Credit Card Dataset:

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import seaborn as sns
from sklearn.preprocessing import StandardScaler

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df = pd.read_csv("CC_GENERAL.csv")
df.head()
```

Out[2]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUEN
0	C10001	40.900749	0.818182	95.40	0.00	95.4	0.000000	0.1666
1	C10002	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	0.0000
2	C10003	2495.148862	1.000000	773.17	773.17	0.0	0.000000	1.0000
3	C10004	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	0.0833
4	C10005	817.714335	1.000000	16.00	16.00	0.0	0.000000	0.0833

In [3]:
```
# Drop any irrelevant columns (e.g., customer IDs)
df.drop('CUST_ID', axis=1, inplace=True)
df.head()
```

Out[3]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	ONEO
0	40.900749	0.818182	95.40	0.00	95.4	0.000000	0.166667	
1	3202.467416	0.909091	0.00	0.00	0.0	6442.945483	0.000000	
2	2495.148862	1.000000	773.17	773.17	0.0	0.000000	1.000000	
3	1666.670542	0.636364	1499.00	1499.00	0.0	205.788017	0.083333	
4	817.714335	1.000000	16.00	16.00	0.0	0.000000	0.083333	

Handling missing values:

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
BALANCE                             0
BALANCE_FREQUENCY                   0
PURCHASES                           0
ONEOFF_PURCHASES                    0
INSTALLMENTS_PURCHASES              0
CASH_ADVANCE                        0
PURCHASES_FREQUENCY                 0
ONEOFF_PURCHASES_FREQUENCY          0
PURCHASES_INSTALLMENTS_FREQUENCY    0
CASH_ADVANCE_FREQUENCY              0
CASH_ADVANCE_TRX                    0
PURCHASES_TRX                       0
CREDIT_LIMIT                        1
PAYMENTS                            0
MINIMUM_PAYMENTS                  313
PRC_FULL_PAYMENT                    0
TENURE                              0
dtype: int64
```

In [5]:
```
df['CREDIT_LIMIT'].fillna(df['CREDIT_LIMIT'].median(),inplace=True)
df['MINIMUM_PAYMENTS'].fillna(df['MINIMUM_PAYMENTS'].median(),inplace=True)
print (df.isnull().sum())
```

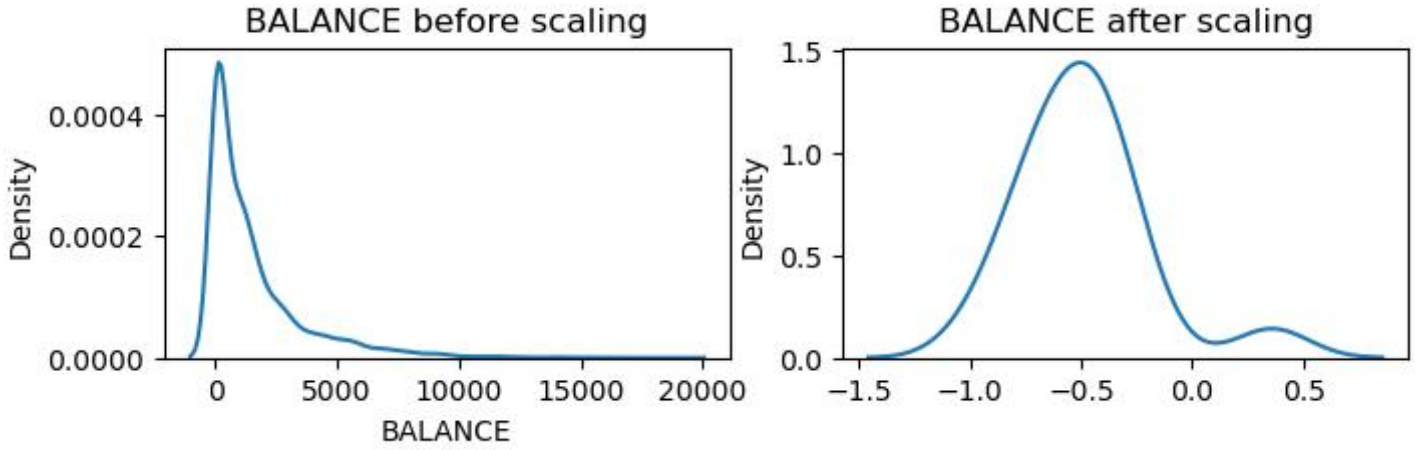
```
BALANCE                             0
BALANCE_FREQUENCY                   0
PURCHASES                           0
ONEOFF_PURCHASES                    0
INSTALLMENTS_PURCHASES              0
CASH_ADVANCE                        0
PURCHASES_FREQUENCY                 0
ONEOFF_PURCHASES_FREQUENCY          0
PURCHASES_INSTALLMENTS_FREQUENCY    0
CASH_ADVANCE_FREQUENCY              0
CASH_ADVANCE_TRX                    0
PURCHASES_TRX                       0
CREDIT_LIMIT                        0
PAYMENTS                            0
MINIMUM_PAYMENTS                    0
PRC_FULL_PAYMENT                    0
TENURE                              0
dtype: int64
```

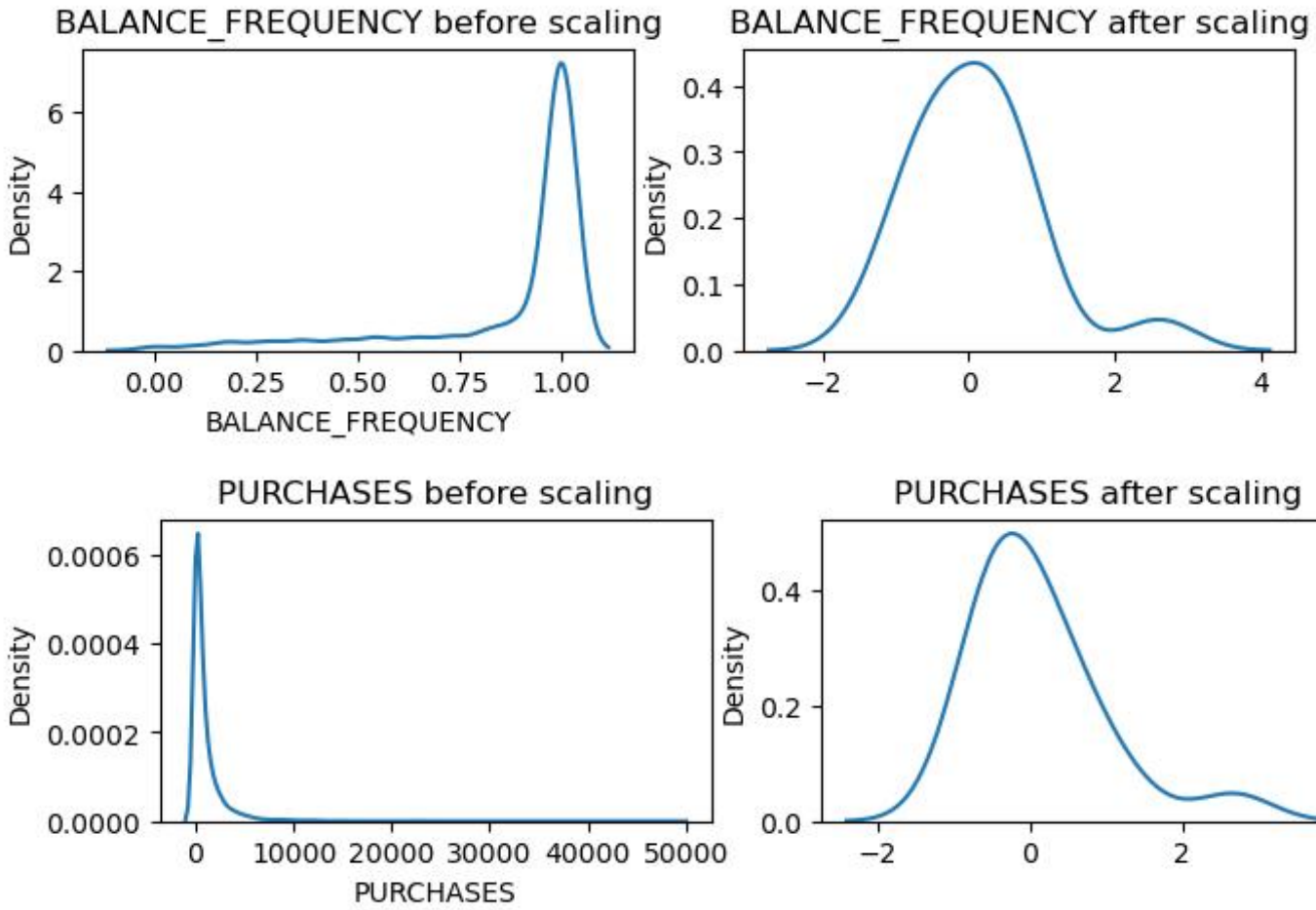
In [6]:
```
def plot(data):
    for i,j in zip(df.columns, range(len(df.columns))):
        plt.figure(figsize=(8,2))

        # 121 for 1 row, 2 columns, 1st position
        plt.subplot(121)
        sns.kdeplot(df[i])
        plt.title(i+' before scaling')

        # 122 for 1 row, 2 columns, 2nd position
        plt.subplot(122)
        sns.kdeplot(data[j])
        plt.title(i+' after scaling')
```

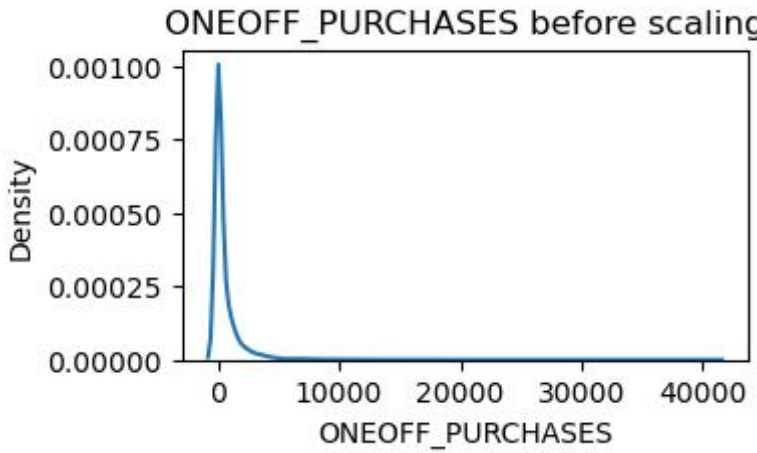
In [7]:
```
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)
print(scaled_data)
```

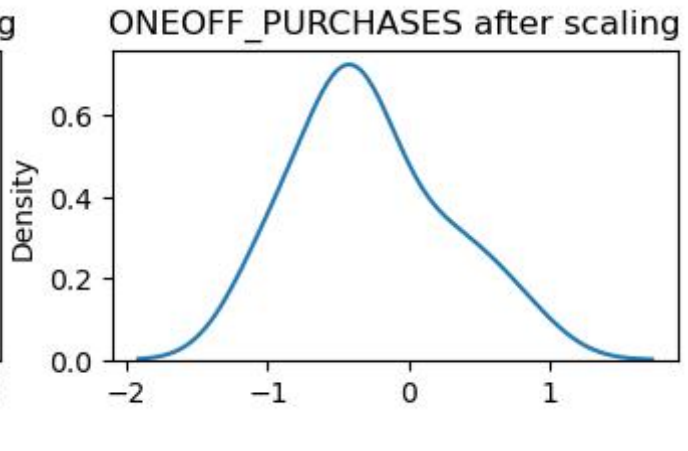
```
[[-0.73198937 -0.24943448 -0.42489974 ... -0.3024     -0.52555097
   0.36067954]
 [ 0.78696085  0.13432467 -0.46955188 ...  0.09749953  0.2342269
   0.36067954]
 [ 0.44713513  0.51808382 -0.10766823 ... -0.0932934  -0.52555097
   0.36067954]
 ...
 [-0.7403981  -0.18547673 -0.40196519 ... -0.32687479  0.32919999
  -4.12276757]
 [-0.74517423 -0.18547673 -0.46955188 ... -0.33830497  0.32919999
  -4.12276757]
 [-0.57257511 -0.88903307  0.04214581 ... -0.3243581  -0.52555097
  -4.12276757]]
```

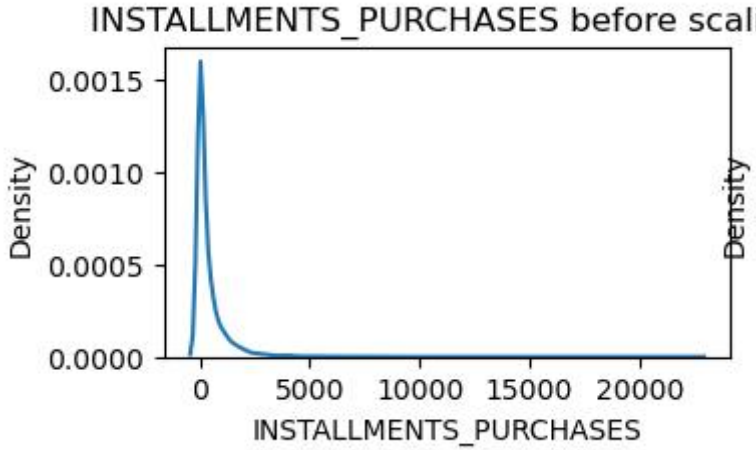
In [8]:
```
plot(scaled_data)
```

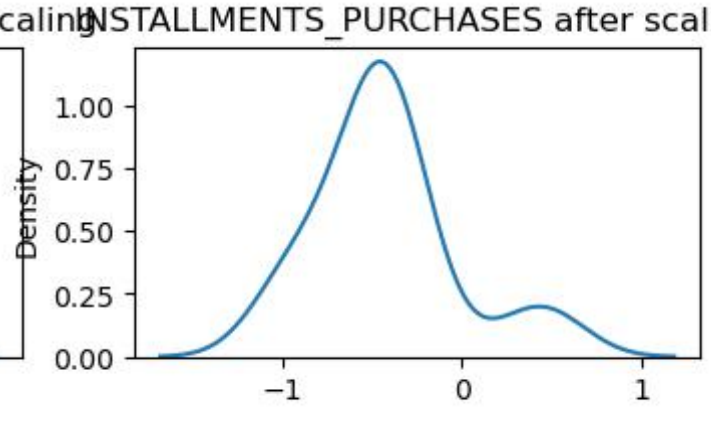


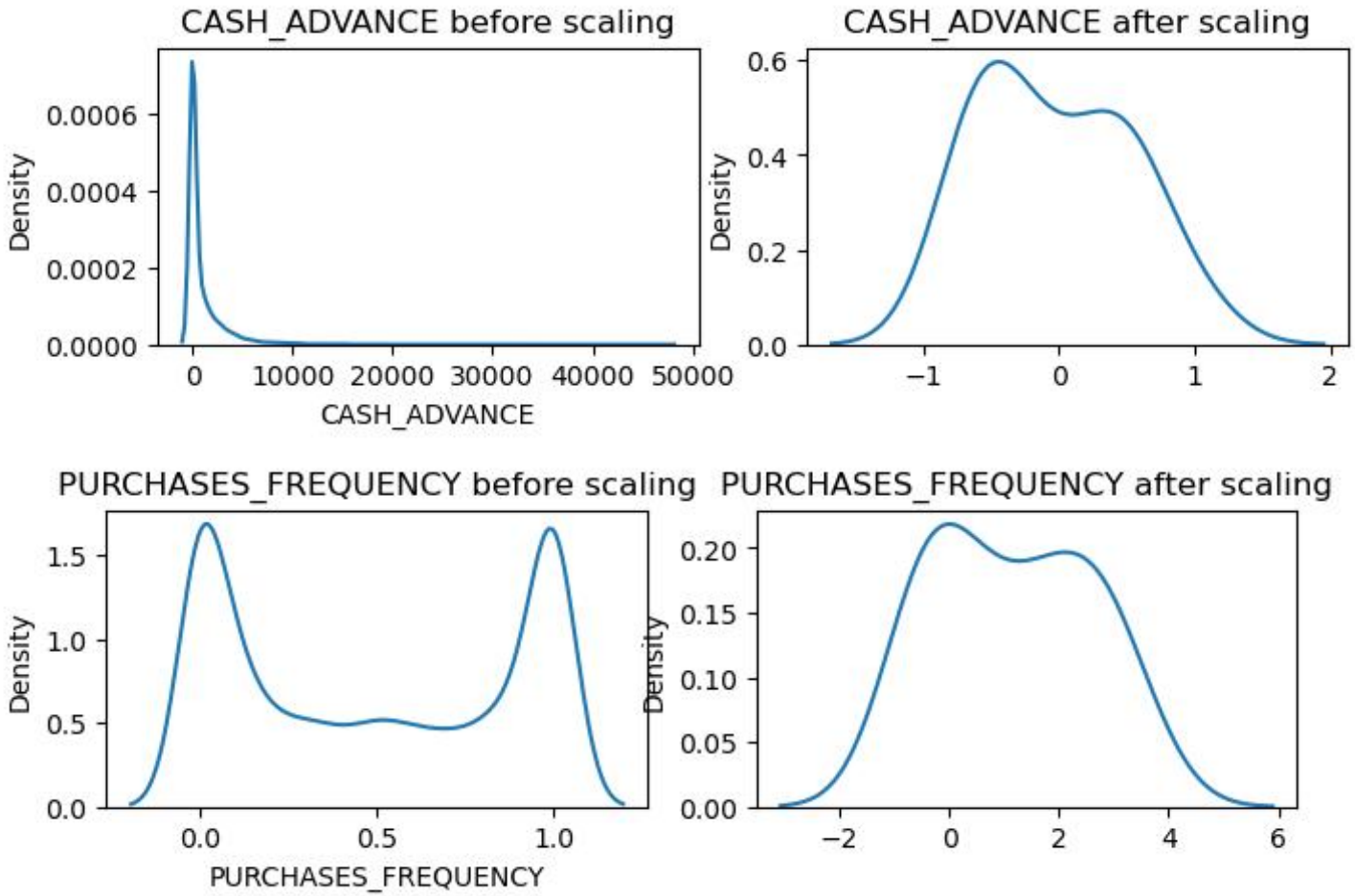

BALANCE_FREQUENCY before scaling
Density
BALANCE_FREQUENCY
BALANCE_FREQUENCY after scaling
Density
PURCHASES before scaling
Density
PURCHASES
PURCHASES after scaling
Density

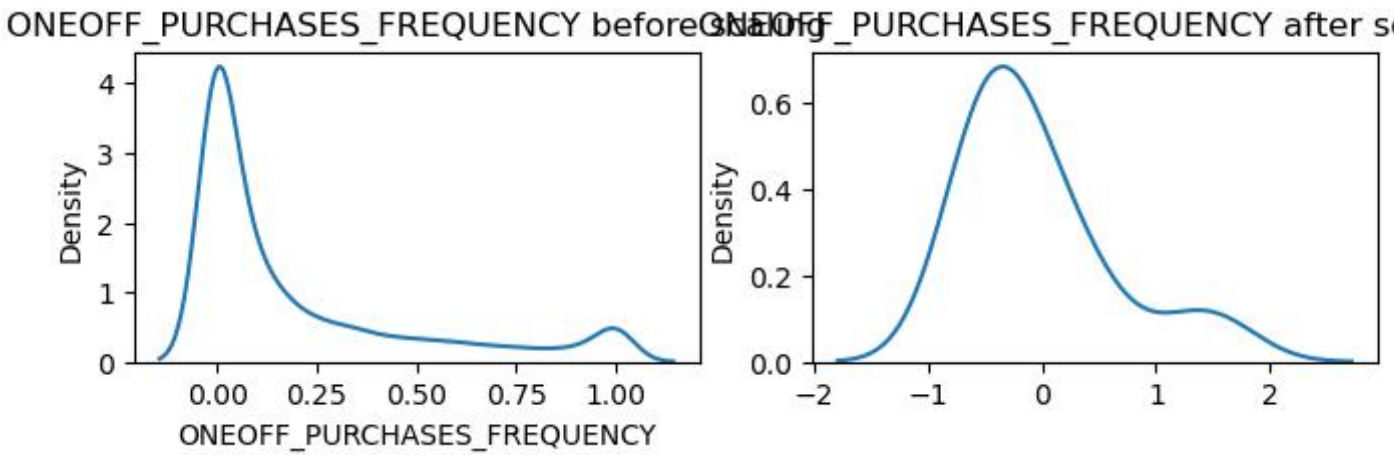

ONEOFF_PURCHASES before scaling
Density
0.00100
0.00075
0.00050
0.00025
0.00000
0
10000
20000
30000
40000
ONEOFF_PURCHASES

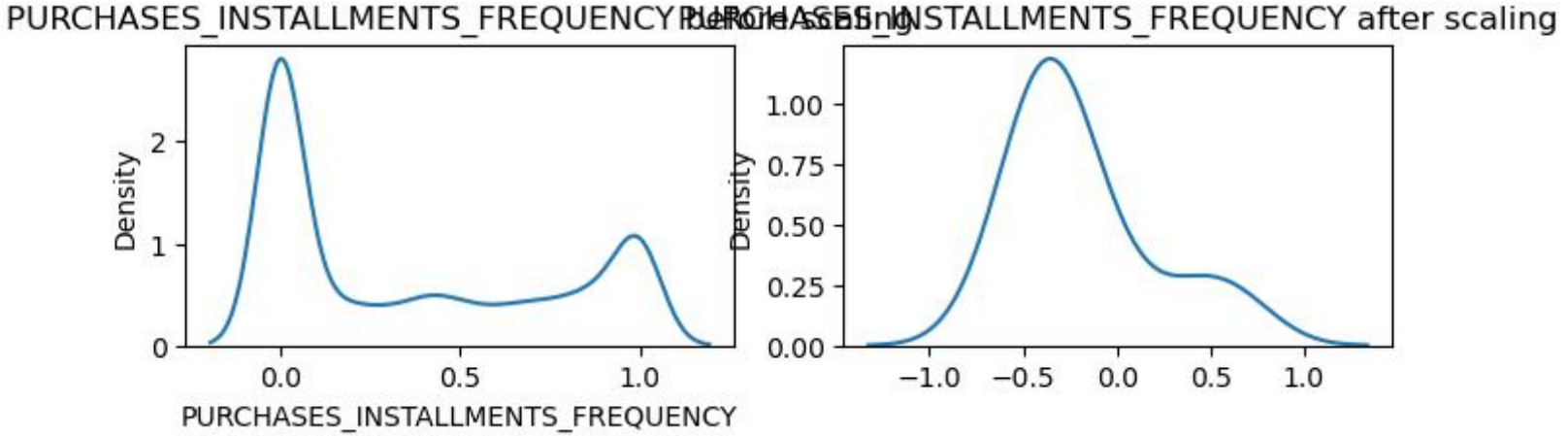

ONEOFF_PURCHASES after scaling
Density
0.6
0.4
0.2
0.0
−2
−1
0
1

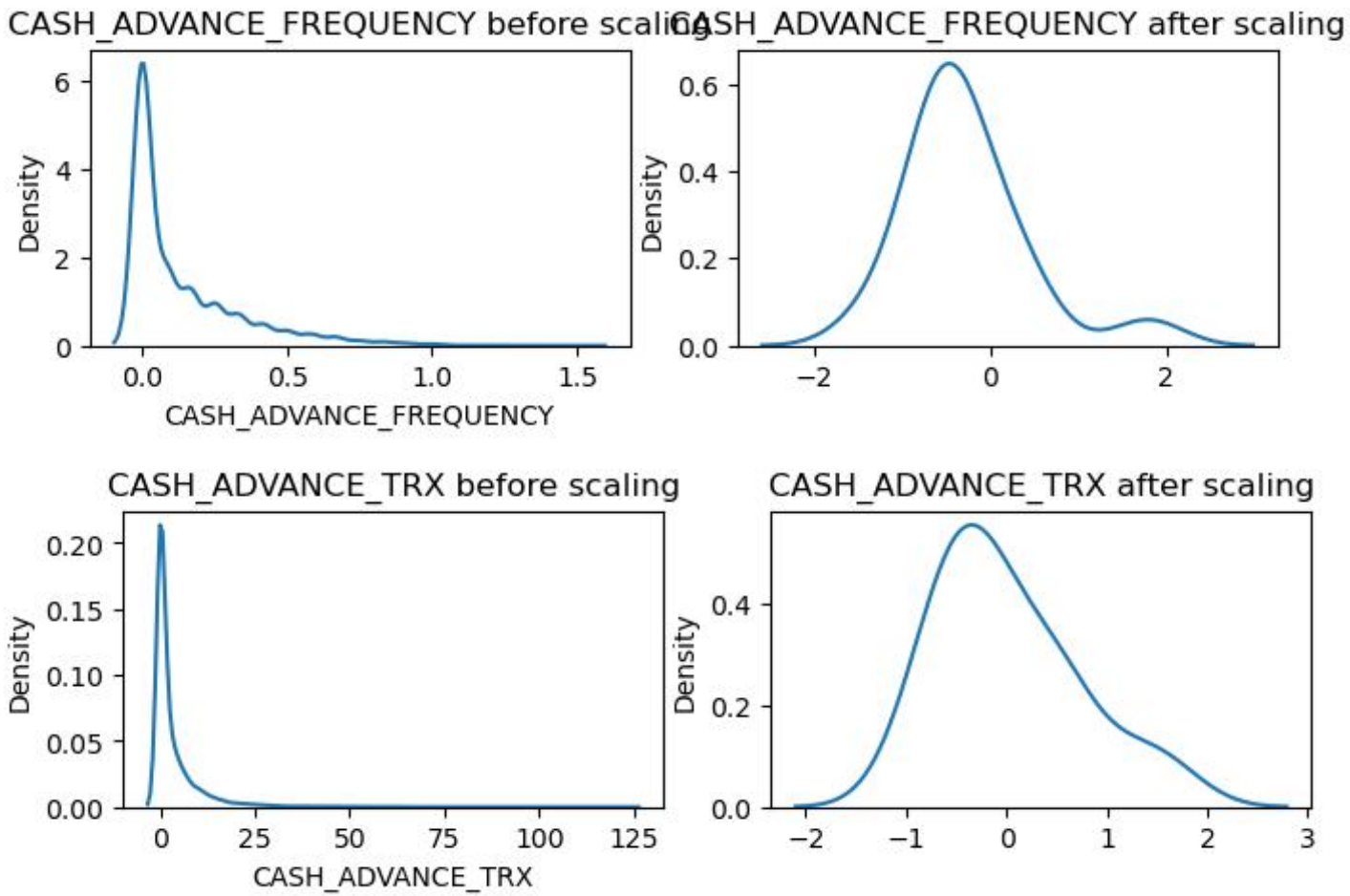

INSTALLMENTS_PURCHASES before scaling
Density
0.0015
0.0010
0.0005
0.0000
0
5000
10000
15000
20000
INSTALLMENTS_PURCHASES

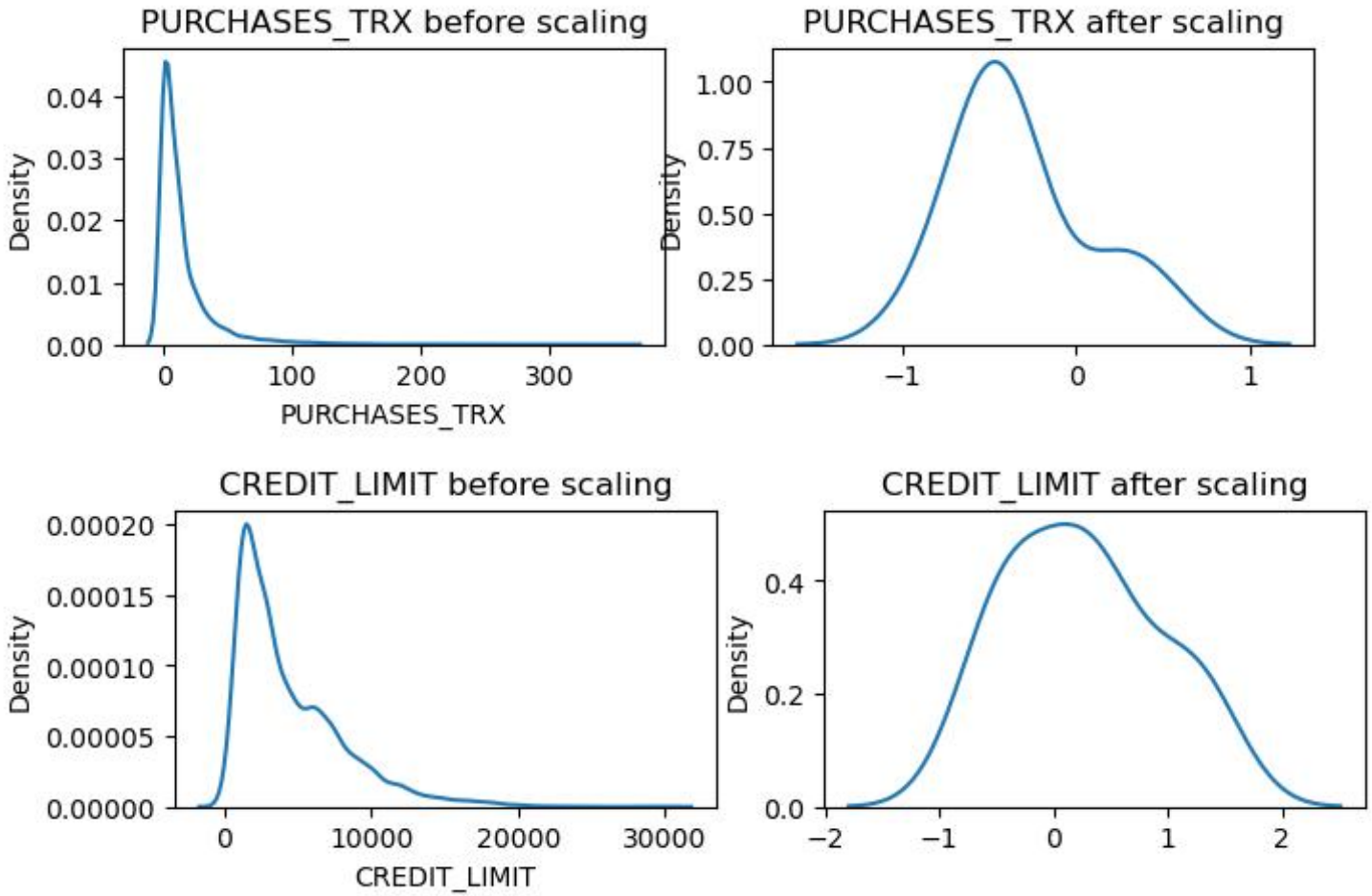

INSTALLMENTS_PURCHASES after scaling
Density
1.00
0.75
0.50
0.25
0.00
−1
0
1

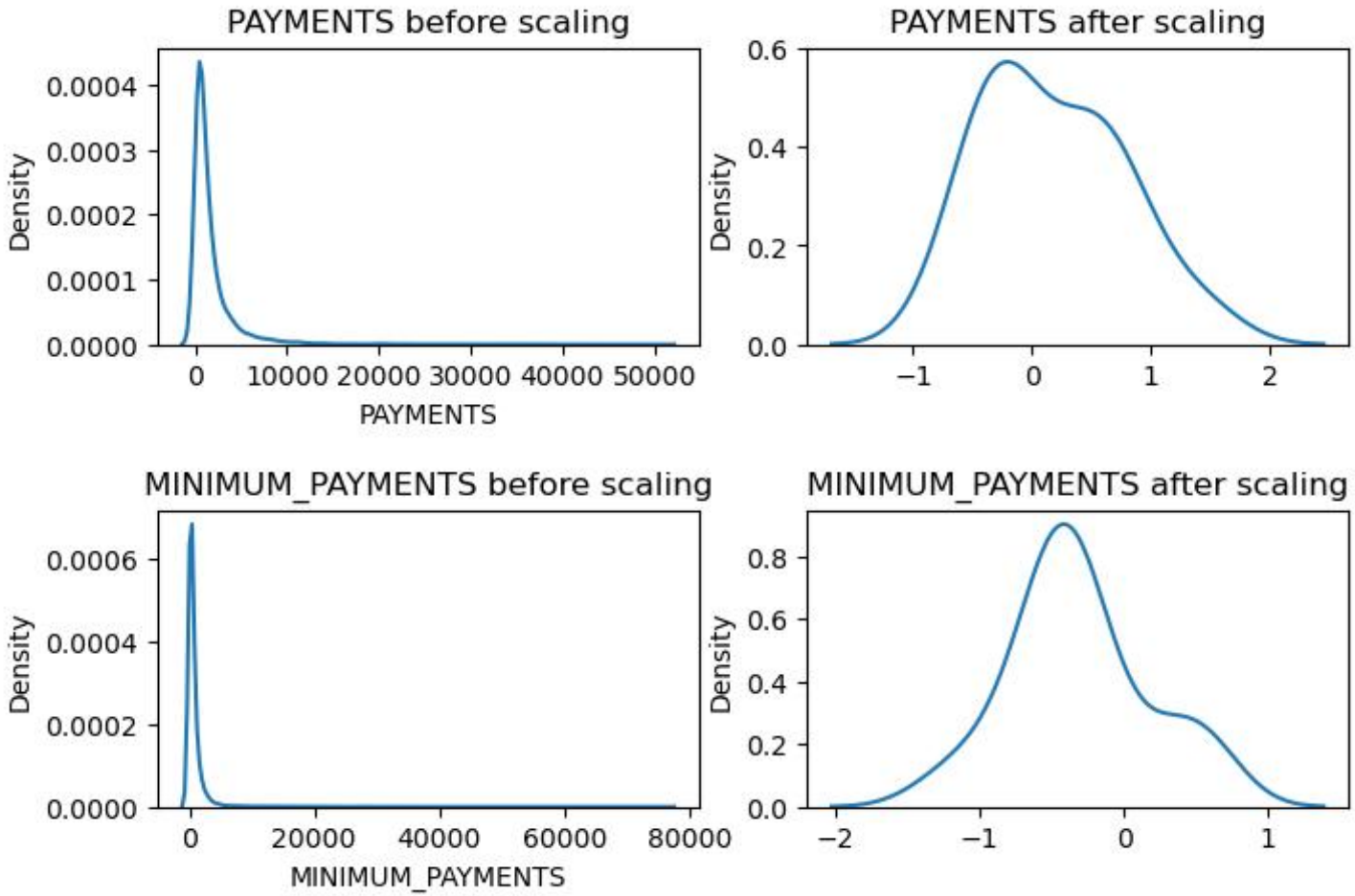

CASH_ADVANCE before scaling
Density
0.0006
0.0004
0.0002
0.0000
0
10000
20000
30000
40000
50000
CASH_ADVANCE
CASH_ADVANCE after scaling
Density
0.6
0.4
0.2
0.0
−1
0
1
2
PURCHASES_FREQUENCY before scaling
Density
1.5
1.0
0.5
0.0
0.0
0.5
1.0
PURCHASES_FREQUENCY
PURCHASES_FREQUENCY after scaling
Density
0.20
0.15
0.10
0.05
0.00
−2
0
2
4
6

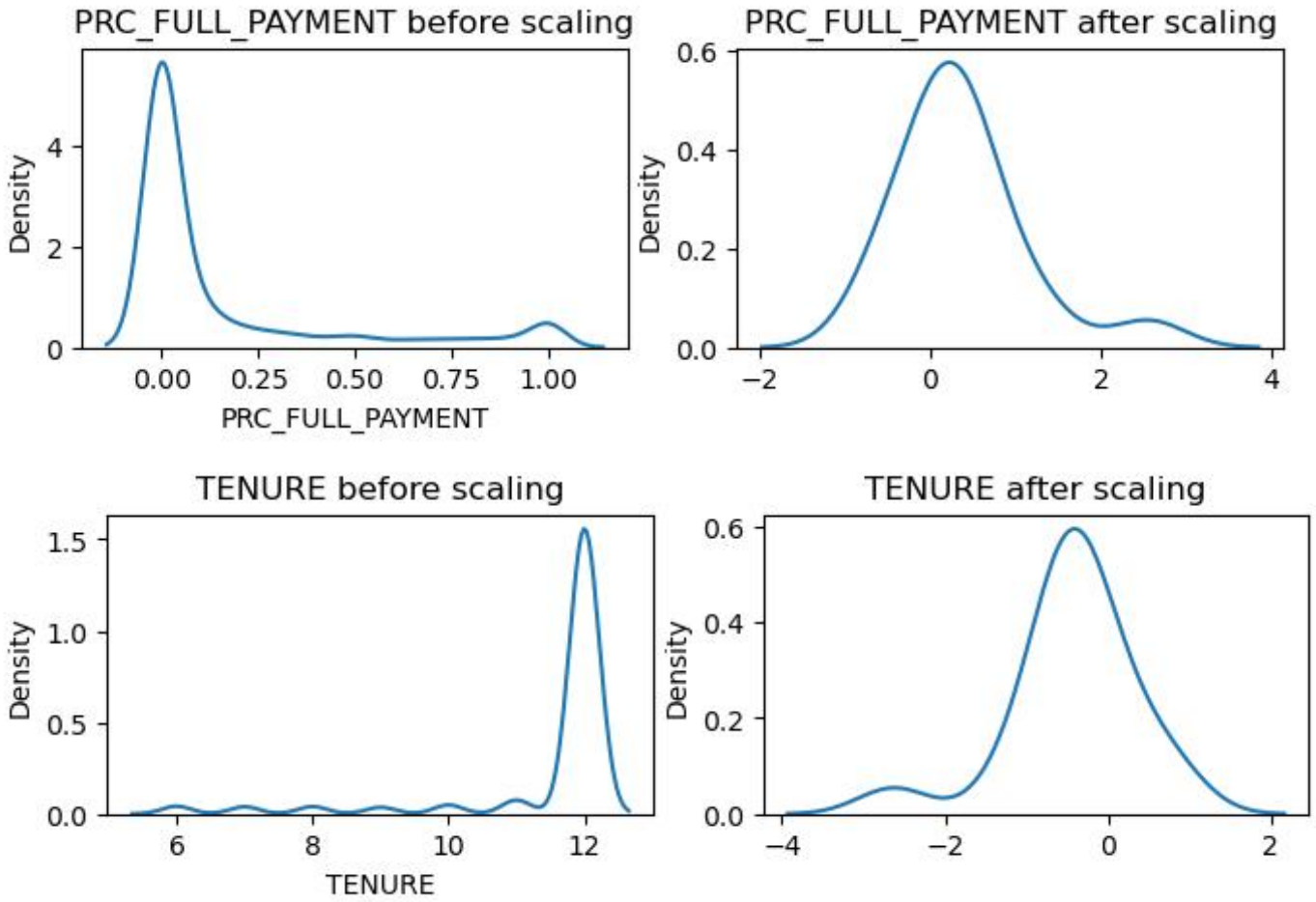

ONEOFF_PURCHASES_FREQUENCY before scaling
Density
0.00
0.25
0.50
0.75
1.00
ONEOFF_PURCHASES_FREQUENCY
ONEOFF_PURCHASES_FREQUENCY after scaling
Density
−2
−1
0
1
2


PURCHASES_INSTALLMENTS_FREQUENCY before scaling
Density
0.0
0.5
1.0
PURCHASES_INSTALLMENTS_FREQUENCY
PURCHASES_INSTALLMENTS_FREQUENCY after scaling
Density
−1.0
−0.5
0.0
0.5
1.0


CASH_ADVANCE_FREQUENCY before scaling
CASH_ADVANCE_FREQUENCY after scaling
Density
CASH_ADVANCE_FREQUENCY
CASH_ADVANCE_TRX before scaling
CASH_ADVANCE_TRX after scaling
CASH_ADVANCE_TRX

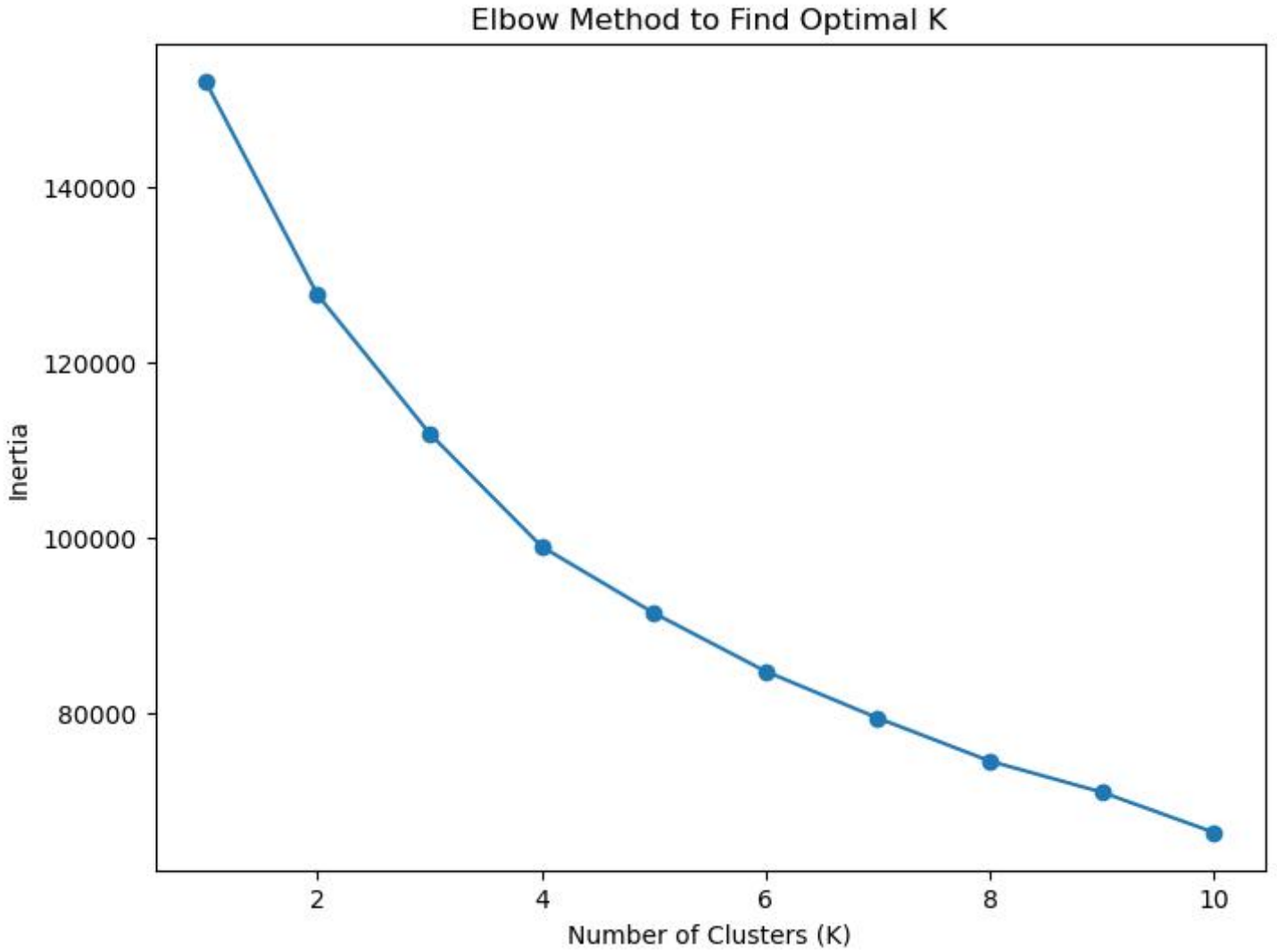

PURCHASES_TRX before scaling
Density
0.04
0.03
0.02
0.01
0.00
0
100
200
300
PURCHASES_TRX
PURCHASES_TRX after scaling
Density
1.00
0.75
0.50
0.25
0.00
−1
0
1
CREDIT_LIMIT before scaling
Density
0.00020
0.00015
0.00010
0.00005
0.00000
0
10000
20000
30000
CREDIT_LIMIT
CREDIT_LIMIT after scaling
Density
0.4
0.2
0.0
−2
−1
0
1
2


PAYMENTS before scaling
Density
0.0004
0.0003
0.0002
0.0001
0.0000
0
10000
20000
30000
40000
50000
PAYMENTS
PAYMENTS after scaling
Density
0.6
0.4
0.2
0.0
−1
0
1
2
MINIMUM_PAYMENTS before scaling
Density
0.0006
0.0004
0.0002
0.0000
0
20000
40000
60000
80000
MINIMUM_PAYMENTS
MINIMUM_PAYMENTS after scaling
Density
0.8
0.6
0.4
0.2
0.0
−2
−1
0
1



In [9]:
```
# To find the optimal number of clusters (K)
# We'll use the 'inertia' attribute of KMeans, which represents the sum of squared distances
# of samples to their closest cluster center
inertia = []
k_range = range(1, 11)

for k in k_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_data)
    inertia.append(kmeans.inertia_)

# Plot the inertia values to find the elbow point
plt.figure(figsize=(8, 6))
```

```
plt.plot(k_range, inertia, marker='o')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.title('Elbow Method to Find Optimal K')
plt.show()
```

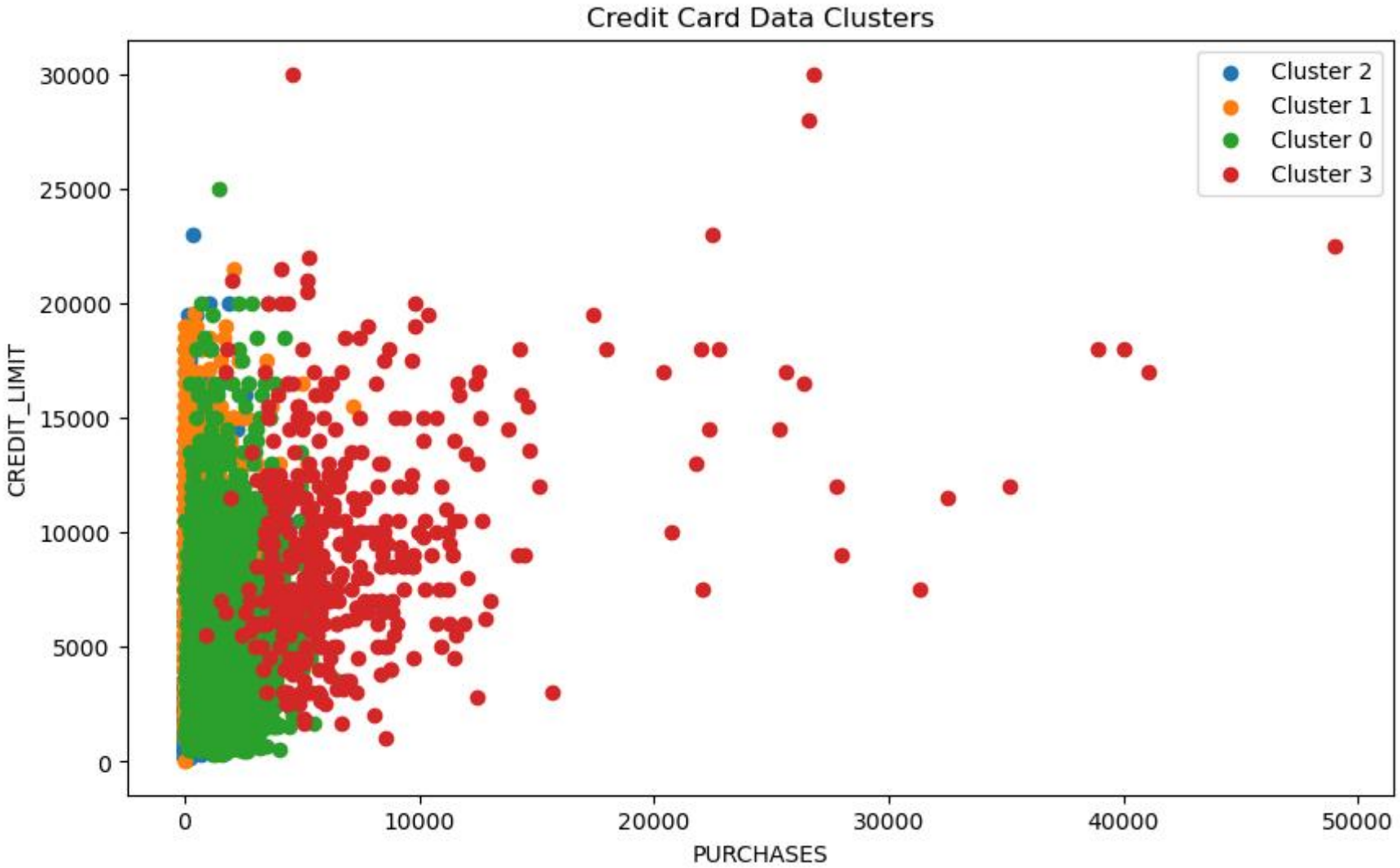


In [10]:
```
# Let's say we choose K=4 (as shown by the elbow plot)

# Create and fit the KMeans model with the chosen K value
```

```
kmeans = KMeans(n_clusters=4, random_state=42)
kmeans.fit(scaled_data)

# Add the cluster labels back to the original dataframe
df['Cluster'] = kmeans.labels_
```

In [11]:

```
# We can now analyze the segments or clusters formed
# For example, we can use groupby to see the average spending behavior of each cluster
cluster_means = df.groupby('Cluster').mean()

# We can also visualize the clusters using scatter plots
# Choose two features for visualization (e.g., 'Spending Score' vs. 'Income')
feature1 = 'PURCHASES'
feature2 = 'CREDIT_LIMIT'

plt.figure(figsize=(10, 6))
for cluster_label in df['Cluster'].unique():
    cluster_data = df[df['Cluster'] == cluster_label]
    plt.scatter(cluster_data[feature1], cluster_data[feature2], label=f'Cluster {cluster_label}')

plt.xlabel(feature1)
plt.ylabel(feature2)
plt.title('Credit Card Data Clusters')
plt.legend()
plt.show()
```


Credit Card Data Clusters
Cluster 2
Cluster 1
Cluster 0
Cluster 3
CREDIT_LIMIT
PURCHASES
0
5000
10000
15000
20000
25000
30000
0
10000
20000
30000
40000
50000