Application of PCA in Text Document Clustering

DWDM PROJECT REPORT

by

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1 Abstract

Clustering is a very powerful data mining technique for topic discovery from text documents. It is a useful technique that organises a large number of unordered text documents into a small number of meaningful and coherent clusters, thereby providing a basis for intuitive and informative navigation and browsing mechanisms. Graph-based clustering algorithms, such as Spectral Clustering, are reported performing well on document clustering. They treat the clustering problem as an optimisation process of grouping documents into K clusters so that a particular criterion function is minimised or maximised. Most of the existing text clustering algorithms take in features vector directly as an input and make the corresponding prediction. This research work aims at applying Dimensionality Reduction techniques such as Principle Component Analysis(PCA) on the features vector instead of feeding-in directly as input to Spectral Clustering so that we can reduce dimensions of input features vector to make the computation faster and achieving the same level of accuracy as we were getting when the dimensions were high. *Euclidean distance*, *Gaussian kernel* was used for computing the weights of the adjacency matrix of the graph. The concluding results show that by applying PCA to input data and using *Gaussian Kernel* as a distance measure, we can achieve the same level of accuracy as compared when the dimensions of input features vectors were relatively high.

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4.1 Introduction

One of the significant questions in areas of information retrieval and text mining is how to explore and utilise the massive amount of text documents. To help users effectively navigate, summarise, and organise text documents, *Text Document Clustering* is one of the most crucial text mining methods which are developed in recent years. A large number of documents can be easily organised into several meaningful clusters using document clustering. Document clustering can also be used to browse a collection of documents or organize the results returned by a search engine in response to a user's query[2]. It can significantly improve the precision and recall in information retrieval systems [3], [2], [4], [5], and it is an efficient way to find the nearest neighbours of a document [6]. The problem of document clustering is generally defined as follows: given a set of documents, we would like to partition them into a predetermined or an automatically derived number of clusters, such that the documents assigned to each cluster are more similar to each other than the documents assigned to different clusters. In other words, the documents in one cluster share the same topic, and the documents in different clusters represent various topics.

Clustering has been among the most active research topics in machine learning and pattern recognition. While many traditional clustering algorithms have been developed over the past few decades [8], [9], some new clustering algorithms emerged over the last few years that give very promising results on some challenging tasks. Among them are *Spectral Clustering* [10], [11], [12], [13] and *Path-based Clustering* [14], [15], [16], which have demonstrated excellent performance on some clustering tasks involving highly non-linear and elongated clusters in addition to compact clusters.

It has been reported that there are two general categories of clustering methods: agglomerative hierarchical and partitional methods. *Agglomerative hierarchical clustering* (AHC) algorithms initially treat each document as a cluster, use different kinds of distance functions to compute the similarity between the pairs of clusters, and then merge the closest pair [17]. This merging step is repeated until the desired number of clusters is obtained. Compared with the bottom-up method of AHC algorithms, the family of *k-means* algorithms [18], [19], [20], [21], which belong to the category of partitional clustering, create one-level partitioning of the documents. The *k-means* algorithm is based on the idea that a centroid can represent a cluster. After selecting k initial centroids, each document is assigned to a cluster based on a distance measure (between the document and each of the k centroids), then k centroids are recalculated. This step is repeated until an optimal set of k clusters are obtained based on a criterion function. Text document clustering is a basic process used in information retrieval, automatic topic extraction and document organization. High quality clustering algorithms play a vital role efficiently in organizing, summarizing and navigating the unstructured documents.

Despite the promising performance of these algorithms demonstrated on some difficult data sets, there exist some other situations when these algorithms do not perform well. Consider some examples in Fig 4.1. Although spectral clustering works perfectly well on the 2-circle data set (Fig. 4.1(a)), it gives very poor results on the 3-spiral data set (Fig 4.1(b)). The poor clustering result is due mainly to the particular choice of the affinity matrix, which is usually defined in a way similar to the Gaussian kernel based on inter-point Euclidean distance in the input space. However, if path-based criteria from path-based clustering are used to define the similarity or dissimilarity between points to form the affinity matrix before spectral clustering is applied, the three clusters in the 3-spiral data set can be found correctly, as shown in Fig 4.1(c).

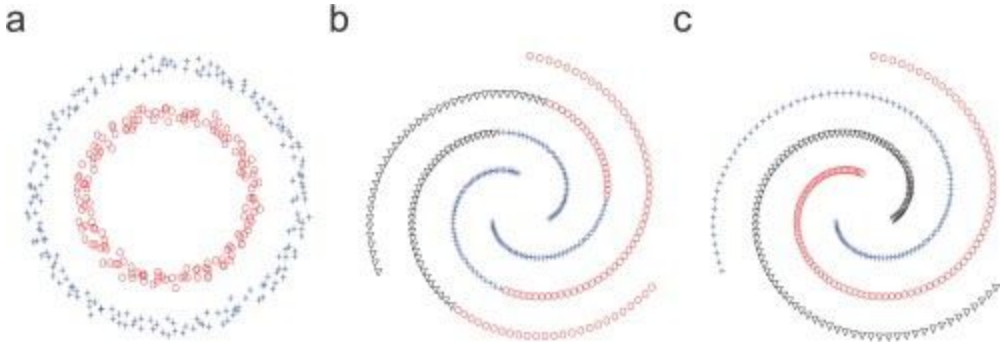

Fig. 4.1 Simple examples of spectral clustering and path-based clustering: (a) spectral clustering result for 2-circle data set; (b) spectral clustering result for 3-spiral data set; and (c) path-based spectral clustering result for 3-spiral data set

In this research work we aim at applying *Principle Component Analysis*(PCA) which is well-known *Dimensionality Reduction* techniques on the input features vector which is very high dimensional vector instead of feeding-in directly as input to *Spectral Clustering* so as to reduce dimensions of input features vector for making the faster computation while achieving the similar level of accuracy when the dimensions of input features vector was high. To achieve this, we made the use of the *Gaussian Kernel* as distance measure and PCA with 270 components.

The rest of this report is organized as follows. Various methods have been explained in Section 4.2 to achieve the results. In Section 4.3, we have shown the results which we have achieved after applying PCA to input features vectors and then applying *Spectral Clustering* on the features vector and showing the accuracy of various types of *Spectral Clustering*. Finally, some concluding remarks are given in Section 4.4.

4.2 Materials And Methods

The objective of the text document clustering is to group the text documents into clusters based on the similarity of the content available in a particular document. When we have the document, the first thing we have to do Document preprocessing. It is the significant phase to represent the documents for efficient document clustering . For doing text preprocessing we have to apply

several techniques such as *Tokenization*, stop word removal and *Stemmization*. *Tokenization* is the process of splitting a stream of text content into words, terms, symbols or certain other expressive features called tokens. The list of tokens goes into an input for further processing which includes parsing or text mining. There are many words in the documents which occur frequently in the text, but they are basically meaningless words as they are used to connect the words well organized to form a sentence. These words are called stop words which does not denote the content or context of text documents. *Stemming* is the process of reducing a word to its word stem that affixes to suffixes and prefixes or to the roots of words known as a lemma.
Now the input text has been preprocessed but it is still in the text format, but the algorithm accepts only vectors, so we have to convert the text into vectors so that we can feed it into the algorithm. To convert the text into vectors there are two representations which exist in the literature. They are:

- **Word-count vector**
- **TF-IDF vector**

The *Word-count* vector is the simplest form of text representation in numbers. Like the term itself, we can represent a sentence as a bag of words. It is a representation that turns arbitrary text into fixed-length vectors by counting how many times each word appears. This process is often referred to as vectorization. Let's understand this with an example. Suppose we wanted to vectorize the following:

- **the cat sat**
- **the cat sat in the hat**
- **the cat with the hat**

We first define our vocabulary, which is the set of all words found in our document set. The only words that are found in the 3 documents above are: the, cat, sat, in, the, hat and with. To vectorize our documents, all we have to do is count how many times each word appears:

Document	the	cat	sat	in	hat	with
the cat sat	1	1	1	0	0	0
the cat sat in the hat	2	1	1	1	1	0
the cat with the hat	2	1	0	0	1	1

Fig 4.2 Word-Count Representation of above sentences

Now we have length-6 vector for each sentences

- **the cat sat: [1,1,1,0,0,0]**
- **the cat sat in the hat: [2,1,1,1,0]**
- **the cat with the hat: [2,1,0,0,1,1]**

TF-IDF stands for *Term Frequency-Inverse Document Frequency*. This is a technique to quantify a word in documents, we generally compute a weight to each word which signifies the

importance of the word in the document and corpus. This method is a widely used technique in *Information Retrieval* and *Text Mining*. *Term Frequency* increases the weight of the terms that occur more frequently in the document. So it can be defined as

`tf(t,d) = F(t,d)` where `F(t,d)` is number of occurrences of term *t* in document

But practically, it seems unlikely that thirty occurrences of a term in a document truly carry thirty times the significance of a single occurrence. So, to make it more pragmatic, we scale TF in a logarithmic way so that as the frequency of terms increases exponentially, we will be increasing the weights of terms in an additive manner.

$$tf(t,d) = \log(F(t,d))$$

Inverse Document Frequency diminishes the weight of the terms that occur in all the documents of the corpus and similarly increases the weight of the terms that occur in rare documents across the corpus. The rare keywords get special treatment and stop words/non-distinguishing words get punished. We define IDF as:

$$idf(t,D) = \log(N/N_t \in d)$$

Here, N is the total number of files in the corpus D and $N_t \in d$ is the number of files in which the term t is present. By now, we can agree to the fact that TF is an intra-document factor which depends on individual documents and idf is a per corpus factor which is constant for a corpus. Finally, We calculate TF-IDFas:

$$tf\text{-}idf(t,d,D) = tf(t,d) \cdot idf(t,D)$$

After converting text into vectors we can feed them into the algorithms for doing clustering. Now comes the part where we have a very high dimensional vector which if fed into the algorithm will take a lot of time for doing the task. So we applied *Dimensionality Reduction* techniques such as *Principle Component Analysis*(PCA) to reduce the dimension from very high numbers to a low value.

PCA is a technique for *feature extraction*, it combines our input variables in a specific way, then we can drop the *least important* variables while still retaining the most valuable parts of all of the variables. It is an unsupervised learning class of statistical techniques used to explain data in high dimensions using a smaller number of variables called the principal components. As an added benefit, each of the new variables after PCA are all independent of one another. This is a benefit because the assumptions of a linear model require our independent variables to be independent of one another. We applied PCA on the input text and reduced the features for visualization. The dimensions were reduced from 1000 to 2 as we can plot only in 2D. We used *Genism library* for

plotting the *Word Embeddings* of the input text which clusters the similar nearer to each other where unsimilar words of the text are far away in the *Embedding* space.

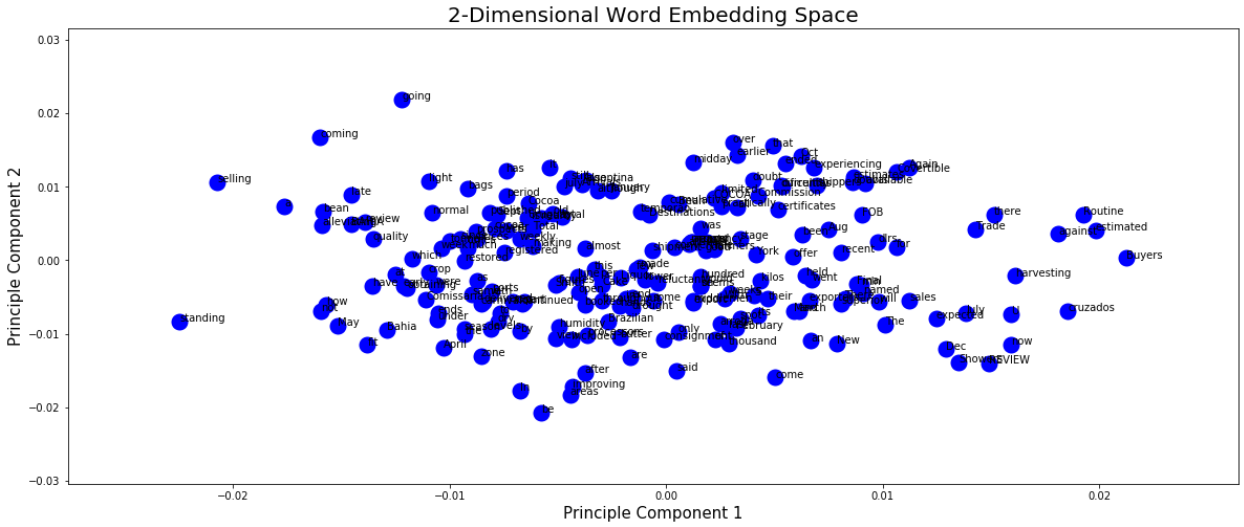

Fig 4.3 Visualization of Input Text in Embedding Space

For fitting the input features vector into the algorithm we tried various values of components such as 2, 50, 100, 150, 250, 270, 300, 500, 750, 900 while applying PCA to input features vectors. The best accuracy is achieved when the features vector has 270 features.

Now we have features vectors with reduced dimension, our vector is ready to feed into *Spectral Clustering* Algorithm. *Spectral Document Clustering* has developed in recent times as a widespread clustering technique, which motivated the emerging criterion functions and the developing algorithm to produce further accurate clusters . It uses the *Eigen Vectors* of the graph matrices which are derived from the documents. This algorithm is based on the concept of the weighted undirected graph. It demonstrates the collection of documents, i.e. document corpus $D = \{d1,d2,\ldots\ldots, dn\}$. as an undirected graph $G(Vs,Es,Ma)$ where V_s is a Vertex Set, E_s denotes the Edge Set and M_a denotes the Graph Affinity Matrix. Each vertex $V_i \in V_s$ signifies the ith document and edge $(i, j) \in E_s$ is allocated to an affinity score. This algorithm consists of the following steps. First we have to construct a *Similarity graph* where there are numerous ways to transform a set of documents $\{d1,d2,\ldots, dn\}$ from document collections with the pair wise similarity ps_{ij} or distance wise similarity ds_{ij}, into a graph. Then we have to construct a *Graph Laplacian Matrix*. It is the most important part of spectral clustering. If there is no unique

resolution then the matrix is precisely called as *Graph Laplacian*. The frequently used graph Laplacian types are as follows: *Un-normalized Graph Laplacian*, *Normalized Graph Laplacian*, *Normalized Graph Laplacian related to Random Walks.*After computing the *Laplacian matrix* we apply *Particle Swarm Optimization* to the *Eigen Vectors* computed from *Laplacian Matrix*.

Particle Swarm Optimization is a global stochastic optimization technique for incessant methods. The K-means algorithm is suitable for the initial clustering conditions, which can cause this algorithm to converge upon suboptimal solutions. But, the PSO algorithm is less sensitive for the initial conditions because of its population based nature. Hence, the PSO is more likely to find the near optimal solution. The ultimate purpose of this algorithm is to have whole particles come across the optima in a high dimensional data volume. The location of the particle in the high dimensional problem space, epitomize to explain a particular problem. While a particle travels from one location to a new location, another solution will be generated. These solutions are assessed by a fitness function which provides the optimal solution. Each particle will recall its recent coordinates and its velocity which shows the particle movement speed along with the dimensions of a problem space, from which the finest fitness value is established. The best value is coupled with its neighbor's best value, impacts the movement of every particle over the problem space.

For analysing how our algorithm has performed we calculated *Adjusted Rand Index*. The *Adjusted Rand index* in data clustering, is a measure of the similarity between two data clusterings. A form of the *Rand index* may be defined that is adjusted for the chance grouping of elements, this is the *Adjusted Rand Index*. From a mathematical standpoint, *Rand index* is related to accuracy, but is applicable even when class labels are not used. The *Adjusted Rand index* is the corrected-for-chance version of the *Rand index*. Such a correction for chance establishes a baseline by using the expected similarity of all pair-wise comparisons between clusterings specified by a random model.

```
ARI = (RI - Expected_RI) / (max(RI) - Expected_RI)
```

The whole above process is summarized in the Fig 4.4

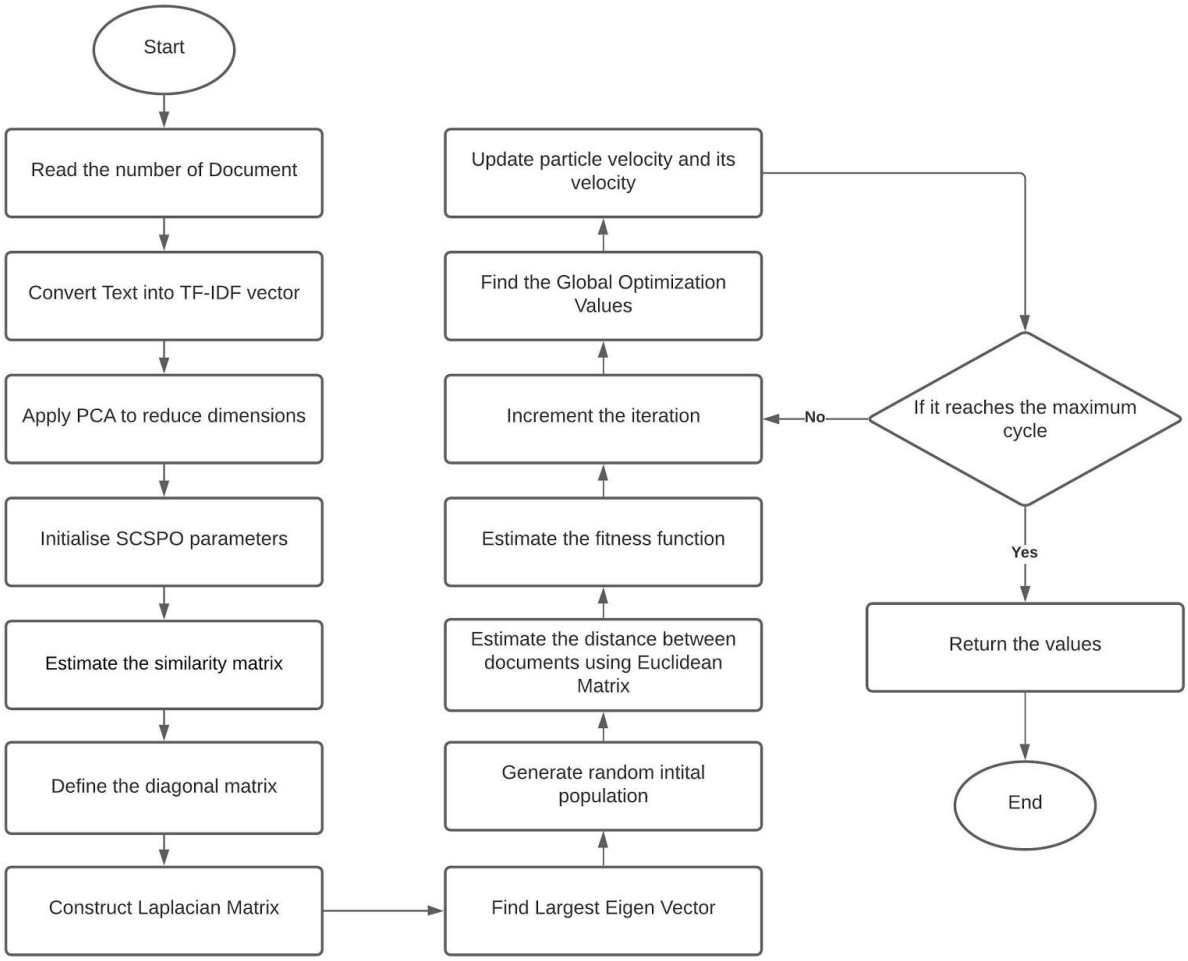

Fig 4.4 Flow chart for Text Document Clustering using while using PCA as Dimensionality Reduction and Spectral Clustering for clustering with Particle Swarm Optimization

4.3 Results & Discussion

Document clustering is a significant problem in the area of text mining and retrieving information. This is an open problem on which contributions are being added from time to time. *Spectral Clustering* with *Particle Swarm Optimization* (SCPSO) is a beneficial method as compared to the existing models like *K-means*.

The figure given below shows the adjusted rand index for different clustering models we applied.

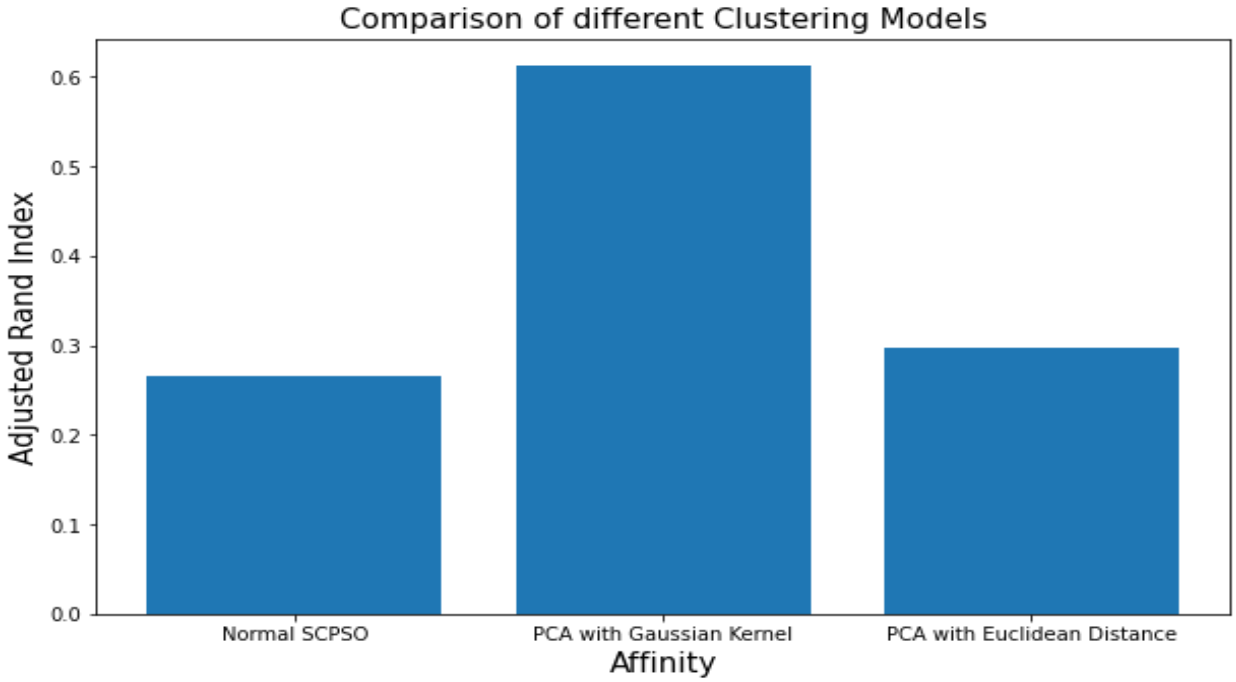

Fig 4.5 Comparing various Clustering Models

For experimentation, the clustering is being performed on the *Reuters* dataset which consists of text documents where each document belongs to some categories. This document corpus contains 90 categories with a total number of 21,578 documents. For the dataset, we applied preprocessing technique which is explained in the above section. For comparing various models, we have used the *Adjusted Rand Index* which gives the idea of how significant is a particular clustering model. A form of the *Rand index* may be defined that is adjusted for the chance grouping of elements; this is the *Adjusted Rand index*. From a mathematical standpoint, the Rand index is related to accuracy but is applicable even when class labels are not used. The *Adjusted Rand index* is the corrected-for-chance version of the Rand index. Such a correction for chance establishes a baseline by using the expected similarity of all pairwise comparisons between clusterings specified by a random model.

```
ARI = (RI - Expected_RI) / (max(RI) - Expected_RI)
```

We have also applied *Principal Component Analysis* (PCA) which is used for reducing the dimensionality while preserving as much information possible. Example - If the dataset has 100 attributes, applying PCA we can get ten features which may maintain over 99% of the information; thus the information is almost entirely retained but reducing dimensionality enables training the model better and faster. PCA has been applied on the TF-IDF vector.

Table 1
Performance measures comparison

Clustering Model	Adjusted Rand Index(ARI)
Normal SCPSO	0.2831796062227219
PCA applied SCPSO with distance metric as Euclidean distance	0.2474655533222179
PCA applied SCPSO with distance metric as Gaussian Kernel	0.6120316575561298

Table 1 reveals the comparison of ARI values on *Reuters* datasets after applying PCA to input features vectors and without applying PCA i.e., existing algorithms. This test shows that the applying PCA on features vectors and then applying SCPSO with distance metric as *Gaussian Kernel* algorithm outperforms the others in terms of ARI. The effectiveness of the proposed algorithm is slightly increased when compared to the PSO clustering algorithm.

4.4 Conclusion

In this research work, we have tried to make the computation faster by applying Dimensionality *Reduction* techniques such as PCA to reduce the dimensions of features vectors while achieving the same level of accuracy as before. Above results shows that the best outcome is shown by the PCA with *Gaussian Kernel* followed by PCA with *Euclidean Distance* and finally by normal SCPSO. The ideas of our experiments proved to be useful as they showed improved results as compared to the typical SCPSO algorithm, the accuracy is still a bit lower as compared to the results in the research paper. We know that the problems that can be solved by *K-means* can be solved by *Spectral Clustering* but not the other way around, also applying PCA is very helpful as it is drastically reducing the dimensions of features vector and making the computation faster while keeping the accuracy as high as earlier. Hence we can conclude from the results, observations and the working of our algorithm that the additional ideas used, proved to be useful for the problem that we were aiming to solve. In future, experiments can include the use of parallel processing for improvement in the training period. *Hybrid clustering* can be applied to increase the robustness of the algorithm. Instead of PCA, other *Dimensionality Reduction* techniques such as *Linear Discriminant Analysis* (LDA) can be applied, and other ideas like transforming the data differently altogether can also be done. Distinct intentions can be introduced to attain the accomplished results of text document clustering. In addition to the above suggestions, changes can be applied to the spectral and optimization algorithms.

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