

Buddy System Based Alpha Numeric Weight Based Clustering Algorithm with User Threshold

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Abstract: Data is present in the data sources like Files and Data bases, Retrieval of information from that data sources is one of the important issue nowadays. So for retrieval information from the data sources clustering is used. In the present market different types of clustering algorithms were available. But opting of the clustering is based on user requirements. This paper focuses on the study of hierarchical clustering approach on different conditions or measures or with customer choices like clustering process number of clusters generated at each level, number of levels, attributes range for performing the clustering on the given data set. In brief overview we discuss the hierarchical approach for clustering algorithm with the user opting choices.

Keywords: Clustering, hierarchical agglomerative clustering, Alpha numeric Weight based of Object Positional Value for a Term / Field / Attribute, Clustering Ranges, Buddy System

1. Introduction

Clustering is a collecting of grouping set of objects where all similar come into one group and dissimilar objects will come into other group [1]. Clustering is a one of the method which is used in the data mining process, feature extraction and data classification. Among all the clustering algorithms, hierarchical clustering approach is a hot topic in the current era. Hierarchical clustering approaches are of two kinds. They were Agglomerative clustering approach and Divisive clustering approach [2]. Divisive approach is a top down approach for clustering the given data set and forms a hierarchical clustering tree. In order to get good clusters from the given data set, we have to go for user preferences. Clustering Process Creates 2 Groups of clusters. They were

Inter cluster

It is the distance between the data items in distinct clusters.

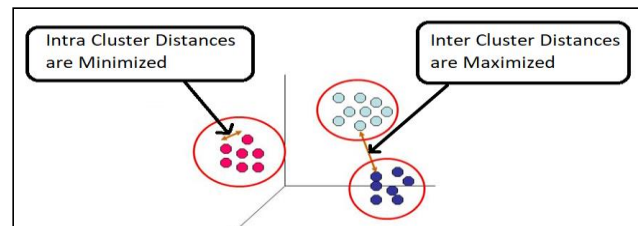


Fig 1. Types of cluster Distances

Table 1. Types of Objects in the clustering Process

Objects Group	Details
Similar	All Objects of same type
Dissimilar	All Objects of different type

1.1 Clustering Distances

For the given data set, the distance between any two clusters is called as Clustering Distance. It is of two types. They were Inter-cluster and Intra cluster Distance

Table 2. Types of cluster Distances

Type of cluster Distance	Details
Intra cluster	It is the distance between the centroid of a cluster and a data item present within a cluster.

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Table 3. Clustering Outline

Techniques of Data Mining	Clustering, Classification, Association mining, Text mining, Sequential patterns, prediction, Decision trees, and Regression.
Technique	Unsupervised
Classes	Used for Finite set of classes
Data Mining Task	Descriptive
Goal	Used for finding similarities in the data set.
Data Set	Used for finite set of data
Objects Similarity	Defined by similarity function

Table 4. Outline of Supervised and Unsupervised Learning [3]

Property	Supervised Learning	Unsupervised Learning
Definition	It uses datasets which are labeled on algorithms to the train, classify data or concepts to understand, predict outcomes correctly.	Machine learning is used in Unsupervised Learning to cluster unlabeled datasets.
Number of Classes	Unknown	Unknown
Labeling	Input data Labeled	Input data unlabeled
Output	Known	Unknown
Uses	Training Data Set	Input Data set
Knowledge Required on	Training Set	No previous knowledge
Classify Used for	later observations	data understanding
performance Measure	Accurately	Indirect / Qualitative
Used for	Analysis	Prediction

1.1. Types of Hierarchical Clustering

It is of two types. They were Divisive and Agglomerative is article.

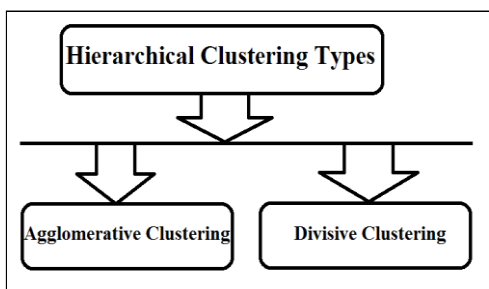


Fig 2. Types of Hierarchical Clustering

Divisive

It starts with complete data set and divides it into successfully small clusters [4].

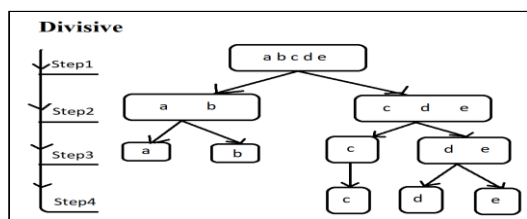


Fig 3. Divisive Clustering Example

1.3 Agglomerative

It starts with single element as a unique cluster and combines them into successfully big clusters [5].i.e. Data mining means extraction of data from data sources. So, whatever the data extracted will be used by the user. So, we have to take the preferences of the user before the clustering process. So, at the end of the clustering the user will get good Clustering results from a given dataset.

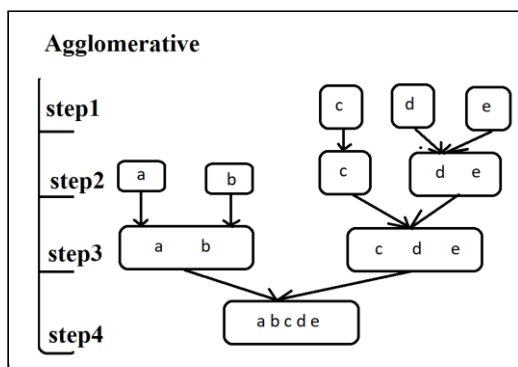


Fig 4. Agglomerative Clustering Example

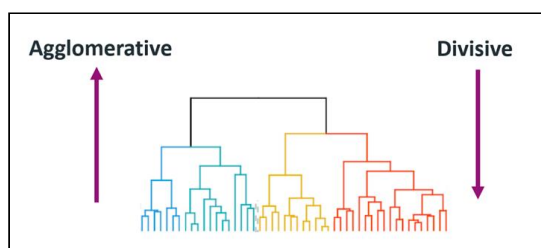


Fig 5. Agglomerative and Divisive clustering indicating dendrograms.

1.4 Applications of Clustering

In the current era the data in the servers is growing day by day so Clustering is used in many Areas such Market Analysis, Outlier Detection, Classification of Documents, Data Mining Function, Pattern Recognition, Image Processing, Anomaly Detection, Medical Image processing, Grouping of Search Results, for the Analysis of Social Networks e.t.c.

Table5: Clustering Application Areas

Clustering Application Areas	Clustering Purpose
Market Analysis	It is used to identify different groups of people in the Market and to identify their requirement to provide the products Required by the Customers [6].
Outlier Detection	It is used in outlier detection applications. Example of credit card fraud [7].
Classification Of Documents	It is used to classify the documents in WWW (world wide web) [8].
Data Mining Function	It is used in cluster analysis (to observe characteristics of each cluster.)[9].
Pattern Recognition	It is used in traffic Pattern Recognition to clear traffic problems [10].
Image Processing	It is used in Image Processing for segmentation of image [11].
Anomaly Detection	It is used in anomaly detection is to study normal modes in the data available and it is used to point out anomalous are there or not [12].
Medical Imaging	It is used in Medical Imaging for segmentation of the images and analyzes it [13].
Search Result Grouping	It is used in the grouping of search results from the WWW when the users so the Search [14].
Social Network Analysis	It is used to merge the entities of a social network into distinct Classes depends on their relationships and links between the classes [15].

1.5 Stages of Clustering

Total there are three stages in the clustering process [16]. They were

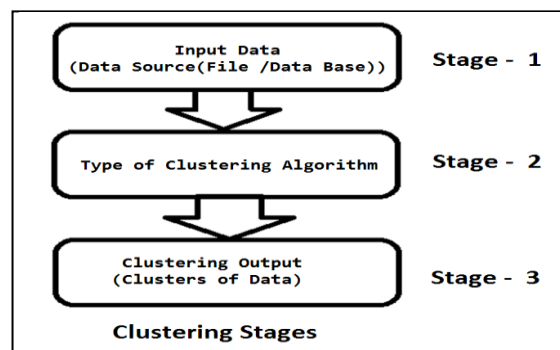


Fig 6. Stage of Clustering

Note:

- 1 In the stage one, Input Data to clustering algorithm is collected from a file or a data base.
- 2 In the stage two, Different Types of clustering algorithm are

utilized to process the stage 1 data. In the current ERA different types of clustering algorithms are available in the market like Constraint Based Method, Soft Computing, Partitioning, Hierarchical, Density Based, Grid Based, Model Based, Bi-clustering, Graph Based, e.t.c.

- 3 In Knowledge Discovery in Database clustering is a part of it. [17].

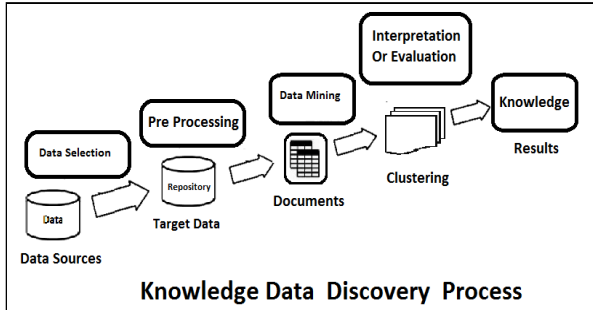


Fig 7. Knowledge Data Discovery Process

1.5 Data preprocessing techniques [18]:

It includes Data Reduction, Cleaning and Transformation.

Table 6. Techniques of Data preprocessing

Techniques of Data preprocessing	Handle Operations
Data Cleaning [19]	Missing Data, Noisy Data
Data Reduction[20]	1. Attribute Subset Selection (Attributes). 2. Numerosity Reduction (Reduces data by replacing original data by smaller form of data representation). 3. Dimensionality Reduction (Compression the data).
Data Transformation[21]	1. Smoothing (Remove Noise). 2. Aggregation (Generates Attributes summary). 3. Generalization (Converts Low level data to high level data). 4. Normalization (Scales the Attributes). 5. Attribute Construction (Create New Attributes)

2. Literature Survey

In the market Different types clustering methods were there proposed by different researcher's persons. For each clustering method there will be one or more sub clustering Algorithms. Each sub clustering algorithm will have its own constraints. The major clustering methods available in the market were.

Table 7. Types of Clustering

S. No	Clustering Type	Details	Sub Clustering Methods
1.	Partitioning	It is used to group data by moving objects from one group to another using relocation technique [22].	1. CLARA. 2. CLARANS. 3. EMCLUSTERING 4. FCM. 5. K MODES. 6. KMEANS. 7. KMEDOIDS. 8. PAM. 9. XMEANS
2.	Hierarchical	It is used to create clusters based on a particular similarity in the objects [23]. It is of	1. AGNES. 2. BIRCH. 3. CHAMELEON. 4. CURE.

		two types. They were Agglomerative and Divisive. Agglomerative clustering clusters the data based on combining clusters up. Divisive clustering clusters the data based on merging clusters down. Other names for hierarchical clustering are hierarchical cluster analysis or HCA.	5. DIANA. 6. ECHIDNA 7. ROCK.
3.	Density Based	It is used radius as a constraint to group the data. Here data points within a particular radius are considered as a group and remaining points are considered as noise [24].	1. DBSCAN. 2. OPTICS. 3. DBCLASD 4. DENCLUE. 5. CENCLUE.
4.	Grid Based	Grid Based calculates the density of cells and based on the cells densities values clustering is done [25].	1. CLIQUE. 2. OPT GRID. 3. STING. 4. WAVE CLUSTER.
5.	Model Based	It uses a statistical approach for clustering the data where each object is assigned a weight (probability distribution) which is used to cluster the data [26].	1. EM. 2. COBWEB. 3. CLASSIT. 4. SOMS.
6.	Soft Computing	In Soft Computing, clusters individual data points are assigned to more than one cluster and after clustering the clusters will have minimum similarity [27].	1. FCM. 2. GK. 3. SOM. 4. GA Clustering
7.	Bicustering	It is the clustering of the rows and columns of a matrix simultaneous using a data mining technique [28].	1. OPSM. 2. Samba 3. JSa
8.	Graph Based	Graph is a collection of nodes (vertices). Clustering of these nodes of a graph based on certain weights assigned to the nodes is called as Graph Based Clustering [29].	1. Click
9	Hard Clustering	In Hard Clustering individual data points are assigned to a unique cluster and after clustering clusters will have maximum similarity [30].	1. KMEANS

Each Clustering method calculates different types of parameters for doing the Clustering on a given data set. The time and space complexity of the algorithms are different for different clustering algorithms.

2.1 Similarity measures used by Different Clustering Methods [50]

Similarity measures are used to identify the good clusters in the given data set. There are so many Similarity measures used in the current market. They were Average Distance, Canberra Metric, Chord, Clustering coefficient, Cosine, Czekanowski Coefficient, Euclidean distance,

Index of Association, Kmean, KullbackLeibler Divergence, Mahalanobis, Manhattan distance or City blocks distance, Mean Character Difference, Minkowski Metric, Pearson coefficient, Weighted Euclidean e.t.c.

Table 8. Similarity measures in Clustering

S.N	Similarity measures Name	Details
1	Average Distance	It is the Euclidean distance but a modified version[31]. Average Distance = $\left(\frac{1}{n} \sum_{i=1}^n (x_i - y_i)^2\right)^{\frac{1}{2}}$ Here x, y are data points in n-dimensional space
2	Weighted Euclidean	It is the modified version of Euclidean distance [32]. Weighted Euclidean Distance = $\left(\sum_{i=1}^n w_i (x_i - y_i)^2\right)^{\frac{1}{2}}$
3	Chord	It is the length calculated between two points which are normalized within a hypersphere of radius one [33].
4	Mahalanobis	It is the distance sample point (outlier) and a distribution [34].
5	Mean Character Difference	It is calculated using all points in the given space [35]. Mean Character Difference = $\frac{1}{n} \sum_{i=1}^n x_i - y_i $
6	Index of Association	It is calculated using all points in the given space [36]. Index of Association = $\frac{1}{n} \sum_{i=1}^n \left \frac{x_i}{\sum_{i=1}^n x_i} - \frac{y_i}{\sum_{i=1}^n y_i} \right $
7	Canberra Metric	It is calculated using all points in the given space [37]. Canberra Metric = $\sum_{i=1}^n \frac{ x_i - y_i }{(x_i + y_i)}$
8	Czekanowski Coefficient	It is calculated using all points in the given space [38]. Czekanowski coefficient = $1 - \frac{\sum_{i=1}^n \min(x_i, y_i)}{\sum_{i=1}^n (x_i + y_i)}$
9	Pearson coefficient	It is calculated using all points in the given space [39]. Pearson coefficient = $\frac{\sum_{i=1}^n (x_i - \mu_x)(y_i - \mu_y)}{\sqrt{\sum_{i=1}^n (x_i - \mu_x)^2} \sqrt{\sum_{i=1}^n (y_i - \mu_y)^2}}$
10	Minkowski Metric	Minkowski Distance / metric are the distance between two vectors and it's a generalization of both the Manhattan and Euclidean distance [40].
11	Manhattan distance or City blocks distance	It is the distance between vectors. It is equal to the one-norm of the distance between the vectors [41].
12	Euclidean distance	Euclidean distance is also known as Pythagorean distance. It is the distance between any two points (Cartesian coordinates) in the Euclidean space [42].
13	KullbackLeibler Divergence	KullbackLeibler Divergence is used to calculate the distance between two independent discrete probability distributions (data and cluster center point). It is used to create cluster group by combining multiple Fuzzy c-means clustering's results [43].
14	Clustering coefficient	It is used to calculate how the nodes of a graph are connected along with the degree [44].
15	Cosine	It is the replacement of Euclidean distance with cosine function [45].
16	Kmean	It is the mean of all the coordinates or points in the in the Euclidean space [46].

2.1. Inputs and Outputs in clustering process

In every clustering algorithm the user gives so many parameters as inputs to the clustering algorithm and gets the outputs

Table 9. Inputs and Outputs in clustering process

S.NO	Inputs and Outputs	Details
1	Number of Inputs for the clustering process	Clustering Algorithm, Algorithm Constraints, Number of Levels and clusters per each level.
2	Number of Levels	In the entire clustering.
3	Number of clusters	At each stage
4	Sum of Square Error (SSE) or other errors	It is a measure of difference between the data obtained by the prediction model that has been done before. [47]
5	Likelihood of Clusters	It is the similarity of clusters in the data points.[48]
6	Unlikelihood of Clusters	It is the dissimilarity of clusters in the data points.
7	Number of variable parameters at each level	These are the input parameters which are changed during the running of the algorithm like threshold.
8	outlier	In the clustering process any object doesn't belong to any cluster it is called as a outlier.[48]
9	Output	Clusters

3. Proposed Algorithm

Buddy Memory Allocation Technique invented by Harry Markowitz for Memory Allocation Technique in the year 1963. Buddy memory allocation technique is used to divide memory into 2 halves and gives a best fit and is easy to implement it [51].Here Modified Buddy system is used for clustering on Alpha numeric weighted based sorted records for clustering.

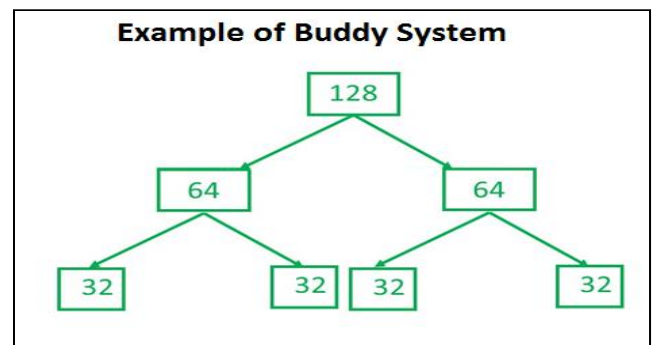


Fig 8. Example of Buddy System

The problem with the buddy system is it works for the even number of records. But it is difficult to work with odd number of records. So I our algorithm it works for both even and odd record count.

3.1 Buddy System with Alpha numeric Weighted based clustering Algorithm

- 1 Take a Sample data set.
- 2 Calculate The Weight of Individual Object by Position of an attribute of a particular column for all records.
 - a. Object individual position is calculated using ASCII Character Binary Table.
 - b. Formula for calculating the Alpha Numeric Weight based Object Positional Value for a Term / Field

(ANWAPVT) of a record.

- 3 ANWAPVT= (First Char) ASCII value* n+ (second Char) ASCII value *(n-1) ----- (Last char-3) + (Last char-2) ASCII value*3+ (Last char-1) ASCII value*2+Last char*ASCII value*1
- 4 Example: Term is AB.AB=65*2+66*1=130+66=196
- 5 Here “A” ASCII value is 65 and “B” ASCII value is 66.
- 6 Sort the records / data in ascending order as per the Alpha Numeric Weight based Object individual position values. For that call the Sort Function or write a sort function to sort the records.
- 7 Compute the number of records (N) in the Data source (data base / set / File). Specify Number of levels (L) that should be generated in the clustering process which should be always $2L < N$.
- 8 Use Modified buddy system for level wise cluster generation. I.e. At each level, every cluster is splits into two sub clusters and adds computed clusters to a list. Here list index indicates the cluster number.

Table 10. Example of Modified buddy system

If No. of elements (N)	Elements in Cluster1	Elements in Cluster2
Even	$N/2$	$N/2$
Odd	$N/2$	$N/2 + 1$

i.e. cluster 1 is divided into two clusters (cluster 2 and cluster 3).

- 9 Repeat the step5 till $2L < N$. where
 L = Number of levels that has to be generated using buddy system.
 N = Number of records in the data set.
- 10 Assign the elements to each cluster in a based on the list from the sorted data set.
- 11 Use the list to generate a pie circle chart.

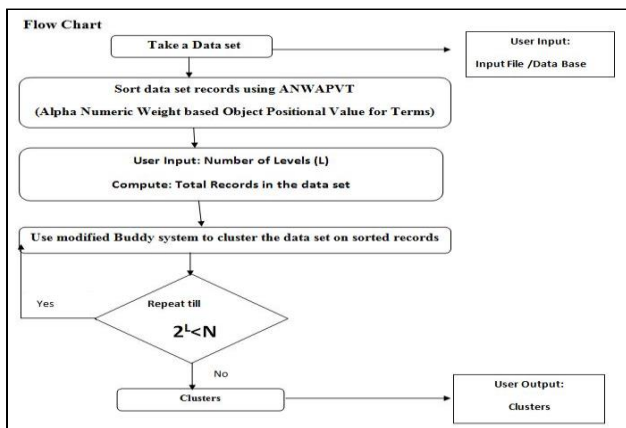


Fig 9. Buddy System Based Alpha Numeric Weight Based Clustering Algorithm with User Threshold

Note

1. The number of elements in each cluster can be known using algorithm.
2. Data set can be collected / downloaded from freely available public repositories. i.e the data set which we have used is twitter data set.
3. At each level the numbers of clusters are equal to $2L$ (Where number of levels L is required by the user.)
4. Data preprocessing techniques applied on the collected data set. This data set will be the input for the proposed Algorithm [52].

5. Clustering output will be saved in the output file / Data base.
6. Data preprocessing has to be done on the data set before clustering algorithm starts [53].
7. Data preprocessing can also be done on multiple data sources to get required data for clustering algorithm [54].
8. Formatted data is given as input for the clustering process and output is patterns [55].
9. Data mining output is the input for the clustering algorithm input.
10. Each clustering algorithm will be associated with a time complexity [56].
11. Patterns can be explored and filtered [57].
12. After data clustering the data is used for visualization and interpretation of results [58].
13. Clustering is used in Association rules [59] and classification [60].

4. Results

Results are being generated using python.

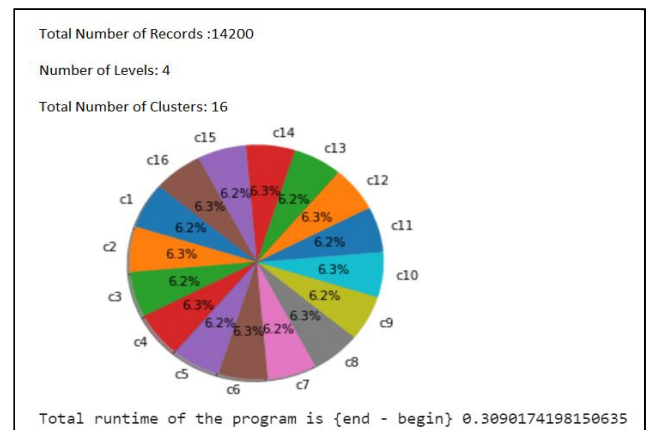


Fig 10. Clustering Result

5. Conclusion

Here we are going to implement Buddy system with Alpha numeric weighted based clustering Algorithm with user preferences to get good clusters. So the efficiency of the clustering algorithm depends on the metrics (Buddy system, Alpha numeric weight of the object with user preferences and number of levels) used in the clustering algorithm.

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Conflicts of interest

The authors declare no conflicts of interest.