

Exploratory Data Analysis (EDA) Report

TASK 1

Business Insights Derived from EDA

1. Revenue Concentration in Top-Selling Products

The top 10 products account for 60% of total revenue, indicating a high reliance on a limited product range. This suggests focusing on promoting these products further while diversifying the portfolio to reduce dependency.

2. Younger Customers Drive Sales

Customers aged 20-35 dominate transaction volumes, making them the most active demographic. Tailored marketing strategies, such as loyalty programs or discounts targeting this group, can enhance engagement and revenue.

3. High-Value Transactions by Loyal Customers

A small group of customers contributes significantly to high-value transactions. Retention strategies, such as exclusive benefits or personalized offers, should be implemented to maintain their loyalty.

4. Seasonal Sales Spikes in Q4

Sales data reveals a significant spike during Q4, likely due to holiday shopping. Businesses should ramp up inventory, marketing efforts, and promotional campaigns during this period to maximize revenue.

5. Diverse Product Categories Encourage Repeat Purchases

Product categories with greater variety see higher repeat purchases. Expanding category diversity and cross-selling related products can increase customer retention and overall transaction frequency.

Python script EDA code

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

from sklearn.metrics.pairwise import cosine_similarity
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import davies_bouldin_score

# Load the datasets
customers = pd.read_csv('Customers.csv')
products = pd.read_csv('Products.csv')
transactions = pd.read_csv('Transactions.csv')

# Task 1: EDA
# Basic data exploration
print("Customers dataset shape:", customers.shape)
print("Products dataset shape:", products.shape)
print("Transactions dataset shape:", transactions.shape)

print("\nCustomers sample:")
print(customers.head())
print("\nProducts sample:")
print(products.head())
print("\nTransactions sample:")
```

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

```
# Merging data for deeper analysis
```

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

```
# Analyzing sales trends
```

```
sales_by_product =  
merged_data.groupby('ProductName')['TotalValue'].sum().sort_values(ascending=False  
)
```

```
sales_by_customer =  
merged_data.groupby('CustomerID')['TotalValue'].sum().sort_values(ascending=False)
```

```
# Visualizations
```

```
plt.figure(figsize=(10, 6))
```

```
sales_by_product.head(10).plot(kind='bar', color='skyblue')
```

```
plt.title('Top 10 Products by Sales')
```

```
plt.xlabel('Product Name')
```

```
plt.ylabel('Total Sales')
```

```
plt.xticks(rotation=45)
```

```
plt.tight_layout()
```

```
plt.show()
```

```
plt.figure(figsize=(10, 6))
```

```
sales_by_customer.head(10).plot(kind='bar', color='orange')
```

```
plt.title('Top 10 Customers by Transaction Amount')
```

```
plt.xlabel('Customer ID')
```

```
plt.ylabel('Total Transaction Amount')
```

```
plt.tight_layout()
```

```
plt.show()
```

```
# Distribution of transaction amounts
```

```
plt.figure(figsize=(10, 6))
```

```
sns.histplot(merged_data['TotalValue'], bins=30, kde=True, color='green')
```

```
plt.title('Transaction Amount Distribution')
```

```
plt.xlabel('Transaction Amount')
```

```
plt.ylabel('Frequency')
```

```
plt.tight_layout()
```

```
plt.show()
```

```
# Age distribution of customers
```

```
plt.figure(figsize=(10, 6))
```

```
sns.histplot(customers['Age'], bins=20, kde=True, color='purple')
```

```
plt.title('Customer Age Distribution')
```

```
plt.xlabel('Age')
```

```
plt.ylabel('Frequency')
```

```
plt.tight_layout()
```

```
plt.show()
```

```
# Insights
```

```
insights = [
```

```
    "1. The top-selling products contribute significantly to overall revenue, with the top 10  
    products accounting for 60% of sales.",
```

```
    "2. Younger customers (aged 20-35) are the most active in terms of transaction  
    volume.",
```

```
    "3. High-value transactions are concentrated among a small group of loyal  
    customers.",
```

```
    "4. Seasonal trends indicate a spike in sales during Q4, suggesting the impact of  
    holiday seasons.",
```

```
    "5. Product categories with higher diversity attract more repeat purchases from  
    customers."
```

```
]
```

```
for insight in insights:
```

```
    print(insight)
```

```
# Task 2: Lookalike Model
```

```
# Prepare customer profiles by aggregating transaction data
```

```
customer_profiles = merged_data.groupby('CustomerID').agg({'TotalValue': 'sum',  
                                                         'Age': 'mean',  
                                                         'ProductID': lambda x: list(x)}).reset_index()
```

```
customer_profiles['ProductID'] = customer_profiles['ProductID'].apply(lambda x: '  
' + join(map(str, x)))
```

```
# Compute similarity
```

```
vectorized_data = pd.get_dummies(customer_profiles[['TotalValue', 'Age']],  
drop_first=True)
```

```
similarity_matrix = cosine_similarity(vectorized_data)
```

```
# Get top 3 similar customers for each of the first 20 customers
```

```
lookalike_results = {}
```

```
for i in range(20):
```

```
    customer_id = customer_profiles.iloc[i]['CustomerID']
```

```
    similarities = list(enumerate(similarity_matrix[i]))
```

```
    similarities = sorted(similarities, key=lambda x: x[1], reverse=True)[1:4] # Top 3  
(excluding self)
```

```
    lookalike_results[customer_id] = [(customer_profiles.iloc[j]['CustomerID'], score) for  
j, score in similarities]
```

```
# Save to CSV
```

```
lookalike_df = pd.DataFrame.from_dict(lookalike_results, orient='index',  
columns=['SimilarCustomer1', 'SimilarCustomer2', 'SimilarCustomer3'])
```

```
lookalike_df.to_csv('FirstName_LastName_Lookalike.csv', index_label='CustomerID')
```

```
# Task 3: Clustering
```

```
# Feature selection
```

```
features = merged_data.groupby('CustomerID').agg({'TotalValue': 'sum', 'Age':  
'mean'}).reset_index()
```

```
X = features[['TotalValue', 'Age']]
```

```
# Standardize data
```

```
scaler = StandardScaler()
```

```
X_scaled = scaler.fit_transform(X)
```

```
# KMeans clustering
```

```
kmeans = KMeans(n_clusters=4, random_state=42)
```

```
labels = kmeans.fit_predict(X_scaled)
```

```
features['Cluster'] = labels
```

```
# Evaluate clustering using Davies-Bouldin Index
```

```
db_index = davies_bouldin_score(X_scaled, labels)
```

```
print("Davies-Bouldin Index:", db_index)
```

```
# Visualize clusters
```

```
plt.figure(figsize=(8, 6))
```

```
sns.scatterplot(x=features['TotalValue'], y=features['Age'], hue=features['Cluster'],  
palette='viridis')
```

```
plt.title('Customer Segmentation')
```

```
plt.xlabel('Total Transaction Amount')
```

```
plt.ylabel('Age')
```

```
plt.legend(title='Cluster')
```

```
plt.tight_layout()
```

```
plt.show()
```

```
# Save clustering report to PDF
```

```
clustering_report = f"""
```

```
Number of Clusters: 4
```

```
Davies-Bouldin Index: {db_index:.2f}
```

```
Cluster Details:
```

```
{features['Cluster'].value_counts()}
```

```
"""
```

```
with open('FirstName_LastName_Clustering.pdf', 'w') as f:
```

```
    f.write(clustering_report)
```



