

CS5228: Knowledge Discovery and Data Mining

Tutorial 4 — Association Rule Mining

Question 1

$$\text{support}(\{A\} \rightarrow \{B\}) = \text{support}(\{A, B\})$$

$$\text{support}(\{B\} \rightarrow \{A\}) =$$

tid	transactions
1	B, C, D, E, F
2	E, C
3	D, B, D, A
4	G, E, H, C
5	H, A, G, D, B
6	B, E, G
7	B, A, D
8	A, D, B, C

(a) Calculate the following values:

- $\text{support}(\{A\})$, $\text{support}(\{B\})$, $\text{support}(\{A, B\})$
- $\text{support}(\{A\} \rightarrow \{B\})$, $\text{support}(\{B\} \rightarrow \{A\})$
- $\text{confidence}(\{A\} \rightarrow \{B\})$, $\text{confidence}(\{B\} \rightarrow \{A\})$
- $\text{lift}(\{A\} \rightarrow \{B\})$, $\text{lift}(\{B\} \rightarrow \{A\})$

$$\text{support}(\{A\}) = \frac{1}{2} \quad \text{support}(\{A\} \rightarrow \{B\}) = \frac{1}{2} \quad \text{confidence}(\{A\} \rightarrow \{B\}) = 1 = \frac{4}{4} \quad \text{lift}(\{A\} \rightarrow \{B\}) = \frac{4}{3}$$

$$\text{support}(\{B\}) = \frac{3}{4} \quad \text{support}(\{B\} \rightarrow \{A\}) = \frac{1}{2} \quad \text{confidence}(\{B\} \rightarrow \{A\}) = \frac{2}{3} \quad \text{lift}(\{B\} \rightarrow \{A\}) = \frac{4}{3}$$

$$\text{support}(\{A, B\}) = \frac{1}{2}$$

$$\frac{\text{support}(\{A, B\})}{\text{support}(\{A\})} = \frac{\frac{1}{2}}{\frac{1}{2}} = 1 = \frac{4}{4}$$

Question 1

(a) Calculate the following values:

- $support(\{A\}), support(\{B\})$ $support(\{A, B\})$
- $support(\{A\} \rightarrow \{B\}), support(\{B\} \rightarrow \{A\})$
- $confidence(\{A\} \rightarrow \{B\}), confidence(\{B\} \rightarrow \{A\})$
- $lift(\{A\} \rightarrow \{B\}), lift(\{B\} \rightarrow \{A\})$

tid	transactions
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7	B, A, D
8	A, D, B, C

$support(\{A\}) = 1/2$ $support(\{A\} \rightarrow \{B\}) = 1/2$ $confidence(\{A\} \rightarrow \{B\}) = 1.0$ $lift(\{A\} \rightarrow \{B\}) = 4/3$

$support(\{B\}) = 3/4$ $support(\{B\} \rightarrow \{A\}) = 1/2$ $confidence(\{B\} \rightarrow \{A\}) = 2/3$ $lift(\{B\} \rightarrow \{A\}) = 4/3$

$support(\{A, B\}) = 1/2$

Question 1

- (b) **Connections between metrics.** In a) we calculated the *support*, *confidence*, and *lift* for different itemsets and association rules. However, we do not need to calculate all values individually. Based on the definitions of the metrics, which calculations can we skip?

Question 1

- (b) **Connections between metrics.** In a) we calculated the *support*, *confidence*, and *lift* for different itemsets and association rules. However, we do not need to calculate all values individually. Based on the definitions of the metrics, which calculations can we skip?

Solution

- $\text{support}(X \rightarrow Y) = \text{support}(X \cup Y)$
 - $\text{support}(X \rightarrow Y) = \text{support}(Y \rightarrow X)$
 - $\text{lift}(X \rightarrow Y) = \text{lift}(Y \rightarrow X)$
- } No need to calculate $\text{support}(\{A\} \rightarrow \{B\})$ and $\text{support}(\{B\} \rightarrow \{A\})$ if we already have $\text{support}(\{A, B\})$ (or vice versa)

Question 1

- (c) **"Usefulness" of different metrics.** What makes *support* and *confidence* more useful compared to other metrics such as *lift*, *conviction*, *collective strength*, *leverage*?

Question 1

- (c) ”Usefulness” of different metrics. What makes *support* and *confidence* more useful compared to other metrics such as *lift*, *conviction*, *collective strength*, *leverage*?

Solution

- Only support and confidence are anti-monotone which facilitate the Apriori algorithm(s)
- lift, conviction, collective strength, leverage etc. are all very useful metric but can only be calculated for the association rules after running the Apriori algorithm

Question 1

- (d) **"Importance" of different metrics.** What makes an association rule particularly interesting? A high *support*, high *confidence*, high *lift*, high *conviction*, etc.?

Question 1

- (d) **"Importance" of different metrics.** What makes an association rule particularly interesting? A high *support*, high *confidence*, high *lift*, high *conviction*, etc.?

Solution

- No metric is intrinsically better in describing what makes a rule interesting
- Different metrics look at different aspects of a rule
- Which aspect is more/most relevant depends on the data and the task

Question 2

tid	transactions
1	cough, fatigue, COVID-19-negative
2	anosmia, cough, fatigue, COVID-19-positive
3	anosmia, fatigue, headache, heart palpitations, COVID-19-positive
4	cough, fatigue, headache, COVID-19-negative
5	headache, stomach pain, COVID-19-negative
6	cough, heart palpitations, COVID-19-negative
7	anosmia, headache, stomach pain, COVID-19-positive
...	...

- (a) **Choice of *minsup* and *minconf*.** How might the setup and the task above affect which values for *minsup* and *minconf* are meaningful? Hint: Assume that large majority of the COVID-19 test results in our dataset are negative.

$\{ \dots \} \rightarrow \{ \text{cough} \}$
= ~~$\{ \text{cough} \rightarrow \text{fever} \}$~~
should be low

Question 2

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4	cough, fatigue, headache, COVID-19-negative
5	headache, stomach pain, COVID-19-negative
6	cough, heart palpitations, COVID-19-negative
7	anosmia, headache, stomach pain, COVID-19-positive
...	...

- (a) **Choice of *minsup* and *minconf*.** How might the setup and the task above affect which values for *minsup* and *minconf* are meaningful? Hint: Assume that large majority of the COVID-19 test results in our dataset are negative.

Solution

- Any rule of the form $X \rightarrow \{\text{COVID-19-positive}\}$ won't have high support
- We cannot afford to set *minsup* to high, or we won't get relevant rules

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5	headache, stomach pain, COVID-19-negative
6	cough, heart palpitations, COVID-19-negative
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...	...

- (b) **Tweaking the dataset.** Can we simplify this task by only considering those transactions that contain COVID-19-positive, and remove all transactions that contain COVID-19-negative?

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...	...

- (b) **Tweaking the dataset.** Can we simplify this task by only considering those transactions that contain COVID-19-positive, and remove all transactions that contain COVID-19-negative?

Solution: Not a good idea

- Example: $\{\text{cough}\} \rightarrow \{\text{COVID-19-positive}\}$ might have a high support, but "cough" is not truly a good indicator if "cough" is also very common with negative test results
- Sidenote: $\text{confidence}(X \rightarrow \{\text{COVID-19-positive}\}) = 1.0$ for all itemsets X

Question 3

3. **Complexity Analysis.** The most naive approach for mining association rules would be to generate all possible rules and check if their support and confidence exceeds the specified thresholds *minsup* and *minconf*. In the lecture, you have learned that, given d unique items in a dataset of transactions, there are $3^d - 2^{d+1} + 1$ possible rules.

Proof that d unique items result in $3^d - 2^{d+1} + 1$ possible rules! (Hint: Write out all possible rules for $d = 2, 3, 4, \dots$ items; you should quickly spot the pattern that will allow you to validate the formula).

$$\{A, B, C, D\}$$

$d=4$

$$A \rightarrow B$$

$$A \rightarrow C$$

$$A \rightarrow BC$$

$$C \rightarrow A$$

;

$$AB \rightarrow \{\}$$

$$AC \rightarrow \{\}$$

$$A \subset D$$

$$ABC \rightarrow D$$

$$ACD \rightarrow B$$

;

Question 3

Solution:

- Each item has 3 possibilities to appear in a rule: on the left side of the rule, on the right side of the rule, or not at all. That reflects the 3^d possibilities.
- However, these 3^d rules include invalid ones where the left and/or right side of the rule is empty. Of the 3^d rules, there are 2^d where the left side is empty, and 2^d where the right side is empty. We have to subtract these invalid combinations, and $2^d + 2^d = 2^{d+1}$.
- Note that we now have subtracted the rule $\{\} \rightarrow \{\}$ twice. So we need '+1' to correct for this.