Experiment 7

Aim: To perform association rule mining on any dataset using any 2 algorithms

Theory:

Association rule learning is a rule-based machine learning method for discovering interesting relations between variables in large databases. It is intended to identify strong rules discovered in databases using some measures of interestingness. Association rule mining finds interesting associations and relationships among large sets of data items. This rule shows how frequently an itemset occurs in a transaction.

Rule Evaluation Metrics

- Support. This says how popular an itemset is, as measured by the proportion of transactions in which an itemset appears. The support of an itemset X, supp(X) is the proportion of transactions in the database in which item X appears. It signifies the popularity of an itemset.

  $$\text{supp(X)}=\frac{Number\ of\ transaction\ in\ which\ X\ appears}{Total\ number\ of\ transactions}$$

  If the sales of a particular product (item) above a certain proportion have a meaningful effect on profits, that proportion can be considered as the support threshold. Furthermore, we can identify itemsets that have support values beyond this threshold as significant itemsets.

- Confidence. This says how likely item Y is purchased when item X is purchased, expressed as {X -> Y}. This is measured by the proportion of transactions with item X, in which item Y also appears. Confidence of a rule is defined as follows:

  $$conf\ (X \rightarrow Y)\ = \frac{supp(\ X \cup Y)}{supp(X)}$$

  It signifies the likelihood of item Y being purchased when item X is purchased. It can also be interpreted as the conditional probability P(Y|X), i.e, the probability of finding the itemset Yin transactions given the transaction already contains X.

- Lift. This says how likely item Y is purchased when item X is purchased, while controlling for how popular item Y is. A lift value greater than 1 means that item Y is likely to be bought if item X is bought, while a value less than 1 means that item Y is unlikely to be bought if item X is bought. The lift of a rule is defined as:

  $$lift\ (X \rightarrow Y)\ = \frac{supp(\ X \cup Y)}{supp(X) * supp(Y)}$$

  This signifies the likelihood of the itemset Y being purchased when item X is purchased while taking into account the popularity of Y. If the value of lift is greater than 1, it means that the itemset Y is likely to be bought with itemset X, while a value less than 1 implies that itemset Y is unlikely to be bought if the itemset X is bought

A typical example is Market Based Analysis. Market Based Analysis is one of the key techniques used by large relations to show associations between items.It allows retailers to identify relationships between the items that people buy together frequently. The “supermarket” dataset (supermarket.arff) is a real world transaction data set from a small NZ supermarket. Each instance represents a customer transaction – products purchased and the departments involved. The data contains 4,500 instances and 220 attributes. Each attribute is binary and either has a value (t for true) or no value (“?” for missing). We can easily understand how difficult it would be to detect the association between such a large number of attributes

We would be using two algorithms for this purpose

1. **Apriori:** The Apriori algorithm is used for mining frequent itemsets and devising association rules from a transactional database. The parameters “support” and “confidence” are used. Support refers to items’ frequency of occurrence; confidence is a conditional probability. Items in a transaction form an item set. The algorithm begins by identifying frequent, individual items (items with a frequency greater than or equal to the given support) in the database and continues to extend them to larger, frequent itemsets.

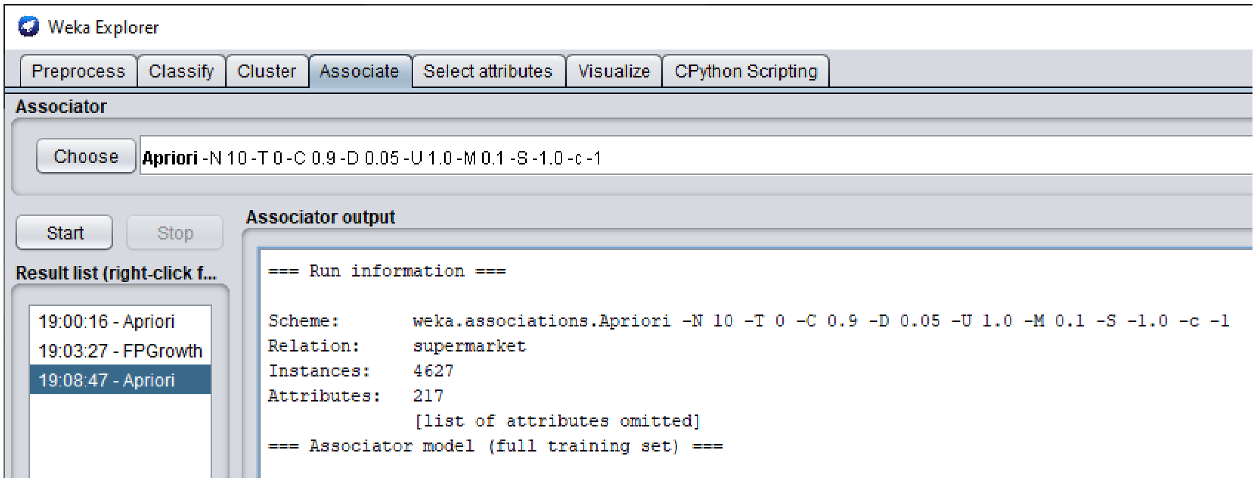
2. **FP Growth**: Fp Growth Algorithm (Frequent pattern growth) is an improvement of apriori algorithm. FP growth algorithm used for finding frequent itemset in a transaction database without candidate generation.FP growth represents frequent items in frequent pattern trees or FP-tree.Advantages of FP growth algorithm:-
    a. Faster than apriori algorithm
    b. No candidate generation
    c. Only two passes over dataset

Procedure:

- Go to Weka Explorer.
- Choose dataset in weka/data (supermarket.arff)
- Go to Associate tab
- Choose an algorithm
- Click start.
- Navigate to Associate tab and under associator choose Apriori and then hit start

Output:

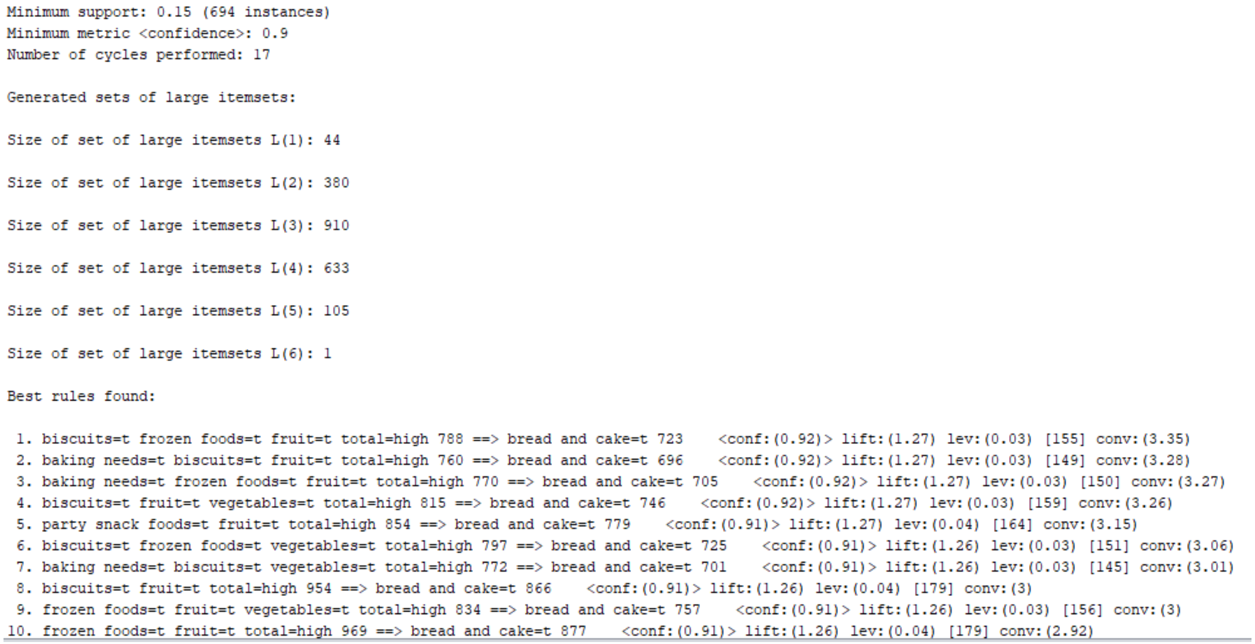
Using Apriori Algorithm



Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1

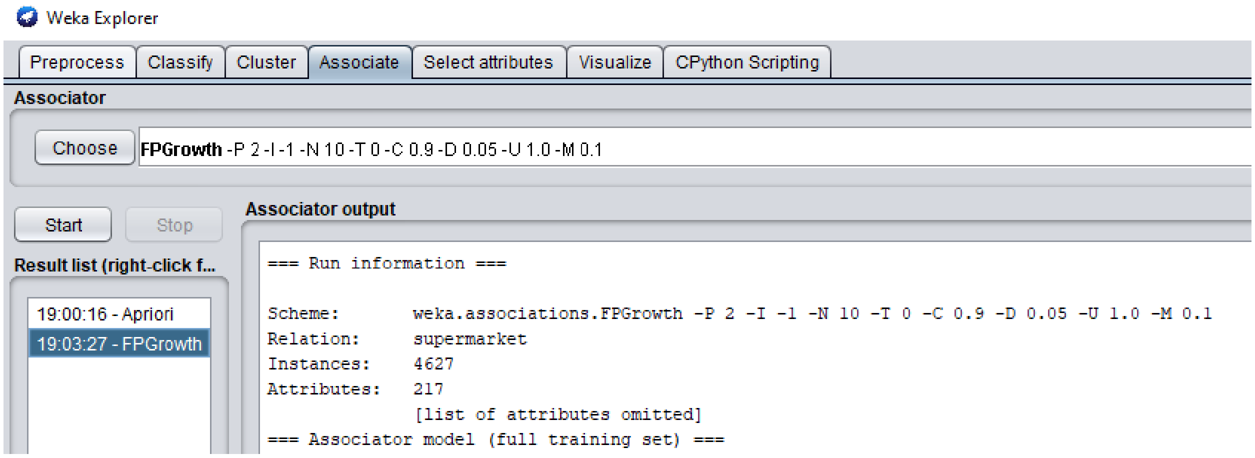
```
=== Run information ===

Scheme:       weka.associations.Apriori -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1 -S -1.0 -c -1
Relation:     supermarket
Instances:    4627
Attributes:   217
              [list of attributes omitted]
=== Associator model (full training set) ===
```

Zoomed Output View



```
Minimum support: 0.15 (694 instances)
Minimum metric <confidence>: 0.9
Number of cycles performed: 17

Generated sets of large itemsets:

Size of set of large itemsets L(1): 44

Size of set of large itemsets L(2): 380

Size of set of large itemsets L(3): 910

Size of set of large itemsets L(4): 633

Size of set of large itemsets L(5): 105

Size of set of large itemsets L(6): 1

Best rules found:

 1. biscuits=t frozen foods=t fruit=t total=high 788 ==> bread and cake=t 723    <conf:(0.92)> lift:(1.27) lev:(0.03) [155] conv:(3.35)
 2. baking needs=t biscuits=t fruit=t total=high 760 ==> bread and cake=t 696    <conf:(0.92)> lift:(1.27) lev:(0.03) [149] conv:(3.28)
 3. baking needs=t frozen foods=t fruit=t total=high 770 ==> bread and cake=t 705    <conf:(0.92)> lift:(1.27) lev:(0.03) [150] conv:(3.27)
 4. biscuits=t fruit=t vegetables=t total=high 815 ==> bread and cake=t 746    <conf:(0.92)> lift:(1.27) lev:(0.03) [159] conv:(3.26)
 5. party snack foods=t fruit=t total=high 854 ==> bread and cake=t 779    <conf:(0.91)> lift:(1.27) lev:(0.04) [164] conv:(3.15)
 6. biscuits=t frozen foods=t vegetables=t total=high 797 ==> bread and cake=t 725    <conf:(0.91)> lift:(1.26) lev:(0.03) [151] conv:(3.06)
 7. baking needs=t biscuits=t vegetables=t total=high 772 ==> bread and cake=t 701    <conf:(0.91)> lift:(1.26) lev:(0.03) [145] conv:(3.01)
 8. biscuits=t fruit=t total=high 954 ==> bread and cake=t 866    <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(3)
 9. frozen foods=t fruit=t vegetables=t total=high 834 ==> bread and cake=t 757    <conf:(0.91)> lift:(1.26) lev:(0.03) [156] conv:(3)
10. frozen foods=t fruit=t total=high 969 ==> bread and cake=t 877    <conf:(0.91)> lift:(1.26) lev:(0.04) [179] conv:(2.92)
```

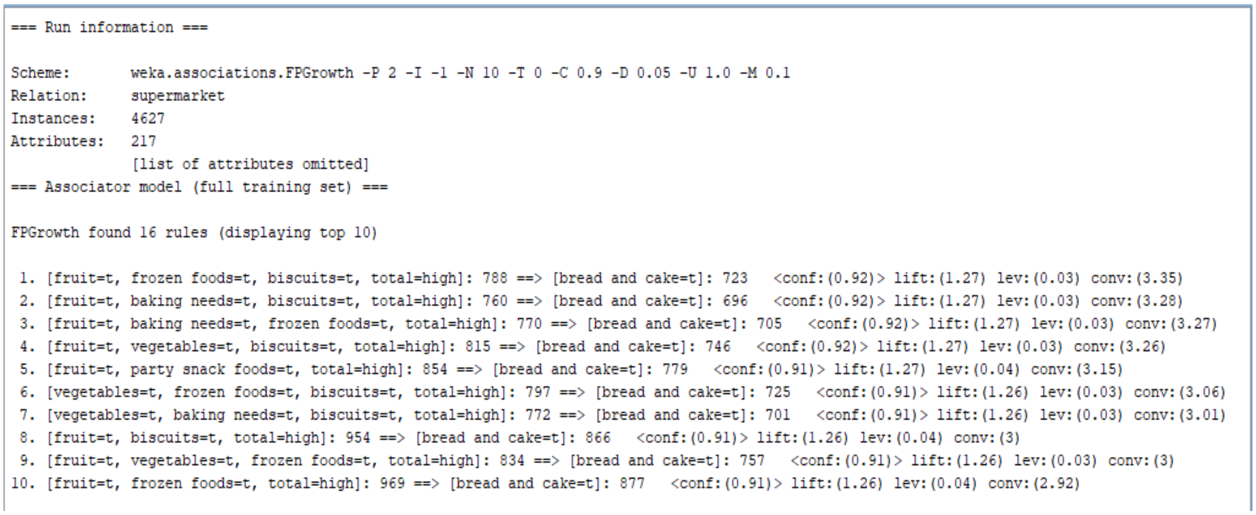
Using FP Growth Algorithm



FPGrowth -P 2 -I -1 -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1

```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Relation:     supermarket
Instances:    4627
Attributes:   217
              [list of attributes omitted]
=== Associator model (full training set) ===
```

Zoomed Output View



```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Relation:     supermarket
Instances:    4627
Attributes:   217
              [list of attributes omitted]
=== Associator model (full training set) ===

FPGrowth found 16 rules (displaying top 10)

 1. [fruit=t, frozen foods=t, biscuits=t, total=high]: 788 ==> [bread and cake=t]: 723   <conf:(0.92)> lift:(1.27) lev:(0.03) conv:(3.35)
 2. [fruit=t, baking needs=t, biscuits=t, total=high]: 760 ==> [bread and cake=t]: 696   <conf:(0.92)> lift:(1.27) lev:(0.03) conv:(3.28)
 3. [fruit=t, baking needs=t, frozen foods=t, total=high]: 770 ==> [bread and cake=t]: 705   <conf:(0.92)> lift:(1.27) lev:(0.03) conv:(3.27)
 4. [fruit=t, vegetables=t, biscuits=t, total=high]: 815 ==> [bread and cake=t]: 746   <conf:(0.92)> lift:(1.27) lev:(0.03) conv:(3.26)
 5. [fruit=t, party snack foods=t, total=high]: 854 ==> [bread and cake=t]: 779   <conf:(0.91)> lift:(1.27) lev:(0.04) conv:(3.15)
 6. [vegetables=t, frozen foods=t, biscuits=t, total=high]: 797 ==> [bread and cake=t]: 725   <conf:(0.91)> lift:(1.26) lev:(0.03) conv:(3.06)
 7. [vegetables=t, baking needs=t, biscuits=t, total=high]: 772 ==> [bread and cake=t]: 701   <conf:(0.91)> lift:(1.26) lev:(0.03) conv:(3.01)
 8. [fruit=t, biscuits=t, total=high]: 954 ==> [bread and cake=t]: 866   <conf:(0.91)> lift:(1.26) lev:(0.04) conv:(3)
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10. [fruit=t, frozen foods=t, total=high]: 969 ==> [bread and cake=t]: 877   <conf:(0.91)> lift:(1.26) lev:(0.04) conv:(2.92)
```

Findings and Learnings :

- We learnt about Association rule mining and the associated terms such as confidence , support and lift.
- We learnt to use Association rule mining in WEKA.
- We learnt the use of Apriori and FP Growth in WEKA.