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An Enhanced Application of Modified PSO for Association Rule Mining

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Abstract

In data mining, association rule learning is a well-liked and well explored technique for finding out interesting relatives in large databases along with variables. It analyzes and present strong rules discovered in databases by means of diverse measures of interestingness. As all know two important parameters, minimal support and confidence, are forever deciding by the decision-maker him/herself or in the course of trial-and-error; and thus, the previous algorithms be deficient in both objectiveness and competence. As a result, the main purpose of proposed work is to recommend an improved algorithm that can provide feasible threshold values for minimal support and confidence. Earliest particle swarm optimization algorithm investigates for the optimum fitness value of each particle and next discovers equivalent support and confidence as minimal threshold values subsequent to the data are distorted into binary values. To improve the feasibility of the work the modified PSO is developed to provide the feasible values. The modified PSO (Particle Swarm Optimization) algorithm has a number of swarm population size, the number of highest generation, and three predetermined parameters will be determined $\mathrm{C_w}, \mathrm{C}_p, \mathrm{C_g}$. In each generation, the particle's position value in all measurements will be reserved or be updated by its pbest value or be updated by the gbest value or restored by generating a new random number.

Keywords: *Data Mining, Particle Swarm Optimization, Modified PSO, Minimal Support and Confidence, Association Rule Learning, Swarm intelligence.*

1. Introduction

Data mining is an emerging technique to address the problem of reconstructing data into useful knowledge information from the user who can mine the results which they really want. That the rules are generated according to the knowledge by data mining algorithms in which one of most problematic steps in an association rule is discovery process knowledge validation. To solve this problem association rules have been widely used in many application domains for finding patterns in data and to generate the association rules. The pattern reveals combinations of events that occur at the same time based on the interesting associations and/or correlation relationships among a large set of data items. The attributes value conditions will be shown by association rule that occur frequently together in a given dataset. Apart from the antecedent (the "if" part) and the consequent (the "then" part), an association rule has two numbers that express the degree of uncertainty about the rule. First is Support: It is simply the number of transactions that include all items in the antecedent and consequent parts of the rule. Second is Confidence: It is the ratio of the number of transactions that include all items in the consequent as well as the antecedent to the number of transactions that include all items in the antecedent. The objective of data mining is to find out significant associations along with items such that the occurrence of various items in a transaction will entail the occurrence of some other items.

To accomplish this principle, suggested quite a lot of mining algorithms depends on the perception of large item sets to discover association rules in the transaction data mining process into two stages. In the first stage, candidate item sets were produced and calculated through scanning the transaction data. The value is called as minimum support if the amount of an item set to emerge in the transactions be larger than a pre-defined threshold value then the item set is considered as a large item set. At the second stage the association rule, rules is generated from the first stage's result of large item sets. For each large item set all feasible association permutations were formed and the value is called as minimum confidence the output will be as association rules, when individuals calculated with confidence values larger than a predefined threshold. Modified PSO has been developed based on the standard PSO [16] in which each particle is implied as a positive integer number. In this work, modified PSO algorithm is exploited to resolve rule mining problem which can manage with the dataset enclosing both the discrete and continuous variables. This advance is significantly diverse from other methods which had only joined data mining and PSO together. Most of their attempts had utilized to compact with the development of PSO as an optimization technique to resolve the data mining problems, for instance classification and clustering. To get better performance of the proposed algorithm planned to integrate the local search scheme to perform globally best solution obtained in each generation.

The main contribution of work is as follows:

1. First the input data from the database are transformed into binary data type
2. A novel technique of application that uses the concept of the particle swarm optimization approach.
3. Applying the modified PSO for a feasible solution of support and confidence.
4. At last Mining the association rule

The remainder of this work is described as follows: In section 2 the related work is dealt and in section 3 the proposed work is explained. In section 4 the experimental results and discussion is explained. In section 5 the conclusion of the work is described.

2. Previous Research

2.1 Association rule mining

Association rule mining is the most important and well researched data mining techniques were first introduced by J. Han [1]. In this method are used to extract the correlation, frequent interaction patterns, frequent item set association or casual relationship between the set of items in the transaction database or repositories. Association rule mining methods used in several areas such as telecommunication networks and risk management, inventory control etc. It is to find out the association rules that satisfy the predefined minimum support and confidence from a given database. Sometimes the association rules are very large to validate the results of each and every generation of rules. Several strategies have been proposed to reduce the number of association rules, such as generating only “interesting” rules, generating only “non redundant” rules, or generating only those rules by satisfying the certain number of criteria such as coverage, lift or strength and leverage.

2.2 Weighted Clustering based Particle Swarm Optimization (PSO) For MANET

Clustering is a method of organizing things into meaningful groups with respect to their similarities or grouping of the data. Clustered results the elements in a group are similar to each other but are different from other groups. The objective of clustering is to identify the groups in such a way that the identified groups are excluded so that any instance belongs to a single group. It is very similar to a graph partitioning problem in the PSO. Optimally portioning a graph is an NP-hard problem with respect to certain parameters. In this method the set of cluster-heads is called the dominating sets S of the graph. Due to the mobility of the network, the nodes can go outside the transmission range of their cluster-head and move into another cluster thus changing their neighborhood. The PSO optimization result changes the number of clusters and the number of nodes in a cluster but this does not result in a change of the dominant set at all.

Clustering of nodes in MANETs is one of the biggest challenges. Finding the optimal number of clusters that cover the entire network becomes essential and an active area of research. Although, several authors have proposed different techniques to find the optimal number of clusters, none of them addresses all the parameters of a mobile ad hoc network. Clustering has numeral advantages in MANETs. The performance of the system can be improved by allowing the reuse of system resources. It can optimally manage the network topology by dividing the task among specified nodes called cluster-heads, which is very useful for network management and routing [2].

The clustering algorithm must be distributed, since every node in the network has only local knowledge and communicates outside its group only through its cluster-head as in the case of cluster-based routing. The algorithm should be robust as the network size increases or decreases; it should be able to adapt to all the changes. The clusters should be reasonably efficient, i.e. the selected cluster heads should cover a large number of nodes as much as possible. In this work, they propose a Comprehensive Learning Particle Swarm Optimization (CLPSO) based clustering algorithm to find the optimal number of clusters for mobile ad hoc networks. Particle swarm optimization is a stochastic search technique. It has simple parameters that need to be tuned during the execution of the algorithm. It has been an efficient and effective technique to solve complex optimization problems. Each particle contains the IDs of all mobile nodes of the network. The algorithm takes a set of parameters of MANETs into consideration such as mobility of nodes, transmission power, battery power and moving speed of the nodes. It is a weighted clustering algorithm in which each of these parameters is assigned a weight such that the sum of all the weights is equal to one.

2.3 Optimization based methods for frequent item set

Genetic algorithms (GA) Optimization techniques have also been applied in ARM [3]. In this Genetic algorithm based system assigns weighted values to the importance of individual items. These weighted values based items apply to the fitness function of heuristic genetic algorithms to estimate the value of different association rules. These genetic algorithms can generate a suitable threshold value for association rule mining. In addition, Saggar et al. Proposed an approach concentrating on optimizing the rules generated using genetic algorithms. The approach predicts the more number negative attributes in the association rule [4] another study, a genetic algorithm was employed to mine the association rule oriented to the dataset in a manufacturing information system (MIS). According to the test results, the conclusion drawn stated that the genetic algorithm had a considerably higher efficiency [5].

In another study, an ant colony based algorithm was also employed in data mining under multi-dimensional constraints. The computational results showed that the ant colony based algorithm could provide more condensed rules than the Apriori method. In addition, the computation time was also reduced [6]. In addition, this method was integrated with the clustering method to provide more precise rules [7]. First, the dataset is clustered with the self-organizing map (SOM) network and the association rules in each cluster are then mined by an ACS-base association rule mining system. The results show that the new mining framework can provide better rules.

2.4 Particle swarm optimization (PSO) for applications

After the PSO algorithm was proposed in 1995, besides the above mentioned modifications, many different kinds of applications have been developed. PSO is applied to learn neural networks and it can classify XOR problem precisely. The results have shown that PSO can learn simple neural networks. Moreover, PSO was also utilized to develop the weight and structure of a neural network in 1998. It is more efficient than traditional training algorithms. Applications of PSO are gradually increasing, like in the medical treatment of human tremors of diseases such as Parkinson's disease, and in industrial automation of computer-aided design and manufacturing (CAD/CAM) [8]. In addition, PSO has been applied in clustering analysis. Cohen and Castro [9] presented a modified PSOA that featured self organization of the updating rule for clustering analysis. In their PSOA, it is not necessary to calculate fitness value. The results show that it is better than the K-means method. Kuo et al. [10] Proposed a PSKO which combined PSO-clustering with K-means. The PSKOA was evaluated in four data sets, and compared with the performance of K-means clustering, PSO-clustering and hybrid PSO. The experimental results show that the PSKO algorithms outperform other algorithms. In addition, Kuo and Lin [11] further used binary PSO to solve a clustering analysis problem and applied it to an order clustering problem. Chen and Ye proposed a PSO based clustering algorithm [12], which they called PSO-clustering. This method used minimal target function in PSO to automatically search for the data group center in multi-dimensional space. Compared with traditional clustering algorithms, PSO-clustering requires fewer parameter settings and avoids local optimal solutions.

2.5 An Optimized Particle Filter based on PSO Algorithm

Optimized PSO-UPF [13] was proposed for nonlinear dynamic systems. Based on the concept of re-sampling step where the particles with larger weights should be re-sampled more time. PSO-UPF optimization filter based algorithm the after calculation of weight values for particles, some particles will join in the refining process which means particles with higher weight values are moving to the region. The proposed PSO-UPF algorithm was compared with other filtering algorithms and variances of PSO-UPF are lower than other filtering algorithms. Major important feature in the particle optimization based filters is that the random measurement of the weight values and is recursively updated. Here three major operations are performed such as sampling, weight computation, and re-sampling. In sampling step one generates a set of new particles that represents the support of the random measure and with weight computation; one calculates the weight values of the particles. Re-sampling is an important operation because without this step proposed system will get poor results. Re-sampling step can be performed in two ways one replicates the particles that have larger weights and removes the ones with negligible weights.

2.6 Quantum Evolutionary based optimization Algorithm

Quantum Evolutionary Algorithm (QEA) is an optimization algorithm proposed by [14] .Here the QEA algorithm is performed by combining both the quantum based computing and Particle Swarm Optimization (PSO). By combining both these methods improves the performance of the system and solve optimization problems it is named as PSEQEA. PSEQEA is the algorithm used to solve multi-objective Optimization (MO) problems and single optimization problems. In this method non trivial points are used to evaluate the performance of the system to detect the Pareto optimal points and the shape of the Pareto optimal points by using both Fixed Weighted Aggregation method and Adaptive Weighted Aggregation method. The global optimization problem is still becoming a major problem in multidimensional functions. Quantum based concept with optimization techniques solves the optimization problems in function or multidimensional data. Hota et al proposed Quantum-behaved particle swarm optimization (QPSO)

[15] algorithm for global optimization of multi-dimensional functions. In this research, a modified and improved QPSO using fitness weighted recombination operator along with a fitness proportionate selection mechanism proposed to improve or solve optimization problems in the data or multidimensional functions. The experimental results are tested with different benchmark functions and compared with PSO and QPSO.

3. PSO and Modified PSO Based Association Rule Mining

3.1 Encoding

According to the definition of association rule mining, the intersection of the association rule of item set X to item set Y (X→Y) must be empty. Items which appear in the item set X do not appear on item set Y, and vice versa. Hence, both the front and back partition points must be given for the purpose of chromosome encoding. The item set before the front partition point is called "item set X," while that between the front partition and back partition points is called "item set Y." The chromosome encoding approach in this study is "string encoding." Each value represents a different item name, which means that item 1 is encoded as "1" and item 2 is encoded as "2." The representative value of each item is encoded into a string type chromosome by the corresponding order.

3.2 Fitness value calculation

The fitness value is utilized to evaluate the importance of each particle. The fitness value of each particle comes from the fitness function.

$$Fitness(k) = confidence(k) \times \log\left(support(k) \times length(k) + 1\right)$$

Fitness (k) is the fitness value of association rule type k. Confidence (k) is the confidence of association rule type k. Support (k) is the actual support of association rule type k. Length (k) is the length of association rule type k. The objective of this fitness function is maximization. The larger the particle support and confidence, the greater the strength of the association, meaning that it is an important association rule. In the equation above, support, confidence and item set length must be calculated before calculating fitness value. This study uses the binary type data search method. This method first arranges the original data into a two-dimensional matrix where rows represent data records and columns represent product items.

3.3 Population generation

In order to apply the evolution process of the PSO algorithm, it is necessary to first generate the initial population. Here we select particles which have larger fitness values as the population. The particles in this population are called initial particles.

3.4 Search the best particle

First, the particle with the maximum fitness value in the population is selected as the "gbest." The initial velocity of the particle is set to be $v_0 = 0$, while the initial position is $x_0 = (2,5,1,3,4)$. The particle's initial "pbest" is its initial position, and it is updated as shown below:

$$v_{id}^{new} = v_{id}^{old} + c_1 rand()(pbest - x_{id}) + c_2 rand()(gbest - x_{id}),\ x_{id}^{new} = x_{id}^{old} + v_{id}^{new}$$

Since the values calculated by these two equations may not always be an integer or fall in the range (1, 5), we designed a method to constrain the search. The constrained method is to calculate the distance between the particle's new position and all the possible particles inside the constrained range before the particle's position is updated. Definitely, the particle with the smallest distance will be selected and treated as the particle's new position. In the distance measuring function, we use traditional "Euclidean distance" as shown below:

$$dist(x^n, y^m) = \sqrt{\textstyle\sum_1^d (x_i^n - y_i^m)^2}.$$

Where x^n the position of the particle at nth update and ym is is the possible particle number m in the constrained range. In addition, d is the dimension of the search space. The nearest possible particle is selected to be the target particle's new position. This method can prevent a particle from falling beyond the search space when its position is updated.

3.5 Termination condition

To complete particle evolution, the design of a termination condition is necessary. The evolution terminates when the fitness values of all particles are the same. In other words, the positions of all particles are fixed. Another termination condition occurs after 100 iterations and the evolution of the particle swarm is completed.

Finally, after the best particle is found, its support and confidence are recommended as the value of minimal support and minimal confidence. These parameters are employed for association rule mining to extract valuable information.

3.6 Item set weight

Based on the item weight $w(i)$, the weight of an item set, denoted as $w(is)$, can be derived from the weights of its enclosing items. One simple way is to calculate the average value of the item weights, denoted as:

$$w(is) = \frac{\sum_{k=1}^{|s|} w(i_k)}{|is|}$$

3.7 Transaction weight

Transaction weight is a type of item set weight. It is a value attached to each of the transactions. Usually the higher a transaction weight, the more it contributes to the mining result. In a supermarket scenario, the weight can be the "significance" of a customer who made a certain transaction.

3.8 Weighted support

Weighted support *WSP* of an item set. A set of transactions T respects a rule R in the form A → B, where A and B are non-empty sub-item sets of the item space I and they share no item in common. Its weighted support is the fraction of the weight of the transactions that contains both A and B relative to the weight of all transactions. This can be formulated as:

$$wsp(AB) = \frac{\sum_{k=1}^{|ws_r|\&(A\cup B)\subseteq t_k} weight(t_k)}{\sum_{k=1}^{|ws_r|} weight(t_k)}$$

By this means, weighted support is modeled to quantify the actual quota of an item set in the transaction space in weighted association rule mining scenario. The weighted support of an item set can be defined as the product of the total weight of the item set (sum of the weights of its items) and the weight of the fraction of transactions that the item set occurs in. The goal of the weighted association rule mining is then changed to determining all rules that are above a user specified minimum weighted support threshold holding a minimum user specified confidence. In order to calculate weighted support of an item set, we need a method to evaluate transaction weight.

The transaction weight (t_k) can be derived from weights of the items presented in the transaction. One may formulate it easily as the average weight of the items presented in the transaction. Note that WS_t (t_k) denotes the inner-transaction space for the k_{th} transaction in transaction space WS_T.

$$weight = \frac{\sum_{i=1}^{|ws_r(t_k)|} weight(item(k))}{|ws_r(t_k)|}$$

This value is used to calculate the weighted support of a potentially significant itemset described above. The item set is then validated as significant if its weighted support is above the pre-defined minimum weighted support.

The Modified PSO the number of swarm population size, the number of maximum generation, and three predetermined parameters will be determined. In every generation, the particle's position value in each dimension will be kept or be updated by its pbest value or be updated by the gbest value or replaced by generating a new random number according to the procedure depicted (1). In this equation, i = 1, 2, . . ., m, where m is the swarm population. $X_i = (x_{i1}, x_{i2}, \ldots, x_{id})$, where x_{id} is the position value of the ith particle with respect to the d^{th} dimension (d = 1, 2, . . ., D) of the feature space. C_w, C_p and C_g are three predetermined positive constant with $C_w < C_p < C_g$. $P_i = (p_{i1}, p_{i2}, \ldots, p_{id})$ denotes the best solution achieved so far by itself (pbest), and the best solution achieved so far by the whole swarm (gbest) is represented by $Gi = (g_{i1}, g_{i2}, \ldots, g_{id})$. X represents the new values for the particle in every dimension which are randomly generated from random function rand(), where the random number is between 0. The update strategy for particles' position value in Modified PSO is presented below.

Step 1: Initialize the swarm size (m), the maximum generation (max_{Gen}), the maximum fitness value (max_{Fit}), C_w, C_p and C_g.

Step 2: In every iteration, a random number R that is in the range of 0 and 1 will be randomly generated for each dimension.

Step 3: Perform the comparison strategy where:
if ($0 \le R < Cw$), then $\{x_{id} = x_{id}\}$;
Else if ($C_w \le R < C_p$), then $\{x_{id} = p_{id}\}$;
Else if ($Cp \le R < Cg$), then $\{x_{id} = g_{id}\}$;
Else if ($Cg \le R \le 1$), then $\{x_{id} = new(x_{id})\}$;

Step 4: This process will be repeated until the termination condition is satisfied.

$$x_{id}^{t} = \begin{cases} x_{id}^{t-1} & if\ rand() \in [0, C_w) \\ p_{id}^{t-1} & if\ rand() \in [C_w, C_p) \\ g_{id}^{t-1} & if\ rand() \in [C_p, C_g) \\ x & if\ rand() \in [C_g, 1) \end{cases}$$

Step 5: Proceed the step 3 until convergence met.

Step 6: Find the best solution.

4. EXPERIMENTAL RESULTS AND DISCUSSON

In this module we measure the performance of the system in terms of the association rule mining accuracy and rule quality. The mining accuracy and result of the rule quality is measured by using the following equations: Data will be divided into two parts: training data and testing data. Training data is used to generate a model according to the given rules in the target problem, and later the model will be used on the testing data to obtain the validation accuracy. How well the rule will perform in the testing phase will depend on the reliability of the mining accuracy measurement. The standard mining accuracy rate can be written as:

$$\textit{Standard mining accuracy rate} = \frac{TP+TN}{TP+TN+FP+FN}.$$

The quality of the resulting rule is evaluated according to the rule-evaluation function

$$Quality = sensitivity \times specificity \frac{TP}{TP+FN} \times \frac{TN}{TN+FP}.$$

True positive (TP): the numbers of examples that covered by the rule that have the class predicted by the rule. False positive (FP): the numbers of examples covered by the rule that have a class different from the class predicted by the rule. True negative (TN): the number of examples that are not covered by the rule that have a class different from the class predicted by the rule. False negative (FN): the number of examples that are not covered by the rule that have the class predicted by the rule.

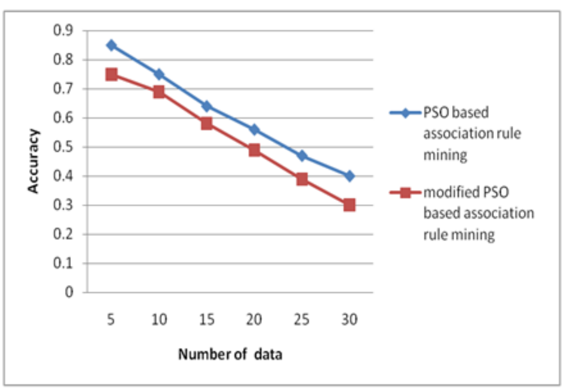

Fig 1: Comparison graph of Accuracy

This graph(Fig 1) shows the accuracy rate of existing and proposed system based on two parameters of accuracy and the number of datasets. From the graph we can see that, when the number of number of datasets is advanced the accuracy also developed in proposed system but when the number of number of datasets is improved the accuracy is reduced somewhat in existing system than the proposed system. From this graph we can say that the accuracy of proposed system is increased which will be the best one.

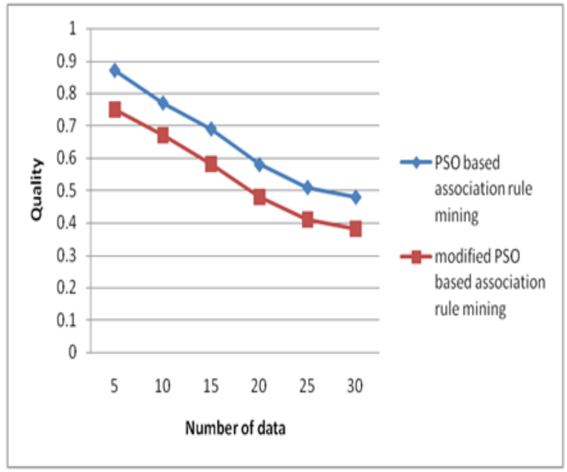

Fig 2: Comparison graph of Quality

This graph(Fig 2) shows the accuracy rate of existing and proposed system based on two parameters of quality and the number of datasets. From the graph we can see that, when the number of number of datasets is advanced the quality also developed in proposed system but when the number of number of datasets is improved the quality is reduced somewhat in existing system than the proposed system. From this graph we can say that the quality of proposed system is increased which will be the best one.

5. CONCLUSION

An important investigate that gets place in the area of data mining is the process of the extracting the exact required information based on the query. Thus the effective information can be retrieved based on the efficient association rules. By focusing on the problem of the generating the association rules, in this paper an effective approach of quantum particle swarm optimization is proposed in this paper. Here we have evaluated the proposed approach with the existing concept of association rule mining. From the experimental result shows that this approach provides an efficient association rule mining application for the information searching from the large databases. On applying this application of quantum particle swarm optimization approach to real time applications, could able to retrieve information effectively such as retrieving the transaction behavior, etc. This approach can be further enhanced by applying the other association rule techniques that can outperform the proposed approach.

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