

Project 1 PCA Report

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Abstract. This report describes the implementation of PCA algorithm for dimensionality reduction. PCA serves the purpose of dimensionality reduction, and helps data visualization when the dimensionality is reduced to 2, and is mainly used in the field of computer vision to reconstruct images. In this project, we illustrate on the implementation details and also demonstrate our experiment results. **Our team made two different original implementations for the PCA algorithm, as can be seen on our team's Github page: <https://github.com/xuanyudo/Pca-Apriori-Algorithm>.**

1 Model Description

1.1 Principle Component Analysis

Principle component analysis is built on linear algebra. It can represent data in a more compact form by (1): get the covariance matrix of the dataset, (2): decompose the covariate matrix into a set of eigen vectors and eigen values, (3) pick out the eigen value, eigen vector pairs with the top k largest eigen value, if we want to visualize the data, then k will be set to 2 or 3. (4) The new set of coordinates for each of the data in the dataset will be the multiplication of original coordinates with each of the k eigen vectors, with each data point having k coordinates.

2 Model Implementation

2.1 Implementation of PCA

In this implementation, we encapsulated the whole functionality of PCA algorithm into one "PCA" class. After reading in the file and parse the dataset into a data matrix, the "compute covariant" function computes the covariance of the data matrix, whose dimensionality is of size *feature No.* \times *feature No.*. Then we called the "np.linalg.eig" function to calculate the eigen value and eigen vector of this covariance matrix, after which the two eigen value, eigen vector pairs with the largest eigen value is kept and serves as the new axes for the plot. Then, we get the coordinates of the each of the data point under this new set of

coordinates, which is done by getting the inner product of the data point with each of the 2 eigen vectors. For the plot, we used a dictionary to store all the available colors which matches with the category that each data point belongs to.

2.2 Application of TSNE Method

Based on the project guidance, we adopted readily available packages from `sklearn.manifold` for creation of the tsne plot. In the package, we call the `TSNE` function and set the parameter `n_components` to be 2, so as it can be plotted as a two dimension scatter graph, and the data matrix is feed into the `fit_transform` method.

2.3 Application of SVD Method

Based on the project guidance, we adopted readily available packages from `np.linalg.svd` for creation of the SVD plot. We attached visualization of the result below.

3 Experiment Result

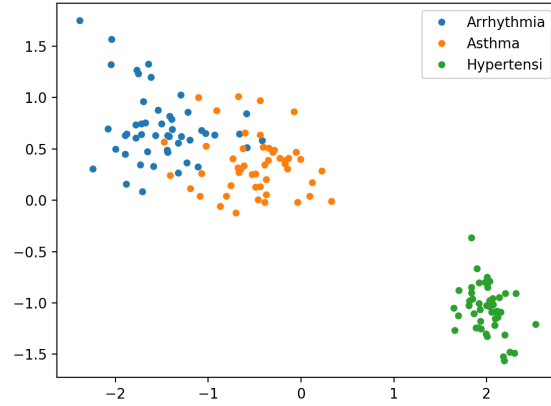
3.1 Result on PCA Analysis

After running PCA algorithm on the three given data files (`pca_a.txt`, `pca_b.txt`, `pca_c.txt`), we plot the result in Figure 1.

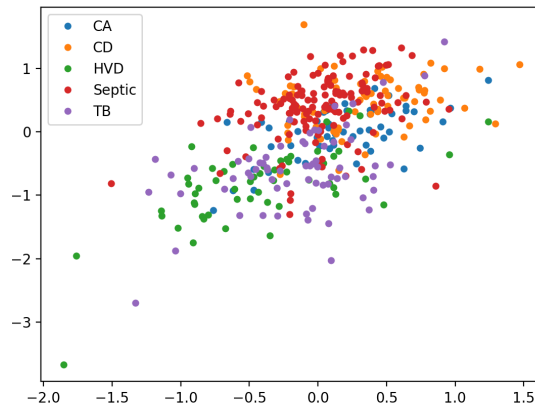
We can see the `pca_a` data is the easiest to separate among all three dataset, as shown by the different colors denoting the different classes, the different categories of data is not overlapping with each other and is easily distinguishable. For `pca_b` and `pca_c`, overlapping among the different clusters exists. Taking a closer look into the result of `pca_c`, we can see the clusters of data for Breast Cancer, AML and COPD are not separable in the PCA plot.

We further adopted the TSNE and SVD method to visualize the data, the result of which are shown in Figure 2 and Figure 3. Comparing the result of PCA with TSNE, we can see the TSNE method is achieving similar performance as PCA in `pca_a` dataset, while having better separation effect for the `pca_b` and `pca_c` dataset. This is in accordance with the observations of researchers in the field, as currently TSNE has become one the most widely adopted visualization methods in the field of data mining and bioinformatics.

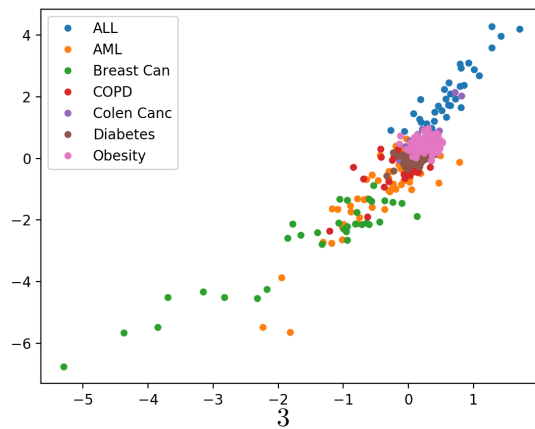
The effectiveness of SVD is similar to PCA, which successfully separates `pca_a` dataset and not effective on `pca_b` dataset. The performance on `pca_c` data lies in between the other two.



(a) PCA visualization of pca_a.txt data file

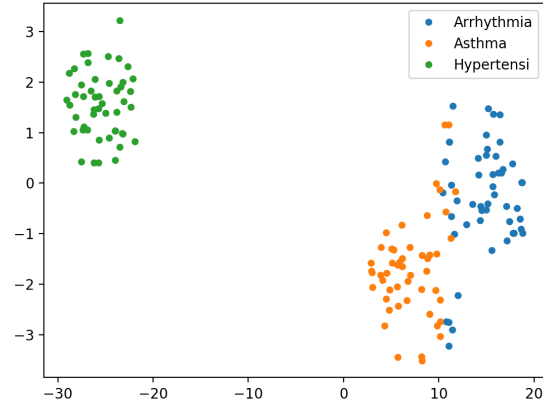


(b) PCA visualization of pca_b.txt data file

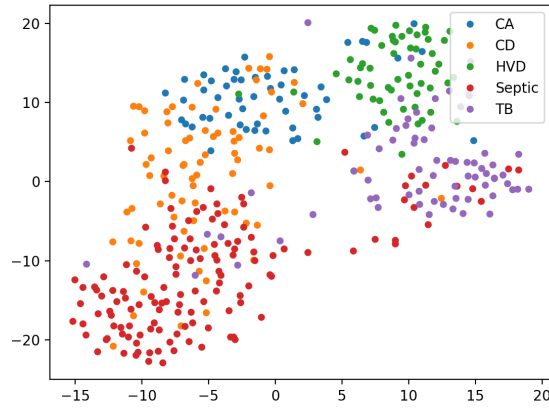


(c) PCA visualization of pca_c.txt data file

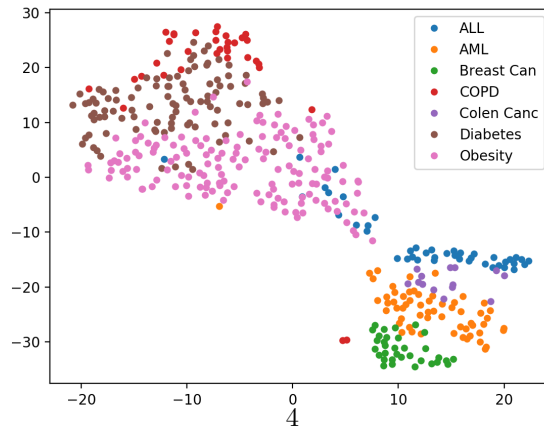
Fig. 1: (a) PCA visualization of pca_a.txt data file, (b) PCA visualization of pca_b.txt data file, (c) PCA visualization of pca_c.txt data file.



(a) TSNE visualization of pca_a.txt data file

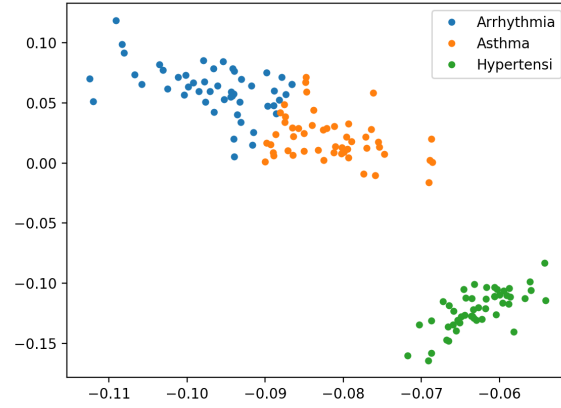


(b) TSNE visualization of pca_b.txt data file

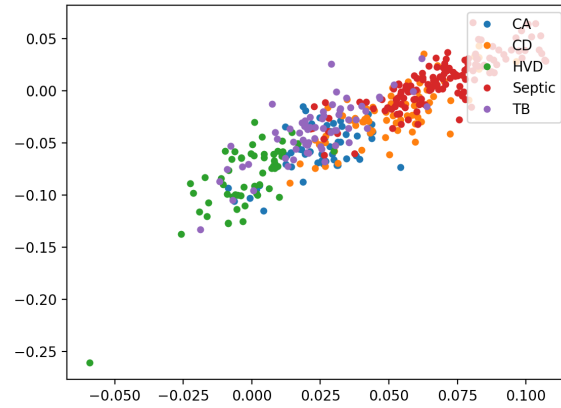


(c) TSNE visualization of pca_c.txt data file

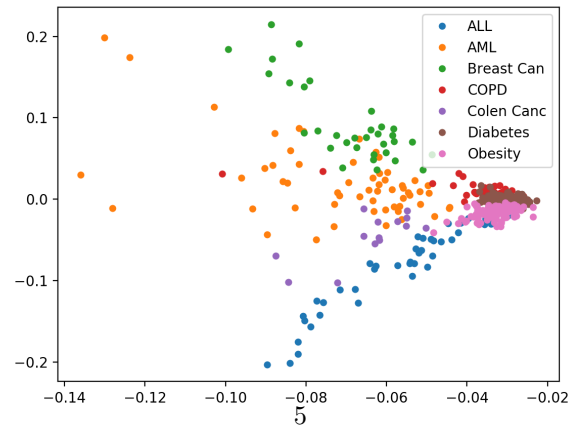
Fig. 2: (a) TSNE visualization of pca_a.txt data file, (b) TSNE visualization of pca_b.txt data file, (c) TSNE visualization of pca_c.txt data file.



(a) SVD visualization of pca_a.txt data file



(b) SVD visualization of pca_b.txt data file



(c) SVD visualization of pca_c.txt data file

Fig. 3: (a) SVD visualization of pca_a.txt data file, (b) SVD visualization of pca_b.txt data file, (c) SVD visualization of pca_c.txt data file.