PRACTICAL NO 8

Aim: To Implement Fp Growth algorithm.

Theory: Frequent Pattern Growth Algorithm

This algorithm is an improvement to the Apriori method. A frequent pattern is generated without the need for candidate generation. FP growth algorithm represents the database in the form of a tree called a frequent pattern tree or FP treeThis tree structure will maintain the association between the itemsets. The database is fragmented using one frequent item. This fragmented part is called a “pattern fragment”. The itemsets of these fragmented patterns are analyzed. Thus with this method, the search for frequent item sets is reduced comparatively.

FP Tree

Frequent Pattern Tree is a tree-like structure that is made with the initial itemsets of the database. The purpose of the FP tree is to mine the most frequent pattern. Each node of the FP tree represents an item of the itemset. The root node represents null while the lower nodes represent the itemsets. The association of the nodes with the lower nodes, that is the itemsets with the other itemsets are maintained while forming the tree.

Frequent Pattern Algorithm Steps

The frequent pattern growth method lets us find the frequent pattern without candidate generation.

Let us see the steps followed to mine the frequent pattern using frequent pattern growth algorithm:

1) The first step is to scan the database to find the occurrences of the itemsets in the database. This step isthe same as the first step of Apriori. The count of 1-itemsets in the database is called support count or frequency of 1-itemset.
2) The second step is to construct the FP tree. For this, create the root of the tree. The root is representedby null.
3) The next step is to scan the database again and examine the transactions. Examine the first transaction and find out the itemset in it. The itemset with the max count is taken at the top, the next itemset with lower count and so on. It means that the branch of the tree is constructed with transaction item sets in descending order of count.
4) The next transaction in the database is examined. The item sets are ordered in descending order of count. If any itemset of this transaction is already present in another branch (for example in the 1st transaction), then this transaction branch would share a common prefix to the root.

This means that the common itemset is linked to the new node of another itemset in this transaction.

#5) Also, the count of the itemset is incremented as it occurs in the transactions. Both the common node and new node count is increased by 1 as they are created and linked according to transactions.

#6) The next step is to mine the created FP Tree. For this, the lowest node is examined first along with the links of the lowest nodes. The lowest node represents the frequency pattern length 1. From this, traverse the path in the FP Tree. This path or paths are called a conditional pattern base.

Conditional pattern base is a sub-database consisting of prefix paths in the FP tree occurring with the lowest node (suffix).

#7) Construct a Conditional FP Tree, which is formed by a count of itemsets in the path. The itemsets meeting the threshold support are considered in the Conditional FP Tree.

#8) Frequent Patterns are generated from the Conditional FP Tree.

Example Of FP-Growth Algorithm

Support threshold=50%, Confidence= 60%Table 1

Transaction	**List of items**
T1	I1,I2,I3
T2	I2 ,I3 ,I4
T3	I4,I5
T4	I1 ,I2 ,I4
T5	I1,I2,I3,I5
T6	I1 ,I2 ,I3 ,I4

Solution:

Support threshold=50% => 0.5*6= 3 => min_sup=3

1. Count of each item

Table 2

Item	Count
I1	4
I2	5
I3	4
I4	4
I5	2

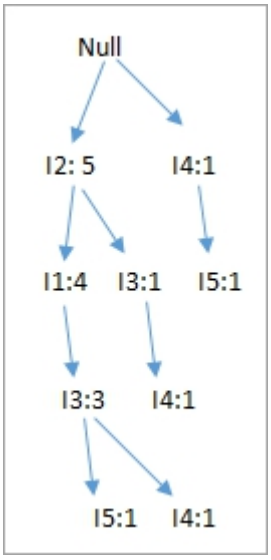
2. Sort the itemset in descending order.

Table 3

Item	Count
I2	5
I1	4
I3	4
I4	4

3. Build FP Tree

1. Considering the root node null.
2. The first scan of Transaction T1: I1, I2, I3 contains three items {I1:1}, {I2:1}, {I3:1}, where I2 is linked as a child to root, I1 is linked to I2 and I3 is linked to I1.
3. T2: I2, I3, I4 contains I2, I3, and I4, where I2 is linked to root, I3 is linked to I2 and I4 is linked to I3. But this branch would share I2 node as common as it is already used in T1.
4. Increment the count of I2 by 1 and I3 is linked as a child to I2, I4 is linked as a child to I3. The count is {I2:2}, {I3:1}, {I4:1}.
5. T3: I4, I5. Similarly, a new branch with I5 is linked to I4 as a child is created.
6. T4: I1, I2, I4. The sequence will be I2, I1, and I4. I2 is already linked to the root node, henceit will be incremented by 1. Similarly I1 will be incremented by 1 as it is already linked with I2 in T1, thus {I2:3}, {I1:2}, {I4:1}.
7. T5:I1, I2, I3, I5. The sequence will be I2, I1, I3, and I5. Thus {I2:4}, {I1:3}, {I3:2}, {I5:1}.
8. T6: I1, I2, I3, I4. The sequence will be I2, I1, I3, and I4. Thus {I2:5}, {I1:4}, {I3:3}, {I4 1}.

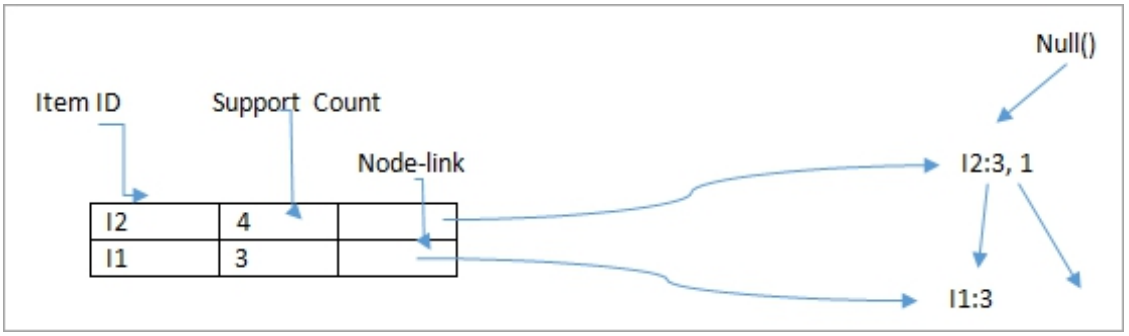


4. Mining of FP-tree is summarized below:

1. The lowest node item I5 is not considered as it does not have a min support count, hence it is deleted.
2. The next lower node is I4. I4 occurs in 2 branches , {I2,I1,I3:,I41},{I2,I3,I4:1}. Therefore considering I4 as suffix the prefix paths will be {I2, I1, I3:1}, {I2, I3: 1}. This forms the conditional pattern base.
3. The conditional pattern base is considered a transaction database, an FP-tree is constructed. This will contain {I2:2, I3:2}, I1 is not considered as it does not meet the min support count.
4. This path will generate all combinations of frequent patterns : {I2,I4:2},{I3,I4:2},{I2,I3,I4:2}
5. For I3, the prefix path would be: {I2,I1:3},{I2:1}, this will generate a 2 node FP-tree : {I2:4, I1:3} and frequent patterns are generated: {I2,I3:4}, {I1:I3:3}, {I2,I1,I3:3}.
6. For I1, the prefix path would be: {I2:4} this will generate a single node FP-tree: {I2:4} and frequent patterns are generated: {I2, I1:4}.

Item	Conditional Pattern Base	Conditional FP-tree	Frequent Patterns Generated
I4	{I2,I1,I3:1},{I2,I3:1}	{I2:2, I3:2}	{I2,I4:2},{I3,I4:2},{I2,I3,I4:2}
I3	{I2,I1:3},{I2:1}	{I2:4, I1:3}	{I2,I3:4}, {I1:I3:3}, {I2,I1,I3:3}
I1	{I2:4}	{I2:4}	{I2,I1:4}

The diagram given below depicts the conditional FP tree associated with the conditional node I3.

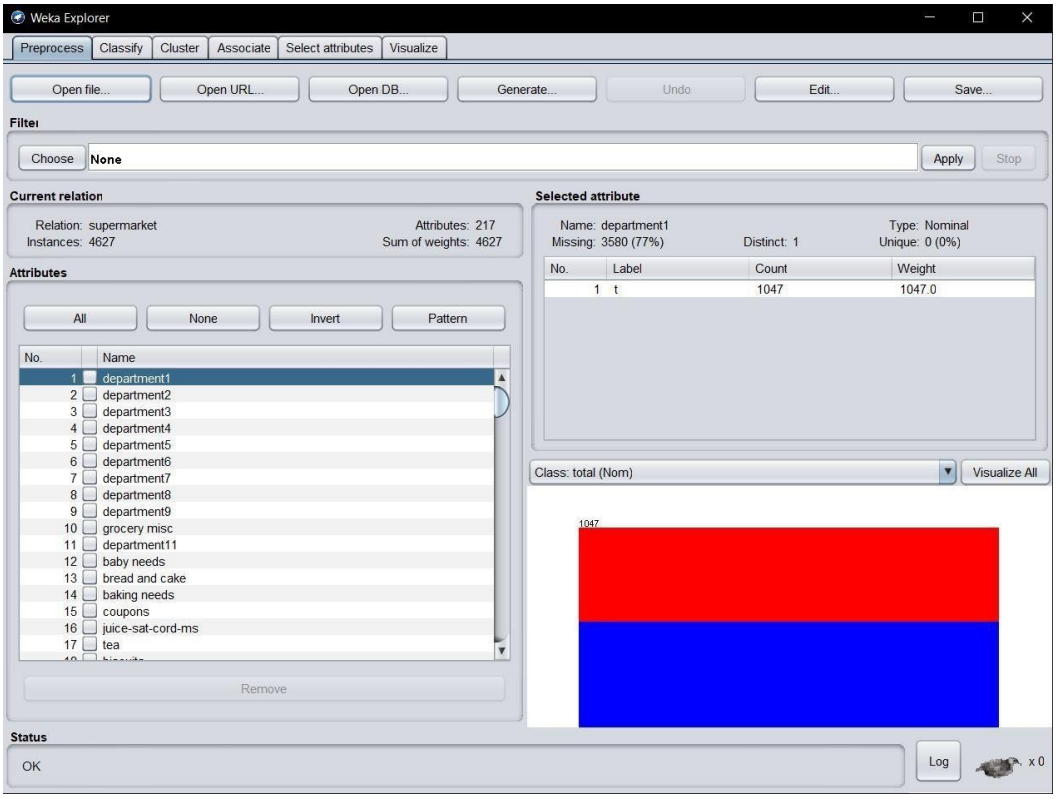


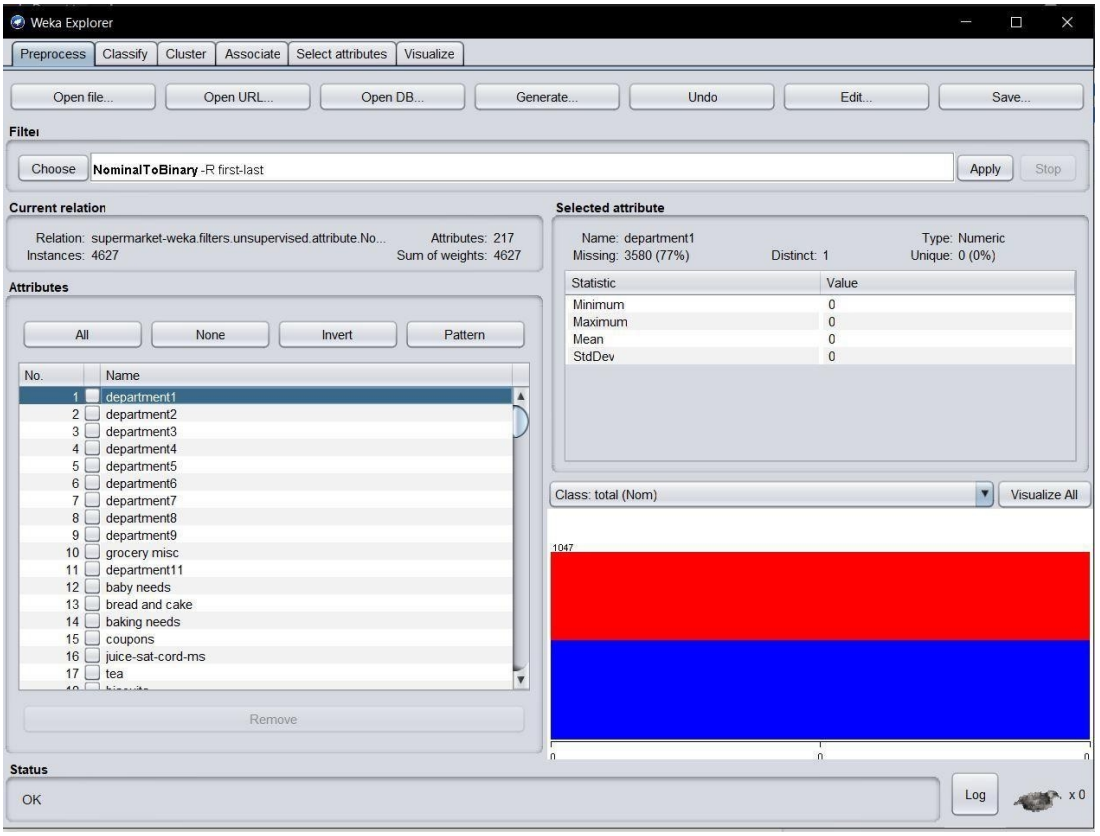
Advantages Of FP Growth Algorithm

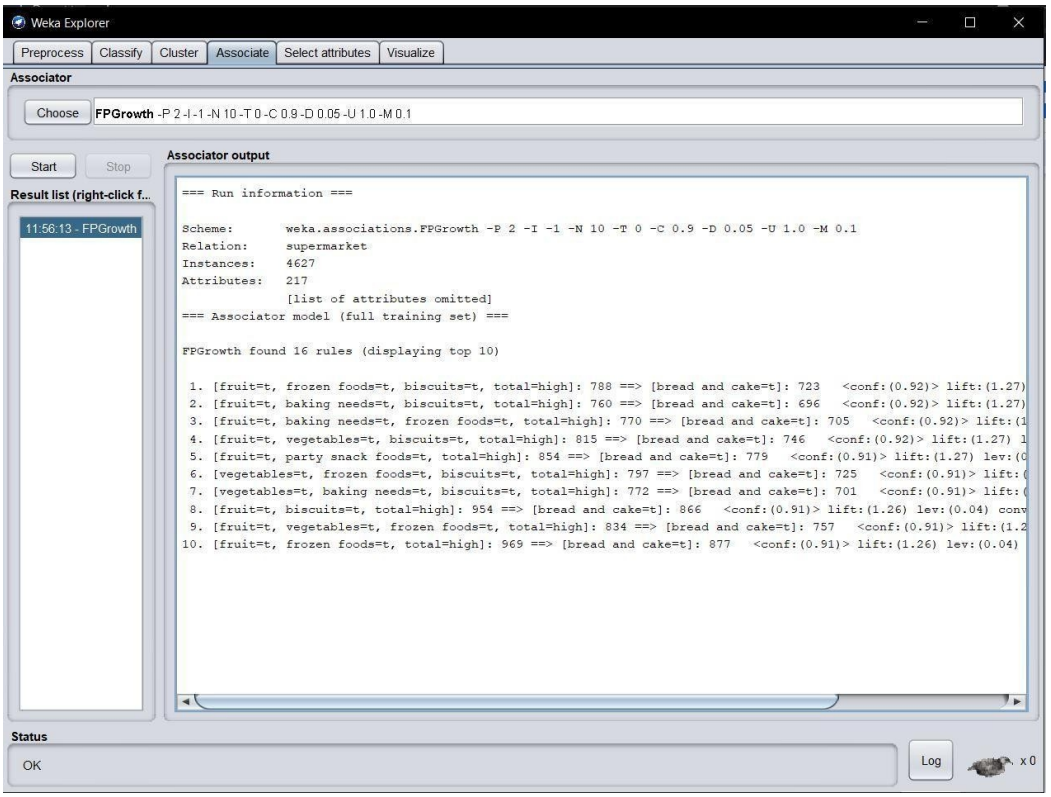
1. This algorithm needs to scan the database only twice when compared to Apriori which scans the transactions for each iteration.
2. The pairing of items is not done in this algorithm and this makes it faster.
3. The database is stored in a compact version in memory.
4. It is efficient and scalable for mining both long and short frequent patterns.

Disadvantages Of FP-Growth Algorithm

1. FP Tree is more cumbersome and difficult to build than Apriori.
2. It may be expensive.
3. When the database is large, the algorithm may not fit in the shared memory.




Weka Explorer
Preprocess
Classify
Cluster
Associate
Select attributes
Visualize
Open file...
Open URL...
Open DB...
Generate...
Undo
Edit...
Save...
Filter
Choose
NominalToBinary -R first-last
Apply
Stop
Current relation
Relation: supermarket-weka.filters.unsupervised.attribute.No...
Attributes: 217
Instances: 4627
Sum of weights: 4627
Selected attribute
Name: department1
Type: Numeric
Missing: 3580 (77%)
Distinct: 1
Unique: 0 (0%)
Statistic
Value
Minimum 0
Maximum 0
Mean 0
StdDev 0
Attributes
All
None
Invert
Pattern
No.
Name
1 department1
2 department2
3 department3
4 department4
5 department5
6 department6
7 department7
8 department8
9 department9
10 grocery misc
11 department11
12 baby needs
13 bread and cake
14 baking needs
15 coupons
16 juice-sat-cord-ms
17 tea
Remove
Class: total (Nom)
Visualize All
1047
Status
OK
Log
x 0


Weka Explorer
Preprocess
Classify
Cluster
Associate
Select attributes
Visualize
Associator
Choose
FPGrowth -P 2 -I -1 -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Start
Stop
Result list (right-click f...
11:56:13 - FPGrowth
Associator output
=== 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)
2. [fruit=t, baking needs=t, biscuits=t, total=high]: 760 ==> [bread and cake=t]: 696 <conf:(0.92)> lift:(1.27)
3. [fruit=t, baking needs=t, frozen foods=t, total=high]: 770 ==> [bread and cake=t]: 705 <conf:(0.92)> lift:(1
4. [fruit=t, vegetables=t, biscuits=t, total=high]: 815 ==> [bread and cake=t]: 746 <conf:(0.92)> lift:(1.27) l
5. [fruit=t, party snack foods=t, total=high]: 854 ==> [bread and cake=t]: 779 <conf:(0.91)> lift:(1.27) lev:(0
6. [vegetables=t, frozen foods=t, biscuits=t, total=high]: 797 ==> [bread and cake=t]: 725 <conf:(0.91)> lift:(
7. [vegetables=t, baking needs=t, biscuits=t, total=high]: 772 ==> [bread and cake=t]: 701 <conf:(0.91)> lift:(
8. [fruit=t, biscuits=t, total=high]: 954 ==> [bread and cake=t]: 866 <conf:(0.91)> lift:(1.26) lev:(0.04) conv
9. [fruit=t, vegetables=t, frozen foods=t, total=high]: 834 ==> [bread and cake=t]: 757 <conf:(0.91)> lift:(1.2
10. [fruit=t, frozen foods=t, total=high]: 969 ==> [bread and cake=t]: 877 <conf:(0.91)> lift:(1.26) lev:(0.04)
Status
OK
Log
x 0

=== 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)

9. [fruit=t, vegetables=t, frozen foods=t, total=high]: 834 ==> [bread and cake=t]: 757 <conf:(0.91)> lift:(1.26) lev:(0.03) conv:(3)

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)

Conclusion: Hence we have studied the implementation of the Fp Growth algorithm successfully.

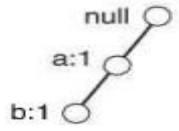
VIVA VOCE

Q1. Define Fp-Growth Algorithm?
Ans: This algorithm is an improvement to the Apriori method. A frequent pattern is generated without the need for candidate generation. FP growth algorithm represents the database in the form of a tree called a frequent pattern tree or FP tree.

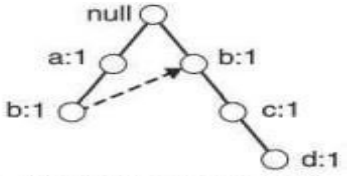
Q2. How to Construct Fp tree?
Ans: To put it simply, an FP-Tree is a compressed representation of the input data. It is constructed by reading the dataset one transaction at a time and mapping each transaction onto a path in the FP-Tree structure. As different transactions can have the same items, their paths may overlap.

Transaction Data Set

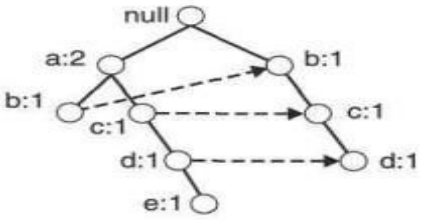
TID	Items
1	{a,b}
2	{b,c,d}
3	{a,c,d,e}
4	{a,d,e}
5	{a,b,c}
6	{a,b,c,d}
7	{a}
8	{a,b,c}
9	{a,b,d}
10	{b,c,e}



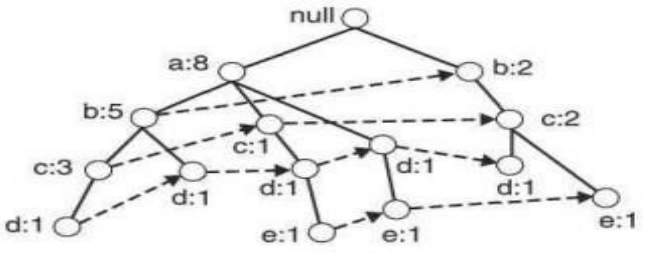
(i) After reading TID=1



(ii) After reading TID=2



(iii) After reading TID=3



(iv) After reading TID=10

Q3. Define Frequent Pattern?
Ans: Frequent Pattern Mining (AKA Association Rule Mining) is an analytical process that finds frequent patterns, associations, or causal structures from data sets found in various kinds of databases such as relational databases, transactional databases, and other data repositories. Givena set of transactions, this process aims to find the rules that enable us to predict the occurrence of aspecific item based on the occurrence of other items in the transaction.