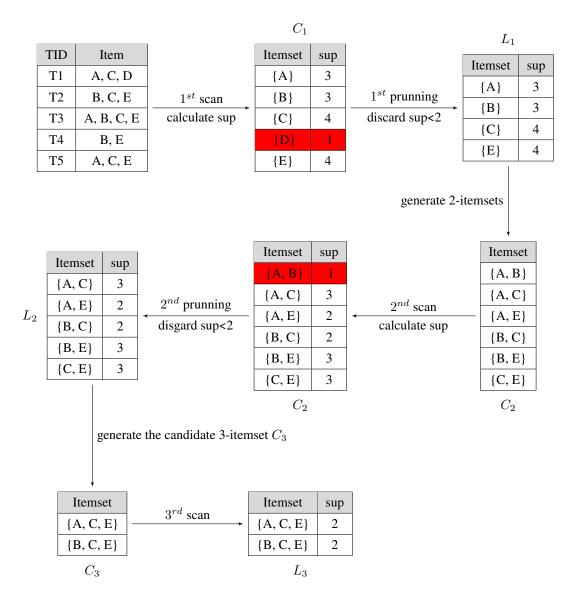
## **DSAA 5002 - HW1**

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# **Q1** [15 Marks]

Given the transaction database below, set the minimum support count to 2 and the minimum confidence level to 60% to find the strong association rule. Generate the set  $C_3$  of the candidate 3-itemset, using prunning on Apriori principle.

### **Solution:**



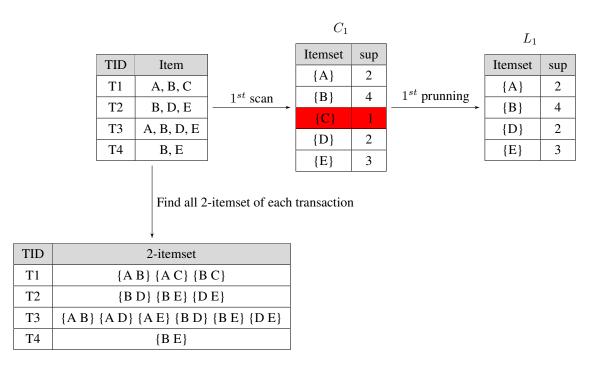
Thus we get the candidate 3-itemset  $C_3$ .

# **Q2** [15 Marks]

Reducing the transactions using dynamic hashing and prunning(DHP) algorithm. Set the minimum support count to 2.

Hash function bucket #=  $h({xy}) = ((order of x) * 10 + (order of y))\%7$ 

## **Solution**



Because we have:

• Items = A, B, C, D, E,

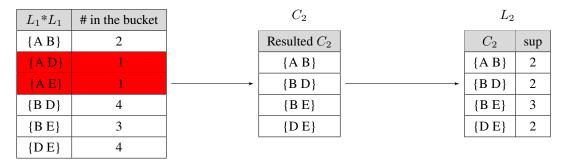
• Order = 1, 2, 3, 4, 5

• Hash function :  $h(\lbrace xy \rbrace) = ((\text{order of } x) * 10 + (\text{order of } y))\%7$ 

Thus we have the hash table below:

bucket	0	1	2	3	4	5	6
count	1	1	1	4	3	2	1
2-itemset	{A D}	{A E}	{B C}	{B D}	{BE}	{AB}	{A C}
				{DE}	{BE}	{AB}	
				{B D}	{BE}		
				{DE}			

Let  $L_1*L_1$  to generate a 2-itemset table, and choose the itemsets where the number of content in its bucket is above the minimum support.



Because if an item occurs in a frequent (k+1)-itemset, it must occur in at least k candidate k-itemsets.

TID	Item	2-itemset occurs			
T1	A, B, C	{A B}	Disgard	TID	Item
T2	B, D, E	{BD} {BE} {DE}	Keep {B D E}	 T2	B, D, E
Т3	A, B, D, E	{AB} {BD} {BE} {DE}	Keep {B D E}	Т3	B, D, E
T4	B, E	{EE}	Disacrd		

Thus we have reduced the transactions.

## **Q3** [35 Marks]

An itemset X is said to be a frequent itemset if the frequency count of X is at least a given support threshold.

An itemset Y is a proper super-itemset of X if  $X \subset Y$  and  $X \neq Y$ .

An itemset X is said to be a closed frequent itemset if (1) X is frequent and (2) there exists no proper super-itemset Y of X such that Y is frequent and Y has the same frequency count as X.

An itemset X is said to be a maximal frequent itemset if (1) X is frequent and (2) there exists no proper superitemset Y of X such that Y is frequent.

Let  $F_c$  be the set of (traditional) frequent itemsets each of which is associated with a frequency in the dataset.

For example, if there are three frequent itemsets,  $\{I_1\}$  with frequency 4,  $\{I_2\}$  with frequency 5, and  $\{I_1, I_2\}$  with frequency 3,  $F = \{\{I_1\}, \{I_2\}, \{I_2, I_2\}\}$  and  $F_c = \{\{\{I_1\}, \{I_2\}, \{I_2\}, \{I_2\}, \{I_3\}, \{I_4\}, \{I_4\},$ 

Similarly, let C be the set of closed frequent itemsets without specifying the frequency of itemsets.

Let  $C_c$  be the set of closed frequent itemsets each of which is associated with a frequency of itemsets.

Let M be the set of maximal frequent itemsets without specifying the frequency of itemsets.

Ler  $M_c$  be the set of maximal frequent itemsets each of which is associated with a frequency in the dataset.

The following shows six transactions with four items. Each row corresponds to a transaction where 1 corresponds to a presence of an item and 0 corresponds to an absence.

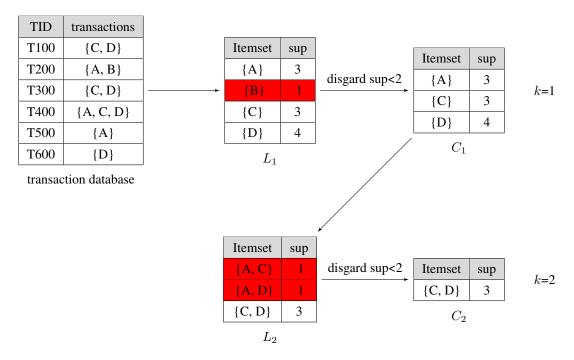
Α	В	C	D
0	0	1	1
1	1	0	0
0	0	1	1
1	0	1	1
1	0	0	0
0	0	0	1

Suppose that the support threshold is 2.

- (a) (i) What is  $F_C$ ?
- (ii) What is  $C_c$ ?
- (iii) What is  $M_c$ ? (5 Marks)
- (b) (i) What is the advantages and the disadvantages of using closed frequent itemsets compared with traditional frequent itemsets? (5 Marks)
- (ii) What are the advantages and the disadvantages of using closed frequent itemsets compared with maximal frequent itemsets? (5 Marks)
- (c) Please adapt algorithm FP-growth with the use of the FP-tree to find all closed frequent item set. Please write down how to adapt algorithm FP-growth and illustrate the adapted algorithm with the above example. (20 Marks)

### **Solution**

(a) According to the topic, we have the following transaction database. And we generate all the k-itemsets which might be frequent itemsets.



i: We have  $F_c = \{ < \{A\}, 3>, < \{C\}, 3>, < \{D\}, 4>, < \{C, D\}, 3> \}$ 

ii: We have 
$$C_c = \{ \langle \{A\}, 3 \rangle, \langle \{D\}, 4 \rangle, \langle \{C, D\}, 3 \rangle \}$$

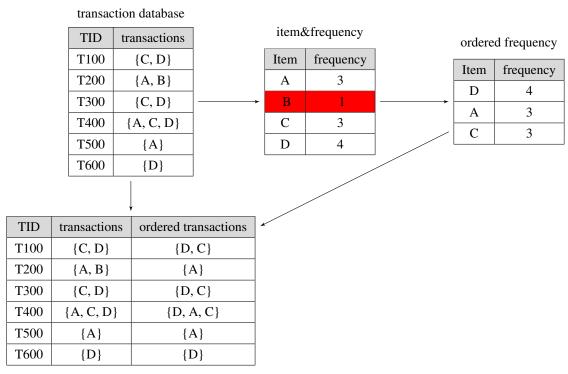
iii: We have 
$$M_c = \{ \langle \{A\}, 3 \rangle, \langle \{C, D\}, 3 \rangle \}$$

#### (b) i:

- Advantages: Compared with traditional frequent itemsets, inclosed itemsets are eliminated, which reduces
  the number of itemsets. And because a lot of frequent itemsets can be considered as subsets of a closed
  super-itemset, it does not lose much information.
- Disadvantages: Finding frequent closed itemsets need more computation, increasing the time complexity.

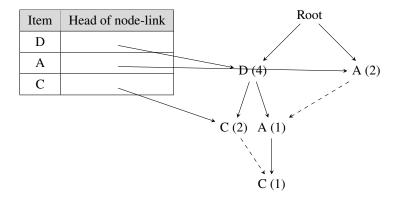
### ii:

- Advantages: Closed itemsets do not lose much information because the closed super-itemsets have same frequency as the sub-itemsets. But maximal frequent itemsets may lose some information.
- Disadvantages: Maximal frequent itemsets are more efficient than closed itemsets, because it does not need to check the frequency of the super-itemsets.
- (c) Generate a FP-tree. Firstly, deduce the ordered frequent items.



ordered transaction database

Then we construct the FP-tree from the above data.

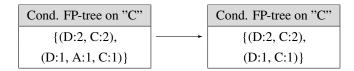


Notice that if X is a frequent itemset but not closed, then there exists a super-itemset Y of X such that Y is frequent and Y has the same frequency count as X. Let Z = Y - X, (Z is not empty), the for every path lying X, Z must lie in the path, too.

So when we construct the FP-conditional tree for a item, we could check if there exists a common item in all the paths, if not, the item is a closed frequent itemset.

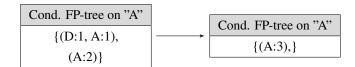
Construct the FP-conditional tree for C, A, D.

for C



Because for every path lying C, D also lies in the path, so C is not a closed frequent itemset. But  $\{D,C\}$  is a closed frequent itemset.

 $\quad \text{for } A$ 



Because there is no other itemsets lies in the right path lying A, so A is a closed frequent itemset.

 ${\bf for}\ D$ 



Because there is a path only lying D, so D is a closed frequent itemset.

Thus we have 
$$C_c = \{ \langle \{D, C\}, 3 \rangle, \langle \{A\}, 3 \rangle, \langle \{D\}, 4 \rangle \}.$$

# **Q4** [35 Marks]

A GSP example: Suppose now we have 5 events: 'Upload Songs', 'Add Tags', 'Share', 'Listen' and 'Comment'. Let min-support be 40%. The sequence database of a Music Platform is shown in following table:

Object	Sequence
A	<{'Upload Songs', 'Add Tags'}>
В	<{'Upload Songs', 'Share'}>
С	<{'Upload Songs'}, {'Share', 'Listen'}>
D	<{'Upload Songs'}, {'Upload Songs', 'Add Tags'}, {'Listen'}>
Е	<{'Listen'}, {'Add Tags', 'Comment'}, {'Share', 'Listen'}>

Please answer the following questions:

- (a) Make the first pass over the sequence database to yield all the 1-element **frequent** sequences and what is the corresponding support? **5 Marks**
- (b) Based on (a), do the 2-sequences Candidate Generation and Candidate Pruning. 10 Marks
- (c) What is the **frequent** 2-sequences based on the result of (b)? **5 Marks**
- (d) Based on (c), do the 3-sequences Candidate Generation and Candidate Pruning. When a sequence should be pruned, you need to explain why. **10 Marks**
- (e) What is the frequent 3-sequences based on the result of (d)? Please calculate the support. 5 Marks

**Remember:** For frequent k-sequences, the support >= min-support

#### **Solution**

For easier reading, we denote 'Upload Songs', 'Add Tags', 'Share', 'Listen' and 'Comment' by U, A, S, L and C respectively. And if there are 2 items in 1 set, we have arranged it in alphabetical order by the first letter. Thus we have:

Object	Sequence
A	<{'Upload Songs', 'Add Tags'}>
В	<{'Upload Songs', 'Share'}>
C	<{'Upload Songs'}, {'Share', 'Listen'}>
D	<{'Upload Songs'}, {'Upload Songs', 'Add Tags'}, {'Listen'}>
Е	<{'Listen'}, {'Add Tags', 'Comment'}, {'Share', 'Listen'}>

Object	Sequence		
A	<{A, U}>		
В	<{S, U}>		
С	<{U}, {L, S}>		
D	<{U}, {A, U}, {L}>		
Е	<{L}, {A, C}, {L, S}>		

(a) Candidate 1-sequences are:

According to the database above, we have:

Sequence	Sup			
-	60%		Sequence	Sup
<{A}>	00%		<{A}>	60%
<{C}>	20%	disgard sup<40%		60%
<{L}>	60%		<{L}>	00%
· , ,	60%		<{S}>	60%
<{S}>	00%		<{U}>	80%
<{U}>	80%		(-)	

The 1-element frequent sequences and the corresponding support are:

- <{'Add Tags'}> (support=60%)
- <{'Listen'}> (support=60%)
- <{'Share'}> (support=60%)
- <{'Upload Songs'}> (support=80%)
- (b) Base case (k=2): Merging two frequent 1-sequences  $<\{i_1\}>$  and  $<\{i_2\}>$  will produce two candidate 2-sequences:  $<\{i_1\}$   $\{i_2\}>$  and  $<\{i_1,i_2\}>$

Candidate 2-sequences are:

$$\{A, L\}$$
>,  $\{A, S\}$ >,  $\{A, U\}$ >,  $\{L, S\}$ >,  $\{L, U\}$ >,  $\{S, U\}$ >,

$$\{L\}, \{A\}>, \{L\}, \{L\}>, \{L\}, \{S\}>, \{L\}, \{U\}>,$$

$$\{U\}, \{A\} >, \{U\}, \{L\} >, \{U\}, \{S\} >, \{U\}, \{U\} >$$

All the 1-sequences we generate 2-sequences from are frequent. So after candidate prunning, the 2-sequences should remain the same.

(c) After candidate elimination, frequent 2-sequences are:

$$<{A, U}> (support=40\%),$$

$$\{L, S\} > (support=40\%),$$

$$\{A\}, \{L\} > (support = 40\%),$$

$$\{U\}, \{L\} > (support=40\%)$$

(d) Generate 3-sequences from the remaining 2-sequences, 3-sequences are:

$$\{A, U\}, \{L\} > (generate from \{A, U\} > and \{U\}, \{L\} > or from \{A, U\} > and \{A\}, \{L\} > ),$$

 $\{A\}, \{L, S\} > (generate from < \{A\}, \{L\} > and < \{L, S\}),$ 

 $\{U\}, \{L, S\} > (generate from < \{U\}, \{L\} > and < \{L, S\})$ 

Pruning:

 $\{A\}, \{L, S\}$  should be pruned because one 2-subsequence  $\{A\}, \{S\}$  is not frequent.

 $\{U\}, \{L, S\}$ > should be pruned because one 2-subsequence  $\{U\}, \{S\}$ > is not frequent.

(e)  $\{A, U\}, \{L\} > (support=20\% < 40\%, should be eliminated)$ 

Thus, there is no frequent 3-sequence.