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Multilevel Interesting Association Rule Mining Using Soft Computing Techniques

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Abstract: Data warehouse contains large amounts of data from a various sources that may contain some noise while using for decision making. Data mining is extraction of knowledge from large data which may contains some amount of missing data along with inaccurate data and outliers. One of the best ways to detect data errors is by properly utilizing association rules that indicates relationships among attributes. Association rule mining algorithms detects patterns which occur in large dataset. Mining association rules at multiple level of concept hierarchy lead to the detection of more specific and actual knowledge from the dataset. The present paper uses various soft computing approaches for mining multilevel interesting association rules. In real-world problems, transaction data contains quantitative values. The fuzzy logic is useful for finding interesting association rules in quantitative transactions. To generate optimized multilevel association rule, optimization techniques such as genetic algorithm, ant colony optimization and particle swarm optimization are used. In this paper, soft computing techniques are reviewed based on approach used, findings and open issues in order to find optimized multilevel interesting association rules.

Keywords: Ant colony system, Fuzzy logic, Genetic algorithm, Interestingness measures, Multilevel association rule mining, Particle swarm optimization.

I. Introduction

Data mining is used to extract the useful information as well as and patterns from dataset. One of the techniques used in data mining is called association rule mining. Association rule mining is the process of finding associations or correlations among a set of items or objects in transaction databases, relational databases, and data warehouses. Association rules are of the form A and B → C, where A, B, and C are items. The rule can be comprehended as "Item A and Item B imply Item C". An itemset is the collection of such items or objects that are being tracked. For example, bread, butter, and jam could be part of an itemset that is of interest for a grocery-food chain. An event that covers the occurrence of one or more items from the given itemset is usually known as a transaction [1]. In the case of the grocery-food chain example this could represent a customer buying a set of grocery items. The portion of the rule to the left of the implication (→) is known as the antecedent (A & B), whereas the right side of the implication is known as the consequent (C). Support is the percentage of transactions contains both the antecedent and consequent (P [A, B, C]). Confidence is the percentage of transactions with the antecedent, that also contain the consequent (P [A, B, C | C]). In other words, support represents the frequency of antecedent and consequent items being together in a dataset of transactions, and confidence measures the strength of a rule [2].

Association rules generated from multiple levels of concept hierarchy are called multiple-level or multilevel association rules. In the concept hierarchy tree, each node represents one item of an itemset and terminal node represents actual items appearing in the transactions set. Classes or concepts formed from lower-level of concept hierarchy are represented by internal nodes. At a single concept level, one might find that 70 percent of customers that purchase computer may also purchase printer. But, it would be more informative to know that 50 percent of people buy HP printer if they buy desktop computer. The process of discovering such association rules at multiple levels and cross levels, gives us more useful and deeper information about the data set, in comparison to the single level association concept.

The purpose of the work described in this paper is to review the soft computing techniques to find interesting association rules at different concept hierarchy using minimum support threshold. The rest of this paper is organized as follows: Section II presents preliminaries for soft computing based multilevel interesting association rules generation. In Section III, Introduction to multiple level association rule mining and different rule mining approaches are explained. Section IV shows the literature survey. Conclusion is drawn in Section V.

II. Preliminaries

This section will briefly review five aspects of literatures. They include fuzzy logic, genetic algorithm, particle swarm optimization, ant colony optimization system and interestingness measures. Detailed information is presented in the following subsections.

A. Fuzzy Logic (FL)

The fuzzy set theory is generally used in intelligent systems [3]. The theory of fuzzy sets is a mathematical tool for dealing with uncertainty. A fuzzy set contains class of different objects with membership function. A membership function which assigns grade of membership ranging between zero and one to each available object. The fuzzy set includes union, intersection, complement, relation, convexity, etc., to set properties of established notions. For generating quantitative multilevel association rules, fuzzy set theory is widely used.

B. Genetic Algorithm (GA)

Genetic algorithm (GA) is an optimization technique which is based on biological mechanisms [4]. GA is basically searching method which is used to find the exact or the approximate solutions of optimized problems. GA is a heuristic optimization technique which is inspired from biological mechanisms of evolution and natural genetics. GA imitates the mechanics of natural selection, crossover and mutation. GA searches for better solutions to a problem by preserving a population of candidate solutions and also makes subsequent generations by selecting the current best solutions using Crossover and Mutation operators. Crossover and mutation operators create new candidate solutions. The algorithm stops when maximum numbers of iterations are reached, or fitness level will reach to an acceptable level [4], [5], and [6].

C. Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm is a biological inspired heuristic search algorithm that is used to simulate the social behavior of a flock of birds which are randomly searching for food in a specific region [7]. In PSO algorithm, each bird is referred as a particle which flown through the problem space by following the current optimal particles. Each particle has a fitness value which is evaluated by the optimized fitness function. The particles contain velocities and positions. It is updated by two best values. First, the best fitness solution of the particle accomplished so far and is called particle best which is denoted by "pbest". Second, global best shortened as "gbest" for global neighborhood version and called local best termed as "lbest" for the local neighborhood [8]. PSO searches for optima by updating each particle's velocity and position using the two best values. For global neighborhood, it updates "pbest" and "gbest" and for local neighborhood "pbest" and "lbest".

D. Ant Colony System (ACS)

The Ant Colony System (ACS) is based on agents that simulate the natural behavior of ants. The ACS also develops mechanisms of cooperation and learns from experience [9]. The heuristics approach is used to robust and versatile for various problems. The ACS is a population based heuristics which enables the study of the positive feedback between agents. ACS is a particular algorithm of ant colony optimization where the real ants are able to communicate information related to food sources via an aromatic essence. While searching for food, ants secrete a pheromone to mark the path leading to food source. When there are more pheromones on a path, the probability is higher to use same path for other ants. Hence, the pheromone trail on such a path will grow faster and also attracts more ants to follow same path. In the ACS, the method whereas ants select the path is changed is known as ACS state transition rule.

E. Interestingness Measures

Interestingness measure is important aspect of extraction of interesting pattern from the dataset. For this experiment, following interestingness measures are used.

i) Confidence

The confidence is the percentage of transactions in the database D with itemset X that also contains the itemset Y. The equation for the confidence is as given by [37] and [14].

$$\text{Confidence}(X \to Y) = \text{P}(Y \mid X) = \frac{\text{Support}(X \cup Y)}{\text{Support}(X)}$$

Here, Support ($X \cup Y$) is the number of transactions containing the itemsets X and Y both, and Support (X) is the number of transactions containing the itemset X.

ii) All-Confidence

All-confidence is defined as [38],

$$\text{All-Confidence}(X \to Y) = \frac{\text{Support}(X \cup Y)}{\text{Max (Support}(X), \text{Support}(Y))}$$

All-confidence satisfies the downward closed closure property. Hence, it is effectively used for interesting association rule mining.

iii) Cosine

Cosine is defined as [39],

$$\text{Cosine } (X \to Y) = \frac{\text{Support } (X \cup Y)}{\sqrt{\text{Support } (X) * \text{Support } (Y)}}$$

If the value of cosine (X → Y) is near to 1 which indicates more transactions containing item X also contains item Y. Similarly, if the value of cosine (X → Y) is near to 0 which indicates more transactions contain item X without containing item Y.

iv) Interestingness of a Rule

Interestingness of a rule, denoted by Interestingness (X → Y), is used to measure how much the rule is surprising for the user. The following expression can be used to define the interestingness of a rule [32] and [40].

$$\text{Interestingness}\ (X \rightarrow Y) = \frac{\text{Support}\ (X \cup Y)}{\text{Support}\ (X)} * \frac{\text{Support}\ (X \cup Y)}{\text{Support}\ (Y)} * \left(1 - \frac{\text{Support}\ (X \cup Y)}{NOT}\right)$$

Where, NOT indicates the total number of transactions in the database.

v) Lift/Interest

Lift/Interest is used to measure frequency of X and Y together, if both are statistically independent of each other [41] and [42]. The lift of rule X → Y is defines as,

$$\text{Lift}\ (X \rightarrow Y) = \frac{\text{Confidence}}{\text{Expected Confidence}} = \frac{\text{Confidence}\ (X \rightarrow Y)}{\text{Support}\ (Y)}$$

If lift value is 1 then X and Y appear as frequently together. In this case, X and Y are said to be independent of each other.

vi) Conviction

Conviction is used to measure strength of the association rule from statistical independence [41]. Conviction is defined as,

$$\text{Conviction}\ (X \rightarrow Y) = \frac{\text{1- Support}\ (Y)}{\text{1- Confidence}\ (X \rightarrow Y)} = \frac{\text{P}(X) * \text{P}(\hat{}Y)}{\text{P}(X \cup \hat{}Y)}$$

Where, P (^Y) is the probability that Y does not appear in a transaction. Conviction is a directed measure as compare to lift [43]. Hence, conviction is monotone in confidence and lift.

III. Multi-Level Association Rule Mining

Association rules generated from multiple levels of concept hierarchy is called multilevel association rules. In multiple-level association rule mining, the items in an itemset are divided by concept hierarchy. At lowest levels, there may be almost no rules which may match the constraints [10]. At highest levels, rules can be enormously general. A top-down approach is used where support is reduced going from higher levels to lower levels [11]. To illustrate, here is an example of a concept hierarchy.

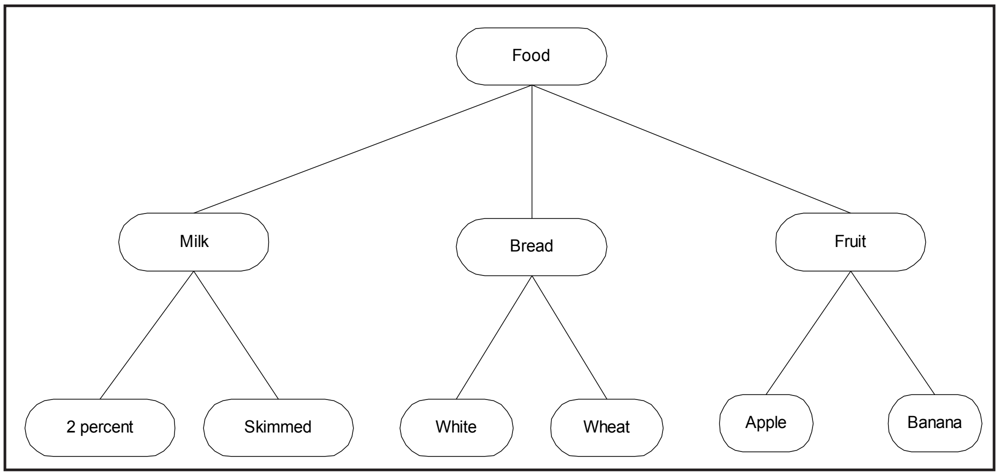

Fig. 1: Concept Hierarchy Tree Example

Each node in the concept-hierarchy tree in Fig. 1 represents one item in the itemset. Here are essentially two levels of tree structure. At the first level, there are three items: Milk, Bread, and Fruit. At level 2, the items are children of their parent items exist at level 1. Items 2 percent and Skimmed are children of Milk. Items White and Wheat are children of parent node Bread. Items Apple and Banana are children of parent item Fruit. In the case of a concept hierarchy as shown in Fig. 2, when the item Organic appears in a transaction, we know that its parent node at level 2 is Fat-Free, but what we don't know is whether the item Organic in that transaction is a grand-child of Milk or Bread at level 1. Notice that inside each node in Fig. 2 is listed a number. The number represents the item id. It also provides encoding that gives us taxonomy information about the hierarchy that the multiple-level association algorithm requires [12]. For example, the item Organic is encoded as 131 and 211. The two codes' first digit, 1 and 2, represent Milk and Bread at level 1. The second digit, 3 and 1, of the codes represent Fat-Free (Milk) and Fat-Free (Bread) respectively. And the third digit, 1 and 1, are for the item Organic (Milk-Fat-Free and Bread-Fat-Free respectively). Encoding the taxonomy information as a sequence of digits in such a way makes multi-level association algorithm not only simpler to work with but also makes it more efficient in terms of memory and processing.

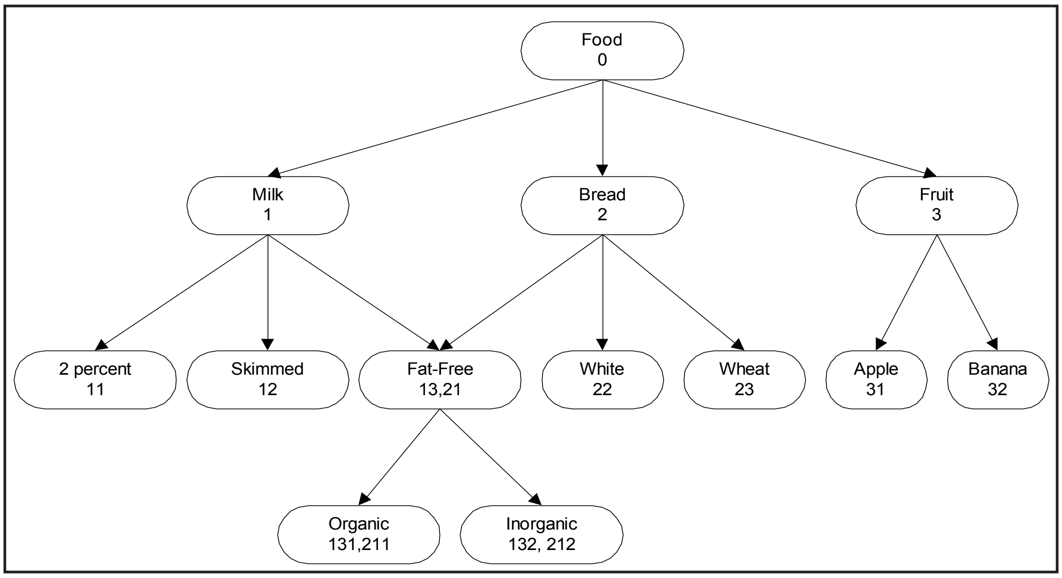

Fig. 2: Concept-Hierarchy Tree with Taxonomy Information

In a top-down strategy, it starts with the concept level one then going towards the lower concept levels until no more frequent itemsets are found [13]. Once all frequent itemsets at concept level 1 are found, then the frequent itemsets at next level are found. The variations to this approach are described below [14].

A. Using Uniform Minimum Support for All Levels

In uniform minimum support, minimum support threshold value remains same for each concept level. An optimization technique can be accepted based on the relationship knowledge of an ancestor and its descendents. An item whose ancestor does not have minimum support that avoids examining item sets. This provides the motivation for the following approach.

B. Using Reduced Minimum Support at Lower Levels

Each level of concept hierarchy has its own minimum support threshold. For lower hierarchical level, the corresponding threshold is smaller.

C. Using Item or Group-Based Minimum Support

Group based minimum support often has insight as to which groups are more important than others. User-specific, item or group-based minimal support thresholds is more desirable while mining multilevel association rules.

IV. Literature Survey

By combining the advantages of both multilevel association rule mining and soft computing techniques, optimized rules can be discovered from the databases. In this section, a literature survey of integration of various soft computing techniques along with interesting measures in multilevel association rule mining is presented.

Author(s)	Year	Approach	Findings	Open Issues
J. Han and Y. Fu [11]	1999	• The enforcement of different interestingness measurements to find more interesting rules, and the relaxation of rule conditions for finding level crossing association rules.	• Multi-level association rules generate interesting and strong rules from large databases.	• Extension of existing methods for mining single-level to multiple-level interesting rule generation.

Author(s)	Year	Approach	Findings	Open Issues
T. P. Hong, K. Y. Lin and S. L. Wang [15]	2003	• Integrates fuzzy set concepts and generalized data mining technologies to find cross-level interesting rules from quantitative data.	• Gets smoother mining results due to its fuzzy membership characteristics. • Achieves better time complexity.	• Assumes that member-ship functions are known in advance. • Propose some fuzzy learning methods to automatically derive membership functions.
M. Kaya and R. Alhajj [16]	2004	• Proposes fuzzy weighted multi-cross-level association rules by taking advantages of fuzziness and level crossing mining, weighted mining and linguistic terms.	• More meaningful rules those are more understandable for human beings. • Proposed approach generates consistent meaningful results.	• An approach proposed in this paper can be extended with the concept of adjacency lattice.
W. Y. Lin and M. C. Tseng [17]	2005	• An automatic support specification for efficiently mining high-confidence and positive lift associations without consulting the users.	• The proposed support specification still can-not find all interesting association rules.	• The proposed approach does not set automatically mini-mum item support.
S. Lallich, O. Teytaud and E. Prudhomme [18]	2007	• Validating the interesting rules against the selected measures.	• A bootstrap based method BS_FD is used for filtering rules.	• Filtering discriminant rules in the context of genomics.
P. W. Peter and B. Venansius [19]	2008	• A multi objective evolutionary algorithm is used based on genetic algorithms.	• It discovered rules with high predictive accuracy and interestingness value.	• Extend the algorithm proposed in this paper to cope with continuous data since the current one handles only categorical data.
Y. B. Wan, Y. Liang and L.Y. Ding [20]	2008	• A novel method is proposed to improve the efficiency, integrality and accuracy. • The proposed method also supports dynamic concept hierarchies.	• Different users get their desired association rules from customized point of view. • Discusses the issues of the calculation of rule support, multilevel association rules at specific levels and the tradeoff between commonsense and specific patterns.	• Dynamic feature of construction of concept hierarchy can be encapsulated as a learning component and integrated with the know ware system to provide the knowledge source for other intelligent components.
T. Aydın and H. A. Guvenir [21]	2009	• Proposes a post-processing method to generate interesting association rules.	• The experimental results show how the model selects the interesting rules.	• As a future work, novelty interesting-ness factor may be incorporated to find better interesting rules.
Y. Xu, G. Shaw and Y. Li [22]	2009	• Remove hierarchically redundant rules from multi level datasets.	• Reduces the size of the association rule set that improves the quality and usefulness without loss of any information. • Proposed an approach which removes hierarchical redundancy through the use of frequent closed item-sets and generators.	• If there is other hierarchical a redundancy in the basic rule sets that should be removed and will investigate.

Author(s)	Year	Approach	Findings	Open Issues
T. P. Hong, Y. F. Tung, S. L. Wang and Y. L. Wu [23]	2009	• Proposed an algorithm that generates fuzzy association rules using ant colony. • The membership functions derived in a level will be refined in the next level.	• Multi-level ACS-based mining algorithm is used to generate fuzzy association rules.	• Further this work can be extended by solving real world mining problems.
G. Shaw, Y. Xu and S. Geva [24]	2009	• Proposed an approach which removes hierarchical redundancy through the use of frequent closed itemsets and generators.	• Removes hierarchical redundancy in multi-level datasets, thus reducing the size of the rule set to improve the quality and useful-ness, without loss of any information.	• More efficient frequent itemset finding algorithm. • This approach can be applied to the approximate basis rule set to remove redundancy.
P. Gautam and K. R. Pardasani [25]	2010	• A Boolean Matrix based approach is used to generate frequent itemsets.	• Number of database scans is one. • Stores all transaction data in bits which improves memory utilization.	• Can be applied to mining large transaction databases.
T. P. Hong, Y. F. Tung, S. L. Wang, Y. L. Wu and M. T. Wu [26]	2012	• Multilevel ant colony framework is designed and an algorithm based on the structure is pro-posed.	• Proposed approach can obtain better member-ship functions, but with more computational time due to the multilevel processing.	• Further this work can be extended by including different encoding methods.
S. Prakash, Vijayakumar and R. M. S. Parvathi [27]	2011	• Mining both the frequent and in-frequent association rules which are more interesting and does not have redundant rules.	• Discovers rules which are complete according to propositional logic.	• Taking an unclassified dataset and perform classification before performing the experiment.
P. Gautam and K. R. Pardasani [28]	2011	• Partition method and • Boolean methods are used for finding frequent itemsets at each level of concept hierarchy. Thus, it reduce database scans, I/O cost and also CPU over-head.	• Partitioning method is used to limit the total memory requirement.	• Further the work can be extended by considering an algorithm for mining very large databases.
R. J. Kuo, C. M. Chao and Y. T. Chiu [29]	2011	• Proposed PSO algorithm which first searches for the optimum fitness value of each particle and then finds corresponding support and confidence as minimal threshold values after the data are transformed into binary values. • The proposed method is compared with a genetic algorithm.	• The results indicate that the PSO algorithm really can suggest suitable threshold values and obtain quality rules. • The mining results provide security for customers' transaction behavior and also provide a reference for the formulation of marketing strategy.	• Future studies can focus on testing different updating rules. • Different product items may have different importance so weighted PSO mining algorithm can be investigated.

Author(s)	Year	Approach	Findings	Open Issues
S. J. Mirabedini, A. M. N. Kousari and M. Sadeghzad [30]	2012	• Proposes a multilevel fuzzy association rule mining model for extraction of implicit knowledge. • Approach adopts a top-down approach and also incorporates fuzzy boundaries instead of sharp boundary intervals.	• The mined rules can be more close to the user's demand. • The run time of the algorithm shall significantly decline.	• New method can be used to generate membership function dynamically to cope with changing conditions.
B. Rani and S. Aggarwal [31]	2013	• The Ant Colony algorithm is proposed which decreases number of association rules compared to Apriori.	• The execution time taken by ACO based Apriori algorithm is less than ACO based FP-Growth algorithm.	• The proposed method can further be extended for multilevel association rule generation. • The time factor as well as number of rules can be reduced by ACO based FP-Growth approach.
M. K. Gupta and G. Sikka [32]	2013	• Proposed approach for optimizing association rules using Multi-objective feature of GA with multiple quality measures i.e. support, confidence, comprehensibility and interestingness.	• It has been observed that proposed algorithm can improve the performance in terms of the interesting association rules extraction. • The numbers of rules generated by proposed algorithm are significantly less as compared to Apriori algorithm.	• To improve the complexity GA can be applied parallel for optimization of Association Rule Mining.
S. Tyagi and K. K. Bharadwaj [33]	2013	• The proposed approach improves the quality of recommendations through Multi Objective PSO (MOPSO) algorithm for association rule mining in the framework of collaborative Filtering.	• The effectiveness of proposed model is evaluated experimentally using MovieLens dataset and it is found that MOPSO based Direct Association Rule Mining (MOPSO-DAR) and MOPSO based Direct & Indirect Association Rule Mining (MOPSO-D&I-AR) models outperform Adaptive Support Association Rule Mining (ASARM), Fuzzy Association Rules and Multiple-level Similarity (FARAMS) and Association Rules based Collaborative Filtering (ARCF) models under different configurations of dataset.	• The proposed work can be analyzed further by evolving the quantitative association rules with the help of PSO algorithm. • Further the work can be extended to mine multi level association rules using evolutionary approach to develop an intelligent system.

Author(s)	Year	Approach	Findings	Open Issues
K. N. V. D. Sarath and V. Ravi [34]	2013	• Proposed a binary particle swarm optimization (BPSO) based association rule mining algorithm to generate rules from the transactional database using combinatorial optimization problem, without considering minimum support and minimum confidence.	• The proposed algorithm generates M (given number) best rules from the given database. • The proposed algorithm automatically extracts the top association rules without using support and confidence threshold. • BPSO does not generate redundant rules, which is a serious drawback of other algorithms.	• Future directions include devising more robust strategies for association rule mining by combining two or more evolutionary algorithms and suggesting newer fitness functions.
A. K. Chandanan, and M. K. Shukla [35]	2015	• The method presented in this paper removes hierarchical duplicate rule. Thus, it reduces the size of the rule set and also improves the quality of rules without any loss.	• The proposed approach removes redundant rules from multilevel dataset. • This reduction in rule set improves the quality and efficiency of mining without information loss.	• The authors suggested to remove redundancy using upper level closed frequent item set by using generator as future scope.
M. Narvekar and S. F. Syed [36]	2015	• Proposed a new algorithm which generates frequent item sets without generating conditional FP tree.	• The proposed frequent item set mining algorithm saves a lot of memory by reducing the number of conditional pattern bases and conditional FP trees.	• As a future work, similar techniques can be applied on XML data.

V. Conclusion

Multiple-level association rule mining is one of the important features of association rule mining. A top-down approach is used for mining association rules based on an itemset that is characterized by a different level of concept hierarchy. The complicated concept level hierarchies can be simplified in order to properly generate frequent multilevel itemsets. The uniform support approach has several limitations. One of limitation is that there is unlikely that items at lower levels of concept hierarchy will occur as frequently as those at higher levels of concept hierarchy. The minimum support threshold can also be set appropriately. If the minimum support threshold is set too high than some of the meaningful association rules generated at low level of concept hierarchy is missed completely. Similarly, if the minimum support threshold is set too low then it may generate many uninteresting association rules occurring at high concept level. Thus, reduced minimum support gives more important association rules as compare to other methods. The soft computing techniques can also be encapsulated in multilevel association rule mining for knowledge discovery in large datasets. The proposed article is intended by focusing more on the latest advances, as well as it also highlights the opportunities by using soft computing techniques for multilevel association rule generation. Based on this, it has been concluded that rule optimization can be applied using ACO and PSO as compared to genetic algorithm.

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