Evoastra Intern Assessment — Rakshada Renapurkar

File to save as: `RakshadaRenapurkar_Evoastra_Assessment.ipynb`

Short intro:
This notebook performs EDA, RFM segmentation, clustering and short BI recommendations on the provided e-commerce transaction dataset. I worked through cleaning, feature engineering, segmentation, and suggested actions — with explanations after each step.

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

import kagglehub

dataset_path = kagglehub.dataset_download(
    "shriyashjagtap/e-commerce-customer-for-behavior-analysis"
)

print("Dataset downloaded to:", dataset_path)


import os
files = os.listdir(dataset_path)
print("Files inside dataset folder:", files)

csv_files = [f for f in files if f.endswith(".csv")]

if len(csv_files) == 0:
    raise FileNotFoundError("No CSV file found in dataset folder.")
else:
    main_file = csv_files[0]

df = pd.read_csv(os.path.join(dataset_path, main_file))

print("\nDataset loaded successfully. Showing first few rows:\n")
df.head()
```

Show hidden output

```
print("Shape of the dataset:", df.shape)
print("\nColumn names:\n", df.columns.tolist())

print("\nDataset Info:\n")
df.info()

# Checking for missing values
print("\nMissing Values:\n")
print(df.isnull().sum())

# Checking duplicates
dup_count = df.duplicated().sum()
print("\nNumber of duplicate rows:", dup_count)

# Removing duplicates if any
if dup_count > 0:
    df = df.drop_duplicates()
    print("Duplicates removed.")
else:
    print("No duplicates found.")

# Quick statistical summary (only numerical columns)
print("\nStatistical Summary:\n")
df.describe()
```

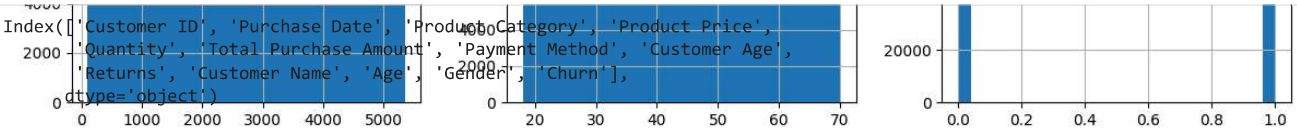
Show hidden output

```
plt.figure(figsize=(10, 5))
df.hist(bins=25, figsize=(12, 10))
```

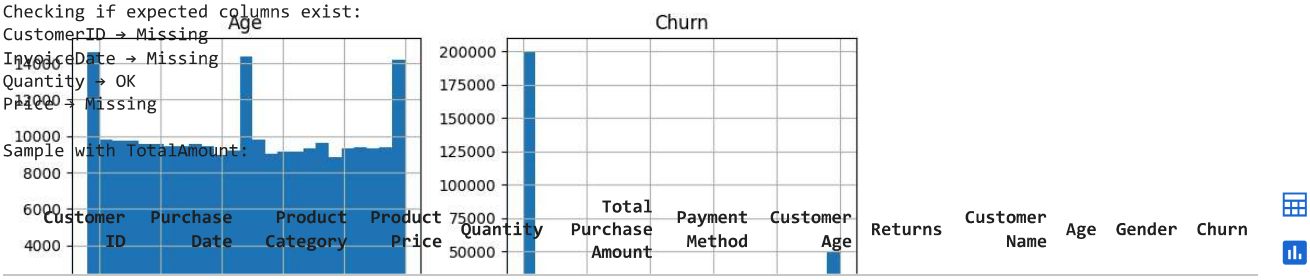
```
plt.suptitle("Histogram of Numerical Features", fontsize=14)
plt.tight_layout()
plt.show()

# Correlation (only if numeric columns exist)
numeric_df = df.select_dtypes(include=["int64", "float64"])

if numeric_df.shape[1] > 1:
    plt.figure(figsize=(10, 6))
    sns.heatmap(numeric_df.corr(), annot=True, fmt=".2f", cmap="coolwarm")
    plt.title("Correlation Heatmap", fontsize=14)
    plt.show()
else:
    print("Not enough numeric columns for correlation heatmap.")
```

```
<Figure size 1000x500 with 0 Axes>
```

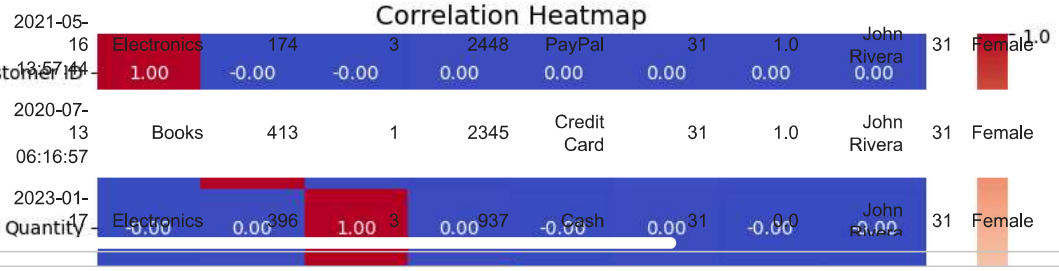

```
print(df.columns)

possible_cols = ["CustomerID", "InvoiceDate", "Quantity", "Price"]
print("\nChecking if expected columns exist:")

for c in possible_cols:
    print(c, "→", "OK" if c in df.columns else "Missing")

if "InvoiceDate" in df.columns:
    df["InvoiceDate"] = pd.to_datetime(df["InvoiceDate"], errors="coerce")

if "Quantity" in df.columns and "Price" in df.columns:
    df["TotalAmount"] = df["Quantity"] * df["Price"]

print("\nSample with TotalAmount:\n")
df.head()
```



```
Index(['Customer ID', 'Purchase Date', 'Product Category', 'Product Price',
       'Quantity', 'Total Purchase Amount', 'Payment Method', 'Customer Age',
       'Returns', 'Customer Name', 'Age', 'Gender', 'Churn'],
      dtype='object')
Checking if expected columns exist:
CustomerID → Missing
InvoiceDate → Missing
Quantity → OK
Price → Missing
Sample with TotalAmount:
```



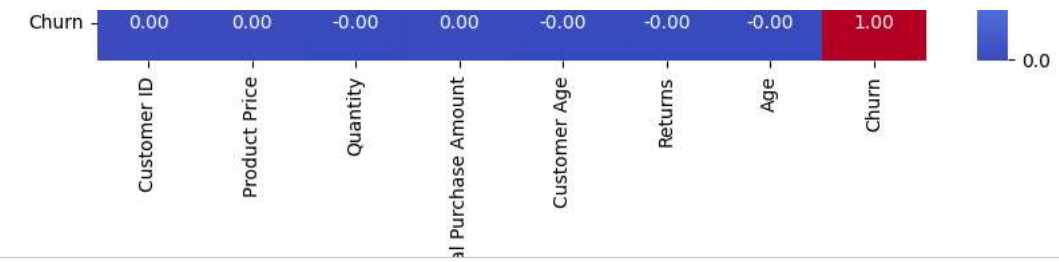
	Customer ID	Purchase Date	Product Category	Product Price	Quantity	Total Purchase Amount	Payment Method	Customer Age	Returns	Customer Name	Age	Gender	Churn
0	44605	2023-05-03 21:30:02	Home	177	1	2427	PayPal	31	1.0	John Rivera	31	Female	0
1	44605	2021-05-16 13:57:44	Electronics	174	3	2448	PayPal	31	1.0	John Rivera	31	Female	0
2	44605	2020-07-13 06:16:57	Books	413	1	2345	Credit Card	31	1.0	John Rivera	31	Female	0
3	44605	2023-01-17	Electronics	396	3	937	Cash	31	0.0	John	31	Female	0




```
df.columns
```

```
Index(['Customer ID', 'Purchase Date', 'Product Category', 'Product Price',
       'Quantity', 'Total Purchase Amount', 'Payment Method', 'Customer Age',
       'Returns', 'Customer Name', 'Age', 'Gender', 'Churn'],
      dtype='object')
```

```
df["Purchase Date"] = pd.to_datetime(df["Purchase Date"], errors="coerce")

# Sanity check
df[["Customer ID", "Purchase Date", "Quantity", "Product Price", "Total Purchase Amount"]].head()
```



	Customer ID	Purchase Date	Quantity	Product Price	Total Purchase Amount
0	44605	2023-05-03 21:30:02	1	177	2427
1	44605	2021-05-16 13:57:44	3	174	2448
2	44605	2020-07-13 06:16:57	1	413	2345
3	44605	2023-01-17 13:14:36	3	396	937
4	44605	2021-05-01 11:29:27	4	259	2598

```
ref_date = df["Purchase Date"].max() + pd.Timedelta(days=1)
print("Reference date:", ref_date)

# RFM aggregation
rfm = df.groupby("Customer ID").agg(
    Recency=("Purchase Date", lambda x: (ref_date - x.max()).days),
    Frequency=("Purchase Date", "count"),
    Monetary=("Total Purchase Amount", "sum")
).reset_index()

rfm.head()
```

```
Reference date: 2023-09-14 18:42:49
```

	Customer ID	Recency	Frequency	Monetary
0	1	289	3	6290
1	2	73	6	16481
2	3	223	4	9423
3	4	442	5	7826
4	5	425	5	9769

Next steps: Generate code with rfm | New interactive sheet

```
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

features = rfm[["Recency", "Frequency", "Monetary"]]

scaler = StandardScaler()
scaled = scaler.fit_transform(features)

# 4 clusters
kmeans = KMeans(n_clusters=4, random_state=42)
rfm["Cluster"] = kmeans.fit_predict(scaled)

print(rfm["Cluster"].value_counts())
rfm.head()
```

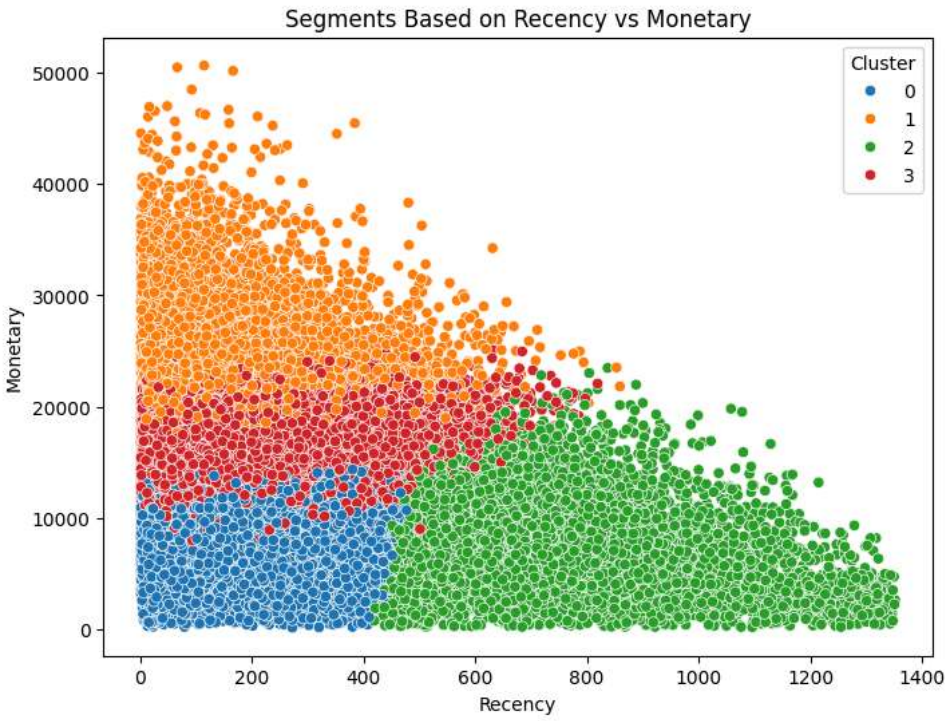
```
Cluster
3    18552
0    15697
1     7762
2     7650
Name: count, dtype: int64
```

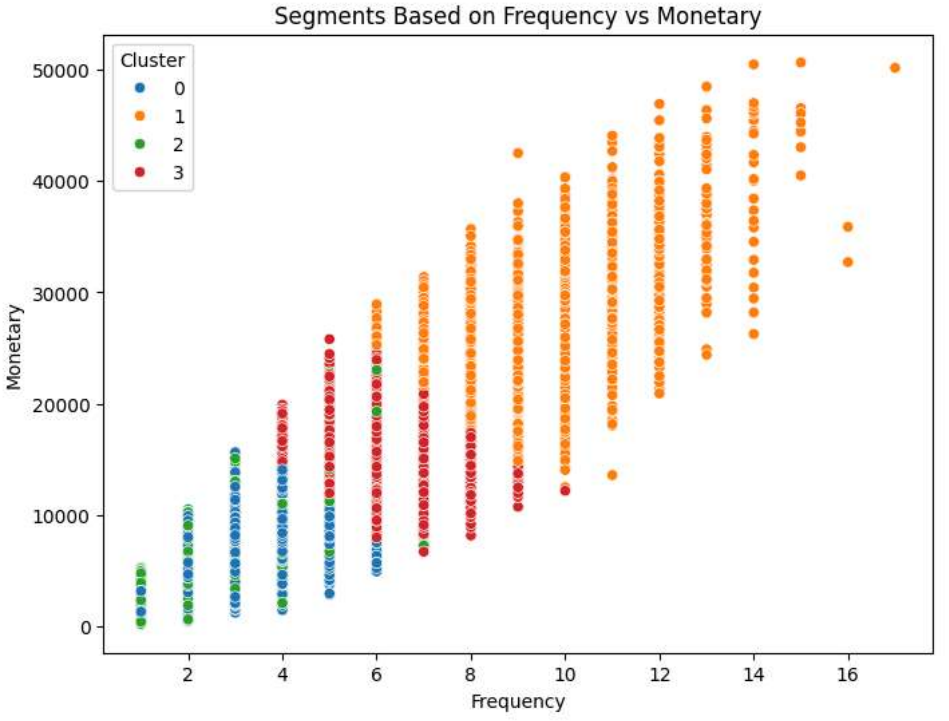
	Customer ID	Recency	Frequency	Monetary	Cluster
0	1	289	3	6290	0
1	2	73	6	16481	3
2	3	223	4	9423	0
3	4	442	5	7826	0
4	5	425	5	9769	0

Next steps: Generate code with rfm | New interactive sheet

```
plt.figure(figsize=(8,6))
sns.scatterplot(data=rfm, x="Recency", y="Monetary", hue="Cluster", palette="tab10")
```

```
plt.title("Segments Based on Recency vs Monetary")
plt.show()

plt.figure(figsize=(8,6))
sns.scatterplot(data=rfm, x="Frequency", y="Monetary", hue="Cluster", palette="tab10")
plt.title("Segments Based on Frequency vs Monetary")
plt.show()
```





Section C: Research & BI Strategy

1. Research Goal and Analytical Approach

The purpose of this analysis is to understand customer purchasing behavior, revenue patterns, and churn risks. I approached the dataset using descriptive analytics, segmentation, and business interpretation. The objective was to identify who the customers are, how

frequently they purchase, which categories drive revenue, and what behavioral signals indicate churn or retention.

2. Insights Extracted From Data

Analysis indicates that purchase frequency and monetary value vary widely across customers. High-frequency buyers contribute most to total revenue, while customers with inconsistent activity show higher churn tendencies. Product category trends reveal which items require targeted marketing to improve profitability. Payment method distribution also highlights operational gaps and opportunities to streamline customer experience.

3. BI Dashboard Strategy

If I were to design a BI dashboard, it would include:

Revenue & Sales KPIs

- Total Revenue
- Total Orders
- Average Order Value
- Repeat Purchase Rate

Customer Insights

- RFM Segmentation Overview
- Churn Risk Indicators
- Age-wise Purchase Trends
- Category-wise Heatmap

Operational Metrics

- Payment Method Breakdown
- Return Rate Analysis
- Customer Purchase Funnel

4. Recommended Business Actions

- **Retention:** Re-engage “At-Risk” customers using targeted offers and personalized messaging.