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Research Article

AN IMPROVED APPROACH FOR WEIGHTED ASSOCIATION RULE MINING BASED ON MULTI-CRITERIAIMPORTANCE

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Abstract

Association Rule Mining (ARM) is used to identify relationships amongst items in transactional databases so it is widely applied to the subjects which are difficult to use statistical and mathematical methods in recent years. A traditional association rule mining (ARM) are assumed to have the same importance for each item included in the transactional database. In fact, the data in the reality vary with the importance of each data and also it is duo to how the criteria and methods of evaluating them are set. Thus, taking this into account, the mining of association rules can lead to more efficient and accurate results. From this point of view, a number of studies have been carried out to determine the Frequent Weighted Itemsets (FWI) by assigning the weight to each item in the transactional database and to mine the association rules. In this paper, we propose a method for determining the weights based on the multi-criteria importance of items in a transactional database. This paper also proposes the method for weighted associated rule mining (WARM) which is based on the multi-criteria importance weight and some applications are introduced to verify its effectiveness. The experimental results show that the proposed method is better than the typical associated rule mining or previous WARM in accuracy and effectiveness. Therefore, we can be sure that the proposed method is more accurate and effective than the previous methods.

Keywords: Multiple criteria analysis, multi-criteriaimportance, Weighted association rule mining, Data mining, Attribute weighting, Grey relational analysis.

INTRODUCTION

According to E.Cohenet al.and R. C.Agarwal et al.[1,2], Data Mining is the technique for finding out the available information(rules or laws or functions) which is included in a number of data. In other words, it is a method for extracting multi-dimensional knowledge or pattern hidden in the huge database. According to S.Sunita et al and M. Indhumathy et al. [3-5], ARMis a datamining technique that allows the discovery of hidden association patterns in a data set, which reveals the association between itemsets of interest and a set of other items in the transaction database under consideration and finds out the rule to the degree of confidence required by the user. Traditional ARM methods [6-9] extract a set of frequent itemsby considering only the equivalent level of occurrence for all datain a database or a data warehouse. In practice, however, user interest on items in the database, that is, the degree of importance of each item, is different, and theimportance is different according to what criteria is evaluated forthe same item.For example, at a library, readers are more likely to browse the relevant book depending on their occupational character or research area, and not much attention is paid to other unrelated books, and even when they are reading, they are more likely to require more recent books than older ones and are more interested in them.In addition, customers who come to the store are more curious about new products with the same variety and price, and are in high demand. However, if the variety is the same but the price or quality is different, there is a person who is interested in the quality only regardless of the price, or who is interested in a product that is cheap regardless of quality.

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That is, everybody has different evaluation criteria which can lead to different levels of interest.This shows that user interest on each item is not same as well as its importance according to the evaluation criteria. In this case, in traditional ARM, a part of afrequentitemset are frequent, but there are some casesof insigni- ficant, and also important items exist among non-frequent items.Therefore, in ARM, the occurrence of an item should be takeninto account, as well as the weight of the item representing the importance of the various evaluation criteria in accordance with the characteristics of the businessdatabase.
In previous studies [4-6,8,10], Frequent Weighted Itemsets were determined by assigning weight according to the importance of frequency and attribute to each item in the transactional database, and a study of weighted ARM was conducted. Previous studies [10,11] have shown that for each item in an large-scale database or a data warehouse, frequent items were deter- mined in a uniform agreement manner and used for ARM, which is not accurate. Thus, the accuracy and efficiency of ARM was improved by determining the frequent itemset used for rule mining using the weights according to the frequency of occurrence of the item and the importance of the item.

X. Kang et al. [11-14] determined the item weight by fuzzy evaluation method, and the weight of itemset was determined by the average of the fuzzy evaluation values of the items (11) or by the membership function (12,13).

J. Gao [15] used web records to perform ARM by weighing the frequency of web pages selected by users.

In this case, the weight of an item is calculated as the ratio of the sum of the average access time of the entire page to the average access time of the web page, and the weight of the itemset is taken as the maximum value among the weight of the included items.

Shao Y. X. et al. [16] proposed a new software defect prediction model based on weighted class ARM.Here, the weight of an item was calculated as the mean value of the correlation function of the total attributesversus the value of the correlation function of the attributes of that item, and the weight of the itemset was determined as the product of the weight of the individual items.

Mallik S. et al. [17-19] determined the weight of an item with the rank to which the hierarchy of items constitutes the itemsets. S. Datta et al. [18] introduced the concept of direct link-based weight and indirect link-based weight based on the hierarchical structure of the items to calculate the weight of the itemset.

Zhong Y. H. et al. [20] calculated the weight of itemsets as the ratio of the sum of the weight of individual items to the product of the weights of individual items in the itemsets, using the weight of items determined by the experts.Weighted support was defined as the weight ratio of the number of totalrecords tothe number of subsets in the transactional database.

Yan L.W. and W. G. Yi [21] determined the weight of an item by combining two weights according to the ration of the number of new added transactions and the number of previous transactions to the total number of transac- tions in the transaction database, and weighted support was also defined as the sum of the respective weighted support.

Pears R. and Y. S. Koh [22] used particle swarm optimization algorithm to determine the weight of each item, and the weight of the itemset was calculated by summing the products of the weights of each item and the coefficients that reflected the relationship with the other items.At this time, the coefficients that reflect the relationship between the items were determined by the number of simultaneous appearances of the two items in the transactional database.

In previous studies, the weight of the item considering the importance of the attributes is determined by using expert evaluation methods, fuzzy evaluation methods and hierarchical analysis methods etc., for most of the single attributes. However, as mentioned earlier they did not determine the item weight taking into account the frequency of the item occurrence as well as the different attributes that match the nature of the transactional database and the degree of importance with the evaluation criteria. From this point of view, we focus on determining the overall weight of an item according to the criteria for evaluation and the various attributes that match the nature of the transactional database with the frequency of occurrence in determining the weight ofthe item.

The rest of this paper is organized as follows.

Section 2 presents the some related works concerning with the ARM and the determination method for FWIs.

Section 3 proposes the method of determining the item weight based on the multi-criteria importance and the method of the weighted ARM using it.

Some of the experiment results are described in the Section 4 and the results of the effectiveness analysis and conclusions are described in the Section 5.

RELATED WORK

Formulation of Related Rule Mining Problem

$i_k(k=1,2,\cdots,m)$is an item and m, n are the number of items and the number of transactions, respectively where $I=\{i_1,i_2,\cdots,i_m\}$ is a itemset, $D=\{t_1,t_2,\cdots,t_n\}(t_i \subseteq I)$ is the transaction database.

D consists of transaction(T) and its id(Tid), each transaction Tconsists of items belonging to I.

In this case, we call the group of items an Itemset.

Definition 2.1. We call $X \Rightarrow Y$an association rule where $X \subseteq I, Y \subseteq I, X \cap Y = \emptyset$ [6,7,20].

Association rule is one of the several knowledge samples obtained as a result of data mining, meaning that a transaction containing an itemset X in a transactional database D tends to include an itemset Y as well.

Definition 2.2. If a transaction T contains all the items of X, we say that the transaction T supports the set X, and we denote it as follows [6,7,16,20].

$$Support(X) = \frac{|\{T:X\subseteq T, T\in D\}|}{|D|} \quad (1)$$

Thus, the support of $X, Support(X)$means the ratio (or percent) of the number of transaction that support Xtoall transaction numbers of D.

At this time, for a given minimum support threshold value $Support_{min}$, if $Support(X) \geq Support_{min}$, the set X is called a frequently occurring set of items, simply a frequent itemset.

Definition 2.3. The support of association rule $X \Rightarrow Y$ is the ratio(or percent) between the number of transactions that simultaneously include the itemsets X,Y and the number of total transactions of D[6,7,16].

This is also the support of the itemset $(X \cup Y)$.

$$Support(X \Rightarrow Y) = \frac{|\{T:X\cup Y\subseteq T, T\in D\}|}{|D|} = Support(X \cup Y) \quad (2)$$

Definition 2.4.The ratio of the number of transactions containing an item X to the number of transactions containing the itemsets X and Y simultaneously is called the confidence of the association rule.That is, the confidence of the association rule is the conditional probability that T supporting $X$and$Y$ is together [7, 20].

$$Confidence(X \Rightarrow Y) = \frac{|\{T:X\cup Y\subseteq T, T\in D\}|}{|T:X\subseteq T, T\in D|} = \frac{P(Y\subseteq T \wedge X\subseteq T)}{P(X\subseteq T)} = \frac{Support(X\cup Y)}{Support(X)} \quad (3)$$

ARM finds out frequent itemsets in a transactional database D and then generates association rules that satisfyminimum confidence.

$AR(D) = \{i_k \Rightarrow i_l | i_k, i_l \subseteq I^\omega, i_k \cap i_l = \emptyset, Support(i_k \Rightarrow i_l) \geq Support_{min}, Confidence(i_k \Rightarrow i_l) \geq Confidence_{min}\}$ (4)

Method for determining a FWI

In general, ARM determines a frequent item by the proportion of transactions that contain item X and item Y together for the entire transactional database D as the support of association rule $X \Rightarrow Y$.The relationship between the items in the set of frequent items obtained above was determined by the ratio of the item X to the item X and Y together, which is the confidence of the association rule, $Confidence(X \Rightarrow Y)$.This assumes that each item in the transactional database has the same importance to each other and only considers the frequency of the item when generating a frequent itemset.However, the user interest for the items in the real databases, that is, the importance of an item is different. It also has different importance depending on what criteria its attribute indices are evaluated for the same item.Therefore, in ARM, the weight of the item must be taken into account, representing the frequency of the itemand the importance across the various criteria that is suitable for the characteristics of the transactional database.

The set$I^\omega = \{(i_1, \omega_1), (i_2, \omega_2), \cdots, (i_n, \omega_m)\}$ obtained when assigning weight $\omega_j, (0 < \omega_j \leq 1, j = \overline{1, m})$ for each item i_j in the m itemset $I = \{i_1, i_2, \cdots, i_m\}$of the transactional database $D = \{t_1, t_2, \cdots, t_n\}$ is called weighted itemset [21, 22].

For the weighted items $(i_k, \omega_k), (i_l, \omega_l)$on $\forall k, l \in m$, if $\omega_k > \omega_l$, then i_k becomes an item that is more important than item i_l.

Definition 2.5. For $\forall(i_k, \omega_k) \in I^\omega$ in a transactional database $D, wSupport(i_k)$ is called the weighted support of a weighted itemset (i_k, ω_k)[9,10,22].

$$wSupport(i_k) = \omega_k \cdot Support(i_k) \tag{5}$$

In equation (5), $Support(i_k)$ is the usual support, which is the ratio of the number of transactions supporting itemset $i_k$to all transaction numbers of$D$calculated by equation (1).

Definition 2.6. For $\forall(i_k, \omega_k), (i_l, \omega_l) \in I^\omega$ in a transactional data- base D, $wSupport(i_k \Rightarrow i_l)$ is called the weighted support of a weighted association rule $i_k \Rightarrow i_l$ [2,9,23].

$$wSupport(i_k \Rightarrow i_l) = \sum_{j=k,l} \omega_j \cdot Support(i_k \cup i_l) \tag{6}$$

In the weighted support of the weighted association rule of equation (6), $Support(i_k \cup i_l)$is the support of the itemset calculated byequation (2).Then, the frequent itemset that satisfy the minimum weighted support (w_min_sup) is defined as a FWIs.

$$wSupport(i_k \Rightarrow i_l) \geq w\_min\_sup \tag{7}$$

METHODOLOGY

Method of weight determining based on the multi-criteria importance

In equation (6), the weights of the individual items of the weighted itemset I^ωvary greatly depending on what criteria and methods each item has, and how they are evaluated. Hence, we set the weight of an item in a transaction database D as a multi-criteria importance assessment index that reflects the frequency of item i_j, the occurrence time characteristic of item i_j, and the interest of item i_j, and then use it to determine the weightω_j for each item in the transaction database as follows.

$$\omega_j = \alpha_1 \omega_j^f + \alpha_2 \omega_j^t + \alpha_3 \omega_j^e \tag{8}$$

In equation (8), ω_j^frepresents the importance of an item i_j in terms of occurrence frequency of item, ω_j^trepresents the importance of the item i_j in terms of the occurrencetime, ω_j^erepresents the importance of the users' interest for item i_j, and α_1,α_2,$\alpha_3$represent the importance of ω_j^f, ω_j^t, ω_j^ein the overall weight of the item, respectively.

In the transactional database $D = \{t_1, t_2, \cdots, t_n\}$, the ratio of the number of occurrence $f_j$of an item $i_j$to n is called the importance of the item due to the frequent occurrence of the item and is expressed as follows.

$$\omega_j^f = f_j / n \tag{9}$$

ω_j^t is the importance which reflects the characteristic of occurrence time of item $i_j$where $t_{max}$is the last occurrence time, $t_{min}$is the longest time and $t_j^k$is the time of k-th item i_j.

- A case of attaching importance to recent transaction

$$\omega_j^t = \sum_{k=1}^{f_j} \left[\left(t_j^k - t_{min}\right) / \left(t_{max} - t_{min}\right) \right] / f_j \tag{10}$$

- A case of attaching importance to longest transaction

$$\omega_j^t = \sum_{k=1}^{f_j} \left[\left(t_{max} - t_j^k\right) / \left(t_{max} - t_{min}\right) \right] / f_j \tag{11}$$

When calculating the importance which reflects the characteristic of occurrencetime of item i_j, we can use equation (10) for attaching importance to recent transaction and equation (11) for attaching importance to longest transaction.

Here, the occurrence times of items t_{max}, t_{min}, t_j^krepresent the value after prescriptive process according to the characteristic of the item i_j. For example, if the time of a transaction occurrence in a transactional databaseis given in the form of"January 2023", then it can be normalized as follows.

$$t_j^k = \left(y_j - y_{min}\right) \times 12 + m_j \tag{12}$$

Here, y_j, $m_j$means the year and month at the k-th occurrence time of the item, respectively, and y_{min}means the year at the occurrence time of the longest transaction.

The importance of an item $i_j$in a transactional database depends on the criteria assessing the degree of interest of the user. We refer to ω_j^eas the importance of the item's interest and set by the grey relational grade that reflects the relationship between each item in the transactional database and the criteria set to evaluate interest.

In the m itemsets$I = \{i_1, i_2, \cdots, i_m\}$ of the transactional database D let us promise sets $I_j = \{i_j(1), i_j(2), \cdots, i_j(n)\}, j = \overline{0, m}, N = \{0,1, \cdots, m\}, L = \{1,2, \cdots, n\}$.

In this case, we call I_0 an reference sequence , I_j an comparison sequence and the grey relational grade reflecting the relationship between et I_0 and I_j calculated by equation (13) [24,25].

$$\gamma(I_0, I_j) = \frac{1}{n}\sum_{k=1}^{n}(i_0(k), i_j(k)) = \frac{1}{n}\sum_{k=1}^{n}\xi_{0j}(k) \quad (13)$$

Association coefficient $\xi_{0j}(k)$ can be calculated as follows [26-28].

$$\xi_{0j}(k) = \frac{\min_{j\in N}\min_{k\in L}\Delta\left(i_0(k), i_j(k)\right) + \zeta\max_{j\in N}\max_{k\in L}\Delta\left(i_0(k), i_j(k)\right)}{\Delta\left(i_0(k), i_j(k)\right) + \zeta\max_{j\in N}\max_{k\in L}\Delta\left(i_0(k), i_j(k)\right)}\quad j = \overline{1,m}, k = \overline{1,n} \quad (14)$$

Here, $\Delta\left(i_0(k), i_j(k)\right) = \left|i_0(k) - i_j(k)\right|$and $\zeta = 0.5$ [29,30].

In this case, let $\gamma_j$be the association degree of the n items in the itemset $I = \{i_j\}$, and the weight of each item is determined by the foll- owing expression.

$$\omega_j^e = \frac{\gamma_j}{\sum_{l=1}^{n}\gamma_l}, j = \overline{1,m} \quad (15)$$

The importance reflecting the interest of an item $i_j$is thus different according to how $I_0$and $I_j$are determined.

In such a weight determination method, all items in the transactional database are assigned weights that reflect frequency of occurrence, occurrencetime and interest, and are used to mine association rules using weighted items.

Weighted ARM based on multi-criteria importance

The weight of an item on the basis of a multi-criteria importance is different from an individual item, whichis less frequent in occurrence but more often is considered important and this is determined as a weighted frequent item. In order to mine association rules using FWIs determined as such, the weighted association rule defines the confidence as follows.

Definition 2.7. For $\forall(i_k, \omega_k), (i_l, \omega_l) \in I^\omega$ in a transactional database D, $wConfidence(i_k \Rightarrow i_l)$ is called the weighted confidence of a weighted association rule.

$$wConfidence(i_k \Rightarrow i_l) = wSupport(i_k \Rightarrow i_l)/wSupport(i_k) \quad (16)$$

Weighted ARM is done by the relationship between weighted items that satisfy the minimum weighted confidence ($w\_\min\ \_conf$). Hence, weighted ARM for $\forall(i_k, \omega_k), (i_l, \omega_l) \in I^\omega$ in the transactional database D is to find out a set of rules that are relatively large in relation by a multi-criteria importance evaluation index in a transactional database.

$$WAR(D) = \{i_k \Rightarrow i_l | i_k, i_l \subseteq \mathrm{I}^\omega, i_k \cap i_l = \emptyset, wSupport(i_k \Rightarrow i_l) \geq w\_\min\ \_sup, wConfidence(i_k \Rightarrow i_l) \geq w\_\min\ \_conf\} \quad (17)$$

The detailed steps for mining weighted association rules based on multi-criteria importance are as follows.

Step 1: Find out all FWIs I_k^ωbased on the multi-criteria importance that satisfy the minimum weighted support ($w\_\min\ \_sup$) in the transactional database D.

Step 2: Find out all sets where $S = \{I_{k_j}^\omega \middle| I_{k_j}^\omega \subset I_k^\omega, I_{k_j}^\omega \neq \emptyset\}$ for FWIs I_k^ω.

Step 3: Generate weighted association rules that satisfy the minimum weight confidence from the weighted subsets. That is, for a non-empty weighted partial frequent itemset S of a weighted frequent itemset I_k^ω, we generate weighted association rules that satisfy $wConfidence(S \Rightarrow (I_k^\omega - S) \geq w\_\min\ \_conf$.

EXPERIMENTAL RESULTS

In order to verify the effectiveness of the proposed weighted ARM method, we used an example of a manage- ment transactional database. Given product investment and revenue scale for five years as Table 1, The importance of reflecting the interest of each item in terms of the producer is by using the investment and revenue respectively as reference and comparison sequence. On this basis, using equation (9),(10),(11),(15), the weights based on the multi-criteria importance, which reflect the frequency, time of occurrence, and interest of each item, are calculated, and the weights of the items calculated are shown in Table 2, with a set to $\alpha_1 = 0.3$,$\alpha_2 = 0.3$,$\alpha_3 = 0.4$ in equation (8).

Table 1. Product investment and revenue scalefor 2019~2023

Product name	2019		2020		2021		2022		2023	
	Investment	Revenue	Investment	Revenue	Investment	Revenue	Investment	Revenue	Investment	Revenue
A	2.728	1.9	3.234	2.32	2.98	1.726	3.56	3.78	7.654	4.339
B	0.432	0.47	0.768	0.83	0.782	0.798	0.702	0.643	0.389	0.43
C	18.3	9.1	18.9	9.2	17.78	8.9	19.27	9.3	16.84	8.3
D	49.13	30.23	48.25	28.67	49.09	29.5	52.65	32.73	50.34	29.12
E	52	21.2	49.67	18.3	50.2	17.6	46.48	15.3	45.1	14.78
F	281.5	114.2	294.5	115.7	308.9	117.2	312.4	119.9	302.1	116.3
G	62.1	20.34	70.04	28.94	64.59	23.32	76.2	32.17	68.78	21
H	31.77	26.77	36.23	32.18	27.42	24.29	40.78	37.69	35.06	31.85
I	62.79	32.47	83.49	43.54	113.2	64.93	61.93	32.78	5.18	2.79
J	36.57	28.63	34.2	26.59	43.85	32.32	37.43	28.93	52.67	41.9
K	54.27	22.24	60.9	27.83	53.48	21.02	57.23	24.58	55.21	22.76
L	322.8	189.5	318.9	183.5	304.6	178.3	295.1	167.9	334.5	190.3
M	66.07	20.73	64.23	19.43	69.87	23.84	64.2	18.92	87.56	33.45
N	187.8	31.098	196.4	38.23	163.2	29	289.3	50.47	153.8	25.66
O	19.74	2.7	28.45	3.4	30.28	3.56	21.31	2.8	27.98	3.2
P	33.45	9.8	43.27	12.34	32.91	9.3	146.7	37.48	137.8	32.31
Q	45.75	27.67	48.74	28.23	53.4	30.09	58.91	33.84	62.32	34.52
R	20.32	9.023	18.7	8.92	26.54	11.4	27.82	12.69	21.3	10.23
S	129.3	55	298.07	130	156.3	78	191.1	89	187.6	85
T	290.2	128.09	342.87	134.2	452.8	164.4	465.9	167.7	502.7	172.1

Table 2. Multi-criteria importance and weight of items

Item	ω_j^f	ω_j^t	ω_j^e	ω_j
A	0.114754	0.607748	0.810859	0.541094
B	0.180328	0.513097	0.718209	0.495311
C	0.196721	0.792373	0.883341	0.650065
D	0.081967	0.813559	0.885870	0.623006
E	0.196721	0.637006	0.873267	0.599425
F	0.360656	0.802774	0.885698	0.703308
G	0.344262	0.801453	0.880197	0.695793
H	0.47541	0.727645	0.868818	0.708444
I	0.344262	0.646489	0.804039	0.618841
J	0.016393	0.864407	0.866812	0.610965
K	0.131148	0.940678	0.887073	0.676377
L	0.032787	0.898305	0.882335	0.632262
M	0.098361	0.954802	0.876877	0.6667
N	0.311475	0.768064	0.846102	0.662303
O	0.016393	0.627119	0.833729	0.526545
P	0.04918	0.627119	0.728214	0.494175
Q	0.016393	0.694915	0.864917	0.559359
R	0.016393	0.847458	0.845867	0.597502
S	0.04918	0.220339	0.775293	0.390973
T	0.180328	0.677966	0.785387	0.571643

At this time, the minimum weighted support is set to 30%, and the weighted support priority of the weighted frequent itemset determined using our proposed method is as Table 3.

As shown in Table 3, the priority of the weighted support priority for the itemset " F, G, N, H, I"is the highest, so this is the maximum frequent itemset.

Table 3. Weighted support priority

Priority	Itemset	Number of items	Weighted support
1	F, G, N, H, I	5	67.77%
2	N, I, C, H	4	39.58%
3	F, G, N, H, K, L, E	7	38.98%
4	F, G, N, I, C, D	6	36.77%
5	F, G, N, H, I, C, A, B	8	33.83%
6	F, G, N, H, I, C	6	33.65%
7	T, H, I, E	4	33.31%
8	F, G, N, I, C, E, D	7	30.74%

For the non-empty subsets of the maximum frequent itemset $l = \{F, G, N, H, I\}$, the case where the weighted subset(S) and its weight confidence to be used for ARM is larger than the minimum weight confidence(60%) is shown in Table 4 below.

Priority	S	Weighted confidence
1	{F, G, N, I}	100%
2	{F, N, H, I}	100%
3	{G, N, H, I}	100%
4	{F, N, I}	100%
5	{G, N, I}	100%
6	{F, G, H, I}	92.31%
7	{F, G, I}	92.31%
8	{F, H, I}	92.31%
9	{G, N, H}	92.31%
10	{G, H, I}	92.31%
11	{F, G, N, H}	66.7%
12	{F, G, N}	66.7%
13	{F, N, H}	66.7%
14	{F, N}	66.7%
15	{F, G, H}	63.16%

Hence the association rules found are as Table 5.

Thus, in the case of weighted ARM based on multi-criteria importance, it shows that subsets of frequent itemsets are not necessarily used for ARM, and also that items outside of the frequent itemset can be used for ARM.

It is because the importance of items in a transactional database is different, it may or may not be a weighted frequent set of items depending on what items are associated with.

Table 5. Association rule mining result

Priority	Association rule	Weighted confidence
1	$\{F, G, N, I\} \Rightarrow \{H\}$	100%
2	$\{F, N, H, I\} \Rightarrow \{G\}$	100%
3	$\{G, N, H, I\} \Rightarrow \{F\}$	100%
4	$\{F, N, I\} \Rightarrow \{G, H\}$	100%
5	$\{G, N, I\} \Rightarrow \{F, H\}$	100%
6	$\{F, G, H, I\} \Rightarrow \{N\}$	92.31%
7	$\{F, G, I\} \Rightarrow \{N, H\}$	92.31%
8	$\{F, H, I\} \Rightarrow \{G, N\}$	92.31%
9	$\{G, N, H\} \Rightarrow \{F, I\}$	92.31%
10	$\{G, H, I\} \Rightarrow \{F, N\}$	92.31%
11	$\{F, G, N, H\} \Rightarrow \{I\}$	66.67%
12	$\{F, G, N\} \Rightarrow \{H, I\}$	66.67%
13	$\{F, N, H\} \Rightarrow \{G, I\}$	66.67%
14	$\{F, N\} \Rightarrow \{G, H, I\}$	66.67%
15	$\{F, G, H\} \Rightarrow \{N, I\}$	63.16%

CONCLUSION

In order to evaluate the effectiveness of our proposed method, we compared the number of rules discovered and the time of mining in three cases, when no weight was applied to the above transactional database, when traditional weighted ARM method ([11]) was used, and when using the proposed method. When the values of the minimum weighted support and minimum weighted confidence are different, the number of extracted rules and the time spent extracting the rules are as follows.

Table 6. Efficiency comparisonof association rule mining

minimum weighted support (%)/ minimum weighted confidence (%)		30/80	30/60	30/40	10/80	10/60	10/40
when the weight is not applied	number of rules (piece)	89	94	106	98	127	142
	extracted time(ms)	162	167	185	170	213	244
traditional weighted ARM method	number of rules (piece)	32	37	48	53	72	86
	extracted time(ms)	138	144	156	161	192	231
proposed method	number of rules (piece)	10	15	19	21	28	33
	extracted time(ms)	117	126	134	142	153	166

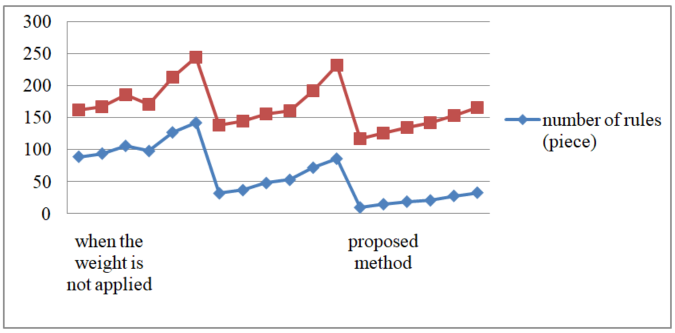

Fig. 1. Efficiency comparison of association rule mining

As shown in the experimental results, weighted ARM method based on the multi-criteria importance proposed in this paper shows that fewer rules are found and the time taken for rule mining is also shorter than the previous methods. That is, by adding weights to the items according to the multi-criteria importance evaluation index proposed in the paper, the ARM can lead to more useful rules for the purpose of ARM comparing to the previous weighted ARM method. Based on such this weight determination method, we have increased the mining efficiency of the association rules for transactional data- bases by assigning the weights that reflects the frequency of occurrence and different criteria to all items in the transactional database and using weighted items.

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