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Clustering with Hierarchal based Approach

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ABSTRACT

Cluster is the one of the technique in the data mining; it is used for arranging the similar data items into classes from a set of data objects. In this paper, we introduced a novel based similarity for grouping the similar objects in to classes. In the existing system, the major difference between the similarity and dissimilarity measure can be found with the single view point and consider it as origin. In Proposed System document clustering is achieved by considering multiple view points, with more similarities.

Index terms: *cluster, data mining, data objects, document clustering.*

Introduction

Imagine that we are having a set of data objects for analysis, but there is no proper classification. So, to identify object, we have to assign label for each object. To assigning label for large data object it is costly process. So we are using the clustering technique in the data mining. Clustering is the process of grouping the data objects in to classes (or clusters), so that objects within the same clusters have the high similarity in comparison to one another but are very dissimilar to objects in another cluster. According to the recent study, more than half a century after it was introduced; the simple algorithm k-means still remains as one of the top 10 data mining algorithms nowadays. The k-means algorithm is the centriod - base partitions algorithm. The clustering algorithm takes the input parameter, k, and partitions a set on n objects into k clusters so that the resulting intracluster similarity is high but the intercluster similarity is low. Cluster similarity is measured in regard to the mean value of the objects in a cluster which can be viewed as the cluster's centriod or center of gravity.

A common approach to the clustering problem is to treat it as an optimization process. An optimal partition is found by optimizing a particular function of similarity among data.

Related work:

The k - means algorithm processed as follows. Given data set D, a data set of **n** objects,and **k** is the number of clusters to form, a partitions algorithm organizes the objects into k partitions(K<=n), where each partition represents a cluster.

First, it randomly selects k of the objects, each of which initially represents a cluster mean or center. For each of the remaining objects, an object is assigned to the cluster to which it is the most similar, based on the distance between the object and the cluster mean. It then computes the new mean for each cluster. This process iterates until the criterion function converges. Typically, the square-error criterion is used, defined as

$$\sum_{i=1}^{k} \sum_{P \in Ci} |p - c_i|^2$$

Where E is the sum of the square error for all objects in the data set; p is the point in space representing a given object; and mi is the mean of cluster C_i.

K means has more than some of drawbacks, such as sensitiveness to initialization and to cluster size, and its performance can be worse than other state of the art algorithms in many domains. In spite of that, its simplicity, understandability and scalability are the reasons for tits tremendous popularity.

Novel hierarchical Approach:

With the help of novel hierarchical approach we are going to find the document clustering.

Document clustering techniques mostly rely on single term analysis of the document data set, such as **the vector space model.** To achieve more accurate document clustering, mote informative features including phrases and their weights are particularly important in such scenarios. Document clustering is particularly useful in many application such as automatic categorization of documents, grouping search engine results, building taxonomy of documents, and others. For hierarchical clustering method provides a better improvement in achieving the result. Our project presents two key parts of successful hierarchical document clustering. The first part is a document index model, the document index graph, which allows for incremental construction of the index of the document set with an emphasis on efficiency, rather than relying on single term indexes only. It provides efficient phrase matching that is used to judge the similarity between documents. This model is flexible in that it could revert to a compact representation of the vector space model if we choose not to index phrases. The second part is an incremental document clustering algorithm based on maximizing the tightness of clusters by carefully watching the pair wise document similarity distribution inside clusters. both the phases are based upon two algorithmic modes called Gaussian Mixture Model and expectation Maximization. The combination of these two components creates an underlying model for robust and accurate document similarity calculation that leads to much improved results in web document clustering over traditional methods.

In this proposed the main work is to develop a novel hierarchical algorithm for document clustering which provides maximum efficiency and performance. It is particularly focused in studying and making use of cluster overlapping phenomenon to design cluster merging criteria. Proposing a new way to compute the overlap rate in order to improve time efficiency and —"the veracity" is mainly concentrated. Based on the Hierarchical Clustering Method, the usage of Expectation-Maximization (EM) algorithm in the Gaussian Mixture Model to count the parameters and make the two sub-clusters combined when their overlap is the largest is narrated.

CHALLENGES OF HIERARCHICAL DOCUMENT CLUSTERING:

High dimensionality: each distinct word in the High dimensionality: Each distinct word in the document set constitutes a dimension. So there may be 15~20 thousands dimensions. This type of high dimensionality greatly affects the scalability and efficiency of many existing clustering algorithms. This is been cleared described in the following paragraphs.

High volume of data: In text mining, processing of data about 10 thousands to 100 thousands documents are involved.

Consistently high accuracy:

Some existing algorithms only work fine for certain type of document sets, but may not perform well in some others.

Meaningful cluster description:

This is important for the end user. The resulting hierarchy should facilitate browsing.

HIERARCHICAL ANALYSIS MODEL:

A hierarchical clustering algorithm creates a hierarchical decomposition of the given set of data objects. Depending on the decomposition approach, hierarchical algorithms are classified as agglomerative (merging) or divisive (splitting). The agglomerative approach starts with each data point in a separate cluster

or with a certain large number of clusters. Each step of this approach merges the two clusters that are
the most similar. Thus after each step, the total number of clusters decreases. This is repeated until the desired number of clusters is obtained or only one cluster
Remains. By contrast, the divisive approach starts with all data objects in the same cluster. In each step, one cluster is split into smaller clusters, until a termination condition holds. Agglomerative algorithms are more widely used in practice. Thus the similarities between clusters are more researched.

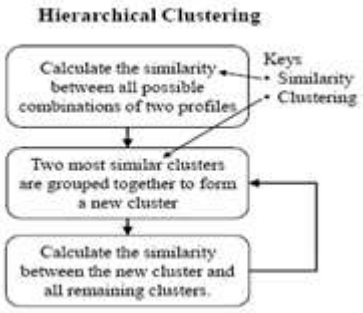

Fig: Hierarchical clustering

How they work?

Given a set of N items to be clustered, and an N*N distance (or similarity) matrix, the basic process
of hierarchical clustering is this:

STEP 1 - Start by assigning each item to a cluster, so that if you have N items, you now have N clusters, each containing just one item. Let the distances (similarities) between the clusters the same as the distances (similarities) between the items they contain.

STEP 2 - Find the closest (most similar) pair of clusters and merge them into a single cluster, so that now you have one cluster less with the help ohtf - itf.

STEP 3 - Compute distances (similarities) between the new cluster and each of the old clusters.

STEP 4 - Repeat steps 2 and 3 until all items are clustered into a single cluster of size N.

Step 3 can be done in different ways, which is what distinguishes single-linkage from complete linkage and average-linkage clustering. In single linkage clustering (also called the connectedness or minimum method), considering the distance between one cluster and another cluster to be equal to the shortest distance from any member of one cluster to any member of the other cluster.

If the data consist of similarities, consider the similarity between one cluster and another cluster to be equal to the greatest similarity from any member of one cluster to any member of the other cluster. In complete linkage clustering (also called the diameter or maximum method), consider the distance between one cluster and another cluster to be equal to the greatest distance from any member of one cluster to any member of the other cluster. In average-linkage clustering, consider the distance between one cluster and another cluster to be equal to the average distance. This kind of hierarchical clustering is called agglomerative because it merges clusters iteratively. There is also adivisivehierarchical clustering which does the reverse by starting with all objects in one cluster and subdividing them into smaller pieces. Divisive methods are not generally available, and rarely have been applied. Of course there is no point in having all the N items grouped in a single cluster but, once the complete hierarchical tree is obtained and need k clusters, **k-1**longest links are eliminated.

TERM FREQUENCY - INVERSE DOCUMENT FREQUENCY

The TF-IDF is a text statistical-based
Technique which has been widely used in many search engines and information retrieval systems. Assume that there is a corpora of 1000 documents and the task is to compute the

similarity between two given documents (or a document and a query). The following describes the steps of acquiring the similarity value:

Document pre-processing steps

- Tokenization: A document is treated as a string (or bag of words), and then partitioned into a list of tokens.
- Removing stop words: Stop words are frequently occurring, insignificant words. This step eliminates the stop words.
- Stemming word: This step is the process of conflating tokens to their root form (connection-> connect).

Document representation

Generating N-distinct words from the corpora and call them as index terms (or the vocabulary). The document collection is then represented as a N-dimensional vector in term space.

Computing Term weights

- Term Frequency.
- Inverse Document Frequency.
- Compute the TF-IDF weighting.

Measuring similarity between two documents:

Capturing the similarity of two documents using cosine similarity measurement. The cosine similarity is calculated by measuring the cosine of the angle between two document vectors. Using the code:

The main class is TFIDF Measure. This is the testing code:

```
void Test (string[] docs, int i, int j)
// docs is collection of parsed documents
{
StopWordHandlerstopWord=new
StopWordsHandler() ;
TFIDFMeasuretf=new TFIDFMeasure(doc) ;
float simScore=tf.GetSimilarity( i, j); //
similarity of two given
documents at the
// position i,j respectively }
```

Extension

This library also includes stemming (Martin Porter algorithm), and N-gram text generation modules. If a tokenbased system did not work as expected, then make another choice with N-gram based. Thus, instead of expanding the list of tokens from the document, generating a list of Ngrams
is adopted, where N should be a predefined number. The extra N-gram based similarities (bi, tri, quad...-gram) also help to compare the result of the statistical-based method with the N-gram based method. Consider two documents as two flat texts and then run the measurement to compare. Example of some N-grams for the word "TEXT":

- uni(1)-gram: T, E, X, T
- bi(2)-gram: T, TE, EX, XT, T
- tri(3)-grams: TE, TEX, EXT, XT, T
- quad(4)-grams: TEX, TEXT, EXT, XT, T

The problem, straight Boolean logic:

To many of users the phrase “relevancy ranked search results” is a mystery. A better phrase might have been ”statistically significant search results”. Taking such an approach, the application of statistical analysis against texts does have its information retrieval advantages over straight Boolean logic.

Take for example, the following three documents consisting of a number of words. A search for “rose” against the corpus will return three hits, but which on should start reading from? The new document? The document by a particular author or in a particular format ? Even if the corpus contained 2,000,000 documents and a search for “rose” returned a mere 100 the problem would remain. Which ones should we spend our valuable time accessing? Yes, we could limit our search in any number of ways, but unless we are doing a known item search it is quite likely the search results will return more than we use, and information literacy skills will only go so far. Ranked search results, a list of hits based on term weighting has proven to be an effective way of addressing this problem. All it

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requires is the application of basic arithmetic against the documents being searched.

Document 1		Document 2		Document 3	
Word	TFIDF	Word	TFIDF	Word	TFIDF
airplane	0.326	Milton	0.439	building	0.367
shoe	0.261	shakespeare	0.293	ceiling	0.245
computer	0.196	car	0.256	cleaning	0.245
perl	0.163	book	0.220	carpet	0.184
chair	0.152	pond	0.146	justice	0.163
justice	0.152	slavery	0.146	perl	0.153
forest	0.130	rose	0.122	rose	0.143
love	0.130	newton	0.110	chair	0.122
might	0.130	chair	0.098	libraries	0.122
rose	0.130	thesis	0.073	newton	0.061
blue	0.065	truck	0.073	science	0.061
thesis	0.065	justice	0.049	car	0.031

Table1: Total Classification

TFIDF Analysis

By taking into account these two actors — term frequency (TF) and inverse document frequency (IDF) — it is possible to assign "weights" to search results and therefore ordering them statistically. Put another way, a search result's score("ranking") is the product of TF and IDF:

TFIDF = TF * IDF

where:

- TF = C / T where C = number of times a given word appears in a document and T = total number of words in a document
- IDF = D / DF where D = total number of documents in a corpus, and DF = total number of documents containing a given word
- Given TFIDF, a search for "rose" still returns three documents ordered by Documents 3, 1, and 2. A search for "newton" returns only two items ordered by Documents 2 (0.110) and 3 (0.061). In the later case, Document 2 is almost one and a half times more "relevant" than document3. TFIDF scores can be summed to take into account Boolean unions (or) or intersections (and).

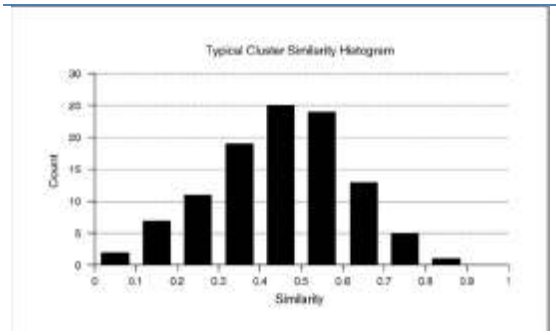
Automatic classification

TDIDF can also be applied a priori to indexing/searching to create browse lists hence, automatic classification. Consider the table where each word is listed in a sorted TFIDF order: Given such a list it would be possible to take the first three terms from each document and call them the most significant subject "tags". Thus, Document #1 is about airplanes, shoes, and computers. Document #2 is about Milton, Shakespeare, and cars. Document #3 is about buildings, ceilings, and cleaning. Probably a better way to assign "aboutness" to each document is to first denote a TFIDF lower bounds and then assign terms with greater than that score to each document. Assuming lower bounds of 0.2, Document #1 is about airplanes and shoes. Document #2 is about Milton, Shakespeare, cars, and books. Document #3 is about buildings, ceilings, and cleaning.

Doc 1	Doc 2	Doc 3
Word	Word	Word
Airplane	book	Building
Blue	car	Car
Chair	chair	Carpet
Computer	justice	Ceiling
Forest	milton	chair
justice	newton	cleaning
Love	pond	justice
Might	rose	libraries
Perl	shakespeare	newton
Rose	slavery	perl
Shoe	thesis	rose
Thesis	truck	science

The clustering approach proposed here is an incremental dynamic method of building the clusters. An overlapped cluster model is adopted here. The key concept for the similarity histogram-based clustering method is to keep each cluster at a high degree of coherency at any time.

Representation of the coherency of a cluster is called as Cluster Similarity Histogram.



Cumulative Document

- The cumulative document is the sum of all the documents, containing meta-tags from all the documents.
- We find the references (to other pages) in the input base document and read other documents and then find references in them and so on.
- Thus in all the documents their meta-tags are identified, starting from the base document.

CONCLUSION

Given a data set, the ideal scenario would be to have a given set of criteria to choose a proper clustering algorithm to apply. Choosing a clustering algorithm, however, can be a difficult task. Even ending just the most relevant approaches for a given data set is hard. Most of the algorithms generally assume some implicit structure in the data set. One of the most important elements is the nature of the data and the nature of the desired cluster. Another issue to keep in mind is the kind of input and tools that the algorithm requires. This report has a proposal of a new hierarchical clustering algorithm based on the overlap rate for cluster merging. The experience in general data sets and a document set indicates that the new method can decrease the time cost, reduce the space complexity and improve the accuracy of clustering. Specially, in the document clustering, the newly proposed algorithm measuring result show great advantages. The hierarchical document clustering algorithm provides a natural way of distinguishing clusters and implementing the basic requirement of clustering as high within-cluster similarity and between-cluster dissimilarity.

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