Combined Mining Approach to Generate Informative Patterns

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Abstract

Business data mining applications involve huge amount of heterogeneous, distributed data. In such a case to use traditional data mining algorithms for obtaining comprehensive information about business, which will be helpful for decision making, is very time and space consuming. Traditional data mining methods involve single step data mining process to generate patterns and also they deal with homogeneous features of dataset. They need to follow join operation to get useful information from multiple large data sources. We consider Combined Mining as an approach to generate more informative patterns by considering multiple data sources or multiple features or multiple methods. Here we are going to discuss multifeature combined mining and multimethod combined mining methods. In multifeature combined mining, we obtained pair patterns, incremental pair patterns and cluster patterns by considering multiple heterogeneous features from data sources. In multimethod combined mining approach, multiple data mining methods has been used to generate more informative knowledge.

Keywords: Actionable knowledge discovery, association rule mining, combined mining, data mining, FP-Growth, interestingness metrics

1. INTRODUCTION

Nowadays, due to increase in number of customers, business data has grown enormously. This data involves heterogeneous, distributed data sources which contain information about business transactions, user preferences and business impact and indirectly this leads to complex data. In data mining application such raw data is used to obtain useful information (in the form of association rules or patterns) which can help to take some important business decisions. Data mining applications are being widely used in many areas such as public services, telecom, share market, shopping malls, online trading, social citing, health care and many more. Data mining algorithms provide association rules and patterns as output. Traditional data mining algorithms use single-step process to mine data. To mine data from multiple data sources, data mining algorithms perform join operation on those data sources which is quite time and space consuming. Also, traditional data mining algorithms find difficult to mine data by considering multiple heterogeneous features from data source.

Combined Mining provides a general approach to mine for more informative patterns which combine components from either multiple data sets or multiple features or by multiple methods [1]. So, there are three different methods of combined mining i.e. multisource combined mining, multifeature combined mining and multisource combined
mining. Final deliverables of combined mining are combined patterns such as combined association rules [3].

A combined association rule is formed by combining multiple heterogeneous itemsets from different datasets. In multisource combined mining, generated combined patterns reflect nature of business. In multifeature combined mining, combined patterns reflect multiple characteristics in business. And in multimethod combined mining, combined patterns disclose a deep and comprehensive knowledge about data. By applying interestingness metrics on combined patterns we can generate more significant patterns considering different perspectives. Pair patterns and cluster patterns can be further generated using combined patterns.

The remaining part of this paper is organized as follows. In section 2, concept of combined mining has been elaborated. Section 3, 4 and 5 provides brief idea about multisource, multifeature and multimethod combined mining respectively. In section 6 different interestingness metrics which can be use to choose better combined association rules has been mentioned. Section 7 concludes the paper.

2. CONCEPT OF COMBINED MINING

Existing single-handed data mining methods do not target the discovery of informative patterns in complex data. Table joining method is widely used to mine more informative patterns (e.g. combined patterns) from multiple relational tables by putting relevant features from individual tables into a consolidated one. But table joining method becomes very costly and time consuming when applied to enterprise applications which involve multiple heterogeneous data sets consisting of large volume of data records. Patterns identified using traditional data mining methods usually only involve homogeneous features from a single source of data. If we consider market-basket analysis, patterns obtained using traditional method involves frequent patterns of customer shopping habits. Such patterns provide single line of business information and it is not very useful for decision making. If attributes from multiple aspects can be included in single pattern then it can completely reflect business situation and can be helpful for business decision making. For example, in market-basket analysis, the shopper personal information along with price of goods and items purchased will provide additional information for shop owner to take more significant actions (i.e. to set up a discount, to arrange more affordable products etc.)

The concept of combined mining has elaborated using following example [3]. Consider there are two datasets, transactional dataset and demographic dataset (Tables [1] and [2]). Here "churn" talks about customer's behavior of switching form one company to another. The few traditional association rules discovered are given in Table [3]. If we follow combined mining approach, few of generated combined association rules are mentioned in Table [4]. In combined mining approach, first we partition the whole population into two groups, male and female, based on demographic data in Table [2]. And then mining the two groups separately, some combined rules are shown in Table [4]. Further, these combined rules are organized in pairs which are shown in Table [5]. Among these combined rules or rule pairs more significant or interesting rules can be found out using different new interestingness metrics such as 'Irule' apart from traditional metrics Confidence and Lift. These interestingness metrics are discussed in section 6.

Patterns which are identified using traditional mining method usually involve single homogeneous feature from single source of data e.g. considering policy or gender value to decide about churning (Table [3]). But combined patterns include heterogeneous features from multiple data sources e.g. policy value along with customer's gender will decide about churning (Table [4]). So combined patterns are more informative during business decision making process.

Table 1: Transactional Data

Customer ID	Policy	Churn
1	a,b	Y
1	A	Y
2	a,c	N
2	b,c	Y
2	b.c.d	N
3	a,c,d	Y
3	a,b,e	Y
4	a,b	N
4	C	N
4	b,d	N

Table 2: Demographic Data

Customer ID	Gender	….
1	F	
2	F	
3	M	
4	M	

Table 3: Traditional Rules

Rules
F → Y
F → N
M → Y
M → N
a → Y
a → N
b → Y
b → N
c → Y

Table 4: Combined Rules

Rules
F ^ a→ Y
F ^ b→Y
F ^ c→N
M ^ a→Y
M ^ b→N

Table 5: Combined Association Rules

Pairs	Combined Rules
P1	M ^ a →Y M ^ b →N
P2	F ^ b →Y M ^ b →N

Combined mining is a two-to-multistep data mining process, consisting of following steps:

1) Mining atomic patterns
2) Merging atomic pattern sets into combined pattern set for each data set by pattern merging method. Pattern merging method is designed or selected as per particular business problem.
3) If multiple data sets are involved, combined patterns indentified in specific data sets are further merged into the combined pattern.

General process of combined mining [1] is shown in figure [1]. This process gives an idea about discovery of combined patterns either in multiple data sets or sub sets through data partitioning. In following process, 1) based on domain knowledge, business understanding and goal definition, one of the data sets (say D1) or certain partial data are selected for initial mining using mining method say, R1. 2) The findings from above step are used to perform either data partition or data set management through the data coordinator and to design strategies for managing and conducting pattern mining on relevant data sets or subsets. The application of mining method Rk (k=2,..L), which could be either in parallel or through combination, is done by the understanding of business objectives or requirement. And if necessary, another step of pattern mining is conducted on data set Dk with the supervision of the results from step k-1. 3) After finishing the mining of all data sets, patterns identified from individual data sets are merged by considering domain knowledge and further lead to final deliverables (P).

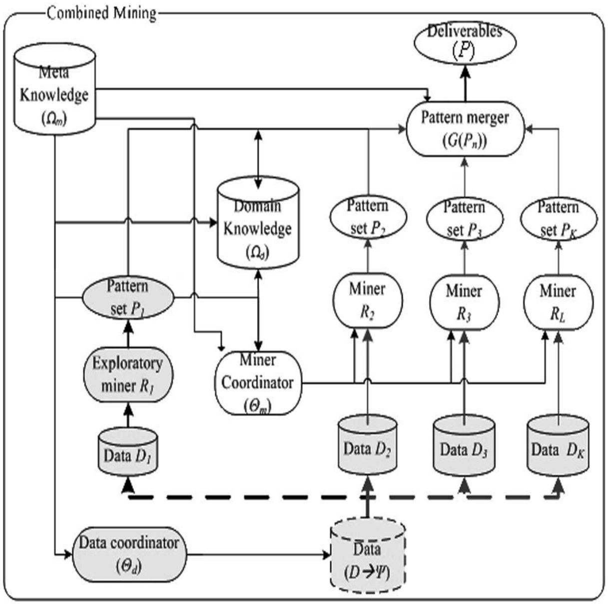

Figure 1: Combined mining for actionable patterns

Real-world enterprise applications often involve multiple heterogeneous and distributed data sets that cannot or are too costly to be joined. Apart from traditional mining, if there is large volume of data then such application data can be partitioned into small and manageable sets or in terms of business categories such as billing, networking, accounting data, warehouse data etc. then such small multiple data sources can be mined implicitly or explicitly. And eventually atomic patterns which are generated by different smaller datasets can be combined to get Combined Patterns. This method is nothing but generalized combined mining method.

These combined patterns are further used to form pair patterns or cluster patterns (discussed in section 6). Pair patterns and cluster patterns represent more informative form of combined patterns.

3. CONCEPT OF MULTISOURCE COMBINED MINING

Multisource combined mining method talks about considering multiple heterogeneous data sources to generate combined patterns. Heterogeneous data sources means, data fetched from different systems, database types, same database type but different tables, subject tables, historical tables, aggregated data, etc. Transactional, demographic and time series data are examples of heterogeneous data sources. Heterogeneous data sources require a different data mining technique or algorithm to fetch or extract atomic patterns (i.e. necessary knowledge) [2]. Two different methods of combined mining i.e. multifeature and multimethod combined mining contribute to multisource combined mining. As, both multifeature and multimethod methods involve considering multiple data sources, which make them part of multisource combined mining method.

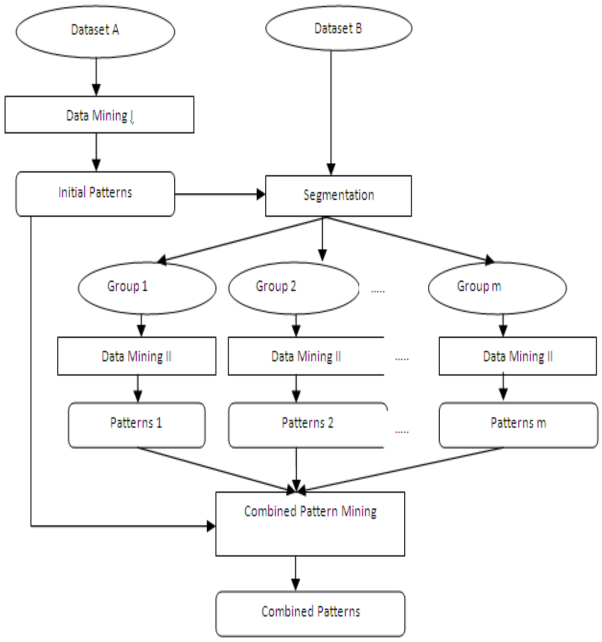

Figure2: Framework for Multisource Combine Mining Process

Framework for multisource combined mining [2] is given in figure [2]. Based on business knowledge or problem definition, one of the datasets is selected for initial mining exploration. Further those findings i.e. patterns are used to guide data partition. After finishing mining of all datasets finally all atomic patterns are merged to find out combined patterns. Any of the traditional data mining algorithms can be used in the place of Data Mining I and II in following figure [2]. Combined patterns are further analyzed using interestingness metrics and more useful or significant patterns can be selected.

Above discussed framework can be instantiated into a number of mutations. For example, for a large volume of data, combined mining can be performed as *data partition + unsupervised + supervised* mining by integrating data partition into combined mining. First the whole data set is partitioned into several subsets based on the data/business understanding and domain knowledge jointly by data miners and domain experts. E.g. data sets 1 and 2. Second, unsupervised learning is developed to mine one of the preference data sets for example, data set 1. Some of the mined results are then used to design new variables for processing the other data set. Supervised learning is further conducted on data set 2 to generate actionable patterns by checking both the technical and business performance. Finally, the individual patterns mined from both data sets are combined into pattern deliverables.

4. CONCEPT OF MULTIFEATURE COMBINED MINING

In multifeature combined pattern (MFCP) mining, combined patterns are formed by considering heterogeneous features of different data types, such as, binary, categorical, ordinal and numerical or of different data categories, such as customer demographics, transactions, and time series. As shown in section 2, Table 4, MFCP example is, F ^ a -> Y. This pattern combines one demographic component with items from transactional data set and business outcome i.e. whether the policy will be churned or not. In MFCP mining, multiple data sources are involved so, it is considered as a part of multisource combined mining.

In MFCP mining approach, initially one of data set is mined using selected feature. Atomic patterns generated are used to partition the entire population (i.e. collection of all related data sets). Then individual partition is mined using same or other mining method. Atomic patterns generated by these two mining are then merged (i.e. combined) to generate combined patterns. The outline of combined association rule mining (by considering multiple features) algorithm [4] is given as,

1. Discovering frequent itemsets I_D and the corresponding support counts C_D;
2. For each frequent itemsets I_D
3. Finding frequent itemsets including target class I_{DC};
4. Recording the support count C_{DC} for each I_{DC};
5. Calculating conditional support ConSup(DC);
6. If (ConSup(DC) > MinSup), for each I_{DC}
7. Finding candidate pattern of three kinds of itemsets I_{DCA};
8. Recording the support count C_{DCA} for each I_{DCA};
9. Calculating conditional support: ConSup(DA);
10. Calculating Conf, Lift and ConLift;
11. If (Conf > min_C & Lift >= min_l & conLift >= min_{cl})
12. Adding the mined frequent itemsets to the rule set

Here, MinSup stands for minimum support value defined as per business requirement, Conf stands for confidence and ConLift stands for contribution. These metrics are discussed in section 6.

MFCP can be further used to generate Pair Patterns and Cluster Patterns, which are often more informative. These different types of combined patterns are given as [5] and [6]:

A. Pair patterns can be formed by combining two atomic patterns. They are of for $\{A1 \rightarrow B1, A2 \rightarrow B2\}$ where A1 and A2 are same but B1 and B2 are different or vice versa. So, combined pair pattern will be $A1 \rightarrow B1 \& B2$. Measure I_{pair} is used to measure the interestingness of pair pattern.
B. Cluster patterns are formed by organizing many similar or related atomic or pair patterns together. They are of form $\{A1 \rightarrow B1, A2 \rightarrow B2, AN \rightarrow BN\}$ where A1, A2 and AN are same but B1, B2 and BN are different or vice versa. So, combined cluster pattern will be $A1 \rightarrow B1 \& B2 \& BN$. Measure $I_{cluster}$ defines how interested is the cluster of patterns.
C. Incremental cluster pattern also called as prefix combined patterns, in which any two neighboring atomic patterns form an incremental relation, namely pattern i+1 sharing some incremental part of features, pattern elements, or impacts on top of pattern i. For example, $\{A1 \rightarrow X, A1, B1 \rightarrow Y, A1, B1, C1 \rightarrow Z\}$. In incremental pair pattern the second pattern is an extension of the first by appending items B1 to A1and this leads to the outcomes of the patterns. The relationship between A1 and B1 can be ordered or unordered.

5.CONCEPT OF MULTIMETHOD COMBINED MINING

Multimethod combined mining is another form of multisource combined mining which helps to discover more informative knowledge in complex data. Multimethod combined mining focus on combining multiple data mining algorithms as per requirement to generate combined patterns (i.e. more informative knowledge). In fact, multimethod combined mining has been recognized as an essential and effective strategy in dealing with complex applications. The general process [1] of multimethod combined mining in dealing with real-world complex enterprise applications is given as follows:

1. Based on domain knowledge, business understanding and problem definition, user determines which methods should be used for implementation of multimethod combined mining.
2. Second, the patterns discovered by each method are combined with patterns by the other methods using user defined merging method. In reality, patterns are merged either serially or parallel.
3. Finally, the combined patterns are further used to form more workable patterns as pair patterns, cluster patterns etc.

There are three general frameworks of multimethod combined mining. They are parallel multimethod combined mining, serial multimethod combined mining, and closed-loop multimethod combined mining.

5.1 PARALLEL MULTIMETHOD COMBINED MINING

One approach to involve multiple mining methods for combined mining is parallel multimethod combined mining. In parallel multimethod combined mining multiple methods are implemented on multiple data sources or partitioned data sets. The resulting patterns are the combination of outputs of individual methods applied to each data sources. Consider there are K data sets Dk (k=1,…K), L data mining methods Rl (l=1,…L) are used to mine them, the parallel multimethod combined mining process is given as [1]:

1) Parallel data mining is performed on each data set using different data mining methods to find respective atomic patterns. i.e. mining of all data sets are performed in parallel using different data mining methods.

$$\begin{cases} D1 \overset{R1}{\rightarrow} P1 \\ D2 \overset{R2}{\rightarrow} P2 \\ \quad \ldots.. \\ Dk \overset{RL}{\rightarrow} Pn \end{cases}$$

2)The atomic patterns identified by individual methods are merged into combined patterns by merging method say G.

$$P := G(P1, P2, \ldots, Pn)$$

An example of parallel multimethod combined mining is to mine demographic patterns on customer demographic data using association rule mining and at the same time, decision-tree-based classification is applied on customer's transactional data to generate policy patterns. The identified results from both methods are then merged to form combined patterns.

5.2 Serial Multimethod Combined Mining

Second type of multimethod combined mining is serial multimethod combined mining. In serial multimethod combined mining, the data mining methods are used one by one according to specific arrangements. That is, one of the methods is selected and it is applied to data source based on the output of previous method applied on same data source. Such serial combination of data mining methods is often very useful for mining complex data sets.

Consider we have L methods Rl (l=1…L), and data source D, the serial multimethod combined mining process is given as follows [1]:

1. Based on the understanding of domain knowledge, business problem, select a suitable method (say R1) on data set D, which gives resulting pattern set P1.

$$D \xrightarrow{R1} P1$$

2. Supervised by the resulting patterns P1 and deeper understanding of business during mining pattern P1, leads to selection of next mining method say, R2 to get pattern set P2. Pattern set P1 contributes towards discovery of P2.

$$D \xrightarrow{R2,P1} P2$$

3. Similarly, select the next method to mine the data with the supervision of corresponding patterns from the previous stages; repeat this process until the data mining objective is met and we eventually get pattern set P.

$$D \xrightarrow{RL,Pn-1} P$$

An example of serial multimethod combined mining is combination of sequential pattern mining and classification, classification and clustering and regression and association rule mining.

5.3 Closed-Loop Multimethod Combined Mining

In above two methods, impact of one method on the other is not is not considered. If feedback from previous method is provided to following method then it may help to refine and enhance the performance and the efficiency of data mining process. Considering this approach, the concept of closed-loop multimethod combined mining has been proposed. The general process of closed-loop multimethod combined mining is given as follows:

Consider, we have data set D and L data mining methods say, Rl (l=1,…L) which are used to mine D. Closed-loop multimethod combined mining is enhancement to serial multimethod combined mining.

1)Loop 1: By following the same process as serial multimethod combined mining, pattern set P is generated. For closed-loop multimethod combined mining, say, pattern set P^1 is generated at the end of first step using serial multimethod combined mining. During this extraction of patterns, there are some samples that cannot be properly identified. This is because of the constraints and conditions applied on the respective data mining methods.

2)Loop 2: The patterns (i.e. pattern set P^1) identified by data mining methods Rl (l=1,…L) are further checked to see whether the identified patterns are valid to all samples in the data set D. Those samples on which patterns are not valid are put together into data set say, D^1 . They are called exceptional itemsets. These exceptional itemsets are further fed back to another loop of mining by reusing mining methods from Rl to RL as needed, with the refinement of parameters etc. The we get another resulting set say, P^2 .

3)Repeat the loop 2 as needed. Suppose we need Z loops, in order to get final exceptional itemsets D^z . So, in entire process we obtain Z pattern sets namely, $\{P^1, P^2, \ldots, P^z\}$.

4)Merge the identified Z pattern sets to generate final combined patterns

$$P := Gc\,(P^1, P^2, \ldots P^z)$$

Where Gc represents the merging methods for closed-loop multimethod combined mining.

Figure 3 [1] represents the process of closed-loop multimethod combined mining. In closed-loop method, whether a pattern is interesting or not does not only depend

on a particular method that extracts that pattern but also depend on other methods used in the system. Hence the performance and efficiency of the system could be much improved by using the same interestingness measures.

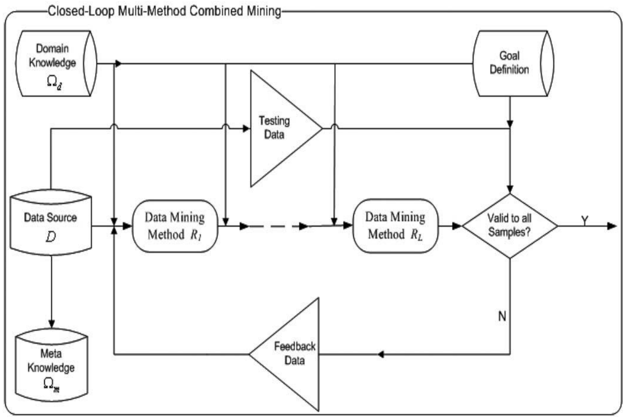

Figure3: Closed-loop multimethod combined mining process

6.INTERESTINGNESS METRICS

Output of each and every data mining method is pattern set. The technical significance of a pattern is called as 'interestingness'. Usefulness and significance of patterns are decided using some metrics. Those metrics are called as interestingness metrics. There are few traditional metrics called as Confidence, Support and Lift. These metrics are given as follows:

Consider pattern $X \rightarrow T$.

Support = $prob(X \cap T)$

Confidence = $prob(X \cap T)/prob(X)$

Lift = $prob(X \cap T)/(prob(X) * prob(T))$

These traditional metrics are explained in detail in [7].

In case of combined pattern, it's a combination of two atomic patterns so, the contribution of each atomic pattern towards the combined pattern becomes essential to be considered. Based on tradition support, confidence and lift, two new metrics contribution and Irule are defined are defined as follows for measuring the interestingness of a single combined pattern. Consider combined pattern as,

$$P : Xp \cap Xe \rightarrow T.$$

The contribution of atomic pattern Xe to impact T in rule P is given as,

$$Cont_e(Xp \cap Xe \rightarrow T) = \frac{Lift\,(Xp \cap Xe \rightarrow T)}{Lift\,(Xp \rightarrow T)}$$

$$= \frac{Conf\,(Xp \cap Xe \rightarrow T)}{Conf\,(Xp \rightarrow T)}$$

$Cont_e(P)$ shows the lift of Xe over Xp i.e. how much Xe contributes to the rule as compare to Xp. Similarly contribution of Xp to the rule is given as,

$$Cont_p(Xp \cap Xe \rightarrow T) = \frac{Lift\,(Xp \cap Xe \rightarrow T)}{Lift\,(Xe \rightarrow T)}$$

$$= \frac{Conf\,(Xp \cap Xe \rightarrow T)}{Conf\,(Xe \rightarrow T)}$$

The value of contribution falls in [0, +∞). A contribution greater than one means that the additional items in the rule contribute to the occurrence of the outcome and contribution less than one suggests reverse effect. Based on definition of contribution more interestingness metric i.e. Irule is defined as follows:

$$Irule\,(Xp \cap Xe \rightarrow T) = \frac{Cont_e(Xp \cap Xe \rightarrow T)}{Lift\,(Xe \rightarrow T)}$$

Irule indicates whether the contribution of Xe or Xp to the occurrence of impact T increases with Xe or Xp. The value of *Irule* falls in [0, +∞). Therefore, if *Irule* < 1 says that $Xp \cap Xe \rightarrow$ is less interesting than $Xp \rightarrow$ and $Xe \rightarrow$ When *Irule* > 1, the higher *Irule* is, the more interesting the combined rule is.

Consider pair pattern P which has the following form

$$P : \begin{cases} X1 \rightarrow T1 \\ X2 \rightarrow T2 \end{cases}$$

Where $X1 \cap X2 = Xp$ where Xp being prefix of pair P, T1 and T2 are contrary to each other, or T1 and T2 are the same, but there is a big difference in the interestingness values of two constituent patterns.

An example of pair pattern in section 2 is

$$M \wedge a \rightarrow Y$$

$$M \wedge b \rightarrow N$$

It shows that a group of male customers leads to different outcomes. If male customers opt for policy 'a' then it leads to churning and if they go for policy 'b' then it does not lead to churning. With these findings, business can encourage male customer to go for policy 'b'.

The interestingness of pair pattern P is given as,

$$Ipair\,(P) = \begin{cases} |\,Conf\,(P1) - Conf\,(P2)\,|\,, & if\ T1 = T2 \\ \sqrt{Conf\,(P1)\,Conf\,(P2)}\,, & if\ T1\ and\ T2\ are\ contrary \\ 0, & otherwise \end{cases}$$

where P1 and P2 are the two constituent patterns in the pair.

Ipair measures the contribution of two constituent pattern to the occurrence of impact. The value of *Ipair* will fall in the range [0,1]. The larger the value the more interesting a pair is. This kind of knowledge can help to design business campaigns and to improve business process.

Atomic or combined patterns can be further organized into clusters by placing similar or related patterns together. Cluster pattern is defined in section 4. Considering *Ipair* of a combined pair pattern, for a cluster rule P with k constituent patterns P1, P2, … Pk, its interestingness is given as

$$Icluster\,(P) = \max_{Pi, Pj\ \in\ i \neq j} Ipair(Pi, Pj)$$

The definition of Icluster indicates that interesting clusters are those rules which include interesting rule pairs and other rules in the cluster provide additional information. The value of Icluster also falls in [0,1].

7.CONCLUSION

Large and day-to-day enterprise applications always involve enormous, distributed and heterogeneous featured data. Such data includes demographic, user preferences, customer behavior, business appearance, service usage and business impact data. So there is a huge need to mine useful and efficient patterns which can represent comprehensive business scenarios and can help for business decision making. For this purpose existing data mining methods such as postanalysis & table joining based, represent inefficiency in terms of time and space.

This paper puts forward a comprehensive and general approach named combined mining for discovering more informative and efficient knowledge in complex data. Combined mining approach is implemented using three different ways as multisource, multifeature and

multimethod mining. Among these multifeature and multimethod mining methods follow multisource combined mining approach. Combined mining methods generate combined association rules (i.e. combined patterns) as an output. These combined patterns can be further used to generate pair pattern and cluster pattern depending upon business requirement and understanding. These combined patterns are further filtered to form more efficient and useful patterns by applying different interestingness metrics which are discussed in this paper.
In future, these combined mining methods are enhanced to more efficient ones. More efficient pattern merging methods and interestingness measures are developed.

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