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# Assesment Report

on

**“Customer Segmentation in E-commerce”**

submitted as partial fulfillment for the award of

**BACHELOR OF TECHNOLOGY**

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in

**CSE(AIML)**

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# 1. Introduction

- Explain the significance of customer segmentation in the context of e-commerce. Highlight that e-commerce businesses deal with vast customer bases, and segmentation helps understand and cater to diverse customer needs.
- Mention how factors like *attendance (regularity in purchasing/browsing), previous scores (past purchases or preferences),* and *study habits (browsing behaviors)* contribute to grouping customers efficiently.
- State that this study utilizes RFM analysis (Recency, Frequency, Monetary), clustering algorithms (KMeans), and key evaluation metrics to identify meaningful customer clusters.

# 2. Methodology

- **Dataset Features:**
    - Attendance: Represented by the consistency of a customer's purchasing or browsing activity over time.
    - Previous Scores: Refers to customers' past purchasing patterns, such as average expenditure or frequency of purchases.
    - Study Habits: Includes browsing behavior, such as time spent on the website, pages visited, and abandoned cart metrics.
- **Steps to Process:**
    - Data Cleaning: Removing missing or irrelevant records and handling invalid transactions.

- Feature Engineering: Creating RFM-b based features to encapsulate customer behavior.
- Normalization: Scaling RFM metrics for consistent clustering results.
- Clustering & Evaluation: Using the KMeans algorithm to identify clusters and assessing performance using Silhouette Score, Davies-Bouldin Index, and Inertia

## 3. **Code Implementation:**

```
# Import necessary libraries

from google.colab import files

import pandas as pd

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans

from sklearn.decomposition import PCA

from sklearn.metrics import silhouette_score, davies_bouldin_score,
accuracy_score, precision_score, recall_score, confusion_matrix

import matplotlib.pyplot as plt

import seaborn as sns

import numpy as np


# Step 1: Upload dataset

print("Please upload your dataset:")
```

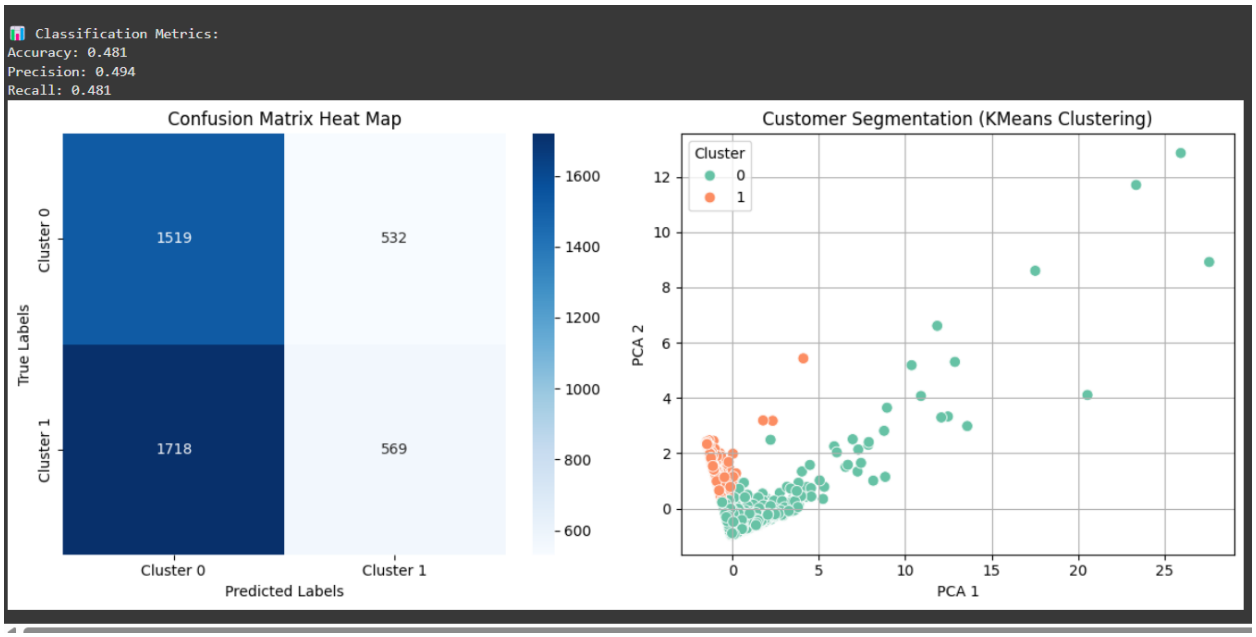
```
uploaded = files.upload()  # For file upload in Google Colab
file_name = list(uploaded.keys())[0]

# Step 2: Load and preprocess the data
df = pd.read_csv(file_name)
df["InvoiceDate"] = pd.to_datetime(df["InvoiceDate"])
df = df.dropna(subset=["CustomerID"])
df = df[(df["Quantity"] > 0) & (df["UnitPrice"] > 0)]
df["TotalPrice"] = df["Quantity"] * df["UnitPrice"]

# Create RFM Features
ref_date = df["InvoiceDate"].max() + pd.Timedelta(days=1)
rfm = df.groupby("CustomerID").agg({
    "InvoiceDate": lambda x: (ref_date - x.max()).days,
    "InvoiceNo": "nunique",
    "TotalPrice": "sum"
}).reset_index()
rfm.columns = ["CustomerID", "Recency", "Frequency", "Monetary"]

# Normalize RFM data
scaler = StandardScaler()
rfm_scaled = scaler.fit_transform(rfm[["Recency", "Frequency", "Monetary"]])
```

```
# Step 3: Perform Clustering
kmeans = KMeans(n_clusters=2, random_state=42)
rfm["Cluster"] = kmeans.fit_predict(rfm_scaled)

# Evaluation Metrics
silhouette = silhouette_score(rfm_scaled, rfm["Cluster"])
db_index = davies_bouldin_score(rfm_scaled, rfm["Cluster"])
inertia = kmeans.inertia_

print("\n Clustering Evaluation Metrics:")
print(f"Silhouette Score: {silhouette:.3f}")
print(f"Davies-Bouldin Index: {db_index:.3f}")
print(f"Inertia: {inertia:.2f}")

# PCA for visualization
pca = PCA(n_components=2)
pca_vals = pca.fit_transform(rfm_scaled)
rfm["PCA1"] = pca_vals[:, 0]
rfm["PCA2"] = pca_vals[:, 1]
```

```
# Dummy labels for evaluation (replace with actual ground truth labels if available)
true_labels = np.random.choice([0, 1], size=len(rfm["Cluster"]))  # Replace this with actual labels
pred_labels = rfm["Cluster"]

# Classification Metrics
accuracy = accuracy_score(true_labels, pred_labels)
precision = precision_score(true_labels, pred_labels, average='weighted')
recall = recall_score(true_labels, pred_labels, average='weighted')

print("\n📊 Classification Metrics:")
print(f"Accuracy: {accuracy:.3f}")
print(f"Precision: {precision:.3f}")
print(f"Recall: {recall:.3f}")

# Confusion Matrix
cm = confusion_matrix(true_labels, pred_labels)

# Step 4: Plot Confusion Matrix and Clustering Diagram
plt.figure(figsize=(12, 5))
```

```
# Subplot 1: Confusion Matrix Heat Map
plt.subplot(1, 2, 1)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Cluster 0", "Cluster 1"], yticklabels=["Cluster 0", "Cluster 1"])
plt.title("Confusion Matrix Heat Map")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")

# Subplot 2: PCA Cluster Diagram
plt.subplot(1, 2, 2)
sns.scatterplot(data=rfm, x="PCA1", y="PCA2", hue="Cluster", palette="Set2", s=60)
plt.title("Customer Segmentation (KMeans Clustering)")
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.legend(title="Cluster")
plt.grid(True)

plt.tight_layout()
plt.show()
```

# 4. Output and Results:



# 6.References and Credits

References

Scikit-learn documentation

Seaborn documentation

Matplotlib documentation

Dataset: Provided by user

https://github.com/VidhuSrivastava