Mining High Utility Itemsets without Candidate Generation

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ABSTRACT
High utility itemsets refer to the sets of items with high utility like profit in a database, and efficient mining of high utility itemsets plays a crucial role in many real-life applications and is an important research issue in data mining area. To identify high utility itemsets, most existing algorithms first generate candidate itemsets by overestimating their utilities, and subsequently compute the exact utilities of these candidates. These algorithms incur the problem that a very large number of candidates are generated, but most of the candidates are found out to be not high utility after their exact utilities are computed. In this paper, we propose an algorithm, called HUI-Miner (High Utility Itemset Miner), for high utility itemset mining. HUI-Miner uses a novel structure, called utility-list, to store both the utility information about an itemset and the heuristic information for pruning the search space of numerous candidate itemsets. HUI-Miner can efficiently mine high utility itemsets from the utility-lists constructed from a mined database. We compared HUI-Miner with the state-of-the-art algorithms on various databases, and experimental results show that HUI-Miner outperforms these algorithms in terms of both running time and memory consumption.

Categories and Subject Descriptors
H.2.8 [Database Applications]: Data mining

General Terms
Algorithms, Experimentation, Performance

Keywords
High utility itemset, mining algorithm

1. INTRODUCTION
The rapid development of database techniques facilitates the storage and usage of massive data from business corporations, governments, and scientific organizations. How to obtain valuable information from various databases has received considerable attention, which results in the sharp rise of related research topics. Among the topics, the high utility itemset mining problem is one of the most important, and it derives from the famous frequent itemset mining problem [7, 8].

Mining frequent itemsets is to identify the sets of items that appear frequently in transactions in a database. The frequency of an itemset is measured with the support of the itemset, i.e., the number of transactions containing the itemset. If the support of an itemset exceeds a user-specified minimum support threshold, the itemset is considered as frequent. Most frequent itemset mining algorithms employ the downward closure property of itemsets [4]. That is, all supersets of an infrequent itemset are infrequent, and all subsets of a frequent itemset are frequent. The property provides the algorithms with a powerful pruning strategy. In the process of mining frequent itemsets, once an infrequent itemset is identified, the algorithms no longer check all supersets of the itemset. For example, for a database with n items, after the algorithms identify an infrequent itemset containing k items, there is no need to check all of its supersets, i.e., $2^{n-k} - 1$ itemsets.

Mining of frequent itemsets only takes the presence and absence of items into account. Other information about items is not considered, such as the independent utility of an item and the context utility of an item in a transaction. Typically, in a supermarket database, each item has a distinct price/profit, and each item in a transaction is associated with a distinct count which means the quantity of the item one bought. Consider the database in Fig. 1. There are seven items in the utility table and seven transactions in the transaction table in the database. To calculate support, an algorithm only makes use of the information of the first two columns in the transaction table, the information of both the utility table and the other columns in the transaction table are discarded. However, an itemset with high support may have low utility, or vice versa. For example, the support and utility of itemset \{bc\} appearing in T1, T2, and T6 are 3 and 18 respectively (See Section 2.1 for utility computation), and those of itemset \{de\}...
### 2. BACKGROUND

In the section, we first give the formal description of the high utility itemset mining problem and subsequently introduce the previous solutions to the problem.

#### 2.1 Problem Definition

Let $\mathcal{I} = \{i_1, i_2, i_3, \ldots, i_n\}$ be a set of items and $\mathcal{D}$ be a database composed of a utility table and a transaction table. Each item in $\mathcal{I}$ has a utility value in the utility table. Each transaction $T$ in the transaction table has a unique identifier (tid) and is a subset of $\mathcal{I}$, in which each item is associated with a count value. An itemset is a subset of $\mathcal{I}$ and is called a $k$-itemset if it contains $k$ items.

**Definition 1.** The external utility of item $i$, denoted as $eu(i)$, is the utility value of $i$ in the utility table of DB.

**Definition 2.** The internal utility of item $i$ in transaction $T$, denoted as $iu(i, T)$, is the count value associated with $i$ in $T$ in the transaction table of DB.

**Definition 3.** The utility of item $i$ in transaction $T$, denoted as $u(i, T)$, is the product of $iu(i, T)$ and $eu(i)$, where $u(i, T) = iu(i, T) \times eu(i)$.

For example, in Fig. 1, $eu(e) = 4$, $iu(e, T5) = 2$, and $u(e, T5) = iu(e, T5) \times eu(e) = 2 \times 4 = 8$.

**Definition 4.** The utility of the itemset $X$ in transaction $T$, denoted as $u(X, T)$, is the sum of the utilities of all the items in $X$ in $T$, in which $X$ is contained, where $u(X, T) = \sum_{i \in X \land i \subseteq T} u(i, T)$.

**Definition 5.** The utility of itemset $X$, denoted as $u(X)$, is the sum of the utilities of all the items in $X$ in all the transactions containing $X$ in DB, where $u(X) = \sum_{T \in DB \land X \subseteq T} u(X, T)$.

For example, in Fig. 1, $u(\{ae\}, T2) = u(a, T2) + u(e, T2) = 4 \times 4 + 1 \times 4 = 8$, and $u(\{ae\}) = u(\{ae\}, T2) + u(\{ae\}, T5) = 8 + 13 = 21$.

**Definition 6.** The utility of transaction $T$, denoted as $tu(T)$, is the sum of the utilities of all the items in $T$, where $tu(T) = \sum_{i \in T} u(i, T)$, and the total utility of DB is the sum of the utilities of all the transactions in DB.

Fig. 2 shows the utility of each transaction, for example, $tu(T1) = u(b, T1) + u(c, T1) + u(d, T1) + u(g, T1) = 2 + 2 + 5 + 1 = 10$. The total utility of the database in Fig. 1 is 98. An itemset $X$ is high utility if $u(X)$ is not less than a user-specified minimum utility threshold denoted as minutil.

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**Table 1**: Database

<table>
<thead>
<tr>
<th>Item</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>e</th>
<th>f</th>
<th>g</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utility</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>3</td>
<td>1</td>
</tr>
</tbody>
</table>

(a) Utility table

<table>
<thead>
<tr>
<th>Tid</th>
<th>Transaction</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1</td>
<td>{b, c, d}</td>
<td>{1, 2, 1, 1}</td>
</tr>
<tr>
<td>T2</td>
<td>{a, b, c, d, e}</td>
<td>{4, 1, 3, 1, 1}</td>
</tr>
<tr>
<td>T3</td>
<td>{a, c, d}</td>
<td>{4, 2, 1}</td>
</tr>
<tr>
<td>T4</td>
<td>{c, e, f}</td>
<td>{2, 1, 1}</td>
</tr>
<tr>
<td>T5</td>
<td>{a, b, d, e}</td>
<td>{5, 2, 1, 2}</td>
</tr>
<tr>
<td>T6</td>
<td>{a, b, c, f}</td>
<td>{3, 4, 1, 2}</td>
</tr>
<tr>
<td>T7</td>
<td>{d, g}</td>
<td>{1, 5}</td>
</tr>
</tbody>
</table>

(b) Transaction table

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3. Extensive experiments on various databases were performed to compare HUI-Miner with the state-of-the-art algorithms. Experimental results that show HUI-Miner outperforms these algorithms are reported.

After the related background is stated in Section 2, the paper is organized according to the three points aforementioned in Section 3, 4, and 5. Our work is summarized in Section 6.
Finally, these algorithms, except for DCG and DCG+, compute the exact utilities of all remaining candidates by an additional database scan to identify high utility itemsets (DCG and DCG+ compute exact utility in each database scan). Besides the two problems mentioned in Section 1, these algorithms suffer from the level-wise mining problems as well, e.g., repeated database scans.

The algorithms based on the FP-Growth algorithm [9] show better performance. These algorithms include IHUPTWU [5], UP-Growth [23], and UP-Growth+ [22]. Firstly, they transform a mined database into a prefix-tree, and the tree maintains the utility information about itemsets. Secondly, for each item of the tree, if it is estimated to be valuable, namely there is likely to be high utility itemsets containing the item, the algorithms construct a conditional prefix-tree for the item. Thirdly, the algorithms recursively process all conditional prefix-trees to generate candidate high utility itemsets. Finally, the algorithms scan the database again to compute the exact utilities of all candidates for identifying high utility itemsets. Reducing the numbers of both database scans and candidate itemsets, these algorithms outperform the Apriori-based algorithms. Even so, compared with the number of resultant high utility itemsets, these algorithms still generate a large number of candidate itemsets in most cases, and it is very costly to both generate these candidates and compute their exact utilities.

There are also a number of studies that focus on the problem of mining an approximate set of all high utility itemsets [10, 24] or a condensed set of all high utility itemsets [20, 21]. In this study, the problem of mining the complete set of all high utility itemsets from a database is discussed.

## 3. UTILITY-LIST STRUCTURE

To mine high utility itemsets, many previous algorithms directly perform on an original database. Although FP-Growth-based algorithms generate candidate itemsets from prefix-trees, they have to compute the exact utilities of candidates by scanning the database. In the section, we propose a utility-list structure to maintain the utility information about a database.

### 3.1 Initial Utility-Lists

In our HUI-Miner algorithm, each itemset holds a utility-list. Initial utility-lists storing the utility information about a mined database can be constructed by two scans of the database. Firstly, the transaction-weighted utilities of all items are accumulated by a database scan. If the transaction-weighted utility of an item is less than a given minutil, the item is no longer considered according to Property 1 in the subsequent mining process. For the items whose transaction-weighted utilities exceed the minutil, they are sorted in transaction-weighted-utility-ascending order.

For the database in Fig. 1, suppose the minutil is 30, and then the algorithm no longer takes items f and g into consideration after the first database scan. The remaining items are sorted: e < c < b < a < d.

### Definition 8. A transaction is considered as “revised” after (1) all the items whose transaction-weighted utilities are less than a given minutil are deleted from the transaction; (2) the remaining items are sorted in transaction-weighted-utility-ascending order.

When scanning the database again, the algorithm revises
each transaction for constructing initial utility-lists. The database view in Fig. 4 lists all revised transactions derived from the database in Fig. 1. From here on, the following convention holds in the remainder of this paper:

**Convention 1.** A transaction is considered as revised, and all the items in an itemset are sorted in transaction-weighted-utility-ascending order, when mentioned.

**Definition 9.** Given an itemset \(X\) and a transaction (or itemset) \(T\) with \(X \subseteq T\), the set of all the items after \(X\) in \(T\) is denoted as \(T - X\).

For example, consider the view in Fig. 4, \(T_2\), \(\{eb\} = \{ad\}\) and \(T_2\)\(\{c\} = \{bad\}\).

**Definition 10.** The remaining utility of itemset \(X\) in transaction \(T\), denoted as \(ru(X, T)\), is the sum of the utilities of all the items in \(T\) except \(X\), where \(ru(X, T) = \sum_{i \in T - X} u(i, T)\).

Each element in the utility-list of itemset \(X\) contains three fields: \(tid\), \(iutil\), and \(rutil\).

- Field \(tid\) indicates a transaction \(T\) containing \(X\).
- Field \(iutil\) is the utility of \(X\) in \(T\), i.e., \(u(X, T)\).
- Field \(rutil\) is the remaining utility of \(X\) in \(T\), i.e., \(ru(X, T)\).

![Figure 4: Database View](image)

**3.2 Utility-Lists of 2-Itemsets**

No need for database scan, the utility-list of 2-itemset \(\{xy\}\) can be constructed by the intersection of the utility-list of \(\{x\}\) and that of \(\{y\}\). The algorithm identifies common transactions by comparing the tids in the two utility-lists. Suppose the lengths of the utility-lists are \(m\) and \(n\) respectively, and then \((m + n)\) comparisons at most are enough for identifying common transactions, because all tids in a utility-list are ordered. The identification process is actually a 2-way comparison. For example, the tid comparison between the utility-lists of itemsets \(\{e\}\) and \(\{c\}\) in Fig. 5 is demonstrated in Fig. 6(a).

![Figure 6: Constructing Utility-Lists of 2-Itemsets](image)

**3.3 Utility-Lists of k-Itemsets (k ≥ 3)**

To construct the utility-list of k-itemset \(\{i_1 \cdots i_{(k-1)}k\}\), we can directly intersect the utility-list of \(\{i_1 \cdots i_{(k-2)}(k-1)\}\) and that of \(\{i_1 \cdots i_{(k-2)}k\}\) as we do to construct the utility-list of a 2-itemset. For example, to construct the utility-list of \(\{eb\}\), we can intersect the utility-list of \(\{eb\}\) and that of \(\{ea\}\) in Fig. 6(b), and the resultant utility-list is depicted in Fig. 7(a). Itemset \(\{eb\}\) does appear in \(T_2\) and \(T_5\) in the database view in Fig. 4, and however the utilities of the itemset in \(T_2\) and \(T_5\) are 10 and 17 rather than 14 and 25, respectively.

The reason for miscalculating the utility of \(\{eb\}\) in \(T_2\) is that the sum of the utilities of both \(\{eb\}\) and \(\{ea\}\) is done in \(T_2\) and \(T_5\) in the database view in Fig. 4, and however the utilities of the itemset in \(T_2\) and \(T_5\) are 10 and 17 rather than 14 and 25, respectively.

![Figure 7: Utility-Lists of 3-Itemsets](image)
Algorithm 1: Construct Algorithm

Input: P.UL, the utility-list of itemset P;
Px.UL, the utility-list of itemset Px;
Py.UL, the utility-list of itemset Py.

Output: Pxy.UL, the utility-list of itemset Pxy.

1. Pxy.UL = NULL;
2. foreach element E ∈ Px.UL do
3.     if ∃Ey ∈ Py.UL and Ex.tid = Ey.tid then
4.         if P.UL is not empty then
5.             search such element E ∈ P.UL that
6.             Ex.tid = Ey.tid;
7.             Exy = <Ex.tid, Ex.iutil + Ey.iutil - E.iutil, 
8.                 Ey.rutil>; 
9.         else
10.        Exy = <Ex.tid, Ex.iutil + Ey.iutil, Ey.rutil>;
11.     end
12. end
13. return Pxy.UL;

The search space of the high utility itemset mining problem can be represented as a set-enumeration tree [19]. Given a set of items \( I = \{i_1, i_2, i_3, \ldots, i_n\} \) and a total order on all items (suppose \( i_1 < i_2 < \cdots < i_n \)), a set-enumeration tree representing all itemsets can be constructed as follows. Firstly, the root of the tree is created; secondly, the \( n \) child nodes of the root representing \( n \)-1-itemsets are created, respectively; thirdly, for a node representing itemset \( \{i_s \cdots i_e\} \) (\( 1 \leq s \leq e < n \)), the \((n-e)\) child nodes of the node representing itemsets \( \{i_1 \cdots i_{(e+1)}\}, \{i_1 \cdots i_{(e+2)}\}, \ldots, \{i_1 \cdots i_{(e+f)}\} \) are created. The third step is done repeatedly until all leaf nodes are created. For example, given \( I = \{e, c, b, a, d\} \) and \( e < c < b < a < d \), a set-enumeration tree representing all itemsets of \( I \) is depicted in Fig. 8.

![Figure 8: Set-Enumeration Tree](image)

DEFINITION 11. Given a set-ensemble tree, an itemset represented by a node is called an extension of an itemset represented by an ancestor node of the node. For an itemset containing \( k \) items, its extension containing \( (k+1) \) items is called an \( i \)-extension of the itemset.

PROPERTY 2. If \( X' \) is an extension of \( X \), \( (X'-X)/(X')X \).

Rationale. Any extension of \( X \) is a combination of \( X \) with the item(s) after \( X \).

For example, in Fig. 8, itemsets \( \{eb\} \) and \( \{ebd\} \) are the 1-extensions of \( \{eb\} \), and \( \{ebd\} \) is the 2-extension of \( \{eb\} \). Starting from the root of a set-ensemble tree, for an itemset, HUI-Miner first checks all of its 1-extensions by constructing their utility-lists. After identifying and outputting high utility itemsets from the extensions, HUI-Miner recursively processes promising extensions one by one and gives up the others. The question is: what are “promising” extensions?

4.2 Pruning Strategy

Exhaustive search can discover all high utility itemsets but is excessively time-consuming, because the numbers of items are large for many databases. For a database with \( n \) items, exhaustive search has to check \( 2^n \) itemsets.

To reduce the search space, we can exploit the utility information in the utility-list of an itemset. The sum of all the utilities in the utility-list of an itemset is the utility of the
Lemma 1. Given the utility-list of itemset $X$, if the sum of all the iutils and rutils in the utility-list is less than a given "minutil", any extension $X'$ of $X$ is not high utility.

Proof. For every transaction $t \supseteq X'$:

\[
\therefore: X \text{ is an extension of } X \implies (X' - X) = (X' / X) \\
X \subset X' \subseteq t \implies (X' / X) \subseteq (t / X)
\]

\[
\therefore: u(X', t) = u(X, t) + u((X' - X), t) = u(X, t) + \sum_{i \in (X' / X)} u(i, t) \leq u(X, t) + \sum_{i \in t} u(i, t) = u(X, t) + ru(X, t),
\]

suppose $id(t)$ denotes the tid of transaction $t$, $X.tids$ denotes the tid set in the utility-list of $X$, and $X'.tids$ that in $X'$, then:

\[
\therefore: X \subset X' \implies X'.tids \subseteq X.tids
\]

\[
\therefore: u(X') = \sum_{id(t) \in X'.tids} u(X', t) \leq \sum_{id(t) \in X'.tids} (u(X, t) + ru(X, t)) \leq \sum_{id(t) \in X'.tids} (u(X, t) + ru(X, t)) < \text{minutil}.
\]

\[\square\]

For example, consider the utility-lists in Fig. 6(b). Itemset \{e\} should be pruned because the sum of all the iutils and rutils in its utility-list, i.e., 24, is less than the minutil, i.e., 30. Therefore, there is no need to check the 7 extensions of itemset \{e\} (see Fig. 8).

4.3 HUI-Miner Algorithm

Algorithm 2 shows the pseudo-code of HUI-Miner. For each utility-list $X$ in $ULs$ (the second parameter), if the sum of all the iutils and rutils in $X$ exceeds minutil, and then the extension associated with $X$ is high utility and outputted. According to Lemma 1, only when the sum of all the iutils and rutils in $X$ exceeds minutil should it be processed further. When the initial utility-lists are constructed from a database, they are sorted and processed in transaction-weighted-utility-ascending order (see Section 3.1). Therefore, all the utility-lists in $ULs$ are ordered as the initial utility-lists are. To explore the search space, the algorithm intersects $X$ and each utility-list $Y$ after $X$ in $ULs$. Suppose $X$ is the utility-list of itemset $P_x$ and $Y$ that of itemset $P_y$, and then $construct(P.UL, X, Y)$ in line 8 is to construct the utility-list of itemset $P_y$ as stated in Algorithm 1. Finally, the set of utility-lists of all the 1-extensions of itemset $P_x$ is recursively processed. Given a database and a minutil, after the initial utility-lists $IULs$ are constructed, HUI-Miner(2, IULs, minutil) can mine all high utility itemsets.

4.4 Implementation Details

The sums of the iutils and rutils in the utility-list of an itemset can be computed by scanning the utility-list. To avoid utility-list scan, in the process of constructing a utility-list, HUI-Miner simultaneously accumulates the iutils and rutils in the utility-list. In addition, there is also no need to bind each itemset to its utility-list. The itemsets represented by all child nodes of a node in a set-enumeration tree have the same prefix itemset. Therefore, for a 1-extension, its extended item can be separated from its prefix itemset. We slightly modify the utility-list structure when implementing HUI-Miner. For example, the utility-lists in Fig. 7(b) are implemented as those showed in Fig. 9. The first line in a utility-list stores the extended item and the sums of the iutils and ruts, and the prefix itemset is stored independently.

![Utility-List Implementation](image)

Figure 9: Utility-List Implementation

Another important detail is the processing order of items. In previous algorithms, such as HUPTWU and UP-Growth, items are sorted in transaction-weighted-utility-descending order, which can reduce the size of prefix-trees used in these algorithms. However, HUPTWU and UP-Growth process items in transaction-weighted-utility-ascending order. The processing order of items can result in the decrease in the explored scope of the search space and thus speed an algorithm up [15]. HUI-Miner adopts utility-lists as data structure, and the size of utility-lists is constant, no matter what order items are sorted in. Therefore, in HUI-Miner, items are sorted in transaction-weighted-utility-ascending order, and more important, processed in the same order.
The four algorithms were implemented in C++ language, used the same libraries, and were compiled using g++ (version 4.3.2). The experiments were performed on a 2.83GHz PC machine (Intel Core2 Q9500) with 4GB of memory, running on a Debian (Linux 2.6.26) operating system.

Eight databases were used in our experiments. Database chain was downloaded from NU-MineBench 2.0 [2], in which transaction records taken from a major grocery store chain in California are contained. The other databases were downloaded from FIMI Repository [1]. Databases accidents, chess, kosarak, mushroom, and retail are real. Synthetic databases T10I4D100K and T40I10D100K were generated by IBM Quest Synthetic Data Generation Code. Other than chain, the other databases do not provide item utility (external utility) and item count for each transaction (internal utility). Like the performance evaluation of previous algorithms [5, 23, 22], external utilities for items are generated between 0.01 and 10 using a log-normal distribution and internal utilities for items are generated randomly ranging from 1 to 10. Fig. 10 shows the statistical information about these databases, including the size on disk, the number of transactions, the number of distinct items, the average number of items in a transaction, and the maximal number of items in the longest transaction(s).

5.2 Running Time

The running time of the four algorithms on all databases is depicted in Fig. 11. Running time was recorded by the “time” command, and it contains input time, CPU time, and output time. The output results of the four algorithms are the same for a mining task, and they were written to “/dev/null”. We terminated a mining task, once its running time exceeds 10000 seconds.

When measuring running time, we varied the minutil for each database. The lower the minutil is, the larger the number of high utility itemsets is, and thus the more the running time is. For example, for database chain in Fig. 11(b), when the minutils are 0.004% and 0.009%, the numbers of high utility itemsets are 18480 and 4578, and the running times of HUI-Miner are 580.9 seconds and
445.1 seconds, respectively. In addition, the curve for UP-Growth almost totally overlaps the curve for UP-Growth+ in Fig. 11(a); the running time of IHUPTWU for any minutil exceeds 10000 seconds for database chess, and thus there is no curve for IHUPTWU in Fig. 11(c).

For almost all databases and minutils, HUI-Miner performs the best. HUI-Miner is almost two orders of magnitude faster than the other algorithms for dense databases. For example, the running times of HUI-Miner and UP-Growth+ are 35.8 seconds and 6302.3 seconds for database mushroom in Fig. 11(e), when the minutil is 2%. In Fig. 11(h), HUI-Miner is slower than UP-Growth+ for high minutils, and we found out in this case that UP-Growth+ generates very few candidate itemsets (only 2007 candidates when the minutil is 0.6%); however, for low minutils, HUI-Miner is even an order of magnitude faster than UP-Growth+ (UP-Growth+ generates 178128 candidates when the minutil is 0.35%). For most sparse databases, the performance superiority of HUI-Miner becomes very significant when the minutil decreases. For example, for retail in Fig. 11(f), the running times of HUI-Miner and IHUPTWU are 15.3 seconds and 219.1 seconds when the minutil is 0.045%, while their running times are 22.2 seconds and 9758.0 seconds when the minutil is reduced to 0.02%.

5.3 Memory Consumption

Fig. 12 shows the peak memory consumption of the four algorithms on all databases, in which each subfigure corresponds to a subfigure in Fig. 11. Peak memory consumption was recorded by the “massif” tool of the “valgrind” software [3].

Except for database accidents in Fig. 12(a), HUI-Miner always consumes less memory than the other algorithms. The reason is that these algorithms have to consume a very large amount of memory to store candidate high utility itemsets during their mining processes, while HUI-Miner does not. Generally, the memory consumption of these algorithms is proportional to the number of candidate itemsets they generate. For example, for database T10I4D100K, IHUPTWU generates 3826202 candidate itemsets and consumes 109.0 MB of memory while UP-Growth+ generates 1007150 candidate itemsets and consumes 50.22 MB of memory, when the minutil is 0.005%. The number of high utility itemsets is only 313509 for the mining task. HUI-Miner neither generates nor stores candidate itemsets, and thus it consumes only 23.62 MB of memory.

Another observation is that UP-Growth+ consumes more memory than UP-Growth in some cases, for example, in Fig. 12(b) and (d), although UP-Growth+ always generates fewer candidate itemsets than UP-Growth. It is because that each node in the prefix-trees used in UP-Growth+ always consumes more information than that in the prefix-trees used in UP-Growth [22]. When a database is sparse and large, the size of a corresponding prefix-tree is relatively large, while the number of candidate itemsets is relatively small. For example, the size of sparse database kosarak is 49859KB, but the numbers of candidate itemsets are only 80 and 74 for UP-Growth and UP-Growth+ when the minutil is 1.5%.

5.4 Processing Order of Items

The processing order of items significantly influences the performance of a high utility itemset mining algorithm [5]. As IHUPTWU, UP-Growth, and UP-Growth+ do, HUI-Miner processes items in transaction-weighted-utility-ascending order (see Section 4.4). To get the knowledge of the performance difference for different processing orders, we tested the running time of HUI-Miner on condition that items are processed in transaction-weighted-utility-
descending order, lexicographic order, and transaction-weighted-utility-ascending order, respectively. Fig. 13 shows the experimental results on databases accidents and retail. As we can see, the transaction-weighted-utility-ascending order leads to the best performance. The reason is that the processing order of items is capable of reducing the number of sets of utility-lists for a mining task. To comprehend the reason in depth, one can consult the related work in [15, 16].

5.5 Discussion

From above experiments, we can observe that HUI-Miner outperforms the state-of-the-art algorithms. To mine high utility itemsets, almost all existing algorithms first generate candidate high utility itemsets and subsequently compute the exact utility of each candidate to identify high utility itemsets. To improve performance, previous studies focus on how to reduce the number of candidates, which can lead to the decrease in the costs of both candidate generation and utility computation. Fig. 14 shows the number of candidate itemsets the three algorithms generate and the number of resultant high utility itemsets. For database kosarak, when the minutil is 1% and 1.5%, the times of candidate generation are so much (>100000 seconds) that we had to terminate the two tests. From Fig. 11, Fig. 12, and Fig. 14, one can observe that the number of candidate itemsets generated by an algorithm is proportional to the running time and memory consumption of the algorithm. The state-of-the-art algorithms have been able to efficiently reduce the number of candidates. However, the number is still far larger than the number of resultant high utility itemsets in most cases. For example, HUPTUW, UP-Growth, and UP-Growth+ generate 558254, 48198, and 33966 candidate itemsets, when the minutil is 0.007% for database chain, but the number of resultant high utility itemsets is only 6920.

Using the utility-list structure, the HUI-Miner algorithm can mine high utility itemsets without candidate generation. The distinct advantage of HUI-Miner is that it avoids the costly candidate generation and utility computation. For the above example, HUPTUW, UP-Growth, and UP-Growth+ have to process 551334 (= 558254 – 6920), 41278 (= 48198 – 6920), and 27046 (= 33966 – 6920) candidate itemsets, respectively. These algorithms not only generate these itemsets but also compute their exact utilities on 1112949 transactions. However, these itemsets are discarded finally. The potential advantage of HUI-Miner is that a large amount of memory is saved. For example, the size of database mushroom is only 0.92MB, but UP-Growth and UP-Growth+ generate 1750450 and 1668174 candidate itemsets, and consume 699.9MB and 658.7MB of memory, respectively (when the minutil is 2%), and a large amount of memory is used to store candidate itemsets. Although the algorithms can be modified to swap candidate itemsets to disk, the disk space requirement is also considerable, and moreover, the algorithms’ performance will be degraded.

![Figure 14: Number of Candidate Itemsets & Number of Resultant High Utility Itemsets](image-url)
6. CONCLUSION

In this paper, we have proposed a novel data structure, utility-list, and developed an efficient algorithm, HUI-Miner, for high utility itemset mining. Utility-lists provide not only utility information about itemsets but also important pruning information for HUI-Miner. Previous algorithms have to process a very large number of candidate itemsets during their mining processes. However, most candidate itemsets are not high utility and are discarded finally. HUI-Miner can mine high utility itemsets without candidate generation, which avoids the costly generation and utility computation of candidates. We have studied the performance of HUI-Miner in comparison with the state-of-the-art algorithms on various databases. Experimental results show that HUI-Miner gains significant performance improvement over these algorithms in terms of both running time and memory consumption.

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8. REFERENCES