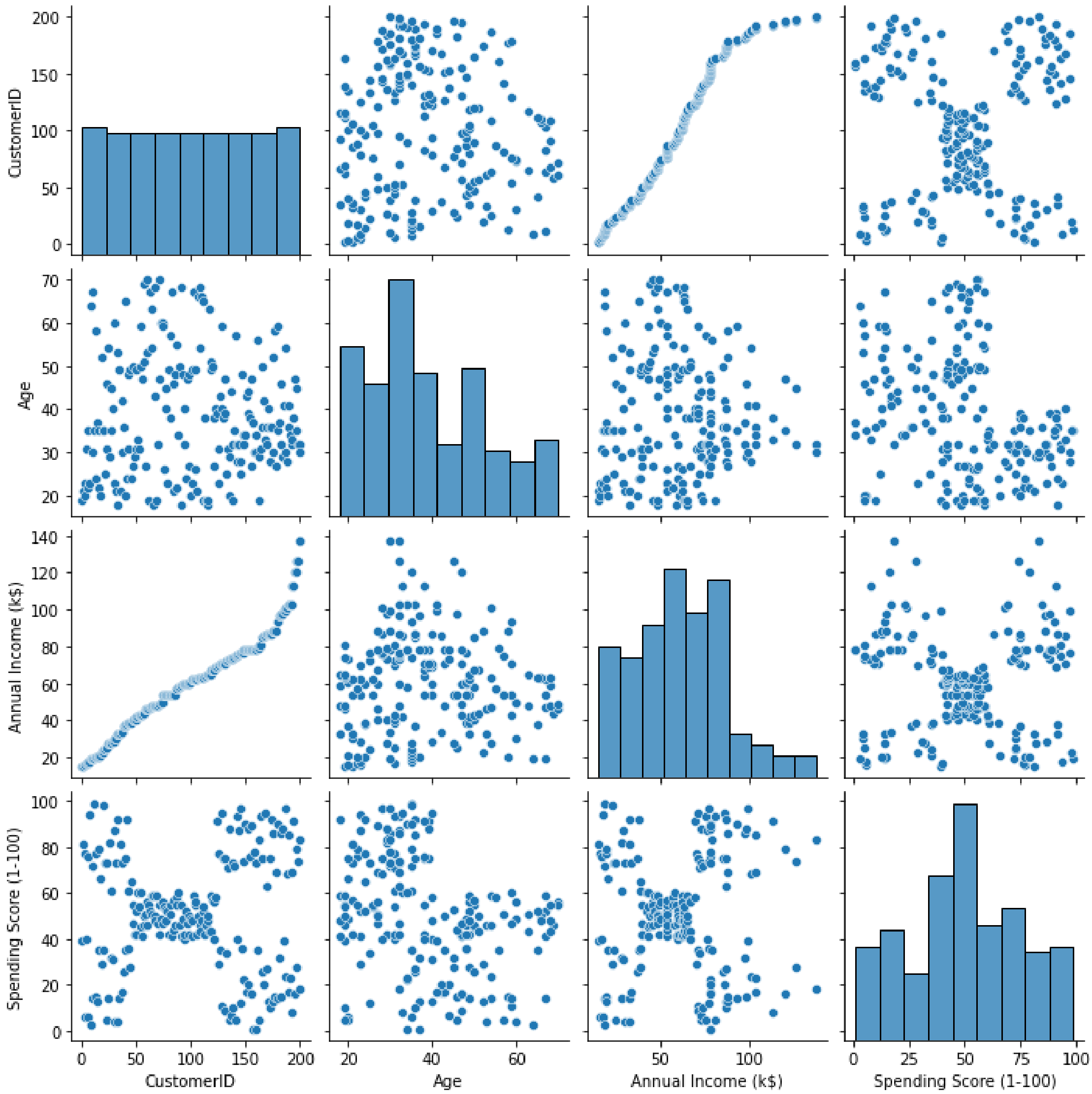


6.Perform descriptive statistics on the dataset

```
#Create a DataFrame
df = pd.DataFrame(customer)

df
```

```
     CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
0           1.0    Male  19.0                15.0
39.0
1           2.0    Male  21.0                15.0
81.0
2           3.0  Female  20.0                16.0
6.0
```

```
3            4.0  Female  23.0                16.0
77.0
4            5.0  Female  31.0                17.0
40.0
..           ...     ...   ...                 ...
...
195        196.0  Female  35.0               120.0
79.0
196        197.0  Female  45.0               126.0
28.0
197        198.0    Male  32.0               126.0
74.0
198        199.0    Male  32.0               137.0
18.0
199        200.0    Male  30.0               137.0
83.0

[200 rows x 5 columns]
```

```
#Create a DataFrame
df = pd.DataFrame(customer)
```

```
df.sum()
```

```
CustomerID
20100.0
Gender
MaleMaleFemaleFemaleFemaleFemaleFemaleFemaleMa...
Age
7770.0
Annual Income (k$)
12112.0
Spending Score (1-100)
10040.0
dtype: object
```

```
#axis=1
df.sum(1)
```

```
0       74.0
1      119.0
2       45.0
3      120.0
4       93.0
       ...
195    430.0
196    396.0
197    430.0
198    386.0
199    450.0
Length: 200, dtype: float64
```

```
df.mean()
```

```
CustomerID                100.50
Age                        38.85
Annual Income (k$)         60.56
Spending Score (1-100)     50.20
dtype: float64
```

```
df.std()
```

```
CustomerID                57.879185
Age                       13.969007
Annual Income (k$)        26.264721
Spending Score (1-100)    25.823522
dtype: float64
```

```
df.describe()
```

```
       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
```

```
 df.describe(include=['object'])
```

```
        Gender
count      200
unique       2
top     Female
freq       112
```

```
df. describe(include='all')
```

```
        CustomerID  Gender         Age  Annual Income (k$)  \
count   200.000000     200  200.000000          200.000000
unique         NaN       2         NaN                 NaN
top            NaN  Female         NaN                 NaN
freq           NaN     112         NaN                 NaN
```

```
mean    100.500000     NaN   38.850000            60.560000
std      57.879185     NaN   13.969007            26.264721
min       1.000000     NaN   18.000000            15.000000
25%      50.750000     NaN   28.750000            41.500000
50%     100.500000     NaN   36.000000            61.500000
75%     150.250000     NaN   49.000000            78.000000
max     200.000000     NaN   70.000000           137.000000

        Spending Score (1-100)
count               200.000000
unique                     NaN
top                        NaN
freq                       NaN
mean                 50.200000
std                  25.823522
min                   1.000000
25%                  34.750000
50%                  50.000000
75%                  73.000000
max                  99.000000
```

```
customer["Age"].mean()
```

```
38.85
```

```
customer["Annual Income (k$)"].median()
```

```
61.5
```

```
customer.max()
```

```
CustomerID                200.0
Gender                     Male
Age                        70.0
Annual Income (k$)        137.0
Spending Score (1-100)     99.0
dtype: object
```

```
customer.min()
```

```
CustomerID                   1.0
Gender                    Female
Age                         18.0
Annual Income (k$)          15.0
Spending Score (1-100)       1.0
dtype: object
```

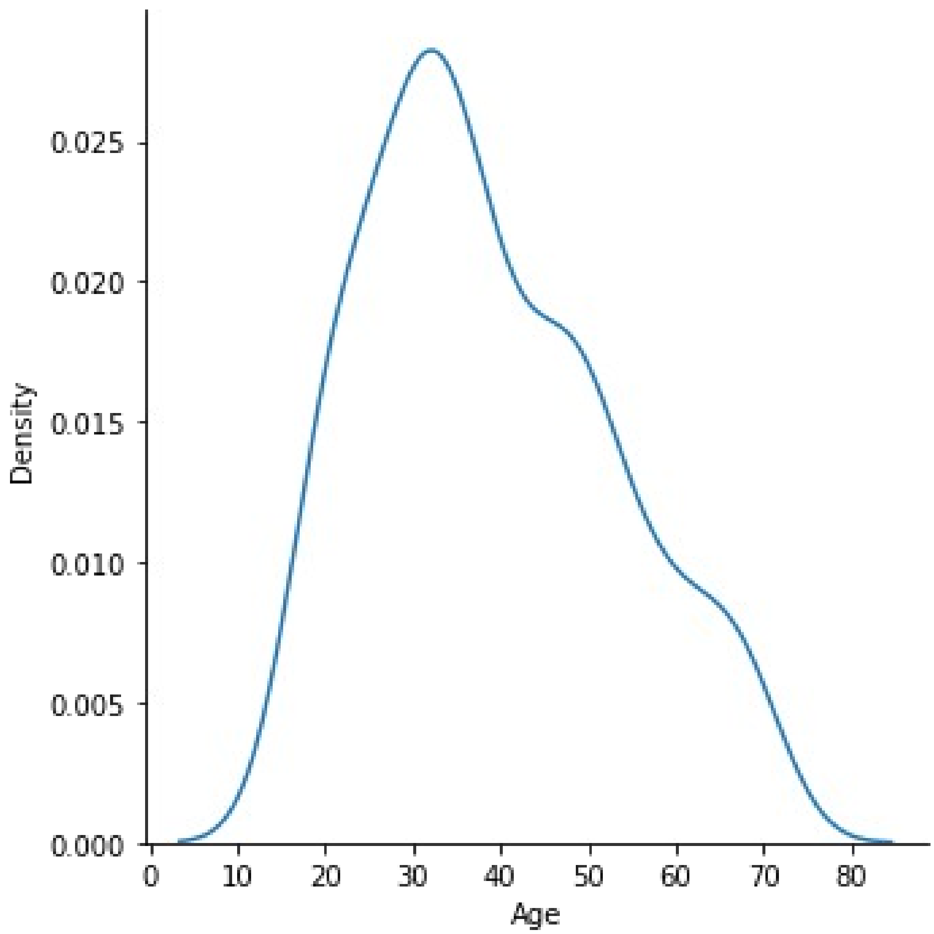
```
customer.kurtosis()
```

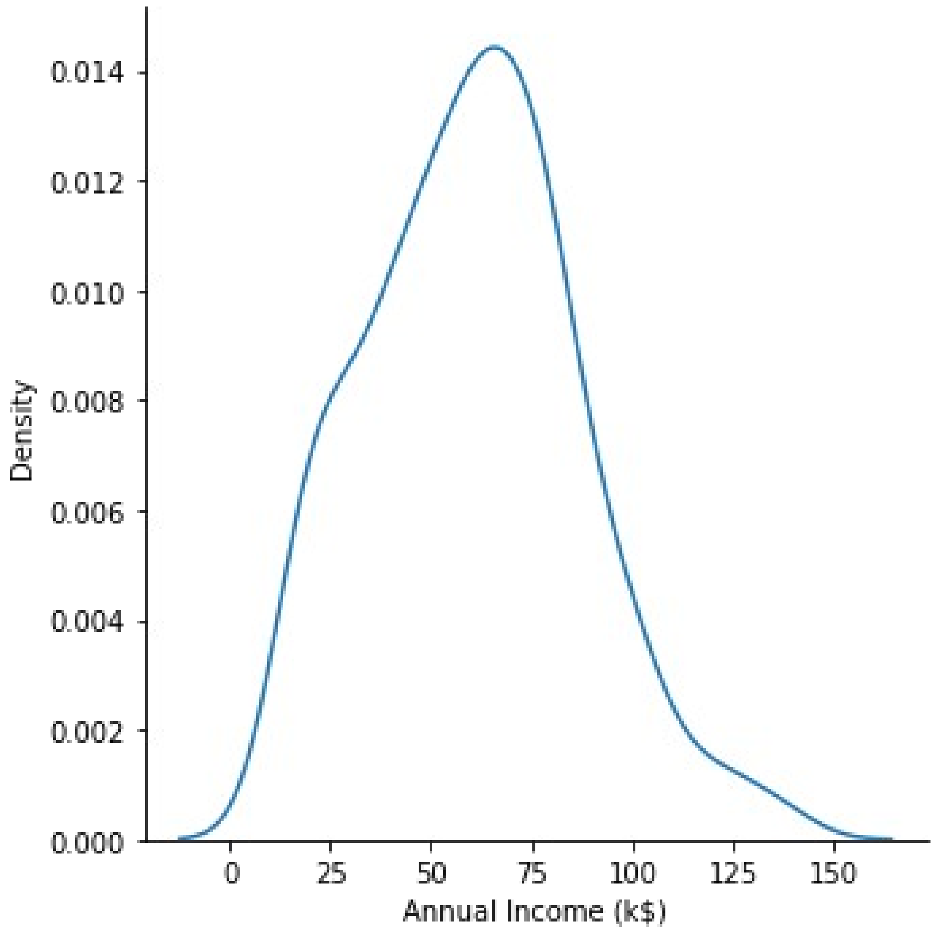
```
CustomerID               -1.200000
Age                      -0.671573
Annual Income (k$)       -0.098487
```

```
Spending Score (1-100)   -0.826629
dtype: float64
```

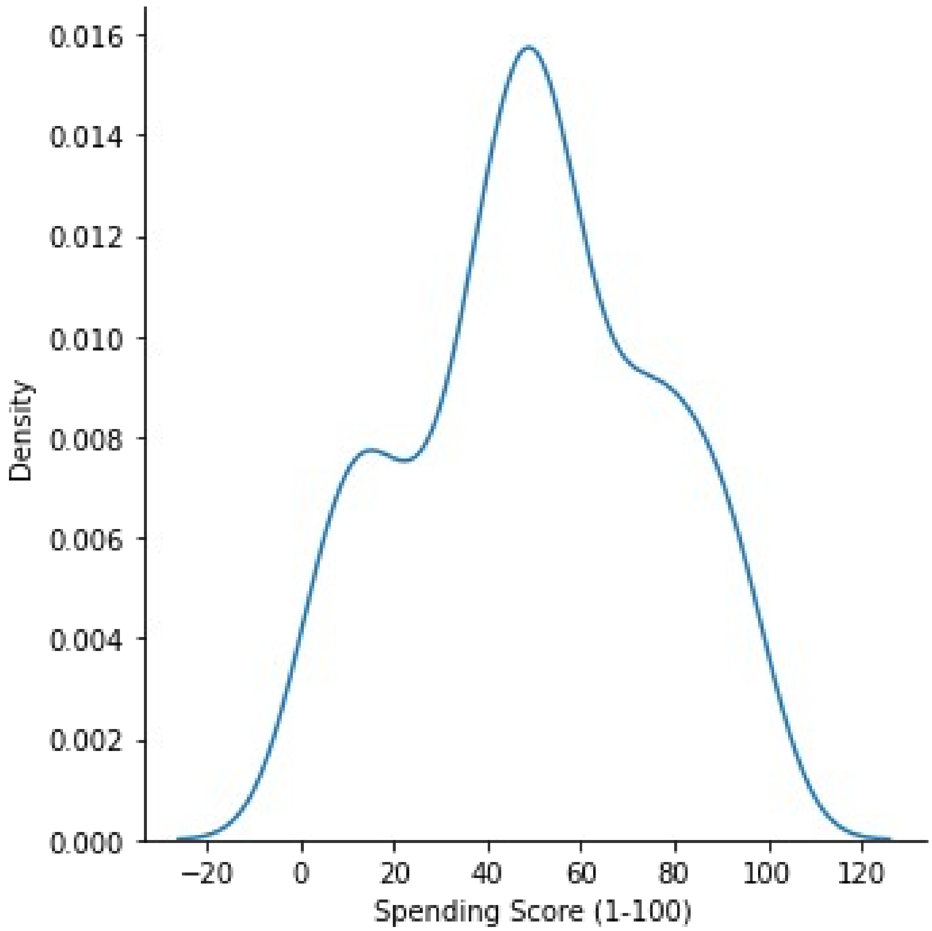
```
print(sns.displot(customer["Age"],kind = "kde")),
print(sns.displot(customer["Annual Income (k$)"],kind = "kde")),
print(sns.displot(customer["Spending Score (1-100)"],kind = "kde"))
```

```
<seaborn.axisgrid.FacetGrid object at 0x7f7e9c366c50>
<seaborn.axisgrid.FacetGrid object at 0x7f7e9e0fc410>
<seaborn.axisgrid.FacetGrid object at 0x7f7e9c30bf50>
```





0.014
0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
0
25
50
75
100
125
150
Annual Income (k$)



7.Check with missing value and deal with them

```
df.fillna(value = 100)
```

```
     CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
0           1.0    Male  19.0                15.0
39.0
1           2.0    Male  21.0                15.0
81.0
2           3.0  Female  20.0                16.0
6.0
3           4.0  Female  23.0                16.0
77.0
4           5.0  Female  31.0                17.0
40.0
..          ...     ...   ...                 ...
...
195       196.0  Female  35.0               120.0
79.0
196       197.0  Female  45.0               126.0
```

```
28.0
197       198.0    Male  32.0               126.0
74.0
198       199.0    Male  32.0               137.0
18.0
199       200.0    Male  30.0               137.0
83.0

[200 rows x 5 columns]
```

```
df
```

```
     CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
0           1.0    Male  19.0                15.0
39.0
1           2.0    Male  21.0                15.0
81.0
2           3.0  Female  20.0                16.0
6.0
3           4.0  Female  23.0                16.0
77.0
4           5.0  Female  31.0                17.0
40.0
..          ...     ...   ...                 ...
...
195       196.0  Female  35.0               120.0
79.0
196       197.0  Female  45.0               126.0
28.0
197       198.0    Male  32.0               126.0
74.0
198       199.0    Male  32.0               137.0
18.0
199       200.0    Male  30.0               137.0
83.0

[200 rows x 5 columns]
```

```
df["Age"].mean()
```

```
38.85
```

```
df["Age"].median()
```

```
36.0
```

```
df["Age"].fillna(df["Age"].mean(),inplace = True)
```

```
df
```

```
     CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
0           1.0    Male  19.0                15.0
39.0
1           2.0    Male  21.0                15.0
81.0
2           3.0  Female  20.0                16.0
6.0
3           4.0  Female  23.0                16.0
77.0
4           5.0  Female  31.0                17.0
40.0
..          ...     ...   ...                 ...
...
195       196.0  Female  35.0               120.0
79.0
196       197.0  Female  45.0               126.0
28.0
197       198.0    Male  32.0               126.0
74.0
198       199.0    Male  32.0               137.0
18.0
199       200.0    Male  30.0               137.0
83.0

[200 rows x 5 columns]
```

```
df["Annual Income (k$)"].fillna(df["Annual Income
(k$)"].median(),inplace = True)
```

```
df
```

```
     CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
0           1.0    Male  19.0                15.0
39.0
1           2.0    Male  21.0                15.0
81.0
2           3.0  Female  20.0                16.0
6.0
3           4.0  Female  23.0                16.0
77.0
4           5.0  Female  31.0                17.0
40.0
..          ...     ...   ...                 ...
...
195       196.0  Female  35.0               120.0
79.0
196       197.0  Female  45.0               126.0
28.0
197       198.0    Male  32.0               126.0
```

```
74.0
198       199.0    Male  32.0               137.0
18.0
199       200.0    Male  30.0               137.0
83.0

[200 rows x 5 columns]
```

```
df= df.replace("Male",np.nan)
```

```
df
```

```
     CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)
0           1.0     NaN  19.0                15.0
39.0
1           2.0     NaN  21.0                15.0
81.0
2           3.0  Female  20.0                16.0
6.0
3           4.0  Female  23.0                16.0
77.0
4           5.0  Female  31.0                17.0
40.0
..          ...     ...   ...                 ...
...
195       196.0  Female  35.0               120.0
79.0
196       197.0  Female  45.0               126.0
28.0
197       198.0     NaN  32.0               126.0
74.0
198       199.0     NaN  32.0               137.0
18.0
199       200.0     NaN  30.0               137.0
83.0

[200 rows x 5 columns]
```

8.Find the outlier and replace them

```
### Method to outlier detection
qnt = customer.quantile(q = (0.25,0.75))
qnt
```

```
      CustomerID    Age  Annual Income (k$)  Spending Score (1-100)
0.25       50.75  28.75                41.5                   34.75
0.75      150.25  49.00                78.0                   73.00
```

```
iqr = qnt.loc[0.75] - qnt.loc[0.25]   # IQR = Q3 - Q1
```

```
iqr
```

```
CustomerID                99.50
Age                       20.25
Annual Income (k$)        36.50
Spending Score (1-100)    38.25
dtype: float64
```

```
lower = qnt.loc[0.25] - 1.5 * iqr
lower
```

```
CustomerID               -98.500
Age                       -1.625
Annual Income (k$)       -13.250
Spending Score (1-100)   -22.625
dtype: float64
```

```
upper = qnt.loc[0.75] + 1.5 * iqr
upper
```

```
CustomerID                299.500
Age                        79.375
Annual Income (k$)        132.750
Spending Score (1-100)    130.375
dtype: float64
```

```
customer.mean()
```

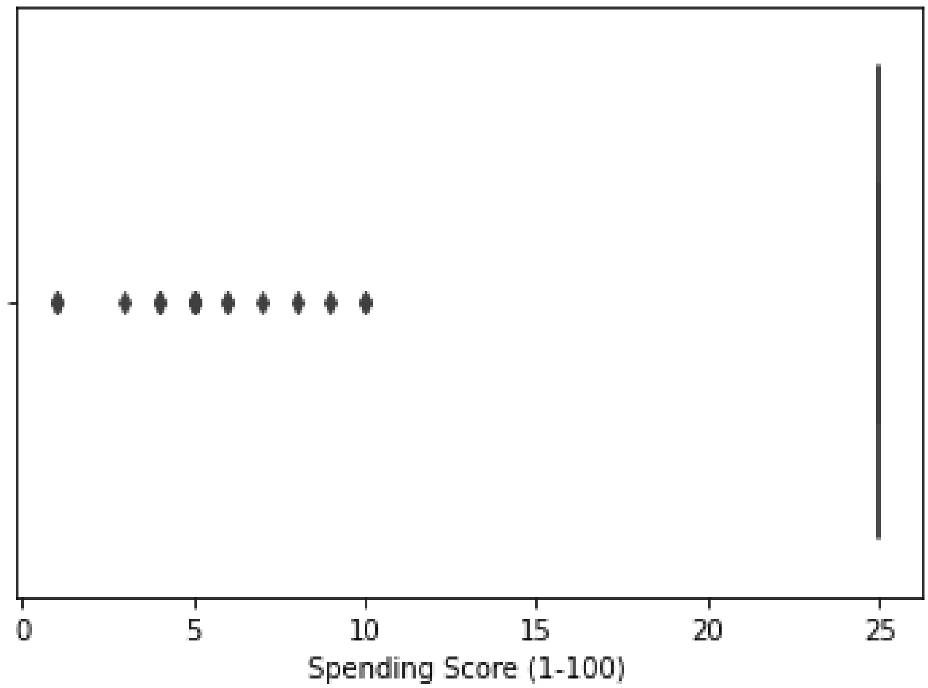
```
CustomerID                100.50
Age                        38.85
Annual Income (k$)         60.56
Spending Score (1-100)     50.20
dtype: float64
```

```
### replacing outlier
```

```
customer["Spending Score (1-100)"] = np.where(customer["Spending Score
(1-100)"] > 10,25,customer["Spending Score (1-100)"])
```

```
sns.boxplot(customer["Spending Score (1-100)"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7ea0febbd0>
```




```
customer.isnull().sum()
```

```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

```
customer = customer.dropna(axis = 0)
```

```
customer.isnull().sum()
```

```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

9.Check for Categorical columns and perform encoding

```
customer['Gender'].unique()
```

```
array(['Male', 'Female'], dtype=object)
```

```
from sklearn.preprocessing import LabelEncoder
```

```
gender = LabelEncoder()
```

```
gender.fit(customer['Gender'])
```

```
LabelEncoder()

marry_values = gender.transform(customer['Gender'])

print("Before Encoding:", list(customer['Gender'][-10:]))

Before Encoding: ['Female', 'Female', 'Male', 'Female', 'Female',
'Female', 'Female', 'Male', 'Male', 'Male']

print("After Encoding:", customer[-10:])

After Encoding:      CustomerID  Gender   Age  Annual Income (k$)
Spending Score (1-100)
190       191.0  Female  34.0               103.0
23.0
191       192.0  Female  32.0               103.0
69.0
192       193.0    Male  33.0               113.0
8.0
193       194.0  Female  38.0               113.0
91.0
194       195.0  Female  47.0               120.0
16.0
195       196.0  Female  35.0               120.0
79.0
196       197.0  Female  45.0               126.0
28.0
197       198.0    Male  32.0               126.0
74.0
198       199.0    Male  32.0               137.0
18.0
199       200.0    Male  30.0               137.0
83.0

print("The inverse from the encoding result:",
gender.inverse_transform(marry_values[-10:]))

The inverse from the encoding result: ['Female' 'Female' 'Male'
'Female' 'Female' 'Female' 'Female' 'Male'
 'Male' 'Male']

residence_encoder = LabelEncoder()
residence_values =
residence_encoder.fit_transform(customer['CustomerID'])

print("Before Encoding:", list(customer['CustomerID'][:5]))

Before Encoding: [1.0, 2.0, 3.0, 4.0, 5.0]

print("After Encoding:", residence_values[:5])

After Encoding: [0 1 2 3 4]
```

```
print("The inverse from the encoding result:",
residence_encoder.inverse_transform(residence_values[:5]))
```

```
The inverse from the encoding result: [1. 2. 3. 4. 5.]
```

```
from sklearn.preprocessing import OneHotEncoder

gender_encoder = OneHotEncoder()
```

```
from sklearn.preprocessing import OneHotEncoder
import numpy as np

gender_encoder = OneHotEncoder()
gender_reshaped = np.array(customer['Gender']).reshape(-1, 1)
gender_values = gender_encoder.fit_transform(gender_reshaped)

print(customer['Gender'][:5])
print()
print(gender_values.toarray()[:5])
print()
print(gender_encoder.inverse_transform(gender_values)[:5])
```

```
0      Male
1      Male
2    Female
3    Female
4    Female
Name: Gender, dtype: object

[[0. 1.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [1. 0.]]

[['Male']
 ['Male']
 ['Female']
 ['Female']
 ['Female']]
```

```
#Create the encoded dataframe
# For 'ever_married' column
Gender = pd.DataFrame(marry_values, columns=['Gender'])

# For 'residence_type' column
Age = pd.DataFrame(residence_values, columns=['Age'])

# For 'gender' column
gender = pd.DataFrame(gender_values.toarray(), columns=['Female',
'Male'])
```

```
# Combine all categorical columns as one dataframe
df_categorical_encoded = pd.concat([Gender,Age], axis=1)

# The preview
print(df_categorical_encoded.shape)
df_categorical_encoded.head()
```

```
(200, 2)

   Gender  Age
0       1    0
1       1    1
2       0    2
3       0    3
4       0    4
```

```
df_new = pd.concat([customer, df_categorical_encoded], axis=1)

print(df_new.shape)
df_new.head()
```

```
(200, 7)

   CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)  \
0         1.0    Male  19.0                15.0
39.0
1         2.0    Male  21.0                15.0
81.0
2         3.0  Female  20.0                16.0
6.0
3         4.0  Female  23.0                16.0
77.0
4         5.0  Female  31.0                17.0
40.0

   Gender  Age
0       1    0
1       1    1
2       0    2
3       0    3
4       0    4
```

```
df_categorical_encoded = pd.get_dummies(customer, drop_first=True)
df_categorical_encoded.head()
```

```
   CustomerID   Age  Annual Income (k$)  Spending Score (1-100)
Gender_Male
```

```
0          1.0  19.0                15.0                       39.0
1
1          2.0  21.0                15.0                       81.0
1
2          3.0  20.0                16.0                        6.0
0
3          4.0  23.0                16.0                       77.0
0
4          5.0  31.0                17.0                       40.0
0
```

```
df_new = pd.concat([customer, df_categorical_encoded], axis=1)
df_new.head()
```

```
   CustomerID  Gender   Age  Annual Income (k$)  Spending Score (1-
100)  \
0          1.0    Male  19.0                15.0
39.0
1          2.0    Male  21.0                15.0
81.0
2          3.0  Female  20.0                16.0
6.0
3          4.0  Female  23.0                16.0
77.0
4          5.0  Female  31.0                17.0
40.0

   CustomerID   Age  Annual Income (k$)  Spending Score (1-100)
Gender_Male
0          1.0  19.0                15.0                       39.0
1
1          2.0  21.0                15.0                       81.0
1
2          3.0  20.0                16.0                        6.0
0
3          4.0  23.0                16.0                       77.0
0
4          5.0  31.0                17.0                       40.0
0
```

10.Scaling the data

```
customer.columns
```

```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

```
x=customer[["Age","CustomerID"]]
```

```
x
```

```
      Age  CustomerID
0    19.0         1.0
1    21.0         2.0
2    20.0         3.0
3    23.0         4.0
4    31.0         5.0
..    ...         ...
195  35.0       196.0
196  45.0       197.0
197  32.0       198.0
198  32.0       199.0
199  30.0       200.0

[200 rows x 2 columns]
```

```
x.head()
```

```
    Age  CustomerID
0  19.0         1.0
1  21.0         2.0
2  20.0         3.0
3  23.0         4.0
4  31.0         5.0
```

```
from sklearn.preprocessing import StandardScaler
```

```
scale = StandardScaler()
```

```
st_scale = scale.fit_transform(x)
```

```
st_scale
```

```
array([[-1.42456879, -1.7234121 ],
       [-1.28103541, -1.70609137],
       [-1.3528021 , -1.68877065],
       [-1.13750203, -1.67144992],
       [-0.56336851, -1.6541292 ],
       [-1.20926872, -1.63680847],
       [-0.27630176, -1.61948775],
       [-1.13750203, -1.60216702],
       [ 1.80493225, -1.5848463 ],
       [-0.6351352 , -1.56752558],
       [ 2.02023231, -1.55020485],
       [-0.27630176, -1.53288413],
       [ 1.37433211, -1.5155634 ],
       [-1.06573534, -1.49824268],
       [-0.13276838, -1.48092195],
       [-1.20926872, -1.46360123],
       [-0.27630176, -1.4462805 ],
       [-1.3528021 , -1.42895978],
       [ 0.94373197, -1.41163905],
       [-0.27630176, -1.39431833],
```

```
[-0.27630176, -1.3769976 ],
[-0.99396865, -1.35967688],
[ 0.51313183, -1.34235616],
[-0.56336851, -1.32503543],
[ 1.08726535, -1.30771471],
[-0.70690189, -1.29039398],
[ 0.44136514, -1.27307326],
[-0.27630176, -1.25575253],
[ 0.08253169, -1.23843181],
[-1.13750203, -1.22111108],
[ 1.51786549, -1.20379036],
[-1.28103541, -1.18646963],
[ 1.01549866, -1.16914891],
[-1.49633548, -1.15182818],
[ 0.7284319 , -1.13450746],
[-1.28103541, -1.11718674],
[ 0.22606507, -1.09986601],
[-0.6351352 , -1.08254529],
[-0.20453507, -1.06522456],
[-1.3528021 , -1.04790384],
[ 1.87669894, -1.03058311],
[-1.06573534, -1.01326239],
[ 0.65666521, -0.99594166],
[-0.56336851, -0.97862094],
[ 0.7284319 , -0.96130021],
[-1.06573534, -0.94397949],
[ 0.80019859, -0.92665877],
[-0.85043527, -0.90933804],
[-0.70690189, -0.89201732],
[-0.56336851, -0.87469659],
[ 0.7284319 , -0.85737587],
[-0.41983513, -0.84005514],
[-0.56336851, -0.82273442],
[ 1.4460988 , -0.80541369],
[ 0.80019859, -0.78809297],
[ 0.58489852, -0.77077224],
[ 0.87196528, -0.75345152],
[ 2.16376569, -0.73613079],
[-0.85043527, -0.71881007],
[ 1.01549866, -0.70148935],
[ 2.23553238, -0.68416862],
[-1.42456879, -0.6668479 ],
[ 2.02023231, -0.64952717],
[ 1.08726535, -0.63220645],
[ 1.73316556, -0.61488572],
[-1.49633548, -0.597565  ],
[ 0.29783176, -0.58024427],
[ 2.091999  , -0.56292355],
[-1.42456879, -0.54560282],
[-0.49160182, -0.5282821 ],
```

```
[ 2.23553238, -0.51096138],
[ 0.58489852, -0.49364065],
[ 1.51786549, -0.47631993],
[ 1.51786549, -0.4589992 ],
[ 1.4460988 , -0.44167848],
[-0.92220196, -0.42435775],
[ 0.44136514, -0.40703703],
[ 0.08253169, -0.3897163 ],
[-1.13750203, -0.37239558],
[ 0.7284319 , -0.35507485],
[ 1.30256542, -0.33775413],
[-0.06100169, -0.3204334 ],
[ 2.02023231, -0.30311268],
[ 0.51313183, -0.28579196],
[-1.28103541, -0.26847123],
[ 0.65666521, -0.25115051],
[ 1.15903204, -0.23382978],
[-1.20926872, -0.21650906],
[-0.34806844, -0.19918833],
[ 0.80019859, -0.18186761],
[ 2.091999  , -0.16454688],
[-1.49633548, -0.14722616],
[ 0.65666521, -0.12990543],
[ 0.08253169, -0.11258471],
[-0.49160182, -0.09526399],
[-1.06573534, -0.07794326],
[ 0.58489852, -0.06062254],
[-0.85043527, -0.04330181],
[ 0.65666521, -0.02598109],
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```python
# normalisation
from sklearn.preprocessing import MinMaxScaler

min_max = MinMaxScaler(feature_range=(0,1))
norm = min_max.fit_transform(x)

norm
```

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```

```
# robust scaler
from sklearn.preprocessing import RobustScaler

Rscale = RobustScaler()

RS = Rscale.fit_transform(x)

RS
```

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       [ 0.04938272,  0.80904523],
       [-0.19753086,  0.81909548],
       [ 0.49382716,  0.82914573],
       [-0.34567901,  0.83919598],
       [ 0.24691358,  0.84924623],
       [-0.2962963 ,  0.85929648],
       [ 0.88888889,  0.86934673],
       [-0.39506173,  0.87939698],
       [ 0.24691358,  0.88944724],
       [ 0.        ,  0.89949749],
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       [-0.19753086,  0.91959799],
       [-0.14814815,  0.92964824],
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       [ 0.44444444,  0.96984925],
       [-0.19753086,  0.9798995 ],
       [-0.19753086,  0.98994975],
       [-0.2962963 ,  1.        ]])
```

11.Perform any of the clustering algorithms

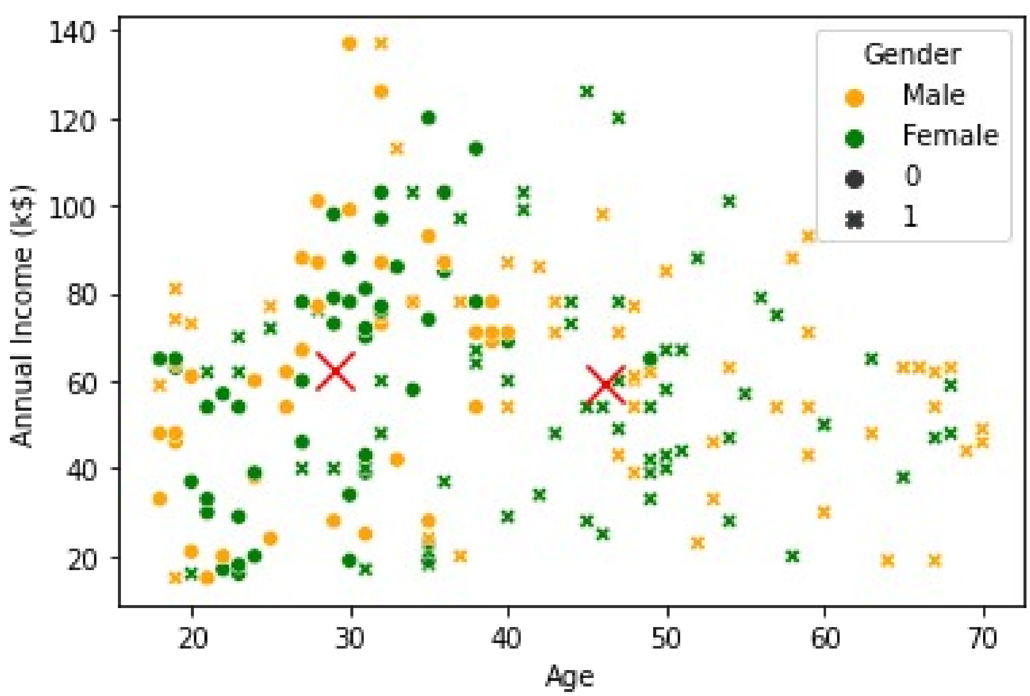
```
#K-MEANS CLUSTERING
yes = df.Gender

df = df.drop("Gender",axis = 1)

df.head()

    Age  Annual Income (k$)  Spending Score (1-100)
0  19.0                15.0                    39.0
1  21.0                15.0                    81.0
2  20.0                16.0                     6.0
3  23.0                16.0                    77.0
4  31.0                17.0                    40.0

from sklearn.cluster import KMeans

km = KMeans(
    n_clusters=2,
    random_state=10,
    init = "k-means++",
    n_init =20,
    max_iter=200
)

import warnings
warnings.filterwarnings("ignore")

km.fit(df)

KMeans(max_iter=200, n_clusters=2, n_init=20, random_state=10)

km.labels_

array([1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
0,
       1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
0,
       1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1,
0,
       1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1,
0,
       0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1,
1,
       1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 1,
0,
       1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
0,
       1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
0,
       1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
0,
       1, 0], dtype=int32)
```

```
df.head()
```

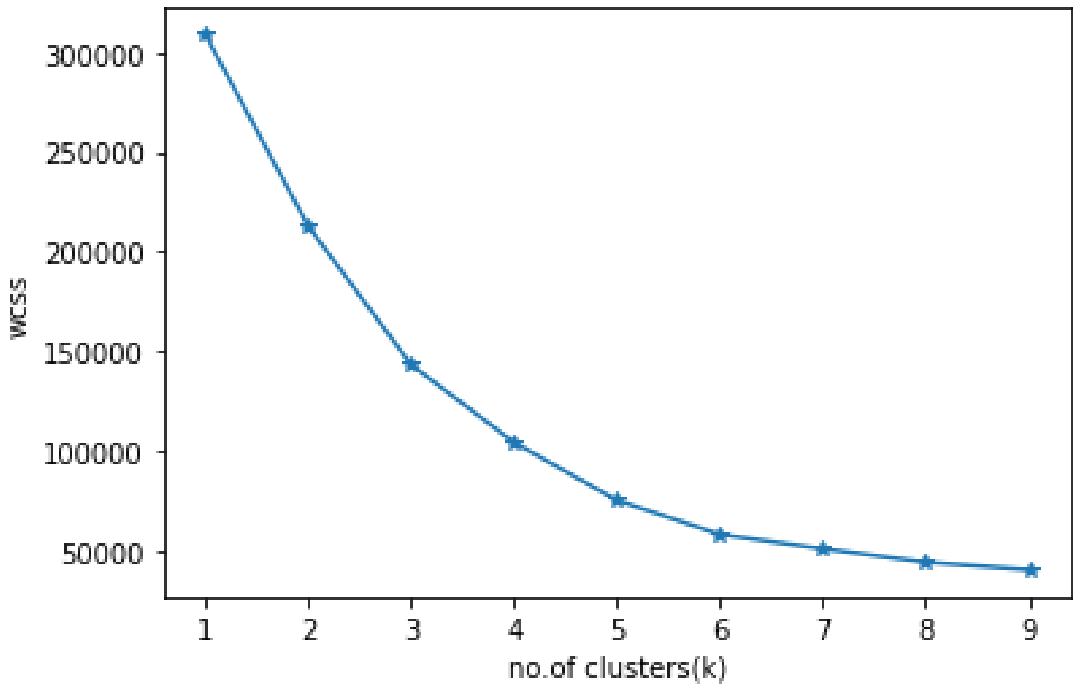
```
    Age  Annual Income (k$)  Spending Score (1-100)
0  19.0                15.0                    39.0
1  21.0                15.0                    81.0
2  20.0                16.0                     6.0
3  23.0                16.0                    77.0
4  31.0                17.0                    40.0
```

```
sns.scatterplot(
        x = "Age",
        y = "Annual Income (k$)",
        data = df,
        hue = yes,
        style = km.labels_,
        palette= ["orange","green"]
)

plt.scatter(
    km.cluster_centers_[:,0],
    km.cluster_centers_[:,1],
    marker= "x",
    s = 200,
    c = "red"
)
```

```
<matplotlib.collections.PathCollection at 0x7f8402caf450>
```



```
from sklearn.metrics import silhouette_score
from sklearn import cluster

silhouette_score(df,km.labels_)

0.293166070535953

k_means_model=cluster.KMeans(n_clusters=3,init='k-means+
+',random_state=0)

k_means_model.fit(df)

KMeans(n_clusters=3, random_state=0)

clustered_data =k_means_model.predict(df)

#Elbow Graph
wcss = []

for k in range(1,10):
    km = KMeans(n_clusters= k ,random_state=1,init = "k-means++",
n_init = 10)
    km.fit(df)
    error = km.inertia_
    wcss.append(error)


plt.plot(range(1,10),wcss,marker = "*")
plt.xlabel("no.of clusters(k)")
plt.ylabel("wcss")
plt.show()
```



12.Add Cluster data with primary set

```
df['Clustered_data'] = pd.Series(clustered_data)
df.head()
```

```
   CustomerID   Age  Annual Income (k$)  Spending Score (1-100)  \
0         1.0  19.0                15.0                    39.0
1         2.0  21.0                15.0                    81.0
2         3.0  20.0                16.0                     6.0
3         4.0  23.0                16.0                    77.0
4         5.0  31.0                17.0                    40.0

   Clustered_data
0               0
1               0
2               0
3               0
4               0
```

13.Split the data into dependent and independent variables

```
df.head(0)
```

```
Empty DataFrame
Columns: [CustomerID, Gender, Age, Annual Income (k$), Spending Score
(1-100)]
Index: []
```

```
x=df.iloc[:,1:2]
```

```
x
```

```
     Gender
0      Male
1      Male
2    Female
3    Female
4    Female
..      ...
195  Female
196  Female
197    Male
198    Male
199    Male

[200 rows x 1 columns]
```

```
y=df.iloc[:,1:]
```

```
y
```

```
      Age  Annual Income (k$)  Spending Score (1-100)  Clustered_data
0    19.0                15.0                    39.0               0
1    21.0                15.0                    81.0               0
2    20.0                16.0                     6.0               0
3    23.0                16.0                    77.0               0
4    31.0                17.0                    40.0               0
..    ...                 ...                     ...             ...
195  35.0               120.0                    79.0               2
196  45.0               126.0                    28.0               2
197  32.0               126.0                    74.0               2
198  32.0               137.0                    18.0               2
199  30.0               137.0                    83.0               2

[200 rows x 4 columns]
```

14.Split the data into training and testing

```
from sklearn.model_selection import train_test_split
```

```
df=df.rename(columns={'fit':'fit-feature'})
```

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,rando
m_state=0)
```

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((160, 1), (40, 1), (160, 4), (40, 4))
```

```
x_test
```

```
     Gender
18     Male
170    Male
107    Male
98     Male
177    Male
182    Male
5    Female
146    Male
12   Female
152  Female
61     Male
125  Female
180  Female
154  Female
80     Male
7    Female
33     Male
130    Male
37   Female
74     Male
183  Female
145    Male
45   Female
159  Female
60     Male
123    Male
179    Male
185    Male
122  Female
44   Female
16   Female
55     Male
150    Male
111  Female
22   Female
189  Female
129    Male
4    Female
83   Female
106  Female
```

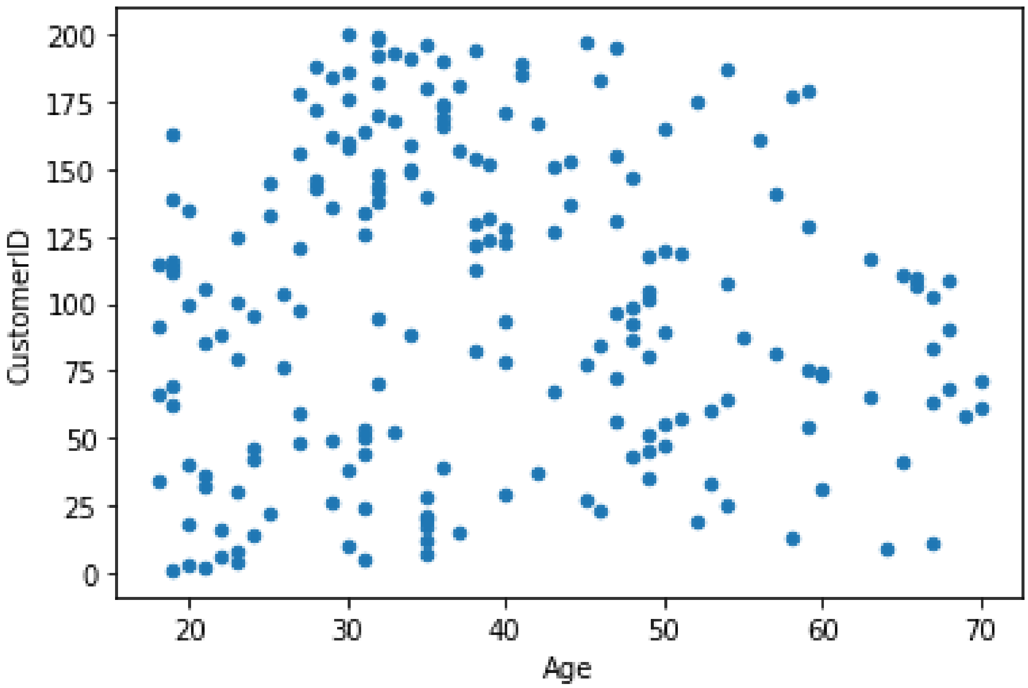
15.Build the model

```
from sklearn.linear_model import LinearRegression
```

```
lr=LinearRegression()
```

```
df.plot.scatter("Age","CustomerID")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f46f13ccd10>
```




```
from sklearn.linear_model import  LinearRegression

model=LinearRegression()

model.fit(x,y)

LinearRegression()

predict=model.predict(x)

predict

array([[19.        , 61.02272279, 62.20768706,  1.08321414],
       [21.        , 60.97610085, 60.99784453,  1.07785252],
       [20.        , 60.99941182, 61.6027658 ,  1.08053333],
       [23.        , 60.9294789 , 59.78800201,  1.07249089],
       [31.        , 60.74299113, 54.94863191,  1.05104438],
       [22.        , 60.95278987, 60.39292327,  1.0751717 ],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [23.        , 60.9294789 , 59.78800201,  1.07249089],
       [64.        , 59.97372906, 34.98623025,  0.96257755],
       [30.        , 60.7663021 , 55.55355317,  1.0537252 ],
       [67.        , 59.90379614, 33.17146646,  0.95453511],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [58.        , 60.11359489, 38.61575783,  0.97866243],
       [24.        , 60.90616793, 59.18308075,  1.06981008],
       [37.        , 60.6031253 , 51.31910434,  1.0349595 ],
       [22.        , 60.95278987, 60.39292327,  1.0751717 ],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [20.        , 60.99941182, 61.6027658 ,  1.08053333],
```

```
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```

```
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```

```
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```

```
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       [32.        , 60.71968016, 54.34371065,  1.04836357],
       [40.        , 60.53319238, 49.50434055,  1.02691706],
       [28.        , 60.81292404, 56.7633957 ,  1.05908682],
       [36.        , 60.62643627, 51.9240256 ,  1.03764032],
       [36.        , 60.62643627, 51.9240256 ,  1.03764032],
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       [30.        , 60.7663021 , 55.55355317,  1.0537252 ],
       [58.        , 60.11359489, 38.61575783,  0.97866243],
       [27.        , 60.83623502, 57.36831696,  1.06176764],
       [59.        , 60.09028392, 38.01083656,  0.97598161],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [37.        , 60.6031253 , 51.31910434,  1.0349595 ],
       [32.        , 60.71968016, 54.34371065,  1.04836357],
       [46.        , 60.39332655, 45.87481297,  1.01083219],
       [29.        , 60.78961307, 56.15847443,  1.05640601],
       [41.        , 60.50988141, 48.89941929,  1.02423625],
       [30.        , 60.7663021 , 55.55355317,  1.0537252 ],
       [54.        , 60.20683878, 41.03544287,  0.98938568],
       [28.        , 60.81292404, 56.7633957 ,  1.05908682],
       [41.        , 60.50988141, 48.89941929,  1.02423625],
       [36.        , 60.62643627, 51.9240256 ,  1.03764032],
       [34.        , 60.67305821, 53.13386812,  1.04300194],
       [32.        , 60.71968016, 54.34371065,  1.04836357],
       [33.        , 60.69636918, 53.73878938,  1.04568276],
       [38.        , 60.57981433, 50.71418307,  1.03227869],
       [47.        , 60.37001558, 45.26989171,  1.00815137],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [45.        , 60.41663752, 46.47973424,  1.013513  ],
       [32.        , 60.71968016, 54.34371065,  1.04836357],
       [32.        , 60.71968016, 54.34371065,  1.04836357],
       [30.        , 60.7663021 , 55.55355317,  1.0537252 ]])
```

16.Train the model

```
train=df.sample(frac=0.8,random_state=200)
```

```
train
```

```
     CustomerID   Age  Annual Income (k$)  Spending Score (1-100)  \
121       122.0  38.0                67.0                    40.0
169       170.0  32.0                87.0                    63.0
194       195.0  47.0               120.0                    16.0
125       126.0  31.0                70.0                    77.0
36         37.0  42.0                34.0                    17.0
..          ...   ...                 ...                     ...
90         91.0  68.0                59.0                    55.0
162       163.0  19.0                81.0                     5.0
3           4.0  23.0                16.0                    77.0
120       121.0  27.0                67.0                    56.0
95         96.0  24.0                60.0                    52.0
```

```
     Clustered_data
121               1
169               2
194               2
125               1
36                0
..              ...
90                1
162               2
3                 0
120               1
95                1

[160 rows x 5 columns]
```

```
pred_train = model.predict(x_train)
pred_train
```

```
array([[20.        , 60.99941182, 61.6027658 ,  1.08053333],
       [43.        , 60.46325947, 47.68957676,  1.01887462],
       [45.        , 60.41663752, 46.47973424,  1.013513  ],
       [19.        , 61.02272279, 62.20768706,  1.08321414],
       [36.        , 60.62643627, 51.9240256 ,  1.03764032],
       [54.        , 60.20683878, 41.03544287,  0.98938568],
       [64.        , 59.97372906, 34.98623025,  0.96257755],
       [26.        , 60.85954599, 57.97323822,  1.06444845],
       [51.        , 60.27677169, 42.85020666,  0.99742812],
       [32.        , 60.71968016, 54.34371065,  1.04836357],
       [47.        , 60.37001558, 45.26989171,  1.00815137],
       [23.        , 60.9294789 , 59.78800201,  1.07249089],
       [41.        , 60.50988141, 48.89941929,  1.02423625],
       [27.        , 60.83623502, 57.36831696,  1.06176764],
       [34.        , 60.67305821, 53.13386812,  1.04300194],
       [54.        , 60.20683878, 41.03544287,  0.98938568],
       [60.        , 60.06697295, 37.4059153 ,  0.9733008 ],
       [56.        , 60.16021683, 39.82560035,  0.98402405],
       [65.        , 59.95041809, 34.38130899,  0.95989673],
       [51.        , 60.27677169, 42.85020666,  0.99742812],
       [39.        , 60.55650335, 50.10926181,  1.02959788],
       [47.        , 60.37001558, 45.26989171,  1.00815137],
       [32.        , 60.71968016, 54.34371065,  1.04836357],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [38.        , 60.57981433, 50.71418307,  1.03227869],
       [48.        , 60.34670461, 44.66497045,  1.00547056],
       [50.        , 60.30008266, 43.45512792,  1.00010893],
       [31.        , 60.74299113, 54.94863191,  1.05104438],
       [33.        , 60.69636918, 53.73878938,  1.04568276],
       [55.        , 60.18352781, 40.43052161,  0.98670487],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
```

```
[68.        , 59.88048517, 32.5665452 ,  0.95185429],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[49.        , 60.32339364, 44.06004919,  1.00278975],
[25.        , 60.88285696, 58.57815948,  1.06712926],
[50.        , 60.30008266, 43.45512792,  1.00010893],
[66.        , 59.92710712, 33.77638773,  0.95721592],
[37.        , 60.6031253 , 51.31910434,  1.0349595 ],
[35.        , 60.64974724, 52.52894686,  1.04032113],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[28.        , 60.81292404, 56.7633957 ,  1.05908682],
[50.        , 60.30008266, 43.45512792,  1.00010893],
[19.        , 61.02272279, 62.20768706,  1.08321414],
[35.        , 60.64974724, 52.52894686,  1.04032113],
[68.        , 59.88048517, 32.5665452 ,  0.95185429],
[67.        , 59.90379614, 33.17146646,  0.95453511],
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[44.        , 60.4399485 , 47.0846555 ,  1.01619381],
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[47.        , 60.37001558, 45.26989171,  1.00815137],
[60.        , 60.06697295, 37.4059153 ,  0.9733008 ],
[45.        , 60.41663752, 46.47973424,  1.013513  ],
[59.        , 60.09028392, 38.01083656,  0.97598161],
[30.        , 60.7663021 , 55.55355317,  1.0537252 ],
[43.        , 60.46325947, 47.68957676,  1.01887462],
[40.        , 60.53319238, 49.50434055,  1.02691706],
[38.        , 60.57981433, 50.71418307,  1.03227869],
[34.        , 60.67305821, 53.13386812,  1.04300194],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[49.        , 60.32339364, 44.06004919,  1.00278975],
[19.        , 61.02272279, 62.20768706,  1.08321414],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[65.        , 59.95041809, 34.38130899,  0.95989673],
[24.        , 60.90616793, 59.18308075,  1.06981008],
[63.        , 59.99704003, 35.59115151,  0.96525836],
[33.        , 60.69636918, 53.73878938,  1.04568276],
[24.        , 60.90616793, 59.18308075,  1.06981008],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[31.        , 60.74299113, 54.94863191,  1.05104438],
[29.        , 60.78961307, 56.15847443,  1.05640601],
[48.        , 60.34670461, 44.66497045,  1.00547056],
[24.        , 60.90616793, 59.18308075,  1.06981008],
[29.        , 60.78961307, 56.15847443,  1.05640601],
[31.        , 60.74299113, 54.94863191,  1.05104438],
[54.        , 60.20683878, 41.03544287,  0.98938568],
[29.        , 60.78961307, 56.15847443,  1.05640601],
[35.        , 60.64974724, 52.52894686,  1.04032113],
[22.        , 60.95278987, 60.39292327,  1.0751717 ],
```

```
[23.        , 60.9294789 , 59.78800201,  1.07249089],
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[31.        , 60.74299113, 54.94863191,  1.05104438],
[23.        , 60.9294789 , 59.78800201,  1.07249089],
[45.        , 60.41663752, 46.47973424,  1.013513  ],
[23.        , 60.9294789 , 59.78800201,  1.07249089],
[63.        , 59.99704003, 35.59115151,  0.96525836],
[50.        , 60.30008266, 43.45512792,  1.00010893],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[35.        , 60.64974724, 52.52894686,  1.04032113],
[19.        , 61.02272279, 62.20768706,  1.08321414],
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[38.        , 60.57981433, 50.71418307,  1.03227869],
[27.        , 60.83623502, 57.36831696,  1.06176764],
[28.        , 60.81292404, 56.7633957 ,  1.05908682],
[37.        , 60.6031253 , 51.31910434,  1.0349595 ],
[18.        , 61.04603376, 62.81260832,  1.08589496],
[30.        , 60.7663021 , 55.55355317,  1.0537252 ],
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[19.        , 61.02272279, 62.20768706,  1.08321414],
[48.        , 60.34670461, 44.66497045,  1.00547056],
[21.        , 60.97610085, 60.99784453,  1.07785252],
[25.        , 60.88285696, 58.57815948,  1.06712926],
[36.        , 60.62643627, 51.9240256 ,  1.03764032],
[20.        , 60.99941182, 61.6027658 ,  1.08053333],
[36.        , 60.62643627, 51.9240256 ,  1.03764032],
[31.        , 60.74299113, 54.94863191,  1.05104438],
[59.        , 60.09028392, 38.01083656,  0.97598161],
[30.        , 60.7663021 , 55.55355317,  1.0537252 ],
[59.        , 60.09028392, 38.01083656,  0.97598161],
[49.        , 60.32339364, 44.06004919,  1.00278975],
[40.        , 60.53319238, 49.50434055,  1.02691706],
[18.        , 61.04603376, 62.81260832,  1.08589496],
[39.        , 60.55650335, 50.10926181,  1.02959788],
[21.        , 60.97610085, 60.99784453,  1.07785252],
[42.        , 60.48657044, 48.29449802,  1.02155544],
[40.        , 60.53319238, 49.50434055,  1.02691706],
[58.        , 60.11359489, 38.61575783,  0.97866243],
[53.        , 60.23014975, 41.64036414,  0.99206649],
[28.        , 60.81292404, 56.7633957 ,  1.05908682],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[32.        , 60.71968016, 54.34371065,  1.04836357],
[23.        , 60.9294789 , 59.78800201,  1.07249089],
```

```
       [20.        , 60.99941182, 61.6027658 ,  1.08053333],
       [67.        , 59.90379614, 33.17146646,  0.95453511],
       [49.        , 60.32339364, 44.06004919,  1.00278975],
       [19.        , 61.02272279, 62.20768706,  1.08321414],
       [34.        , 60.67305821, 53.13386812,  1.04300194],
       [38.        , 60.57981433, 50.71418307,  1.03227869],
       [60.        , 60.06697295, 37.4059153 ,  0.9733008 ],
       [40.        , 60.53319238, 49.50434055,  1.02691706],
       [29.        , 60.78961307, 56.15847443,  1.05640601],
       [36.        , 60.62643627, 51.9240256 ,  1.03764032],
       [38.        , 60.57981433, 50.71418307,  1.03227869],
       [41.        , 60.50988141, 48.89941929,  1.02423625],
       [52.        , 60.25346072, 42.2452854 ,  0.99474731],
       [34.        , 60.67305821, 53.13386812,  1.04300194],
       [20.        , 60.99941182, 61.6027658 ,  1.08053333],
       [27.        , 60.83623502, 57.36831696,  1.06176764],
       [57.        , 60.13690586, 39.22067909,  0.98134324],
       [34.        , 60.67305821, 53.13386812,  1.04300194],
       [70.        , 59.83386323, 31.35670268,  0.94649267],
       [22.        , 60.95278987, 60.39292327,  1.0751717 ],
       [42.        , 60.48657044, 48.29449802,  1.02155544],
       [25.        , 60.88285696, 58.57815948,  1.06712926],
       [30.        , 60.7663021 , 55.55355317,  1.0537252 ],
       [26.        , 60.85954599, 57.97323822,  1.06444845],
       [68.        , 59.88048517, 32.5665452 ,  0.95185429],
       [33.        , 60.69636918, 53.73878938,  1.04568276],
       [49.        , 60.32339364, 44.06004919,  1.00278975],
       [27.        , 60.83623502, 57.36831696,  1.06176764],
       [36.        , 60.62643627, 51.9240256 ,  1.03764032]])
```

17.Test the Model

```
y_test
```

	Age	Annual Income (k$)	Spending Score (1-100)	Clustered_data
18	52.0	23.0	29.0	0
170	40.0	87.0	13.0	2
107	54.0	63.0	46.0	1
98	48.0	61.0	42.0	1
177	27.0	88.0	69.0	2
182	46.0	98.0	15.0	2
5	22.0	17.0	76.0	0
146	48.0	77.0	36.0	2
12	58.0	20.0	15.0	0
152	44.0	78.0	20.0	2
61	19.0	46.0	55.0	0
125	31.0	70.0	77.0	1
180	37.0	97.0	32.0	2
154	47.0	78.0	16.0	2
80	57.0	54.0	51.0	1
7	23.0	18.0	94.0	0

```
33   18.0                33.0                     92.0              0
130  47.0                71.0                      9.0              1
37   30.0                34.0                     73.0              0
74   59.0                54.0                     47.0              1
183  29.0                98.0                     88.0              2
145  28.0                77.0                     97.0              2
45   24.0                39.0                     65.0              0
159  30.0                78.0                     73.0              2
60   70.0                46.0                     56.0              0
123  39.0                69.0                     91.0              1
179  35.0                93.0                     90.0              2
185  30.0                99.0                     97.0              2
122  40.0                69.0                     58.0              1
44   49.0                39.0                     28.0              0
16   35.0                21.0                     35.0              0
55   47.0                43.0                     41.0              0
150  43.0                78.0                     17.0              2
111  19.0                63.0                     54.0              1
22   46.0                25.0                      5.0              0
189  36.0               103.0                     85.0              2
129  38.0                71.0                     75.0              1
4    31.0                17.0                     40.0              0
83   46.0                54.0                     44.0              1
106  66.0                63.0                     50.0              1
```

```
pred_test=model.predict(x_test)
pred_test
```

```
array([[52.        , 60.25346072, 42.2452854 ,  0.99474731],
       [40.        , 60.53319238, 49.50434055,  1.02691706],
       [54.        , 60.20683878, 41.03544287,  0.98938568],
       [48.        , 60.34670461, 44.66497045,  1.00547056],
       [27.        , 60.83623502, 57.36831696,  1.06176764],
       [46.        , 60.39332655, 45.87481297,  1.01083219],
       [22.        , 60.95278987, 60.39292327,  1.0751717 ],
       [48.        , 60.34670461, 44.66497045,  1.00547056],
       [58.        , 60.11359489, 38.61575783,  0.97866243],
       [44.        , 60.4399485 , 47.0846555 ,  1.01619381],
       [19.        , 61.02272279, 62.20768706,  1.08321414],
       [31.        , 60.74299113, 54.94863191,  1.05104438],
       [37.        , 60.6031253 , 51.31910434,  1.0349595 ],
       [47.        , 60.37001558, 45.26989171,  1.00815137],
       [57.        , 60.13690586, 39.22067909,  0.98134324],
       [23.        , 60.9294789 , 59.78800201,  1.07249089],
       [18.        , 61.04603376, 62.81260832,  1.08589496],
       [47.        , 60.37001558, 45.26989171,  1.00815137],
       [30.        , 60.7663021 , 55.55355317,  1.0537252 ],
       [59.        , 60.09028392, 38.01083656,  0.97598161],
       [29.        , 60.78961307, 56.15847443,  1.05640601],
       [28.        , 60.81292404, 56.7633957 ,  1.05908682],
       [24.        , 60.90616793, 59.18308075,  1.06981008],
```

```
       [30.        , 60.7663021 , 55.55355317,  1.0537252 ],
       [70.        , 59.83386323, 31.35670268,  0.94649267],
       [39.        , 60.55650335, 50.10926181,  1.02959788],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [30.        , 60.7663021 , 55.55355317,  1.0537252 ],
       [40.        , 60.53319238, 49.50434055,  1.02691706],
       [49.        , 60.32339364, 44.06004919,  1.00278975],
       [35.        , 60.64974724, 52.52894686,  1.04032113],
       [47.        , 60.37001558, 45.26989171,  1.00815137],
       [43.        , 60.46325947, 47.68957676,  1.01887462],
       [19.        , 61.02272279, 62.20768706,  1.08321414],
       [46.        , 60.39332655, 45.87481297,  1.01083219],
       [36.        , 60.62643627, 51.9240256 ,  1.03764032],
       [38.        , 60.57981433, 50.71418307,  1.03227869],
       [31.        , 60.74299113, 54.94863191,  1.05104438],
       [46.        , 60.39332655, 45.87481297,  1.01083219],
       [66.        , 59.92710712, 33.77638773,  0.95721592]])
```

```
from sklearn.linear_model import LinearRegression
```

```
lr = LinearRegression()
```

18.Measure the performance using evaluation metrics

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

```
customer= pd.read_excel("Mall_Customers.xlsx")
```

```
x=df.iloc[:,1:]
```

```
x
```

```
      Age  Annual Income (k$)  Spending Score (1-100)
0    19.0                15.0                    39.0
1    21.0                15.0                    81.0
2    20.0                16.0                     6.0
3    23.0                16.0                    77.0
4    31.0                17.0                    40.0
..    ...                 ...                     ...
195  35.0               120.0                    79.0
196  45.0               126.0                    28.0
197  32.0               126.0                    74.0
198  32.0               137.0                    18.0
199  30.0               137.0                    83.0

[200 rows x 3 columns]
```

```
y=df.iloc[:,1:]
```

```
y
```

```
      Age  Annual Income (k$)  Spending Score (1-100)
0    19.0                15.0                    39.0
1    21.0                15.0                    81.0
2    20.0                16.0                     6.0
3    23.0                16.0                    77.0
4    31.0                17.0                    40.0
..    ...                 ...                     ...
195  35.0               120.0                    79.0
196  45.0               126.0                    28.0
197  32.0               126.0                    74.0
198  32.0               137.0                    18.0
199  30.0               137.0                    83.0

[200 rows x 3 columns]
```

```
from sklearn.model_selection import train_test_split
```

```
df=df.rename(columns={'fit':'fit-feature'})
```

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,rando
m_state=0)
```

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((160, 3), (40, 3), (160, 3), (40, 3))
```

```
x_test
```

	Age	Annual Income (k$)	Spending Score (1-100)
18	52.0	23.0	29.0
170	40.0	87.0	13.0
107	54.0	63.0	46.0
98	48.0	61.0	42.0
177	27.0	88.0	69.0
182	46.0	98.0	15.0
5	22.0	17.0	76.0
146	48.0	77.0	36.0
12	58.0	20.0	15.0
152	44.0	78.0	20.0
61	19.0	46.0	55.0
125	31.0	70.0	77.0
180	37.0	97.0	32.0
154	47.0	78.0	16.0
80	57.0	54.0	51.0
7	23.0	18.0	94.0
33	18.0	33.0	92.0
130	47.0	71.0	9.0
37	30.0	34.0	73.0
74	59.0	54.0	47.0
183	29.0	98.0	88.0
145	28.0	77.0	97.0
45	24.0	39.0	65.0
159	30.0	78.0	73.0
60	70.0	46.0	56.0
123	39.0	69.0	91.0
179	35.0	93.0	90.0
185	30.0	99.0	97.0
122	40.0	69.0	58.0
44	49.0	39.0	28.0
16	35.0	21.0	35.0
55	47.0	43.0	41.0
150	43.0	78.0	17.0
111	19.0	63.0	54.0
22	46.0	25.0	5.0
189	36.0	103.0	85.0
129	38.0	71.0	75.0
4	31.0	17.0	40.0

```
83   46.0                54.0                     44.0
106  66.0                63.0                     50.0
```

```
from sklearn.metrics import r2_score
```

```
from sklearn.linear_model import LinearRegression
```

```
lr = LinearRegression()
```

```
df = df.replace("Male",2)
```

```
lr.fit(x_train,y_train)
```

```
LinearRegression()
```

```
lr.coef_  , lr.intercept_
```

```
(array([[ 1.00000000e+00,  1.32312315e-17, -7.16567384e-18],
        [-1.26527940e-16,  1.00000000e+00, -3.33066907e-16],
        [ 3.03558876e-17,  0.00000000e+00,  1.00000000e+00]]),
 array([-1.42108547e-14,  4.26325641e-14, -1.42108547e-14]))
```

```
y_pred = lr.predict(x_test)
```

```
y_pred
```

```
array([[ 52.,  23.,  29.],
       [ 40.,  87.,  13.],
       [ 54.,  63.,  46.],
       [ 48.,  61.,  42.],
       [ 27.,  88.,  69.],
       [ 46.,  98.,  15.],
       [ 22.,  17.,  76.],
       [ 48.,  77.,  36.],
       [ 58.,  20.,  15.],
       [ 44.,  78.,  20.],
       [ 19.,  46.,  55.],
       [ 31.,  70.,  77.],
       [ 37.,  97.,  32.],
       [ 47.,  78.,  16.],
       [ 57.,  54.,  51.],
       [ 23.,  18.,  94.],
       [ 18.,  33.,  92.],
       [ 47.,  71.,   9.],
       [ 30.,  34.,  73.],
       [ 59.,  54.,  47.],
       [ 29.,  98.,  88.],
       [ 28.,  77.,  97.],
       [ 24.,  39.,  65.],
       [ 30.,  78.,  73.],
       [ 70.,  46.,  56.],
       [ 39.,  69.,  91.],
       [ 35.,  93.,  90.],
```

```
       [ 30.,  99.,  97.],
       [ 40.,  69.,  58.],
       [ 49.,  39.,  28.],
       [ 35.,  21.,  35.],
       [ 47.,  43.,  41.],
       [ 43.,  78.,  17.],
       [ 19.,  63.,  54.],
       [ 46.,  25.,   5.],
       [ 36., 103.,  85.],
       [ 38.,  71.,  75.],
       [ 31.,  17.,  40.],
       [ 46.,  54.,  44.],
       [ 66.,  63.,  50.]])
```

```
score = r2_score(y_test,y_pred)
```

```
score
```

```
1.0
```