

# Mae Fah Luang University

หมู่ที่ 1 ถนนสุธรรมราษฎร์  
หมู่ที่ 1 333, Tha Sut, Mueang,  
Chiang Rai 57100, Thailand



1501413 : Big Data Management & Analytics

## *Mini Project Report*

### **----- Title -----**

**Customer Segmentation for E-Commerce using k-Means Clustering**

**Student ID: 6531501208      Student NAME: Sai Hae Naing Lay**

**Student ID: 6531501202      Student NAME: Aung Ko Hein**

**Student ID: 6531501237      Student NAME: Zwe Lulin Maung**

*Under the guidance of*

**Dr. Prof. Shanmugam Nandagopalan**



**School of Applied Digital Technology**

School of Applied Technology, MFU

## **Objectives**

To segment customers based on their purchasing behavior using **Recency, Frequency, and Monetary (RFM)** features and apply **K-Means Clustering** to group similar customers for targeted marketing strategies.

### **1. Data Loading and Cleaning**

- **Source:** `data.csv`
- **Encoding:** ISO-8859-1
- **Cleaning Steps:**
  - Dropped rows with missing `CustomerID` or `Description`.
  - Filtered only positive values for `Quantity` and `UnitPrice`.
  - Converted `InvoiceDate` to datetime format.
  - Created a new feature `TotalAmount = Quantity × UnitPrice`.

### **2. RFM Feature Engineering**

- **Reference Date:** One day after the latest `InvoiceDate` in the dataset.
- **RFM Metrics:**
  - **Recency:** Days since the customer's most recent purchase.
  - **Frequency:** Number of unique invoices (transactions).
  - **Monetary:** Total amount spent.

These metrics were grouped by `CustomerID` to profile each customer.

### **3. Feature Scaling**

- **Tool Used:** `StandardScaler` from `sklearn`
- **Reason:** To normalize the RFM features so that each contributes equally to distance calculations in clustering.

### **4. Finding Optimal Number of Clusters (k)**

- **Method Used:** Elbow Method
- **Metric:** SSE (Sum of Squared Errors/Inertia)
- **Range Tested:** 1 to 10 clusters
- **Observation:** A bend (elbow) around  $k=4$ , suggesting 4 is the optimal number of clusters.

### **5. K-Means Clustering**

- **Chosen k:** 4
- **Model:** `KMeans` with `random_state=42` for reproducibility
- **Assignment:** Each customer was assigned to one of the 4 clusters.

## **6. Cluster Analysis**

### **Summary Table:**

Cluster Summary:		Recency	Frequency	Monetary	NumCustomers
Cluster					
0	43.70	3.68	1359.05	3054	
1	248.08	1.55	480.62	1067	
2	7.38	82.54	127338.31	13	
3	15.50	22.33	12709.09	204	

### **Interpretation Tips:**

- **Lower Recency** = More recent customers.
- **Higher Frequency and Monetary** = More valuable and loyal customers.
- This analysis helps in understanding customer segments like:
  - Loyal customers
  - High spenders
  - At-risk customers
  - New customers

## **7. Visualization**

- **Tool Used:** Seaborn PairPlot
- **Dimensions:** Recency, Frequency, and Monetary
- **Colored by:** Cluster
- **Purpose:** To visually explore the separation and distribution of customers across clusters.

### **Complete Code / Program**

```

import pandas as pd
import matplotlib.pyplot as plt
from datetime import timedelta
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import seaborn as sns

df = pd.read_csv("data.csv", encoding='ISO-8859-1')

df = df.dropna(subset=["CustomerID", "Description"])
df = df[(df["Quantity"] > 0) & (df["UnitPrice"] > 0)]
df["InvoiceDate"] = pd.to_datetime(df["InvoiceDate"])
df["TotalAmount"] = df["Quantity"] * df["UnitPrice"]

reference_date = df["InvoiceDate"].max() + timedelta(days=1)
rfm = df.groupby("CustomerID").agg({
    "InvoiceDate": lambda x: (reference_date - x.max()).days,
    "InvoiceNo": "nunique",
    "TotalAmount": "sum"
}).reset_index()

rfm.columns = ["CustomerID", "Recency", "Frequency", "Monetary"]

scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm[["Recency", "Frequency", "Monetary"]])

sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(rfm_scaled)
    sse.append(kmeans.inertia_)

plt.figure(figsize=(8, 4))
plt.plot(range(1, 11), sse, marker='o')
plt.title("Elbow Method For Optimal K")
plt.xlabel("Number of clusters")
plt.ylabel("SSE (Inertia)")
plt.grid(True)
plt.show()

k = 4
kmeans = KMeans(n_clusters=k, random_state=42)
rfm["Cluster"] = kmeans.fit_predict(rfm_scaled)

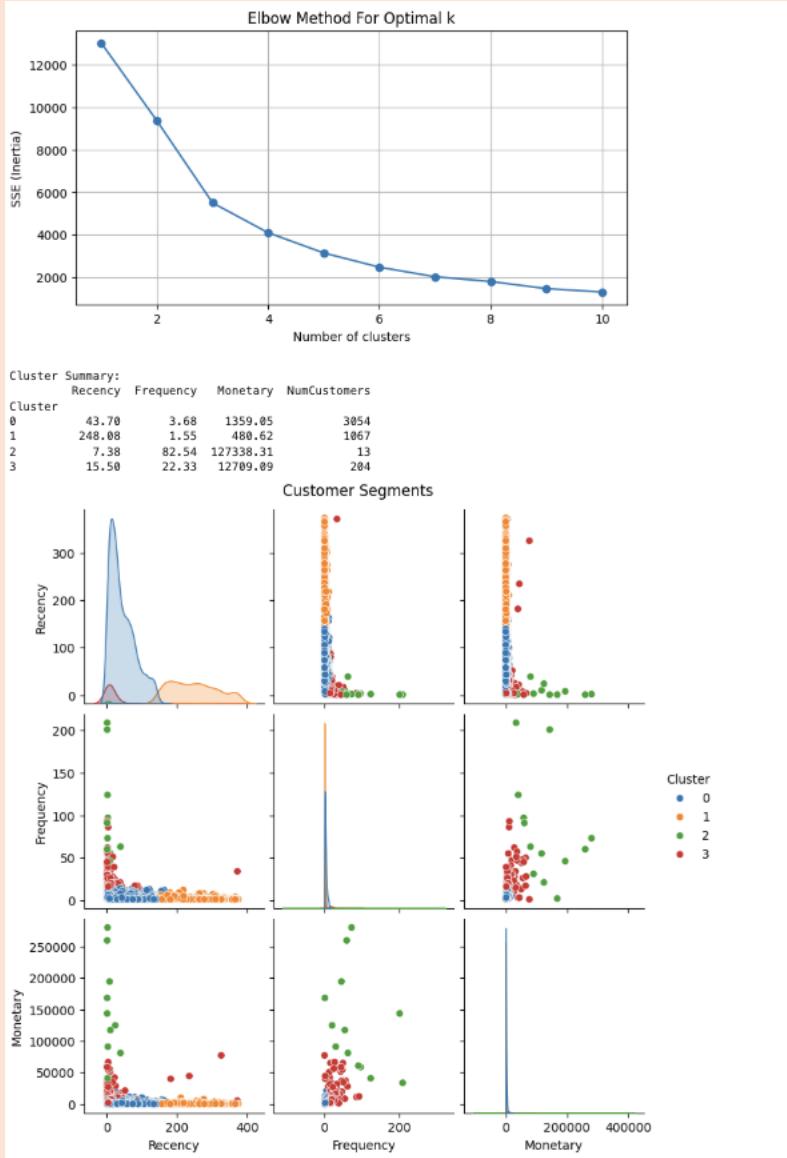
cluster_summary = rfm.groupby("Cluster").agg({
    "Recency": "mean",
    "Frequency": "mean",
    "Monetary": "mean",
    "CustomerID": "count"
}).rename(columns={"CustomerID": "NumCustomers"}).round(2)

print("\nCluster Summary:")
print(cluster_summary)

sns.pairplot(rfm, hue="Cluster", palette="tab10", vars=["Recency", "Frequency", "Monetary"])
plt.suptitle("Customer Segments", y=1.02)
plt.show()

```

## Result



## Conclusion

This project successfully performed customer segmentation using the RFM model and k-means clustering. The insights derived from the cluster profiles can help businesses:

- Tailor marketing strategies
- Prioritize high-value customers
- Re-engage inactive customers
- Optimize customer service efforts

## Reference

<https://www.kaggle.com/datasets/carrie1/ecommerce-data?resource=download>

