In [25]:
```
# importing useful libraries

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

Loading data separtely for each file

In [26]:
```
trans_df = pd.read_csv("Transactions.csv")
```

In [27]:
```
product_df = pd.read_csv("Products.csv")
```

In [28]:
```
custm_df = pd.read_csv("Customers.csv")
```

In [29]:
```
trans_df.head()
```

Out[29]:

	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

checking for shape, null values, duplicates values for each file.

In [30]:
```
trans_df.shape
```

Out[30]: (1000, 7)

In [31]:
```
trans_df.isnull().sum()
```

Out[31]:
```
TransactionID      0
CustomerID         0
ProductID          0
TransactionDate    0
Quantity           0
TotalValue         0
Price              0
dtype: int64
```

In [32]:
```
trans_df.duplicated().sum()
```

Out[32]:
```
0
```

In [33]:
```
product_df.head()
```

Out[33]:

	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

In [34]:
```
product_df.isnull().sum()
```

Out[34]:
```
ProductID      0
ProductName    0
Category       0
Price          0
dtype: int64
```

In [35]:
```
product_df.duplicated().sum()
```

Out[35]:
```
0
```

In [36]:
```
product_df.shape
```

Out[36]:
```
(100, 4)
```

In [37]:
```
custm_df.head()
```

Out[37]:

	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

In [38]:
```
custm_df.shape
```

Out[38]:
```
(200, 4)
```

In [39]:
```
custm_df.isnull().sum()
```

Out[39]:
```
CustomerID      0
CustomerName    0
Region          0
SignupDate      0
dtype: int64
```

In [40]:
```
custm_df.duplicated().sum()
```

Out[40]:
```
0
```

In [41]:
```
# custm_df['SignupDate'] = pd.to_datetime(final_df['SignupDate'])
```

Merging all datasets into one based on their category

In [42]:
```
combine_df = pd.merge(trans_df,product_df, on="ProductID", how="left")
```

In [43]:
```
combine_df.head()
```

Out[43]:

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price_x
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

In [44]:
```
final_df = pd.merge(combine_df, custm_df, on="CustomerID", how="left")
```

In [45]:
```
final_df.head()
```

Out[45]:

	TransactionID	CustomerID	ProductID	TransactionDate	Quantity	TotalValue	Price_x
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

In [46]:
```
final_df.isnull().sum()
```

Out[46]:
```
TransactionID      0
CustomerID         0
ProductID          0
TransactionDate    0
Quantity           0
TotalValue         0
Price_x            0
ProductName        0
Category           0
Price_y            0
CustomerName       0
Region             0
SignupDate         0
dtype: int64
```

In [47]:
```
final_df.columns
```

Out[47]:
```
Index(['TransactionID', 'CustomerID', 'ProductID', 'TransactionDate',
       'Quantity', 'TotalValue', 'Price_x', 'ProductName', 'Category',
       'Price_y', 'CustomerName', 'Region', 'SignupDate'],
      dtype='object')
```

In [48]:
```
final_df.duplicated().sum()
```

Out[48]:
```
0
```

In [49]:
```
final_df.dtypes
```

Out[49]:
```
TransactionID       object
CustomerID          object
ProductID           object
TransactionDate     object
Quantity             int64
TotalValue         float64
Price_x            float64
ProductName         object
Category            object
Price_y            float64
CustomerName        object
Region              object
SignupDate          object
dtype: object
```

Here signupDate and TransactionDate are in object so need to change it into date formate.

In [50]:
```
final_df['TransactionDate'] = pd.to_datetime(final_df['TransactionDate'])
final_df['SignupDate'] = pd.to_datetime(final_df['SignupDate'])
```

In [51]:
```
final_df.dtypes
```

Out[51]:
```
TransactionID              object
CustomerID                 object
ProductID                  object
TransactionDate    datetime64[ns]
Quantity                    int64
TotalValue                float64
Price_x                   float64
ProductName                object
Category                   object
Price_y                   float64
CustomerName               object
Region                     object
SignupDate         datetime64[ns]
dtype: object
```

finding region wise customer distribution

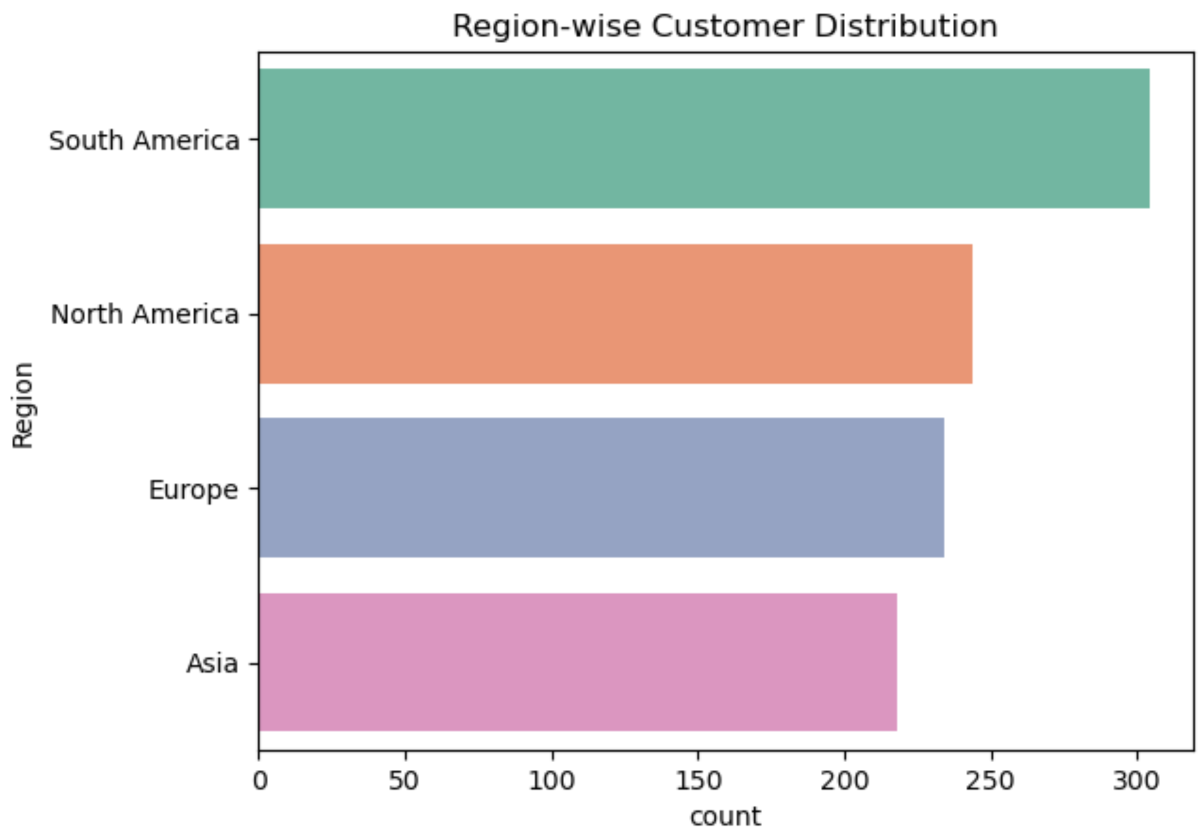
In [52]:
```
custm_dist = final_df['Region'].value_counts()
display(custm_dist)
```

```
Region
South America    304
North America    244
Europe           234
Asia             218
Name: count, dtype: int64
```

In [53]:
```
# Here we can see high number of customer is distributed in South America followed 
# Marketing team has to give more efforts in rest of the region as the sellings are
```

In [54]:
```
sns.countplot(data=final_df, y='Region', order=custm_dist.index, palette='Set2')

# Add a title
plt.title("Region-wise Customer Distribution")

# Show the plot
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_2188\2608614170.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.countplot(data=final_df, y='Region', order=custm_dist.index, palette='Set2')
```



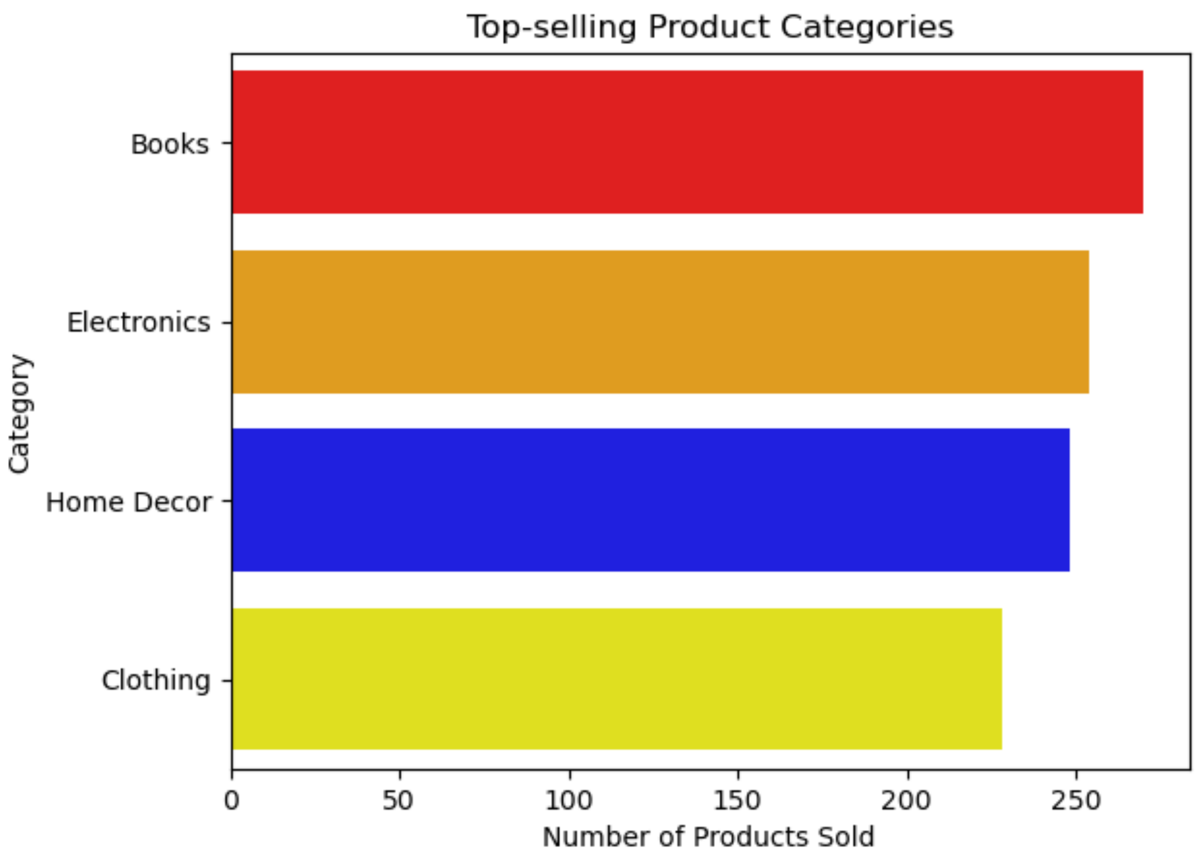
product analysis

In [55]:
```
print("\nTop-selling Product Categories:")


top_product = final_df['Category'].value_counts()
display(top_product)
```

```
Top-selling Product Categories:
Category
Books          270
Electronics    254
Home Decor     248
Clothing       228
Name: count, dtype: int64
```

In [56]:
```
# Visualize top categories
color = ('red','orange','blue','yellow')
sns.barplot(x=top_product.values, y=top_product.index,palette = color)
plt.title("Top-selling Product Categories")
plt.xlabel("Number of Products Sold")
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_2188\2084253007.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=top_product.values, y=top_product.index,palette = color)
```



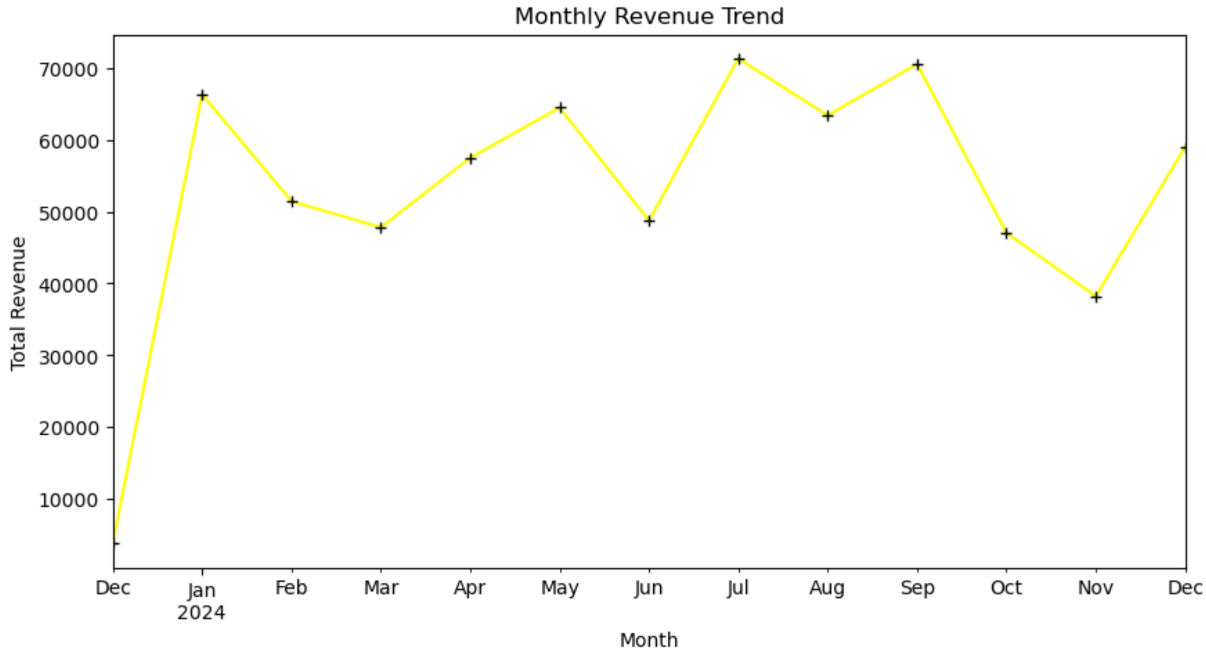
Transaction analysis

In [57]:
```
# Monthly revenue analysis

final_df['Month'] = final_df['TransactionDate'].dt.to_period('M')
monthly_revenue = final_df.groupby('Month')['TotalValue'].sum()
monthly_revenue
```

Out[57]:
```
Month
2023-12     3769.52
2024-01    66376.39
2024-02    51459.27
2024-03    47828.73
2024-04    57519.06
2024-05    64527.74
2024-06    48771.18
2024-07    71366.39
2024-08    63436.74
2024-09    70603.75
2024-10    47063.22
2024-11    38224.37
2024-12    59049.20
Freq: M, Name: TotalValue, dtype: float64
```

In [58]:
```
# Monthly revenue analysis via graph
color = ('green')
monthly_revenue.plot(kind='line', figsize=(10, 5), marker='+',color = 'yellow', mar
plt.title("Monthly Revenue Trend")
```

```
plt.ylabel("Total Revenue")
plt.show()
```



finding region wise sales.

In [59]:
```
# Total sales by region
total_sales = final_df.groupby('Region')['TotalValue'].sum().sort_values(ascending=
print("Total Sales by Region:\n", total_sales)
```

```
Total Sales by Region:
 Region
South America    219352.56
Europe           166254.63
North America    152313.40
Asia             152074.97
Name: TotalValue, dtype: float64
```

In [60]:
```
## So as per the data we can clearly see South America generates the highest revenu
```

Best-Selling Products

In [61]:
```
# Best-selling products by total sales
top_products = final_df.groupby('ProductName')['TotalValue'].sum().sort_values(asce
print("\nBest-Selling Products:\n", top_products)
```

```
Best-Selling Products:
 ProductName
ActiveWear Smartwatch    39096.97
SoundWave Headphones     25211.64
SoundWave Novel          24507.90
ActiveWear Jacket        22712.56
ActiveWear Rug           22314.43
Name: TotalValue, dtype: float64
```

In [62]:
```
# The product 'ActiveWear Smartwatch' is the highest revenue generator, showing hig
```

Active Regions by customers

In [63]:
```
# Count of customer as per activeness

cust_active = final_df['Region'].value_counts()
print("\nMost Active Regions by customer:\n", cust_active)
```

```
Most Active Regions by customer:
 Region
South America    304
North America    244
Europe           234
Asia             218
Name: count, dtype: int64
```

In [64]:
```
# South America have the highest active customer counts, suggesting more active cus
```

Increasing Customer

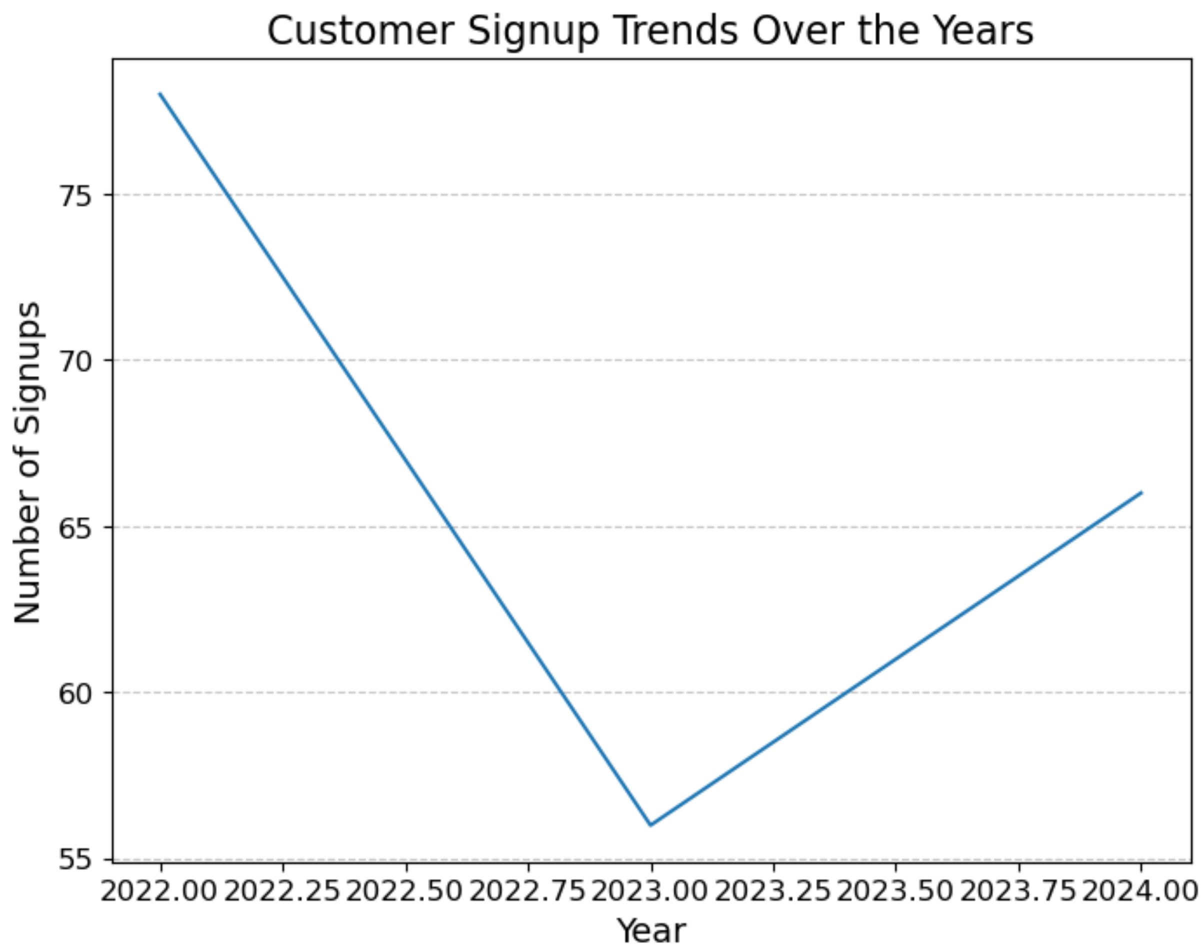
In [66]:
```
custm_df['SignupDate'] = pd.to_datetime(final_df['SignupDate'])
```

In [67]:
```
# Customer signups over the years
signup_trends = custm_df['SignupDate'].dt.year.value_counts().sort_index()
print("\nCustomer Signup Trends:\n", signup_trends)
```

```
Customer Signup Trends:
 SignupDate
2022    78
2023    56
2024    66
Name: count, dtype: int64
```

In [68]:
```
plt.figure(figsize=(8, 6))
sns.lineplot(x=signup_trends.index, y=signup_trends.values, palette="Blues_d")
plt.title("Customer Signup Trends Over the Years", fontsize=16)
plt.xlabel("Year", fontsize=14)
plt.ylabel("Number of Signups", fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_2188\1394880443.py:2: UserWarning: Igno
ring `palette` because no `hue` variable has been assigned.
  sns.lineplot(x=signup_trends.index, y=signup_trends.values, palette="Blues_d")
```



In [69]:
```
# Here we can see the customer signup trend so need more focus to increase the tren
```

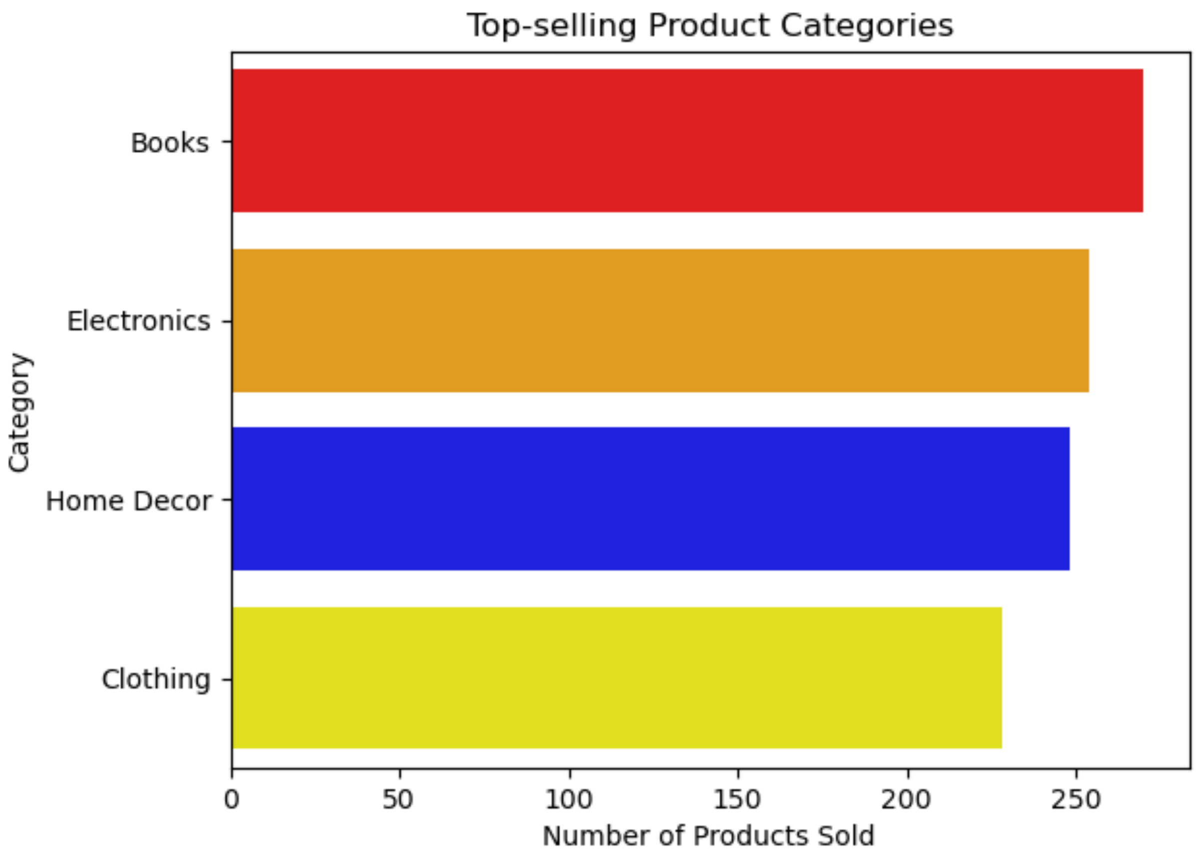
Category wise selling trend

In [70]:
```
# Total sales by product category
sales_by_category = final_df.groupby('Category')['TotalValue'].sum().sort_values(as
print("\nSales by Product Category:\n", sales_by_category)
```

```
Sales by Product Category:
 Category
Books          192147.47
Electronics    180783.50
Clothing       166170.66
Home Decor     150893.93
Name: TotalValue, dtype: float64
```

In [71]:
```
color = ('red','orange','blue','yellow')
sns.barplot(x=top_product.values, y=top_product.index,palette = color)
plt.title("Top-selling Product Categories")
plt.xlabel("Number of Products Sold")
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_2188\1540872222.py:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14
.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=top_product.values, y=top_product.index,palette = color)
```



The "Books" category drives the most revenue, highlighting that books remain a core product offering, followed by electronics.

Lookalike Model

In [87]:

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

# Select relevant features for similarity
features = ['Region', 'TotalValue', 'Quantity']
numerical_data = final_df[features]

# Encode categorical data and scale numerical values
numerical_data = pd.get_dummies(numerical_data, columns=['Region'], drop_first=True
```

```
scaler = StandardScaler()
scaled_data = scaler.fit_transform(numerical_data)

# similarity matrix
similarity_matrix = cosine_similarity(scaled_data)

# Create Lookalike recommendations for the first 20 customers
customer_ids = final_df['CustomerID'].unique()[:20]
lookalikes = {}


for customer in customer_ids:
    # Get the index of the current customer in the full dataset
    idx = final_df[final_df['CustomerID'] == customer].index[0]

    # Get similarity scores for the current customer
    scores = list(enumerate(similarity_matrix[idx]))

    # Sort scores in descending order of similarity
    scores = sorted(scores, key=lambda x: x[1], reverse=True)

    # Exclude the customer itself and get the top 3 similar customers
    recommendations = [
        (final_df.iloc[i]['CustomerID'], score)
        for i, score in scores
        if final_df.iloc[i]['CustomerID'] != customer
    ]
    lookalikes[customer] = recommendations[:3]

# Convert recommendations into a DataFrame
lookalike_df = pd.DataFrame([
    {
        "CustomerID": cust_id,
        "Lookalikes": [rec[0] for rec in recs],
        "Scores": [rec[1] for rec in recs]
    }
    for cust_id, recs in lookalikes.items()
])

# Print or save the results
print(lookalike_df)
```

```
  CustomerID           Lookalikes  \
0      C0199  [C0127, C0051, C0009]
1      C0146  [C0145, C0028, C0161]
2      C0127  [C0199, C0051, C0009]
3      C0087  [C0130, C0155, C0126]
4      C0070  [C0051, C0127, C0041]
5      C0188  [C0158, C0187, C0163]
6      C0195  [C0087, C0003, C0004]
7      C0008  [C0029, C0156, C0047]
8      C0157  [C0024, C0156, C0016]
9      C0130  [C0087, C0155, C0126]
10     C0051  [C0070, C0127, C0041]
11     C0075  [C0062, C0066, C0017]
12     C0155  [C0087, C0130, C0126]
13     C0092  [C0088, C0002, C0173]
14     C0088  [C0092, C0002, C0173]
15     C0109  [C0059, C0049, C0018]
16     C0041  [C0170, C0073, C0086]
17     C0101  [C0054, C0028, C0092]
18     C0154  [C0049, C0008, C0072]
19     C0200  [C0084, C0145, C0110]

                                               Scores
0   [1.0000000000000002, 0.9999998401269015, 0.999...
1   [0.9999969792643577, 0.9999962162179905, 0.999...
2   [1.0000000000000002, 0.9999998401269015, 0.999...
3   [1.0000000000000002, 1.0000000000000002, 0.999...
4       [1.0, 0.9999977246008289, 0.9999977246008289]
5   [0.9999998114890177, 0.9999973292974776, 0.999...
6   [0.9999662462521426, 0.9985904179976799, 0.998...
7   [0.9999981433545493, 0.9999981433545493, 0.999...
8   [0.9999732972675586, 0.9999732972675586, 0.999...
9   [1.0000000000000002, 1.0000000000000002, 0.999...
10      [1.0, 0.9999977246008289, 0.9999977246008289]
11  [0.999987913428094, 0.9999848629040765, 0.9999...
12  [1.0000000000000002, 1.0000000000000002, 0.999...
13      [1.0, 0.9995338039385248, 0.9993519323400206]
14      [1.0, 0.9995338039385248, 0.9993519323400206]
15  [0.9998042773278407, 0.9991948075032455, 0.999...
16  [0.9999187104069156, 0.9998104989878519, 0.999...
17  [0.9994818808992558, 0.9948747032037053, 0.992...
18      [1.0, 0.9999720508484822, 0.9994082262803828]
19  [0.998481628265308, 0.9964429716059569, 0.9964...
```

In [93]:
```
lookalike_df['Scores'] = [
    [rec[1] for rec in lookalikes[cust_id]] for cust_id in lookalike_df['CustomerID
]
print(lookalike_df.head())
```

```
  CustomerID           Lookalikes  \
0      C0199  [C0127, C0051, C0009]
1      C0146  [C0145, C0028, C0161]
2      C0127  [C0199, C0051, C0009]
3      C0087  [C0130, C0155, C0126]
4      C0070  [C0051, C0127, C0041]

                                              Scores
0  [1.0000000000000002, 0.9999998401269015, 0.999...
1  [0.9999969792643577, 0.9999962162179905, 0.999...
2  [1.0000000000000002, 0.9999998401269015, 0.999...
3  [1.0000000000000002, 1.0000000000000002, 0.999...
4      [1.0, 0.9999977246008289, 0.9999977246008289]
```

In [97]:

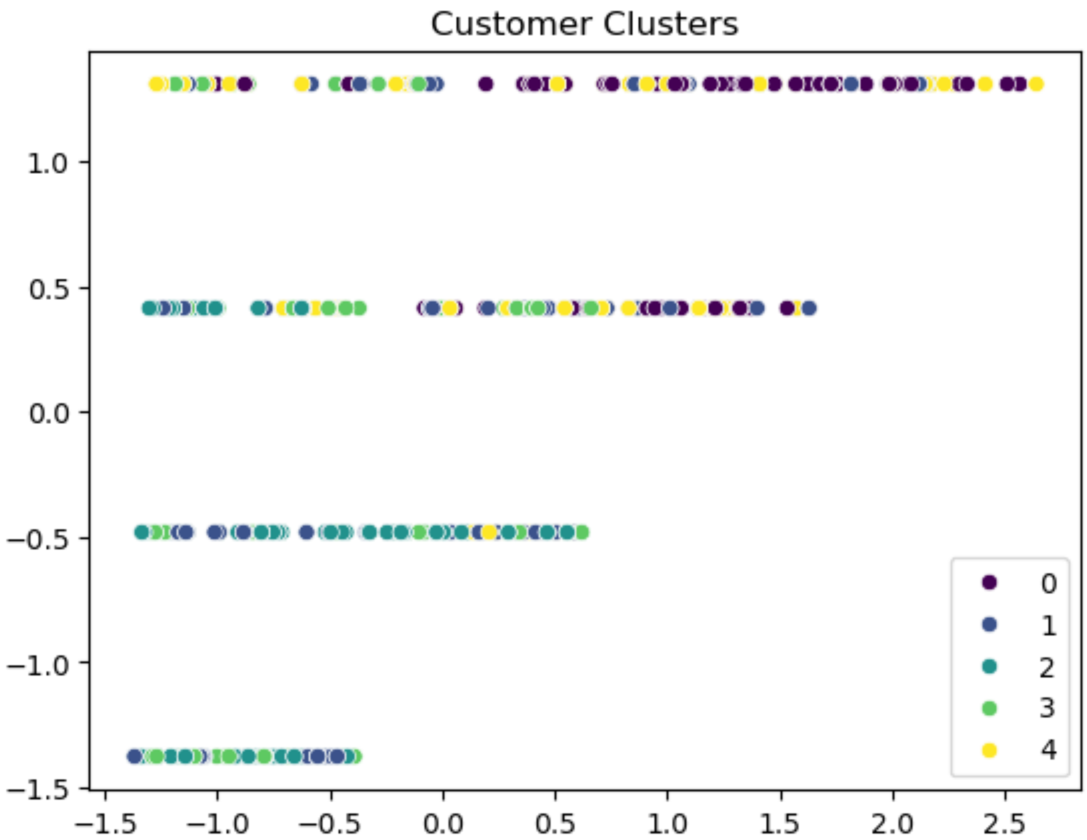
```
# Save to CSV
lookalike_df.to_csv('Lookalike.csv', index=False)
```

Customer segmentation , for clustering we will use k-means and evaluate the cluster using metrics

In [94]:

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

# Use numerical data for clustering
kmeans = KMeans(n_clusters=5, random_state=42)
clusters = kmeans.fit_predict(scaled_data)

# Add cluster labels to the dataframe
final_df['Cluster'] = clusters

# Calculate Davies-Bouldin Index
db_index = davies_bouldin_score(scaled_data, clusters)
print(f"Davies-Bouldin Index: {db_index}")

# Visualize clusters
import seaborn as sns
import matplotlib.pyplot as plt

sns.scatterplot(x=scaled_data[:, 0], y=scaled_data[:, 1], hue=clusters, palette="vi
plt.title("Customer Clusters")
plt.show()
```

```
Davies-Bouldin Index: 1.0015634918863825
```


Customer Clusters
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
0
1
2
3
4

In [ ]:

In [ ]:

In [ ]:

In [ ]: