eCommerce Transactions Dataset EDA

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

```
#Load the all file:

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

```
#Check Data:
customers.head()
```

	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

Next steps: Generate code with customers View recommended plots New interactive sheet

```
products.head()
```

	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

Next steps: Generate code with products View recommended plots New interactive sheet

```
transactions.head()
```

	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
3	T00272	C0087	P067	2024-03-26 22:55:37	2	601.36	300.68
4	T00363	C0070	P067	2024-03-21 15:10:10	3	902.04	300.68

Next steps: Generate code with transactions View recommended plots New interactive sheet

#Data UnderStanding

```
#Check the data shape
print(customers.info())
print()
print(products.info())
print()
print(transactions.info())
print()
```

```
<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    object
dtypes: object(4)
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   object
 4   Quantity         1000 non-null   int64
 5   TotalValue       1000 non-null   float64
 6   Price            1000 non-null   float64
dtypes: float64(2), int64(1), object(4)
memory usage: 54.8+ KB
None
```

```
#Check missing Value
print(customers.isnull().sum())
print()
print(products.isnull().sum())
print()
print(transactions.isnull().sum())
print()
```

```
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
```

```
#Check duplicate Value

print(customers.duplicated().sum())
print()
print(products.duplicated().sum())
print()
print(transactions.duplicated().sum())
print()
```

```
0

0

0
```

```
#Describe the transaction Table

round(transactions.describe()).T
```

	count	mean	std	min	25%	50%	75%	max
Quantity	1000.0	3.0	1.0	1.0	2.0	3.0	4.0	4.0
TotalValue	1000.0	690.0	493.0	16.0	295.0	589.0	1012.0	1991.0
Price	1000.0	273.0	141.0	16.0	148.0	300.0	404.0	498.0

#Data Cleaning:

```
print(customers.head())
print()
print(products.head())
print()
```

```
  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
```

```
#Remove the time from TransactionDate column of transaction Table:

transactions['TransactionDate'] = pd.to_datetime(transactions['TransactionDate'])
transactions['TransactionDate'] = transactions['TransactionDate'].dt.date
```

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

```
print(customers.head())
print()
print(transactions.head())
print()
```

```
  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

  TransactionID CustomerID ProductID TransactionDate  Quantity  TotalValue  \
0        T00001      C0199      P067      2024-08-25         1      300.68
1        T00112      C0146      P067      2024-05-27         1      300.68
2        T00166      C0127      P067      2024-04-25         1      300.68
3        T00272      C0087      P067      2024-03-26         2      601.36
4        T00363      C0070      P067      2024-03-21         3      902.04

    Price
0  300.68
1  300.68
2  300.68
3  300.68
4  300.68
```

```
#Check the data shape
print(customers.info())
print()
print(products.info())
print()
print(transactions.info())
print()
```

```
<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
```

Exploratory Analysis (Lets analyze all the file indivisual)

customers file:

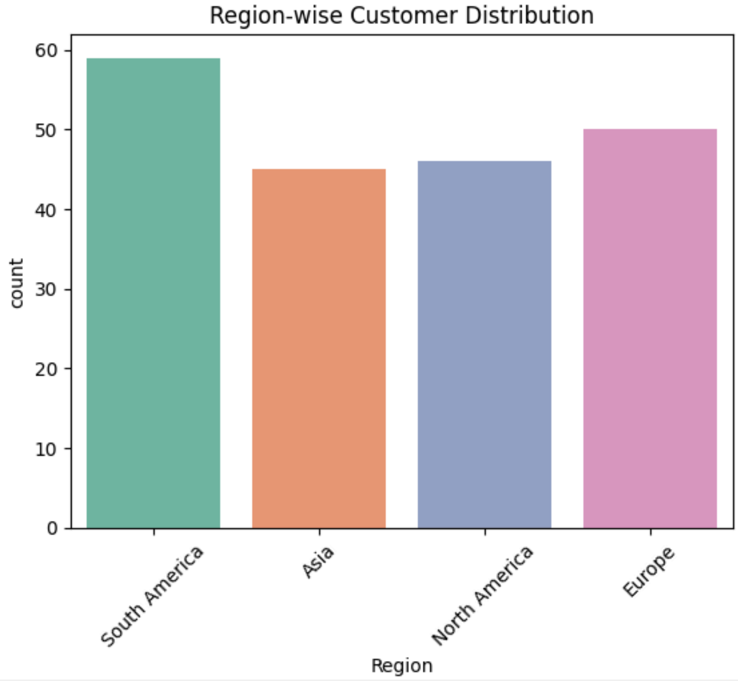
```
customers.head()
```

	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

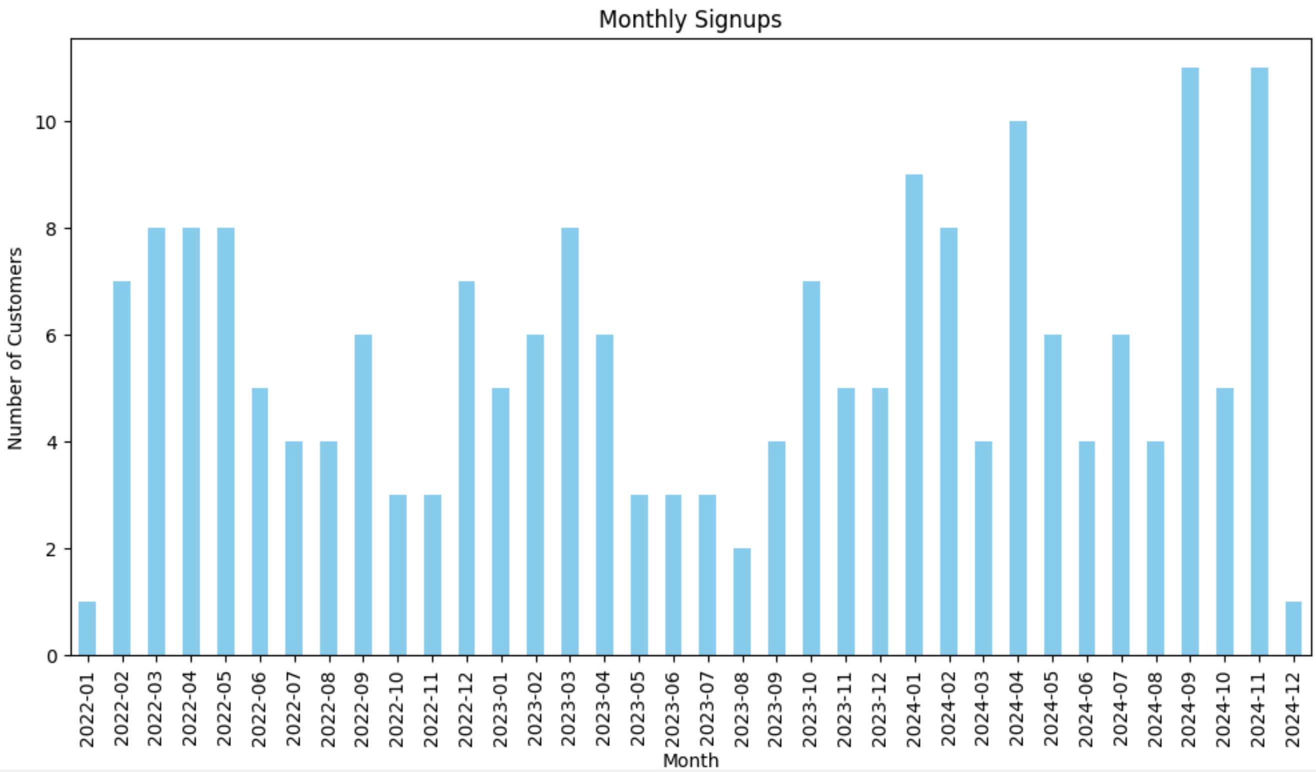
Next steps: Generate code with customers | View recommended plots | New interactive sheet

```
#Distributed region wise:

sns.countplot(data=customers, x='Region', palette='Set2')
plt.xticks(rotation=45)
plt.title("Region-wise Customer Distribution")
plt.show()
```

```
<ipython-input-65-e2c8c2e5aadd>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and s

  sns.countplot(data=customers, x='Region', palette='Set2')
```



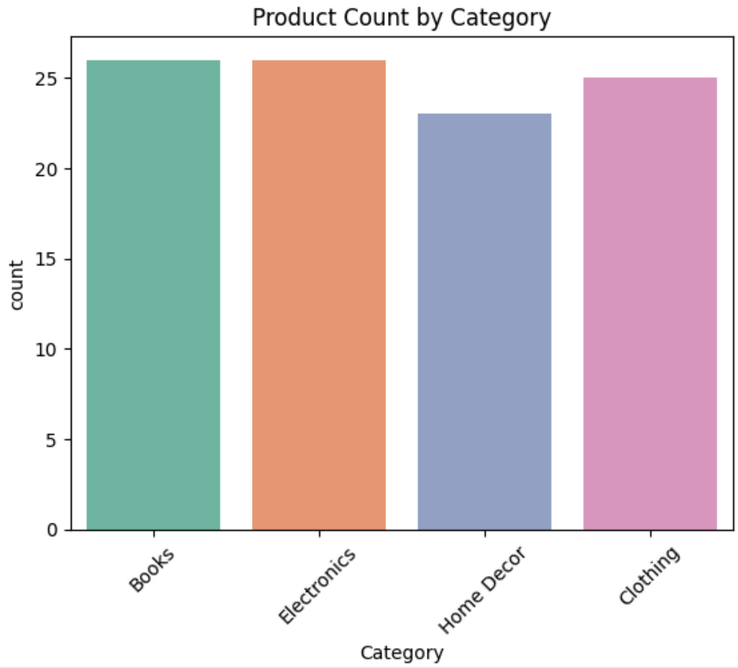

```
#Analysis by Signup date
customers['SignupMonth'] = customers['SignupDate'].dt.to_period('M')
monthly_signups = customers.groupby('SignupMonth').size()

monthly_signups.plot(kind='bar', figsize=(12, 6), color='skyblue')
plt.title("Monthly Signups")
plt.xlabel("Month")
plt.ylabel("Number of Customers")
plt.show()
```



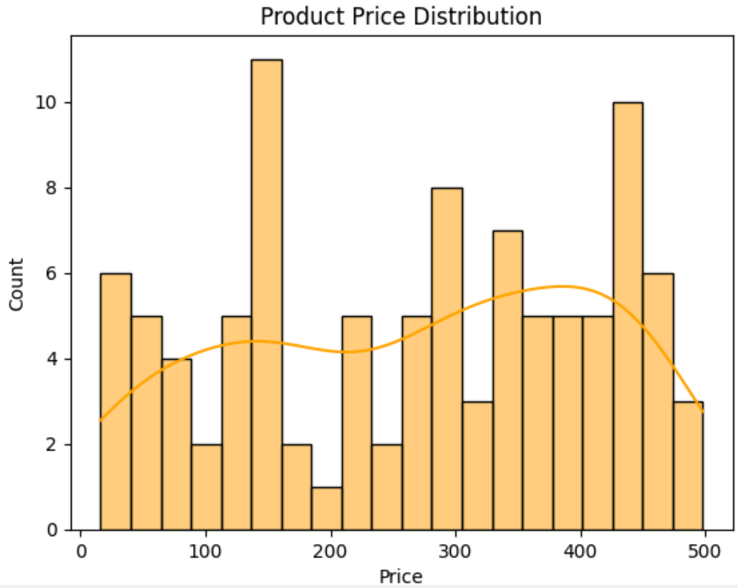
From Product File:

```
#Category_wise product count:

sns.countplot(data=products, x='Category', palette='Set2')
plt.title("Product Count by Category")
plt.xticks(rotation=45)
plt.show()
```

```
<ipython-input-54-2fad0c645677>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and s

  sns.countplot(data=products, x='Category', palette='Set2')
```




```
#price Distribution:
sns.histplot(products['Price'], bins=20, kde=True, color='orange')
plt.title("Product Price Distribution")
plt.show()
```



Transactions File

```
transactions.head()
```

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price
0	T00001	C0199	P067	2024-08-25	1	300.68	300.68
1	T00112	C0146	P067	2024-05-27	1	300.68	300.68
2	T00166	C0127	P067	2024-04-25	1	300.68	300.68
3	T00272	C0087	P067	2024-03-26	2	601.36	300.68
4	T00363	C0070	P067	2024-03-21	3	902.04	300.68

Next steps: Generate code with transactions | View recommended plots | New interactive sheet

```
#calculate Toral revenue:

total_revenue = transactions['TotalValue'].sum()
print(f"Total Revenue: {total_revenue}")
```

```
Total Revenue: 689995.56
```

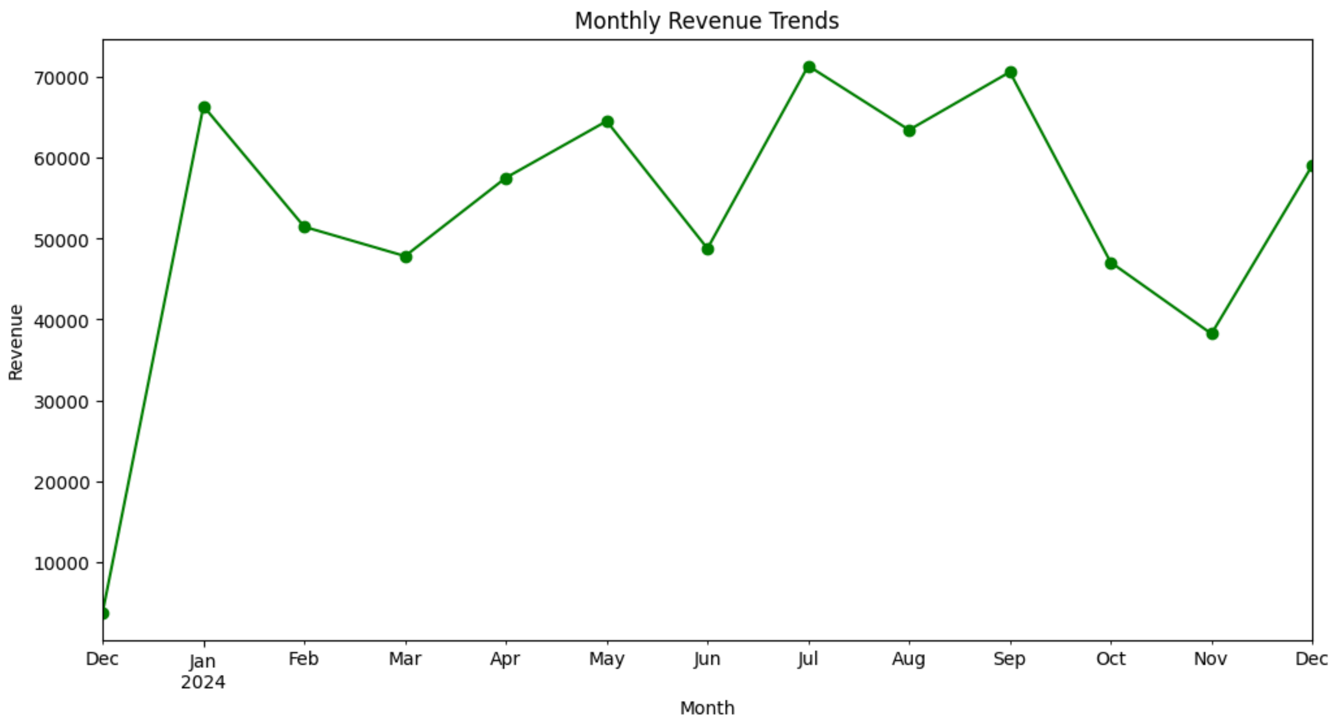
```
# Top 10 customers by revenue:

top_customers = transactions.groupby('CustomerID')['TotalValue'].sum().sort_values(ascending=False).head(10)
print(top_customers)
```

```
CustomerID
C0141    10673.87
C0054     8040.39
C0065     7663.70
C0156     7634.45
C0082     7572.91
C0188     7111.32
C0059     7073.28
C0028     6819.57
C0099     6715.72
C0165     6708.10
Name: TotalValue, dtype: float64
```

```
# Top 10 products by sales:
top_products = transactions.groupby('ProductID')['Quantity'].sum().sort_values(ascending=False).head(10)
print(top_products)
```

```
ProductID
P059    46
P054    46
P029    45
P079    43
P061    43
P057    43
P048    43
P062    39
P020    38
P028    38
Name: Quantity, dtype: int64
```

```
#Monthly revenue trends:

transactions['TransactionMonth'] = transactions['TransactionDate'].dt.to_period('M')
monthly_revenue = transactions.groupby('TransactionMonth')['TotalValue'].sum()

monthly_revenue.plot(kind='line', figsize=(12, 6), marker='o', color='green')
plt.title("Monthly Revenue Trends")
plt.xlabel("Month")
plt.ylabel("Revenue")
plt.show()
```



Business Insghts:

1. Customer Demographics and Signup Trends:

A.South America has the highest number of customers compared to other regions. This indicates that South America is a key market for the business.

B.Most customers signed up during February, March, and April, whereas January consistently shows the lowest number of new signups.

2. Product Category and Pricing Trends:

A.Products across categories have almost equal distribution, with a slight dip in the Home Decor category. This might indicate either lower demand or limited product variety in this segment.

B.Price distribution highlights two key ranges: $100-$200 and $400-$500,
showing these are the most popular pricing brackets among customers.

3. Revenue and Customer Trends:

A.The total revenue generated is $689,995.56, withCustomerID: C0141beingthetopcontributor, generating$10,673 in revenue.

B.The top-selling product is P059, sold 46 times, indicating strong demand for this product.

4. Monthly Revenue Trends:

A.In December 2023, revenue was critically low (below $1,000), butitshowedasharprecoverytoover$6,000 in January 2024.

B.Post-recovery, the monthly revenue stabilized in the range of $5,000-$7,000 for the rest of the year, showing consistent performance after an initial spike.

TASK 2 : Looklike Model

```
#import sklearn library
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import MinMaxScaler
```

```
# visit the Data:

print(customers.head())
print()
```

```
print(products.head())
print()
print(transactions.head())
```

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

  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  TotalValue  \
0        T00001      C0199      P067      2024-08-25         1      300.68
1        T00112      C0146      P067      2024-05-27         1      300.68
2        T00166      C0127      P067      2024-04-25         1      300.68
3        T00272      C0087      P067      2024-03-26         2      601.36
4        T00363      C0070      P067      2024-03-21         3      902.04

    Price TransactionMonth
0  300.68          2024-08
1  300.68          2024-05
2  300.68          2024-04
3  300.68          2024-03
4  300.68          2024-03
```

```
# Merge 3 Dataset
# Merge transactions with products
transactions = transactions.merge(products, on='ProductID', how='left')

# Merge transactions with customers
data = transactions.merge(customers, on='CustomerID', how='left')

# Check the final dataset
data.head()
```

TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price_x	TransactionMonth	ProductName_x	Categor
T00001	C0199	P067	2024-08-25	1	300.68	300.68	2024-08	ComfortLiving Bluetooth Speaker	Electro
T00112	C0146	P067	2024-05-27	1	300.68	300.68	2024-05	ComfortLiving Bluetooth Speaker	Electro
T00166	C0127	P067	2024-04-25	1	300.68	300.68	2024-04	ComfortLiving Bluetooth Speaker	Electro
T00272	C0087	P067	2024-03-26	2	601.36	300.68	2024-03	ComfortLiving Bluetooth Speaker	Electro
T00363	C0070	P067	2024-03-21	3	902.04	300.68	2024-03	ComfortLiving Bluetooth Speaker	Electro

Next steps: Generate code with data | View recommended plots | New interactive sheet

```
# Aggregate transaction data
customer_agg = data.groupby('CustomerID').agg({
    'TotalValue': 'sum','Quantity': 'sum','Price': 'mean'}).reset_index()

# Add region encoding
region_encoding = pd.get_dummies(customers[['CustomerID', 'Region']], columns=['Region'])
customer_agg = customer_agg.merge(region_encoding, on='CustomerID', how='left')

# Check aggregated features
customer_agg.head()
```

	CustomerID	TotalValue	Quantity	Price	Region_Asia	Region_Europe	Region_North America	Region_South America
0	C0001	3354.52	12	278.334000	False	False	False	True
1	C0002	1862.74	10	208.920000	True	False	False	False
2	C0003	2725.38	14	195.707500	False	False	False	True
3	C0004	5354.88	23	240.636250	False	False	False	True
4	C0005	2034.24	7	291.603333	True	False	False	False

Next steps: Generate code with customer_agg View recommended plots New interactive sheet

Normalize the Features

```
# Normalize numerical features
scaler = MinMaxScaler()
features = customer_agg.drop('CustomerID', axis=1)  # Exclude CustomerID for scaling
normalized_features = scaler.fit_transform(features)

# Convert back to DataFrame
normalized_features = pd.DataFrame(normalized_features, columns=features.columns, index=customer_agg['CustomerID'])
normalized_features.head()
```

CustomerID	TotalValue	Quantity	Price	Region_Asia	Region_Europe	Region_North America	Region_South America
C0001	0.308942	0.354839	0.519414	0.0	0.0	0.0	1.0
C0002	0.168095	0.290323	0.367384	1.0	0.0	0.0	0.0
C0003	0.249541	0.419355	0.338446	0.0	0.0	0.0	1.0
C0004	0.497806	0.709677	0.436848	0.0	0.0	0.0	1.0
C0005	0.184287	0.193548	0.548476	1.0	0.0	0.0	0.0

Next steps: Generate code with normalized_features View recommended plots New interactive sheet

Calculate similirity score (Build the lookalike model)

```
# Compute pairwise cosine similarity
similarity_matrix = cosine_similarity(normalized_features)

# Convert to DataFrame for easy manipulation
similarity_df = pd.DataFrame(similarity_matrix, index=customer_agg['CustomerID'], columns=customer_agg['CustomerID'])
similarity_df.head()
```

CustomerID	C0001	C0002	C0003	C0004	C0005	C0006	C0007	C0008	C0009	C0010	...	C0191	C0192
CustomerID													
C0001	1.000000	0.253518	0.986950	0.959271	0.286969	0.995359	0.330221	0.348553	0.241389	0.224175	...	0.999278	0.989804
C0002	0.253518	1.000000	0.221730	0.289222	0.984924	0.277859	0.969086	0.272393	0.185625	0.178380	...	0.247901	0.224718
C0003	0.986950	0.221730	1.000000	0.968405	0.229577	0.968467	0.262941	0.326945	0.176962	0.211370	...	0.984116	0.970527
C0004	0.959271	0.289222	0.968405	1.000000	0.287091	0.953520	0.328818	0.447073	0.205789	0.284352	...	0.948407	0.910928
C0005	0.286969	0.984924	0.229577	0.287091	1.000000	0.322382	0.995295	0.274389	0.248972	0.179873	...	0.285261	0.271305

5 rows × 199 columns

Generate recoomendations

```
# Function to get top 3 lookalikes for each customer
def get_top_lookalikes(similarity_df, top_n=3):
    lookalike_list = []
    for customer_id in similarity_df.index:
        # Sort customers by similarity score, skip self (iloc[1:top_n+1])
        similar_customers = similarity_df.loc[customer_id].sort_values(ascending=False).iloc[1:top_n+1]
        # Add results to the list
```

```
        lookalike_list.append(
            [customer_id] + list(similar_customers.index) + list(similar_customers.values)
        )
    return lookalike_list

# Get top 3 lookalikes for all customers
lookalike_list = get_top_lookalikes(similarity_df)

# Convert the list into a DataFrame
lookalike_df = pd.DataFrame(
    lookalike_list,
    columns=['CustomerID', 'Lookalike1', 'Lookalike2', 'Lookalike3', 'Score1', 'Score2', 'Score3']
)

# Save the DataFrame as a CSV file
lookalike_df.to_csv('Lookalike.csv', index=False)

# Show the first few rows
lookalike_df.head()
```

	CustomerID	Lookalike1	Lookalike2	Lookalike3	Score1	Score2	Score3
0	C0001	C0137	C0191	C0011	0.999479	0.999278	0.999276
1	C0002	C0088	C0142	C0027	0.998965	0.998596	0.996510
2	C0003	C0190	C0147	C0174	0.998906	0.997914	0.996201
3	C0004	C0113	C0169	C0012	0.999112	0.995818	0.994859
4	C0005	C0186	C0140	C0146	0.998743	0.998450	0.996784

Next steps: Generate code with lookalike_df View recommended plots New interactive sheet

```
#Top 3 similar customers and their scores for all customers
lookalike_df.head(3)
```

	CustomerID	Lookalike1	Lookalike2	Lookalike3	Score1	Score2	Score3
0	C0001	C0137	C0191	C0011	0.999479	0.999278	0.999276
1	C0002	C0088	C0142	C0027	0.998965	0.998596	0.996510
2	C0003	C0190	C0147	C0174	0.998906	0.997914	0.996201

Next steps: Generate code with lookalike_df View recommended plots New interactive sheet

Task 3: Customer Segmentation / Clustering

To group customers into segments based on their profiles and transaction history, enabling better targeting and personalized marketing.

```
# Merge Customers.csv and Transactions.csv
merged_df = pd.merge(transactions, customers, on='CustomerID', how='left')

# Aggregate transaction-level data for each customer
customer_agg = merged_df.groupby('CustomerID').agg({
    'TotalValue': 'sum',       # Total revenue per customer
    'TransactionID': 'count',  # Total number of transactions
    'Quantity': 'mean',        # Average basket size
}).rename(columns={
    'TotalValue': 'TotalRevenue',
    'TransactionID': 'TotalTransactions',
    'Quantity': 'AvgBasketSize'
}).reset_index()

# Merge aggregated transaction data back to customer profile
customer_profile = pd.merge(customers, customer_agg, on='CustomerID', how='left')

# Fill any missing values (e.g., customers with no transactions)
customer_profile.fillna({
    'TotalRevenue': 0,
    'TotalTransactions': 0,
    'AvgBasketSize': 0
}, inplace=True)

# Convert SignupDate to a datetime object for tenure calculation
customer_profile['SignupDate'] = pd.to_datetime(customer_profile['SignupDate'])
```

```
# Calculate tenure in days since signup
current_date = pd.Timestamp.now()
customer_profile['TenureDays'] = (current_date - customer_profile['SignupDate']).dt.days

# Drop unneeded columns for clustering
customer_clustering_data = customer_profile.drop(['CustomerName', 'SignupDate'], axis=1)
customer_clustering_data.head()
```

	CustomerID	Region	SignupMonth	TotalRevenue	TotalTransactions	AvgBasketSize	TenureDays
0	C0001	South America	2022-07	3354.52	5.0	2.400000	932
1	C0002	Asia	2022-02	1862.74	4.0	2.500000	1079
2	C0003	South America	2024-03	2725.38	4.0	3.500000	326
3	C0004	South America	2022-10	5354.88	8.0	2.875000	841
4	C0005	Asia	2022-08	2034.24	3.0	2.333333	896

Next steps: Generate code with customer_clustering_data | View recommended plots | New interactive sheet

Feature Scaling:

```
from sklearn.preprocessing import StandardScaler

# Select numeric columns for clustering
numeric_columns = ['TotalRevenue', 'TotalTransactions', 'AvgBasketSize', 'TenureDays']
scaler = StandardScaler()
scaled_data = scaler.fit_transform(customer_clustering_data[numeric_columns])

# Convert scaled data back to a DataFrame for easier handling
scaled_df = pd.DataFrame(scaled_data, columns=numeric_columns)
scaled_df['CustomerID'] = customer_clustering_data['CustomerID']
scaled_df.head()
```

	TotalRevenue	TotalTransactions	AvgBasketSize	TenureDays	CustomerID
0	-0.051884	0.000000	-0.201382	1.152884	C0001
1	-0.862714	-0.451294	-0.030924	1.605593	C0002
2	-0.393842	-0.451294	1.673655	-0.713387	C0003
3	1.035375	1.353881	0.608293	0.872636	C0004
4	-0.769499	-0.902587	-0.315021	1.042017	C0005

Next steps: Generate code with scaled_df | View recommended plots | New interactive sheet

1. K-Means Clustering:

What is it?:

K-Means is a popular clustering algorithm that partitions data into K distinct clusters. Each customer is assigned to the cluster whose center (centroid) is nearest.

Why use it?:

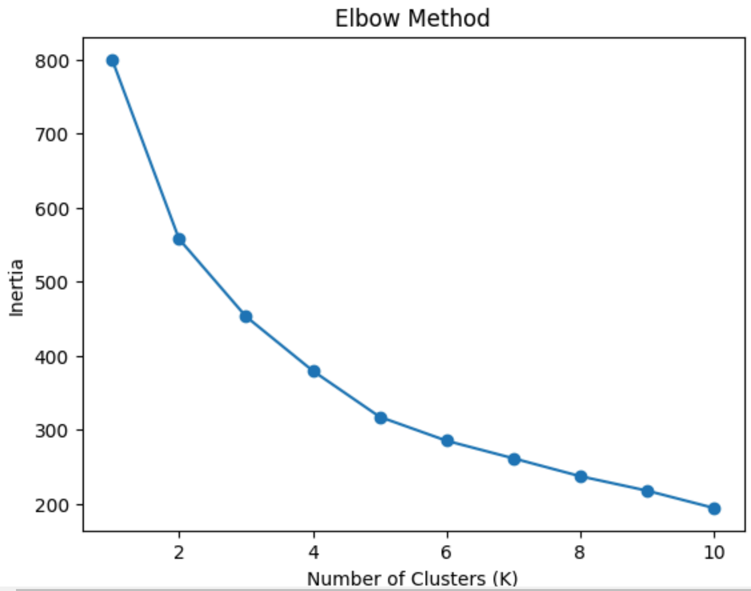
Easy to understand and implement.

Works well when clusters are spherical or circular and data is relatively well-separated.

Good for large datasets.

```
#Step 1: Elbow Method to Find Optimal K

import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

# Elbow method to find the optimal number of clusters
inertia = []

# Try different values of K from 1 to 10
for k in range(1, 11):
```

```
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(scaled_df[numeric_columns])  # Fit the KMeans model on the scaled data
    inertia.append(kmeans.inertia_)  # Store inertia (sum of squared distances to the nearest cluster center)

# Plot the Elbow Method graph
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Elbow Method')
plt.xlabel('Number of Clusters (K)')
plt.ylabel('Inertia')
plt.show()
```




```
#Step 2: Apply K-Means with Chosen K:

# Apply K-Means clustering with K=4 (example)
kmeans = KMeans(n_clusters=4, random_state=42)
customer_profile['Cluster'] = kmeans.fit_predict(scaled_df[numeric_columns])

# Check the first few rows to see which customer belongs to which cluster
customer_profile.head()
```

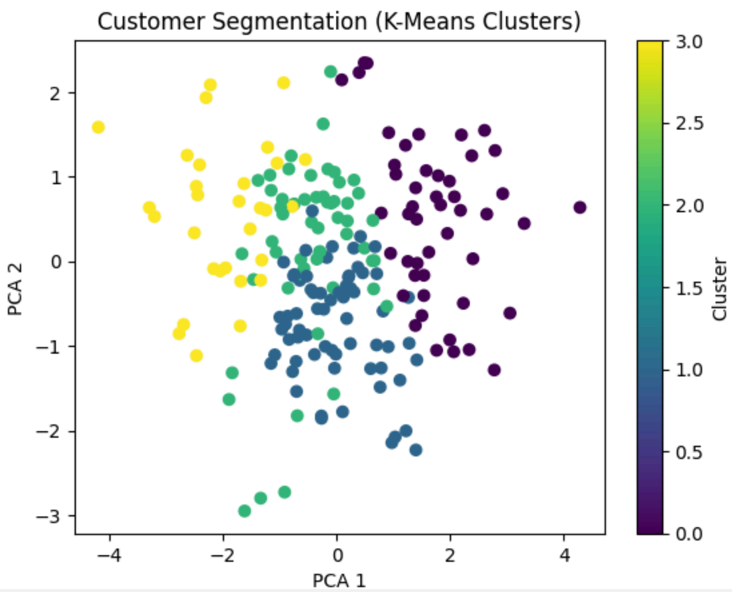
	CustomerID	CustomerName	Region	SignupDate	SignupMonth	TotalRevenue	TotalTransactions	AvgBasketSize	TenureDays	Cluste
0	C0001	Lawrence Carroll	South America	2022-07-10	2022-07	3354.52	5.0	2.400000	932	
1	C0002	Elizabeth Lutz	Asia	2022-02-13	2022-02	1862.74	4.0	2.500000	1079	
2	C0003	Michael Rivera	South America	2024-03-07	2024-03	2725.38	4.0	3.500000	326	
		Kathleen	South							

Next steps: Generate code with customer_profile | View recommended plots | New interactive sheet

```
#Step 3: Optional - Evaluate Clustering:

from sklearn.metrics import davies_bouldin_score

# Evaluate clustering quality
db_index = davies_bouldin_score(scaled_df[numeric_columns], customer_profile['Cluster'])
print('Davies-Bouldin Index:', db_index)


from sklearn.metrics import davies_bouldin_score

# Evaluate clustering quality
db_index = davies_bouldin_score(scaled_df[numeric_columns], customer_profile['Cluster'])
print('Davies-Bouldin Index:', db_index)
```

```
Davies-Bouldin Index: 1.215035501264994
Davies-Bouldin Index: 1.215035501264994
```

```
#Step 4: Optional - Visualize the Clusters

from sklearn.decomposition import PCA

# Reduce the features to 2D using PCA
pca = PCA(n_components=2)
pca_components = pca.fit_transform(scaled_df[numeric_columns])

# Add PCA components to the DataFrame
customer_profile['PCA1'] = pca_components[:, 0]
customer_profile['PCA2'] = pca_components[:, 1]

# Plot the clusters
plt.scatter(customer_profile['PCA1'], customer_profile['PCA2'], c=customer_profile['Cluster'], cmap='viridis')
plt.title('Customer Segmentation (K-Means Clusters)')
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
plt.colorbar(label='Cluster')
plt.show()
```




```
#Step 5: Analyze the Clusters:

# Group by clusters and calculate the average for each feature
cluster_summary = customer_profile.groupby('Cluster').agg({
    'TotalRevenue': 'mean',
    'TotalTransactions': 'mean',
    'AvgBasketSize': 'mean',
    'TenureDays': 'mean'
}).reset_index()

# Print the cluster summary
print(cluster_summary)
```

```
   Cluster  TotalRevenue  TotalTransactions  AvgBasketSize  TenureDays
0        0   5755.758125           7.708333       2.657543  709.958333
1        1   3476.467463           5.179104       2.505467  255.194030
2        2   2684.503091           3.709091       2.824545  775.872727
3        3   1104.939333           2.633333       1.761667  589.333333
```

```
#Step 6: Label the Clusters

# Create a new column for cluster labels based on the summary
def label_cluster(cluster_id):
    if cluster_id == 0:
        return 'High-Value, Frequent Shoppers'
    elif cluster_id == 1:
        return 'Moderate Shoppers'
    elif cluster_id == 2:
        return 'Loyal, Moderate Spenders'
    elif cluster_id == 3:
        return 'Low-Value, Infrequent Shoppers'

# Apply the label function to the Cluster column
customer_profile['ClusterLabel'] = customer_profile['Cluster'].apply(label_cluster)
```

```
# Check the updated customer profile
customer_profile.head()
```

	CustomerID	CustomerName	Region	SignupDate	SignupMonth	TotalRevenue	TotalTransactions	AvgBasketSize	TenureDays	Cluste
0	C0001	Lawrence Carroll	South America	2022-07-10	2022-07	3354.52	5.0	2.400000	932	
1	C0002	Elizabeth Lutz	Asia	2022-02-13	2022-02	1862.74	4.0	2.500000	1079	
2	C0003	Michael Rivera	South America	2024-03-07	2024-03	2725.38	4.0	3.500000	326	
3	C0004	Kathleen	South	2022-10-09	2022-10	5354.88	8.0	2.875000	841	

Next steps: Generate code with customer_profile View recommended plots New interactive sheet

Cluster:

Cluster 0: High revenue, frequent transactions, and larger average basket size.

Cluster 1: Moderate revenue, fewer transactions, shorter tenure.

Cluster 2: Moderate revenue, larger basket size, longer tenure.

Cluster 3: Low revenue, infrequent transactions, small basket size.

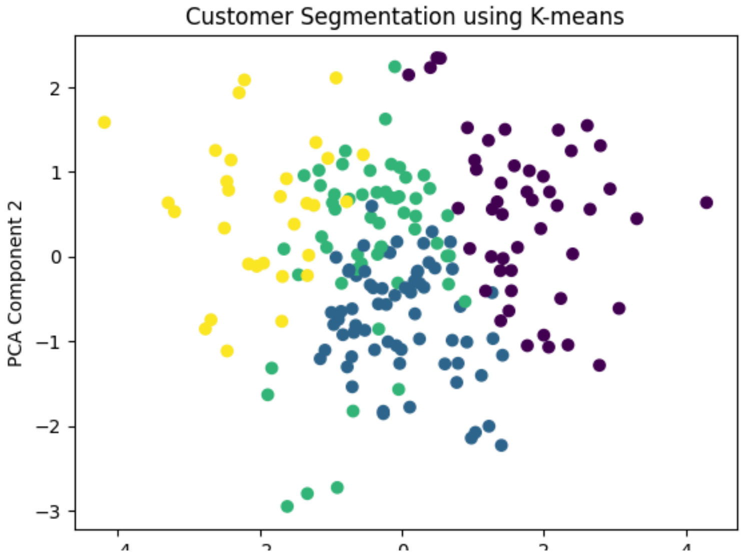
```
# Save the customer profile with cluster labels to a new CSV
customer_profile.to_csv('CustomerProfile_with_Clusters.csv', index=False)
```

Evaluate the Clustering Performance:

```
from sklearn.metrics import davies_bouldin_score
db_index = davies_bouldin_score(scaled_df[numeric_columns], kmeans.labels_)
print("DB Index:", db_index)
```

```
DB Index: 1.215035501264994
```

```
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
pca_components = pca.fit_transform(scaled_df[numeric_columns])

plt.scatter(pca_components[:, 0], pca_components[:, 1], c=kmeans.labels_, cmap='viridis')
plt.title("Customer Segmentation using K-means")
plt.xlabel("PCA Component 1")
plt.ylabel("PCA Component 2")
plt.show()
```


Customer Segmentation using K-means
PCA Component 2
2
1
0
−1
−2
−3