COMP9318 Tutorial 4: Association Rule Mining

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Show that if $A \to B$ does not meet the minconf constraint, $A \to BC$ does not either.

Solution to Q1 I

$$conf(A \to BC) = \frac{supp(ABC)}{supp(A)}$$

 $\leq \frac{supp(AB)}{supp(A)} = conf(A \to B)$

Like Apriori, we can utilize this rule when generating association rules.

Given the following transactional database

1	C, B, H
2	B, F, S
3	A, F, G
4	C, B, H
5	B, F, G
6	B, E, O

- 1. We want to mine all the frequent itemsets in the data using the Apriori algorithm. Assume the minimum support is 30%. (You need to give the set of frequent itemsets in L_1, L_2, \ldots , candidate itemsets in C_2, C_3, \ldots).
- Find all the association rules that involves only B, C, H (in either left or right hand side of the rule). The minimum confidence is 70%.

Solution to Q2 I

1. Apriori

- 1.1 minsup = $30\% \times 6 = 1.8$. In other words, the support of a frequent itemset must be no less than 2.
- 1.2 $C_1 = \{A, B, C, E, F, G, H, O, S\}$, scanning the DB and collect the supports as

A	В	С	Е	F	G	Н	0	S
1	5	2	1	3	2	2	1	1

Therefore, $L_1 = \{ B, C, F, G, H \}.$

1.3 C_2 is generated from L_1 by enumerating all pairs as $\{BC, BF, BG, BH, CF, CG, CH, FG, FH, GH\}$. Scan the DB and collect the supports as (you may want to sort items in each transaction and remove non-frequent items from the DB)

BC	BF	BG	ВН	CF	CG	СН	FG	FH	GH
2	2	1	2	0	0	2	2	0	0

Therefore, $L_2 = \{BC, BF, BH, CH, FG\}.$

1.4 C_3 is generated from L_2 by a special enumeration-and-pruning procedure. The result is $\{BCH\}$. Scan the DB and collect the support as

Therefore, $L_3 = \{BCH\}.$

- 1.5 C_4 will be the empty set, therefore we stop here.
- 2. We list the frequent itemsets related to B, C, and H below:

Solution to Q2 II

В	С	Н	ВС	ВН	СН	ВСН
5	2	2	2	2	2	2

- 2.1 For BC, we need to consider candidate rules: $B \to C$, and $C \to B$. The former has confidence $\frac{supp(BC)}{supp(B)} = 40\%$ and does not meet the minconf requirement. The latter rule has confidence $\frac{supp(BC)}{supp(C)} = 100\%$ and it is qualified.
- 2.2 It is easy to see that any rule in the form of $B \to \dots$ will not meet the minconf requirement for the dataset. Therefore, we can repeat the above procedure and find the following rules:
 - ► *H* → *B* (100%)
 - ► C → H (100%)
 - \rightarrow $H \rightarrow C (100\%)$
 - \triangleright BC \rightarrow H (100%)
 - \triangleright BH \rightarrow C (100%)
 - ightharpoonup CH
 ightharpoonup B (100%)
 - ightharpoonup CH oup B (100%)
 - C → BH (100%)
 - ► *H* → *BC* (100%)

Q3 I

Compute the frequent itemset of for the data in $\ensuremath{\mathsf{Q2}}$ using the FP-growth algorithm.

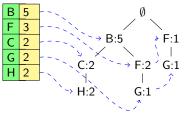
Solution to Q3 I

 Similar to the first step in Apriori, count the support of all items and normalize the original transaction db as follows: (by removing non-frequent items and sort items in the decreasing order of their support)

					_	DR	
Ord	der					1 2	B, C, H B, F
B 5	F 3	C 2	G 2	H 2		3 4	F, G B, C, H
						5 6	B, F, G B

We can output all frequent item: B, C, F, G, H.

2. Construct the FP-tree as:



Solution to Q3 II

3. H's conditional pattern base is:

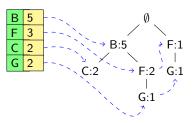
All of the items are frequent, and thus we can output: BH, CH. Construct the H-conditional FP-tree as



Since it is a single-path tree, we directly output all its combinations: BCH.

4. We track back and can now safely remove all H nodes from the initial FP-tree, as shown below.

Solution to Q3 III



We now find G's conditional pattern base as:

BF: 1 F: 1

Only F is frequent. We output FG. It is clear that we can stop.

5. We track back and can now safely remove all G nodes from the FP-tree, and then process C's conditional pattern base:

B: 2

B is frequent, output BC, and we can stop here.

6. We track back and can now safely remove all C nodes from the FP-tree, and then process F's conditional pattern base:

Solution to Q3 IV

B : 2

B is frequent, output BF, and we can stop here.

7. Since we are left with one item (B) only, we can output stop the whole mining process.