

Knowledge Extraction by Fuzzy Association Rules: An Extension Approach to the Fuzzy Case

Youssef FAKIR, Salim KHALIL

Sultan Moulay Slimane University, Morocco

Email : info.dec07@yahoo.fr, khalilsalim1@gmail.com

Abstract

Numerous studies have explored association rule extraction within the research domain. Yet, prevalent algorithms are typically constrained to processing binary data, indicating merely the presence or absence of elements. It is crucial to acknowledge that a significant portion of real-world data is quantitative and numeric. In this article, we introduce an innovative approach aimed at accommodating such data types through the incorporation of fuzzy logic. Our proposed algorithm is tailored to extract fuzzy association rules, offering a more nuanced and flexible perspective on the relationships within quantitative and numeric datasets.

Keywords: fuzzy logic, association rules, optimization algorithm, extended Apriori algorithm,

1. Introduction

Extracting knowledge from large data sets is of crucial importance in today's information-rich world. The rapid evolution of technology has led to an exponential accumulation of data in diverse domains such as e-commerce, healthcare, social media and many others. At the heart of this evolution, association rules have emerged as a powerful methodology for discovering hidden relationships and meaningful patterns within these data sets. Association rules, first popularized by Agrawal et al. [1] and Srikant Savasere et al. [2] in 1994, aim to identify frequent associations between different elements in a dataset. However, the binary and absolute nature of the relationships discovered by traditional association rule methods may not always capture the complexity and uncertainty present in many real-world situations. This is where the extension to the fuzzy case comes in. The fuzzy extension to association rules aims to introduce the notion of fuzziness into the knowledge extraction process, enabling partial or uncertain relationships between data elements to be modelled. Fuzziness is inherent in many problems and reflects the reality of uncertainty and imprecision that often characterize real data. By incorporating this fuzzy extension, association rules can be made more adaptable to the nuances present in complex data sets. This intersection between association rule-based knowledge extraction and fuzzy extension offers exciting

opportunities to deepen our understanding of the underlying patterns in diverse data. Many studies explore association rule generation, whether using fuzzy logic or classical logic. Sharmila and Vijayarani [3] have proposed a technique called Fuzzy Rules Using Whale Optimization Algorithm (FRUWOA). This method unfolds through several stages to optimize the discovery of associations in datasets. First, FRUWOA performs data fuzzification using triangular membership functions to represent data uncertainty. Next, it categorizes items based on their type, such as food or electronic products, and assigns individual thresholds to them. Utilizing the whale optimization algorithm (WOA), WOA effectively identifies frequent items that surpass their predefined individual thresholds. Lastly, the method generates fuzzy rules from frequent items to capture potential relationships between them in transactions. This approach combines fuzzy logic with the advanced optimization capabilities of the whale optimization algorithm, thus offering a promising method to enhance the accuracy and efficiency of association rule generation in transactional datasets. Arora et al. [4] presented the Extended Apriori Star algorithm, aiming to extract fuzzy association rules based on fuzzy data from various tables constructed using the entity-relationship model. In this article, we will explore this innovative approach in detail, analyzing its fundamental

components. We will also highlight how incorporating fuzziness into the association rule extraction process can improve modelling capability and open up new avenues for meaningful knowledge discovery. Through this exploration, we hope to provide an enlightening perspective on the evolution of association rules and how their extension to the fuzzy case can enrich our ability to extract relevant and actionable information from complex and uncertain data. The main objective of this study is to extend traditional association rules to the fuzzy domain, using fuzzy logic to handle uncertainty and nuanced relationships. We aim to create a robust methodology that can discover meaningful associations in complex and uncertain data. After this introduction, we will undertake a literature review to explore previous work on association rules. We will identify the gaps that our approach, to extending association rules to the fuzzy case, seeks to fill. Subsequent to this, we will elaborate on the methodology we have designed to broaden association rules into the realm of fuzziness. We will elucidate the seamless integration of fuzzy logic into the process of extracting association rules and its adept handling of uncertainty and fuzziness inherent in the data. Our ensuing discourse will encompass the presentation of experiments and results gleaned from both authentic and simulated datasets. We will scrutinize the efficacy of our approach vis-à-vis conventional methods, delineating its advantages in the realm of knowledge discovery. Ultimately, we will wrap up by succinctly summarizing our contributions, outlining the ramifications of our approach for prospective research in the domain of knowledge extraction, and spotlighting potential application areas for our methodology.

2. Review of Literature

In this section, we will conduct a literature review to explore previous work related to knowledge extraction through association rules, highlighting advances in rule induction and adaptations to handle uncertainty and complexity. Early work in the field of association rule extraction saw the emergence of algorithms such as:

- The C5.0 Kantardzic [5] algorithm is a

powerful tool used in machine learning to solve classification problems. Based on decision trees, it operates by constructing a hierarchical tree where each node represents a feature of the data, and each branch a decision based on that feature. One of the most remarkable aspects of C5.0 is its rule selection process. It uses metrics such as entropy to assess rule quality, and thus guides the growth of the decision tree. Entropy measures the uncertainty in a data set, and C5.0 seeks to minimize this uncertainty by choosing rules that maximize the purity of classes in each branch of the tree. This approach enables C5.0 to generate simple, interpretable classification models, while maintaining high accuracy in class prediction. What's more, C5.0 is robust to noisy data and can efficiently handle large datasets, making it a popular choice for many classification applications in diverse fields such as medicine, finance and marketing research.

- FP-Growth Han et al. [6] algorithm, developed in 2000 by Han et al. effectively solves the two main challenges faced by the Apriori algorithm. Unlike the latter, FP-Growth requires only two passes over the database, and does not need to generate sets of candidate articles to produce sets of frequent articles. It uses a deep search method and compresses the database on the first visit, storing it as a tree structure called FP-Tree. This approach speeds up the frequent pattern discovery process by dividing large items into smaller units. The discovery process takes place in two distinct stages.

The first stage consists of data pre-processing, where all items retrieved during the first visit are first compared with a threshold. Those that do not meet this threshold are deleted, and the remaining item sets are used to build the FP-Tree. Each node of this tree contains three values: the name of the article, its medium and a link to neighboring nodes. The second step involves creating the FP-Tree in a top-down structure, where the items with the greatest support are at the top and form the root node, while those with the least support are at the bottom and form the leaves of the tree. The FP- Growth algorithm recursively traverses this tree to discover frequent patterns.

- The Apriori Agrawal et al. [7] algorithm,

first proposed in 1994 by Aggarwal and Srikant, represents the first algorithmic method for generating association rules. Its main advantage is its ease of use for this task. The Apriori Algorithm works in two distinct phases to generate association rules.

Firstly, it explores frequent patterns, which is the most complex process in the production of association rules, as it requires repeated access to the database. The definition of a pattern as frequent at level k is based on its frequency at level $k-1$ and a support greater than or equal to a given threshold. The Apriori Algorithm starts by finding sets of frequent items, thus initiating the generation of the candidate set.

Once this complex process of finding frequent patterns has been completed, the actual generation of association rules begins. These rules can only be generated from the sets of frequent items, using the confidence measure. An association rule is accepted if its confidence is greater than or equal to a specified threshold. The Apriori Algorithm faces two major challenges in generating these rules: repeated visits to the database, which slow down the process, and the generation of candidate sets, a source of additional cumbersomeness and complexity. The main limitations of these algorithms include the difficulty in dealing with uncertainty and gradation in relationships between items, as well as the inability to represent degrees of membership and to model graded relationships. Traditional approaches based on frequency criteria may not be flexible enough to handle data where patterns are present with varying degrees of certainty.

3. Fuzzy association rules

Fuzzy logic, applied to association rules, offers an innovative perspective in data mining, going beyond the limits of traditional binary association rules. Traditionally, the search for association rules considers the attributes of a database as binary data, represented by the set $\{0,1\}$ where 1 means the presence of an attribute in a record and 0 its absence. However, in reality, data can be of various types, such as numeric, integer, etc. Numerous studies have been carried out on quantitative data processing Kuok et al. [8] de

Graaf et al. [9], Gyenesei [10] to incorporate the theory of fuzzy subsets into the process of extracting association rules. This advance has given rise to a new methodology called “fuzzy association rules”. To better understand this approach, we will look at some of the concepts and notions used throughout this article.

A fuzzy item (Fiot et al. [11]) is a pair (Item, fuzzy subset). For example, (Chocolate, a lot) is a fuzzy Item where a lot is a fuzzy subset defined by its membership function.

A fuzzy itemset (Fiot et al. [11]) is a collection of fuzzy items, where each item is associated with a fuzzy subset. This association can be expressed as a pair of sets, consisting of a set of items and a set of corresponding fuzzy subsets for each item. Alternatively, it can be represented as a list of fuzzy items, exemplified by expressions like ((chocolate, a lot); (milk, a little)).

Membership function: is a function represented by a curve which associates each fuzzy item with a value between 0 and 1 which measures the degree to which an element x belongs to a fuzzy subset A . There are no precise rules for defining such a membership function. Each fuzzy set is represented by its own membership function. In general, a membership function can take different forms. In general, a membership function can take different forms which are given by Godjevac [12]:

- Monotonic (increasing or decreasing)
- Triangular
- Trapezoidal
- Gaussian shape

4. Methodology

In this section, we will elaborate on the approach we have formulated for extracting fuzzy association rules. This method builds upon an extension of the Apriori algorithm. Our approach involves three fundamental stages, each playing a pivotal role in the extraction of nuanced association rules. The methodology approach flow chart is given in Fig.1.

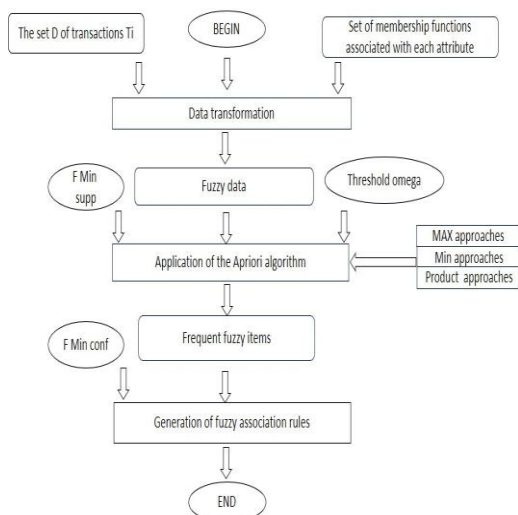


Fig 1: Methodology of the approach

Step 1: Transforming data into fuzzy data
Our methodology begins by transforming the raw data into fuzzy data. This transformation is essential to take account of the quantitative attributes in the database. Each quantitative attribute is expanded into several fuzzy attributes, with each fuzzy attribute representing a subset of the possible values of the original attribute. Fuzzy partitions are usually defined by a domain expert who uses membership functions to assign degrees of membership to attribute values. This step creates a new transaction table T' , where the values of the quantitative attributes are now expressed in degrees of membership.

Step 2: Generating Frequent Fuzzy Items

The second stage of our methodology consists of generating frequent fuzzy itemsets from the T' table. We use an extension of the Apriori algorithm for this task. Unlike traditional Apriori, our approach calculates the support of fuzzy itemsets using different strategies, such as the minimum strategy, the maximum strategy or the product of the degrees of membership of the items making up the itemset. This step allows us to identify the fuzzy itemsets that are frequent in the database according to the minimum thresholds set by the user.

Step 3: Generation of Fuzzy Association Rules
Finally, the third stage of our methodology consists of generating fuzzy association rules from the

frequent fuzzy itemsets. The fuzzy association rules we extract are of the form $(X, A) \rightarrow (Y, B) F \supset F\%, Fconf\%$, where (X, Y) are itemsets and (A, B) are fuzzy subsets, and $F \supset F\%$ and $Fconf\%$ are the fuzzy support and fuzzy confidence respectively. We set a threshold $Fminconf$ for confidence, and only rules with confidence above this threshold are retained. This step makes it possible to deduce significant fuzzy association rules from the frequent fuzzy itemsets, thus representing nuanced relationships between the data. The pseudo-code of the extension of the Apriori algorithm is as follows:

Input:

- T' : the set of transactions
- $Fminsup$: minimum support threshold
- Ω : threshold of membership degrees
- F_s : variable for the support of a fuzzy Itemset

Output:

LF: frequent fuzzy Itemsets.

Algorithm:

```

1   $LF_1 = 1$ -itemsets of frequent fuzzy items
2   $k = 2$  ;
3  While  $LF_{k-1}$  is not empty do
4   $CF_k = Aprioriflou-Gen(LF_k)$ 
5  For each  $t$  in  $T'$  do
6       $CF_t = Subset (CF_k, t)$ ; the candidates
       contained in  $CF_k$ ;
7   $F_s = 0$  ;
8  For each  $cf$  of in  $CF_t$  do
9                                      $F_s = F_s$ 
+  $\perp(\mu(a_j)(t_i[x_j]))$            where
 $j = 1..k$ 
10  Endfor
11  Endfor
12   $LF_k = cf$  in  $CF_t/F_s \geq Fminsup$ ;
13   $k++$  ;
14  End while
15  Return:  $\cup LF_{k-1}$ 

```

ALG.Aprioriflou-Gen :

```

Insert Into  $CF_k$ 
Select  $p.item_1, p.item_2, p.item_3, \dots, p.item_{k-1},$ 
 $q.item_{k-1}$ 
From  $LF_{k-1} p, LF_{k-1} q$ 
Where  $p.item_1 = q.item_1; \dots; p.item_{k-2} =$ 
 $p.item_{k-2} q ;$ 
 $p.item_{k-1} < q.item_{k-1};$ 
For each fuzzy itemset  $cf$  in  $CF_k$  do For each

```

$s = \text{Subset}(k-1) \text{ of } cf \text{ do}$

| ID | Chocolate | Bread | Milk | Cheese | Chips | Sausage |
|----|-----------|-------|------|--------|-------|---------|
| 1 | 2 | 0 | 0 | 0 | 0 | 0 |
| 2 | 1 | 3 | 1 | 0 | 0 | 0 |
| 3 | 2 | 0 | 1 | 0 | 0 | 0 |
| 4 | 3 | 2 | 3 | 4 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 2 |
| 6 | 2 | 0 | 0 | 1 | 0 | 0 |
| 7 | 0 | 0 | 2 | 0 | 0 | 0 |
| 8 | 0 | 4 | 1 | 0 | 0 | 0 |
| 9 | 3 | 0 | 1 | 0 | 5 | 0 |
| 10 | 0 | 0 | 1 | 0 | 2 | 3 |
| 11 | 3 | 1 | 0 | 0 | 0 | 0 |
| 12 | 0 | 0 | 0 | 4 | 0 | 5 |
| 13 | 0 | 0 | 2 | 0 | 0 | 0 |
| 14 | 0 | 2 | 0 | 0 | 0 | 0 |
| 15 | 0 | 0 | 0 | 0 | 2 | 0 |
| 16 | 2 | 0 | 0 | 0 | 0 | 4 |
| 17 | 0 | 0 | 3 | 0 | 0 | 0 |
| 18 | 0 | 2 | 0 | 0 | 0 | 0 |
| 19 | 0 | 0 | 2 | 0 | 0 | 0 |

If $s \notin LF_{k-1}$ then

Remove cf from CF_k

End for End for

Return CF_k

Step3 : used to generate fuzzy association rules

Begin

$ER = \{\}$; //empty set

For each fuzzy itemset l in LF where $k > 1$ do

For $i = 1$ to k do

$l = LH_{k-i} \cup LH_i$;

$FConf = Fsup(LH_k)/Fsup(LH_{k-i})$ If $FConf \geq$

$Fminconf$ then

Add $(LH_{k-i} \rightarrow LH_i)$ to ER

End for

End for End

5. Simulation Results of Our Approach on a Real Example

In this section, we implement the method proposed in this article by illustrating it with an example. We are also going to present the results of our research into fuzzy association rule extraction using the methodology we described. The results are essential for evaluating the effectiveness of the approach and for highlighting the knowledge uncovered from real data.

We will apply our approach to a table that represents a set of nine-ten transactions, which contain six items: Chocolate, Bread, Milk, Cheese, Chips and Sausage (Table 1). The fuzzy partitions are depicted in the Fig.2. They correspond to the functions of the membership degrees associated with the quantitative attributes of the table. Using the membership functions above, we define table T' , which represents the membership degrees of the fuzzy subsets of each quantitative attribute (Table 2). By fixing the thresholds ($Fsupp = 0.7$), the outcomes are presented in the

Table 3, showcasing the frequent fuzzy itemsets.

Table 1: Quantitative transaction table

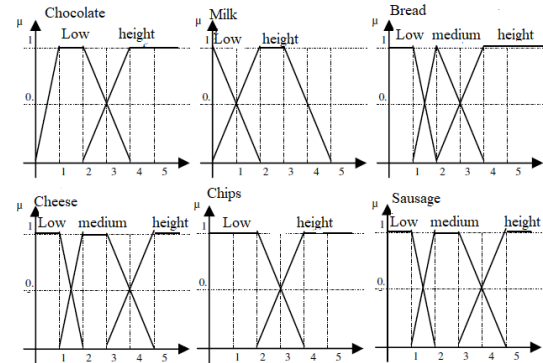


Fig 2: Fuzzy partitioning

Table 2: Quantitative transaction table(T')

| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P | Q | R |
|----|-----------|-----------|-----------|-------|-------|-------|------|------|------|--------|--------|--------|---------|---------|---------|---------|---------|---------|
| 1 | Chocolate | Chocolate | Chocolate | Bread | Bread | Bread | Milk | Milk | Milk | Cheese | Cheese | Cheese | Chips | Chips | Chips | Sausage | Sausage | Sausage |
| 2 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 3 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 4 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 1 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 5 | 0 | 0 | 0 | 0.75 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 6 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 7 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 1 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 8 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 9 | 0.75 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 10 | 0 | 0 | 0 | 0.75 | 0 | 0 | 1 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 11 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 1 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 12 | 0 | 0 | 0 | 1 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 13 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 14 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 15 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 16 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 17 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 18 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 19 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |
| 20 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.75 | 0 | 0 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 | 0.33333 |

After calculating the support, we determine the fuzzy association rules. It is essential to set a minimum confidence threshold, for example ($Fconf = 80\%$). Then, the algorithm provides the set of fuzzy association rules, which are illustrated in Table 4. The instance illustrates that our approach to extracting fuzzy association rules presents notable benefits concerning adaptability, precision, intelligibility, and straightforward implementation. In contrast to existing methods, our approach excels in:

Adaptability and Precision:

Departing from the conventional binary model that overlooks uncertainty, our method accommodates intricate and uncertain data through the incorporation of membership degrees and relevance functions. Consequently, it produces rules characterized by heightened precision, offering a closer alignment with real-

world scenarios.

Table 3 : Fuzzy itemsets

| Itemset | Support |
|--|--------------------|
| ['ChocolateLow'] | 0.8421052631578947 |
| ['BreadLow'] | 0.8947368421052632 |
| ['MilkLow'] | 0.8947368421052632 |
| ['CheeseLow'] | 0.8947368421052632 |
| ['BreadLow', 'ChocolateLow'] | 0.7368421052631579 |
| ['MilkLow', 'ChocolateLow'] | 0.7894736842105263 |
| ['CheeseLow', 'ChocolateLow'] | 0.7894736842105263 |
| ['MilkLow', 'BreadLow'] | 0.7894736842105263 |
| ['BreadLow', 'CheeseLow'] | 0.7894736842105263 |
| ['MilkLow', 'CheeseLow'] | 0.8421052631578947 |
| ['MilkLow', 'CheeseLow', 'ChocolateLow'] | 0.7368421052631579 |
| ['MilkLow', 'BreadLow', 'CheeseLow'] | 0.7368421052631579 |

Table 4: Generated rules

| Antecedent | Consequent | Support | Confidence |
|-------------------------------|-------------------------------|--------------------|--------------------|
| ['BreadLow'] | ['ChocolateLow'] | 0.7368421052631579 | 0.8235294117647058 |
| ['ChocolateLow'] | ['BreadLow'] | 0.7368421052631579 | 0.875 |
| ['MilkLow'] | ['ChocolateLow'] | 0.7894736842105263 | 0.8823529411764706 |
| ['ChocolateLow'] | ['MilkLow'] | 0.7894736842105263 | 0.9375000000000001 |
| ['CheeseLow'] | ['ChocolateLow'] | 0.7894736842105263 | 0.8823529411764706 |
| ['ChocolateLow'] | ['CheeseLow'] | 0.7894736842105263 | 0.9375000000000001 |
| ['MilkLow'] | ['BreadLow'] | 0.7894736842105263 | 0.8823529411764706 |
| ['BreadLow'] | ['MilkLow'] | 0.7894736842105263 | 0.8823529411764706 |
| ['BreadLow'] | ['CheeseLow'] | 0.7894736842105263 | 0.8823529411764706 |
| ['CheeseLow'] | ['BreadLow'] | 0.7894736842105263 | 0.8823529411764706 |
| ['MilkLow'] | ['CheeseLow'] | 0.8421052631578947 | 0.9411764705882353 |
| ['CheeseLow'] | ['MilkLow'] | 0.8421052631578947 | 0.9411764705882353 |
| ['MilkLow', 'CheeseLow'] | ['ChocolateLow'] | 0.7368421052631579 | 0.875 |
| ['MilkLow', 'ChocolateLow'] | ['BreadLow'] | 0.7368421052631579 | 0.9333333333333332 |
| ['CheeseLow', 'ChocolateLow'] | ['MilkLow'] | 0.7368421052631579 | 0.9333333333333332 |
| ['MilkLow'] | ['CheeseLow', 'ChocolateLow'] | 0.7368421052631579 | 0.8235294117647058 |
| ['CheeseLow'] | ['MilkLow', 'ChocolateLow'] | 0.7368421052631579 | 0.8235294117647058 |
| ['ChocolateLow'] | ['MilkLow', 'CheeseLow'] | 0.7368421052631579 | 0.875 |
| ['MilkLow', 'BreadLow'] | ['CheeseLow'] | 0.7368421052631579 | 0.9333333333333332 |
| ['MilkLow', 'CheeseLow'] | ['BreadLow'] | 0.7368421052631579 | 0.875 |
| ['BreadLow', 'CheeseLow'] | ['MilkLow'] | 0.7368421052631579 | 0.9333333333333332 |
| ['MilkLow'] | ['BreadLow', 'CheeseLow'] | 0.7368421052631579 | 0.8235294117647058 |
| ['BreadLow'] | ['MilkLow', 'CheeseLow'] | 0.7368421052631579 | 0.8235294117647058 |
| ['CheeseLow'] | ['MilkLow', 'BreadLow'] | 0.7368421052631579 | 0.8235294117647058 |

Interpretability:

Fuzzy rules prove more accessible for human comprehension compared to intricate probabilistic models that demand statistical expertise. The inherent simplicity of fuzzy logic facilitates understanding and interpretation, fostering a more user-friendly experience.

Simplicity of Implementation:

The fuzzy logic paradigm maintains a relatively uncomplicated implementation process in contrast to probabilistic models, which may necessitate extensive data and computational resources. Our approach prioritizes simplicity, easing the burden of implementation while preserving effectiveness.

Efficiency:

In terms of efficiency and performance, our approach emerges as a compelling alternative to probabilistic models. It delivers precise and

pertinent outcomes with reduced complexity, underscoring its capacity to achieve results competently and resource-effectively.

This underscores the multifaceted advantages our fuzzy association rule extraction method brings to the table, positioning it as a robust and efficient choice in comparison to existing approaches.

6. Conclusion

Association rules have garnered significant attention within the research community since their inception. Multitudes of techniques and strategies have been devised to derive these rules, applicable to both binary and fuzzy datasets. Within this discourse, we introduce a novel method for extracting fuzzy association rules, predicated on an extension of the Apriori algorithm. Despite the relatively nascent status of fuzzy association rules in research, their potential for diverse applications is substantial. We advocate for continued exploration and investigation in this domain, emphasizing the necessity to advance research efforts for the development of more streamlined methodologies in extracting fuzzy association rules.

References

- [1] Rakesh Agrawal, Tomasz Imielinski, and Arun Swami. Mining association rules between sets of items in large databases. In *Proceedings of the 1993 ACM SIGMOD international conference on Management of data*, pages 207–216, 1993.
- [2] Ashoka Savasere, Edward Omiecinski, and Shamkant Navathe. An efficient algorithm for mining association rules in large databases. In *Proceedings of the 21st International Conference on Very Large Databases (VLDB)*, pages 432–444, 1995.
- [3] S. Sharmila and S. Vijayarani. Association rule mining using fuzzy logic and whale optimization algorithm. *Soft Computing*, 25:1431–1446, 2021.
- [4] Praveen Arora, Priyanka Gandhi, Geeta Sharma, and Sanjive Saxena. Study about rule mining for multiple tables with fuzzy data. *Novel Research Aspects in*

Mathematical and Computer Science, 1:38–47, 2022.

- [5] Mehmed Kantardzic. Data mining: Concepts, models, methods, and algorithms. *Technometrics*, 45(3):277, 2003.
- [6] Jiawei Han, Jian Pei, and Yiwen Yin. Mining frequent patterns without candidate generation. *ACM sigmod record*, 29(2):1–12, 2000.
- [7] Rakesh Agrawal, Ramakrishnan Srikant, et al. Fast algorithms for mining association rules. In *Proc. 20th int. conf. very large databases, VLDB*, volume 1215, pages 487–499. Santiago, Chile, 1994.
- [8] Chan Man Kuok, Ada Fu, and Man Hon Wong. Mining fuzzy association rules in databases. *ACM Sigmod Record*, 27(1):41–46, 1998.
- [9] Jeannette M de Graaf, Walter A Kusters, and Jeroen JW Witteman. Interesting fuzzy association rules in quantitative databases. In *Principles of Data Mining and Knowledge Discovery: Fifth European Conference, PKDD 2001, Freiburg, Germany, September 3–5, 2001 Proceedings 5*, pages 140–151. Springer, 2001.
- [10] Céline Fiot, Gérard Dray, Anne Laurent, and Maguelonne Teisseire. A la recherche des motifs séquentiels flous. In *12ème Rencontres Francophones sur la Logique Floue et ses Applications (LFA)*, pages 131–138. Cépadues Editions, 2004.
- [11] Attila Gyenesi. A fuzzy approach for mining quantitative association rules. *Acta Cybernetica*, 15(2):305–320, 2001.
- [12] Jelena Godjevac. *Idées nettes sur la logique floue*. PPUR presses polytechniques, 1999.