Improved Intelligent Techniques of Ensemble Data Clustering Method Using Bees Swarm Optimization Ensemble Approach

N. Yuvaraj and C. Suresh Gnana Dhas

Abstract--- *Clustering is considered as an unsupervised partitioning method which is an intelligent self-organizing system that partitions the datasets in a comparable or a different way, where each data cluster consists of similar data points. As of late, the clustering ensemble is regarded as a solution to extract the categorical data points into relevant clusters in a more effective way. However, it encounters a serious problem related to data imperfection during data partitioning into clusters. The present examination thinks about this as the primary issue and improves it using following thought. Right now the ensemble clustering over clear cut datasets using Bees Swarm Optimization (BSO) based cluster ensemble approach. The similarity measurement is carried out using entropy weighted triple quality to finds the similarity difference between the clusters. The knowledge paradigms including cognitive science and systems is intended to improve the clustering quality over categorical datasets. The result shows that the proposed method is accurate than existing methods over categorical datasets in terms of clustering accuracy, normalized mutual information and adjusted rand. -based .This shows the effectiveness of the BSO ensemble clustering algorithm than the existing link clustering ensemble algorithm.*

Keywords--- *Clustering, Bees Swarm Optimization, Cluster Ensemble, Intelligent Data Analytics.*

I. INTRODUCTION

Data clustering is a basic instrument to realize the informational index structure. It assumes a significant job in machine learning, data mining, pattern retrieval and pattern recognition. Clustering clusters the data into clusters, where the cluster information is comparable than other clusters. The present study works on clustering the categorical data sets into suitable clusters using its own value.

As of late, cluster ensembles have developed as a method for beating issues with clustering algorithms. It is notable that clustering strategies may find diverse examples in a given arrangement of information. This is on the grounds that each clustering algorithm has its very own inclination coming about because of the improvement of various criteria. Besides, there is no ground truth against which the clustering result can be approved. Hence, no cross-approval strategy can be maintained out for tuning the input parameters associated with the clustering procedure. As a result, the client is outfitted without any rules for picking the best possible clustering strategy for a given dataset.

A symmetrical issue identified with clustering is high dimensionality. High dimensional information represents a troublesome test to the clustering procedure. Different clustering algorithms can deal with information with low

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dimensionality, however as the dimensionality of the information expands, these algorithms will in general separate.

A cluster ensemble comprises of various segments. Such parcels can be acquired from numerous utilizations of any single algorithm with various introductions, or from the use of various algorithms to the equivalent dataset. Cluster ensembles offer an answer for difficulties unchallengeable to clustering emerging from its not well-presented nature: they can give increasingly hearty and stable arrangements by utilizing the agreement over numerous clustering results while averaging out rising fake structures that emerge because of the different inclinations to which each partaking algorithm is tuned.

To upgrade the clustering results, a clustering ensemble is investigated. A cluster ensemble system is portrayed by two segments: the component to create different partitions and the consensus function to join the info segments into the last clustering. One prominent procedure uses a co-association matrix, which is used as a consensus function. Graph-based partitioning have been utilized with progress to produce the consolidated clustering.

Categorical data clustering using clustering ensembles have not received much consideration in the literatures. The methodology in produces a segment for each absolute quality, with the goal that focuses in each cluster share a similar incentive for that characteristic. The subsequent clustering are consolidated utilizing the accord capacities exhibited in. The study develops cluster ensembles for information with numerical and categorical features.

This paper presents the ensemble clustering over categorical datasets using Bees Swarm Optimization (BSO) based cluster ensemble approach. The similarity measurement is carried out using entropy weighted triple quality to finds the similarity difference between the clusters. The proposed method is intended to improve the clustering quality over categorical datasets in terms of clustering accuracy, normalized mutual information and adjusted rand.

The outline of the paper is present as follows: Section 2 provides the related works. Section 3 provides the proposed method. Section 4 evaluates the proposed method. Section 5 concludes the work.

II. RELATED WORKS

Several approaches are used to construct the link based cluster ensemble. These techniques use a base clustering algorithm to improve the performance of link-based cluster ensemble.

In [Iam-on, N,] the authors present a LinkCluE MATLAB package, which uses link-based cluster ensemble framework. Various functional methods are used for evaluating the results of the clustering algorithm based on internal and external condition. It further presents the evaluating condition on both real and synthetic conditions using the algorithms used.

In [Iam-on, N], the authors introduce an investigation that offers a solution to the issue that corrupts the clustering result. This method uses a link based clustering approach, which finds the unknown entries from the conventional matrix using similarity ensemble approach. The similarity measurement between the ensemble clusters is carried out using a link based algorithm. The final clusters are then obtained using graph-based partitioning, which is applied on a weighted bipartite graph, which is framed using refined matrix.

In [Iam-on, N], the authors present a link clustering ensemble approach for data clustering. This method extends significantly the hybrid bipartite graph formulation through the application of applying a graph-based consensus function. This helps to improve the cluster association matrix rather than a binary matrix. This method is tested specifically on gene cluster microarray samples.

In [Iam-on, N], the authors present a link based ensemble approach to improve the clustering and it attains improve similarity measurement between the clusters, which is found using link-based ensemble model. This method proposes a three link based algorithm to assess the similarity measurement. The refined matrix generates the final clusters using consensus function namely, graph-based partitioning and feature based partitioning.

In [Iam-on, N], the authors present a link based cluster ensemble approach that uses cluster ensemble and it summaries the information matrix through a classification process. This method attains high accurate clusters that are coupled with ensemble diversity driven generation providing diversified and informative clusters.

In [Yuvaraj,], the authors provide a solution to the problem of clustering degradation during partitioning of data. The base clusters are formed using the firefly algorithm, the similarity measurement is carried out with link-based ensemble approach that uses multi-viewpoint and weighted triple quality using entropy measurements to combine the clustered data points.

This method avoids the problems related to local optimum and avoids the issues arising out from high-dimensional datasets. The final partitioning of data is carried out with similarity measurement and bipartite spectral algorithm [Akbari, R].

In [Deng, S], the relationships between clustering categorical data and clustering ensemble are carried out. Categorical data clustering through maximal K-partite cliques [Zaki, M. J] determines he clusters in categorical datasets using K-partite maximal cliques. The clustering ensemble process possess two stages: population generation with clustering partitions through resampling [Jia, J., Xiao] attribute subspace [Al-Razgan, M] homogenous algorithm [Ayad, H. G] and others.

Second stage integrates clustering results into a final solution. Clustering ensemble using supervised bagging and boosting algorithms. In [Minaei-Bidgoli, B] an adaptive approach, ensemble individual partitions are generated sequentially by subsamples of dataset. Also, clustering the categorical dataset related issue is analyzed and investigated in the proposed study. A suggested generic framework is effectively applicable in all the other data types.

2.1 Cluster Ensemble Methodology

The study uses link-based cluster ensemble approach (Figure 2.1) for clustering the categorical datasets and aims at reducing the degradation of the quality of clusters arising from different clustering algorithms. The data partitioning is generated using ensemble even in the presence of incomplete information. The matrix obtained presents the clustering relation and avoids unknown entries.

The similarity measurement is used to bridges the gap between clustering and link analysis over categorical datasets, where the architecture of which is presented in (Figure.2.2) The estimation is utilized to overcomes any issues among bunching and connection examination over categorical datasets, where the design of which is exhibited in The connection based group troupe (LCE) strategy, introduced here, executes these thoughts and shows exceptional execution.

Analysis results on genuine quality articulation and engineered datasets demonstrate that LCE: (I) as a rule outflanks the current group troupe calculations in singular tests and, generally speaking, is obviously class-driving; (ii) produces great, hearty execution across various kinds of information, particularly with the nearness of commotion and imbalanced information bunches; (iii) gives an elevated level information network that is material to numerous numerical grouping procedures; and (iv) is computationally effective for enormous datasets and quality grouping.

Cluster ensembles offer an answer for difficulties unchallengeable to clustering emerging from its not well-presented nature: they can give increasingly hearty and stable arrangements by utilizing the agreement over numerous clustering results while averaging out rising fake structures that emerge because of the different inclinations to which each partaking algorithm is tuned.

Clustering can refer to the following: In computing: Computer cluster, the technique of linking many computers together to act like a single computer; Data cluster, an allocation of contiguous storage in databases and file systems; Cluster analysis, a set of machine learning algorithms to group.

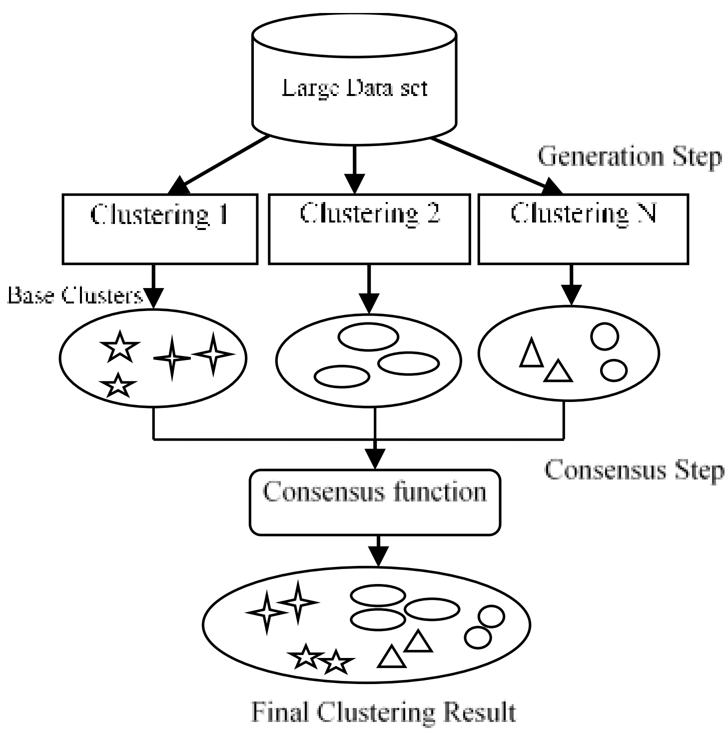

Figure 2.1: General Cluster Ensemble Process

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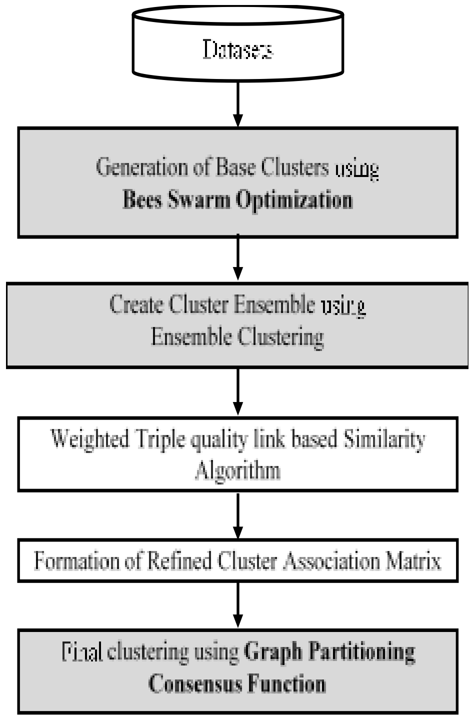

Figure 2.2: Proposed Architecture of BSO based Cluster Ensemble Technique

2.2 BSO Algorithm for Categorical Datasets

The database from the categorical dataset is selected and the base clusters are formed using Bees Swarm Optimization technique.

The BSO algorithm includes three types of bees: forger, viewer and scout bees who fly in a search area in a D-Dimension to find the best solution. Suppose that we have a series of bees in a swarm, they are divided according to their fitness. The fitness of a bee is a quality of the food source that this bee has found in the BSO algorithm. The percentage is determined by the scout, forager and forger.

We are exploring a little piece of the honey bees. The other segment of honey bees is likewise isolated into watchers and experienced honey bees. Every honey bee is related to a positions vector that is a potential arrangement in a D-dimensional quest zone for an ideal issue. Each vector with nourishment source has the related quality in BSO calculations. The calculation of which is given underneath.

Although the combination of BA and PSO is given by BSO, Bee Swarm Optimization, this algorithm uses the velocity vector and the collective memories of PSO and the search based on the BA and the results are much better. We use the Greedy Algorithm, which it's an approximate algorithm, to compare the results from these met heuristics and thus be able to tell which is which gives better result

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2.2.1 Algorithm of Bees Swarm Optimization

Step 1: Initialize

Step 2: Find number of bees, percentage of experienced foragers, scouts, on alookers, dimension, radius and end condition

Step 3: For all the bees

a. Initialize the bees randomly inside the search space
b. Do
c. Compute fitness of bees
d. Sort bees using its fitness value
e. Partition the swarm into the experienced forager, onlooker and scout

Step 4: End

Step 5: For all the experienced forager bees

a. For D-dimensional search space
    i. Update the previous best position
    ii. Select elite bee for all the experienced forager bees
b. For update the position of an experienced forager bee
c. End
d. End

Step 6: End

Step 7: For each onlooker bee

a. Select an elite bee from experienced forager bee for onlooker
b. For D-dimensional search space
    i. Update the position of an onlooker bee
c. End

Step 8: End

Step 9: For each scout bee

a. For D-dimensional search space
    i. Walk randomly around the search space
b. End

Step 10: End

Step 11: Adjust the radius and step size of the search space for scout bees

End until the termination criterion is met

2.3 Cluster Ensemble

The cluster ensembles are motivated by the performance of clustering techniques that entirely depending on the data. A particular cluster model can yield for one dataset an acceptable result but may be ineffective for others. Generally, the clustering of algorithms involves two major challenges.

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To start with, different methods find different structures from a solitary arrangement of information objects. Second, a solitary bunching calculation can likewise uncover various structures for the equivalent dataset with various parameter settings. A few, however not all datasets may have a specific setting. Clients face these difficulties, which make it hard to choose a right grouping procedure.

The ultimate goal remains a solution to this dilemma. To achieve this, researchers have invented an ensemble method to combine different types of clusters into one consensus clusters. The so-called process cluster ensemble provides a stable and robust solution across various data sets and domains.

However, it is far from trivial to model a mechanism effective in integrating multiple data partitions into a cluster group. This task is difficult, as the different cluster results are not well defined. There is a great deal of interest among researchers as well as challenges associated with combining data partitions and generating improving clustering results without prior knowledge.

The agreement bunching arrangement evades the old style ensemble issue is stayed away from, explicitly on unaided learning. The information sources are changed over the clear cut dataset and the nearness of the base group is utilized to decide a solitary accord bunch. This gets compromise of bunching from different sources utilizing three different techniques to be specific: Direct ensemble, Full-Space Ensemble and Subspace en-semble.

2.4 Refined Matrix

The better combination is accomplished utilizing the framework change technique and operation timal intermingling request is acquired by consolidating the network change strategy with Euler time discretization. This diminishes the blunder in finding the positive or negative affiliations.

Then, weights over each edge,$w_{de} \in w$, which gets connects to clusters of c_d and $c_e \in v$. This is estimated finally by the overlapping members proportion.

$$w_{de} = |L_d \cap L_e| \,/\, |L_d \cup L_e| \qquad (1)$$

The value lies in [0,1]. The value is 0 if two data points are considered disjoint and the value is 1 if two data points are equal. This is a common indicator for measuring the similarity between the two dataset clusters. If $w_{xy}$is nearer to 1, the clusters are dissimilar and if w_{de} is nearer to 0, the clusters are similar.

Hence, total duplicated the datasets are removed from the clusters. This is calculated based on hash value and that uses Division Reminder Hashing (DRH) over two datasets L_d, L_e. In DRH, L_d key is divided by a number greater than the total L_d keys, and the remainder value is regarded as the index over the hash table i.e.

$$H\,(L_d) = L_d \mathrm{mod}_m \qquad (2)$$

The number is chosen as prime number and this reduces the total collisions. The hash function over each cluster maps the keys and that lies between 0 to m-1. Here, if the hash lies between 1 to m rather 0 to m-1.

2.5 Link-Based Similarity

The study uses weighted triple quality to cluster the similar vertices in each cluster. The weighted triple quality is determined to be reciprocal of the triple the amount of weight. In like manner, the triple weight is the summation of

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the entire triple of gathering set and each triple weight. Further, the score of group weighted triple quality over entire triples exists between the between bundles. The closeness is therefore evaluated between triple gatherings and this makes interfacing with exist between the clusters.ns Entropy Based Weighted Triple Quality

When the comparability estimation between the information focuses is discovered, the entropy is expanded and have certain revision dependent on grouping closeness. Also, the clusters entropy merges two different clusters is formally explored.

The present work utilizes entropy in weighted triple quality and the bipartite chart is produced refined matrix and afterwards, the refined matrix is built with comparative information focuses. Here, the downright name likeness settles the refined matrix development issue. In this manner, loads are determined with the weighted triple quality for entropy enhances the nature of clustering.

LC first calculates the link similarity of the neighbor links and then builds a transform matrix, which is then subjected to a hierarchical clustering technique to generate a dendrogram. By calculating the partition density of each level of the dendrogram, the maximum density value can be determined and used to determine the appropriate cutoff level of the dendrogram. The resulting communities are the communities detected.

2.7 Bipartite Spectral Graph Partitioning

Here, the datasets are connected over different clustering procedure and it gives diverse yield, which is picked as base groups. This base cluster is connected with connection closeness method, which produces the last grouping with otherworldly chart parcel. The last groups are created dependent on entire data ensemble. Here, the datasets are connected over various clustering strategy and it gives di-section yield, which is picked as base gatherings. This base cluster is connected with connection closeness method, which produces the last grouping with otherworldly outline package. The last gatherings are made reliant on whole information troupe.

Thus, the downright datasets are grouped with better quality utilizing the above system and elements are additionally incorporated into the concluded cluster. Higher precision is accomplished utilizing join based ghastly chart segment in a modest way. This connection approach can locate the invalid or obscure qualities. To additionally enhance the precision bipartite chart segment is utilized with connection comparability.

III. RESULTS

The proposed BSO based link cluster ensemble algorithm is evaluated on UCI datasets, namely. Zoo, lymphography, primary tumor, breast cancer and 20 newsgroup datasets. The proposed method is tested in terms of clustering accuracy, normalized mutual information and adjusted rand against existing methods. The proposed method is compared against existing methods that includes link-based cluster ensemble (LCE) Similarity matrix (CO) with single linkage (CO+SL) Algorithm, Similarity matrix (CO) with average linkage (CO+AL) Algorithm, Cluster-based Similarity Partitioning Algorithm (CSPA) and Hyper-Graph Partitioning (HGPA).

The results of clustering accuracy are shown in Figure 3.1, the results show that the proposed method is improved in terms of clustering than the existing methods. The results of normalized mutual information are shown in Figure 3.2, the results show that the proposed method is improved in terms of normalized mutual information than the existing methods. The results of adjusted rand are shown in Figure 3.3, the results show that the proposed method is improved in terms of adjusted rand than the existing methods.

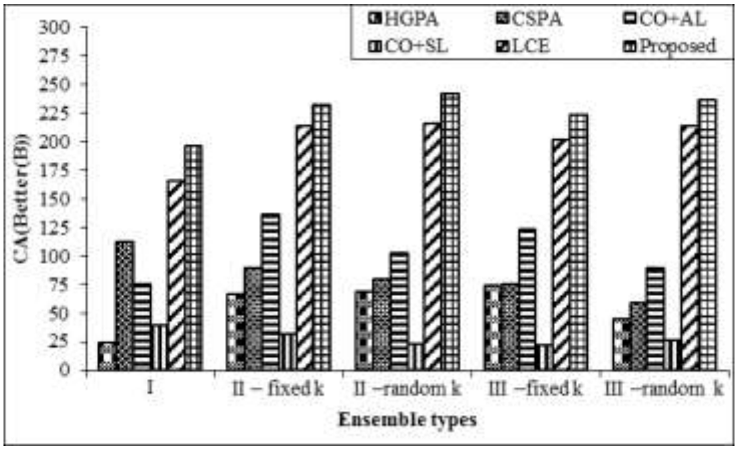

Figure 3.1: Clustering Accuracy (B) vs. Ensemble Type

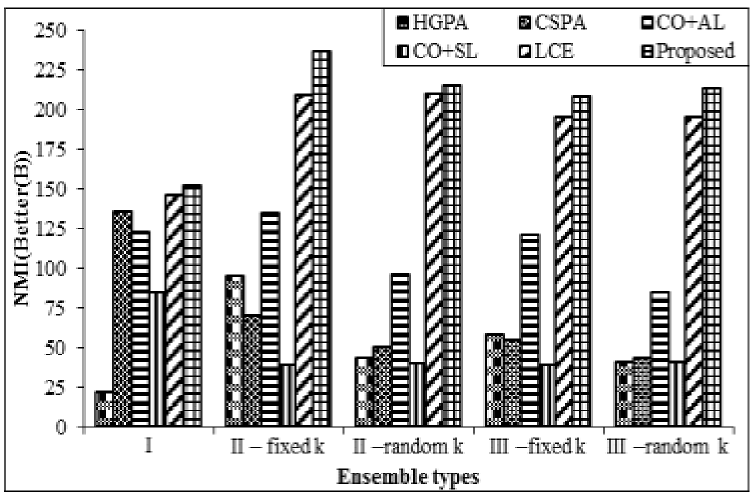

Figure 3.2: Normalized Mutual Information vs. Ensemble Type

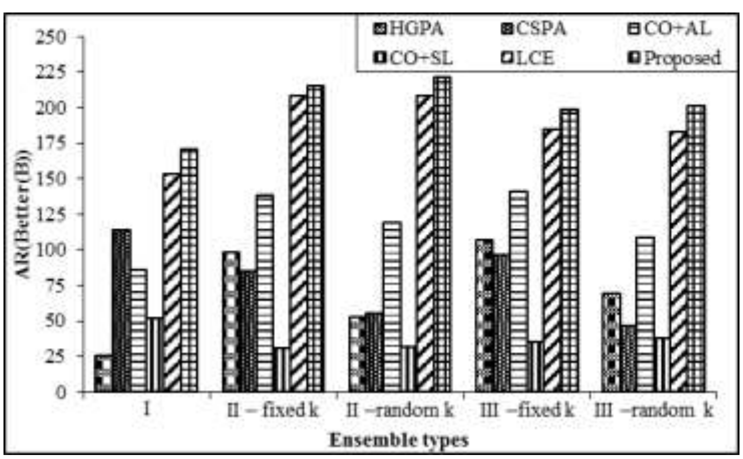

Figure 3.3: Adjusted Rand vs. Ensemble Types

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IV. SUMMARY

This paper presents the ensemble clustering over categorical datasets using Bees Swarm Optimization (BSO) based cluster ensemble approach. The similarity measurement is carried out using entropy weighted triple quality to finds the similarity difference between the clusters. The proposed method is intended to improve the clustering quality over categorical datasets. The clustering accuracy, normalized mutual information and adjusted rand result shows that the proposed method is accurate than existing methods over categorical datasets. This shows the effectiveness of the BSO ensemble clustering algorithm than existing link-based clustering ensemble algorithm.

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