A Study on Quantitative Association Rules Mining Algorithm Based on Clustering Algorithm

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Abstract: In order to develop a data mining system for huge database mainly composed of numerical attributes, there exists necessary process to decide valid quantization of the numerical attributes. Though the clustering algorithm can provide useful information for the quantization problem, it is difficult to formulate appropriate clusters for rule extraction in terms of appropriate dimension, cluster size, and shape. In this paper, we propose a new method of quantitative association rules extraction that can quantize the attribute by applying clustering algorithm and extract rules simultaneously. From the results of numerical experiments using benchmark data, the method is found to be effective for actual applications.

Keywords Data Mining, Association Rule, Clustering, Fuzzy c-means, Quantitative Association Rule, Database.

1. Introduction
Recently, Data Mining to extract knowledge or rules from massive data sets stored in database or dataware house is studied for utilizing in various business scenes. As promising applications of Data Mining, Association Rules [1-7] have been applied to various marketing problems. The association rules mining technique is attractive and effective for actual marketing applications because valuable rules can be extracted from huge database in feasible computation time. As for the other needs like in manufacturing area, there still exist many problems to cope with the stored legacy data, such as business decision, process improvement, quality control, and so on. In such domain, it seems that conventional approach such as computer assisted data analysis technique of stored data has been still applied depending highly upon the human skill. However, the work is complicated, conservative and time consuming even for skilled engineer. Several reasons can be stated why the approach based on Data Mining methods is not applicable for such problems, one of the main reasons is that the mining system should deal with quantitative attributes appropriately in large database.

In order to deal with the quantitative attributes in mining association rules, algorithms based on the generalized association rules that handle the continuous attributes as the Boolean vector by partitioning into several intervals are proposed [1,2]. Though several methods [20] were also proposed to improve the performance such as computational time and quality of the rules, the results applying the algorithms are still time consuming and complicated to the user. Fuzzy association rules mining approaches [3-7,15-18] are proposed to overcome such disadvantages based on the fuzzy set concept. These approaches are based on the fuzzy extensions to the classical association rules mining by defining support and confidence of the fuzzy rule. Though the mining results are easy to understand by human operator, two drawbacks are still remained for applying such fuzzy approaches to the actual problems. One is the computational time for mining from database, and the other is accuracy of extracted rules. The accuracy of extracted rules depends upon defined fuzzy sets and the fineness of their partition. In existing approaches, it is assumed that the input space is divided by grid-type fuzzy partition in ad-
vance[4,5,7] or fuzzy partition based on 1-dimensional fuzzy clustering[16-18]. In other words, quantization of numerical attribute is fixed independent with extracting rules in advance. However, this assumption leads to deterioration of accuracy as well as to waste of computation time when the true fuzzy set exists just between the grids or a boundary of the partition. The problem is also well known as “boundary problem”[16][17] in quantization.

On the other hands, subspace clustering methods[12-14] are also proposed. The methods try to identify appropriate clusters of subspace effectively in large dimensional input space by combining interval partitioned inputs. Although the methods seem to meet the issue interested in this study, it is difficult to apply the methods to extract fuzzy association rules. Furthermore, the “boundary problem” will be also emerged.

In this paper, we propose a new method of quantitative association rules extraction that can quantize the attribute by applying clustering algorithm and extract rules simultaneously, in order to improve accuracy of quantization and rule expression in the association rules mining technique. We propose a naïve algorithm that conducts clustering calculations along with association rules mining iteratively, in contrast with the conventional algorithm such as subspace clustering.

The paper is organized as follows. In section 2, extraction technique of association rules from database is introduced. In section 3, quantization technique based on clustering algorithm is described. The synchronous algorithm of association rules extraction and clustering based quantization is proposed in section 4. In section 5, results of numerical experiments are described. Finally, conclusions are drawn in section 6.

2. Extraction of Association Rules from Database

2.1. Extraction of Quantitative Association Rules

Assume that the database consists of numerical attributes. Let \( X \) denote the set of numerical attributes(items) as:

\[
X = \{x_1, x_2, \ldots, x_i, \ldots, x_n\}
\]  

\( k \)th transaction data is defined as:

\[
X^k = [x_1^k, x_2^k, \ldots, x_i^k, \ldots, x_n^k]^T, \quad k = 1, 2, \ldots, m
\]  

where \( m \) is the number of transactions in the database. Since it is assumed that the database is composed of only numerical attributes for simplicity, the transaction data can be also handled with \( n \)-dimensional input vector. In order to express discovered knowledge as rule form, the item in Eq.(1) is transformed to quantized items in each attribute as:

\[
Q = \{C_{11}, C_{12}, \ldots, C_{1,f(i)}, C_{21}, C_{22}, \ldots, C_{2,f(2)}, \ldots\} \\
= \{C_{i1}, C_{i2}, \ldots, C_{i,f(i)}, \ldots, C_{n1}, C_{n2}, \ldots, C_{n,f(n)}\}
\]

where \( C_{i,f(i)} \) denotes quantized item of \( x_i \) and \( f(i) \) denotes the number of partition(fineness) of \( x_i \). This transformation is performed by interval division in the generalized association rules or by definition of fuzzy sets(fuzzy partition) in fuzzy association rules. Let \( F \) denote the itemset which consists of items in Eq.(3). Support of the itemset \( F \) is defined as:

\[
s(F) = \frac{\sum \mu_F(X^k)}{m}
\]

where \( \mu_F(X^k) \) denotes the membership value to the quantized set \( F \), i.e. multidimensional interval set or fuzzy set, calculated by the product operation(t-norm) of each membership value of each item in \( F \). From the support value, confidence of the association rule \( G \Rightarrow H \) is calculated by:

\[
c(G \Rightarrow H) = \frac{s(G \cup H)}{s(G)}
\]

where \( G \) and \( H \) are quantized itemsets. Association rule is extracted when the support value of the rule is more than pre-defined minimal support and the confidence value is more than pre-defined minimal confidence. When we apply the mining algorithm to the actual huge problems, the support calculation is critical calculation concerning with the number of queries to the database. The itemset which has the value greater than the predefined minimal support is called “frequent itemset.” One of the main problems of quantitative association rules mining is how efficiently find the “frequent itemsets” from the database.
2.2. The Apriori Algorithm

The Apriori algorithm[19] is an essential and effective algorithm for finding the frequent itemsets. The basic principle is that the frequent itemset should contain the subset itemsets of the frequent itemsets. Owing to this characteristic, frequent itemsets can be compounded from the smaller frequent itemsets one after another. Let \( k \)-itemset denote an itemset having \( k \) items. Let \( L_k \) represent the set of “frequent” \( k \)-itemsets, and \( D_k \) the set of candidate \( k \)-itemsets. The algorithm to generate the frequent itemsets is as follows:

A1) \( D_k \) is generated by joining the itemsets in \( L_{k-1} \).
A2) The itemsets in \( D_k \) which have some \((k-1)\)-subset that is not in \( L_{k-1} \) are deleted.
A3) The support of itemsets in \( D_k \) is calculated through database scan to decide \( L_k \).

After \( L_1 \) is decided first through database scan, the above A1-A3 procedures are iterated until \( L_k \) becomes empty set. The association rules are decided by calculating the confidence of the rule combining the extracted frequent itemsets in Eq.(5).

3. Quantization Based on Clustering Algorithm

3.1. Quantization for Association Rules Mining

In above described extraction of the quantitative association rule, the precision of extracted rules depends highly upon validness of quantization of numerical attributes. In traditional approach, the numerical attribute is quantized by means of definition of interval sets or fuzzy sets in general. The necessary itemsets are generated by combining the quantized items in Eq.(1) together through the mining process. In other words, multidimensional area for rule expression is formulated as the Cartesian product set of the 1-dimensional quantized sets. The clustering algorithm is effective approach for such quantization process. In this paper, fuzzy clustering algorithm (FCM) and hard clustering (HCM) are applied for the quantization in association rules mining.

3.2. Fuzzy Clustering

When the numerical attribute should be quantized by fuzzy partition, fuzzy clustering algorithm, i.e. fuzzy \( c \)-means, is effective. The regulation of the algorithm is as follows:

\[
M_f = \{(u_{ik})|u_{ik} \in [0,1], \sum_{k=1}^{(T)} u_{ik} = 1 \, \forall \, k \} \quad (6)
\]

\[
J_{fs}(U,F) = \sum_{k=1}^{(T)} \sum_{i=1}^{(q_k)} (u_{ik})^p |X_i - v|^2 \quad (7)
\]

where \( v_i \) denotes the center of \( i \)th cluster and \( u_{ik} \) denotes the membership degree to \( i \)th cluster. \( p \) denotes the parameter for the degree of fuzziness. From the equations, fuzzy clustering is fulfilled based on iterative calculation.

3.3. Hard Clustering

In Eq.(7), “hard clustering” is realized when the parameter \( p \) is set as 1.0. The process is equivalent to the \( k \)-means clustering algorithm. In the clustering, each data belongs only to a certain cluster(crisp partition). The quantization is expressed as the interval value.

4. A Simultaneous Algorithm of Association Rules Extraction and Clustering Based Quantization

4.1. Basic Concepts

Though the clustering algorithm is effective for quantization of numerical attribute selected from massive database that the data mining technique deals with, appropriate items should be selected for proper representation of “area” in \( n \)-dimensional space for the association rule. It is not applicable manner to calculate every combination of items(attributes) for quantization by clustering. This issue is similar to the extraction of frequent itemsets in Association Rules mining. Instead of using the whole Cartesian product for multidimensional rule expression as described above, our idea is to use the clusters of arbitrary multi-dimensional subspace for quantization.

Let \( T \) denote whole set of itemsets for clustering as:

\[
T = 2^X - \phi = \{\{x_1\}, \{x_2\}, \ldots, \{x_n\} \} \cup \{\{x_1, x_2\}, \ldots, \{x_1, x_2, \ldots, x_n\}\}
\]

\[
= \{q_i|i=1,\ldots,2^n-1\}
\]

(8)

where \( 2^X \) denotes the power set of \( X \), i.e. set of all subsets, \( \phi \) is the empty set, and \( q_i \) denotes the itemset in \( T \). From Eq.(8), the quantization is performed using clustering algorithm with \( q_i \) as the
input variables. Then the quantized cluster is defined as follows:

\[
Q = \left\{ C_{q_i,1}, C_{q_i,2}, \ldots, C_{q_i,1}\cdot f(q_i), C_{q_i,2}, \ldots, C_{q_i,1}\cdot f(q_i) \cdot \ldots \right\}
\]

(9)

where \( f(q_i) \) denotes the number of clusters calculated with input data represented as itemset \( q_i \). For example, cluster set \( \{C_{q_i,1}, C_{q_i,2}, C_{q_i,1}\cdot f(q_i)\} \) is generated by 2-dimensional clustering calculation with inputs \( \{x_1, x_3\} \) corresponding to the itemset \( q_i = \{x_1, x_3\} \) when \( f(q_i) \) is 3. It is obvious that all clusters based on the itemsets(combination of input variables) in Eq.(9) cannot be calculated practically in actual huge database because of its combinatorial explosion.

Our idea is to generate the clusters of appropriate dimension in turn through the mining process. We propose a naïve simultaneous algorithm of association rule extraction and clustering based quantization. Figure 1 shows the conceptual diagram of the algorithm. For reducing the database scan, \( q_i \) is generated in tern like the apriori algorithm.

### 4.2. Algorithm

Let us define that a cluster is the “frequent cluster” when \( C \) in Eq.(9) satisfies the support restriction. It is also defined that an itemset \( q_i \) is “frequent itemset” when some frequent \( w \)th cluster \( C_{q_i,w} \) exist. The flowchart of the algorithm is shown in Fig.2. First, “Candidate 1-Itemsets” is set as \( \{\{x_1\}, \{x_2\}, \ldots, \{x_n\}\} \). Then “1-dimensional clustering” procedures using the clustering algorithm are employed based on the input variable corresponding to the “Candidate 1-Itemset”. The frequent 1-dimensional clusters are selected based on the support restriction. Then “Frequent 1-Itemsets” are selected when there exist some frequent clusters in “Frequent 1-dimensional clusters” of the itemset. For example, 1-Itemset \( q_{i} = \{x_1\} \) is frequent when there exist frequent cluster \( C_{q_i,1} \) in “Frequent 1-dimensional clusters” of itemset \( q_i \). “Candidate 2-Itemsets” are generated by joining the itemsets in “Frequent 1-Itemsets”. 2-dimensional process is employed in the same manner. These procedures are iterated until “Frequent n-Itemsets” becomes empty set. It should be noted that an anti-monotone behavior of the support values of the clusters is not guaranteed strictly in this algorithm, in contrast to the Apriori algorithm. However, it is empirically expected that appropriate itemsets and clusters can be decided through the algorithm.

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**Fig.1. Conceptual Diagram of Proposed Algorithm**

**Fig. 2. Flowchart of Proposed Algorithm**

In the clustering procedure in the algorithm, the number of clusters should be decided appropriately. In order to save the computation, the numbers of clusters might be fixed reasonably in advance. In
this study, threshold of the proportion of variance explained by the clusters is adopted as the necessary parameter. The number of clusters is decided as minimum number of clusters over the threshold value. For applying the number decision, several iterations are needed in each clustering process.

As shown in the figures, the quantization and the rule extraction are performed simultaneously. It is expected that the quantization and the extraction can be fulfilled in reduced computation time avoiding combinatorial explosion neatly.

5. Numerical Experiments

5.1. Classification Problem

We develop a mining system based on the proposed algorithm and evaluate the performance through numerical experiments. In order to evaluate the precision of extracted rules, we apply the system to the classification problems such as “Iris”[9], “Wine”[9], “Liver”[10], and “Diabetes”[11]. Table 1 shows the parameter settings for numerical experiments. In Table 1, “Decision coefficient” denotes the threshold parameter for decision of the number of clusters.

Let \( W = \{e_1, e_2, ..., e_p\} \) denote class(output) set where \( p \) is the number of classes. The extracted \( i \)th rule by the mining algorithm is expressed as:

\[
R^i: IF \ X^* \ belongs \ to \ C_i, \ THEN \ class \ is \ E_i \ with \ CV_i, \ E_i \in W
\]

where \( X^* \) is the input vector, \( C_i \) denotes the cluster of \( i \)th rule, \( CV_i \) denotes the confidence value of the \( i \)th rule decided by the mining algorithm in extraction, and \( E_i \) denotes the class of \( i \)th rule. Association rules are extracted corresponding to the classification class of the data. From the rules extracted as Eq.(10), the performance of classification is investigated. In order to evaluate the extracted rules, a proper reasoning method should be defined. In this study, the reasoning output is calculated by the following two manners as:

\[
E^* = E_{cl}, \ cl = \arg \max_k (u_k(X) \cdot CV_k)
\]

(11)

\[
E^* = e_{cl}, \ cl = \arg \max_k \left( \sum_j u_j(X) \cdot CV_j \right)
\]

(12)

where \( u_k() \) denotes the membership value of the \( k \)th rule, \( E^* \) is the output class, and \( N(e_k) \) denotes the set of rule numbers that consequent part is class \( e_k \). Eq.(11) corresponds to the output decision using the rule of maximum membership value. Eq.(12) corresponds to the output decision applying aggregation of the rules. These two different reasoning manners are used for evaluation in the numerical experiments.

5.2. Evaluation Results of Association Rules Extraction

The performance of the proposed algorithm is compared with the conventional method described in Section 2 through the experiments. In the conventional algorithm, quantization of each attribute is performed using 1-dimensional clustering calculation, first. After that, association rules mining is fulfilled based on combination(Cartesian product) of the 1-dimensional quantization. This is also equivalent to use the subspace clustering and association rule extraction. Figures 3-6 show the number of itemsets (clusters) through mining process. Where “Proposed_C” stands for the number of candidate clusters, “Proposed_F” stands for the number of frequent clusters in the proposed algorithm, “Conventional_C” the number of candidate itemsets, and “Conventional_F” stands for the number of frequent itemsets in the conventional method.

<table>
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<tr>
<th></th>
<th>Iris</th>
<th>Wine</th>
<th>Liver</th>
<th>Diabetes</th>
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<tbody>
<tr>
<td>The Minimal Support [%]</td>
<td>15</td>
<td>15</td>
<td>3</td>
<td>15</td>
</tr>
<tr>
<td>The Minimal Confidence [%]</td>
<td>75</td>
<td>75</td>
<td>70</td>
<td>75</td>
</tr>
<tr>
<td>Decision Coefficient</td>
<td>0.85</td>
<td>0.85</td>
<td>0.70</td>
<td>0.85</td>
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</table>

Table 1. Parameter Settings for Mining
Fig. 3. The number of candidate itemsets and frequent itemsets (Iris)

Fig. 4. The number of candidate itemsets and frequent itemsets (Wine)

Fig. 5. The number of candidate itemsets and frequent itemsets (Liver)

Fig. 6. The number of candidate itemsets and frequent itemsets (Diabetes)
From these results, the number of database scan and the number of clustering procedures can be restrained to applicable level by the proposed algorithm. The redundant candidates are drastically reduced by the proposed algorithm compared with the conventional algorithm. It is noted that the database scan is desirable to be reduced as the database scan is the most time consuming task in the association rules mining using Apriori algorithm. The computational performance of the proposed algorithm could be expected to lead the reduction of the database scan in huge problems.

Tables 2-5 show the classification results compared with the conventional method. Where “Maximum Rule” stands for using Eq.(11) as the output reasoning, “Majority Rule” stands for using Eq.(12) as the output reasoning, “with Revision” denotes using CV as it is, and “without Revision” denotes using CV as 1.0. The classification performance by the proposed algorithm is improved for almost benchmark databases, especially using “Majority Rule”. The results show that the accuracy of extracted rules tends to be improved respectively by the proposed algorithm, though they have some variations depending on the objective data. From the results of representative performance of each benchmark data, quality of the association rule is improved by the proposed construction of the mining algorithm. As for clustering algorithms(HCM, FCM), it cannot be said that there exists obvious biased difference between both algorithms. Moreover, in many cases, effects of confidence value of the extracted association rules (CV) are also confirmed.

In order to compare the proposed algorithm with traditional clustering and classification approach, we performed clustering using all attributes at the same time in advance and extracted the rules from the clusters in the view point of “association”. For keeping the same classification performance with our proposed method, the parameter settings are needed as shown in Table 6. The numbers of extracted rules are shown in Table 7. The number of rules(Clusters) by the traditional clustering and classification approach is bigger than the data mining approach except for the “Diabetes”. The number of rules extracted by the proposed algorithm is relatively small especially in “Wine” that includes 13 dimensional inputs, i.e. more inputs compared with the other benchmark data. This characteristic of association rules mining by the proposed algorithm is indispensable for actual huge database applications.

<table>
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<tr>
<th>Table 2. Evaluation Results (Iris)</th>
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<tr>
<td>Maximum Rule</td>
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<tr>
<td>Without Revision</td>
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<tr>
<td>Proposed FCM [%]</td>
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<tr>
<td>Conventional FCM [%]</td>
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<tr>
<td>Proposed HCM [%]</td>
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<td>Conventional HCM [%]</td>
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<th>Table 3. Evaluation Results (Wine)</th>
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<tr>
<td>Maximum Rule</td>
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<tr>
<td>Without Revision</td>
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<tr>
<td>Proposed FCM [%]</td>
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<td>Conventional FCM [%]</td>
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<td>Proposed HCM [%]</td>
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<td>Conventional HCM [%]</td>
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<th>Table 4. Evaluation Results (Liver)</th>
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<td>Maximum Rule</td>
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<td>Without Revision</td>
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<td>Proposed FCM [%]</td>
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<td>Conventional FCM [%]</td>
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<td>Proposed HCM [%]</td>
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<td>Conventional HCM [%]</td>
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<th>Table 5. Evaluation Results (Diabetes)</th>
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<tr>
<td>Maximum Rule</td>
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<td>Without Revision</td>
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<td>Proposed FCM [%]</td>
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<td>Conventional FCM [%]</td>
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<td>Proposed HCM [%]</td>
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<td>Conventional HCM [%]</td>
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<th>Table 6. Parameter Settings for Whole Clustering</th>
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<tr>
<td>Iris</td>
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<tr>
<td>The Number of Clusters</td>
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<tr>
<td>The Minimal Support [%]</td>
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<tr>
<td>The Minimal Confidence [%]</td>
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<th>Table 7. Comparison of the Number of Rules</th>
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<td>Whole Clustering</td>
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<td>Conventional Mining</td>
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<tr>
<td>Proposed Mining</td>
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Through the numerical experiments, it is confirmed that the proposed algorithms extracting association rules with clustering based quantization outperform the conventional algorithm based on Cartesian product type quantization such as general- ized association rules mining and fuzzy association rules mining, in terms of total precision of quantization and rule extraction. Furthermore anti-monotone characteristic of the itemset(cluster) support value in the proposed algorithm is empirically confirmed through numerical experiments, because the number of DB scans, which is equivalent to the number of itemset dimensions, is neither increased nor decreased compared with the conventional algorithm. The proposed algorithms are significant for application of tasks that need to quantize the numerical attributes and to extract association rules simultaneously from huge database. However, the difference caused by the clustering algorithms, i.e. fuzzy clustering and hard clustering, could not be observed clearly. In [16,17], the similar numerical comparisons for “fuzzy quantization versus crisp quantization” were conducted utilizing the conventional mining algorithm based on Cartesian product type quantization and showed that extracted rules were different substantially. Comparative study about precision of extracted rules was not performed in [17]. In this study, though we cannot confirm the difference between precisions corresponding to the clustering algorithm, we can suppose that the extracted rules are different from the results of the numerical experiments. Since the classification system is to attain appropriate crisp partition corresponding to the classes in the input space, it can be considered that the merit of fuzzy quantization tends not to be embodied clearly. Moreover, we might need to improve evaluation manner, e.g. using pruned rules, instead of utilizing the whole extracted rules as in this study.

Two issues are still remained in order to apply the proposed algorithm. One is computational efficiency of the algorithm. Though it is significant in terms of rule precision, computational time is increased because of performing clustering based quantization corresponding to each itemset, compared with the conventional algorithms based on Cartesian product type quantization. In order to apply the proposed algorithm to actual application, we consider that some techniques are necessary to reduce the computational time. For example, the technique that deals with quantization of low dimensional itemset by Cartesian product type quantization and high dimensional itemset by clustering, will be effective. The other issue is evaluation in applying the proposed algorithm to the other types of problem than classification. In order to apply the proposed algorithm to the problem such as original association rules mining, minor modification and extension are considered to be needed. For such objective, we consider that the concept of output field specification[7] will be effective.

6. Conclusions

In this paper, we proposed a new algorithm of quantitative association rules extraction that could quantize the attribute by applying clustering algorithm and extract rules simultaneously in the mining procedure. From the results of numerical experiments using benchmark data, the method was found to be promising for actual applications. The computation performance of mining algorithm is important for actual application. Our method was confirmed to satisfy the requirement through numerical experiments. Furthermore precision of extracted rules was improved totally, though quality of the extracted rules depends on the distribution of the datasets to some degree. In order to verify the approach more definitely, we plan to apply the method to the actual huge problems in future.

References


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