

## Report on Frequent Itemsets and Association Rules Analysis

### Dataset Overview

The dataset represents transaction records of grocery items, where each row corresponds to a transaction and each column represents the presence or absence of an item in that transaction. Items include categories like UHT-milk, beef, yogurt, whisky, white wine, etc. The data consists of 5 rows and 167 columns, with True indicating the presence of an item and False indicating its absence.

### Frequent Itemsets Analysis

We applied two algorithms for discovering frequent itemsets from the transaction data: **Apriori** and **FP-growth**. The key objective was to identify which items frequently appear together in transactions. The following summaries provide insights into the results from both algorithms.

#### 1. Apriori Frequent Itemsets

The Apriori algorithm identifies itemsets that occur together in a significant proportion of transactions. Some frequent itemsets identified are as follows:

##### Support Itemsets

0.021386 (UHT-milk)

0.033950 (beef)

0.021787 (berries)

0.016574 (beverages)

0.045312 (bottled beer)

... ..

From the Apriori algorithm, itemsets with relatively high support values include:

- **(UHT-milk)** with a support of 0.021386
- **(beef)** with a support of 0.033950
- **(berries)** with a support of 0.021787

#### 2. FP-growth Frequent Itemsets

FP-growth is another method for mining frequent itemsets and often performs faster than Apriori for larger datasets. The results from FP-growth are as follows:

Support	Itemsets
0.157923	(whole milk)

Support	Itemsets
0.051728	(pastry)
0.018780	(salty snack)
0.085879	(yogurt)
0.060349	(sausages)
...	...

Notable frequent itemsets from FP-growth include:

- **(whole milk)** with a support of 0.157923
- **(pastry)** with a support of 0.051728
- **(salty snack)** with a support of 0.018780

The FP-growth algorithm tends to show a higher support for certain items like **whole milk**, which appears significantly more frequently than others.

### Association Rules Analysis

After identifying the frequent itemsets, we generated association rules based on the Apriori and FP-growth algorithms. The rules reveal relationships between itemsets, showing how the presence of one item in a transaction can suggest the presence of another item.

#### 1. Apriori Association Rules

For the Apriori algorithm, we considered the "lift" metric to assess the strength of the association between items. Some association rules derived from Apriori are:

Antecedents	Consequents	Support	Confidence	Lift	Leverage	Conviction
(rolls/buns)	(other vegetables)	0.010559	0.095990	0.786	-0.002872	0.971
(whole milk)	(other vegetables)	0.014837	0.093948	0.769	-0.004446	0.968
(rolls/buns)	(whole milk)	0.013968	0.126974	0.804	-0.003404	0.964
(whole milk)	(rolls/buns)	0.013968	0.088447	0.804	-0.003404	0.976

#### 2. FP-growth Association Rules

Association rules derived from the FP-growth algorithm are as follows:

Antecedents	Consequents	Support	Confidence	Lift	Leverage	Conviction
(yogurt)	(whole milk)	0.011161	0.129961	0.823	-0.002401	0.968
(whole milk)	(yogurt)	0.011161	0.070673	0.823	-0.002401	0.984
(soda)	(whole milk)	0.011629	0.119752	0.758	-0.003707	0.957
(whole milk)	(soda)	0.011629	0.073635	0.758	-0.003707	0.975

The rules highlight frequent co-occurrences such as:

- **(yogurt) => (whole milk)** with high confidence and lift values.
- **(whole milk) => (yogurt)** with a similar pattern.

### Insights & Conclusion

From the analysis of frequent itemsets and association rules, we can conclude:

- **Whole milk** is a dominant item in both the frequent itemsets and association rules, appearing in many strong associations with other products like **yogurt**, **soda**, and **rolls/buns**.
- **Apriori** and **FP-growth** yield slightly different results in terms of itemsets with FP-growth showing a higher support for products like **whole milk**, while Apriori identifies more diverse sets of items.
- The association rules with high lift values suggest significant relationships between products, which could be useful for marketing strategies or product placement decisions.

