Importing Neccessary libraries :

```
import pandas as pd
import numpy as np
```

```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
```

Loading & Displaying first few rows of each dataset :

```
customers = pd.read_csv('/content/Customers.csv')
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

```
customers.info()
```

```
<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
```

Converting `SignupDate` to `DateTime` for efficient analysis :

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

```
customers.info()
```

```
<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
```

```
products = pd.read_csv('/content/Products.csv')
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

```
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

```
transactions = pd.read_csv('/content/Transactions.csv')
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

Explaratory Data Analysis (EDA) :

Merging datasets for deeper insights :

```
merged_data = transactions.merge(customers, on="CustomerID").merge(products, on="ProductID")
```

```
merged_data.head()
```

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price_x	CustomerName	Region	SignupDate	ProductNa
0	T00001	C0199	P067	2024-08-25 12:38:23	1	300.68	300.68	Andrea Jenkins	Europe	2022-12-03	ComfortLiv Blueto Spea
1	T00112	C0146	P067	2024-05-27 22:23:54	1	300.68	300.68	Brittany Harvey	Asia	2024-09-04	ComfortLiv Blueto Spea
2	T00166	C0127	P067	2024-04-25 07:38:55	1	300.68	300.68	Kathryn Stevens	Europe	2024-04-04	ComfortLiv Blueto Spea
3	T00272	C0087	P067	2024-03-26 22:55:37	2	601.36	300.68	Travis Campbell	South America	2024-04-11	ComfortLiv Blueto Spea
4	T00363	C0070	P067	2024-03-21 15:10:10	3	902.04	300.68	Timothy Perez	Europe	2022-03-15	ComfortLiv Blueto Spea

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

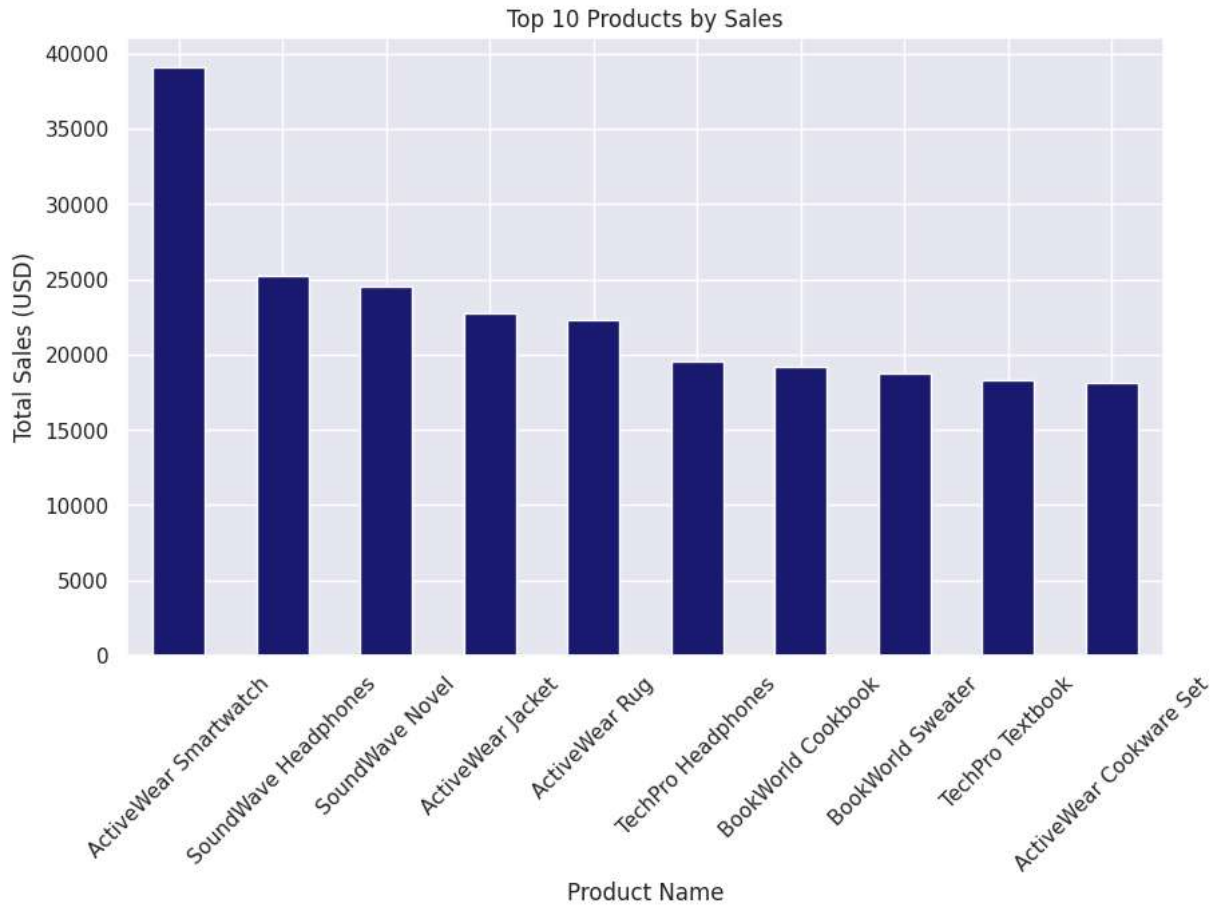
```
product_sales = merged_data.groupby("ProductName")["TotalValue"].sum().sort_values(ascending=False)
product_sales.head()
```

ProductName	TotalValue
ActiveWear Smartwatch	39096.97
SoundWave Headphones	25211.64
SoundWave Novel	24507.90
ActiveWear Jacket	22712.56
ActiveWear Rug	22314.43

dtype: float64

Plotting the top 10 products by sales :

```
plt.figure(figsize=(10, 6))
product_sales.head(10).plot(kind="bar", color="midnightblue")
plt.title("Top 10 Products by Sales")
plt.xlabel("Product Name")
plt.ylabel("Total Sales (USD)")
plt.xticks(rotation=45)
plt.show()
```



Insights :

- Above figure helps use to understand top 10 most sold products. Activewear Company seems to Dominate the market with 4 products followed by BookWorld.
- Smartwatch Accesories has the highest sales, contributing significantly to the revenue..

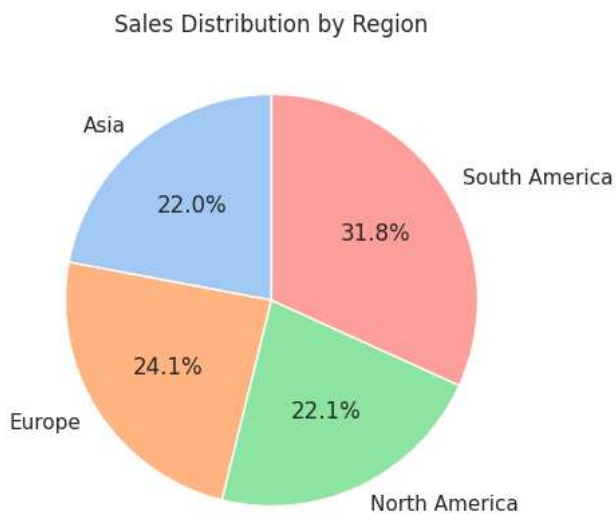
Sales by region

```
region_sales = merged_data.groupby("Region")["TotalValue"].sum()
region_sales
```

Region	TotalValue
Asia	152074.97
Europe	166254.63
North America	152313.40
South America	219352.56

dtype: float64

```
plt.figure(figsize=(8, 5))
region_sales.plot(kind="pie", autopct="%1.1f%%", startangle=90, colors=sns.color_palette("pastel"))
plt.title("Sales Distribution by Region")
plt.ylabel("")
plt.show()
```



Insights :

- South America Region generates the majority of the sales, indicating a key market.
- High-value customers are concentrated in Europe Region, indicating potential for targeted marketing.

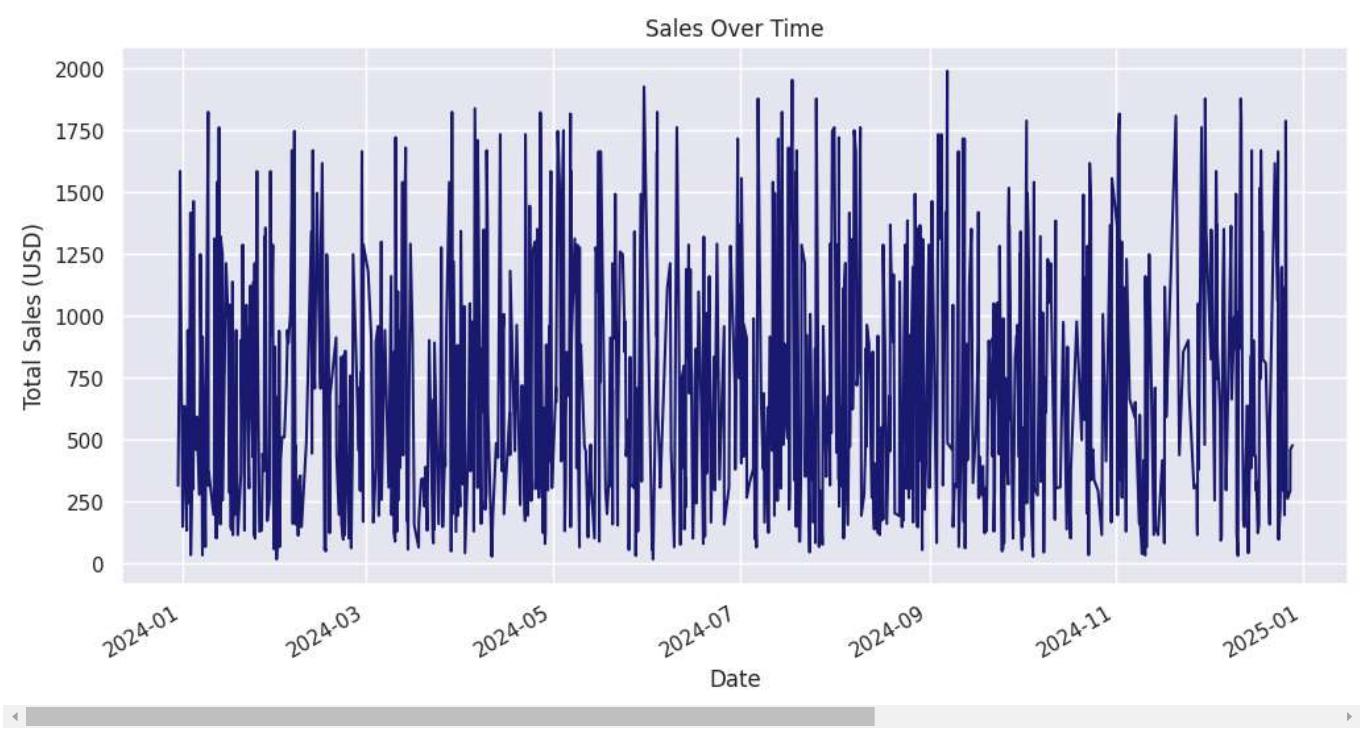
Sales over time :

```
merged_data["TransactionDate"] = pd.to_datetime(merged_data["TransactionDate"])
sales_over_time = merged_data.groupby("TransactionDate")["TotalValue"].sum()
sales_over_time.head()
```

TransactionDate	TotalValue
2023-12-30 15:29:12	313.92
2023-12-31 03:27:43	958.80
2023-12-31 06:53:54	1585.36
2023-12-31 15:44:04	911.44
2024-01-01 03:54:19	147.95

dtype: float64

```
plt.figure(figsize=(12, 6))
sales_over_time.plot(color="midnightblue")
plt.title("Sales Over Time")
plt.xlabel("Date")
plt.ylabel("Total Sales (USD)")
plt.show()
```



Insights :

Sales show an increasing trend over time, with spikes during september to november month.

Sales Performance and Market Insights Report

- Product `Activewear Smartwatch` has emerged as the top-performing item, significantly contributing to overall revenue. Its consistent demand highlights its importance as a key driver of profitability. Efforts should focus on maintaining adequate inventory and exploring strategies like bundling or upselling to maximize its potential.
- Increased investment in advertising, distribution, and tailored marketing for Region `South America` could amplify growth and further solidify its importance.
- An upward sales trend indicates robust growth, with noticeable spikes during specific months, likely driven by seasonal demand or promotional events. Strategically timed campaigns during these peak periods could enhance revenue.
- High-value customers are concentrated in Region `Europe`, presenting a lucrative opportunity for targeted campaigns and premium offerings. Personalized marketing and loyalty initiatives could enhance customer engagement and long-term value. These insights underscore the need for data-driven decisions to capitalize on strengths and address inefficiencies for sustainable growth.

Lookalike Model Code :

```
from sklearn.metrics.pairwise import cosine_similarity
from sklearn.preprocessing import StandardScaler
```

Step 1: Prepare data for the model

Combine customer and transaction data :

```
customer_transactions = merged_data.groupby("CustomerID").agg({"TotalValue": "sum", "Quantity": "sum"}).reset_index()
```

```
customer_profiles = customers.merge(customer_transactions, on="CustomerID", how="left")
customer_profiles.fillna(0, inplace=True)
```

```
customer_profiles.head()
```

	CustomerID	CustomerName	Region	SignupDate	TotalValue	Quantity
0	C0001	Lawrence Carroll	South America	2022-07-10	3354.52	12.0
1	C0002	Elizabeth Lutz	Asia	2022-02-13	1862.74	10.0
2	C0003	Michael Rivera	South America	2024-03-07	2725.38	14.0
3	C0004	Kathleen Rodriguez	South America	2022-10-09	5354.88	23.0
4	C0005	Laura Weber	Asia	2022-08-15	2034.24	7.0

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

Encode categorical data using one-hot encoding (for Region)

```
customer_profiles = pd.get_dummies(customer_profiles, columns=["Region"], drop_first=True)
```

Standardize numerical features :

```
scaler = StandardScaler()
numerical_features = ["TotalValue", "Quantity"]
customer_profiles[numerical_features] = scaler.fit_transform(customer_profiles[numerical_features])
```

Compute cosine similarity

```
feature_columns = numerical_features + [col for col in customer_profiles.columns if col.startswith("Region_")]
customer_similarity = cosine_similarity(customer_profiles[feature_columns])
```

Step 2: Find Top 3 Lookalike Customers for each Customer

```
lookalike_data = {}
```

```
for idx, customer_id in enumerate(customer_profiles["CustomerID"]):
    similarity_scores = list(enumerate(customer_similarity[idx]))
    similarity_scores = sorted(similarity_scores, key=lambda x: x[1], reverse=True)
    top_3 = [(customer_profiles.iloc[i[0]]["CustomerID"], i[1]) for i in similarity_scores[1:4]]
    lookalike_data[customer_id] = top_3
```

Step 3: Create `Lookalike.csv` :

```
lookalike_rows = []
```

```
for customer_id, lookalikes in lookalike_data.items():
    for lookalike_id, score in lookalikes:
        lookalike_rows.append([customer_id, lookalike_id, round(score, 4)])
```

```
lookalike_df = pd.DataFrame(lookalike_rows, columns=["CustomerID", "LookalikeID", "SimilarityScore"])
```

```
lookalike_df.head()
```

	CustomerID	LookalikeID	SimilarityScore
0	C0001	C0107	0.9895
1	C0001	C0137	0.9879
2	C0001	C0184	0.9877
3	C0002	C0142	0.9973
4	C0002	C0088	0.9968

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

```
lookalike_df.to_csv("ANUBHAV_PANDEY_Lookalike.csv", index=False)
```

Customer Segmentation / Clustering :

```
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score
```

Step 1: Prepare data for clustering

```
clustering_data = customer_profiles[feature_columns]
```

```
clustering_data.head()
```

	TotalValue	Quantity	Region_Europe	Region_North America	Region_South America
0	-0.051884	-0.110735	False	False	True
1	-0.862714	-0.434049	False	False	False
2	-0.393842	0.212579	False	False	True
3	1.035375	1.667493	False	False	True
4	-0.769499	-0.919021	False	False	False

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

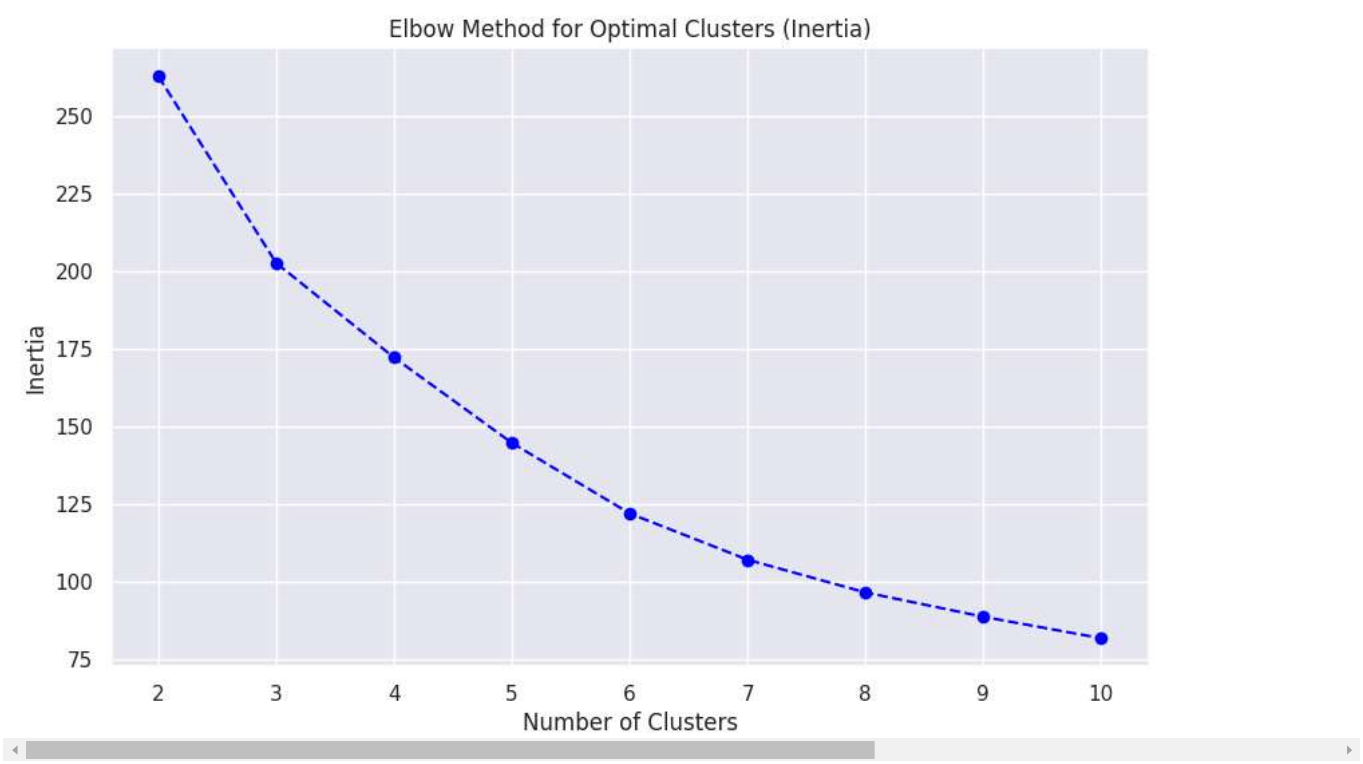
Step 2: Determine the optimal number of clusters using the elbow method

```
inertia = []
db_scores = []
clusters_range = range(2, 11)
```

```
for k in clusters_range:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(clustering_data)
    inertia.append(kmeans.inertia_)
    db_scores.append(davies_bouldin_score(clustering_data, kmeans.labels_))
```

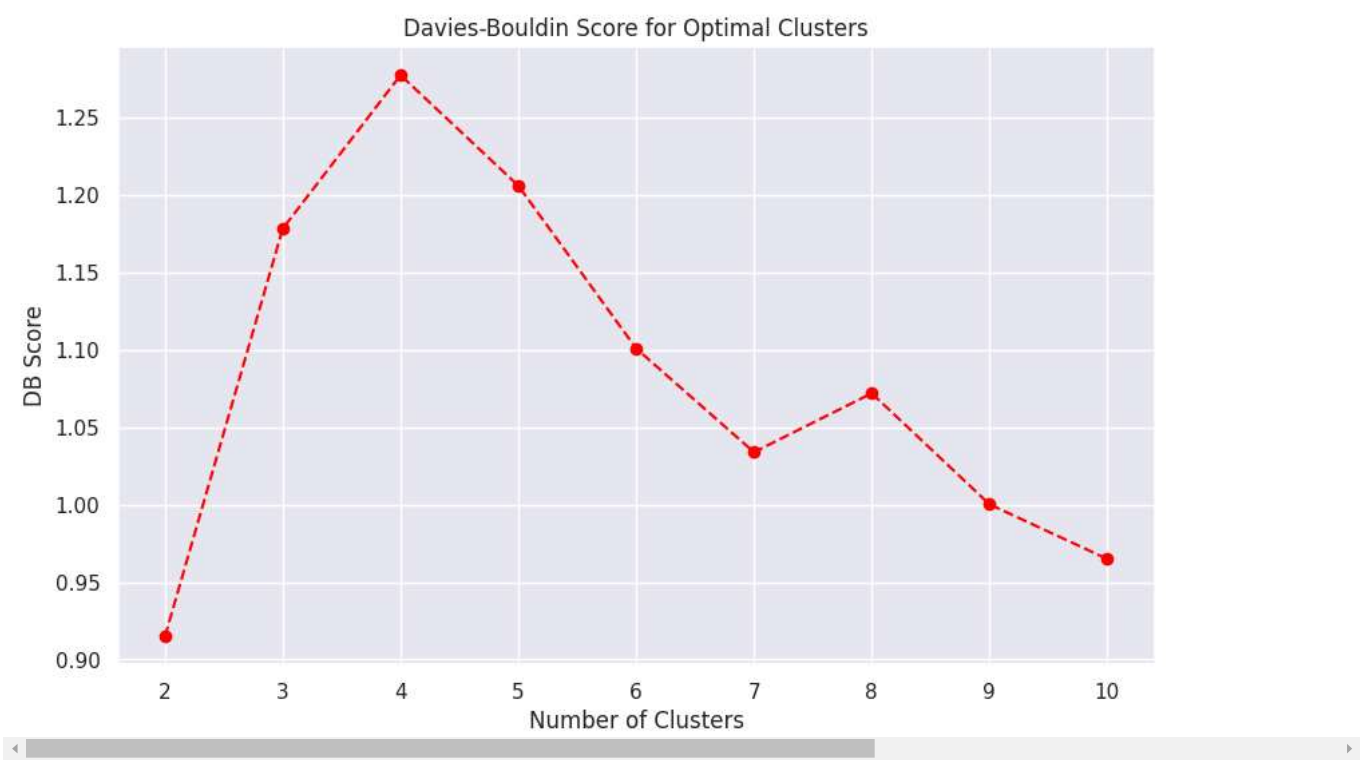
Plot the elbow curve for inertia

```
plt.figure(figsize=(10, 6))
plt.plot(clusters_range, inertia, marker='o', linestyle='--', color='blue')
plt.title("Elbow Method for Optimal Clusters (Inertia)")
plt.xlabel("Number of Clusters")
plt.ylabel("Inertia")
plt.show()
```



Plot Davies-Bouldin Score

```
plt.figure(figsize=(10, 6))
plt.plot(clusters_range, db_scores, marker='o', linestyle='--', color='red')
plt.title("Davies-Bouldin Score for Optimal Clusters")
plt.xlabel("Number of Clusters")
plt.ylabel("DB Score")
plt.show()
```



Step 3: Choose the optimal number of clusters (based on elbow or DB Score)

```
optimal_clusters = 4
kmeans = KMeans(n_clusters=optimal_clusters, random_state=42)
customer_profiles['Cluster'] = kmeans.fit_predict(clustering_data)
```

Step 4: Visualize clusters

```
plt.figure(figsize=(12, 8))
sns.scatterplot(
    x=customer_profiles['TotalValue'],
    y=customer_profiles['Quantity'],
    hue=customer_profiles['Cluster'],
    palette='viridis',
    s=100
)
plt.title("Customer Clusters")
plt.xlabel("Total Value (Standardized)")
plt.ylabel("Quantity (Standardized)")
plt.legend(title="Cluster")
plt.show()
```

Step 5: Evaluate clustering

```
db_index = davies_bouldin_score(clustering_data, customer_profiles['Cluster'])
print(f"Davies-Bouldin Index: {db_index}")
```

```
Davies-Bouldin Index: 1.2775830636839256
```

Step 6: Save clustering results :

```
customer_profiles[['CustomerID', 'Cluster']]
```

	CustomerID	Cluster
0	C0001	1
1	C0002	1
2	C0003	1
3	C0004	0
4	C0005	2