

Programming Assignment 3: PCA and fastmap

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In this assignment, we will implement two algorithms, PCA and Fastmap. Both of them is used to reduce the dimensions. First of all, PCA (principle component analysis) is to treat the data as matrix and calculate their means, sigma, and the eigenvectors of this matrix. Only store the first k eigenvectors. The Fastmap is not easy to understand. This method is used to calculate different values' distance, and project them to different axis. In this assignment, we will treat 6000 values with PCA and treat 10 words with fastmap method. In the first section, we will show you the pseudocodes of them. In the second section, we will show you the library in different programming languages. In the third section, we will show you the applications of these two different algorithms.

1 pseudocode of PCA and Fastmap (Yu Hou)

(1) pseudocode

PCA method:

Call miu method to calculate the mean.

Call sigma method to calculate the sigma.

Call U matrix to calculate a new matrix which is consist of first k eigenvectors.

Call z method to times original data (matrix) with U matix.

Fastmap method has two ways to implement. We can use two for loop to get k dimension matrix. Also, we can use recursion to get k dimension matrix.

Fastmap method 1:

Determine the A point and B point and distance to point A of every point

Using $x_i = (d_{ai}^2 + d_{ab}^2 - d_{ib}^2) / 2d_{ab}$, i means different point

Get the x value of different points

Get the new distance of every points

Using $D_{new}^2(O_i O_j) = D_{old}^2(O_i O_j) - (x_i - x_j)^2$

Determine the A point and B point again and calculate the distance to point A of every point

Get the y value of different point.

Fastmap method 2 (recursion):

If it is the base case:

K=k' means we already get the k dimension

If it is not the base case:

Determine the A point and B point and distance to point A of every point

Using $x_i = (d_{ai}^2 + d_{ab}^2 - d_{ib}^2) / 2d_{ab}$, i means different point

Get the K_i dimension of different points

Update the new distance of every points Using $D_{new}^2(O'_i O'_j) = D_{old}^2(O'_i O'_j) - (x_i - x_j)^2$
Recursion and $k=k+1$

Because in the assignment, we just had to represent 10 words in 2D, so we used the method 1 without recursion.

(2) Results

PCA:

Shown as the figure 1, the 6000 point can be plotted in 3D view. In the figure2, they are the same 6000 points plotted in 2D view after dimension reduction.

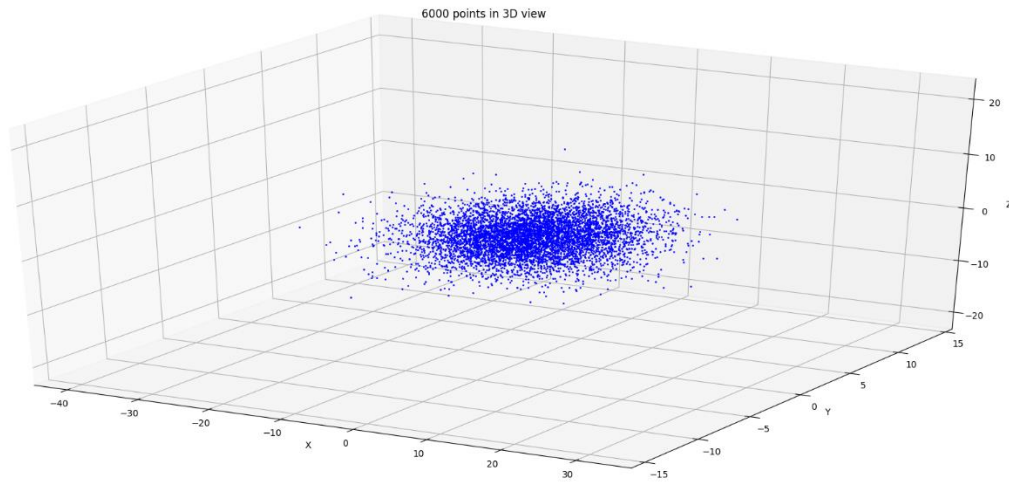


Figure 1 6000 points in 3D view

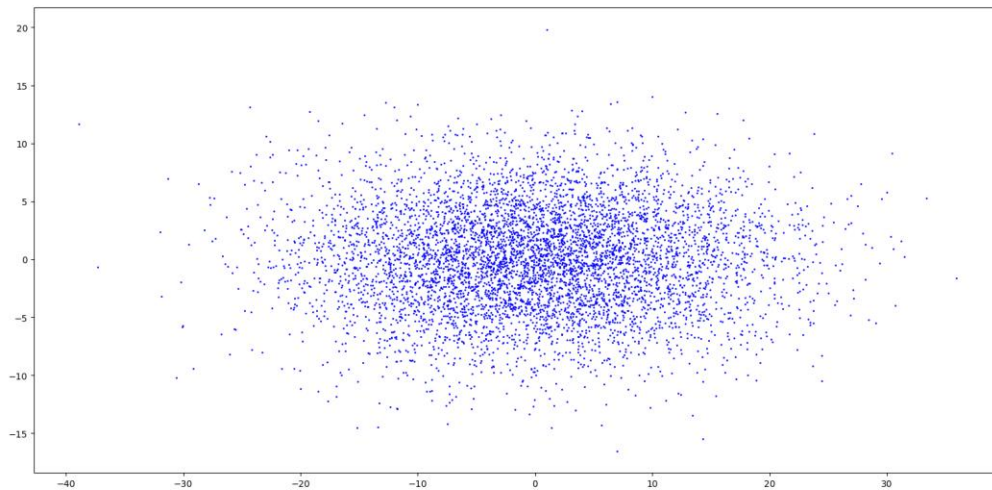


Figure 2 6000 points in 2D view

If we print out the 6000 points in 2D in matrix, it will be as follows:

```
[[ 10.87667009  7.37396173]
 [-12.68609992 -4.24879151]
 [ 0.43255106  0.26700852]
 ...,
 [-2.92254009  2.41914881]
 [ 11.18317124  4.20349275]
 [ 14.2299014  5.64409544]]
```

Fastmap:

If we print out the results, it can be as follows, there will be two different results. In the first iteration, the farthest two points are 3.0 and 10.0, and the distance is 12.0. In the second iteration, there are two cases. One the farthest two points are 5.0 and 7.0, and the distance is 8.0. The other farthest two points are 7.0 and 9.0, the distance is also 8.0. The matrixes of these two cases are shown as follows.

First case:

```
[[ 3.875      6.0625 ]
 [ 3.        7.75   ]
 [ 0.        4.     ]
 [ 1.04166667 1.1875 ]
 [ 2.45833333 0.     ]
 [ 9.5        5.1875 ]
 [ 2.45833333 8.     ]
 [ 1.5        1.5625 ]
 [ 2.45833333 1.     ]
 [ 12.        4.     ]]
```

Second case:

```
[[ 3.875      2.75   ]
 [ 3.        0.25   ]
 [ 0.        4.     ]
 [ 1.04166667 5.5    ]
 [ 2.45833333 7.     ]
 [ 9.5        4.     ]
 [ 2.45833333 0.     ]
 [ 1.5        7.75   ]
 [ 2.45833333 8.     ]
 [ 12.        4.     ]]
```

However, according to the requirement of assignment, we should use the one that includes the smallest object ID. If we plot these 10 points in the 2D view, it can be as follows in figure3. Also, we can calculate the distances between each pair of objects, the Damerau-Levenshtein distances between them. Then, we label them on the Fastmap.

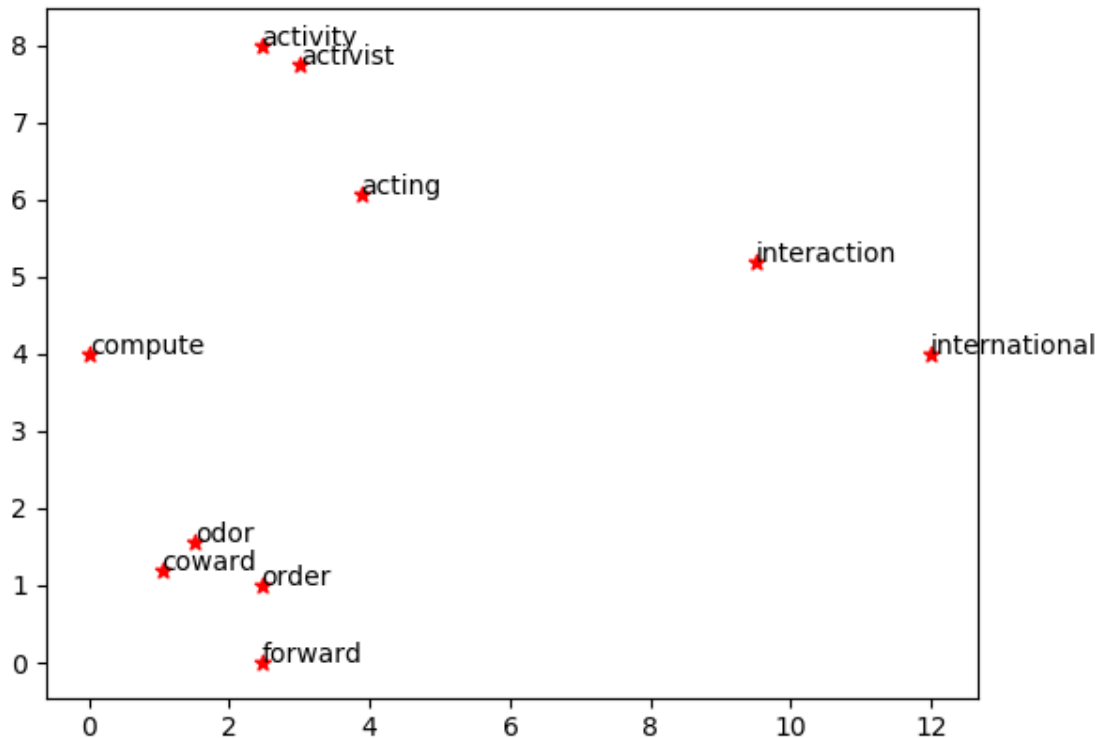


Figure3 10 words using Fastmap

(3) data structure

PCA

This algorithm is easy to store the data. We create a matrix to store all 6000 3D points, matrix [6000] [3]. This is easy to calculate the mean, sigma, eigenvector using matrix. We also store the mean, sigma, and eigenvector in different matrix. After computation, we will get a matrix [6000] [2] to store all 2D points after reduction.

Fastmap

There are two ways to store data in fastmap method.

First method is using a 2D array. Shown as the table 1.

Table 1 store the distance between each two record.

	01	02	03	09	10
01	0.0	4.0	7.0	6.0	10.0
02	4.0	0.0	7.0	8.0	11.0
03	7.0	7.0	0.0		6.0	12.0
.....
09	6.0	8.0	6.0	0.0	11.0
10	10.0	11.0	12.0	11.0	0.0

In this 2D array, for example, the intersection of the “01” column and the “02” row is 4.0 means the

2 Software Familiarization (Yu Hou, Haoteng Tang)

(1) Python for principle component analysis(PCA)

In Python programming, we have a library called sklearn. In the library, we can find some statements to implement this algorithm. Here is the main statements.

```
>>> import numpy as np
>>> from sklearn.decomposition import PCA
>>> X = np.array([[ -1, -1], [-2, -1], [-3, -2], [1, 1], [2, 1], [3, 2]])           //data set need to reduce
>>> pca = PCA(n_components=2)
>>> pca.fit(X)
PCA(copy=True, iterated_power='auto', n_components=2, random_state=None, svd_solver='auto',
tol=0.0, whiten=False)
```

In this statement, number of components to keep. if n components are not set all components are kept, so `n_components == min(n_samples, n_features)`.

(2) MATLAB for principle component analysis(PCA)

In order to do the PCA of a set of data X which is showed in an m*n dimension matrix by using MATLAB library function, we can code as below:

```
[COEFF,SCORE,Latent]=princomp(X);
```

COEFF is a p-by-p matrix, each column containing coefficients for one principal component. The columns are in order of decreasing component variance. For data matrix in assignment, the COEFF matrix is:

```
[0.866671367084373  -0.496277304498303  -0.0508879014698239
-0.232764816475979  -0.492479204508382   0.838620756562641
0.441249681798195   0.714963684509004   0.542333521134645];
```

which is the same as the result based on our own code.

SCORE is the principal component scores that is the representation of X in the principal component space. Rows of SCORE correspond to observations, columns to components.

Latent, a vector containing the eigenvalues of the covariance matrix of X.

(3) Python for fastmap

It is very hard to find a library using python to implement fastmap. However, teaching assistance suggested us to search a code somebody else wrote on the website. We found one on Github, <https://github.com/mahmoudimus/pyfastmap>.²The author is "mahmoudimus". We used his code to run our data and get some results as follows.

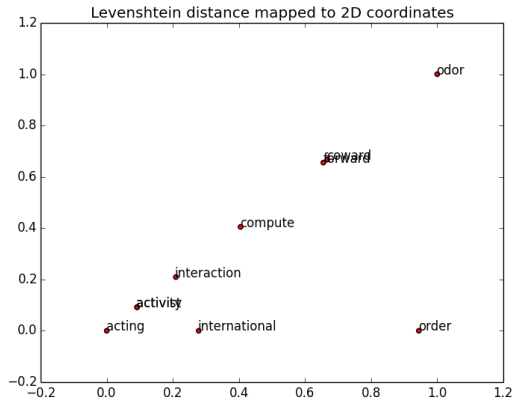


Figure 7

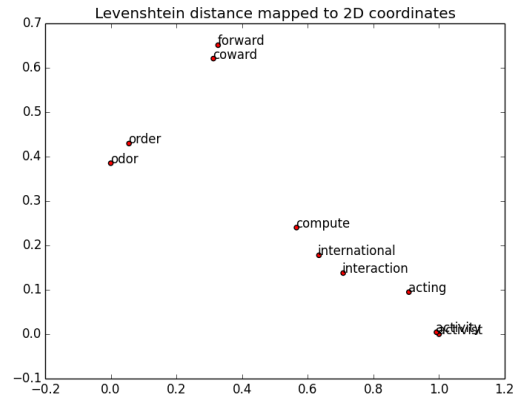


Figure 8

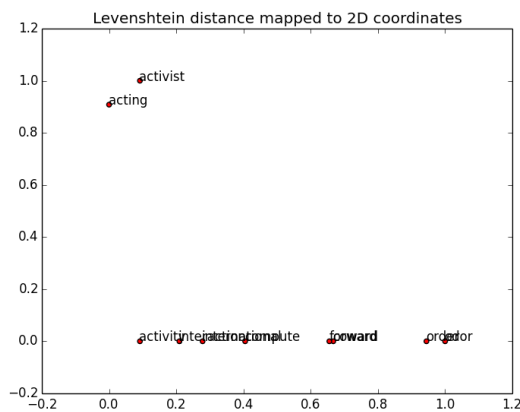


Figure 9

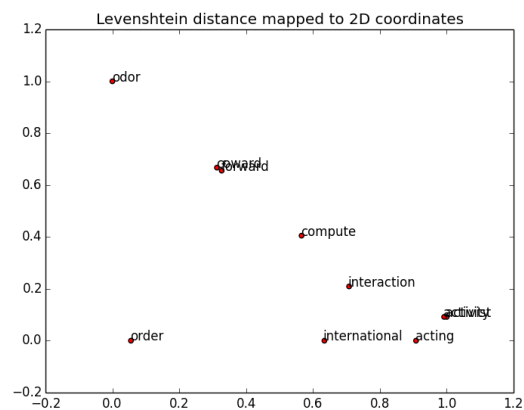


Figure 10

However, we found that the results cannot make sense. In these four pictures above, we can find that there were great possibilities that some words were in a line. Because the author found the farthest distance between two points randomly, but there were some mistakes in his code. Sometimes, the code will choose the same two words as the two farthest distance words. In the author's code, he wrote a test code to generate 10 5-D points randomly distributed between [0-10]. Here are twice running his test code.

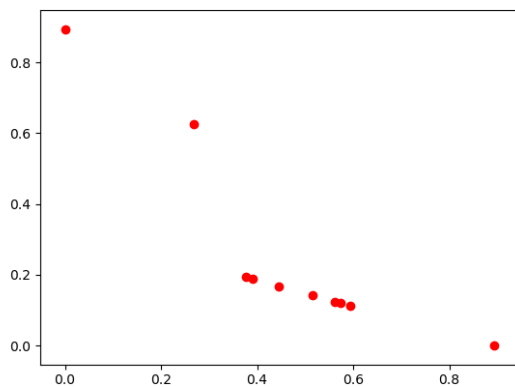


Figure 11

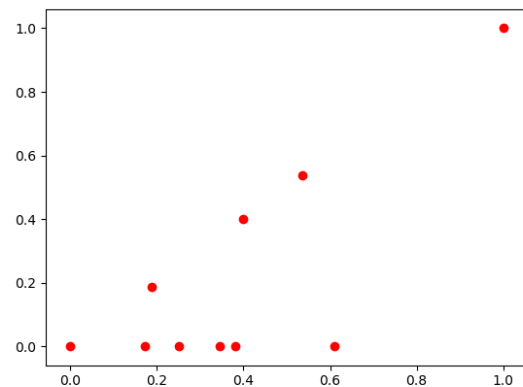


Figure 12

In the figure 11, the first iteration, the code picked point 2 and 1, the same as the second iteration. In

the figure12, the first iteration picked point 9 and 3, the same as the second iteration. Here are the results printed.

Picked 2, 1 at K = 2

Picked 1, 2 at K = 1

Picked 9, 3 at K = 2

Picked 9, 3 at K = 1

So, this library should be improved.

3 Application (Haoteng Tang)

Both PCA and fast-map are a kind of method to reduce the dimension. It will be complicated for our algorithm to be executed and be a lot of time and space cost if the attributes (dimensions) of the data is very high when we use machine learning algorithms such as neural network to process the data. For instance, if the dimension is very high, each level of the neural network should be implanted many perceptron which is very complex. However, by using this kind of dimension reduction, we can use a few representative dimensions to replace previous whole dimensions. This is a logical and wise preprocess before we deal with our data into following steps.

For example, in construction management. We want to find the most appropriate architectural designer. We have a big dataset with many attributes. Here are some of these attributes.

1Gender

2Age

3Worktime in this company (how many years)

4Salary

5Education background

6Designer style

7Position in the company

8Marriage

9Kids (number)

10Work time (how many hours a week)

11Work delay (how many days)

12Extra work time (how many hours a week)

13Design mistakes

14Typical design mistakes, account the number

15Design omissions

16Typical design omission, account the number

17Design conflicts

18Typical design conflicts, account the number

19Type of work (new-build, rebuild, extension)

20Discipline of work (Steel, concrete, wood, combination)

21Complexity of the work

22Profitable of the work

23Service fee of the work

24Priority of the work

There are too much attributes, we need to reduce the dimension of the dataset. So we can use PCA and fastmap and other methods.

Reference

¹ Christos Faloutsos, King-Ip Lin. FastMap: a fast algorithm for indexing, data-mining and visualization of traditional and multimedia datasets. 1995: 163-174

² Fastmap Github: <https://github.com/mahmoudimus/pyfastmap>.