A Hybrid Meta Heuristic Algorithm for Discovering Classification Rule in Data Mining

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Abstract

The Meta heuristics provide acceptable solutions in a reasonable time for solving hard and complex problems in medical, science and engineering. In this paper we present a meta heuristic based technique for mining rule over a medical data base were the use of the ABC and PSO algorithm as new tool for data mining particularly in classification task. This new found tool, hybrid ABC and PSO, surely help the medical fraternity and diagnosis. The diagnosis quickly and accurately by applying the hybrid Meta heuristic algorithm. The proposed algorithm is compared with an existing algorithm.

Key words: Meta Heuristic, Classification Rule mining Artificial Bee Colony, Particle Swarm Optimization.

1. Introduction

Data mining is a step in Knowledge Discovery in Database (KDD) approach that is used to extract and discover meaningful knowledge from large amount of data. Besides that, among the major functions of data mining are classification and prediction; concept description; association; cluster analysis; outlier analysis; trend and evaluation analysis; statistical analysis and many others. Classification and prediction are among the popular function in Data mining. The technique is supervised learning, which is class level or prediction target is known. There are many areas that have adapted this approach such as finance, medical, marketing, stock, telecommunication, manufacturing, health care, customer relationship and etc.

In other words, the data you wish to analyze by data mining techniques are incomplete (lacking attribute values or certain attributes of interest, or containing only aggregate data), noisy (containing errors, or outlier values which deviate from the expected), and inconsistent (e.g. containing discrepancies in the department). The classification analysis is by analyzing the data in the demonstration database, to make the accurate description or establish the accurate model or mine the classifying rule for each category, and then use the classifying rule to classify records in other databases.

1.1 Data Mining Classification Rule

Classification is aimed at finding set of efficient rules from the dataset. A rule of the form: IF (conditions) THEN (class), meaning that if a case (record) satisfies the rule conditions, it is predicted to have the class specified in the rule. The classification rule is of the form: IF <term1 AND Term2 AND … > THEN < class >. Each term is a triple <attribute, operator, value>, where value is one of the values belonging to the domain of attribute. An example of a term is: <Sex =female>. Class is the value of the goal attribute predicted by the rule for any case that satisfies all the terms of the rule antecedent. An example of a rule is: IF <Salary = high> AND <Mortgage = No> THEN <Credit = good>.

1.2 Meta Heuristic Algorithm

A Meta heuristic is formally defined as an iterative generation process which guides a subordinate heuristic by combining intelligently different concepts for exploring and exploiting the search space, learning strategies are used to structure information in order to find efficiently near-optimal solutions.

The core component of the proposed algorithm is a simulated annealing that utilizes three types of memories, two short-term memories and one long-term memory. The purpose of the two short-term memories is to guide the search toward good solutions. While the aim of the long term memory is to provide means for the search to escape local optima through increasing the diversification phase in a logical manner. The long-term memory is considered as a population list. In specific circumstances, members of the population might be employed to generate a new population from which a new initial solution for the simulated annealing component is generated.

This paper is organized as follows: section 2 presents study of Meta heuristic algorithm, section 3 presents ABC algorithm, section 4 presents PSO algorithm, section 5 presents Hybrid ABC and PSO algorithm for classification, section 6 presents experiments and results techniques section 7 presents summary and conclusions.

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2. Study of Meta Heuristic Algorithm

In this paper we study of Meta heuristic algorithms and following algorithms are part and parcel of whole of Meta heuristic algorithm. These Simulated Annealing, Tabu Search, Genetic Algorithm, Harmony Search, Ant Colony Optimization , Hill Climbing , Iterated Local Search , Scatter Search and Guided Local Search.

2.1 The Simulated Annealing

The Simulated Annealing algorithm (SA) [2] is a kind of heuristic random searching method. It is different from the traditional random searching method in searching strategy. In the iterative process, it not only accepts the solution which making the objective function value get "better", but can also accept the solution which making the objective function value get "worse" at a definite probability, and the accepting probability will gradual decrease in company with the temperature reduction. This searching strategy of SA can avoid the search process trapping in the local optimum solution, so the SA is a kind of effective global optimization algorithm. Due to the SA simulates the annealing process, although it can obtain a global optimum solution, but it needs lots of iterative computation, lead to the slow convergence rate.

2.2 Tabu Search

The Tabu Search (TS) approach was first proposed by Glover [3]. It is a global optimization technique with short-term memory, it can be used to solve a lot of hard combinatorial optimization problems, designed to guide other methods (or their components process) to escape the trap of local optimality. It sues flexible structure memory (to permit search information to be exploited more thoroughly than by rigid memory system or memory less systems) , conditions for strategically constraining and freeing the search space , and memory function of varying time spans for intensifying and diversifying the search .

2.3 Genetic Algorithm

The Genetic Algorithm (GA) is a search algorithm based on natural selection and the mechanisms of population genetics. The theory was proposed by Holland [4] and further developed by Goldberg [5] and others. A simple GA is comprised of three operators: reproduction, crossover, and mutation. Reproduction is the process of survival of-the-fittest selection. Crossover is the partial swapping between two parent strings to produce two offspring strings. Mutation is the occasional random inversion of bit values that generates non-recursive offspring. The main characteristic of the GA is the simultaneous evaluation of many solutions.

2.4 Harmony Search

The Harmony Search (HS) was first developed by Zong Woo Geem et al. in 2001 [6], it is a music-based Meta heuristic optimization algorithm. It was inspired by the observation that the aim of music is to search for a perfect state of harmony. This harmony in music is analogous to find the optimality in an optimization process. The search process in optimization can be compared to a jazz musician's improvisation process. On the one hand, the perfectly pleasing harmony is determined by the audio aesthetic standard. A musician always intends to produce a piece of music with perfect harmony.

On the other hand, an optimal solution to an optimization problem should be the best solution available to the problem under the given objectives and limited by constraints. Both processes intend to produce the best or optimum.

2.5 Ant Colony Optimization

The Ant Colony Optimization (ACO) was initially proposed by M.Dorigo [7]. The main underlying idea, loosely inspired by the behavior of real ants, is that of a parallel search over several constructive computational threads based on local problem data and on a dynamic memory structure containing information on the quality of previously obtained result. The collective behavior emerging from the interaction of the different search threads has proved effective in solving combinatorial optimization (CO) problems.

2.6 Hill Climbing

The Hill Climbing (HC**)** [8] is an optimization algorithm which historically was first used for maximization tasks. Like gradient descent algorithms in continuous spaces it approaches a local extreme but instead of using the gradient, hill climbing uses random local search to determine the direction and size of each new step. Hill climbing type algorithms can be regarded as evolutionary algorithms for populations of size two which only use a mutation operator.

2.7 Iterated Local Search

The Iterated local search (ILS) [9] is a general meta-heuristic. It has two basic operators for generating new solutions. One is a local search and the other is a perturbation operator. When its local search is trapped in a local optimal solution, a perturbation operator is applied to the local optimum to generate a new starting point for its local search. It is desirable that the generated starting point should be in a promising area in the search space. A commonly-used perturbation operator is a conventional mutation, which can produce a starting point in a neighboring area of the local optimum.

In this paper, we use the guided mutation operator as the perturbation operator in iterated local search for the quadratic assignment problem. The guided mutation operator can generate a new starting point for the further local search, which is in a promising area characterized by a probability model and not far away for the best solution found so far.

In [11] and [10], we have used guided mutation operators in evolutionary algorithms with guided local search and 2- opt local search for the QAP. The algorithms in [11] and [10] are population-based methods, while the algorithm in this paper is a single-point based iteration method. One of the major contributions of this paper is the introduction of guided mutation operators to iterated local search. We show that a guided mutation operator can improve the performance of ILS.

2.8 Scatter Search

Introduced as early as 1977 by Glover *[12;* 13; 14], Scatter Search (SS) is a population-based approach that starts with a collection of reference points obtained by the application of preliminary heuristic processes. Weighted combinations of the reference points are created to produce trial points, and these in turn are submitted to a generalized rounding operator to handle discrete components. **A** fundamental element of scatter search includes submitting a preferred subset of the resulting combined trial solutions to heuristic processes to yield further improvement before selecting new reference points from these outcomes. This represents a marria.ge of population-based strategies and local search strategies that more recently has emerged in some genetic algorithm hybrids. The maintenance of the reference points and the selection of generators are also influenced by the history of the search with the use of special memory structures. These memory-based proposals provide a link between alternative classes of solution approaches, by introducing notions that have also become establish among the early cornerstones of tabu search.

2.9 Guided Local Search

The Guided Local Search (GLS) [15] is a penalty-based approach that sits on top of local search methods to bring them out of local optima. When the given local search algorithm is trapped in a local optimum, GLS dynamically changes the objective function, by penalizing some selected features (i.e. increasing the associated penalties) that present in this local optimum. Then, the local search continues to search using the augmented objective function which will guide the search to escape from the current local optimum toward promising areas by giving incentive to remove unfavorable features. The novelty of GLS is mainly in the way that it selects which features to penalize, which is determined by two factors: feature’s cost (i.e. influence on the objective function) and the frequency of penalizing a feature.

3. Artificial Bee Colony Algorithm

Our aim is to combine the better of this two algorithm before we deal with this concept, let see the best side of the two algorithms i.e., ABC and PSO. Artificial Bee Colony (ABC) algorithm [16] a new swarm intelligent algorithm, which proposed by Karabog in Erciyes University of Turkey in 2005 (D. Karaboga, 2005). Since ABC algorithm is simple in concept, easy to implement, and has fewer control parameters, it has been widely used in many optimization applications such as protein tertiary structures (H.A A. Bahamish, R. Abdullah, & R.A. Salam, 2009), digital IIR filters (N. Karaboga, 2009), artificial neural networks (D. Karaboga & Akay, 2005) and others.

3.1 Description of Honey Bee Behaviors

The minimal model of foraging selection that leads to the emergence of collective intelligence of honey bee swarms consists of three essential components: food sources, employed foragers and unemployed foragers. There are two basic behaviors: recruitment to a food source and the abandonment of a food source [17].

Food Sources: In order to select a food source, a forager bee evaluates several properties related with the food source such as its closeness to the hive, richness of the energy, taste of its nectar, and the ease or difficulty of extracting this energy. For the simplicity, the quality of a food source can be represented by only one quantity although it depends on various parameters mentioned above.

Employed foragers: An employed forager is employed at a specific food source which she is currently exploiting. She carries information about this specific source and shares it with other bees waiting in the hive. The information includes the distance, the direction and the profitability of the food source.

Unemployed foragers: A forager bee that looks for a food source to exploit is called unemployed. It can be either a scout who searches the environment randomly or an onlooker who tries to find a food source by means of the information given by the employed bee.

In ABC algorithm, each cycle of the search consists of three steps: sending the employed bees onto their food sources and evaluating their nectar amounts; after sharing the nectar information of food sources, the selection of food source regions by the onlookers and evaluating the nectar amount of the food sources; determining the scout bees and then sending them randomly onto possible new food sources. At the initialization stage, a set of food sources is randomly selected by the bees and their nectar amounts are determined.

The Main Steps for ABC Algorithm

1: Initialize Population
2: repeat
3: Place the employed bees on their food sources
4: Place the onlooker bees on the food sources depending on their nectar amounts
5: Send the scouts to the search area for discovering new food sources
6: Memorize the best food source found so far
7: until requirements are met

At the initialization stage, a set of food sources is randomly selected by the bees and their nectar amounts are determined.

At the first step of the cycle, these bees come into the hive and share the nectar information of the sources with the bees waiting on the dance area. A bee waiting on the dance area for making decision to choose a food source is called onlooker and the bee going to the food source visited by herself just before is named as employed bee. After sharing their information with onlookers, every employed bee goes to the food source area visited by self at the previous cycle since that food source exists in her memory, and then chooses a new food source by means of visual information in the neighborhood of the one in her memory and evaluates its nectar amount.

At the second step, an onlooker prefers a food source area depending on the nectar information distributed by the employed bees on the dance area. As the nectar amount of a food source increases, the probability of that food source chosen also increases. After arriving at the selected area, she chooses a new food source in the neighborhood of the one in the memory depending on visual information as in the case of employed bees.

The determination of the new food source is carried out by the bees based on the comparison process of food source positions visually. At the third step of the cycle, when the nectar of a food source is abandoned by the bees, a new food source is randomly determined by a scout bee and replaced with the abandoned one.

In our model, at each cycle at most one scout goes outside for searching a new food source and the number of employed and onlooker bees are selected to be equal to each other. These three steps are repeated through a predetermined number of cycles called Maximum Cycle Number (MCN) or until a termination criterion is satisfied.

Pseudo Code of ABC Algorithm

Require: *Max_Cycles, Colony Size and Limit*
1: Initialize the food sources
2: Evaluate the food sources
3: Cycle=1
4: **while** $Cycle \leq Max\_Cycles$ **do**
5: Produce new solutions using employed bees
6: Evaluate the new solutions and apply greedy selection process
7: Calculate the probability values using fitness values
8: Produce new solutions using onlooker bees
9: Evaluate the new solutions and apply greedy selection process
10: Produce new solutions for onlooker bees
11: Apply Greedy selection process for onlooker bees
12: Determine abandoned solutions and generate new solutions randomly using scouts
13: Memorize the best solution found so far
14: Cycle = Cycle + 1
15: ***end while***
16: ***return*** *best solution*

4. Particle Swarm Optimization

The Particle swarm optimization (PSO) [18] is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behaviour of bird flocking or fish schooling. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space which are associated with the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called *pbest*. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the neighbours of the particle. This location is called *lbest*. When a particle takes all the population as its topological neighbours, the best value is a global best and is called *gbest*. The particle swarm optimization concept consists of, at each time step, changing the velocity of (accelerating) each particle toward its p*best* and *lbest* locations (local version of PSO). Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pbest* and *lbest* locations. PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest. After finding the two best values, the particle updates its velocity and positions with following equation (1) and (2).

$$V[\ ]=V[\ ]+C_1*rand(\ )*(pbest[\ ]-present[\ ]) + C_2*rand(\ )*(gbest[\ ]-present[\ ]) \quad (1)$$

$$prsent[\ ]=present[\ ]+V[\ ] \quad (2)$$

The $V[\ ]$ particle velocity $present[\ ]$ is the current particle (solution). The *pbest* [ ] and *gbest* [ ] are defined as stated before. The *rand ( )* is a random number between (0, 1). C_1, C_2 are learning factors. Usually $c_1 = c_2 = 2$.

Pseudo Code of PSO Algorithm

For each particle
Initialize particle
END
Do
For each particle
Calculate fitness value
If the fitness value is better than the best fitness value (pbest) in history
set current value as the new pbest
End
Choose the particle with the best fitness value of all the particles as the gbest
For each particle
Calculate particle velocity according equation (1)
Update particle position according equation (2)
End
While maximum iterations or minimum error criteria is not attained

5. Hybrid ACO and PSO

Finally we come to the heart of the part where we tend to combine the algorithm ACO and PSO and produce a new hybrid which makes increase accuracy of the classification rule. The goal of ABC and PSO algorithm is to discover classification rules form the training data set. The hybrid algorithm aimed at mixing the components from ABC and PSO algorithm to easily solve the problem. The PSO algorithms make use of particle moving in an n-dimensional space to search for solution for an n-variable function optimization problem.

A particle decides where to move next considering its own experience so that PSO find the global best position in the neighborhood are maintained by using ABC , update the global position velocity associated with each dimension which is an increment to be made in each iteration , to the dimension associated equation(3). Produce a new solution V_{ij} in the neighborhood of x_{ij} for the employee bee using the equation (3).

$$V_{ij} = x_{i,j} + \phi_{ij}(x_{ij} - x_{kj}) \quad (3)$$

Where k is a solution in the neighborhood of i, ϕ is a random number in the range of (-1, 1) and evaluate them apply the greedy solution process between process.

Hybrid ACO and PSO Algorithm

RS= { } / Initially Rule Set Empty*/*
For Each Class C
TS= {all training sample belonging to all classes}
While (number of uncovered training sample of class c > max uncover example per class)
For any particle i do
Update velocity

$$V_{ij} = \omega V_{ij} + C_1 r_1 (pbest_{ij} - x_{ij}) + C_2 r_2 (gbest_{ij} - x_{ij})$$

Update position

$$x_{ij} = x_{ij} + V_{ij}$$

IF $f(pbest) \le f(x_i)$ *then*

$$pbest = x_i$$

End if
End For
Update $gbest$
For every particle i do
Choose random problem variable
Apply ABC update rule to $pbest$
Update $pbest_i$ *and* $gbest$
End For
Iter_no=iter_no+1
End wile
End For
Return $gbest$

6. Experimental Result and Discussion

Our experiment used data set from the UCI data set repository stat log-heart data set which contains 70 instances and 12 integral attribute and two classes.

We have evaluated comparative performance of the proposed method and PSO using 10 fold cross validation. Each dataset divided into ten partitions, each method is run ten times, using different portions as test set as the training set each time. We run the classifier ten times using a different random, seed to initialize search each time for each cross validate ion fold. The comparison was carried out across three criteria, namely 1. Predictive accuracy of the discovered rule list 2. Their simplicity and attribute. 3. Computational cost. In the first step of our two step approach, we apply the PSO feature selection criteria to reduce the number of attribute and remove the duplicate the examples (sample values for all attribute) from the resulting reduce dataset to avoid the possibility that a test set contains an example that is same as the training is dataset example. In the second step our hybrid approach we run the ABC on the new reduce dataset. For the dataset we performed experiments using Java and Myra software for comparing accuracy, simplicity and computational cost between the proposed our algorithm and PSO.

The result from heart dataset also shows that PSO convergence faster but less than optimum solution. Here proposed algorithm provides best result in terms of accuracy and time among the heuristic.

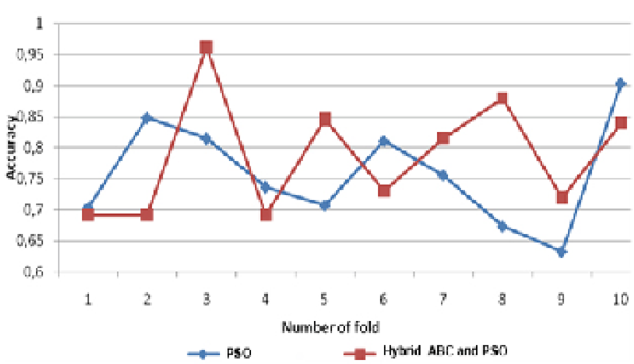

Figure 1: Compare PSO with ABC and PSO for accuracy

However we note our conclusion for all the cases tested. On the heart data set, the proposed algorithm achieved better accuracy compare to the original PSO. It is obtained clearly better accuracy in the figure 1, compare to the PSO with simpler rule list in the figure 2, 3 and less computational cost.

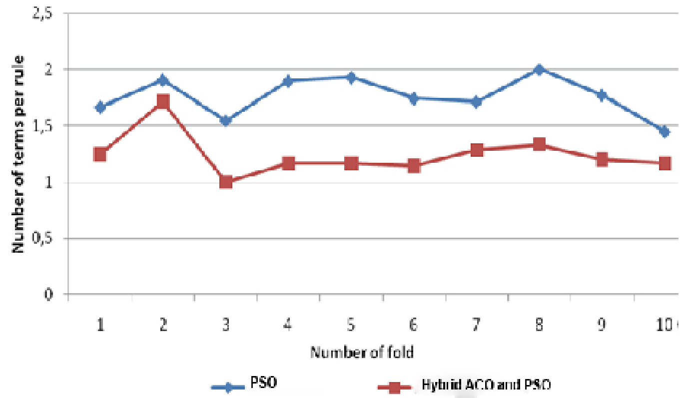

Figure 2: Compare PSO with ABC and PSO for instance Rule

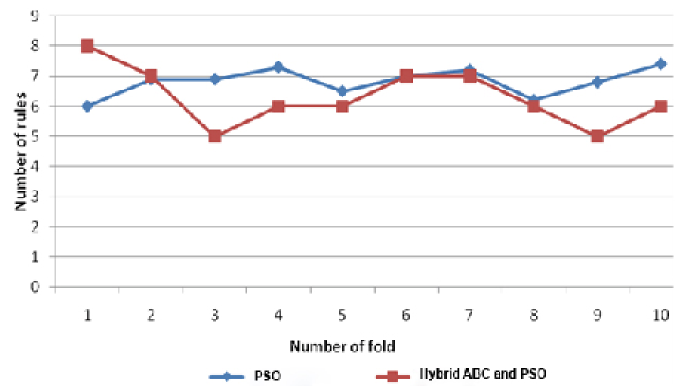

Figure 3: Compare PSO with ABC and PSO for Rules

7. Conclusion

The ABC is new search algorithm under SI technology many approach like ant colonies have been successfully used in Data Mining. From the best of our knowledge, previous work has never applied the ABC algorithm in Data mining.

In this work, we proposed a hybridization approach between ABC and PSO. The rule quality can be viewed in terms of its accuracy. A rule framed, using this hybridization method, to enhance the accuracy and higher efficiency of the result. So that it will be useful to medical field to treat the patients. This is achieved by incorporating an ABC corresponding to PSO, which update the bpest information of the particle in every interaction using the ABC update equation. This method penalize false positive severely, which is desirable characteristic for data mining in the medical domain.

In future work, we plan to compare the performance of the proposed ABC and PSO algorithm with other heuristic algorithm we also plan to discover a new effort, by changing the parameter values of ABC and PSO.

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