Optimization of Association Rule Using Heuristic Approach

Shivika[1], Mr. Manish Mahajan[2]
[1]M.Tech Student, Graphic Era University, Dehradun, India
[2]Associate professor, Computer Science Department, Graphic Era University, Dehradun, India
shivika0892@gmail.com , *Manish.mahajan@outlook.com*

Abstract- Apriori algorithm is used to create all possible association rules among the items in the database, on the behalf of Association Rule Mining and Apriori Algorithm. Here proposed a new algorithm based on the Ant Colony Optimization algorithm to improve the result of association rule mining. Ant Colony Optimization (ACO) is a meta-heuristic approach that inspired by the real behaviour of ant colonies. The association rules create by Apriori algorithm after that find the rules from weakest set based on threshold value that will used the Ant Colony algorithm to reduce the association rules and discover the better quality of rules than apriori. In this research work proposed method focuses on reducing the scans of datasetss by optimization and improving the quality of rules generated for ACO.

Keywords: *Data Mining, Association Rule Mining (ARM), Apriori Algorithm, Ant Colony Optimization (ACO), FP-Growth.*

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I. INTRODUCTION

Association principles are one of the significant strategies of information mining. The volume of information is expanding significantly as the information created by everyday exercises. Hence, mining Association rules from monstrous measure of information in the database is intrigued for some commercial enterprises which help in much business can basic leadership procedures, for example, cross showcasing, Basket information investigation, and advancement arrangement. It finds the Association relationship among the expansive number of database things and its most commonplace application is to locate the new valuable rules in the business exchange database, which mirrors the client buying conduct examples, for example, the effect on alternate products in the wake of purchasing a specific sort of merchandise.

These guidelines can be utilized as a part of numerous fields, for example, client shopping examination, extra deals, products racks outline, stockpiling arranging and grouping the clients as per the purchasing designs, and so on. The information have customarily centered around recognizing connections between things letting some know part of Human conduct, more often than not purchasing conduct for deciding things that clients purchase together. All Rules of this write depict a specific nearby example. The gathering of Association standards can be effectively translated and conveyed.

Information is gathered and accessible in each circle of life. Handling and investigation of the created information as a rule gives helpful bits of knowledge and learning about the framework which has delivered that information. The field of information mining manages transformation of crude information into valuable data. Information mining is an accumulation of strategies utilized for removing or mining of already obscure, valuable and reasonable examples from extensive databases. Information mining coordinates strategies from numerous orders, for example, database innovation, machine learning, intelligences, design acknowledgment, neural systems, and picture preparing and information perception. There is dependably a necessity for productive and versatile information mining calculations and it is a subject of continuous exploration [1].

The initial step is to concentrate information from the database and after that perform preprocessing ventures on it. Information mining procedures are utilized to concentrate information designs. Assessment and presentation intends to speak to the learning in a way which is reasonable to clients. The outcome is strengthening off clients with learning.

There are diverse information mining procedures including directed order, association rules mining or market wicker container investigation, unsupervised bunching, web information mining, and relapse.

One imperative procedure of information mining is arrangement. The target of characterization is to fabricate one or more models in view of the preparation information, which can effectively anticipate the class of test articles. There are a few issues from an extensive size of spaces which can be given a role as characterization issues [1]. Grouping has a few vital applications in our lives [2-5]. Illustrations incorporate client conduct forecast, portfolio hazard administration, recognizing suspects, therapeutic applications, sports, extortion recognition, and biometric identification. This postulation bargains for the most part with the order system of information mining.

Swarm intelligence [6-11], which manages the aggregate conduct of little and straightforward elements, has been utilized as a part of numerous application areas. It is a savvy, innovational, and circulated, worldview for taking care of enhancement issues. It might appear that information mining and swarm knowledge don't have a considerable measure in like manner. In any case, late research ponders recommend that both can be utilized together for extensive variety of genuine information mining issues including grouping, bunching, relapse, and picture handling. It is particularly reasonable for those situations when different strategies would be hard to actualize or excessively costly [12]. To grow more exact models of swarm intelligence in the field of information mining that perform superior to those that are as of now known is a continuous examination region.

Ant colony optimization (ACO) is a well-known system under the protection of swarm knowledge [13]. Ant Colony settlements are conveyed elements. In spite of the straightforwardness of their people they demonstrate a profoundly organized aggregate association. By using this association, subterranean insect settlements can accomplish complex assignments, which ascend over the individual capacities of a solitary insect. Cases are agreeable transport, searching, and division of work. In every one of these cases, ants organize their activities. It is a sort of roundabout correspondence between ants utilizing alterations of the earth. For instance, a searching Ant Colony drops a compound on the ground that expands the likelihood that different ants will take after the same way.

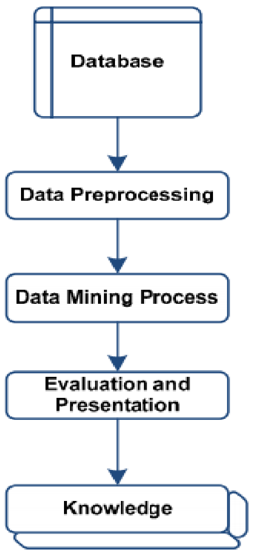

Figure 1-1 Steps of data mining for knowledge discovery

ACO is energized by the searching conduct of subterranean insect provinces, and appropriate for discrete streamlining issues [13]. Since its commencement, ACO has been connected to determine extensive quantities of issues. It is normally suited to discrete streamlining issues, for example, quadratic task [14], work booking [15], subset issues [16], system directing [17], vehicle steering [18], diagram shading issue [19], bioinformatics [20-22] and information mining [23] which is the subject of this proposition.

II. LITERATURE REVIEW

Determination of association rule mining, email (messages about criminal movement) is suspected. Adverse feeling words double-cross hypothesis, another individual pronoun, notwithstanding basic words, the high-recurrence words and uncommon words were composed in the body is described by misleading email composing preprocessed. Terms of apriori calculation [36] is utilized to make. Information created via the post office soon. It is utilized for computerized examination and assessment to distinguish criminal exercises and the declaration.

Apriori calculation for association guideline mining, and all email messages utilizing the activity verbs, past strained, utilizing prospects and assessed, It's an activity verb, such sort of messages later on strained addition and another with a message by email on the off chance that you are suspicious. Cautioning email to ""murder and bomb" future strained of words, for example, ""will and might," which alludes to such terms. Step number.

With a specific end goal to group the email box, all HTML from the content component, header, body, and so on expelled, before the words are stop words tokenizing. After detachment of the body, starts to move email arrangement. Preparing information "Bomb/Blast/Kill " key and " will/may " they, vital that the class data, messages, a move "assaulted/terrorist" and strained "was" in them utilizing apriori calculation.. The preparation set apriori calculation to discover the email database of words every now and again utilized as a part of the mining successive thing sets. Apriori calculation for association rules and the rules used to set this thing as takes after.

Tense=past, Attack= Y, Bomb =Y - >Email = Suspicious enlightening Email.

Tense=future, Attack= Y, Bomb =Y-> Email =Suspicious ready Email.

Tense=future, Attack= N, Bomb =N->Email =Normal Email.

An enhanced incessant example tree in light of the strategy named dynamic regular example tree is proposed by Gyorodi [36]. The new technique is productively connected on genuine size database. A correlation between traditional successive example mining calculations that are competitor set era, test and without hopeful era is proposed in paper. Apriori calculation, regular example development, dynamic incessant example development are analyzed and introduced together. Apriori calculation in used to govern mining in enormous exchange database and Apriori calculation is a base up methodology. Successive example development is utilized to novel, minimal information structure, alluded to as regular example tree, fp tree based ones are parcel based, separate and vanquish strategies.

Advancement of association rule mining and apriori calculation Using Ant state streamlining [37].This paper is on Apriori calculation and association principle mining to enhanced calculation in view of the Ant settlement improvement calculation.

ACO was presented by dorigo and has advanced fundamentally in the most recent couple of years. Numerous associations have gathered monstrous sum information. This information set is normally put away on capacity database frameworks. Two noteworthy issues emerge in the investigation of the data framework. One is diminishing pointless protests and ascribes in order to get the base subset of traits guaranteeing a decent guess of classes and a satisfactory nature of characterization. Another is speaking to the data framework as a choice table which indicates conditions between the base subset of qualities and specific class numbers without excess. In Apriori calculation, is working procedure clarified in steps. Two stage procedures is utilized to locate the continuous thing set to join and prune.

ACO calculation was enlivened from characteristic conduct of subterranean insect settlements. ACO is utilized to fathom to various hard enhancements including the voyaging sales representative issue. ACO framework contains two principles .One is nearby pheromone overhaul guideline, which is connected in building arrangement. Another is worldwide pheromone redesign guideline which is connected in insect construction.ACO calculation incorporates two more systems, to be specific trail dissipation and alternatively deamonactions.ACO calculation is utilized for the particular issue of minimizing the quantity of association standards. Apriori calculation utilizes exchange information set and uses a client intrigued backing and certainty esteem then creates the association principle set. These association principle set is discrete and proceeds. Subsequently feeble rule set are required to prune.

III. APRIORI ALGORITHM

Apriori calculation is, the most established and imperative calculation for mining continuous itemsets, proposed by R.Agrawal and R.Srikant in 1994. Apriori is utilized to locate all regular itemsets in a given database DB. The key thought of Apriori calculation is to make numerous disregards the database. It utilizes an iterative methodology known as a broadness first inquiry (level-wise pursuit) through the hunt space, where k-itemsets are utilized to investigate (k+1)-itemsets. The working of Apriori calculation is reasonably relies on the Apriori property which expresses that" All nonempty subsets of a successive itemsets must be incessant". It likewise portrayed the counter monotonic property which says if the framework can't finish the base bolster test, all its supersets will neglect to breeze through the test. In this manner if the one set is occasional then all its supersets are likewise incessant and the other way around. This property is utilized to prune the rare competitor components. To start with, the arrangement of successive 1-itemsets is found. The arrangement of that contains one thing, which fulfill the bolster limit, is meant by L. In each resulting pass, we start with a seed set of itemsets observed to be vast in the past pass. This seed set is utilized for creating new conceivably substantial itemsets, called applicant itemsets, and number the real backing for these hopeful itemsets amid.

Toward the end of the pass, we figure out which of the competitor itemsets are very (continuous), and they turn into the seed for the following pass. Accordingly, L is utilized to discover L!, the arrangement of successive 2-itemsets, which is utilized to discover L , etc, until not any more incessant k-itemsets can be found. The fundamental strides to mine the incessant components are as per the following:

• Generate and test: In this first discover the 1-itemset successive components L by examining the database and expelling every one of those components from C which can't fulfill the base bolster criteria.

• Join venture: To accomplish the following level components Ck join the past successive components independent from anyone else join i.e. Lk-1* Lk-1 known as Cartesian result of Lk-1 . I.e. This progression produces new applicant k-itemsets taking into account joining Lk-1 with itself which is found in the past emphasis. Let Ck indicate hopeful k-itemset and Lk be the continuous k-itemset.

• Prune step: Ck is the superset of Lk so individuals from Ck might possibly be visit yet all K " 1 regular itemsets are incorporated into Ck in this way prunes the Ck to discover K successive itemsets with the assistance of Apriori property. I.e. This progression kills a portion of the applicant k-itemsets utilizing the Apriori property An output of the database to decide the include of every hopeful Ck would bring about the determination of Lk (i.e., all competitors having a tally no not exactly the base bolster number are continuous by definition, and along these lines have a place with Lk). Ck, be that as it may, can be tremendous, thus this could include grave calculation. To shrivel the extent of Ck, the Apriori property is utilized as takes after. Any (k-1)- itemset that is not visit can't be a subset of a successive k-itemset. Henceforth, assuming any (k-1)- subset of hopeful k-itemset is not in Lk-1 then the competitor can't be visit either thus can be expelled from Ck. Step 2 and 3 is rehashed until no new applicant set is created.

It is undoubtedly Apriori calculation effectively finds the continuous components from the database. Be that as it may, as the dimensionality of the database increment with the quantity of things then:

• More look space is required and I/O expense will increment.

• Number of database output is expanded along these lines competitor era will build results in expansion in computational expense.

In this way numerous varieties have been happens in the Apriori calculation to minimize the above impediments emerges because of expansion in size of database. These in this manner proposed calculations receive comparative database examine level by level as in Apriori calculation, while the techniques for hopeful era and pruning, bolster numbering and competitor representation may contrast. The calculations enhance the Apriori calculations by:

- Reduce passes of transaction database scans.
- Shrink number of candidates
- Facilitate support counting of candidates

IV. ACO ALGORITHM

Our proposed associative arrangement calculation utilizes ACO calculation for finding intriguing connections among information things. It utilizes its transformative ability to productively discover all the more fascinating subsets of affiliation standards. It doesn't thoroughly hunt down all conceivable affiliation rules as ordinary ARM approaches does. In every era of the calculation various standards that fulfills least backing and certainty limit are chosen for the last classifier. After every era pheromones qualities are redesigned in a manner that better standards can be separated in next coming eras.

The last found standard set is the prescient model and is utilized to order inconspicuous test tests

The final discovered rule set is the predictive model and is used to classify unseen test samples.

2. Discovered_RuleList = {}; /* initialize the rule list with empty set */

3. TrainingSet = {all training samples};

4. Initialize min_support, min_confidence, min_coverege, /* minimum support, confidence and coverge threshold */

5. Initialize No_ants; */ initialize the maximum number of ants */

6. FOR EACH CLASS C IN THE TRAINING SET

7. Rule_Set_Class = {}; /* initialize the rule set of the selected class with empty set */

8. Initialize pheromone value of all trails;

9. Initialize the heuristic values;

10. Calculate the support of all 1-itemset (item => C) of the training set;

11. IF(support(item) < min_support)

12. Set the pheromone value 0 of all those items;

13. END IF

14. g = 1; /* generation count */

15. WHILE(g != no_attributes && coverege < min_coverege)

16. Temp_Rule_Set_Class = {};

17. t = 1; /* counter for ants */

18. DO

19. Antt construct a class based association rule with a maximum g number of items in the rule;

20. t = t + 1;

21. WHILE(t <= no_ants);

22. FOR EACH RULE CONSTRUCTED BY THE ANTS

23. IF(support(Rule)>=min_support AND confidence(Rule)>=min_confidence)

24. Insert the rule in Temp_Rule_Set_Class;

25. END IF

26. END FOR

27. Sort all the rules in Temp_Rule_Set_Class according to confidence and then support;

28. Insert the rule one by one from Temp_Rule_Set_Class into Rule_Set_Class until coverage of Rule_Set_Class is greater than or equal to min_coverage;

29. Update pheromones;

30. g = g + 1; /* increment generation count */

31. END WHILE

32. Insert Rule_Set_Class in Discovered_RuleList

33. END FOR

34. Pruning discovered rule set;

35. Output: Final classifier;

V. Artificial Bee Colony Algorithm With Crossover

Here, one more phase in the form of crossover operator of genetic algorithm is added to original Artificial Bee Colony algorithm. In standard ABC algorithm, there are only 4 phases that described the overall working of this algorithm, but here one additional phase after the employed bee phase of ABC algorithm is added in the form of crossover operator. Now ABC with crossover algorithm works in five phases: initialization phase followed by employed bee phase then crossover phase, onlooker bee phase and finally scout bee phase.

In order to adapt the ABC algorithm for solving constrained optimization problems, we adopted Deb's constrained handling method [13] instead of the selection process (greedy selection) of the ABC algorithm described in the previous section since Deb's method consists of very simple three heuristic rules. Deb's method uses a tournament selection operator, where two solutions are compared at a time, and the following criteria are always enforced:

1) Any feasible solution is preferred to any infeasible solution,
2) Among two feasible solutions, the one having better objective function value is preferred,
3) Among two infeasible solutions, the one having smaller constraint violation is preferred.

The basic steps of this algorithm are given below:

Initialization phase.
REPEAT
(a) In the Memory, Employed bees are placed on the food sources;
(b) Generate new offspring from older offspring after Applying crossover operator.
(c) In the memory, onlooker bees are placed on the food sources;
(d) For finding new food sources, Send the scout bee to the search space.

Pseudo-code of the ABC algorithm proposed for solving constrained problems is given below:

1: Initialize the population of solutions $x_{i,j}$, $i = 1 \ldots SN, j = 1 \ldots D$
2: Evaluate the population
3: cycle=1
4: repeat
5: Produce new solutions $\upsilon_{i,j}$ for the employed bees by using (4) and evaluate them
6: Apply selection process based on Deb's method
7: Calculate the probability values $P_{i,j}$ for the solutions $x_{i,j}$ by (1)
8: Produce the new solutions $\upsilon_{i,j}$ for the onlookers from the solutions $x_{i,j}$ selected depending on $P_{i,j}$ and evaluate them
9: Apply selection process based on Deb's method

10: Determine the abandoned solution for the scout, if exists, and replace it
with a new randomly produced solution xi,jby (3)
11: Memorize the best solution achieved so far
12: cycle=cycle+1
13: until cycle=Finish

VI. RESULT SIMULATION

- **Apriori Optimization Results**

Final Rules:

- Rule #1: 5 --> 1

Support = 0.22222
Confidenec = 1
Lift = 1.5

- Rule #2: 4 --> 2

Support = 0.22222
Confidenec = 1
Lift = 1.2857

- Rule #3: 5 --> 2

Support = 0.22222
Confidenec = 1
Lift = 1.2857

- Rule #4: 5 --> [1 2]

Support = 0.22222
Confidenec = 1
Lift = 2.25

- Rule #5: [1 5] --> 2

Support = 0.22222
Confidenec = 1
Lift = 1.2857

- Rule #6: [2 5] --> 1

Support = 0.22222
Confidenec = 1
Lift = 1.5

- Rule #7: 1 --> 3

Support = 0.44444
Confidenec = 0.66667
Lift = 1

- Rule #8: 3 --> 1

Support = 0.44444
Confidenec = 0.66667
Lift = 1

- **ACO Optimization Results**

Time comparison is done using execution time, which is the time to mine the frequent itemsets, against probabilistic factor and also done the number of comparison against probablistic factor. Experimental results of number of rules comparison, time comparison have been shown graphically in figure 1.2 and figure 1.3. with black line indicating performance of the Apriori with ACO based algorithm and Figure 1.4 to Figure 1.5 indicating performance of the Apriori with Artificial Bee Coloney based algorithm for dataset.

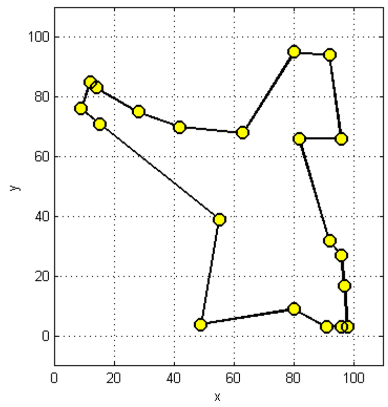

Figure 1.2 ACO optimization algorithms over the Apriori algorithm.

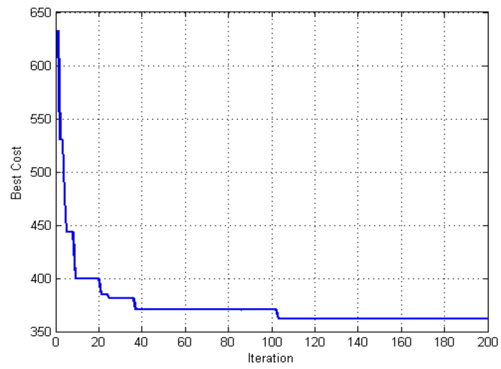

Figure 1.3 ACO optimization algorithm best cost over the Apriori algorithm.

- **Proposed Optimization Results**

Layer 1: Neurons = 15	Min Error = 3.4519
Layer 2: Neurons = 15	Min Error = 2.5807
Layer 3: Neurons = 15	Min Error = 2.4493
Layer 4: Neurons = 1	Min Error = 2.3897

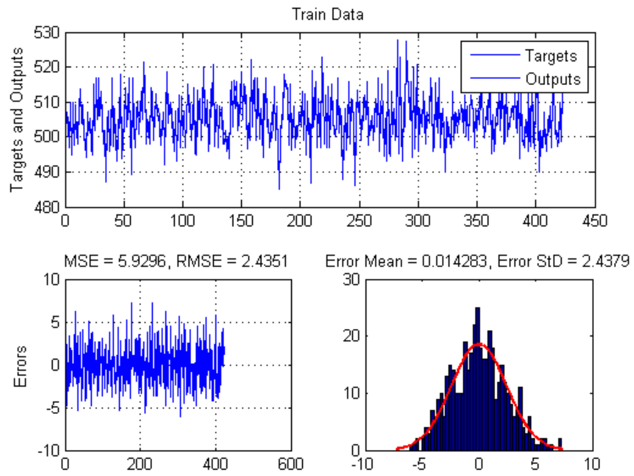

Figure 1.4 Train data with performance and error values with representations.

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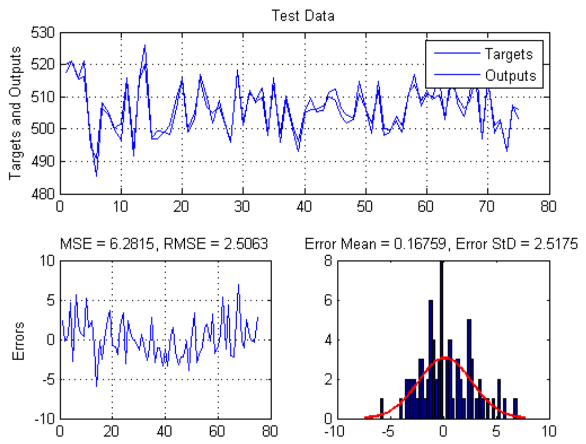

Figure 1.5 Test data with performance and error values with representations.

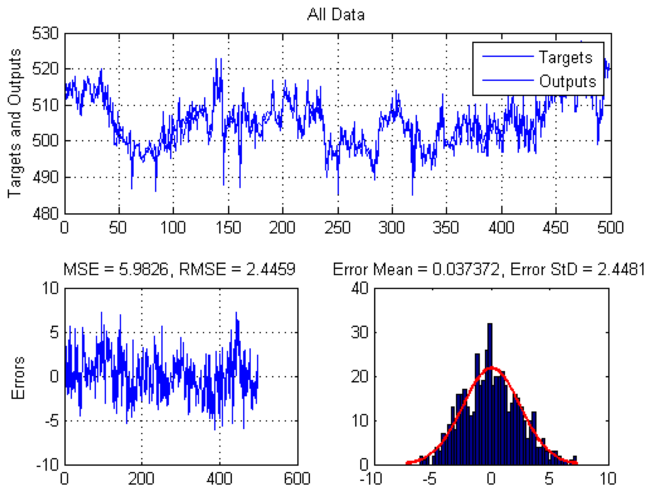

Figure 1.6 Train & test combine data with performance and error values with representations.

Plotregression is linear regression. Plotregression (targets, outputs) takes a target and output data and generates a regression plot.
Plotregression
(targets,1, outputs1,'name1',targets2,outputs2,names2,...) generates a variable number of regression plots in one figure.
Here a feed-forward network is used to solve a simple problem here showing way to plot regression plot of the three data.

```
figure; PlotResults(TrainTargets, TrainOutputs, 'Train Data');

figure; PlotResults(TestTargets, TestOutputs, 'Test Data');

figure; PlotResults(Targets, Outputs, 'All Data');

if ~isempty(which('plotregression'))
   figure; plotregression(TrainTargets, TrainOutputs, 'Train Data', ...
            TestTargets, TestOutputs, 'TestData', ...
            Targets, Outputs, 'All Data');
end
```

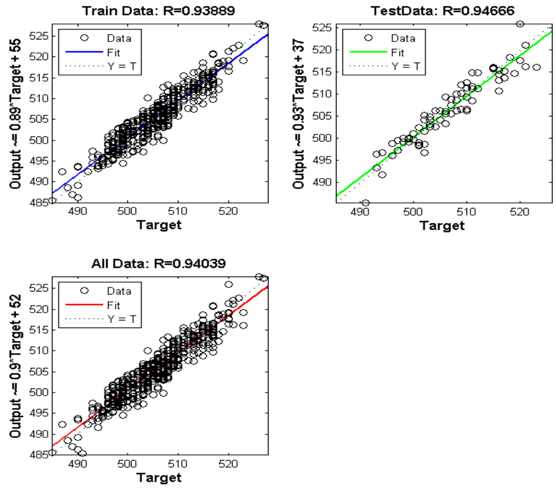

Figure 1.7 Regression plot representations of all three data.

VI. CONCLUSION

The ACO algorithm for optimizing the association rules, generated through apriori algorithm. ACO is a meta-heuristic approach for solving hard combinatorial optimization problems. The good quality of rules helps in better decision making. On the basis of the association rule mining and Apriori algorithm, a new algorithm is proposed based on the Ant Colony Optimization algorithm to improve the result of association rule mining. Ant Colony Optimization optimized the result generated by Apriori Algorithm by introducing probabilistic scheme. In probabilistic section, set of good rules are found from the weakest set rules based on the support and confidence value. For this, rules are reduced and number of rules is compared with the probabilistic value. If the probabilistic value is increased, then the number of rules is decreased or vice versa. From this research work which compares the rules with the time factor it was found that if number of rules is decreased then time of work process is also decreased. Performance comparison results indicated that proposed methodology was better than the Apriori approach in rule generation approach.
Comparative analysis also proves that apriori and Artificial Bee Colony based approach is better than apriori and ACO based approach as the time taken in processing of the algorithm on dataset using former approach is less than the later approach. As it can be seen that the proposed technique was found very useful from the existing techniques, but still there is a scope for improvement in the proposed approach to extend this approach to handle variety of situations and information. Proposed methodology which is implemented for single level association rules can be adopted for multi-level association rule mining. Time factor and number of rules can be reduced for Artificial Bee Colony and ACO approach.

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