```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from sklearn.cluster import DBSCAN
from sklearn.neighbors import NearestNeighbors
```

```
df= pd.read_csv(r"C:\Users\navde\Downloads\Lab3_data_mod2.csv")
```

```
df.head(20)
```

	CustomerID	Gender	Age	Income	Spending Score
0	1	Male	19.0	15000.0	39
1	2	Male	21.0	15000.0	81
2	3	Female	20.0	16000.0	6
3	4	Female	23.0	16000.0	77
4	5	Female	31.0	17000.0	40
5	6	Female	22.0	17000.0	76
6	7	Female	35.0	18000.0	6
7	8	Female	23.0	18000.0	94
8	9	Male	64.0	19000.0	3
9	10	Female	30.0	19000.0	72
10	11	Male	67.0	NaN	14
11	12	Female	35.0	19000.0	99
12	13	Female	58.0	20000.0	15
13	14	Female	24.0	20000.0	77
14	15	Male	37.0	20000.0	13
15	16	Male	22.0	20000.0	79
16	17	Female	35.0	21000.0	35
17	18	Male	20.0	21000.0	66
18	19	Male	52.0	23000.0	29
19	20	Female	35.0	23000.0	98

```
df.describe()
```

	CustomerID	Age	Income	Spending Score
count	200.000000	197.000000	197.000000	200.000000
mean	100.500000	39.142132	61670.065990	50.200000
std	57.879185	14.412300	27733.398489	25.823522
min	1.000000	18.000000	15000.000000	1.000000
25%	50.750000	28.000000	42000.000000	34.750000
50%	100.500000	36.000000	62000.000000	50.000000
75%	150.250000	49.000000	78000.000000	73.000000
max	200.000000	85.000000	150753.000000	99.000000

```
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             197 non-null    float64
 3   Income          197 non-null    float64
 4   Spending Score  200 non-null    int64  
dtypes: float64(2), int64(2), object(1)
memory usage: 7.9+ KB
```

Create plots to understand the distribution of the each feature in the data

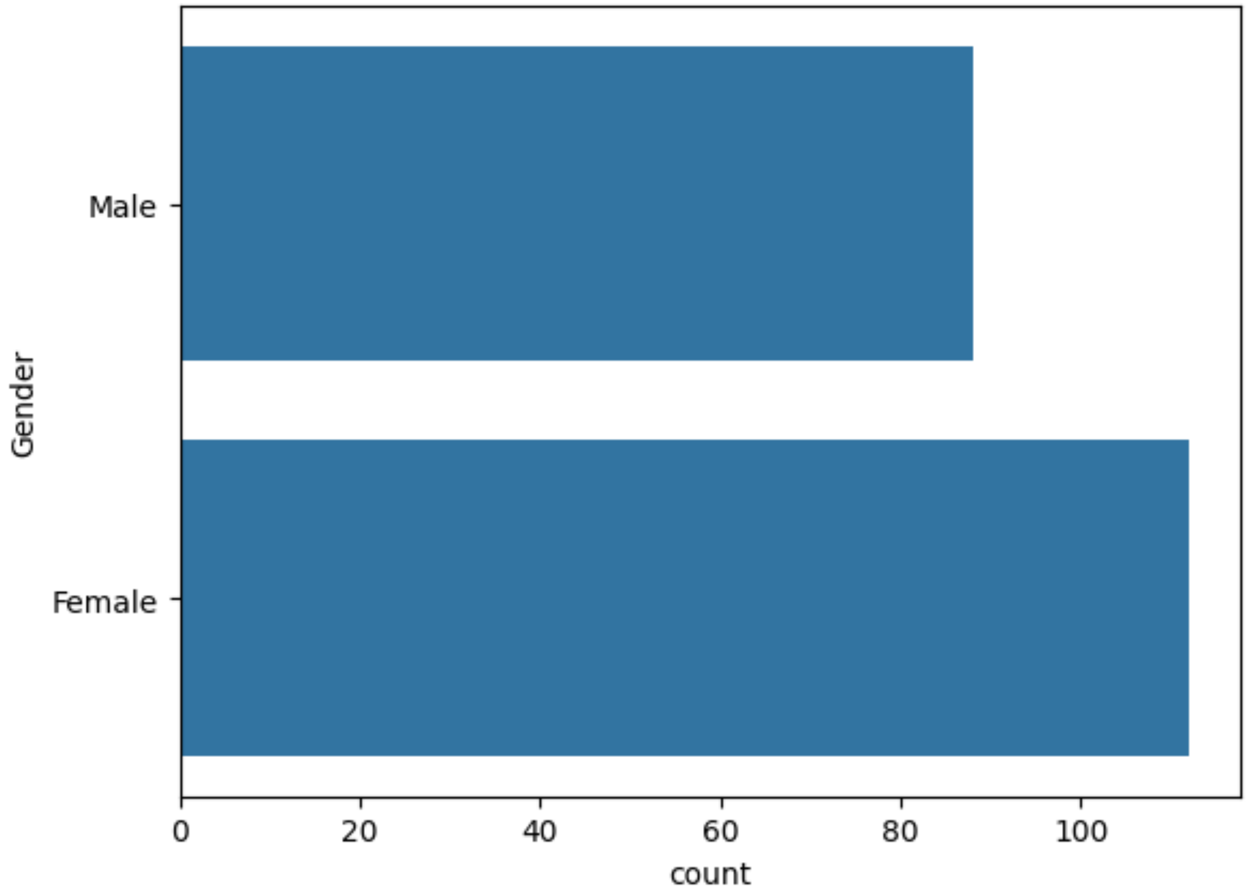
Create plots to understand the distribution of data with respect to the other features

```
#checking for null values in the data
df.isnull().sum()
```

```
CustomerID        0
Gender            0
Age               3
Income            3
Spending Score    0
dtype: int64
```

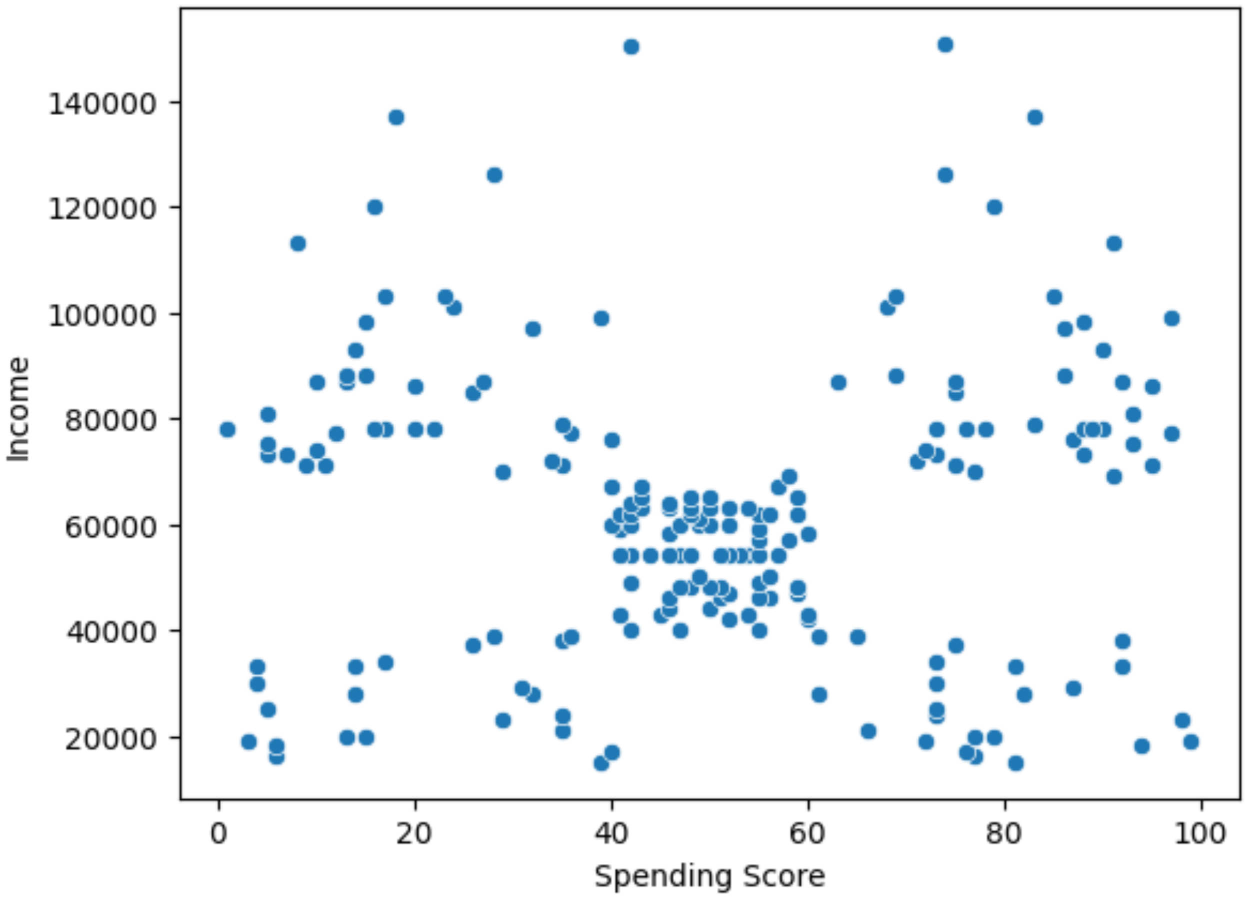
```
sns.countplot(df['Gender'])
```

```
<Axes: xlabel='count', ylabel='Gender'>
```



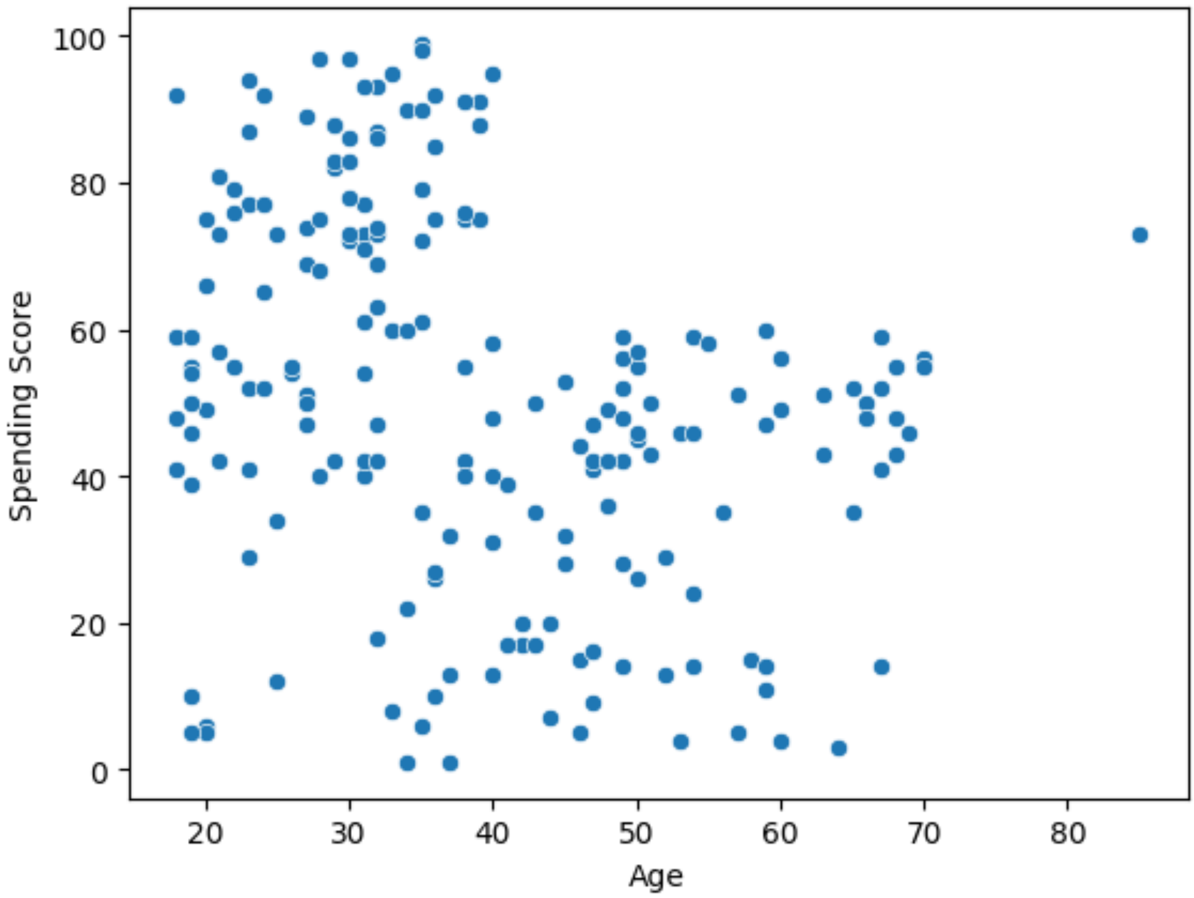
```
sns.scatterplot(x='Spending Score', y='Income', data=df)
```

```
<Axes: xlabel='Spending Score', ylabel='Income'>
```

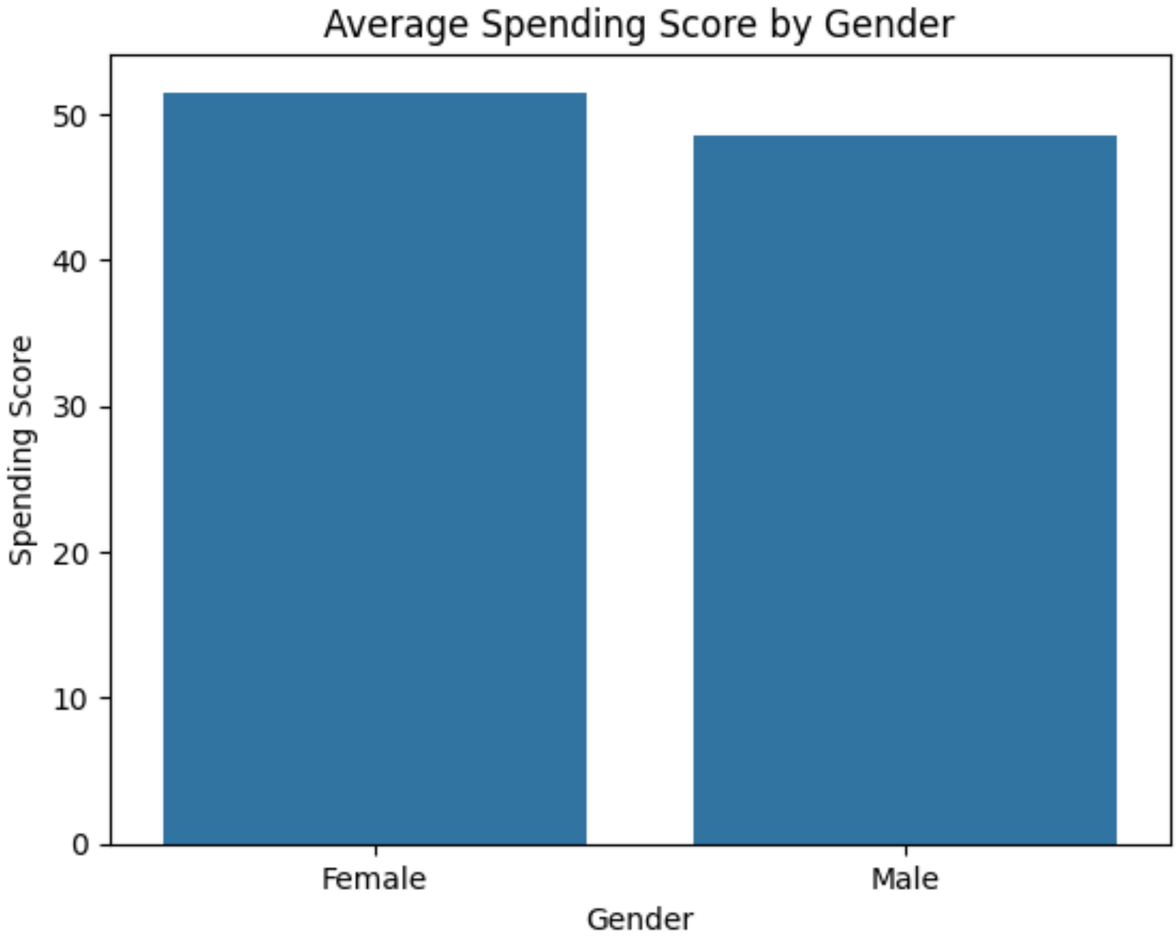


```
sns.scatterplot(x='Age', y='Spending Score', data=df)
```

```
<Axes: xlabel='Age', ylabel='Spending Score'>
```

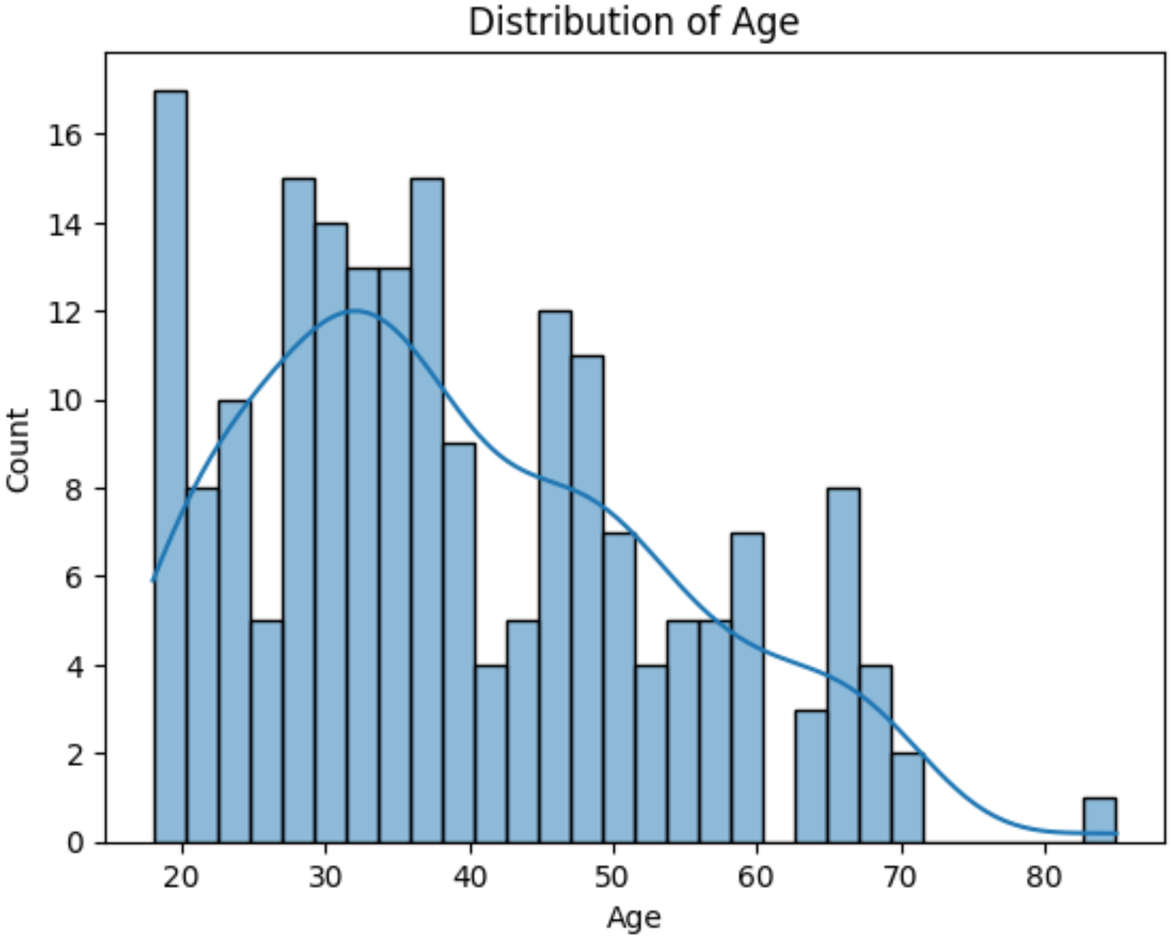


```
# Calculate the average spending score for each gender
average_spending = df.groupby('Gender')['Spending Score'].mean().reset_index()

sns.barplot(x='Gender', y='Spending Score', data=average_spending)

plt.title('Average Spending Score by Gender')
plt.show()
```



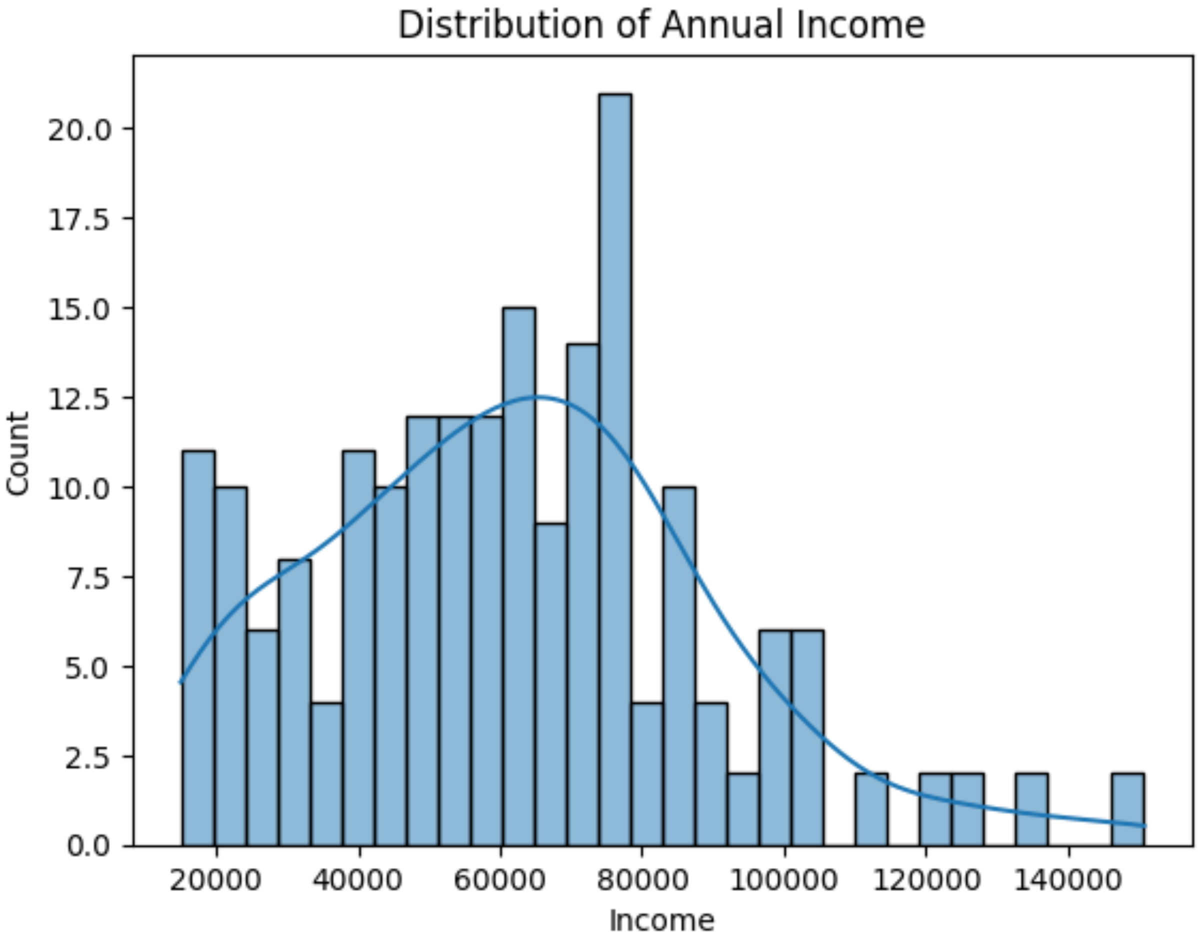
```
sns.histplot(df['Age'], bins=30, kde=True)
plt.title('Distribution of Age')
```

```
Text(0.5, 1.0, 'Distribution of Age')
```



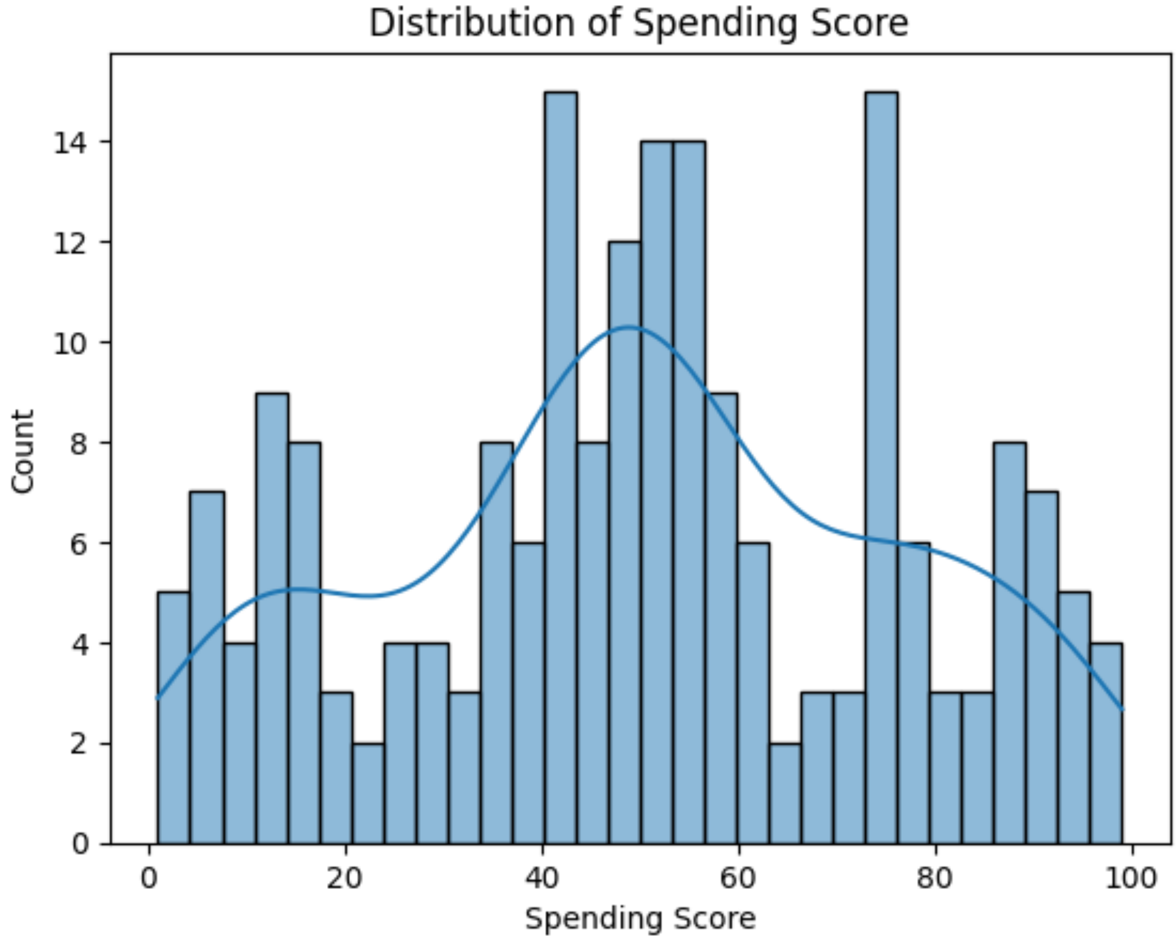
```
sns.histplot(df['Income'], bins=30, kde=True)
plt.title('Distribution of Annual Income')
```

```
Text(0.5, 1.0, 'Distribution of Annual Income')
```

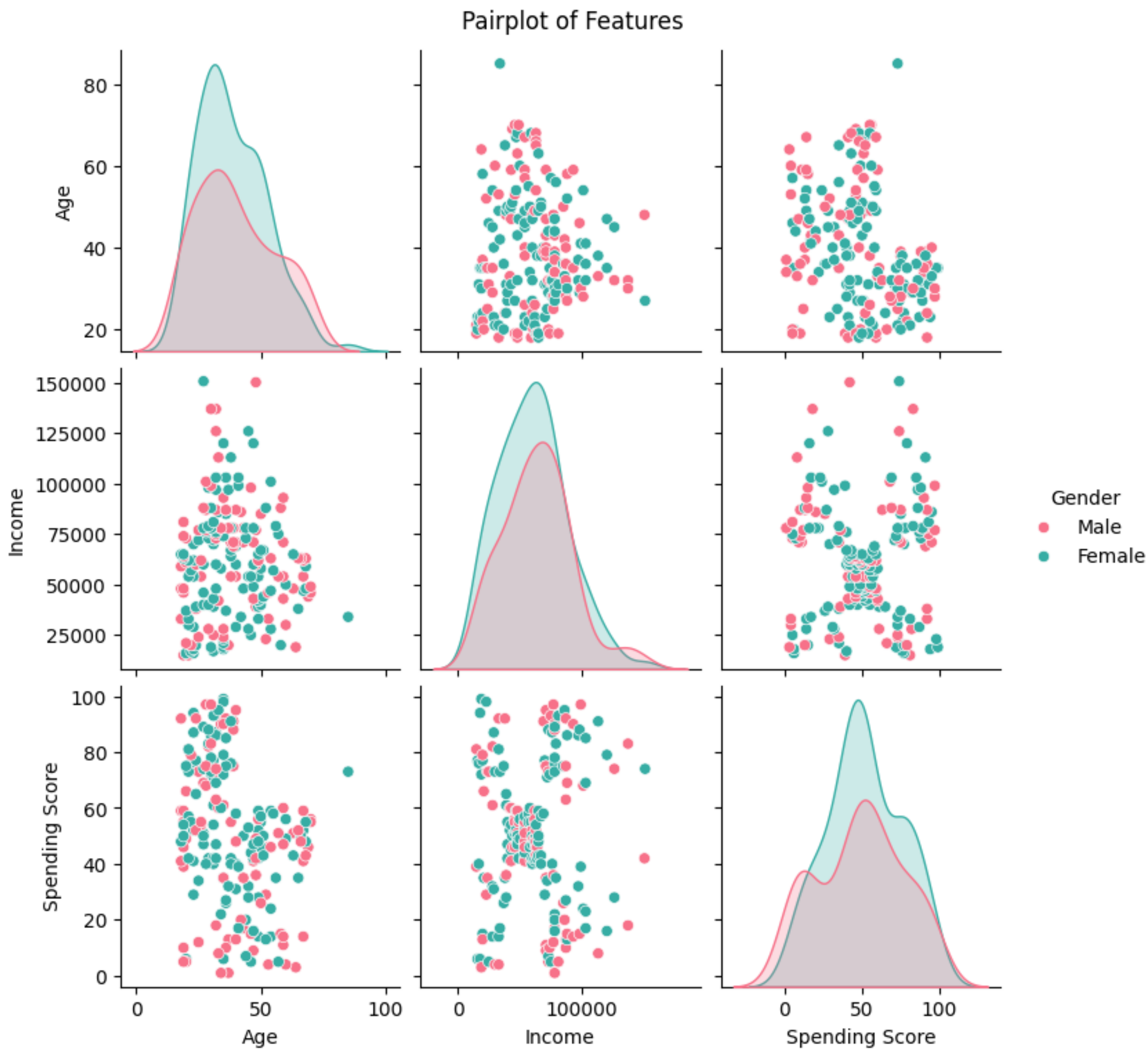


```
sns.histplot(df['Spending Score'], bins=30, kde=True)
plt.title('Distribution of Spending Score')
```

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



```
pairplot_columns = ['Age', 'Income', 'Spending Score', 'Gender']
sns.pairplot(df[pairplot_columns], hue='Gender', palette='husl')
plt.suptitle('Pairplot of Features', y=1.02)
plt.show()
```



Filling missing values in the data

Identify any outliers

feature scaling

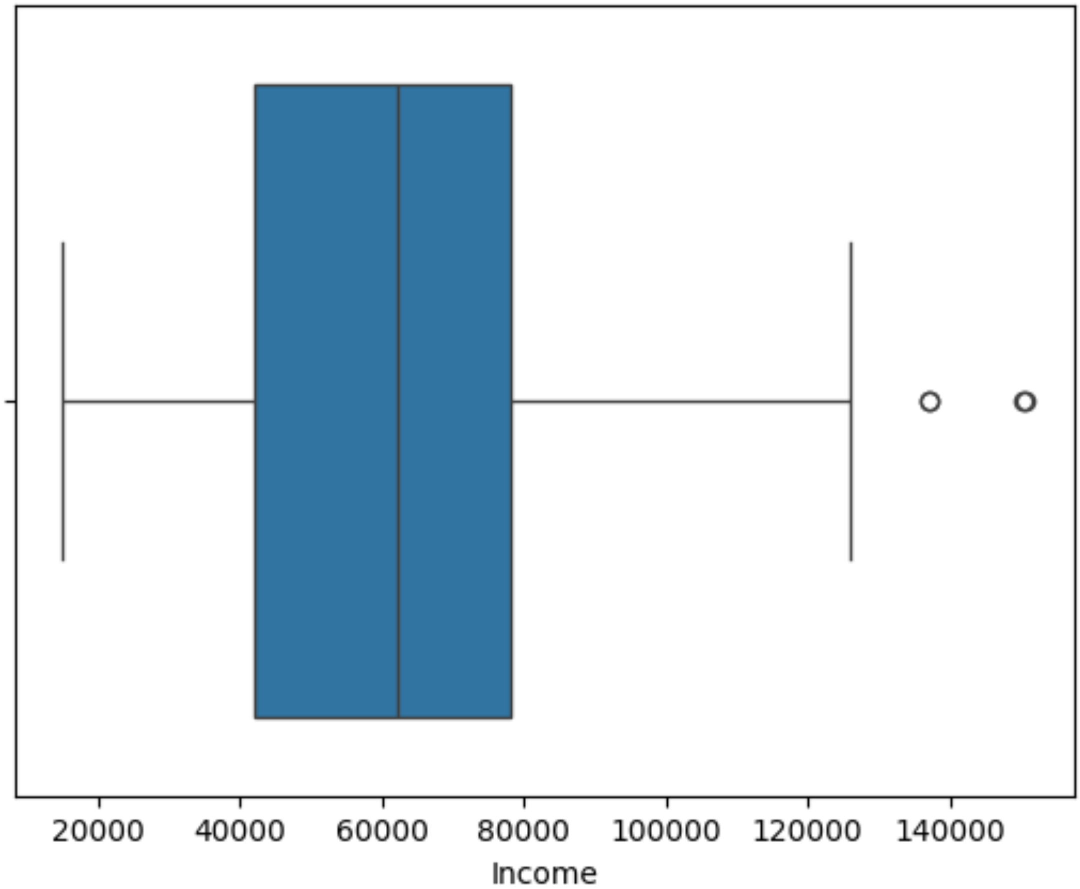
Encode categorical features into numerical data

```
#rows with all the nan values

nan_rows = df[df.isnull().any(axis=1)]
nan_rows
```

	CustomerID	Gender	Age	Income	Spending Score
10	11	Male	67.0	NaN	14
49	50	Female	31.0	NaN	42
85	86	Male	NaN	54000.0	46
120	121	Male	NaN	NaN	56
190	191	Female	NaN	103000.0	23

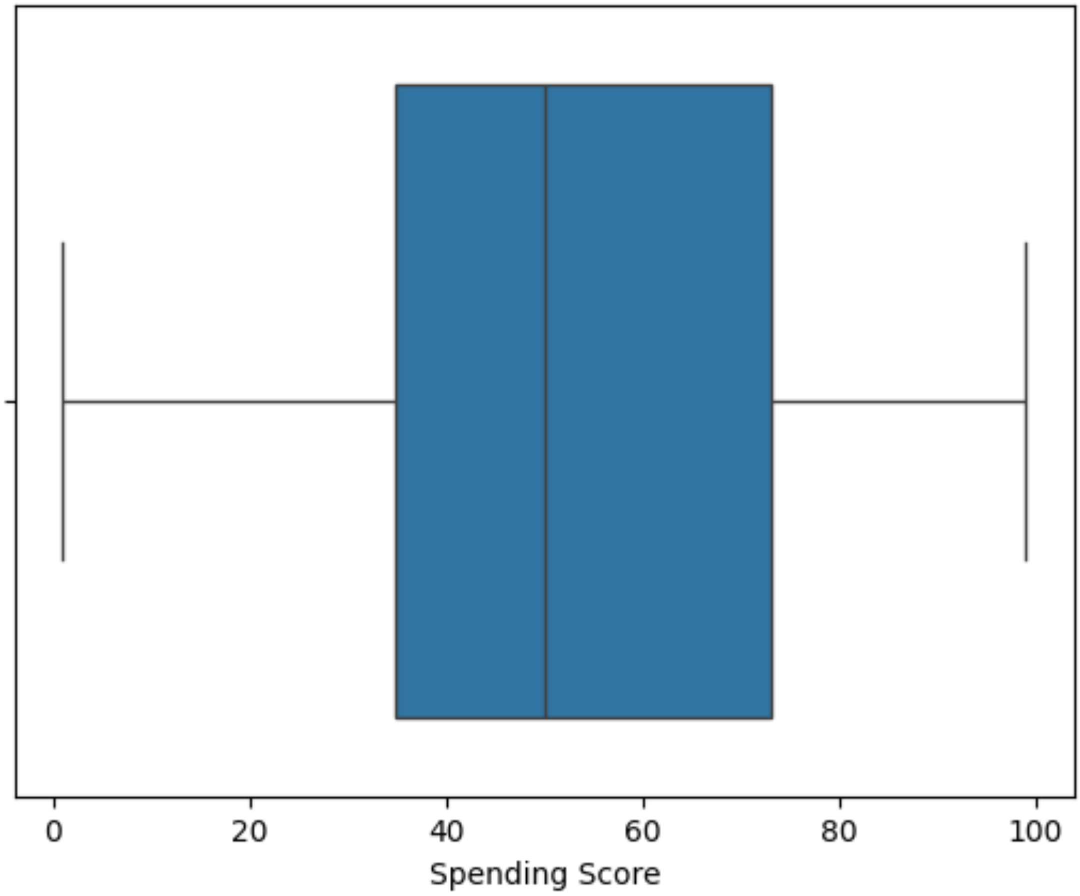
```
sns.boxplot(x='Income', data=df)
```

```
<Axes: xlabel='Income'>
```



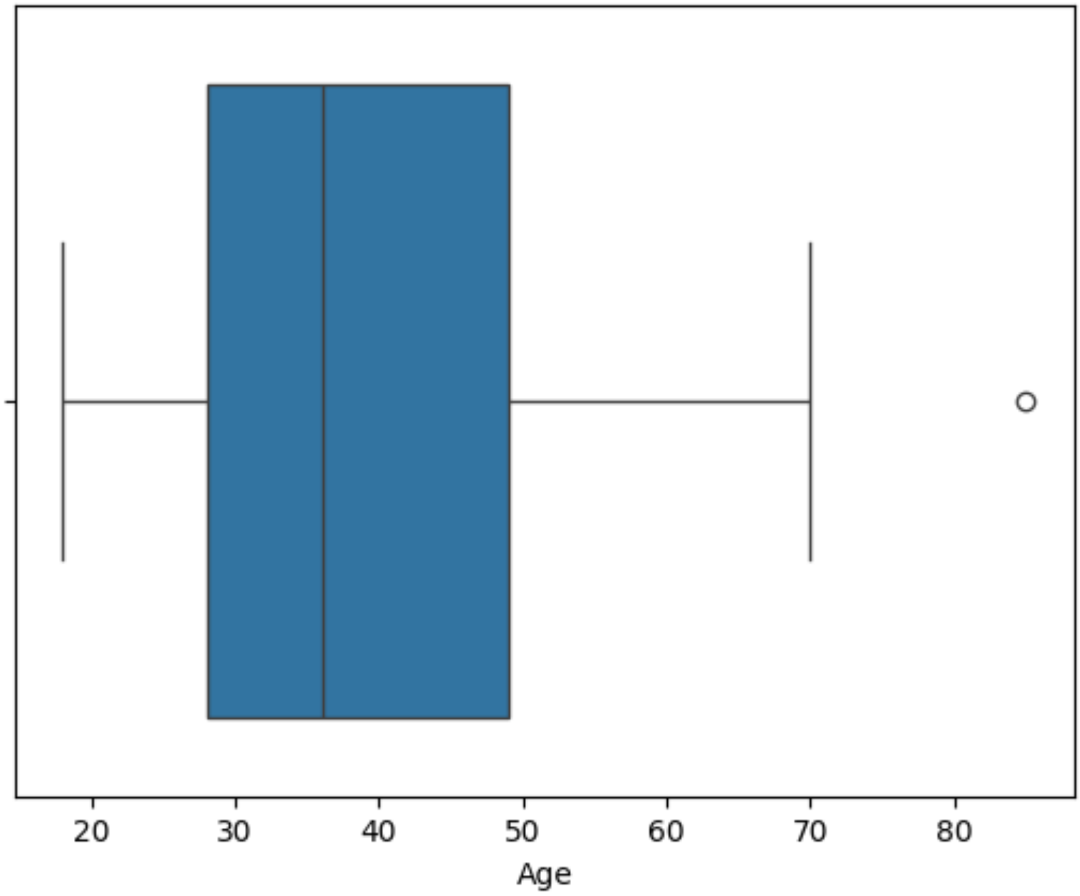
```
sns.boxplot(x='Spending Score', data=df)
```

```
<Axes: xlabel='Spending Score'>
```



```
sns.boxplot(x='Age', data=df)
```

```
<Axes: xlabel='Age'>
```



```
Q1 = df['Income'].quantile(0.25)
Q3 = df['Income'].quantile(0.75)
IQR = Q3 - Q1

# Create a boolean mask for outliers
outlier_mask = (df['Income'] < (Q1 - 1.5 * IQR)) | (df['Income'] > (Q3 + 1.5 *

outliers_income= df[outlier_mask]
outliers_income
```

	CustomerID	Gender	Age	Income	Spending Score
98	99	Male	48.0	150250.0	42
147	148	Female	27.0	150753.0	74
198	199	Male	32.0	137000.0	18
199	200	Male	30.0	137000.0	83

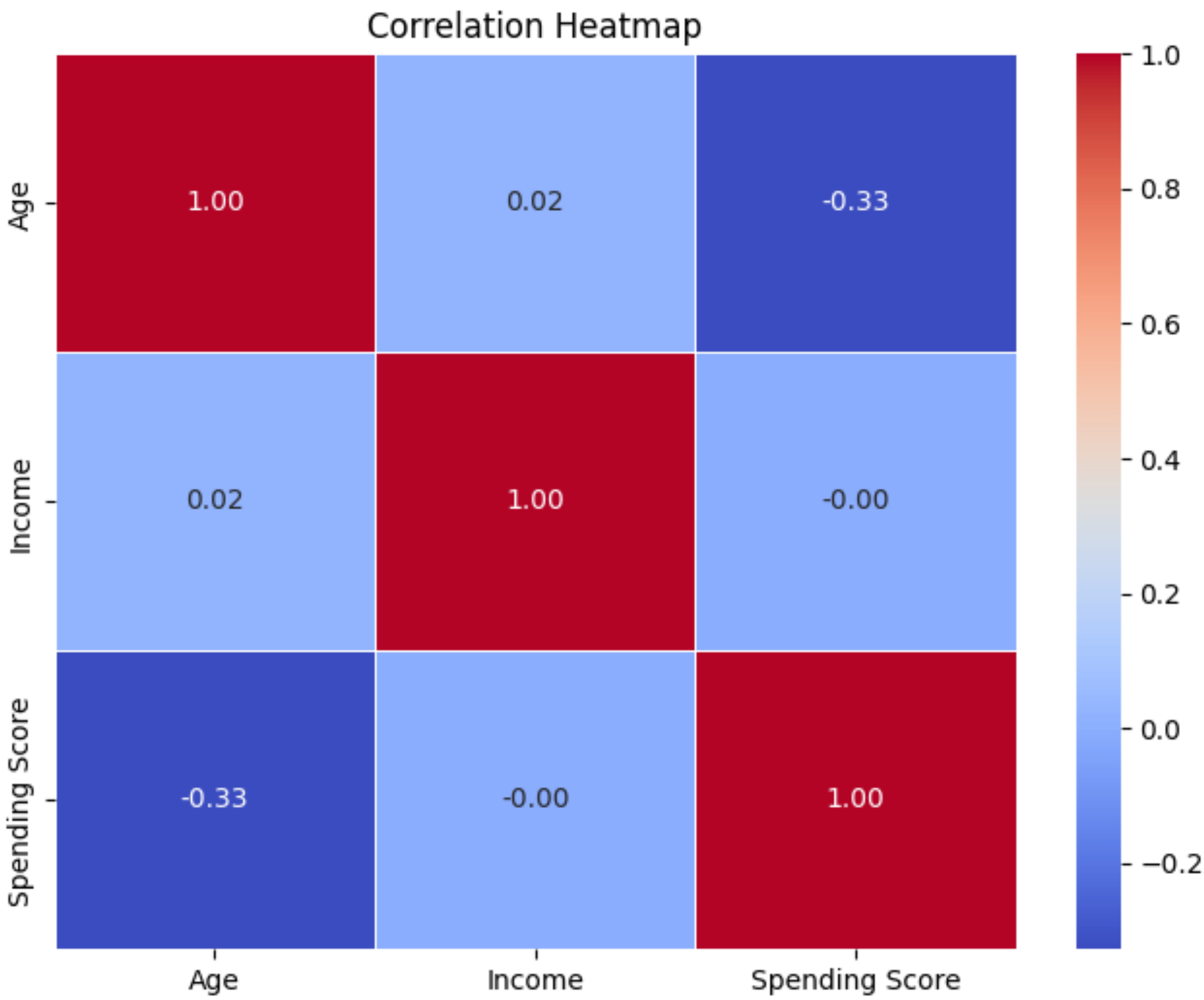
```
# Remove outliers from the DataFrame
df = df[~outlier_mask]
```

```
Q1 = df['Age'].quantile(0.25)
Q3 = df['Age'].quantile(0.75)
IQR = Q3 - Q1

# Create a boolean mask for outliers
outlier_mask = (df['Age'] < (Q1 - 1.5 * IQR)) | (df['Age'] > (Q3 + 1.5 * IQR))

outliers_age= df[outlier_mask]
outliers_age
```

	CustomerID	Gender	Age	Income	Spending Score
37	38	Female	85.0	34000.0	73

```
# Remove outliers from the DataFrame
df = df[~outlier_mask]
```

```
selected_columns = ['Age', 'Income', 'Spending Score']

# Calculate the correlation matrix
correlation_matrix = df[selected_columns].corr()

# Create a heatmap for the correlation matrix
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f', linewic
plt.title('Correlation Heatmap')
plt.show()
```



```
# Calculate gender-specific mean for numerical columns
gender_means = df_clean.groupby('Gender').transform('mean')

# Fill missing values based on gender-specific mean
df_clean_filled = df_clean.copy()
df_clean_filled[['Age', 'Income']] = df_clean_filled[['Age', 'Income']].fillna(
```

```
df_clean_filled
```

	CustomerID	Gender	Age	Income	Spending Score
0	1	Male	19.0	15000.0	39
1	2	Male	21.0	15000.0	81
2	3	Female	20.0	16000.0	6
3	4	Female	23.0	16000.0	77
4	5	Female	31.0	17000.0	40
...	...	...	...	...	...
195	196	Female	35.0	120000.0	79
196	197	Female	45.0	126000.0	28
197	198	Male	32.0	126000.0	74
198	199	Male	32.0	137000.0	18
199	200	Male	30.0	137000.0	83

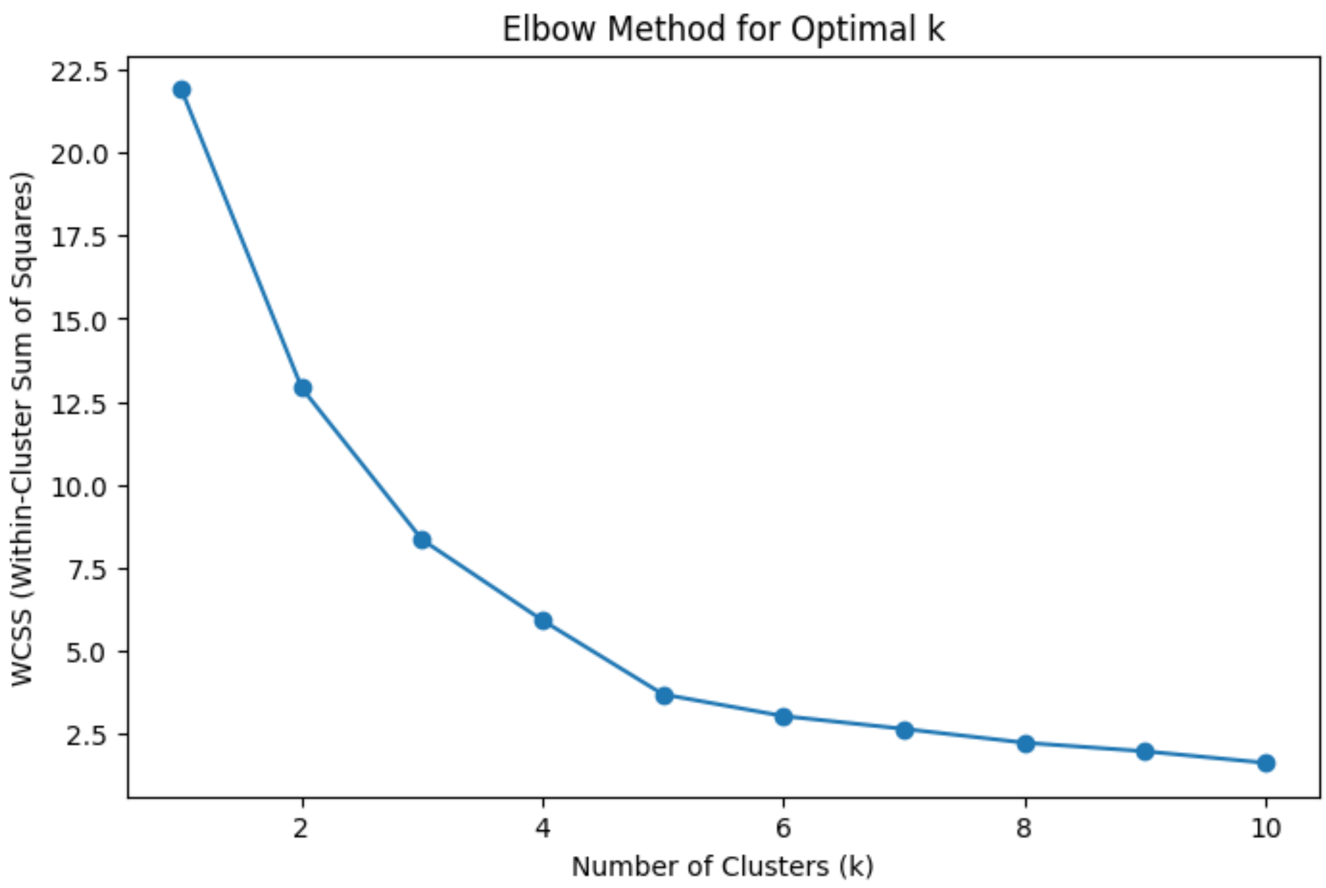
199 rows × 5 columns

```
# Assuming a simple approach: use Min-Max normalization for numerical features
numerical_columns = ['Age', 'Income', 'Spending Score']

scaler = MinMaxScaler()
df_clean_copy = df_clean_filled.copy()  # Create a copy

# Apply Min-Max scaling to numerical columns
df_clean_copy[numerical_columns] = scaler.fit_transform(df_clean_copy[numerical

# Encode categorical features into numerical data using Label Encoder for 'Genc
label_encoder = LabelEncoder()
df_clean_copy['Gender'] = label_encoder.fit_transform(df_clean_copy['Gender'])
df_clean_copy
```

	CustomerID	Gender	Age	Income	Spending Score
0	1	1	0.019231	0.000000	0.387755
1	2	1	0.057692	0.000000	0.816327
2	3	0	0.038462	0.007366	0.051020
3	4	0	0.096154	0.007366	0.775510
4	5	0	0.250000	0.014733	0.397959
...	...	...	...	...	...
195	196	0	0.326923	0.773464	0.795918
196	197	0	0.519231	0.817661	0.275510
197	198	1	0.269231	0.817661	0.744898
198	199	1	0.269231	0.898691	0.173469
199	200	1	0.230769	0.898691	0.836735

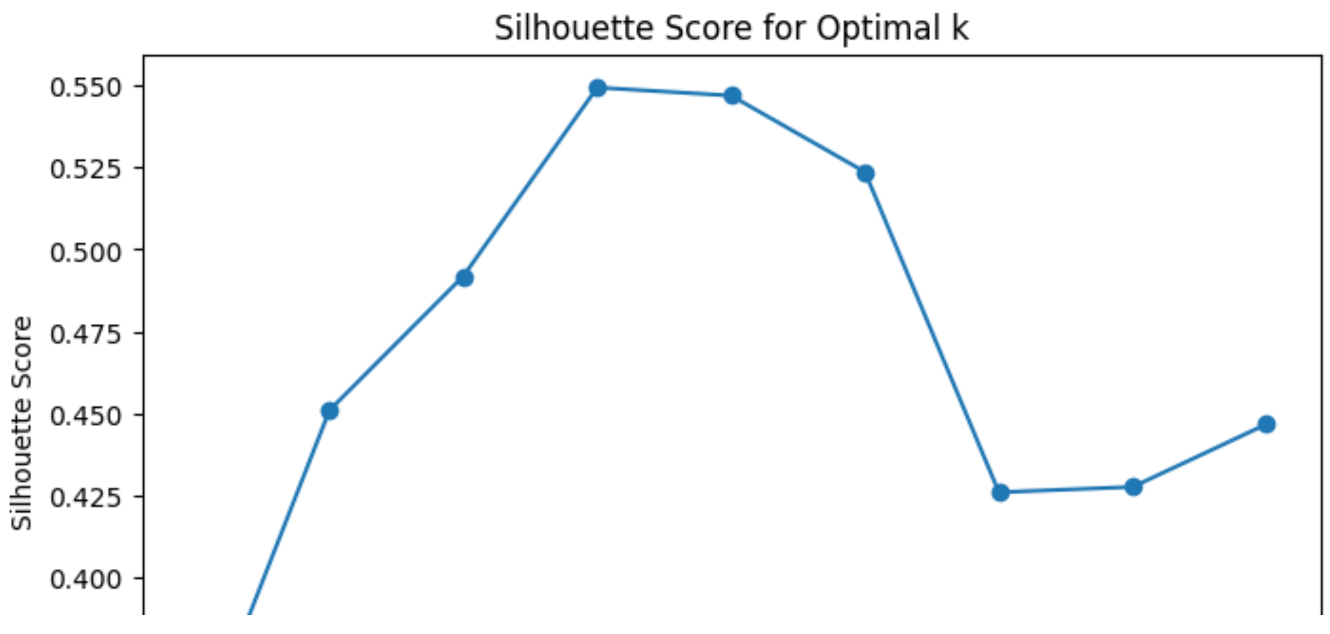
199 rows × 5 columns

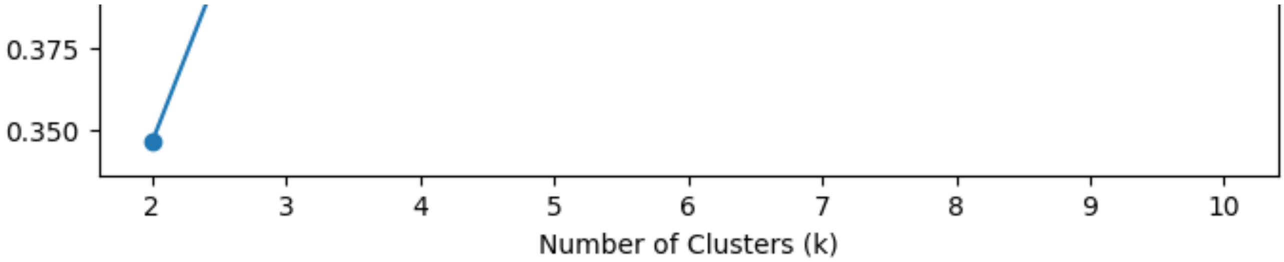
```
features_for_clustering = ['Income', 'Spending Score']
x= df_clean_copy[features_for_clustering]
wcss = []  # Within-Cluster Sum of Squares

# Try different values of k
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42,n_init=10)
    kmeans.fit(x)
    wcss.append(kmeans.inertia_)

# Plot the Elbow Method
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.show()
```

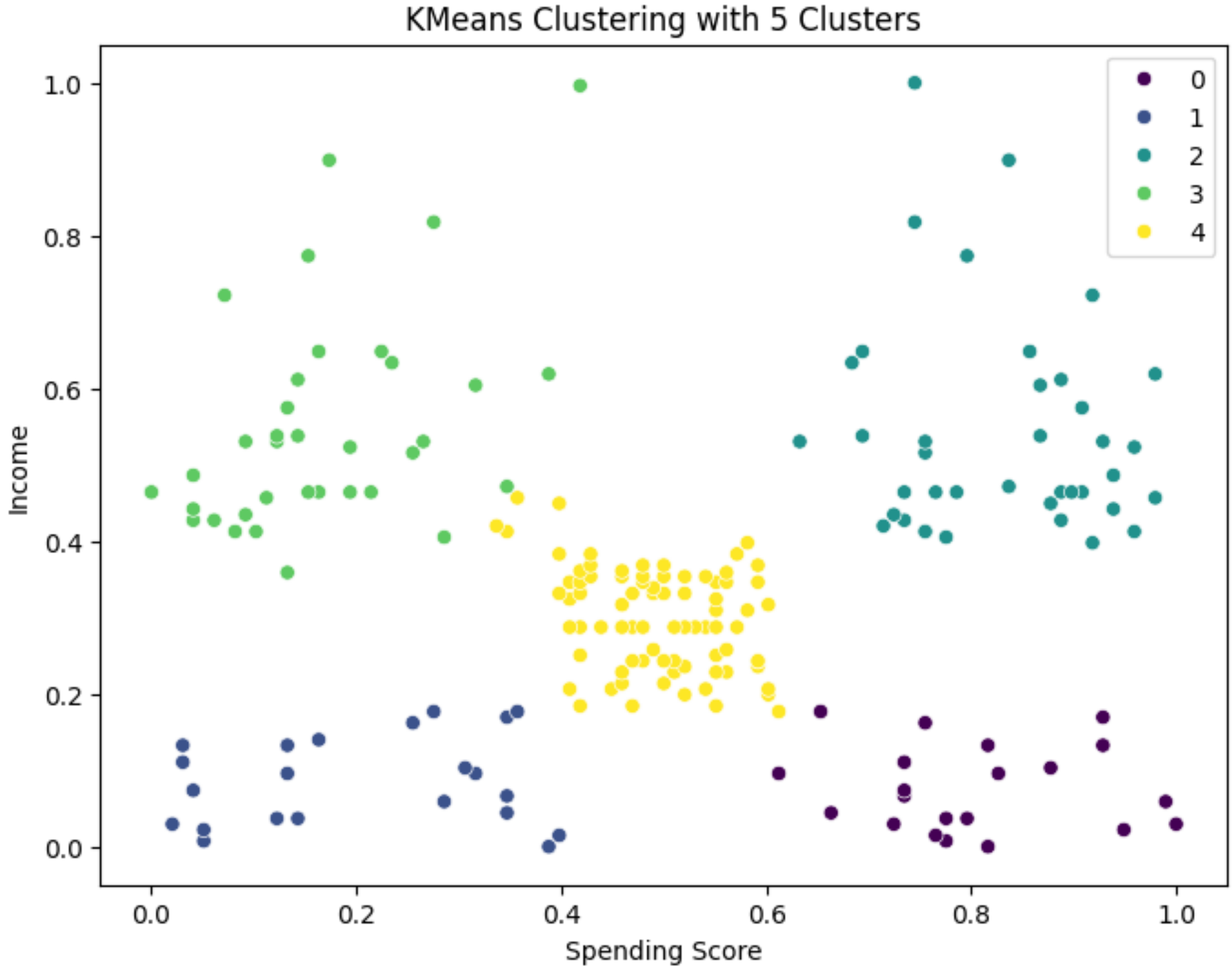



```
# Step 7: Determine the optimum number of clusters using Silhouette Score
```

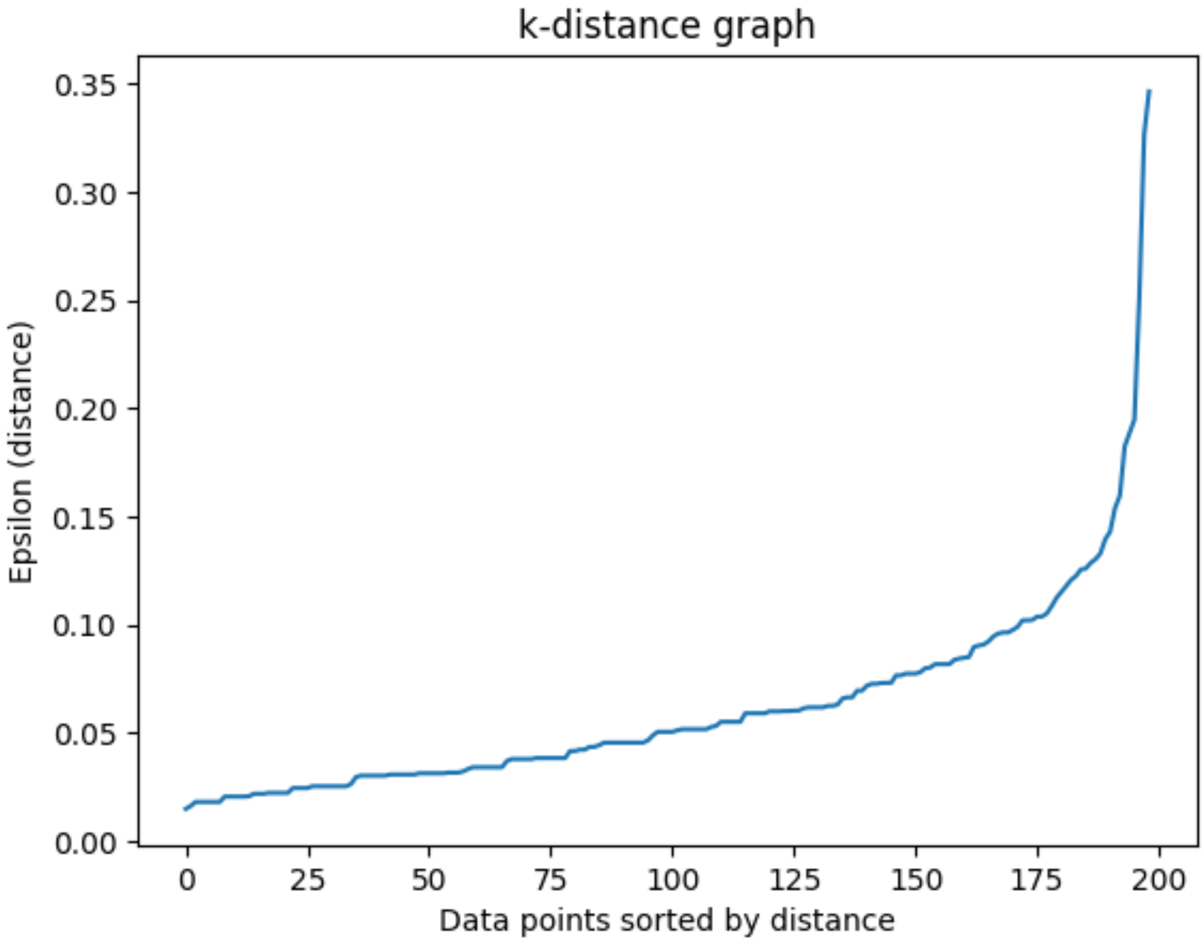
```
silhouette_scores = []

# Try different values of k
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42,n_init=10)
    labels = kmeans.fit_predict(x)
    silhouette_avg = silhouette_score(x, labels)
    silhouette_scores.append(silhouette_avg)

# Plot the Silhouette Score
plt.figure(figsize=(8, 5))
plt.plot(range(2, 11), silhouette_scores, marker='o')
plt.title('Silhouette Score for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Silhouette Score')
plt.show()

# Step 8: Visualize clustering with the optimal number of clusters
# Choose the value of k based on the Elbow Method or Silhouette Score
optimal_k = 5  # Adjust based on the analysis from the Elbow Method or Silhouet

# Fit KMeans with the optimal number of clusters
kmeans_optimal = KMeans(n_clusters=optimal_k, random_state=42,n_init=10)
labels_optimal = kmeans_optimal.fit_predict(x)

# Visualize the clustering
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Spending Score', y='Income', data=df_clean_copy, hue=labels_
plt.title(f'KMeans Clustering with {optimal_k} Clusters')
plt.xlabel('Spending Score')
plt.ylabel('Income')
plt.show()
```




0.375
0.350
2
3
4
5
6
7
8
9
10
Number of Clusters (k)

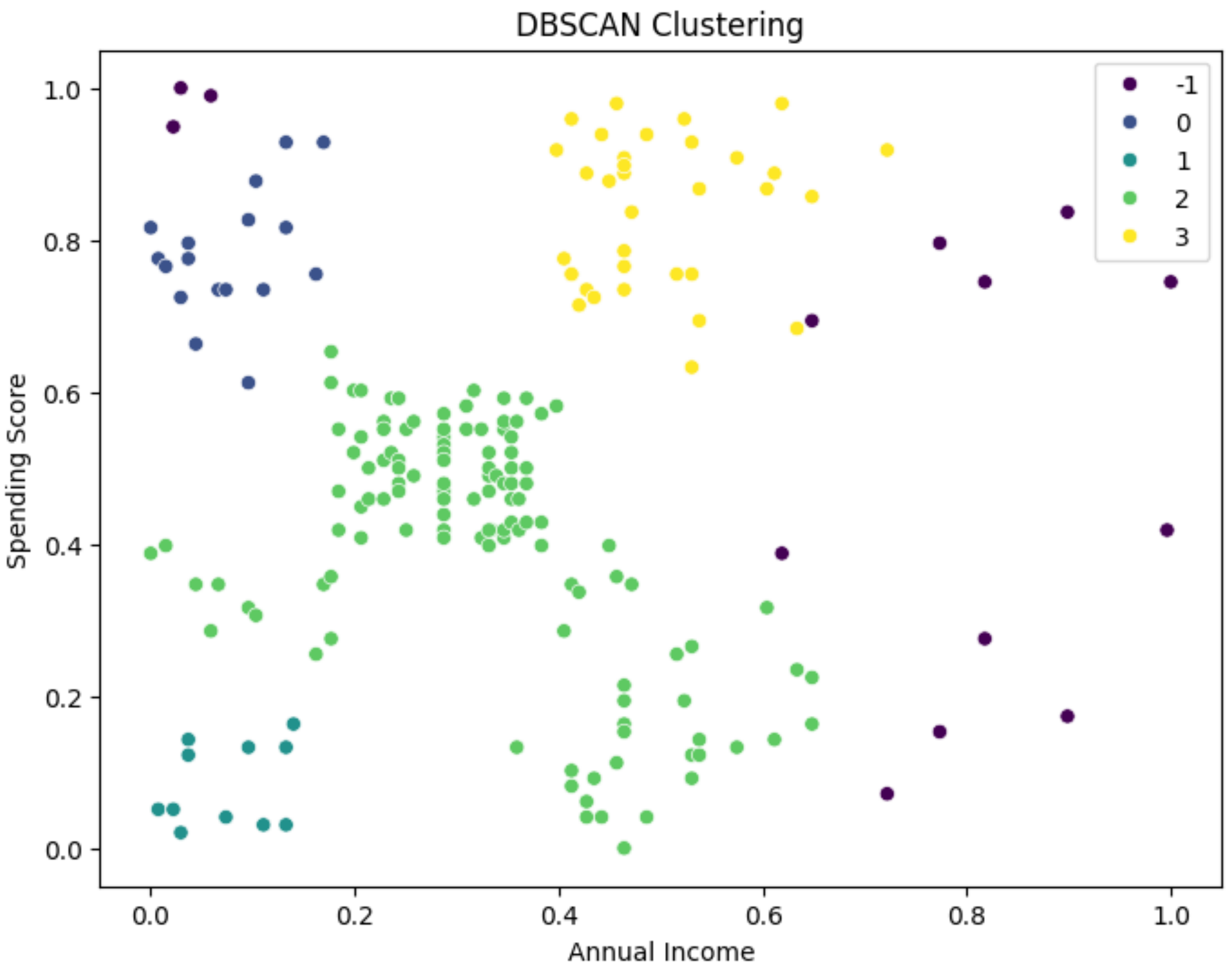

KMeans Clustering with 5 Clusters
Income
Spending Score
0.0
0.2
0.4
0.6
0.8
1.0
0
1
2
3
4

```
# Assuming X is your standardized data
neighbors = NearestNeighbors(n_neighbors=5)  # You can adjust the value of n_ne
neighbors_fit = neighbors.fit(x)
distances, indices = neighbors_fit.kneighbors(x)

# Sort the distances and plot the k-distance graph
distances = np.sort(distances[:, -1])
plt.plot(distances)
plt.title("k-distance graph")
plt.xlabel("Data points sorted by distance")
plt.ylabel("Epsilon (distance)")
plt.show()
```

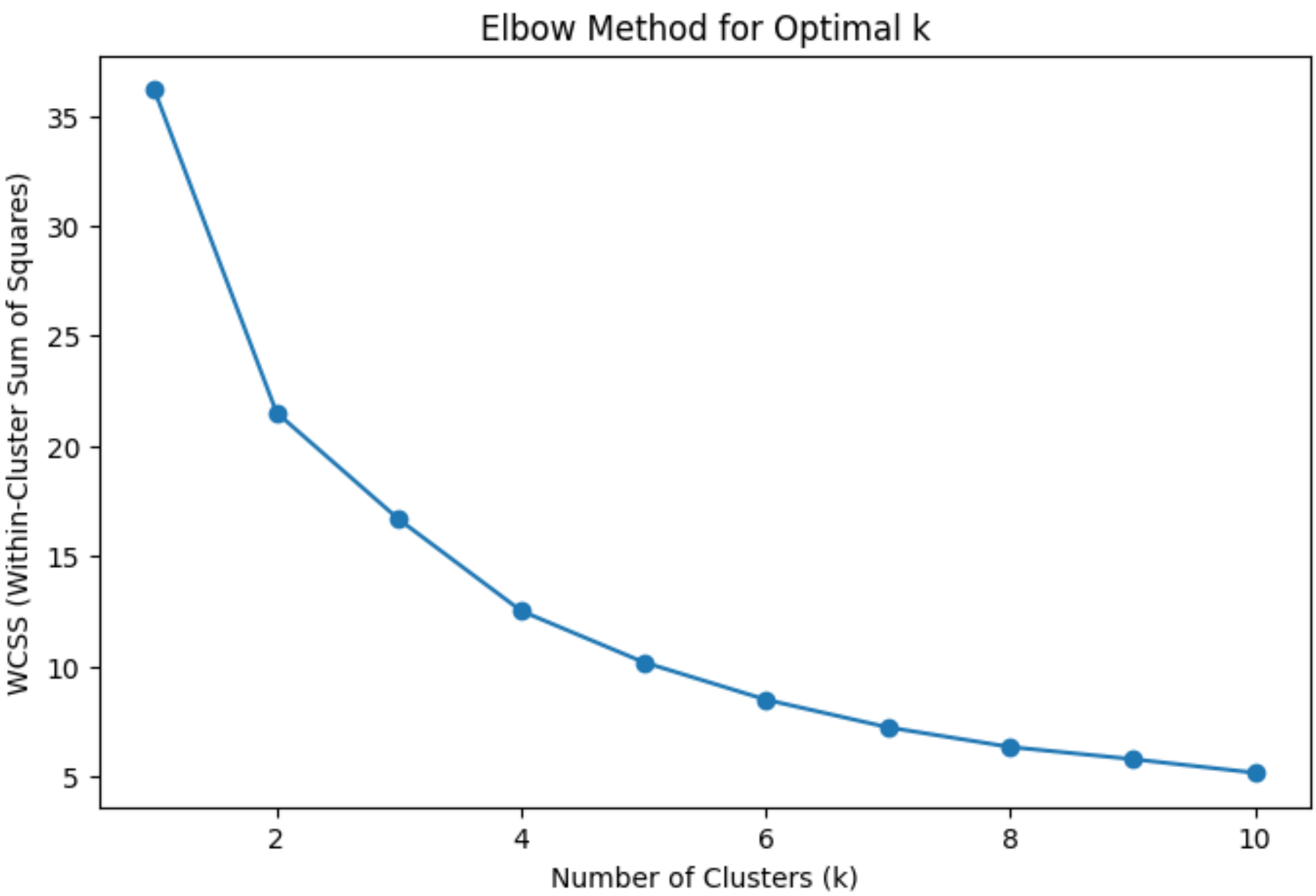


to know the optimum value of eps i have used k distance graph and to see the optimum no of cluster i used k means and silhoutte score

```
# Step 6: Fit the DBSCAN model
# Adjust parameters such as epsilon (eps) and min_samples based on your data
dbscan_model = DBSCAN(eps=.1, min_samples=5)
clusters = dbscan_model.fit_predict(x)

# Step 7: Visualize the clusters
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Income', y='Spending Score', data=df_clean_copy, hue=cluster
plt.title('DBSCAN Clustering')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.show()
```



```
features_for_clustering = ['Income', 'Age', 'Spending Score']
y= df_clean_copy[features_for_clustering]



wcss = []  # Within-Cluster Sum of Squares

# Try different values of k
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42,n_init=10)
    kmeans.fit(y)
    wcss.append(kmeans.inertia_)

# Plot the Elbow Method
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), wcss, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.show()
```



```
# Step 6: Fit the DBSCAN model
# Adjust parameters such as epsilon (eps) and min_samples based on your data
# Adjust parameters such as epsilon (eps) and min_samples based on your data
dbscan_model = DBSCAN(eps=0.1, min_samples=5)
labels = dbscan_model.fit_predict(y)

# Step 7: Visualize clustering with DBSCAN in 3D
# Create a 3D scatter plot
fig = plt.figure(figsize=(10, 8))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(y['Spending Score'], y['Income'], y['Age'], c=labels, cmap='viridis'
ax.set_xlabel('Annual Income')
ax.set_ylabel('Age')
ax.set_zlabel('Spending Score')
ax.set_title('DBSCAN Clustering in 3D')
```

```
Text(0.5, 0.92, 'DBSCAN Clustering in 3D')
```