# Machine Learning Project

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# Customer Segmentation of Mall - using K-means clustering

### -:OVERVIEW:-

1)It has always been important for businesses to understand customer behaviours in order to ensure that products or services are tailored towards maximum profit.

2) For this case study, we will refer to a dataset with customer shopping data on customer's gender, , city, customer's annual income, credit score, and spending score found here.

3) This data was obtained on several cities in India as will see in the dataset

4)Data visualization is going to be done ( in Python & ML) to make comparisons between the different features of the dataset.

5) Customer segmentation is the practice of dividing a company's customers into groups that reflect similarity among customers in each group. Hence here we are using unsupervised algorithm i.e K-means clustering to group the data in the form of similar properties .

6) customer segmentation is a process of dividing the datapoints into the clusters on the basis of similar or dissimilar categories.

# GOAL OF THIS PROJECT *

1) To increase the sales.

2) To Increase the turnover of the Mall

3) To Increase brand awareness.

4) Improving market positioning from competitors.

5) Identifying new marketing opportunities.

6) Developing customized product offer strategies.

# Analyse and visualize the dataset:

Here we have the following features -

1. Customer_ID: It is the unique ID given to a customer
2. Gender: Gender of the customer
3. Age: The age of the customer
4. Annual Income ($): It is the annual income of the customer
5. Spending Score: It is the score (out of 100) given to a customer by the mall authorities, based on the money spent and the behaviour of the customer

# steps to be performed :

1)Import the libraries

2 Read the Dalaset

3)Apply Exploratory Data Analysis (EDA) -a) Handle Missing Values. -b) find outliers /Skewness -c) Encoding -d) feature scaling

4)Data Visualizatiq,/ Analysis

5)Baseline Model ( 1st model)

6) Evaluate Model -a) check Bias & variance -b) Performance (Error/reports)

7)again check skewnes/outliers/scaling

8)Next model

9)Re-Evaluate the Model (2nd model)

10)Apply Hyperparameter tuning (if needed) -( for loop , Grid search cv)

11)Tuned Model (3rd Model) .

12)cross validation

# 1) Importing the Libraries

In [1]:
```python
import pandas as pd                                 #for data processing,read cs
import numpy as np                                  #for Linear algebra
import matplotlib.pyplot as plt                     #for Data Visualization
import seaborn as sns                               #python Library fot Visualiz
import warnings                                     #to prevent warnings
warnings.filterwarnings("ignore")
import plotly as py                                 #for Data plotting
```

# 2) Importing the Dataset

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

Out[2]:

| | 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 |
| **...** | ... | ... | ... | ... | ... |
| **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 | 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 |

# 3) EDA

In [4]:
```
print("No.of Rows",df.shape[0])
print("No.of cols",df.shape[1])
```

```
No.of Rows 200
No.of cols 5
```

In [5]:
```
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   Gender                  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
```

### The above dataset cosist 200 rows and 5 colums and there is no null values in the dataset and datatypes of the column are in the int64 & object values.

In [6]:
```
df.isnull().sum()               #data cleaning
```

Out[6]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [7]:
```
df.duplicated().sum()          # there is no duplicate values are present
```
Out[7]:
```
0
```

In [8]:
```
df.head()             # it shows inital 5 rows of Dataset
```
Out[8]:

| | 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 |

In [9]:
```
df.tail()             # it shows last 5 rows of Dataset
```
Out[9]:

| | CustomerID | Gender | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|---|
| **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 |

In [10]:
```
df["Spending Score (1-100)"].value_counts()
```
Out[10]:
```
42    8
55    7
46    6
73    6
35    5
     ..
31    1
44    1
53    1
65    1
18    1
Name: Spending Score (1-100), Length: 84, dtype: int64
```

In [11]:
```
df.value_counts().sum()
```
Out[11]:
```
200
```

In [12]:
```
1 df.describe()
```

Out[12]:

| | 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 the above dataset it gives the statitical value of the columns where the Mean value of CutomerId is 100.5 and median is 100.5, for Age mean is 38.85 and median is 36.00, for annual income mean is 60.56 and median is 61.50, and for column spending score mean is 50.20 and median is 50.00 after looking upon the values of the column there is no far difference is the mean and median. we can say (mean = median) hence this data is called Normal distribution which hes zero (0) skewness and te outlier might be situated at both the side

In [13]:
```
1 x = df.iloc[:,[3,4]]                  # selecting feature variable
```

In [14]:
```
1 x
```

Out[14]:

| | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|
| **0** | 15 | 39 |
| **1** | 15 | 81 |
| **2** | 16 | 6 |
| **3** | 16 | 77 |
| **4** | 17 | 40 |
| **...** | ... | ... |
| **195** | 120 | 79 |
| **196** | 126 | 28 |
| **197** | 126 | 74 |
| **198** | 137 | 18 |
| **199** | 137 | 83 |

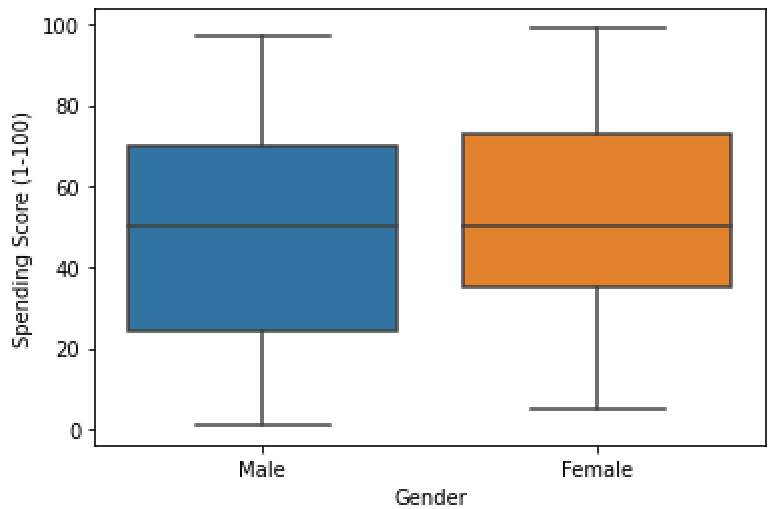
200 rows × 2 columns

In [15]:
```
from scipy.stats import skew                    #import skew fro check outliers
```

# 4) Finding outliers

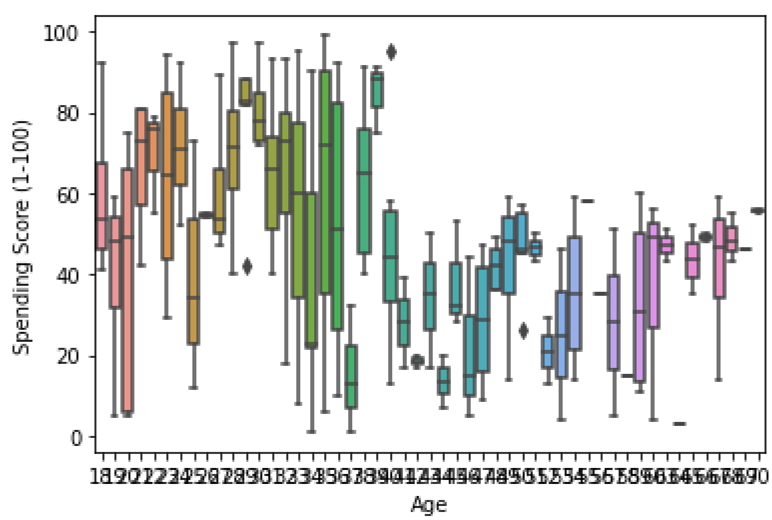
In [16]:
```
sns.boxplot(data=df,y="Spending Score (1-100)", x="Gender")
```

Out[16]: <AxesSubplot:xlabel='Gender', ylabel='Spending Score (1-100)'>



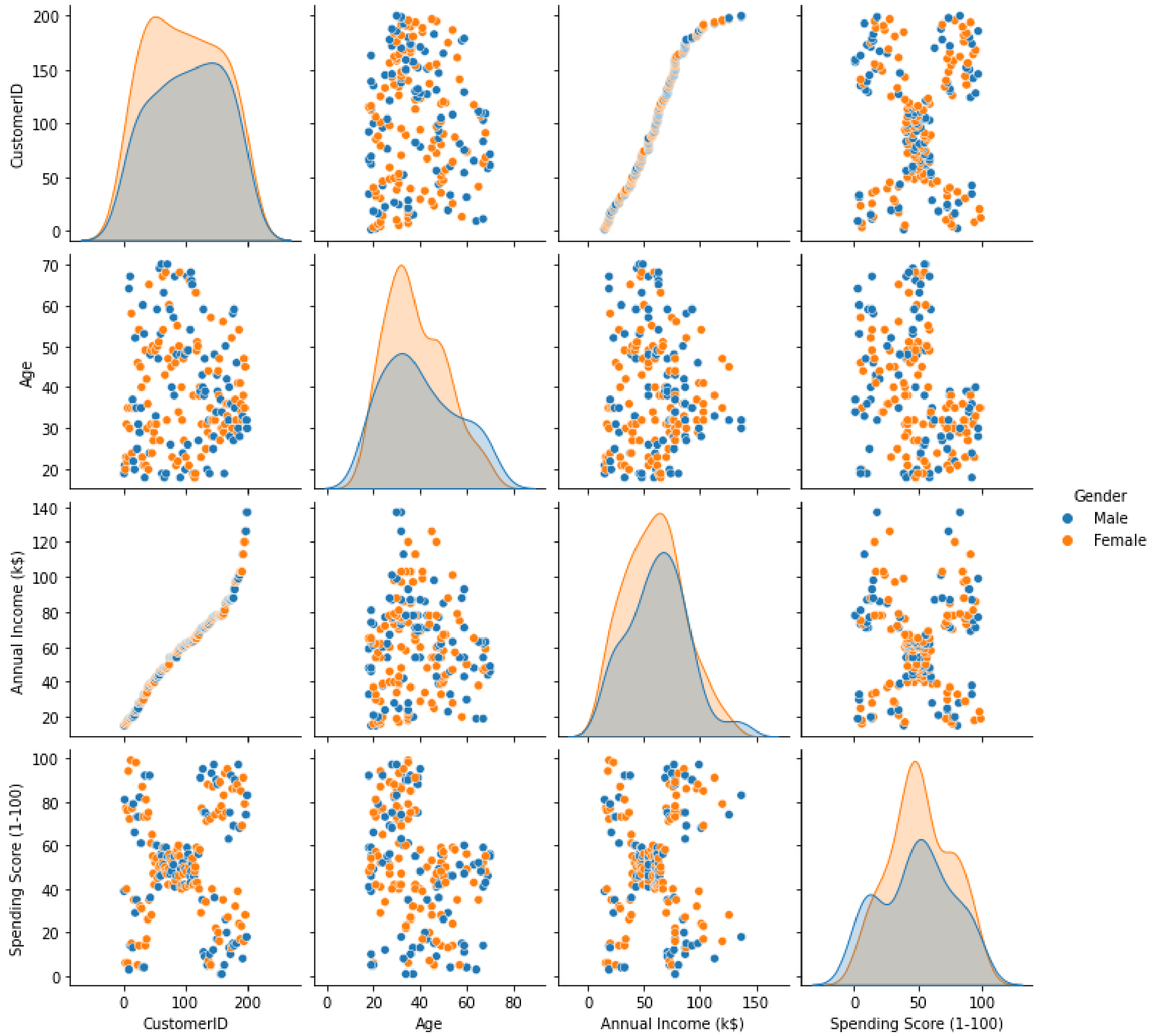

In [17]:
```
sns.boxplot(data=df,y="Spending Score (1-100)",x="Age")
```

Out[17]: <AxesSubplot:xlabel='Age', ylabel='Spending Score (1-100)'>



In [18]:
```
sns.pairplot(data=df,hue="Gender")
```

Out[18]:
```
<seaborn.axisgrid.PairGrid at 0x13178ff24f0>
```




In [19]:
```
df.groupby("Gender").size().max
```

Out[19]:
```
<bound method NDFrame._add_numeric_operations.<locals>.max of Gender
Female    112
Male       88
dtype: int64>
```

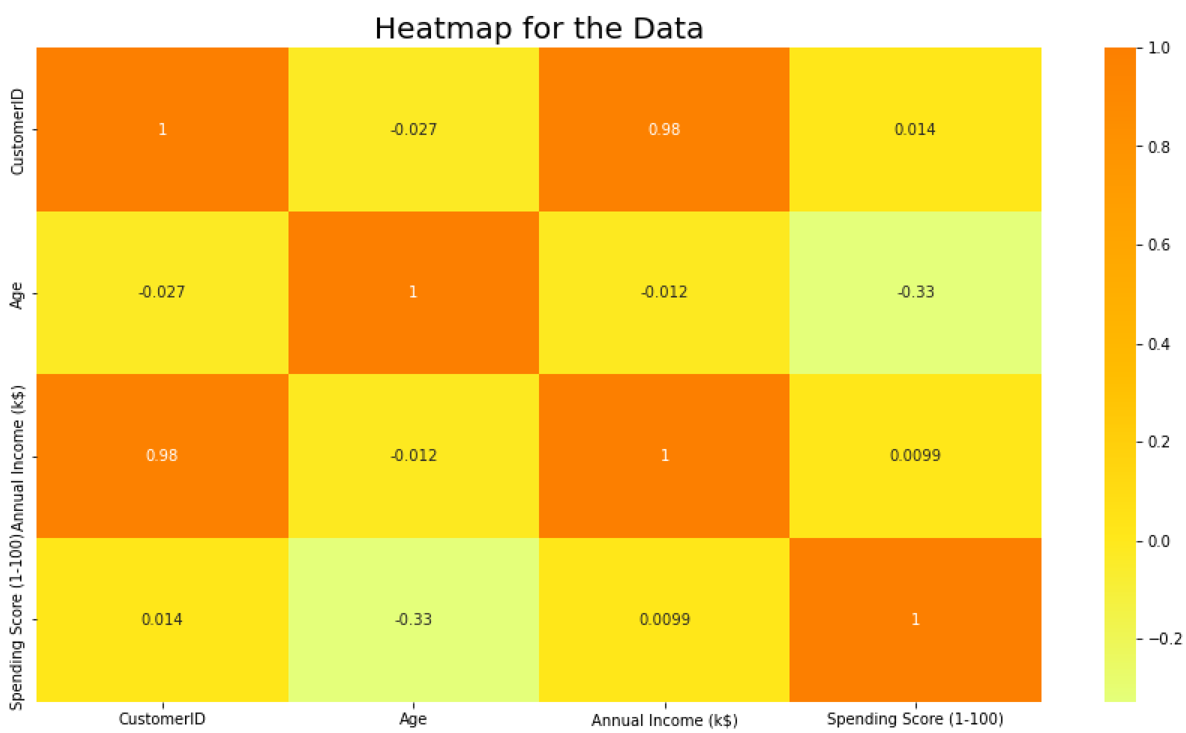
# After visualizing the graph using pairplot the Female age is highly skewed near theage group of 50 years and the spending score is lie between the 90-100. Hence we can conclude that the female customers are raked as that most shopping cutomers at the mall generating high lead score.

In [20]:
```
df.corr().style.background_gradient()
```

Out[20]:

| | 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 [21]:
```
# We now check for Correlation between the different attributes of the mal

plt.rcParams["figure.figsize"] = (15,8)
sns.heatmap(df.corr(), cmap = "Wistia", annot = True)
plt.title("Heatmap for the Data", fontsize = 20)
plt.show()
```



### The above graph shows the correlation between the different attributes of the mall customer segementation Dataset, This Heatmap reflects the most correlated features with Orenge Colour and least correlated features with yellow colour.

In [22]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x = sc.fit_transform(x)
x
```

```
       [-1.20462718,  1.42863343],
       [-1.16645776, -1.7935561 ],
       [-1.16645776,  0.88513158],
       [-1.05194947, -1.7935561 ],
       [-1.05194947,  1.62274124],
       [-1.05194947, -1.4053405 ],
       [-1.05194947,  1.19570407],
       [-1.01378004, -1.28887582],
       [-1.01378004,  0.88513158],
       [-0.89927175, -0.93948177],
       [-0.89927175,  0.96277471],
       [-0.86110232, -0.59008772],
       [-0.86110232,  1.62274124],
       [-0.82293289, -0.55126616],
       [-0.82293289,  0.41927286],
       [-0.82293289, -0.86183865],
       [-0.82293289,  0.5745591 ],
       [-0.78476346,  0.18634349],
       [-0.78476346, -0.12422899],
       [-0.78476346, -0.3183368 ],
```

# Model Evaluate - KMeans clustering

### K-means Algorithum :- it is an iteative algorithum that divides the unlabelled data into K difference clusters in such a way that each dataset belongs to only one group that has similar properties and from centroids.

### K-means clustering is a clustering algorithum that aims to partition N observations into K clusters. intialisation - K initial "means" (centroids) are generated Randomly.

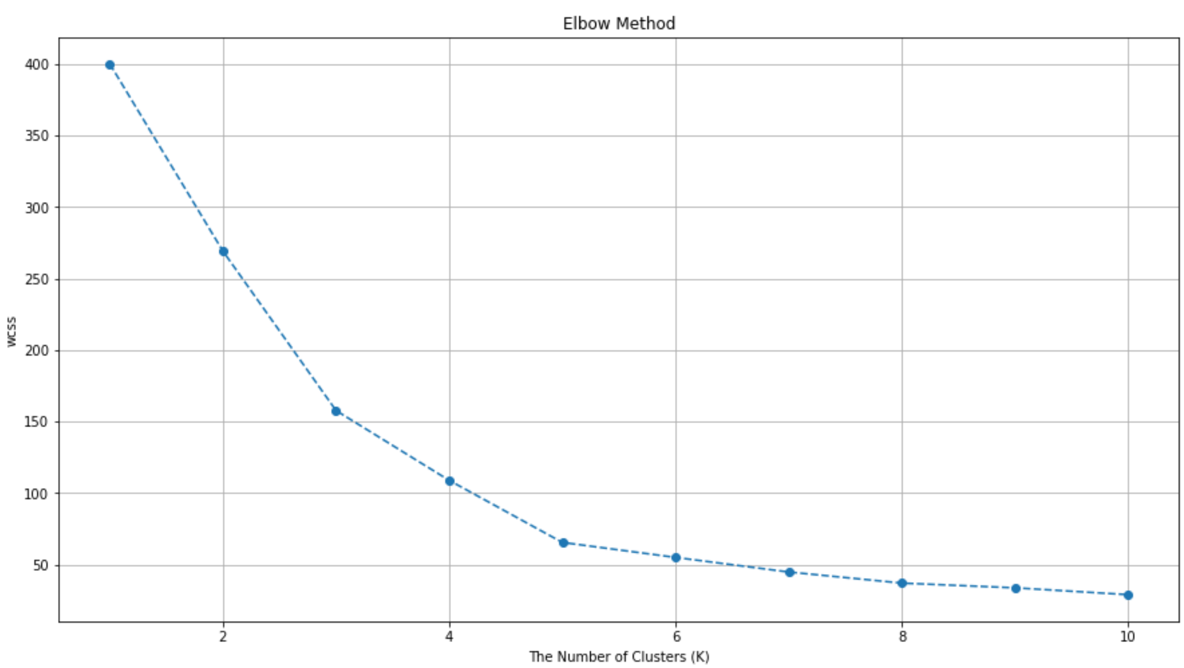
-K clusters are created by associating each observation with the nearest centroid Update - The centroid of the clusters becomes the new mean, Assignment and Update are repeated iteratively until convergence The end result is that the sum of squared errors is minimised between points and their respective centroids. We will use Means Clustering. At first we will find the optimal clusters based on inertia and using elbow method. The distance between the centroids and the data points should be less.

In [23]:
```
from sklearn.cluster import KMeans                        # import KMeans libr

wcss = []

for i in range(1,11):
    kmeans = KMeans(n_clusters=i, random_state=1)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

wcss
```

Out[23]:
```
[400.0,
 269.1425070447921,
 157.70400815035947,
 108.92131661364357,
 65.56840815571681,
 55.10377812115057,
 44.91118554999014,
 37.15135706793106,
 33.854106217363686,
 29.076176851244274]
```

In [24]:
```
#wcss = within clusters sum of square
```

In [25]:
```
plt.plot(range(1,11), wcss, "o--")
plt.grid()
plt.title("Elbow Method")
plt.ylabel("wcss")
plt.xlabel("The Number of Clusters (K)")
plt.show()
```



### from the above graph using Elbow method, we can say that the point which is gradually decreases deeper at the value5. therefore we can say the optimal no. of cluster k=5.

# Customer Gender Visualization

### we now create a bar graph and pie chart to check on customer Gender(Male and Female) distribution on our customer mall data set.

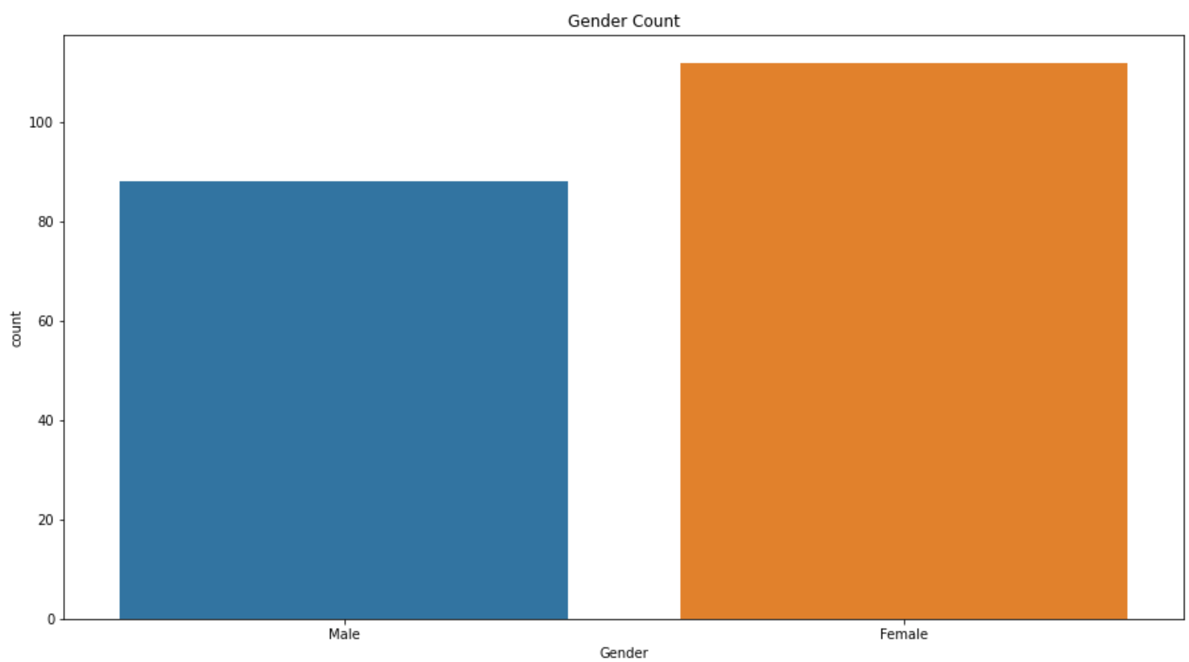
In [26]:
```
#We now check for the data Gender Unique
a = df.Gender.unique()
a
```

Out[26]:
```
array(['Male', 'Female'], dtype=object)
```

In [27]:
```
#Lets now check on Data Gender counts for our data set
df.Gender.value_counts()
```

Out[27]:
```
Female    112
Male       88
Name: Gender, dtype: int64
```

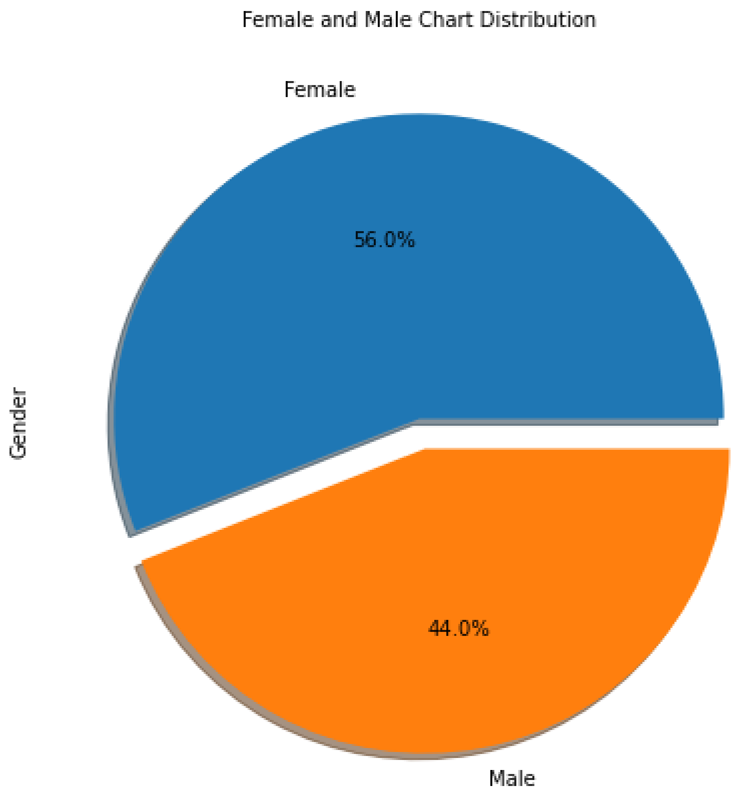
In [28]:
```
#We plot a graph on data gender count for women and man for our data set
sns.countplot(df.Gender)
plt.title("Gender Count")
plt.show()
```



# from above graph we can conclude that females preferences is higher as compare to male.

In [29]:

```
#We now match lable on dataset gender. assign arange to male and pink to f

#We now carry out the visualization
plt.figure(figsize=(7,7))

df["Gender"].value_counts().plot.pie(autopct="%1.1f%%", explode=(0,0.1),sh
plt.title("Female and Male Chart Distribution", color="black", fontsize=10
plt.show()
```

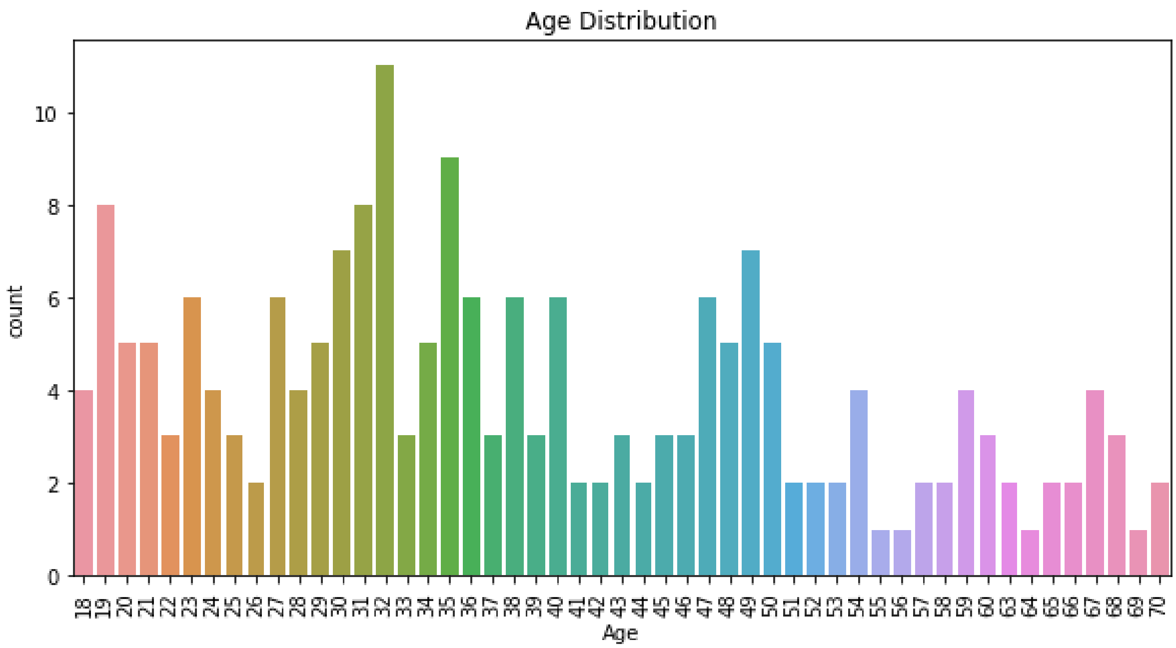


# Now From the above piechart, we conclude that the percentage of females is 56%, whereas the percentage of male in the customer dataset is 44%.

In [30]:

```
#Customer's distribution based on age
plt.figure(figsize=(10,5))
sns.countplot(df["Age"])
plt.xticks(rotation=90)
plt.title("Age Distribution")
```

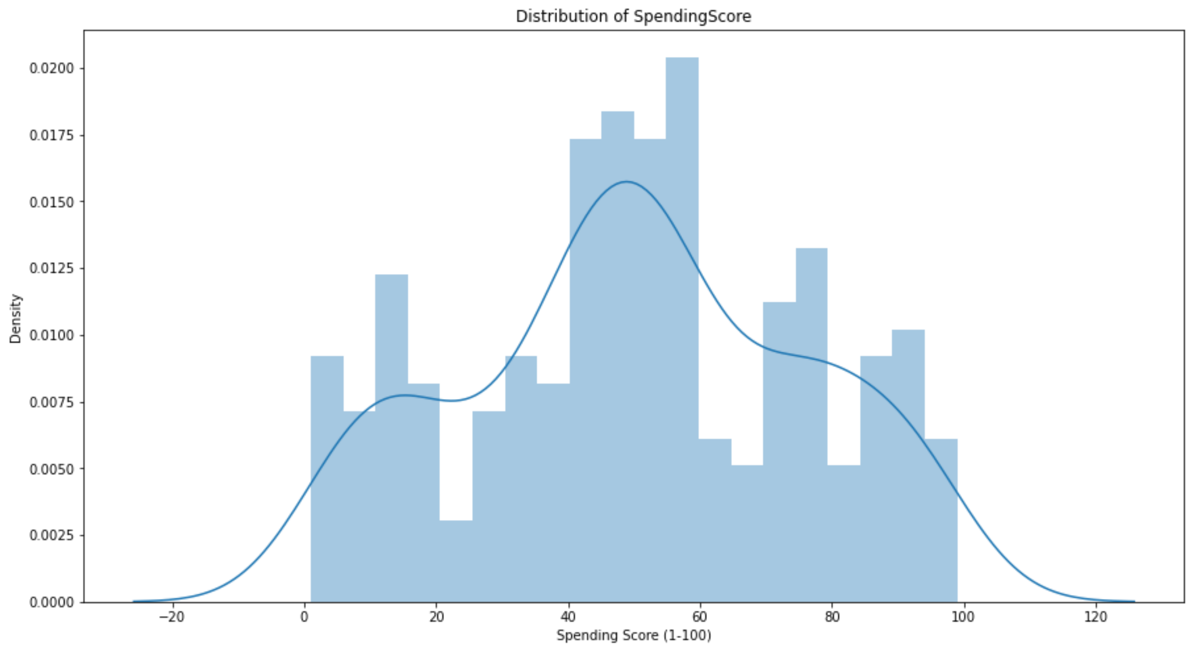
Out[30]: Text(0.5, 1.0, 'Age Distribution')



## We notethat people who's age group belong to 30-35 are mostly visiting mall then the order age groups. People at Age 32 are the Most Frequent Visitors in the Mall. People of Age 55, 56, 64, 69 are very less frequent in the malls (older agre, above 50s groups are lesser frequent in comparison). Ages from 19 and 31 are very much frequent.

In [31]:

```
#We now visualize our data using Histogram to show Spending scoure Distrib

plt.title("Distribution of SpendingScore")
sns.distplot(df["Spending Score (1-100)"], bins=20)
plt.figure(figsize=(18,8))
plt.show()
```

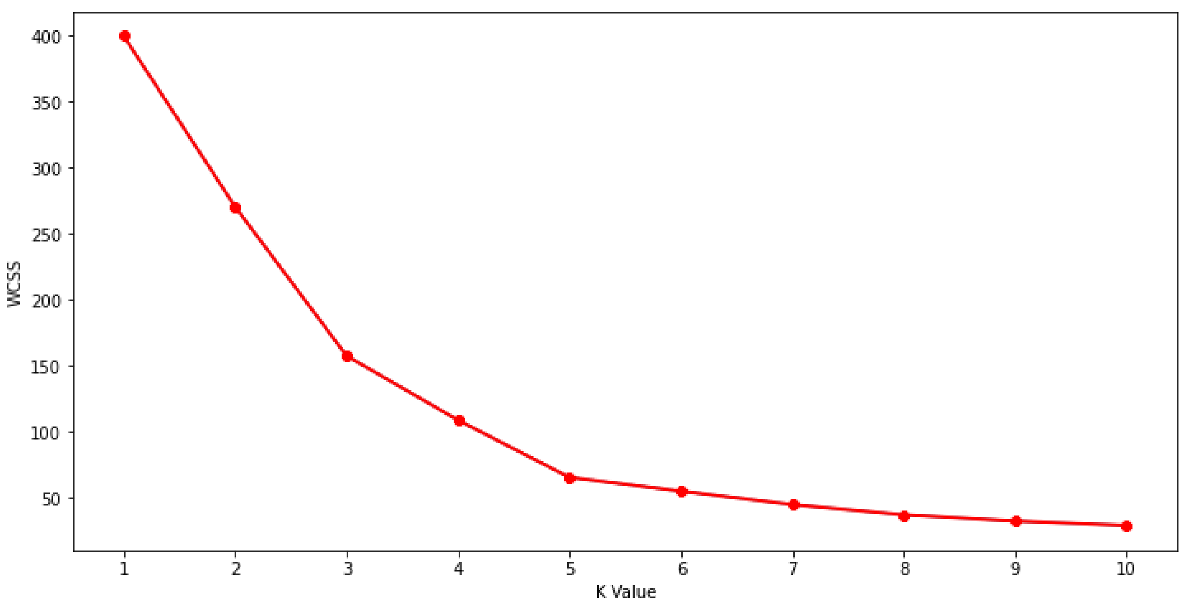



```
<Figure size 1296x576 with 0 Axes>
```

### Now we will visualize the dataset using matplotlib and seaborn to understand the relationship between columns. From this, we understand that 40-60 spending score is higher. And the person whose annual income is between "50,000-1,00,000 dollars do more shopping in comparison to others

In [32]:

```
wcss=[]
for i in range(1,11):
    km=KMeans(n_clusters=i)
    km.fit(x)
    wcss.append(km.inertia_)

#The Elbow Curve
plt.figure(figsize=(12,6))
plt.plot(range(1,11),wcss)
plt.plot(range(1,11),wcss, linewidth=2, color="red", marker="8")
plt.xlabel("K Value")
plt.xticks(np.arange(1,11,1))
plt.ylabel("WCSS")
plt.show()
```




### This is known as the elbow graph, the x-axis being the number of clusters, the number of clusters is taken at the elbow joint point. This point is the point where making clusters is most relevant as here the value of WCSS suddenly stops decreasing Here in the graph, after 5 the drop is minimal, so we take 5 to be the number of clusters.

In [33]:

```
kmeans = KMeans(n_clusters=5, random_state=1)
ylabel = kmeans.fit_predict(x)
```

In [34]:

```
df
```

Out[34]:

| | 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 |
| **...** | ... | ... | ... | ... | ... |
| **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 [35]:

```
df["ykmeans"] = ylabel
df
```

Out[35]:

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

200 rows × 6 columns

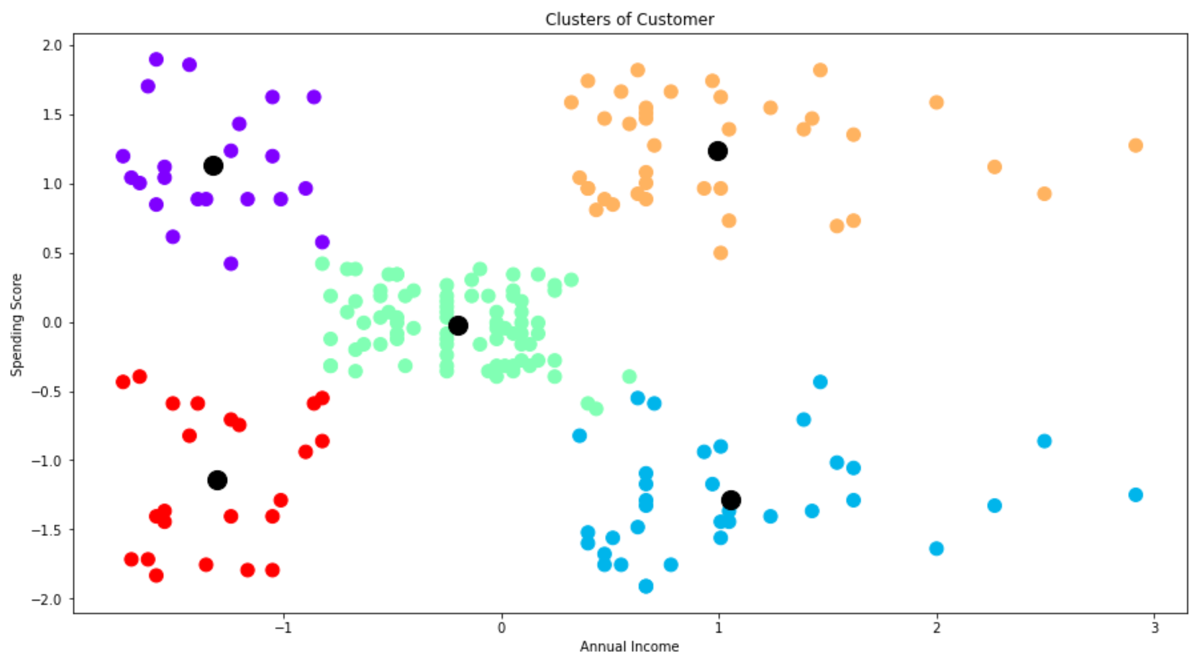
In [36]:
```
kmeans.cluster_centers_
```

Out[36]:
```
array([[-1.32954532,  1.13217788],
       [ 1.05500302, -1.28443907],
       [-0.20091257, -0.02645617],
       [ 0.99158305,  1.23950275],
       [-1.30751869, -1.13696536]])
```

In [37]:
```
df["ykmeans"].value_counts()
```

Out[37]:
```
2    81
3    39
1    35
4    23
0    22
Name: ykmeans, dtype: int64
```

In [38]:
```
plt.scatter(x[:,0], x[:,1], c=ylabel, s=100, cmap="rainbow")
plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], c=

plt.xlabel("Annual Income")
plt.ylabel("Spending Score")
plt.title("Clusters of Customer")
plt.show()
```



In [39]:
```
df[df.ykmeans==0].describe()
```

Out[39]:

| | CustomerID | Age | Annual Income (k$) | Spending Score (1-100) | ykmeans |
|---|---|---|---|---|---|
| **count** | 22.000000 | 22.000000 | 22.000000 | 22.000000 | 22.0 |
| **mean** | 23.090909 | 25.272727 | 25.727273 | 79.363636 | 0.0 |
| **std** | 13.147185 | 5.257030 | 7.566731 | 10.504174 | 0.0 |
| **min** | 2.000000 | 18.000000 | 15.000000 | 61.000000 | 0.0 |
| **25%** | 12.500000 | 21.250000 | 19.250000 | 73.000000 | 0.0 |
| **50%** | 23.000000 | 23.500000 | 24.500000 | 77.000000 | 0.0 |
| **75%** | 33.500000 | 29.750000 | 32.250000 | 85.750000 | 0.0 |
| **max** | 46.000000 | 35.000000 | 39.000000 | 99.000000 | 0.0 |

In [40]:
```
df[df.ykmeans==1].describe()
```

Out[40]:

| | CustomerID | Age | Annual Income (k$) | Spending Score (1-100) | ykmeans |
|---|---|---|---|---|---|
| **count** | 35.000000 | 35.000000 | 35.000000 | 35.000000 | 35.0 |
| **mean** | 164.371429 | 41.114286 | 88.200000 | 17.114286 | 1.0 |
| **std** | 21.457325 | 11.341676 | 16.399067 | 9.952154 | 0.0 |
| **min** | 125.000000 | 19.000000 | 70.000000 | 1.000000 | 1.0 |
| **25%** | 148.000000 | 34.000000 | 77.500000 | 10.000000 | 1.0 |
| **50%** | 165.000000 | 42.000000 | 85.000000 | 16.000000 | 1.0 |
| **75%** | 182.000000 | 47.500000 | 97.500000 | 23.500000 | 1.0 |
| **max** | 199.000000 | 59.000000 | 137.000000 | 39.000000 | 1.0 |

In [41]:
```
df.groupby("ykmeans")[["Annual Income (k$)", "Spending Score (1-100)"]].me
```

Out[41]:

| | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|
| **ykmeans** | | |
| **0** | 25.727273 | 79.363636 |
| **1** | 88.200000 | 17.114286 |
| **2** | 55.296296 | 49.518519 |
| **3** | 86.538462 | 82.128205 |
| **4** | 26.304348 | 20.913043 |

# Performing classification

In [42]:
```
x = df.iloc[:,[3,4]]
y = df.iloc[:, -1]
```

In [43]:
```
x
```

Out[43]:

| | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|
| **0** | 15 | 39 |
| **1** | 15 | 81 |
| **2** | 16 | 6 |
| **3** | 16 | 77 |
| **4** | 17 | 40 |
| **...** | ... | ... |
| **195** | 120 | 79 |
| **196** | 126 | 28 |
| **197** | 126 | 74 |
| **198** | 137 | 18 |
| **199** | 137 | 83 |

200 rows × 2 columns

In [44]:
```
y
```

Out[44]:
```
0      4
1      0
2      4
3      0
4      4
      ..
195    3
196    1
197    3
198    1
199    3
Name: ykmeans, Length: 200, dtype: int32
```

In [45]:
```
# Applying train test split model
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=
```

In [46]:
```
def mymodel(model):
    model.fit(xtrain,ytrain)
    ypred = model.predict(xtest)

    train = model.score(xtrain,ytrain)
    test = model.score(xtest,ytest)

    print(f"Traning Accuracy:-{train}\n Testing Accuracy:- {test}\n\n")
    print(classification_report(ytest,ypred))
    return model
```

In [47]:
```
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import MultinomialNB,GaussianNB,BernoulliNB
```

In [48]:
```
logreg = mymodel(LogisticRegression())
```

```
Traning Accuracy:-0.9928571428571429
 Testing Accuracy:- 0.95


              precision    recall  f1-score   support

           0       1.00      0.88      0.93         8
           1       1.00      0.91      0.95        11
           2       0.88      1.00      0.93        21
           3       1.00      1.00      1.00        11
           4       1.00      0.89      0.94         9

    accuracy                           0.95        60
   macro avg       0.97      0.93      0.95        60
weighted avg       0.96      0.95      0.95        60
```

In [49]:
```
knn = mymodel(KNeighborsClassifier(n_neighbors=5))
```

```
Traning Accuracy:-0.9714285714285714
 Testing Accuracy:- 0.9833333333333333


              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       1.00      1.00      1.00        11
           2       0.95      1.00      0.98        21
           3       1.00      1.00      1.00        11
           4       1.00      0.89      0.94         9

    accuracy                           0.98        60
   macro avg       0.99      0.98      0.98        60
weighted avg       0.98      0.98      0.98        60
```

In [50]:
```
svm = mymodel(SVC())
```

```
Traning Accuracy:-0.9785714285714285
 Testing Accuracy:- 0.9833333333333333


              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       1.00      1.00      1.00        11
           2       0.95      1.00      0.98        21
           3       1.00      1.00      1.00        11
           4       1.00      0.89      0.94         9

    accuracy                           0.98        60
   macro avg       0.99      0.98      0.98        60
weighted avg       0.98      0.98      0.98        60
```

In [51]:
```
dt = mymodel(DecisionTreeClassifier())
```

```
Traning Accuracy:-1.0
 Testing Accuracy:- 0.9666666666666667


              precision    recall  f1-score   support

           0       1.00      0.88      0.93         8
           1       1.00      1.00      1.00        11
           2       0.91      1.00      0.95        21
           3       1.00      1.00      1.00        11
           4       1.00      0.89      0.94         9

    accuracy                           0.97        60
   macro avg       0.98      0.95      0.97        60
weighted avg       0.97      0.97      0.97        60
```

In [52]:
```
1 bnb = mymodel(BernoulliNB())
```

```
Traning Accuracy:-0.42857142857142855
 Testing Accuracy:- 0.35


              precision    recall  f1-score   support

           0       0.00      0.00      0.00         8
           1       0.00      0.00      0.00        11
           2       0.35      1.00      0.52        21
           3       0.00      0.00      0.00        11
           4       0.00      0.00      0.00         9

    accuracy                           0.35        60
   macro avg       0.07      0.20      0.10        60
weighted avg       0.12      0.35      0.18        60
```

In [53]:
```
1 mnb = mymodel(MultinomialNB())
```

```
Traning Accuracy:-0.6857142857142857
 Testing Accuracy:- 0.6166666666666667


              precision    recall  f1-score   support

           0       0.89      1.00      0.94         8
           1       1.00      0.82      0.90        11
           2       0.53      0.86      0.65        21
           3       0.33      0.09      0.14        11
           4       0.20      0.11      0.14         9

    accuracy                           0.62        60
   macro avg       0.59      0.58      0.56        60
weighted avg       0.58      0.62      0.57        60
```

In [54]:
```
gnb = mymodel(GaussianNB())
```

```
Traning Accuracy:-0.9785714285714285
 Testing Accuracy:- 0.9833333333333333


              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       1.00      1.00      1.00        11
           2       0.95      1.00      0.98        21
           3       1.00      1.00      1.00        11
           4       1.00      0.89      0.94         9

    accuracy                           0.98        60
   macro avg       0.99      0.98      0.98        60
weighted avg       0.98      0.98      0.98        60
```

# Applying Hyperperameter tuning - on svm

In [55]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
```

In [56]:
```
pipe = Pipeline(
                 steps=[
                     ("scaler",StandardScaler()),
                     ("svm",SVC())
                 ]
)
```

In [57]:
```
pipe
```

Out[57]:
```
Pipeline(steps=[('scaler', StandardScaler()), ('svm', SVC())])
```

In [58]:
```
pipe.fit(xtrain,ytrain)
ypred = pipe.predict(xtest)
```

In [59]:
```python
from sklearn.metrics import classification_report
print(classification_report(ytest,ypred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       1.00      1.00      1.00        11
           2       0.95      1.00      0.98        21
           3       1.00      1.00      1.00        11
           4       1.00      0.89      0.94         9

    accuracy                           0.98        60
   macro avg       0.99      0.98      0.98        60
weighted avg       0.98      0.98      0.98        60
```

In [60]:
```python
train = pipe.score(xtrain,ytrain)
test = pipe.score(xtest,ytest)

print(f"Traning Accuracy:-{train}\n Testing Accuracy:- {test}")
```

```
Traning Accuracy:-0.9785714285714285
 Testing Accuracy:- 0.9833333333333333
```

In [61]:
```python
from sklearn.model_selection import GridSearchCV
parameter = {
             "C":[0.001,0.01,0.1,1,10,100],
             "gamma":[0.001,0.01,0.1,1,10,100],
             "kernel":["rbf"]
}
```

In [62]:
```python
grid = GridSearchCV(SVC(), parameter, verbose=2)
grid.fit(xtrain,ytrain)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
[CV] END ..................C=0.001, gamma=0.001, kernel=rbf; total time=
0.0s
[CV] END ..................C=0.001, gamma=0.001, kernel=rbf; total time=
0.0s
[CV] END ..................C=0.001, gamma=0.001, kernel=rbf; total time=
0.0s
[CV] END ..................C=0.001, gamma=0.001, kernel=rbf; total time=
0.0s
[CV] END ..................C=0.001, gamma=0.001, kernel=rbf; total time=
0.0s
[CV] END ...................C=0.001, gamma=0.01, kernel=rbf; total time=
0.0s
[CV] END ...................C=0.001, gamma=0.01, kernel=rbf; total time=
0.0s
[CV] END ...................C=0.001, gamma=0.01, kernel=rbf; total time=
0.0s
[CV] END ...................C=0.001, gamma=0.01, kernel=rbf; total time=
0.0s
```

In [63]:
```
grid.best_params_
```

Out[63]: {'C': 1, 'gamma': 0.001, 'kernel': 'rbf'}

In [64]:
```
grid.best_score_
```

Out[64]: 0.9714285714285715

In [65]:
```
grid.best_estimator_
```

Out[65]: SVC(C=1, gamma=0.001)

In [66]:
```
svm = grid.best_estimator_
svm.fit(xtrain,ytrain)
ypred = svm.predict(xtest)
```

In [67]:
```
svm = mymodel(SVC())
```

```
Traning Accuracy:-0.9785714285714285
 Testing Accuracy:- 0.9833333333333333


              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       1.00      1.00      1.00        11
           2       0.95      1.00      0.98        21
           3       1.00      1.00      1.00        11
           4       1.00      0.89      0.94         9

    accuracy                           0.98        60
   macro avg       0.99      0.98      0.98        60
weighted avg       0.98      0.98      0.98        60
```

### Hence from the above Algorithm i can conclude that both the SM model are giving the best accuracy -

# CONCLUSION

1) This study demonstrates that client segmentation in shopping malls is achievable despite the fact that this form of machine learning application is highly useful in the market, a manager can concentrate all of his or her attention on each cluster that has been discovered an meet all of their requirements.

1) Mall managers must be able to understand what customers require and, more importantly, how to meet those needs. analyze their purchasing habits, and establish frequent encounters with customers that make them feel comfortable in order to satisty their demands.