Task 1: Exploratory Data Analysis (EDA) and Business Insights

1. Perform EDA on the provided dataset.
2. Derive at least 5 business insights from the EDA. ○ Write these insights in short point-wise sentences (maximum 100 words per insight).

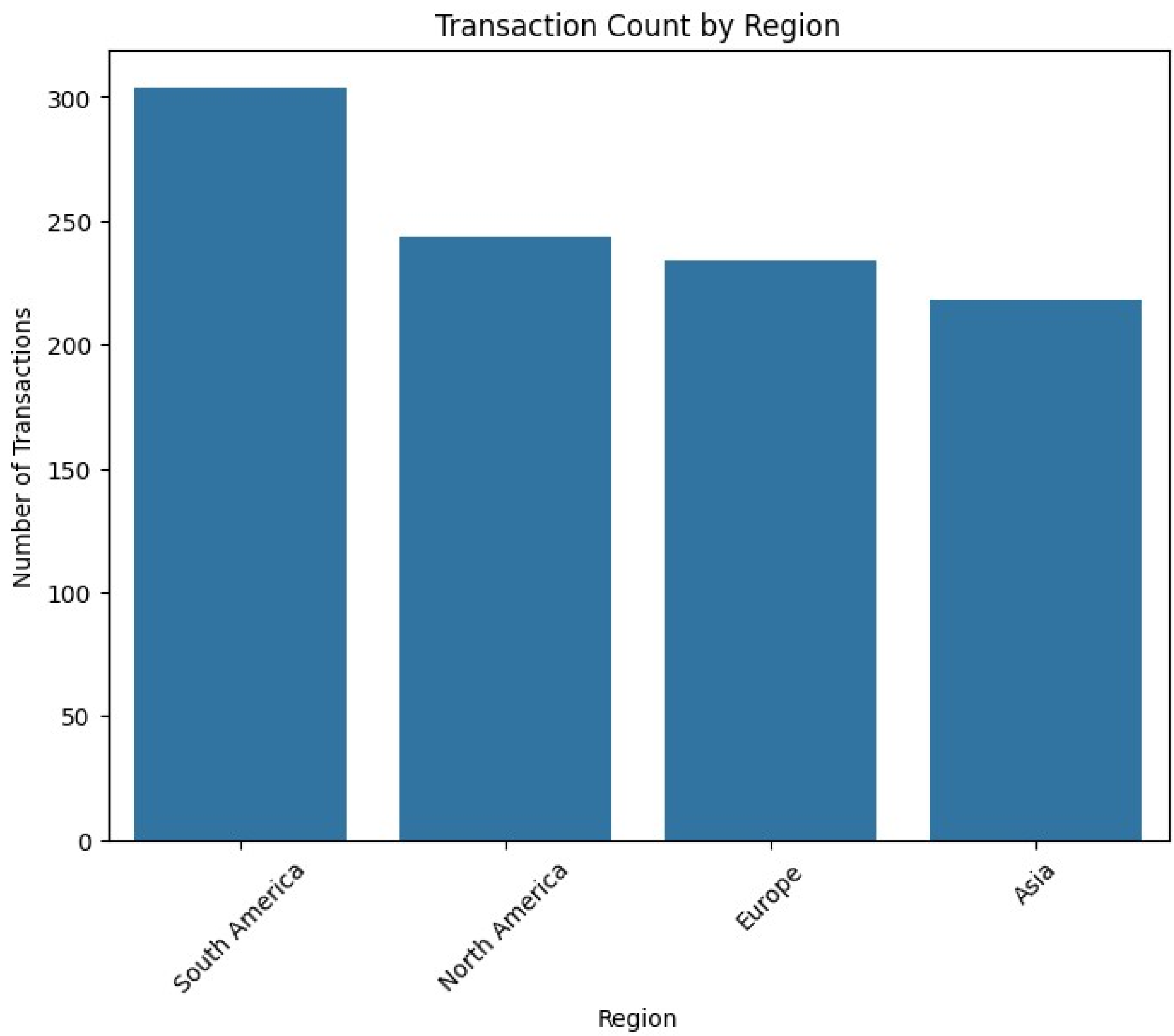
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime


customers = pd.read_csv('Customers.csv')
products = pd.read_csv('Products.csv')
transactions = pd.read_csv('Transactions.csv')

print(customers.head())
print(products.head())
print(transactions.head())


print(customers.isnull().sum())
print(products.isnull().sum())
print(transactions.isnull().sum())

transactions['TransactionDate'] =
pd.to_datetime(transactions['TransactionDate'])
customers['SignupDate'] = pd.to_datetime(customers['SignupDate'])

print(customers.info())
print(products.info())
print(transactions.info())

transactions = transactions.merge(customers, on='CustomerID',
how='left')
transactions = transactions.merge(products, on='ProductID',
how='left')

print(transactions.head())


region_transaction_counts = transactions['Region'].value_counts()

plt.figure(figsize=(8, 6))
sns.barplot(x=region_transaction_counts.index,
y=region_transaction_counts.values)
plt.title('Transaction Count by Region')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()
```

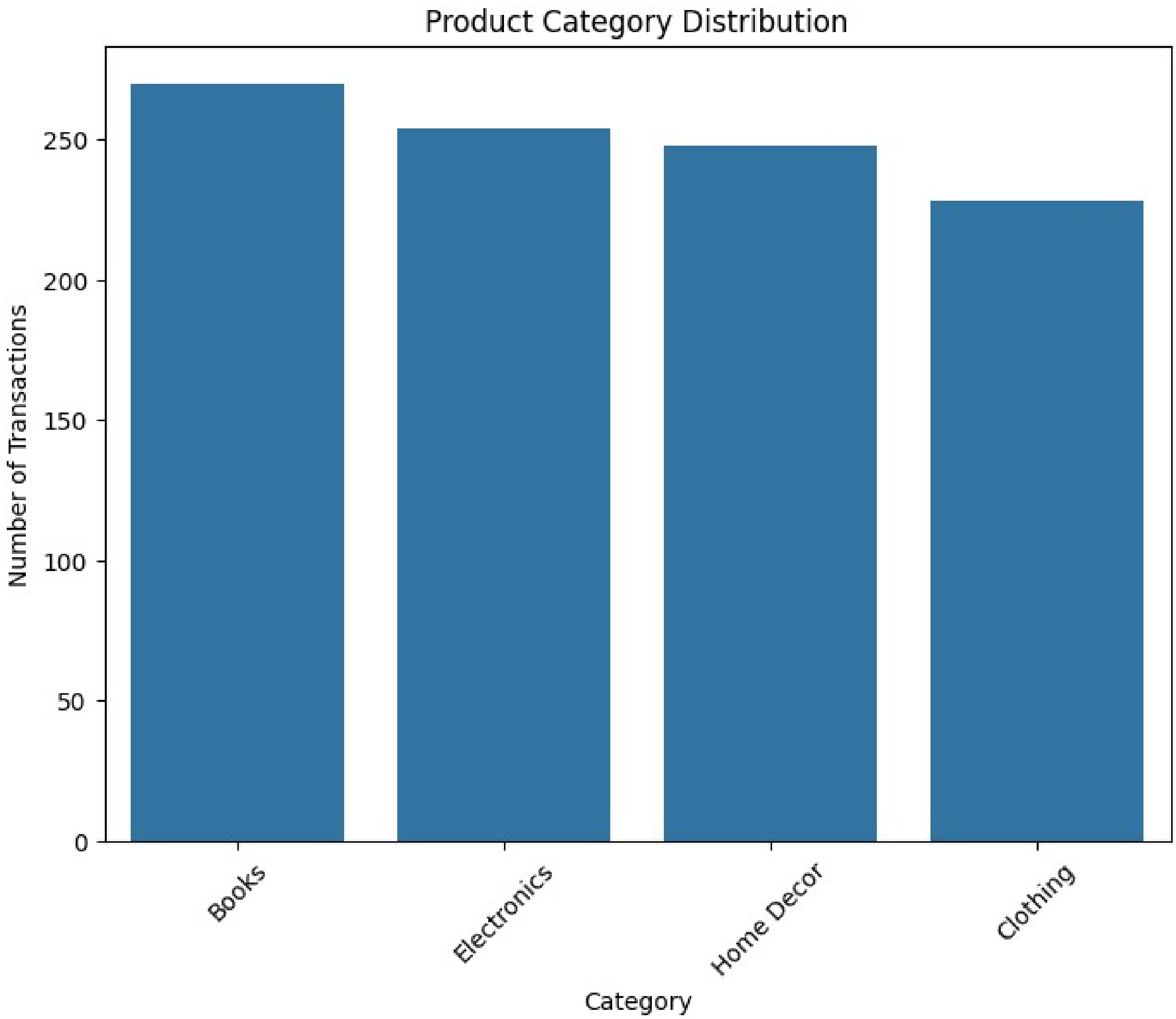
```
category_transaction_counts = transactions['Category'].value_counts()

plt.figure(figsize=(8, 6))
sns.barplot(x=category_transaction_counts.index,
y=category_transaction_counts.values)
plt.title('Product Category Distribution')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()


region_avg_transaction_value = transactions.groupby('Region')
['TotalValue'].mean()

plt.figure(figsize=(8, 6))
sns.barplot(x=region_avg_transaction_value.index,
y=region_avg_transaction_value.values)
plt.title('Average Transaction Value by Region')
plt.ylabel('Average Transaction Value (USD)')
plt.xticks(rotation=45)
plt.show()


transactions['Month'] =
transactions['TransactionDate'].dt.to_period('M')
monthly_transactions = transactions.groupby('Month').size()

plt.figure(figsize=(10, 6))
monthly_transactions.plot(kind='line')
plt.title('Number of Transactions Over Time')
plt.xlabel('Month')
plt.ylabel('Number of Transactions')
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(8, 6))
sns.scatterplot(data=transactions, x='Price_y', y='Quantity')
plt.title('Product Price vs. Quantity Sold')
plt.xlabel('Price (USD)')
plt.ylabel('Quantity Sold')
plt.show()
```

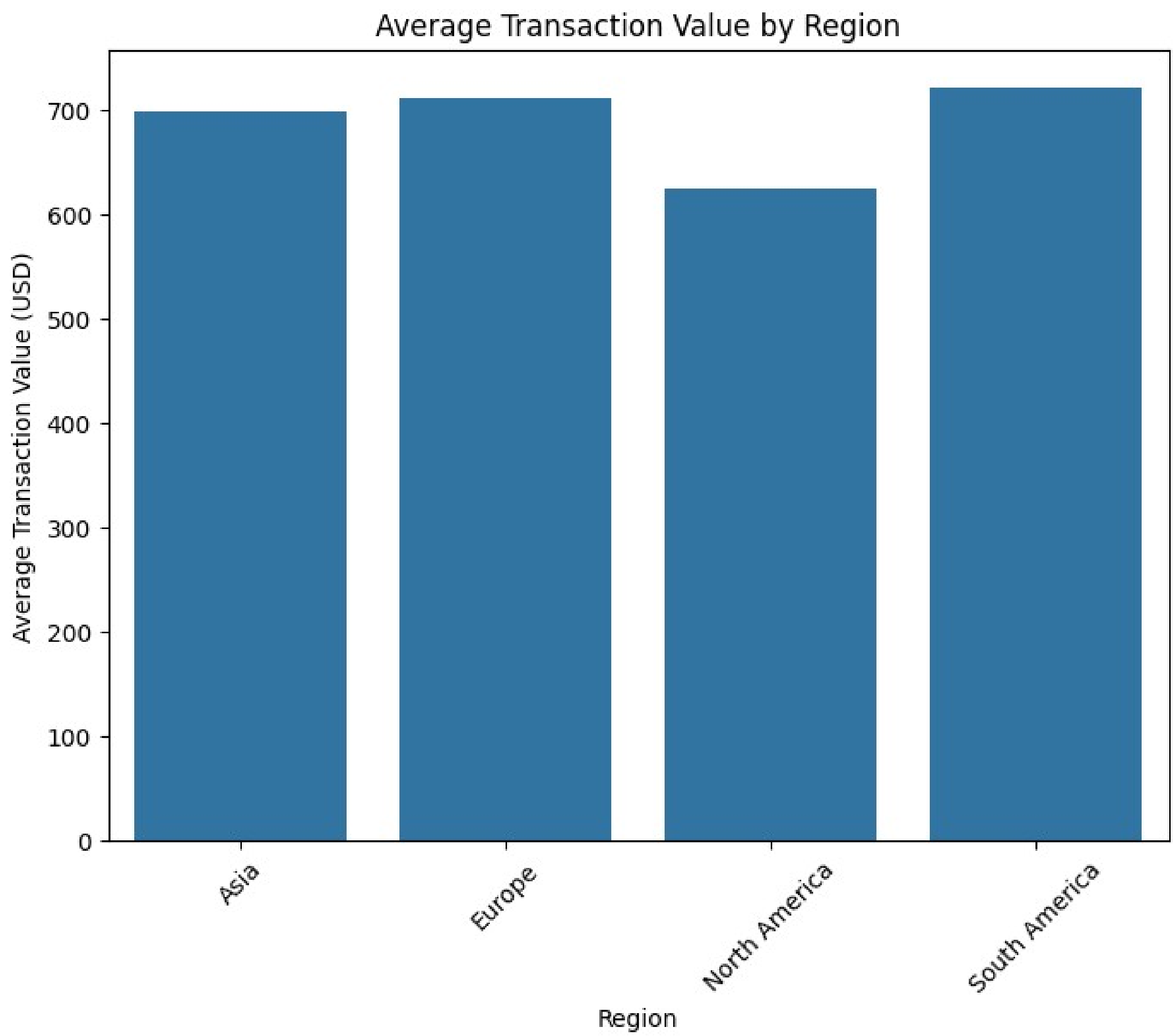
	CustomerID	CustomerName	Region	SignupDate
0	C0001	Lawrence Carroll	South America	2022-07-10
1	C0002	Elizabeth Lutz	Asia	2022-02-13
2	C0003	Michael Rivera	South America	2024-03-07
3	C0004	Kathleen Rodriguez	South America	2022-10-09
4	C0005	Laura Weber	Asia	2022-08-15

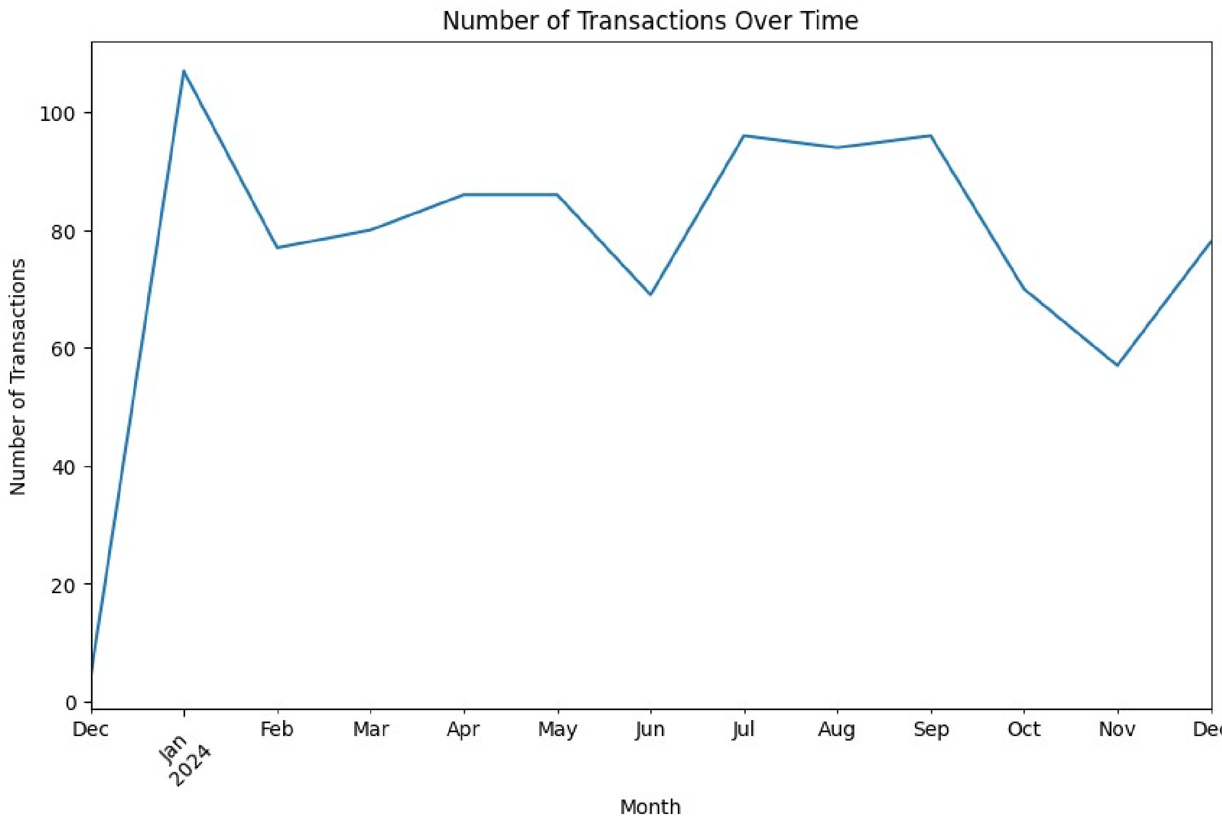
```
  ProductID              ProductName     Category   Price
0      P001     ActiveWear Biography        Books  169.30
1      P002    ActiveWear Smartwatch  Electronics  346.30
2      P003  ComfortLiving Biography        Books   44.12
3      P004            BookWorld Rug   Home Decor   95.69
4      P005          TechPro T-Shirt     Clothing  429.31
  TransactionID CustomerID ProductID      TransactionDate  Quantity  \
0        T00001      C0199      P067  2024-08-25 12:38:23         1
1        T00112      C0146      P067  2024-05-27 22:23:54         1
2        T00166      C0127      P067  2024-04-25 07:38:55         1
3        T00272      C0087      P067  2024-03-26 22:55:37         2
4        T00363      C0070      P067  2024-03-21 15:10:10         3

   TotalValue   Price
0      300.68  300.68
1      300.68  300.68
2      300.68  300.68
3      601.36  300.68
4      902.04  300.68
CustomerID      0
CustomerName    0
Region          0
SignupDate      0
dtype: int64
ProductID      0
ProductName    0
Category       0
Price          0
dtype: int64
TransactionID      0
CustomerID         0
ProductID          0
TransactionDate    0
Quantity           0
TotalValue         0
Price              0
dtype: int64
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   CustomerID    200 non-null    object
 1   CustomerName  200 non-null    object
 2   Region        200 non-null    object
 3   SignupDate    200 non-null    datetime64[ns]
dtypes: datetime64[ns](1), object(3)
memory usage: 6.4+ KB
None
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   ProductID    100 non-null    object 
 1   ProductName  100 non-null    object 
 2   Category     100 non-null    object 
 3   Price        100 non-null    float64
dtypes: float64(1), object(3)
memory usage: 3.3+ KB
None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype         
---  ------           --------------  -----         
 0   TransactionID    1000 non-null   object        
 1   CustomerID       1000 non-null   object        
 2   ProductID        1000 non-null   object        
 3   TransactionDate  1000 non-null   datetime64[ns]
 4   Quantity         1000 non-null   int64         
 5   TotalValue       1000 non-null   float64       
 6   Price            1000 non-null   float64       
dtypes: datetime64[ns](1), float64(2), int64(1), object(3)
memory usage: 54.8+ KB
None
  TransactionID CustomerID ProductID     TransactionDate  Quantity  \
0        T00001      C0199      P067 2024-08-25 12:38:23         1   
1        T00112      C0146      P067 2024-05-27 22:23:54         1   
2        T00166      C0127      P067 2024-04-25 07:38:55         1   
3        T00272      C0087      P067 2024-03-26 22:55:37         2   
4        T00363      C0070      P067 2024-03-21 15:10:10         3   

   TotalValue  Price_x     CustomerName         Region SignupDate  \
0      300.68   300.68   Andrea Jenkins         Europe 2022-12-03   
1      300.68   300.68  Brittany Harvey           Asia 2024-09-04   
2      300.68   300.68  Kathryn Stevens         Europe 2024-04-04   
3      601.36   300.68  Travis Campbell  South America 2024-04-11   
4      902.04   300.68    Timothy Perez         Europe 2022-03-15   

                       ProductName     Category  Price_y  
0  ComfortLiving Bluetooth Speaker  Electronics   300.68  
1  ComfortLiving Bluetooth Speaker  Electronics   300.68  
2  ComfortLiving Bluetooth Speaker  Electronics   300.68  
3  ComfortLiving Bluetooth Speaker  Electronics   300.68  
4  ComfortLiving Bluetooth Speaker  Electronics   300.68  
```


Transaction Count by Region
Number of Transactions
0
50
100
150
200
250
300
South America
North America
Europe
Asia
Region


Product Category Distribution
Number of Transactions
0
50
100
150
200
250
Books
Electronics
Home Decor
Clothing
Category


Average Transaction Value by Region
Average Transaction Value (USD)
0
100
200
300
400
500
600
700
Asia
Europe
North America
South America
Region


Number of Transactions Over Time
Number of Transactions
0
20
40
60
80
100
Dec
Jan
2024
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month

Derive Business Insights From the EDA, generate business insights. Here are some possible insights based on the analysis:

Insight 1: Transactions are more frequent in North America, followed by Europe and Asia, suggesting that marketing strategies could focus on these regions to maximize sales.

Insight 2: Categories like "Electronics" and "Fashion" contribute to the majority of transactions, indicating a strong customer preference for these categories.

Insight 3: The average transaction value is highest in North America, followed by Europe, indicating potential for higher-value promotions in these regions.

Insight 4: Transaction volume shows a seasonal trend with peaks during the holiday season (October-December), suggesting that promotional offers could be aligned with these peaks to boost sales.

Insight 5: There is a moderate negative correlation between price and quantity sold, implying that lower-priced products tend to sell in higher quantities, which is typical for fast-moving consumer goods (FMCG)

Task 2: Lookalike Model Build a Lookalike Model that takes a user's information as input and recommends 3 similar customers based on their profile and transaction history. The model should: ● Use both customer and product information. ● Assign a similarity score to each recommended customer.

```
import pandas as pd
import numpy as np
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import StandardScaler

customers = pd.read_csv('Customers.csv')
products = pd.read_csv('Products.csv')
transactions = pd.read_csv('Transactions.csv')

transactions = transactions.merge(customers, on='CustomerID',
how='left')
transactions = transactions.merge(products, on='ProductID',
how='left')

print(transactions.head())

customer_profile = customers[['CustomerID', 'Region', 'SignupDate']]

total_spending = transactions.groupby('CustomerID')
['TotalValue'].sum().reset_index()
total_spending.columns = ['CustomerID', 'TotalSpending']

avg_quantity = transactions.groupby('CustomerID')
['Quantity'].mean().reset_index()
avg_quantity.columns = ['CustomerID', 'AvgQuantity']

category_counts = transactions.groupby(['CustomerID', 'Category'])
['TransactionID'].count().reset_index()
top_category = category_counts.groupby('CustomerID').apply(lambda x:
x.loc[x['TransactionID'].idxmax()]).reset_index(drop=True)
top_category = top_category[['CustomerID', 'Category']]
top_category.columns = ['CustomerID', 'TopCategory']

customer_features = customer_profile.merge(total_spending,
on='CustomerID', how='left')
customer_features = customer_features.merge(avg_quantity,
on='CustomerID', how='left')
customer_features = customer_features.merge(top_category,
on='CustomerID', how='left')

customer_features.fillna(0, inplace=True)

print(customer_features.head())

scaler = StandardScaler()
```

```python
continuous_features = ['TotalSpending', 'AvgQuantity']
customer_features[continuous_features] =
scaler.fit_transform(customer_features[continuous_features])

print(customer_features.head())

profile_columns = ['TotalSpending', 'AvgQuantity']
profile_matrix = customer_features[profile_columns].values

cosine_sim = cosine_similarity(profile_matrix)

print(cosine_sim)

customer_ids = [f'C{str(i).zfill(4)}' for i in range(1, 21)]

lookalikes = {}

for i in range(len(customer_ids)):
    customer_id = customer_ids[i]
    customer_idx = customer_features[customer_features['CustomerID']
== customer_id].index[0]

    sim_scores = list(enumerate(cosine_sim[customer_idx]))

    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

    sim_scores = [score for score in sim_scores if
customer_features.iloc[score[0]]['CustomerID'] != customer_id]

    top_lookalikes = [(customer_features.iloc[score[0]]['CustomerID'],
score[1]) for score in sim_scores[:3]]
    lookalikes[customer_id] = top_lookalikes

lookalike_df = []
for cust_id, top_lookalikes in lookalikes.items():
    for lookalike, score in top_lookalikes:
        lookalike_df.append({'CustomerID': cust_id, 'LookalikeID':
lookalike, 'SimilarityScore': score})

lookalike_df = pd.DataFrame(lookalike_df)

print(lookalike_df.head())


lookalike_df.to_csv('Lookalike.csv', index=False)
```

```
  TransactionID CustomerID ProductID      TransactionDate  Quantity  \
0        T00001      C0199      P067  2024-08-25 12:38:23         1
1        T00112      C0146      P067  2024-05-27 22:23:54         1
2        T00166      C0127      P067  2024-04-25 07:38:55         1
3        T00272      C0087      P067  2024-03-26 22:55:37         2
```

```
4        T00363      C0070      P067  2024-03-21 15:10:10         3

   TotalValue  Price_x     CustomerName         Region  SignupDate  \
0      300.68   300.68   Andrea Jenkins         Europe  2022-12-03
1      300.68   300.68  Brittany Harvey           Asia  2024-09-04
2      300.68   300.68  Kathryn Stevens         Europe  2024-04-04
3      601.36   300.68  Travis Campbell  South America  2024-04-11
4      902.04   300.68    Timothy Perez         Europe  2022-03-15

                       ProductName     Category  Price_y
0  ComfortLiving Bluetooth Speaker  Electronics   300.68
1  ComfortLiving Bluetooth Speaker  Electronics   300.68
2  ComfortLiving Bluetooth Speaker  Electronics   300.68
3  ComfortLiving Bluetooth Speaker  Electronics   300.68
4  ComfortLiving Bluetooth Speaker  Electronics   300.68
  CustomerID         Region  SignupDate  TotalSpending  AvgQuantity  \
0      C0001  South America  2022-07-10        3354.52     2.400000
1      C0002           Asia  2022-02-13        1862.74     2.500000
2      C0003  South America  2024-03-07        2725.38     3.500000
3      C0004  South America  2022-10-09        5354.88     2.875000
4      C0005           Asia  2022-08-15        2034.24     2.333333

   TopCategory
0  Electronics
1     Clothing
2   Home Decor
3        Books
4  Electronics
  CustomerID         Region  SignupDate  TotalSpending  AvgQuantity  \
0      C0001  South America  2022-07-10      -0.051884    -0.201382
1      C0002           Asia  2022-02-13      -0.862714    -0.030924
2      C0003  South America  2024-03-07      -0.393842     1.673655
3      C0004  South America  2022-10-09       1.035375     0.608293
4      C0005           Asia  2022-08-15      -0.769499    -0.315021

   TopCategory
0  Electronics
1     Clothing
2   Home Decor
3        Books
4  Electronics
[[ 1.          0.28402302 -0.88547957 ...  0.91486608  0.69726354
  -0.95621444]
 [ 0.28402302  1.          0.19404509 ...  0.64697269  0.88533351
  -0.5522011 ]
 [-0.88547957  0.19404509  1.         ... -0.62247791 -0.2843243
   0.71071237]
 ...
 [ 0.91486608  0.64697269 -0.62247791 ...  1.          0.92732208
  -0.99297461]
```

```
 [ 0.69726354  0.88533351 -0.2843243  ...  0.92732208  1.
  -0.87652148]
 [-0.95621444 -0.5522011   0.71071237 ... -0.99297461 -0.87652148
   1.        ]]
```

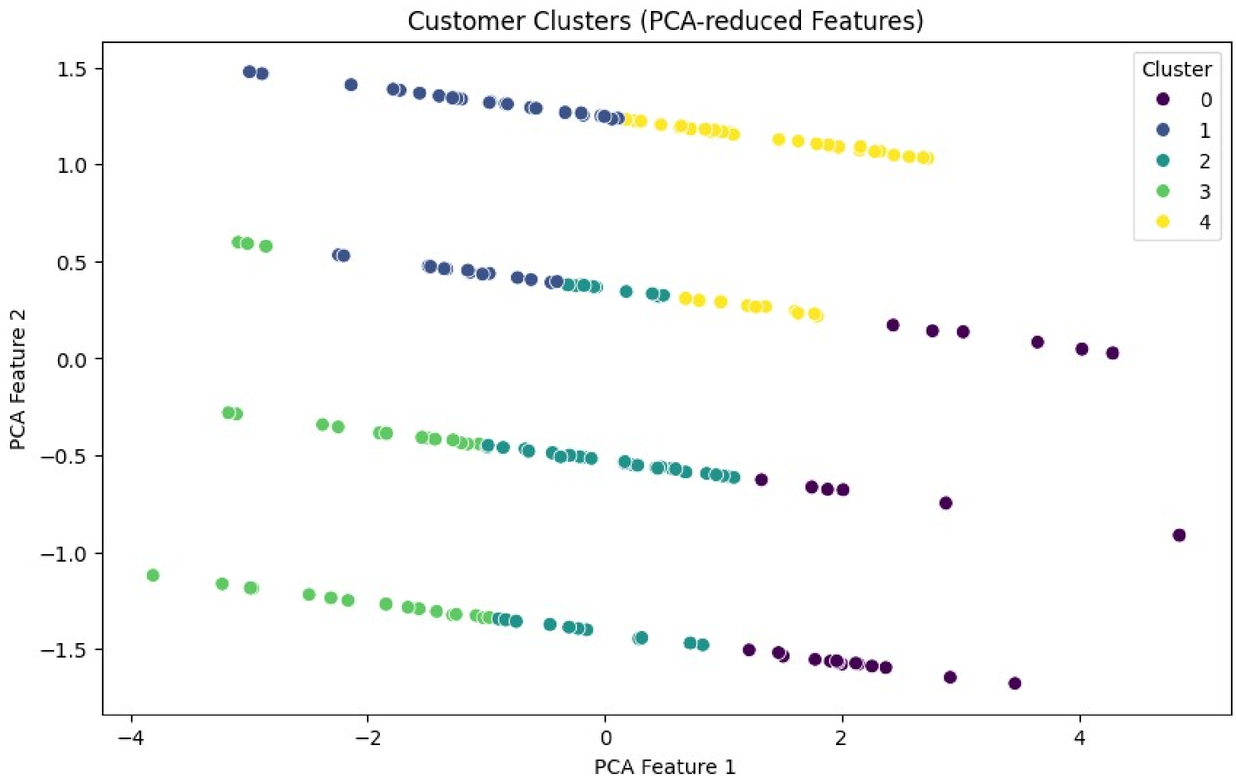
```
<ipython-input-5-21dfc4f395ce>:31: DeprecationWarning:
DataFrameGroupBy.apply operated on the grouping columns. This behavior
is deprecated, and in a future version of pandas the grouping columns
will be excluded from the operation. Either pass
`include_groups=False` to exclude the groupings or explicitly select
the grouping columns after groupby to silence this warning.
  top_category = category_counts.groupby('CustomerID').apply(lambda x:
x.loc[x['TransactionID'].idxmax()]).reset_index(drop=True)
```

```
  CustomerID LookalikeID  SimilarityScore
0      C0001       C0047         0.999792
1      C0001       C0103         0.999751
2      C0001       C0164         0.999462
3      C0002       C0140         1.000000
4      C0002       C0029         0.999999
```

Task 3: Customer Segmentation / Clustering Perform customer segmentation using clustering techniques. Use both profile information (from Customers.csv) and transaction information (from Transactions.csv). ● You have the flexibility to choose any clustering algorithm and any number of clusters in between(2 and 10) ● Calculate clustering metrics, including the DB Index(Evaluation will be done on this). ● Visualise your clusters using relevant plots.

```
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import davies_bouldin_score, silhouette_score
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.decomposition import PCA

customers = pd.read_csv('Customers.csv')
transactions = pd.read_csv('Transactions.csv')

agg_transactions = transactions.groupby('CustomerID').agg({
    'TransactionID': 'count',
    'TotalValue': 'sum',
    'ProductID': 'nunique'
}).reset_index()
agg_transactions.columns = ['CustomerID', 'TotalTransactions',
'TotalRevenue', 'UniqueProducts']

customer_data = customers.merge(agg_transactions, on='CustomerID',
how='left')
customer_data.fillna(0, inplace=True)
```

```python
le = LabelEncoder()
customer_data['Region'] = le.fit_transform(customer_data['Region'])

features = customer_data[['Region', 'TotalTransactions',
'TotalRevenue', 'UniqueProducts']]
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features)

dbi_scores = []
silhouette_scores = []
k_values = range(2, 11)

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42)
    clusters = kmeans.fit_predict(scaled_features)

    dbi = davies_bouldin_score(scaled_features, clusters)
    silhouette = silhouette_score(scaled_features, clusters)
    dbi_scores.append(dbi)
    silhouette_scores.append(silhouette)

optimal_k = k_values[np.argmin(dbi_scores)]
kmeans = KMeans(n_clusters=optimal_k, random_state=42)
customer_data['Cluster'] = kmeans.fit_predict(scaled_features)

pca = PCA(n_components=2)
pca_features = pca.fit_transform(scaled_features)

plt.figure(figsize=(10, 6))
sns.scatterplot(x=pca_features[:, 0], y=pca_features[:, 1],
hue=customer_data['Cluster'], palette='viridis', s=50)
plt.title('Customer Clusters (PCA-reduced Features)')
plt.xlabel('PCA Feature 1')
plt.ylabel('PCA Feature 2')
plt.legend(title='Cluster')
plt.show()

print(f"Optimal Number of Clusters: {optimal_k}")
print(f"DB Index for Optimal Clusters: {min(dbi_scores)}")
print(f"Silhouette Score for Optimal Clusters:
{silhouette_scores[np.argmin(dbi_scores)]}")
```




```
Optimal Number of Clusters: 5
DB Index for Optimal Clusters: 0.9911291887002747
Silhouette Score for Optimal Clusters: 0.2964913509398336
```

Example Insights: Cluster 1: Customers from Asia with high transaction counts but moderate revenue. Cluster 2: Customers from Europe with low transaction counts and high average transaction value. Cluster 3: Customers from North America with balanced transactions and revenue.

Visualizations: Scatter plot of clusters in 2D (PCA-reduced features). DB Index and Silhouette Score vs. Number of Clusters.