

Research Article

Neutrosophic Fuzzy Association Rule Generation-Based Big Data Mining Analysis Algorithm

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As a very common and classic big data (BD) mining algorithm, the association rule data mining (DM) algorithm is often used to determine the internal correlation between different items and set a certain threshold to determine the size of the correlation. However, the traditional association rule algorithm is more suitable for establishing Boolean association rules between different items of different types of data, and hardening the sharp boundaries of the data causes the performance of the association rules to decrease. In order to overcome this shortcoming of classic DM, this article introduces association rules, support and confidence, the Apriori algorithm and fuzzy association rules based on the neutrosophic fuzzy association rule (NFAR). This paper is based on the data set of the supermarket purchase goods database, by drawing a radar chart to describe the correlation between different goods and different item sets support, and confidence calculation based on association rules support. Finally, the association rules are generated. Compared to the results produced by NFAR and ordinary association rules, the accuracy of the NFAR association rules algorithm in small data sets is 88.48%, while the accuracy of traditional association rules algorithm is only 80.87%, nearly 8 percentage points higher. On large data sets, the prediction accuracy of the neutral fuzzy association rules algorithm is 95.68%, while that of the traditional method is only 89.63%. Therefore, the NFAR algorithm can improve the accuracy and effectiveness of DM. This algorithm has great application prospects and development space in big DM and analysis.

1. Introduction

The reason why well-known scholars at home and abroad use BD technology to extract the information value contained in massive data stems from the advancement of Internet technology and the establishment of database systems. BD analysis, as one of the efficient and rapid means of obtaining data and information, can discover the connections between different projects. By analyzing which products users often buy at the same time, you can discover hidden relationships between different products. Association analysis can help merchants carry out product promotion, product placement, price list formulation, and customer division.

DM is a related privacy issue, looking at various ways that you can help protect sensitive information [1]. Based on the success of information systems (IS), BD analytics (BDA), and

the business value of information technology (IT), Wamba S. F. proposed a BD analytics capability (BDAC) model based on resource perspectives and literature. This study explores practical and research implications by examining the direct impact of BDAC on firm performance. However, the complexity of the study led to inaccurate results [2]. Mai T believes that traditional association rule mining algorithms only generate a set of frequently used rules [3].

The innovations of this paper are: (1) the fuzzy theory is introduced into the risk association rule mining model, which improves the success rate of mining potential connections between data; and (2) the traditional modular association rule mining algorithm has quantitative preprocessing of language words. Due to the shortcomings of relying too much on human experience, the traditional fuzzy association rule mining algorithm is improved on the basis of the neutron subset theory.

2. Proposed Method

2.1. Association Rule Mining Model. Association rules are the analysis process to discover the association between things, a typical example of which is the shopping basket analysis. Association rule mining is used for knowledge discovery rather than prediction, so it is an unsupervised machine learning method. The following articles will begin with a brief introduction to some basic concepts of association rules and some common rules [4, 5], as shown in Figure 1.

Products with strong associations must meet certain requirements [6, 7]. The text below introduces this model through the purchase of a simple sports product.

As shown in Table 1, we can see the sales information of the supermarket. Transaction 1 purchased tennis rackets, tennis balls, and sports shoes, but did not purchase badminton. In transaction 2, tennis rackets and tennis balls were purchased, and in transaction 3, only tennis rackets were purchased. Transaction 4 purchased tennis rackets and sports shoes but did not purchase tennis and badminton. Transaction 5 purchased tennis balls, sports shoes, and badminton equipment, but did not purchase tennis rackets. Transaction 6 only bought tennis rackets and tennis balls [7, 8].

2.2. Introduction to Support and Confidence. The data in the abovementioned table introduces the concepts of support and confidence.

Assuming that the transaction database contains N pieces of data, the formula for calculating the support degree is referred in [9, 10]:

$$\text{Sup}(y) = \frac{\text{sum}(y)}{n}. \quad (1)$$

Assuming that there are N transactions in the transaction database, the confidence is calculated by the following formula and refer [11, 12]:

$$\text{Conf}X \Rightarrow Y = \frac{\text{Sup}X \cup Y}{\text{Sup}X}. \quad (2)$$

2.3. Apriori Algorithm. Agrawal proposed the association model algorithm in 1994. Apriori uses historical transaction data to mine. Any nonempty subset of frequent items; all supersets of infrequent items are also infrequent items [13, 14]. The main idea of the Apriori algorithm is to first find all frequent itemsets that satisfy the support threshold, then, recursively find all frequent itemsets, and finally, by comparing the minimum confidence threshold, the rules that satisfy the conditions have valuable rules [15, 16]. The process of generating candidate itemsets is called joining, and pruning is the process of removing impossible frequent itemsets. The main steps of the Apriori algorithm are as follows [17]:

- (1) Find all the frequent itemsets and calculate their support.

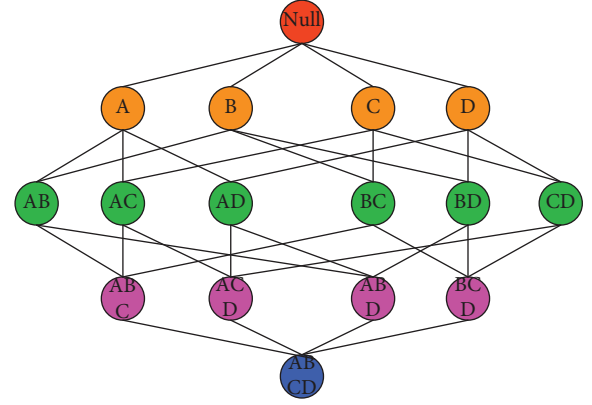


FIGURE 1: Lattice structure of frequent itemsets.

TABLE 1: Commodity purchase form.

Tid	Tennis racket	Net ball	Sports shoes	Badminton
1	1	1	1	0
2	1	1	0	0
3	1	0	0	0
4	1	0	1	0
5	0	1	1	1
6	1	1	0	0

- (2) Repeat steps (2) and (3) until all frequent itemsets are found.
- (3) Operate the obtained frequent itemsets using the rule generation function to generate association rules, and finally, calculate their confidence.
- (4) Compare the calculated confidence with the set confidence threshold, and call the association rules that meet the conditions as strong association rules.
- (5) End the algorithm and output the final result.

The combination of elements should not appear in the process, and at the same time, when calculating the support of the itemset, the database needs to be scanned multiple times, which requires a large IO load [18].

2.4. Fuzzy Association Rules. Traditional association rule mining algorithms usually do not consider the order within a transaction or between events. Traditional association rule mining algorithms directly and rigidly divide numerical data into multiple categories. Although this classification method is simple, it is easy to cause the loss of data edge information due to the strong division, and the mined association rules may not conform to the actual operation law [19]. The fuzzy set classification based on fuzzy theory can better describe the essential attributes of things, soften the distinction between numerical variables, and make the mining association rules more practical [20].

For all attribute sets in database A are $B = \{B_1, B_2, \dots, B_n\}$, for attribute B_i , there are q_i fuzzy membership functions related to it. The fuzzy database A_f is obtained by fuzzy A , and the value range of the new attribute is $[0, 1]$. For a fuzzy

attribute set $Y = \{y_1, y_2, \dots, y_p\}$, the fuzzy support of record i for y is defined as follows:

$$Fsup_i(Y) = y_1^i \wedge y_2^i \wedge \dots \wedge y_p^i, \quad (3)$$

where the fuzzy attribute Y_j represents the value on the i -th record y_j^i .

The parameter optimization process based on fuzzy association rules can be divided into three stages: data preprocessing, fuzzy association rule mining, fuzzy association rule interpretation, and evaluation [21]. These three stages can be subdivided into five processes, namely: data selection, data preprocessing, data fuzzification, fuzzy association rule mining, fuzzy association rule interpretation, and evaluation. The data selection is to filter data related to parameters from the database according to mining requirements. Since the acquisition of data is affected by various environmental factors, there will also be interference factors in the acquisition process, and the obtained operating data may contain outliers, missing values, or noisy data [22]. The existence of bad data will not only affect the efficiency of the mining algorithm but also reduce the accuracy of the mining results, so it is necessary to preprocess the original data. The original data is still of the numerical type after preprocessing. The association rule mining algorithm cannot directly mine numerical data. Numerical data needs to be fuzzified. Therefore, the fuzzy C clustering algorithm is first used to construct the fuzzy set, and then the fuzzy set is used. The association rule mining algorithm digs out all the strong fuzzy association rules. Finally, the obtained strong fuzzy association rules are interpreted and evaluated, the invalid rules are eliminated, the low energy consumption data in the historical data is filtered according to the final retained rules, this part of the data is analyzed and calculated, and the parameter optimization strategy is determined [23].

2.5. The NFAR Model. In this paper, the basic theorem and operation rules of a neutral set are given based on the content of the subject, and then, a neutral fuzzy association rule mining model is constructed. The model of neutrosophic association rules is $X \longrightarrow Y$, and where is an empty set, X and Y are Chinese intelligence sets. First, we find the frequent set, the corresponding support degree, and the corresponding association rule generation criteria. Combined with the definition and properties of fuzzy association rules, the Chinese intelligence set is added to the set L , where L is all possible data sets, M is the Chinese intelligence set, and N is the classical itemset. The general form of association rules is as follows $X \longrightarrow Y, X \subseteq I, Y \subseteq I, X \cap Y = \emptyset$.

The maximum confidence measure claims that the measure treats both as neutral. The maximum confidence measure claims that these cases are all strongly positively correlated. These cases are strongly positively correlated. Based on the above analysis, to establish a NFAR framework model of association rules, we must first understand that neutrosophic association rules are a joint distribution model of random variables $X = X_1, X_2, \dots$, the joint probability

formula of the neutrosophic association rule for each clique in the graph is

$$P(X = x) = \frac{1}{Z} \prod_k \varphi(x\{k\}). \quad (4)$$

In the following formula, X is the state of the random variable, and Z is the partition function, defined as

$$Z = \sum_{x \in \chi} \prod_k \varphi_k(x_{((k))}). \quad (5)$$

Log-linear models describe the relationship between probability and covariates; log-linear models are also used to describe the relationship between expected frequencies and covariates. In order to better understand the joint probability distribution of the NFAR algorithm, the joint probability distribution of the NFAR algorithm is expressed as a log-linear model, and all the potential functions of each clique in the following formula are after the eigenvalues are weighted, and then, summed, and then, exponentiated, formula (7) can be obtained:

$$P(X = x) = \frac{1}{Z} \exp\left(\sum_j w_j f_j(x)\right). \quad (6)$$

Probability distribution refers to the probability law used to express the value of a random variable. The probability of an event expresses the probability of an outcome occurring in an experiment. According to the definition of the NFAR, the probability distribution of NFAR algorithm can be obtained as follows:

$$P(X = x) = \frac{1}{Z} \exp\left(\sum_i w_i n_i(x)\right) = \frac{1}{Z} \prod_i \varphi_i(x_{(i)})^{n_i(x)}. \quad (7)$$

This formula expresses the probability distribution of the NFAR algorithm very well. However, when learning the weights in the formula, the parameters in the formula are learned through multiple relational databases. In order to make learning more convenient, they generally only learn in one relational database.

3. The Experiment of Neutrosophic Fuzzy Association Rules in Supermarket Purchases

3.1. The Data Processing. This chapter conducts an example analysis through a data set about goods purchased in supermarkets. Some of the data are shown in Table 2. These data contains 5 fields and 2800 records, mainly, including customer information, purchase amount, and items purchased. Basket Contents: indicators of the presence of a product category: fruit and vegetable, fresh meat, dairy, milk, canned meat, frozen meat, beer, wine, drink, fish, and sweet food. We use a portion of this data, the purchase item information, to do an association rule analysis.

The Markov model is a statistical model, which is widely used in speech recognition, automatic part-of-speech tagging, phonetic-to-word conversion, probabilistic grammar,

TABLE 2: Part of the basket data table.

Member ID	Commodity	Number	Unit price	Subtotal
36405	Canned meat	1	15.68	15.68
109884	Canned meat	2	15.68	31.36
85259	Canned meat	1	15.68	15.68
78428	Canned meat	1	15.68	15.68
78626	Canned meat	1	15.68	15.68
78967	Canned meat	1	15.68	15.68
109798	Canned meat	1	15.68	15.68
50064	Canned meat	2	15.68	31.36
63420	Canned meat	1	15.68	15.68

and other natural language processing applications. Through the introduction of the first two chapters, we know that in the network of association rule analysis, we regard the item set in the association rule as every node in the Markov logic network. Therefore, we need to process the data first. A shopping message corresponds to a Markov logical network, such as the canned meat of the first message of the shopping basket message. By summarizing the same member ID number, the shopping information of the same customer can be obtained, and the count and support degree of different goods can be obtained, as shown in Table 3.

3.2. Correlation Analysis. This experiment is to analyze the association rules of shopping basket data. Through the NFAR algorithm established in the subsections, the data in the examples are used to learn the parameters in the model. The principle of the shopping basket analysis model: I do not know if you have noticed when you go to the supermarket. In the supermarket, baby diapers and beer are often sold together. The rules obtained according to the NFAR algorithm model are compared with the traditional association rule analysis results. Use the data in the example to learn the parameters in the Markov logic network model, and get Figure 2.

As can be seen from Figure 2, as the number of iteration samples (i.e., transactions) increases, the sum of the average sample $\log(* (X = x))$ begins to converge around 500, ensuring the accuracy of the algorithm. According to the parameters learned, the rules are inferred to get the association rules. In order to see the rules more intuitively, the rules are represented visually, and Figure 3 is obtained.

Figure 3 shows the relationship of association rules obtained by the fuzzy association rules algorithm. Figure 3 shows: (canned vegetable, frozen meal), (canned vegetable, beer), (frozen meal, beer), (fruit and vegetable, fish), milk, wine, (wine, canned vegetable), (frozen meat, fish) (fruit and vegetable, beer) (fruit and vegetable, canned vegetable) (canned vegetable, frozen meat, beer), (confectionery, wine, canned vegetable), and so on. There are strong correlations between them.

3.3. Validation of Algorithm. In order to verify the effectiveness of the proposed MWF association rules algorithm, the prediction ability of MWF association rules algorithm and traditional association rules is compared by comparing

TABLE 3: single item count and support.

Single item set	Count	Support (%)
Beer	293	10.46
Canned meat	204	7.29
Canned vegetable	303	10.82
Drink	184	6.57
Fresh meat	183	6.54
Frozen meat	302	10.79
Milk	177	6.32
Sweet food	276	9.86
Vegetables and fruits	299	10.68
Wine	287	10.25

the accuracy and repetition rate. In this experiment, the number of attractions is set at 50 products, 100 products, and 200 products for testing. The test results are shown in Figure 4.

Common classification recommendation algorithms include logistic regression and naive Bayes, both of which are characterized by strong interpretability. But the effect is not obvious. With the increase in the number of items, the traditional classification recommendation effect is not, obviously, the recommendation effect of the NFAR algorithm is better and more advantageous.

4. Accuracy Rate of the NFAR

The Apriori algorithm is the first association rule mining algorithm and also the most classic algorithm. It uses the iterative method of layer-by-layer search to find out the relationship of itemsets in the database to form rules. The process consists of joining (matrix-like operations) and pruning (removing those unnecessary intermediate results). In this paper, a small data set of supermarket purchases is used to carry out accuracy experiments on the rules obtained from the Apriori algorithm and the fuzzy association rules algorithm.

Commonly used methods are mean absolute error and mean square error, expressed as follows:

$$\begin{aligned}
 MAE &= \frac{1}{|E^P|} \sum |r_a - r'_a|, \\
 MSE &= \frac{1}{|E^P|} \sum (r_a - r'_a)^2, \\
 RMSE &= \sqrt{\frac{1}{|E^P|} \sum (r_a - r'_a)^2}, \\
 NMAE &= \frac{MAE}{r_a - r'_a}.
 \end{aligned} \tag{8}$$

A mean squared error is a measure that reflects the degree of difference between the estimator and the estimator. Let t be an estimator of the overall parameter determined according to the subsample, which is called the mean square error of the estimator. In this paper, the mean square error method is used to calculate the accuracy.

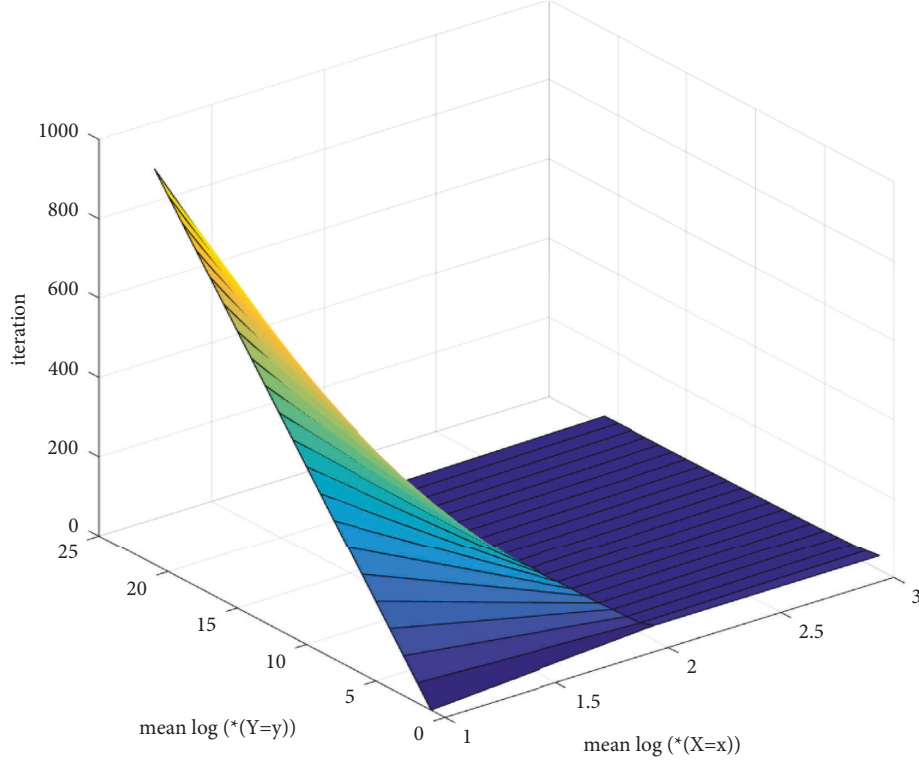


FIGURE 2: Example convergence graph of neutrosophic fuzzy algorithm.

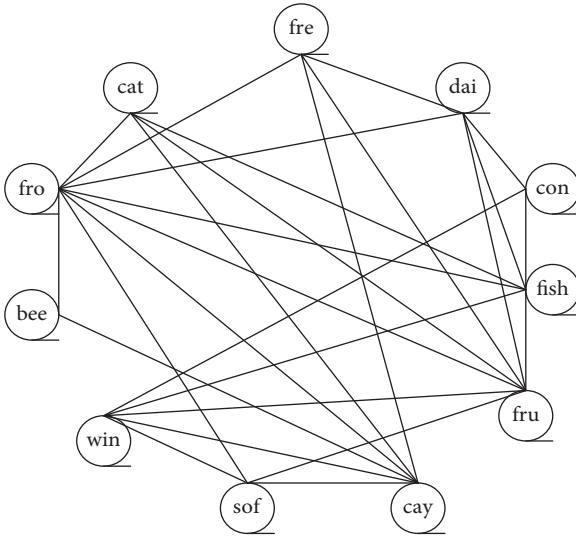


FIGURE 3: The relation schema of association rules.

On the data set, the Apriori algorithm uses test samples to mine the data for association rules and obtains 1986 rules. A total of 86,350 numbers are needed to predict the outcome. Through the rules obtained by the Apriori algorithm, the prediction samples were predicted, and it was found that a total of 69832 prediction results were correct, with an accuracy of 80.87% through the formula.

$$P_{\text{accuracy}} = \frac{n_2}{n_1} = \frac{69832}{86350} = 80.87\%. \quad (12)$$

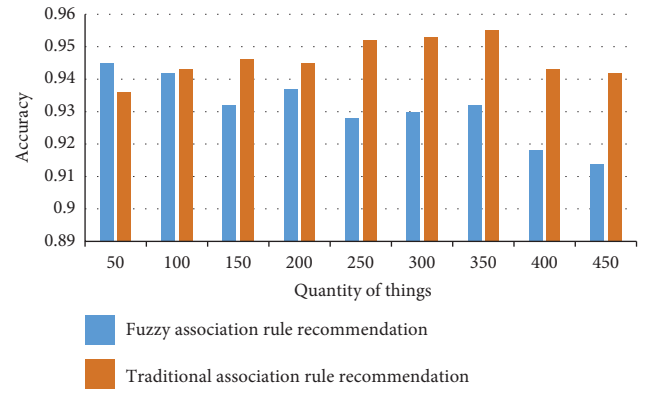


FIGURE 4: Accuracy comparison results.

The predicted occurrence times of samples are 40269, and the actual occurrence times of results are 35280. The recall rate was obtained by the formula, and the accuracy of the Apriori algorithm rule prediction was 87.61%.

$$R_{\text{recall}} = \frac{n_4}{n_3} = \frac{35280}{40269} = 87.61\%. \quad (13)$$

In the NFAR algorithm, the test samples are used to mine the association rules of the data, and 3678 rules are obtained. It can be known that a total of 88,567 predictions are needed. The rules obtained by the neutral fuzzy association rule algorithm were used to predict the predicted samples. The correct number of the predicted results was 78363, and the accuracy rate was 88.48%.

TABLE 4: Comparison of accuracy and recall rates of two methods in small data.

	Accuracy (%)	Recall (%)
Apriori algorithm	80.87	87.61
Fuzzy association rule recommendation	88.48	89.74

TABLE 5: Comparison of accuracy and recall rates of two methods in BD.

	Fuzzy association rule recommendation (%)	Traditional association rule recommendation (%)
Accuracy	95.68	89.63
Recall	90.63	89.16

$$P_{\text{accuracy}} = \frac{n_2}{n_1} = \frac{78363}{88567} = 88.48\%. \quad (14)$$

The number of occurrences of the predicted sample is 39437, and the number of occurrences of the actual result is 35392. The recall rate is obtained through the formula, and the prediction accuracy rate of the NFAR algorithm is 89.74%.

$$R_{\text{recall}} = \frac{n_4}{n_3} = \frac{35392}{39437} = 89.74\%. \quad (15)$$

It can be seen from Table 4 that the accuracy of rule prediction using two algorithms on a small data set shows that on this data set, the prediction accuracy of the NFAR algorithm for association rules has reached 88.48%. The prediction accuracy of the traditional association rule algorithm is only 80.87%, which is nearly 8 percentage points higher. The results show that the proposed neutral fuzzy association rules algorithm has higher accuracy than the traditional one.

In the BD set, the same test is performed, and Table 5 is obtained. Through the large data set, it can be found that the prediction accuracy of the NFAR algorithm reaches 95.68%, while the traditional method is only 89.63%. In terms of recall rate, the NFAR algorithm is also better than the traditional association rule algorithm.

It shows that the rules obtained by the NFAR algorithm are more accurate than the rules obtained by the traditional association rule algorithm. The NFAR algorithm can effectively mine positive association rules, negative association rules, quantitative rules, and rare rules. In traditional methods, these rules cannot be mined at the same time, so the rules obtained by traditional methods are not as accurate as those obtained by the NFAR algorithm proposed in this paper. Moreover, in the process of forming the rules, the traditional association rule method needs to set the support and confidence values. Their settings need to be constantly adjusted and rely on expert knowledge. The NFAR algorithm proposed in this paper uses machine learning to solve the parameters of the model during the solving process, which improves the efficiency of the model.

As can be seen from Figure 5, in the Boolean mining algorithm, the number of generated association rules tends

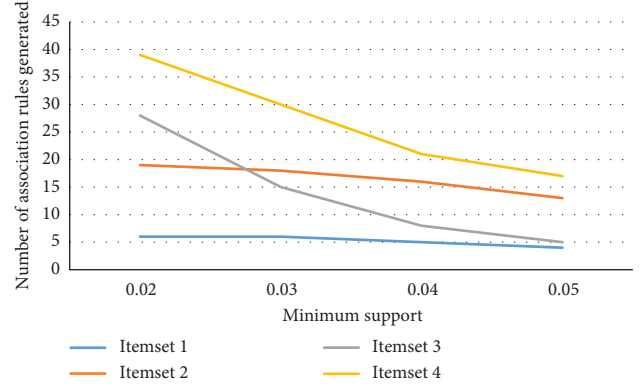


FIGURE 5: The trend of the number of Boolean association rules with the number of itemsets.

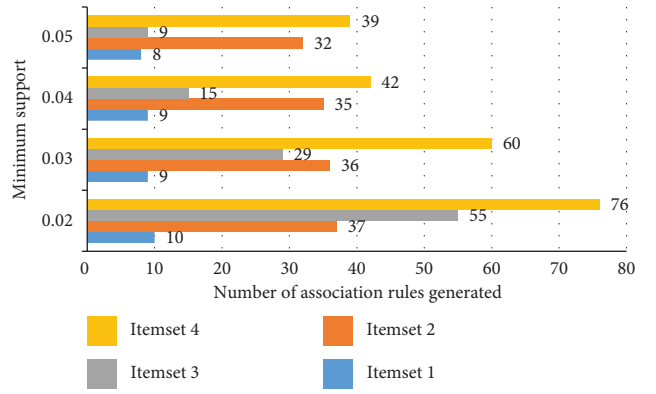


FIGURE 6: The trend of the number of fuzzy association rules with the number of itemsets.

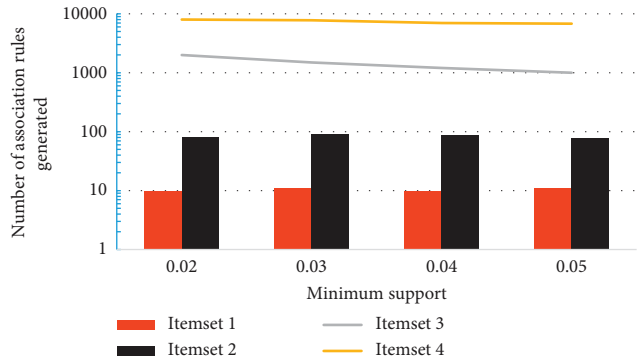


FIGURE 7: The change trend of the number of association rules generated by CIIC with the number of itemsets.

to decrease as the minimum confidence increases. From Figure 6 and Figure 7, it can be seen that when the minimum support threshold is set to small and the number of itemsets is small, the performance of the NFAR mining algorithm is similar to that of the fuzzy association rule generation algorithm, while the Boolean mining algorithm, due to the small number of associations generated, performed poorly.

5. Conclusions

Mining association rules are a popular research direction in the context of today's BD era. As far as association rule

mining research is concerned, people have achieved good results in this field, but there are still some shortcomings. For example, mining positive association rules have its own limitations: mining negative association rules, mining sparse association rules, and mining the scale of association rules of interest. To solve these problems, this paper proposes the NFAR algorithm. Construct most of the current association rule mining algorithms into a unified framework model. The NFAR algorithm effectively constructs the positive association rule mining method, the negative association rule mining method, the sparse association rule mining method, and the association rule mining method of the index of interest in a unified framework model. Moreover, the Markov network framework model of association rules only needs to learn the parameters in the model and does not need to set the values of interest measurement methods such as support, confidence, and promotion like other association rule algorithms. The work content of this article mainly includes that, combination of the neutrosophic fuzzy algorithm and association rules, a new framework model for the NFAR algorithm is proposed. The Zhongzhi fuzzy association rule algorithm builds most of the current association rule mining algorithms into a unified framework model.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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