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An Efficient Concept-Based Mining Model for Analysis Partitioning Clustering

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Abstract - Data clustering is an important task in the area of data mining. Clustering is the unsupervised classification of data items into homogeneous groups called clusters. Clustering methods partition a set of data items into clusters, such that items in the same cluster are more similar to each other than items in different clusters according to some defined criteria. Clustering algorithms are computationally intensive, particularly when they are used to analyze large amounts of data.With the development of information technology and computer science, high-capacity data appear in our lives. In order to help people analyzing and digging out useful information, the generation and application of data mining technology seem so significance. Clustering is the mostly used method of data mining. Clustering can be used for describing and analyzing of data. In this paper, the approach of Kohonen SOM and K-Means and HAC are discussed. After comparing these three methods effectively and reflect data characters and potential rules syllabify. This work will present new and improved results from large-scale datasets.

Keywords- SOFM, CURE, C4.5, K-MEANS, HAC

I. INTRODUCTION

A self-organizing map (SOM) or self-organizing feature map (SOFM) is a kind of artificial neural network that [1] is trained using unsupervised learning to produce a low-dimensional (typically two dimensional), discretized representation of the input space of the training samples, called a map. Self-organizing maps are different than other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space.

SOM is a clustering method. Indeed, it organizes the data in clusters (cells of map) such as the instances in the same cell are similar, and the instances in different cells are different. In this point of view, SOM gives comparable results to state-of-the-art clustering algorithm such as K-Means.

SOM is also used as a visualization technique. It allows us to visualize in a low dimensional [2] representation space (2D) the original dataset. Indeed, the individuals located in adjacent cells are more similar than individuals located in distant cells. In this point of view, it is comparable to visualization techniques such as Multidimensional scaling or PCA (Principal Component Analysis). Through this, it can be showed how to implement the Kohonen's SOM algorithm with a particular tool. After implementation it has been tried to assess the properties of this approach by comparing the results with those of the PCA algorithm. Then, compare the results to those of K-Means, which is a clustering algorithm. Finally implement [3] the Two-step Clustering process by combining the SOM algorithm with the HAC process (Hierarchical Agglomerative Clustering). It is a variant of the Two-Step clustering where combine K-Means and HAC.

The Kohonen algorithm is a very powerful tool for data analysis. It was originally designed to model organized connections between some biological neural networks. It was also immediately considered as a very good algorithm to realize vectorial quantization, and at the same time pertinent classification, with nice properties for visualization. If the individuals are described by quantitative variables (ratios, frequencies, measurements, amounts, etc.), the straightforward application of the original algorithm leads to build code vectors and to associate to each of them the class of all the individuals which are more similar to this code-vector than to the others. But, in case of individuals described by categorical (qualitative) variables having a finite number of modalities (like in a survey), it is necessary to define a specific algorithm. In this paper, we present a new algorithm inspired by the SOM algorithm, which provides a simultaneous classification of the individuals and of their modalities.

II. RELATED WORK

According to Ji Dan, Qiu Jianlin [14], with the development of information technology and computer science, high-capacity data appear in our lives . In order to help people analyzing and digging out useful information, the generation and application of data mining technology seem so significance. Clustering and decision tree are the mostly used methods of data mining. Clustering can be used for describing and decision tree can be applied to analyzing. After combining these two methods effectively, it can reflect data characters and potential rules syllabify. This paper presents a new synthesized data mining algorithm named CA which improves the original methods of CURE and C4.5. CA introduces principle component analysis (PCA), grid partition and parallel processing which can achieve feature reduction and scale reduction for large-scale datasets. This paper applies CA algorithm to maize seed breeding and the results of experiments show that our approach is better than original methods.

According to Timothy C. Havens et James C. Bezdek [15], very large (VL) data or “Big Data” are any data that you cannot load into your computer’s working memory.

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This is not an objective definition, but a definition that is easy to understand and one that is practical, because there is a data set too big for any computer you might use; hence, this is VL data for you. Clustering is one of the primary tasks used in the pattern recognition and data mining communities to search VL databases (including VL images) in various applications, and so, clustering algorithms that scale well to VL data are important and useful. This article compares the efficacy of three different implementations of techniques aimed at extending fuzzy c-means (FCM) clustering to VL data. Specifically, we compare methods based on (i) sampling followed by non-iterative extension; (ii) incremental techniques that make one sequential pass through subsets of the data; and (iii) kernelized versions of FCM that provide approximations based on sampling, including three proposed algorithms. it will use both loadable and VL data sets to conduct the numerical experiments that facilitate comparisons based on time and space complexity, speed, quality of approximations to batch FCM (for loadable data), and assessment of matches between partitions and ground-truth. Empirical results show that random sampling plus extension FCM, bit-reduced FCM, and approximate kernel FCM are good choices for approximating FCM for VL data. it conclude by demonstrating the VL algorithms on a data set with 5 billion objects and presenting a set of recommendations regarding the use of the different VL FCM clustering schemes.

III. METHODOLOGY

a. Kohonen-SOM's approach

Kohonen's SOM is called a topology-preserving map because there is a topological structure imposed on the nodes in the network. A topological map is simply a mapping that preserves neighborhood relations.

Algorithm for Kohonen's Self Organizing Map

- Assume output nodes are connected in an array (usually 1 or 2 dimensional)
- Assume that the network is fully connected - all nodes in input layer are connected to all nodes in output layer.
- Use the competitive learning algorithm as follows:

1. Randomly choose an input vector x

2. Determine the "winning" output node i, where wi is the weight vector connecting the inputs to output node i. Note: the above equation is equivalent to

w_i x >= w_k x only if the weights are normalized.

$$|\omega_i - X| \leq |\omega_K - X| \quad \forall k$$

Given the winning node i, the weight update is

$$\omega_k(new) = \omega_k(old) + \Delta\omega_k(n)$$

where $\Delta\omega_k(n)$ represesnts the change in weight.

b. K-Means's approach

The **K-Means** algorithm clusters data by trying to separate samples in n groups of equal variance, minimizing a criterion known as the 'inertia' of the groups. This algorithm requires the number of cluster to be specified. It scales well to large number of samples and has been used across a large range of application areas in many different fields. It is also equivalent to the expectation-maximization algorithm when setting the covariance matrix to be diagonal, equal and small. The K-means algorithm aims to choose centroids C that minimize the within cluster sum of squares objective function with a dataset X with n samples:

$$J(X,C) = \sum_{i=0}^{n} \min \left(\|X_j - \mu_i\|^2 \right) \text{ where, } \mu_i \varepsilon C$$

K-means is often referred to as Lloyd's algorithm. In basic terms, the algorithm has three steps. The first step chooses the initial centroids, with the most basic method being to choose k samples from the dataset X. After initialization, k-means consists of looping between the other two major steps. The first step assigns each sample to its nearest centroid. The second step creates new centroids by taking the mean value of all of the samples assigned to each previous centroid. The difference between the old and the new centroids is the inertia and the algorithm repeats these last two steps until this value is less than a threshold.

IV. RESULTS & DISCUSSION

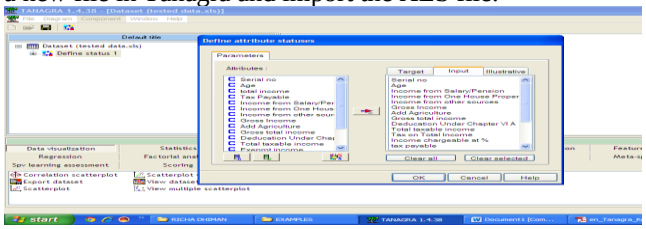
a. Data Set

I am using "Tax Audit" dataset it has real values there are approximately 20 descriptors and 19800 instances. Some of them will be used as an input attributes and other are used as an output attributes.

Table 1: Attributes of Data Set

First Name
Permanent Account Number
Income from Salary/Pension
Income from One House Property
Income from other sources
Gross Total Income
Tax Paid
Deduction Under Chapter VI A
Total Income
Add Agriculture Income
Tax on Total Income
Net Tax Payable
Interest Payable
Total Tax and Interest Payable
Total Advance Tax Paid
Total self assessment Tax Paid
Total TDS Deducation
Total TCS Deducation
Total Prepaid Taxes
Tax Payable
Refund

The easiest way to import a XLS file in Tanagra is to create a new file in Tanagra and import the XLS file.



Figur1: Check the integrity of the dataset by computing some descriptive statistics indicators.

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We insert the DEFINE STATUS component into the diagram using the shortcut into the toolbar. Then set all the variables as INPUT.

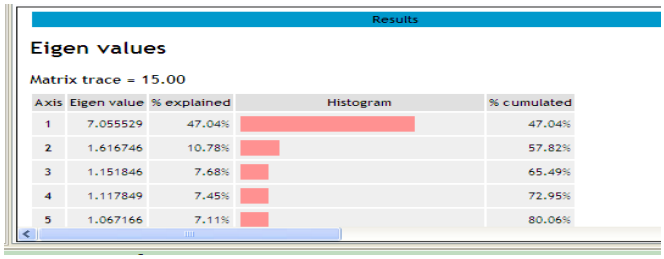


Figure 2: Individuals who are in adjacent cells are also close in the original representation space. This is one of the main interests of this method. Let us check this assertion on the Tax dataset I cannot visualize the dataset into the original space. So we use a PCA in order to obtain a 2D representation. We try to visualize the relative positions of groups (clusters) in the scatter plot.

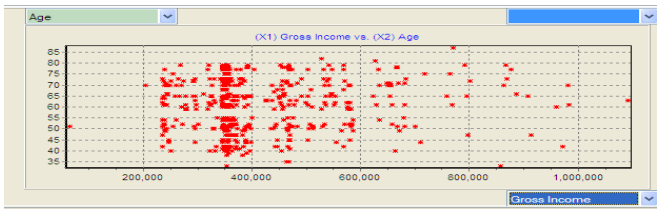


Figure 3. Fig 6: Add the SCATTERPLOT component (DATA VISUALIZATION tab) into the diagram. set the first factor as the horizontal axis, the second one as vertical axis

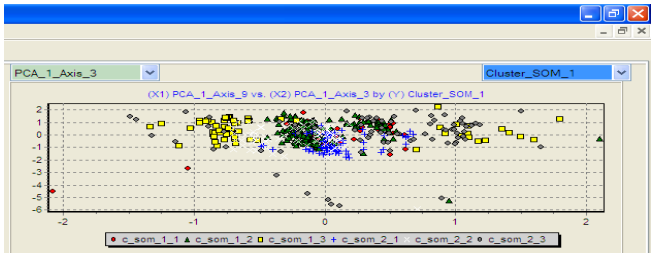
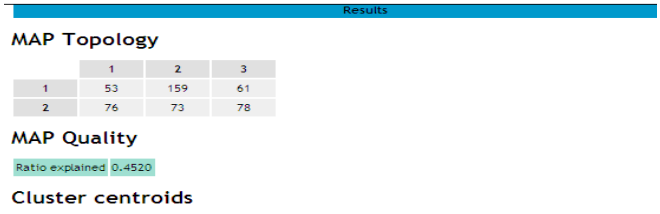


Figure 4. Correspondence between the proximities into the SOM map and the proximities into the 2 first factors of PCA.



Figurw 5: The number of instances into each cell is displayed. See that 45.20 % (Error Rate) of the TSS (Total Sum of Squares) is explained by the partitioning into 6 classes. I can compare this result to those of the other methods below.

b. Result

After implementation of these algorithms on Academic Activities data set, the following results obtained:

Table 2: Comparative results of both algorithms

Parameters	Kohonen SOM	K-MEANS
No. of clusters	6	6
MAP TOLOPLOGY	6	6
ERROR RATE	0.7654	0.8765
COMPUTAION TIME	432 MS	1281 MS
ACEESING TIME	FAST	SLOW

V. CONCLUSION

In this comparative study found that Kohonen SOM gives the better performance as compare to K-Means with minimum error rate or high accuracy, minimum computation time on same data set and parameters.

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