



Assesment Report

on

“Market Analysis”

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

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By

Shreya Mittal (202401100300240)

Under the supervision of

“Mr. Abhishek Shukla Sir”

KIET Group of Institutions, Ghaziabad

Affiliated to

Dr. A.P.J. Abdul Kalam Technical University, Lucknow
(Formerly UPTU)

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Introduction

Market Basket Analysis (MBA) is a data mining technique used to uncover relationships between items frequently purchased together. It plays a vital role in understanding customer purchasing behavior and supporting business strategies such as product placement, bundling, and targeted marketing.

In this project, we simulate customer transactions based on real-world retail data and apply the Apriori algorithm to discover frequent itemsets and generate association rules. Additionally, we classify customers into high and low spenders using a logistic regression model and perform clustering to segment customers based on their shopping patterns. These insights help in making data-driven decisions to improve customer engagement and sales.

Methodology

The project follows a structured approach to perform Market Basket Analysis using simulated transaction data and machine learning techniques:

1. Data Preparation

We begin by uploading a real-world dataset and randomly selecting a subset of aisle names. Using these, we simulate 500 customer transactions with varying item counts. Customers purchasing more than 4 items are labeled as high spenders, while others are labeled as low spenders.

2. Association Rule Mining

The transaction data is one-hot encoded using `TransactionEncoder`. The **Apriori algorithm** is applied to identify frequent itemsets with a minimum support of 0.05. From these, **association rules** are generated using a confidence threshold of 0.3, helping us uncover meaningful item relationships.

3. Customer Classification

We use the number of items in a transaction as a feature to train a **logistic regression** model that predicts whether a customer is a high or low spender. The model's performance is evaluated using accuracy, precision, recall, and a confusion matrix.

4. Customer Segmentation

To understand different customer profiles, we apply **K-Means clustering** on the one-hot encoded transaction data. **PCA (Principal Component Analysis)** is used to reduce dimensions and visualize customer clusters based on their purchase behavior.

CODE

```
# STEP 1: Load and Simulate Transaction Data

import pandas as pd

import numpy as np

import random

import seaborn as sns

import matplotlib.pyplot as plt


from google.colab import files

uploaded = files.upload() # Upload your "10. Market Basket Analysis.csv"


df_aisles = pd.read_csv("10. Market Basket Analysis.csv")

aisles = df_aisles['aisle'].sample(20, random_state=42).tolist()


transactions = []

customer_labels = []


np.random.seed(42)

for _ in range(500):

    num_items = np.random.randint(1, 8)

    items = random.sample(aisles, num_items)

    transactions.append(items)

    customer_labels.append(1 if num_items > 4 else 0) # High spender if more than 4 items
```

```
# STEP 2: Association Rule Mining (Apriori)
```

```
!pip install mlxtend
```

```
from mlxtend.preprocessing import TransactionEncoder
```

```
from mlxtend.frequent_patterns import apriori, association_rules
```

```
te = TransactionEncoder()
```

```
te_array = te.fit(transactions).transform(transactions)
```

```
df_trans = pd.DataFrame(te_array, columns=te.columns_)
```

```
frequent_itemsets = apriori(df_trans, min_support=0.05, use_colnames=True)
```

```
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.3)
```

```
print("Top 5 Association Rules:")
```

```
display(rules.sort_values(by='confidence', ascending=False).head())
```

```
# STEP 3: Classification (High vs. Low Spender)
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.linear_model import LogisticRegression
```

```
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score
```

```
X = np.array([len(t) for t in transactions]).reshape(-1, 1)
```

```
y = np.array(customer_labels)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
model = LogisticRegression()
```

```
model.fit(X_train, y_train)
```

```
y_pred = model.predict(X_test)
```

```
cm = confusion_matrix(y_test, y_pred)
```

```
acc = accuracy_score(y_test, y_pred)
```

```
prec = precision_score(y_test, y_pred)
```

```
rec = recall_score(y_test, y_pred)
```

```
plt.figure(figsize=(6, 4))
```

```
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["Low", "High"],  
yticklabels=["Low", "High"])
```

```
plt.xlabel("Predicted")
```

```
plt.ylabel("Actual")
```

```
plt.title("Confusion Matrix")
```

```
plt.show()
```

```
print(f'Accuracy: {acc:.2f}')
```

```
print(f'Precision: {prec:.2f}')
```

```
print(f'Recall: {rec:.2f}')
```

```
# STEP 4: Clustering and Customer Segmentation

from sklearn.cluster import KMeans

from sklearn.decomposition import PCA

item_df = pd.DataFrame(te_array.astype(int), columns=te.columns_)

kmeans = KMeans(n_clusters=3, random_state=42)

clusters = kmeans.fit_predict(item_df)

reduced = PCA(n_components=2).fit_transform(item_df)

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

sns.scatterplot(x=reduced[:, 0], y=reduced[:, 1], hue=clusters, palette="Set2")

plt.title("Customer Segmentation Based on Aisle Preferences")

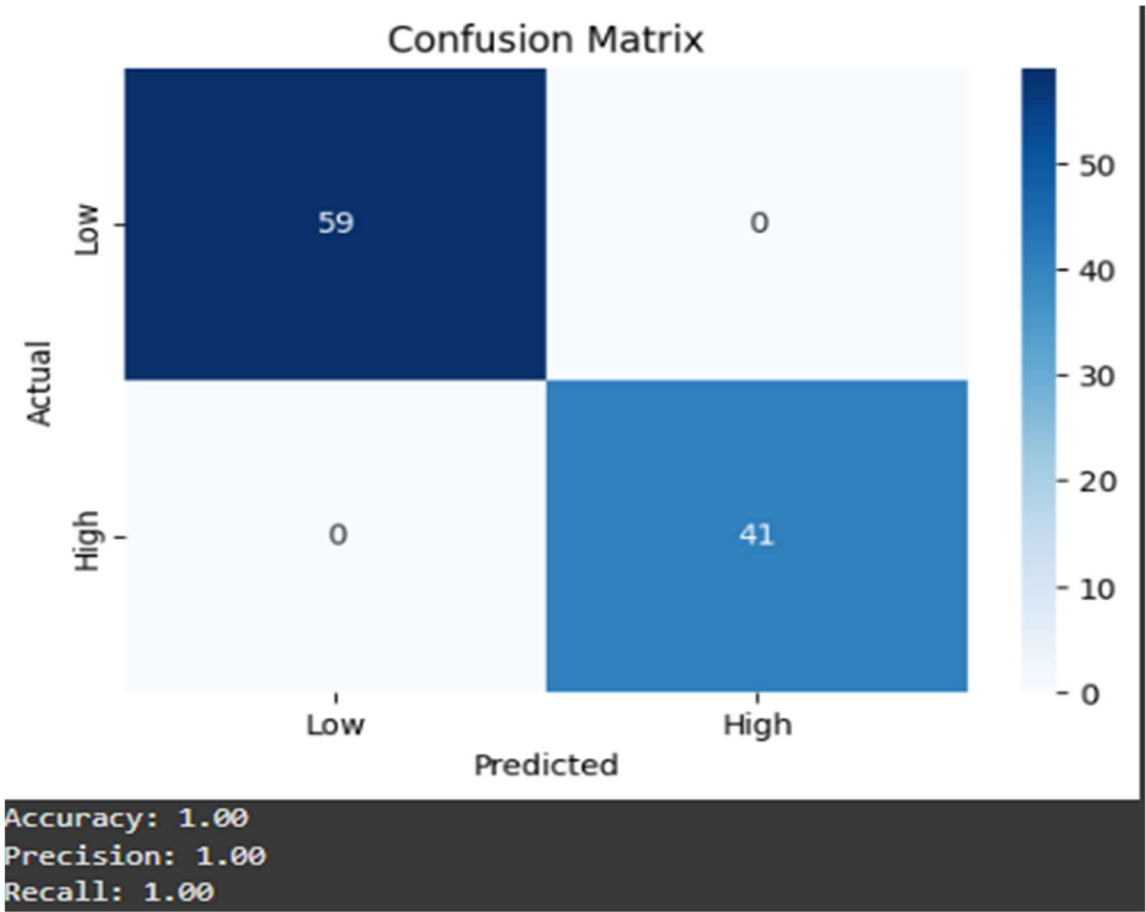
plt.xlabel("PCA 1")

plt.ylabel("PCA 2")

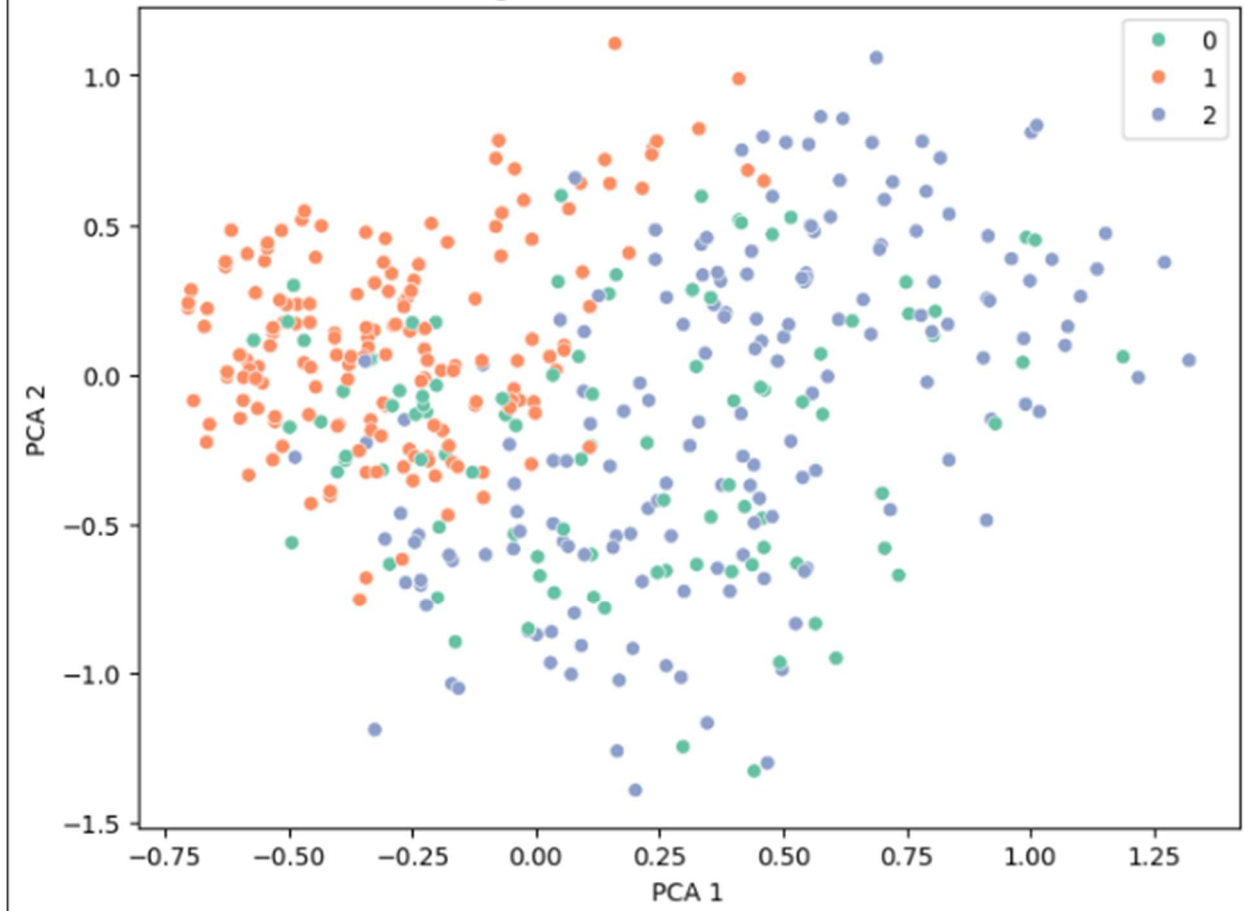
plt.show()
```

OUTPUT

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_metric	jaccard	certainty	kulczynski
8	(pickled goods olives)	(dish detergents)	0.170	0.266	0.062	0.364706	1.371075	1.0	0.016780	1.155370	0.326079	0.165775	0.134477	0.298894
6	(juice nectars)	(dish detergents)	0.222	0.266	0.080	0.360360	1.354738	1.0	0.020948	1.147521	0.336568	0.196078	0.128556	0.330556
3	(cookies cakes)	(dish detergents)	0.172	0.266	0.060	0.348837	1.311418	1.0	0.014248	1.127214	0.286795	0.158730	0.112857	0.287201
1	(cookies cakes)	(buns rolls)	0.172	0.200	0.056	0.325581	1.627907	1.0	0.021600	1.186207	0.465839	0.177215	0.156977	0.302791
2	(buns rolls)	(dish detergents)	0.200	0.266	0.064	0.320000	1.203008	1.0	0.010800	1.079412	0.210937	0.159204	0.073569	0.280301



Customer Segmentation Based on Aisle Preferences



References/Credits

- [Mlxtend Documentation](#)
- [Scikit-learn Documentation](#)
- [Dataset: Market Basket Analysis](#)
- [Google Colab](#)