Customer_Seg_CLV_Project

September 19, 2023

In this section, we import the necessary Python libraries, such as pandas, numpy, seaborn, and matplotlib, for data analysis and visualization.

[ ]:
```
import pandas as pd
import seaborn as sns

df = pd.read_csv('DATA/Mall_Customers.csv')

df.head()
```

[ ]:

	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

We load the dataset into a pandas DataFrame for further analysis. The dataset contains information about customers, including their gender, age, annual income, and spending score.

[ ]:
```
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
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
CustomerID              0
Gender                  0
```

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

[ ]:
```
df.drop(columns='CustomerID').describe()
```

[ ]:

	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

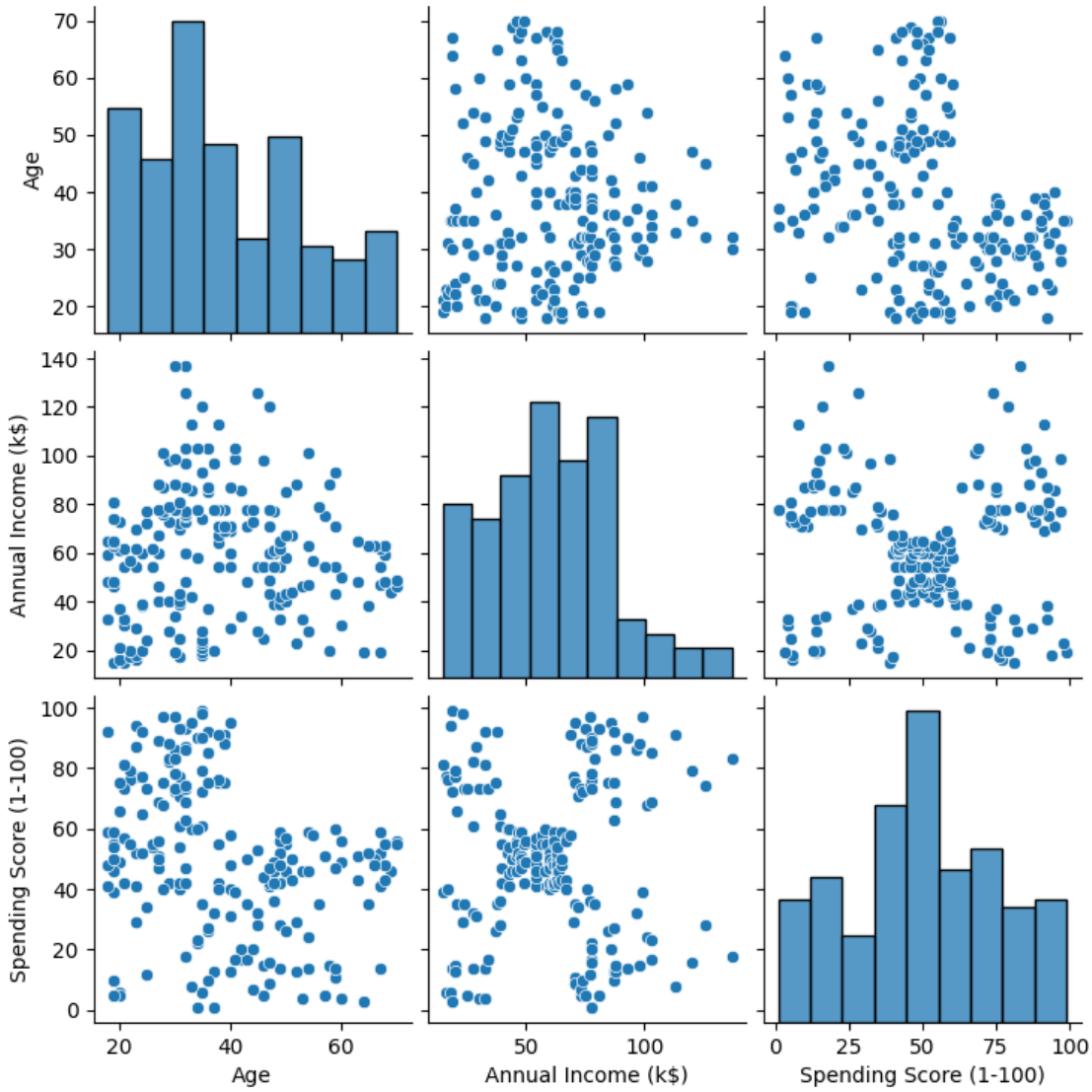
[ ]:
```
df.describe(include='O')
```

[ ]:

	Gender
count	200
unique	2
top	Female
freq	112

[ ]:
```
sns.pairplot(df.drop(columns='CustomerID'));
```

```
C:\Users\pnrde\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\seaborn\axisgrid.py:118: UserWarning: The figure layout has changed to
tight
  self._figure.tight_layout(*args, **kwargs)
```

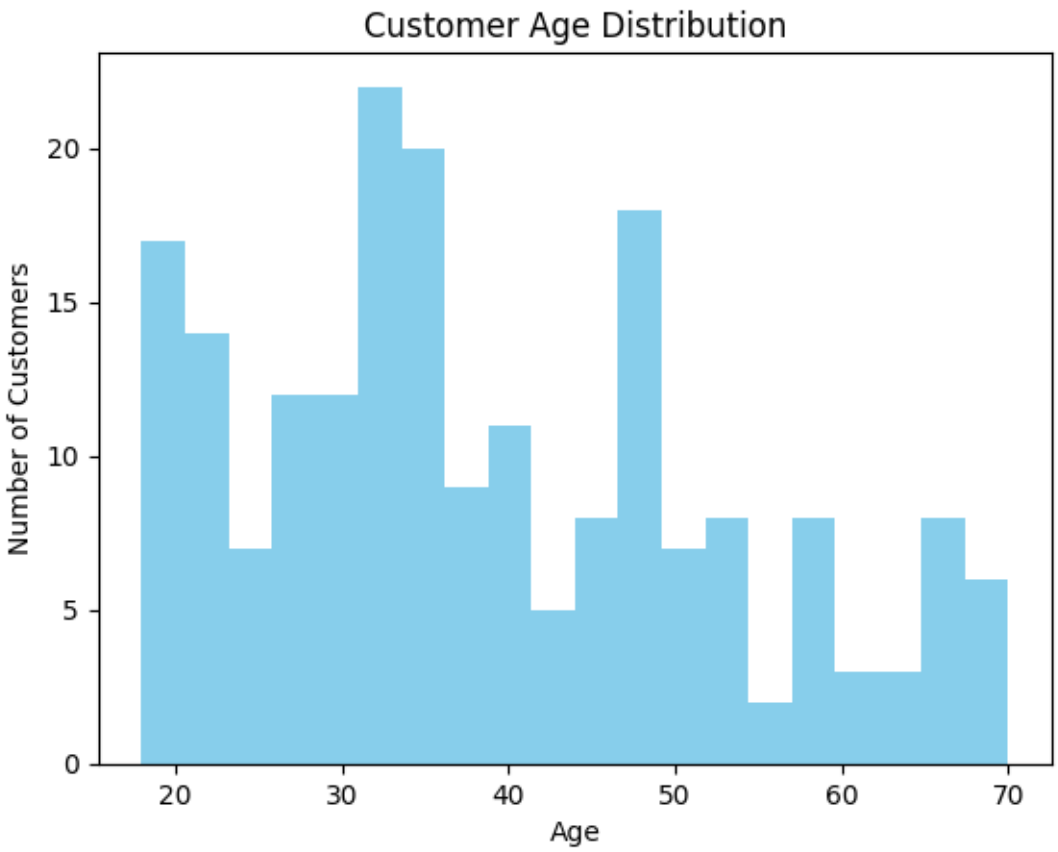


[ ]:
```
df.columns
```

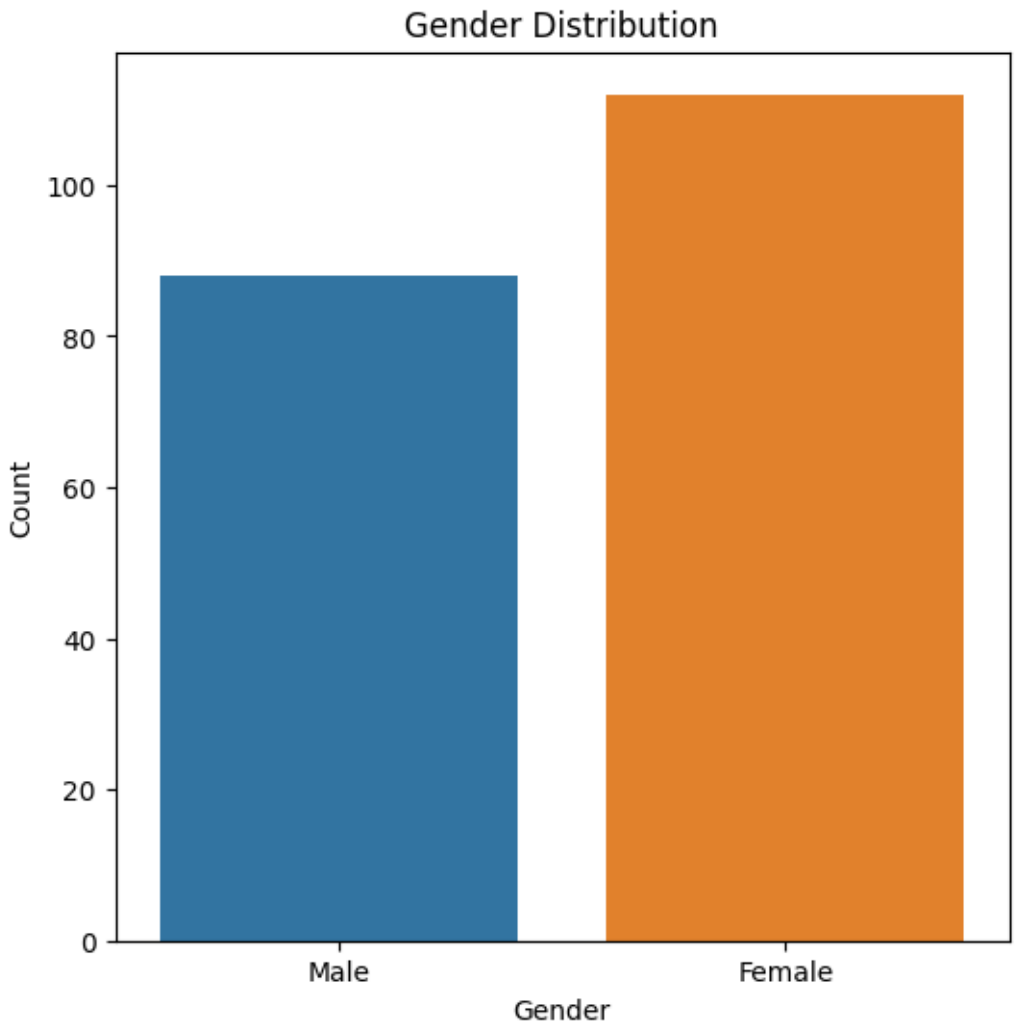
[ ]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

[ ]:
```
import matplotlib.pyplot as plt

plt.hist(df['Age'], bins=20, color='skyblue')
plt.xlabel('Age')
plt.ylabel('Number of Customers')
plt.title('Customer Age Distribution')
plt.show()
```



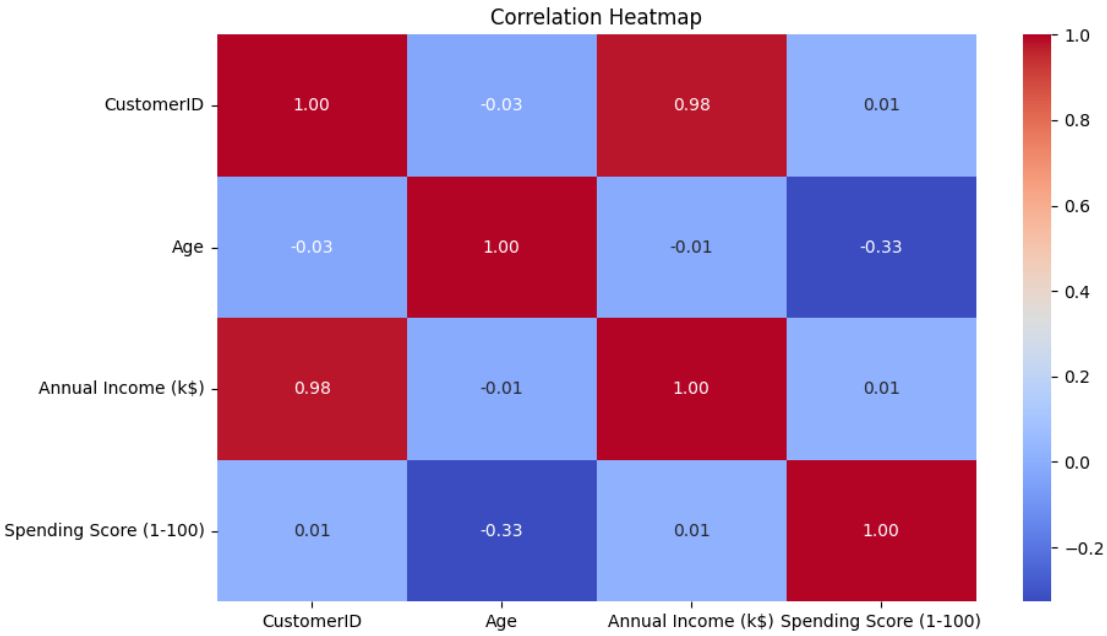
[ ]:
```
plt.figure(figsize=(6, 6))
sns.countplot(data=df, x='Gender')
plt.title('Gender Distribution')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```



[ ]:
```
import numpy as np


numeric_columns = df.select_dtypes(include=[np.number])
correlation_matrix = numeric_columns.corr()

plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```



[ ]:
```
sns.scatterplot(x='Spending Score (1-100)', y='Annual Income (k$)', data=df,␣
↪hue='Gender', palette='Set1')
plt.xlabel('Spending Score (1-100)')
plt.ylabel('Annual Income (k$)')
plt.title('Spending Score vs. Annual Income by Gender')
plt.show()
```

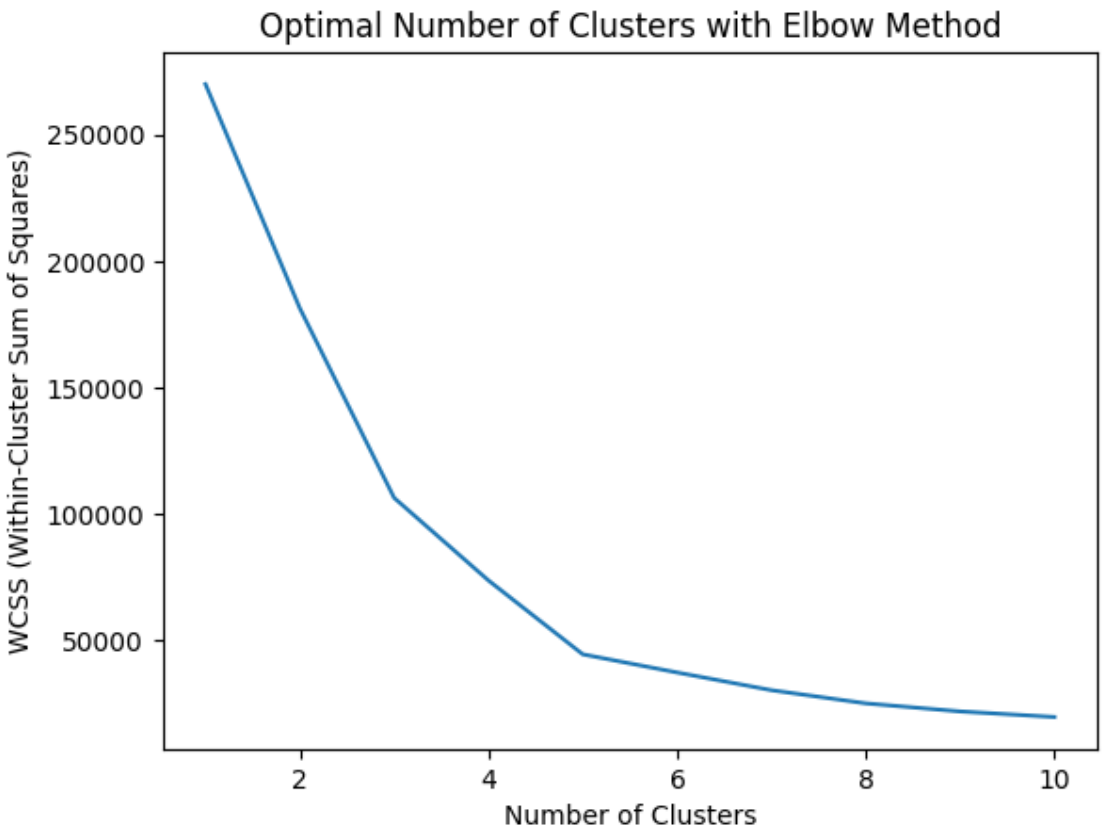
Using techniques such as K-means clustering, we segment customers into different groups based on their spending behavior and demographics.

[ ]:
```
from sklearn.cluster import KMeans
```

[ ]:
```
X = df[['Annual Income (k$)', 'Spending Score (1-100)']]
```

[ ]:
```
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10,␣
 ↪random_state=0)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
```

[ ]:
```
plt.plot(range(1, 11), wcss)
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS (Within-Cluster Sum of Squares)')
plt.title('Optimal Number of Clusters with Elbow Method')
plt.show()
```

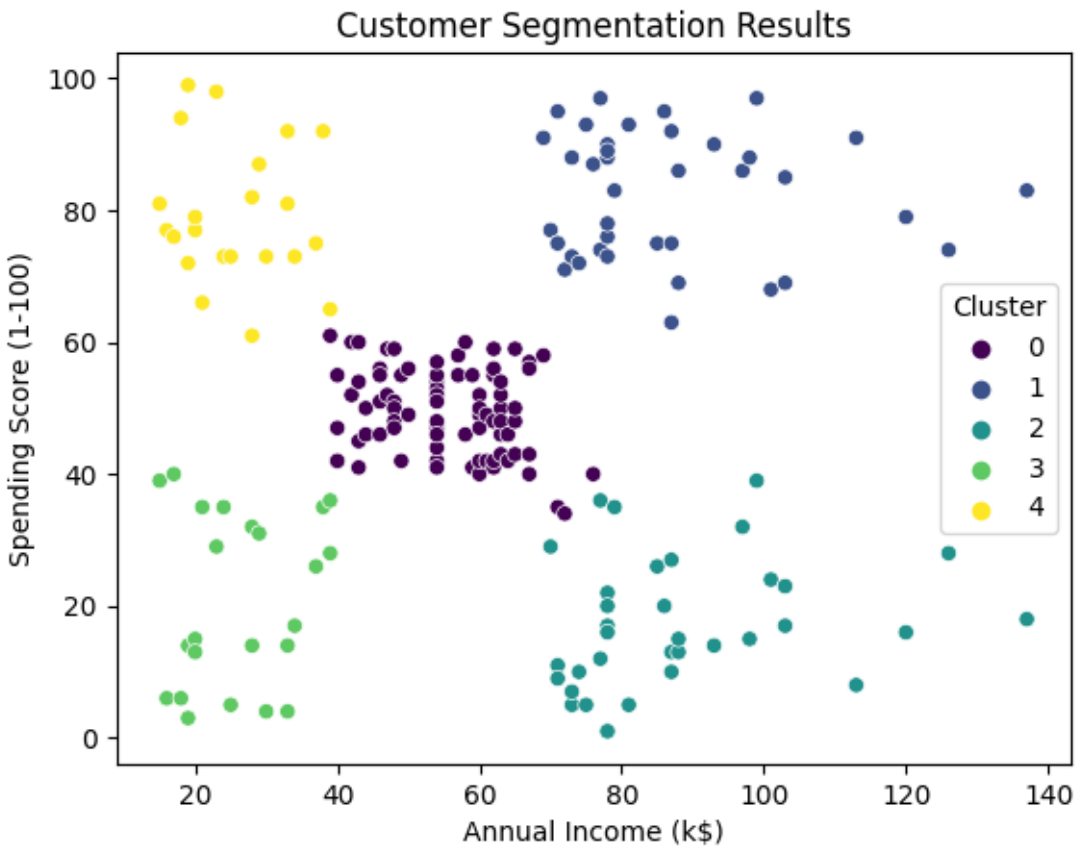


[ ]:
```
optimal_kume_count = 5
```

[ ]:
```
kmeans = KMeans(n_clusters=optimal_kume_count, init='k-means++', max_iter=300,␣
↪n_init=10, random_state=0)
```

[ ]:
```
df['Cluster'] = kmeans.fit_predict(X)
```

[ ]:
```
sns.scatterplot(x='Annual Income (k$)', y='Spending Score (1-100)', data=df,␣
↪hue='Cluster', palette='viridis')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Customer Segmentation Results')
plt.show()
```



We calculate the Customer Lifetime Value (CLV) for each customer using historical data. This helps us understand the long-term value of customers.

[ ]:
```
from sklearn.cluster import k_means


df["Target"]=k_means
```

[ ]:
```
Clustered_df=df
Clustered_df.head()
```

[ ]:
```
   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

   Cluster                                      Target
0        3  <function k_means at 0x000002430305ADE0>
```

```
1         4  <function k_means at 0x0000024303305ADE0>
2         3  <function k_means at 0x0000024303305ADE0>
3         4  <function k_means at 0x0000024303305ADE0>
4         3  <function k_means at 0x0000024303305ADE0>
```

[ ]:
```
data = {
    'CustomerID': [1, 2, 3, 4, 5],
    'Recency': [10, 5, 3, 8, 1],
    'Frequency': [3, 8, 4, 2, 12],
    'Monetary': [150, 300, 200, 50, 800],
}

df = pd.DataFrame(data)
```

[ ]:
```
quantiles = df.quantile(q=[0.25, 0.5, 0.75])
quantiles = quantiles.to_dict()



def r_score(x, col):
    if x <= quantiles[col][0.25]:
        return 1
    elif x <= quantiles[col][0.5]:
        return 2
    elif x <= quantiles[col][0.75]:
        return 3
    else:
        return 4

def fm_score(x, col):
    if x <= quantiles[col][0.25]:
        return 4
    elif x <= quantiles[col][0.5]:
        return 3
    elif x <= quantiles[col][0.75]:
        return 2
    else:
        return 1

df['R_Score'] = df['Recency'].apply(r_score, args=('Recency',))
df['F_Score'] = df['Frequency'].apply(fm_score, args=('Frequency',))
df['M_Score'] = df['Monetary'].apply(fm_score, args=('Monetary',))
```

[ ]:
```
df['RFM_Score'] = df['R_Score'].map(str) + df['F_Score'].map(str) +␣
↪df['M_Score'].map(str)
```

[ ]:
```
average_purchase_value = df['Monetary'].mean()
```

[ ]:
```
average_purchase_frequency = df['Frequency'].mean()
```

[ ]:
```
average_customer_lifespan = df['Recency'].mean()
```

[ ]:
```
df['CLV'] = (average_purchase_value * average_purchase_frequency *␣
 ↪average_customer_lifespan)
```

[ ]:
```
print(df)
```

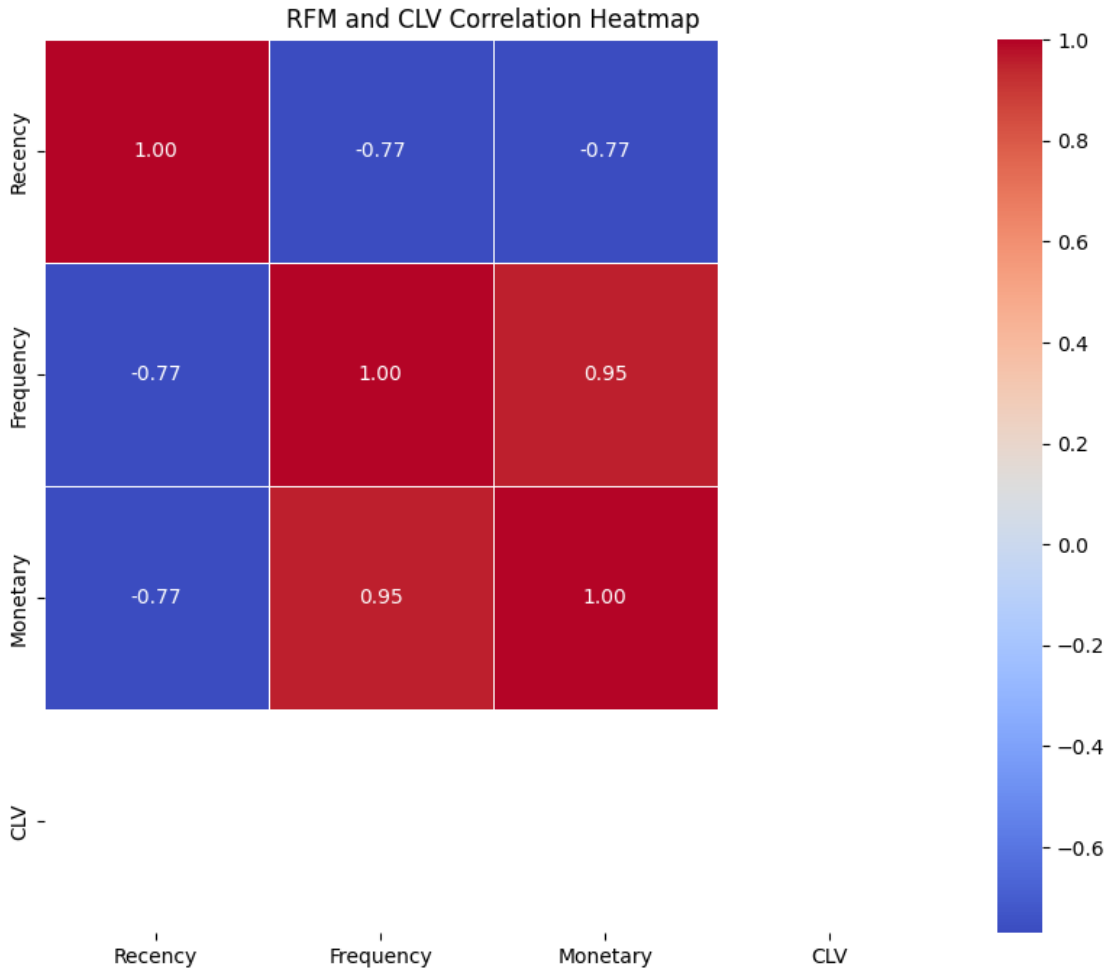
```
   CustomerID  Recency  Frequency  Monetary  R_Score  F_Score  M_Score  \
0           1       10          3       150        4        4        4
1           2        5          8       300        2        2        2
2           3        3          4       200        1        3        3
3           4        8          2        50        3        4        4
4           5        1         12       800        1        1        1

  RFM_Score     CLV
0       444  9396.0
1       222  9396.0
2       133  9396.0
3       344  9396.0
4       111  9396.0
```

[ ]:
```
rfm_clv_df = df[['Recency', 'Frequency', 'Monetary', 'CLV']]
```

[ ]:
```
correlation_matrix = rfm_clv_df.corr()
```

[ ]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
 ↪linewidths=0.5)
plt.title('RFM and CLV Correlation Heatmap')
plt.show()
```



[ ]:
```
X = df[['Recency', 'Frequency', 'Monetary']]
```

[ ]:
```
kmeans = KMeans(n_clusters=3)
df['Segment'] = kmeans.fit_predict(X)
```

```
C:\Users\pnrde\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\cluster\_kmeans.py:1412: 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
  super()._check_params_vs_input(X, default_n_init=10)
```

[ ]:
```
segment_statistics = df.groupby('Segment').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'Monetary': 'mean',
    'CLV': 'mean'
```

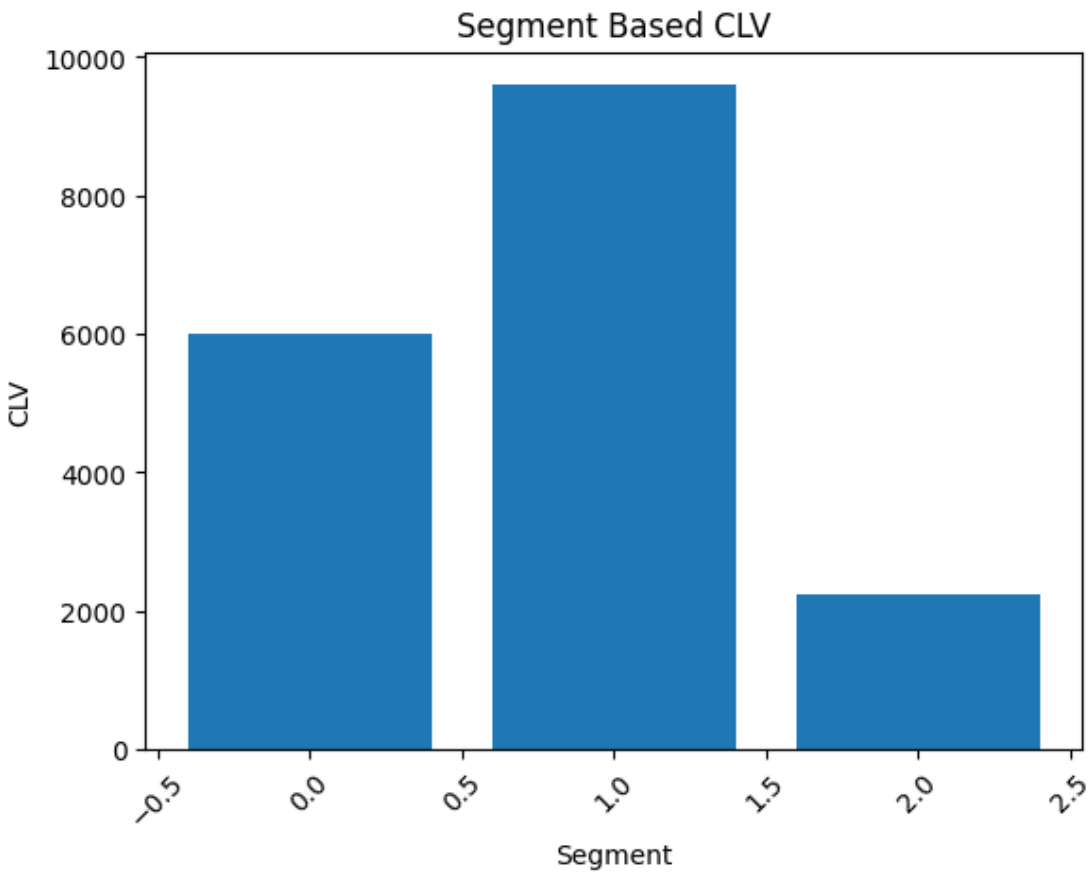
```
})
print(segment_statistics)
```

```
         Recency  Frequency  Monetary     CLV
Segment
0            4.0        6.0     250.0  9396.0
1            1.0       12.0     800.0  9396.0
2            9.0        2.5     100.0  9396.0
```

[ ]:
```
segmented_data = df.groupby('Segment')
```

[ ]:
```
segment_clv = {}
for segment, data in segmented_data:
    average_purchase_value = data['Monetary'].mean()
    average_purchase_frequency = data['Frequency'].mean()
    average_customer_lifespan = data['Recency'].mean()
    segment_clv[segment] = (average_purchase_value * average_purchase_frequency␣
 ↪* average_customer_lifespan)
```

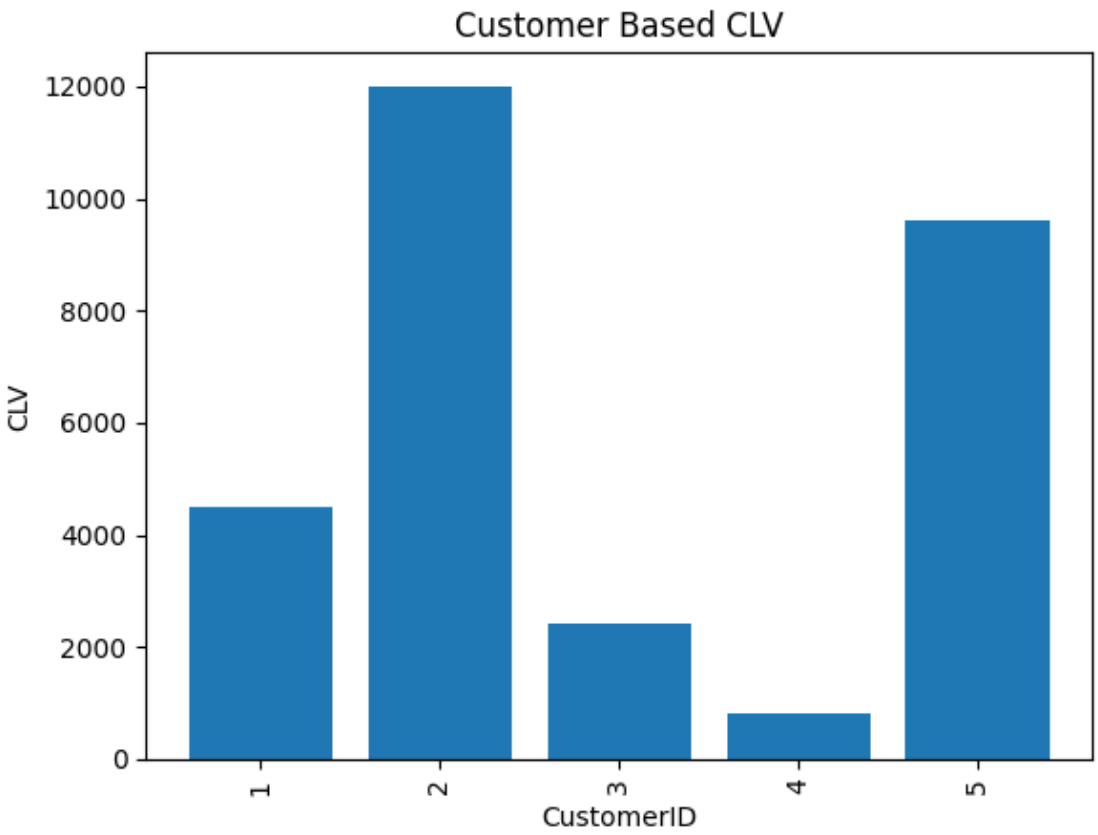
[ ]:
```
plt.bar(segment_clv.keys(), segment_clv.values())
plt.xlabel('Segment')
plt.ylabel('CLV')
plt.title('Segment Based CLV')
plt.xticks(rotation=45)
plt.show()
```



[ ]:
```
product_grouped_data = df.groupby('CustomerID')
```

[ ]:
```
customer_product_clv = {}
for (customer), data in product_grouped_data:
    average_purchase_value = data['Monetary'].mean()
    average_purchase_frequency = data['Frequency'].mean()
    average_customer_lifespan = data['Recency'].mean()
    customer_product_clv[(customer)] = (average_purchase_value *␣
 ↪average_purchase_frequency * average_customer_lifespan)
```

[ ]:
```
plt.bar(customer_product_clv.keys(), customer_product_clv.values())
plt.xlabel('CustomerID')
plt.ylabel('CLV')
plt.title('Customer Based CLV')
plt.xticks(rotation=90)
plt.show()
```


Customer Based CLV
12000
10000
8000
6000
4000
2000
0
CLV
1
2
3
4
5
CustomerID