

```
In [18]: import pandas as pd
```

```
In [19]: # Read the dataset
data = pd.read_csv('MB.csv', header=None)
data.head()
```

Out[19]:

	0	1	2	3	4	5
0	Wine	Chips	Bread	Butter	Milk	Apple
1	Wine	NaN	Bread	Butter	Milk	NaN
2	NaN	NaN	Bread	Butter	Milk	NaN
3	NaN	Chips	NaN	NaN	NaN	Apple
4	Wine	Chips	Bread	Butter	Milk	Apple

```
In [20]: data
```

Out[20]:

	0	1	2	3	4	5
0	Wine	Chips	Bread	Butter	Milk	Apple
1	Wine	NaN	Bread	Butter	Milk	NaN
2	NaN	NaN	Bread	Butter	Milk	NaN
3	NaN	Chips	NaN	NaN	NaN	Apple
4	Wine	Chips	Bread	Butter	Milk	Apple
5	Wine	Chips	NaN	NaN	Milk	NaN
6	Wine	Chips	Bread	Butter	NaN	Apple
7	Wine	Chips	NaN	NaN	Milk	NaN
8	Wine	NaN	Bread	NaN	NaN	Apple
9	Wine	NaN	Bread	Butter	Milk	NaN
10	NaN	Chips	Bread	Butter	NaN	Apple
11	Wine	NaN	NaN	Butter	Milk	Apple
12	Wine	Chips	Bread	Butter	Milk	NaN
13	Wine	NaN	Bread	NaN	Milk	Apple
14	Wine	NaN	Bread	Butter	Milk	Apple
15	Wine	Chips	Bread	Butter	Milk	Apple
16	NaN	Chips	Bread	Butter	Milk	Apple
17	NaN	Chips	NaN	Butter	Milk	Apple
18	Wine	Chips	Bread	Butter	Milk	Apple
19	Wine	NaN	Bread	Butter	Milk	Apple
20	Wine	Chips	Bread	NaN	Milk	Apple
21	NaN	Chips	NaN	NaN	NaN	Apple

```
In [21]: # Convert the dataset into a transactional format
transactions = []
for i in range(len(data)):
    transaction = []
    for j in range(len(data.columns)):
        if pd.notna(data.iloc[i,j]):
            transaction.append(str(data.iloc[i,j]))
    transactions.append(transaction)
transactions
```

```
Out[21]: [['Wine', 'Chips', 'Bread', 'Butter', 'Milk', 'Apple'],
 ['Wine', 'Bread', 'Butter', 'Milk'],
 ['Bread', 'Butter', 'Milk'],
 ['Chips', 'Apple'],
 ['Wine', 'Chips', 'Bread', 'Butter', 'Milk', 'Apple'],
 ['Wine', 'Chips', 'Milk'],
 ['Wine', 'Chips', 'Bread', 'Butter', 'Apple'],
 ['Wine', 'Chips', 'Milk'],
 ['Wine', 'Bread', 'Apple'],
 ['Wine', 'Bread', 'Butter', 'Milk'],
 ['Chips', 'Bread', 'Butter', 'Apple'],
 ['Wine', 'Butter', 'Milk', 'Apple'],
 ['Wine', 'Chips', 'Bread', 'Butter', 'Milk'],
 ['Wine', 'Bread', 'Milk', 'Apple'],
 ['Wine', 'Bread', 'Butter', 'Milk', 'Apple'],
 ['Wine', 'Chips', 'Bread', 'Butter', 'Milk', 'Apple'],
 ['Chips', 'Bread', 'Butter', 'Milk', 'Apple'],
 ['Chips', 'Butter', 'Milk', 'Apple'],
 ['Wine', 'Chips', 'Bread', 'Butter', 'Milk', 'Apple'],
 ['Wine', 'Bread', 'Butter', 'Milk', 'Apple'],
 ['Wine', 'Chips', 'Bread', 'Milk', 'Apple'],
 ['Chips', 'Apple']]
```

```
In [22]: from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori

# Encode the transactions
te = TransactionEncoder()
te_ary = te.fit(transactions).transform(transactions)
df = pd.DataFrame(te_ary, columns=te.columns_)

# Apply the Apriori algorithm
frequent_itemsets = apriori(df, min_support=0.2, use_colnames=True)
```

```
In [23]: from mlxtend.frequent_patterns import association_rules

# Generate association rules
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.7)
```

```
In [24]: # Print the frequent itemsets
print("Frequent itemsets:")
print(frequent_itemsets)
```

Frequent itemsets:

	support	itemsets
0	0.727273	(Apple)
1	0.727273	(Bread)
2	0.681818	(Butter)
3	0.636364	(Chips)
4	0.772727	(Milk)
5	0.727273	(Wine)
6	0.545455	(Apple, Bread)
7	0.500000	(Apple, Butter)
8	0.500000	(Apple, Chips)
9	0.500000	(Milk, Apple)
10	0.500000	(Apple, Wine)
11	0.590909	(Butter, Bread)
12	0.409091	(Bread, Chips)
13	0.590909	(Milk, Bread)
14	0.590909	(Wine, Bread)
15	0.409091	(Butter, Chips)
16	0.590909	(Milk, Butter)
17	0.500000	(Butter, Wine)
18	0.454545	(Milk, Chips)
19	0.409091	(Wine, Chips)
20	0.636364	(Milk, Wine)
21	0.409091	(Apple, Butter, Bread)
22	0.363636	(Apple, Bread, Chips)
23	0.409091	(Milk, Apple, Bread)
24	0.454545	(Apple, Wine, Bread)
25	0.363636	(Apple, Butter, Chips)
26	0.409091	(Milk, Apple, Butter)
27	0.363636	(Apple, Butter, Wine)
28	0.318182	(Milk, Apple, Chips)
29	0.272727	(Apple, Wine, Chips)
30	0.409091	(Milk, Apple, Wine)
31	0.363636	(Butter, Bread, Chips)
32	0.500000	(Milk, Butter, Bread)
33	0.454545	(Wine, Butter, Bread)
34	0.318182	(Milk, Bread, Chips)
35	0.318182	(Wine, Bread, Chips)
36	0.500000	(Milk, Wine, Bread)
37	0.318182	(Milk, Butter, Chips)
38	0.272727	(Butter, Wine, Chips)
39	0.454545	(Milk, Butter, Wine)
40	0.363636	(Milk, Wine, Chips)
41	0.318182	(Apple, Butter, Bread, Chips)
42	0.318182	(Milk, Apple, Butter, Bread)
43	0.318182	(Apple, Wine, Butter, Bread)
44	0.272727	(Milk, Apple, Bread, Chips)
45	0.272727	(Apple, Wine, Bread, Chips)
46	0.363636	(Milk, Apple, Wine, Bread)
47	0.272727	(Milk, Apple, Butter, Chips)
48	0.227273	(Apple, Butter, Wine, Chips)
49	0.318182	(Milk, Apple, Butter, Wine)
50	0.227273	(Milk, Apple, Wine, Chips)
51	0.272727	(Milk, Butter, Bread, Chips)
52	0.272727	(Wine, Butter, Bread, Chips)
53	0.409091	(Milk, Wine, Butter, Bread)
54	0.272727	(Milk, Wine, Bread, Chips)
55	0.227273	(Milk, Butter, Wine, Chips)

```

56 0.227273 (Milk, Butter, Bread, Chips, Apple)
57 0.227273 (Wine, Butter, Bread, Chips, Apple)
58 0.272727 (Milk, Wine, Butter, Bread, Apple)
59 0.227273 (Milk, Wine, Bread, Chips, Apple)
60 0.227273 (Milk, Wine, Butter, Bread, Chips)

```

```

In [25]: # Print the association rules
print("Association rules:")
print(rules)

```

Association rules:

	antecedents	consequents	antecedent support \
0	(Apple)	(Bread)	0.727273
1	(Bread)	(Apple)	0.727273
2	(Butter)	(Apple)	0.681818
3	(Chips)	(Apple)	0.636364
4	(Butter)	(Bread)	0.681818
5	(Bread)	(Butter)	0.727273
6	(Milk)	(Bread)	0.772727
7	(Bread)	(Milk)	0.727273
8	(Wine)	(Bread)	0.727273
9	(Bread)	(Wine)	0.727273
10	(Milk)	(Butter)	0.772727
11	(Butter)	(Milk)	0.681818
12	(Butter)	(Wine)	0.681818
13	(Chips)	(Milk)	0.636364
14	(Milk)	(Wine)	0.772727
15	(Wine)	(Milk)	0.727273
16	(Apple, Butter)	(Bread)	0.500000
17	(Apple, Bread)	(Butter)	0.545455