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An efficient algorithm for mining temporal high utility itemsets from data streams

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Abstract

Utility of an itemset is considered as the value of this itemset, and utility mining aims at identifying the itemsets with high utilities. The temporal high utility itemsets are the itemsets whose support is larger than a pre-specified threshold in current time window of the data stream. Discovery of temporal high utility itemsets is an important process for mining interesting patterns like association rules from data streams. In this paper, we propose a novel method, namely *THUI* (*Temporal High Utility Itemsets*)-*Mine*, for mining temporal high utility itemsets from data streams efficiently and effectively. To the best of our knowledge, this is the first work on mining temporal high utility itemsets from data streams. The novel contribution of *THUI-Mine* is that it can effectively identify the temporal high utility itemsets by generating fewer candidate itemsets such that the execution time can be reduced substantially in mining all high utility itemsets in data streams. In this way, the process of discovering all temporal high utility itemsets under all time windows of data streams can be achieved effectively with less memory space and execution time. This meets the critical requirements on time and space efficiency for mining data streams. Through experimental evaluation, *THUI-Mine* is shown to significantly outperform other existing methods like Two-Phase algorithm under various experimental conditions.
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Keywords: Utility mining; Temporal high utility itemsets; Data stream mining; Association rules

1. Introduction

The mining of association rules for finding the relationship between data items in large databases is a well studied technique in the data mining field with representative methods like *Apriori* (Agrawal et al., 1993, 1996). The problem of mining association rules can be decomposed into two steps. The first step involves finding of all frequent itemsets (or say large itemsets) in databases. Once the frequent itemsets are found, generating association rules is straightforward and can be accomplished in linear time.

An important research issue extended from the mining of association rules is the discovery of temporal association patterns in data streams due to the wide applications on various domains. Temporal data mining can be defined as the activity of discovering interesting correlations or patterns in large sets of temporal data accumulated for other purposes (Bettini et al., 1996). For a database with a specified transaction window size, we may use an algorithm like Apriori to obtain frequent itemsets from the database. For time-variant data streams, there is a strong demand to develop an efficient and effective method to mine various temporal patterns (Das et al., 1998). However, most methods designed for traditional databases cannot be directly applied to the mining of temporal patterns in data streams because of their high complexity.

In many applications, we would like to mine temporal association patterns from the most recent data in data

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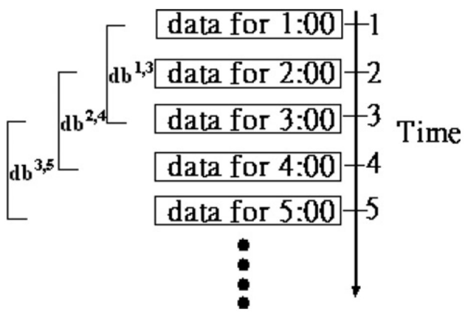


Fig. 1. An example of online transaction flows.

streams. That is, in temporal data mining, one should not only include new data (i.e., data in the new hour) but also remove the old data (i.e., data in the most obsolete hour) from the mining process. Without loss of generality, consider a typical market-basket application as illustrated in Fig. 1, where the transactional data of customer purchases are shown as time advances.

In Fig. 1, for example, data was accumulated as a function of time. Data obtained prior to some specified time interval in the past becomes useless for reference. People might be most interested in the temporal association patterns in the latest three hours (i.e., $db^{3,5}$) as shown in Fig. 1. It can be seen that in such a data stream environment it is intrinsically difficult to conduct the frequent pattern identification due to the constraints of limited time and memory space. Furthermore, it takes considerable time to find temporal frequent itemsets in different time windows. However, the frequency of an itemset may not be a sufficient indicator of interestingness, because it only reflects the number of transactions in the database that contain the itemset. It does not reveal the *utility* of an itemset, which can be measured in terms of cost, profit or other expressions of user preferences. On the other hand, frequent itemsets may only contribute a small portion of the overall profit, whereas non-frequent itemsets may contribute a large portion of the profit. In reality, a retail business may be interested in identifying its most valuable customers (customers who contribute a major fraction of the profits to the company). Hence, frequency is not sufficient to answer questions such as whether an itemset is highly profitable, or whether an itemset has a strong impact. Utility mining is thus useful in a wide range of practical applications and was recently studied in Chan et al. (2003), Liu et al. (2005) and Yao et al. (2004). This also motivates our research in developing a new scheme for finding *temporal high utility itemsets* (*THUI*) from data streams.

Recently, a *utility mining* model was defined in Yao et al. (2004). Utility is considered as a measure of how "useful" (e.g., "profitable") an itemset is. The definition of utility $u(X)$ of an itemset X is the sum of the utilities of X in all transactions containing X. The goal of utility mining is to identify high utility itemsets which drive a large portion of the total utility. Traditional association rules mining models assume that the utility of each item is always 1 and the sales quantity is either 0 or 1, thus it is only a special case of utility mining, where the utility or the sales quantity of each item could be any number. If $u(X)$ is greater than a utility threshold, X is a high utility itemset. Otherwise, it is a low utility itemset. 1 is an example of utility mining in a transaction database. The number in each transaction in Table 1(panel a) is the sales volume of each item, and the utility of each item is listed in Table 2(panel b). For example, $u(\{B, D\}) = (6 \times 10 + 1 \times 6) + (1 \times 10 + 7 \times 6) + (3 \times 10 + 2 \times 6) = 160$. $\{B, D\}$ is considered as a high utility itemset if the utility threshold is set at 120.

However, a high utility itemset may consist of some low utility items. Another attempt is to adopt the level-wise searching schema that exists in fast algorithms such as Apriori (Agrawal and Srikant, 1995). However, this algorithm does not apply to the *utility mining* model. For example, consider $u(D) = 84 < 120$ as shown in 1, D is a low utility item. However, its superset $\{B, D\}$ is a high utility itemset. If Apriori is used to find high utility itemsets, all combinations of the items must be generated. Moreover, the number of candidates is prohibitively large in discovering a long pattern. The cost of either computation time or memory will be intolerable, regardless of what implementation is applied. The challenge of utility mining is not only in restricting the size of the candidate set but also in simplifying the computation for calculating the utility. Another challenge of utility mining is how to find temporal high utility itemsets from data streams as time advances.

In this paper, we explore the issue of efficiently mining high utility itemsets in temporal databases like data streams. We propose an algorithm named *THUI-Mine* that can discover temporal high utility itemsets from data streams efficiently and effectively. The underlying idea of *THUI-Mine* algorithm is to integrate the advantages of Two-Phase algorithm (Liu et al., 2005) and SWF algorithm (Lee et al., 2001) with augmentation of the incremental mining techniques for mining temporal high utility itemsets efficiently. The novel contribution of *THUI-Mine* is that it can efficiently identify the utility itemsets in data streams so that the execution time for mining high utility itemsets can be substantially reduced. That is, *THUI-Mine* can discover the temporal high utility itemsets in current time window and also discover the temporal high utility itemsets in the next time window with limited memory space and less computation time by sliding window filter method. In this way, the process of discovering all temporal high utility itemsets under all time windows of data streams can be achieved effectively under less memory space and execution time. This meets the critical requirements of time and space efficiency for mining data streams. Through experimental evaluation, *THUI-Mine* is shown to produce fewer candidate itemsets in finding the temporal high utility itemsets, so it outperforms other methods in terms of execution efficiency. It is observed that the average improvement of *THUI-Mine* over Two-Phase algorithm reaches to about 67%. Moreover, it also achieves high scalability in dealing with large databases. To our best knowledge, this is the

Table 1
A transaction database and its utility table

Panel a: Transaction table

			ITEM / TID	A	B	C	D	E	
			T_1	0	0	26	0	1	
		P_1	T_2	0	6	0	1	1	
			T_3	12	0	0	1	0	
			T_4	0	1	0	7	0	
$db^{1,3}$		P_2	T_5	0	0	12	0	2	
	D		T_6	1	4	0	0	1	
			T_7	0	10	0	0	1	
		P_3	T_8	1	0	1	3	1	$db^{2,4}$
			T_9	1	1	27	0	0	
			T_{10}	0	6	2	0	0	
	+	P_4	T_{11}	0	3	0	2	0	
			T_{12}	0	2	1	0	0	

Item	Profit ($) (per unit)
Panel b: The utility table	
A	3
B	10
C	1
D	6
E	5

first work on mining temporal high utility itemsets from data streams.

The rest of this paper is organized as follows: Section 2 provides an overview of the related work. Section 3 describes the proposed approach, *THUI-Mine*, for finding the temporal high utility itemsets. In Section 4, we describe the experimental results for evaluating the proposed method. The conclusion of the paper is provided in Section 5.

2. Related work

In association with rules mining, Apriori (Agrawal and Srikant, 1995), DHP (Park et al., 1997) and partition-based ones (Lin and Dunham, 1998; Savasere et al., 1995) were proposed to find frequent itemsets. Many important applications have called for the need of incremental mining due to the increasing use of record-based databases to which data are being added continuously. Many algorithms like FUP (Cheung et al., 1996), FUP_2 (Cheung et al., 1997) and UWEP (Ayn et al., 1999;Ayn et al., 1999) have been proposed to find frequent itemsets in incremental databases. The FUP algorithm updates the association rules in a database when new transactions are added to the database. Algorithm FUP is based on the framework of Apriori and is designed to discover the new frequent itemsets iteratively. The idea is to store the counts of all the frequent itemsets found in a previous mining operation. Using these stored counts and examining the newly added transactions, the overall count of these candidate itemsets are then obtained by scanning the original database. An extension to the work in Cheung et al. (1996) was reported in Cheung et al. (1997) where the authors propose an algorithm FUP_2 for updating the existing association rules when transactions are added to and deleted from the database. UWEP (Update With Early Pruning) is an efficient incremental algorithm, that counts the original database at most once, and the increment exactly once. In addition, the number of candidates generated and counted is minimized.

In recent years, processing data from data streams becomes a popular topic in data mining. A number of algorithms like Lossy Counting (Manku and Motwani, 2002), FTP-DS (Teng et al., 2003) and RAM-DS (Teng et al., 2004) have been proposed to process data in data streams. Lossy Counting divided incoming stream conceptually into buckets. It uses bucket boundaries and maximal possible error to update or delete the itemsets with frequency for mining frequent itemsets. FTP-DS is a regression-based algorithm for mining frequent temporal patterns from data streams. A wavelet-based algorithm, RAM-DS, performs pattern mining tasks for data streams by exploring both temporal and support count granularities.

Some algorithms like SWF (Lee et al., 2001) and Moment (Chi et al., 2004) were proposed to find frequent itemsets over a stream sliding window. By partitioning a transaction database into several partitions, algorithm SWF employs a filtering threshold in each partition to deal with the candidate itemset generation. The Moment algorithm uses a closed enumeration tree (CET) to maintain a dynamically selected set of itemsets over a sliding window.

A formal definition of utility mining and theoretical model was proposed in Yao et al. (2004), namely MEU, where the utility is defined as the combination of utility information in each transaction and additional resources. Since this model cannot rely on downward closure property of Apriori to restrict the number of itemsets to be examined, a heuristic is used to predict whether an itemset should be added to the candidate set. However, the prediction usually overestimates, especially at the beginning stages, where the number of candidates approaches the number of all the combinations of items. The examination of all the combinations is impractical, either in computation cost or in memory space cost, whenever the number of items is large or the utility threshold is low. Although this algorithm is not efficient or scalable, it is by far the best one to solve this specific problem.

Another algorithm named Two-Phase was proposed in Liu et al. (2005), which is based on the definition in Yao et al. (2004) and achieves the finding of high utility itemsets. The Two-Phase algorithm is used to prune down the number of candidates and can obtain the complete set of high utility itemsets. In the first phase, a model that applies the "transaction-weighted downward closure property" on the search space is used to expedite the identification of candidates. In the second phase, one extra database scan is performed to identify the high utility itemsets. However, this algorithm must rescan the whole database when new transactions are added from data streams. It incurs more cost on I/O and CPU time for finding high utility itemsets. Hence, the Two-Phase algorithm is focused on traditional databases and is not suited for mining data streams.

Although there existed numerous studies on high utility itemsets mining and data stream analysis as described above, there is no algorithm proposed for finding temporal high utility itemsets in data streams. This motivates our exploration of the issue of efficiently mining high utility itemsets in temporal databases like data streams in this research.

3. Proposed method: THUI-Mine

In this section, we present the *THUI-Mine* method. Section 3.1 describes the basic concept of *THUI-Mine*. Section 3.2 gives an example for mining temporal high utility itemsets. The procedure of the*THUI-Mine* algorithm is provided in Section 3.3.

3.1. Basic concept of THUI-Mine

The goal of utility mining is to discover all the itemsets whose utility values are beyond a user specified threshold in a transaction database. In Yao et al. (2004), the goal of utility mining is defined as the discovery of all high utility itemsets. An itemset X is a *high utility itemset* if $u(X) \geqslant \varepsilon$, where $X \subseteq I$ and ε is the minimum utility threshold; otherwise, it is a *low utility itemset*. For example, in 1, $u(A, T_8) = 1 \times 3 = 3$, $u(\{A, C\}, T_8) = u(A, T_8) + u(C, T_8) = 1 \times 3 + 1 \times 1 = 4$, and $u(\{A, C\}) = u(\{A, C\}, T_8) + u(\{A, C\}, T_9) = 4 + 30 = 34$. If $\varepsilon = 120$, $\{A, C\}$ is a low utility itemset. However, if an item is a low utility item, its superset may be a high utility itemset. For example, consider $u(D) = 84 < 120$, D is a low utility item, but its superset $\{B, D\}$ is a high utility itemset since $u(\{B, D\}) = 160 > 120$. Intuitively, all combinations of items should be processed so that it never loses any high utility itemset. However, this will incur intolerable cost on computation time and memory space. A set of terms leading to the formal definition of utility mining problem can be generally defined as follows by referring to (Yao et al., 2004):

- $I = \{i_1, i_2, \ldots, i_m\}$ is a set of items.
- $D = \{T_1, T_2, \ldots, T_n\}$ is a transaction database where each transaction $T_i \in D$is a subset of I.
- $o(i_p, T_q)$, *local transaction utility value*, represents the quantity of item i_p in transaction T_q. For example, $o(A, T_3) = 12$, as shown in Table 1(panel a).
- $s(i_p)$, *external utility*, is the value associated with item i_p in the Utility Table. This value reflects the importance of an item, which is independent of transactions. For example, in Table 1(panel b), the external utility of item A, $s(A)$, is 3.
- $u(i_p, T_q)$, *utility*, the quantitative measure of utility for item i_p in transaction T_q, is defined as $o(i_p, T_q) \times s(i_p)$. For example, $u(A, T_3) = 12 \times 3$, in 1.
- $u(X, T_q)$, *utility of an itemset X in transaction Tq*, is defined as $\sum_{ip \in X}^{u(ip,Tq)}$, where $X = \{i_1, i_2, \ldots, i_m\}$ is a k-itemset, $X \subseteq T_q$ and $1 \leqslant k \leqslant m$.
- $u(X)$, *utility of an itemset X*, is defined as $\sum_{Tq \in D \wedge X \subseteq Tq}^{u(X,Tq)}$.

Liu et al. (2005) proposed the Two-Phase algorithm for pruning candidate itemsets and simplifying the calculation of utility. First, the Phase I overestimates some low utility itemsets, but it never underestimates any itemsets. For the example in 1, the *transaction utility of transaction Tq*, denoted as $tu(T_q)$, is the sum of the utilities of all items in Tq: $tu(T_q) = \sum_{ip \in Tq}^{u(ip,Tq)}$. Moreover, the *transaction-weighted utilization of an itemset X*, denoted as $twu(X)$, is the sum of the transaction utilities of all the transactions containing $X : twu(X) = \sum_{X \subseteq Tq \in D}^{tu(Tq)}$. For example, $twu(\mathrm{A}) = tu(T_3) + tu(T_6) + tu(T_8) + tu(T_9) = 42 + 48 + 27 + 40 = 157$ and $twu(\{D, E\}) = tu(T_2) + tu(T_8) = 71 + 27 = 98$. In fact, $u(A) = u(\{A\}, T_3) + u(\{A\}, T_6) + u(\{A\}, T_8) + u(\{A\}, T_9) = 36 + 3 + 3 + 3 = 45$ and $u(\{D, E\}) = u(\{D, E\}, T_2) + u(\{D, E\}, T_8) = 11 + 23 = 34$. Table 2 gives the transaction

Table 2
Transaction utility of the transaction database

TID	Transaction utility	TID	Transaction utility
T_1	31	T_7	105
T_2	71	T_8	27
T_3	42	T_9	40
T_4	52	T_{10}	62
T_5	22	T_{11}	42
T_6	48	T_{12}	21

utility for each transaction in 1. Second, one extra database scan is performed to filter the overestimated itemsets in phase II. For example, by observing that $twu(A) = 157 > 120$ and $u(A) = 45 < 120$, the item $\{A\}$ is pruned. Otherwise, it is a high utility itemset. Finally, all high utility itemsets are discovered in this way.

We illustrate the detail process of Two-Phase algorithm by the following example in $\text{db}^{1,3}$ of 1. Suppose the utility threshold is set as 120 with nine transactions in $\text{db}^{1,3}$. In Phase I, the high transaction-weighted utilization 1-itemsets $\{A,B,C,D,E\}$ are generated since $twu(A) = tu(T_3) + tu(T_6) + tu(T_8) + tu(T_9) = 42 + 48 + 27 + 40 = 157 > 120$, $twu(B) = tu(T_2) + tu(T_4) + tu(T_6) + tu(T_7) + tu(T_9) = 71 + 52 + 48 + 105 + 40 = 361 > 120$, $twu(D) = tu(T_2) + tu(T_3) + tu(T_4) + tu(T_8) = 71 + 42 + 52 + 27 = 192 > 120$ and $twu(\text{E}) = tu(T_1) + tu(T_2) + tu(T_5) + tu(T_6) + tu(T_7) + tu(T_8) = 31 + 71 + 22 + 48 + 105 + 27 = 304 > 120$. Then, 10 candidate 2-itemsets $\{AB, AC, ADAE, BC, BD, BE, CD, CE, DE\}$ are generated by the high transaction-weighted utilization 1-itemsets $\{A,B,C,D,E\}$ in the first database scan. In the same way, the high transaction-weighted utilization 2-itemset $\{BE\}$ are generated since $twu(AB) = tu(T_6) + tu(T_9) = 48 + 40 = 88 < 120$, $twu(AC) = tu(T_8) + tu(T_9) = 27 + 40 = 67 < 120$, $twu(AD) = tu(T_3) + tu(T_8) = 42 + 27 = 69 < 120$, $twu(\text{AE}) = tu(T_6) + tu(T_8) = 48 + 27 = 75 < 120$, $twu(BC) = tu(T_9) = 40 < 120$, $twu(BD) = tu(T_4) = 52 < 120$, $twu(BE) = tu(T_2) + tu\quad(T_6) + tu(T\quad_7) = 71 + 48 + 105 = 224 > 120$, $twu(CD) = tu(T_8) = 27 < 120$, $twu(CE) = tu(T_1) + tu(T_5) + tu(T_8) = 31 + 22 + 27 = 80 < 120$ and $twu(\text{DE}) = tu(T_2) + tu(T_8) = 71 + 27 = 98 < 120$. After processing $\text{db}^{1,3}$, the high transaction-weighted utilization itemsets in $\text{db}^{1,3}$ are obtained as $\{A,B,C,D,E,BE\}$.

In phase II, the high transaction-weighted utilization itemsets $\{A,B,C,D,E,BE\}$ is used to scan $\text{db}^{1,3}$ to find high utility itemsets. The resulting high utility itemsets are $\{B\}$ and $\{BE\}$ since $u(A) = u(\{A\},\ T_3) + u(\{A\},\ T_6) + u(\{A\},\ T_8) + u(\{A\},\ T_9) = 45 < 120$, $u(B) = u(\{B\},\ T_2) + u(\{B\},\ T_4) + u(\{B\},\ T_6) + u(\{B\},\ T_7) + u(\{B\},\ T_9) = 220 > 120$, $u(C) = u(\{C\}, T_1) + u(\{C\},\ T_5) + u(\{C\}, T_8) + u(\{C\},\ T_9) = 66 < 120$, $u(D) = u(\{D\}, T_2) + u(\{D\},\ T_3) + u(\{D\},\ T_4) + u(\{D\},\ T_8) = 72 < 120$, $u(E) = u(\{E\},\ T_1) + u(\{E\},\ T_2) + u(\{E\}, T_5) + u(\{E\},\ T_6) + u(\{E\},\ T_7) + u(\{E\}, T_8) = 35 < 120$ and $u(\{B,E\}) = u(\{B,E\},\ T_2) + u(\{B,E\},\ T_6) + u(\{B,E\}, T_7) = 215 > 120$.

Our algorithm *THUI-Mine* is based on the principle of the Two-Phase algorithm (Liu et al., 2005), and we extend it with the sliding window filtering (SWF) technique and focus on utilizing incremental methods to reduce the candidate itemsets and execution time. In essence, by partitioning a transaction database into several partitions from data streams, algorithm *THUI-Mine* employs a filtering threshold in each partition to deal with the *transaction-weighted utilization itemsets* (*TWUI*) generated. The cumulative information in the prior phases is selectively carried over toward the generation of TWUI in the subsequent phases by *THUI-Mine*. In the processing of a partition, a progressive transaction-weighted utilization set of itemsets is generated by *THUI-Mine*. Explicitly, a progressive transaction-weighted utilization set of itemsets is composed of the following two types of TWUI: (1) the TWUI that were carried over from the previous progressive candidate set in the previous phase and remain as TWUI after the current partition is taken into consideration; (2) the TWUI that were not in the progressive candidate set in the previous phase but are newly selected after taking only the current data partition into account. As such, after the processing of a phase, algorithm *THUI-Mine* outputs a *cumulative filter*, denoted as CF, which consists of a progressive transaction-weighted utilization set of itemsets with their occurrence counts and the corresponding partial support required.

THUI-Mine is different from other existing methods like Lossy Counting (Manku and Motwani, 2002), which uses bucket boundaries and maximal possible error to update or delete the itemsets with frequency. The CF computes the occurrence counts of itemsets in memory and then deletes itemsets that do not satisfy utility threshold in every partial database. With these design considerations, algorithm *THUI-Mine* is shown to have very good performance for mining temporal high utility itemsets from data streams. In Section 3.2, we give an example for mining temporal high utility itemsets from a data stream. The details of *THUI-Mine* algorithm is described in Section 3.3.

3.2. An example for mining temporal high utility itemsets

The proposed *THUI-Mine* algorithm can be best understood by the illustrative transaction database in 1 and Fig. 2 where a scenario of generating high utility itemsets from data streams for mining temporal high utility itemsets is given. For real life applications, this illustrative transaction database can be mapped to the customer transactions in a supermarket. We set the utility threshold as 120 with nine transactions. Without loss of generality, the temporal mining problem can be decomposed into two procedures:

1. Pre-processing procedure: This procedure deals with mining on the original transaction database.
2. Incremental procedure: The procedure deals with the update of the high utility itemsets from data streams.

The pre-processing procedure is only utilized for the initial utility mining in the original database, e.g., $\text{db}^{1,n}$. For mining high utility itemsets in $\text{db}^{2,n+1}$, $\text{db}^{3,n+2}$, $\text{db}^{i,j}$ and

	P_1		
	C_2	start	transaction-weighted utility
	AB	1	0
◎	AD	1	42
	AE	1	0
◎	BD	1	71
◎	BE	1	71
◎	DE	1	71

	P_2		
	C_2	start	transaction-weighted utility
◎	AB	2	48
	AD	1	42
◎	AE	2	48
◎	BD	1	123
◎	BE	1	119
	DE	1	71

	P_3		
	C_2	start	transaction-weighted utility
◎	AB	2	88
◎	AC	3	67
	AD	3	27
	AE	2	75
◎	BC	3	40
◎	BD	1	123
◎	BE	1	224
	CE	3	27

	$db^{1,3} - \Delta^- = D^-$		
	C_2	start	transaction-weighted utility
◎	AB	2	88
◎	AC	3	67
◎	BC	3	40
	BD	2	52
◎	BE	2	153

	$D^- + \Delta^+ = db^{2,4}$		
	C_2	start	transaction-weighted utility
	AB	2	88
	AC	3	67
◎	BC	3	123
◎	BD	4	42
◎	BE	2	153
	CD	4	0

Fig. 2. Temporal high utility itemsets generated from data streams by THUI-Mine.

so on, the incremental procedure is employed. Consider the database in 1. Assume that the original transaction database $db^{1,3}$ is segmented into three partitions, namely, $\{P_1, P_2, P_3\}$, in the pre-processing procedure. Each partition is scanned sequentially for the generation of candidate 2-itemsets in the first scan of the database $db^{1,3}$. Since there are three partitions, the utility threshold of each partition is $120/3 = 40$. Such a partial utility threshold is called the filtering threshold in this paper. After scanning the first segment of the three transactions, 1-itemsets $\{A, B, D, E\}$ are kept to generate 2-itemsets because $twu(A) = 42 > 40$, $twu(B) = 71 > 40$, $twu(C) = 31 < 40$, $twu(D) = 113 > 40$ and $twu(E) = 102 > 40$. Then, 2-itemsets $\{AB, ADAE, BD, BE, DE\}$ are generated by 1-itemsets $\{A, B, D, E\}$ in partition P_1 as shown in Fig. 2. In addition, each potential candidate itemset $c \in C_2$ has two attributes: (1) c.start, which contains the identity of the starting partition when c was added to C_2 and (2) transaction-weighted utility which is the sum of the transaction utilities of all the transactions containing c since c was added to C_2. Itemsets whose transaction-weighted utility are below the filtering threshold are removed. Then, as shown in Fig. 2, only $\{AD, BD, BE, DE\}$, marked by "◎", remain as *temporal high transaction-weighted utilization 2-itemsets* (*TWU2I*) whose information is then carried over to the next phase of processing. Similarly, after scanning partition P_2, the temporal high TWU2I are recorded.

From Fig. 2, it is noted that since there are also three transactions in P_2, the filtering threshold of those itemsets carried out from the previous phase is $40 + 40 = 80$ and that of newly identified candidate itemsets is 40. It can be seen from Fig. 2 that we have four temporal high TWU2I in C_2 after the processing of partition P_2, and two of them are carried from P_1 to P_2 and two of them are newly identified in P_2. Finally, partition P_3 is processed by algorithm *THUI-Mine*. The resulting temporal high TWU2I are $\{AB, AC, BC, BD, BE\}$ as shown in Fig. 2. Note that although itemset $\{AE\}$ appears in the previous phase P_2, it is removed from temporal high TWU2I once P_3 is taken into account since its transaction-weighted utility does not meet the filtering threshold then, i.e., $75 < 120$. However, we do have two new itemsets, i.e., AC and BC, which join the C_2 as temporal high TWU2I. Consequently, we have five temporal high TWU2I generated by *THUI-Mine*, where two of them are carried from P_1 to P_3, one of them is carried from P_2 to P_3, and two of them are newly identified in P_3. Note that only five temporal high TWU2I are generated by *THUI-Mine*, while 10 candidate itemsets would be generated if Two-Phase algorithm were used as mentioned in Section 3.1. After processing P_1 to P_3, those temporal high TWUI in $db^{1,3}$ are obtained as $\{A, B, C, D, E, AB, AC, BC, BD, BE\}$.

After generating temporal high TWU2I from the first scan of database $db^{1,3}$, we use a skill to reduce the number of database scan. In fact, it will take $k - 1$ database scan to generate k-candidate itemsets by using temporal high transaction-weighted utilization $(k - 1)$-itemsets directly. Instead, we use temporal high TWU2I to generate C_k $(k = 3, 4, \ldots, n)$, where C_n is the candidate last itemset. It can be verified that temporal high TWU2I generated by *THUI-Mine* can be used to generate the candidate 3-itemsets. Clearly, a C_3 can be generated from temporal high TWU2I. For example, the 3-candidate itemset $\{ABC\}$ is generated from temporal high TWU2I $\{AB, AC, BC\}$ in $db^{1,3}$. However, the temporal high TWU2I generated by *THUI-Mine* is very close to the high utility itemsets. Similarly, all C_k can be stored in main memory and we can find temporal high utility itemsets together when the second scan of the database $db^{1,3}$ is performed. Thus, only two scans of the original database $db^{1,3}$ are required in the pre-processing step. In this way, the number of database scan is reduced effectively. The resulting temporal high utility itemsets are $\{B\}$ and $\{BE\}$ since $u(B) = 220 > 120$ and $u(\{B, E\}) = 215 > 120$.

One important merit of THUI-Mine lies in its incremental procedure. As depicted in Fig. 2, the mining of database will be moved from $db^{1,3}$ to $db^{2,4}$. Thus, some transactions like T_1, T_2 and T_3 are deleted from the mining database and other transactions like T_{10}, T_{11} and T_{12}, are added. To illustrate it more clearly, this incremental step can also be divided into three sub-steps: (1) generating temporal high TWU2I in $D^- = db^{1,3} - \Delta^-$, (2) generating temporal high TWU2I in $db^{2,4} = D^- + \Delta^+$ and (3) scanning the database $db^{2,4}$ only once for the generation of all temporal high utility itemsets. In the first sub-step, $db^{1,3} - \Delta^- = D^-$, we check the pruned partition P_1 and reduce the value of transaction-weighted utility and set c.start = 2 for those temporal TWU2I where c.start = 1. It can be seen that itemset $\{BD\}$ was removed. Next, in the second sub-step, we scan the incremental transactions in P_4. The process in $D^- + \Delta^+ = db^{2,4}$is similar to the operation of scanning partitions, e.g., P_2, in the pre-processing step. The new itemset $\{BD\}$ joins the temporal high TWU2I after the scan of P_4. In the third sub-step, we use temporal high TWU2I to generate C_k as mentioned above. Finally, those temporal high TWUI in $db^{2,4}$ are $\{B, C, D, E, BC, BD, BE\}$. By scanning $db_{2,4}$ only once, THUI-Mine obtains temporal high utility itemsets $\{B, BC, BE\}$ in $db^{2,4}$.

Table 3
Meanings of symbols used

$db^{i,j}$	Partitioned_database (D) from P_i to P_j
s	Utility threshold in one partition
$\lvert P_k \rvert$	Number of transactions in partition P_k
$TUP_k\ (I)$	Transactions in P_k that contain itemset I with transaction utility
$UP_k\ (I)$	Transactions in P_k that contain itemset I with utility
$\lvert db^{1,n}, (I) \rvert$	Transactions number in $db^{1,n}$ that contain itemset I
$C^{i,j}$	The progressive candidate sets of $db^{i,j}$
$Thtw^{i,j}$	The progressive temporal high transaction-weighted utilization 2-itemsets of $db^{i,j}$
$Thu^{i,j}$	The progressive temporal high utility itemsets of $db^{i,j}$
Δ^-	The deleted portion of an ongoing database
D^-	The unchanged portion of an ongoing database
Δ^+	The added portion of an ongoing database

```
1. n = Number of partitions;
2. |db^{1,n}| = Σ_{k=1,n} |P_k|;
3. CF = φ;
4. begin for k = 1 to n                    // 1st scan of db^{1,n}
5.         begin for each 2-itemset I ∈ P_k
6.              if ( I ∉ CF )
7.                   I.twu = TUP_k (I);
8.                   I.start = k;
9.                   if (I.twu ≥ s×P.count )     // P.count is number of partitions
10.                             CF = CF ∪ I;
11.             if ( I ∈ CF )
12.                  I.twu = I.twu + TUP_k (I);
13.                  if (I.twu < s×P.count )
14.                            CF = CF − I;
15.        end
16. end
17. select Thtw^{1,n} from I where I ∈ CF;
18. keep Thtw^{1,n} in main memory;
19. h = 2;
20. begin while (Thtw^{1,n} ≠ φ)         //Database scan reduction
21.     if (h=2)
22.          C^{1,n}_{h+1} = Thtw^{1,n} * Thtw^{1,n} ;
23.     else
24.          C^{1,n}_{h+1} = C^{1,n}_h * C^{1,n}_h
25.     h = h + 1;
26. end
27. refresh I.twu = 0 where I ∈ Thtw^{1,n} ;
28. begin for k = 1 to n                   //2nd scan of db^{1,n}
29.      for each itemset I ∈ Thtw^{1,n} ∪ C^{1,n}_{h+1}
30.             I.u = I.u + UP_k (I);
31. end
32. for each itemset I ∈ Thtw^{1,n} ∪ C^{1,n}_{h+1}
33.      if (I.u ≥ s×P.count )
34.             Thu^{1,n} = Thu^{1,n} ∪ I;
35. end
36. return Thu^{1,n};
```

Fig. 3. Pre-processing procedure of THUI-Mine.

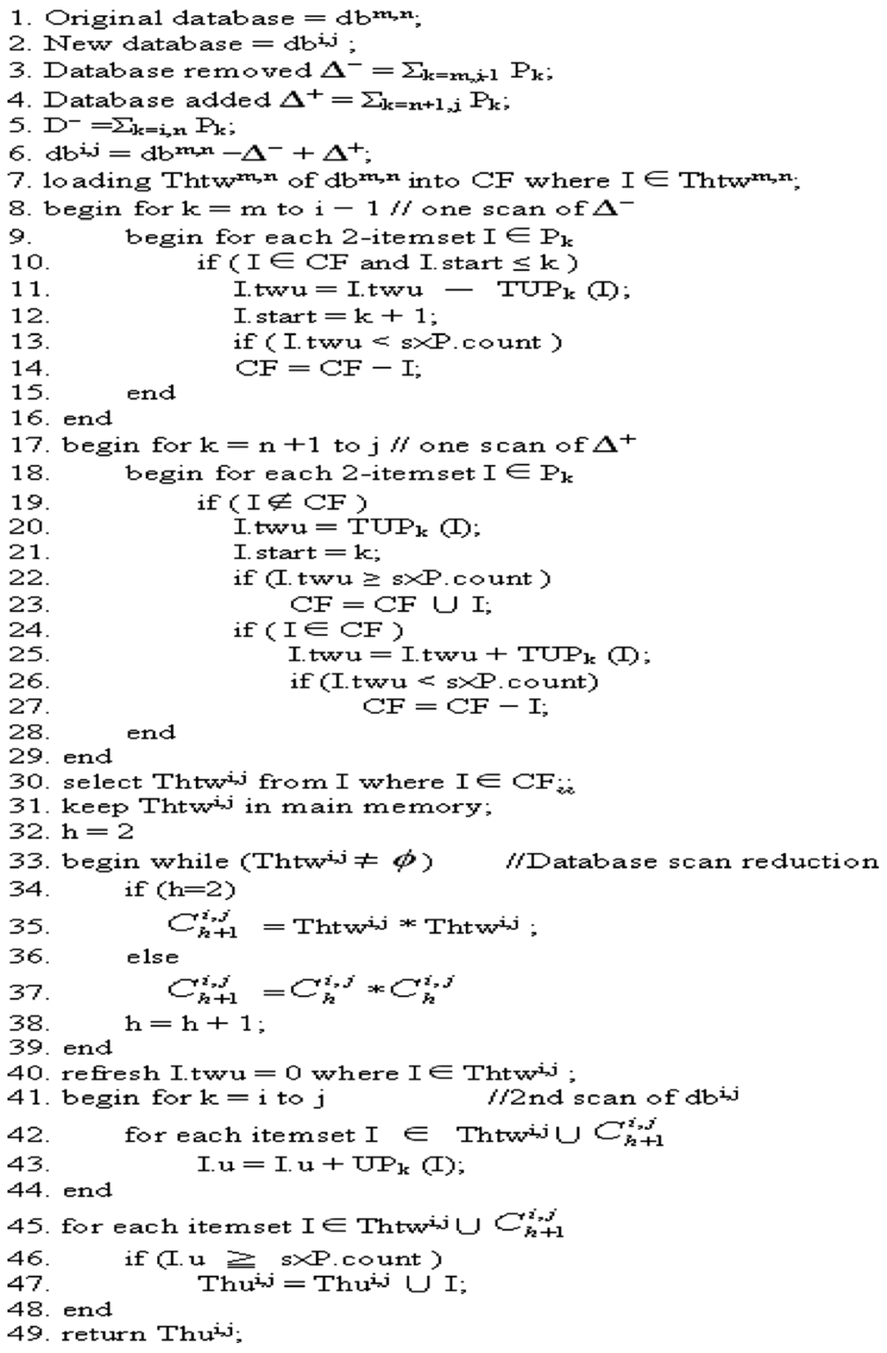
In contrast, Two-Phase algorithm has to scan the whole database like $db^{2,4}$ and more candidate itemsets, i.e., $\{BC, BD, BE, CD, CE, DE\}$, will be generated whenever some transactions are deleted and other transactions are added. Then, Two-Phase algorithm needs one more database scan than THUI-Mine to obtain temporal high TWU2I. Finally, Two-Phase algorithm scans database again to produce temporal high utility itemsets. Hence, more database scans and candidate itemsets are incurred by Two-Phase algorithm in comparison with THUI-Mine.

3.3. THUI-Mine algorithm

For easier illustration, the meanings of various symbols used are given in Table 3. The pre-processing procedure and the incremental procedure of algorithm *THUI-Mine* are described in Sections 3.3.1 and 3.3.2, respectively.

3.3.1. Pre-processing procedure of THUI-Mine

The pre-processing procedure of Algorithm *THUI-Mine* is shown in Fig. 3. Initially, the database $db^{1,n}$ is partitioned into n partitions by executing the pre-processing



```
1. Original database = $db^{m,n}$;
2. New database = $db^{i,j}$ ;
3. Database removed $\Delta^- = \Sigma_{k=m,i-1} P_k$;
4. Database added $\Delta^+ = \Sigma_{k=n+1,j} P_k$;
5. $D^- = \Sigma_{k=i,n} P_k$;
6. $db^{i,j} = db^{m,n} - \Delta^- + \Delta^+$;
7. loading $Thtw^{m,n}$ of $db^{m,n}$ into CF where $I \in Thtw^{m,n}$;
8. begin for k = m to i − 1 // one scan of $\Delta^-$
9.         begin for each 2-itemset $I \in P_k$
10.                if ( $I \in CF$ and I.start $\le$ k )
11.                    I.twu = I.twu  −  $TUP_k$ (I);
12.                    I.start = k + 1;
13.                    if ( I.twu < s×P.count )
14.                    CF = CF − I;
15.        end
16. end
17. begin for k = n +1 to j // one scan of $\Delta^+$
18.        begin for each 2-itemset $I \in P_k$
19.                if ( $I \notin CF$ )
20.                    I.twu = $TUP_k$ (I);
21.                    I.start = k;
22.                    if (I.twu $\ge$ s×P.count )
23.                          CF = CF $\cup$ I;
24.                    if ( $I \in CF$ )
25.                          I.twu = I.twu + $TUP_k$ (I);
26.                          if (I.twu < s×P.count)
27.                                 CF = CF − I;
28.        end
29. end
30. select $Thtw^{i,j}$ from I where $I \in CF_{i,i}$;
31. keep $Thtw^{i,j}$ in main memory;
32. h = 2
33. begin while ($Thtw^{i,j} \ne \phi$)        //Database scan reduction
34.        if (h=2)
35.              $C^{i,j}_{h+1}$ = $Thtw^{i,j}$ * $Thtw^{i,j}$ ;
36.        else
37.              $C^{i,j}_{h+1} = C^{i,j}_{h} * C^{i,j}_{h}$
38.        h = h + 1;
39. end
40. refresh I.twu = 0 where $I \in Thtw^{i,j}$ ;
41. begin for k = i to j                   //2nd scan of $db^{i,j}$
42.        for each itemset I  $\in$  $Thtw^{i,j} \cup C^{i,j}_{h+1}$
43.                I.u = I.u + $UP_k$ (I);
44. end
45. for each itemset $I \in Thtw^{i,j} \cup C^{i,j}_{h+1}$
46.        if (I.u  $\ge$  s×P.count )
47.                $Thu^{i,j} = Thu^{i,j} \cup I$;
48. end
49. return $Thu^{i,j}$;
```

Fig. 4. Incremental procedure of THUI-Mine.

procedure (in Step 2), and CF, the cumulative filter, is empty (in Step 3). Let $\text{Thtw}^{1,n}$ be the set of progressive temporal high TWU2I of $\text{db}^{i,j}$. Algorithm *THUI-Mine* only records $\text{Thtw}^{1,n}$ which is generated by the pre-processing procedure to be used by the incremental procedure. From Step 4 to Step 16, the algorithm processes one partition at a time for all partitions. When partition P_i is processed, each potential candidate 2-itemset is read and saved to CF. The transaction-weight utility of an itemset I and its starting partition are recorded in I.twu and I.start, respectively. An itemset, whose I.twu $\geqslant$ s, will be kept in CF. Next, we select $\text{Thtw}^{1,n}$ from I where $I \in CF$ and keep I.twu in main memory for the subsequent incremental procedure. By employing the scan reduction technique from Step 19 to Step 26, $C_h^{1,n}$ ($h \geqslant 3$) are generated in main memory. After refreshing I.count = 0 where I.twu = 0 where $I \in \text{Thtw}^{1,n}$, we begin the last scan of database for the pre-processing procedure from Step 28 to Step 31. Finally, those itemsets satisfying the constraint that I.u $\geqq s \times$ P.count are finally obtained as the temporal high utility itemsets.

3.3.2. Incremental procedure of THUI-Mine

As shown in Table 3, D^- indicates the unchanged portion of an ongoing transaction database. The deleted and added portions of an ongoing transaction database are denoted by Δ^- and Δ^+, respectively. It is worth mentioning that the sizes of Δ^+ and Δ^-, i.e., $|\Delta^+|$ and $|\Delta^-|$ respectively, are not required to be the same. The incremental procedure of *THUI-Mine* is devised to maintain temporal high utility itemsets efficiently and effectively. This procedure is shown in Fig. 4. As mentioned before, this incremental step can also be divided into three sub-steps: (1) generating temporal high TWU2I in $D^- = \text{db}^{1,3} - \Delta^-$, (2) generating temporal high TWU2I in $\text{db}^{2,4} = D^- + \Delta^+$ and (3) scanning the database $\text{db}^{2,4}$ only once for the generation of all temporal high utility itemsets. Initially, after some update activities, old transactions Δ^- are removed from the database $\text{db}^{m,n}$ and new transactions Δ^+ are added (in Step 6). Note that $\Delta^- \subset \text{db}^{\text{m,n}}$. Denoting the updated database as $\text{db}^{i,j}$, note that $\text{db}^{i,j} = \text{db}^{m,n} - \Delta^- + \Delta^+$. We denote the unchanged transactions by $D^- = \text{db}^{m,n} - \Delta^- = \text{db}^{i,j} - \Delta^+$. After loading $\text{Thtw}^{m,n}$ of $\text{db}^{m,n}$ into CF where $I \in \text{Thtw}^{m,n}$, we start the first sub-step, i.e., generating temporal high TWU2I in $D^- = \text{db}^{\text{m,n}} - \Delta^-$. This sub-step reverses the cumulative processing which is described in the pre-processing procedure. From Step 8 to Step 16, we prune the occurrences of an itemset I, which appeared before partition P_i, by deleting the value I.twu where $I \in CF$ and I.start < i. Next, from Step 17 to Step 39, similarly to the cumulative processing in Section 3.3.1, the second sub-step generates temporal high TWU2I in $\text{db}^{i,j} = D^- + \Delta^+$ and employs the scan reduction technique to generate $C_{h+1}^{i,j}$. Finally, to generate temporal high utility itemsets, i.e., $\text{Thu}^{i,j}$, in the updated database, we scan $\text{db}^{i,j}$ only once in the incremental procedure to find temporal high utility itemsets. Note that $\text{Thtw}^{i,j}$ is kept in main memory for the next generation of incremental mining.

4. Experimental evaluation

To evaluate the performance of *THUI-Mine*, we conducted experiments using synthetic datasets generated via a randomized dataset generator provided by IBM Quest project (Agrawal and Srikant, 1995). However, the IBM Quest data generator only generates the quantity of 0 or 1 for each item in a transaction. In order to fit databases into the scenario of utility mining, we randomly generate the quantity of each item in each transaction, ranging from 1 to 5, as is similar to the model used in Liu et al. (2005). Utility tables are also synthetically created by assigning a utility value to each item randomly, ranging from 1 to 1000. Because it is observed from real world databases that most items are in the low profit range, we generate the utility values using a log normal distribution, as is similar to the model used in Liu et al. (2005). Fig. 5 shows the utility value distribution of 1000 items.

The simulation is implemented in C++ and conducted in a machine with 2.4 GHz CPU and 1 GB memory. For comparison with THUI-Mine algorithm, the two-Phase algorithm is extended with sliding window scenario. The extended Two-Phase algorithm scans the database according to the set time window and then performs the computation within the time window. This process is repeated over sliding time window for the database. The main performance metric used is execution time. We recorded the execution time of *THUI-Mine* in finding temporal high utility itemsets. The comparison on the number of generated itemsets for *THUI-Mine*, Two-Phase and MEU is presented in Section 4.1. Section 4.2 shows the performance comparison of *THUI-Mine* and Two-Phase. The results of scale-up experiments are presented in Section 4.3. Section 4.4 shows the performance comparison of *THUI-Mine* and Two-Phase on another dense dataset.

4.1. Evaluation on number of generated candidates

In this experiment, we compare the average number of candidates generated in the first database scan on the sliding windows and incremental transaction number d10K

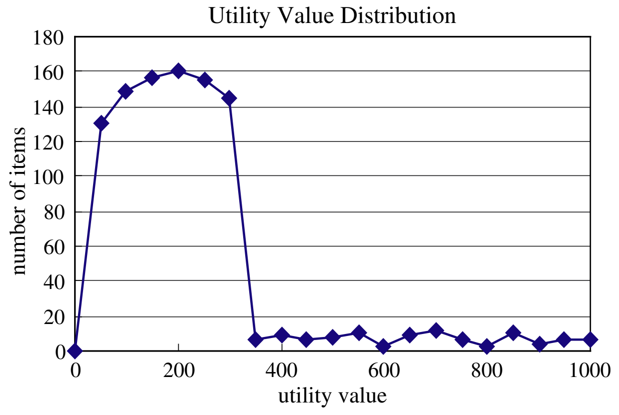


Fig. 5. Utility value distribution in utility table.

with different support values for *THUI-Mine*, Two-Phase (Liu et al., 2005) and MEU (Yao et al., 2004). Without loss of generality, we set $|d| = |\Delta^+| = |\Delta^-|$ for simplicity. Thus, by denoting the original database as $db^{1,n}$ and the new mining database as $db^{i,j}$, we have $|db^{i,j}| = |db^{1,n} - \Delta^- + \Delta^+| = |D|$, where $\Delta^- = db^{1,i-1}$ and $\Delta^+ = db^{n+1,j}$. Tables 4 and 5 show the average number of candidates generated by *THUI-Mine*, Two-Phase and MEU on two datasets, respectively. The number of items is set at 1000, and the minimum utility threshold varies from 0.2% to 1%. The experimental results show that the number of candidate itemsets generated by *THUI-Mine* at the first database scan decreases dramatically as the threshold goes up. Especially, when the utility threshold is set as 1%, the number of candidate itemsets is 0 in database T10.I6.D100 K.d10 K where T denotes the average size of the transactions and I the average number of frequent itemsets. The default size of the sliding window is set as 30K. In fact, we also varied the size of sliding window and the experimental results show that THUI-Mine outperforms Two-Phase algorithm under different sliding windows sizes. Due to space limitation, we only show the representative results with the sliding window size set as 30K. However, the number of candidates generated by Two-Phase is still very large and that for MEU is always 499,500 because it needs to process all combinations of 1000 items. *THUI-Mine* generates far fewer candidates when compared to Two-Phase and MEU.

We obtain similar experimental results for different datasets. For example, only 118 candidate itemsets are generated by *THUI-Mine*, but 183,921 and 499,500 candidate itemsets are generated by Two-Phase and MEU, respectively, when the utility threshold is set as 1% in dataset T20.I6.D100K.d10K. In the case of dataset T20.I6. D100K.d10K, more candidates are generated, because the transaction is longer than that in T10.I6.D100K.d10K. In overall, our algorithm *THUI-Mine* always generates far fewer candidates compared to Two-Phase and MEU for various kinds of databases. Hence, *THUI-Mine* is verified to be very effective in pruning candidate itemsets to find temporal high utility itemsets.

Table 4
The number of candidate itemsets generated on database T10.I6.D100K.d10K

Threshold (%)	Databases, T10.I6.D100K.d10K		
	THUI-Mine	Two-Phase	MEU
0.2	3433	361,675	499,500
0.3	666	303,810	499,500
0.4	161	258,840	499,500
0.6	7	182,710	499,500
0.8	1	129,286	499,500
1	0	91,378	499,500

Table 5
The number of candidate itemsets generated on database T20.I6.D100K.d10K

Threshold (%)	Databases, T20.I6.D100K.d10K		
	THUI-Mine	Two-Phase	MEU
0.2	27357	401,856	499,500
0.3	11659	371,953	499,500
0.4	5389	337,431	499,500
0.6	1364	278,631	499,500
0.8	371	229,503	499,500
1	118	183,921	499,500

4.2. Evaluation of execution efficiency

In this experiment, we compare only the relative performance of Two-phase and *THUI-Mine* since MEU spends much higher execution time and becomes incomparable. Figs. 6 and 7 show the execution times for the two algorithms on datasets T20.I6.D100K.d10K and T10.I6.D100 K.d10K, respectively, as the minimum utility threshold is decreased from 1% to 0.2%. It is observed that when the minimum utility threshold is high, there are only a limited number of high utility itemsets produced. However, as the minimum utility threshold decreases, the performance difference becomes prominent in that *THUI-Mine* significantly outperforms Two-Phase. As shown in Figs. 6 and 7, *THUI-Mine* leads to prominent performance improvement under different sizes of transaction. Explicitly, *THUI-Mine* is significantly faster than Two-Phase and the margin grows as the minimum utility threshold decreases. For example, THUI-Mine is 10 times faster than Two-Phase when threshold is 0.2 for T20.I6.D100K.d10K. In overall, *THUI-Mine*spends much less time than Two-Phase with higher stability in finding temporal high utility itemsets. This is because the Two-Phase algorithm produces more candidate itemsets and needs more database scans to find high utility itemsets than *THUI-Mine*. To measure the improvement on execution time for *THUI-Mine* compared to Two-Phase algorithm, we define the *Improvement Ratio* as follows:

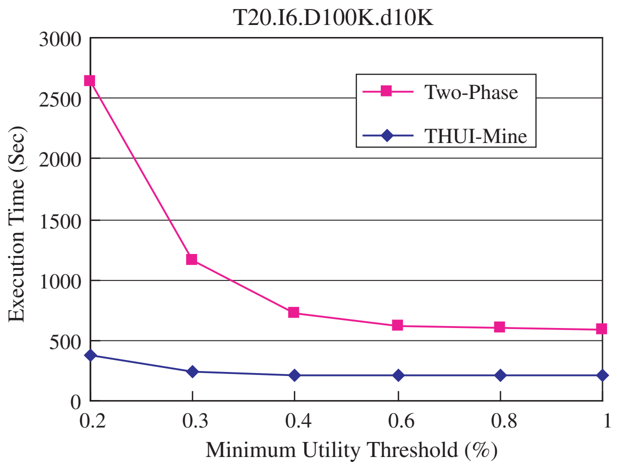


Fig. 6. Execution time for Two-Phase and THUI on T20.I6.D100K. d10K.

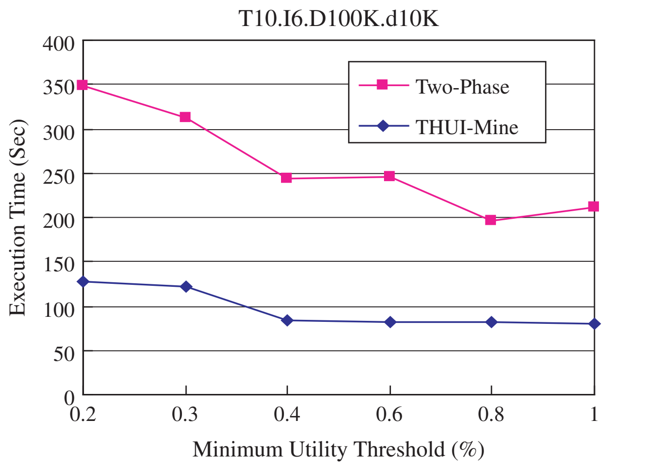


Fig. 7. Execution time for Two-Phase and THUI on T10.I6.D100K.d10K.

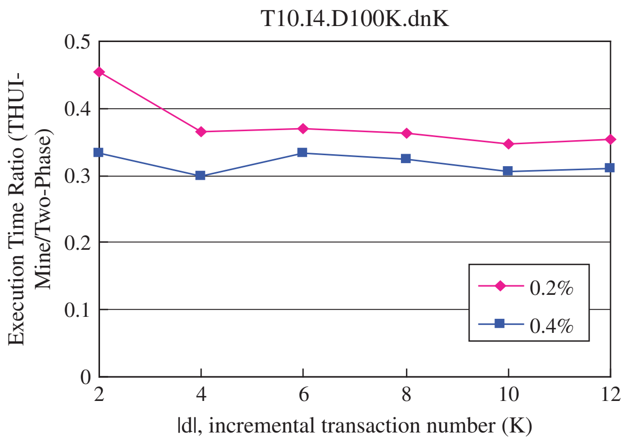


Fig. 8. Scale-up performance results for THUI vs. Two-Phase.

$$\text{Improvement Ratio} = \frac{(\text{execution time of Two} - \text{Phase}) - (\text{execution time of THUI} - \text{Mine})}{\text{execution time of Two} - \text{Phase}}$$

From the data illustrated in Fig. 6, we see that the Improvement Ratio is about 85.6% with the threshold set as 0.2%. In Fig. 7, the average improvement is about 67% with minimum utility threshold varied from 0.2% to 1%. Obviously, *THUI-Mine* reduces substantially the time in finding high utility itemsets. Moreover, the high utility itemsets obtained by Two-Phase are not suitable for applications in data streams since Two-Phase needs more database scans and increased execution time in finding high utility itemsets. Hence, *THUI-Mine* meets the requirements of high efficiency in terms of execution time for data stream mining.

4.3. Scale-up on incremental mining

In this experiment, we investigate the effects of varying incremental transaction size on the execution time of mining results. To further understand the impact of $|d|$ on the relative performance of *THUI-Mine* and Two-Phase, we conduct scale-up experiments which are similar to those described in Lee et al. (2001) with minimum support thresholds being set as 0.2% and 0.4%, respectively. Fig. 8 shows the experimental results where the value in y-axis corresponds to the ratio of the execution time of *THUI-Mine* to that of Two-Phase under different values of $|d|$. It can be seen that the execution-time ratio remains stable with the growth of the incremental transaction number $|d|$ since the size of $|d|$ has little influence on the performance of *THUI-Mine*. Moreover, the execution time ratio of the scale-up experiments with minimum support thresholds varied from 0.6% to 1% remains constant at approximately 0.4%. This implies that the advantage of *THUI-Mine* over Two-Phase is stable and less execution time is taken as the amount of incremental portion increases. This result also indicates that *THUI-Mine* is useful for mining data streams with large transaction size.

4.4. Evaluation on dense data

Typically, the synthetic data sets are very sparse. For testing various kinds of databases, we evaluate another dense dataset, the gazelle data set as used in Zaki and Hsiao (2005). The gazelle data set comes from click-stream data from a dot-com company named Gazelle.com, a

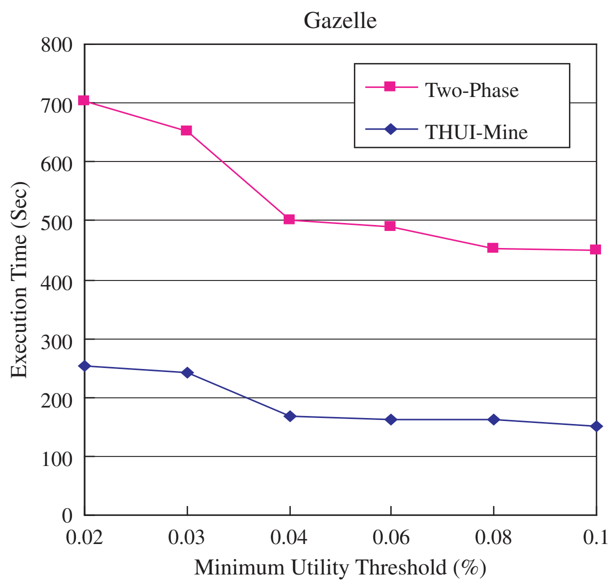


Fig. 9. Execution time for Two-Phase and THUI on gazelle dataset.

legware and legcare retailer. This data set was used in the KDD-Cup 2000 competition and publicly available from www.ecn.purdue.edu/ KDDCUP. In order to fit databases into the scenario of utility mining, we also randomly generate the quantity of each item in each transaction, ranging from 1 to 5. The utility tables are also synthetically created by assigning a utility value to each item randomly, ranging from 1 to 1000.

Fig. 9 shows the execution time for the two algorithms as the minimum utility threshold is varied from 0.1% to 0.02%. It is observed that *THUI-Mine* still spends less time than Two-Phase with higher stability for finding temporal high utility itemsets even under the dense data. This is because the Two-Phase algorithm produces more candidate itemsets and needs more database scans to find high utility itemsets than *THUI-Mine*. Hence, this result also indicates that *THUI-Mine* is effective for mining temporal high utility itemsets under both of sparse and dense datasets.

5. Conclusions

In this paper, we addressed the problem of discovering temporal high utility itemsets in data streams. Under the stream database situation, the memory is often limited and it is hard to store large itemsets in memory. We propose a new algorithm, namely *THUI-Mine*, which can discover temporal high utility itemsets from data streams efficiently and effectively. The novel contribution of *THUI-Mine* is that it can effectively identify the temporal high utility itemsets with less candidate itemsets such that the execution time can be reduced efficiently. In this way, the process of discovering the temporal high utility itemsets in data streams can be achieved effectively with less memory space and execution time. This meets the critical requirements of time and space efficiency for mining data streams.

The experimental results show that *THUI-Mine* can discover the temporal high utility itemsets with higher performance by generating less candidate itemsets as compared to other algorithms under different experimental conditions, including both of sparse and dense datasets. Across the experiments, THUI-Mine is faster than Two-Phase by 2–10 times, and the performance gain becomes more significant as the minimum utility threshold decreases. For example, THUI-Mine is 10 times faster than Two-Phase when the threshold is 0.2 for dataset T20.I6.D100K.d10K. This performance enhancement comes mainly from the good feature of THUI-Mine in producing far fewer candidate itemsets. Moreover, the experimental results also show that *THUI-Mine* is scalable with large databases. Therefore, it is indicated that the advantage of *THUI-Mine* over Two-Phase is stable and less execution time is taken as the amount of incremental portion of databases increases. Hence, *THUI-Mine* is promising for mining temporal high utility itemsets in data streams. For future work, we would extend the concepts proposed in this work to discover other interesting patterns in data streams like utility items with negative profit.

References

Agrawal, R., Imielinski, T., Swami, A., 1993. Mining association rules between sets of items in large databases. In: Proceedings of 1993 ACM SIGMOD International Conference on Management of Data, Washington, DC, pp. 207–216.

Agrawal, R., Mannila, H., Srikant, R., Toivonen, H., Verkamo, A.I., 1996. Fast discovery of association rules. Advances in Knowledge Discovery and Data Mining. AAAI/MIT Press, pp. 307–328.

Agrawal, R., Srikant, R., 1995. Mining sequential patterns. In: Proceedings of the 11th International Conference on Data Engineering, March 1995. pp. 3–14.

Ayn, N.F., Tansel, A.U., Arun, E., 1999. An efficient algorithm to update large itemsets with early pruning. Technical Report BU-CEIS-9908, Dept. CEIS Bilkent Uniiversity, June 1999.

Ayn, N.F., Tansel, A.U., Arun, E., 1999. An efficient algorithm to update large itemsets with early pruning. In: Proceedings of the Fifth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Diego.

Bettini, C., Wang, X.S., Jajodia, S., 1996. Testing complex temporal relationships involving multiple granularities and its application to data mining. In: Proceedings of the 15th ACM Symposium on Principles of Database Systems, Montreal, Canada, pp. 68–78.

Chan, R., Yang, Q., Shen, Y., 2003. Mining high utility Itemsets. In: Proceedings of IEEE ICDM, Florida.

Cheung, D., Han, J., Ng, V., Wong, C.Y. 1996. Maintenance of discovered association rules in large databases: an incremental updating technique. In: Proceedings of 1996 International Conference on Data Engineering, February 1996, pp. 106–114.

Cheung, D., Lee, S.D., Kao. B., A general incremental technique for updating discovered association rules. In: Proceedings of the International Conference On Database Systems For Advanced Applications, April 1997.

Chi, Y., Wang, H., Yu, P.S., Richard, R., 2004. Muntz: moment: maintaining closed frequent itemsets over a stream sliding window. In: Proceedings of the 2004 IEEE International Conference on Data Mining (ICDM'04).

Das, G., Lin, K.I., Mannila, H., Renganathan G., Smyth, P. 1998. Rule discovery from time series. In: Proceedings of the 4th ACM SIGKDD, August 1998, pp. 16–22.

Lee, C.H., Lin, C.R., Chen, M.S. 2001. Sliding-window filtering: an efficient algorithm for incremental mining. In: International Conference on Information and Knowledge Management (CIKM01), November 2001, pp. 263–270.

Lin, J.L., Dunham, M.H., 1998. Mining association rules: anti-skew algorithms. In: Proceedings of 1998 International Conference on Data Engineering, pp. 486–493.

Liu, Y., Liao, W., Choudhary, A., 2005. A fast high utility itemsets mining algorithm. In: Proceedings of the Utility-Based Data Mining Workshop, August.

Manku, G.S., Motwani, R., 2002. Approximate frequency counts over data streams. In: Proceedings of the 28th International Conference on Very Large Data Bases, Hong Kong, China.

Park, J.S., Chen, M.S., Yu, P.S., 1997. Using a hash-based method with transaction trimming for mining association rules. IEEE Transactions on Knowledge and Data Engineering 9 (5), 813–825.

Savasere, A., Omiecinski, E., Navathe, S. An efficient algorithm for mining association rules in large databases. In: Proceedings of the 21th International Conference on Very Large Data Bases, September 1995, pp. 432–444.

Teng, W.G., Chen, M.S., Yu, P.S., 2003. A regression-based temporal pattern mining scheme for data streams. In: Proceedings of the 29th International Conference on Very Large Data Bases, September 2003, pp. 93–104.

Teng, W.G., Chen, M.S., Yu, P.S., 2004. Resource-aware mining with variable granularities in data streams. In: Proceedings of the 4th SIAM International Conference on Data Mining, Florida, USA.

Yao, H., Hamilton, H.J., Butz, C.J., 2004. A foundational approach to mining itemset utilities from databases. In: Proceedings of the4th SIAM International Conference on Data Mining, Florida, USA.

Zaki, M.J., Hsiao, C.J., 2005. Efficient algorithm for mining closed itemsets and their lattice structure. IEEE Transactions on Knowledge and Data Engineering 17 (3), 462–478.