Importing Libraries

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

In [2]:
```
df = pd.read_csv('/content/Customer_Data.csv')
```

Data Cleaning and Exploration

In [3]:
```
df.head()
```

Out[3]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLME
0	C10001	40.900749	0.818182	95.40	0.00	
1	C10002	3202.467416	0.909091	0.00	0.00	
2	C10003	2495.148862	1.000000	773.17	773.17	
3	C10004	1666.670542	0.636364	1499.00	1499.00	
4	C10005	817.714335	1.000000	16.00	16.00	

In [4]:
```
# Removing English Letter from CUST_ID using regular expression

df['CUST_ID'] = df['CUST_ID'].str.replace(r'\D', '', regex = True)

# Change Data Type from object to int
df['CUST_ID'] = df['CUST_ID'].astype('int64')
```

In [5]:
```
df.head()
```

Out[5]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLME
0	10001	40.900749	0.818182	95.40	0.00	
1	10002	3202.467416	0.909091	0.00	0.00	
2	10003	2495.148862	1.000000	773.17	773.17	
3	10004	1666.670542	0.636364	1499.00	1499.00	
4	10005	817.714335	1.000000	16.00	16.00	

In [6]:
```
# Checking the Data Types of All Columns

df.dtypes
```

Out[6]:
```
CUST_ID                              int64
BALANCE                            float64
BALANCE_FREQUENCY                  float64
PURCHASES                          float64
ONEOFF_PURCHASES                   float64
INSTALLMENTS_PURCHASES             float64
CASH_ADVANCE                       float64
PURCHASES_FREQUENCY                float64
ONEOFF_PURCHASES_FREQUENCY         float64
PURCHASES_INSTALLMENTS_FREQUENCY   float64
CASH_ADVANCE_FREQUENCY             float64
CASH_ADVANCE_TRX                     int64
PURCHASES_TRX                        int64
CREDIT_LIMIT                       float64
PAYMENTS                           float64
MINIMUM_PAYMENTS                   float64
PRC_FULL_PAYMENT                   float64
TENURE                               int64
dtype: object
```

In [7]:
```
# Change all the Data Types to float
for col in df.columns:
  if df[col].dtypes == 'int64':
    df[col] = df[col].astype('float64')
```

In [8]:
```
# Information of the whole dataset

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8950 entries, 0 to 8949
Data columns (total 18 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   CUST_ID                           8950 non-null   float64
 1   BALANCE                           8950 non-null   float64
 2   BALANCE_FREQUENCY                 8950 non-null   float64
 3   PURCHASES                         8950 non-null   float64
 4   ONEOFF_PURCHASES                  8950 non-null   float64
 5   INSTALLMENTS_PURCHASES            8950 non-null   float64
 6   CASH_ADVANCE                      8950 non-null   float64
 7   PURCHASES_FREQUENCY               8950 non-null   float64
 8   ONEOFF_PURCHASES_FREQUENCY        8950 non-null   float64
 9   PURCHASES_INSTALLMENTS_FREQUENCY  8950 non-null   float64
 10  CASH_ADVANCE_FREQUENCY            8950 non-null   float64
 11  CASH_ADVANCE_TRX                  8950 non-null   float64
 12  PURCHASES_TRX                     8950 non-null   float64
 13  CREDIT_LIMIT                      8949 non-null   float64
 14  PAYMENTS                          8950 non-null   float64
 15  MINIMUM_PAYMENTS                  8637 non-null   float64
 16  PRC_FULL_PAYMENT                  8950 non-null   float64
 17  TENURE                            8950 non-null   float64
dtypes: float64(18)
memory usage: 1.2 MB
```

Checking the total missing values of each columns

In [9]:
```
missing_values = []
for col in df.columns:
  missing_values.append(df[col].isna().sum())
```

In [10]:
```
Col = df.columns
```

In [11]:
```
Col = pd.DataFrame(Col)
missing_values= pd.DataFrame(missing_values)
```

In [12]:
```
result_missing = pd.concat([Col, missing_values], axis = 1)
result_missing.columns = ['Columns', 'Missing_values']
```

In [13]:
```
result_missing
```

Out[13]:

	Columns	Missing_values
0	CUST_ID	0
1	BALANCE	0
2	BALANCE_FREQUENCY	0
3	PURCHASES	0
4	ONEOFF_PURCHASES	0
5	INSTALLMENTS_PURCHASES	0
6	CASH_ADVANCE	0
7	PURCHASES_FREQUENCY	0
8	ONEOFF_PURCHASES_FREQUENCY	0
9	PURCHASES_INSTALLMENTS_FREQUENCY	0
10	CASH_ADVANCE_FREQUENCY	0
11	CASH_ADVANCE_TRX	0
12	PURCHASES_TRX	0
13	CREDIT_LIMIT	1
14	PAYMENTS	0
15	MINIMUM_PAYMENTS	313
16	PRC_FULL_PAYMENT	0
17	TENURE	0

Filling Missing Values

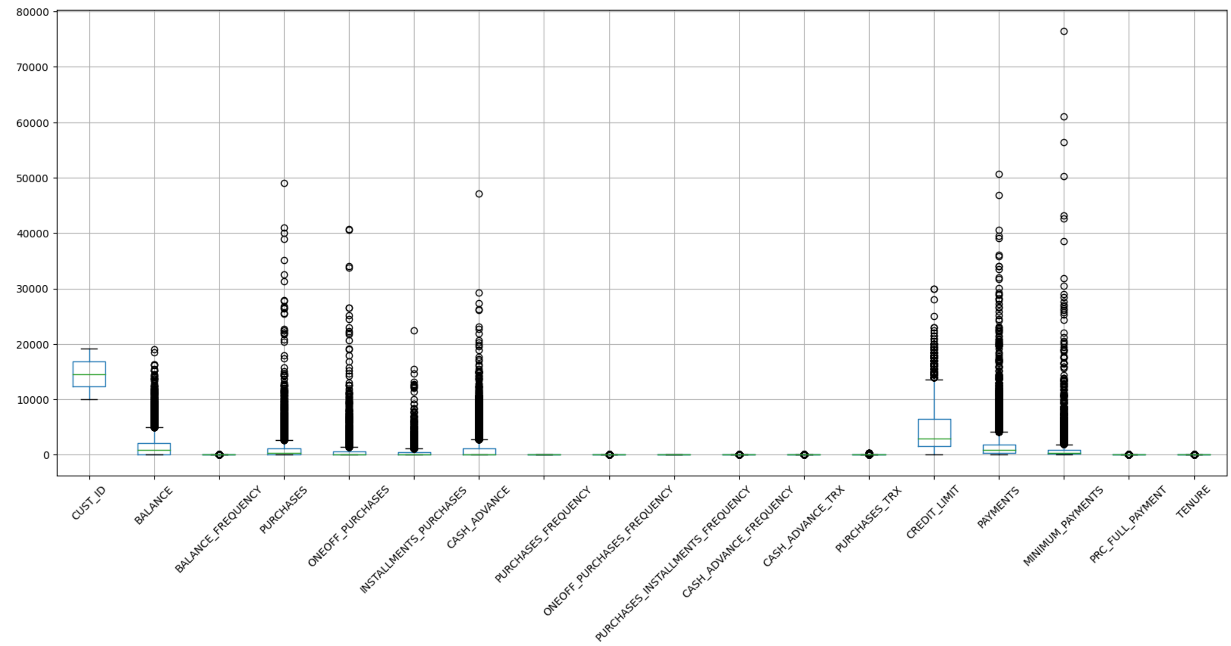
In [14]:
```
df['CREDIT_LIMIT'].fillna(df['CREDIT_LIMIT'].mean(), inplace=True)
```

In [15]:
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(missing_values = np.nan, strategy = 'mean')
df[['MINIMUM_PAYMENTS']] = imputer.fit_transform(df[['MINIMUM_PAYMENTS']])
```

Outlier Detection using Boxplot

In [16]:
```
plt.figure(figsize = (20, 8))
df.boxplot(rot = 45)
```

Out[16]:
```
<Axes: >
```



Check the total outliers of each columns

In [17]:
```
total_outliers = []

for col in df.columns[1:]:
  percentile25 = df[col].quantile(0.25)
  percentile75 = df[col].quantile(0.75)
  iqr = percentile75 - percentile25
  upper_bound = percentile75 + 1.5 * iqr
  lower_bound = percentile25 - 1.5 * iqr
  total_outliers.append(sum((df[col] < lower_bound) | (df[col] > upper_bound)))
```

In [18]:
```
total_outliers = pd.DataFrame(total_outliers)
```

In [19]:
```
result_outlier = pd.concat([Col, total_outliers], axis = 1)
result_outlier.columns = ['Columns', 'Sum of Outliers']
```

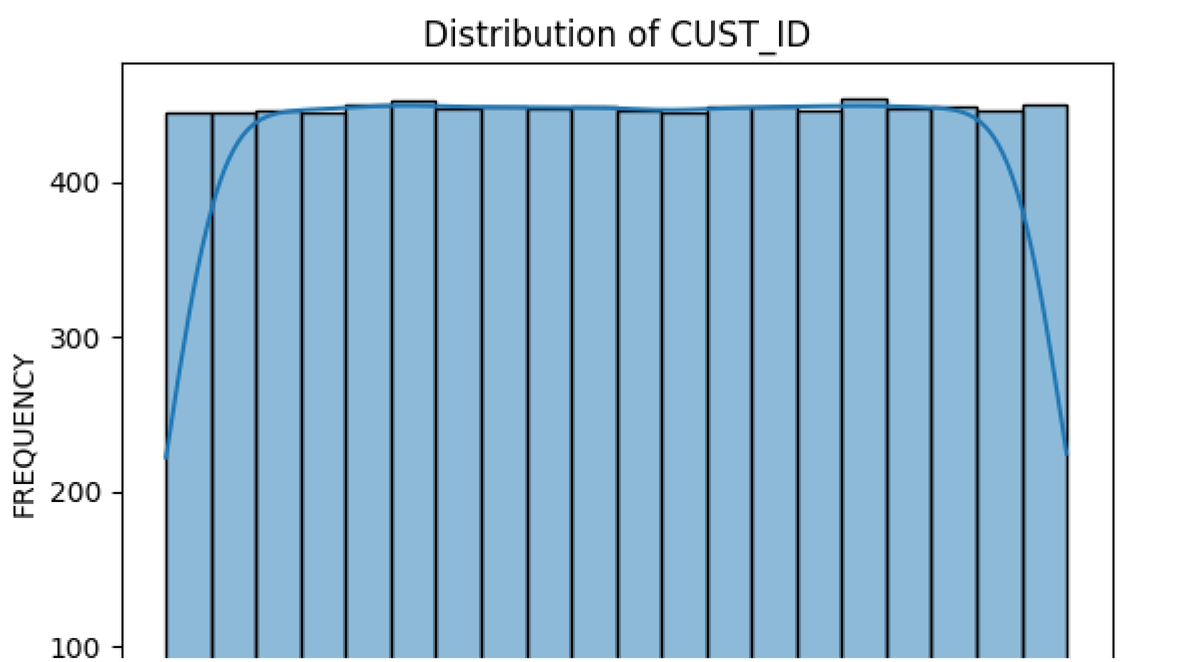
In [20]:
```
result_outlier
```

Out[20]:

	Columns	Sum of Outliers
0	CUST_ID	695.0
1	BALANCE	1493.0
2	BALANCE_FREQUENCY	808.0
3	PURCHASES	1013.0
4	ONEOFF_PURCHASES	867.0
5	INSTALLMENTS_PURCHASES	1030.0
6	CASH_ADVANCE	0.0
7	PURCHASES_FREQUENCY	782.0
8	ONEOFF_PURCHASES_FREQUENCY	0.0
9	PURCHASES_INSTALLMENTS_FREQUENCY	525.0
10	CASH_ADVANCE_FREQUENCY	804.0
11	CASH_ADVANCE_TRX	766.0
12	PURCHASES_TRX	248.0
13	CREDIT_LIMIT	808.0
14	PAYMENTS	774.0
15	MINIMUM_PAYMENTS	1474.0
16	PRC_FULL_PAYMENT	1366.0
17	TENURE	NaN

Checking the Distribution of Data

In [ ]:
```
for col in df.columns:
  sns.histplot(df[col], kde = True, bins = 20)
  plt.title('Distribution of {}'.format(col))
  plt.xlabel(col)
  plt.ylabel('FREQUENCY')
  plt.show()
```



Statistical Analysis

In [21]:
```
df.describe()
```

Out[21]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	II
count	8950.000000	8950.000000	8950.000000	8950.000000	8950.000000	
mean	14600.040670	1564.474828	0.877271	1003.204834	592.437371	
std	2651.305875	2081.531879	0.236904	2136.634782	1659.887917	
min	10001.000000	0.000000	0.000000	0.000000	0.000000	
25%	12307.250000	128.281915	0.888889	39.635000	0.000000	
50%	14598.500000	873.385231	1.000000	361.280000	38.000000	
75%	16899.750000	2054.140036	1.000000	1110.130000	577.405000	
max	19190.000000	19043.138560	1.000000	49039.570000	40761.250000	

In [22]:
```
# Data Splitting

X = df.iloc[:,:]
```

In [23]:
```
# Checking the number of Rows and Columns
X.shape
```

Out[23]: (8950, 18)

Algorithm Selection

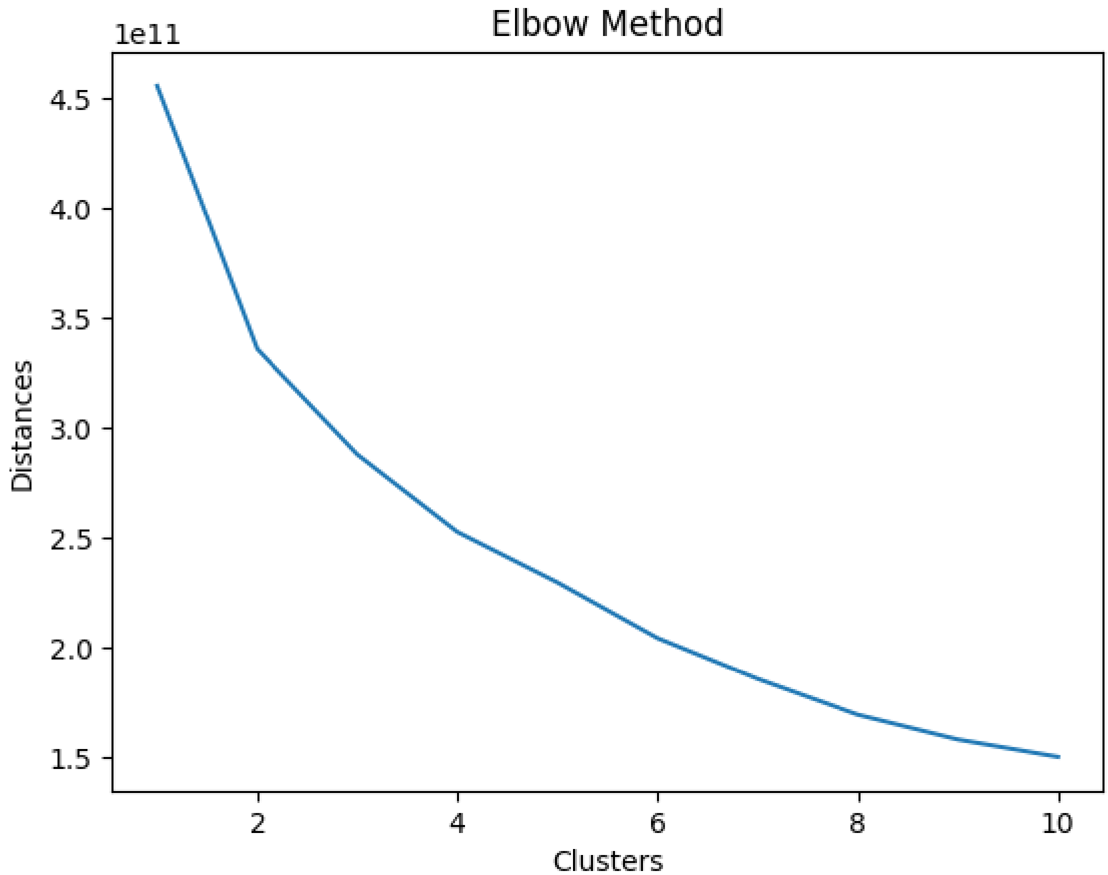
K-Means with Elbow Method

In [24]:
```
distances = []
from sklearn.cluster import KMeans
for i in range(1,11):
  kmeans = KMeans(n_clusters=i, init = 'k-means++', random_state = 42)
  kmeans.fit(X)
  distances.append(kmeans.inertia_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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(
```

Plot distance with their respective number of clusters

In [25]:
```
plt.plot(range(1,11), distances)
plt.title('Elbow Method')
plt.xlabel('Clusters')
plt.ylabel('Distances')
plt.show()
```



Silhouette Score

In [33]:

```
distances = []
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
for i in range(2,11):
  kmeans = KMeans(n_clusters=i, init = 'k-means++')
  kmeans.fit(X)
  score = silhouette_score(X, kmeans.labels_)
  distances.append(score)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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: FutureW
arning: 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(
```

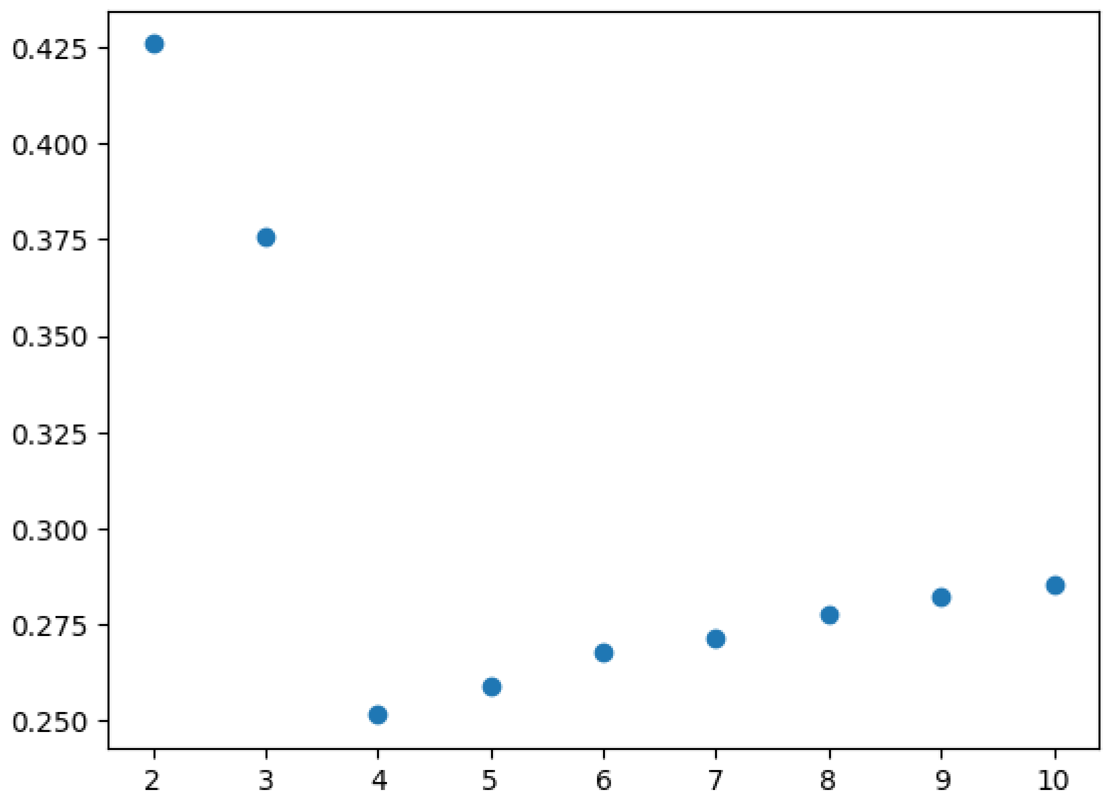
In [34]:
```
# Find suitable number of clusters with high silhouette score
distances
```

Out[34]:
```
[0.42593449979764775,
 0.3758402535764535,
 0.25130717076663545,
 0.2590742535484474,
 0.2678799817209666,
 0.2713220741254244,
 0.2775015035460162,
 0.2824372102444667,
 0.28558068256430075]
```

Plotting # of Clusters with their Silhouette Score

In [35]:
```
plt.scatter(range(2,11), distances)
```

Out[35]:
```
<matplotlib.collections.PathCollection at 0x7e4ececc6bf0>
```



Model Implementation with KMeans Clustering

In [26]:
```
k_cluster = KMeans(n_clusters=2, init = 'k-means++', random_state = 42)
elbow_pred = k_cluster.fit_predict(X)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureW
arning: 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 Clustering using Iterative Method

In [37]:
```
# Converting DataFrame to Numpy array

X = np.array(X)
X.shape
```

Out[37]: (8950, 18)

Find Closest Centroid

In [29]:
```
def find_close_centroid(X, initial_centroids):
  idx = np.zeros(X.shape[0], 'float64')
  lst = []
  for i in range(X.shape[0]):
    lst = np.sum((X[i] - initial_centroids) ** 2, axis = 1)
    idx[i] = np.argmin(lst)

  return idx
```

Compute Centroid to get Mean

In [30]:
```
def compute_centroid(X, idx, K):
  m,n = X.shape
  centroids = np.zeros((K,n))
  for i in range(K):
    centroids[i] = np.mean(X[idx == i], axis = 0)

  return centroids
```

Find the best Centroid using iteration

In [31]:
```
def Run_KMean(X, initial_centroids,max_iteration = 10):
  idx = np.zeros(X.shape[0])
  centroids = initial_centroids.copy()
  K = initial_centroids.shape[0]
  for i in range(max_iteration):

    idx = find_close_centroid(X, initial_centroids)
    centroids = compute_centroid(X, idx, K)
  return idx, centroids
```

Parameter Initialization

In [36]:
```
k = 2
rand_data = np.random.permutation(X.shape[0])
initial_centroids = X[rand_data[:k]]
max_iter = 10
idx, centroids = Run_KMean(X, initial_centroids, max_iter)
idx
centroids
```

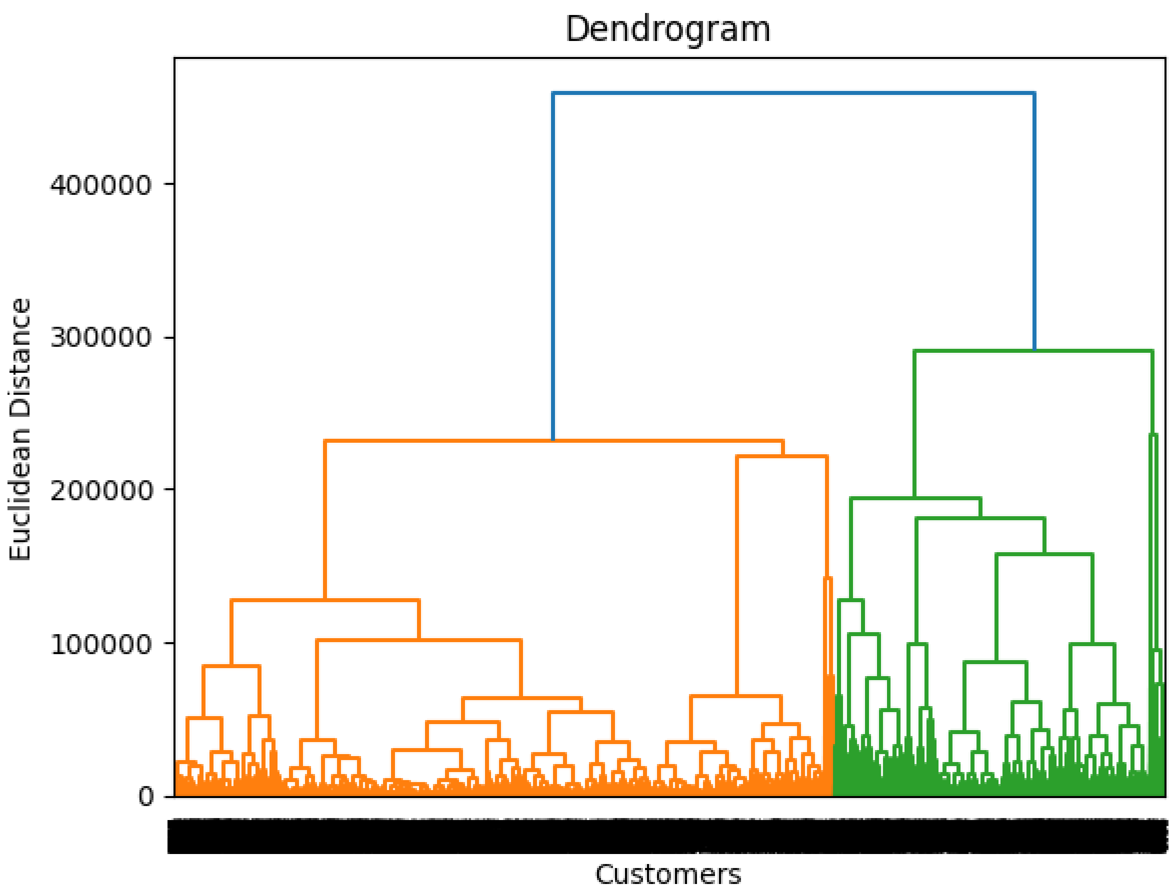
Out[36]:
```
array([[1.46622152e+04, 6.95757523e+02, 8.46045865e-01, 6.60864763e+02,
        3.50396867e+02, 3.10773477e+02, 3.20648284e+02, 4.94836389e-01,
        1.75282869e-01, 3.69355034e-01, 8.23233760e-02, 1.60431428e+00,
        1.14906314e+01, 3.21609479e+03, 9.46435686e+02, 4.22468591e+02,
        1.80652394e-01, 1.14885845e+01],
       [1.44481089e+04, 3.68730038e+03, 9.53572800e-01, 1.83975804e+03,
        1.18389533e+03, 6.56149700e+02, 2.58732559e+03, 4.79388805e-01,
        2.68862935e-01, 3.52420310e-01, 2.64218866e-01, 7.26741054e+00,
        2.25763755e+01, 7.61827801e+03, 3.65556923e+03, 1.94365161e+03,
        8.78887076e-02, 1.15875337e+01]])
```

Hierarchical Clustering

Plot Dendrogram

In [ ]:
```
# Plotting Dendrogram for appropriate number of clusters

import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean Distance')
plt.show()
```



Model Implementation with Hierarchical Clustering

In [38]:
```
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 2, affinity = 'euclidean', linkage = 'w
hc_pred = hc.fit_predict(X)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_agglomerative.py:983:
FutureWarning: Attribute `affinity` was deprecated in version 1.2 and will be r
emoved in 1.4. Use `metric` instead
  warnings.warn(
```

Compute the Differences of each Model

In [39]:
```
elbow_new = pd.DataFrame(elbow_pred)
hc_new = pd.DataFrame(hc_pred)
idx_new = pd.DataFrame(idx)
```

In [40]:
```
table = pd.concat([elbow_new, idx_new, hc_new], axis = 1)
```

In [41]:
```
table.columns = ['Elbow Cluster', 'IDX Cluster', 'Hierarchy Cluster',]
```

In [42]:
```
table
```

Out[42]:

	Elbow Cluster	IDX Cluster	Hierarchy Cluster
0	0	0.0	1
1	1	1.0	0
2	1	0.0	0
3	1	0.0	0
4	0	0.0	1
...	...	...	...
8945	0	0.0	1
8946	0	0.0	1
8947	0	0.0	1
8948	0	0.0	1
8949	0	0.0	1

8950 rows × 3 columns