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A Survey on Application of Particle Swarm Optimization in Text Mining

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Abstract:
Text Mining is the discovery of new previously unknown information, by automatically extracting information from a usually large amount of data set. Many algorithms have been developed in recent years for solving problems of numerical and combinatorial optimization problems. Most efficient among them are swarm intelligence algorithms. Clustering using PSO is being used as an alternative to more conventional clustering techniques. PSO is population-based stochastic search algorithms that impersonate the capability of swarm. Data clustering with PSO algorithms are being used to produce better outcomes in a wide variety of real-world data. In this paper, a brief survey on PSO application in data clustering is described.

General Terms*: Data clustering, K-mean clustering*
Key words*: Data mining, Data clustering, Particle swarm optimization*

1. Introduction

The rapid advancement in computer networks, data acquisition, improved in computing performance and explosive growth in generation of electronic information has led to collection and storage of huge amount of data in databases. The amount of data stored in databases is increasing rapidly. This huge amount of stored data contains meaningful knowledge, which can be used to improve the decision-making in an organization. Such large databases have led to the emergence of a field of study called data mining and knowledge discovery in databases [1].

Data Mining is an analytical process exploring large amount of data to find consistent patterns and systematic relationships between variables, and then legitimize the outcomes by applying the detected patterns to new subsets of data. It generally aims at making a prediction. Technically it is the process of finding correlation and patterns among various fields in relational database by using advanced analytical techniques such as neural network, fuzzy logic and rough set[2],[3]. There are various methods of finding these patterns in a large database. Summarization, association, clustering etc. are some of these methods. Data clustering is the most popular of these methods.

Data clustering is a common approach of automatically finding classes, concepts, or groups of patterns. It aims to. partition an unstructured set of objects into clusters. This signifies wanting the objects to be as similar to objects in the same cluster and as dissimilar to objects from other clusters as possible. Clustering is being used in almost every field. Clustering techniques have been applied to a wide variety of research problems.

Data clustering algorithms can be either hierarchical or partitioned [4],[5]. In Hierarchical clustering a nested set of clusters is created. Every level in this hierarchy has a separate set of clusters is such a way that at the lowest level, each item is in its unique cluster and at the highest level, all items belong to the same cluster. Such hierarchical algorithms can be agglomerative (bottom-up) or divisive (top-down). Agglomerative algorithms are those that begin with each element as a separate cluster and merge them in successively larger clusters. Divisive algorithms, on the other hand, begin with the whole set and proceed to divide it into successively smaller clusters. Hierarchical algorithms have two basic advantages[4]. One is that the number of classes need not be specified a priori, and two, they are independent of the initial conditions. The main disadvantage of hierarchical clustering techniques is that they are static; which means that data points assigned to a cluster cannot move to another cluster. Besides this they may fail to separate overlapping clusters due to a lack of information about the global shape or size of the clusters[6].

The partitioned clustering technique is well suited for clustering a large dataset on account of their computational requirements being relatively low[7],[8]. The time complexity of this technique is almost linear making it widely usable. The best known partitioning clustering algorithm is the K-means algorithm and its variants [9]. This algorithm is simple, straightforward and is based on the firm foundation of the analysis of variances.

The K-mean algorithm seeks to find a partition that minimizes mean square error (MSE) measure. Although it is an extensively useful clustering algorithm, it suffers from many shortcomings. The objective function of the K-means is not convex[10] and hence it may contain local minima. As a consequence, while minimizing the objective function, there is possibility of getting stuck at local minima as well as at local maxima and at saddle point [11].

In order to overcome the problem of partitonal clustering various heuristic algorithms have been proposed in the literature surveyed such as Genetic Algorithm (GA), Ant Colony Optimization (ACO), Differential Evolution (DE) and Particle Swarm Optimization (PSO). Literature survey revealed that clustering techniques based on Evolutionary Computing and Swarm Intelligence algorithms outperformed many classical methods of clustering.

2. Particle Swarm Optimization

PSO is a population-based search algorithm which is initialized with a population of random solutions, called particles[21]. As against the other evolutionary computation techniques, each particle in this algorithm, called PSO is also associated with a velocity. Particles fly through the search space with velocities that are dynamically adjusted as per their historical behaviors. The particles, therefore have the tendency to fly towards the better and better search area all over the course of the process of search. In PSO a number of simple entities—the particles—are placed in the search space of some problem or function, and each one of these evaluates the objective function at its current location. Thereafter, each particle then determines its movement through the search space by combining some aspect of the history of its own current and best (best-fitness) locations with those of one or more members of the swarm, with some random perturbations. The next iteration takes place after all particles have moved. Eventually the swarm as a whole, like a flock of birds collectively foraging for food, is likely to move close to an optimum of the fitness function.

The particle swarm is actually more than just a collection of particles. A particle by itself has almost does not solve any problem; progress takes place only when they i.e. The particles interact. Populations are organized according to some sort of communication structure or topology. This is often thought of as a social network.

The main advantage of PSO is that it has less parameter to adjust. Other advantages are that PSO does not have any complicated evolutionary operators such as crossover, mutation as in genetic algorithm [23]. It has shortcomings too. PSO gives good results and accuracy for single objective optimization, but for multi objective problem it stuck into local optima[24]. Another problem in PSO is its nature to a fast and premature convergence in mid optimum points. Several PSO variants have been developed to solve this problem.[25]

The PSO algorithm consists of just three steps, which are repeated until some stopping condition is met [4]:

- Evaluate the fitness of each particle
- Update individual and global best fitnesses and positions
- Update velocity and position of each particle

The first two steps are fairly trivial. Fitness evaluation is conducted by supplying the candidate solution to the objective function. Individual and global best fitnesses and positions are updated by comparing the
newly evaluated fitnesses against the previous individual and global best fitnesses, and replacing the best
fitnesses and positions as necessary.

The velocity and position update step is responsible for the optimization ability of the PSO algorithm.

The velocity of each particle in the swarm is updated using the following equation:

$vi(t + 1) = wvi(t) + c1r1[\hat{\ }xi(t) - xi(t)] + c2r2[g(t) - xi(t)]$

The PSO algorithm works by simultaneously maintaining several candidate solutions in the search space. During each iteration of the algorithm, each candidate solution is evaluated by the objective function being optimized, determining the fitness of that solution. Each candidate solution can be thought of as a particle“flying” through the fitness landscape finding the maximum or minimum of the objective function.

Initially, the PSO algorithm chooses candidate solutions randomly within the search space.

The search space is composed of all the possible solutions along the x-axis; the curve denotes the objective function. It should be noted that the PSO algorithm has no knowledge of the underlying objective function, and thus has no way of knowing if any of the candidate solutions are near to or far away from a local or global maximum. The PSO algorithm simply uses the objective function to evaluate its candidate solutions, and operates upon the resultant fitness values.

3. Application of PSO in Data Clustering

Van der merwe and Engelhrecht[26] proposed two methods to cluster data using PSO. While in one method standard best PSO was used to find the centroid of a user specified number of clusters. In the second method the algorithm is then extended to use K-means clustering to seed the initial swarm. The results of two PSO approaches were compared to K-mean algorithm. This showed that the PSO approaches have better convergence to lower quantization errors, and in general, larger inter-cluster distances and smaller intra cluster distances.

Ahmadyfard and Modares [27] proposed another clustering algorithm, which is a hybrid of PSO and K-mean, named as PSO-KM algorithm. In this PSO algorithm is initially applied to search all space for a global solution. When global solution is found, K-mean clustering algorithm is used for faster convergence to finish the clustering process.

Ghali et al.[28] presented a exponential particle swarm optimization (EPSO) to cluster data. In EPSO exponential inertia weight is used instead of linear inertia weight. A comparison between EPSO clustering algorithm and particle swarm optimization (PSO) was made. It showed that EPSO clustering algorithm has a smaller quantization error than PSO clustering algorithm, i.e. EPSO clustering algorithm more accurate than PSO clustering algorithm.

Chen and Ye[17] proposed a algorithm based on PSO, called PSO-clustering that automatically search cluster centre in the arbitrary data set This proposed algorithm overcomes the shortcomings of K-Means algorithm, performance of which is highly dependent upon its nature of selection of initial cluster centre.

Omran [31] proposed a new clustering method based on PSO (DCPSO) for image segmentation. It was proposed to tackle the color image quantization. The method used binary PSO algorithm to automatically determines the ‘‘optimum’’ number of clusters and simultaneously clusters the data set.

Srinoy and Kurutach [32] proposed a novel model for the intrusion detection system, based on hybridization artificial ant cluster algorithm and k-mean particle swarm optimization. In this approach, initially artificial ant clustering algorithm is used to create raw clusters and then these clusters are refined using K-mean particle swarm optimization (KPSO). This approach is capable of recognizing only the known attacks as well as to detecting suspicious activity that may cause new, unknown attack.

Cui et al.[43] proposed a hybrid PSO based algorithm for document clustering. In this algorithm, they applied the PSO, K-means and a hybrid PSO clustering algorithm on four different text document datasets. The results have shown that the hybrid PSO algorithm can generate more compact clustering results than the K-means algorithm.

Hwang et al.[44] stated that one of the big issue with clustering algorithm was to define the number of clusters at the start of the clustering process by the user. To overcome such a problem, they proposed an algorithm based on particle swarm optimization (PSO) and fuzzy theorem which automatically determines the appropriate number of clusters and their centers. The results revealed that the proposed algorithm is able to determine the number of clusters accurately.

Das et al.[45] worked out a modified PSO based algorithm, called Multi-Elitist PSO (MEPSO) model for clustering complex and linearly non-separable datasets. In this algorithm kernel—induced similarity measure was used instead of Euclidean distance metric. They also reported that for nonlinear and complex data Euclidean distance causes severe misclassifications but it works well when data is hyper spherical and linearly separable.

Fun and Chen[46] worked out an evolutionary PSO learning-based method to optimally cluster N data points into K clusters. The hybrid PSO and K-means, with a novel alternative metric algorithm is called Alternative KPSO- clustering (AKPSO) method. It developed to automatically detect the cluster centers of geometrical structure data sets. In AKPSO algorithm, the special alternative metric is considered to improve the traditional K-means clustering algorithm to deal with various structure data sets.

Sridevi and Nagaveni[47] presented a clustering algorithm that employs semantic similarity measure. They have proposed a model by combining ontology and optimization technique to improve the clustering. In this model the ontology similarity is used to identify the importance of the concepts in the document and the particle swarm optimization is used to cluster the document.

Johnson and Sahin[48] introduced four methods of PSO, (Interia methods, Inertia with predator prey option, Constriction method and Constriction with predator prey option) to explain the PSO application in data clustering. The four methods were evaluated in a number of well-known benchmark data sets and were compared with K-mean and fuzzy c-means. The results have shown significant increase in performance and lower quantization error.

Paper referred	**Clustering Algorithm**	**Dataset**	**Evaluation parameters**	**Future Work**
DW van der Merwe AP Engelhrecht [26]	Gbest PSO, Hybrid PSO and K-means algorithm	Iris , Breast Cancer, Wine, Automotives	Quantization error, Inter cluster distance and intra cluster distance	Extend the fitness function to optimize the inter and intra cluster distances, Experiment on higher dimensional problems-and large number of patterns , determination of optimal number of clusters dynamically.
Neveen I. Ghali, Nahed El- Dessouki, Mervat A. N., and Lamiaa Bakrawi [28]	PSO, Exponential Particle Swarm Optimization (EPSO)	Breast cancer, Iris, Yeast, Lences, Glass	Quantization error	-------

Surat Srinoy and Werasak Kurutach [32]	Hybrid artificial ant cluster algorithm and kmean particle swarm optimization	KDD'99 data set	Recognition of known network attacks	-------
Esmaeil Mehdizadeh[34]	Fuzzy PSO alogrithm	Artificial data set, iris, wine and image segmentation	Objective function value and CPU time	-------
Hesam Izakian, Ajith Abraham, Václav Snášel[33]	Hybrid fuzzy c-means fuzzy particle swarm algorithm for clustering	Iris , Cancer, Wine, glass, CMC, vowel	Objective function values	-------
T. Niknam, M. Nayeripour and B.Bahmani Firouzi [35]	Particle swarm optimization - ant colony optimization (PSO-ACO) algorithm	Iris, Wine, Vowel and CMC	Function value, Standard deviation and number of function evaluation	-------
K. Premalatha and A.M. Natarajan[36]	PSO with local search	Iris , Wine, glass	Fitness value , Inter and Intra Cluster similarity	-------
Xiang Xiao, Ernst R. Dow, Russell Eberhart, Zina Ben Miled and Robert J. Oppelt [37]	Hybrid SOM –PSO algorithm	Yeast data set and rat data set	Average merit, execution time	-------
N. M. Abdul Latiff, C. C. Tsimenidis, B. S. Sharif and C. Ladha [38]	Binary PSO with multi-objective clustering approach (DCBMPSO)	100 nodes	Number of cluster, network lifetime and delivery of data messages	To investigate the DC-BMPSO algorithm properties such as the effect of varying algorithm parameter, *init p* on the number of clusters, as well as on network performance
Sandeep Rana, Sanjay Jasola, Rajesh Kumar [39]	PSO in sequence with K-Means	Artificial problem, Iris and wine	Quantization error, Inter and Intra Cluster distance	Variations in PSO algorithm and its hybridization with K-Means algorithm
Jakob R. Olesen, Jorge	*AutoCPB*	Artificial dataset,	QEF metric, ID metric, number of	To identify a rule to minimize local optima, to apply to other domains such

Jen-Ing G. Hwang, Chia- Jung Huang [44]	Hybrid scheme of differential evolution based PSO and fuzzy *c*-means(EDPSO)	Iris, Breast Cancer, Wine	Effect of perturbed velocity, determine an appropriate number of Clusters, Jaccard index	-------
Mahamed G. H. Omran , Ayed Salman and Andries P. Engelbrecht[31]	Dynamic clustering algorithm based on PSO (DCPSO)	Synthetic images,Lenna, mandrill, jet, peppers, MRI and Lake Tahoe	Mean and Standard deviation	Application of the DCPSO algorithm to general data, to investigate the effect of high dimensionality on the performance of the DCPSO, use of other clustering algorithms such as FCM and KHM to refine the cluster centroids, incorporation of spatial information into the DCPSO algorithm
Xiaohui Cui, Thomas E. Potok [43]	Hybrid Particle Swarm Optimization (PSO) and K-means document clustering	TREC-5, TREC-6, and TREC-7	Average distance between documents and the cluster centroid(ADVDC)	-------
Sridevi.U. K., Nagaveni. N. [47]	PSO clustering using ontology similarity	NewsGroups	Sum of squared error, Precision, Recall, F-measure, Time in minutes	Fuzzy ontology based methodology for clustering knowledge and personalized searching method
Ching-Yi Chen and Fun Ye[17]	PSO clustering algorithm	Artificial data set	Object function and Cluster centre	
Shi M. Shan, Gui S. Deng, Ying H. He[49]	Hybridization of Clustering Based on Grid and Density with PSO	Artificial dataset	Shape of clusters	To devise an application and finding a way of adaptively tuning the parameters.

Table 1: Comparison of various PSO based data clustering methods

4. Conclusion

This paper has presented a review of previous researches conducted in the areas of Particle Swarm Optimization (PSO), PSO hybrids and their application to data clustering.

Researches in this field shows that if PSO is hybridized with other clustering algorithms, then it yields better results in various optimization problems in terms of efficiency and accuracy when compared with other evolutionary algorithms

Such as GA, SA etc. The implementation of hybrid PSO algorithms for data clustering yields optimal number of clusters which results in better prediction and analysis of data. A comprehensive survey of literature in this area has therefore been given to help provide more insight in this subject. After having done the survey we would like to do the following:

- We would like to analyze and evaluate existing PSO based approaches in data clustering to know about the strengths and shortcomings of the existing systems.
- Improvement in earlier proposed solutions, if possible.

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