# ASSIGNMENT – 4

| | |
|---|---|
| Assignment Date | 28 october |
| Student Name | Ms. M. Priyadharshini |
| Student Roll Number | 913219106004 |
| Maximum Marks | 2 marks |

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

**2) LOAD DATASET**

InÂ [2]:
```
f1=pd.read_csv("Mall_Customers.csv")
```

InÂ [3]:
```
f1.head()
```

Out[3]:

| | CustomerID | Gender | 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 |

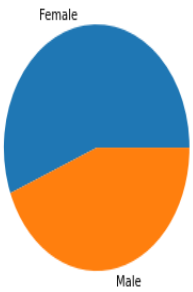
InÂ [4]:
```
f1.columns
```

Out[4]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

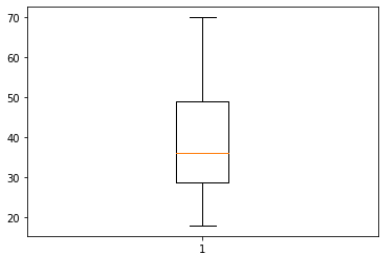
**3) PERFORM VISUALIZATIONS**

**3.1 UNIVARIATE ANALYSIS**

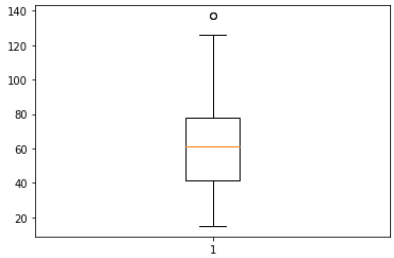
[nÂ [5]:
```
#pie chart
data1=f1.groupby("Gender",axis=0)
plt.pie(data1.count()["Age"], labels=data1.indices)
plt.show()
```



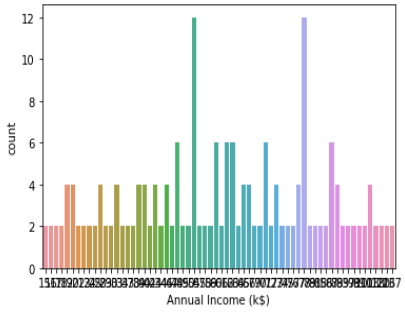
InÂ [6]:
```
#boxplot
plt.boxplot(f1["Age"])
plt.show()
```




InÂ [7]:
```
#boxplot
plt.boxplot(f1["Annual Income (k$)"])
plt.show()
```

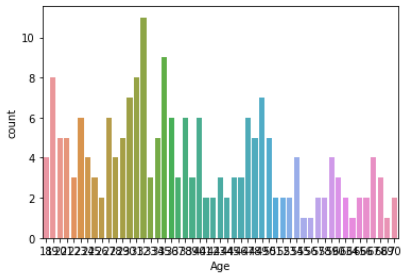



InÂ [11…
```
#countplot
sns.countplot(x=f1["Annual Income (k$)"])
plt.show()
```



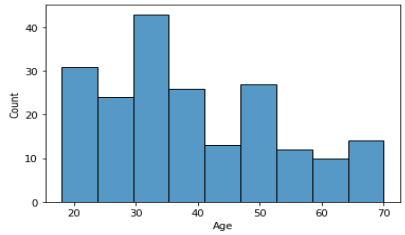
InÂ [12…

```
#countplot
sns.countplot(x=f1["Age"])
plt.show()
```




InÂ [13…

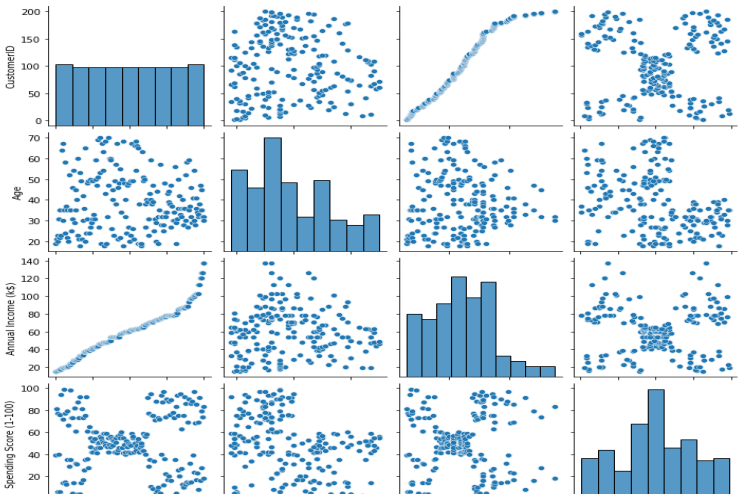
```
#histplot
sns.histplot(f1["Age"])
plt.show()
```

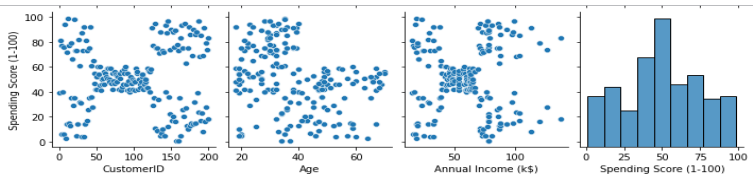



### 3.2 BI-VARIATE ANALYSIS

[15…

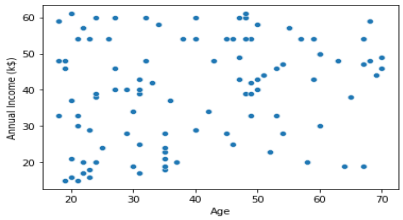
```
#pairplot
sns.pairplot(f1)
plt.show()
```






InÂ [17…

```
#scatterplot for Age and Annual Income (k$)
sns.scatterplot(x=f1.iloc[:100,:]["Age"],y=f1.iloc[:100,:]["Annual Income (k$)"])
plt.show()
```

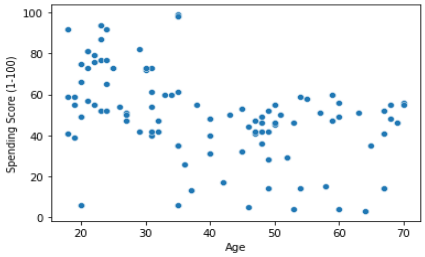



InÂ [18…

```
#scatterplot for Age and Spending Score (1-100)
sns.scatterplot(x=f1.iloc[:100,:]["Age"],y=f1.iloc[:100,:]["Spending Score (1-100)"])
plt.show()
```

In […

```
#scatterplot for Age and Spending Score (1-100)
sns.scatterplot(x=f1.iloc[:100,:]["Age"],y=f1.iloc[:100,:]["Spending Score (1-100)"])
plt.show()
```




### 3.3 MULTI-VARIATE ANALYSIS

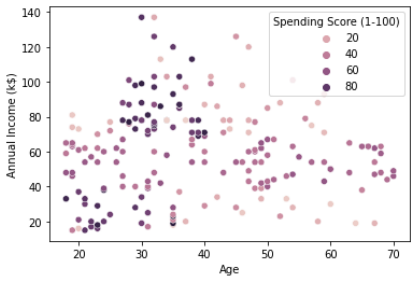
In […

```
#scatterplot for Age, Annual Income (k$) and Spending Score (1-100)
sns.scatterplot(x=f1.iloc[:200,:]["Age"],y=f1.iloc[:200,:]["Annual Income (k$)"],hue=f1.iloc[:200,:]["Spending Score (1-100)"])
plt.show()
```

### 3.3 MULTI-VARIATE ANALYSIS

InÂ [19…

```
#scatterplot for Age, Annual Income (k$) and Spending Score (1-100)
sns.scatterplot(x=f1.iloc[:200,:]["Age"],y=f1.iloc[:200,:]["Annual Income (k$)"],hue=f1.iloc[:200,:]["Spending Score (1-100)"])
plt.show()
```



### 4) PERFORM DESCRIPTIVE STATISTICS ON THE DATASET

InÂ [20…
```
f1.describe()
```

Out[20]:

| | 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 |

InÂ [21…
```
f1.mode(numeric_only=True)
```

Out[21]:

| | CustomerID | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|
| **0** | 1 | 32.0 | 54.0 | 42.0 |
| **1** | 2 | NaN | 78.0 | NaN |
| **2** | 3 | NaN | NaN | NaN |
| **3** | 4 | NaN | NaN | NaN |
| **4** | 5 | NaN | NaN | NaN |
| **...** | ... | ... | ... | ... |
| **195** | 196 | NaN | NaN | NaN |
| **196** | 197 | NaN | NaN | NaN |
| **197** | 198 | NaN | NaN | NaN |
| **198** | 199 | NaN | NaN | NaN |
| **199** | 200 | NaN | NaN | NaN |

200 rows ÃƒÂ— 4 columns

InÂ [22…
```
f1.median(numeric_only=True)
```

Out[22]:
```
CustomerID                100.5
Age                        36.0
Annual Income (k$)         61.5
Spending Score (1-100)     50.0
dtype: float64
```

InÂ [23…
```
f1.skew(numeric_only=True)
```

Out[23]:
```
CustomerID                0.000000
Age                       0.485569
Annual Income (k$)        0.321843
Spending Score (1-100)   -0.047220
dtype: float64
```

InÂ [24…
```
f1.kurt(numeric_only=True)
```

Out[24]:
```
CustomerID               -1.200000
Age                      -0.671573
Annual Income (k$)       -0.098487
Spending Score (1-100)   -0.826629
dtype: float64
```

### 5) HANDLE MISSING VALUES

InÂ [25…
```
#find the null columns
f1.isnull().sum()
```

Out[25]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

InÂ [23…
```
f1.skew(numeric_only=True)
```

Out[23]:
```
CustomerID              0.000000
Age                     0.485569
Annual Income (k$)      0.321843
Spending Score (1-100)  -0.047220
dtype: float64
```

InÂ [24…
```
f1.kurt(numeric_only=True)
```

Out[24]:
```
CustomerID              -1.200000
Age                     -0.671573
Annual Income (k$)      -0.098487
Spending Score (1-100)  -0.826629
dtype: float64
```

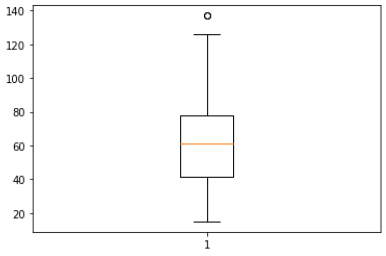
**5) HANDLE MISSING VALUES**

InÂ [25…
```
#find the null columns
f1.isnull().sum()
```

Out[25]:
```
CustomerID              0
Gender                  0
Age                     0
Annual Income (k$)      0
Spending Score (1-100)  0
dtype: int64
```

**6) FIND THE OUTLIERS AND REPLACE THE OUTLIERS**

InÂ [36…
```
#find outliers-Annual Income (k$)
plt.boxplot(f1["Annual Income (k$)"])
plt.show()
```




InÂ [37…
```
#handling outliers: InterQuartile Range(IQR)
Q3=np.percentile(f1["Annual Income (k$)"],75,interpolation='midpoint')
Q1=np.percentile(f1["Annual Income (k$)"],25,interpolation='midpoint')
IQR=Q3-Q1
print("Q1: ", Q1)
print("Q3:", Q3)
print("IQR: ", IQR)
```

```
Q1:  41.0
Q3: 78.0
IQR:  37.0
```

InÂ [38…
```
upperOutlayers=Q3+1.5*IQR
lowerOutlayers=Q1-1.5*IQR
print(upperOutlayers)
print(lowerOutlayers)
```

```
133.5
-14.5
```

InÂ [39…
```
f1.drop(np.where(f1["Annual Income (k$)"]>=upperOutlayers)[0],inplace=True)
f1.drop(np.where(f1["Annual Income (k$)"]<=lowerOutlayers)[0],inplace=True)
```

InÂ [40…
```
#find outliers-Spending Score (1-100)
plt.boxplot(f1["Spending Score (1-100)"])
plt.show()
```

InÂ [37…
```
#handling outliers: InterQuartile Range(IQR)
Q3=np.percentile(f1["Annual Income (k$)"],75,interpolation='midpoint')
Q1=np.percentile(f1["Annual Income (k$)"],25,interpolation='midpoint')
IQR=Q3-Q1
print("Q1: ", Q1)
print("Q3:", Q3)
print("IQR: ", IQR)
```

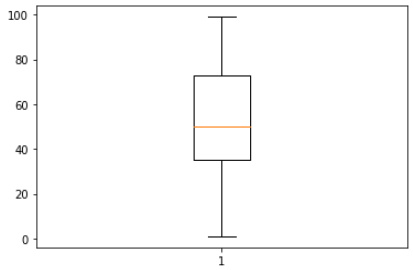
```
Q1:  41.0
Q3: 78.0
IQR:  37.0
```

InÂ [38…
```
upperOutlayers=Q3+1.5*IQR
lowerOutlayers=Q1-1.5*IQR
print(upperOutlayers)
print(lowerOutlayers)
```

```
133.5
-14.5
```

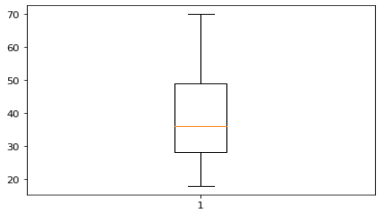
InÂ [39…
```
f1.drop(np.where(f1["Annual Income (k$)"]>=upperOutlayers)[0],inplace=True)
f1.drop(np.where(f1["Annual Income (k$)"]<=lowerOutlayers)[0],inplace=True)
```

InÂ [40…
```
#find outliers-Spending Score (1-100)
plt.boxplot(f1["Spending Score (1-100)"])
plt.show()
```




1…
```
#find outliers-Age
plt.boxplot(f1["Age"])
plt.show()
```

InÂ [41…
```
#find outliers-Age
plt.boxplot(f1["Age"])
plt.show()
```




**7) CHECK FOR CATEGORICAL COLUMNS AND PERFORM ENCODING**

InÂ [42…
```
f1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 198 entries, 0 to 197
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   CustomerID              198 non-null    int64 
 1   Gender                  198 non-null    object
 2   Age                     198 non-null    int64 
 3   Annual Income (k$)      198 non-null    int64 
 4   Spending Score (1-100)  198 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 17.4+ KB
```

InÂ [43…
```
from sklearn.preprocessing import LabelEncoder
```

InÂ [45…
```
encod=LabelEncoder()
f1['Spending Score (1-100)']=encod.fit_transform(f1['Spending Score (1-100)'])
```

InÂ [48…
```
print(f1["Spending Score (1-100)"].unique())
```

```
[29 66  4 63 30 62 78  1 58 12 82 13 11 65 27 54 23 81 59  3 67 25 51 24
 71  2 76 15 20 61 28 22 53 45 37 32 42 50 44 35 31 40 36 41 46 49 38 39
 43 34 47 48 33 75 79  9  7 26 57 72  5  8 77 10 80 60 17 74 16 14 73  0
 64 68 21 52 70 56 19 55 69 18  6]
```

[46…
```
f1.head()
```

:[46]:

| | CustomerID | Gender | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|---|
| **0** | 1 | Male | 19 | 15 | 29 |
| **1** | 2 | Male | 21 | 15 | 66 |
| **2** | 3 | Female | 20 | 16 | 4 |
| **3** | 4 | Female | 23 | 16 | 63 |
| **4** | 5 | Female | 31 | 17 | 30 |

[47…
```
f1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 198 entries, 0 to 197
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   CustomerID              198 non-null    int64 
 1   Gender                  198 non-null    object
 2   Age                     198 non-null    int64 
 3   Annual Income (k$)      198 non-null    int64 
 4   Spending Score (1-100)  198 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 17.4+ KB
```

### 8) SCALING THE DATA

InÂ [49…
```
from sklearn.preprocessing import scale
```

InÂ [50…
```
x=f1.drop(columns=['Gender'],axis=1)
x.head()
```

Out[50]:

| | CustomerID | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|
| **0** | 1 | 19 | 15 | 29 |
| **1** | 2 | 21 | 15 | 66 |
| **2** | 3 | 20 | 16 | 4 |
| **3** | 4 | 23 | 16 | 63 |
| **4** | 5 | 31 | 17 | 30 |

InÂ [52…
```
x.mean()
```

Out[52]:
```
1.570012358055777e-17
```

InÂ [54…
```
x.std()
```

Out[54]:
```
1.0
```

### 9) PERFORM CLUSTERING ALGORITHM

InÂ [56…
```
from sklearn.cluster import KMeans
wcss=[]
for i in range (1,11):
  kmeans=KMeans(n_clusters=i, init='k-means++',random_state=0)
  kmeans.fit(x)
  wcss.append(kmeans.inertia_)
```

InÂ [57…
```
wcss
```

Out[57]:
```
[791.9999999999998,
 508.44874485439107,
 368.58328054500737,
 257.0929393027723,
 206.35125359279914,
 156.94571620133905,
 140.89593744774663,
 125.07516278994356,
 114.55898071571418,
 101.0295653122749]
```

InÂ [52…
```
x.mean()
```

Out[52]:
```
1.570012358055777e-17
```

InÂ [54…
```
x.std()
```

Out[54]:
```
1.0
```

### 9) PERFORM CLUSTERING ALGORITHM

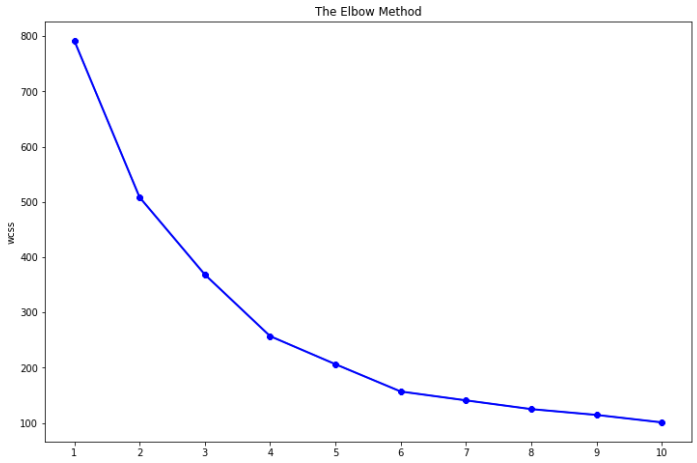
InÂ [56…
```
from sklearn.cluster import KMeans
wcss=[]
for i in range (1,11):
  kmeans=KMeans(n_clusters=i, init='k-means++',random_state=0)
  kmeans.fit(x)
  wcss.append(kmeans.inertia_)
```

InÂ [57…
```
wcss
```

Out[57]:
```
[791.9999999999998,
 508.44874485439107,
 368.58328054500737,
 257.0929393027723,
 206.35125359279914,
 156.94571620133905,
 140.89593744774663,
 125.07516278994356,
 114.55898071571418,
 101.0295653122749]
```

InÂ [60…

```
plt.figure(figsize=(12,8))
plt.plot(range(1,11),wcss)
plt.title('The Elbow Method')
plt.plot(range(1,11),wcss, linewidth=2, color="red", marker ="8")
plt.xlabel("No. of clusters/ k-value")
plt.xticks(np.arange(1,11,1))
plt.ylabel("wcss")
plt.show()
```




InÂ [62…

```
#BUILD MODEL
kmodel=KMeans(n_clusters=5,init='k-means++',random_state=0)
y_kmeans=kmodel.fit_predict(x)
```

InÂ [64…

```
kmodel.labels_
```

Out[64]:

```
array([0, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0,
       4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 1, 0, 4, 0,
       4, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0,
       1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0,
       0, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1,
       1, 0, 2, 0, 0, 0, 1, 1, 1, 1, 3, 2, 3, 3, 2, 3, 2, 3, 2, 3, 2, 3,
       2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3,
       2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3,
       2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3],
      dtype=int32)
```

InÂ [75…

```
plt.scatter(x[y_kmeans==0,0],x[y_kmeans==0,1],s=100,c='red',label='Cluster 1')
plt.scatter(x[y_kmeans==1,0],x[y_kmeans==1,1],s=100,c='blue',label='Cluster 2')
plt.scatter(x[y_kmeans==2,0],x[y_kmeans==2,1],s=100,c='pink',label='Cluster 3')
plt.scatter(x[y_kmeans==3,0],x[y_kmeans==3,1],s=100,c='green',label='Cluster 4')
plt.scatter(x[y_kmeans==4,0],x[y_kmeans==4,1],s=100,c='orange',label='Cluster 5')
plt.scatter(kmeans.cluster_centers_[:, 0],kmeans.cluster_centers_[:, 1],s=300,c='black',label='Centroids')
plt.title('Clusters of cutomers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score(1-100)')
plt.show()
```