Multidimensional Multi-Granularity Data Mining for Healthcare Service Management

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ABSTRACT: *Data Mining is getting increasingly important for discovering association patterns for health service innovation and Customer Relationship Management (CRM) etc. Yet, there are deficits of existing data mining techniques. Since most of them perform a plain mining based on predefined schemata through the data warehouse as a whole, a re-scan must be done whenever new attributes are added. Secondly, an association rule may be true on a certain granularity but fail on a smaller one and vise verse. Last but not least, they are usually designed to find either frequent or infrequent rules.*

After a survey of a category of significant health services, we propose a data mining algorithm alone with a forest data structure to solve aforementioned weaknesses at the same time. At first, we construct a forest structure of concept taxonomies that can be used for representing the knowledge space. On top of it, the data mining is developed as a compound process to find the large-itemsets, to generate, to update and to output association rules that can represent services portfolio. After a set of benchmarks derived to measure the performance of data mining algorithms, we present the performance with respect to efficiency, scalability, information loss, etc. The results show that the proposed approach is better than existing methods with regard to the level of efficiency and effectiveness.

Keywords: Multidimensional Data Mining, Healthcare Services, Customer Relationship Management (CRM), Association Pattern, Granular Computing

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1. Introduction

In the era of information economy, markets offer more variances of services and customers become demanding on more intensive information and better quality of services. While the term of Service Innovation becomes a focus in the scientific and business communities, data mining turns out to be increasingly important for knowledge discovery of innovative services. As a whole, the conventional process of mass-marketing is being replaced by the customer-oriented view. As the second reason for seeking new way of services, healthcare institutions in many countries are facing a tail-off of healthcare assurance payments. Healthcare institutions need thus to target patients with new portfolios of service variances.

Under this condition, hospitals like to provide various new services such as prevention methods with education on patient with changing habits to prevent chronic illness and disease, treatment and physical check-up periodically to assist patients to improve their health quality. Moreover, hospitals like to improve their performance and to offer better quality of services. New tools and approaches such as CRM via data mining are needed to address this change.

Using association rules, we figure out simple yet useful insights on services [5, 13, 17]. Significant examples are finding new therapies and drugs for cancer cure as well as new portfolios of rationale services. For instance, "52% *of the patients those take therapy X also take treatment Y*". With such association rules, we can reduce the costs of the therapy *X*, and raise the service level of the treatment *Y* to make more benefits.

However, most conventional data mining approaches only perform a plane scan over the databank based on a predefined schema for searching. Questions often arise such as: Should there be any other influencing factor like W for treatment Y taken into account? Since most association rules apply in a context of certain breadth, the knowledge usually exists in multidimensional insides [5]. In the in the meantime, adding attributes to the databank is meant to change the schema and lead to a full re-scan that consumes extra time.

The second problem of the conventional mining approaches lies in the assumption that the rules derived should be effective throughout a database as a whole. Nevertheless, this obviously is not true for real-life cases [5]. Different association rules can be found in different segments of the database. If the mining tool deals only with the database as a whole, meaningful rules that are partially true may be ignored.

The goal of this research is to invent an approach with novel data structure and efficient multi-dimensional data mining algorithm for association patterns in various granularities. The crucial issue here lies on a more efficient and accurate multidimensional mining approach to explore association patterns on different granularities. Last but not least, the data mining approach has to be very flexible and robust.

2. Baseline of the Researh

2.1 Data Mining for healthcare services

Data mining technology can contribute to hospitals with more understanding of patients' illness status and to improve quality of service (QoS). Hospitals use databases of patient's records, physical check-up, pathology etc. to analyze patients' status with aids of data mining and knowledge management. Based on the findings of above activities, hospitals can then select different type of patient categories for different prevention, treatment services. Regarding data mining technology, they are now exploring five constructs for better service such as patient segmentations with respect to different type of service, different insurance reimbursement for varies type of patient, chronic illness, self-pay treatment and physical check-up services. Significant service categories can be summarized as follow:

2.1.1 Patient segmentations on different type of service

By analyzing different types of patient illness, hospitals can provide various services for patients with their customization of treatment service, education, and wellness maintenance. Hospital notify patient to return back to the hospital for planning the best services for patient treatment.

2.1.2 Different insurance reimbursement for varies type of patients

Hospital will analyze patients' insurance types of reimbursement, and also applies data mining to provide appropriate service to earn the maximum reimbursement. Furthermore, hospital will classify the contributions of different patient types to provide the best services to attract the higher level of patients to generate more revenue.

2.1.3 Chronic illness

Hospital will analyze the patient's check-up results to define and predict different chronic illness types as well as different services for patients. Furthermore, hospital will notify patient back to hospital for routine check-up and treatments.

2.1.4 Self- pay services

Hospital is capable of mining the patients' needs for self-pay services such as tumor/ cancer MRI check-up, skin disease for skin beauty treatments, hypertension for brain stoke check-up, cardiac disease for VCT cardiac service etc.

2.1.5 Physical check up patient services

Hospital applies data mining to retrieve patient illness status to notify patient for physical check up.

2.2 Finding Association Rules

T_ID	Transaction content
001	Diagnosis-2, Therapy1.
002	Check-up-N, Therapy1.
003	MRI-Check, Diagnosis-3, Treatment-3
004	Check-up-N, Therapy1

Table 1. An Example of Transaction Database

T_ID	Date	POS_No	Occupation	Sex	Age	Transaction content
001	05/03/01	003	Student	F	23	Diagnosis-2,Therapy1.
002	05/03/01	003	Student	M	14	Check-up-1, Diagnosis-2
003	05/03/01	003	Manager	M	47	MRI-Check, Diagnosis-3,Treatment-3
004	05/03/01	003	Teacher	F	34	Check-up-N,Therapy1

Table 2. An Example of Multidimensional Transaction Database

We are used to storing data in the transaction database containing simple items identified by the Transaction IDs (TID) as in Table I. Let $I = \{i1, i2, .., in\}$ be the set of all n different items in D, each transaction in D is a subset of I. An itemset is defined as a subset of I. [4, 13, 17].

Rather than in an uni-dimensional transaction database, services and related information on customers are usually gathered in a relational database or data warehouse. Apart from keeping track of the item fed, a relational database may record other attributes associated with the transactions, and another table to record profile of patients, viz. a fact table. After joining several relational tables, a big data table can be obtained to store not only the items saved in the transaction [13, 17], but also 5W1H information corresponding to the transactions as Zachman Framework intends [4]. Table 2 illustrates an example of multidimensional transaction database MD, assuming each attribute is a dimension.

There are two important factors for association rules, viz. support, and confidence [13, 17]. Support means how often the rule applies, i.e. repeatability; Confidence means how often the rule is true, i.e. reliability [4]. Suppose we have a database MD as in Table 2, the support of an itemset X is the fraction of transactions containing X in MD. The confidence of $A \rightarrow B$ is the fraction of transactions containing A and B, and simultaneously also in transactions containing A. The formulas for support and confidence are as follows:

$$Support\ (X) = \frac{|\ Transactions\ in\ containing\ X\ |}{|Transactions\ in\ D\ |} \tag{1}$$

$$Confidence\ (A \div B) = \frac{|\ Transactions\ in\ D\ containing\ both\ A\ and\ B|}{|\ Transactions\ in\ D\ containing\ A|} \tag{2}$$

Given a set of transaction MD and a threshold ó as minimum support, X is a large itemset in MD if the support of X in MD exceeds ó [13, 17]. The task for discovering association rules is to generate all association rules that own support and confidence greater than the user-specified minimum support (called minSup) and minimum confidence (called minConf) respectively [4, 12, 13, 17].

We are more likely to find association rules with high support and confidence, viz. frequent rules. Recently, the importance of vital few association rules is perceived, viz. infrequent rules [4].

2.3 Multidimensional Data Mining

Finding association rules involving various attributes efficiently is an important subject for data mining. Association Rule

Clustering System (ARCS) was proposed in [], where association rule clustering is proposed for a 2-dimensional space. The restriction of ARCS is that it generates one rule in once of clustering. Hence, it takes massive redundant scans to find all rules.

The method proposed in [16] mines all large itemsets at first and then use a directed graph to assign attributes according the user given priorities of each attribute. Since the method is meant to discover the large itemsets over a database as the whole, it may loss some rules that hold only in specific segments of the database. Different priorities of the condition attributes will induce different rules so that user may need to try with all possible priorities to discover all possible rules.

2.4 Apriori Algorithm

2.4.1 Apriori Algorithm

The Apriori algorithm is a level-wise iterative search algorithm for mining frequent itemsets w.r.t association rules [1, 3, 5, 7, 13, 14, 17]. The key drawback of the Apriori algorithm is that it requires k passes of database scans when the cardinality of the longest frequent itemsets is k. In addition, the algorithm is computation intensive in generating the candidate itemsets and computing the support values, especially for applications with very low support threshold and/or vast amount of items. In this algorithm, if the number of first itemsets element is k, the database will be scanned k times at least. So, it is not efficient enough. The key point for improving the algorithm is to reduce the number of itemsets.

2.4.2 AprioriTID Algorithm [9]

The AprioriTID is a variant of the aforementioned Apriori algorithm which reduces the time needed for the frequency counting procedure by replacing every transaction in the database by the set of candidate sets that occur in that transaction [9]. This is done by iterating each candidate sets repeatedly.

While the AprioriTID algorithm is much faster in later iterations, it is much slower than original Apriori in early iterations. This is mainly due to the additional overhead that is created when the adapted transaction database Ck does not fit into main memory and has to be written into disk [4]. If a transaction does not contain any candidate k-sets, then Ck will not have an entry for the transaction. Hence, the number of entries in Ck may be smaller than the number of transactions in the database, especially at later iterations of the algorithm. Other drawbacks of ApririTID are that the database modified by Apriori-Gen can be much larger than the initial database and only faster in the later stages of the scans.

2.5 Concept Description and Knowledge Taxonomy

The issues of data structures and concept description models for data mining when comparing works dealing with algorithms are less discussed till. The concept description task is problematic, since the term "concept description" is used in quite different ways in related discussions. In this situation, researchers argue for a de facto standard definition for the concept description [8, 18]. At this beginning stage, it is easier to deal with common criterion on higher abstraction level for the concept description, such as comprehension [8] and compatibility [4].

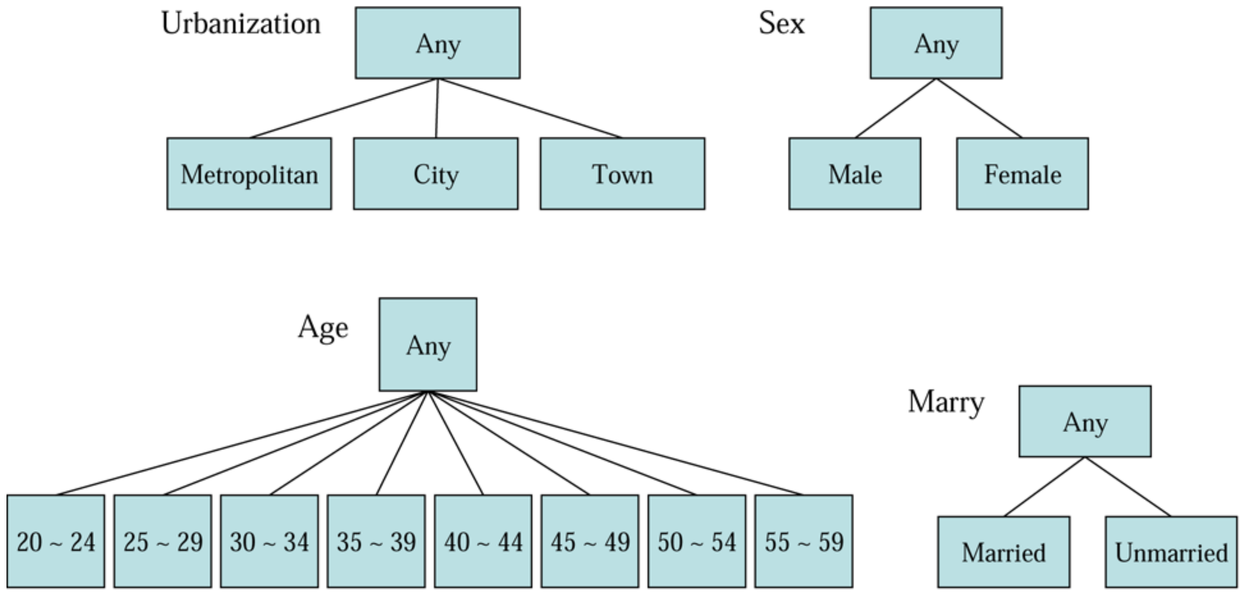
Researchers view concept description as a form of data generalization and define the concept description as a task that generates descriptions for the characterization and comparison of the data [8]. Similar concept appears in the development of ontology for Semantic Web/GRID. Semantic Web can be described as an extension of the existing Web where information is considered with priori well-defined meaning, enabling computer and people to work in cooperation centric to Internet [11]. The objective of such techniques is to enhance ill-structured content so that it can be interpreted universally by machines or humans.

In practical applications, ontology provides a vocabulary for specific domains and defines the meaning of the terms and relationships between them. In this article, ontology refers to the shared understanding (comprehension) of domains of interests which is often conceived as a set of concepts, relations, axioms etc. Hence, the term "*Taxonomy*" is hereby similar to "*Ontology*" and both terms can be used to denote the classification or categorization of concepts that describe entities and relations among them. This article applies the term Taxonomy rather than Ontology because the former is more flexible and even can cover the case with no semantic meaning.

3. Methodology

3.1 Representation schema and data structure

For the sakes of comprehension and compatibility, we use the forest structure consisting of Concept-Taxonomies to represent



Pattern such as [Urban = Taipei, Sex = Male, Age = 40-50, Married]

Figure 1. An Example for Forest of Concept Taxonomies

the overall searching space, i.e. the set of all the propositions of the concepts. On top of this structure, the sets of association patterns can be formed by selecting concepts from individual taxonomies. The notions can be clarified with examples as follows:

3.1.1 Taxonomy

A category consists of domain concepts in a latticed hierarchical structure, while each member per se can be in turn taxonomy. An Example for customer's characteristics can be [Age, Sex, Occupation,.], while for instance the taxonomy of occupation can [manager, labor, teacher, Engineer,...].

3.1.2 Forest of concept taxonomies

A hyper-graph for representing the universe of discourse or the closed-world of interests is built with taxonomies under consideration. An example of forest of taxonomies with respect to the location and Sex of customers is shown in Figure 2 below:

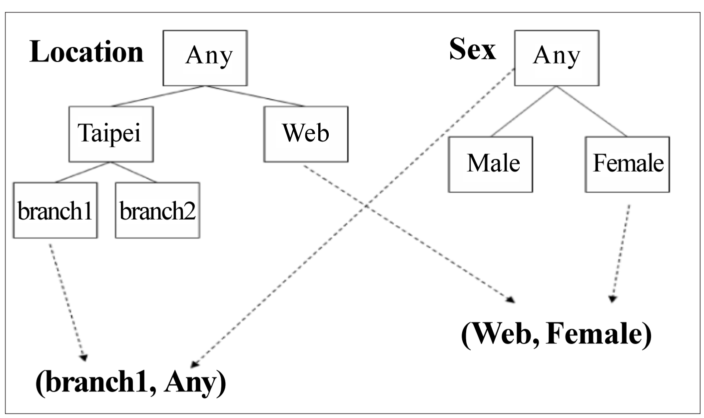


Figure 2. Examples of Forest Concept Taxonomies

3.1.3 Association Rule

An association rule typically refers to a portfolio's pattern which consists of elements taken from various concept taxonomies such as [(Address = TPE), (Sex=female), (Cares = VCT & CDG)]. It owns support and confidence greater than the user-specified minSup and minConf respectively [4].

By the proposed multidimensional data mining of association rules, the notion of relation will be implemented by the belonging relationship between elementary patterns and generalized patterns rather than the semantics [4]. Other notations to be used in the following text are shown in Table 3 below:.

Notation	Meaning
CT	Concept Taxonomy
Ei.	The *i*-th element segment
$T\,[Ei]$	an element segment over *Ei* in *MD*
Gi	The *j*-th generalized pattern
$T\,[Gj]$	The *j*-th combined segment over *G*
RE i	Rules w.r.t the *i*-th element segment
R*Gj*	Rules w.r.t the *j*-th generalized pattern
$(Gj\,, r)$	association rules over *Gj* w.r.t to match ratio *r*

Table 3. Concepts and Notations

3.2 The Multidimensional Multi-granularity data mining algorithm

```
Input:
    Multidimensional Transaction Database MD
    Concept taxonomies for each dimension: CT × (X = 1–n)
    User given threshold: minSup, minConf, match ratio m
Procedure:
    Phase ():
        to generate all Ei and Gj by CT  (x = 1 to n);
        bulid the pattern table;
    Phase 1:
        For all Ei ⊂ G
            to discover all association rules r in T⌈Ei⌉ as R_Ei
    Phase 2:
        for all Ei
            for all Gj that Ei ⊂ Gj
                to update R_Gj using R_Ei;
    Phase 3:
        for all Gj
            For all r (which satisfy m) in R_Gj
                output (Gj, r);
Output:
all multidimensional association rules ( p, r)
```

Figure 3. Outline of the proposed algorithm

The proposed data mining process can be formulated essentially with two cascading steps: (1) finding all itemsets in each elementary segment and (2) updating all combinations of the segments by the output of Phase 0. For the practical reason, the algorithm in Phase 0 can be replaced by any tool available elsewhere such as the Apriori algorithm so that an easy realization the phase 0 and then a segregation of the two steps enable the flexible mining on a distributed environment like Cloud and Grid. Figure 3 shows outline of the proposed algorithm extending the mining process into four phases.

Outline of the proposed algorithm is shown in Figure 3. The input of the mining process involves 5 entities, namely (1) a multidimensional transaction database MD which is optional when a default MD is assigned, (2) a set of concept taxonomies for each dimension (CTs), (3) a minimal support, viz. minSup, (4) a minimal confidence, viz. minConf, and (5) a match ratio m for the relaxed match. The output of the algorithm encompasses all multi-dimensional associations with respect to the fully-relaxed match within the MD. The last three settings can help with finding frequent or infrequent rules.

The most significant feature of the algorithm is it's capablity to discover both frequent and infrequent associations rules R_{Ei} (based on different levels of granularities) in the element segment $T[Ei]$ for each element pattern Ei. After it, R_{Ei} is used to update R_{Gj}, i.e. the set of association patterns for every generalized pattern Gj which includes Ei. The heuristic regarding each element pattern is to find the large-itemsets per se and acknowledge its super generalized patterns with the result. The task of each generalized pattern is to decide which rules hold within it, according to the acknowledgements from the element patterns. The mining procedure needs only to work on each element segment to determine which rules hold in the compound segments. Thus, it is not necessary to scan all of the potential segments for finding the rules.

3.3 Pattern Generation and the Pattern Table

Being a pre-processing mechanism, the algorithm generates at first all elementary and generalized patterns with the given forest, where a pattern table for recording the belonging relationship between the elementary and generalized patterns is built. Given a set of concept taxonomies, a multi-dimensional pattern can be generated by choosing a node from each of the taxonomy. The compound of different choices represents all the multidimensional patterns.

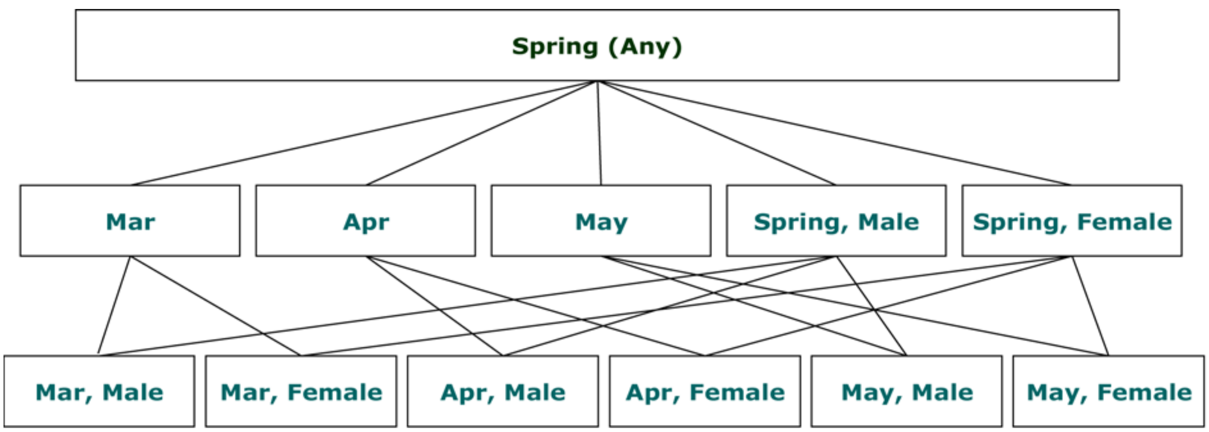


Figure 4. Belonging relationships between patterns

	(Mar)	(Apr)	(May)	(Spring, Male)	(Spring, Female)	(Spring)
(Mar, Male)	1	0	0	1	0	1
(Mar, Female)	1	0	0	0	1	1
(Apr, Male)	0	1	0	1	0	1
(Apr, Female)	0	1	0	0	1	1
(May, Male)	0	0	1	1	0	1
(May, Female)	0	0	1	0	1	1

Figure 5. The pattern table (for the relations in Figure 4)

Figure 4 shows an example of the belonging relationship between 12 patterns in a lattice structure. The relationships are recorded in the form of bit map as shown in Figure 5 which includes element patterns and generalized patterns. In the table, a "1" indicates that the element pattern belongs to the corresponding generalized pattern and "0" indicates the case vice versa.

3.4 Update process

After all patterns and the pattern table have been generated, the procedure reads the transactions of each element segment and then discovers all the association rules. The output of this phase is all R_{Ei} for each element pattern Ei that will be fed as the input to the next phase for updating each R_{Gj} using R_{Ei}. For a full match illustrated in Figure 6, the update is done by intersection of the set R_{Gj} and the set R_{Ei}, where Ei belongs to Gj , let $R_{Gj} = R_{Ei}$ if R_{Gj} is updated for the first time. After all the intersections, the association pattern r left in R_{Gj} holds in all element segments covered by $T[Gj]$.

```
for all R_Ei
    for all G_j ⊃ E_i
        if (R_Gj never be updated)
            R_Gj = R_Ei;
        else
            R_Gj = R_Gj ∩ R_Ei
```

Figure 6. The "*Update*" algorithm with full match

```
for all R_Ei
    for all G_j ⊃ E_i
        for all r in R_Ei
        if (r ∉ R_Gj)
            add r to R_Gj;
            R_Gj. r. count = 1;
        else
            R_Gj. r. count++;
```

Figure 7. The "*Update*" procedure for relaxed match

For the relaxed match as shown in Figure 7, a counter for each rule in R_{Gj} is set. While using R_{Ei} for updating R_{Gj}, the counters of both R_{Gj} and R_{Ei} are incremented by one and the rules, those appear in R_{Ei} but not in R_{Gj}, will be added to R_{Gj} while setting the counter to one. After all the update process, the association rule r in R_{Gj} whose counts exceed $m|T[Gj]|$ holds in at least m *100% of the element segments $T[E_i]$ that are covered by $T[Gj]$, and thus (Gj, r) is a multidimensional association rule for the relaxed match in MD.

3.5 The Output Function

For a full match, the algorithm outputs all the (Gj, r) pairs for every r left in each v. For a relaxed match, it outputs all the (Gj, r) pair for every r in each R_{Gj} where the count exceed $|m\, T[Gj]\,|$. By means of this approach, loss of finding the rules that only hold in some segments can be prevented. And, pickup of multidimensional association rules that do not hold over all the range of the domain can also be avoided. For example, the full match can guarantee that the corresponding rules, those hold only in two months of spring but fail in the rest one, will never be counted as an association rules with respect to whole spring.

3.6 The Breakthroughs for Incremental Data Mining

A breakthrough hereby is that the incremental data mining can be realized with the proposed approach. By keeping out the rules deduced in each element segment, we only need to search the new data. That is, using the proposed approach, we can produce the new association rules by combining the rules discovered from the new data with existing rules to reduce redundant scan on the old data. The following section will present our experimentation results.

3.7 Design of metrics for measuring data mining

In order to assure the performance, we need to design metrics for measuring the mining performance, at least to measure whether it is better than the prior algorithms. By cascade evaluating the results of a hypothetical measurement, we can evaluate the consequence from any sequence of measurements to determine the optimal next measure. For this reason, a one-step look-ahead strategy based on Shannon's Entropy Function is adopted and the capacity of ICT systems can be described in the following form [4, 15]:

$$C = B * [\log 2\ (1 + S/N)] \quad (3)$$

where B is the bandwidth, (S/N) is Signal-to-Noise(S/N) ratio.

Drawing on this equation, the function for the performance of data mining can be formulated as follow:

$C = |D|$ [log2 (1 + information lost ratio)], where $|D|$ is the number of transactions in whole transaction database [4].

While $WSEi$ denotes each element segment in the measure, the $WSEi$ of an element segment $T[Ei]$ can be generated by a uniform distribution between 0 and SM. Suppose there are N element segments, the number of transactions in the element segment $T[Ei]$ is:

$$|D_{Ei}| = \frac{|D|}{\sum_{a \to 0}^{n} WS_{Ea}} WS_{Ei} \quad (4)$$

Thereafter, the definitions of information loss are:

$$discrete\ ratio = \frac{|\{r \mid r\ holds\ in\ T[Gj] < Gj, r > doesn't\ hold\ in\ MD\}|}{|\{r \mid r\ holds\ in\ T[Gj]\}|} \quad (5)$$

Definition 1: discrete ratio is the ratio of the number of rules pruned by the improved algorithm to the number of rules discovered by prior mining approaches.

$$lost\ ratio = \frac{|\{< Gj, r >\}| < Gj, r > holds\ in\ MD\ r\ doesn't\ hold\ in\ T[Gj]\}|}{|\{< Gj, r >\}| < Gj, r > holds\ in\ MD\}|} \quad (6)$$

Definition 2: lost ratio is the ratio of the number of rules discovered by the improved algorithm but lost in the previous mining approaches to the number of rules discovered by the improved algorithm.

4. Experiment and Evaluation

4.1 Experiment scenario on a case of hospital

A scenario for a medical center and related data were established to evaluate the performance of the proposed approach. The center contains various departments and a web-site for e-services. The test bench is implemented with Java on a PC Server with an AMD processor and the data mining software is implemented with Java.

Data from different departments of the medical center and the website are gathered for the experiment (ref. Figure 1). There are various attributes in the database of patients' records that may influence the healthcare behaviors. We take five of them, *viz*. (Address, Sex, Occupation, Age, Marriage) as the dimensions for the test. Adding with the therapy/service catalog and the cost records, there are 7 dimensions, *i.e.* 7 concept-taxonomies for each dimension.

4.2 Experiment Data

The medial center provided basic patterns resulted from their mining tool and ca. 50K basic data. We then generated with Apriori-Generator three types of synthetic data sets respectively, as shown in table 4. There are 110 multidimensional patterns with respect to these taxonomies, where 40 of them are element patterns and the other 70 of them are generalized patterns. The proposed mining tool should find all large itemsets for the 70 generalized patterns.

The first task for the evaluation is to determine the size of the transactions, where the size is picked from a Poisson distribution with the mean value μ equal to the average transaction size $|T|$. As the second step, each transaction is assigned a series of potentially large-itemsets. If the large-itemset on hand does not fit in the transaction, the itemset is put in the transaction randomly in half of the cases, and the itemset is fed to the next transaction of the rest. The number of maximal potentially large itemsets is set to the maximal size of potential large itemsets $|L|$. A maximal potentially large itemsets is generated by picking the size of the itemset from a Poisson distribution with mean μ equal to its average size $|I|$.

Type 1	To generate a single set of maximal potentially large itemsets and then generate transactions for each element pattern *Ei* following apriori-gen. [4]
Type 2	Besides a set of common maximal potential large itemsets, to genreate maximal potentially large itemsets for each element pattern *Ei*, and then genreate transactions for each element pattern *Ei*. The common maximal potentially large itemsets respectively following the apriori-gen. [4]
Type 3	Generating a set of maximal potentially large itemsets for each element pattern *Ei*, and generating transactions for each element pattern *Ei* from its own maximal potentially large items following the apriori-gen. [4]

Table 4. Three Types of data Sets

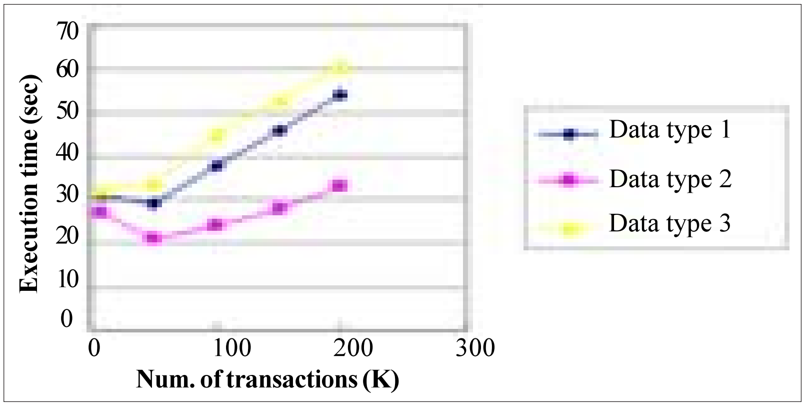


Figure 8. Scalability test w.r.t. the no. of transactions

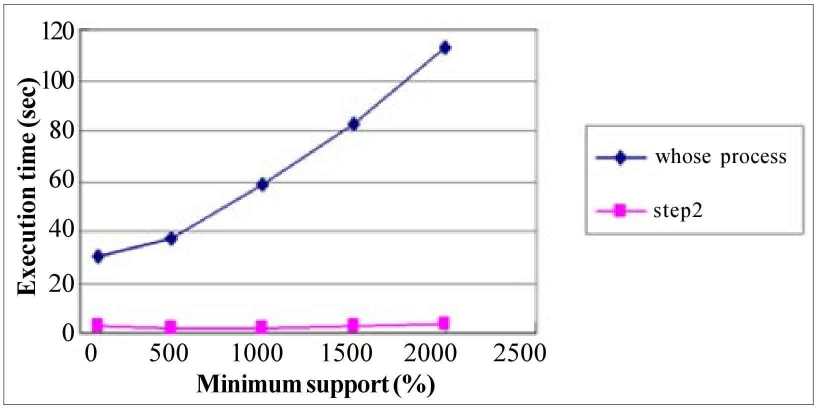


Figure 9. Scalability test w.r.t. the no. of records

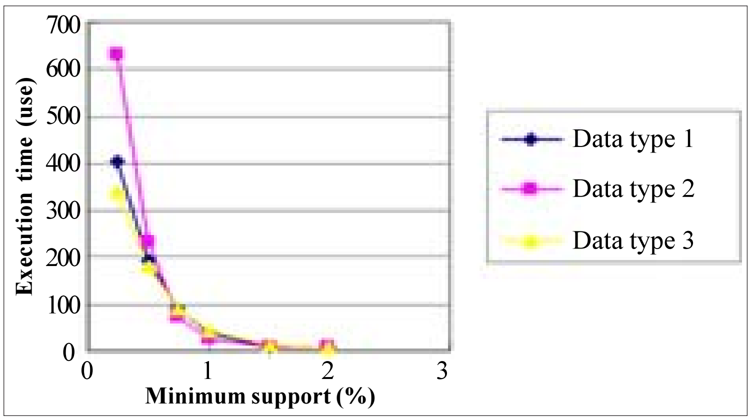


Figure 10. Efficiency in Relation to Minimum Support

4.3 The Results of Experiment

At first, the scalability of the algorithm is examined. A series of data sets is generated for the experiments. The default value of MinSup is 0.5%, match ratio $m = 1$, and the number of element patterns is 40. The experimental results in Figure 7 show that the algorithm takes time linear to the number of transactions of all the three data types. The execution time needed for processing itemsets is linear to the number of records in general, shown in Figure 8.

The next step of experiment is to evaluate the effect of minimum support minsup on the algorithm. The experimental results are

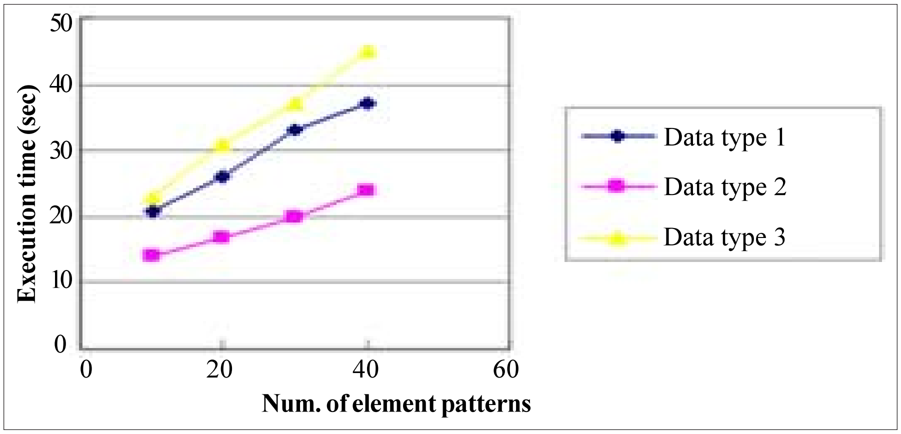


Figure 11. Efficiency in relation to the number of element patterns

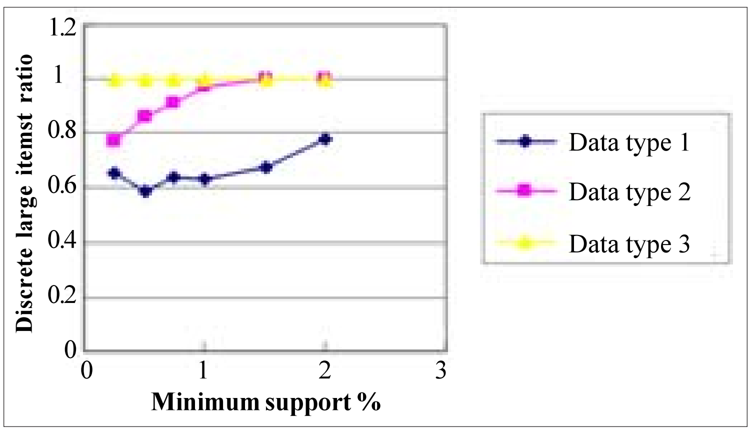


Figure 12. Effects of minSup on Discrete Large Itemsets Ratio

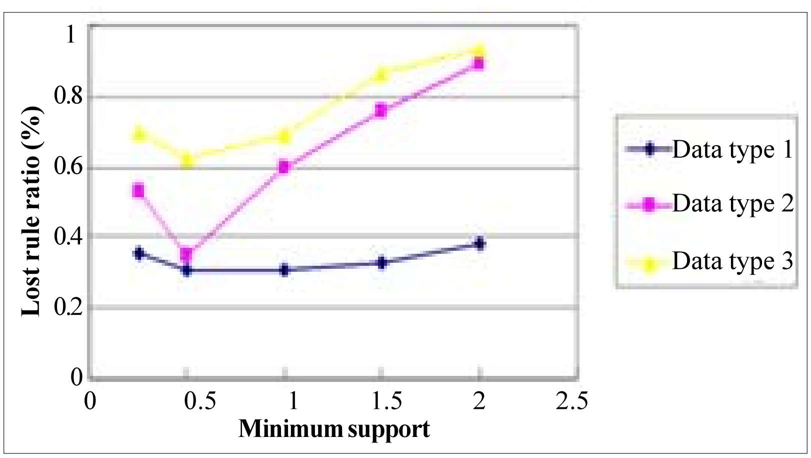


Figure 13. Effects of minSup on Lost Itemsets

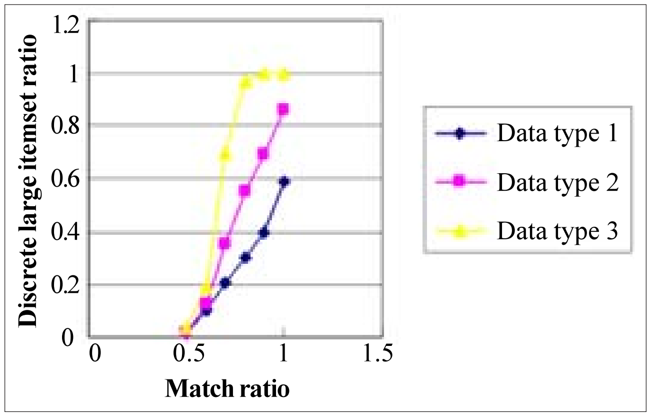


Figure 14. Effects of match ratio on discrete large itemsets ratio

shown in Figure 9. All of this kind of algorithms is sensitive to the minimum support; the smaller the minimum support, the longer the execution time. However, the real execution time of the update step in the proposed algorithm is relativity much shorter than the whole process (see Figure 8).

We then evaluate the effect of number of element patterns on the algorithm and the result is shown in Figure 10. This result shows that the algorithm takes time linear to the number of element patterns on all three data types. The linearity of the performance reveals the proposed approach runs faster than the most of existing tools that possess the nature of non-linearity.

One of the ultimate goals of this work is to discover association rules those hold in the meaningful element data segments belonging to the domain, and to mine rules that are lost in traditional mining tools. The discrete ratio and lost ratio are defined to evaluate the discovered rules.

5. Summary

This paper presents at first the categories of innovative healthcare services as well as the way to find new service patterns. Then, we propose a data mining approach for managing such new healthcare services, including a novel data structure and an effective algorithm for multi-dimensional mining association rules on various granularities. It is proved to be very useful for discovering new service patterns. The advantages of this approach over existing approaches include (1) more comprehensive and easy-to-use (2) more efficient with limited scans (3) more effective with finding rules hold in different granularity levels (4) capable of finding frequent patterns and infrequent patterns while users can choose the full match and the relaxed match (5) low information loss rate (6) capable of incremental mining of association rules to avoid unnecessary re-scan.

The design and evaluation of the multidimensional multi-granularity data mining approach were discussed in this paper. Since there is in our knowledge no metrics serving as the base for the measuring the data mining methods, we derive new metrics from Shannon's Entropy Function. The evaluation results prove the performances of the proposed approach, including efficiency, scalability and information loss rate, are better than existing approaches we know. The results show that we can use the proposed approach to find frequent and infrequent rules on different granularities by user-defined minSup value and match ratio.

Beyond the research so far, the effects of perceived issues and potential development of data mining without thresholds as well as concept description are worthy of further investigation.

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