International Journal of Technical Research and Applications e-ISSN: 2320-8163,
www.ijtra.com Volume 3, Issue 3 (May-June 2015), PP. 169-172

AN IMPROVED TECHNIQUE FOR DOCUMENT CLUSTERING

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Abstract— **Data mining , knowledge discovery is the process of analyzing data from different perspectives and summarizing it into useful information - information that can be used to increase revenue, cuts costs, or both. Data mining software is one of a number of analytical tools for analyzing data. It allows users to analyze data from many different dimensions or angles, categorize it, and summarize the relationships identified. Technically, data mining is the process of finding correlations or patterns among dozens of fields in large relational databases. The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data. But how to decide what constitutes a good clustering? It can be shown that there is no absolute "best" criterion which would be independent of the final aim of the clustering. Consequently, it is the user which must supply this criterion, in such a way that the result of the clustering will suit their needs.**

For instance, we could be interested in finding representatives for homogeneous groups (*data reduction*), in finding "natural clusters" and describe their unknown properties (*"natural" data types*), in finding useful and suitable groupings (*"useful" data classes*) or in finding unusual data objects (*outlier detection*).Of late, clustering techniques have been applied in the areas which involve browsing the gathered data or in categorizing the outcome provided by the search engines for the reply to the query raised by the users. In this paper, we are providing a comprehensive survey over the document clustering.

Keywords—Data Mining, Clustering, Classification, Similarity Measure, Term Frequency.

I. INTRODUCTION

Document clustering is also applicable in producing the hierarchical grouping of document (Ward 1963). In order to search and retrieve then information efficiently in Document Management Systems (DMS), the metadata set should be created for the documents with adequate details. But just one metadata set is not enough for the whole document management systems. This is because various document types need different attributes to be distinguished appropriately.

So clustering of documents is an automatic grouping of text documents into clusters such that documents within a cluster have high resemblance in comparison to one another, but are different from documents in other clusters. Hierarchical document clustering (Murtagh 1984) categorizes clusters into a tree or a hierarchy that benefits browsing.

Information Retrieval (IR) (Baeza 1992) is the field of computer science that focuses on the processing of documents in such a way that the document can be quickly retrieved based on keywords specified in a user's query. IR technology is the foundation of web-based search engines and plays a key role in biomedical research, as it is the basis of software that aids literature search.

II. LITERATURE SURVEY

Document clustering is the process of categorizing text document into a systematic cluster or group, such that the documents in the same cluster are similar whereas the documents in the other clusters are dissimilar. It is one of the vital processes in text mining. Liping (2010) emphasized that the expansion of internet and computational processes has paved the way for various clustering techniques. Text mining especially has gained a lot of importance and it demands various tasks such as production of granular taxonomies, document summarization etc., for developing a higher quality information from text.

Likas *et al.* (2003) proposed the global K-means clustering technique that creates initial centers by recursively dividing data space into disjointed subspaces using the K-dimensional tree approach. The cutting hyper plane used in this approach is the plane that is perpendicular to the maximum variance axis derived by Principal Component Analysis (PCA). Partitioning was carried out as far as each of the leaf nodes possess less than a predefined number of data instances or the predefined number of buckets has been generated. The initial center for K-means is the centroids of data that are present in the final buckets. Shehroz Khan and Amir Ahmad (2004) stipulated iterative clustering techniques to calculate initial cluster centers for K-means. This process is feasible for clustering techniques for continuous data.

Agrawal *et al.* (2005) ascribed data mining applications and their various requirements on clustering techniques. The main requirements considered are their ability to identify clusters embedded in subspaces. The subspaces contain high dimensional data and scalability. They also consist of the comprehensible ability of results by end-users and distribution of unpredictable data transfer.

The main limitation of K-means approach is that it generates empty clusters based on initial center vectors. However, this drawback does not cause any significant problem for static execution of K-means algorithm and the problem can be overcome by executing K-means algorithm for a number of times. However, in a few applications, the cluster issue poses problems of erratic behavior of the system and affects the overall performance. Malay Pakhira et al. (2009) mooted a modified version of the K-means algorithm that effectively eradicates this empty cluster problem. In fact, in the experiments done in this regard, this algorithm showed better performance than that of traditional methods.

Uncertainty heterogeneous data streams (Charu Aggarwal *et .al* 2003) are seen in most of the applications. But the clustering quality of the existing approaches for clustering heterogeneous data streams with uncertainty is not satisfactory. Guo-Yan Huang *et al.* (2010) posited an approach for clustering heterogeneous data streams with uncertainty. A frequency histogram using H-UCF helps to trace characteristic categorical statistic. Initially, creating 'n' clusters by a K-prototype algorithm, the new approach proves to be more useful than UMicro in regard to clustering quality.

Alam *et al.* (2010) designed a novel clustering algorithm by blending partitional and hierarchical clustering called

HPSO. It utilized the swarm intelligence of ants in a decentralized environment. This algorithm proved to be very effective as it performed clustering in a hierarchical manner.

Shin-Jye Lee *et al.* (2010) suggested clustering-based method to identify the fuzzy system. To initiate the task, it tried to present a modular approach, based on hybrid clustering technique. Next, finding the number and location of clusters seemed the primary concerns for evolving such a model. So, taking input, output, generalization and specialization, a HCA has been designed. This three-part input-output clustering algorithm adopts several clustering characteristics simultaneously to identify the problem.

Only a few researchers have focused attention on partitioning categorical data in an incremental mode. Designing an incremental clustering for categorical data is a vital issue. Li Taoying *et al.* (2010) lent support to an incremental clustering for categorical data using clustering ensemble. They initially reduced redundant attributes if required, and then made use of true values of different attributes to form clustering memberships.

Crescenzi *et al.* (2004) cited an approach that automatically extracts data from large data-intensive web sites. The "data grabber" investigates a large web site and infers a scheme for it, describing it as a directed graph with nodes. It describes classes of structurally similar pages and arcs representing links between these pages. After locating the classes of interest, a library of wrappers can be created, one per class with the help of an external wrapper generator and in this way suitable data can be extracted.

Miha Grcar *et al.* (2008) mulled over a technique about the lack of software mining technique, which is a process of extracting knowledge out of source code. They presented a software mining mission with an integration of text mining and link study technique. This technique is concerned with the inter links between instances. Retrieval and knowledge based approaches are the two main tasks used in constructing a tool for software component. An ontology-learning framework named LATINO was developed by Grcar *et al.* (2006). LATINO, an open source purpose data mining platform, offers text mining, link analysis, machine learning, etc.

Similarity-based approach and model-based approaches (Meila and Heckerman 2001) are the two major categories of clustering approaches and these have been described by Pallav Roxy and Durga Toshniwal (2009). The former, capable of maximizing average similarities within clusters and minimizing the same among clusters, is a pairwise similarity clustering approach. The latter tries to generate techniques from the documents, each approach representing one document group in particular.

Document clustering is becoming more and more important with the abundance of text documents available through World Wide Web and corporate document management systems. But there are still some major drawbacks in the existing text clustering techniques that greatly affect their practical applicability. The drawbacks in the existing clustering approaches are listed below:

- Text clustering that yields a clear cut output has got to be the most favorable. However, documents can be regarded differently by people with different needs vis-à-vis the clustering of texts. For example, a businessman looks at business documents not in the same way as a technologist sees them (Macskassy *et al.* 1998). So clustering tasks depend on intrinsic parameters that make way for a diversity of views.
- Text clustering is a clustering task in a high-dimensional space, where each word is seen as an important attribute for a text. Empirical and mathematical analysis have revealed that clustering in high-dimensional spaces is very complex, as every data point is likely to have the same distance from all the other data points (Beyer *et al.* 1999).
- Text clustering is often useless, unless it is integrated with reason for particular texts are grouped into a particular cluster. It means that one output preferred from clustering in practical settings is the explanation why a particular cluster result was created rather than the result itself. One usual technique for producing explanations is the learning of rules based on the cluster results. But this technique suffers from a high number of features chosen for computing clusters.

III. EXISTING SYSTEM

Clustering is sometimes erroneously referred to as automatic classification; however, this is inaccurate, since the clusters found are not known prior to processing whereas in case of classification the classes are pre-defined. In clustering, it is the distribution and the nature of data that will determine cluster membership, in opposition to the classification where the classifier learns the association between objects and classes from a so called training set, i.e. a set of data correctly labeled by hand, and then replicates the learnt behavior on unlabeled data.

Drawbacks of Existing System

1) K-Medoid Clustering Algorithm

Weaknesses:

a) Relatively more costly; complexity is O(i k (n-k)2), where i is the total number of iterations, is the total number of clusters, and n is the total number of objects.
b) Relatively not so much efficient.
c) Need to specify k, the total number of clusters in advance.
d) Result and total run time depends upon initial partition.

2) Hierarchical Clustering Algorithm

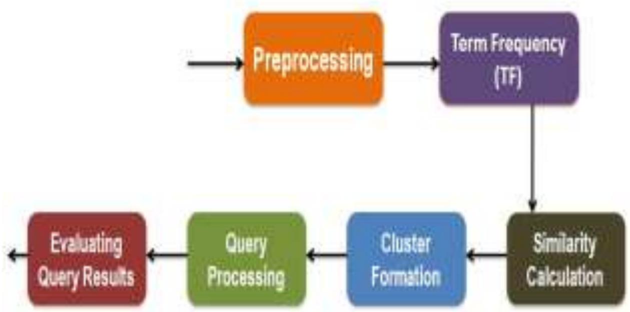
Weaknesses:

a) Depends on the scale of data.
b) Computationally complex for large datasets.
c) Different methods sometimes lead to very different dendrograms

IV. PROPOSED SYSTEM

A. Architecture of Proposed System

The outline of the proposed system is as follows:



1) Preprocessing Module

Before running clustering algorithms on text datasets, I performed some pre-processing steps. In particular, stop words (prepositions, pronouns, articles, and irrelevant document metadata) have been removed. Also, the Snow balls stemming algorithm for Portuguese words has been used. Then, I adopted a traditional statistical approach for text mining, in which documents are represented in a vector space model. In this model, each document is represented by a vector containing the frequencies of occurrences of words, which are defined as delimited alphabetic strings, whose number of characters is between 4 and 25. I also used a dimensionality reduction technique known as Term Variance (TV) that can increase both the effectiveness and efficiency of clustering algorithms. TV selects a number of attributes (in our case 100 words) that have the greatest variances over the documents. In order to compute distances between documents, two measures have been used, namely: cosine-based distance and Levenshtein-based distance. The later has been used to calculate distances between file (document) names only.

2) Calculating the number of clusters

In order to estimate the number of clusters, a widely used approach consists of getting a set of data partitions with different numbers of clusters and then selecting that particular partition that provides the best result according to a specific quality criterion (e.g., a relative validity index). Such a set of partitions may result directly from a hierarchical clustering dendrogram or, alternatively, from multiple runs of a partitional algorithm (e.g., K-means) starting from different numbers and initial positions of the cluster prototypes.

3) Clustering techniques

The clustering algorithms adopted in our study the partitional K-means and K-medoids, the hierarchical Single/Complete/Average Link, and the cluster ensemble based algorithm known as CSPA are popular in the machine learning and data mining fields, and therefore they have been used in our study. Nevertheless, some of my choices regarding their use deserve further comments. For instance, K-medoids is similar to K-means. However, instead of computing centroids, it uses medoids, which are the representative objects of the clusters. This property makes it particularly interesting for applications in which (i) centroids cannot be computed; and (ii) distances between pairs of objects are available, as for computing dissimilarities between names of documents with the Levenshtein distance.

4) Removing Outliers

I assess a simple approach to remove outliers. This approach makes recursive use of the silhouette. Fundamentally, if the best partition chosen by the silhouette has singletons (i.e., clusters formed by a single object only), these are removed. Then, the clustering process is repeated over and over again until a partition with-out singletons is found. At the end of the process, all singletons are incorporated into the resulting data partition (for evaluation purposes) as single clusters.

V. IMPLEMENTATION

A. Algorithm for Stop Word-Removal

A typical method to remove stopwords is to compare each term with acompilation of known stopwords

```
Input:A document Data Base D and List of Stop words L
D=fd1,d2,d3,.,dkg ;where 1<=k<=i
tij is the jth term in ith document
Output: All valid stem text term in D
for (all di in D) do
for (1 to j) do
Extract tij from di
If(tij in list L)
Remove tij from di
End for
End for
```

B. Calculating Similarity between two documents

```
For i:=0 to N(total documents)
For j:=0 to N (total documents)
Simvalue :=((doc[i]_doc[j]))/Math.sqrt(doc[i]_doc[j])
Add simvalue to the list Build matrix;
Next
Next
```

Where N is total number of documents
doc[i] for i=1,2.....n are documents

C. Clustering Technique

K means & improved method are used.
Steps of K Means method:

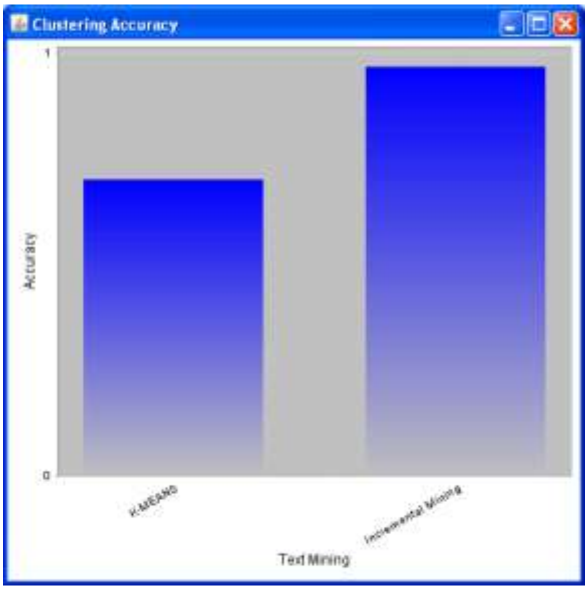
1) Initialization In this first step data set, number of clusters and the centroid that we defined for each cluster.
2) Classification The distance is calculated for each data point from the centroid and the data point having minimum distance from the centriod of a cluster is assigned to thatparticular cluster.
3) Centroid Recalculation Clusters generated previously, the centriod is again repeatly calculated means recalculation of the centriod.
4) Convergence Condition Some convergence conditions are given as below:
   - Stopping when reaching a given or defined number of iterations.
   - Stopping when there is no exchange of data point between the clusters.
   - Stopping when a threshold value is achieved.
5) If all of the above conditions are not satisfied, then go to step 2 and the whole process repeat again, until the given conditions are not satisfied.

Steps of improved method:
Output: D = d1, d2, d3,..., di,..., dn== set of documents
di = x1, x2, x3,..., xi,..., xm k == Number of desired clusters.
Input: A set of k clusters.

1) Calculate distance for each document or data point from the origin.
2) Arrange the distance (obtained in step 1) in ascending order.
3) Split the sorted list in K equal size sub sets. Also the middle point of each sub set is taken as the centroid of that set.
4) Repeat this step for all data points. Now the distance between each data point & all the centroids is calculated. Then the dataset is assigned to the closest cluster.
5) In this step, the centroids of all the clusters are recalculated.

6) Now for all data points. Now the distance between each data point & all the centroids is calculated.If this distance is less than or equal to the present nearest distance then the data point stays in the same cluster. Else it is shifted to the nearest new cluster.

VI. RESULT



VII. CONCLUSION

As clustering plays a very vital role in various applications, many researches are still being done. The upcoming innovations are mainly due to the properties and the characteristics of existing methods. These existing approaches form the basis for the various innovations in the field of clustering. From the existing clustering techniques, it is clearly observed that the clustering techniques provide significant results and performance. Hence, this research concentrates mainly on the clustering for better performance.

VIII. ACKNOWLEDGEMENT

I would like to express my profound gratitude and deep regard to my Project Guide Prof. M.M. Naoghare, for her exemplary counsel, valuable feedback and constant fillip throughout the duration of the project. Her suggestions were of immense help throughout my project work. Working under her was an extremely knowledgeable experience for me.

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