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# Extracting Repitative Patterns from Fuzzy Temporal Data

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***Abstract:*** *Association rules mining from temporal dataset is to find associations between items that hold within certain time frame but not throughout the dataset. This problem involves first discovering frequent itemsets which are frequent at certain time intervals and then extracting association rules from such frequent itemsets. In practice, we may have datasets having imprecise or fuzzy time attributes, we term such datasets as fuzzy temporal datasets. In such datasets, as the time of transaction is imprecise, we may have frequent itemsets that are frequent in certain fuzzy time intervals. The algorithm [1] finds all such frequent itemsets along with a collection of list of fuzzy time intervals where each frequent itemset is having an associated list of fuzzy time intervals where it is frequent. The list of fuzzy time intervals may show some interesting features e.g. the itemsets may be repetitive in nature. In this paper we propose a method of finding all repetitive frequent itemsets. The method's efficacy is demonstrated with experimental results.*

***Keywords:*** *Fuzzy time intervals, Fuzzy temporal datasets, Frequent itemsets, Similarity measure on fuzzy sets, Similar fuzzy intervals, Similar trapezoidal fuzzy numbers, Fuzzy distance between fuzzy intervals, Aggregation of fuzzy intervals*

## I. Introduction

Mining association rules from datasets has been proposed initially [2] by R. Agarwal *et al* for application in large super markets. Large supermarkets have huge collection of records of customer's daily sales. Analyzing the buying patterns of the customers may help the management in taking strategic business decisions such as what are the things to put on sale, how to put the goods on the shelves, how to make strategy for future purchase etc.

Association rules mining in temporal databases has been considered as a vital data-mining problem. Super market transaction data are normally temporal because each transaction (purchase of customer) will have an associated time of transaction (purchase). The problem of super market data mining has been considered as well-researched problem.

Mining from dataset having fuzzy temporal features have been considered as an exciting data mining problem. A method of finding frequent itemsets from such datasets have been discussed in [1]. The method [1] mines all frequent itemsets along with a collection of list of fuzzy time intervals where every frequent itemset is coupled with a fuzzy time intervals list. The fuzzy time intervals list associated with any frequent itemsets can be exploited to extract some interesting patterns. For example, some fuzzy intervals may be repetitive in nature i.e. it may be repeating or re-appears in the list after certain gap. We call the associated frequent itemset as repetitive frequent itemsets. In this article, we intend to study the problem of repetitive nature of a fuzzy time intervals list which is associated with a frequent itemset. Here we devise a technique to extract all frequent itemsets which are repetitive in nature. First, we define a similarity measure on the fuzzy time intervals present in the list. Two consecutive fuzzy time intervals present in a list are said to be similar if their similarity measure is less than or equal to a pre-assign threshold and similarly two consecutive fuzzy time gaps (gap between two consecutive fuzzy time intervals) are said to be similar if their similarity measure is also less than or equal to a pre-assign threshold.

The article is organized as follows. In section II, we give a brief discussion on the recent developments of the works which are closely related to our work. In section III, we give important definitions, terms and notations available in the literature and are used in this paper. In section IV, we present our algorithm for mining repetitive frequent itemsets. Experimental results are discussed on section V. Finally, we conclude the paper with conclusion and possible future extension in section VI.

## II. Recent Works

Agrawal *et al*, has formulated the problem of association rule mining in 1993 [2]. Given a large set *I*, of items and a large transactions sets *D* of involving the items, the problem of association rule mining is to find relationships among the items i.e. the occurrence of various items in the transactions. A transaction *T* supports an item 'a' if 'a' is present in *T*. An itemset {a, b} is said to be supported by a transaction *T* if *T* contains each of 'a' and 'b' of the itemset. An association rule is an expression of the form $A \Rightarrow B$ where $A \subseteq I$ and $B \subseteq I$. We say, the association rule $A \Rightarrow B$ holds with confidence $\rho$ if $\rho$% of the transaction of *D* supporting *A* also supports *B*. The rule has support $\varnothing$ if $\varnothing$% of the transactions supports

$A \cup B$. A technique of association rules discovery is discussed in [3], known as the A-priori algorithm. Then there is a lot of subsequent refinements, generalizations, extensions and improvements of works [3].

Mining from temporal Data is considered as an extension of conventional data mining. Lately it has been able to attract more people to work in the area. By considering into account the time features, some more appealing patterns that are dependent on time can be extracted. Usually there are two wide directions of temporal data mining [4]. One deals with the discovery of causal relationships among temporally oriented events. The other deals with the finding of similar patterns within the same time sequence or among different time sequences. The underlying problem is to extract frequent sequential patterns in the temporal datasets. The underlying problem is termed as sequence mining problem. In [5] the authors have discussed the problem of recognizing frequent episodes in an event sequence.

Incorporating the time aspects the traditional association rule mining process is extended which is termed as temporal association rule mining. In temporal association rules every rule is associated with a time interval in which the rule holds. In such problem, it is required to find valid time intervals in which association rules hold. In [6], [7], [8] and [9], the authors have not only discussed the problem of temporal data mining in details but also devised techniques and algorithms for finding such patterns. In [6], a method for temporal association rules discovery is described. In [10], two algorithms for finding cyclic association rules from temporal dataset are discussed. The method discussed in [10], requires the time interval to be specified by user to split the data into disjoint segments like months, weeks, days etc. The works similar to [10], are done in [11] and [12] adding multiple granularities of time intervals (e.g. first working day of every month) from which both cyclic and user defined calendar patterns can be found. In [13], an algorithm for discovering locally and periodically frequent itemsets and periodic association rules are discussed. The method [13], is an improvement of other existing methods in the sense it is dynamic in nature and it is less user-dependent.. Fuzzy calendric data mining and fuzzy temporal data mining are discussed in [14] and [15]. In [14], a method is discussed which extracts user specified ill-defined fuzzy temporal patterns from temporal datasets. The algorithm discussed in [15], discovers user-defined calendric patterns from the similar dataset.

Mining from fuzzy temporal dataset is discussed initially [1], and subsequently [16] and [17]. In [16], an algorithm for clustering of frequent itemsets from fuzzy temporal dataset is discussed. In their work they have used a similarity measure on the fuzzy time intervals which is defined in terms of variance of fuzzy intervals [18]. In [17], similar works are done using a new similarity measures and aggregation of fuzzy numbers [19]. An efficient hash tree based implementation of the algorithm for finding patterns from fuzzy temporal data is discussed in [20]. A trie-based implementation of the algorithm for finding patterns from fuzzy temporal dataset is discussed in [21]

## III. Problem Definition

### *A. Fuzzy sets*

A fuzzy set $A$ in $E$ (universe of discourse) is characterized by a membership function $\mu_A(x) \in [0,1]$. $\mu_A(x)$ for $x \in E$ represents the membership grade of x in $A$. Therefore, a fuzzy set $A$ is defined as

$$A=\{(x, \mu_A(x)), x \in E\}$$

A fuzzy set $A$ is termed as normal if $\mu_A(x) = 1$ for at least one $x$ in $E$

In general, a generalized fuzzy number $A$ is expressed as any fuzzy subset of the real line $R$, whose membership function $\mu_A(x)$ satisfying the following conditions.

(1) $\mu_A(x)$ is continuous mapping from $R$ to the closed interval [0, 1]
(2) $\mu_A(x)=0$, $-\infty < x \le c$
(3) $\mu_A(x)= L(x)$ is strictly increasing on $[c, a]$
(4) $\mu_A(x)=w$, $a \le x \le b$
(5) $\mu_A(x)= R(x)$ is strictly decreasing on $[b, d]$
(6) $\mu_A(x)=0$, $d \le x < \infty$,

where $0 < w \le 1$, $a$, $b$, $c$ and $d$ are all real numbers. The above type of generalized fuzzy number is denoted by $A=(c, a, b, d; w)_{LR}$. For w=1, it will be a fuzzy interval denoted by $A=(c, a, b, d)_{LR}$. When the functions $L(x)$ and $R(x)$ are straight line, then $A$ will be a trapezoidal fuzzy number denoted by $(c, a, b, d)$. If $a=b$, then the above trapezoidal number will become a triangular fuzzy number denoted by $(c, a, d)$.

The $\alpha$-cut of the fuzzy number $[s_1-a, s_1, s_1+a]$ is a closed interval of the form $[s_1+(\alpha-1).a, s_1+(1-\alpha).a]$. Similarly the $\alpha$-cut of the fuzzy interval $[s_1-a, s_1, s_2, s_2+a]$ is also a closed interval of the form $[s_1+(\alpha-1).a, s_2+(1-\alpha).a]$.

***B. Fuzzy distance***

The concept fuzzy distance between any two trapezoidal fuzzy numbers is proposed in [22] as follows: Suppose $A=(a_1, a_2, a_3, a_4)$, $B=(b_1, b_2, b_3, b_4)$ be two trapezoidal fuzzy numbers (fuzzy intervals), having graded mean integration representation are P($A$), P($B$) respectively. Also suppose

$$d_i=(a_i-P(A)+b_i-P(B))/2,\ i=1, 2, 3, 4;$$

$$c_i=|P(A)-P(B)|+d_i\ ,\ i=1, 2, 3, 4; \qquad \dots \qquad (1)$$

then the fuzzy distance of $A$, $B$ is $C=(c_1, c_2, c_3, c_4)$ and is expressed in equation (1). Obviously the fuzzy distance between two trapezoidal numbers (fuzzy intervals) is also a trapezoidal number (fuzzy intervals).

Where the graded mean integration P(A) and P(B) for the fuzzy intervals are given below:

$$P(A)=\int_0^w \alpha\left(\frac{L^{-1}(\alpha)+R^{-1}(\alpha)}{2}\right)d\alpha \Big/ \int_0^w \alpha d\alpha \qquad \dots \qquad (2)$$

$$\text{and } P(B)=\int_0^w \beta\left(\frac{L^{-1}(\beta)+R^{-1}(\beta)}{2}\right)d\beta \Big/ \int_0^w \beta d\beta \quad \text{[see e.g. [23], [24], [25]]} \qquad \dots \qquad (3)$$

$\alpha$, $\beta$ are between 0 and w, $0<w\le1$

***C. Similarity measure between two fuzzy intervals.***

Let $F$ be a frequent itemset which is frequent in two fuzzy intervals $T=[a_1, a_2, a_3, a_4]$ and $S=[b_1, b_2, b_3, b_4]$, then the degree of similarity between $T$ and $S$ is given by

$$sim(T, S)=1-\frac{\sum_{i=1}^{4}|a_1-b_i|}{4} \qquad \text{[see e.g. [23]]} \qquad \dots \qquad (4)$$

If the value of $sim(T, S)$ is less than or equal to some pre-assigned threshold say $\theta$, then $S$ and $T$ are said to be *almost similar*.

***D. Aggregation operator***

Suppose that $[a_1, b_1, c_1, d_1]$ and $[a_2, b_2, c_2, d_2]$, ...... $[a_n, b_n, c_n, d_n]$ be n trapezoidal fuzzy numbers (fuzzy intervals), the arithmetic mean aggregation operator [26] will produces a trapezoidal fuzzy number (fuzzy interval) say [a, b, c, d] where $a=\frac{1}{n}\sum_{i=1}^{n}a_i$ , $b=\frac{1}{n}\sum_{i=1}^{n}b_i$ , $c=\frac{1}{n}\sum_{i=1}^{n}c_i$ and $d=\frac{1}{n}\sum_{i=1}^{n}d_i$ ... (5)

For a particular frequent itemset say $F$, if it's all fuzzy time intervals (which are actually trapezoidal fuzzy numbers) in which $F$ is frequent are found to be almost similar and if any two consecutive fuzzy time intervals of $F$ are found to be equi-distant in terms *similarity measure*, then $F$ is called as repetitive frequent itemset with a period average of all its fuzzy time intervals. The averaging or aggregation is done using the method defined in equation (5).

## IV. Algorithm Proposed

For finding repetitive frequent itemsets, we apply two measures on the list of time intervals associated with a frequent itemset namely the fuzzy distance and similarity measure on any two consecutive fuzzy time intervals associated with that frequent itemset (the definitions of fuzzy distance and similarity measure are given by equation (1) and equation (4) respectively). The frequent itemsets along with their list time intervals are extracted by the method discussed in [1]. It is to be mentioned here the fuzzy distance between any two fuzzy intervals is also a fuzzy interval. If the fuzzy distance (fuzzy time gap) between any two consecutive fuzzy time intervals associated any frequent itemset are found to be *almost similar* and also the same fuzzy time intervals are *almost similar* (the definition of *almost similar* fuzzy time interval is given in *section III*) then we call such frequent itemsets as repetitive frequent itemsets. Now, to find out such type of repetitive patterns from frequent itemsets extracted by the method discussed in [1], we proceed as follows. If the first fuzzy time interval is *almost similar* to the second fuzzy time interval then we see whether the fuzzy distance (fuzzy time gap) between the first and the second fuzzy time interval is *almost similar* to the fuzzy distance (fuzzy time gap) between the second and third fuzzy time intervals. If both fuzzy time intervals and their fuzzy time gaps are *almost similar*, then we take the aggregate of the first fuzzy time gap ( fuzzy distance between first two fuzzy time intervals) and second fuzzy time gap (fuzzy distance between second and third fuzzy time intervals) and see whether it is *almost similar* to the fuzzy distance (fuzzy time gap) between the third and the fourth fuzzy time intervals associated with frequent itemset. Also we take aggregate of first and second fuzzy time intervals to check whether it is *almost similar* to third fuzzy time intervals. If the aggregate of first and second fuzzy time interval is *almost similar* to the third fuzzy time interval and if the aggregate of the fuzzy distance of the first two fuzzy time intervals is *almost similar* to the fuzzy distance of the third and fourth fuzzy time interval we proceed further. Otherwise the process will be stopped with message that the given frequent itemset is not repetitive . In general if the aggregate of the first (*n*-1) fuzzy time intervals associated with a frequent itemset is *almost similar* to the *n*-th fuzzy time interval and that of first (*n*-2) fuzzy distances (fuzzy time gaps) are *almost similar* to the (*n*-1)-th fuzzy time gap, then the aggregate of *n* fuzzy time intervals is compared with (*n*+1)-th fuzzy time interval and that of the first *n*-1 fuzzy time gaps is compared with the *n*-th fuzzy time gap to check the repetitiveness of the frequent itemsets. Using this procedure, we can extract repetitive frequent itemsets if such frequent itemsets exist in the fuzzy temporal datasets. We describe below the algorithm's pseudo code for extracting such repetitive frequent itemsets.

***Algorithm for finding repetitive frequent itemsets from fuzzy temporal datasets***

```
for each frequent itemset i having a list fuzzy time intervals in which i is frequent do
  { I1 ← first fuzzy time interval for i
    I2 ← second fuzzy time interval for i
    compute sim(I1, I2)
     if (sim(I1, I2)!≤ θ)
      { then I1,I2 are not almost similar
        report that i is not repetitive in nature
       continue /* proceed to the next frequent itemset */
           }
     n=1
     fIg1 ← fuzzydist(I1,I2)
       avgint ←aggregate(I1,I2)
        flag = 0
 while ( not end of fuzzy interval list for i) do
     { Cint ← current fuzzy time interval
        fCint ←fuzzydist(Cint, I2)
       Compute sim(Cint, I2),
        if (sim(,fIg1, fCint) ≤ θ) then
              avv(gftg) ← aggregatr(n* fIg1 , fCint)
        else
           { flag = 1; break;}
           avg=aggregate(Cint, I2)
   if ( upto nth fuzzy time intervals are almost similar) then
         avg ← aggregate((n+1)* avgint, avg)
    else
       {flag = 1; break;}
         I2 ← tint;
     n ←n+1;
              }
     if (flag == 1)
        report that i is not repetitive in nature
      else
        report that i is repetitive in nature
   }
```

Here the function, *fuzzydist*() returns fuzzy distance between any two consecutive fuzzy time intervals associated with a frequent itemset i.e. fuzzy time gap, *sim*() returns the similarity value of any two fuzzy time intervals *aggregate()* returns the aggregate of the fuzzy time intervals, $\theta$ is the threshold value upto which the variation of *similarity measure* can be acceptable.

## V. Experimental Results And Discussions

For experiments, we have used a dataset which is actually a super market dataset. The dataset is a retail dataset from an anonymous *Belgian* store and is donated by *Tom Brijs* [27]. The dataset contains 17000 items and 88162 transactions besides other details like minimum number of items in a transaction, maximum number of items in a transaction and average number of items. The dataset does not contain fuzzy time stamp (fuzzy temporal features). So, we incorporate the fuzzy time attribute in it which is are fuzzy numbers to make it compatible for the execution of our algorithm. With these details our experimental evaluation will be as follows.

We break the dataset into different sizes based on number of transaction. For example, 10,000 transactions, 20,000 transactions, 30,000 transactions, 40,000 transactions, 50,000 transactions, 60,000 transactions, 70,000 transactions and whole dataset, then execute the algorithm discussed in [1] to find frequent itemsets with their list of fuzzy time intervals in which they are frequent. Now, we apply our algorithm on the list of fuzzy time intervals associated with each frequent itemsets to find the repetitive nature of the frequent itemsets. A partial view of experimental results are given in table-1, figure-1 and figure-2.

| Transaction sizes | No. of repetitive frequent itemsets |
|---|---|
| 10,000 | 0 |
| 20,000 | 1 |
| 30,000 | 1 |
| 40,000 | 2 |
| 50,000 | 3 |
| 60,000 | 3 |
| 70,000 | 3 |
| 88162 | 3 |

**Table-1:** Repetitive frequent itemsets for different transaction sizes

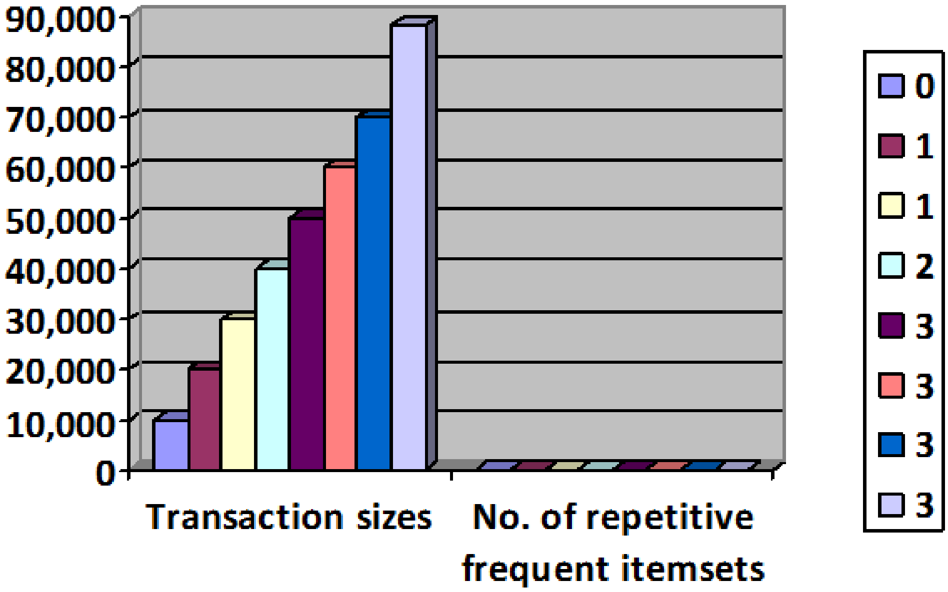


**Figure-1:** Transaction vs. Repetitive frequent itemsets

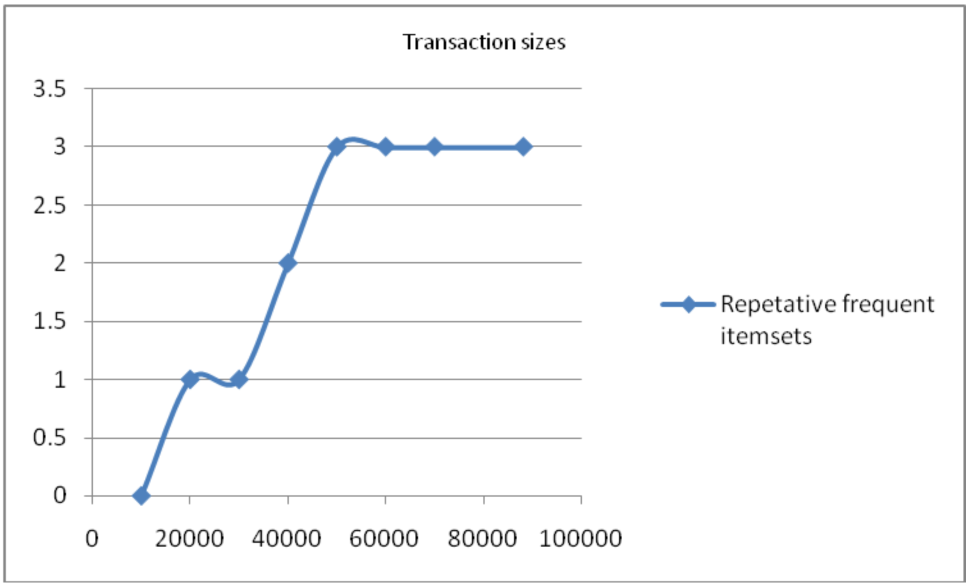


**Figure-1:** Transaction vs. Repetitive frequent itemsets

## VI. Conclusions And Lines For Future Works

An algorithm for finding repetitive frequent itemsets from fuzzy temporal data is proposed in this paper. The algorithm takes input from the results obtained by the method discussed in [1]. The method discussed in [1] extracts all frequent itemsets where each frequent itemset is associated with a sequence of fuzzy time intervals where it is frequent. Our algorithm works on the list of fuzzy time intervals associated with every frequent itemsets to find the repetitive nature of the frequent itemsets. For this purpose, we take two parameters, namely similarity measure of fuzzy time intervals and fuzzy distance between any two consecutive fuzzy time intervals associated with a frequent itemset. The algorithm works on the list of fuzzy time intervals in the following manner. For a frequent itemset say $A$, having a list of fuzzy time intervals say ($T_1$, $T_2$, $T_3$, ...$T_n$.), if $T_1$ is *almost similar* to $T_2$ also fuzzy distance ($T_1$, $T_2$) is *almost similar* to fuzzy distance ($T_2$, $T_3$), then similarity of aggregate ($T_1$, $T_2$) and $T_3$ is checked. Similarly the aggregate of first two fuzzy distances is checked with the next. The process continues till end of the fuzzy time interval list or there is a dissimilarity at certain stage i.e. two consecutive fuzzy time intervals are *not almost similar* or two consecutive fuzzy time gaps are *not almost similar.* The output to the algorithm are those frequent itemsets for which any two consecutive fuzzy time intervals are *almost similar* and any two consecutive fuzzy time gaps are *almost similar*. Such frequent itemsets are called as repetitive frequent itemsets It is to be mentioned here that the fuzzy distance of any two consecutive fuzzy intervals is same as the fuzzy time gap of the intervals which is a fuzzy number or fuzzy intervals.

In practice, we may have certain frequent itemsets, which are not repetitive in nature. For example we may have some itemsets in which fuzzy time gaps are *almost similar*, but the fuzzy time intervals in which the itemsets are frequent may not be *almost similar*. We may have some frequent itemsets where the fuzzy time intervals are *almost similar*, but the corresponding fuzzy time gaps may not be *almost similar*. Also we may have frequent items for which both fuzzy time intervals and fuzzy time gaps may not be *almost similar*. Our algorithm can be suitably modified to extract all such frequent itemsets if they exist in the datasets. In future, we may work in the following lines

(1) We may extract association rules from such frequent itemsets.
(2) We may optimize our algorithm to capture the patterns more efficiently
(3) We may do clustering of frequent itemsets based some parameters.
(4) We may classify the frequent sets.
(5) We may also do outlier analysis on the set of such frequent itemsets.

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