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ANALYZING IMPACT OF SINGLE VIEW AND MULTI VIEW BIG DATA BASED ONCLUSTERING QUALITY VIA K-MEANS TECHNIQUE

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ABSTRACT

Due to the revolutionary advancements in the signal sensing devices and its availability to civilians, the real time datasets are now having multiple views. Thus such a multi-view datasets are quite common in era of big data domain. As against learning of single-view, learning of multi-view has plenty of benefits. Clustering has been very useful technique in machine learning and data mining. Traditional clustering techniques use only single set of features of the available dataset. However for the multi-view dataset with multiple features, how to ensemble all of these data views is a major concern. Thus problem is termed as multi-view clustering problem. The key benefits of multi-view clustering against single view clustering are accurate description of data, reducing noises of data, and wider range of applications. This paper studies the impact multi view K-means clustering available in mvlearn python package with the traditional K-means clustering technique. To assess the impact of simple K-means technique and multi-view version of K-means technique, two datasets are utilized namely, nutrimouse and simulated dataset. In order to analyze the impact of multi view clustering on clustering quality, traditional k-means technique is applied to individual views, concatenated view of the both the datasets, followed by the application of multi-view version of K-means technique on the both the datasets. We analyzed the clustering quality of multi-view K-means technique using various performance evaluation parameters such as Jaccard Coefficient (Jacc), Fowlkes Mallows Index (FM), Normalized Mutual Information (NMI), Rand Index (RI), and clustering execution times.

Keywords – Multi-view dataset, Multi view clustering techniques, K-means, Jaccard Coefficient (Jacc), Fowlkes Mallows Index (FM), Normalized Mutual Information (NMI), Rand Index (RI)

I. INTRODUCTION

Due to advancement in the micro electro mechanical devices (MEMS), multi-view datasets are quite common in many real time data mining and clustering applications. Clustering is important category of unsupervised learning techniques. It has been very successfully deployed for heterogeneous data analysis, gene expression analysis, social network analysis, as well as market analysis [1]-[3]. The main aim of the clustering is to divide (partition) the given dataset into several sub-clusters such that data elements in one cluster are with similar features than those in different sub-clusters. However, the existing clustering techniques are suitable for single- view data. Due to high revolution in Internet and computing devices, enormous data are generated from different sources for an underlying application. The data associated with each of these sources carries valuable information, which in turn enforces the requirement mining the valuable and intrinsic hidden patterns in the data; it is a necessity to take full advantage of the information contained in multiple sources [4]. This process is termed as multi-view learning. In general, each data view corresponds to one important source of valuable information. For instance, web pages can be simultaneously considered by both the page-contents (one view) as well as page hyperlink information (another view). That means the web page itself consists of lot information in terms of words appearing on it. The same web page generally has many links pointing to other web pages which in turn contain other sort of related information in terms of words. The multimedia data is also simultaneously described by video signal obtained from camera as well as audio signal from mic. Similarly, an image can be described by its color, shape as well as location.

Integrating all the information available in multiple data views can provide great benefits to data clustering. The straightforward solution to utilize this total information of all data views is to concatenate the data features of each view together and then apply suitable traditional single view clustering technique. However, this approach generally fails to distinguish the information available in inter-linkage of different data views [5]. In other words in the concatenation let single view clustering approach, the important data views and less important data views are treated equally. This would in turn deteriorate the ultimate clustering performance. To take better advantage of the multi-view information, the ideal approach is to simultaneously perform the clustering using each view of data features and integrate their results based on their importance to the clustering task. The availability of such multi-view data has forced the research community to go for multi-view learning of multi- view data especially in the context unsupervised learning [6]. However in unsupervised learning set up for multi-view clustering, it is not possible for the traditional single view clustering techniques to make a full use of the multi-data. Merely concatenating the features from all the data views into a single data union, and then applying the single-view clustering technique usually may not work out effectively in unsupervised clustering. In order to solve the problem associated with the clustering of the multi-view dataset, the approach based on the Multi-view clustering is must.

1. In this work we implemented the multi view K-means clustering algorithm using mvlearn python package as well as traditional (single view) K-means clustering algorithm using sklearn python package.

2. We investigated the efficacy of the multi-view K-means technique on two multi-view datasets namely, nutrimouse and simulated dataset. We investigated the efficacy of multi-view K-means algorithm in two phases namely, Phase I (Multi-view Clustering of Nutrimouse Dataset via K-means technique), and Phase II (Multi-view Clustering of Simulated multi view Dataset via K-means technique).

3. We analyzed the clustering quality of multi-view K-means technique using various performance evaluation parameters such as Normalized Mutual Information (NMI), Jaccard Coefficient (Jacc), Fowlkes Mallows Index (FM), Rand Index (RI). We also compared the execution times of single view K-means clustering and multi view K-means clustering. From the values of these clustering quality performance evaluation parameters, it is proved that multi-view version of K-means algorithm has high clustering quality as compared to its single view counterpart. Additionally, the execution time for multi-view K-means algorithm is very low as compared its single view counterpart in both Phase I and Phase II.

II. RELATED WORK

Traditional clustering techniques mainly deal with single view data. To deal with multi-view data, traditional clustering techniques generally consider each data view separately, and then deploy a simple integration (ensemble) based mechanism to get the final clustering results. Therefore to utilize the total information, all data views are concatenated together and then a suitable traditional single view clustering technique is applied [2]- [5]. However, this approach generally fails to distinguish the information available in inter-linkage of different data views. In other words in the concatenation let single view clustering approach, the important data views and less important data views are treated equally. This would in turn deteriorate the ultimate clustering performance. To meet with this challenge, multi-view learning technology is required. Different from traditional single view clustering algorithms, multi-view clustering methods integrate the information from different views to achieve the better performance. Hence, multi-view learning has become an important topic in the field of machine learning.

The research community has proposed many novel algorithms to solve the problem of multi-view clustering. Based on the K-means algorithm, a two-level variable automatic weighted clustering algorithm called TW-k-means was proposed [13]. A novel multi-view K-means clustering method was presented to solve the problem of large-scale multi-view data clustering [14]. It can learn the weight of each view adaptively, and is robust to the outliers. Based on the Fuzzy clustering means (FCM) based technique, a large number of multi-view clustering algorithms has been proposed. By introducing collaborative mechanism into classical FCM, a collaborative clustering algorithm called Co-FC algorithm was developed in [15]. Based on FCM algorithm, a multi-view fuzzy clustering algorithm called Co-FKM was proposed in [16], which reduced the disagreement between the partitions on different views by introducing a penalty term in the objective function. A multi-view fuzzy clustering algorithm called Co-FCM was also proposed based on the classical FCM algorithm in [17]. It was further developed into the multi-view weighted collaborative fuzzy clustering algorithm (WV-Co-FCM) by applying different weights to different views.

To deal with the clustering of high dimensional data, a correlational spectral clustering algorithm based on kernel canonical correlation analysis has been proposed in [18]. This algorithm initially projects the multi-view data from different feature spaces to a common low-dimensional subspace. K-means or other clustering algorithm was then used to cluster the data in the low- dimensional space. The authors in [19] has proposed novel multi-view clustering algorithm based on canonical correlation analysis, wherein the algorithm uses canonical correlation analysis to project the multi-view data to a common low-dimensional subspace, and then used K-means or other clustering algorithms to cluster the generated low-dimensional data. Some researchers apply non-negative matrix factorization technology to multi-view data clustering, and propose some multi-view clustering algorithms. A multi-view clustering algorithm based on joint non-negative matrix factorization was proposed in [20], where a joint non-negative matrix factorization method was used to normalize the coefficient matrix from each view into a common consistent matrix that was considered as a potential representation of the original data. K-means and other clustering algorithms were then used directly to cluster the consistent matrix. The authors in [21] proposed a multi-view kernel k-means (MVKKM) algorithm which assigns a weight for each view according to the view's contribution to the clustering result and then combines the kernels derived from the weighted views together. However, it is based on the inner product kernels for all views, and has no explicit mechanism for feature selection. To address the above issues, there are some other efforts that investigate feature selection in multi-view data clustering. A framework was proposed in [22], which constructs models respectively for the multi-source learning and feature selection. However, this work is designed for supervised learning and cannot deal with the unsupervised situation.

III. PROPOSED K-MEANS BASED MULTI-VIEW CLUSTERING APPROACH

The traditional K-means is one of the widely used of clustering single view datasets [6], [7], [21]. Being simple to use, it has a huge potential to deal with the large-scale datasets. It has been successfully utilized in wide variety of applications ranging from computer vision, and social network analysis to market segmentation. Let, the dataset contains N samples, then corresponding matrix can be represented as $X = [x_1,x_2,\ldots..x_N]$. Taking Euclidean distance as the similarity measure, data samples are clustered into $C(2 \leq C \leq N)$ clusters. The cluster centers can be presented by matrix $Z = [z_1,z_2,\ldots..z_N]$. The objective function of the K-means algorithm is defined as

$$P(U,Z) = \sum_{i=1}^{C} \sum_{j=1}^{N} \boldsymbol{u}_{i,j} (x_j-y_i)^2 \qquad (1)$$

As can be seen, Eq. (1) adopts the Euclidean distance to measure the similarities between data samples. However, there are many data structures or data distributions in real world. Thus, it is not always suitable to apply this basic form of K-means to accurately identify the hidden patterns of datasets. What is more, some datasets may be not separable in the low-dimensional space. Thanks to mvlearn python package which has built in K-means function for clustering multi-view dataset.

Multi-view data, in which each sample is represented by multiple views of distinct features, are often seen in real-world data, and related methods have grown in popularity. mvlearn is a Python library which implements the leading multi-view machine learning methods. It’s simple API closely follows that of scikit-learn for increased ease of-use. The package can be installed from Python Package Index (PyPI) or the conda package manager and is released under the Apache 2.0 open-source license. Additionally, mvlearn can be used to generate multiple views from a single original data matrix, expanding the use-cases of multi-view methods and potentially improving results over typical single-view methods with this data [23]. The experimentation in this research work is split in two phases namely, Phase I and Phase II. The Phase II experimentation is further divided into two cases. Single view and multi view K-means technique is applied on simulated dataset with highseparation and high overlapping in View 1 and View 2 in Case A, and case B respectively.

Phase I: Multi-view Clustering of Nutrimouse Dataset via K-means technique

Phase II: Multi-view Clustering of Simulated multi views Dataset via K-means technique

a. Performance when cluster components in both views are well separated,

b. Performance when cluster components in both views are highly overlapping.

In this research work, we investigated the efficacy of the multi-view K-means technique on two multi-view datasets namely, and simulated dataset [23], and nutrimouse [24]. The nutrimouse dataset comes from a nutrition study in the mouse. It was provided by Pascal Martin from the Toxicology and Pharmacology Laboratory (French National Institute for Agronomic Research). It contains the following components:

a. gene: data frame (40 * 120) with numerical variables

b. lipid: data frame (40 * 21) with numerical variables

c. diet: factor vector (40)

d. genotype: factor vector (40)

In order to evaluate the clustering quality of multi-view K-means technique, various performance evaluation parameters such as Normalized Mutual Information (NMI), Jaccard Coefficient (Jacc), Fowlkes Mallows Index (FM), Rand Index (RI), and clustering execution times, are used. The details of these metrics are given below.

1. Normalized Mutual Information (NMI)

NMI gives us the reduction in entropy of class labels when we are given the cluster labels. In a sense, NMI tells us how much the uncertainty about class labels decreases when we know the cluster labels. It is similar to the information gain in decision trees. It is mathematically given by Equation (2).

$$NMI\ (Y,C) = \frac{2*I\ (Y;C)}{[H(Y)+H(C)]} \tag{2}$$

2. Jaccard Cofficient (Jacc)

If the true labels of a dataset are known, the quality of the applied clustering technique can be computed by finding out the difference between the true labels and the predicted labels. The useful quality measures in this context are Jacc and FM. Thus the generated feature subset quality can be measured using Jacc and FM. Both Jacc and FM can vary between 0 and 1, with 1 indicating complete overlap and 0 indicating no overlap. Thus higher the value of these two coefficients, higher would be the clustering quality.

The Jacc is a statistical method of comparing the similarity between two sets. It is defined as the size of the intersection divided by the size of the union of two label sets, is used to compare set of predicted labels for a sample to the corresponding set of actual labels. Let $K = K_{1,} K_{2,..,} K_m$ and $P=P_{1,} P_{2,..,} P_n$ be two clustering result set, then Jacc index can be computed using Equation (3).

$$\text{Jacc} = \frac{a}{(a+b+c)} \tag{3}$$

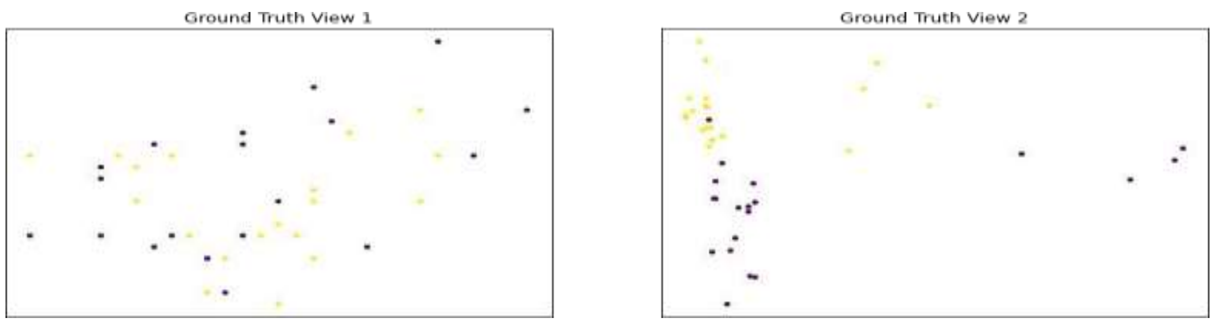
Where,
a: Number of point pairs belonging to same cluster set of two clustering results K and P

b: Number of point pairs belonging to same cluster set in K but not in P
c: Number of point pairs belonging to different cluster set in K but same in P.

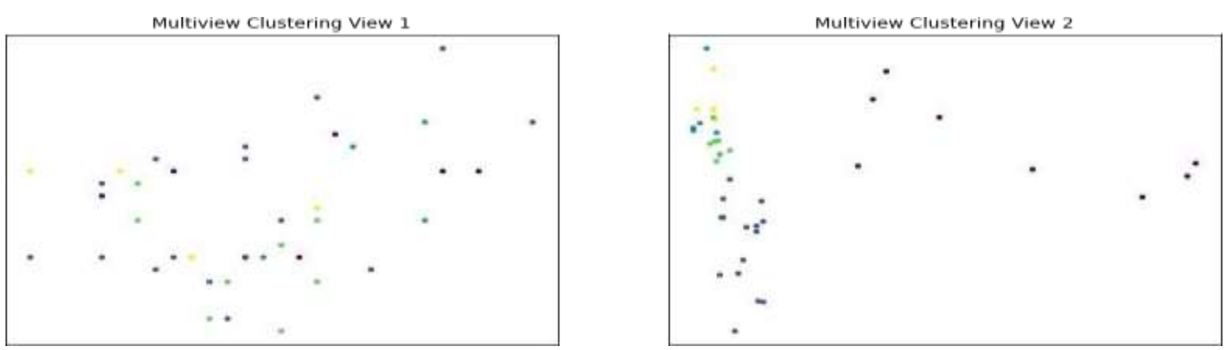
IV. DISCUSSION ON RESULTS:

Phase I: Multi-view Clustering of Nutrimouse Dataset via K-means technique:

In order to analyze the impact of multi view clustering on clustering quality, traditional k-means technique is applied to individual views, concatenated view of the both the datasets, followed by the application of multi-view version of K-means technique on the multi view Nutrimouse dataset in Phase I. We analyzed the clustering quality of multi-view K-means technique using various performance evaluation parameters such as Jacc, FM, NMI, RI, and clustering execution times. Fig. 1 illustrates the clustering results on multi view Nutrimouse dataset, wherein we observe that the clustering quality with multi view approach is little bit improved than its single view counterpart. Clearer picture on clustering quality, we can get from Table 1 values of performance evaluation parameters of clustering. We can see that NMI, Jacc, FM, and RI values obtained for multi view clustering are better than its single view counterpart. Although the improvement is not much convincing, but the execution time required to run multi view K-means clustering algorithm is far less than its single view counterpart.



(a) Single View vs Multi View Clustering on View 1 of Nutrimouse Dataset



(b) Single View vs Multi View Clustering on View 2 of Nutrimouse Dataset

Fig. 1: K-means technique based Clustering on Nutrimouse Dataset (Phase I)

Table 1: Comparison of Clustering Quality of Single view and Multi view K-means based approaches for

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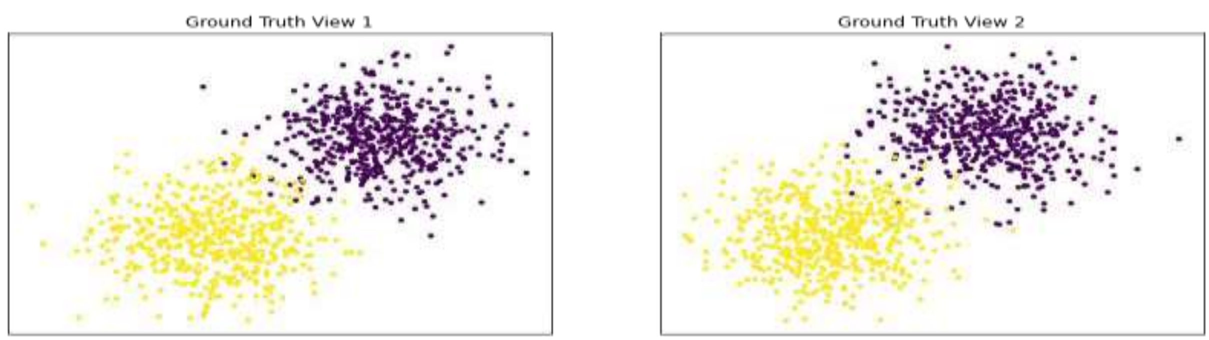
Nutrimouse Dataset for Phase I

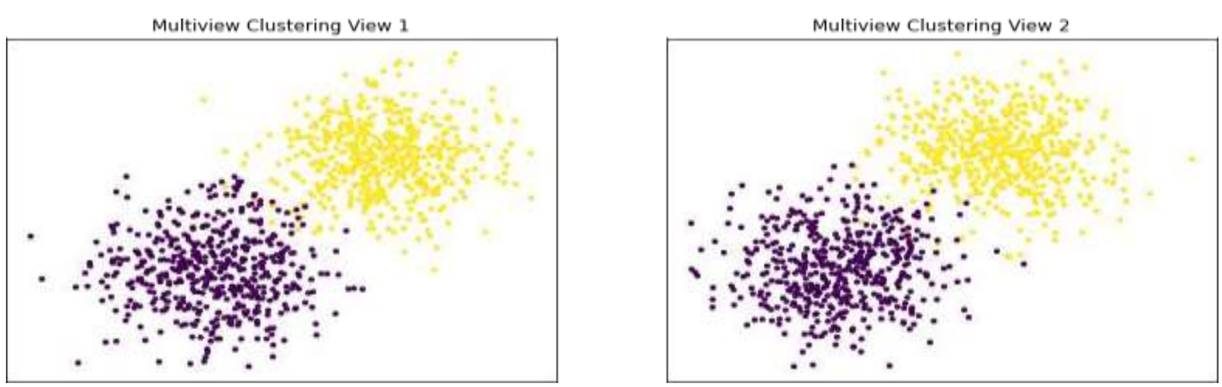
Clustering Approach	NMI	Jacc	FM	RI	Execution Time
Single view K-means for View 1 of Dataset	0.547	0.075	0.664	0.446	0.38
Single view K-means for View 2 of Dataset	0.422	0.225	0.535	0.284	0.36
Single view K-means for Concatenated Dataset	0.422	0.225	0.535	0.284	0.38
Multi view K-means for whole dataset	0.448	0.423	0.605	0.468	0.23

Phase II: Multi-view Clustering of Simulated multi views Dataset via K-means technique
In this phase, we apply single view and multi view K-means algorithms on simulated multi view dataset. In this two experiments are conducted which are indexed (A), and (B) as given below. For each of these experiments, we run both single view K-means clustering and multi view K-means clustering. For evaluating single view performance, we run the algorithm on each view separately as well as all views concatenated together. We run each algorithm across 100 random cluster initializations in both the experiments. The clustering results are discussed below in detail.

A. Performance when Cluster Components in Both Views are well Separated:
Here we can see that multi-view K-means clustering performs about as well as single view K-means clustering for the concatenated views, and both of these perform better than on single view clustering for just one view. The results of clustering for Case A are illustrated and summarized with Fig. 2, and Table 2 respectively.



(a) Single View vs Multi View Clustering on View 1 of Simulated Dataset for Case A



(b) Single View vs Multi View Clustering on View 2 of Simulated Dataset for Case A

Fig. 2: K-means technique based Clustering on Simulated Dataset for Phase II

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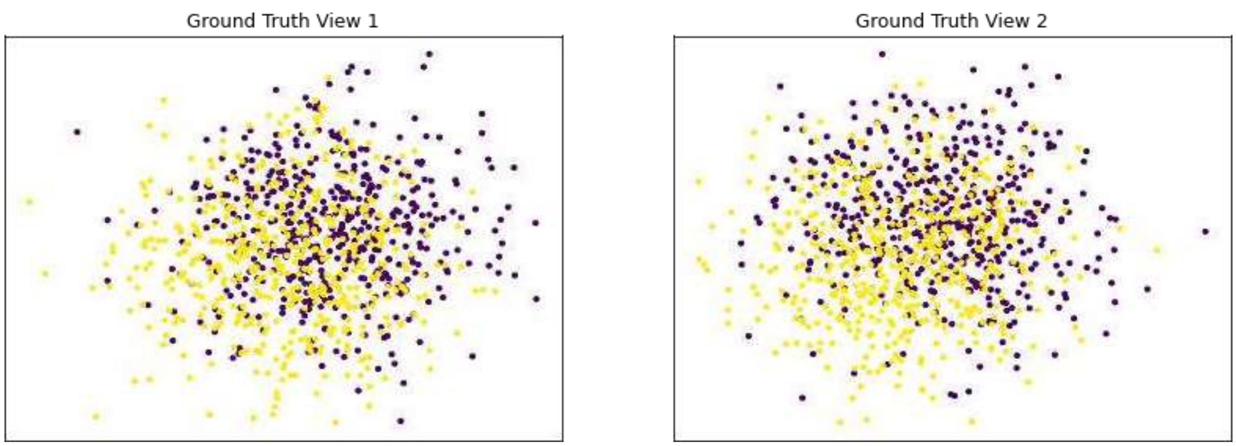
(Case A: When cluster components in both views are well separated)

Table 2: Comparison of Clustering Quality of Single view and Multi view K-means based approaches for Simulated Dataset for Phase II, Case A

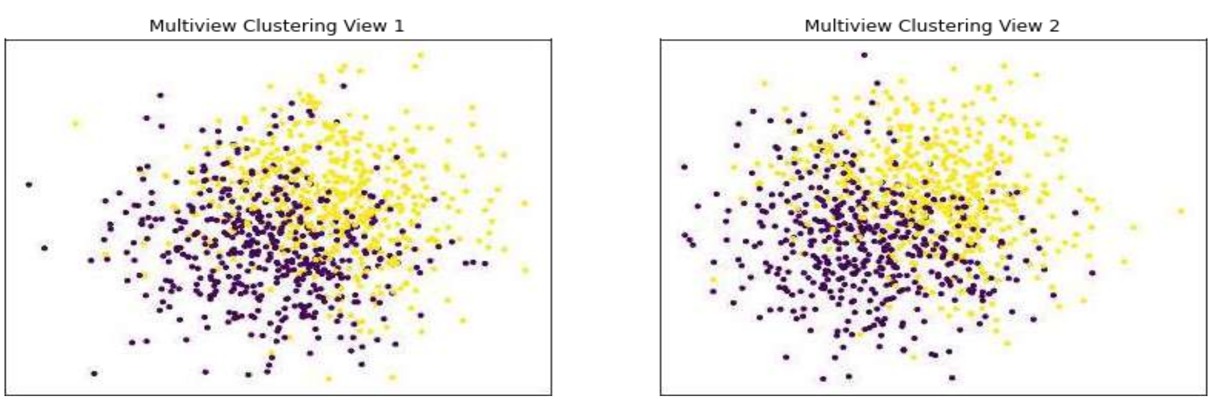
Clustering Approach	NMI	Jacc	FM	RI	Execution Time (in sec)
Single view K-means for View 1 of Dataset	0.901	0.987	0.974	0.994	0.72
Single view K-means for View 2 of Dataset	0.888	0.985	0.970	0.941	0.74
Single view K-means for Concatenated Dataset	0.99	0.99	0.998	0.996	0.75
Multi view K-means for whole dataset	0.99	0.993	0.999	0.997	0.275

B. Performance When Cluster Components Are Relatively Inseparable (Highly Overlapping) In BothViews:

Here we can see that multi-view K-means clustering performs about as poorly as single view K-means clustering across both individual views and concatenated views as inputs. The results of clustering for Case B are illustrated and summarized with Fig. 3, and Table 3 respectively.



(a) Single View vs Multi View Clustering on View 1 of Simulated Dataset for Case B



(b) Single View vs Multi View Clustering on View 2 of Simulated Dataset for Case B

Fig. 3: K-means technique based Clustering on Simulated Dataset for Phase II

(Case B: When cluster components are relatively overlapping)

Table 3: Comparison of Clustering Quality of Single view and Multi view K-means based approaches for Simulated Dataset for Phase II, Case B

Clustering Approach	NMI	Jacc	FM	RI	Execution Time (in sec)
Single view K-means for View 1 of Dataset	0.062	0.445	0.541	0.083	0.72
Single view K-means for View 2 of Dataset	0.044	0.378	0.530	0.059	0.74
Single view K-means for Concatenated Dataset	0.098	0.318	0.566	0.132	0.75
Multi view K-means for whole dataset	0.109	0.508	0.573	0.147	0.275

Thus from the values of clustering quality performance evaluation parameters NMI, Jacc, FM, and RI obtained in Phase I and Phase II experiments, it is proved that multi-view version of K-means algorithm has high clustering quality as compared to its single view counterpart. Additionally, the execution time for multi-view K-means algorithm is almost half than that with its single view counterpart in both Phase I and Phase II

V. CONCLUSION

Clustering has been very useful technique in machine learning and data mining. Traditional clustering techniques use only single set of features of the available dataset. However for the multi-view dataset with multiple features, how to ensemble all of these data views is a major concern. Thus problem is termed as multi- view clustering problem. The key benefits of multi-view clustering against single view clustering are accurate description of data, reducing noises of data, and wider range of applications. This paper studies the impact multi view K-means clustering available in mvlearn python package with the traditional K-means clustering technique. To assess the impact of simple K-means technique and multi-view version of K-means technique,two datasets are utilized namely, nutrimouse and simulated dataset.

We investigated the efficacy of multi-view K-means algorithm in two phases namely, Phase I (Multi-view Clustering of Nutrimouse Dataset via K-means technique), and Phase II (Multi-view Clustering of Simulated multi view Dataset via K-means technique). We analyzed the clustering quality of multi-view K-means technique using various performance evaluation parameters such as Normalized Mutual Information (NMI), Jaccard Coefficient (Jacc), Fowlkes Mallows Index (FM), Rand Index (RI). We also compared the execution times of single view K-means clustering and multi view K-means clustering. From the values of these clustering quality performance evaluation parameters, it is proved that multi-view version of K-means algorithm has high clustering quality as compared to its single view counterpart. Additionally, the execution time for multi-view K- means algorithm is very low as compared its single view counterpart in both Phase I and Phase II.

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