

Association Rules – the Apriori Algorithm

V.S. Subrahmanian

University of Maryland

vs@cs.umd.edu

Basic Idea

- An association rule (AR) tries to find dependencies of the form $A_1, \dots, A_n \rightarrow B$ where A_1, \dots, A_n, B are attributes (or conditions over attributes). B is different from all of the A 's.
- Intuitively this says: When A_1, \dots, A_n occur together, B is also likely to occur.
- The “goodness” of an AR is captured by two quantities
 - Support,
 - Confidence

Classical Example: Market Basket Analysis

- You work for a grocery store.
- Every time a person checks out, the system identifies the set of items the person bought.
- Thus, each transaction at the checkout register is a row in a table and the items bought are listed.

Transaction	Items
1	A,B,D
2	A,B,F
3	B,C,F
4	C,E
5	A,C,F
6	A,B,E
7	B,E,F

6 items: A, B, C, D, E, F

Itemset

- An *itemset* is a set of items – in our example, any subset of $\{A,B,C,D,E,F\}$.
- An itemset is *frequent* if it occurs often enough, i.e. if it occurs over a certain number of times.
- Suppose $r = A_1, \dots, A_n \rightarrow B$ is an AR.
- $\text{Support}(r)$ = Probability that a random transaction contains $\{A_1, \dots, A_n, B\}$. NOTE: *Sometimes people just use the number of transactions whose itemsets contain $\{A_1, \dots, A_n, B\}$.*
- $\text{Confidence}(r)$ = Probability of B being in an itemset, given that $\{A_1, \dots, A_n\}$ are in it.

Classical Example: Market Basket Analysis

- Let $r = A \rightarrow B$
- $\text{Support}(r) = 3/7$ as A,B occur together in 3 out of 7 transactions.
- $\text{Confidence}(r) = 3/4$ as B occurs in 3 out of 4 transactions in which A occurs.

Transaction	Items
1	A,B,D
2	A,B,F
3	B,C,F
4	C,E
5	A,C,F
6	A,B,E
7	B,E,F

6 items: A, B, C, D, E, F

Classical Example: Market Basket Analysis

- Let $r = A, B \rightarrow F$
- $\text{Support}(r) = 1/7$ as A,B,F occur together in 1 out of 7 transactions.
- $\text{Confidence}(r) = 1/3$ as F occurs in 1 out of 3 transactions in which A and B both occur.

Transaction	Items
1	A,B,D
2	A,B,F
3	B,C,F
4	C,E
5	A,C,F
6	A,B,E
7	B,E,F

6 items: A, B, C, D, E, F

Association Rule Mining Problem

- Given a database DB having the schema (Transaction, Itemset) and two integers s, c find all association rules r having
 - $Support(r) \geq s$,
 - $Confidence(r) \geq c$.

Apriori Algorithm

- For each $i \geq 1$, L_i denotes the set of all frequent itemsets of cardinality i .
- The idea is to iteratively expand L_i to L_{i+1} .
- Once $L_j = \emptyset$ for some j , we can stop.
- At this stage, L_1, L_2, \dots, L_{j-1} would represent the set of all frequent itemsets (i.e. satisfying the support requirement).
- Check these to see if the confidence levels hold.

Join Operation

- Compute $L_{\{j+1\}}$ by joining L_j with itself.
- Suppose $j=2$ and $L_j = \{\{A, B\}, \{A, C\}, \{C, D\}\}$.
- The *join* of L_j with itself is
 - $\{A, B, C\}$: join $\{A, B\}$ with $\{A, C\}$
 - $\{A, B, C, D\}$: join $\{A, B\}$ with $\{C, D\}$ but rejected in join as it has 4 elements;
 - $\{A, C, D\}$: join $\{A, C\}$ with $\{C, D\}$.
- So the returned join is $\{\{A, B, C\}, \{A, C, D\}\}$.

Pruning Step

- **Theorem.** If X is a frequent itemset (i.e. it occurs in a sufficiently high percentage of transactions) then so must any subset $Y \subseteq X$.
- **Proof ?**
- **Implication.**
 - If X is a candidate to be inserted into L_i but some subset Y of cardinality $(i-1)$ is not in $L_{\{i-1\}}$, then X should not go into L_i .

Apriori Algorithm, Phase I: Find AR conditions having enough support

$L_1 = \{ \{x\} \mid x \text{ is an item} \};$ %singletons

$j=1;$

While ($L_j \neq \emptyset$) **do**

$\{ j=j+1;$

$C_j = \text{join}(L_j, L_j) ;$ % find candidates

$L_j = \{x \mid x \in C_j \& \text{support}(x) \geq c\};$

$\}$

Return $\bigcup_j L_j$

Classical Example: Market Basket Analysis

- Let $s = 0.2$.
- COUNTs are as follows:

Item	COUNT
A	4
B	5
C	3
D	1
E	3
F	4

Transaction	Items
1	A,B,D
2	A,B,F
3	B,C,F
4	C,E
5	A,C,F
6	A,B,E
7	B,E,F

So $L_1 = \{\{A\}, \{B\}, \{C\}, \{E\}, \{F\}\}$

Classical Example: Market Basket Analysis

- Let $s = 0.2$.
- *Pruning Step*: Nothing containing D can be in L_2 . Why?
- Instead of considering 18 pairs, we only need to consider 10 pairs.
- What makes it into L_2 ?
- $\{A,B\}:3, \{A,F\}:2$
- $\{B,E\}:2, \{B,F\}:2$
- $\{C,F\}:2$
- All of these occur at least twice in the data, so support is enough.

Transaction	Items
1	A,B,D
2	A,B,F
3	B,C,F
4	C,E
5	A,C,F
6	A,B,E
7	B,E,F

So

$$L_2 = \{\{A, B\}, \{A, F\}, \{B, E\}, \{B, F\}, \{C, F\}\}$$

Classical Example: Market Basket Analysis

- What makes it into L_3 ?
- $\{A,B,F\}:1$
- $\{A,B,E\}:1$. Can prune because AE is not in L_2 .
- $\{A,C,F\}:1$. Can prune because AC is not in L_2 .
- $\{A,B,E,F\}:0$ **X**
- $\{B,E,F\}:1$. Can prune because EF is not in L_2 .
- $\{B,C,F\}:1$. Can prune as BC is not in L_2 .

Transaction	Items
1	A,B,D
2	A,B,F
3	B,C,F
4	C,E
5	A,C,F
6	A,B,E
7	B,E,F

So $L_3 = \emptyset$.
So our iteration can stop.

Apriori Algorithm, Phase II: Find ARs satisfying confidence condition

SOL = {};

foreach itemset X , $|X| \geq 2$ ret. by Phase I **do**

foreach a in X **do**

if $\text{conf}(X - \{a\} \rightarrow a) \geq c$ **then**

 SOL = SOL **U** $\{X - \{a\} \rightarrow a\}$;

Return SOL.

Apriori Algorithm, Phase II: Find ARs satisfying confidence condition

SOL = {};

foreach itemset X , $|X| \geq 2$ ret. by Phase I **do**

foreach $a \subseteq X$ s.t. $|X - a| \geq 1$ **do**

if $\text{conf}(X - \{a\} \rightarrow a) \geq c$ **then**

SOL = SOL $\cup \{X - \{a\} \rightarrow a\}$;

Return SOL.

Allows rule heads to have multiple items.

Candidate Itemsets

- Itemsets with enough support are:
- $L = \left\{ \begin{array}{l} \{A\}, \{B\}, \{C\}, \{E\}, \\ \{F\}, \{A, B\}, \{A, F\}, \\ \{B, E\}, \{B, F\}, \{C, F\} \end{array} \right\}.$
- Of these, the only ones that can give rise to a rule are the doubletons [singletons can't generate a rule – why?]

Assoc. Rule	Confidence
A => B	
B => A	
A => F	
F => A	
B => E	
E => B	
B => F	
F => B	
C => F	
F => C	

Candidate Itemsets

Transaction	Items
1	A,B,D
2	A,B,F
3	B,C,F
4	C,E
5	A,C,F
6	A,B,E
7	B,E,F

The association rules discovered are now based on the confidence threshold. For example, if the threshold is 65%, then the rules returned are highlighted in red.

Assoc. Rule	Confidence
A => B	$\frac{3}{4} = 75\%$
B => A	$\frac{3}{5} = 60\%$
A => F	$\frac{1}{4} = 25\%$
F => A	$\frac{2}{4} = 50\%$
B => E	$\frac{2}{5} = 50\%$
E => B	$\frac{2}{3} = 66.67\%$
B => F	$\frac{3}{5} = 60\%$
F => B	$\frac{3}{4} = 75\%$
C => F	$\frac{2}{3} = 66.67\%$
F => C	$\frac{2}{4} = 50\%$

Are ARs good?

- Not necessarily – why?
- Give an example

Lift

- $\text{Lift}(A \rightarrow B) = \frac{P(B|A)}{P(B)}.$
- Intuition:
 - Rule could have high support.
 - Rule could have high confidence.
 - But if $P(B)$ is almost the same as $P(B|A)$, then A could not have much to do with B being true.
 - On the other hand, if “lift” is high, then having A be true makes a difference in whether B is true.

Flaws with A Priori Algorithm

- Too slow !
- Number of possible candidates (C_j step) can be enormous when the join is done in Phase I.

In Class Exercise

Transaction	Items
1	A,B,D
2	A,B,E,F
3	A,B,C,F
4	C,E,D
5	A,C,E,F
6	A,B,E
7	B,C,F
8	A,D,E,F
9	A,C,D
10	B,E,F

Support = 3/10
Confidence = 55%