Temporal High Utility Rare Itemset Mining using Fuzzy Approach – FTHURI algorithm

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***Abstract*— Business strategies use information about any organization's past performance that can be used to predict its future performance. Innovative business strategies should be designed to achieve the predefined goals, policies mission and vision of the business. The right business strategy can be formulated by clearly understanding the dynamically changing business environment.**

Temporal data mining can be instrumental in tracking the changes in the business environment over time and in enhancing the quality of business strategies.

In market basket analysis, significant associationships between transactional data items is found using Association Rule Mining (ARM). The temporal transactional dataset may consist of imprecise or vague data which can be efficiently and easily handled by Fuzzy Logic. One of the recent mining research paradigms is Utility Mining which gives stress on all types of utility factors and integrates utility concepts in data mining tasks. The utility-based ARM which aims at generating itemsets having high total utility is defined as High utility itemset mining.

Jyothi et al proposed a novel algorithm THURI in [100] which efficiently and effectively mine high utility rare itemsets from databases with temporal consideration of utility values. Fuzzy Logic is very useful for representing diverse data in a synthetic way, as it is capable to adapt according to changes in the user's environmental parameters and express data uniquely. Hence Fuzzy Logic is used in THURI for improving the performance of mining high utility rare itemsets from temporal databases.

An integrated approach of HURI and THURI, named FTHURI algorithm is defined in this paper. To handle uncertainty, this temporal itemset utility mining with fuzzy modeling, FTHURI, allows item utility values to assume fuzzy values and be dynamic *over time.*

Keywords*-Association Rule Mining, Fuzzy Logic, High Utility *Itemset Mining, Temporal Mining, Utility Mining.

I. INTRODUCTION

One of the descriptive Data mining tasks; ARM is used to derive strong relationships between different data items of transactional dataset. ARM is useful in many applications such as business, medical, security, bioinformatics, telecommunications, banking and many other areas.

The business strategies can be enhanced by keeping track of all business activities and updating them accordingly with time. Temporal Data Mining is a process of Knowledge Discovery in Temporal Databases that derives patterns over the temporal data. Temporal data mining has recently received increasing attention, as many processes in business and science have interesting time changing aspects. Traditional temporal association rules mining doesn't consider the utility of every item. Utility of an itemset is considered as the value of this itemset, and utility mining aims at identifying the itemsets with high utilities [3]. The goal of utility mining is to identify high utility itemsets which drive a large portion of the total utility. 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.

Temporal utility mining is a new research paradigm which is an extension of temporal ARM and utility mining. An important question in retail marketing that can be addressed by temporal mining of business operations is which areas can be temporally optimized so as to increase business profitability and customer satisfaction. The most profitable products or services of the company can be found out by applying temporal data mining techniques to business data. The temporal significant rare utility itemsets are those itemsets which appear infrequently in the current time window of large databases. Accordingly, high utility values can be assigned to products which are more preferred by customers in a particular time period [16].

In Data mining systems where ARM is performed, Fuzzy Logic plays a very significant role. An algorithm FHURI (Fuzzy High Utility Rare Itemset Mining) is presented in [17] for mining high utility rare itemsets using fuzzy utility values.

Also temporal transactional data may contain some vague or uncertain data and to deal with fuzzy or uncertain data Fuzzy Logic can be used which helps users in dealing with temporal data. Fuzzy Logic is a powerful tool to categorize numerical data in an abstract manner and also provides more flexibility to data mining systems.

Jyothi et al presented a new foundational approach to temporal itemset utility mining where item utility values are allowed to be dynamic within a specified period of time, unlike traditional approaches where these values are static within those times [18]. The approach incorporates a fuzzy model where utilities can assume fuzzy values. The conceptual model presented allows development of an efficient and applicable algorithm to real world data and captures real-life situations in fuzzy temporal utility association rule mining. An integrated approach of FHURI [16] and THURI [17], named FTHURI algorithm is defined in this paper. The Conceptual model presented in [18] has been implemented in as Temporal High Utility Rare Itemset

Mining using Fuzzy Approach – FTHURI algorithm FTHURI. Fuzzy model is incorporated in THURI to fuzzify utilities and to improve performance of high utility rare itemset mining from temporal databases.

The rest of paper is organized as follows. In section 2, some related works are discussed: section 3 presents the FTHURI algorithm and section 4 presents conclusion and future work.

II. RELATED WORK

Wai-Ho introduced a novel technique, called FARM (Fuzzy Association Rule Miner) to mine fuzzy association rules [25] which uses linguistic terms for representing revealed regularities and exceptions. The linguistic representation is based on fuzzy set theory and thus the rules generated are called fuzzy association rules. FARM uses fuzzy techniques for dealing with noises such as inaccuracies and missing values. FARM is also capable to discover interesting associations between different quantitative values. Wai-Ho et al discuss that experimental results show FARM to be capable of discovering meaningful and useful fuzzy association rules. Sourabh Jain et al presented an overview of Fuzzy Temporal Association Rule Mining in [19].

Sulaiman et al propose a new Fuzzy Healthy Association Rule Mining Algorithm (FHARM) which introduces new quality measures for generating more interesting and quality rules effectively and efficiently [23]. Using FHARM, edible attributes are extracted from transactional input data and transformed to Required Daily Allowance (RDA) numeric values. The RDA values from database are then converted to fuzzy values. Analysis of normalized fuzzy transactional database is performed for getting nutritional information.

Veeramalai et al proposed a novel fuzzy temporal association rule mining algorithm new rule mining technique which incorporate fuzzy logic in temporal association rule mining to mine multidimensional medical data [24]. The authors present that the new system is able to provide useful and interesting patterns to the user.

Wan-Jui Lee et al put forward the fuzzy calendar algebra to deal with uncertainty in temporal expressions [26]. By using the proposed fuzzy calendar algebra system, complicated calendars can be defined by users within multiple time granularities, where different weights are assigned according to different time intervals. Then fuzzy temporal association rules are mined from temporal databases and interesting knowledge can be discovered by the users.

Stephen G. Matthews et al presented a novel method for association rule mining having both quantitative and temporal itemsets which use multi-objective evolutionary search and optimization [21]. The proposed procedure determines temporal frequent quantitative itemsets from data set which are represented with fuzzy sets. The authors conclude that the interpretation of quantitative association rules can be enhanced by using fuzzy association rules.

Stephen G. Matthews et al put forward an approach which deals with fuzzy association rules mining consisting of hidden temporal patterns [22]. Th e 2- tuple linguistic representation of fuzzy association rules mining discovers fuzzy association rules within temporal constraints.

One of the popular and essential fields in medical diagnosis is Expert Decision Making System. As clinical databases are complicated and huge, traditional Data mining techniques are convenient method for mining such databases.

As neural networks are flexible with incomplete, imprecise, missing and noisy data, they are capable of mining large clinical databases efficiently. Sethukkarasi et al proposed a new neuro-fuzzy technique for mining temporal rules from the clinical dataset for early prediction of heart disease to minimize the patient's risk [27]. The proposed fuzzy neural network consists of five input nodes, hidden layers of training and normalization and an output layer with one output node.

The proposed technique is used for diagnosing cardio vascular disease effectively from patients' records.

As stock market is dynamic and volatile, Temporal Data mining is widely used in financial markets and stock-price forecasting. Gerasimos Marketos et al proposed an Intelligent Stock Market Assistant which serves as a portfolio management solution having business intelligence characteristics for finding all possible relations between stocks [5]. The proposed tool uses a sequence mining algorithm consisting of pre-processing and pattern evaluation steps. The technical analysis focuses on the stock chart and discovers

III. TEMPORAL HIGH UTILITY RARE ITEMSET MINING USING FUZZY APPROACH – FTHURI ALGORITHM

A. HURI Algorithm

Rare itemset mining is very important as rare itemsets may bring adequate profits to the business. In [6], Jyothi et al proposed High Utility Rare Itemset Mining [HURI] to find high utility rare-itemsets based on minimum threshold values and user preferences. The utility of items is decided by considering factors such as profit, sale, temporal aspects, etc. of items.

B. FHURI Algorithm

FHURI algorithm is an extension of HURI algorithm which adopts fuzzy logic for fuzzification of total utility value of itemsets. The crisp support and utility values of rare itemsets are transformed into fuzzy values using FHURI. The novelty of FHURI is that very-high and high rare itemsets are generated, according to fuzzy support and fuzzy utility thresholds.

C. THURI Algorithm

THURI algorithm is based on HURI algorithm which incorporates temporal concept within HURI algorithm. THURI can effectively extract high utility rare itemsets from different quarters. The temporal aspect is incorporated by dividing the data set into quarters, months or seasonal time windows and then mining has been performed accordingly.

D. Extraction of HURI using FTHURI Algorithm

In Temporal High Utility Rare Itemset Mining using Fuzzy Approach – FTHURI algorithm (Figure 3), both THURI and

FHURI is merged to mine fuzzy high utility rare itemsets from temporal databases.

FTHURI is an extension of HURI algorithm where utilities of itemsets are considered according to users' preference. Different utility values are assigned to itemsets for different time periods according to itemsets' importance in a particular time period. The linguistic terms *Very-low*, *Low*, *Medium*, *High* and *Very-high* are defined for *Support* and *Utility* according to Figure 1.

FTHURI algorithm incorporates a fuzzy model where utilities can assume fuzzy values. Fuzzy Logic is used in THURI for improving the performance of mining high utility rare itemsets from temporal databases. Figure 2 shows the membership functions or linguistic terms for support and utility.

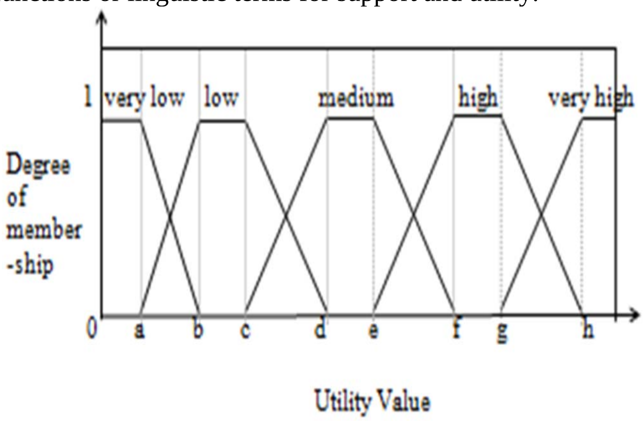


Figure 1. Defined linguistic terms for Utility

$\mu_x^{verylow}$ = Z-function(x: a, b)

$$\mu_x^{verylow} = \begin{cases} 1 & , x <= a \\ 1- (2 * ((x - a) / (b - a))^2) & , a <= x <= (a+b)/2 \\ 2 * ((b-x)) / (b - a))^2 & , (a+b)/2 <= x <= b \\ 0 & , x >= b \end{cases}$$

μ_x^{low} = Trapezoidal-function(x: a, b, c,d)

$$\mu_x^{low} = \begin{cases} 0 & , x <= a \\ (x - a) / (b - a) & , a <= x <= b \\ 1 & , b <= x <= c \\ (d - x) / (d - c) & , c <= x <= d \\ 0 & , d <= x \end{cases}$$

Similarly,

μ_x^{medium} = Trapezoidal-function(x: c,d,e,f)

μ_x^{high} = Trapezoidal-function(x: e,f,g,h)

$\mu_x^{very\ high}$ = S-function(x: g,h),

$$\mu_x^{very\ hig} = \begin{cases} 0 & , x <= g \\ 2 * ((x - g) / (h- g))^2 & , g <= x <= (g + h)/2 \\ 1- (2 * ((h - x) / (h - g))^2) & , (g+h)/2 <= x <= h \\ 1 & , h <= x \end{cases}$$

Figure. 2. Fuzzy Membership functions for proposed *FTHURI* algorithm

Algorithm FTHURI

Description: Finding Fuzzy High Utility Rare Itemsets of users' interest from each time partition

C_k: Candidate itemset of size k
L_k: Rare itemset of size k
n: Number of time partitions

BEGIN
for k = 1 to n
For each transaction ***t*** in database
begin
increment support for each item ***i*** present in *t*
End

//loop for fuzzification of support and utility values
For each itemset ***iset*** in rare itemset table ***R***
begin
Transform support and utility μ_j of each itemset *iset* into linguistic terms f_j
End

L_1={Rare 1-itemset with support greater than user provided min_low_sup and min_very_low_sup}
for(*k*= 1; L_k!=Ø; *k*++)
begin
C_{k+1}= candidates generated from L_k;

//loop to calculate total utility of each item
For each transaction ***t*** in database
begin
Calculate total quantity of each item ***i*** in ***t***
Find total utility for item ***i*** using formula:-
u(i,t)=quantity[i]* external_utility for i
End

//loop to find rare itemsets and their utility
For each transaction ***t*** in database
begin
Increment the count of all candidates in C_{k+1} that are contained in *t*
L_{k+1} = candidates in C_{k+1} *greater than* min_high_support and min_very_low_support
Add L_{k+1} to the Itemset_Utility table by calculating rare itemset utility using formula:
Utility(R,t) = $\Sigma_{\text{for each individual item i in R}}$ (u(i,t));
End

//loop to find very-high and high utility rare itemsets
For each itemset ***iset*** in rare itemset table ***R***
begin
If (**Utility(iset)** > user_provided_threshold for_very-high or high_utility_rare_itemset)
then **iset** is a rare_itemset that is of user interest i.e. very-high or high_utility_rare_itemset
else **iset** is a rare itemset but is not of user interest
End

Return high_utility_rare_itemsets
End

END

Figure. 3. Pseudo Code for FTHURI

E. Performance Evaluation of FTHURI

In FTHURI Algorithm (Figure 3), high utility rare itemsets are generated in three phases:-

- In first phase, different values of Utilities are assigned to itemsets in different time periods (monthly, bimonthly or quarterly).

For example; FTHURI was implemented on Mushroom Dataset found in fimi.ua.ac.be/data having 8124 records. The dataset was sliced vertically to keep a maximum of 7 items per transaction forming Mushroom_Modified dataset(Figure 4). The external utility of items was generated randomly(Figure 4).

- In second phase, rare itemsets are generated from temporal database by considering those itemsets which have fuzzy support value less than the maximum support threshold.

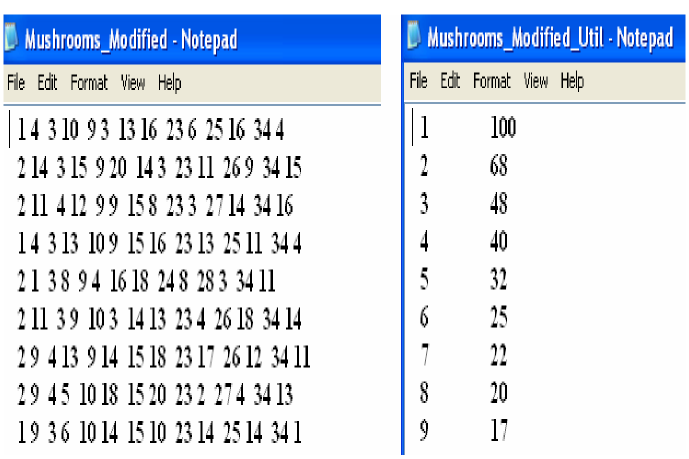
For example; by setting the value of maximum support threshold to 5%, some of the rare itemsets generated from Mushroom_Modified dataset (Figure 4) are listed in Table 1.

- In third phase, the utilities of rare itemsets are fuzzified by using membership functions for

U(Utility) = {Very Low, Low, Medium, High, Very High }as defined in Figure 2.

- Finally, by inputting very_high_utility and high_utility threshold values according to users' interest, rare itemsets having utility value greater than the utility thresholds are generated. Hence, both very_high and high_utility rare itemsets are generated from different time periods using FTHURI algorithm.

For example; on application of FTHURI algorithm on Mushroom_Modified dataset (Figure 4) and by setting the threshold values of fuzzy parameters, support, very-high_utility and high_utility, some of the high and very-high utility rare itemsets generated are listed in table 2.


Mushrooms_Modified - Notepad
File Edit Format View Help

1 4 3 10 9 3 13 16 23 6 25 16 34 4
2 14 3 15 9 20 14 3 23 11 26 9 34 15
2 11 4 12 9 9 15 8 23 3 27 14 34 16
1 4 3 13 10 9 15 16 23 13 25 11 34 4
2 1 3 8 9 4 16 18 24 8 28 3 34 11
2 11 3 9 10 3 14 13 23 4 26 18 34 14
2 9 4 13 9 14 15 18 23 17 26 12 34 11
2 9 4 5 10 18 15 20 23 2 27 4 34 13
1 9 3 6 10 14 15 10 23 14 25 14 34 1

Mushrooms_Modified_Util - Notepad
File Edit Format View Help

1 100
2 68
3 48
4 40
5 32
6 25
7 22
8 20
9 17

Figure. 4. Snapshots of text files containing Mushroom_modified data and item external utilities.

Table 1. Rare Itemsets Table

S.No.	Rare Itemsets	S.No.	Rare Itemsets
1	[2, 23]	23	[2, 13, 23, 36]
2	[2, 3]	24	[2, 14, 24, 34]
3	[2, 3, 34]	25	[2, 11, 24, 36]
4	[2, 3, 23]	26	[2, 16, 24, 36]
5	[2, 9, 23]	27	[2, 10, 13, 34, 36]
6	[2, 23, 34]	28	[2, 10, 16, 34, 36]
7	[22, 10, 13]	29	[2, 11, 16, 34, 36]
8	[2, 9, 23, 34]	30	[2, 10, 17, 34, 36]
9	[2, 3, 23, 34]	31	[2, 11, 24, 29, 34]
10	[2, 9, 24, 36]	32	[2, 11, 24, 29, 36]
11	[2, 16, 29, 36]	33	[2, 11,16, 24, 34]
12	[2, 16, 29, 34]	34	[2, 16, 29, 34, 36]
13	[2, 9, 24, 34]	35	[2, 14, 24, 29, 36]
14	[2, 11, 16, 24]	36	[2, 14, 24, 29, 34]
15	[2, 10, 17, 34]	37	[2, 16, 24, 34, 36]
16	[2,11, 16, 36]	38	[2, 14, 24, 34, 36]
17	[2, 10, 17, 36]	39	[2, 13, 23, 34, 36]
18	[2, 11, 24, 29]	40	[2, 16, 23, 34, 36]
19	[2, 14, 24, 29]	41	[2, 11, 24, 34, 36]
20	[2, 10, 13, 34]	42	[2, 16, 24, 29, 34, 36]
21	[2, 10, 13, 36]	43	[2, 11, 24, 29, 34, 36]
22	[2, 13, 24, 36]	44	[2, 14, 24, 29, 34, 36]

Table 2. High utility rare itemsets table for First, Second and Third Quarter using Fuzzy Utility

S. No.	Rare Itemsets	Support	High utility	very high utility	Time Period (in quarters)
1	[2, 23]	4.99	1	0	Q1
2	[2, 3, 23]	2.48	0.3	0	
3	[2, 23, 34]	4.99	1	0	
4	[2, 3, 34]	3.05	1	0	
5	[3,9,23,34]	4.92	1	0	Q2
6	[3, 9, 24, 36]	4.75	0.9	0	
7	[3, 9, 23]	4.92	1	0	
8	[3,9,24,34,36]	4.16	0.4	0	
9	[3, 10, 13, 36]	4.32	0.8	0	Q3
10	[3, 11, 16, 24]	3.66	0.3	0	
11	[3, 11, 24, 36]	4.82	1	0	
12	[3, 16, 24, 34, 36]	4.48	0.4	0	
13	[3, 13, 23, 34, 36]	4.55	0.6	0	
14	[3, 13,24, 29, 34, 36]	3.98	0.4	0	

IV CONCLUSION

Fuzzy environment is suitable for customer classification, finding profitable transactions and products based upon customers purchasing behaviour and items utilities in different time periods. In fuzzy temporal database the utility concept can be used to assign external utility to the item based on their importance in a particular time period.

An integrated approach of FHURI and THURI, named FTHURI algorithm is defined in this paper. To handle uncertainty, the temporal itemset utility mining with fuzzy modeling, FTHURI, allows item utility values to assume fuzzy values and be dynamic over time. FTHURI algorithm has been implemented to evaluate the performance in terms of generation of high utility and very high utility rare itemsets from temporal datasets.

In this paper, the temporal aspect is incorporated by dividing the data set into four quarters and then mining has been performed accordingly. Also seasonal, bimonthly, monthly time windows have been considered. In future, as per users' requirements, more time windows such as cyclic, can be considered for the temporal concept included in the proposed concept. FTHURI has been implemented on business data and would be implemented on other real-time applications in future.

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