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A Fast Clustering - Correlation Preserving Indexing for High Dimensional Data

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Abstract- Correlation Preserving Indexing can discover the intrinsic structures implanted in high-dimensional document space. To predict the result of one variable based on another variable is not suitable for all the situations since two variable prediction problems takes places. In this paper, Directed Ridge Regression is introduced to predict two or more variables which are highly correlated in high dimensional document space. Directed Ridge Regression is a statistical technique to estimate the relationship among the variables based on the Eigen values to find the similarity between the documents. The directed ridge estimator alters the diagonal elements of the Eigen values. The objective of the Directed Ridge Regression is to achieve efficient document clustering in similarity measure. Experimental results shows that compared to Correlation Preserving Indexing, the Directed Ridge Regression achieves efficient document clustering.

Keywords: Correlation Similarity Measure, Directed Ridge Regression, Document Clustering, Latent Semantic Indexing

I. INTRODUCTION

Document clustering [1] is a fundamental operation used in unsupervised document organization and information retrieval. Document clustering is to group automatically related documents into clusters. It is one of the most significant tasks in machine learning and artificial intelligence and has received much attention in recent years [2, 3, and 4]. Based on a variety of distance measures, a number of methods have been proposed to handle document clustering. A distinctive and widely used distance measure is the euclidean distance. The k-means method is one of the ways that use the euclidean distance, it minimizes the sum of the squared euclidean distance between the data points and their corresponding cluster centers. The document space is of high dimensionality forever, it is preferable to find a low-dimensional representation of the documents to reduce computation complexity. Low computation cost is attained in spectral clustering methods, in which the documents are first projected into a low-dimensional semantic space and then a traditional clustering algorithm is applied to finding document clusters. Latent semantic indexing (lsi)[8] is one of the effective spectral clustering methods, intended at finding the best subspace approximation to the original document space by minimizing the global reconstruction error (euclidean distance). It because of the high dimensionality of the document space, a certain representation of documents usually resides on a nonlinear manifold embedded in the similarities between the data points. The euclidean distance is a dissimilarity measure which describes the dissimilarities rather than similarities between the documents. It is not bright to effectively capture the nonlinear manifold structure embedded in the similarities between them. An effective document clustering method must be able to find a low-dimensional representation of the documents that can best preserve the similarities between the data points.

Locality preserving indexing (lpi) method is a different spectral clustering method based on graph partitioning speculation. The lpi method applies a weighted function to each pair wise distance attempting to focus on capturing the similarity structure, instead of dissimilarity structure, of the documents. It does not overcome the essential limitation of Euclidean distance. Moreover, the selection of the weighted functions is often a difficult task. Correlation as a similarity measure can capture the intrinsic structure embedded in high-dimensional data, especially the input data is sparse. It is a scale-invariant association measure usually used to calculate the similarity between two vectors. In a lot of cases, correlation can effectively represent the distributional structure of the input data to conventional euclidean distance cannot explain. The usage of correlation as a similarity measure can be found in the canonical correlation analysis (cca) method. The cca method is to find projections for paired data sets such that the correlations between their low-dimensional representatives in the projected spaces are mutually maximized.

As a great statistical technique, the cca method has been applied in the field of pattern recognition and machine structure embedded in the similarities between the documents. It aims to find an optimal semantic subspace by simultaneously maximizing the correlations between the documents in the local patches and minimizing the correlations between the documents outside these patches. Learning to propose a new document clustering method based on correlation preserving indexing (cpi), it clearly considers the manifold structure embedded in the similarities between the documents. It aims to locate an optimal semantic subspace by simultaneously maximizing the correlations between the documents in the local patches and minimizing the correlations between the documents outer these patches. This is different from lsi and lpi, that are based on a dissimilarity measure (euclidean distance), and are focused n detect the intrinsic structure between widely separated documents rather than on detecting the intrinsic structure between nearby documents. The similarity-measure-based cpi method focuses on detecting the intrinsic structure between nearby documents rather than on detecting the intrinsic structure between widely separated documents. As the intrinsic semantic structure of the document space is often embedded in the similarities between the documents cpi can effectively detect the intrinsic semantic structure of the high dimensional document space. In multivariate statistics and the clustering of data, spectral clustering techniques make use of the spectrum (eigen values) of the similarity matrix of the data to perform dimensionality reduction before clustering in fewer dimensions. The similarity matrix is provided as an input and consists of a quantitative assessment of the relative similarity of each pair of points in the dataset. An efficiency improvement of spectral clustering is the spectral neighborhood (span) algorithm, it performs spectral clustering without explicitly computing the similarity matrix, and therefore dramatically improves the scalability of the standard spectral clustering algorithm.

II. RELATED WORKS

In Document Clustering [1] in Correlation Similarity Measure Space proposed by Taiping Zhang[15] an effective document clustering method must be able to find a low-dimensional representation of the documents that can best preserve the similarities between the data points. Low computation cost is achieved in spectral clustering methods, in that the documents are first projected into a low dimensional semantic space and then a traditional clustering algorithm is applied to finding document clusters. Because of the high dimensionality of the document space, a certain representation of documents usually reside on a nonlinear manifold embedded in the similarities between the data points .Unfortunately, the Euclidean distance is a dissimilarity measure and describes the dissimilarities rather than similarities between the documents. Thus, it is not able to efficiently capture the nonlinear manifold structure embedded in the similarities between them. So a new document clustering method based on correlation preserving indexing (CPI), it clearly considers the manifold structure embedded in the similarities between the documents. It aims to locate an optimal semantic subspace by simultaneously maximizing the correlations between the documents in the local patches and minimizing the correlations between the documents outside these patches. The traditional vector space information retrieval model in document clustering use words as measure to find similarity between documents [14]. In reality the concepts, semantics, and topics are used to describe the documents. VSM ignores semantic relations in the middle of terms. For instance, having “automobile” in one document and “car” in another document does not contribute to the similarity measure among these two documents. Several factors Contribute to this problem and motivate our explore. The semantic relationships between documents are not explored in the most of the clustering methods. In Document Clustering Using Locality Preserving Indexing [11] the document space is of high dimensionality, in broad ranging from several thousands to tens of thousands. Learning in a high-dimensional space is extremely difficult due to the curse of dimensionality. Consequently, document clustering necessitates some form of dimensionality reduction. One of the basic assumptions at the back data clustering is that, the two data points are close to each other in the high dimensional space, they be inclined to be grouped into the same cluster. The optimal document indexing method should be able to discover the local geometrical structure of the document space. To this last part, the LPI algorithm is of particular attention. LSI is optimal in the sense of renovation. It respects the global Euclidean structure while failing to discover the intrinsic geometrical structure, especially the document space is nonlinear. Another consideration is due to the discerning power. One can expect that the documents should be projected into the subspace in which the documents with different semantics can be well alienated, while the documents with common semantics can be clustered. As indicated LPI is an optimal unsupervised approximation to the Linear Discriminate Analysis algorithm is supervised. So, LPI can have additional discriminate power than LSI. There are a quantity of other linear subspace learning algorithms, such as informed projection and Linear Dependent Dimensionality Reduction. However, none of them has shown discriminating power. Finally, it would be interesting to note that LPI is fundamentally based on manifold theory. LPI tries to find a linear approximation to the Eigen functions of the Laplace Beltrami operator on the compact Riemannian manifold. Therefore, LPI is capable of discovering the nonlinear structure of the document space to some extent. Document Clustering Based on Non-negative Matrix Factorization Wei Xu, Xin Liu, Yihong Gong Clusters each of which 0corresponds to a coherent topic. Each document in the corpus either completely belongs to a particular topic, or is more or less related to several topics. To accurately cluster the given document corpus, it is ideal to project the document corpus into a k-dimensional semantic space in which each axis corresponds to a particular topic. In such a semantic space, each document can be represented as a linear combination of the k topics. Because it is more normal to consider each document as an additive rather than subtractive mixture of the underlying topics, the linear combination coefficients should all take non-negative values. Furthermore, it is also quite common that the topics comprising a document corpus are not completely independent of each other, and there are some overlaps among them. In such a case, the axes of the semantic space that capture each of the topics are not necessarily orthogonal.

III. PROPOSED WORK

In high-dimensional document space, the semantic structure is typically implicit. It is pleasing to find a low dimensional semantic subspace in which the semantic structure can become clear. Consequently, discovering the intrinsic structure of the document space is often a primary concern of document clustering. Since the manifold structure is frequently embedded in the similarities between the documents, correlation as a similarity measure is appropriate for capturing the manifold structure embedded in the high dimensional document space.

Online document clustering aims to group documents into clusters, it belongs unsupervised learning. Though, it can be transformed into semi-supervised learning by using the following side information: 1) If two documents are close to each other in the original document space, then they tend to be grouped into the same cluster [8]. 2) If two documents are far away from each other in the original document space, they tend to be grouped into different clusters.

A. Document preprocessing

Preprocessing is the phase to remove stop words, stemming and identification of unique words. Identification of unique words in the document is necessary for clustering of document with similarity measure. And after that we remove the stop words that is the non informative word for example the, end, have, more etc. The stop words which should be removed are given directly. It need to eliminate those stop words for finding such similarity between documents. Stemming is the processes for reducing derived words to their stem, base or origin form generally a written word form. The stem need not be identical to the root of the word it is usually sufficient that related words map to the same stem, even if this stem is not in itself a valid root. A stemming algorithm is a process in the variant forms of a word are reduced to a frequent form, the following all the example,

- Removal of suffix to generate word Stem
- Groping words
- Increase the relevance

Finally term weighting is to provide the information retrieval and text categorization. In document clustering groups together conceptually related documents.

B. Term Frequency and Inverse Document Frequency.

Every document is represented as a term frequency vector. The term frequency vector can be computed as follows:

1. Transform the documents to a list of terms following words stemming operations.
2. Remove stop words. Stop words are common words that contain no semantic content.
3. Compute the term frequency vector using the TF/IDF weighting scheme.

Clustering Algorithm Based on CPI

1. Input text document from dataset.
2. Transform the documents to a list of terms after words stemming operations.
3. Construct the local neighbor patch, and compute the matrices.
4. Compute CPI projection based on the multipliers
tf *idf.
5. Compute CPI Projection.
6. Finding correlation between the numbers of documents.
7. Finding distance between the numbers of documents.

IV. PERFORMANCE ANALYSIS

In this module the proposed approaches were illustrated and evaluated to compare the performance of all the approaches. We analyze our proposed scheme in terms of memory, storage, computation complexity, generalization error, performance. Based on the comparison and the results from the experiment show the proposed approach works better than the other existing systems.

V. DATASET DESCRIPTION

The 20 newsgroups corpus3 consists of roughly 20,000 documents that come from 20 specific Usenet newsgroups. We repeated the experiment [5] to illustrate the performance of the proposed CPI algorithm and other competing algorithms. The first set of experiments involved binary clustering. In each experiment, we randomly chose 50 documents from the two selected newsgroups and 100 runs were conducted for each algorithm to obtain statistically reliable clustering result. The means and standard deviations of the test results were recorded. We also tested other competing methods under same experimental setting, including K-means, pK-means, p-QR and Spectral. It can be seen from Table that CPI achieves the best clustering accuracy on all six data sets. LPI performs the second best, pK-means and p-QR outperform K-means, and K-means performs the worst. Under Normalized mutual information metric, CPI also performs the best. K-means performs better than p-K-means and p-QR, and pK-means or p-QR performs the worst. It can see that the CPI method outperforms with statistical significance other competing methods in most of the data sets.

Reuter

The Reuters corpus4 contains 21,578 documents in 135 topics. Many documents have multiple category labels. A subset of Reuters contained the total 8,067 documents in 30 categories with unique category labels are used in this experiment. The proposed method was compared with five methods, including .Kmeans on original data used with cosine similarity measure. Kmeans with cosine similarity measure after LSI. Kmeans with cosine similarity measure after LPI. von Mises-Fisher model (vMF) nonnegative matrix factorization (NMF) . The experiments were performed with the number of clusters ranging from 2 to 8. For each given c that is the number of clusters, 50 document sets with different clusters were randomly selected from the corpus. Since all the tested algorithms depend heavily on the initial partition, we performed 100 runs for each set of documents.

VI. RESULTS

The proposed technique is done using correlation preserving indexing, this technique improves the document clustering accuracy based on similarity between the documents. Experiments were performed on NG20, Reuters, and OHSUMED data sets. . We compared the proposed algorithm with other competing algorithms under same experimental setting. In all experiments, our algorithm performs better than or competitively with other algorithms.

VII. CONCLUSION

A new document clustering method based on correlation preserving indexing and the use of natural language processing tool is presented. It simultaneously maximizes the correlation between the documents in the local patches and minimizes the correlation between the documents outside these patches. A low dimensional semantic subspace is derived where the documents corresponding to the same semantics are close to each other. Extensive experiments on NG20 show that the proposed CPI method outperforms other classical clustering methods. CPI method has good generalization capability.

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