

IE 529 Fall 2016 Assignment 2

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1 PCA

Following the procedures of PCA, the mean value is:

$$\vec{m} = [1.87275, 1.48783, 1.87275]$$

And the variance is:

$$variance = [2.38297, 0.234668, 2.54 \times 10^{-16}]$$

And the corresponding eigenvector is:

$$eig1 = [-0.6694 \ -0.3220 \ -0.6694]^T$$

$$eig2 = [0.2277 \ -0.9467 \ 0.2277]^T$$

$$eig3 = [-0.7071 \ -1.4140 \times 10^{-15} \ 0.7071]^T$$

The de-biased dataset and corresponding eigenvectors are plotted in Figure 1.

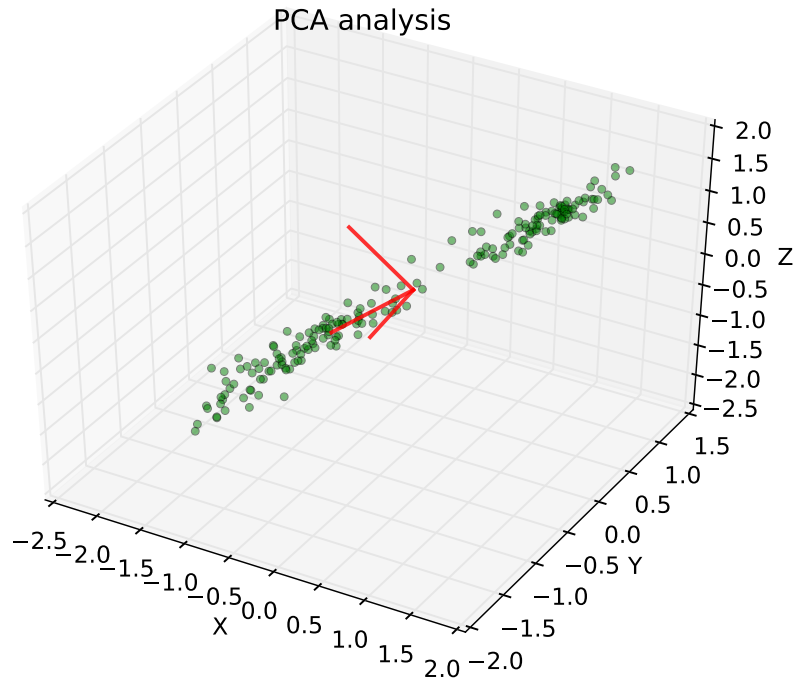


Figure 1: PCA eigenvector and scatter plot

The original dataset can be projected onto the first two principal components, the result is shown in Figure 2.

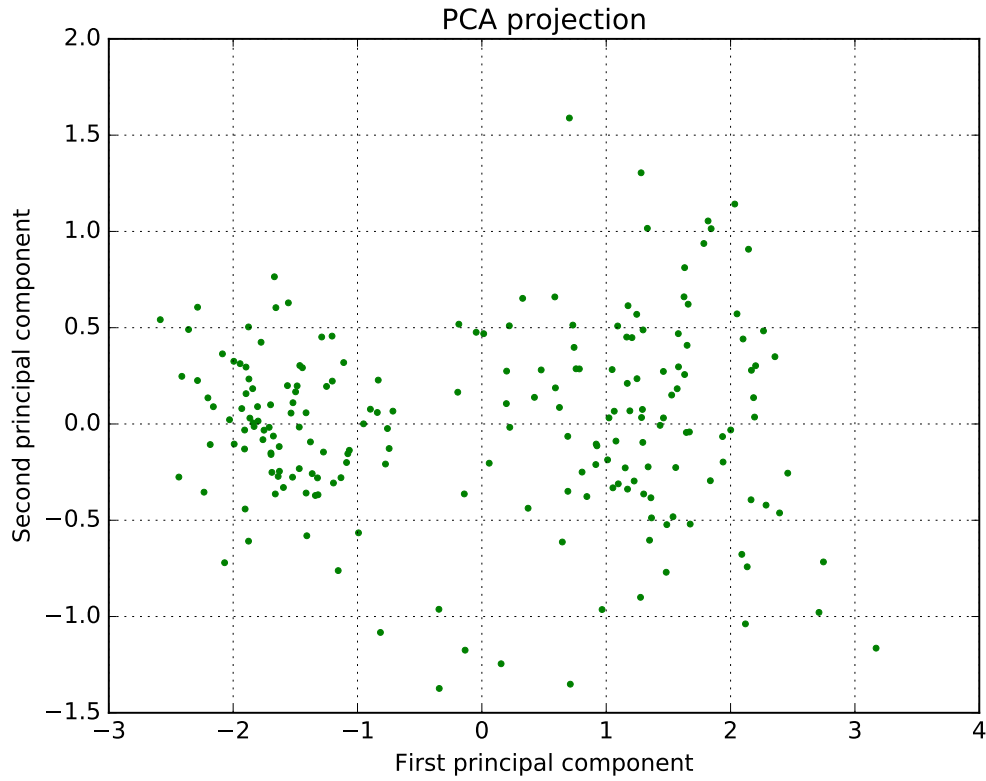


Figure 2: PCA Projection

2 Discussion

Currently the PCA is conducted through

$$[U, S, V] = SVD(A * A^T)$$

In fact this process can be simplified to:

$$[U', S', V'] = SVD(A)$$

Then, we can get that:

$$U = U'$$

$$S = S'^2$$

In this way, this process can be directly performed on the original data, rather than the new data.

The Python code is attached.

```

1 #!/usr/bin/env python3
2 # -*- coding: utf-8 -*-
3 """
4 __author__      = "Jifu Zhao"
5 __email__       = "jzhao59@illinois.edu"
6 __date__        = "09/29/2016"
7 """
8
9 import warnings
10 warnings.simplefilter('ignore')
11 import copy
12 import numpy as np
13 import pandas as pd
14 import matplotlib.pyplot as plt
15 from mpl_toolkits.mplot3d import Axes3D
16
17 def pca(data):
18     """ function to perform PCA """
19     data = copy.deepcopy(data)
20     n, m = data.shape
21     mean = np.mean(data, axis=0)
22     data -= mean
23     covariance = np.dot(data.T, data) / (n - 1)
24     U, S, V = np.linalg.svd(covariance)
25     return S, mean, U
26
27
28 def main():
29     # PCA analysis
30     data = pd.read_csv('./PCAdata.csv', header=None).values.T
31     variance, mean, component = pca(data)
32     project = np.dot(data - mean, component)
33     data = data - mean
34
35     print('Mean:\t', mean)
36     print('Variance:\t', variance)
37     print('Eigenvector 1\t', component[:, 0])
38     print('Eigenvector 2\t', component[:, 1])
39     print('Eigenvector 3\t', component[:, 2])
40
41     # 3D plot
42     fig = plt.figure()
43     ax = fig.add_subplot(111, projection='3d')
44     ax.plot(data[:, 0], data[:, 1], data[:, 2], 'o', markersize=4, color='green',
45             alpha=0.5)
46     for i in range(3):
47         ax.plot([0, component[0, i]], [0, component[1, i]], [0, component[2, i]],
48                 color='red', alpha=0.8, lw=2)
49     ax.set_xlabel('X')
50     ax.set_ylabel('Y')
51     ax.set_zlabel('Z')
52     ax.set_title('PCA analysis')
53     ax.view_init(40)
54     fig.savefig('./result/3d.pdf')
55     plt.show()
56
57     # PCA projection
58     fig, ax = plt.subplots()
59     ax.plot(project[:, 0], project[:, 1], 'g.')

```

```
59     ax.set_title('PCA projection')
60     ax.set_xlabel('First principal component')
61     ax.set_ylabel('Second principal component')
62     ax.grid('on')
63     fig.savefig('./result/projection.pdf')
64     plt.show()
65
66
67 if __name__ == '__main__':
68     main()
```