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An Initilization Method for Subspace Clustering Algorithm*

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***Abstract*—Soft subspace clustering is an important part and research hotspot in clustering research. Clustering in high dimensional space is especially difficult due to the sparse distribution of the data and the curse of dimensionality. By analyzing limitations of the existing algorithms, the concept of subspace difference and an improved initialization method are proposed. Based on these, a new objective function is given by taking into account the compactness of the subspace clusters and subspace difference of the clusters. And a subspace clustering algorithm based on *k*-means is presented. Theoretical analysis and experimental results demonstrate that the proposed algorithm significantly improves the accuracy.**

Index Terms- k-means type clustering; subspace clustering; subspace difference; initialization method;

I. INTRODUCTION

Data mining is the analysis of data and the use of software techniques for finding patterns and regularities in sets of data. In most clustering approaches, the data points in a given dataset are partitioned into clusters such that the points within a cluster are more similar among themselves than data points in other clusters [1]. However, conventional clustering techniques fall short when clustering is performed in high dimensional spaces [2]. A key challenge to most conventional clustering algorithms is that, in many real world problems, data points in different clusters are often correlated with different subsets of features, clusters may exist in different subspaces that are comprised of different subsets of features [3].

As a branch of data mining, some progresses have made to solve this problem [4-13]. Subspace clustering has been proposed to overcome this challenge, and has been studied extensively in recent years. The goal of subspace clustering is to locate clusters in different subspaces of the same dataset. In general, a subspace cluster represents not only the cluster itself, but also the subspace where the cluster is situated [14]. The two main categories of subspace clustering algorithms are hard subspace clustering and soft subspace clustering. Hard subspace clustering methods identifies the exact subspaces for different clusters. While the exact subspaces are identified in hard subspace clustering, a weight is assigned to each dimension in the clustering process of soft subspace cluster to measure the contribution of each dimension to the formation of a particular cluster. Soft subspace clustering can be considered as an extension of the conventional feature weighting clustering [15], which employs a common weight vector for the whole dataset in the clustering procedure. However, it is also distinct in that different weight vectors are assigned to different clusters. Most of soft subspace clustering techniques are *k*-means type algorithm due to the efficiency and scalability in clustering large datasets, e.g. FWKM [16] and EWKM [17].

Although many soft subspace clustering algorithms have been developed and applied to different areas, their performance can be further enhanced; a major weakness of k-means type algorithms is that almost all of them are developed based on within-class information only, the commonly used within-cluster compactness [18]. And these kind algorithms which converge to locally optimal solution are commonly sensitive to initial cluster centers [19], it is assumed that clusters distribute with certain high density in the dataset in most soft subspace clustering. Accordingly, taking initial cluster centers form each high density area in the dataset would benefit clustering efficiency [20].

These algorithms are expected to be improved if more discrimination information and an efficient initialization method are utilized for clustering. Motivated by this idea, we proposed a new algorithm DBNDI (Distance-Based Neighborhood Density Initialization) which improved initialization efficiency in high dimensional space with a new density measure by considering the distribution of each point’s neighborhoods. It means the density of a point is composed of the similarity and the structure between neighbors. And then, we develop a novel soft subspace clustering algorithm SDSC (Soft Subspace Clustering based on Subspace Difference) in this study. Experiments of some high dimensional datasets demonstrated that the novel algorithm with new initial centers performs much better than other *k*-means type techniques.

The rest of this paper is organized as follows. Section II presents an overview of the existing *k*-means clustering algorithms and our contributions. The novel initialization method and the proposed SDSC algorithm are presented in Section III and Section IV. Experimental results and analysis are presented in Section V. In Section VI, we summarize this work and point out the future work.

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II. SUBSPACE CLUSTERING ALGORITHMS

In this paper, the dataset is denoted by X, where $X = \{x_1, x_2, x_3, ..., x_n\}, X_i = \{x_n | y_n = i\}$, specify 'n' points in D-dimensional spaces and the size of clusters is *K*, let $C = \{C_1, ..., C_k\}$ be K clusters. Where C_k denotes a partition of dataset. $\forall k \neq l, 1 \leq k,\ l \leq K, C_k \cap C_l = \varnothing$. $|C_k|$ represents the data point's number of C_k.

A. The existing k-means algorithms

k-means clustering is one of the most widely used clustering methods in data mining. Considering efficiency and scalability in clustering large datasets, various *k*-means type clustering have been proposed for clustering high dimensional data. *k*-means clustering have similar steps like *k*-means to calculate centroids and find members for them. In order to discover subspaces in which the clusters exist, an additional step for calculating the corresponding weight vectors for every cluster is added in the iterative clustering process. The process of *k*-means clustering is showed in Fig.1.

```
Algorithm: A k-means-type projective clustering algorithm
Input: the dataset, and the number of clusters $K$;
Output: the partition $C$ and the associated weights $W$;
1. Find the initial cluster centers $V$ and set $W$ with equal values;
2. Repeat
3.     Re-group the dataset into $C$ according to $V$ and $W$;
4.     Re-compute $V$ according to $C$;
5.     Re-compute $W$ according to $C$;
6. Until convergence is reached.
7. Return $C$ and $W$.
```

Figure 1. Process of *k*-means type algorithm

A soft subspace clustering algorithm known as the fuzzy weighting *k*-means algorithm (FWKM) [16] has been derived by using Eq.(1). A similar algorithm known as fuzzy subspace clustering (FSC) was also developed in [25]; detailed analysis of the properties of FSC can be found in [25].

$$F(C,V,W) = \sum_{k=1}^{K}\sum_{j=1}^{D} w_{kj}^{\beta} \sum_{x_i \in C_k} (x_{ij} - v_{kj})^2 \quad (1)$$

$$\sum_{j=1}^{D} w_{kj} = 1,\ k = 1,2,...,K.$$

where $\mathbf{w}_k = < w_{k1}, w_{k2}, ..., w_{kD} >$ and $\mathbf{v}_i = < v_{i1}, v_{i2}, ..., v_{iD} >$ are the cluster center vector and the cluster weight vector, β is a parameter to control the influence of weight. It is clear from Eq.(1)-(3) that weight w_{kj} is assigned to the features of different clusters.

The latest advance in soft subspace clustering is the introduction of the concept of entropy. Unlike fuzzy weighting subspace clustering, the weights in this kind of subspace clustering algorithm are controllable by entropy, and the developed algorithms are therefore referred to as entropy weighting subspace clustering algorithms (EWKM) [27], the objective function of which can be formulated as:

$$E(\mathbf{C},\mathbf{W}) = \sum_{k=1}^{K}\sum_{j=1}^{D}(w_{kj}\sum_{x_i \in C_k}\left(x_{ij} - v_{kj}\right)^2 + r w_{kj}\log w_{kj}) + \sum_{k=1}^{K}\lambda_k(1 - \sum_{j=1}^{D} w_{kj}) \quad (2)$$

Besides EWKM, entropy is also taken into account in the local adaptive clustering (LAC) [17] algorithm for subspace clustering; the objective function of LAC can be expressed as:

$$L(C,W) = \sum_{k=1}^{K}\sum_{j=1}^{D}\left(w_{kj}\frac{\sum_{x_i \in C_i}(x_{ij} - v_{kj})^2}{|C_k|} + h w_{kj}\log w_{kj}\right) + \sum_{k=1}^{K}\lambda_k\left(1 - \sum_{j=1}^{D} w_{kj}\right) \quad (3)$$

By comparing Eq.(2) and Eq.(3), it is found that their objective functions are very similar and the only difference is that the effect of cluster size is considered in Eq.(3) but omitted in Eq.(2).

By inspecting these soft subspace clustering techniques, it is clear that the within-cluster compactness is only considered to develop the corresponding algorithms. It is however anticipated that the performance of clustering can be further enhanced by including more discriminative information. Recently, Chen has proposed an adaptive algorithm for soft subspace clustering (ASC) [26] by taking into account both minimization of the compactness of the subspace clusters and maximization of the subspace in which the clusters exist. The objective function of ASC can be expressed as:

$$A(C,V,W) = \sum_{k=1}^{K}\left(\sum_{j=1}^{D}\sum_{x_i \in C_i} w_{kj}\left(x_{ij} - v_{kj}\right)^2 - h_k \times size(S_k)\right) + \sum_{k=1}^{K}\lambda_k\left(\sum_{j=1}^{D} w_{kj} - 1\right)$$

where h_k is a balance parameter and $size(S_k)$ the size of the subspace. We can observe that ASC considers subspace information in clustering besides the within-cluster compactness which is omitted in other soft subspace clustering, however, this subspace clustering algorithm requires an additional step to obtain the adaptive parameter which increase the running time.

By inspecting the existing soft subspace clustering algorithms, the problems we find out are as follows:

1. Most of the existing subspace clustering techniques focus on the within-compactness and omitted the other important information of the subspace.
2. Require to set or spend more time to figure out the value of additional parameter.
3. Lack of effective initialization method to achieve a better clustering result.

B. Our contributions

The major contributions of this paper are as follows.

1. Unlike most existing soft subspace clustering algorithms, we proposed the concept of subspace difference to develop the within-subspace information. Both the within-cluster compactness and subspace difference are employed at the same time to develop a new optimization objective function, which is used to derive the proposed soft subspace clustering based on subspace difference (SDSC) algorithm.
2. We proposed an improved initialization algorithm in high dimensional space with a new density measure by considering the distribution of each point's neighborhoods. It means the density of a point is composed of the similarity and the structure between neighbors.
3. The performance of the proposed SDSC algorithm was investigated using real high-dimensional data, and achieved better clustering result.

III. THE NOVEL INITIALIZATION METHOD

A. The existing initialization algorithms

Currently, cluster center initializing methods have been categorized into three major families, namely random sampling methods, distance optimization methods, and density estimation methods [21]. Random sampling methods are the most widely used methods which usually initialize cluster centers either by using randomly selected input samples, or random non-heuristic parameters. Being one of the earliest references in literature, Forgy [22] adopted uniformly random input samples as seed clusters. Distance optimization methods are proposed to optimize the inter-cluster separation. Among them, SCS [23] is a variable K-Means implemented in SAS. However, it is sensitive to both initial parameter and presentation order of inputs. Density estimation methods are based on the assumption that dataset follow Gaussian mixture distribution, which identifies the dense areas to the initial cluster centers. Algorithm KR [24] proposed by Kaufman estimates the density through pairwise distance comparison, and initializes seed clusters using input samples from areas with high local density. KR also has the drawback of huge computational complexity. As a result, it is ineffective with large datasets.

These methods are limited to huge computational complexity and presentation order of inputs. Moreover, these approaches would loss effectiveness in high dimensional space due to "curse of dimensionality" [4] and the inherently sparse data.

B. Algorithm DBNDI

Searching initial centers in high dimensional space is an interesting and important problem which is relevant for the wide various types of *k*-means algorithm. However, this is a very difficult problem, due to the "curse of dimensionality" and the inherently sparse data. Motivated by these problems, we propose a new algorithm DBNDI, which explores a new method to calculate the density for improving the search accuracy. We explore a novel density measure by considering the distribution of each point's neighborhoods. It means the density of a point is composed of the similarity and the structure between neighbors. The notions of similarity and density can be describe as follows.

Definition 2[19]. Let $tNN(p)$ be the *t*-nearest neighbors set of p. For $\forall q \in tNN(p)$, the similarity between p and q, is defined as:

$$Sim(p,q) = \begin{cases} |StNN(p,q)|/t & p \in tNN(q) \\ 0 & p \notin tNN(q) \end{cases} \qquad (12)$$

where $StNN(p,q) = \{x \mid x \in tNN(p) \quad and \quad x \in tNN(q)\}$. $|StNN(p,q)|$ is the amount of elements in $StNN(p,q)$. Then we can assign different weights to each point according to their unique structure of neighbors. The algorithm calculates a new weight for each neighbor of a point based on the distances proportion between the point and its neighbors. Let $dist(p,q)$ be the distance between any two points in the dataset by using traditional Euclidean distance measure[20]. The sum distance between p and its near neighbors can be measured, and it can be formally defined as:

$$D_p = \sum_{i=1}^{t} dist(p,q_i) \qquad (13)$$

where $q_i \in tNN(p), i = 1,...,k$ .Given the influents imposed by different distances proportion of near neighbors, we assign weights $w_i^{'}$ in the following definition.

Definition 3.The notion of probability density of point *p*, named DBNDF (Distance-Based Neighborhood Density Factor), is calculated as:

$$NBNDF(p) = \sum_{i=1}^{t} w_i^{'} S_i \qquad (14)$$

where $w_i^{'} = \frac{D_p - dist(p,q_i)}{(t-1)D_p}$ and $S_i = \begin{cases} 1 & Sim(p,q_i) \geq \theta \\ 0 & Sim(p,q_i) < \theta \end{cases}$, $i = 1,...,t$. t is the size of near neighbor list of p , θ is the value of similarity threshold for $Sim(p,q)$, and q_i is the $i-th$ nearest neighbor of p .It's easy to get $0 < w_i^{'} < 1$ and $\sum_{i=1}^{t} w_i^{'} = 1$ to one point in high dimensional space.

To identify the similarity requires determining the value of θ . This is a very experience-dependent process. Owing to the existing problems of high dimensional space, the number of low similarity is numerous, and the number of high similarity is relatively lack. The ideal value of parameter can filter out low similarity and distinguish the reasonable scope of similarity.

Based on these ideas, a counting-based approach is adopted to facilitate the calculation of θ . In this approach, as for the whole pairs of the point and its neighbors, we can find all different similarities by definition 3. Let V be a vector to record the different similarities and their numbers. Then we use $sum(V)$ to state the total number of all similarities and $avg(V)$ as the average value of $sum(V)$. If the amount of any similarity in V gets most close to $avg(V)$, it means this element divided all similarities into two parts, the similarities of each part have approximately same amount. And the similarity of this element can be the value of θ . Based on a large number of experiments, we find that the above rule is appropriate in most cases. Fig.2 shows the process of calculating the value of θ .

```
Step1: Declare a vector $V$ of two elements, one
       stores similarity, and the other represents its
       amount.
Step2: Filling in the vector $V$.
Step3: Calculate $sum(V)$.
Step4: Compute $avg(V)$.
Step5: Filter out the similarity in V which is most
```

Figure 2.The calculation of θ

After determining the parameter, Fig.3 describes the process of proposed algorithm. It is deviated from IMSND that the improved algorithm could obtain the adaptive parameter θ according to the similarity distribution. In this wise, DBNDI is able to improve the clustering accuracy and the ability of detecting the noise.

```
Algorithm DBNDI
Input: dataset $X=\{x_1,x_2,x_3,...,x_n\}$, the size of
       neighborhood t, density threshold $\sigma$, and the
       number of clusters k
Output: cluster center set CS
Steps:
1. Initialization. $CS=\varnothing$.
2. Declare a membership matrix U of size $n\times t$ to store
   neighbors of each point, Fill in this matrix by using
   traditional Euclidean distance measure. The value in
   matrix is the index of each point's neighbors.
3. Declare a similarity matrix W of size $n\times t$ to store the
   similarity of each point. Calculate all similarities
   using Definition 1.
4. Declare a parameter $\theta$ to be similarity threshold. As
   mentioned in Fig.1, determine the value of similarity
   threshold $\theta$.
5. Based on Definition 2, count the density factor
   DBNDF of each data point and rank them in order.
6. Given the density threshold $\sigma$, mark and eliminate
   the data points as outliers while their DBNDF values
   are below the threshold.
7. According to the order of DBNDF values generated
   in Step 5, points with higher density neighborhoods
   and lower similarity are chosen as the initial centers
   until the number of centers achieves k.
```

Figure 3.The process of DBNDI algorithm

While reviewing some research works on initializing cluster centers [4, 5, 7, 9], the following are typical criterions of cluster initialization algorithms:

(1) **Ability to deal with noise:** According to density threshold, the point with low density will be detected. It can greatly reduce the influence of noise for choosing the initial cluster centers.

(2) **Deterministic results:** The cluster centers generated by DBNDI are deterministic. In other words, for the same data the result with each running of the algorithm is the same. Other algorithms based on probability, such as Forgy [9], give non-deterministic results as the cluster centers may be different with each running.

(3) **High dimensionality:** Contrary to traditional initialization approaches, DBNDI is based on the new density measure which lies in the data distribution structure so that it can avoid the curse of dimensionality.

(4) **Immunity to the order of inputs:** From the discussion in section 3.2, it is obvious that DBNDI is implemented in whole data space. However, most of the other algorithms, such as SCS [4], limited to the order of inputs.

IV. Clustering Algorithm SDSC

In this section, we first introduce the notions of subspace difference, and then describe the subspace clustering algorithm SDSC.

A. Subspace difference

Soft subspace techniques have a common feature: the value of the weight is relevant to the distribution of its projection subspace [27]. It means that the more compact the data distributed, the greater the dimension weight will be. Hence, the information of the weight distribution reflects the dispersion of data points in the subspace. Taken the weight of each clusters as a data object, the greater the compactness of the weight is, the more centralized the data distributed, and the subspace is more optimal. Therefore, considering the compactness of dimension weight in the objective function will benefit the clustering process to obtain better clustering results. Unlike existing soft subspace clustering, Traditional clustering is not related to the concept of dimension weight, we assumed the weight of each dimension is equal [26]. Based on the refinement of $w_{k1}+w_{k2}+...+w_{kD}=1$, the compactness of dimensional weight can be expressed as follows:

$$diff^{'}(S_k)=\sum_{j=1}^{D}(1-w_{kj})^2 \tag{4}$$

Where S_k refers to the *k*th subspace. We could calculate $diff^{'}(S_k)\in[(D-1),(D-1)^2/D]$ using the refinement of $w_{k1}+w_{k2}+...+w_{kD}=1$, then normalize it to the range of [0, 1], and give the formal definition as follows.

Definition 1(subspace difference): Given $diff(S_k)$ to represent subspace difference of the *k*th subspace:

$$diff(S_k)=D\sum_{j=1}^{D}\left(1-w_{kj}\right)^2\Big/\left(D-1\right)-D+1 \tag{5}$$

The new objective function is written as follows:

$$J(C,V,W)=\sum_{k=1}^{K}\left(\sum_{j=1}^{D}\sum_{x_i\in C_i}w_{kj}\left(x_{ij}-v_{kj}\right)^2-p_k\times diff(S_k)\right) \tag{6}$$

The first term in Eq.(6) is the within-cluster compactness, and the second term is the subspace difference. The positive parameter p_k controls each dimension's balance[26], we can definite it as:

$$p_k=\frac{1}{D}\sum_{j=1}^{D}X_{kj}$$

where $X_{kj}=\sum_{x_i\in C_k}\left(x_{ij}-v_{kj}\right)^2$.

B. Objective function

Minimization of *J* with the constraints forms a class of constrained nonlinear optimization problems whose solutions are unknown. The usual method toward optimization of J is to use the partial optimization for W and V. In this method, we first fix V and minimize J with respect to W. Then, we fix W and minimize J with respect to V. we use the Lagrangian multiplier technique to obtain the minimization problem:

$$J_1(C,V,W)=\sum_{k=1}^{K}\sum_{j=1}^{D}w_{kj}X_{kj} -\sum_{k=1}^{K}\left(\frac{1}{D}\sum_{j=1}^{D}X_{kj}\times\left(\frac{D\sum_{j=1}^{D}\left(1-w_{kj}\right)^2}{D-1}-D+1\right)\right) +\sum_{k=1}^{K}\lambda_k\left(\sum_{j=1}^{D}w_{kj}-1\right) \quad (7)$$

By setting gradient to J_1 with respect to v_{kj}, w_{kj} and λ_k, from $\frac{\partial J_1}{\partial v_{kj}}=0$, we obtain

$$v_{kj}=\frac{1}{|C_k|}\sum_{x_i\in C_k}x_{ij}\ . \quad (8)$$

From $\frac{\partial J_1}{\partial w_{kj}}=0$, we obtain

$$w_{kj}=\frac{\left(X_{kj}+\lambda_k\right)\left(D-1\right)}{2\sum_{l=1}^{D}X_{kj}}+1\ . \quad (9)$$

From $\frac{\partial J_1}{\partial \lambda_k}=\sum_{j=1}^{D}w_{kj}-1=0$, we obtain

$$\lambda_k=\frac{-\sum_{j=1}^{D}X_{kj}}{D}\ . \quad (10)$$

Substituting this expression back to Eq.(9), we obtain

$$w_{kj}=\frac{X_{kj}\left(D-1\right)}{2\sum_{l=1}^{D}X_{kj}}+\frac{1+D}{2D} \quad (11)$$

C. Clustering Algorithm SDSC

The SDSC algorithm that minimizes J_1, using Eq.(8) and Eq.(10), is summarized as follows:

```
Algorithm SDSC
Input: dataset $X=\{x_1,x_2,x_3,...,x_n\}$, the size of
    neighborhood $t$, density threshold $\sigma$, and the
    number of clusters $k$
Output: $C=\{C_1,C_2,...,C_k\}$ and W
Initialization Method: Algorithm DBNDI or
                       Random Initialization
Let $p$ be the number of iteration, $p$=0;
Denote V, W as $\mathbf{V}^{(0)}$ and $\mathbf{W}^{(0)}$, respectively.
Repeat
1.  For each center $\mathbf{v}_k$, and for each point $x_i$:
    Set $C_k=\left\{x_i \middle| k=\arg\min_{l=1,2,...,K} dist_{s_l}\left(v_l,x_i\right)\right\}$,
    where $dist_{s_l}\left(v_l,x_i\right)=\sqrt{\sum_{j=1}^{D}w_{lj}(x_{ij}-v_{lj})^2}$ ;
2.  $p$=$p$+1;
3.  Using Eq.() to calculate $\mathbf{V}^{(p)}$;
4.  Using Eq.() to calculate $\mathbf{W}^{(p)}$;
Until $\left\|\mathbf{V}^{(p)}-\mathbf{V}^{(p-1)}\right\|<\varepsilon$ and $\left\|\mathbf{W}^{(p)}-\mathbf{W}^{(p-1)}\right\|<\varepsilon$
```

Figure 3.The process of SDSC algorithm

where ε is a small positive number aiming to control the algorithm process. SDSC algorithm is based on the classical framework of *k*-means. Unlike the other *k*-means type soft subspace algorithms, SDSC algorithm pays attention to the subspace difference and re-defines the iterative formula. Correspondingly, the new algorithm not only continues the convergence conditions of *k*-means (cluster centers converge), also focuses on the dimension weights convergence.

The SDSC algorithm is scalable to the number of dimensions and the number of objects. This is because SDSC only adds a new step to the *k*-means clustering process to calculate the dimension weights of each cluster. Next, we only consider the three major computational steps to analyze the runtime complexity. First, partitioning the objects, this step simply compares the summation of $dist_{s_l}\left(v_l,x_i\right)=\sqrt{\sum_{j=1}^{D}w_{lj}(x_{ij}-v_{lj})^2}$ for each object in all k clusters. Thus, the complexity for this step is O(*KND*) operations. Similarly, the complexity of updating cluster centers and calculating dimension weights are all O(*KND*) . If the clustering process needs p iterations to converge, the total computational complexity of this algorithm is O(*KNDP*).

V. Experiments and Analysis

The main purpose of this section is to verify the accuracy of our proposed SDSC algorithm. The performance of SDSC is evaluated both on real world high dimensional data and artificial data. Each dataset is normalized into a range between 0 and 1 using maxing-min normalization.

A. Datasets

In order to demonstrate the superiority of our proposed method on high dimensional data, we used five real datasets to examine the effectiveness of SDSC. The first one is Spam-Base [29] datasets is obtained from UCI Machine learning Repository. The second one is Email-1431 [30] dataset. It is an English email corpus which contains 642 normal emails and 789 spam emails. After preprocessing, each email document is mapped to a 2002-dimensional vector by employing the vector space mode (VSM). The Third one is Ling-Spam [31] dataset. It contains 2412 linguist messages and 481 spam messages. We have removed low frequency words (frequency less than 0.5%) and high frequency words (frequency higher than 40%) in the preprocessing stage. Finally we have 4435 words. The last two datasets extracted from TanCorp [32], after preprocessing, we choose 1191 words, and then we have Tan-5711-1191 dataset and Tan-6301-1191 dataset. Their detailed parameters are summarized in Table 1.

To measure the scalability of SDSC to the number of dimensions and the number of objects, we generated 8 datasets based on the method suggested by Aggarwal et al [8], the detailed descriptions are summarized in Table

2. D_{1-4} datasets validate the scalability to the number of objects. Each of them contains 4 clusters and 1000 dimensions. D_{5-8} datasets validate the scalability to the number of dimensions. Each of them contains 4 clusters and 5000 objects.

Table 1. Some information about the real-world datasets

Datasets	Size	Dimension	Cluster number
SpamBase	4601	54	2
Email-1431	1431	2002	2
Ling-Spam	2893	4435	2
Tan-5711-1191	5711	1191	3
Tan-6301-1191	6301	1191	4

Table 2. Summarized parameters of the synthetic datasets

D_{1-4}	4 clusters and 1000 dimensions			
the number of objects	D_1 10000	D_2 20000	D_3 30000	D_4 40000
D_{5-8}	4 clusters and 5000 objects.			
the number of dimensions	D_5 1000	D_6 2000	D_7 3000	D_8 4000

B. *Experiment Setup*

We have implemented SDSC in C++ and all experiments were run on a PC with a 2.99GHz CPU and 2GB RAM. In order to evaluate the performance of our algorithm SDSC, we compare its performance with FWKM [16], EWKM [17] and FSC [25]. As mentioned in section 2, we explore a novel initialization method for high dimensional data. To have a better comparable results, first, like the other soft subspace algorithm, we will implement SDSC algorithm with the same initialization method (random initialization), and then we apply DBNDI technique to SDSC algorithm and the other algorithms. Three comparable algorithms all require input parameters; we specify their parameters based on the value suggested by [16], [17] and [25]. The input parameters of DBNDI are specified in Table 2.

To measure the goodness of clustering, we employ two well-known indexes Micro-F1 [27] and Macro-F1 [27] . Where F1 [27] is defined as.

$$\mathrm{F1} = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{15}$$

where *recall* is ratio between the number of correct positive predictions and the number of positive examples; *precision* is ratio between the numbers of correct positive predictions [27].

Table 3. Specified Values of Input Parameters for DBNDI

Datasets	Parameter settings
SpamBase	t=50, σ =0.02
Email-1431	t=50, σ =0.02
Ling-Spam	t=50, σ =0.02
Tan-5711-1191	t=45, σ =0.02
Tan-6301-1191	t=40, σ =0.025

C. *Experimental results on Real-World Data*

According to the use of sampling or approximation techniques, the *k*-means type algorithms are no longer determinate and may vary with different runs of the algorithm. Hence the experiments randomly run 100 times using these methods and analyze their average accuracy.

Table 4 and Table 5 show the accuracy of four methods with the random initialization. As they show, SDSC yields better results than the competing algorithms on four datasets, in terms of both Micro-F1 and Macro-F1. We noted that the average accuracy of our proposed algorithm is almost beyond 80% which is improved while it compares to the other three techniques. As for the uneven distribution of Ling-Spam dataset, the average accuracy of the other three algorithms is almost 60%; however, SDSC continues to show advantages and achieves the clustering accuracy of 80%. To the highest dimensional dataset, Emial-1431, other clustering algorithms on average only receives the clustering precision of 70% which is given 90% using SDSC algorithm.

The comparisons results with the DBNDI algorithm are shown in table 6 and table 7. Experimental results demonstrate that the initial centers chosen by DBNDI can benefit clustering results. The obvious improvements indicate that the proposed initial algorithm is more suitable for K-Means type algorithm in high dimensional space.

As Fig.5 shows, while clustering the same dataset, the time for EWKM clustering is significantly more than other three algorithms, this is because selecting the appropriate algorithm parameters for EWKM algorithm is a time-consuming process. The average running time of other three algorithms are almost same; however, SDSC algorithm has a better clustering accuracy in the same operating conditions.

D. *Simulation Result*

We conducted extensive experiments on the eight synthetic datasets, investigated the scalability of our proposed to the number of data points and the number of dimensions. The results are reported below.

Fig.6 shows the relationships between the runtime and the number of dimensions and objects, repectively. We can see that the runtime of SDSC increased linearly as the number of dimensions and objects increased. These results were consistent with the algorithm annlysis in Sction 3 and demonstrated that SDSC is scalable.

Table 4. Comparison of the clustering results on the real-world datasets (Micro-F1) with the random initialization

	SpamBase	Email-1431	Ling-Spam	Tan-5711-1191	Tan-6301-1191
SDSC	**0.7013**	**0.9257**	**0.7962**	**0.8954**	**0.8091**
EWKM(γ =0.5)	0.5673	0.5829	0.6543	0.5783	0.4984
FWKM(β =1.5)	0.6411	0.6027	0.8402	0.6683	0.5648
FSC(α =2.1)	0.5984	0.6542	0.6146	0.6428	0.6184

Table 5. Comparison of the clustering results on the real-world datasets (Miaro-F1) with the random initialization

	SpamBase	Email-1431	Ling-Spam	Tan-5711-1191	Tan-6301-1191
SDSC	**0.8001**	**0.9146**	**0.7849**	**0.9028**	**0.8054**
EWKM(γ =0.5)	0.4192	0.4634	0.5184	0.4793	0.5012
FWKM(β =1.5)	0.4996	0.4871	0.4957	0.5839	0.5237
FSC(α =2.1)	0.4735	0.6157	0.4843	0.4918	0.4896

Table 6. Comparison of the clustering results on the real-world datasets (Micro-F1) with the DBNDI initialization

	SpamBase	Email-1431	Ling-Spam	Tan-5711-1191	Tan-6301-1191
SDSC	**0.8123**	**0.9620**	**0.8892**	**0.9527**	**0.8956**
EWKM(γ =0.5)	0.6098	0.6247	0.7016	0.6234	0.5761
FWKM(β =1.5)	0.6983	0.6672	0.8714	0.7029	0.6172
FSC(α =2.1)	0.6483	0.7037	0.6749	0.7011	0.6798

Table 7. Comparison of the clustering results on the real-world datasets (Miaro-F1) with the DBNDI initialization

	SpamBase	Email-1431	Ling-Spam	Tan-5711-1191	Tan-6301-1191
SDSC	**0.8793**	**0.9309**	**0.8094**	**0.9164**	**0.9034**
EWKM(γ =0.5)	0.5092	0.5783	0.6035	0.5672	0.6092
FWKM(β =1.5)	0.5004	0.5267	0.5861	0.6049	0.5984
FSC(α =2.1)	0.5284	0.7035	0.5283	0.5381	0.5436

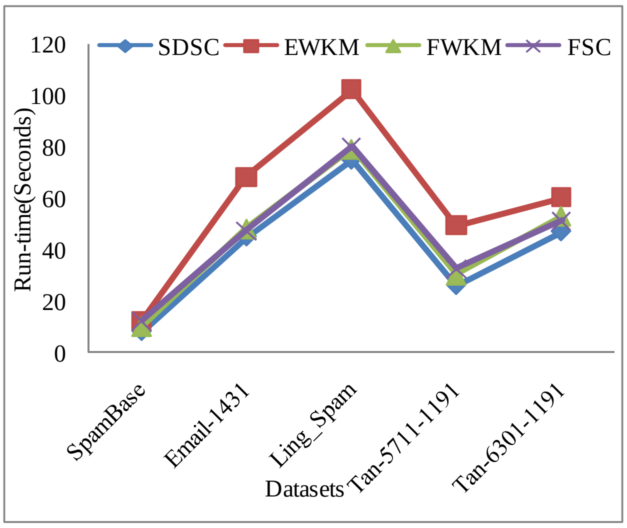
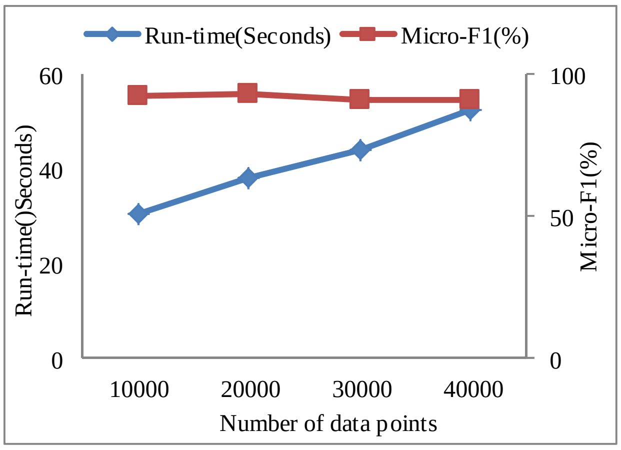


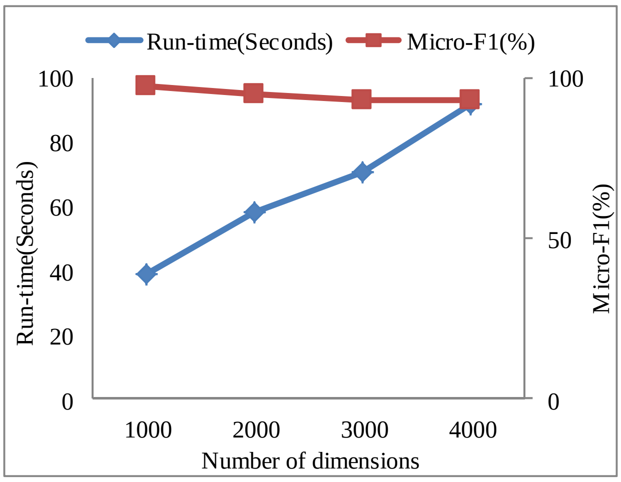
Figure 5.Comparison of the runtime of different algorithms

I. Conclusions and Future Work

In this paper, we have proposed a new *k*-means type subspace clustering algorithm, SDSC, with a novel initialization method for high dimensional sparse data. In this algorithm, we simultaneously minimize the within-cluster compactness and optimize the subspace by evaluating the subspace difference. Besides, we introduce a novel initialization method which suitable for high dimensional data, and benefit the clustering results. SDSC requires no additional input parameters. The experimental results on both synthetic and real datasets have shown that the new algorithm outperformed other *k*-means type algorithms, such as FWKM, EWKM and FSC. Except for clustering accuracy, the new algorithm is scalable to high dimensional data and easy to use because it has no input parameters. Future work will focus on how to develop a more effective way to specify the input parameters of our proposed initialization algorithm according to the various structure of dataset.



(a)



(b)

Figure 6.The relationships between the runtime of SDSC, and different numbers of data points and dimensions.

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