

Representing and Discovering Frequent Patterns with Negation

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Layout

- ♦ Quick reminding of basic notions
- ♦ Deriving supports of patterns with negation
- ♦ Deriving supports of patterns by means of generalized disjunctive rules
- ♦ Representations of frequent patterns using generalized disjunctive rules
- ♦ Naive approach to computing the GDFLR representation
- ♦ Upper bound on the length of elements in the GDFLR representation
- ♦ Advanced approach to computing the GDFLR representation
- ♦ Some experimental results
- ♦ Summary

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Informal introduction to problem

- ♦ Let item $\{fish\}$ occur in 5% of sales transactions and set $\{fish, white\ wine\}$ occur in 4% of transactions. This information allows us to derive an *association rule* stating that 80% of *customers who buy fish also buy white wine*.
- ♦ Let item $\{coke\}$ occur in 3% of sales transactions and set $\{coke, chips, -beer, -milk\}$ occur in 4% of transactions. A sample association rule with negation could state that 75% of *customers who buy coke also buy chips and neither beer nor milk*.
- ♦ In order to derive such rules we need to know how many transactions support respective *sets of items* (or *itemsets*).

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Quick reminding of basic notions

- ♦ Let $I = \{i_1, i_2, \dots, i_m\}$ be a set of distinct *items*.
- ♦ Let dataset D be a set of *transactions* (or *records*), where each transaction is a subset of I .
- ♦ *Support of an itemset* (or *pattern*) X , denoted by $sup(X)$, is the number of transactions in D that contain all items in X .
- ♦ An itemset X is defined *frequent*, if $sup(X) > minSup$, where $minSup$ is the user-defined threshold value.
- ♦ **Basic property of itemsets:** supports of supersets of an itemset X are not greater than $sup(X)$.

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Quick reminding of basic notions

- ♦ A pattern consisting of items x_1, \dots, x_m and negations of items x_{m+1}, \dots, x_n will be denoted by $\{x_1, \dots, x_m, -x_{m+1}, \dots, -x_n\}$.
- ♦ *Support of pattern* $\{x_1, \dots, x_m, -x_{m+1}, \dots, -x_n\}$ is the number of transactions in which all items in set $\{x_1, \dots, x_m\}$ occur and no item in set $\{x_{m+1}, \dots, x_n\}$ occurs.
- ♦ A pattern X is called *positive*, if it does not contain any negated item. Otherwise, X is called a *pattern with negation*.
- ♦ A pattern obtained from X by negating any number of items in X is called a *variation of X* .

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Quick reminding of basic notions

Sample database D .

Id	Transaction
T_1	acefh
T_2	af
T_3	abch
T_4	abe
T_5	abce
T_6	abcef
T_7	bef
T_8	h

} $sup(\{a(-b)\}) = 2$

$\{ab\}$ is a *positive pattern*

$\{a(-b)\}$ is a *pattern with negation*

All variations of $\{ab\}$:

$\{ab\}_{[4]}, \{a(-b)\}_{[2]}, \{(-a)b\}_{[1]}, \{(-a)(-b)\}_{[1]}$

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Calculating supports of patterns with negation

$$\text{sup}(X(-a)) = \text{sup}(X) - \text{sup}(Xa)$$

$$\text{sup}(X(-a_1) \dots (-a_n)) = \sum_{Z \subseteq \{a_1, \dots, a_n\}} (-1)^{|Z|} \times \text{sup}(XZ)$$

Id	Transaction
T ₁	abce
T ₂	abch
T ₃	abcef
T ₄	abe
T ₅	acefh
T ₆	bef
T ₇	h
T ₈	af

$$\text{sup}(abc(-f)) = \text{sup}(abc) - \text{sup}(abcf) = 3 - 1 = 2$$

$$\begin{aligned} \text{sup}(abe(-f)(-h)) &= \text{sup}(abe(-f)) - \text{sup}(abe(-f)h) = \\ &= (\text{sup}(abe) - \text{sup}(abef)) - (\text{sup}(abe) - \text{sup}(abefh)) = \\ &= \text{sup}(abe) - \text{sup}(abef) - \text{sup}(abeh) + \text{sup}(abefh) = \\ &= 3 - 1 - 0 + 0 = 2 \end{aligned}$$

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Pattern with negation may be more frequent

Id	Transaction
T ₁	abce
T ₂	h
T ₃	abch
T ₄	abe
T ₅	acefh
T ₆	bef
T ₇	abcef
T ₈	af

$$\text{sup}(\{f\}) = 4; \text{sup}(\{fh\}) = 1; \text{sup}(\{f(-h)\}) = 3.$$

Let $\text{minSup} = 2$. Then:

$\{f\}$ is frequent,
 $\{fh\}$ is infrequent,
 $f(-h)$ is frequent.

$$\text{sup}(\{f(-h)\}) = \text{sup}(\{f\}) - \text{sup}(\{fh\})$$

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Knowing frequent positive patterns is not enough

Id	Transaction
T ₁	abce
T ₂	h
T ₃	abch
T ₄	abe
T ₅	acefh
T ₆	bef
T ₇	abcef
T ₈	af

Let $\text{minSup} = 2$. Then:

$\{f\}_{[4]}, \dots$
 $\{fh\}$ is not frequent



$$\text{sup}(\{f(-h)\}) = \text{sup}(\{f\}) - \text{sup}(\{fh\}) = ?$$

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Generalized disjunctive rules

- Let Z be an itemset. The expression:

$$X \rightarrow a_1 \vee \dots \vee a_n$$

is defined a *generalized disjunctive rule based on Z* (and Z is the base of $X \rightarrow a_1 \vee \dots \vee a_n$) if $X \subset Z$ and $\{a_1, \dots, a_n\} = Z \setminus X$.

- Example.** Let $Z = \{abc\}$. There are $2^3 - 1$ gen. dis. rules:

$$\begin{array}{lll} \emptyset \rightarrow a \vee b \vee c & & \\ a \rightarrow b \vee c & b \rightarrow a \vee c & c \rightarrow a \vee b \\ ab \rightarrow c & ac \rightarrow b & bc \rightarrow a \end{array}$$

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Errors of generalized disjunctive rules

- $\text{sup}(X \rightarrow a_1 \vee \dots \vee a_n)$ is defined as the number of transactions in which X occurs together with a_1 or a_2 , or ... or a_n .
- $\text{err}(X \rightarrow a_1 \vee \dots \vee a_n)$ is defined as the number of transactions that contain X and do not contain any item in $\{a_1, \dots, a_n\}$; that is:

$$\text{sup}(X) \left\{ \begin{array}{|c|c|} \hline X & a \\ \hline X & b \\ \hline X & c \\ \hline X & d \\ \hline \end{array} \right\} \begin{array}{l} \text{sup}(X \rightarrow a \vee b \vee c) \\ \text{err}(X \rightarrow a \vee b \vee c) \end{array}$$

- $X \rightarrow a_1 \vee \dots \vee a_n$ is defined as a *certain rule* if $\text{err}(X \rightarrow a_1 \vee \dots \vee a_n) = 0$.

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Reasoning with certain rules...

- Example.**

$$\text{err}(X \rightarrow a \vee b) = 0$$

$$\text{sup}(X) = \text{sup}(X \rightarrow a \vee b)$$

$$\text{sup}(X) = \text{sup}(Xa) + \text{sup}(Xb) - \text{sup}(Xab)$$

$$\text{sup}(Xab) = \text{sup}(Xa) + \text{sup}(Xb) - \text{sup}(X)$$

Generalized conclusion.

$$\text{err}(X \rightarrow \vee Y) = 0 \text{ iff } \text{sup}(XY) = (-1)^{|Y|} \times [\sum_{Z \subset Y} (-1)^{|Z|} \times \text{sup}(XZ)].$$

- Thus, if $X \rightarrow \vee Y$ is certain, then $\text{sup}(XY)$ is determinable from the supports of proper subsets of XY .

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	a	
X	a	
X	a	
X	a	b
X		b
		b

Reasoning with certain rules

♦ **Example.**

$$err(X \rightarrow a \vee b) = 0$$



$$err(YX \rightarrow a \vee b) = 0$$

		a	
	X	a	
Y	X	a	
Y	X	a	b
Y	X		b
			b

- ♦ **Generalized conclusion.** If $X \rightarrow \forall Y$ is certain, then $ZX \rightarrow \forall Y$ is also certain and determines a method of calculating $sup(ZXY)$ from the supports of proper subsets of ZXY .
- ♦ **Corollary.** If there is a certain rule based on itemset Z, then the supports of all supersets of Z are derivable from their proper subsets.

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Generalized disjunctive (derivable) sets and generalized disjunction-free (non-derivable) sets

- ♦ Itemset X is defined as a *generalized disjunctive set* (or *derivable*) if there is a certain generalized disjunctive rule based on X.
- ♦ **Note:** There is $2^{|X|}-1$ generalized disjunctive rules based on X.
- ♦ Itemset X is defined as a *generalized disjunction-free set* (or *non-derivable*) if there is no certain generalized disjunctive rule based on X.

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Generalized disjunctive (derivable) sets and generalized disjunction-free (non-derivable) sets

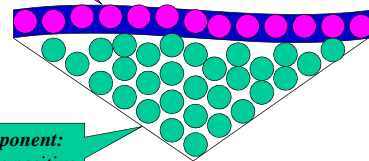
- ♦ Supersets of a generalized disjunctive (derivable) set are generalized disjunctive (derivable).
- ♦ Subsets of a generalized disjunction-free set (non-derivable) are generalized disjunction-free set (non-derivable)

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Representing all positive patterns

Border:

minimal derivable
positive patterns



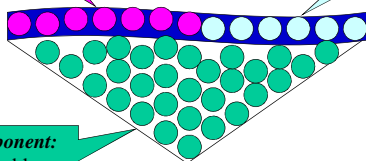
Main Component:
non-derivable positive
patterns

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GDFSR: Representing all frequent positive patterns

Border:
minimal derivable
frequent pos. patterns

Border:
minimal infrequent
pos. patterns



Main Component:
non-derivable
frequent pos. patterns

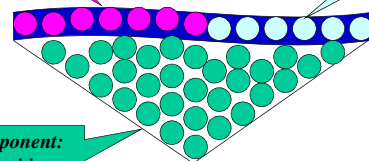
17

GDFSR: Representing all frequent positive patterns

Border:
minimal derivable
frequent pos. patterns

each other pattern is infrequent
or derivable

Border:
minimal infrequent
pos. patterns

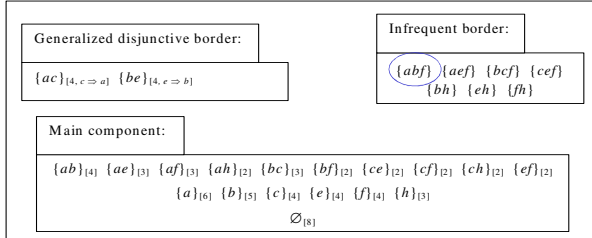


Main Component:
non-derivable
frequent pos. patterns

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GDFSR: Deriving frequent and infrequent positive patterns

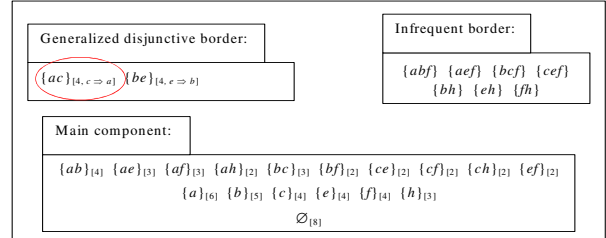
Example. Pattern $\{abcf\}$ problem: We note that $\{abcf\}$ has a subset, e.g. $\{abf\}$, in the infrequent border. This means that all supersets of $\{abf\}$, in particular $\{abcf\}$, are infrequent.



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GDFSR: Deriving frequent and infrequent positive patterns

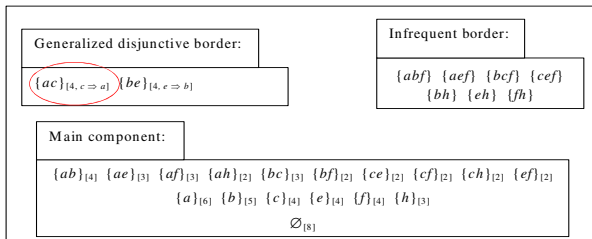
Example. Pattern $\{abce\}$ problem: It does not have any subset in the infrequent border, but has a subset, e.g. $\{ac\}$, in the generalized disjunctive border.



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GDFSR: Deriving frequent and infrequent positive patterns

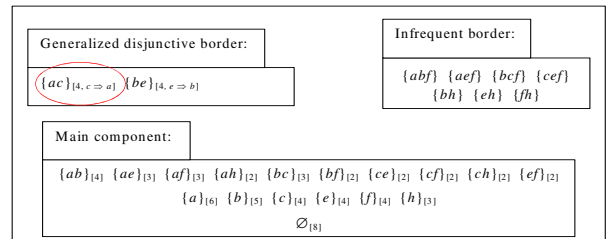
Example. Pattern $\{abce\}$ problem: Property $c \Rightarrow a$, associated with set $\{ac\}$ implies property $bce \Rightarrow a$ related to set $\{abce\}$.



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GDFSR: Deriving frequent and infrequent positive patterns

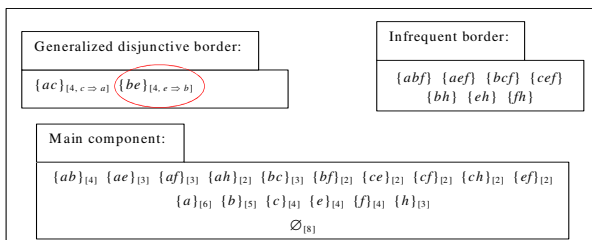
Example. Pattern $\{abce\}$ problem: Property $c \Rightarrow a$, associated with set $\{ac\}$ implies property $bce \Rightarrow a$ related to set $\{abce\}$. Hence, $\sup(\{abce\}) = \sup(\{bce\}) = ?$



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GDFSR: Deriving frequent and infrequent positive patterns

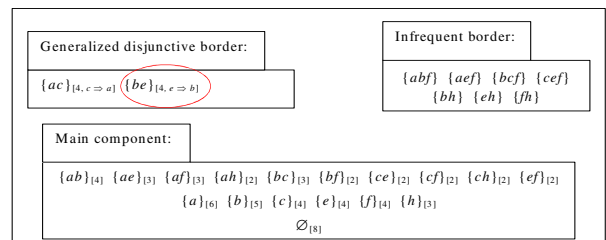
Example. Pattern $\{bce\}$ subproblem: $\{bce\}$ has subset $\{be\}$ in the generalized disjunctive border.



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GDFSR: Deriving frequent and infrequent positive patterns

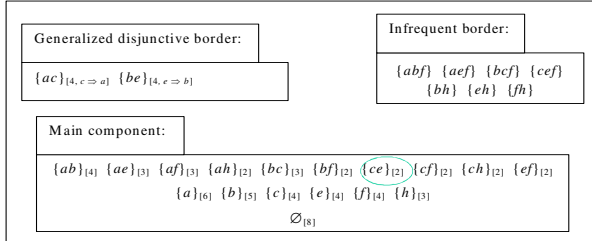
Example. Pattern $\{bce\}$ subproblem: Property $e \Rightarrow b$ associated with $\{be\}$ implies property $ce \Rightarrow b$ related to $\{bce\}$. Hence, $\sup(\{bce\}) = \sup(\{ce\}) = ?$



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GDFSR: Deriving frequent and infrequent positive patterns

Example. Pattern $\{ce\}$ subproblem: Pattern $\{ce\}$ belongs to the main component, so its support is known: $sup(\{ce\}) = 2$.

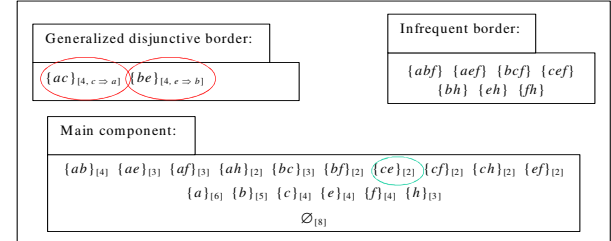


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GDFSR: Deriving frequent and infrequent positive patterns

Example. Summarizing pattern $\{abce\}$ problem:

$$sup(\{abce\}) = sup(\{bce\}) = sup(\{ce\}) = 2.$$

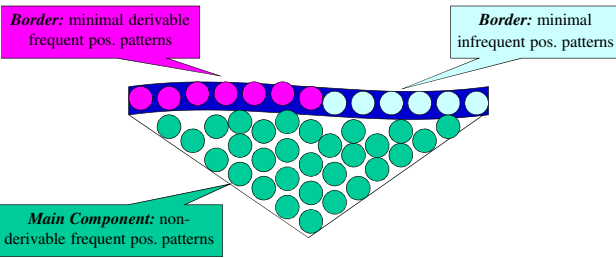


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GDFSR: Represents all frequent patterns with negation?

Problem

An infrequent non-derivable positive pattern \circ may have a frequent variation \bullet with negation



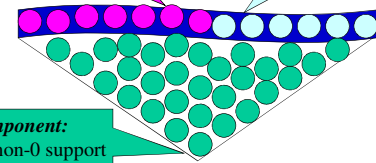
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GDFLR: Representing all frequent patterns (also with negation)

Border: minimal derivable or 0-support pos. patterns having a frequent variation

Border: minimal pos. patterns having all variations infrequent

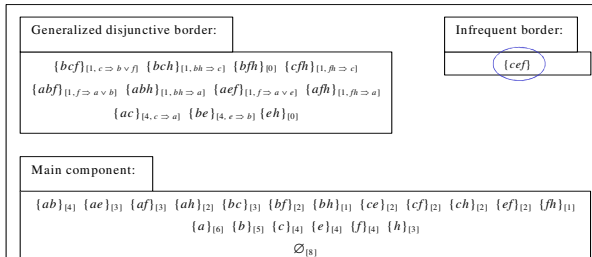
Main Component: non-derivable non-0 support pos. patterns having a frequent variation



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GDFLR: Deriving frequent and infrequent patterns with negation

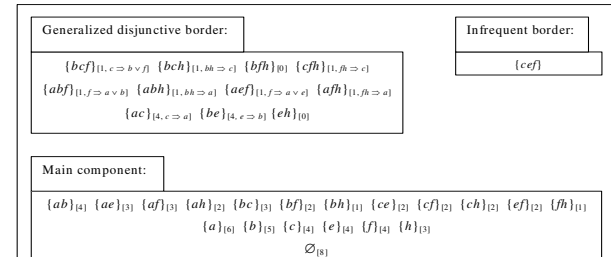
Example. Pattern $\{a(-c)(-e)f\}$ problem: $\{acef\}$ - positive variation of the evaluated pattern - has subset $\{cef\}$ in the infrequent border. This means that all supersets of $\{cef\}$ and all their variations, including $\{acef\}$ and $\{a(-c)(-e)f\}$, are infrequent.



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GDFLR: Deriving frequent and infrequent patterns with negation

Example. Pattern $\{bef(-h)\}$ problem. The positive variation $\{befh\}$ of $\{bef(-h)\}$ does not have any subset in the infrequent border, so $\{bef(-h)\}$ has a chance to be frequent.



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GDFLR: Deriving frequent and infrequent patterns with negation

Example. Pattern $\{bef(-h)\}$ problem:

$$\sup(\{bef(-h)\}) = \sup(\{bef\}) - \sup(\{befh\}) = \dots = 2 - 0 = 2.$$

Generalized disjunctive border:

$\{bcef\}_{[1, c \supset b \vee f]}$ $\{bch\}_{[1, bh \supset c]}$ $\{bfh\}_{[0]}$ $\{cfh\}_{[1, fh \supset c]}$
 $\{abf\}_{[1, f \supset a \vee b]}$ $\{abh\}_{[1, bh \supset a]}$ $\{aef\}_{[1, f \supset a \vee e]}$ $\{afh\}_{[1, fh \supset a]}$
 $\{ac\}_{[4, c \supset a]}$ $\{be\}_{[4, e \supset b]}$ $\{eh\}_{[0]}$

Infrequent border:

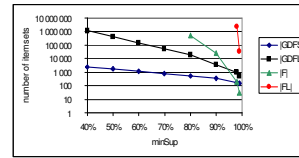
$\{cef\}$

Main component:

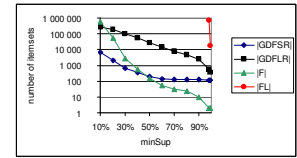
$\{ab\}_{[4]}$ $\{ae\}_{[3]}$ $\{af\}_{[3]}$ $\{ah\}_{[2]}$ $\{bc\}_{[3]}$ $\{bf\}_{[2]}$ $\{bh\}_{[1]}$ $\{ce\}_{[2]}$ $\{cf\}_{[2]}$ $\{ch\}_{[2]}$ $\{ef\}_{[2]}$ $\{fh\}_{[1]}$
 $\{a\}_{[6]}$ $\{b\}_{[5]}$ $\{c\}_{[4]}$ $\{e\}_{[4]}$ $\{f\}_{[4]}$ $\{h\}_{[3]}$
 $\emptyset_{[8]}$

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Conciseness of the representation



connect-4 data set



mushroom data set

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Basic steps in GDFLR-Apriori algorithm

Assertion: candidate elements are positive patterns

- Calculate supports of candidates w.r.t. database.
- Calculate errors of all generalized disjunctive rules for each candidate.**
- Determine supports of all variations for each candidate.**
- Split candidates into *Main Component* and *Borders* based on errors of rules and supports of variations of candidates.
- Create longer candidates by merging pairs of elements of *Main Component*.
- Prune all new candidates that do not have all proper subsets in *Main Component*.

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Errors of rules and supports of variations

♦ **Example.**

$$\text{err}(X \rightarrow a \vee b) = \sup(X(-a)(-b))$$

X	a
X	b
X	
X	d

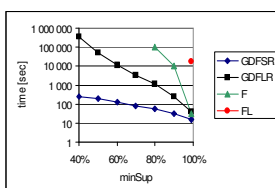
Generalized conclusion.

$$\text{err}(X \rightarrow a_1 \vee \dots \vee a_n) = \sup(X(-a_1) \dots (-a_n)).$$

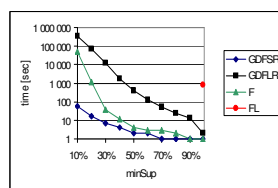
- For a pattern P , the set of the errors of all generalized disjunctive rules based on P equals the set of the supports of all variations of P that are different from P .

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Extraction time



connect-4 data set



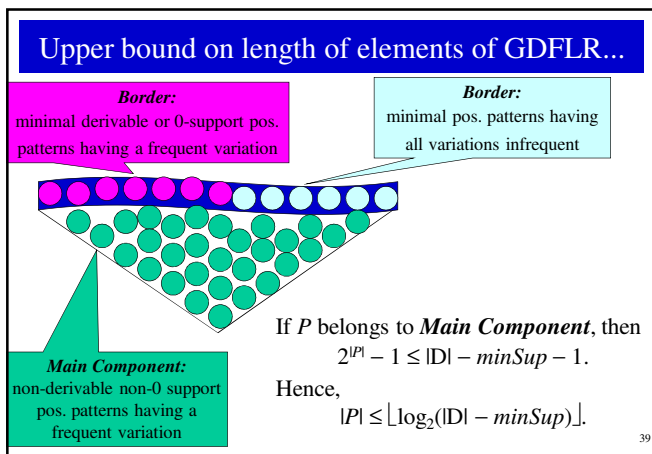
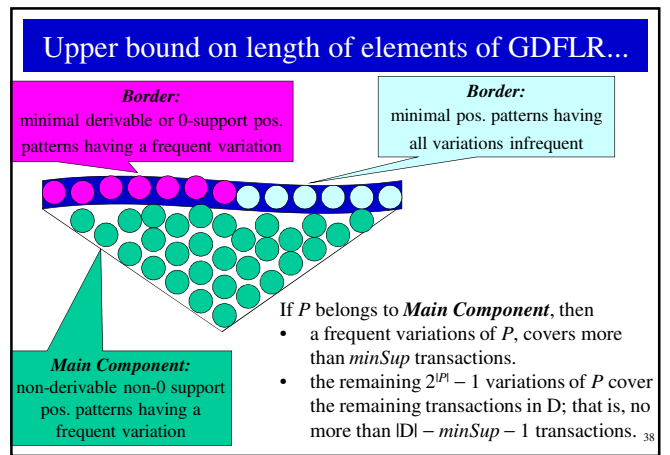
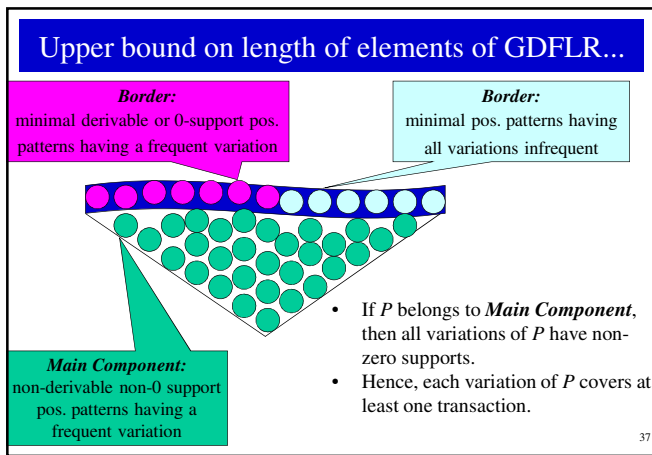
mushroom data set

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Upper bound on length of elements of GDFLR...

- Earlier conclusion:** For a pattern P , the set of the errors of all generalized disjunctive rules based on P equals the set of the supports of all variations of P that are different from P .
- Corollary 1:** For a **positive** pattern P , the set of the errors of all generalized disjunctive rules based on P equals the set of the supports of all variations **with negation** of P .
- Corollary 2:** The following statements are equivalent for a generalized disjunction-free (non-derivable) positive pattern P :
 - all rules based on P are not certain
 - the errors of all rules based on P are different from 0
 - all variations with negation of P have non-zero supports.

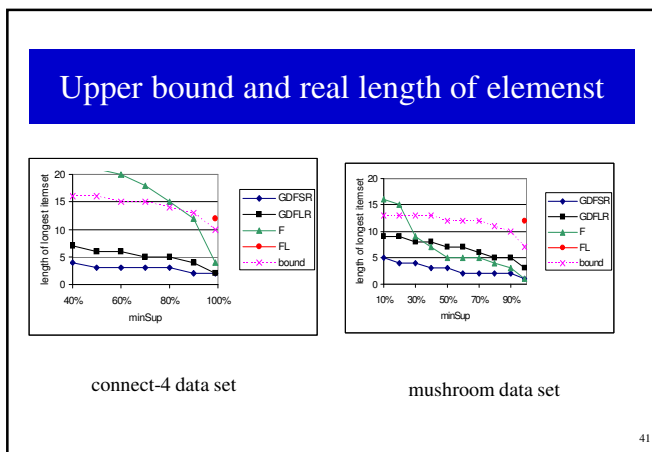
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Upper bound on length of GDFLR' s elements

data set	# items	avg. length	std. dev	# records	$minSup / D $	length of longest frequent itemset	$\lfloor \log_2(D - minSup) \rfloor + 1$
chess	76	37	0	3196	20%	23	12
connect-4	129	43	0	67557	10%	29	16
mushroom	119	23	0	8124	0.075%	21	13
pumsb*	7117	50	2	49046	5%	40	16
pumsb	7117	74	0	49046	60%	22	15
gazelle	498	2,5	4,9	59601	0.01%	154	16
T10I4D100K	1000	10	3,7	100000	0.025%	11	17
T40I10D100K	1000	40	8,5	100000	0.001%	25	17

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Addressed problem:

calculating rule errors /supports of variations

- Calculation of errors of all rules based on X (or supports of all variations of X that are different from X) requires:

$$\sum_{n=1..|X|} \binom{|X|}{n} (2^n - 1)$$

accesses to proper subsets of X .

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Absolute ordering of variations

- ♦ n^{th} variation of pattern X ($\mathcal{V}_n(X)$) is defined as this variation of X that differs from X on all and only bit positions with value 1 in the binary representation of n ($0 \leq n < 2^{|X|}$).

For variation $\mathcal{V}_n(X)$, n is called its (absolute) ordering number.

- ♦ **Example.** Let $X = \{abc\}$.

$$\mathcal{V}_5(X) = \mathcal{V}_{2+2^0}(X) = \mathcal{V}_{(101)_2}(X) = \{(-a)b(-c)\}$$

5th variation of X

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Clusters of variations

- ♦ k^{th} cluster ($C_k(X)$) for pattern X is defined as the set of all variations of X such that k is the leftmost bit position with value 1 in the binary representation of their ordering numbers ($0 \leq k < |X|$).

- ♦ **Example.**

$$\begin{array}{ll} \text{basic pattern: } X : \mathcal{V}_{(000)_2}(X) & 2^{\text{nd}} \text{ cluster } C_2(X): \mathcal{V}_{(100)_2}(X) \\ 0^{\text{th}} \text{ cluster } C_0(X): \mathcal{V}_{(001)_2}(X) & \mathcal{V}_{(101)_2}(X) \\ 1^{\text{th}} \text{ cluster } C_1(X): \mathcal{V}_{(010)_2}(X) & \mathcal{V}_{(110)_2}(X) \\ & \mathcal{V}_{(111)_2}(X) \end{array}$$

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Ordering variations in clusters

- ♦ $\mathcal{V}_{2^k+j}(X)$, where $j < 2^k$, is called j^{th} variation of pattern X in cluster $C_k(X)$.

$$\text{cluster } C_2(X) = \{ \mathcal{V}_{(100)_2}(X), \mathcal{V}_{(101)_2}(X), \mathcal{V}_{(110)_2}(X), \mathcal{V}_{(111)_2}(X) \}$$

absolute ordering:

5th variation of X

relative ordering:

1th variation

in cluster $C_2(X)$

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Relationships between variations

Let X be a non-empty pattern, $k \in \{0, \dots, |X|-1\}$ and $j < 2^k$.

- ♦ **Note.** j^{th} variation in k^{th} cluster ($\mathcal{V}_{2^k+j}(X)$) differs from j^{th} variation ($\mathcal{V}_j(X)$) only on position k .

$$\sup(\mathcal{V}_{2^k+j}(X)) = \sup(\mathcal{V}_j(X \setminus X[k])) - \sup(\mathcal{V}_j(X))$$

- ♦ **Conclusion (principle of GDFLR-SO-Apriori).** The supports of all variations of X belonging to the same cluster are determinable from:
 - the supports of variations of the same subset of X , and
 - the supports of variations of X with less absolute ordering number.

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Calculating the supports of variations

X - non-empty pattern, $i \in \{0, \dots, |X|-1\}$ and $j < 2^i$.

$$\sup(\mathcal{V}_{2^i+j}(X)) = \sup(\mathcal{V}_j(X \setminus \{X[i]\})) - \sup(\mathcal{V}_j(X))$$

$X = \{abc\}$	$\sup(\mathcal{V}_{2^0+0}(X)) = \sup(\mathcal{V}_0(X \setminus X[0])) - \sup(\mathcal{V}_0(X))$	
$\begin{matrix} i & j \end{matrix}$		
0 0	$\sup(\{ab(-c)\}) =$	$\sup(\{ab\}) - \sup(\{abc\})$
1 0	$\sup(\{a(-b)c\}) =$	$\sup(\{ac\}) - \sup(\{abc\})$
1 1	$\sup(\{a(-b)(-c)\}) =$	$\sup(\{a(-c)\}) - \sup(\{ab(-c)\})$
2 0	$\sup(\{(-a)bc\}) =$	$\sup(\{bc\}) - \sup(\{abc\})$
1 1	$\sup(\{(-a)b(-c)\}) =$	$\sup(\{b(-c)\}) - \sup(\{ab(-c)\})$
2 1	$\sup(\{(-a)(-b)c\}) =$	$\sup(\{(-b)c\}) - \sup(\{a(-b)c\})$
3	$\sup(\{(-a)(-b)(-c)\}) =$	$\sup(\{(-b)(-c)\}) - \sup(\{a(-b)(-c)\})$

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Advanced versus naive calculation of rule errors /supports of variations

- ♦ New calculation of supports of all variations of X requires:
 - $|X|$ accesses to $(|X|-1)$ -item subsets of X , and
 - knowing the supports of all variations for all these subsets of X .

- ♦ Previous calculation of errors of all rules based on X requires:

$$\sum_{n=1..|X|} \binom{|X|-1}{n} (2^n - 1)$$

accesses to proper subsets of X .

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Experimental results for the connect-4 dataset

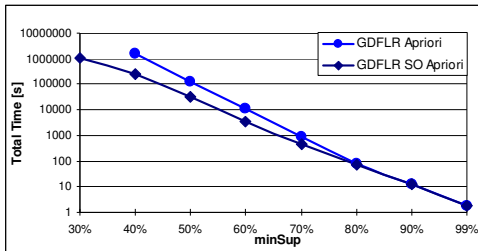


Figure. Duration of *GDFLR-SO-Apriori* and *GDFLR-Apriori* (logarithmic scale)

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Experimental results for the mushroom dataset

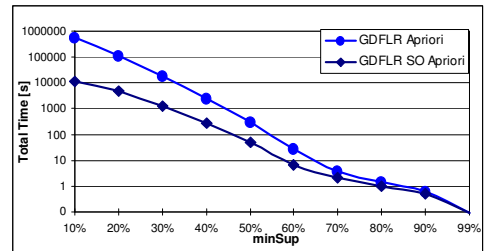


Figure. Duration of *GDFLR-SO-Apriori* and *GDFLR-Apriori* (logarithmic scale)

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Experimental results for the connect-4 dataset

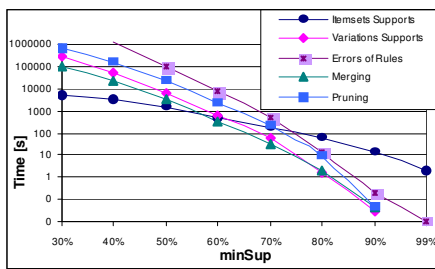


Figure. Duration of particular phases of *GDFLR-SO-Apriori* and *GDFLR-Apriori* (log. scale)

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Experimental results for the mushroom dataset

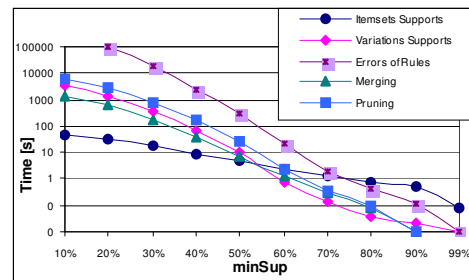


Figure. Duration of particular phases of *GDFLR-SO-Apriori* and *GDFLR-Apriori* (log. scale)

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Experimental results for the connect-4 dataset

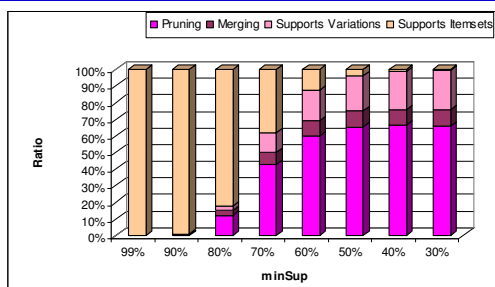


Figure. The proportion of runtime of individual phases of *GDFLR-SO-Apriori*

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Experimental results for the mushroom dataset

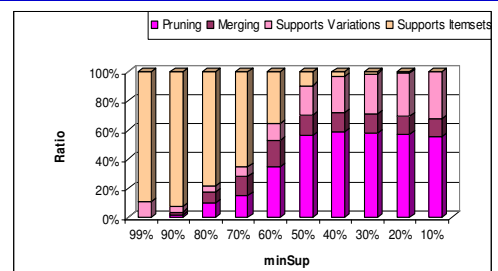


Figure. The proportion of runtime of individual phases of *GDFLR-SO-Apriori*

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Experimental results

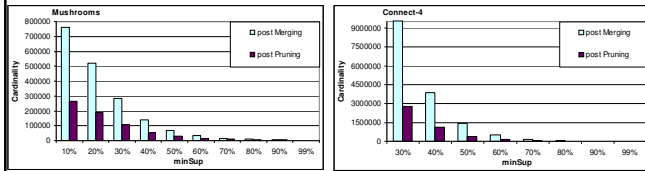


Figure. Number of candidates generated in the merging phase versus number of candidates remained after pruning phase

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Experimental results for the mushroom dataset

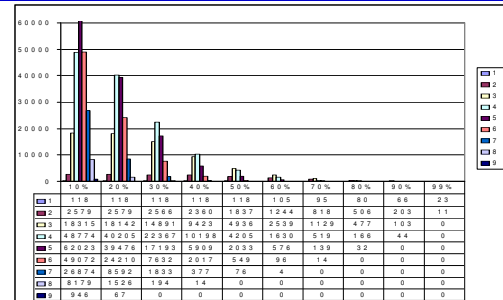


Figure. Number of patterns of the Main component found in each iteration

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Experimental results for the connect-4 dataset

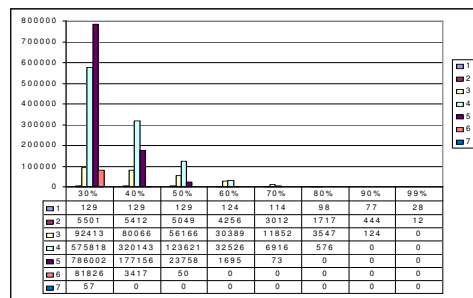


Figure. Number of patterns of the Main component found in each iteration

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Summary

- ◆ The set of all positive patterns can be treated as a lossless representation of all frequent patterns, nevertheless it is not concise.
- ◆ The set of all frequent positive patterns neither guarantees derivation of all frequent patterns with negation, nor is concise in practice.
- ◆ GDFLR representations, which consists of a subset of positive patterns, admits derivation of both all frequent positive patterns and patterns with negation.

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Summary

- ◆ The experiments carried out on real benchmark data sets show that GDFLR is by several orders of magnitude more concise than all frequent patterns.
- ◆ The length of longest elements in GDFLR depends logarithmically on the number of records in the data set, which implies that the number of scans of the data set carried out by *Apriori*-like algorithms discovering GDFLR also depends logarithmically on the number of records in the data set.

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Summary

- ◆ The *GDFLR-SO-Apriori* algorithm is faster than the *GDFLR-Apriori* algorithm by up to two orders of magnitude for low support threshold values.
- ◆ The speed-up is obtained as a result of proposing an ordering of variations and calculating their supports in accordance with that order, which admits re-use of the partial results.

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References...

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**Thank you
for your
attention**

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