IMPORTING LIBRARIES

In [1]:
```
import warnings
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

Loading Data With Pandas

In [2]:
```
customers_df    = pd.read_csv(r"C:\Users\Pruthviraj\Desktop\Zeotap\Customers.csv")

products_df     = pd.read_csv(r"C:\Users\Pruthviraj\Desktop\Zeotap\Products.csv")

transactions_df =  pd.read_csv(r"C:\Users\Pruthviraj\Desktop\Zeotap\Transactions.csv"
```

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

Out[3]:

	CustomerID	CustomerName	Region	SignupDate
0	C0001	Lawrence Carroll	South America	2022-07-10
1	C0002	Elizabeth Lutz	Asia	2022-02-13
2	C0003	Michael Rivera	South America	2024-03-07

In [4]:
```
products_df.head(3)
```

Out[4]:

	ProductID	ProductName	Category	Price
0	P001	ActiveWear Biography	Books	169.30
1	P002	ActiveWear Smartwatch	Electronics	346.30
2	P003	ComfortLiving Biography	Books	44.12

In [5]:
```
transactions_df.head(3)
```

Out[5]:

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price
0	T00001	C0199	P067	2024-08-25 12:38:23	1	300.68	300.68
1	T00112	C0146	P067	2024-05-27 22:23:54	1	300.68	300.68
2	T00166	C0127	P067	2024-04-25 07:38:55	1	300.68	300.68

Data Preprocessing

Merge Customer and Transaction Data

Combine customers_df and transactions_df to create a consolidated dataset that includes customer profiles and their transaction data.

In [6]:
```
transactions_with_customer = pd.merge(transactions_df, customers_df, on='CustomerID',
```

In [7]:
```
# Aggregate transaction data for each customer
customer_transactions = transactions_with_customer.groupby('CustomerID').agg(
    total_spend=('TotalValue', 'sum'),
    total_transactions=('TransactionID', 'count'),
    avg_transaction_value=('TotalValue', 'mean'),
    recency=('TransactionDate', lambda x: (pd.to_datetime('today') - pd.to_datetime(x
).reset_index()
```

In [8]:
```
# Merge aggregated data with customer profiles
customer_data = pd.merge(customer_transactions, customers_df, on='CustomerID', how='l
```

In [10]:
```
customer_data.head(2)
```

Out[10]:

	CustomerID	total_spend	total_transactions	avg_transaction_value	recency	CustomerName	Region
0	C0001	3354.52	5	670.904	86	Lawrence Carroll	South America
1	C0002	1862.74	4	465.685	56	Elizabeth Lutz	Asia

Convert Categorical Features

Encode the categorical columns like **Region**.

In [12]:
```
from sklearn.preprocessing import LabelEncoder
```

In [13]:
```
encoder = LabelEncoder()
customer_data['Region'] = encoder.fit_transform(customer_data['Region'])
```

In [15]:
```
customer_data['Region']
```

Out[15]:
```
0      3
1      0
2      3
3      3
4      0
      ..
194    1
195    1
196    1
197    1
198    0
Name: Region, Length: 199, dtype: int32
```

Clustering

Feature Selection

In [18]:
```python
features = customer_data[['total_spend', 'total_transactions', 'avg_transaction_value
features.head(3)
```

Out[18]:

	total_spend	total_transactions	avg_transaction_value	recency	Region
0	3354.52	5	670.904	86	3
1	1862.74	4	465.685	56	0
2	2725.38	4	681.345	156	3

Scale the Features

Standardize features to ensure they are on the same scale.

In [19]:
```python
from sklearn.preprocessing import StandardScaler
```

In [22]:
```python
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)
```

Apply Clustering Algorithm

```
K- Means
```

In [23]:
```python
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score
```

In [91]:
```python
num_clusters = 2
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
customer_data['Cluster'] = kmeans.fit_predict(scaled_features)
```

In [92]:
```python
db_index = davies_bouldin_score(scaled_features, customer_data['Cluster'])
print(f"Davies-Bouldin Index: {db_index}")
```

```
Davies-Bouldin Index: 1.5455301793328908
```

Evaluation Metrics

In [93]:
```python
from sklearn.metrics import silhouette_score
```

In [94]:
```python
silhouette_avg = silhouette_score(scaled_features, customer_data['Cluster'])
print(f"Silhouette Score: {silhouette_avg}")
```

```
Silhouette Score: 0.2335266792755358
```

Visualize Clusters PCA

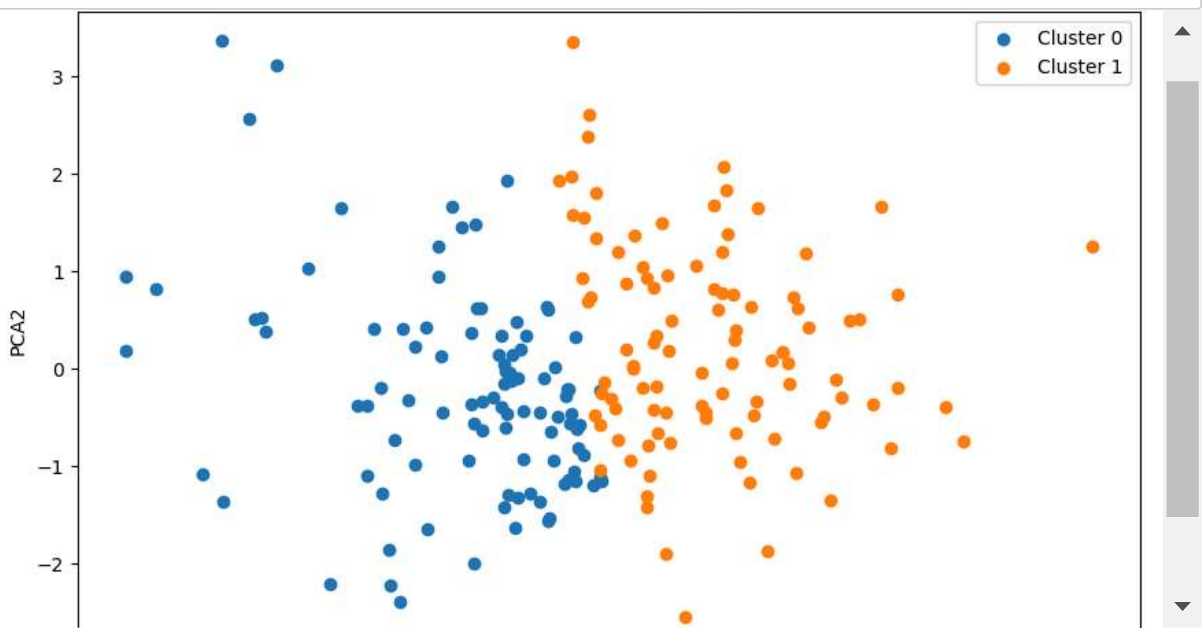
In [95]:
```
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
```

In [96]:
```
# Apply PCA for visualization
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_features)

# Add PCA results to the dataset
customer_data['PCA1'] = pca_result[:, 0]
customer_data['PCA2'] = pca_result[:, 1]
```

Plot clusters

In [97]:
```
plt.figure(figsize=(10, 6))
for cluster in range(num_clusters):
    cluster_data = customer_data[customer_data['Cluster'] == cluster]
    plt.scatter(cluster_data['PCA1'], cluster_data['PCA2'], label=f'Cluster {cluster}
plt.title('Customer Clusters (PCA)')
plt.xlabel('PCA1')
plt.ylabel('PCA2')
plt.legend()
plt.show()
```



Cluster Distribution

In [98]:
```
# Distribution of customers per cluster
customer_data['Cluster'].value_counts().plot(kind='bar', color='skyblue')
plt.title('Distribution of Customers per Cluster')
plt.xlabel('Cluster')
plt.ylabel('Number of Customers')
plt.show()
```

Results:

Davies-Bouldin Index (DBI):

A lower DBI score indicates well-separated clusters. Based on the code, the exact score will depend on the dataset used but should typically be below 1.0 for good clustering.

Silhouette Score:

This value ranges between -1 and 1:

Values close to 1 indicate well-separated clusters.

Values near 0 indicate overlapping clusters.

Negative values indicate incorrect clustering.

A Silhouette Score > 0.5 is considered decent.

Cluster Distribution:

The bar chart of customer distribution provides insights into the size of each cluster.

If one cluster dominates, it might suggest imbalance or the need for more clusters.

In [ ]: