IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 20, 2020, accepted June 5, 2020, date of publication June 22, 2020, date of current version July 20, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3004095

Cluster-Based Membership Function Acquisition Approaches for Mining Fuzzy Temporal Association Rules

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This work was supported by the Ministry of Science and Technology of China under Grant MOST 108-2221-E-032-037 and MOST 108-2218-E-390-001.

ABSTRACT In real-world applications, transactions are typically represented by quantitative data. Thus, fuzzy association rule mining algorithms have been proposed to handle these quantitative transactions. In addition, items generally have certain lifespans or temporal periods in which they exist in a database. Therefore, fuzzy temporal association rule mining algorithms have also been proposed in the literature. A key factor in the acquisition of fuzzy temporal association rules (FTARs) is the design of appropriate membership functions. Because current approaches have been designed to generate membership functions for mining fuzzy association rules (FARs) in market-basket analysis, in this paper, we propose a membership function tuning mechanism for a fuzzy temporal association rule mining algorithm. The proposed approach modifies an existing cluster-based method to generate unique membership functions that are specifically tailored to each item in a dataset. Two factors are utilized to decide the appropriate membership functions of each item: (1) the density similarity among intervals corresponding to the density similarity within intervals, and (2) the information closeness within an interval corresponding to the similarity in the number of data points between intervals. A parameter θ is used to indicate the relative importance of these two factors. As a result, the membership functions are generated based on the quantitative ranges of individual items, and the generated membership functions of items are different in terms of the values of each interval and the number of intervals. The generated membership functions are subsequently used in a fuzzy temporal association rule mining algorithm. Computational experiments were conducted on both a synthetic dataset and a real-world one to demonstrate the effectiveness of the proposed approach.

INDEX TERMS Clustering algorithm, fuzzy association rule, fuzzy temporal association rule, item lifespan, membership functions.

I. INTRODUCTION

Association rule mining is the process of extracting rules from a transaction dataset. For example, a rule might indicate that the presence of certain items implies the presence of other items in a transaction. This mining approach has many useful practical applications, one of them is market-basket analysis [1], [7].

The associate editor coordinating the review of this manuscript and approving it for publication was Zhipeng Cai.

In real-life applications, items in a transactional database tend to have different quantitative values. In other words, the transaction may involve varying units of each purchased item. To handle quantitative values in transactions, a fuzzy set is used to transform these varying quantity ranges into linguistic terms that can be understood by humans. As a result, many algorithms have been designed to mine fuzzy association rules [2], [10], [11], [22]. These algorithms transform quantitative values into fuzzy values using predefined membership functions for generating fuzzy large itemsets;

then, these derived larger itemsets are used to find the fuzzy association rules.

Additionally, items usually have a certain lifespan or a specific time period in which they are available for purchasing. To extract FARs from a transactional database of items in a manner that considers their quantity and time period, several approaches have been proposed in the literature [4], [5]. The existing literature shows that more rules can be found than those derived by fuzzy association rule mining approaches because the lifespan of every item is considered. In addition to the use of fuzzy calendar algebra to consider each item's temporal lifespan, some studies proposed algorithms for obtaining fuzzy periodic association rules [17], [18].

A requirement for mining such rules is to have a set of membership functions. However, defining an appropriate set of membership functions that can obtain useful rules is a challenging task. To address this challenge, Chien *et al.* proposed a granulation-based approach to derive item membership functions from quantitative transactions to mine FARs [6]. This approach is based on two factors: (1) density similarity among intervals and (2) information closeness which is utilized to evaluate the similarity in the number of data points between intervals. Algorithms that capitalize on evolutionary computation techniques to optimize membership functions for items have also been proposed [8], [9], [20]. In general, these approaches are composed of two phases, i.e., membership function optimization and fuzzy association rule mining. First, they encode the membership functions for items into a chromosome. The suitability and number of large 1-itemsets are used as the fitness function to evaluate chromosomes for membership function optimization. Subsequently, these optimized membership functions are used to mine the fuzzy association rules.

However, those membership function learning approaches, e.g., granulation and evolutionary-based approaches, are used only in fuzzy association rule mining. A set of non-tuned membership functions is used in fuzzy temporal association mining. In this paper, we propose an approach to generate fuzzy temporal association rules using a membership function tuning mechanism. The overall goal of the proposed approach is to first generate a set of membership functions specifically tailored to each item in a given dataset and then use these custom membership functions to acquire rules from the transactional database. To obtain the appropriate membership functions, we apply Chien's approach in the membership function learning phase [6], which uses the information density similarity and information closeness to construct an abstract hierarchy of intervals. A determination function is designed to obtain the best interval level for each item from the interval hierarchy based on threshold factors. After the membership functions are generated for each item, they are used to mine the fuzzy temporal association rules from the dataset using the mining algorithm published in [4]. Finally, computational experiments performed on one synthetic dataset and one real-world dataset are conducted to show the effectiveness of the proposed approach.

Hence, the contributions of this paper are listed as follows. (1) A framework consisting of two phases including cluster-based membership function generation and fuzzy temporal association rule mining has been proposed for finding suitable membership functions and fuzzy temporal association rules. (2) Based on the framework, three algorithms are designed and named as granulation on numeric attributes for association rules mining (GNAAR), granulation on numeric attributes for association rules mining overlap half (GNAAROH), and granulation on numeric attributes for association rules mining overlap quarter (GNAAROQ), respectively. (3) Experiments were conducted on two quite different datasets to show the effectiveness of the proposed approaches.

The remainder of this paper is organized as follows. Related work is reviewed in Section 2. The proposed fuzzy temporal association rule mining algorithm with the membership function tuning mechanism is described in Section 3. The experimental results that demonstrate the effectiveness of the proposed approach are presented in Section 4, and conclusions and future work are stated in Section 5.

II. RELATED WORK

In this section, fuzzy data mining algorithms are first described in Section II.A, and the membership function tuning approaches are presented in Section II.B.

A. FUZZY DATA MINING

In real-world applications, purchased items always have quantitative values in transactions. Hence, how to show the meanings of those quantitative values is highly important. Because fuzzy set theory is good at translating the meanings of quantitative values to linguistic terms, many algorithms have been proposed to mine fuzzy association rules [2], [11], [15], [16], [21], [22]. A subset of these algorithms is designed for fuzzy mining with a single minimum support [2], [11], [21], [22], whereas others are intended for fuzzy mining with multiple minimum supports [15], [16]. More efficient approaches based on the defined tree structure have recently been proposed to mine fuzzy association rules [13], [14].

For temporal data mining, the progressive partition miner (PPM) algorithm was proposed to extract general temporal association rules from a given publication database, which consists of a set of transactions in which the database items each have their own lifespans [19]. Chang *et al.* proposed the segmented progressive filter (SPF) algorithm based on the PPM [3]. Compared with PPM, the main contribution of the SPF is that it offers an efficient approach for mining temporal association rules from items with different lifespans in transactions, but it uses them to discover temporal rules from binary transactions.

Lee [12] presented two temporal patterns for fuzzy temporal data mining: fuzzy temporal association rules and fuzzy periodic association rules based on fuzzy calendar algebra. This approach allows users to easily state the temporal requirements. Three types of temporal components (i.e., crisp, cyclic and fuzzy types) were designed to indicate the temporal expressions. In accordance with the three temporal components, the transformed transactions were used to obtain the fuzzy temporal rules. Based on Lee's approach and using a relativity-based interest-measure value, Zhuo *et al.* proposed an algorithm to mine fuzzy calendar-based temporal association rules [23].

Taking the lifespan of items into consideration, Chen *et al.* also proposed a fuzzy data-mining algorithm to extract temporal fuzzy rules that more accurately reflect item associations [4]. This approach first transformed the quantitative values into fuzzy regions using predefined membership functions and simultaneously collected the item lifespans in a temporal information table. Subsequently, the scalar cardinalities of fuzzy item regions were calculated. Finally, using the scalar cardinalities and item lifespans, the mining process was performed to extract the fuzzy temporal association rules.

B. MEMBERSHIP FUNCTION TUNING APPROACHES

The determination of membership functions is necessary prior to the application of FAR mining to a database. That is, both the number of intervals and the values of these intervals must be determined, and they can be user-defined values or determined by an algorithm. Many different approaches have been proposed to generate membership functions [6], [8], [9], [20]. Chien *et al.* developed an approach that partitions quantitative values into intervals and generates membership functions based on the degree of information closeness between intervals and the density similarity between intervals [6]. The advantage of Chien's approach is that it generates membership functions efficiently. To optimize membership functions for fuzzy data mining, Hong *et al.* proposed a genetic algorithm-based fuzzy mining approach to extract suitable membership functions from a set of quantitative data [8]. This approach first encoded the center and width values of membership functions for the items into a chromosome. Subsequently, the number of larger 1-itemsets and the suitability of the membership functions were used to evaluate the quality of a chromosome. Due to the use of the genetic algorithm, this approach can be time-consuming, depending on the size of transactions. The idea was extended to include a divide-and-conquer strategy that greatly improved the efficiency of chromosome evolution [9]. Matthews *et al.* developed an approach using a genetic algorithm to tune the membership functions and mine temporal fuzzy association rules [20]. However, this approach is related to mining rules with respect to web usage and not to market-basket analysis. The comparison of the existing membership function turning approaches for rule mining is given in Table 1.

From Table 1, we can see that the existing approaches can be divided into two types: clustering and genetic algorithms. Generally, genetic algorithm-based approaches are more time consuming than other approaches like clustering. In addition, based on the rule type, we can also know that the existing approaches were proposed for fuzzy association rule or fuzzy temporal association rule mining.

TABLE 1. Comparison of the existing membership function turning approaches.

Approach	Category	Rule Type
Chien et al. [6]	Clustering	FAR
Hong et al. [8]	Genetic Algorithms	FAR
Hong & Chen et al. [9]	Genetic Algorithms	FAR
Matthews et al. [20]	Genetic Algorithms	FTAR

III. PROPOSED MINING FRAMEWORK AND ALGORITHMS

In this section, the proposed mining framework, which contains two main phases for fuzzy temporal fuzzy association rule mining, is stated in Section III.A. Then, the proposed algorithm with a membership function tuning mechanism for fuzzy temporal association rule mining from given temporal transactions is described, including its membership-function generation and fuzzy temporal association rule generation in Sections III.B and III.C, respectively. An example is given to illustrate the proposed approach in Section III.D.

A. PROPOSED MINING FRAMEWORK

The proposed framework combining clustering and fuzzy temporal association rule mining techniques is shown in Fig. 1.

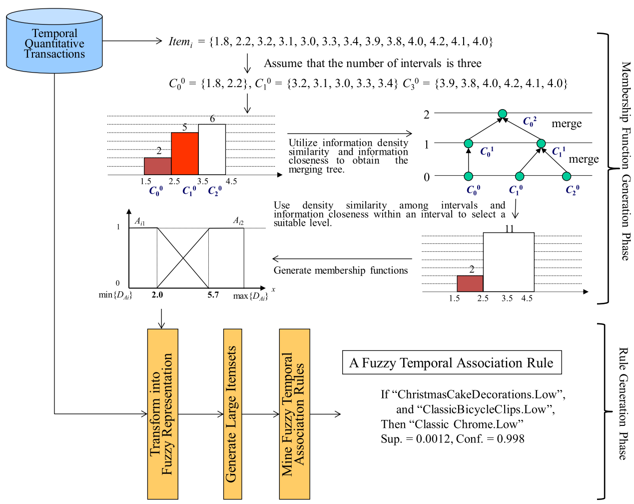

FIGURE 1. The proposed mining framework.

As Fig. 1 shows, the proposed framework consists of membership-function generation and rule-generation phases. The first phase uses a clustering-based approach to generate membership functions for every item. It groups the quantitative values of each item and divides them into predefined intervals. Then, the merging tree is built using information density similarity and information closeness, and the membership functions for items are generated according to the density similarity among intervals and the information closeness within an interval. In the rule-generation phase, using the generated membership functions, the fuzzy temporal association rules are extracted. Based on the framework, the algorithm of the proposed mining method is shown in Table 2.

TABLE 2. The proposed mining algorithm.

The proposed mining algorithm
Input: A given temporal transactions data set *TempTrans* that contains m items and the parameters τ and θ, initial number of intervals on an item r, a predefined minimum support threshold α and a given minimum confidence threshold λ.
Output: A set of fuzzy temporal association rules *fuzzyTemporalRuleSet*.
1. *SetMF* = membershipFunctionGeneration(*TempTrans, r, τ, θ*);
2. *fuzzyTemportalRuleSet* = ruleGeneration(*TempTrans, SetMF, α,* λ);
3. output *fuzzyTemportalRuleSet*;

Table 2 shows that the proposed approach consists of two procedures, namely, membership-function generation and rule-generation, whose purposes are to extract membership functions and to mine fuzzy temporal-association rules. The details of these two procedures are described in the following subsections.

B. PHASE I: MEMBERSHIP-FUNCTION GENERATION PHASE

Before describing the membership-function generation procedure for Phase I, the notations stated in [6] used in the procedure are listed in Table 3.

Based on Chien's approach [6], the procedure for the membership-function generation phase is modified and shown in Table 4.

The goal of the procedure shown in Table 4 is to generate sets of membership functions tailored to the items in a dataset. When presented with an item in a dataset of quantitative transactions, the first step is to split each item's quantitative values into a predefined number of equal-length intervals if the equal-length interval strategy is adopted (Lines 4 to 5). The width of each interval is calculated as the range of quantitative values for an item divided by a user-defined number of intervals. The range of the first interval begins at the lowest value and ends at the lowest value added to the width. The subsequent intervals start at the endpoint of the previous interval and end at their start point plus the width. Excepting the equal-length interval strategy, other two strategies that are the half-overlap-length and quarter-overlap-length interval strategies could also be utilized for initializing intervals. Therefore, three strategies for the membership-function generation procedure are named as the granulation on numeric attributes for association rules mining (GNAAR), granulation on numeric attributes for association rules mining overlap half (GNAAROH), and granulation on numeric attributes for association rules mining overlap quarter (GNAAROQ). In the GNAAROH, when the intervals of an item are initialized, the left and right values of an interval are then extended to

TABLE 3. Notation for the first phase.

n	Total number of transactions in the given dataset.
r	Initial number of intervals for an item.
w	Total range of the dataset.
k	Current level of a granular hierarchy, $k = 0$ for the initial level.
N^k	Number of intervals at level k. Note that $N^0 = r$.
C_i^k	The i-th interval at level k (i.e., the subset of the dataset in the i-th interval at level k).
h_i^k	Number of data values in the i-th interval at level k.
$x_{i,j}^k$	Data in the i-th interval at level k (i.e., $C_i^k = \{x_{i,0}^k, x_{i,1}^k, \dots, x_{i,h_i^k-1}^k\}$).
l_i^k	Length of the i-th interval at level k.
ψ_i^k	Centroid of i-th interval at level k, $\psi_i^k = \frac{\sum_{j=0}^{h_i^k-1} x_{i,j}^k}{h_i^k}$.
$\delta_{i,i+1}^k$	Difference between the density of interval $C_i^k C_i^k$ and the density of the interval merged by neighbor intervals of $C_i^k C_i^k$ and C_{i+1}^k, calculated by $\delta_{i,i+1}^k = \lvert \frac{h_i^k + h_{i+1}^k}{l_i^k + l_{i+1}^k} - \frac{h_i^k}{l_i^k} \rvert$ and $\delta_{i+1,i}^k = \lvert \frac{h_i^k + h_{i+1}^k}{l_i^k + l_{i+1}^k} - \frac{h_{i+1}^k}{l_{i+1}^k} \rvert$.
$\sigma_{i,i+1}^k$	Distance that the centroid of interval C_i^k moves after merging of the neighbor intervals C_i^k and C_{i+1}^k, calculated by $\sigma_{i,i+1}^k = \lvert \psi'^k_{i,i+1} - \psi_i^k \rvert$ and $\sigma_{i+1,i}^k = \lvert \psi'^k_{i,i+1} - \psi_{i+1}^k \rvert$, where $\psi'^k_{i,i+1} = \lvert \frac{h_i^k \psi_i^k + h_{i+1}^k \psi_{i+1}^k}{h_i^k + h_{i+1}^k} \rvert$.
$IDS_{i,i+1}^k$	Information density similarity is the degree of density similarity between two neighbor intervals C_i^k and C_{i+1}^k, represented as $\mathrm{DS}_{i,i+1}^k = \frac{h_i^k \delta_{i,i+1}^k + h_{i+1}^k \delta_{i+1,i}^k}{h_i^k + h_{i+1}^k}$.
$IC_{i,i+1}^k$	Information closeness is the degree of information closeness between two neighbor intervals C_i^k and C_{i+1}^k, represented as $\mathrm{IC}_{i,i+1}^k = \frac{\mathrm{h}_i^k \sigma_{i,i+1}^k + \mathrm{h}_{i+1}^k \sigma_{i+1,i}^k}{\mathrm{h}_i^k + \mathrm{h}_{i+1}^k}$.
$E_{i,i+1}^k$	Threshold value used to evaluate whether C_i^k and C_{i+1}^k should be merged. $E_{i,i+1}^k = IC_{i,i+1}^k \times (DS_{i,i+1}^k)^\tau$, where τ is the parameter used in adjusting the importance between $DS_{i,i+1}^k$ and $IC_{i,i+1}^k$, $\tau > 0$.
U^k	Set of all N^k intervals at level k after k merging processes. Let $U^k = \{C_0^k, C_1^k, \dots, C_{N^k-1}^k\}$.
ξ^k	Information density-similarity variance of U^k, $\xi^k = \sum_{i=0}^{N^k-1} \lvert \frac{n}{w} - \frac{h_i^k}{l_i^k} \rvert$, where h_i^k is the number of data values in interval C_i^k at level k.
η^k	Information closeness variance of U^k, $\eta^k = \sum_{i=0}^{N^k} \sum_{C_j^0 \subseteq C_i^k} \lvert \frac{h_i^k}{l_i^k} - \frac{h_j^0}{l_j^0} \rvert$, where h_j^0 is the number of data values in the initial interval C_i^k.

include an additional half of its width on either side, creating an overlap. In the same way, the values are extended to include an additional quarter of its width on either side to create an overlap in the GNAAROQ.

After the initial set of intervals is assigned, the intervals are assessed to determine which intervals are the best two to merge. This decision is based on two factors, information closeness (IC) and information density similarity (IDS) (Lines 6-10). Because using equal-length intervals to generate MFs could result in a gap between two adjacent MFs when an interval contains no quantitative value (i.e., the interval is empty), the half-overlap-length and quarter-overlap-length

TABLE 4. The membership-function generation phase.

Membership-function generation procedure

Input: A temporal transactions dataset *TempTrans* containing *m* items, the parameters τ and θ, and the initial number of intervals on an item *r*.
Output: Sets of membership functions, *SetMF*.

1. FOR each item I_j ($1 \le j \le m$)
2. Let $k = 0$, $N^0 = r$ and $U^k = \{C_0^k, C_1^k, \ldots, C_{N^k-1}^k\}$;
3. DO{
4. *quanValueItem*$_j$ = findValueForAnItem(*TempTrans*, I_j);
5. *intervalsItem*$_j$ = divideDataIntoIntervals(*quanValueItem*$_j$, l_i^k);
/* Note that there are three ways to divide data into intervals, including **equal-length**, **half-overlap-length** and **quarter-overlap- length interval strategies** to generate MFs. */
6. FOR any C_i^k and C_{i+1}^k in U^k
7. $IDS_{i,i+1}^k$ = calculateInformationDensitySimilarity(C_i^k, C_{i+1}^k);
8. $IC_{i,i+1}^k$ = calculateInformationCloseness(C_i^k, C_{i+1}^k);
9. END FOR
10. U^{k+1} = *mergeTwoIntervalsByMinEValue*(U^k, $DS_{i,i+1}^k$, $IC_{i,i+1}^k$, τ);
11. ξ^k = calculateInformationDensitySimilarityVar(*intervalsItem*$_j$);
12. η^k = calculateInformationClosenessVar(*intervalsItem*$_j$);
13. } while ($N^{k+1} > 1$, $k = k + 1$)
14. Set U^k for item I_j with $\min_k\{\theta \cdot \xi^k + (1-\theta) \cdot \eta^k\}$;
15. *SetMF* = *SetMF* $\cup$ U^k;
16. END FOR
17. Return *SetMF*;

intervals are employed to generate MFs to solve this problem. To determine the most suitable level for generating membership functions, two factors are evaluated: density-similarity among intervals (ξ^k) and information closeness within an interval (η^k) (Lines 11-12). After these two factors have been recorded for all levels, they are used to identify the optimum level based on the weighting parameter θ. The θ value is used to set the relative weights between density similarity among intervals and information closeness within an interval for determining a suitable number of membership functions. The generated membership functions are added to *SetMF* (Lines 14-15). When a level is evaluated as the optimal level, triangular membership functions are generated by calculating the centroid of each interval on that level.

C. PHASE II: FUZZY TEMPORAL-ASSOCIATION RULE GENERATION

After the first phase, the sets of generated membership functions are gathered for mining fuzzy temporal association rules. Based on the previous mining algorithm [4], the procedure for the fuzzy temporal association rule mining phase is stated in Table 5.

Table 5 shows that the process first transforms each quantitative value into fuzzy sets using the sets of generated membership functions (Line 2). During the transformation process, the lifespans of the items are collected and recorded in the temporal information table (Lines 3-4). Then, the process calculates the scalar cardinality of each fuzzy region of the items to find large items (Lines 6-32). The support values of items are calculated according to their corresponding periods to represent the true importance of each item (Lines 10 and 23). Using the scalar cardinalities

TABLE 5. Rule-generation procedure.

Fuzzy temporal association rule mining procedure

Input: A temporal transactions data set *TempTrans*, the generated membership function sets *SetMF* and the minimum support and confidence thresholds α and λ, respectively.
Output: A set of fuzzy temporal association rules *fuzzyTemportalRuleSet*.

1. FOR each *time period* p_t (t = 1 *to* h)
2. *fuzzyRepresentation* = transformToFuzzy(*TempTrans*, *SetMF*);
3. *tempInforTable* = getItemLPAndNumTransInPeriod(*TempTrans*);
4. *TS* = ∅; //Each tuple has a fuzzy temporal subitemset, start period and *count*.
5. END FOR
6. L_1 = ∅;
7. FOR each *fuzzy region* R_{jk}
8. *scalarCardinalityValue*$_{jk}$ = scalarCardinality(R_{jk}, *fuzzyRepresentation*);
9. *numTrans*$_{jk}$ = getTransaction(R_{jk}, *tempInformationTable*);
10. *tempFuzzySupport*$_{jk}$ = *scalarCardinalityValue*$_{jk}$ / *numTrans*$_{jk}$;
11. IF *tempFuzzySupport*$_{jk} \ge \alpha$
12. $L_1 = L_1 \cup R_{jk}$;
13. END IF
14. END FOR
15. IF $L_1 \ne \varnothing$
16. r = 1;
17. END IF
18. *LargeItemset* = ∅;
19. *candidateItemset*$_{r+1}$ = generateCandItemset(L_r, r+1);
20. FOR each *candidate* (r+1)-*itemset s* in *candidateItemset*$_{r+1}$
21. *scalarCardinalityValue*$_s$ = scalarCardinality(s, *fuzzyRepresentation*);
22. *numTrans*$_s$ = getTransaction(s, *tempInformationTable*);
23. *tempFuzzySupport*$_s$ = *scalarCardinalityValue*$_s$ / *numTrans*$_s$;
24. If *tempFuzzySupport*$_s \ge \alpha$
25. $L_{r+1} = L_{r+1} \cup s$;
26. *TS* = *TS* ∪ genrateSubItemsetAndCount(L_{r+1});
27. END IF
28. END FOR
29. *LargeItemset* = *LargeItemset* ∪ L_{r+1};
30. IF $L_{r+1} \ne \varnothing$
31. Go to Line 19;
32. END IF
33. FOR each Itemset *s* in *LargeItemset*
34. *candidateRules* = generateCandidateRules(s);
35. *confidenceOfRules* = calculateConfidenceOfRule(*candidateRules*);
36. *fuzzyTemportalRuleSet* = generateRules(*confidenceOfRules*, λ);
37. END FOR
38. Return *fuzzyTemportalRuleSet*;

of fuzzy regions, the mining process is performed to find the fuzzy temporal association rules (Lines 33-37). Finally, the algorithm outputs the derived fuzzy temporal association rules (Line 38).

D. AN EXAMPLE

The following is an example of how the proposed algorithm is used to generate a set of suitable membership functions from a simple data set of temporal quantitative transactions for one item.

1) MEMBERSHIP FUNCTION GENERATION WITH QUARTER-OVERLAP-LENGTH INTERVAL STRATEGY

The quantitative transactions with a certain item used in this example are shown in Table 6. The quantitative values for item *A* are listed in Table 7.

Table 7 shows that the item appears in 22 quantitative transactions, which can be seen in Table 6.

STEP 1: The range of the items' quantitative values is calculated by subtracting the lowest value from the highest value. The value is 80 (= 100 – 20) in this case.

TABLE 6. The quantitative transactions.

TID	Items	TID	Items
$Trans_1$	(A, 22)	$Trans_{12}$	(A, 64)
$Trans_2$	(A, 22)	$Trans_{13}$	(A, 67)
$Trans_3$	(A, 23)	$Trans_{14}$	(A, 71)
$Trans_4$	(A, 25)	$Trans_{15}$	(A, 76)
$Trans_5$	(A, 27)	$Trans_{16}$	(A, 83)
$Trans_6$	(A, 30)	$Trans_{17}$	(A, 83)
$Trans_7$	(A, 32)	$Trans_{18}$	(A, 87)
$Trans_8$	(A, 39)	$Trans_{19}$	(A, 88)
$Trans_9$	(A, 45)	$Trans_{20}$	(A, 88)
$Trans_{10}$	(A, 53)	$Trans_{21}$	(A, 90)
$Trans_{11}$	(A, 61)	$Trans_{22}$	(A, 100)

TABLE 7. The quantitative values for item A.

Item	Quantitative Values
A	20, 22, 23, 25, 27, 30, 32, 39, 45, 53, 61, 64, 67, 71, 76, 83, 83, 87, 88, 88, 90, 100

STEP 2: The intervals are then decided as follows:

SUBSTEP 2.1: The range is split equally into a predefined number of maximum intervals. Here, let r is set at 4, so there are four intervals initially. This set of intervals is represented as $U^0 = \{C_0^0, C_1^0, C_2^0, C_3^0\}$ and the individual intervals are represented as $C_{00} = \{20, 22, 23, 25, 27, 30, 32, 39\}$, $C_1^0 = \{45, 53\}$, $C_2^0 = \{61, 64, 67, 71, 76\}$ and $C_3^0 = \{83, 83, 87, 88, 88, 90, 100\}$ respectively. The width of each interval is 20, which is represented as $l_0^0 = l_1^0 = l_2^0 = l_3^0 = 20$. The number of instances in each partition is represented as follows: $h_0^0 = 8$, $h_1^0 = 2$, $h_2^0 = 5$, $h_3^0 = 7$.

SUBSTEP 2.2: The width of each interval is then extended to include a quarter of it's neighbouring intervals. The intervals become $C_0^0 = \{20, 22, 23, 25, 27, 30, 32, 39\}$, $C_1^0 = \{39, 45, 53, 61, 64\}$, $C_2^0 = \{61, 64, 67, 71, 76, 83, 83\}$ and $C_3^0 = \{76, 83, 83, 87, 88, 88, 90, 100\}$ respectively. The width of each interval becomes 30, which is represented as $l_0^0 = l_1^0 = l_2^0 = l_3^0 = 30$. The number of instances in each partition becomes: $h_0^0 = 8$, $h_1^0 = 5$, $h_2^0 = 7$, $h_3^0 = 8$. After extending, the intervals are shown in Fig. 2.

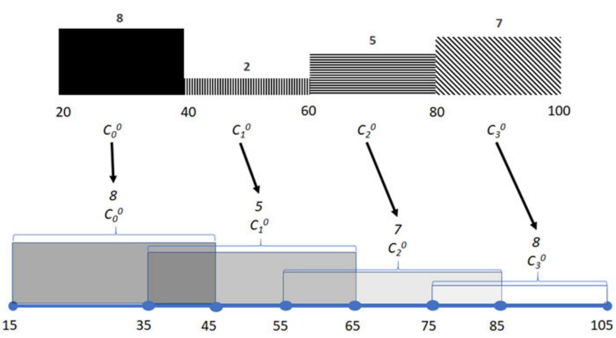

FIGURE 2. GNAAROQ interval extension.

STEP 3: The information density similarity (DS) of C_0^0 and C_1^0 is calculated using following substeps.

SUBSTEP 3.1: The difference between the density of interval C_0^0 and the density of the merged intervals C_0^0 and C_1^0 is calculated as follows:

$$\delta_{0,1}^0 = \left|\frac{h_0^0 + h_1^0}{l_0^0 + l_1^0} - \frac{h_0^0}{l_0^0}\right| = \left|\frac{8+5}{30+30} - \frac{8}{30}\right| = 0.05$$

SUBSTEP 3.2: The difference between the density of interval C_1^0 and the density of the merged intervals C_0^0 and C_1^0 is then calculated as follows:

$$\delta_{1,0}^0 = \left|\frac{h_0^0 + h_1^0}{l_0^0 + l_1^0} - \frac{h_1^0}{l_1^0}\right| = \left|\frac{8+5}{30+30} - \frac{5}{30}\right| = 0.05$$

SUBSTEP 3.3: These values are used to calculate the information density-similarity between intervals C_0^0 and C_1^0 as follows:

$$DS_{0,1}^0 = \frac{h_0^0\delta_{0,1}^0 + h_1^0\delta_{1,0}^0}{h_0^0 + h_1^0} = \frac{8 \times 0.05 + 5 \times 0.05}{8+5} = 0.05$$

STEP 4: The information closeness (IC) between intervals 1 and 2 is calculated using following substeps.

SUBSTEP 4.1: ψ_i^k represents the centroid of the i-th interval at level k. The centroid for interval C_0^0 is determined as follows:

$$\psi_0^0 = \frac{\sum_{j=0}^{h_i^k - 1} x_{0,1}^0}{h_0^0} = \frac{20+22+23+25+27+30+32+39}{8} = 27.25$$

SUBSTEP 4.2: The centroid for interval C_1^0 is then calculated as follows:

$$\psi_1^0 = \frac{\sum_{j=0}^{h_i^k - 1} x_{1,2}^0}{h_1^0} = \frac{39+45+53+61+64}{5} = 52.4$$

SUBSTEP 4.3: The centroid of the two intervals combined is determined.

$$\psi_{0,1}^{'0} = \left|\frac{h_0^0\psi_0^0 + h_1^0\psi_1^0}{h_0^0 + h_1^0}\right| = \frac{8 \cdot 27.25 + 5 \cdot 52.4}{8+5} = 36.92$$

SUBSTEP 4.4: The distance that the centroid of the interval moved after the merging of intervals C_0^0 and C_1^0 is calculated. These two values are:

$$\sigma_{0,1}^0 = \left|\psi_{0,1}^{'0} - \psi_0^0\right| = 9.67 \quad \text{and } \sigma_{1,0}^0 = |36.92 - 52.4| = 15.48$$

SUBSTEP 4.5: The value for information closeness is then calculated as:

$$IC_{0,1}^0 = \frac{h_0^0\sigma_{0,1}^0 + h_1^0\sigma_{1,0}^0}{h_0^0 + h_1^0} = \frac{8 \times 9.67 + 5 \times 15.48}{8+5} = 11.9$$

STEP 5: The threshold value (E) for C_0^0 and C_1^0 is then calculated as follows, with a user-defined value $\alpha = 2$ being used.

$$E_{0,1}^0 = IC_{0,1}^0 \times (DS_{0,1}^0)^{\alpha} = 11.9 \times 0.05^2 = 0.02975$$

Step 6: STEPs 3 to 5 are repeated and the threshold value is calculated for both C_1^0 and C_2^0, and C_2^0 and C_3^0, respectively. The results are shown in Table 8.

TABLE 8. The threshold values of all intervals.

Intervals	*IC*	*DS*	*E*
C_0^0 and C_1^0	11.9	0.05	0.0298
C_1^0 and C_2^0	9.6	0.0333	0.0106✓
C_2^0 and C_3^0	7.334	0.0166	0.0204

Step 7: The threshold value $E_{1,2}^0$ is smaller than the threshold values $E_{0,1}^0$ and $E_{2,3}^0$. Therefore, the intervals C_1^0 and C_2^0 are merged at level 0. We obtain the new set of intervals $U^1 = \{C_0^1, C_1^1, C_2^1\}$, where $C_0^1 = C_0^0$, $C_1^1 = C_1^0 \cap C_2^0$, and $C_2^1 = C_3^0$. These set of intervals are used to granulate the next level.

Step 8: STEPs 3 to 7 are repeated until only one interval remains. The final set of intervals for each level is shown in Figs. 3-6.

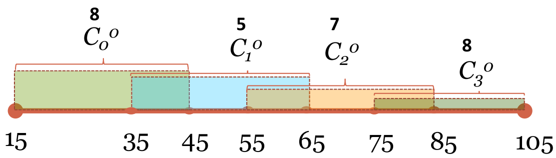

FIGURE 3. Intervals at level 0.

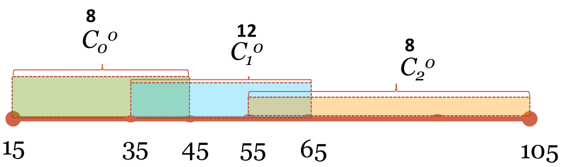

FIGURE 4. Intervals at level 1.

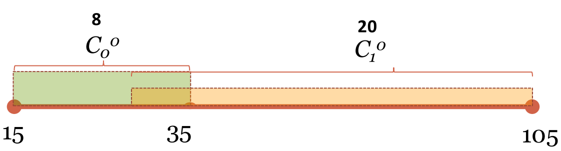

FIGURE 5. Intervals at level 2.

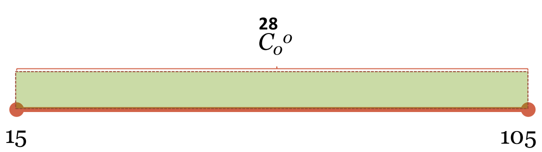

FIGURE 6. Intervals at level 3.

STEP 9: In order to decide which interval is the most suitable, the parameters that are the density similarity among intervals ξ^k and the information closeness within an interval η^k, must be calculated for each level using following substeps.

SUBSTEP 9.1: The ξ^k is first decided through the formula showed in Table 3. The values of the density similarity among intervals at the four levels are 0.311, 0.332, 0.203 and 0, respectively.

SUBSTEP 9.2: The η^k value for the most suitable interval is then decided by the formula showed in Table 2. The values at the four levels are 0, 0.045, 0.133 and 0.311.

STEP 10: The formula $\theta \times \xi^k + (1-\theta) \times \eta^k$ is used to decide on the most suitable level to use to generate membership functions. θ is a user-defined parameter which is used to decide on the respective weights of the two values ξ^k and η^k. In this example, $\theta = 0.4$. The results can be seen in Table 9.

TABLE 9. Formula $\theta * \xi^k + (1-\theta) * \eta^k$ used to decide on the most suitable level.

Level	ξ^k	η^k	$\theta \times \xi^k + (1-\theta) \times \eta^k$
0	0.311	0	0.124✓
1	0.332	0.045	0.160
2	0.203	0.133	0.161
3	0	0.311	0.187

Table 9 indicates that level 1 has the lowest value, and it is deemed to be the most suitable level to generate membership functions.

STEP 11: The centroid of each interval for level 1 is calculated is follows. Since $C_0^0 = \{20, 22, 23, 25, 27, 30, 32, 39\}$, $C_1^0 = \{39, 45, 53, 61, 64\}$, $C_2^0 = \{61, 64, 67, 71, 76, 83, 83\}$ and $C_3^0 = \{76, 83, 83, 87, 88, 88, 90, 100\}$, the centroid of the three intervals are calculated as $\psi_0^0 = 27.25$, $\psi_1^0 = 52.4$, $\psi_2^0 = 72.14$ and $\psi_3^0 = 86.875$.

STEP 12: These centroids generated from previous step are then used as the center of each interval in the membership function. The centroid forms the center of each fuzzy interval. At last, the generated membership functions are shown in Fig. 7.

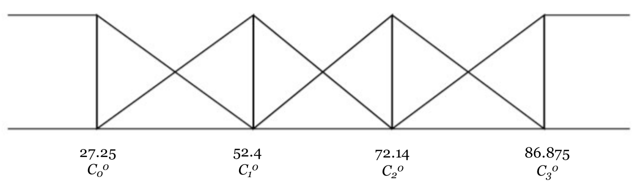

FIGURE 7. The derived membership functions.

2) FUZZY TEMPORAL ASSOCIATION RULE MINING

After membership function generation, the generated membership functions are gathered for fuzzy temporal association rule mining. The details and an example of the rule mining process can be found in [4].

IV. EXPERIMENTAL RESULTS

This section describes the experiments conducted to demonstrate the performance of the proposed approach. The datasets are described in Section IV.A. The approach chosen for comparison is discussed in Section IV.B. The experimental evaluations of these datasets are presented to show the merits of the proposed approach in Section IV.C.

A. EXPERIMENTAL DATASETS

Two rather different datasets were selected to demonstrate the application of the proposed approach in different situations. The first is a synthetic dataset containing 88,000 transactions involving 16,470 items. All the quantitative values in the dataset fall in the range of 1 to 11. The second is a real-life online retail dataset retrieved from the UCI Machine Learning Repository. This database contains all the transactions from a UK-based online retail store between 01/12/2010 and 09/12/2011 and contains 17,485 transactions involving 3,877 items.

Some of the customers of this online retail store are wholesalers who purchase items in bulk; thus, the quantitative values in this dataset are much higher: the quantitative values fall in the range of 1 to 4,800 (excluding 3 outliers). However, the majority of the customers is not wholesalers and is much more likely to buy items in smaller quantities. Therefore, if the number of times that a purchase is made for each quantitative value is counted, the dataset is highly unbalanced in favor of the lower end of the quantitative range. In total, there are 73,314 instances where a customer purchases a single item (a quantitative value of 1), whereas there are only 4 instances when a customer purchases bulk items (with a quantitative value of 4,800). This point is illustrated in Fig. 8.

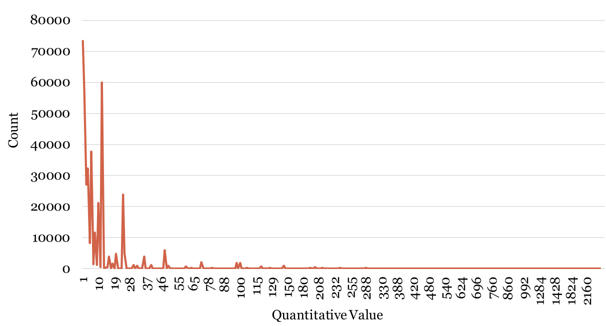

FIGURE 8. Distribution of quantitative values.

B. APPROACH CHOSEN FOR COMPARISON

When a membership function generation algorithm is not used to find appropriate membership functions, predefined membership functions are generally utilized to discover association rules. One commonly used technique considers the quantitative range of the entire dataset and divides that range into an equal number of predefined fuzzy regions. This user-defined membership function is subsequently applied as a communal membership function to mine rules for all of the items. The previous approach of using predefined membership functions is chosen for comparison [4]. The membership functions used in each of the two datasets are shown in Figs. 9 and 10, respectively. The previous approach is referred to as the PMF (predefined membership function) approach in the following sections.

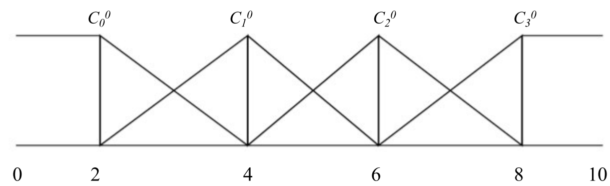

FIGURE 9. Membership functions used in the synthetic dataset.

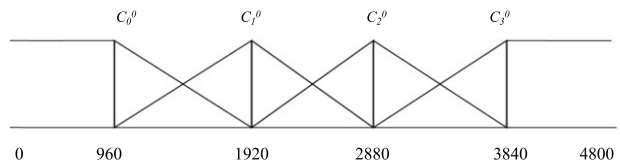

FIGURE 10. Membership functions used in the online retail dataset.

C. EVALUATION OF THE PROPOSED APPROACH

To illustrate the merits of the proposed approach, as discussed in the previous section, there are three ways to generate membership functions in which the allowed intervals overlap. Hence, based on the proposed approach using equal-length, half-overlap-length and quarter-overlap-length intervals for generating membership functions, three approaches, named GNAAR, GNAAROH and GNAAROQ, are used to compare the PMF approach.

Experiments were first performed to compare the three proposed approaches with the PMF approach in terms of the number of rules generated at different minimum supports. The theta value and minimum confidence were set to 0.5 and 0.1, respectively. The relationship between the number of rules and the minimum support for the three proposed approaches and the compared approach, the PFM, for the two datasets are shown in Fig. 11 and Fig. 12.

Fig. 11 shows that the three proposed approaches are capable of generating considerably more rules than the PMF at all minimum supports. Each item in the proposed approaches has a membership function generated specifically for that item based on its quantitative range; thus, the fuzzy regions have significance. However, the PMF approach assigns the same membership function to every item without considering the characteristics of individual items. Consequently, the three proposed approaches generate additional rules.

Fig. 12 shows that the PMF approach is capable of producing many more rules than the three proposed approaches. At first glance, this statement seems counterintuitive, especially considering the results on the synthetic dataset. However, when the distribution of the quantitative values in

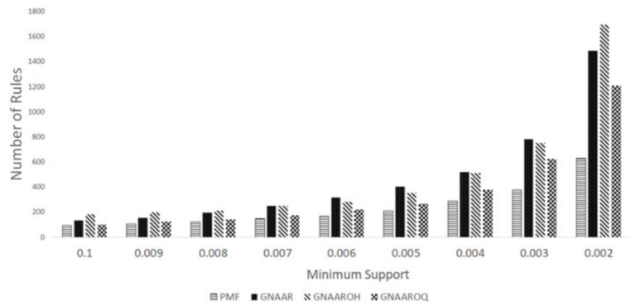

FIGURE 11. Relationship between number of rules and minimum support on the synthetic dataset.

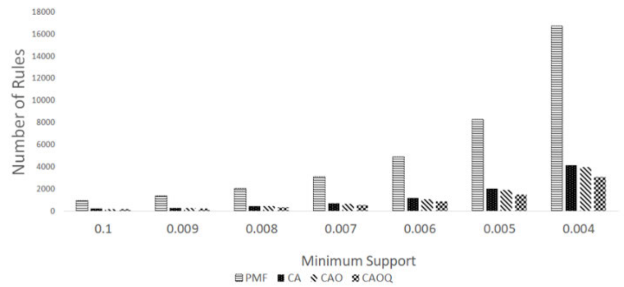

FIGURE 12. Relationship between number of rules and minimum support on the online retail dataset.

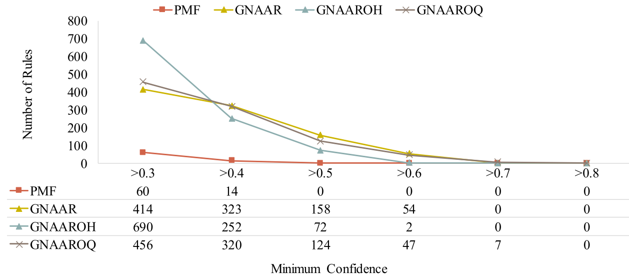

FIGURE 13. Relationship between number of rules and minimum confidence on the synthetic dataset.

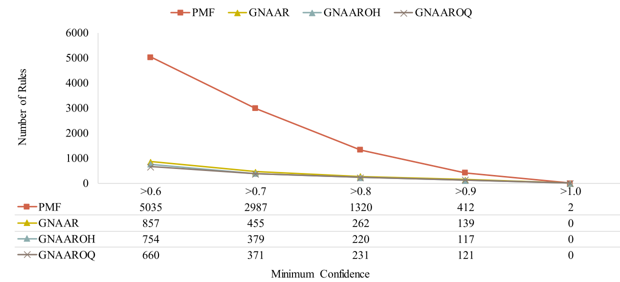

FIGURE 14. Relationship between number of rules and minimum confidence on the online retail dataset.

the second dataset is considered, these results make more sense. As mentioned previously, the dataset is highly unbalanced in favor of the lower end of the quantitative range. The vast majority of items are purchased in quantities of less than 100. Therefore, the proposed approaches generate membership functions with multiple fuzzy regions inside this range. However, using the PMF approach, the lowest fuzzy region C_0^0 ranges from 0 to 1920. Therefore, the quantitative value of almost every single item falls into the fuzzy region C_0^0. As a result, the PMF approach generates many rules such that the presence of one item in the fuzzy region C_0^0 suggests the presence of another item in the fuzzy region C_0^0. Furthermore, these rules might have notably high support and confidence. However, because of the large size of the fuzzy region to which these rules refer, these rules are essentially useless. In contrast, the proposed approaches segment an item's quantitative range into intervals and generate membership functions accordingly, which results in fewer rules but whose quantitative values are far more specific, making them much more useful.

To show the effectiveness of the proposed approach, experiments were conducted to compare the three proposed approaches with the PMF approach in terms of the number of rules generated at different minimum confidences. Note that a θ value of 0.5 and a minimum support value of 0.004 were used. The relationship between number of rules and minimum confidence for the three proposed approaches and the PFM for the two datasets are shown in Fig. 13 and Fig. 14, respectively.

Fig. 13 shows that the three proposed approaches are capable of generating more rules with a higher confidence than is the PMF approach. Comparing the three proposed approaches, the GNAAROQ approach was the only one capable of discovering rules with a confidence of approximately 0.7, which suggests that the GNAAROQ is the most suitable approach for this dataset.

Fig. 14 shows that—for the same reasons outlined in the previous section—the PMF approach outperforms the three proposed approaches in terms of the number of rules generated. Additionally, for the same reasons described previously, the generated rules refer to notably large fuzzy regions, which essentially make them useless. Below, we selected two rules discovered by PMF and the proposed approach and show them in Fig. 15 and Fig. 16 to explain the differences.

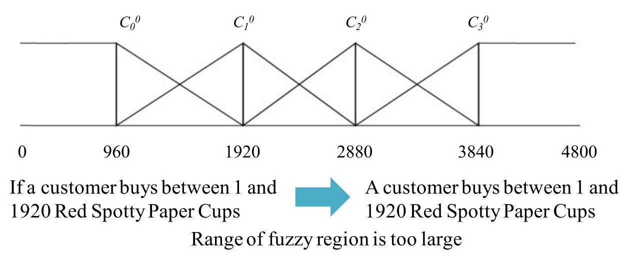

FIGURE 15. A fuzzy temporal association rule extracted by PMF.

Fig. 15 shows that if a customer buys "Red Spotty Paper Cups", then that customer will also buy "Red Spotty Paper Plates" under linguistic term C_0^0 whose quantitative value is within 1 to 1920. From the rule derived by PFM, we can obtain the relationship between two items, but it is difficult to extract useful information for C_0^0 because its range is too large.

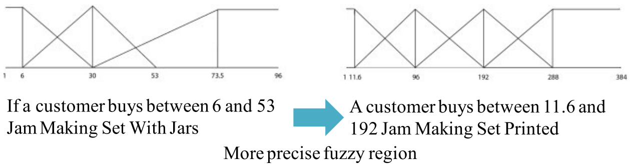

FIGURE 16. A fuzzy temporal association rule extracted by the proposed approach.

In contrast, Fig. 16 shows a rule mined by the proposed approach. The rule indicates that customers who buy "Jam Making Set with Jars" will also buy "Jam Making Set Printed." It is easy to understand that the quantitative values of those two items belong to the fuzzy regions "6–53" and "11.6–192", respectively, which refer to more precise fuzzy regions. Comparing the fuzzy regions of the PMF-derived rules those derived by the proposed approach, we can see that the fuzzy regions of the rules derived by the proposed approach can be more easily understood and that they provide more useful information to users.

At last, because the weighting parameter θ that is utilized to identify the optimum level for generating membership functions will influence the final result, the experiments were conducted to show the number of rules mined by the proposed approaches with different θ values. The results on the two datasets are shown in Fig. 17 and Fig. 18.

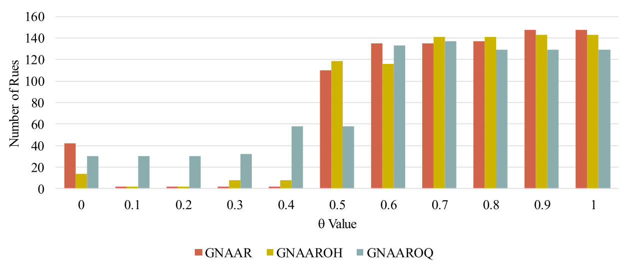

FIGURE 17. Number of rules extracted by the proposed approaches with different theta values on the synthetic dataset.

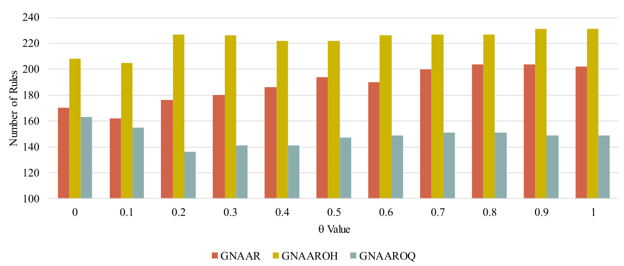

FIGURE 18. Number of rules extracted by the proposed approaches with different theta values on the online retail dataset.

From Fig. 17, we can observe that the proposed approaches can mine more rules when the θ value is larger than 0.5. In addition, the GNAAROQ is better than other two approaches when the θ values were set at small values. Based on the results, for the synthetic dataset, the θ value can be set larger than 0.5 if a decision maker wants to get more rules.

From Fig. 18, it is easy to observe that the number of rules mined by the GNAAROH is larger than that by the GNAAR and GNAAROQ on the online retail dataset. Thus, for the real-life dataset, the GNAAROH is suggested to find membership functions for fuzzy temporal rule mining.

V. CONCLUSIONS AND FUTURE WORK

Because discovering useful fuzzy temporal association rules from transactional data is a challenging task, various approaches have been presented to address this issue. However, the membership functions used in the previous approaches that might critically influence the final results are predefined. In this paper, we proposed an algorithm that first generates membership functions specifically tailored to each item in a temporal quantitative transactional database. The generated membership functions are subsequently used to mine the fuzzy temporal association rules. To show the effectiveness of the proposed approach, experiments were conducted on two vastly different datasets: one was synthetic and the other was a real-life dataset. The synthetic dataset contained transactions that have a notably small range of quantitative values. The second data set contained transactions with largely different quantitative values. In the first dataset, the results indicate that the proposed approach can greatly outperform an approach that uses predefined membership functions in terms of the number of generated rules. In the second dataset, the proposed approach generated a smaller number of rules, but the rules were related to much more specific fuzzy regions, making them more useful.

In the future, the proposed approaches can be improved by using the evolutionary algorithms, e.g., how to design a GA-based approach for finding the suitable θ value to tune the membership functions. In addition, efficient rule mining approaches can also be considered for designing the fitness function to speed up the evolution process and obtain more accurate membership functions. To verify them, analysis of the execution time or memory usage of them can be conducted. Another possibility for future work is to explore different approaches for calculating item lifespans.

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