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Optimization of Artificial Bee Colony Algorithm for Clustering in Data Mining

Dr. Anil Kumar
Associate Professor, DCSA Department,
HCTM Kaithal, Haryana, India

Abstract: ***Data mining is a powerful new technology, which aims at the extraction of hidden predictive information from large databases. Data pre-processing involves many tasks including detecting outliers, recovering incomplete data and correcting errors. Outlier detection is an important pre-processing task. It is a task that finds objects that are dissimilar or inconsistent with respect to the remaining data. It has many uses in applications like fraud detection, network intrusion detection and clinical diagnosis of diseases. Using clustering algorithms for outlier detection is a technique that is frequently used. The clustering algorithms consider outlier detection only to the point they do not interfere with the clustering process. In this paper, an efficient method has been proposed which is based on Fuzzy clustering using Artificial Bee Colony algorithm for detecting the outliers.***

Keywords: FCM, ACO, PSO

I. INTRODUCTION

Outlier detection is a research problem in "small-pattern" mining in databases. It aims at finding a specific number of objects that are considerably dissimilar, exceptional and inconsistent with respect to the majority records in an input database. In many data analysis tasks, a large number of variables are being recorded or sampled. One of the first steps towards obtaining a coherent analysis is the detection of outlaying observations. Although outliers are often considered as an error or noise, they may carry important information. There is a need for pre-processing of the raw data in many fields, such as data mining, information retrieval, machine learning and pattern recognition. Zhang et. al [1] argue for the importance of data preprocessing and present the following reasons: (1) real world data is impure; (2) high performance data mining systems require high quality data and (3) quality data yields high quality patterns. Therefore, developing efficient data-preprocessing techniques is a critical task that requires considerable research efforts. Using clustering algorithms for outlier detection is a technique that is frequently used. The clustering algorithms consider outlier detection only to the point they do not interfere with the clustering process. Several clustering-based outlier detection techniques have been developed, most of which rely on the key assumption that normal objects belong to large and dense clusters, while outliers form very small clusters. The Fuzzy C-Means algorithm (FCM), as one of the best known and the most widely used fuzzy clustering algorithms. However, FCM is an effective algorithm; the random selection in center points makes iterative process falling into the local optimal solution easily. To tackle this problem, evolutionary algorithms such as genetic algorithm (GA), differential evolution (DE), ant colony optimization (ACO), and particle swarm optimization (PSO) have been successfully applied. Recently a family of nature inspired algorithms, known as Swarm Intelligence (SI), has attracted several researchers from the field of pattern recognition and clustering. Inspired from this, in our work Artificial Bee Colony Algorithm is applied to Fuzzy clustering for outlier detection.

II. FCM CLUSTERING

Fuzzy c-means clustering involves two processes: the calculation of cluster centers and the assignment of points to these centers using a form of Euclidian distance. This process is repeated until the cluster centers stabilize. The algorithm is similar to k-means clustering in many ways but it assigns a membership value to the data items for the clusters within a range of 0 to 1. So it incorporates fuzzy set's concepts of partial membership and forms overlapping clusters to support it. The objective function of the fuzzy clustering is to minimize the equation (1), Where m is any real number greater than 1, it is set to 2.00 by Bezdek, u_{ij} is the degree of membership of x_i in the cluster j and $\|xi - c_j\|^2$ is the Euclidean distance from sample points x_i to cluster center c_j. The algorithm needs a fuzzification parameter m in the range [1,n] which determines the degree of fuzziness in the clusters. When m reaches the value of 1 the algorithm works like a crisp partitioning algorithm and for larger values of m the overlapping of clusters is tend to be more.

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2 \qquad (1)$$

The algorithm calculates the membership value μ with the equation (2),

$$\mu_j(x_i) = \frac{\left(\frac{1}{d_{ji}}\right)^{\frac{1}{m-1}}}{\sum_{k=1}^{p}\left(\frac{1}{d_{ki}}\right)^{\frac{1}{m-1}}} \qquad (2)$$

Where,
$\mu_j(x_i)$: is the membership of x_i in the j^{th} cluster
d_{ji} : is the distance of x_i in cluster C_j
m: is the fuzzification parameter
p: is the number of specified clusters
d_{ki}: is the distance of x_i in cluster C_k
This is a special form of weighted average. We modify the degree of fuzziness in x_i's current membership and multiply this by x_i. The product obtained is divided by the sum of the fuzzified membership. In this way new centroids are calculated with these membership values using equation (2) for clusters.

$$C_j = \frac{\sum_i \left[\mu_j(x_i)\right]^m x_i}{\sum_i \left[\mu_j(x_i)\right]^m} \qquad (3)$$

Where,
C_j : is the center of the j^{th} cluster
x_i : is the i^{th} data point
μ_j : the function which returns the membership
m: is the fuzzification parameter

$$\sum_{j=1}^{p} \mu_j(x_i) = 1 \qquad (4)$$

The first loop of the algorithm calculates membership values for the data points in clusters and the second loop recalculates the cluster centers using these membership values. When the cluster center stabilizes (when there is no change) the algorithm ends. The fuzzy c-means approach to clustering suffers from several constrains that affect the performance [4].

The main drawbacks are due to the restriction that the sum of membership values of a data point x_i in all the clusters must be equal to one as in expression (3). This restriction tends to give high membership values for the outlier points. So the algorithm has difficulty in handling outlier points.

III. ARTIFICIAL BEE COLONY-FCM

Artificial Bee Colony (ABC) algorithm is a new swarm intelligence method which simulates intelligent foraging behavior of honey bees. In the model of ABC algorithm, there are three groups of bees; employed bees, onlooker bees and scout bees in the colony of artificial bees [5].

Firstly, half of the colony consists of the employed bees and the second half consist the onlookers. Employed bees go to the food sources, and then they share the nectar and the position information of the food sources with the onlooker bees which are waiting on the dance area determine to choose a food source. The employed bee whose food source has been abandoned by the bees becomes a scout bee that carries out random search in the simulating model. The goal of bees in the ABC model is to find the best solution, the position of a food source represents a possible solution to the optimization problem and the nectar amount of a food source corresponds to the quality (fitness) of the associated solution. The detail pseudo code of ABC [6] fuzzy clustering (ABC-FC) is:

Step 1 Initialize the population of solutions x_{ij} and evaluate the population;
Step 2 Repeat;
Step 3 cycle=1;
Step 4 Produce new solutions (food source positions) v_{ij} in the neighborhood of x_{ij} for the employed bees using the formula

$$v_{ij} = x_{ij} + \Phi_{ij}(x_{ij} - x_{kj}) \qquad (5)$$

Here k is a solution in the neighborhood of i, Φ is a random number in the range [-1, 1]. Evaluate the new solutions;
Step 5 Apply the greedy selection process between x_i and v_i;
Step 6 Calculate the probability values P_i for the solutions x_i by means of their fitness values using the equation:

$$P_i = \frac{f_i}{\sum_{i=1}^{SN} f_i} \qquad (6)$$

Here SN denotes the number of solutions, and f denotes the fitness value;
Step 7 Normalize P_i values into [0, 1];
Step 8 Produce the new solutions (new positions) v_i for the onlookers from the solutions x_i, selected depending on P_i, and evaluate them;
Step 9 Apply the greedy selection process for the onlookers between x_i and v_i;

Step 10 Determine the abandoned solution (source), if exists, and replace it with a new randomly produced solution xi for the scout using the equation

$x_{ij} = min_j + \Phi_{ij} * (max_j - min_j)$ (7)

Here Φ_{ij} is a random number in [0, 1];

Step 11 Memorize the best food source position (solution) achieved so far;

Step 12 cycle= cycle+1;

Step 13 cycle= MCN

It is clear from the above explanation that there are three control parameters in the basic ABC: the number of food sources which is equal to the number of employed or onlooker bees SN, the value of limit and the maximum cycle number MCN. The survival and progress of the bee colony are dependent upon the rapid discovery and efficient utilization of the best food resources. Similarly the successful solution of difficult engineering problems is connected to the relatively fast discovery of good solutions especially for the problems that need to be solved in real time. In a robust search process, exploration and exploitation processes must be carried out together. In the ABC algorithm, while onlookers and employed bees carry out the exploitation process in the search space, the scouts control the exploration process.

The main title (on the first page) should begin 1-3/8 inches (3.49 cm) from the top edge of the page, centered, and in Times 14-point, boldface type. Capitalize the first letter of nouns, pronouns, verbs, adjectives, and adverbs; do not capitalize articles, coordinate conjunctions, or prepositions (unless the title begins with such a word). Leave two blank lines after the title.

IV. RELATED WORK

Many approaches have been proposed to detect outliers. These approaches can be classified into four major categories based on the techniques used [7] which are: distribution-based, distance-based, density-based and clustering-based approaches. Distribution-based approaches develop statistical models from the given data and then apply a statistical test to determine if an object belongs to this model or not. Objects that have low probability to belong to the statistical model are declared as outliers. However, Distribution-based approaches cannot be applied in multidimensional scenarios. In the distance-based approach [8], outliers are detected as follows. Given a distance measure on a feature space, a point q in a data set is an outlier with respect to the parameters M and d, if there are less than M points within the distance d from q, where the values of M and d are decided by the user. The problem with this approach is that it is difficult to determine the values of M and d. Density-based approaches [9] compute the density of regions in the data and declare the objects in low dense regions as outliers. In [9], the authors assign an outlier score to any given data point, which is known as the Local Outlier Factor (LOF), depending on its distance from its local neighborhood.

Clustering-based approaches [10, 11] consider clusters of small sizes as clustered outliers. In these approaches, small clusters (i.e., clusters containing significantly less points than other clusters do) are considered outliers. The advantage of the clustering-based approaches is that they do not have to be supervised. Moreover, clustering-based techniques are capable of being used in an incremental mode (i.e., after learning the clusters, new points can be inserted into the system and tested for outliers).

A method is presented in [8] a method based on fuzzy clustering. In order to test the absence or presence of outliers, two hypotheses are used. However, the hypotheses do not account for the possibility of multiple clusters of outliers.

A two-phase method has been defined in [10] to detect outliers. In the first phase, the authors proposed a modified k-means algorithm to cluster the data, and then, in the second phase, an Outlier-Finding Process (OFP) is proposed. The small clusters are selected and regarded as outliers, using minimum spanning trees. In [14], clustering methods have been applied. The key idea is to use the size of the resulting clusters as indicators of the presence of outliers. The authors use a hierarchical clustering technique.

The PAM algorithm [13] is performed and followed by the Separation Technique (henceforth, the method will be termed PAMST). The separation of a cluster A is defined as the smallest dissimilarity between two objects; one belongs to Cluster A and the other does not. If the separation is large enough, then all objects that belong to that cluster are considered outliers. In order to detect the clustered outliers, one must vary the number k of clusters until obtaining clusters of a small size with a large separation from other clusters.

As mentioned in [13], the K-means is sensitive to outliers, and hence may not give accurate results. In [12], Al- Zoubi proposed an effective clustering-based method to detect outliers. First, the PAM algorithm is performed, producing a set of clusters and a set of medoids. To detect the outliers, the Absolute Distances between the Medoids, μ, of the current cluster and each one of the Points, pi, in the same cluster (i. e., $| pi - \mu |$) are computed. The produced value is termed (*ADMP*). If the *ADMP* value is greater than a calculated threshold, *T*, then the point is considered an outlier; otherwise, it is not. The value of *T* is calculated as the average of all *ADMP* values of the same cluster multiplied by (1.5).

V. PROPOSED METHOD

A new clustering-based approach for outlier detection is proposed. First, we execute the ABCFCM algorithm, producing an objective function. Small clusters are then determined and considered as outlier clusters. We follow [3] to define small clusters. A small cluster is defined as a cluster with fewer points than half the average number of points in the k clusters. To detect the outliers in the rest of clusters, we (temporarily) remove a point from the data set and re-execute the ABC-FCM algorithm. If the removal of the point causes a noticeable decrease in the objective function value,

the point is considered an outlier; otherwise, it is not. The idea is based on the objective function calculated by performing Fuzzy clustering [16] using Artificial Bee Colony method. The Objective Function (OF) produced by the ABC-FCM algorithm represents the distances between the cluster centers and the points belonging to these clusters. Removing a point from the data set will cause a decrease in the OF value because of the total sum of distances between each point and the cluster center belonging to it. If this decrease is greater than a certain threshold, the point is then considered to be an outlier. The following parameters are used:

OF: the objective function of the whole cluster, OF_i: the objective function after removing point P_i from the cluster, DOF_i: $OF-OF_i$ and T= 1.5. The basic structure of the algorithm is explained with the help of following flow chart:

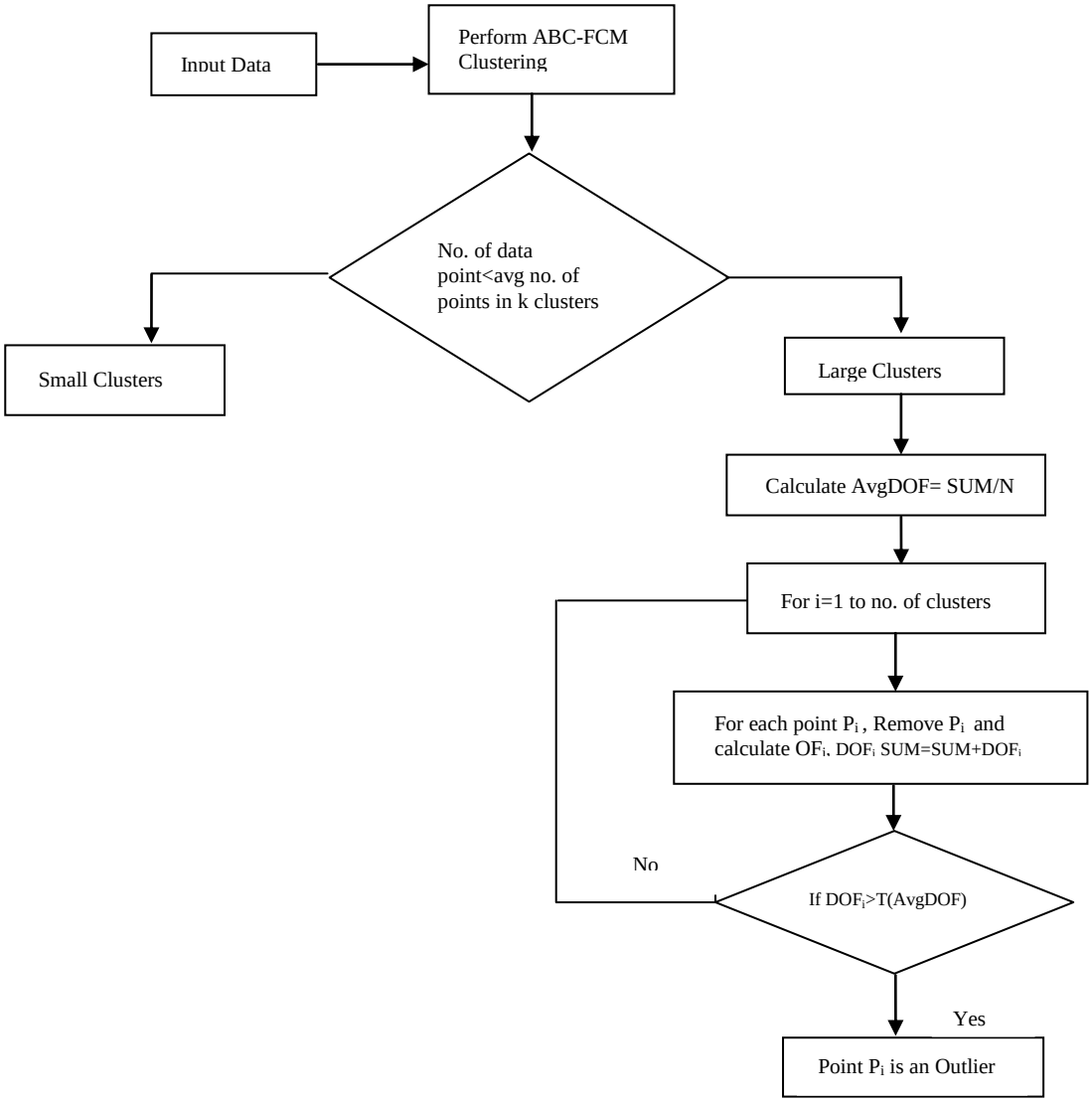

Figure 5.1: Flow Chart of Proposed Method

VI. RESULTS

In this work, we implemented the proposed approach on data set1 which is the well-known Iris data set [15]. The Iris data set has three classes of 50 instances each: Iris-setosa, Iris-versicolor and Iris-viginica, where each class refers to a type of iris plant. One class is linearly separable from the other two, the latter are not linearly separable from each other. The data set contain four attribute which are: Sepal length in cm, Sepal width in cm, Petal length in cm, Petal width in cm. Firstly clusters are formed of the given Iris data set.

It is known that the Iris data have some outliers. When defined number of clusters is three, then step 3 will classify the some points as outliers. Table I shows the result for the detected outliers in Class 1 of the Iris data set. The first column shows the data point no. and second column shows the OFi values when the current point is removed from the set. The third column shows the DOFi values. The value of the objective function for Iris data set, OF, is (6058.68). The AvgDOF is (28.6284). Multiplying the average values by (1.5) will give us the T(AvgDOF) is (42.9426), which is the threshold value used to determine the outliers. The fourth column shows whether the point is detected as outlier or not.

Table I: The data points detected by our proposed method from class 1 of the Iris data set

Data Point No.	OFi	DOFi	Point Detected	Data Point No.	OFi	DOFi	Point Detected

1	6056.34	2.34	F	26	6039.98	18.7	F
2	6039.53	19.15	F	27	6055.08	3.6	F
3	6041.2	17.48	F	28	6053.71	4.97	F
4	6032.49	26.19	F	29	6053.77	4.91	F
5	6054.18	4.5	F	30	6043.18	15.5	F
6	6014.71	43.97	T	31	6042.99	15.69	F
7	6041.43	17.25	F	32	6040.9	17.78	F
8	6058.34	0.34	F	33	6007.71	50.97	T
9	5998.1	60.58	T	34	5978.32	80.36	F
10	6045.29	13.39	F	35	6047.34	11.34	F
11	6034.78	23.9	F	36	6045.73	12.95	F
12	6052.76	5.92	F	37	6030.18	28.5	F
13	6034.53	24.15	F	38	6051.01	7.67	F
14	5979.98	78.7	T	39	6003.82	54.86	T
15	5962.82	95.86	T	40	6057.4	1.28	F
16	5932.54	126.14	T	41	6054.32	4.36	F
17	6015.43	43.25	T	42	5926.55	132.13	T
18	6056.07	2.61	F	43	6015.24	43.44	T
19	5995.87	62.81	T	44	6044.57	14.11	F
20	6042.61	16.07	F	45	6024.61	34.07	F
21	6038.21	20.47	F	46	6036.62	22.06	F
22	6047.34	11.34	F	47	6041.24	17.44	F
23	6016.28	42.4	F	48	6036.9	21.78	F
24	6045.66	13.02	F	49	6041.45	17.23	F
25	6037.11	21.57	F	50	6056.36	2.32	F

Similarly, we calculated outliers for class 2 and class 3 of Iris data set. By using proposed method eleven outliers detected in class 1, seven outliers in class 2 and nine outliers have detected in class 3 of the Iris data set.

VII. CONCLUSION

An efficient method for outlier detection is proposed in this paper. The proposed method is based on fuzzy clustering techniques. In this work, Artificial Bee Colony algorithm which is a recently introduced optimization algorithm is used to fuzzy clustering of Iris data. The ABC-FCM algorithm is first performed, and then small clusters are determined and considered as outlier clusters. Other outliers are then determined based on computing differences between objective functions values when points are temporally removed from the data set. If a noticeable change occurred on the objective function values, the points are considered outliers. Different experimentation have been conducted in [11] and showed that there are 10 outliers in class 3 of the Iris data set. Applying our proposed method, nine outliers are detected in class 3 and 7 outliers in class 2.The test results show that the proposed approach gave effective results. However, our proposed method is very time consuming. This is because the ABC-FCM algorithm has to be executed n times, where n is the number of data points in a set. We had applied proposed algorithm for small data set.

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