```
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import transactionencoder


# Data Preperation:-
## df= pd.read_csv('data.csv')

# Data Preperation:-
df = pd.read_csv('data.csv', encoding='latin-1') # Try 'latin-1' encoding
df.head()
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Coun
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	Un Kingd
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	Un Kingd
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	Un Kingd

Data Cleaning and Preprocessing

```
# Removing leading/trailing spaces
df['Description'] = df['Description'].str.strip()

# Dropping raws without invoice numbers
df.dropna(axis=0, subset=['InvoiceNo'], inplace=True)

# Converting invoice numbers to strings
df['InvoiceNo'] = df['InvoiceNo'].astype('str')

# Removing credit transactions:-
df = df[~df['InvoiceNo'].str.contains('C')]
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
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```

```
# Creating a list of Transactions (each Transaction is a list of items):-
basket = (df[df['Country']=="France"]
          .groupby(['InvoiceNo','Description'])['Quantity']
          .sum().unstack().reset_index().fillna(0)
          .set_index('InvoiceNo'))
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
# Converting all positive values to 1 (presence of item) and others to 0 (absence of item):-
def encode_units(x):
  if x <= 0:
    return 0
  if x >= 1:
    return 1

basket_sets = basket.applymap(encode_units)
basket_sets.drop('POSTAGE', inplace=True, axis=1)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

Frequent Itemset Mining (Apriori)

```
frequent_itemsets = apriori(basket_sets, min_support=0.07, use_colnames=True)
```

```
10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will
code)
10/dist-packages/mlxtend/frequent_patterns/fpcommon.py:110: DeprecationWarning: DataFram
```

Association Rule Generation

```
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

Rules Evaluation and Filtering

```
# Sort rules by confidence in descending order:-
rules= rules.sort_values(by='confidence', ascending= False)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
# Filtering rules by Confidence and Lift:
filtered_rules = rules[(rules['lift'] >= 1) &
                       (rules['confidence'] >= 0.5)]
print(filtered_rules.to_markdown(index=False, numalign="left", stralign="left"))
```

```
| antecedents                                                                    | c
|:-------------------------------------------------------------------------------|:-
| frozenset({'SET/6 RED SPOTTY PAPER CUPS', 'SET/20 RED RETROSPOT PAPER NAPKINS'})   | f
| frozenset({'SET/6 RED SPOTTY PAPER PLATES', 'SET/20 RED RETROSPOT PAPER NAPKINS'}) | f
| frozenset({'SET/6 RED SPOTTY PAPER PLATES'})                                   | f
| frozenset({'SET/6 RED SPOTTY PAPER CUPS'})                                     | f
| frozenset({'ALARM CLOCK BAKELIKE RED'})                                        | f
| frozenset({'ALARM CLOCK BAKELIKE GREEN'})                                      | f
| frozenset({'SET/6 RED SPOTTY PAPER PLATES', 'SET/6 RED SPOTTY PAPER CUPS'})        | f
| frozenset({'SET/6 RED SPOTTY PAPER PLATES'})                                   | f
| frozenset({'ALARM CLOCK BAKELIKE RED'})                                        | f
| frozenset({'SET/6 RED SPOTTY PAPER PLATES'})                                   | f
| frozenset({'SET/20 RED RETROSPOT PAPER NAPKINS'})                              | f
| frozenset({'SET/20 RED RETROSPOT PAPER NAPKINS'})                              | f
| frozenset({'ALARM CLOCK BAKELIKE GREEN'})                                      | f
| frozenset({'PLASTERS IN TIN SPACEBOY'})                                        | f
| frozenset({'SET/20 RED RETROSPOT PAPER NAPKINS'})                              | f
| frozenset({'SET/6 RED SPOTTY PAPER CUPS'})                                     | f
| frozenset({'ALARM CLOCK BAKELIKE PINK'})                                       | f
| frozenset({'ALARM CLOCK BAKELIKE PINK'})                                       | f
| frozenset({'SET/6 RED SPOTTY PAPER CUPS'})                                     | f
| frozenset({'DOLLY GIRL LUNCH BOX'})                                            | f
| frozenset({'PLASTERS IN TIN SPACEBOY'})                                        | f
| frozenset({'PLASTERS IN TIN WOODLAND ANIMALS'})                                | f
| frozenset({'PLASTERS IN TIN CIRCUS PARADE'})                                   | f
| frozenset({'PLASTERS IN TIN WOODLAND ANIMALS'})                                | f
| frozenset({'SPACEBOY LUNCH BOX'})                                              | f
| frozenset({'PLASTERS IN TIN CIRCUS PARADE'})                                   | f
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
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```

Start coding or generate with AI.

Visualizing Network Graph

```
import networkx as nx
import matplotlib.pyplot as plt

# Calculate node positions using a layout algorithm (e.g., spring layout)
pos = nx.spring_layout(G)  # Add this line to calculate node positions
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

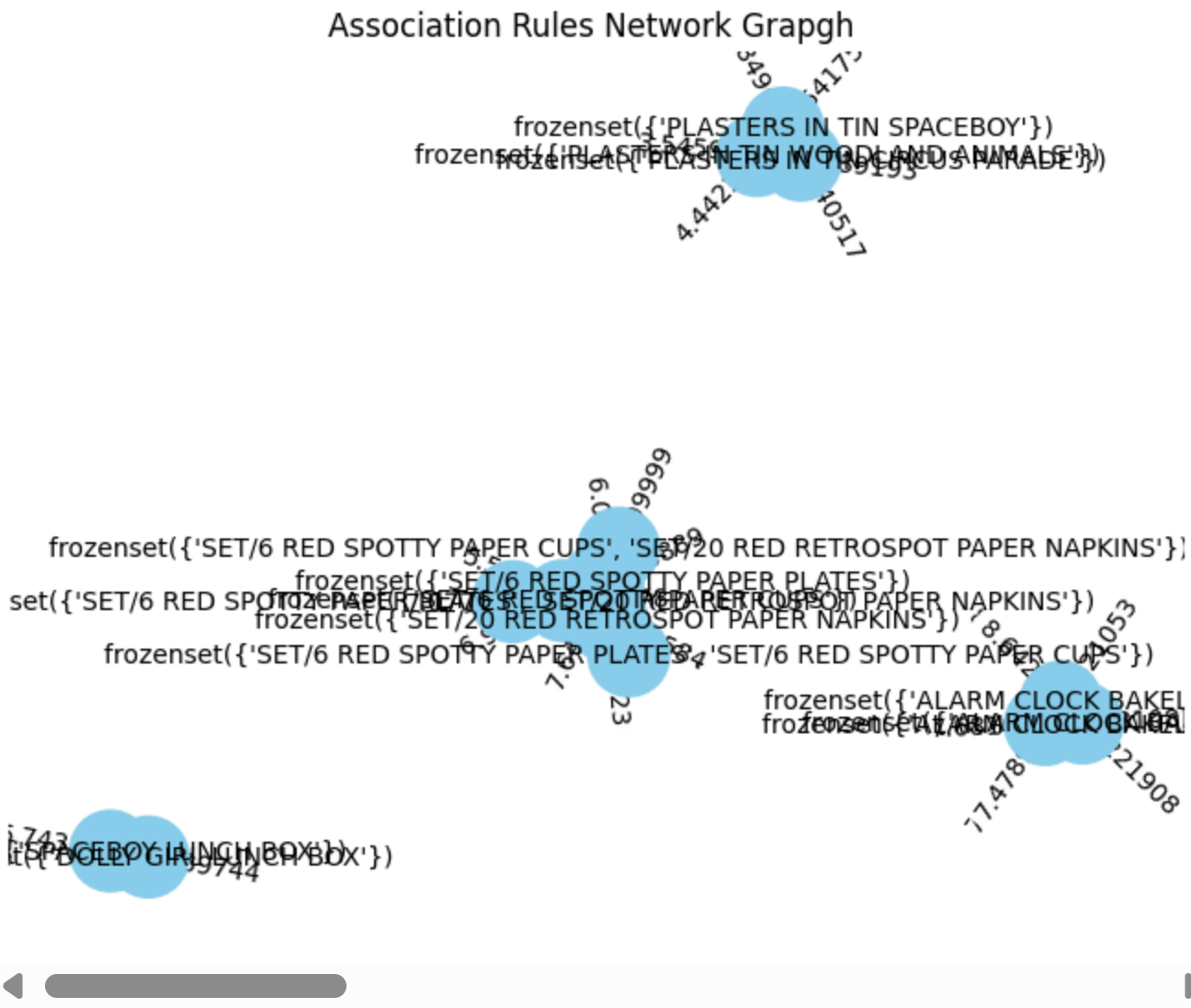
```
# Creating a grapgh from the filtered rules:-
G = nx.DiGraph()
for i, row in filtered_rules.iterrows():
  G.add_edge(row['antecedents'], row['consequents'], weight= row['lift'])
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
# Fix: Extract node values, handle non-numeric types, and ensure a non-empty list
node_sizes = [float(v) * 1000 if isinstance(v, (int, float)) else 1000
              for v in dict(G.nodes).values()]
nx.draw(G, pos, with_labels=True, node_size=node_sizes,
        node_color='skyblue', font_size=10, font_color='black',
        width=[d['weight'] / 2 for (u, v, d) in G.edges(data= True)])

edge_labels = nx.get_edge_attributes(G, 'weight')
nx.draw_networkx_edge_labels(G, pos, edge_labels= edge_labels)
plt.title('Association Rules Network Grapgh ')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```



Validation

```
from sklearn.model_selection import train_test_split

# Splitting the dataset
X_train, X_test= train_test_split(basket_sets, test_size=0.2, random_state=42)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
# Evaluateing the Association Rules on the Test set(X_test):

for _, row in filtered_rules.iterrows():
  antecedent = list(row['antecedents'])
  consequent = list(row['consequents'])
  support_test = X_test[X_test[antecedent].all(axis=1)][consequent].all(axis=1).mean()
  print(f"Rule: {antecedent} -> {consequent}, Support on Test Set: {support_test: .2f}")
```

```
ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transfor

ET/20 RED RETROSPOT PAPER NAPKINS'] -> ['SET/6 RED SPOTTY PAPER PLATES'], Support on Test
'SET/20 RED RETROSPOT PAPER NAPKINS'] -> ['SET/6 RED SPOTTY PAPER CUPS'], Support on Test
-> ['SET/6 RED SPOTTY PAPER CUPS'], Support on Test Set:  0.92
 ['SET/6 RED SPOTTY PAPER PLATES'], Support on Test Set:  0.92
ALARM CLOCK BAKELIKE GREEN'], Support on Test Set:  1.00
['ALARM CLOCK BAKELIKE RED'], Support on Test Set:  0.83
'SET/6 RED SPOTTY PAPER CUPS'] -> ['SET/20 RED RETROSPOT PAPER NAPKINS'], Support on Test
-> ['SET/20 RED RETROSPOT PAPER NAPKINS'], Support on Test Set:  0.83
ALARM CLOCK BAKELIKE PINK'], Support on Test Set:  1.00
-> ['SET/6 RED SPOTTY PAPER CUPS', 'SET/20 RED RETROSPOT PAPER NAPKINS'], Support on Test
NS'] -> ['SET/6 RED SPOTTY PAPER PLATES'], Support on Test Set:  0.83
NS'] -> ['SET/6 RED SPOTTY PAPER CUPS'], Support on Test Set:  0.83
['ALARM CLOCK BAKELIKE PINK'], Support on Test Set:  1.00
PLASTERS IN TIN WOODLAND ANIMALS'], Support on Test Set:  0.80
NS'] -> ['SET/6 RED SPOTTY PAPER PLATES', 'SET/6 RED SPOTTY PAPER CUPS'], Support on Test
 ['SET/20 RED RETROSPOT PAPER NAPKINS'], Support on Test Set:  0.83
'ALARM CLOCK BAKELIKE GREEN'], Support on Test Set:  0.86
'ALARM CLOCK BAKELIKE RED'], Support on Test Set:  0.71
 ['SET/6 RED SPOTTY PAPER PLATES', 'SET/20 RED RETROSPOT PAPER NAPKINS'], Support on Test
EBOY LUNCH BOX'], Support on Test Set:  0.71
PLASTERS IN TIN CIRCUS PARADE'], Support on Test Set:  0.60
'] -> ['PLASTERS IN TIN SPACEBOY'], Support on Test Set:  0.62
-> ['PLASTERS IN TIN WOODLAND ANIMALS'], Support on Test Set:  0.70
'] -> ['PLASTERS IN TIN CIRCUS PARADE'], Support on Test Set:  0.54
GIRL LUNCH BOX'], Support on Test Set:  0.45
-> ['PLASTERS IN TIN SPACEBOY'], Support on Test Set:  0.60
```

```
from sklearn.model_selection import KFold
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
# Initializing k-fold cross-validation:-
kf = KFold(n_splits=5, shuffle=True, random_state=42)

# Metrices to track:-
total_support = []
total_confidence = []
total_lift= []
rule_counts = []

# Cross-validation loop:
for train_index, test_index in kf.split(basket_sets):
  X_train, X_test = basket_sets.iloc[train_index], basket_sets.iloc[test_index]
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
# Rule Evaluation on Test Data:-
for _, rule in rules.iterrows():
  antecedent = set(rule['antecedents'])
  consequent = set(rule['consequents'])

  # Check if the rule applies to any transaction in the test set
  rule_applicable= X_test[(X_test[list(antecedent)]==1).all(axis=1)]
  rule_match = rule_applicable[(rule_applicable[list(consequent)]==1).all(axis=1)]

  # Calculating Support, Confidence and Lift for the rule on Test Set:-
  support_test = len(rule_match)/ len(X_test)
  confidence_test = len(rule_match)/ len(rule_applicable) if len(rule_applicable)>0 else 0

  # Convert the consequent column to numeric type before calculating the sum
  X_test_numeric = X_test[list(consequent)].apply(pd.to_numeric, errors='coerce') # to avoic
  lift_test = confidence_test/ (X_test_numeric.sum() / len(X_test))

  total_support.append(support_test)
  total_confidence.append(confidence_test)
  total_lift.append(lift_test)

rule_counts.append(len(rules))
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `
  and should_run_async(code)
```

```
import numpy as np
# Summarize Cross-Validation Results
print(f"Average Support: {np.mean(total_support):.4f}")
print(f"Average Confidence: {np.mean(total_confidence):.4f}")

print(f"Average Number of Rules: {np.mean(rule_counts):.2f}")
```

```
Average Support: 0.1045
```

Average Support: 0.1045

- Interpretation: This means that, on average, the itemsets involved in our association rules appear together in about 10.45% of the transactions across all folds of our dataset.
- Implication: This indicates that the rules I have discovered capture associations that are not extremely rare but also not universally common. They represent patterns that occur with a moderate frequency in our customer's purchasing behavior.

```
Start coding or generate with AI.
```

Average Confidence: 0.7416

- Interpretation: On average, when the antecedent itemset (the "if" part of the rule) is present in a transaction, there is a 74.16% probability that the consequent itemset (the "then" part of the rule) will also be present.
- Implication: This suggests that our rules have a reasonably high predictive power. If a customer buys the items in the antecedent, there's a good chance they'll also buy the items in the consequent.

Average Number of Rules: 26.00

- Interpretation: On average, the model generates 26 association rules per cross-validation fold.
- Implication: This tells that the approximate number of potentially interesting relationships the model is identifying in the data. However, remember that the number of rules alone doesn't indicate quality. We will need to evaluate the rules based on support, confidence, lift, and their