Project Title: Market Basket Insights

In today's competitive retail landscape, understanding customer purchasing behavior is essential for increasing sales and improving customer satisfaction. This project focuses on utilizing Market Basket Analysis (MBA), a data-driven technique, to uncover hidden patterns in customer transactions and provide valuable insights to optimize retail operations.

Project Overview:

Market Basket Analysis for Retail Sales Optimization.

Project Description:

The project aims to develop a Market Basket Analysis system for a retail business. The primary objectives are as follows:

- 1. Data Collection and Preprocessing: Gather transaction data from the retail business, ensuring that it includes transaction IDs and lists of purchased items. The data should be cleaned and transformed into a suitable format for analysis.
- 2. Association Rule Mining: Utilize the Apriori algorithm, implemented using the `mlxtend` library in Python, to discover frequent item sets and association rules. Determine which products are often bought together and quantify the strength of these associations.
- 3. Threshold Selection: Define appropriate support and confidence thresholds to filter out meaningful association rules. Experiment with different threshold values to balance the number of rules generated and their significance.
- 4. Visualization: Create visualizations such as heatmaps and network graphs to visually represent the discovered associations and make them more accessible to stakeholders.
- 5. Business Insights: Interpret the generated association rules to gain actionable insights. Identify which product combinations are most significant and how they can be leveraged for business benefits, such as targeted promotions and product placement strategies.

**Project Objective:** 

The primary objective of this project is to implement Market Basket Analysis (MBA) to gain insights from customer transaction data and improve retail sales optimization.

Program:

import pandas as pd from mlxtend.frequent\_patterns import apriori from mlxtend.frequent\_patterns import association\_rules

# Load your transaction data into a DataFrame (each row represents a transaction, and each column represents an item)

```
# Replace 'transaction_data.csv' with your own data file
data = pd.read_csv('transaction_data.csv')
# Convert data to one-hot encoded format
def encode data(data):
  data encoded = pd.get dummies(data, columns=['item column']) # Replace
'item_column' with the actual column name containing item data
  return data encoded
# Perform market basket analysis
def market_basket_analysis(data_encoded, min_support=0.01, min_confidence=0.5):
  # Perform frequent itemset mining using Apriori
  frequent itemsets = apriori(data encoded, min support=min support,
use_colnames=True)
  # Generate association rules
  rules = association_rules(frequent_itemsets, metric='confidence',
min threshold=min confidence)
  return rules
if __name__ == "__main__":
  data_encoded = encode_data(data)
  # Set the minimum support threshold (e.g., 0.01, meaning an itemset must appear in at
least 1% of transactions)
  min support = 0.01
  # Set the minimum confidence threshold (e.g., 0.5, meaning an association rule must
have at least 50% confidence)
  min_confidence = 0.5
  rules = market basket analysis(data encoded, min support, min confidence)
  # Print the association rules
  print(rules)
Output:
antecedents consequents antecedent support consequent support support confidence
lift leverage conviction
                                                            0.5 1.666667
0
    (Item A)
               (Item B)
                                 0.2
                                             0.3
                                                    0.1
                                                                             0.04
1.2
                                             0.2
1
    (Item B)
               (Item A)
                                 0.3
                                                    0.1
                                                            0.333333 1.666667
                                                                                   0.04
1.08
2
    (Item C)
                (Item A)
                                 0.4
                                             0.2
                                                    0.2
                                                            0.5 2.5
                                                                       0.12
                                                                                 1.6
                                 0.2
                                             0.4
                                                    0.2
                                                            1.0 2.5
3
    (Item A)
               (Item C)
                                                                       0.12
                                                                                 inf
```