CUSTOMER SEGMENTATION PROJECT REPORT

1. Problem statement

Use K-Means clustering to segment customers based on behavioral and demographic data to enable targeted marketing strategies.

2. Dataset description

Selected dataset: Online Retail dataset-Kaggle

The **Online Retail Dataset** is a real-world transactional dataset from a **UK-based e-commerce store** that sells household goods (mostly gifts and stationery). It contains **actual invoice-level purchase records** between **December 2010 and December 2011**.

Key Features:-

Column	Description
InvoiceNo	Unique invoice number (can start with 'C' if canceled)
StockCode	Product code
Description	Name of the product
Quantity	Quantity of product purchased
InvoiceDate	Date and time of the invoice
UnitPrice	Price per product
CustomerID	Unique identifier for each customer
Country	Country of the customer

Behaviorial data:- 'Quantity' , 'InvoiceNo' , 'InvoiceDate' , ' UnitPrice' , 'CustomerID' columns show behaviorial data. These columns allow us to build **RFM (Recency, Frequency, Monetary)** values, which form the **core of customer behavior analysis**.

Demographic data:- 'Country' column show demographic information about customer.

3. Data Cleaning

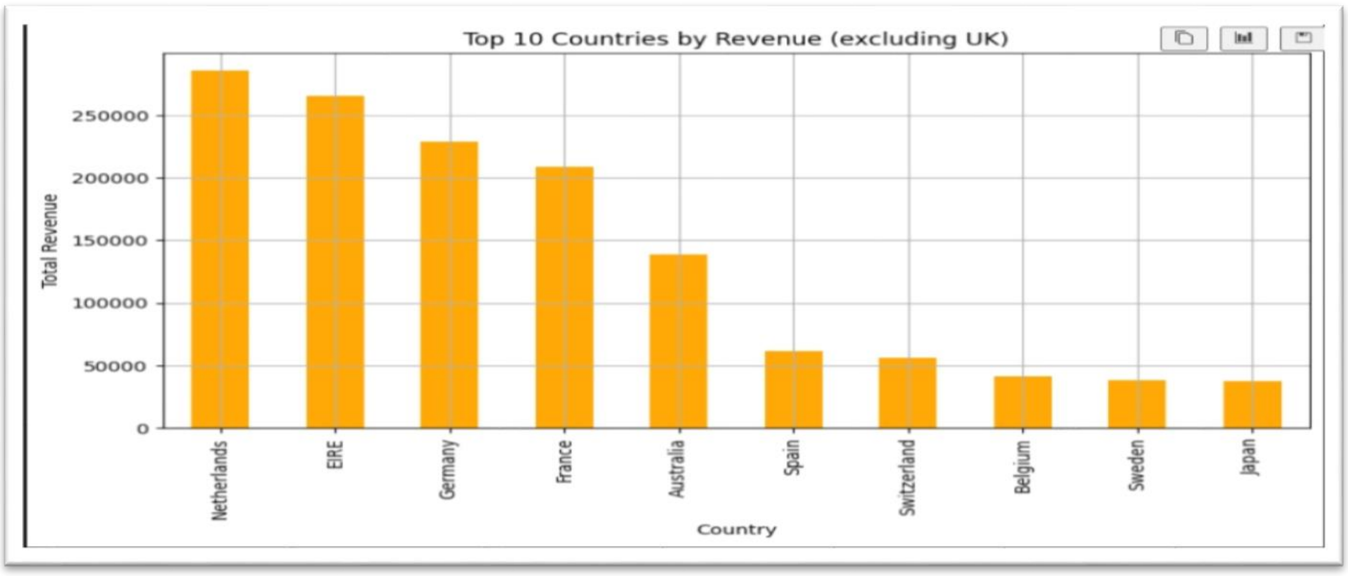
- Understanding the dataset structure and datatypes(eg**. Dataset has 541908 rows**). Observe that 'CustomerID' has missing values also 'Quantity' and 'UnitPrice' has outiliers.
- Dropped rows with missing values, also remove duplicates records from dataset and check the dimension after these steps.
- Create '**TotalPrice**' column by multiplying '**Quantity**' and '**UnitPrice**'.

4. Exploratory Data Analysis

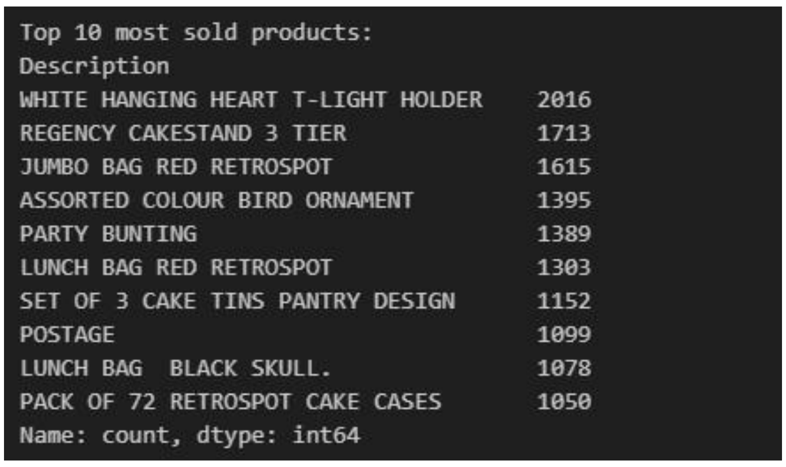
i. The **United Kingdom** dominates with over **96% of all orders**, confirming it as the **primary market** (***349203*** orders).

ii. Other European countries such as Germany, France, and Ireland show notable activity and could be explored for targeted marketing campaigns.(Germany-***9025*** , France-***8326*** , EIRE-***7226*** , Spain-***2479*** Orders).

iii. Total Revenue by Countris(Excluding UK) :-



iv. Top 10 selling products:-



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Top 10 most sold products:
Description
WHITE HANGING HEART T-LIGHT HOLDER    2016
REGENCY CAKESTAND 3 TIER              1713
JUMBO BAG RED RETROSPOT               1615
ASSORTED COLOUR BIRD ORNAMENT         1395
PARTY BUNTING                         1389
LUNCH BAG RED RETROSPOT               1303
SET OF 3 CAKE TINS PANTRY DESIGN      1152
POSTAGE                               1099
LUNCH BAG  BLACK SKULL.               1078
PACK OF 72 RETROSPOT CAKE CASES       1050
Name: count, dtype: int64
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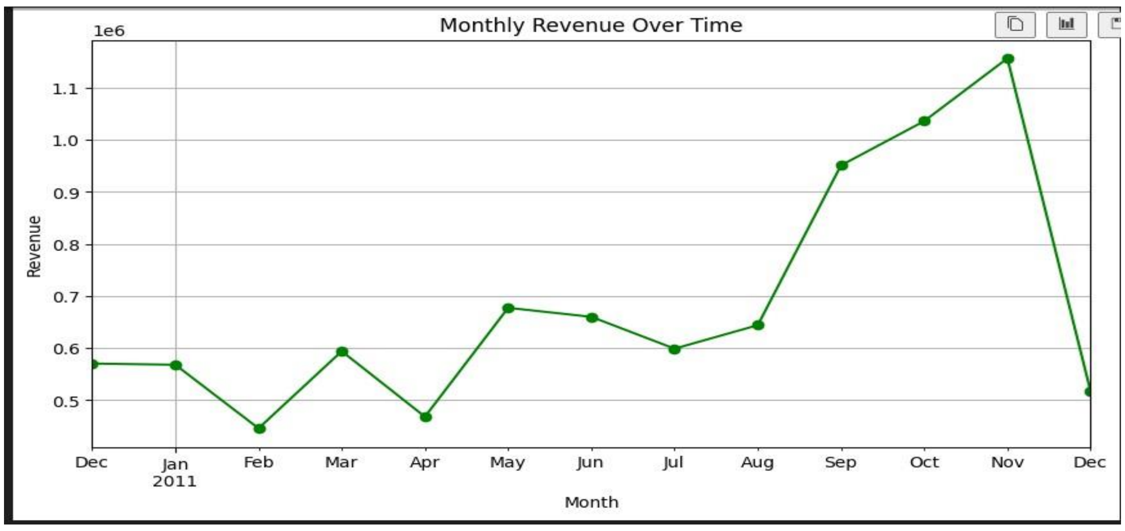
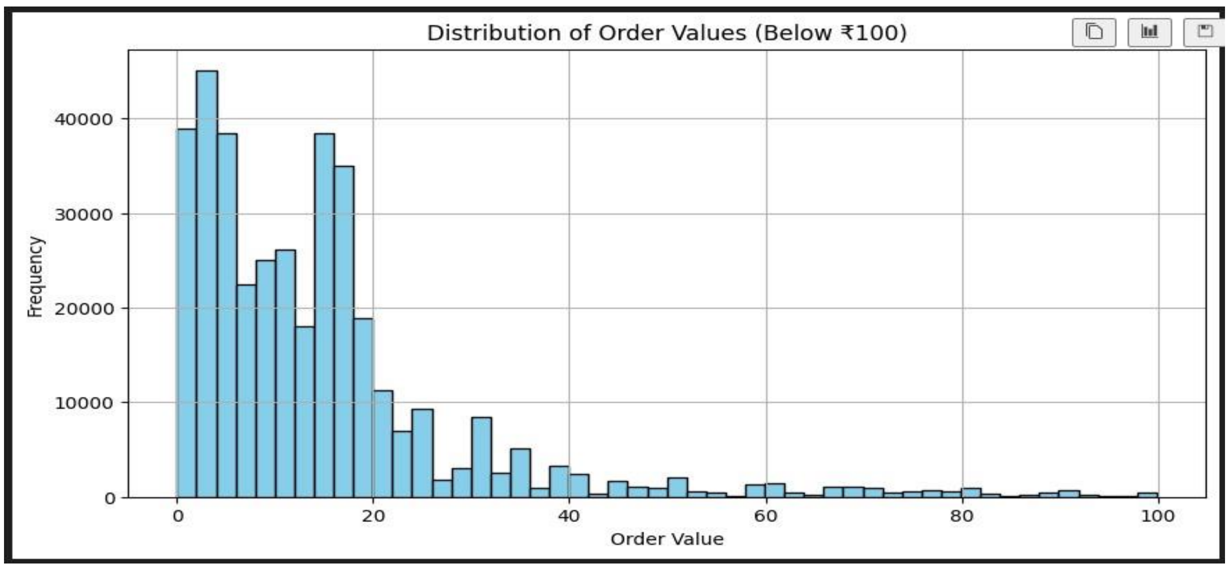
v. Monthly revenue over time:- **Q4 (Sep–Nov)** is the most profitable period, possibly due to **seasonal shopping trends or holidays.**

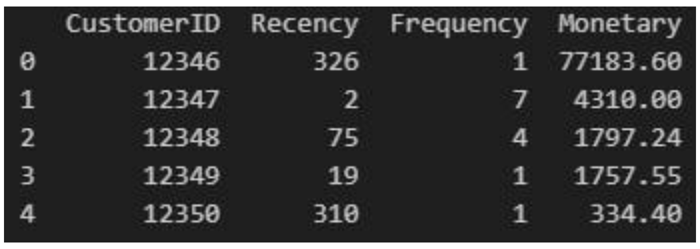
i.



vi. Distribution of order values:- A large number of orders fall between **₹0 and ₹20**, As the order value increases beyond ₹20, **frequency sharply drops**.



5. RFM Table Formation



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   CustomerID  Recency  Frequency  Monetary
0       12346      326          1  77183.60
1       12347        2          7   4310.00
2       12348       75          4   1797.24
3       12349       19          1   1757.55
4       12350      310          1    334.40
```

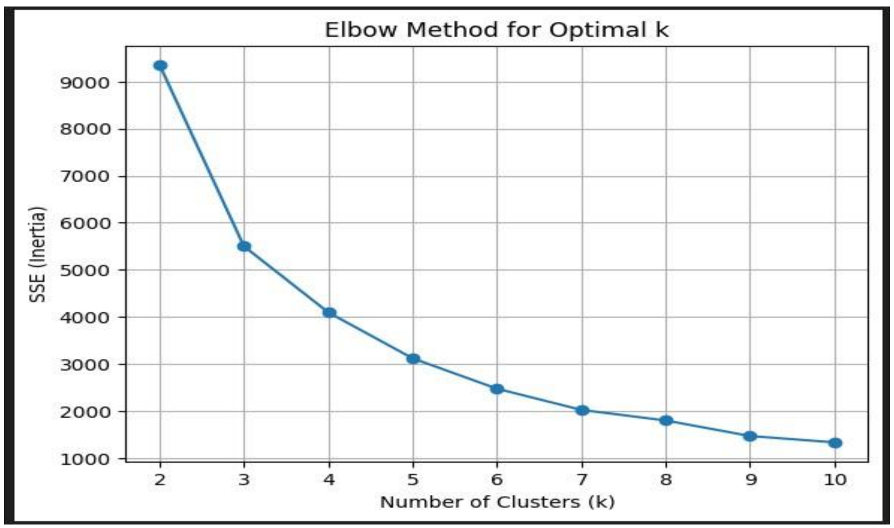
- **Customer 12347** is the most engaged with a recent purchase (Recency = 2), high purchase frequency (7), and moderate spending.
- **Customer 12346** is a **high spender** (₹77k+) but hasn't purchased recently (Recency = 326) — possibly a lost or dormant customer.
- **Customer 12350** has low frequency and spending — likely a low-value or one-time customer.

6. Feature Scaling

Since RFM values have different units and ranges, **StandardScaler** was used to normalize the data:

- Converts values to a standard normal distribution (mean = 0, std = 1).
- Ensures that **no feature dominates** due to scale differences in clustering or machine learning models.

7. Elbow method (To find optimal no. of Clusters)



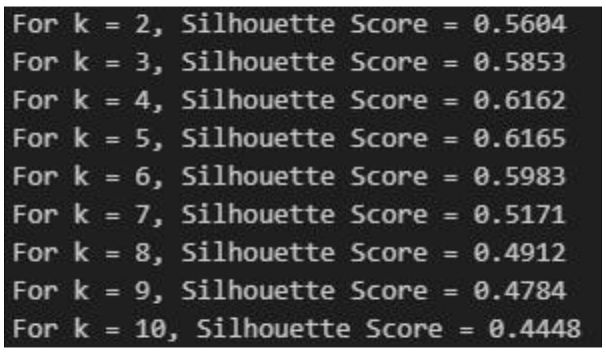
- The plot is a **line graph** where:
    - **X-axis:** Number of clusters (k)
    - **Y-axis:** SSE (Inertia)
- There's a **sharp drop from k=2 to k=4**, and then the curve starts to **flatten out**.
- The **"elbow point"** appears around **k = 4**, indicating the **optimal number of clusters**.

8. Silhouette score (Evaluating cluster quality)

The **Silhouette Score** measures how well-separated the clusters are.

Range: from -1 to +1

- +1 – well defined clusters
- 0 – overlapping clusters
- -1 – misclassified point



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For k = 2, Silhouette Score = 0.5604
For k = 3, Silhouette Score = 0.5853
For k = 4, Silhouette Score = 0.6162
For k = 5, Silhouette Score = 0.6165
For k = 6, Silhouette Score = 0.5983
For k = 7, Silhouette Score = 0.5171
For k = 8, Silhouette Score = 0.4912
For k = 9, Silhouette Score = 0.4784
For k = 10, Silhouette Score = 0.4448
```

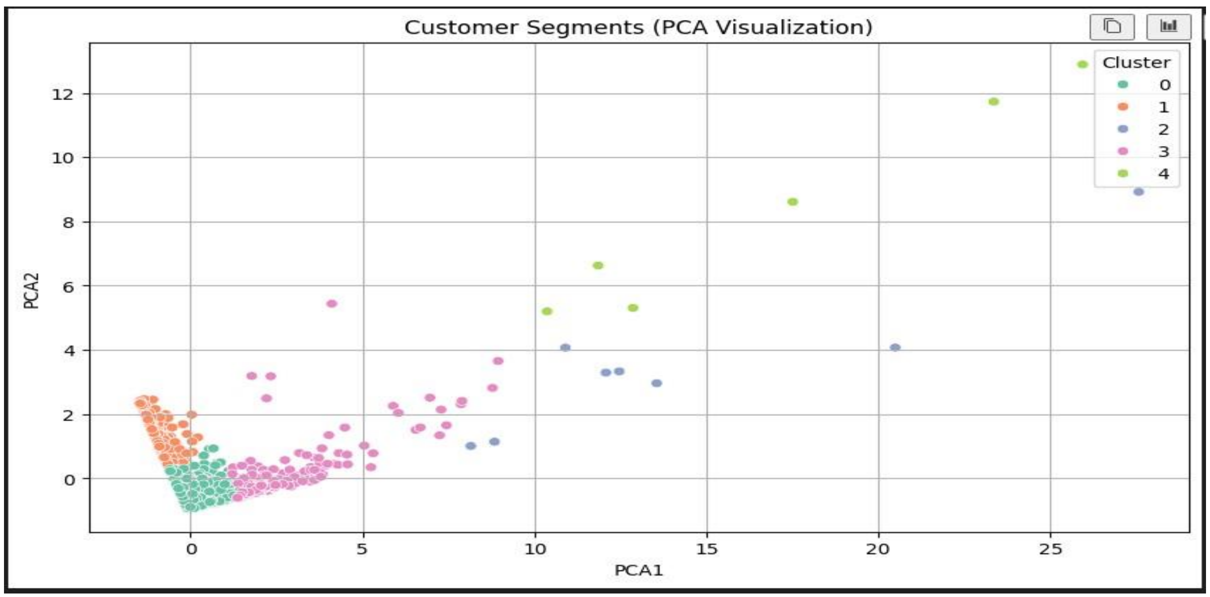
- From the output:
    - Scores increase from **k=2 to k=5**, peaking at **k=5 (score = 0.6165)**.
    - Beyond k=5, the score steadily **declines**, indicating reduced clustering quality.
- Thus, **k=5** is the optimal number of clusters based on silhouette analysis, offering the best balance of cohesion and separation.

9. Kmeans Clustering

The **K-Means algorithm** was applied to the **normalized RFM data** (rfm_scaled) to segment customers into different groups based on their purchasing behavior. This process groups customers into segments that behave similarly, helping businesses tailor marketing strategies to different customer types.

10. Dimensionality reduction using PCA (Cluster Visualization)

To visualize customer segments in 2D space, we applied **Principal Component Analysis (PCA)** to the scaled 3D RFM data. PCA helps reduce high-dimensional data into fewer components while retaining most of the variance. PCA helps **visually separate clusters** by projecting them onto **2 principal components (PCA1 and PCA2)**.



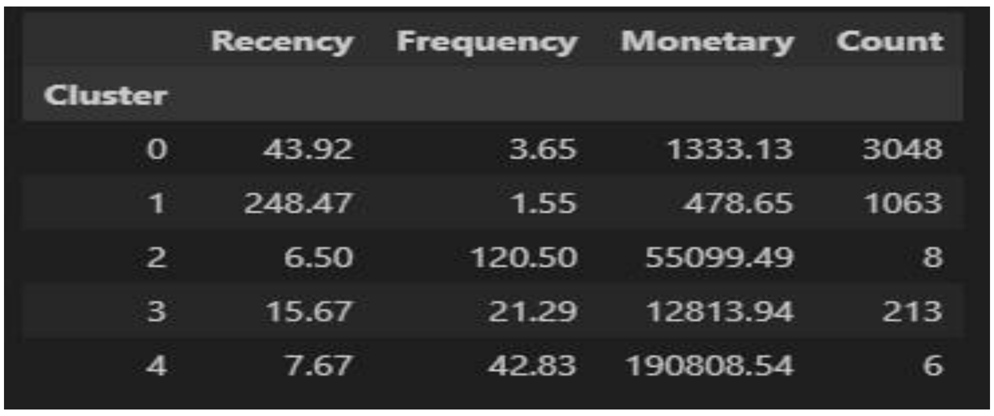
The plot shows customer segments projected onto two principal components: **PCA1 (x-axis)** and **PCA2 (y-axis)**. Each color represents a unique cluster obtained from KMeans clustering with **k = 5**.

i. **Cluster 0 (Green):** These are likely **high-value outliers** — customers who might purchase infrequently but spend significantly when they do. (Possibly **VIP** customers or **seasonal** big spenders.)
ii. **Cluster 1 (Orange):** These customers are **very similar to each other** — likely **frequent buyers with moderate spending**. (Represents your **core customer base** with regular activity.)
iii. **Cluster 2 (Blue):** This group shows moderate diversity — could be **occasional buyers** with average spend.
iv. **Cluster 3 (Pink):** These are **low-value or inactive customers** — probably recent customers or those who haven't made significant purchases.
v. **Cluster 4 (Yellow):** A very **diverse and scattered group**, likely **anomalies** or **niche customers**. (Could represent business buyers, gift shoppers, or inconsistent patterns.)

11. Final Profiling of Clusters

Adding cluster labels back to the original (scaled) RFM data , then group by cluster to analyze:

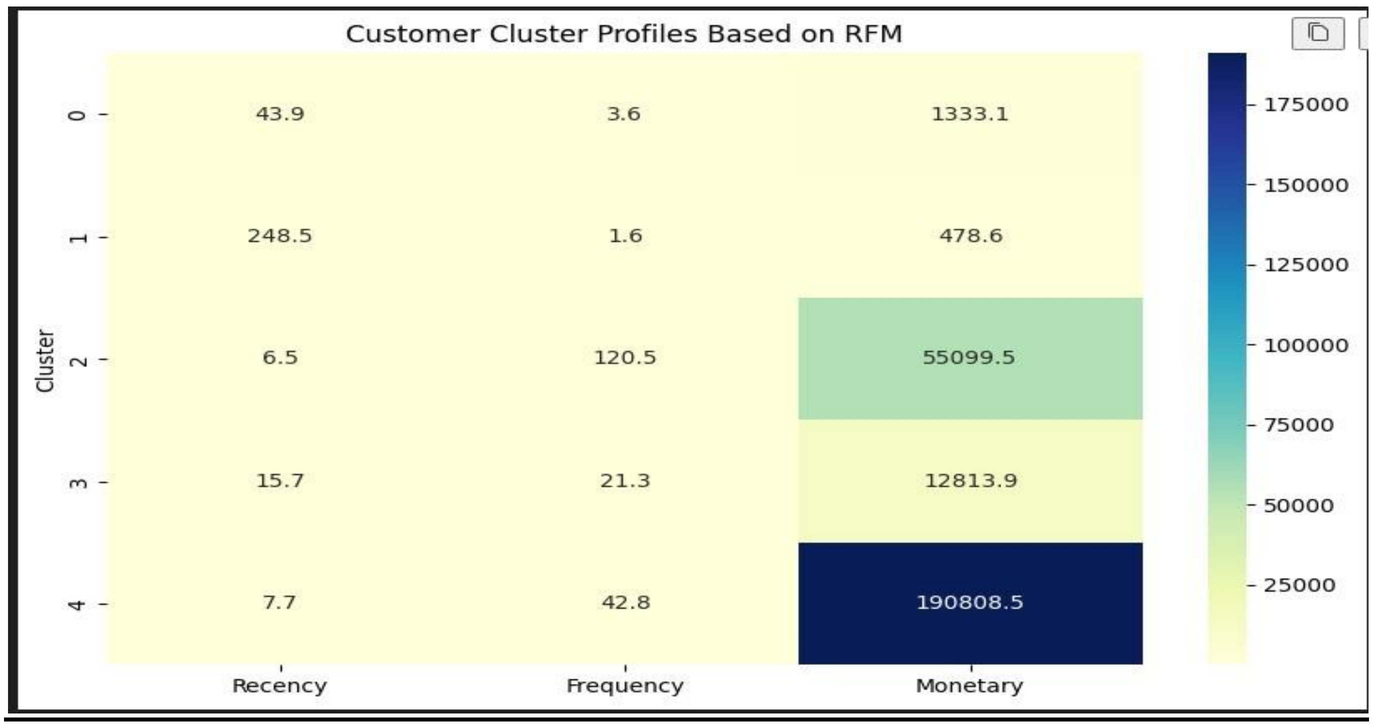
- **Recency:** How recently a customer made a purchase (Lower is better).
- **Frequency:** How often they purchase (Higher is better).
- **Monetary:** How much they spend (Higher is better).
- **Count:** Number of customer in that cluster.



	Recency	Frequency	Monetary	Count
Cluster				
0	43.92	3.65	1333.13	3048
1	248.47	1.55	478.65	1063
2	6.50	120.50	55099.49	8
3	15.67	21.29	12813.94	213
4	7.67	42.83	190808.54	6

i. **0 : Largest group** (3048 customers). Moderate recency, low frequency, low spending. Likely **inactive or low-value** customers.
ii. **1 :** Very **old recency**, lowest frequency and spending. These are **churned or lost customers** (need re-engagement).
iii. **2 :** Extremely **high frequency** and **high spending**, very recent. These are **top VIP customers** (only 8 customers).
iv. **3 :** Good frequency and spending, recent activity. These are **loyal and active customers** worth retaining and upselling.
v. **4 : Very recent**, very high spenders with decent frequency. Likely **new but premium** customers (6 in total), high-value targets.

12. Visualization of cluster profiles



- **Cluster 0**: Low frequency (3.6), low spenders (~1333), moderate recency → **Occasional buyers**
- **Cluster 1**: Very high recency (248.5), lowest frequency (1.6), very low spend (~478) → **Dormant/Churned customers**
- **Cluster 2**: Very low recency (6.5), highest frequency (120.5), high spend (~55K) → **Most Loyal & Active**
- **Cluster 3**: Recent (15.7), good frequency (21.3), decent spend (~12.8K) → **Loyal Customers**
- **Cluster 4**: Very recent (7.7), high frequency (42.8), **highest spend (~190K)** → **Top Premium Customers**

13. Cluster-Based Targeted marketing strategies

I. **Occasional Buyers(cluster 0): (**Low-Mid Value | 3,048 customers)

- **Behavior:** Moderate recency, low frequency, low monetary.
- **Goal:** Increase engagement and spending.
- **Strategies:**
  - Offer **combo deals** or **limited-time discounts** to encourage repeat purchases.
  - Use **email reminders** with personalized recommendations.
  - Introduce a **points-based loyalty program** to build frequency.
  - **Product Recommendations:** Based on browsing history.

II. **Dormant/Churned(cluster 1):** (Low Value | 1,063 customers)

- **Behavior:** High recency (inactive), very low frequency and spending.
- **Goal:** Re-engage or win back lost customers.
- **Strategies:**
  - Launch a **"We Miss You" reactivation campaign** with a strong incentive (e.g., ₹200 off).
  - Run **exit surveys** to understand drop-offs and improve offerings.
  - Provide **low-barrier re-entry deals**, such as free shipping or free trials.
  - **Flash Sales:** Create urgency through time-limited offers.

III. **Most loyal & active(cluster 2):** (Top-Tier | 8 customers)

- **Behavior:** Very recent, extremely frequent, very high spenders.
- **Goal:** Retain and reward loyalty.
- **Strategies:**
  - Offer **exclusive benefits**: early access to sales, loyalty tiers, or luxury packaging.
  - **Upsell & Cross-sell:** Suggest premium or related products.
  - Encourage **referrals** with high-value rewards.
  - **Surprise Rewards:** Gift cards, handwritten thank-you notes.

IV. **Loyal customers(cluster 3):** (Mid-High Value | 213 customers)

- **Behavior:** Recent activity, moderate frequency, good spending.
- **Goal:** Strengthen loyalty and encourage upselling.
- **Strategies:**
  - **Frequency Boosters:** Loyalty stamps, buy X get 1 free.
  - **Conversion Discounts:** Encourage upgrading purchases.
  - **Seasonal Promotions:** Target holidays and festivals.
  - **Content Engagement:** Product tips, user stories, newsletters.

V. **Top Premium Customer(cluster 4):** (Elite VIPs | 6 customers)

- **Behavior:** Very recent, moderately frequent, **highest monetary value**.
- **Goal:** Retain and deepen emotional connection.
- **Strategies:**
  - Offer **ultra-personalized experiences** (e.g., birthday gifts, handwritten notes).
  - Invite to **VIP-only events** or provide **lifetime value discounts**.
  - Treat as **brand advocates** — promote referrals and testimonials.
  - **Personalized Offers:** Early access to premium launches.