

High Confidence Rule Mining for Microarray Analysis

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Outline

- Introduction
- Row Enumeration
- Confidence-based Prune Strategy
- MAXCONF Algorithm
- Evaluation
- References

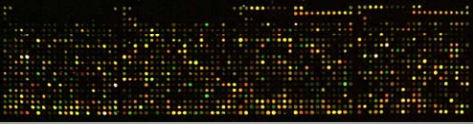
"High Confidence Rule Mining for Microarray Analysis", by Tara McIntosh, Sanjay Chawla, 2006

- 27 pages
- 14 definitions
- 2 lemmas
- 4 tables
- Figures, formulas, etc

Algorithm 1 MAXCONF - High Confidence Rule Mining
Input: Transaction database T , minimum confidence minconf
Output: High confidence spanning rules satisfying minconf
Notation:
 Let N = set of parent nodes corresponding to each transaction in T . Let $\text{children}(n)$ = children represented by node n with support $\sigma(n)$. For each transaction node, $\sigma(n) = 1$ initially. Let $\delta(n)$ be the set of maximal child item sets.
Procedure MAXCONF $(\text{support}, N)$
 $\text{foreach node } n \in N \text{ do}$
 $\text{if } \sigma(n) \geq \text{minconf}$ then $\text{delete } n$, and return;
 $\text{Level 1 Conf. Pruning:}$
 $\text{foreach } \text{child } c \in \text{children}(n) \text{ do}$
 $\text{if } \sigma(c) \geq \text{minconf}$ then $\text{delete } c$, and continue;
 Expand children.
 Calculate $\sigma(c)$ and form children of c .
 Minimal Rule Generation:
 $M = \text{getMinFeatures}(c)$
 $\text{foreach } m \in M \text{ do}$
 $\text{if } m \in \sigma(c)$ then $\text{add rule } m \Rightarrow (c, \text{items} - m)$ into R .
 $\text{Level 2 Conf. Pruning:}$
 $\text{foreach child } c \in \text{children}(n) \text{ do}$
 $\text{if } \sigma(c) \geq \text{minconf}$ then $\text{delete } c$.
 $\text{if } \sigma(n) \geq \text{minconf}$ then $\text{MAXCONF}(\text{support}, \text{children}(n))$
Procedure getMinFeatures (c)
 $\text{minFeatures} = \emptyset$.
 $\text{foreach item } i \in \text{items}(c) \text{ do}$
 $\text{if } \sigma(i) \geq \text{minconf}$ then $\text{minFeatures.add}(i)$
 return minFeatures .

What is Microarrays?

- A DNA microarray is a collection of microscopic DNA spots, commonly representing single genes, arrayed on a solid surface by covalent attachment to a chemical matrix.



~~genes~~ items
~~samples~~ transactions

Our Task

- One main objective of molecular biology is to develop a deeper understanding of how genes are functionally related.

~~minimum support~~

minimum confidence

Minimum Support = 30%, Minimum Confidence = 80%

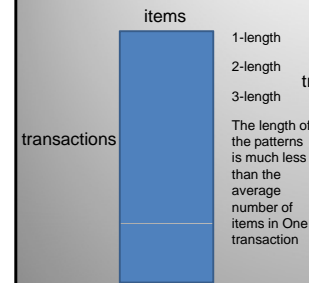
GENE1 ⇒ GENE2 (support 10%, confidence 90%)

We do not mine association rules, but Confidence Rules.

Row Enumeration

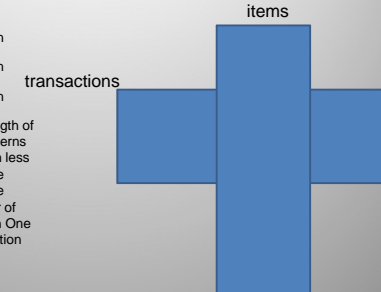
Explosive increase of candidates

- Traditional Dataset



Width: 12 Length: 10000

- Microarray Dataset



Width: <500 Length: >>6000

How can we make the right rectangle like the left one?

EXPLOSION!!!

Outline

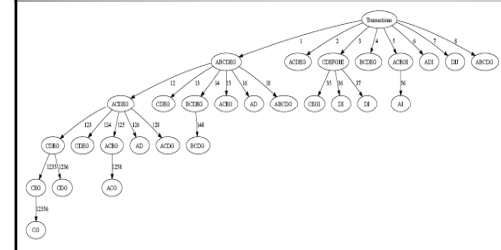
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Row Enumeration

Transposed table & Tree

Transaction	Items
1	A B C D E G
2	A C D E G
3	C D E F G H I
4	B C D E G
5	A C E G I
6	A D I
7	D I J
8	A B C D G

Items	Transactions
A	1,2,5,6
B	1,4,8
C	1,2,3,4,5,8
D	1,2,3,4,6,7,8
E	1,2,3,4,5
F	3
G	1,2,3,4,8
H	3
I	3,5,6,7
J	7



Row Enumeration

Row Enumeration Tree

If the current parent node, *n*, is completely contained within a sibling node, a child node is not constructed. For Example, node 2.

Confidence-based Strategy

RER II, "Mining frequent closed patterns in microarray data." by G. Cong, K.-L. Tan, A. Tung, and F. Pan, 2004

Support-based pruning strategy
 Minimum Support = 30%, Minimum Confidence = 80%

GENE1 ⇒ GENE2 (support 10%, confidence 90%)

In Biology, we care confidence rules, but not support

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Confidence-based Strategy Prune #1

Definition 5 (Maximum Support [4]): Given a node *n* with *k* sibling nodes, the maximum support of the itemset at *n*, represented as $\sigma_{max}(n)$, or any of *n*'s potential child nodes is:

$$\sigma_{max}(n) = n.initial_support + k \quad (5)$$

$\sigma_{max}(5) = 1 + 2 = 3$

Confidence-based Strategy Prune #1

Definition 7 (Minimum Feature): The item i_1 in the itemset I is the *minimum feature* if:

$$\sigma(i_1) \leq \sigma(i_2) \quad \forall i_2 \in I$$

In the itemset {A,B,C}, Support(A) ≤ Support(B), Support(A) ≤ Support(C)
So, A is the minimum feature in {A,B,C}

Definition 8 (I-Spanning Rule): Given an itemset I , a rule r is an *I-spanning rule* if:

$$\text{antecedent}(r) \cup \text{consequent}(r) = I \text{ and}$$

$$|\text{antecedent}(r)| = 1$$

(A) → (B, C) is an I-spanning rule; (B, C) → (A) is not

Definition 9 (Maximum Confidence): Given a node n with minimum feature i , the *maximum confidence* of any spanning rule of the itemset at n is:

$$\text{conf}_{\max}(n) = \frac{\sigma_{\max}(n)}{\sigma(i)} \quad (11)$$

Confidence-based Strategy Prune #1

(I) → (ACEG) This rule has the highest confidence

(AI) → (CEG) What about this one? ✓

Itemset becomes larger, the support of it will not change or even become smaller

$$\sigma(AI) \leq \sigma(I)$$

$$\uparrow \text{confidence} = \frac{\sigma(\text{itemset})}{\sigma(\text{antecedent})} \downarrow$$

Confidence-based Strategy Prune #1

Maximum Support of 5 $\sigma_{\max}(5) = 1 + 2 = 3$

Minimum Feature in this itemset is I $\sigma(I) = 4$

Maximum Confidence of 5: $\text{conf}_{\max}(5) = \frac{\sigma_{\max}(5)}{\sigma(I)} = 3/4$

If minimum confidence is 4/5, the child of node #5 will be pruned

$$\sigma(\text{antecedent}) \downarrow \quad \sigma(I) \uparrow$$

Confidence-based Strategy Prune #2

Definition 10 (Maximum features): Given an itemset I , let R_I be the set of all confident I -spanning rules. The set of *maximum features*, M_I , is the set of all antecedents of the spanning rules.

Itemset: {CDEG} $C \rightarrow DEG, E \rightarrow CDG, G \rightarrow CDE$

The maximum feature of CDEG is CEG

Prune Strategy #2:
If maximum feature set M of an itemset at node n is not empty, we can prune all child nodes of n whose itemsets are subsets of M .

Confidence-based Strategy Prune #2

Itemset: (1234){CDEG} $C \rightarrow DEG, E \rightarrow CDG, G \rightarrow CDE$

The maximum feature of CDEG is CEG

Node (12345)generates: $C \rightarrow EG, E \rightarrow CG, G \rightarrow CE$ **Sub-rules**

MAXCONF Algorithm

Algorithm 1: MAXCONF - High Confidence Rule Mining
Input: Transaction database \mathcal{D} , minimum confidence $minconf$
Output: High confidence spanning rules satisfying $minconf$

Initialization:
 Let N = set of parent nodes corresponding to each transaction in \mathcal{D} . Let $n.items = itemset$ represented by node n with support $\sigma(n)$. For each transaction node, $\sigma(n) = 1$ initially. Let $R = \emptyset$ be the set of maximal confident rules.

Procedure: MAXCONF_depthfirst(N)

- foreach node $n_i \in N$ do
- if n_i has been discovered then delete n_i and return;
- Level 1 Confidence Pruning:**
if n_i cannot form a confident spanning rule then delete n_i and continue;
- Expand subtree.**
Calculate $\sigma(n_i)$ and form children of n_i ;
- Maximal Rule Generation:**
 $M = getMaxFeatures(n_i)$;
foreach $m \in M$ do
if $m \in n_i.parentMaxFeatures$ then add rule $m := \{n_i.items - m\}$ into R ;
- Level 2 Confidence Pruning:**
foreach child $c \in n_i.children$ do
if $c.items \subset M$ then delete c ;
- if $n_i.children \neq \emptyset$ then MAXCONF_depthfirst($n_i.children$);

Procedure: getMaxFeatures(n)

- maxFeatures := \emptyset ;
- foreach item $i \in n.items$ do
if $\sigma(n) \sigma(i) \geq minconf$ then maxFeatures.insert(i);
- return maxFeatures;

Pruning #2
Itemset: (1234){CDEG}
 $C \rightarrow DEG, E \rightarrow CDG, G \rightarrow CDE$
 Maximum Feature {CEG}
 Itemset of child node {CEG}

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Evaluation

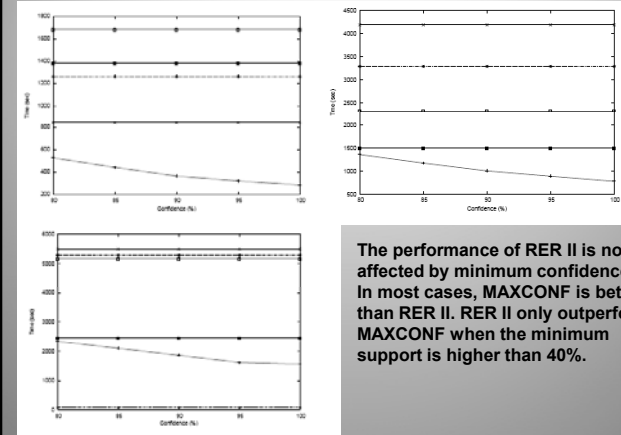
MICROARRAY DATASETS USED IN EXPERIMENTS

Dataset	# Genes	# Items	#Trans.	Mean trans. size	Min. trans. size	Max. trans. size
Hughes <i>et al.</i> (2000) [19]	6316	10044	300	198	2	2339
Masamneh <i>et al.</i> (2004) [20]	6316	8330	215	228	7	1111
Spellman <i>et al.</i> (1999) [9]	6178	6179	82	1397	205	2613

MAXCONF vs RER II
Two Aspect:
1. Rule Generation
2. Scalability

Evaluation

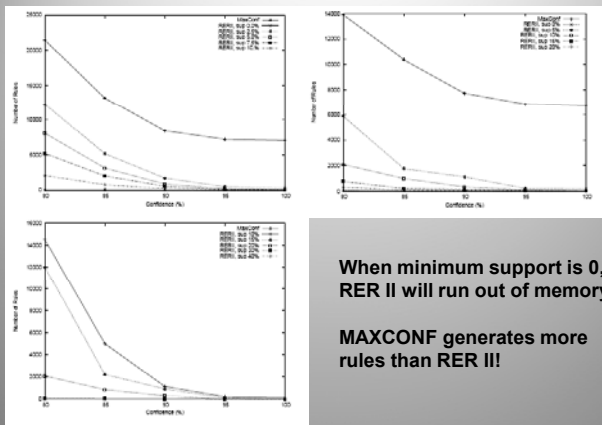
Scalability



The performance of RER II is not affected by minimum confidence. In most cases, MAXCONF is better than RER II. RER II only outperforms MAXCONF when the minimum support is higher than 40%.

Evaluation

Rule Generation



When minimum support is 0, RER II will run out of memory

MAXCONF generates more rules than RER II!

References

- MAXCONF, "High Confidence Rule Mining for Microarray Analysis", by Tara McIntosh, Sanjay Chawla, 2006
- RER II, "Mining frequent closed patterns in microarray data." by G. Cong, K.-L. Tan, A. Tung, and F. Pan, 2004

Any Question?

Thanks for your Attentions