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UCLA CS 145, Fall 2018, Homework 5

1. Frequent Pattern Mining for Set Data

1a. Find all the frequent patterns using Apriori Algorithm. Details of the procedure are expected.

C_1

Itemset	sup
{a}	6
{b}	8
{c}	6
{d}	4
{e}	2
{i}	1
{j}	1
{k}	1

L_1

Itemset	sup
{a}	6
{b}	8
{c}	6
{d}	4
{e}	2

C_2

Itemset	sup
{a,b}	4
{a,c}	4
{a,d}	2
{a,e}	2
{b,c}	4
{b,d}	4
{b,e}	2
{c,d}	1
{c,e}	1
{d,e}	0

L_2

Itemset	sup
{a,b}	4
{a,c}	4
{a,d}	2
{a,e}	2
{b,c}	4
{b,d}	4
{b,e}	2

C_3

Itemset	sup
{a,b,c}	2
{a,b,d}	2
{a,b,e}	2
{a,c,d}	1
{a,c,e}	1
{a,d,e}	0
{b,c,d}	1
{b,c,e}	1
{b,d,e}	0

L_3

Itemset	sup
{a,b,c}	2
{a,b,d}	2
{a,b,e}	2

C_4

Itemset	sup
{a,b,c,d}	1
{a,b,c,e}	1
{a,b,d,e}	0

L_4 : $\emptyset$

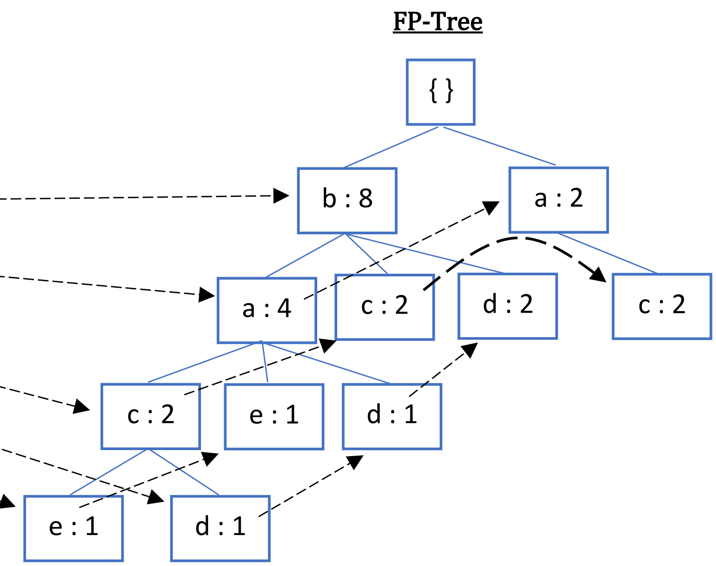
1b. Construct and draw the FP-tree of the transaction database.

Frequent 1-itemset:

Item	Frequency
{a}	6
{b}	8
{c}	6
{d}	4
{e}	2
{i}	1
{j}	1
{k}	1

Sort Frequent 1-itemset, prune for min_support = 2:

Item	Frequency
{b}	8
{a}	6
{c}	6
{d}	4
{e}	2



Scan database again:

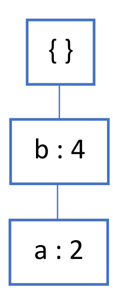
TID	Items	Frequent Items (Ordered)
1	{b,c,j}	{b,c}
2	{a,b,d}	{b,a,d}
3	{a,c}	{a,c}
4	{b,d}	{b,d}
5	{a,b,c,e}	{b,a,c,e}
6	{b,c,k}	{b,c}
7	{a,c}	{a,c}
8	{a,b,e,i}	{b,a,e}
9	{b,d}	{b,d}
10	{a,b,c,d}	{b,a,c,d}

1c. For the item d, show its conditional pattern base and conditional FP-tree.

Conditional pattern base of item **d: {b:2, bac: 1, ba: 1}**

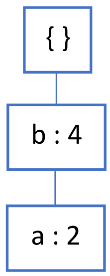
Using min_support = 2, **b:2, bac: 1, ba: 1** → **b:4, ba:2**

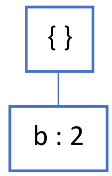
d-conditional FP-tree:



1d. Find frequent patterns based on d's conditional FP-tree.

d-conditional FP-tree: **ad-conditional FP-tree:**





Frequent patterns with item d:

d: 4

bd: 4, ad: 2

bad: 2

2. Apriori for Yelp

Command output:

```
C:\Users\kyles\Desktop\CS145\hw5

λ python2 apriori.py

min_support: 50 min_conf: 0.25

item: "Wicked Spoon","Holsteins Shakes & Buns" , 51.000

item: "Wicked Spoon","Secret Pizza" , 52.000

item: "Wicked Spoon","Earl of Sandwich" , 52.000

item: "The Cosmopolitan of Las Vegas","Wicked Spoon" , 54.000

item: "Mon Ami Gabi","Wicked Spoon" , 57.000

item: "Bacchanal Buffet","Wicked Spoon" , 63.000


------------------------ RULES:

Rule: "Secret Pizza" ==> "Wicked Spoon" , 0.256

Rule: "The Cosmopolitan of Las Vegas" ==> "Wicked Spoon" , 0.277

Rule: "Holsteins Shakes & Buns" ==> "Wicked Spoon" , 0.315

66.7090001106 sec
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What patterns and rules do you see?

I got the following frequent itemsets:

{"Wicked Spoon", "Holsteins Shakes & Buns"}, {"Wicked Spoon", "Secret Pizza"}, {"Wicked Spoon", "Earl of Sandwich"}, {"The Cosmopolitan of Las Vegas", "Wicked Spoon"}, {"Mon Ami Gabi", "Wicked Spoon"} and {"Bacchanal Buffet", "Wicked Spoon"}

I got the following association rules:

"Secret Pizza" ➔ "Wicked Spoon" with confidence 0.256

"The Cosmopolitan of Las Vegas" ➔ "Wicked Spoon" with confidence 0.277

"Holsteins Shakes & Buns" ➔ "Wicked Spoon" with confidence 0.315

Where are these businesses located?

The businesses are restaurants located at the Las Vegas strip, specifically near or in the hotel "The Cosmopolitan of Las Vegas". The "Wicked Spoon" which appears in all the frequent itemsets found is a popular high-end buffet located in "The Cosmopolitan of Las Vegas".

What do these results mean?

These results indicate that visitors of the restaurant "Wicked Spoon" frequently also visit some of the other popular restaurants in its vicinity. This may be because most of these visitors are guests of "The Cosmopolitan of Las Vegas" based on its relatively strong association rule with the "Wicked Spoon".

3. Correlation Analysis

3a. Calculate the confidence, lift, and all_confidence between buying beer and buying nuts.

Confidence:

buys beer => buys nuts	150/500 = 30.0%
buys beer => not buys nuts	350/500 = 70.0%
not buys beer => buys nuts	700/9500 = 7.4%
not buys beer => not buys nuts	8800/9500 = 92.6%

Lift:

lift(buys beer, buys nuts) = (150/10000) / [(500/10000) * (850/10000)] = 3.53

lift(buys beer, not buys nuts) = (350/10000) / [(500/10000) * (9150/10000)] = 0.77

lift(not buys beer, buys nuts) = (700/10000) / [(9500/10000) * (850/10000)] = 0.87

lift(not buys beer, not buys nuts) = (8800/10000) / [(9500/10000) * (9150/10000)] = 1.01

All_confidence:

all_conf(buys beer, buys nuts) = min{150/500 = 30.0%, 150/850 = 17.6%} = 17.6%

all_conf(buys beer, not buys nuts) = min{350/500 = 70.0%, 350/9150 = 3.8%} = 3.8%

all_conf(not buys beer, buys nuts) = min{700/9500 = 7.4%, 700/850 = 82.4%} = 7.4%

all_conf(not buys beer, not buys nuts) = min{8800/9500 = 92.6%, 8800/9150 = 96.2%} = 92.6%

3b. What are your conclusions of the relationship between buying beer and buying nuts, based on the above measures?

We can conclude that people are likely to buy beer and nuts together. From the data, there is relatively high confidence for both *buys beer => buys nuts* and the inverse *not buys beer => not buys nuts*. However, we also see that there is high confidence for *buys beer => not buys nuts* at 70% but this could be a misleadingly strong association rule since the overall probability of people who do not buy nuts is 9150/10000 = 91.5% >> 70%.

This conclusion is further supported by the lift values we calculated, where only *lift(buys beer, buys nuts)* and *lift(not buys beer, not buys nuts)* have values > 1 which indicate positive correlation between buying beer and buying nuts as well as the inverse (not buying beer and not buying nuts). In addition, the all_confidence values calculated also support this with the two highest values coming from *all_conf(buys beer, buys nuts)* and *all_conf(not buys beer, not buys nuts)* at 17.6% and 92.6% respectively.

4. Sequential Pattern Mining (GSP Algorithm)

4a. For a sequence s = <ab(cd)(ef)>, how many events or elements does it contain? What is the length of s? How many non-empty subsequences does s contain?

Number of events/elements = 4

Length of s = 6

Let k be the length of a subsequence, then we have:

k	Number of length-k subsequences
1	$\binom{6}{1} = 6$
2	$\binom{6}{2} = 15$
3	$\binom{6}{3} = 20$
4	$\binom{6}{4} = 15$
5	$\binom{6}{5} = 6$
6	$\binom{6}{6} = 1$

Number of non-empty subsequences = 63

4b. Suppose we have L_3 = {<(ac)e>, <b(cd)>, <bce>, <a(cd)>, <(ab)d>, <(ab)c>} as the frequent 3-sequences, write down all the candidate 4-sequences C_4 with the details of the join and pruning steps.

Join step:

<(ac)e> can join with no other 3-sequence

<b(cd)> can join with no other 3-sequence

<bce> can join with no other 3-sequence

<a(cd)> can join with no other 3-sequence

<(ab)d> can join with no other 3-sequence

<(ab)c> join <b(cd)> = <(ab)(cd)>

<(ab)c> join <bce> = <(ab)ce>

Hence, we get *C_4 = {<(ab)(cd)>, <(ab)ce>}*

Prune step:

Length 3 subsequences of <(ab)(cd)> = <(ab)c>, <(ab)d>, <a(cd)>, <b(cd)>

All subsequences are in L_3.

Length 3 subsequences of <(ab)ce> = <(ab)c>, <(ab)e>, <ace>, <bce>

<(ab)e> is not in L_3, so we prune <(ab)ce> from C_4.

Hence, L_4 = {<(ab)(cd)>}.