Using Tree Structure to Mine High Temporal Fuzzy Utility Itemsets

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ABSTRACT Data mining is a critical technology for extracting valuable knowledge from databases. It has been used in many fields, like retail, finance, biology, etc. In computational intelligence, fuzzy logic has been applied in many intelligent systems widely because it is simple and similar to human inference. Fuzzy utility mining combines utility mining and fuzzy logic for getting linguistic utility knowledge. In this paper, we study a more challenging, complicated, but practical topic called temporal fuzzy utility data mining, which considers the temporal periods in transactions, purchased amounts, item profits, and understandable linguistic terms as important factors. Although an Apriori-based algorithm was proposed previously, its execution was not efficient. We thus use a modified tree structure based on the classical frequent-pattern tree to improve its performance. A tree-based mining algorithm is also proposed to mine temporal fuzzy utility itemsets from quantitative transactional databases. The tree structure is built to keep all temporal fuzzy utility 1-itemsets in a database. All the high temporal fuzzy utility itemsets in a database can be obtained by traversing the tree-based structure. The proposed algorithm gets the final results through two phases. In the first phase, a procedure like FP-Growth is used to find the candidate itemsets. In the second phase, the temporal fuzzy utility database is scanned to decide whether the candidate itemsets are desired. Experimental results show that the proposed algorithm is superior to the existing algorithm for temporal fuzzy utility mining in terms of processing time and used memory.

INDEX TERMS Fuzzy set, quantitative database, temporal fuzzy utility mining, tree structure, utility mining.

I. INTRODUCTION Most data-mining methods [1]–[3] use item frequencies in transaction databases to decide the degrees of importance. They are expected to find useful data and make practical decisions in different domains, such as finance, retail industry, and biology. For example, Enke et al. combined data mining with neural networks to forecast the stock market [8]. Chen et al. applied data mining methods in the online retail industry [7]. Hirschman et al. reviewed data mining methods used in the literature for biology, analyze them, and summarize their accomplishments and challenges [11]. However, frequent itemsets with low prices typically make little contribution to the total benefit of a company; on the contrary, non-frequent itemsets with highly beneficial rates may be desired and worth of promotion. For example, a car gets much higher profit than a motorcycle, even though the former is less sold than the latter. In business, combinations of items that can earn well are more critical than those with high frequencies. Consequently, Yao et al. [36] proposed utility mining by simultaneously considering purchased quantities and actual profits to find itemsets with high utility values. An itemset with its utility value larger than a specified minimum utility threshold is regarded as relevant and called a high utility itemset. A disadvantage of Yao et al.’s method is that mining steps do not keep the downward-closure property. Hence, it consumes more processing time than mining association rules.

To mine desired utility itemsets efficiently, a two-phase method proposed by Liu et al. [24], [25] could have the downward-closure property in the mining process. Upper-bound values for itemsets were designed to keep the...
monotonic property in Phase 1. Unpromising itemsets were thus pruned as early as possible. In Phase 2, the mined itemsets found in Phase 1 as the candidates were used to decide the actual high utility itemsets by rescanning the database.

Besides, the temporal factor is very critical to the analysis of business behavior. In real situations, the transactions in supermarkets are recorded with check-out time. Furthermore, different products may begin their sales at different times. If all the products are mined using the same duration, it will cause some biases for their real utility associations. The temporal relationship among purchased products is complex and not easily found out in utility mining. Some scholars thus proposed mining approaches to reveal ordered correlation among items from temporal transactions. For example, Lee et al. used the common exhibition periods for items in a publication database to obtain corresponding temporal rules [21]. Chang et al. considered different exhibition times for all products in a dataset [5] to find temporal association rules. Weng discussed the marked times of products as their on-shelf times [34]. He designed a measurement to find more relevant patterns than before by avoiding generating useless itemsets.

The fuzzy set theory provides good linguistic representation for bridging the gap between computers and human beings. People are perceived as linguistic more than quantitative representation. The fuzzy logic was proposed by Zadeh [38] and had a literal concept analogous to human perception. This concept had also been used in intelligent information systems with many good applications. In data mining, when a transactional database with sold quantitative information is processed, the idea of the fuzzy sets can be used to transform the item quantity into linguistic representation. It uses semantic terms to represent concepts, which better matches the way of human thought. Some fuzzy data mining algorithms were proposed for finding linguistic association rules [6], [13], [39]. During the last years, fuzzy utility mining algorithms [15], [20] have been proposed as well. They transformed the quantity values of purchased items in each transaction into fuzzy terms by using pre-defined membership functions and then designed mining steps to find linguistic knowledge from the fuzzy terms. For example, Lan et al. [20] used an upper-bound model based on the fuzzy concept to hold the monotonic property for estimating high fuzzy utility patterns level by level [25].

Huang et al. applied the fuzzy sets to handle the temporal utility data mining [15]. They considered both the transaction time and the purchased quantities of items in a temporal quantitative transactional database and designed a temporal fuzzy utility mining algorithm to mine pertinent linguistic itemsets with the temporal property. It provided a two-phase model to hold the monotonic property in solving the problem. Nevertheless, its execution time is slow due to the consideration of the time factor and level-wise processing.

In this paper, a tree-structure algorithm is proposed to overcome the execution efficiency of the previous temporal fuzzy utility mining algorithm [15]. The proposed approach uses the concept of the FP-tree [10] to reduce the multiple scans to a temporal quantitative database, thus speed up the execution. A tree-structure is mainly used to maintain information for candidates in the first phase. The designed method utilizes it to confirm whether the candidate was desired in a second database scan. The experimental results show that the proposed approach can indeed improve performance.

The rest of the paper is organized as follows. The relevant background information is given in Section II. The problem to be solved and some related definitions are described in Section III. The proposed algorithm is stated and explained in Section IV. An example is used to illustrate the proposed algorithm in Section V. Experimental results are shown and discussed in Section VI. We make a conclusion in Section VII.

II. REVIEW OF RELATED WORKS

In this section, some related works on frequent-pattern growth mining, utility mining, and fuzzy utility mining are briefly reviewed.

A. FREQUENT-PATTERN GROWTH MINING

The Apriori algorithm is the most well-known data mining method, which was proposed by Agrawal et al. to find association rules [1]–[3]. At each iteration, the Apriori method needs to capture the set of frequent $k$-itemsets by scanning a database once. Its major drawback is that a substantial amount of candidates are generated during the mining process. If a dataset has $n$ items, then $2^n − 1$ candidates may be generated and examined in the worst case. Therefore, this method needs multiple database scans for deciding frequent itemsets.

FP-Growth [10], called Frequent-Pattern Growth, is a popular algorithm for mining frequent itemsets without generating candidates. To find all frequent itemsets efficiently, this method only scans the dataset twice. It thus shortens computational time to find frequent itemsets. In the beginning, FP-Growth conducts the first database scan to mine all frequent 1-itemsets. It then scans the database again to remove irrelevant items and compress the whole dataset into a tree structure named FP-Tree to store the frequent items with corresponding information needed for mining. Every node in an FP-Tree has an item and its frequency (support). After the tree is built up, the complete set of frequent itemsets can be found by recursively finding conditional trees and traversing them. The FP-Growth [10] algorithm is stated as follows.

**Step 1:** Scan the database once to get the frequency value of each item (1-itemset) in the database and keep the items with their values larger than the pre-defined minimum support as the frequent 1-itemsets.

**Step 2:** Sort the frequent 1-itemsets in descending order of their frequencies and then build the header table according to the order.

**Step 3:** Scan the database again to remove in each transaction non-frequent items, sort the remaining items according to the order above, and insert them into the FP-Tree.
Step 4: Find the conditional pattern base of each 1-itemset in the header table from the last item to the first one.

Step 5: Use the conditional pattern base of each 1-itemset in the header table to build the conditional sub-tree and then to find frequent itemsets.

Step 6: Repeat Step 5 until no frequent itemsets are found.

B. UTILITY MINING

Frequent itemset mining (FIM) is useful, but it only considers binary databases. Therefore, it has some restrictions. From the perspective of business marketing, the first restriction is that purchasing some quantities of an item in a market is considered equally important to buy a single one. It is not in line with the actual situation in real life. The second restriction is that all items in a market are viewed as equally important. But in a retail store, the sale of a mobile phone is more important than that of a headset since the former has a higher profit than the latter. The third restriction is that frequent itemsets derived by FIM may be less attractive to users because some high-profit item combinations may be hard to find, especially if the items are with low frequencies. The products with high profits but low frequencies in a market may be important as well.

To overcome these restrictions, utility mining has recently evolved into an important research topic. It was first proposed by Yao et al. [36]. They designed a utility measure to represent the importance of an item in a dataset. Different from FIM, utility mining simultaneously considers the quantity values of items in a dataset and their profits as critical factors. If the utility values of items satisfy the minimum utility threshold set by a user, they can be viewed as high utility itemsets. However, utility mining is more complicated than FIM because the latter holds the monotonic property, but the former does not. That is, the utility value of an itemset may be larger, smaller, or equal to those of its subsets. Liu et al. thus proposed the two-phase method [24], [25] to estimate the set of high utility itemsets efficiently. The designed model, called transaction-weighted utility, provides the monotonic property for the utility measure to reduce the search space in mining. They applied the sum of the utility values of all items in each transaction to recognize the upper-bound value of that transaction. Consequently, the upper-bound value of an itemset in a dataset is the sum of the upper-bound values of transactions, which include the itemset. Other related methods [23], [30] used by this model were proposed to find high utility itemsets.

Several variants of mining high utility itemsets were also proposed. Vo et al. presented the MCH-Miner to find high utility itemsets with varying unit profits of items in a dataset by parallel processing [32]. It was assumed that the profit values of all items might change along with item promotion, supply chain cost, or other factors. Besides, a divide-and-conquer strategy was adopted to overcome the performance in the mining process. Nam et al. proposed the DHUPL algorithm to find high utility itemsets in an incremental circumstance. A list structure was designed to reveal the different importance of the items. The method used a damped window model to prune itemsets and considered newly inserted data more important than the previous ones [28].

C. FUZZY UTILITY MINING

Fuzzy sets, which are similar to human thought, can easily represent quantitative information when mining quantitative datasets. The item quantities in a dataset are turned into linguistic representations based on fuzzy membership functions defined in advance. The transformed linguistic representation can imply uncertain features which are interposed within a specific range of numbers. For instance, “three apples and five bananas are sold” is a transaction in a database. The transformed linguistic terms can be treated as a “low” amount of apples to represent people’s feelings.

Based on the above concept, several algorithms about fuzzy data mining [12], [22], [26] have been developed. These mining approaches start by turning the item quantity (the number of items sold) into fuzzy terms that are assigned in advance in line with the different membership functions of individual items. For example, Hong et al. mined fuzzy association rules to reveal amusing patterns with quantitative information. They extended the Apriori algorithm and used the fuzzy concept to mine interesting linguistic patterns [12]. For example, the mining pattern \{A.Low, B.High\} may be mined out and can be interpreted as “If someone buys a low amount of product A, then he/she may also buy a high amount of product B.” Although the results derived from the fuzzy data mining algorithm are useful, its execution cost is high. To solve this problem, a fuzzy frequent pattern tree based on the structure of the FP-Tree was designed by Lin et al. to handle fuzzy data efficiently [22]. The mining method based on the tree can find fuzzy frequent itemsets with two database scans.

In contrast to frequent itemset mining, utility mining [24], [25] was designed to find high-utility itemsets which can get more profits than ordinary ones in a dataset. However, high utility itemsets contain just items without quantitative information and are difficult for users to understand their quantitative occurrence relationship. As mentioned before, fuzzy itemsets [18], [35] could represent the linguistic meaning of item quantity relationships, such as the example \{A.Low, B.High\}. Thus, fuzzy utility mining [20] has been developed into another new research issue for being more suitable for practical applications. Considering item quantities in a dataset, profit values of the items, and linguistic meaning of the quantities, fuzzy utility mining turns the items with quantitative information into fuzzy sets to derive high fuzzy utility itemsets. To reduce the search space in mining, Lan et al. developed an upper-bound method to retain the downward-closure property in fuzzy utility mining. Based on the extension of the concept, Huang et al. then considered different transaction periods in a dataset to discover linguistic temporal utility patterns [15].

III. PROBLEM DEFINITIONS

In this section, some critical terms about mining high temporal fuzzy utility itemsets (HTFUIS) based on the temporal
TABLE 1. A quantitative database.

| Period | TID | Items and Quantities |
|--------|-----|----------------------|
| P₁     | Trans₁ | {6ₐ, 2C}          |
| P₃     | Trans₂ | {Aₐ, 4B}          |
| P₃     | Trans₃ | {1A, 1C}          |
| P₄     | Trans₄ | {3ₐ, 3B, 4C, 4D, 2E} |
| P₅     | Trans₅ | {5ₐ, 6B, 2E} |
| P₆     | Trans₆ | {3ₐ, 4D, 2E} |

TABLE 2. Item utilities.

| Item | Profit |
|------|--------|
| A    | 2      |
| B    | 6      |
| C    | 4      |
| D    | 2      |
| E    | 4      |

fuzzy utility mining problem [15] are described below. Let $I = \{i₁, i₂, i₃, \ldots, iₘ\}$ be a finite set of $m$ distinct items in the temporal quantitative transaction database $TQD = \{Trans₁, Trans₂, \ldots, Transₙ\}$, where $Trans_y \in TQD$ and $Trans_y$ is the $y$-th transaction in $TQD$. Each transaction $Trans_y$ includes items sold $iₘ$ and quantity sold $v_{ym}$. According to the membership function of the quantitative value $v_{ym}$ of the item $iₘ$, assume that $R_{m₁}$ to $R_{mₘ}$ are the elements in fuzzy set $f_{ym}$, and $t_{m₁}$ to $t_{mₘ}$ are their membership values in $f_{ym}$. Besides, each item $iₘ$ has external utility value, denoted as $s(iₘ)$, for the profit of $iₘ$. Let a fuzzy region of an item is denoted as a fuzzy item, and a fuzzy itemset includes at least two fuzzy items with no fuzzy items are originated from the same item. A pre-defined minimum temporal fuzzy utility threshold is set as $\lambda$.

Definition 1: A time period set $T = \{p₁, p₂, p₃, \ldots, pₘ\}$ in the temporal quantitative transaction database $TQD$, $m$ is the number of the time periods, and $pₘ$ denotes the $m$-th time period.

For example, assume that three time periods are defined in Table 1 for the running example.

Definition 2: For the quantitative value $v_{ym}$ of an item $iₘ$, the fuzzy utility $fu_{ymh}$ of its $h$-th fuzzy item $R_{mh}$ in the transaction $Trans_y$, is denoted as

$$fu_{ymh} = \mu_{ymh} * v_{ym} * s(iₘ).$$

For example, assume that the membership functions and profits of all items in $TQD$ are defined in Figure 1 and Table 2. The quantity of $A$ in $Trans₂$ in Table 1 are transformed as (0.67/A.Low, 0.33/A.Middle, 0/A.High). Therefore, the fuzzy utility of A.Low in $Trans₂$ is calculated as $0.67 * 4^2 = 5.36$.

Definition 3: The transactional fuzzy utility in a transaction $Trans_y$ is denoted as $fu_y$, and defined as the sum of the fuzzy utility values for all fuzzy items in the transaction $Trans_y$, that is:

$$tfu_y = \sum_{iₘ \in Trans_y} fu_{ym}.$$ 

Definition 4: The fuzzy utility value of a fuzzy itemset $X$ in the transaction $Trans_y$ is denoted as $fu_X$ and defined as the sum of the fuzzy utility values of all items in $X$ and also in $Trans_y$, which is denoted as:

$$fu_X = \mu_X * \sum_{R_{mh} \subseteq X} v_{ym} * s(iₘ),$$

where the $\mu_X$ can use the smallest membership grade in $R_{mh}$ in $X$.

Definition 5: The start transaction period of an item $iₘ$, denoted as $STP_{iₘ}$, is the first occurring time of the transaction period in the $TQD$.

Definition 6: The last transaction period of an itemset $X$, denoted as $LTP_X$, is the last occurring time of transaction period originated from all items of an itemset that are purchased simultaneously last.

A designed upper-bound model [15], which is used to keep the monotonic property, was proposed to find all candidate itemsets to avoid information loss. A set of terms is defined as follows.

Definition 7: For an item $iₘ$, its maximal fuzzy utility $mfu_{ym}$ in $Trans_y$ is represented as

$$mfu_{ym} = \max \{fu_{ym₁}, fu_{ym₂}, \ldots, fu_{ymₘ}\}.$$

Definition 8: The maximal transactional fuzzy utility of $Trans_y$ is represented as $mfu_y$. That is:

$$mfu_y = \sum_{iₘ \in Trans_y} mfu_{ym}.$$ 

Definition 9: The start transaction period $STP_{all}$ of all items is represented as

$$STP_{all} = \min_{TP} \{STP₁, STP₂, \ldots, STPₘ\}.$$

Definition 10: Let $LTP_{all}$ be the time periods from $STP_{all}$ to the last time period of $TQD$. The temporal fuzzy utility upper bound ratio of fuzzy itemset $X$ is denoted as

$$tfuub_X = \sum_{X \in Trans_y \cap Trans_z \in LTP_X} mfu_{yz} / \sum_{Trans_z \in LTP_{all}} tfu_y.$$ 

Definition 11: If the $tfuub_X$ value is no less than minimum temporal fuzzy utility threshold $\lambda$, fuzzy itemset $X$ is a high temporal fuzzy utility upper bound itemsets ($HTFUUBIs$).

According to the above definitions, the possible candidate itemsets ($HTFUUBIs$) can be found by using the upper-bound model [15] and then determined whether these candidate itemsets are desired. The following terms with satisfying high temporal fuzzy utility itemsets ($HTFUIs$) are defined as below.
**Definition 12:** The temporal fuzzy utility ratio of the fuzzy itemset $X$ is defined as $tfu_r X$. That is:

$$tfu_r X = \sum_{X \in Trans_i \cap Trans_j \in LTP_X} fu_{yX} / \sum_{Trans_i \in LTP_X} tfu_y.$$

**Definition 13:** If $tfu_r X$ is no less than minimum temporal fuzzy utility threshold $\lambda$, fuzzy itemset $X$ is an HTFUI.

Temporal fuzzy utility mining includes quantity, profit, transformed linguistic terms, and temporal behavior to mine high fuzzy utility itemsets with the temporal property. These itemsets derived from [15] include more useful and meaningful knowledge than those derived from fuzzy utility mining [20] despite the former has more the number of itemsets than those of the latter. Because of this, late-on-shelf or time-limited items may be found by using [15].

However, the monotonic property, which is the leading spirit for association rule, is not held in temporal fuzzy utility mining to prune unnecessary itemsets efficiently. Lan et al. designed a practical model with fuzzy utility upper-bounds to prune unpromising candidates early and also proposed a fuzzy-utility algorithm and adopted the minimum operator for the intersection. Afterward, Huang et al. proposed an extended upper-bound model and function to find more relevant patterns with considering temporal property as an essential factor. Those algorithms [15], [20] for mining high fuzzy utility itemsets were based on the Apriori-based approach and found knowledge patterns by scanning multiple databases. However, the Apriori-based approach generated explosive candidate itemsets and resulted in the execution time highly.

**IV. THE PROPOSED ALGORITHM**

A Fast High Temporal Fuzzy Utility Pattern tree (FHTFUP) algorithm, in this paper, is proposed to find HTFUIs based on the two-phase upper bound model [15] and FP-tree [10]. Using this model is mainly to find all possible temporal fuzzy utility upper bound itemsets based on downward closure property. The concept of FP-tree is thus used to decrease explosive candidates compared with the generate-and-test method. Based on the above definitions, there are mainly two phases in the proposed algorithm: (1) Finding the possible candidate itemsets by using similar FP-Growth and (2) Scanning the temporal fuzzy utility database to decide whether the candidate itemsets are HTFUIs.

The Proposed FHTFUP Algorithm for Mining Temporal Fuzzy Utility Itemsets:

**INPUT:**

1. $TQD$, a temporal quantitative database with $n$ quantitative transactions,
2. $m$ items in $TQD$,
3. membership functions for $m$ items,
4. $p$ time periods, and
5. a pre-defined minimum temporal fuzzy utility threshold $\lambda$.

**OUTPUT:** All HTFUIs itemsets satisfying $\lambda$.

**Phase I (Find Candidate Itemsets):**

**STEP 1:** Transform the occurring time of each transaction in $TQD$ into a unique time period.

**STEP 2:** Calculate the $STP_{im}$ value of each item $i_m$ in $TQD$.

**STEP 3:** For each item $i_m$ in $Trans_m$, turn its quantitative value $y_{im}$ into a fuzzy set $f_{ym}$ denoted as $\frac{\mu_{y_{im1}}}{R_{y_{im1}}} + \frac{\mu_{y_{im2}}}{R_{y_{im2}}} + \ldots + \frac{\mu_{y_{imr}}}{R_{y_{imr}}}$ based on the membership grade for the quantity of each item $i_m$.

**STEP 4:** For each transaction $Trans_y$ which exists in each period $y$ of $TQD$, carry out the following substeps to process:

- (a) Calculate the $f_{ymh}$ of the $h$-th fuzzy item of item $i_m$ in $Trans_y$.
- (b) Find the $mfu_{ymh}$ of $i_m$ in $Trans_y$.
- (c) Determine the $tfu_{y}$ and the $mtfu_{y}$ of each $Trans_y$.

**STEP 5:** Build the $HTFUBI_1$ table as empty, where each tuple has a fuzzy 1-itemset, the total $mfu$ value, and the occurrence frequency value.

**STEP 6:** Calculate the $tfuab$ value of each fuzzy 1-itemset. If its $tfuab$ is larger than or equal to $\lambda$, it is $HTFUBI_1$.

**STEP 7:** Insert the fuzzy 1-itemset into the $HTFUBI_1$ table, including their total $mfu$ value and the occurrence frequency.

**STEP 8:** For $TQD$, delete the fuzzy 1-itemsets not existed in the $HTFUBI_1$ table.

**STEP 9:** According to the descending order of their frequency in the $HTFUBI_1$ table, sort the fuzzy 1-itemsets in the $HTFUBI_1$ table as the header table of the $FHTFUP$ tree.

**STEP 10:** For each transaction $Trans_y$ in $TQD$, insert each transaction into the $FHTFUP$ tree. If an item in a transaction does not exist at the corresponding branch of the $FHTFUP$ tree, insert the item to the end of the branch, and add the $mfu$ value of $Trans_y$. If yes, just add the $mfu$ value of $Trans_y$ to the $mfu$ value of the corresponding node.

**STEP 11:** After STEP 10, the final $FHTFUP$ tree is constructed. Along with the $FHTFUP$ tree, the candidate high temporal fuzzy utility itemsets $HTFUIs$ can then be found in a way similar to FP-Growth mining, but much more complex. After finding the candidate $HTFUIs$, and Phase II needs to be executed.

**Phase II (Find HTFUIs):**

**STEP 12:** Obtain the fuzzy utility $fu_X$ of each candidate $HTFUI$ by scanning $TQD$.

**STEP 13:** Carry out the following substeps for each candidate $HTFUI$:

- (a) Get $LTP_X$ of itemset $X$ and figure the sum of $tfu$ in $LTP_X$.
- (b) If the $fu_X$ value divided by the sum of $tfu$ is larger than the threshold $\lambda$, $X$ is $HTFUI$; otherwise, remove it.

**STEP 14:** Output the $HTFUIs$ to users.
V. AN EXAMPLE FOR THE PROPOSED ALGORITHM

The following is a running example of the proposed algorithm. Table 1 shows a database (TOD) containing temporal and quantitative properties. In utility mining, the item profits must be known in advance; they are given in Table 2. Besides, the fuzzy concept is also concerned with our algorithm. Thus we assume the membership functions of the above five items shown in Figure 1. A user-defined mining threshold is considered as 40% for this example.

Steps 1 to 3: The start time periods of items are found in Table 1: the results are shown in Table 3. For example, Trans1 contains A and C at quantities of 6 and 2, respectively. Given Figure 1, the quantity values are transformed into fuzzy sets (0, 1, 0) and (0.67, 0, 0). The results are shown in Table 4; other transactions are processed likewise.

Step 4: The fuzzy utility values of the items in each transaction in Table 4 are calculated. For instance: item C in Trans1. The fuzzy utility values of three fuzzy items of the item C are 0.67∗2.4 = 5.36, 0∗2.4 = 0 and 0∗2.4 = 0, respectively. The same process is applied to the other items. The results are shown in Table 5.

According to definitions 3, 7 and 8, the mfu values of items A and C in Trans1 are 12 and 5.36, respectively. The mfu of Trans1 is 12 + 5.36 = 17.36. The tfu of Trans1 is 12 + 5.36 = 17.36. The other transactions are processed in the same way. The mfu and tfu are represented in the last columns of Table 5.

Steps 8 to 7: Find each fuzzy 1-itemset in Table 5 and calculate the corresponding tfuub. If its tfuubr is not smaller than the given threshold, put it into the HTFUUBI1 table. For instance, the fuzzy 1-itemset {A.Low} occurs in Trans3, Trans4, Trans5, and Trans6, and the mfu values in these transactions are 21.44, 1.98, 45.42, 47.36, and 23.36, respectively. And then, STP_all is P2, and the pre-defined threshold is 40%. The tfu values in the range from STP_all to LTP_all are 1.98, 53.34, 47.36, and 26, respectively. Consequently, the tfuub of 1-itemset {A.Low} is 1.98 + 53.34 + 47.36 + 26 (≈ 128.68). The tfuubr value of {A.Low} is (21.44 + 1.98 + 45.42 + 47.36 + 23.36)/128.68 = 108.4% which is larger than predefined threshold. Therefore, itemset {A.Low} is inserted into the HTFUUBI1 table. The other fuzzy 1-itemsets are processed likewise. The results are shown in Table 6.

Step 8: Remove those fuzzy itemsets not included in the HTFUUBI1 table from Table 4. For instance, {A.Middle} is not in the HTFUUBI1 table. Consequently, {A.Middle} and its fuzzy utility value in each transaction must be removed. The results are shown in Table 7.

Step 9: The fuzzy 1-itemsets in Table 6 are then sorted according to the descending order of the frequency of each fuzzy 1-itemset. For instance, the frequency of {A.Low} is 5 because {A.Low} exists in Trans2, Trans3, Trans4, Trans5, and Trans6 in Table 7. The sorted results are shown in Table 8 as the header table.

Steps 10 to 11: The difference between our proposed algorithm and the FP-Tree [10] is to use the values of

### Table 3. Start periods of items in the example.

| Period | STP |
|--------|-----|
| A      | 1P1 |
| B      | 2P1 |
| C      | 1P1 |
| D      | 2P2 |
| E      | 2P2 |

### Table 4. Converted linguistic representations of transactions in Table 1.

| TID   | Linguistic representation |
|-------|---------------------------|
| Trans1| 0.67 A.Low, 0.33 A.Middle, 0.33 A.High, 0.67 C.Low, 0.33 C.Middle, 0.33 C.High |
| Trans2| 0.67 A.Low, 0.33 A.Middle, 0.33 A.High, 0.67 B.Low, 0.33 B.Middle, 0.33 B.High |
| Trans3| 0.33 A.Low, 0.67 A.Middle, 0.67 A.High, 0.33 B.Low, 0.67 B.Middle, 0.67 B.High |
| Trans4| 0.33 A.Low, 0.67 A.Middle, 0.67 A.High, 0.33 C.Low, 0.67 C.Middle, 0.67 C.High |
| Trans5| 0.67 A.Low, 0.33 A.Middle, 0.33 A.High, 0.67 B.Low, 0.33 B.Middle, 0.33 B.High |

### Table 5. All fuzzy utility values for all transactions.

| TID   | A    | B    | C    |
|-------|------|------|------|
|       | L    | M    | H    | L    | M    | H    | L    | M    | H    |
| Trans1| 0    | 12   | 0    | 0    | 0    | 0    | 5.36 | 0    | 0    |
| Trans2| 5.36 | 2.64 | 16.08| 7.92 | 0    | 0    | 0    |
| Trans3| 0.66 | 0    | 0    | 0    | 0    | 0    | 1.32 | 0    | 0    |
| Trans4| 6.00 | 0    | 18.00| 0    | 0    | 0    | 10.72| 5.28 | 0    |
| Trans5| 6.00 | 0    | 36.00| 0    | 0    | 0    | 0    |
| Trans6| 6.00 | 0    | 0    | 0    | 0    | 0    | 0    |

### Table 6. The HTFUUBI1 table.

| fuzzy itemset  | mfu | frequency |
|----------------|-----|-----------|
| A.Low          | 139.56 | 5        |
| B.Low          | 66.86  | 2        |
| B.Middle       | 68.88  | 2        |
| C.Low          | 64.76  | 3        |
| D.Low          | 68.78  | 2        |
| D.Middle       | 68.78  | 2        |
| E.Low          | 116.14 | 3        |
TABLE 7. Fuzzy utility values in transactions after removing unsuitable fuzzy items.

| TID  | A   | B   | C   | D   | E   | tfu | mfu |
|------|-----|-----|-----|-----|-----|-----|-----|
|      | L   | L   | L   | L   | M   |     |     |
| Trans1 | 0   | 0   | 0   | 5.36| 0   | 0   | 17.36|
| Trans2 | 5.36| 16.08| 7.92| 0   | 0   | 0   | 32  |
| Trans3 | 0.66| 0   | 0   | 1.32| 0   | 0   | 1.98|
| Trans4 | 6   | 18  | 0   | 10.72| 5.36| 2.64| 53.34 |
| Trans5 | 6   | 0   | 36  | 0   | 0   | 5.36| 47.36| 47.36|
| Trans6 | 6   | 0   | 0   | 0   | 5.36| 2.64| 12  | 26  | 23.36|

TABLE 8. Header table in FHTFUP tree.

| itemset | mfu  | frequency |
|---------|------|-----------|
| A.Low   | 139.56 | 5         |
| C.Low   | 64.76  | 3         |
| E.Low   | 116.14 | 3         |
| B.Low   | 66.86  | 2         |
| B.Middle| 68.8   | 2         |
| D.Low   | 68.78  | 2         |
| D.Middle| 68.78  | 2         |

FIGURE 2. Trans1 is inserted into the tree.

The nodes of the FHTFUP tree with the mfu to replace the item frequencies in the FP-Tree. All transactions in Table 7 are inserted into the FHTFUP tree tuple by tuple. The construction process is stated below.

The first transaction is then inserted into the FHTFUP tree as the first branch. Take Trans1 as an example. This transaction Trans1 just contains a fuzzy item {C.Low}, which appears in Trans1, and the mfu value of Trans1 is 17.36. The fuzzy item {C.Low} is inserted into the FHTFUP tree as the child of the root, and the node is assigned the corresponding mfu value. The results after inserting the first transaction are shown in Figure 2.

The second transaction is next processed. Trans2 contains fuzzy items {A.Low}, {B.Low} and {B.Middle} and the mfu value of Trans2 is 21.44. {A.Low} is then inserted into the FHTFUP tree as the second branch because the node of the fuzzy item {A.Low} does not share the same prefix with the first transaction in the FHTFUP tree. The node {A.Low} is created to connect with the root and attached the mfu value of Trans2, which is 21.44. The next node, which is a fuzzy item {B.Low} is then inserted as the child of the first node {A.Low}. The same procedure is processed for {B.Middle}. Each node in the branch is attached to the mfu value of Trans2. The results after inserting the second transaction are shown in Figure 3.

The remaining transactions in Table 7 are processed in the same way. The final result of the FHTFUP tree is shown in Figure 4.

After the FHTFUP tree is constructed, the candidate HTFUIs with one or more fuzzy items can then be found in a similar way to the FP-Growth [10]. The fuzzy 1-itemsets of header table in Table 8 are then processed bottom-up and one by one. The corresponding conditional temporal fuzzy pattern tree is thus build from the prefix paths of the item in the FHTFUP tree. In this case, itemset {D.Middle} is first processed. For node {D.Middle}, two paths in Figure 4 can be derived: [{A.Low}, {C.Low}, {E.Low}, {B.Low}, {D.Low}, {D.Middle}], [{A.Low}, {E.Low}, {D.Low}, {D.Middle}]

After completing the conditional temporal fuzzy utility pattern tree for fuzzy 1-itemset {D.Middle}, the fuzzy itemsets with {D.Middle} can then be generated by the recursive method of the FP-Growth. And generated candidates are check whether their mfu values are satisfying the pre-defined threshold in temporal fuzzy utility mining, the fuzzy 1-itemset {D.Low} in Figure 5 needs to be removed because of {A.Low} and {D.Middle} that have identical item D. After deleting {D.Low}, the conditional temporal fuzzy utility pattern tree for fuzzy 1-itemset {D.Middle} is shown in Figure 6. Besides, it can be observed that STP_all...
is $P_2$, and the pre-defined threshold is 40%. The $tfu$ values in the range from $STP_{all}$ to $LTP_{all}$ are 1.98, 53.34, 47.36, and 26. Therefore, the threshold value is calculated as $(1.98 + 53.34 + 47.36 + 26)\times 40% = 51.472$.

Next, all fuzzy 1-itemsets in Figure 6 need to check whether their values are satisfying threshold value. In this case, the two paths in Figure 6 have the node $\{D.Middle\}$. Their value for $\{D.Middle\}$ in the two branches is 45.42 + 23.36 (68.78), which is larger than the threshold value (51.472). Therefore, keep this node $\{D.Middle\}$ in this tree. For another example, the left path in Figure 6 has the node $\{E.Low\}$. Their value for $\{E.Low\}$ in the left branch is 45.42, which is smaller than the threshold value (51.472), so it is omitted in this tree. Similarly, remaining fuzzy 1-itemsets in Figure 5 need to be check in the same way, the final result for conditional temporal fuzzy utility pattern tree for fuzzy 1-itemset $\{D.Middle\}$ is shown in Figure 7.

Next, the conditional temporal fuzzy utility pattern tree for fuzzy 1-itemset $\{D.Middle\}$ can derive the candidate $HTFUIs$, which are $\{E.Low, D.Middle\}$, $\{A.Low, D.Middle\}$, $\{A.Low, E.Low, D.Middle\}$, and $\{D.Middle\}$. The conditional temporal fuzzy utility pattern tree for other fuzzy 1-itemsets is processed in the same way.

Step 12: After completing the above step, all candidate $HTFUIs$ can be found, and the rescan database is executed to get the $tfu$ values of the candidate $HTFUIs$.

Step 13: Using $\{E.Low, D.Middle\}$ as an example. It can be observed that the $STP$ value of the two items, $E$ and $D$, is $P_2$. The $LTP_{\{E.Low, D.Middle\}}$ are $P_2$ to $P_4$. Therefore, the $tfu$ values of each transaction in $LTP_{\{E.Low, D.Middle\}}$ are 1.98 + 53.34 + 47.36 + 26 = 128.68. According to the ninth definition, the $tfu_{\{E.Low, D.Middle\}}$ value can be gotten. First, the fuzzy values of $\{E.Low\}$ and $\{D.Middle\}$ are $\{0.67, 0.33\}$ in $Trans_4$ and $\{0.67, 0.33\}$ in $Trans_6$. And then the fuzzy values of $\{E.Low, D.Middle\}$ in $Trans_4$ and $Trans_6$ are 0.33 and 0.33, respectively. The fuzzy utility value of $\{E.Low, D.Middle\}$ is calculated as $0.33\times[(4^{*4}) + (2^{*4})] + 0.33\times[(4^{*2}) + (3^{*4})] = 11.88$. As such, $tfu_{\{E.Low, D.Middle\}}$ is 11.88 / 128.68, which is smaller than the threshold. It is not $HTFUI$. The same process can handle other itemsets.

VI. PERFORMANCE EVALUATION

Extensive experiments, in this section, were used to evaluate the proposed $FHTFUP$ approach on some synthetic datasets. Because the temporal fuzzy utility data mining problem is interesting, it considers temporal property, quantity information for each item, its profit, and transformed linguistic terms. The existing $TP-TFU$ method [15] is used as a benchmark algorithm for comparison with the proposed $FHTFUP$ algorithm.

A. EXPERIMENTAL SETUP AND DATASET DESCRIPTION

Some synthetic datasets produced from [17] and two real datasets [9], [27] were applied to evaluate the performance of the proposed $FHTFUP$ and previous $TP-TFU$ method on a computer. We implemented two algorithms in Java code and executed on a desktop computer with Dual-Core Processor 3.3GHZ, 16GB RAM, and Windows 7. In those datasets, the quantitative attributes were generated the quantitative values randomly in the $[1, 10]$ interval. The profit values for items were set from 1 to 1000 at random. Besides, the membership functions of all items were used 3-fuzzy terms in Figure 1. Time periods are assigned 2. The parameters of the synthetic databases are described in Table 9.
TABLE 9. Synthetic dataset parameters.

|   | Description                                      |
|---|--------------------------------------------------|
| $T$ | The average length of items in a transaction     |
| $I$ | The average length of maximal potentially frequent itemsets |
| $N$ | The total number of different items in a dataset |
| $D$ | The number of transactions in a dataset          |

B. THE PERFORMANCE OF EXECUTION TIME

This subsection compared the computation time of the proposed FHTFUP approach on different test datasets with varying $D$, $T$, $N$ parameters was evaluated.

For example, the computation time of the proposed FHTFUP approach is shown in Figures 8 to 10. The size of the synthetic datasets is changed, and the pre-defined minimum temporal fuzzy utility threshold is varied from 2% to 5% with a 1% increment on different test datasets. Other parameters, $T$ and $N$, are set to 7 and 4K, respectively.

The execution times along with distinct thresholds, are shown in Figures 8 to 10. We observed that the proposed FHTFUP algorithm is slower, especially when the size of the test datasets as the $D$ parameter increased. On the same dataset, the proposed approach was also slower when the threshold decreased. It is because when the size of the synthetic datasets is set larger, the proposed FHTFUP method has to keep many fuzzy 1-itemsets of different transactions in the FHTFUP tree, which is more time-consuming.

For example, Figures 11 to 13 show the execution time of the proposed FHTFUP method. The total items $N$ and the number of transaction $D$ in test datasets are fixed, the average items in a transaction $T$ are changed, and the pre-defined minimum temporal fuzzy utility threshold is also varied from 2% to 5% with a 1% increment on different test datasets. The running times along with the different $T$ are shown in Figures 11 to 13. We observed that the proposed FHTFUP
The algorithm is slower when the $T$ parameter is increasing. This is because each transaction in a dataset included more distinct items. For each one on three different datasets, the proposed approach was slower when the threshold decreased. In other words, when the threshold decreased, a large amount of candidate $k$-HTFUIs derived from the proposed tree was generated.

For example, the execution time of the proposed FHTFUP method on three different datasets are revealed in Figures 14 to 16. The number of items in a dataset as the $N$ parameter is changed except the other parameters ($T$ and $D$) are fixed, and the pre-defined minimum temporal fuzzy utility threshold is set from 2\% to 5\%.

The running times along with different items in a dataset are shown in Figure 14 to 16. It can be seen that the proposed FHTFUP method is slower when the number of items in a dataset, considered as the $N$ parameter raised. This is because more different fuzzy regions derived from distinct items according to membership functions were generated. Also, you can see that the computation time of the proposed method was slower in a dataset when the threshold decreased. This is because when the $N$ parameter raised, many generated fuzzy 1-itemsets with satisfying the threshold were used to build the proposed tree, and then many candidate HTFUIs are produced.

C. THE PERFORMANCE OF CONSUMED MEMORY

With varying $D$, $T$, $N$ parameters, this subsection discusses the peak consumed memory of the proposed FHTFUP approach on varying datasets as an essential measure.

For example, Figures 17 to 19 show the consumed memory of the proposed FHTFUP approach. Except for $T$ and $N$ parameters, the size of the synthetic datasets is unfixed from 150K to 300K, and the pre-defined minimum temporal fuzzy utility threshold is set from 2\% to 5\%.
utility threshold is varied from 2% to 5% with a 1% increment on different synthetic datasets.

The consumed memory along with the different number of transactions was shown in Figure 17 to 19. Along with the \( D \) value increased, the proposed method needed memory space more. Besides, as you can see that when the threshold is raised, fewer HTFUIS are produced by the proposed FHTFUP algorithm, and the consumed memory was also decreased. In summary, those results showed that used memory space increased in the same threshold of three different datasets when the \( D \) parameter raised. The reason is that numerous fuzzy 1-itemsets in the different transactions were then used to build the proposed tree, and thus algorithm needs more memory.

For example, the memory consumption of the proposed FHTFUP method on three different \( T \) of datasets was shown in Figures 20 to 22. The total items and the number of transactions in synthetic datasets are fixed, the average items in a transaction are changed, and the pre-defined minimum temporal fuzzy utility threshold is set from 2% to 5%.

The consumed memory along with the different \( T \) parameters was shown in Figure 20 to 22. As you can see, the proposed FHTFUP method on three different datasets consumed memory when \( T = 8 \), \( T = 9 \), and \( T = 10 \). It is clear that the FHTFUP method with larger \( T \) needed more memory space than that with smaller \( T \). When the \( T \) parameter grew, it meant the different items in a transaction increased. Hence, many fuzzy 1-items were kept in the proposed tree, and the memory space also raised. On one of three different datasets, the proposed algorithm consumed more memory when the threshold declined because of more fuzzy itemsets with satisfying the threshold.

For example, Figures 23 to 25 show the consumed memory of the proposed FHTFUP method. The number of items in a
dataset is changed except the other parameters are fixed and the pre-defined minimum temporal fuzzy utility threshold is set from 2% to 5%.

Used memory space along with the different number of items in a dataset was shown in Figures 23 to 25. We observed that the proposed FHTFUP algorithm needed more memory space when the $N$ parameter raised. This main reason is that when the number of items in a dataset was raised, the produced fuzzy 1-itemsets with their $	ext{tfuubr}$ values satisfying the threshold value became more and more. The consumed memory in each dataset was larger when the threshold decreased.

**D. COMPARISON WITH TP-TFU**

To gain insights into the advancement of the proposed FHTFUP method, this subsection compared the running time and memory consumption by the two algorithms. Two test datasets of T6I4N4KD200K and T7I4N4KD200K were then performed. Here the minimum temporal fuzzy utility threshold was set from 5% to 3.2%. The experimental results are displayed in Figures 26 to 29.

The results in Figures 26 and 27 showed that the running time of the FHTFUP approach was faster than that of the TP-TFU approach when the threshold varied from 5% to 3.2%. In Figures 28 and 29, the memory space of the FHTFUP approach is less than that of the TP-TFU approach when the threshold varied from 5% to 3.2%.

**E. THE PERFORMANCE EVALUATION ON REAL DATASETS**

In this subsection, two real datasets, Foodmart [27] and Mushroom [9], were used to evaluate the execution time and memory consumption by the two methods.

In the Foodmart dataset, the minimum temporal fuzzy utility threshold was set at 1% to 0.7%. The experimental results on the running time and used memory are shown in Figures 30 and 31.
In the Mushroom dataset, the minimum temporal fuzzy utility threshold was set at 70% to 55%. The experimental results on the running time and used memory are shown in Figures 32 and 33.

From Figures 30 and 32, it can be observed that the \textit{FHTFUP} approach ran faster than the \textit{TP-TFU} approach when the threshold decreased.

The results in Figure 31 showed the memory consumption of the \textit{FHTFUP} approach was less than that of the \textit{TP-TFU} approach when the threshold varied from 1% to 0.7%. In Figure 33, the memory usage of the \textit{TP-TFU} method was always the same because it had used the maximum memory (a quarter of the actual physical memory) in Java Virtual Machine. Therefore, we observed that the \textit{TP-TFU} algorithm needed more memory space than the proposed method.

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