UF-EVOLVE - UNCERTAIN FREQUENT PATTERN MINING

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Abstract: Many frequent-pattern mining algorithms were designed to handle precise data, such as the FP-tree structure and the FP-growth algorithm. In data mining research, attention has been turned to mining frequent patterns in uncertain data recently. We want frequent-pattern mining algorithms for handling uncertain data. A common way to represent the uncertainty of a data item in record databases is to associate it with an existential probability. In this paper, we propose a novel uncertain-frequent-pattern discover structure, the mUF-tree, for storing summarized and uncertain information about frequent patterns. With the mUF-tree, the UF-Evolve algorithm can utilize the shuffling and merging techniques to generate iterative versions of it. Our main purpose is to discover new uncertain frequent patterns from iterative versions of the mUF-tree. Our preliminary performance study shows that the UF-Evolve algorithm is efficient and scalable for mining additional uncertain frequent patterns with different sizes of uncertain databases.

1 INTRODUCTION

Data uncertainty is often found in real-world applications because of measurement inaccuracy, sampling discrepancy, outdated data sources, or other errors. One type of data uncertainty is existential uncertainty. In existential uncertainty, there are applications in which it is uncertain about the presence or absence of some items or events. For example, we may highly suspect, while cannot guarantee, that a patient suffers from an illness based on a few symptoms. The uncertainty of such suspicion can be expressed in terms of existential probability. If R_i represents a patient record, then each item within R_i represents an illness and is associated with an existential probability expressing the likelihood of the patient suffering from that illness in R_i. As an example, in R_i, the patient can have an 80% likelihood of suffering from fever, and a 60% likelihood of suffering from H1N1.

Han et al. (Han, 2004) proposed the FP-tree structure, which is an extended prefix-tree structure for storing compressed, crucial information about frequent patterns, and developed an efficient FP-growth algorithm. In our work, we extend the FP-tree for mining uncertain data. The key contributions are (i) the development of the mUF-tree structure to summarize the content of records consisting of uncertain data, and (ii) the idea of shuffling and merging nodes of mUF-tree, whose difference is small, to derive more uncertain frequent patterns by the UF-Evolve algorithm.

The remainder of the paper is organized as follows. Section 2 gives a literature review and Section 3 gives the problem statement. Section 4 introduces the mUF-tree and its construction algorithm. Next, Section 5 discusses an mUF-tree-based uncertain-frequent-pattern mining algorithm, the UF-Evolve algorithm, and Section 6 presents our performance study. Finally, Section 7 concludes our work.

2 LITERATURE REVIEW

For uncertain data representation, Antova et al. (Antova, 2007) proposed U-relations, a succinct and purely relational representation system for uncertain databases. U-relations support attribute-level uncertainty using vertical partitioning. When considering positive relational algebra extended by an operation for computing possible answers, a query on the logical level can be translated into, and evaluated as, a single relational algebra query on the U-relation representation. The approach takes full advantage of query evaluation and optimization techniques on vertical partitions. Chui et al. (Chui, 2007) proposed an algorithm called U-Apriori. They

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also introduced a trimming strategy to reduce the number of candidates that need to be counted based on the Apriori approach. The Apriori heuristic achieves good performance gained by (possibly significantly) reducing the size of candidate sets. However, in situations with a large number of frequent patterns, long patterns, or low minimum support thresholds, an Apriori-like algorithm may suffer from the following two nontrivial issues: it is costly to handle a huge number of candidate sets; and it is tedious to repeatedly scan the database and check a large set of candidates by pattern matching, which is especially true for mining long patterns.

Han et al. (Han, 2004) proposed the FP-tree structure and the FP-growth algorithm for efficiently mining frequent patterns without generation of candidate itemsets for precise data. It consists of two phases. The first phase focuses on constructing the FP-tree from the database, and the second phase focuses on applying FP-growth to derive frequent patterns from the FP-tree. Each node in the FP-tree consists of three attributes, item-name, count and node-link. In the FP-tree, each entry in the header table consists of two fields: (1) item-name, and (2) head of node-links (a pointer pointing to the first node in the FP-tree carrying the item-name). Below, an example is used to illustrate the uses of the FP-tree. Suppose there is a precise transaction database as shown in Table 1, and the minimum support threshold is 3. The FP-tree together with the associated node-links are shown in Figure 1.

Table 1: A precise transaction database.

TID	Items
1	f, a, c, d, g, i, m, p
2	a, b, c, f, l, m, o
3	b, f, h, j, o
4	b, c, k, s, p
5	a, f, c, e, l, p, m, n

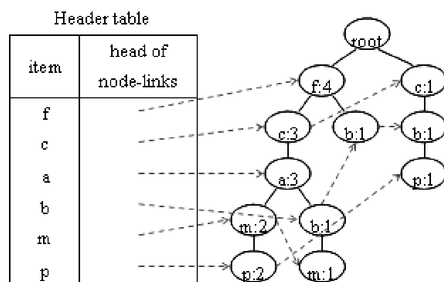

Figure 1: The FP-tree for data in Table 1.

Leung et al. (Leung, 2007 and 2008) proposed the UF-tree structure, a different tree structure than the FP-tree for capturing the content of transactions consisting of uncertain data, and the UF-growth algorithm, a mining algorithm for finding frequent patterns from the UF-tree. Each node in the UF-tree stores item, expected support and occurrence (i.e. the number of transactions containing such an item). UF-growth computes expected support of itemsets and finds frequent patterns from the UF-tree. The expected support of an itemset in a transaction is the expected probability (over all "possible worlds") of coexistence of all the items in the itemset. The expected support of an itemset in a database is the sum of the expected probability of the itemset over all transactions. This calculation incurs much information loss.

3 PROBLEM STATEMENT

Here, in this section, we give some definitions of uncertain data before introducing our target problem. First, we define what an uncertain record and an uncertain database are.

Definition 1. Uncertain Record (R). Let $I = \{a_1, a_2, \ldots, a_k\}$ be a set of items. An uncertain record $R = \{(a_1:p_1), (a_2:p_2), \ldots, (a_m:p_m)\}$, where $(a_i \in I) \wedge (a_i$ appears once with p_i as the probability indicating its existence).

Definition 2. Uncertain Database (UDB). An uncertain database UDB consists of multiple uncertain records, i.e. $UDB = \langle R_1, R_2, \ldots, R_n \rangle$.

An example uncertain database is shown in Table 2.

Table 2: An uncertain database.

Record ID	Item:probability pairs
1	(a:0.2), (f:0.8), (g:0.1), (d:0.3), (c:0.2)
2	(a:0.2), (d:0.3), (c:0.2), (f:0.8)
3	(b:0.3), (f:0.8), (a:0.2)
4	(a:0.4), (c:0.7), (d:0.6), (f:0.8)
5	(f:0.8)
6	(a:0.7), (c:0.4), (b:0.5)
7	(a:0.7)
8	(f:0.8), (a:0.4), (c:0.7), (d:0.6)
9	(b:0.5), (a:0.7), (c:0.4)
10	(d:0.4), (e:0.5), (f:1.0), (a:0.1)
11	(e:0.6), (c:0.3), (d:0.5), (a:0.1), (f:1.0)
12	(a:0.1), (f:1.0), (c:0.3), (d:0.5)
13	(a:0.1), (f:1.0)
14	(f:1.0)
15	(d:0.4), (c:0.4), (b:0.2)
16	(b:0.2)
17	(b:0.2), (f:0.6)
18	(b:0.2)

In an uncertain database, it is often that an item with a probability appears in a record while the same item with another probability appears in another

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record. For example, in Table 2, (d:0.4) appears in the 10th record while (d:0.5) appears in the 11th record. Given a predefined minimum support threshold, an item with a specific probability may not have sufficient support (i.e. the number of records containing it in UDB) to be a frequent pattern.

In order to improve the chance of having more and longer frequent patterns, one can consider to merge the same items with only small differences in their various probabilities for satisfying the support. For example, we can merge (d:0.4) and (d:0.5) as d with a probability range [0.4-0.5]. Hence, for a group of item:probability pairs in which all items are the same, we can use (lowerbound-upperbound) to represent the spread of probabilities for the item. Once the item:probability pairs are grouped, more general frequent patterns can be found.

With the above arrangement, we define what a maximum merging threshold and an uncertain frequent pattern are.

Definition 3. Maximum Merging Threshold (γ). A maximum merging threshold γ is used to determine whether two item:probability pairs can be merged. Assume that an item with a probability ($a:p_1$) appears in a record while the same item with another probability ($a:p_2$) appears in another record. If $abs(p_1 - p_2) \leq \gamma$, then ($a:p_1$) and ($a:p_2$) can be merged as (a:[l-u]), where ($l = min(p_1, p_2)$) $\wedge$ ($u = max(p_1, p_2)$). Here, (a:[l-u]) denotes the item with its (lowerbound-upperbound).

Definition 4. Uncertain Frequent Pattern (UFP). Let an item with its (lowerbound-upperbound) be denoted as (a:[l-u]). An uncertain frequent pattern UFP is represented as $(a_1:[l_1\text{-}u_1])(a_2:[l_2\text{-}u_2])\ldots(a_k:[l_k\text{-}u_k])$:s, where (s is the support for UFP) $\wedge$ ($s \geq$ a predefined minimum support threshold). A record R contains an UFP if for each $(a_i:[l_i\text{-}u_i]) \in$ UFP, $\exists$ $(a_j:p_j) \in$ R, such that $(a_i = a_j) \wedge (l_i \leq p_j \leq u_i)$.

Given an uncertain database, a minimum support threshold and a maximum merging threshold, we are interested in mining a possible set of uncertain frequent patterns. Our approach is to solve the problem in two phases.

- In the first phase, an mUF-tree is constructed for storing summarized and uncertain information about frequent patterns.
- In the second phase, the UF-Evolve algorithm, which utilizes the shuffling and merging techniques to generate iterative versions of the mUF-tree, is applied for discovering new uncertain frequent patterns.

4 MUF-TREE: DESIGN AND CONSTRUCTION

Given an uncertain database, we propose to use an mUF-tree to store summarized and uncertain information about frequent patterns. An mUF-tree with its header table is shown in Figure 2.

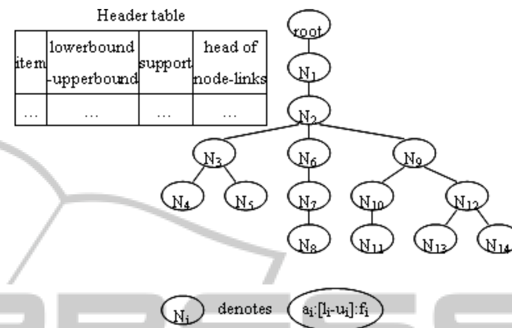


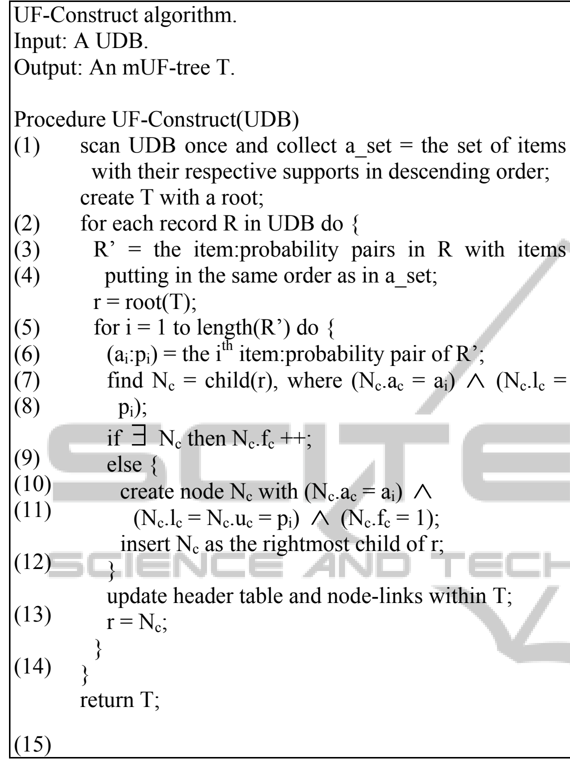
Figure 2: mUF-tree.

Definition 5. Uncertain Frequent Pattern Tree (mUF-tree). An mUF-tree has the following characteristics.

1. An mUF-tree has a virtual root. Each node in the mUF-tree consists of five attributes, item, lowerbound, upperbound, frequency and node-link. Lowerbound and upperbound register the spread of probabilities of the corresponding item. To facilitate tree traversal, nodes with the same item:(lowerbound-upperbound) are linked in sequence via node-links. In Figure 2, $a_i:[l_i\text{-}u_i]:f_i$ in each node N_i represents item:(lowerbound-upperbound):frequency.
2. In the mUF-tree, each entry in the header table consists of four fields: (1) item, (2) lowerbound-upperbound, (3) support (the cumulative frequency of the item:(lowerbound-upperbound) in the mUF-tree), and (4) head of node-links (a pointer pointing to the first node in the mUF-tree carrying the item:(lowerbound-upperbound)).
3. In the header table, item:(lowerbound-upperbound) pairs are in the descending order of supports.

The UF-Construct algorithm is used to construct an mUF-tree from an uncertain database, and its output is the initial mUF-tree. Unlike the FP-tree construction algorithm, UF-Construct scans the database without specifying a minimum support threshold. With this change, the mUF-tree built contains all information. Compared with FP-tree, the mUF-tree stores uncertain information about items, and maintains the structure to be further modified

for discovering more uncertain frequent patterns. Figure 3 shows the steps of the UF-Construct algorithm.



UF-Construct algorithm.
Input: A UDB.
Output: An mUF-tree T.

Procedure UF-Construct(UDB)
(1) scan UDB once and collect a_set = the set of items with their respective supports in descending order;
create T with a root;
(2) for each record R in UDB do {
(3) R' = the item:probability pairs in R with items
(4) putting in the same order as in a_set;
r = root(T);
(5) for i = 1 to length(R') do {
(6) (a_i:p_i) = the ith item:probability pair of R';
(7) find N_c = child(r), where ($N_c.a_c = a_i$) ∧ ($N_c.l_c$ =
(8) p_i);
if ∃ N_c then $N_c.f_c$ ++;
(9) else {
(10) create node N_c with ($N_c.a_c = a_i$) ∧
(11) ($N_c.l_c = N_c.u_c = p_i$) ∧ ($N_c.f_c$ = 1);
insert N_c as the rightmost child of r;
(12) }
update header table and node-links within T;
(13) r = N_c;
}
(14) }
return T;

(15)

Figure 3: UF-Construct.

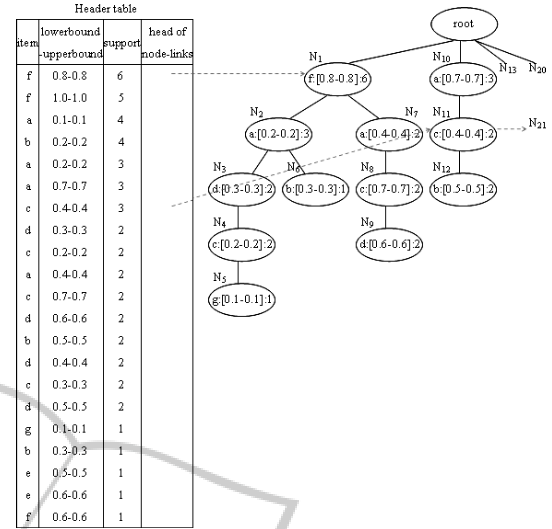
With the records in Table 2, the mUF-tree together with the associated node-links are shown in Figure 4. Since the constructed mUF-tree is large, we split it into two parts. Figure 4(a) shows the header table with the left half of the mUF-tree, and Figure 4(b) shows the right half of the mUF-tree. For the ease of understanding, we only show several node-links.

5 DISCOVERING NEW UNCERTAIN FREQUENT PATTERNS

If we want to use the FP-growth algorithm to mine frequent patterns with mUF-tree(right) in Figure 4(b), we can consider a_i:[l_i-u_i] as an item.

Then FP-growth will discover a set of frequent patterns {(b:[0.2-0.2]):4, (a:[0.1-0.1]):4, (f:[1.0-1.0])(a:[0.1-0.1]):4, (f:[1.0-1.0]):5} with the minimum support threshold be 3.

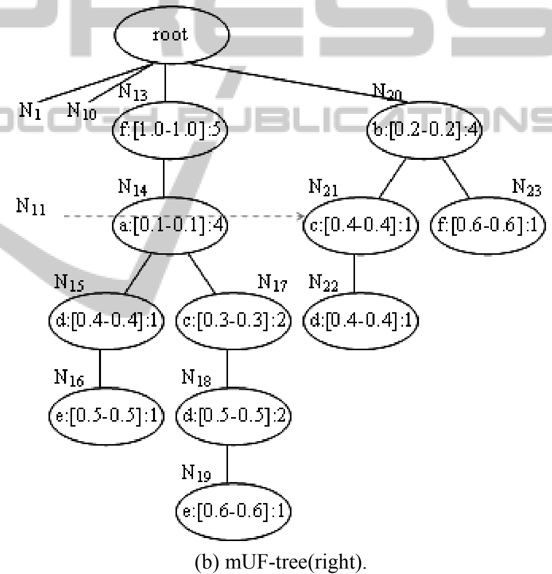
In an mUF-tree, it is often that an item with a



Header table

item	lowerbound -upperbound	support	head of node-links
f	0.8-0.8	6	
f	1.0-1.0	5	
a	0.1-0.1	4	
b	0.2-0.2	4	
a	0.2-0.2	3	
a	0.7-0.7	3	
c	0.4-0.4	3	
d	0.3-0.3	2	
c	0.2-0.2	2	
a	0.4-0.4	2	
c	0.7-0.7	2	
d	0.6-0.6	2	
b	0.5-0.5	2	
d	0.4-0.4	2	
c	0.3-0.3	2	
d	0.5-0.5	2	
g	0.1-0.1	1	
b	0.3-0.3	1	
e	0.5-0.5	1	
e	0.6-0.6	1	
f	0.6-0.6	1	

(a) mUF-tree(left).



(b) mUF-tree(right).

Figure 4: The mUF-tree for data in Table 2.

(lowerbound-upperbound) appears in a node while the same item with another (lowerbound-upperbound) appears in another node. For example, in Figure 4(b), d:[0.4-0.4] appears in N_{15} while d:[0.5-0.5] appears in N_{18}. One can consider to merge the same items with only small differences in their various (lowerbound-upperbound) for satisfying the support. For example, we can merge d:[0.4-0.4] and d:[0.5-0.5] as d:[0.4-0.5]. Hence, for a group of item: (lowerbound-upperbound) pairs of the same item, we can use a combined (lowerbound-upperbound) to represent it. Once the item:(lowerbound-upperbound) pairs are grouped, more general frequent patterns can be found.

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Hence, we are proposing to further discover new uncertain frequent patterns by utilizing shuffling and merging of the mUF-tree. Nodes can be merged to evolve into another mUF-tree for further pattern mining. The steps can be repeated until merging is not possible.

5.1 Preliminary Definitions

For the ease of future discussion, we have further definitions before presenting the algorithms.

Definition 6. Within Range. Given a maximum merging threshold γ, we define two nodes N_b and N_c are **within range** if $(N_b.a_b = N_c.a_c) \wedge (abs(N_b.u_b - N_c.l_c) \leq \gamma) \wedge (abs(N_c.u_c - N_b.l_b) \leq \gamma)$.

In Figure 4(b), given a maximum merging threshold 0.3, then N_{15} and N_{18} are within range, as well as N_{16} and N_{19} are within range.

Definition 7. Common Items (CI). Given a pair of paths PB = $\langle N_{b1}N_{b2}\ldots N_{bk}\rangle$ and PC = $\langle N_{c1}N_{c2}\ldots N_{cm}\rangle$, we define CI(PB, PC) = $\{a_1, a_2, \ldots, a_n\}$ as a sequence of ordered items, where $(n \leq k) \wedge (n \leq m) \wedge (\forall\ i \in \{1, 2, \ldots, n\}$, there is a node in PB and a node in PC, such that these two nodes contain a_i and are within range).

In Figure 4(b), given a pair of paths PB = $\langle N_{15}N_{16}\rangle$ and PC = $\langle N_{17}N_{18}N_{19}\rangle$, then CI(PB, PC) = {d, e}.

We want to merge the nodes corresponding to common items in the two paths. However, it is difficult to merge N_{15} with N_{18} and N_{16} with N_{19} directly. We need to shuffle these nodes to be in the same order. Here, we define the Maximum Attainable Peak (MAP) of a node in a path first.

Definition 8. Maximum Attainable Peak (MAP). Given a_set = $\{a_{11}, a_{12}, \ldots, a_{1k}\}$ as a sequence of ordered items, and a path PB = $\langle N_{21}N_{22}\ldots N_{2m}\rangle$, where the items in a_set is a subset of the items in PB. We take out each item a_{1i} in a_set sequentially and trace along PB. If the position of a_{1i} in PB is not as in a_set, the node N_{2j} containing a_{1i} will be shuffled upward until the position of a_{1i} in PB is as in a_set. The final position is called the MAP of N_{2j} in PB.

Now, we are ready to describe two cases for shuffling the node N_{2j} with its parent node N_q.

- Case 1: $N_{2j}.f_{2j} = N_q.f_q$. Swap N_{2j} and N_q.
- Case 2: $N_{2j}.f_{2j} < N_q.f_q$. Create a new node, N_r, with the same property of N_q except $N_r.f_r = N_q.f_q - N_{2j}.f_{2j}$. Make N_r as another child of the parent of N_q. Set $N_q.f_q = N_{2j}.f_{2j}$. Update the header table and node-links within the mUF-tree, and then follow the handling of Case 1 for N_{2j} and N_q.

The node N_{2j} will be shuffled until it reaches its MAP in PB.

In Figure 4(b), given a_set = {d, e}, then the MAP of N_{18} in the path $\langle N_{17}N_{18}N_{19}\rangle$ is the 1st position. We shuffle N_{18} with N_{17}, which follows Case 1. mUF-tree(right) evolves into mUF-tree(right)$_2$, as shown in Figure 5.

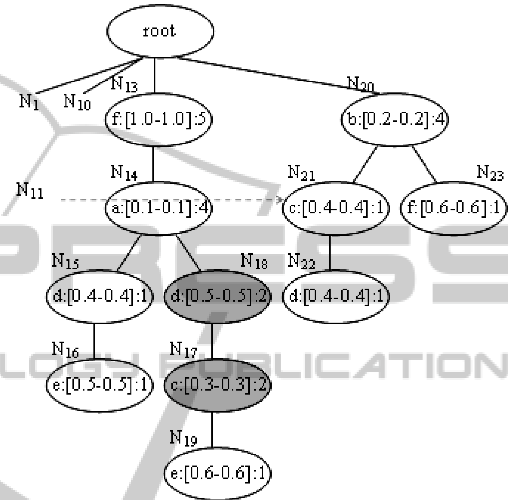

Figure 5: mUF-tree(right)$_2$.

After shuffling N_{18} to its MAP, the MAP of N_{19} in the updated path $\langle N_{18}N_{17}N_{19}\rangle$ is the 2nd position. We shuffle N_{19} with N_{17}, which follows Case 2. We create a new node N_{24} and modify N_{17}, which evolves into mUF-tree(right)$_3$, as shown in Figure 6. Then we shuffle N_{19} with N_{17}, which evolves into mUF-tree(right)$_4$, as shown in Figure 7.

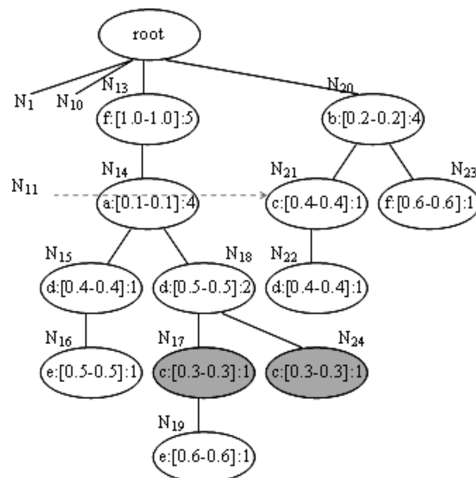

Figure 6: mUF-tree(right)$_3$.

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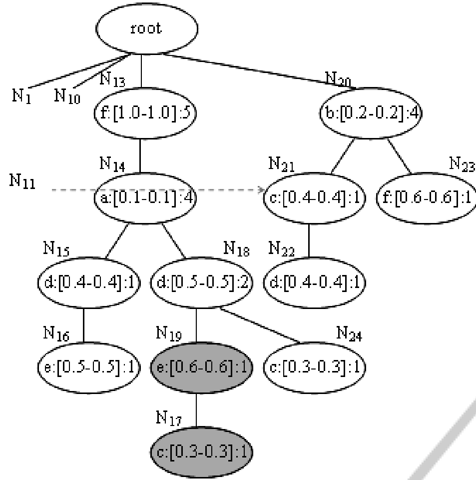

Figure 7: mUF-tree(right)$_4$.

After shuffling, the nodes corresponding to common items are above the other nodes in the two paths. It is much easier to merge N_{15} with N_{18} and N_{16} with N_{19}.

Next, we define the merging criteria, which determine how two candidate nodes can be merged to a new node.

Definition 9. Merging Criteria. If two nodes N_b and N_c are within range, they can be merged as a new node N_q, where $(N_q.a_q = N_b.a_b) \wedge (N_q.l_q = \min(N_b.l_b, N_c.l_c)) \wedge (N_q.u_q = \max(N_b.u_b, N_c.u_c)) \wedge (N_q.f_q = N_b.f_b + N_c.f_c)$.

We merge N_{15} with N_{18} as a new node N_{25}, which evolves into mUF-tree(right)$_5$, as shown in Figure 8. And then we merge N_{16} with N_{19} as a new node N_{26}, which evolves into mUF-tree(right)$_6$, as shown in Figure 9.

Definition 10. Overlap. Given a path PB, overlap(PB) is true if PB shares common nodes with any other path in the mUF-tree.

In Figure 4(b), given PB = $<N_{13}N_{14}N_{15}N_{16}>$, PC = $<N_{13}N_{14}N_{17}N_{18}N_{19}>$ and PD = $<N_{17}N_{18}N_{19}>$, then overlap(PB) since PB shares N_{13} and N_{14} with PC, and !overlap(PD) since PD does not share common nodes with any other path.

Definition 11. Above. Given a_set = $\{a_{11}, a_{12}, \ldots, a_{1k}\}$ and a path PB = $<N_{21}N_{22}\ldots N_{2m}>$, above(a_set , PB) is true if $(k \leq m) \wedge (\forall\ i \in \{1, 2, \ldots, k\}, a_{1i} = N_{2i}.a_{2i})$.

In Figure 4(b), given a_set = {d, e}, PB = $<N_{15}N_{16}>$ and PC = $<N_{17}N_{18}N_{19}>$, then above(a_set, PB) since d and e are above other items in PB, and !above(a_set, PC) since d and e are not above other items in PC.

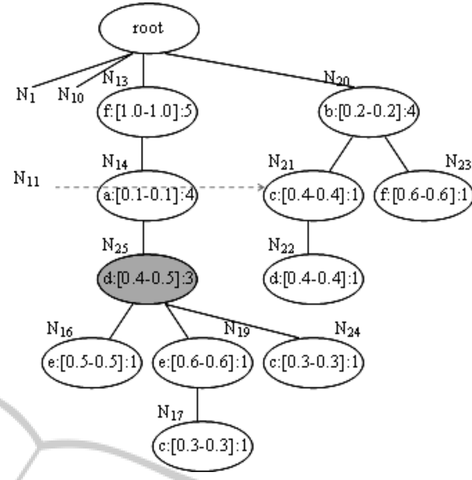

Figure 8: mUF-tree(right)$_5$.

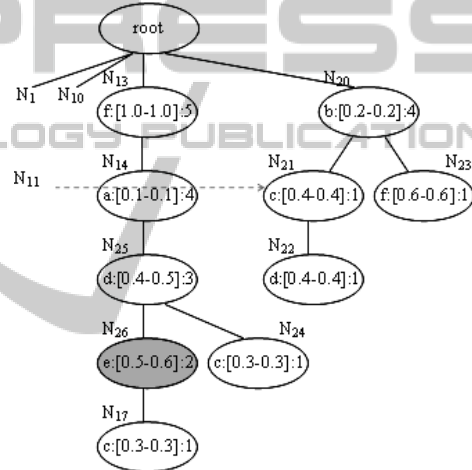

Figure 9: mUF-tree(right)$_6$.

There can be five cases for shuffling a pair of paths PB and PC. In Case 1, both PB and PC do not share common nodes with any other path in the mUF-tree. Therefore, PB and PC can be shuffled without influencing others. In Case 2, PB does not share common nodes with any other path, but PC does. However, in PC, the nodes with common items are above other nodes. Therefore, we do not need to shuffle PC. Case 3 is similar to Case 2 with the information in PB and PC inter-changed. In Case 4, both PB and PC share common nodes with other paths, but with nodes having common items above other nodes. Therefore, neither PB nor PC needs to be shuffled. For all the four cases, PB and PC can be merged after shuffling if necessary.

All other conditions beside the above are considered as Case 0. In Case 0, shuffling is not allowed. Since shuffling in the two paths may induce much effort in re-structuring of the whole mUF-tree.

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Definition 12. Shuffle Case (SC). Given a pair of paths PB and PC, and a_set = CI(PB, PC), there are five shuffle cases.

- SC(PB, PC) = 1 if !overlap(PB) $\wedge$!overlap(PC).
- SC(PB, PC) = 2 if !overlap(PB) $\wedge$ overlap(PC) $\wedge$ above(a_set, PC).
- SC(PB, PC) = 3 if overlap(PB) $\wedge$ above(a_set, PB) $\wedge$!overlap(PC).
- SC(PB, PC) = 4 if overlap(PB) $\wedge$ above(a_set, PB) $\wedge$ overlap(PC) $\wedge$ above(a_set, PC).
- SC(PB, PC) = 0 for other conditions.

For the ease of understanding, the shuffle cases are shown in Table 3.

Table 3: Shuffle cases.

SC(PB, PC)	!overlap(PC)	overlap(PC) $\wedge$ above(a_set, PC)
!overlap(PB)	1	2
overlap(PB) $\wedge$ above(a_set, PB)	3	4

Take the mUF-tree in Figure 4 as an example. Given a maximum merging threshold 0.3, then the shuffle cases with the corresponding path pairs are shown in Table 4.

Table 4: Shuffle cases with corresponding path pairs.

PB	PC	CI(PB, PC)	SC(PB, PC)
$<N_{15}N_{16}>$	$<N_{17}N_{18}N_{19}>$	{d, e}	1
$<N_{10}N_{11}N_{12}>$	$<N_{20}N_{21}N_{22}>$	{b, c}	2
$<N_2N_3N_4N_5>$	$<N_7N_8N_9>$	{a, d}	3
$<N_1N_2N_3N_4N_5>$	$<N_{13}N_{14}N_{15}N_{16}>$	{f, a, d}	4
$<N_{10}N_{11}N_{12}>$	$<N_{13}N_{14}N_{17}N_{18}N_{19}>$	{c}	0
$<N_1N_7N_8N_9>$	$<N_{20}N_{23}>$	{f}	0
$<N_1N_2N_6>$	$<N_{10}N_{11}N_{12}>$	{b}	0
$<N_1N_2N_6>$	$<N_{20}N_{23}>$	{b, f}	0
$<N_1N_7N_8N_9>$	$<N_{20}N_{21}N_{22}>$	{c, d}	0

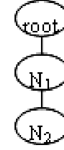
Definition 13. Common Ancestor Path (CAP). Given a pair of paths PB = $<N_{b1}N_{b2}\ldots N_{bk}>$ and PC = $<N_{c1}N_{c2}\ldots N_{cm}>$, we define CAP(PB, PC) = $<N_{b1}N_{b2}\ldots N_{bn}>$, where $(n \leq k) \wedge (n \leq m) \wedge (\forall i \in \{1, 2, \ldots, n\}$, N_{bi} and N_{ci} are the same node).

In Figure 4(b), given a pair of paths PB = $<N_{13}N_{14}N_{15}N_{16}>$ and PC = $<N_{13}N_{14}N_{17}N_{18}N_{19}>$, then CAP(PB, PC) = $<N_{13}N_{14}>$.

Definition 14. Single Prefix-Path Part and Multipath Part. The single prefix-path part of an mUF-tree consists of a single path from the root to N_k, the first node containing more than one child. The multipath part of an mUF-tree consists of the descendants of N_k, with a virtual root connecting to the children of N_k as the parent.

For the mUF-tree shown in Figure 2, the single prefix-path part and the multipath part are shown in Figure 10.

Single prefix-path part:



Multipath part:

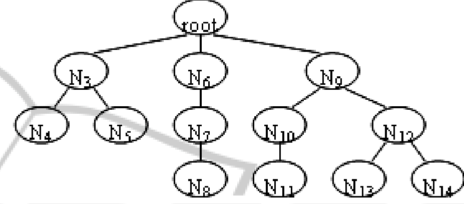


Figure 10: Single prefix-path part and multipath part of mUF-tree.

5.2 The UF-Evolve Algorithm

With the aforementioned definitions, we present the UF-Evolve algorithm for mining frequent patterns in an uncertain database by using an mUF-tree. The algorithm integrates the UF-Mine algorithm for finding out the possible frequent patterns and the UF-Shuffle algorithm for moving and merging the nodes in the mUF-tree iteratively. Figure 11 shows the steps of the UF-Evolve algorithm.

```
UF-Evolve algorithm.
Input: An mUF-tree T, a minimum support threshold
  σ , and a maximum merging threshold γ .
Output: A set of uncertain frequent patterns.

Procedure UF-Evolve(T, σ , γ )
(1)     FPS = ϕ ;  // Frequent pattern set
(2)     do {
(3)       FPS = FPS ∪ UF-Mine(T, null, σ );
(4)       T = UF-Shuffle(T, γ );
(5)     } while T has been modified;
(6)     return FPS;
```

Figure 11: UF-Evolve.

In line (17) of Figure 12, (FPS(P) × FPS(Q)) means concatenating each frequent pattern FP_i in FPS(P) with each frequent pattern FP_j in FPS(Q), with support equal to FP_j.support.

In order to illustrate how the different algorithms work, we will use a running example with mUF-tree(right) in Figure 4(b). Suppose the minimum support threshold is 3, and the maximum merging threshold is 0.3. UF-Evolve calls UF-Mine, and UF-

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```
UF-Mine algorithm.
Input: An mUF-tree T, an uncertain frequent pattern α =
  (a1:[l1-u1])(a2:[l2-u2])…(ak:[lk-uk]):s, and a minimum
  support threshold σ.
Output: A set of uncertain frequent patterns.

Procedure UF-Mine(T, α, σ)
(1)   P = the single prefix-path part of T;
(2)   Q = the multipath part of T;
(3)   FPS(P) = ϕ; // Frequent pattern set in P
(4)   FPS(Q) = ϕ; // Frequent pattern set in Q
(5)   for each pattern β formed from P where all
        nodes in β have sufficient support do {
(6)       β.support = minimum support of nodes in
            β;
(7)     append α to the end of β;
(8)     FPS(P) = FPS(P) ∪ β;
      }
(9)   for each (ai:[li-ui]) in Q with sufficient support do {
(10)      β = (ai:[li-ui]);
(11)      β.support = (ai:[li-ui]).support;
(12)    append α to the end of β;
(13)    FPS(Q) = FPS(Q) ∪ β;
(14)    find cond_tree from Q constructed with the
          conditional pattern-base of β;
          // Conditional mUF-tree of β
(15)    if ∃ cond_tree then
(16)      FPS(Q) = FPS(Q) ∪
            UF-Mine(cond_tree, β, σ);
      }
(17)  return FPS(P) ∪ FPS(Q) ∪
        (FPS(P) × FPS(Q));
```

Figure 12: UF-Mine.

Mine returns a set of uncertain frequent patterns, which is {(b:[0.2-0.2]):4, (a:[0.1-0.1]):4, (f:[1.0-1.0])(a:[0.1-0.1]):4, (f:[1.0-1.0]):5}.

The core algorithm is the UF-Shuffle algorithm, which is shown in Figure 13. Each time it is called by UF-Evolve, it collects the set of paths under the root and finds the most suitable pair of paths to shuffle and merge.

There can be different versions of the UF-Shuffle algorithm. Figure 14 shows UF-Shuffle_2, which is a variant of UF-Shuffle. Each time it is called by UF-Evolve, it collects the set of paths under the root and tries to shuffle and merge each pair of paths. If a pair of paths are shuffled and merged, they will be removed from the set of paths since they have been modified and no longer exist.

After shuffling, candidate nodes can then be merged with some updating. The algorithm of UF-Merge is shown in Figure 15.

```
UF-Shuffle algorithm.
Input: An mUF-tree T, and a maximum merging threshold γ.
Output: A shuffled mUF-tree T.
Procedure UF-Shuffle(T, γ)
(1)   scan T once and collect P_set = the set of paths under
        root(T);
(2)   for each pair of paths PB and PC in P_set do {
        P = CAP(PB, PC);
(3)     PB = PB excludes P;
(4)     PC = PC excludes P;
(5)     get CI(PB, PC) and SC(PB, PC);
(6)   }
      suppose (PB', PC') is a pair of paths that (has maximum
(7)     length(CI(PB, PC))) ∧ (length(CI(PB', PC')) > 0) ∧
        (SC(PB', PC') > 0);
      if ∃ (PB', PC') then {
        switch SC(PB', PC') {
(8)       case 1: shuffle the nodes corresponding to CI(PB',
(9)         PC') to their MAP in PB' and PC';
(10)      case 2: shuffle the nodes corresponding to CI(PB',
            PC') to their MAP in PB';
          case 3: shuffle the nodes corresponding to CI(PB',
(11)        PC') to their MAP in PC';
          case 4: do nothing;
(12)    }
        T = UF-Merge(T, PB', PC',
(13)      length(CI(PB', PC')));
      }
(14)  return T;

(15)
```

Figure 13: UF-Shuffle.

```
Procedure UF-Shuffle_2(T, γ)
(1)   scan T once and collect P_set = the set of paths under
        root(T);
(2)   for each pair of paths PB and PC in P_set do {
        P = CAP(PB, PC);
(3)     PB = PB excludes P;
(4)     PC = PC excludes P;
(5)     if (length(CI(PB, PC)) > 0) ∧
(6)       (SC(PB, PC) > 0) then {
          switch SC(PB, PC) {
(7)         case 1: shuffle the nodes corresponding to CI(PB,
(8)           PC) to their MAP in PB and PC;
            case 2: shuffle the nodes corresponding to CI(PB,
(9)           PC) to their MAP in PB;
            case 3: shuffle the nodes corresponding to CI(PB,
(10)          PC) to their MAP in PC;
            case 4: do nothing;
(11)      }
          T = UF-Merge(T, PB, PC,
(12)        length(CI(PB, PC)));
          remove PB and PC from P_set;
(13)      // Updates will be used in loop at line (2)
        }
      }
      return T;
(14)
```

Figure 14: UF-Shuffle_2.

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UF-Merge algorithm.
Input: An mUF-tree T, a pair of paths PB = $<N_{b1}N_{b2}\ldots N_{bk}>$ and PC = $<N_{c1}N_{c2}\ldots N_{cm}>$, and n, the number of nodes to be merged in each path.
Output: A merged mUF-tree T.

Procedure UF-Merge(T, PB, PC, n)
(1) for i = 1 to n do {
(2) N_q = the new node formed by merging N_{bi} and N_{ci} and updating its item, lowerbound, upperbound, frequency, node-link, parent and children;
remove N_{bi} and N_{ci} from T;
(3) update header table and node-links within T;
(4) }
return T;
(5)

Figure 15: UF-Merge.

In continuing the example, UF-Evolve calls UF-Shuffle to shuffle mUF-tree(right) in Figure 4(b), and UF-Shuffle generates mUF-tree(right)$_4$, as shown in Figure 7.

UF-Shuffle calls UF-Merge and recommends the pair of paths to be merged (i.e. $<N_{15}N_{16}>$ and $<N_{18}N_{19}N_{17}>$). UF-Merge merges the pair of paths, and returns the generated mUF-tree(right)$_6$, as shown in Figure 9.

UF-Evolve calls UF-Mine, and UF-Mine returns a new set of uncertain frequent patterns, which is {(d:[0.4-0.5]):3, (a:[0.1-0.1])(d:[0.4-0.5]):3, (f:[1.0-1.0])(d:[0.4-0.5]):3, (f:[1.0-1.0])(a:[0.1-0.1])(d:[0.4-0.5]):3, (b:[0.2-0.2]):4, (a:[0.1-0.1]):4, (f:[1.0-1.0])(a:[0.1-0.1]):4, (f:[1.0-1.0]):5}.

UF-Evolve combines the original set of uncertain frequent patterns with the new set. Now, the set of uncertain frequent patterns becomes {(b:[0.2-0.2]):4, (a:[0.1-0.1]):4, (f:[1.0-1.0])(a:[0.1-0.1]):4, (f:[1.0-1.0]):5, (d:[0.4-0.5]):3, (a:[0.1-0.1])(d:[0.4-0.5]):3, (f:[1.0-1.0])(d:[0.4-0.5]):3, (f:[1.0-1.0])(a:[0.1-0.1])(d:[0.4-0.5]):3}.

The algorithms continue to attempt building new mUF-trees until not successful. At the end, the patterns are stabilized.

6 PERFORMANCE STUDY

6.1 Experimental Environment and Data Preparation

In this section, we present some performance comparison of UF-Evolve with FP-growth. All the experiments are performed on a 2.83 GHz Xeon server with 3.00 GB of RAM, running Microsoft Windows Server 2003. The programs are written in Java. Runtime here means the total execution time, i.e. the period between input and output, instead of CPU time. Also, all the runtime measurements of UF-Evolve/FP-growth included the time of constructing mUF-trees/FP-trees from the original databases.

The experiments are done on a synthetic database (T10.I4.D3K), which is generated by using the methods in (IBM). In this database, the average record length is 10, the average length of pattern is 4, and the number of records is 3K. Besides, we set the number of items as 1000. All the probabilities for the items are randomly generated.

For UF-Evolve, each record in the database consists of multiple item:probability pairs. However, for FP-growth, each record in the database consists of multiple items. These two representations have different semantic meanings. In order to carry out a consistent comparison of UF-Evolve with FP-growth, we make the following arrangements.

- First we generate UDB for UF-Evolve. Each record in UDB consists of multiple (a_i:p_i).
- Based on UDB, we generate a special database UDB' for FP-growth. Each record in UDB' consists of multiple (a_j:[l_j-u_j]), where $a_j = a_i$, and $l_j = u_j = p_i$. FP-growth treats each (a_j:[l_j-u_j]) as an item.
- While constructing an mUF-tree from UDB, we keep the Record IDs in the corresponding nodes. When UF-Evolve generates iterative versions of the mUF-tree, we record the changes of (lowerbound-upperbound) in the nodes together with their Record IDs.
- We use the Record IDs to trace back to the records in UDB' and change the corresponding l_j and u_j. Then there will be iterative versions of UDB' for discovering new frequent patterns by FP-growth.

With these arrangements, we will have a consistent comparison for the runtime and number of mined frequent patterns from the two algorithms.

6.2 Experiments

In the first experiment, we measured the runtime, number of shuffles and number of mined frequent patterns with different numbers of records for UF-Evolve and FP-growth. The number of records varies from 0.1K to 3K, the minimum support threshold is 3%, and the maximum merging threshold is 0.3. The runtime of UF-Evolve and FP-growth are shown in Figure 16. UF-Evolve is faster and more scalable than FP-growth. The number of shuffles of UF-Evolve is shown in Figure 17. Since when the number of records increases, UF-Evolve shuffles a bigger mUF-tree. The numbers of mined

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frequent patterns of UF-Evolve and FP-growth are shown in Figure 18. The two algorithms mined the same numbers and the same sets of frequent patterns.

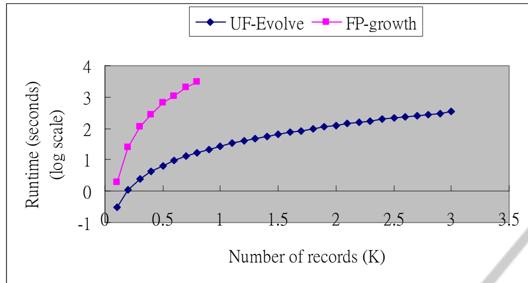

Figure 16: Runtime with number of records for UF-Evolve and FP-growth.

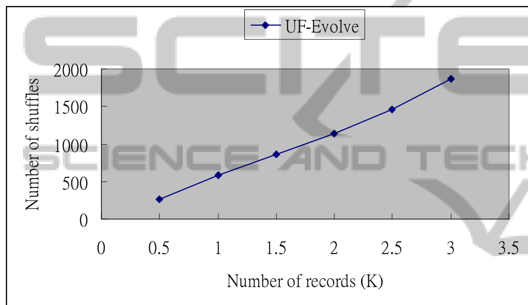

Figure 17: Number of shuffles with number of records for UF-Evolve.

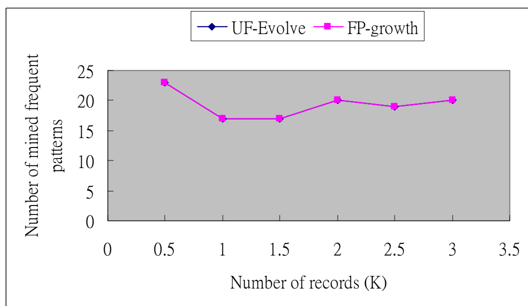

Figure 18: Number of mined frequent patterns with number of records for UF-Evolve and FP-growth.

In the second experiment, we measured the runtime, number of shuffles and number of mined frequent patterns with different minimum support thresholds for UF-Evolve and FP-growth. The minimum support threshold varies from 0.1% to 8%, the number of records is 3K, and the maximum merging threshold is 0.3. The runtime of UF-Evolve and FP-growth are shown in Figure 19. UF-Evolve is faster and more scalable than FP-growth. When the minimum support threshold increases, the runtime of both UF-Evolve and FP-growth decreases. Since when the minimum support threshold is high, UF-Evolve processes fewer and smaller conditional mUF-trees. The number of shuffles of UF-Evolve is shown in Figure 20. When the minimum support threshold increases, the number of shuffles of UF-Evolve remains the same. This is because UF-Evolve always shuffles the same mUF-tree. The numbers of mined frequent patterns of UF-Evolve and FP-growth are shown in Figure 21. The two algorithms mined the same numbers and the same sets of frequent patterns. When the minimum support threshold increases, the numbers of mined frequent patterns of both UF-Evolve and FP-growth decrease. This is because when the minimum support threshold is high, the frequent patterns are short and the set of such patterns is not large.

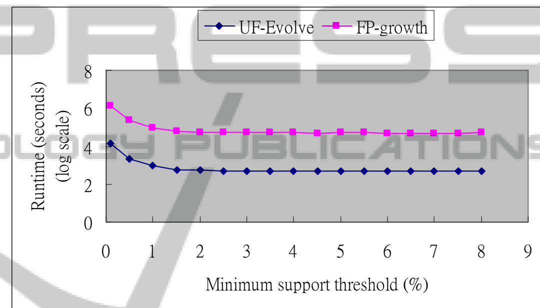

Figure 19: Runtime with minimum support threshold for UF-Evolve and FP-growth.

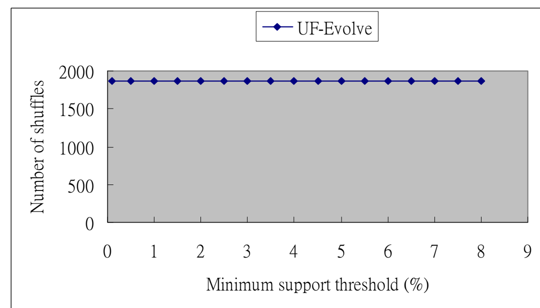

Figure 20: Number of shuffles with minimum support threshold for UF-Evolve.

In the third experiment, we measured the number of mined frequent patterns in each iteration for UF-Evolve. The number of records is 3K, the minimum support threshold is 0.1%, and the maximum merging threshold is 0.3. As shown in Figure 22, UF-Evolve discovers new frequent patterns from iterative versions of mUF-tree, and the number of mined frequent patterns keeps increasing until stabilized.

For the above experiments, UF-Evolve and FP-

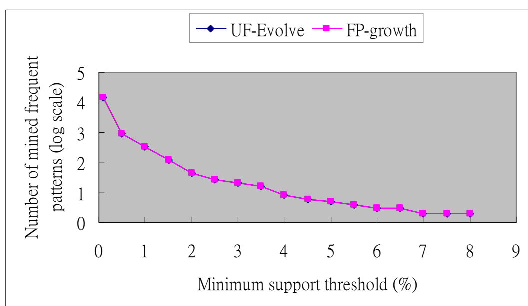

Figure 21: Number of mined frequent patterns with minimum support threshold for UF-Evolve and FP-growth.

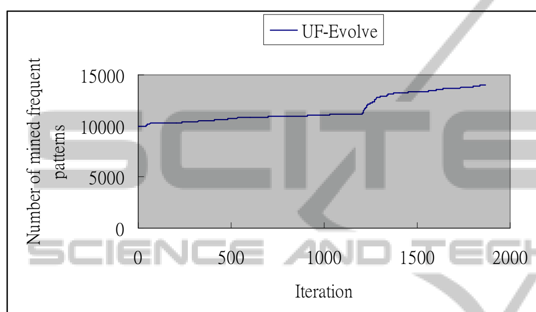

Figure 22: Number of mined frequent patterns in each iteration for UF-Evolve.

growth mined the same numbers and the same sets of frequent patterns. Some of the discovered frequent patterns are shown in Table 5. Here, the supports for frequent patterns are shown as (support count)/(number of records in UDB) in percentage.

Table 5: Discovered frequent patterns.

Frequent patterns mined in 1st iteration	New frequent patterns mined in 2nd iteration	New frequent patterns mined in 3rd iteration
(59757:[0.3-0.3]) :4% (45370:[0.7-0.7]) :5% …	(29340:[0.1-0.3]) :3% (59757:[0.3-0.4]) (22360:[0.3-0.3]) (18474:[0.5-0.7]) (29340:[0.1-0.3]) :3% …	(45973:[0.2-0.3]) :4% (38212:[0.8-0.8]) (8885:[0.2-0.5]) (45973:[0.2-0.3]) :4% …

7 CONCLUSIONS

We have proposed the mUF-tree structure, which is a novel uncertain-frequent-pattern discover structure, and the UF-Evolve algorithm, which utilizes the shuffling and merging techniques on the mUF-tree for repeatedly discovering new uncertain frequent patterns. Also, we proposed a variant of the UF-Shuffle algorithms. Our preliminary performance study shows that the UF-Evolve algorithm is efficient and scalable for mining additional uncertain frequent patterns with different sizes of uncertain databases.

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