퍼지 및 지능시스템학회 논문지 2004, Vol. 14, No. 6, pp. 764-770

하이브리드 데이터마이닝 메커니즘에 기반한 전문가 지식 추출

Extraction of Expert Knowledge Based on Hybrid Data Mining Mechanism

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Abstract

This paper presents a hybrid data mining mechanism to extract expert knowledge from historical data and extend expert systems' reasoning capabilities by using fuzzy neural network (FNN)-based learning & rule extraction algorithm. Our hybrid data mining mechanism is based on association rule extraction mechanism, FNN learning and fuzzy rule extraction algorithm. Most of traditional data mining mechanisms are depended on association rule extraction algorithm. However, the basic association rule-based data mining systems has not the learning ability. Therefore, there is a problem to extend the knowledge base adaptively. In addition, sequential patterns of association rules can't represent the complicate fuzzy logic in real-world. To resolve these problems, we suggest the hybrid data mining mechanism based on association rule-based data mining, FNN learning and fuzzy rule extraction algorithm. Our hybrid data mining mechanism is consisted of four phases. First, we use general association rule mining mechanism to develop an initial rule base. Then, in the second phase, we adopt the FNN learning algorithm to extract the hidden relationships or patterns embedded in the historical data. Third, after the learning of FNN, the fuzzy rule extraction algorithm will be used to extract the implicit knowledge from the FNN. Fourth, we will combine the association rules (initial rule base) and fuzzy rules. Implementation results show that the hybrid data mining mechanism can reflect both association rule-based knowledge extraction and FNN-based knowledge extension.

Key words : Association rules, Data mining, Fuzzy neural networks (FNN), Knowledge management, Rule extraction.

1. Introduction

During the past decade, a variety of application of knowledge management (KM) has been implemented in various fields. Data mining is one of interested topics in the field of knowledge management and knowledge discovery in database (Bonchi, et al., 2001; Chakrabarti et al., 1999; Changchien & Lu, 2001; Hui & Jha, 2000; Lee et al., 2002; Song et al., 2001), and has been recognized as a new area for database research. The area can be defined as efficiently discovering interesting rules from large collections of data. Recently, due to the increasing use of very large databases and data warehouses, mining useful information and helpful knowledge from transaction is evolving into an important research area (Hong et al., 2003).

One of the most popular tools in data mining is the association rule extraction mechanism, which was proposed by Agrawal et al. (1993). Given a set of transactions, where each transaction is a set of item, an association rule is an expression of the form X → Y. X and Y means the sets of items. An example of an association rule is: "20% of transactions that contain beer also contain diapers; 10% of all transactions contain both these items." Here 20% is called the *confidence* of the rule, and 10% the *support* of the rule.

Confidence (accuracy) of X→Y: P(Y|X) = (# of transactions containing both X and Y) / (# of transactions containing X).

Support (coverage) of X→Y: P(X,Y) = (# of transactions containing both X and Y) / (total # of transactions)

접수일자 : 2004년 6월 21일
완료일자 : 2004년 10월 4일

However, one of the most critical problems with basic data mining mechanism is the lack of learning ability. In addition, it couldn't represent the fuzzy logic embedded in real world database. Combine the fuzzy logic with the association rule mining is very difficult for general decision makers because they require high expertise in data mining, artificial intelligence and fuzzy logic (Lee et al., 2002). In this sense, we propose a hybrid data mining mechanism based on association rule mining, fuzzy neural network, and fuzzy rule extraction algorithm. Fuzzy neural networks and fuzzy rule extraction algorithm were used to extract the implicit fuzzy knowledge from database. This paper thus focuses on designing a sophisticated fuzzy-logic based data mining and combining algorithm. The remaining parts of this paper are organized as follows. Agrawal et al.'s (1993) association rule extraction method and former researches related to FNN rule extraction are described in Section 2. A hybrid data mining mechanism is proposed in Section 3. An example and experimental results to illustrate the proposed mechanism are given in Section 4. Conclusions are finally given in Section 5.

2. Research Background

2.1 Association rules extraction

Data mining also known as knowledge discovery in databases, has been recognized as a new approach for knowledge management. The area can be defined as efficiently discovering interesting rules from large collection of data. Among the data mining techniques, association rules mining algorithm has been popular in marketing intelligence fields (Lee et al., 2002). Therefore, we applied the association rule mining to the Web mining task. Web log database, which has been used in data mining, include the Web surfing log files (time, frequency, duration, products, etc.) users made on a target shopping mall or Web site. From a data pre-processing viewpoint, the Web log data poses the following challenges, (1) large errors, (2) unequal sampling, and (3) missing values. To remove these noises included in data, we applied pre-processing techniques to Web log data. As a result of Web mining, we can usually find out the hidden informative relationships between those products and inter-related hyperlinks users visited while Web surfing. Association rules are similar to IF-THEN rules in which a condition clause (IF) triggers a conclusion clause (THEN). In addition, association rules include the support and confidence (Agrawal et al., 1993). Association rules mining algorithm was shown in Table 1.

Table 1 Pseudo code of the association rules mining

```
C_k : Candidate transaction set of size k
L_k : Frequency transaction set of size k
L_j = {frequent items};
For (k=1; L_k !=φ; k++) Do Begin
C_{k+1} = Candidates generated from L_k;
For Each transaction t in database Do
  Increment the count of all candidates in C_{k+1}
that are contained in tL_{k+1} = candidates in C_{k+1} with
min_support
End Return L_k;
```

2.2 Fuzzy neural network & rule extraction

During the past decade, a variety of applications of fuzzy set theory and fuzzy logic have been implemented in various fields. One of the most important applications of fuzzy logic is fuzzy controller developed by engineers. Meanwhile, in the area of artificial intelligence (AI), interesting in artificial neural networks (ANN) has grown up rapidly after two decades of eclipse. In addition, many network topologies and learning methodologies have been explored to utilize the fuzzy logic. Especially, among these learning methodologies, the backpropagation algorithm has had an enormous influence in research on neural networks (NN) (Shann & Fu, 1995). After these kinds of researches, many researches have been published research papers concerning the integration of fuzzy systems and ANN.

One of the initial researches concerned to ANN and artificial learning, Lin & Lee (1991) proposed a multilayered feedforward connectionist model for fuzzy logic controllers and decision-making systems. In Lin & Lee's (1991) research, they used a hybrid two-step learning scheme that combined self-organized and supervised learning algorithms for learning fuzzy logic rules and membership functions.

Kong & Kosko (1992) and Kosko (1992) supposed an adaptive fuzzy associative memory (AFAM) to integrate a NN and fuzzy logic. Unsupervised differential competitive learning (DCL) and product-space clustering adaptively generated fuzzy rules from training sample.

In Wang & Mendel's (1992) research, fuzzy systems were viewed as a three-layer feedforward dedicated network with heterogeneous neurons. The network was trained by traditional backpropagation algorithm for membership function learning.

Horikawa et al. (1992) presented a fuzzy modeling method using fuzzy neural networks. In their research, they proposed three types of fuzzy neural networks, 6, 7, and 10 layers respectively. These FNNs could acquire fuzzy inference rules and tune the membership functions of nonlinear systems.

Krishnapuram & Lee (1992) proposed a fuzzy-set-based hierarchical network for information fusion in computer vision. The proposed scheme could be trained as a NN in which parameterized families of operators were used an activation functions and the gradient descent and backpropagation learning procedure was performed to generate degrees of the parameters of these operators. After training, the network could be interpreted as a set of rules for decision making. In addition, some heuristics were described to eliminate redundant criteria.

Mitra & Pal (1994) had developed a multilayered fuzzy neural network to operate the fuzzy classification and generate the fuzzy rules. In their research, they used MLP (MultiLayered Perceptron) and fuzzy logical operators.

In general, most of the methodologies for learning knowledge are in one of the following two categories: backpropagation type and competitive type. Backpropagation-type learning algorithms learn more precisely than competitive-type algorithms because they are based on time and numerous training epochs to converge. In contrast, competitive-type learning algorithms learn more rapidly than backpropagation -type algorithms because they are based on unsupervised clustering, but the knowledge learned may not be precise enough. Therefore, one of the goals in the filed of knowledge learning is to learn knowledge both precisely and rapidly (Shann & Fu, 1995). With the same purpose, in this research, we use a fuzzy neural network (FNN) to learn our prepared knowledge.

3. Methodology

Our proposed hybrid data mining mechanism was based on fuzzy membership function, association rule mining, FNN, and fuzzy rule extractions. They were aimed at enriching adaptability of traditional knowledge-based decision-making. The proposed mechanism consists of the four phases-association rule extraction, fuzzy neural networks, and fuzzy rule extractions. Figure 1 shows our hybrid data mining mechanism and methodology.

3.1 Phase I: Association rule extractions

The first phase is to preprocess the raw database and association rule mining. In this phase, we adopted the association rules mining technique to extract the relationships among items and attributes.

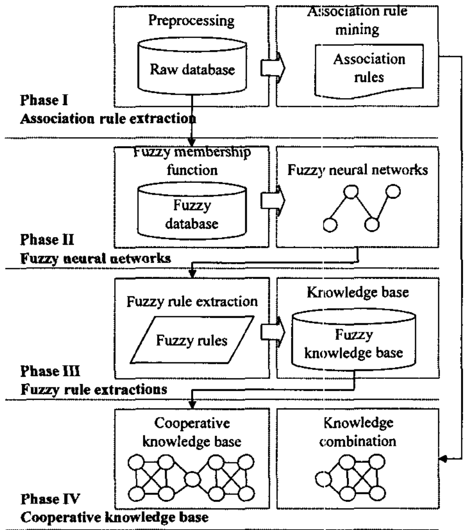

Figure 1. Research methodology

3.2 Phase II: Fuzzy neural networks

The second phase is to adapt the fuzzy membership function to traditional databases. As a result, raw database was transformed into fuzzy database. Then, we used the fuzzy neural networks to learn the implicit knowledge from the fuzzy database.

3.3 Phase III: Fuzzy rule extractions

The fourth stage of the proposed hybrid data mining mechanism is to apply the fuzzy rule extraction algorithm the fuzzy neural networks. Then, initial knowledge base was extended by these fuzzy rules. To this purpose we propose the three-phased fuzzy rule extraction algorithm as follows:

Phase-1: path generation by backtracking
Phase-2: syntax generation for generated path
Phase-3: compute the certainty value

Detailed path and rule generation algorithm was presented in Mitra & Pal's (1994) research paper.

3.4 Phase IV: Cooperative knowledge base

The final stage of our proposed mechanism starts with the transformation of association rules into knowledge base. Then, association rule-based knowledge base was combined and with fuzzy rules extracted from fuzzy neural networks.

4. Implementation

To prove the quality of hybrid causal knowledge base construction mechanism, we used hepatitis data stored in University of California Irvine's machine learning data repository. First, totally 155 data was selected. After the pre-processing such as missing data elimination, however, totally 80 data was used for validation. Which was composed of 19 input variables and 1 output variable (two classes 1:die, 2:live). The prototype system was implemented by using the Excel and VBA language in a Windows XP environment. In addition, SPSS and Clementine 6.0.1 was also used to preprocess the raw-data and extract the association rules. We call this prototype system as AFC (Association rule and Fuzzy neural network-based Cooperative knowledge base). Figure 2 shows the raw database for hepatitis check.

No	Class	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20
1	2	30	2	1	2	2	2	2	1	2	2	2	2	2	1	85	18	4	?	1
2	2	50	1	1	2	1	2	2	1	2	2	2	2	2	0.9	135	42	3.5	?	1
3	2	78	1	2	2	1	2	2	2	2	2	2	2	2	0.7	96	32	4	?	1
4	2	31	1	?	1	2	2	2	2	2	2	2	2	2	0.7	46	52	4	80	1
5	2	34	1	2	2	2	2	2	2	2	2	2	2	2	1	?	200	4	?	1
6	2	34	1	2	2	2	2	2	2	2	2	2	2	2	0.9	95	28	4	75	1
7	1	51	1	1	2	1	2	1	2	2	1	1	2	2	?	?	?	?	?	1
8	2	23	1	2	2	2	2	2	2	2	2	2	2	2	1	?	?	?	?	1
9	2	39	1	2	2	1	2	2	2	1	2	2	2	2	0.7	?	48	4.4	?	1
10	2	30	1	2	2	2	2	2	2	2	2	2	2	2	1	?	120	3.9	?	1
11	2	39	1	1	1	2	2	2	1	1	2	2	2	2	1.3	78	30	4.4	85	1
12	2	32	1	2	1	1	2	2	2	1	2	1	2	2	1	59	249	3.7	54	1
13	2	41	1	2	1	1	2	2	2	1	2	2	2	2	0.9	81	60	3.9	52	1
14	2	30	1	2	2	1	2	2	2	1	2	2	2	2	2.2	57	144	4.9	78	1
15	2	47	1	1	1	2	2	2	2	2	2	2	2	2	?	?	60	?	?	1
16	2	38	1	1	2	1	1	1	2	2	2	2	1	2	2	72	89	2.9	46	1
17	2	66	1	2	2	1	2	2	2	2	2	2	2	2	1.2	102	53	4.3	?	1
18	2	40	1	1	2	1	2	2	2	1	2	2	2	2	0.6	62	166	4	63	1
19	2	38	1	2	2	2	2	2	2	2	2	2	2	2	0.7	53	42	4.1	85	2
20	2	38	1	1	1	2	2	2	1	1	2	2	2	2	0.7	70	28	4.2	62	1

Figure 2. Raw data for hepatitis check

4.1 Phase I: Association rule extraction

The association rule mining algorithm we adopted here is an APRIORI algorithm (Agrawal et al., 1993), which was known to yield a set of association rules. Based on the hepatitis data in Figure 2, the corresponding association rules were extracted with a threshold of 80% confidence.

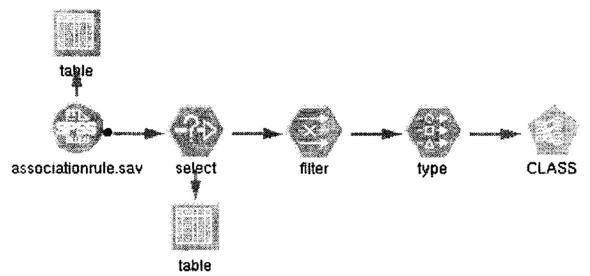

Figure 3. Association rule extraction process

Figure 3 shows the association rule extraction process using Clementine.

Table 1 shows an excerpt of the derived association rules. The association rules shown in Table 1 are straightforward and easy to understand and interpret.

Table 1. Example of association rules from the database

CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V11 = 2 AND V20 = 2 (9:22.5%, 0.889)
CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V5 = 2 AND V20 = 2 (13:32.5%, 0.846)
CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V6 = 1 AND V20 = 2 (11:27.5%, 0.909)
CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V4 = 1 AND V20 = 2 (7:17.5%, 1.0)
CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V7 = 1 AND V20 = 2 (9:22.5%, 0.889)
CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V20 = 2 AND V12 = 1 (9:22.5%, 0.889)
CLASS = 2 <= V9 = 2 AND V8 = 2 AND V14 = 2 AND V20 = 1 AND V7 = 2 (16:40.0%, 1.0)
CLASS = 2 <= V9 = 2 AND V8 = 2 AND V11 = 2 AND V20 = 1 AND V7 = 2 (16:40.0%, 1.0)
CLASS = 2 <= V9 = 2 AND V8 = 2 AND V13 = 2 AND V20 = 1 AND V7 = 2 (16:40.0%, 1.0)

4.2 Phase II: Fuzzy neural networks

In the first phase, we adapted Mitra & Pal's (1994) fuzzy membership functions to transform the real data into fuzzy sets. Fuzzy membership functions used in this phase was as follows:

$$\pi(F_j : c, \lambda) = \begin{cases} 2\left(1-\dfrac{|F_j-c|}{\lambda}\right)^2, & \text{for} \dfrac{\lambda}{2} \leq |F_j-c| \leq \lambda \\ 1-2\left(\dfrac{|F_j-c|}{\lambda}\right)^2, & \text{for} 0 \leq |F_j-c| \leq \dfrac{\lambda}{2} \\ 0, & \text{otherwise} \end{cases}$$

$$\lambda_{medium} = \frac{1}{2}(F_{\max} - F_{\min})$$
$$C_{medium} = F_{\min} + \lambda_{medium}$$
$$\lambda_{low} = \frac{1}{fdenom}(c_{medium} - F_{\min})$$
$$C_{low} = C_{medium} + 0.5 * \lambda_{low}$$
$$\lambda_{high} = \frac{1}{fdenom}(F_{\max} - C_{medium})$$
$$C_{high} = C_{medium} + 0.5 * \lambda_{high}$$

Figure 4 shows fuzzified database transformed by fuzzy membership functions. In this phase, we developed a (31*20*2 structured) FNN and used it to learn the relationships among historical data and its attributes. Finally, after the learning of 357 iteration with 43 data FNN stopped at RMSE = 0.0009.

4.3 Phase III: Fuzzy rule extractions

After the learning of fuzzy neural networks, we adopted Mitra & Pal's (1994) fuzzy rule extraction

No	V2_L	V2_M	V2_H	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15_L	V15_M	V15_H		Class	Class
1	0.96	0.61	0.04	0.10	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.98	0.14	0.00		0.90	0.10
2	0.78	0.91	0.22	0.10	0.10	0.10	0.90	0.90	0.90	0.10	0.10	0.90	0.90	0.90	0.90	0.99	0.40	0.01		0.90	0.10
3	0.99	0.43	0.01	0.10	0.90	0.10	0.10	0.90	0.90	0.90	0.10	0.90	0.10	0.90	0.90	0.99	0.19	0.00		0.90	0.10
4	0.67	0.97	0.33	0.10	0.90	0.10	0.10	0.90	0.90	0.90	0.10	0.90	0.90	0.90	0.90	0.98	0.14	0.00		0.90	0.10
5	1.00	0.28	0.00	0.10	0.90	0.90	0.10	0.90	0.90	0.90	0.10	0.90	0.90	0.90	0.90	0.72	0.95	0.28		0.90	0.10
6	0.83	0.87	0.17	0.10	0.10	0.90	0.10	0.10	0.10	0.90	0.90	0.90	0.90	0.10	0.90	0.81	0.88	0.19		0.90	0.10
7	0.73	0.95	0.27	0.10	0.10	0.90	0.10	0.90	0.90	0.90	0.10	0.90	0.90	0.90	0.90	0.93	0.04	0.00		0.90	0.10
8	0.83	0.87	0.17	0.10	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.95	0.06	0.00		0.90	0.10
9	0.83	0.87	0.17	0.10	0.10	0.10	0.90	0.90	0.90	0.10	0.10	0.90	0.90	0.90	0.90	0.95	0.06	0.00		0.90	0.10
10	0.82	0.00	0.00	0.90	0.90	0.10	0.10	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.90	0.98	0.14	0.00	…	0.90	0.10

Figure 4. Fuzzified database

algorithm to fuzzy neural network. Our revised fuzzy rule extraction algorithm was shown in Table 2.

Table 2. Fuzzy rule extraction algorithm

Step I: Path generation by backtracking

Step 1.1: Find the intermediate node i which has a positive effect on output node j in H(output) layer. If $w_{ji}^{H-1} > 0$, *Then select node i in H-1 layer*

Step 1.2: Select the connection weights between i and j.

Step 1.3: Select the input node, which has an output value more than 0.5. Then, find the connection weight from the lower layer until there's no connection weight.

Step 1.4: Sort the selected connection weight list.

Step 2: Sentence generation

Adapt two conditions as follows:

Condition 1: Define the conditions for sorting. Then, generate the If-Then rules.

Condition 2: Select the linguistic hedge or real values.

Table 3 shows the fuzzy rules extracted from fuzzy neural networks. Where, each value means the fuzzy membership value.

Table 3. Sample of fuzzy rules extracted from fuzzy neural networks

CLASSS = 1 <= V2= low or medium AND V3=0.9 AND V4=0.9 AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V12=0.9 AND V13=0.9 AND V14=0.9 AND V15= low or medium AND V16= medium or high AND V17= high AND V18= medium or high AND V19= medium or high (95%)

CLASSS = 1 <= V2= low or medium AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V12=0.9 AND V13=0.9 AND V14=0.9 AND V15= low AND V16= low or medium AND V17=low AND V18= high AND V19= high (95%)

CLASSS = 2 <= V2= medium of high AND V4=0.9 AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V12=0.9 AND V13=0.9 AND V14=0.9 AND V15= low or medium AND V16= low or medium AND V17= low or medium AND V18= medium or high AND V19= low or medium AND V20=0.9 (90%)

CLASSS = 2 <= V2= medium or high AND V4=0.9 AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V13=0.9 AND V15= low or medium AND V16= low AND V17= low AND V18= medium or high AND V19= medium or high AND V20=0.9 (90%)

4.4 Phase IV: Cooperative knowledge base

After the extraction of association rules and fuzzy rules, we combined two different kinds of knowledge bases into cooperative knowledge base. Table 4 shows the cooperative knowledge base.

Table 4. Example of cooperative knowledge base

CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V11 = 2 AND V20 = 2 (89%)

CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V5 = 2 AND V20 = 2 (85%)

CLASS = 1 <= V9 = 2 AND V8 = 2 AND V3 = 1 AND V6 = 1 AND V20 = 2 (91%)

CLASS = 2 <= V9 = 2 AND V8 = 2 AND V14 = 2 AND V20 = 1 AND V7 = 2 (100%)

CLASS = 2 <= V9 = 2 AND V8 = 2 AND V11 = 2 AND V20 = 1 AND V7 = 2 (100%)

CLASS = 2 <= V9 = 2 AND V8 = 2 AND V13 = 2 AND V20 = 1 AND V7 = 2 (100%)

CLASSS = 1 <= V2= low or medium AND V3=0.9 AND V4=0.9 AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V12=0.9 AND V13=0.9 AND V14=0.9 AND V15= low or medium AND V16= medium or high AND V17= high AND V18= medium or high AND V19= medium or high (95%)

CLASSS = 1 <= V2= low or medium AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V12=0.9 AND V13=0.9 AND V14=0.9 AND V15= low AND V16= low or medium AND V17=low AND V18= high AND V19= high (95%)

CLASSS = 2 <= V2= medium of high AND V4=0.9 AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V12=0.9 AND V13=0.9 AND V14=0.9 AND V15= low or medium AND V16= low or medium AND V17= low or medium AND V18= medium or high AND V19= low or medium AND V20=0.9 (90%)

CLASSS = 2 <= V2= medium or high AND V4=0.9 AND V5=0.9 AND V6=0.9 AND V7=0.9 AND V8=0.9 AND V9=0.9 AND V10=0.9 AND V11=0.9 AND V13=0.9 AND V15= low or medium AND V16= low AND V17= low AND V18= medium or high AND V19= medium or high AND V20=0.9 (90%)

5. Conclusions

Basic association rule extraction mechanism did not consider learning ability of the data mining systems and extension of its knowledge base. One of efficient solutions to that problem, in this study, we suggested the replacement of each former knowledge base with '*extended fuzzy rules*' which contained implicit knowledge of FNNs. To this purpose, we proposed four phased new hybrid data mining mechanism. Empirical evaluation showed that this mechanism could extract & extend the implicit knowledge more flexible, and the result of experiment with a hepatitis database was proved to be a valid and robust solution.

In conclusion, this study has shown how the association rules and FNN can be brought together to create cooperative expert knowledge base. It is expected that the proposed hybrid knowledge extraction mechanism will have a significant impact on the research domain related to the human perception and knowledge management. However, this 'basic and hybrid' data mining approach is complicate and not very fast. Further research topics still remaining are as follows:

(1) The basic technology of association rule mining used for this study needs to be improved so that more fuzzy knowledge can be analyzed.
(2) Fuzzy membership functions need to be integrated with other rule refining and reasoning mechanism.
(3) Complicate FNN construction processes and fuzzy rule refinement algorithm was need to be improved with other useful knowledge management mechanisms.
(4) Fuzzy logic-based inference mechanism is needed to solve more complicate problem.
(5) Knowledge cooperation mechanism to combine several types of knowledge is critical key points to construct an efficient knowledge management system.

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