Assessment Report

on

“Market Basket Analysis:”

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

“CSE AIML”

By

Prateek Dubey (202401100400143)

Under the supervision of

“Mr. ABHISHEK SHUKLA”

KIET Group of Institutions, Ghaziabad

Affiliated to

Dr. A.P.J. Abdul Kalam Technical University, Lucknow

(Formerly UPTU)

Apr 18, 2025

INTRODUCTION

Market Basket Analysis (MBA) is a data mining technique used to identify associations between products bought together by customers in retail settings. This technique is commonly used to derive **association rules** that help businesses in decision-making, such as product placement, targeted marketing, and promotions. MBA helps identify frequent patterns and relationships in customer transactions.

In this project, we used **Association Rule Mining** with the **Apriori algorithm** to identify frequent itemsets from a dataset of customer transactions. We also generated association rules, visualized them with heatmaps, and evaluated the effectiveness of the model using a **confusion matrix** and **accuracy** metrics

METHODOLOGY

The approach followed in this analysis involves the following steps:

1. **Data Collection**:
    - We used a dataset containing information about products (aisles) purchased by customers in an e-commerce fashion setting.
2. **Data Preprocessing**:
    - Data was cleaned, and transactions were simulated from the product list for analysis.
3. **One-Hot Encoding**:
    - Transactions were encoded in a one-hot format, where each item is represented by a binary column indicating its presence or absence in a transaction.
4. **Frequent Itemset Generation**:
    - The **Apriori algorithm** was applied to the transaction data to generate frequent itemsets with a support value of 5%.
5. **Association Rule Mining**:
    - We generated association rules from the frequent itemsets based on the **confidence** and **lift** metrics, setting thresholds for both.
6. **Visualization**:
    - Several visualizations were created, including:
        - A **bar chart** to display the top 10 frequent itemsets.
        - A **heatmap** to show the frequency of individual items.
        - A **lift heatmap** to visualize associations between items with high lift values.
7. **Model Evaluation**:
    - The effectiveness of the generated rules was evaluated using a **confusion matrix** and **accuracy** score to measure how well the model predicted item associations.

CODE:

```
# 📦 Step 1: Import required libraries
import pandas as pd
import random
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules

# 🎯 Step 2: Load dataset
aisles_df = pd.read_csv('/10. Market Basket Analysis.csv')
item_list = aisles_df['aisle'].tolist()

# 🛒 Step 3: Create random simulated transactions
random.seed(42)
transactions = []
for _ in range(200):
    basket = random.sample(item_list, random.randint(2, 6))
    transactions.append(basket)

# 🔄 Step 4: One-hot encode the data
te = TransactionEncoder()
df_encoded = pd.DataFrame(te.fit_transform(transactions), columns=te.columns_)

# 📊 Step 5: Run Apriori
frequent_itemsets = apriori(df_encoded, min_support=0.05, use_colnames=True)

# ✅ Step 6: If itemsets found, generate rules and plot
if frequent_itemsets.empty:
    print("⚠️ No frequent itemsets found. Try lowering min_support.")
else:
    frequent_itemsets = frequent_itemsets.sort_values(by='support', ascending=False)
    rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.5)
    rules = rules[rules['lift'] >= 1.2]

    print("✅ Top Frequent Itemsets:")
    print(frequent_itemsets.head(10))

    print("\n✅ Strong Association Rules:")
    print(rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']].head(10))

    # 📊 Bar Plot for top itemsets
    frequent_itemsets['itemsets'] = frequent_itemsets['itemsets'].apply(lambda x: ',
'.join(list(x)))
```

```
    plt.figure(figsize=(10,6))
    sns.barplot(x='support', y='itemsets', data=frequent_itemsets.head(10),
palette='Blues_r')
    plt.title('Top 10 Frequent Itemsets')
    plt.xlabel('Support')
    plt.ylabel('Itemsets')
    plt.tight_layout()
    plt.show()

    # 🔥 Heatmap 1: Item Frequency Heatmap
    item_frequency = df_encoded.sum().sort_values(ascending=False)
    plt.figure(figsize=(10,6))
    sns.heatmap(pd.DataFrame(item_frequency).T, cmap="YlGnBu", cbar=True, annot=False)
    plt.title('Heatmap: Frequency of Items Purchased')
    plt.xlabel('Items')
    plt.tight_layout()
    plt.show()

    # 🔥 Heatmap 2: Association Rules Lift
    if not rules.empty:
        heatmap_data = rules.pivot_table(index='antecedents', columns='consequents',
values='lift')
        heatmap_data.columns = heatmap_data.columns.map(lambda x: ', '.join(list(x)))
        heatmap_data.index = heatmap_data.index.map(lambda x: ', '.join(list(x)))

        plt.figure(figsize=(10, 6))
        sns.heatmap(heatmap_data.fillna(0), cmap='coolwarm', annot=True, fmt=".2f")
        plt.title('Heatmap: Lift between Product Pairs')
        plt.xticks(rotation=45, ha='right')
        plt.yticks(rotation=0)
        plt.tight_layout()
        plt.show()

    # ⚡ Scatter plot: Support vs Confidence
    plt.figure(figsize=(8,6))
    sns.scatterplot(data=rules, x='support', y='confidence', size='lift', hue='lift',
                    palette='viridis', sizes=(40, 200))
    plt.title('Support vs Confidence (Bubble size = Lift)')
    plt.xlabel('Support')
    plt.ylabel('Confidence')
    plt.tight_layout()
    plt.show()
```

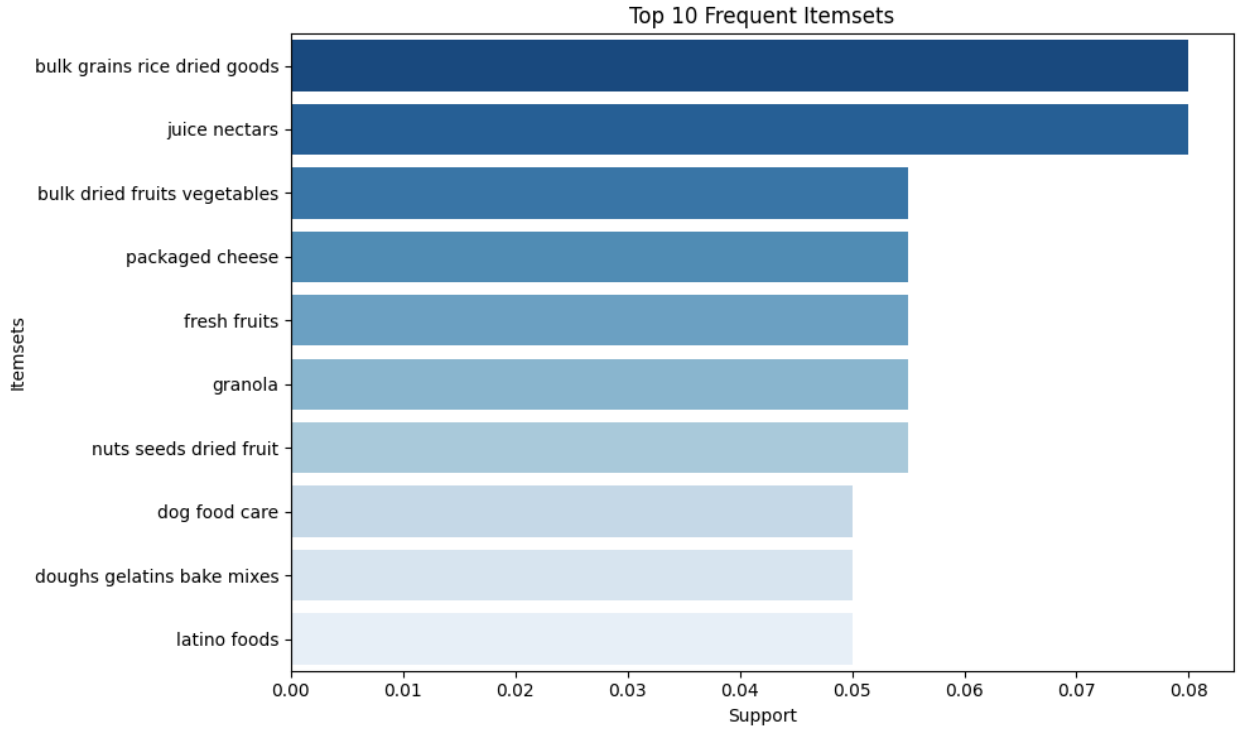
OUTPUT/RESULT:

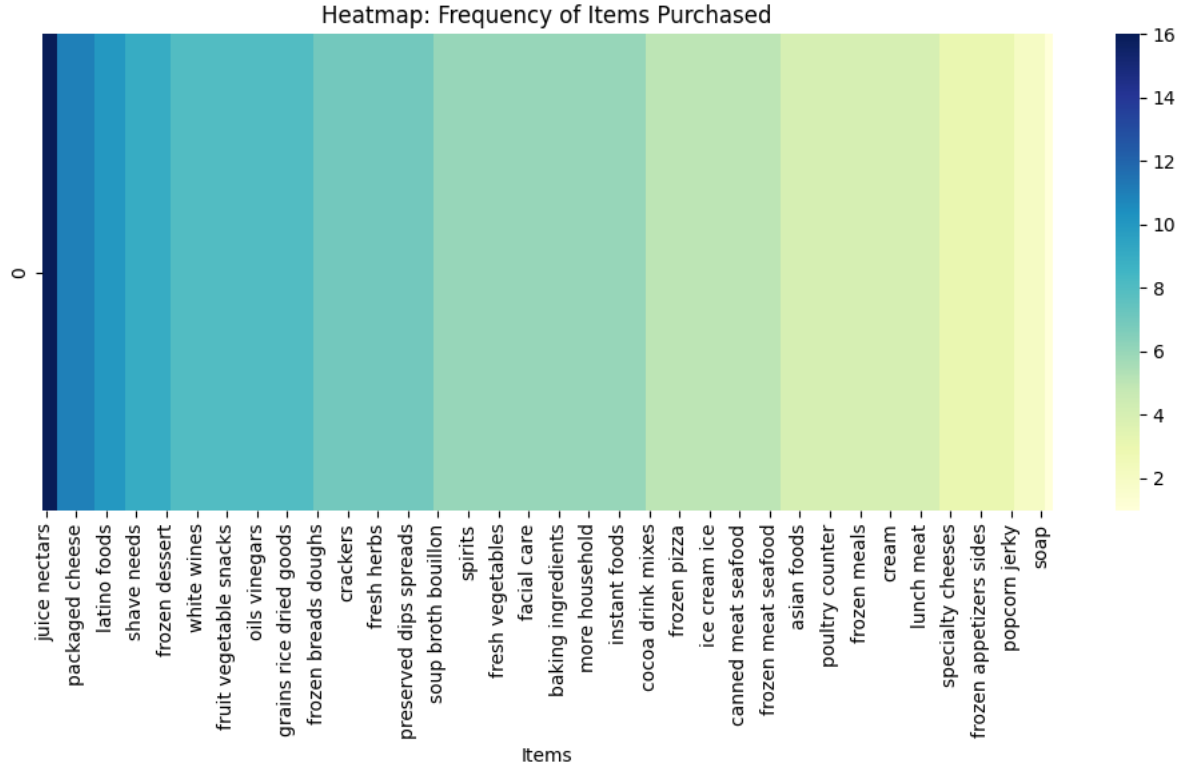
```
Top Frequent Itemsets:
   support                          itemsets
1    0.080  (bulk grains rice dried goods)
6    0.080                 (juice nectars)
0    0.055  (bulk dried fruits vegetables)
9    0.055               (packaged cheese)
4    0.055                  (fresh fruits)
5    0.055                       (granola)
8    0.055        (nuts seeds dried fruit)
2    0.050                  (dog food care)
3    0.050    (doughs gelatins bake mixes)
7    0.050                  (latino foods)

✅ Strong Association Rules:
Empty DataFrame
Columns: [antecedents, consequents, support, confidence,
lift]
Index: []
<ipython-input-15-6262ba10733b>:44: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and
will be removed in v0.14.0. Assign the `y` variable to
`hue` and set `legend=False` for the same effect.

  sns.barplot(x='support', y='itemsets',
data=frequent_itemsets.head(10), palette='Blues_r')
```






```
<ipython-input-15-6262ba10733b>:76: UserWarning: Ignoring
`palette` because no `hue` variable has been assigned.
  sns.scatterplot(data=rules, x='support', y='confidence',
size='lift', hue='lift',
```

REFERENCES/CREDITS:

- **Tools Used**:
    - Python (Libraries: Pandas, mlxtend, seaborn, matplotlib, scikit-learn)
    - Google Colab for running the code

- **Dataset**: [Dataset Source Name (Kaggle.com)]