```python
import pandas as pd
import numpy as np

df=pd.read_csv('Customer_Data.csv')
print(df.head())
```

```
   Customer ID  Age Gender  Annual Income  Spending Score
0            1   62   Male          56564              86
1            2   65   Male          25393              73
2            3   18   Male         143520              39
3            4   21   Male          64711              43
4            5   21   Male         147014              98
```

```python
print("Shape of the dataset:",df.shape)
print("Column names:",df.columns)
```

```
Shape of the dataset: (1000, 5)
Column names: Index(['Customer ID', 'Age', 'Gender', 'Annual Income',
'Spending Score'], dtype='object')
```

```python
missing=df.isnull().sum()
print(missing)
```

```
Customer ID       0
Age               0
Gender            0
Annual Income     0
Spending Score    0
dtype: int64
```

```python
print(df.describe())
```

```
       Customer ID          Age  Annual Income  Spending Score
count  1000.000000  1000.000000    1000.000000     1000.000000
mean    500.500000    43.267000   84856.809000       47.859000
std     288.819436    15.242311   38393.323903       28.606038
min       1.000000    18.000000   20359.000000        1.000000
25%     250.750000    30.000000   51173.750000       23.000000
50%     500.500000    43.000000   84462.000000       47.000000
75%     750.250000    56.000000  118356.250000       73.000000
max    1000.000000    69.000000  149870.000000       99.000000
```

```python
!pip install matplotlib
!pip install seaborn
import matplotlib.pyplot as plt
import seaborn as sns
```

```
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.2.1)
```

```
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (4.51.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)
Requirement already satisfied: numpy>=1.20 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.25.2)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (24.0)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (2.8.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7-
>matplotlib) (1.16.0)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.10/dist-packages (0.13.1)
Requirement already satisfied: numpy!=1.24.0,>=1.20 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (1.25.2)
Requirement already satisfied: pandas>=1.2 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (2.0.3)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in
/usr/local/lib/python3.10/dist-packages (from seaborn) (3.7.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (1.2.1)
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/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
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>seaborn) (4.51.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (1.4.5)
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/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (24.0)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in
```
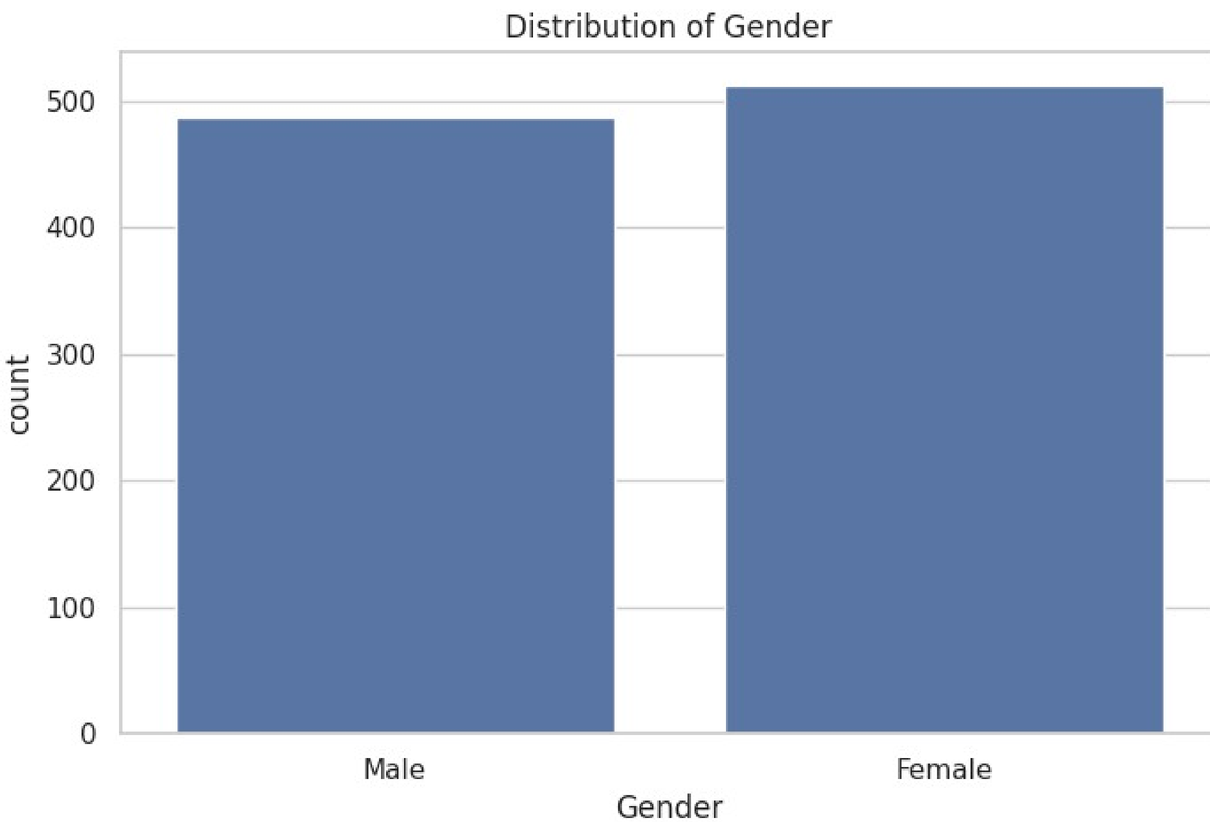

```
/usr/local/lib/python3.10/dist-packages (from matplotlib!=3.6.1,>=3.4-
>seaborn) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn)
(2023.4)
Requirement already satisfied: tzdata>=2022.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=1.2->seaborn)
(2024.1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7-
>matplotlib!=3.6.1,>=3.4->seaborn) (1.16.0)

sns.set(style="whitegrid")
plt.figure(figsize=(15,5))
#numerical variables visualization
plt.subplot(1,3,1)
sns.histplot(df['Age'],bins=10,kde=True,color='skyblue')
plt.title('Distribution of Age')

plt.subplot(1,3,2)
sns.histplot(df['Annual Income'],bins=10,kde=True,color='salmon')
plt.title('Distribution of Annual Income')

plt.subplot(1,3,3)
sns.histplot(df['Spending Score'],bins=10,kde=True,color='green')
plt.title('Distribution of Spending Score')

Text(0.5, 1.0, 'Distribution of Spending Score')
```


```
plt.figure(figsize=(8,5))
sns.countplot(data=df,x='Gender')
plt.title('Distribution of Gender')
plt.show()
```




```
!pip install scikit-learn
from sklearn.preprocessing import StandardScaler, LabelEncoder
```

```
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.10/dist-packages (1.2.2)
Requirement already satisfied: numpy>=1.17.3 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.25.2)
Requirement already satisfied: scipy>=1.3.2 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.11.4)
Requirement already satisfied: joblib>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)
```

```
label=LabelEncoder()
df['Gender']=label.fit_transform(df['Gender'])
print(df.head())
```

```
   Customer ID  Age  Gender  Annual Income  Spending Score
0            1   62       1          56564              86
1            2   65       1          25393              73
2            3   18       1         143520              39
3            4   21       1          64711              43
4            5   21       1         147014              98
```

```
scaler=StandardScaler()
num=['Age','Annual Income','Spending Score']
df[num]=scaler.fit_transform(df[num])
print(df.head())
```

```
   Customer ID       Age  Gender  Annual Income  Spending Score
0            1  1.229628       1      -0.737289        1.333987
1            2  1.426547       1      -1.549581        0.879310
2            3 -1.658518       1       1.528717       -0.309845
3            4 -1.461599       1      -0.524984       -0.169944
4            5 -1.461599       1       1.619768        1.753689
```

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

```
X= df.drop(columns=['Customer ID'])
y=df['Customer ID']
X_train,X_test,y_train,y_test =
train_test_split(X,y,test_size=0.2,random_state=42)
print(X_train.shape)
print(X_test.shape)
```

```
(800, 4)
(200, 4)
```

```
from sklearn.cluster import KMeans
kmeans=KMeans(random_state=42)
inertia=[]
for k in range(1,11):
    kmeans=KMeans(n_clusters=k,random_state=42)
    kmeans.fit(X_train)
    inertia.append(kmeans.inertia_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
_kmeans.py:870: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly
to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870
: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
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: FutureWarning: The default value of `n_init` will change from 10 to
'auto' in 1.4. Set the value of `n_init` explicitly to suppress the
warning
  warnings.warn(
```
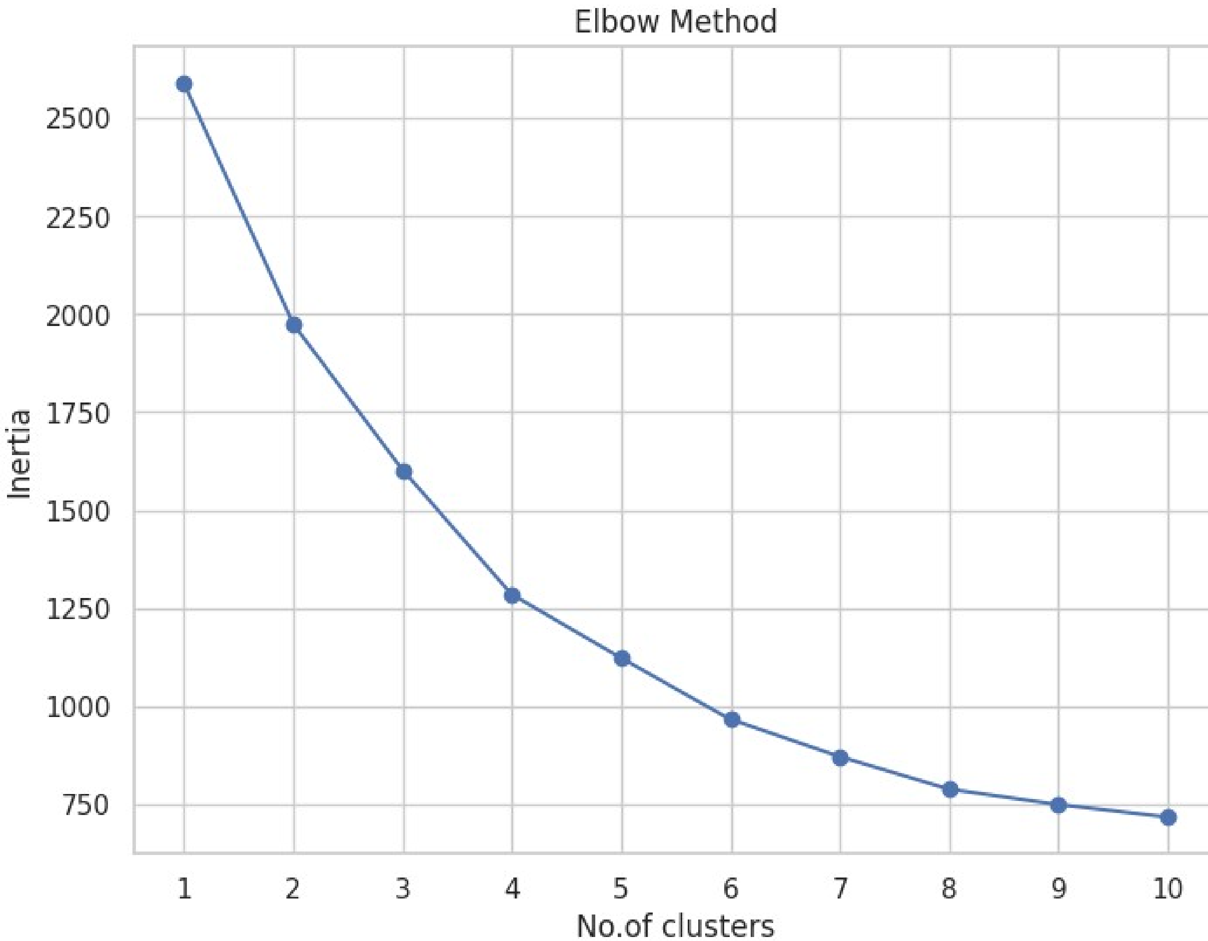

```python
plt.figure(figsize=(8,6))
plt.plot(range(1,11),inertia,marker='o')
plt.title('Elbow Method')
plt.xlabel('No.of clusters')
plt.ylabel('Inertia')
plt.xticks(np.arange(1,11,1))
plt.show()
```

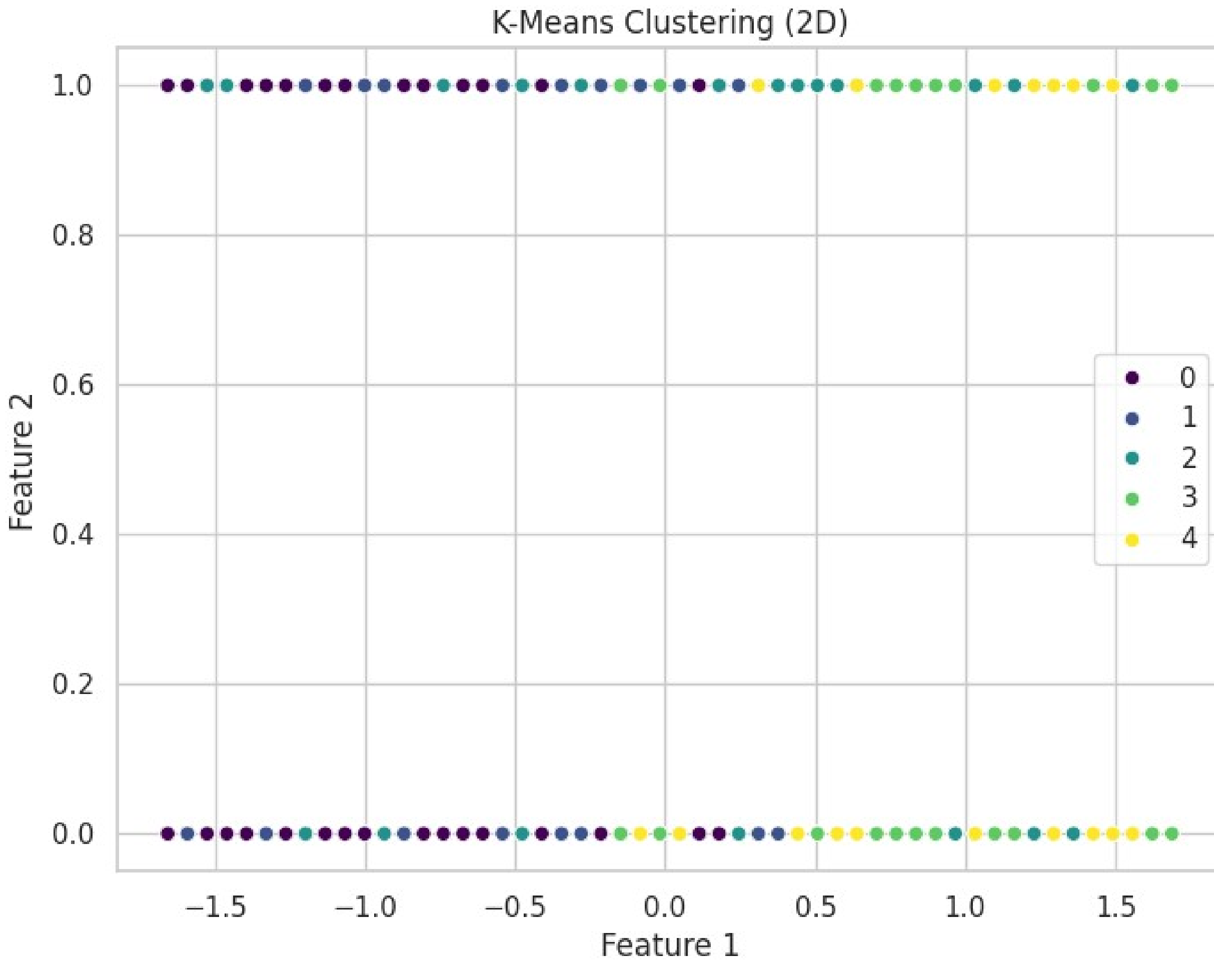



```
k=5
kmeans=KMeans(n_clusters=k,random_state=42)
kmeans.fit(X_train)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/
_kmeans.py:870: FutureWarning: The default value of `n_init` will
change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly
to suppress the warning
  warnings.warn(
```

```
KMeans(n_clusters=5, random_state=42)
```

```
plt.figure(figsize=(8,6))
sns.scatterplot(x=X_train.iloc[:,0],y=X_train.iloc[:,1],hue=kmeans.lab
els_,palette='viridis',legend='full')
plt.title('K-Means Clustering (2D)')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()
```




```
from sklearn.metrics import silhouette_score,davies_bouldin_score
silhouette=silhouette_score(X_train,kmeans.labels_)
print(silhouette)

0.23938393558789123

davies=davies_bouldin_score(X_train,kmeans.labels_)
print(davies)

1.2370478276957144

"""
Discussion of strengths and limitations of K-means clustering
 Strengths:
 - K-means is computationally efficient and scales well to large
datasets.
 - It is simple to implement and easy to understand.
 - K-means can produce tight clusters if the data is well-separated
and spherical in shape.

 Limitations:
```

```
 - K-means requires the number of clusters (k) to be specified in
advance, which can be challenging in practice.
 - It assumes that clusters are isotropic and have similar densities,
which may not always hold true.
 - K-means is sensitive to the initial choice of cluster centers and
may converge to suboptimal solutions.
 """

{"type":"string"}

"""
Insights and Recommendations
 Based on the clustering results, we have identified distinct customer
segments. Let's provide actionable insights and marketing strategies
tailored to each segment:

 Cluster 0: High Spending Customers
 - Offer premium loyalty programs or rewards to encourage repeat
purchases.
 - Introduce exclusive products or services targeting this segment.
 - Personalize marketing communications to enhance engagement.

 Cluster 1: Moderate Spending Customers
 - Provide targeted discounts or promotions to incentivize higher
spending.
 - Implement referral programs to increase customer acquisition.
 - Improve product visibility through targeted advertising campaigns.

 Cluster 2: Low Spending Customers
 - Offer introductory discounts or bundle deals to attract this
segment.
 - Focus on improving the value proposition of products or services.
 - Gather feedback to understand barriers to spending and address
customer concerns.

 Cluster 3: High Income, Low Spending Customers
 - Create personalized experiences to entice this segment to spend
more.
 - Showcase the luxury aspects of products or services to appeal to
their higher income.
 - Offer exclusive perks or benefits to increase loyalty.

 Cluster 4: Low Income, High Spending Customers
 - Provide budget-friendly options or payment plans to accommodate
their spending habits.
 - Focus on building brand loyalty through exceptional customer
service.
 - Implement targeted marketing campaigns emphasizing affordability
and value.
```

```
 The company can use these insights to tailor marketing strategies and
improve customer engagement:
 - Personalize marketing messages and offers based on the
characteristics of each customer segment.
 - Utilize customer segmentation for targeted advertising and
promotional campaigns.
 - Continuously analyze customer feedback and interactions to refine
marketing strategies and offerings.
"""

{"type":"string"}
```