

ai-phase4

October 31, 2023

```
[10]: import pandas as pd
import numpy as np
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
```

```
[11]: !pip install openpyxl
```

```
Requirement already satisfied: openpyxl in c:\users\d e l
l\appdata\local\programs\python\python310\lib\site-packages (3.1.2)
Requirement already satisfied: et-xmlfile in c:\users\d e l
l\appdata\local\programs\python\python310\lib\site-packages (from openpyxl)
(1.1.0)
```

```
[notice] A new release of pip available: 22.2.1 -> 23.3.1
```

```
[notice] To update, run: python.exe -m pip install --upgrade pip
```

```
[12]: data = pd.read_excel('Assignment-1_Data.xlsx')

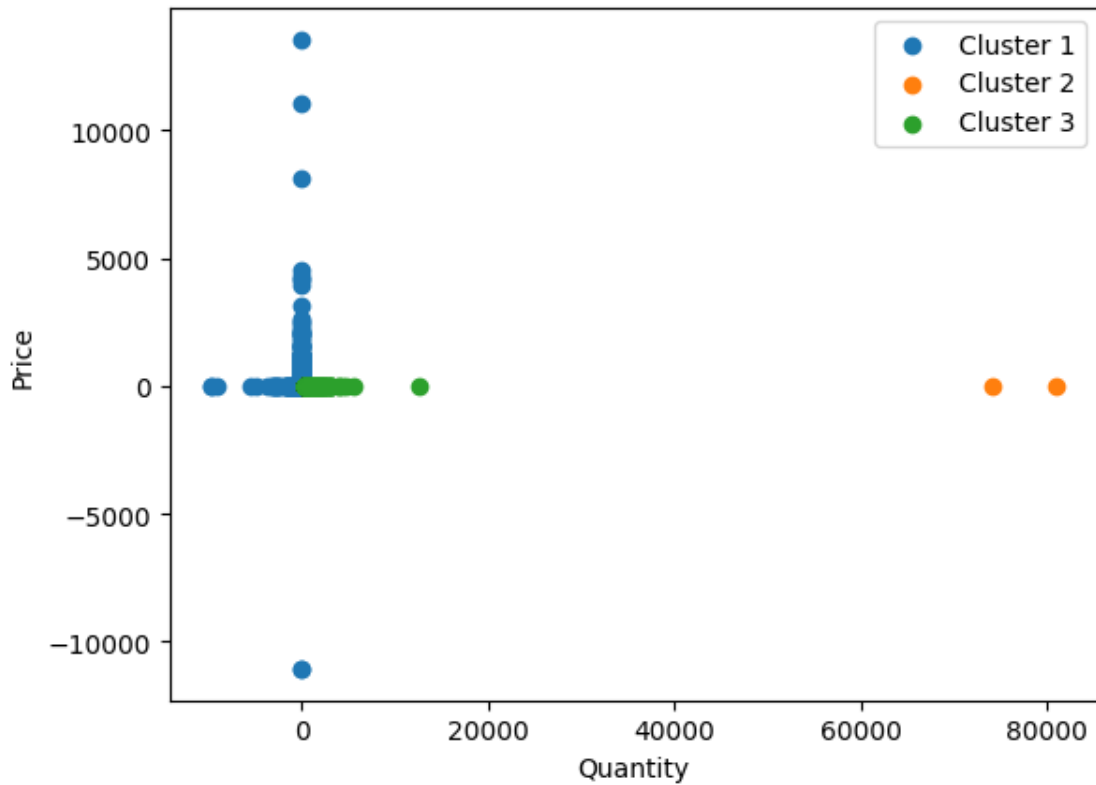
selected_features = data[['Quantity', 'Price']]
num_clusters = 3
kmeans = KMeans(n_clusters=num_clusters)
data['Cluster'] = kmeans.fit_predict(selected_features)
```

```
C:\Users\D E L L\AppData\Local\Programs\Python\Python310\lib\site-
packages\sklearn\cluster\_kmeans.py:1416: FutureWarning: The default value of
`n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init`
explicitly to suppress the warning
  super()._check_params_vs_input(X, default_n_init=10)
```

```
[13]: for cluster in range(num_clusters):
    cluster_data = data[data['Cluster'] == cluster]
    plt.scatter(cluster_data['Quantity'], cluster_data['Price'],
        label=f'Cluster {cluster + 1}')

plt.xlabel('Quantity')
plt.ylabel('Price')
plt.legend()
```

```
plt.show()
```



```
[14]: for cluster in range(num_clusters):
    cluster_data = data[data['Cluster'] == cluster]
    print(f'Cluster {cluster + 1}:')
    print(cluster_data.describe())
    centroid = kmeans.cluster_centers_[cluster]
    print(f'Centroid for Cluster: {cluster + 1}')
    print(f'Quantity: {centroid[0]}')
    print(f'Price: {centroid[1]}')
    plt.figure(figsize=(10, 6))
    plt.hist(cluster_data['Quantity'], bins=20, alpha=0.5, label='Quantity')
    plt.hist(cluster_data['Price'], bins=20, alpha=0.5, label='Price')
    plt.xlabel('Feature Values')
    plt.ylabel('Frequency')
    plt.title(f'Cluster {cluster + 1} Feature Distributions')
    plt.legend()
    plt.show()
```

Cluster 1:

	Quantity	Date	Price \
count	521308.000000	521308	521308.000000

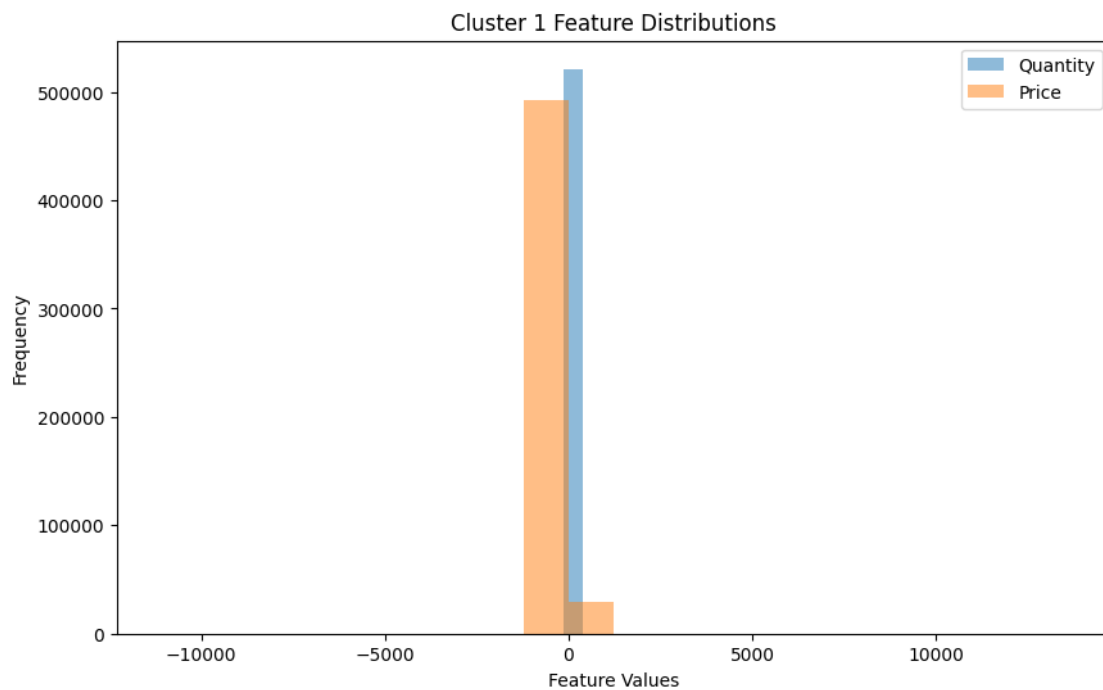
mean	8.723591	2011-07-04 12:57:38.102695680	3.830624
min	-9600.000000	2010-12-01 08:26:00	-11062.060000
25%	1.000000	2011-03-28 10:15:00	1.250000
50%	3.000000	2011-07-20 08:59:00	2.080000
75%	10.000000	2011-10-19 14:22:00	4.130000
max	378.000000	2011-12-09 12:50:00	13541.330000
std	36.890530	NaN	41.930819

	CustomerID	Cluster
count	387303.000000	521308.0
mean	15315.979801	0.0
min	12347.000000	0.0
25%	13950.000000	0.0
50%	15261.000000	0.0
75%	16837.000000	0.0
max	18287.000000	0.0
std	1721.397926	0.0

Centroid for Cluster: 1

Quantity: 8.72359142771426

Price: 3.830624436993143



Cluster 2:

	Quantity	Date	Price	CustomerID	Cluster
count	2.000000	2	2.000000	2.000000	2.0
mean	77605.000000	2011-06-29 21:38:00	1.560000	14396.000000	1.0

min	74215.000000	2011-01-18 10:01:00	1.040000	12346.000000	1.0
25%	75910.000000	2011-04-09 15:49:30	1.300000	13371.000000	1.0
50%	77605.000000	2011-06-29 21:38:00	1.560000	14396.000000	1.0
75%	79300.000000	2011-09-19 03:26:30	1.820000	15421.000000	1.0
max	80995.000000	2011-12-09 09:15:00	2.080000	16446.000000	1.0
std	4794.183976		NaN 0.735391	2899.137803	0.0

Centroid for Cluster: 2
Quantity: 77605.0
Price: 1.56

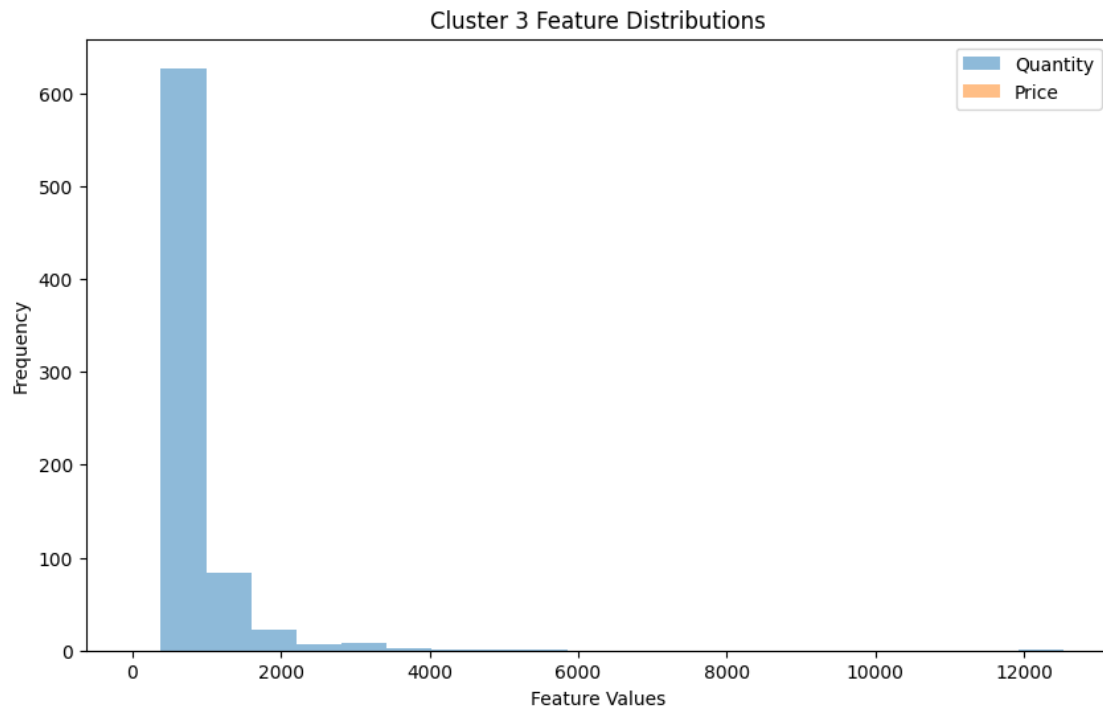


Cluster 3:

	Quantity	Date	Price	CustomerID \
count	754.000000	754	754.000000	718.000000
mean	749.290451	2011-07-01 12:41:03.740052992	1.189589	15832.974930
min	384.000000	2010-12-01 09:58:00	0.000000	12415.000000
25%	432.000000	2011-04-01 12:25:30	0.360000	14101.000000
50%	576.000000	2011-07-24 12:58:30	0.720000	16333.000000
75%	748.500000	2011-10-05 10:06:00	1.650000	17450.000000
max	12540.000000	2011-12-08 18:46:00	8.150000	18251.000000
std	694.918323	NaN	1.327377	1879.120714

	Cluster
count	754.0
mean	2.0
min	2.0

25% 2.0
 50% 2.0
 75% 2.0
 max 2.0
 std 0.0
 Centroid for Cluster: 3
 Quantity: 749.2904509283826
 Price: 1.1895888594164465



```

[15]: from mlxtend.frequent_patterns import apriori
      from mlxtend.frequent_patterns import association_rules

      basket = (data.groupby(['BillNo', 'Itemname'])['Quantity']
                .sum().unstack().reset_index().fillna(0)
                .set_index('BillNo'))
      basket_sets = basket.applymap(lambda quantity: bool(quantity >= 1))
      frequent_itemsets = apriori(basket_sets, min_support=0.01, use_colnames=True)
      rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1.0)
      print("Association Rules:")
      print(rules)
  
```

C:\Users\D E L L\AppData\Local\Temp\ipykernel_12816\3169484420.py:10:
 FutureWarning: DataFrame.applymap has been deprecated. Use DataFrame.map
 instead.

```

basket_sets = basket.applymap(lambda quantity: bool(quantity >= 1))

```

Association Rules:

```

                                antecedents \
0      (JAM MAKING SET PRINTED)
1      (6 RIBBONS RUSTIC CHARM)
2      (6 RIBBONS RUSTIC CHARM)
3      (JAM MAKING SET WITH JARS)
4      (6 RIBBONS RUSTIC CHARM)
...
2999   (STRAWBERRY CHARLOTTE BAG)
3000   (CHARLOTTE BAG SUKI DESIGN)
3001   (RED RETROSPOT CHARLOTTE BAG)
3002   (CHARLOTTE BAG PINK POLKADOT)
3003   (WOODLAND CHARLOTTE BAG)

```

```

                                consequents antecedent support \
0      (6 RIBBONS RUSTIC CHARM)                0.055226
1      (JAM MAKING SET PRINTED)                0.046615
2      (JAM MAKING SET WITH JARS)              0.046615
3      (6 RIBBONS RUSTIC CHARM)                0.053890
4      (JUMBO BAG RED RETROSPOT)              0.046615
...
2999   (RED RETROSPOT CHARLOTTE BAG, CHARLOTTE BAG PI... 0.035432
3000   (CHARLOTTE BAG PINK POLKADOT, STRAWBERRY CHARL... 0.043300
3001   (CHARLOTTE BAG PINK POLKADOT, STRAWBERRY CHARL... 0.050871
3002   (RED RETROSPOT CHARLOTTE BAG, STRAWBERRY CHARL... 0.036520
3003   (RED RETROSPOT CHARLOTTE BAG, STRAWBERRY CHARL... 0.040924

```

```

consequent support  support confidence lift leverage \
0      0.046615  0.011530   0.208781  4.478826  0.008956
1      0.055226  0.011530   0.247346  4.478826  0.008956
2      0.053890  0.010095   0.216561  4.018599  0.007583
3      0.046615  0.010095   0.187328  4.018599  0.007583
4      0.102138  0.010689   0.229299  2.245001  0.005928
...
2999   0.012371  0.010046   0.283520  22.917453  0.009607
3000   0.011926  0.010046   0.232000  19.453344  0.009529
3001   0.010936  0.010046   0.197471  18.056517  0.009489
3002   0.012767  0.010046   0.275068  21.544841  0.009579
3003   0.012074  0.010046   0.245466  20.329375  0.009551

```

```

conviction  zhangs_metric
0      1.204957      0.822130
1      1.255257      0.814705
2      1.207637      0.787884
3      1.173148      0.793942
4      1.164995      0.581681

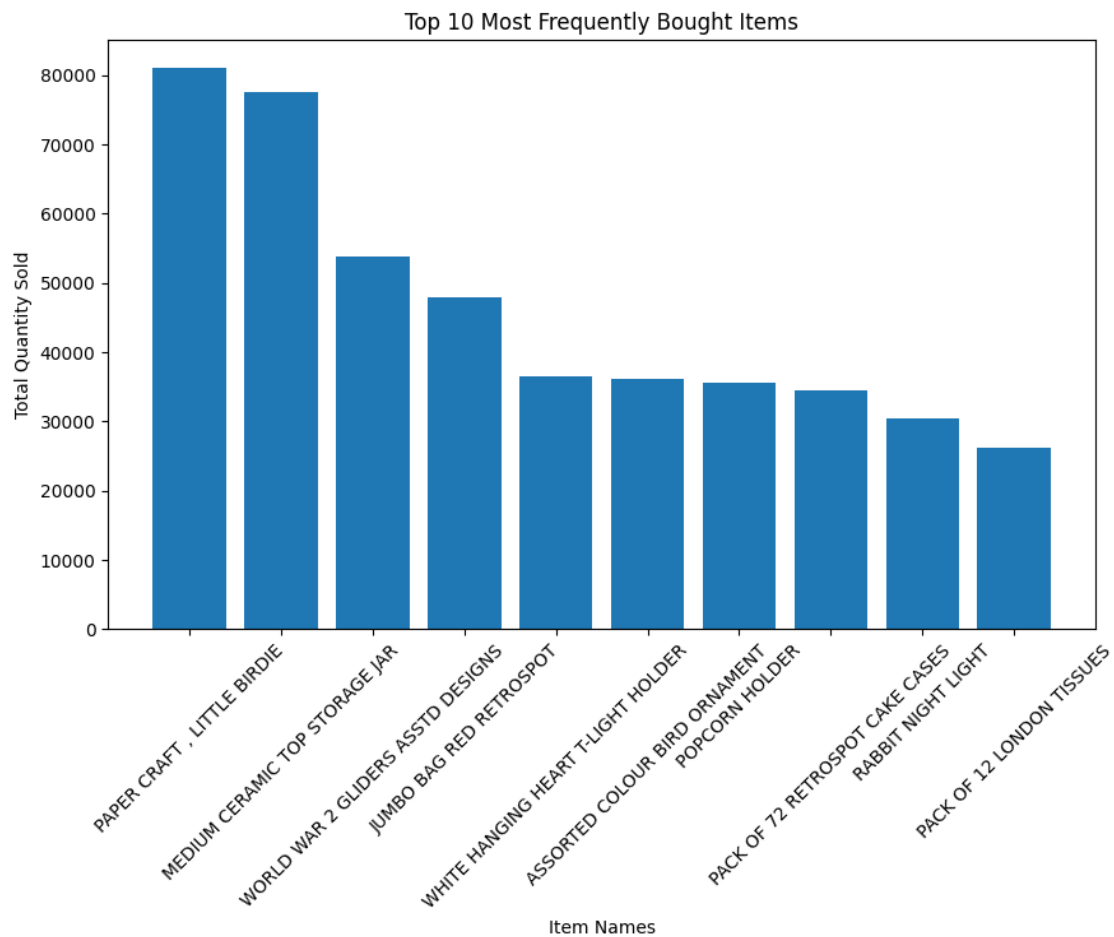
```

...
2999	1.378445	0.991495
3000	1.286555	0.991528
3001	1.232433	0.995248
3002	1.361828	0.989730
3003	1.309318	0.991382

[3004 rows x 10 columns]

```
[16]: item_sales = data.groupby('Itemname')['Quantity'].sum().
      ↪sort_values(ascending=False)

top_n = 10;
plt.figure(figsize=(10, 6))
plt.bar(item_sales.index[:top_n], item_sales.values[:top_n])
plt.xlabel('Item Names')
plt.ylabel('Total Quantity Sold')
plt.title(f'Top {top_n} Most Frequently Bought Items')
plt.xticks(rotation=45)
plt.show()
```



```
[17]: basket = (data.groupby(['BillNo', 'Itemname'])['Quantity']
            .sum().unstack().reset_index().fillna(0)
            .set_index('BillNo'));
basket_sets = basket.applymap(lambda quantity: bool(quantity >= 1))
frequent_itemsets = apriori(basket_sets, min_support=0.01, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1.0)
print("Association Rules:")
print(rules)
plt.figure(figsize=(10, 6))
plt.scatter(rules['support'], rules['confidence'], alpha=0.5)
plt.xlabel('Support')
plt.ylabel('Confidence')
plt.title('Association Rules')
plt.show()
```

C:\Users\D E L L\AppData\Local\Temp\ipykernel_12816\303242403.py:11:
FutureWarning: DataFrame.applymap has been deprecated. Use DataFrame.map
instead.

```
    basket_sets = basket.applymap(lambda quantity: bool(quantity >= 1))
```

Association Rules:

	antecedents \
0	(JAM MAKING SET PRINTED)
1	(6 RIBBONS RUSTIC CHARM)
2	(6 RIBBONS RUSTIC CHARM)
3	(JAM MAKING SET WITH JARS)
4	(6 RIBBONS RUSTIC CHARM)
...	...
2999	(STRAWBERRY CHARLOTTE BAG)
3000	(CHARLOTTE BAG SUKI DESIGN)
3001	(RED RETROSPOT CHARLOTTE BAG)
3002	(CHARLOTTE BAG PINK POLKADOT)
3003	(WOODLAND CHARLOTTE BAG)

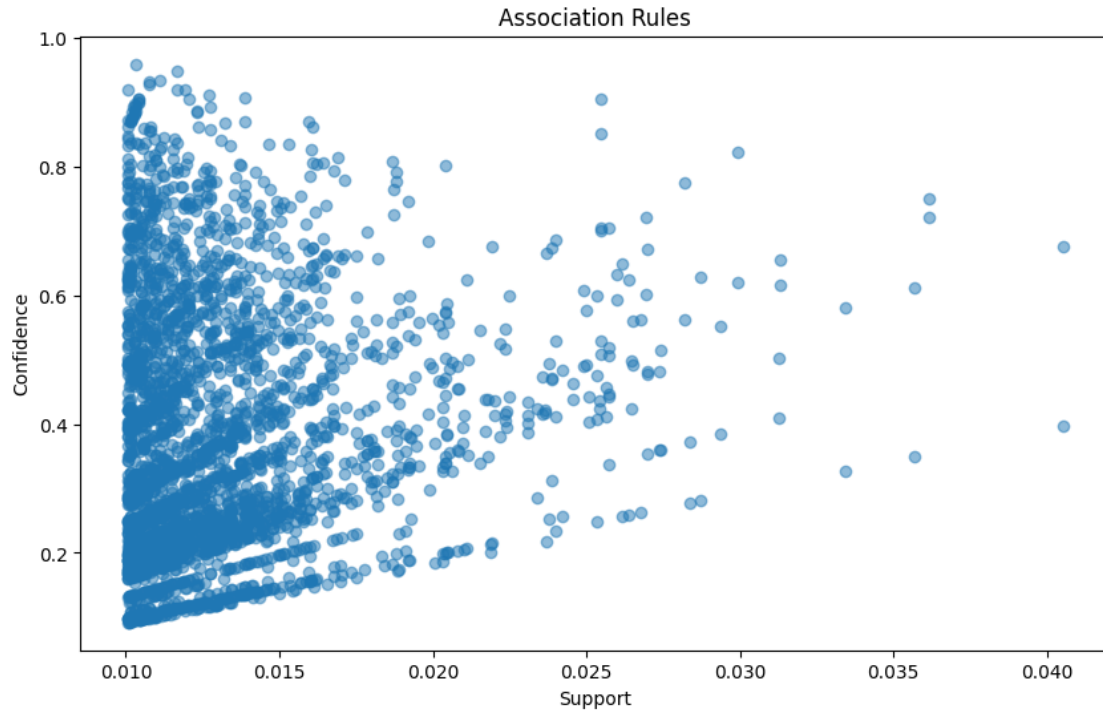
	consequents	antecedent support \
0	(6 RIBBONS RUSTIC CHARM)	0.055226
1	(JAM MAKING SET PRINTED)	0.046615
2	(JAM MAKING SET WITH JARS)	0.046615
3	(6 RIBBONS RUSTIC CHARM)	0.053890
4	(JUMBO BAG RED RETROSPOT)	0.046615
...
2999	(RED RETROSPOT CHARLOTTE BAG, CHARLOTTE BAG PI...	0.035432
3000	(CHARLOTTE BAG PINK POLKADOT, STRAWBERRY CHARL...	0.043300
3001	(CHARLOTTE BAG PINK POLKADOT, STRAWBERRY CHARL...	0.050871
3002	(RED RETROSPOT CHARLOTTE BAG, STRAWBERRY CHARL...	0.036520

3003 (RED RETROSPOT CHARLOTTE BAG, STRAWBERRY CHARL... 0.040924

	consequent	support	support	confidence	lift	leverage \
0	0.046615	0.011530	0.011530	0.208781	4.478826	0.008956
1	0.055226	0.011530	0.011530	0.247346	4.478826	0.008956
2	0.053890	0.010095	0.010095	0.216561	4.018599	0.007583
3	0.046615	0.010095	0.010095	0.187328	4.018599	0.007583
4	0.102138	0.010689	0.010689	0.229299	2.245001	0.005928
...
2999	0.012371	0.010046	0.010046	0.283520	22.917453	0.009607
3000	0.011926	0.010046	0.010046	0.232000	19.453344	0.009529
3001	0.010936	0.010046	0.010046	0.197471	18.056517	0.009489
3002	0.012767	0.010046	0.010046	0.275068	21.544841	0.009579
3003	0.012074	0.010046	0.010046	0.245466	20.329375	0.009551

	conviction	zhangs_metric
0	1.204957	0.822130
1	1.255257	0.814705
2	1.207637	0.787884
3	1.173148	0.793942
4	1.164995	0.581681
...
2999	1.378445	0.991495
3000	1.286555	0.991528
3001	1.232433	0.995248
3002	1.361828	0.989730
3003	1.309318	0.991382

[3004 rows x 10 columns]



```
[18]: basket = (data.groupby(['BillNo', 'Itemname'])['Quantity']
               .sum().unstack().reset_index().fillna(0)
               .set_index('BillNo'));
basket_sets = basket.applymap(lambda quantity: bool(quantity >= 1));
frequent_itemsets = apriori(basket_sets, min_support=0.01, use_colnames=True);
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1.0);
print("Association Rules:")
print(rules)
sorted_rules = rules.sort_values(by=['lift'], ascending=False)
print("Sorted Association Rules:")
print(sorted_rules)
```

C:\Users\D E L L\AppData\Local\Temp\ipykernel_12816\3757603289.py:9:
FutureWarning: DataFrame.applymap has been deprecated. Use DataFrame.map
instead.

```
    basket_sets = basket.applymap(lambda quantity: bool(quantity >= 1));
```

Association Rules:

	antecedents \
0	(JAM MAKING SET PRINTED)
1	(6 RIBBONS RUSTIC CHARM)
2	(6 RIBBONS RUSTIC CHARM)
3	(JAM MAKING SET WITH JARS)
4	(6 RIBBONS RUSTIC CHARM)
...	...

2999 (STRAWBERRY CHARLOTTE BAG)
 3000 (CHARLOTTE BAG SUKI DESIGN)
 3001 (RED RETROSPOT CHARLOTTE BAG)
 3002 (CHARLOTTE BAG PINK POLKADOT)
 3003 (WOODLAND CHARLOTTE BAG)

	consequents	antecedent support \
0	(6 RIBBONS RUSTIC CHARM)	0.055226
1	(JAM MAKING SET PRINTED)	0.046615
2	(JAM MAKING SET WITH JARS)	0.046615
3	(6 RIBBONS RUSTIC CHARM)	0.053890
4	(JUMBO BAG RED RETROSPOT)	0.046615
...
2999	(RED RETROSPOT CHARLOTTE BAG, CHARLOTTE BAG PI...	0.035432
3000	(CHARLOTTE BAG PINK POLKADOT, STRAWBERRY CHARL...	0.043300
3001	(CHARLOTTE BAG PINK POLKADOT, STRAWBERRY CHARL...	0.050871
3002	(RED RETROSPOT CHARLOTTE BAG, STRAWBERRY CHARL...	0.036520
3003	(RED RETROSPOT CHARLOTTE BAG, STRAWBERRY CHARL...	0.040924

	consequent support	support	confidence	lift	leverage \
0	0.046615	0.011530	0.208781	4.478826	0.008956
1	0.055226	0.011530	0.247346	4.478826	0.008956
2	0.053890	0.010095	0.216561	4.018599	0.007583
3	0.046615	0.010095	0.187328	4.018599	0.007583
4	0.102138	0.010689	0.229299	2.245001	0.005928
...
2999	0.012371	0.010046	0.283520	22.917453	0.009607
3000	0.011926	0.010046	0.232000	19.453344	0.009529
3001	0.010936	0.010046	0.197471	18.056517	0.009489
3002	0.012767	0.010046	0.275068	21.544841	0.009579
3003	0.012074	0.010046	0.245466	20.329375	0.009551

	conviction	zhangs_metric
0	1.204957	0.822130
1	1.255257	0.814705
2	1.207637	0.787884
3	1.173148	0.793942
4	1.164995	0.581681
...
2999	1.378445	0.991495
3000	1.286555	0.991528
3001	1.232433	0.995248
3002	1.361828	0.989730
3003	1.309318	0.991382

[3004 rows x 10 columns]
 Sorted Association Rules:

antecedents \

```

482          (HERB MARKER ROSEMARY)
483          (HERB MARKER THYME)
481          (HERB MARKER THYME)
480          (HERB MARKER PARSLEY)
479          (HERB MARKER PARSLEY)
...
1429        (REGENCY CAKESTAND 3 TIER)
1308 (WHITE HANGING HEART T-LIGHT HOLDER)
1309        (PAPER CHAIN KIT 50'S CHRISTMAS)
827          (JUMBO BAG RED RETROSPOT)
826          (REGENCY CAKESTAND 3 TIER)

```

	consequents	antecedent support \
482	(HERB MARKER THYME)	0.011580
483	(HERB MARKER ROSEMARY)	0.011530
481	(HERB MARKER PARSLEY)	0.011530
480	(HERB MARKER THYME)	0.011481
479	(HERB MARKER ROSEMARY)	0.011481
...
1429	(WHITE HANGING HEART T-LIGHT HOLDER)	0.094220
1308	(PAPER CHAIN KIT 50'S CHRISTMAS)	0.108967
1309	(WHITE HANGING HEART T-LIGHT HOLDER)	0.056562
827	(REGENCY CAKESTAND 3 TIER)	0.102138
826	(JUMBO BAG RED RETROSPOT)	0.094220

	consequent support	support	confidence	lift	leverage \
482	0.011530	0.010738	0.927350	80.428744	0.010605
483	0.011580	0.010738	0.931330	80.428744	0.010605
481	0.011481	0.010392	0.901288	78.505254	0.010260
480	0.011530	0.010392	0.905172	78.505254	0.010260
479	0.011580	0.010392	0.905172	78.169761	0.010259
...
1429	0.108967	0.016973	0.180147	1.653230	0.006707
1308	0.056562	0.010095	0.092643	1.637910	0.003932
1309	0.108967	0.010095	0.178478	1.637910	0.003932
827	0.094220	0.013757	0.134690	1.429524	0.004133
826	0.102138	0.013757	0.146008	1.429524	0.004133

	conviction	zhangs_metric
482	13.605998	0.999136
483	14.393872	0.999086
481	10.014131	0.998778
480	10.423865	0.998728
479	10.423343	0.998673
...
1429	1.086821	0.436224
1308	1.039765	0.437094
1309	1.084612	0.412815

827	1.046769	0.334647
826	1.051371	0.331721

[3004 rows x 10 columns]