Principal Component Analysis

import library

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors as colors
from matplotlib import cm
```

load data

```
In []:
    fname_data = 'assignment_12_data.txt'
    feature0 = np.genfromtxt(fname_data, delimiter=',')

    number_data = np.size(feature0, 0)
    number_feature = np.size(feature0, 1)

    print('number of data : {}'.format(number_data))
    print('number of feature : {}'.format(number_feature))

number of data : 50
    number of feature : 2
```

plot the input data

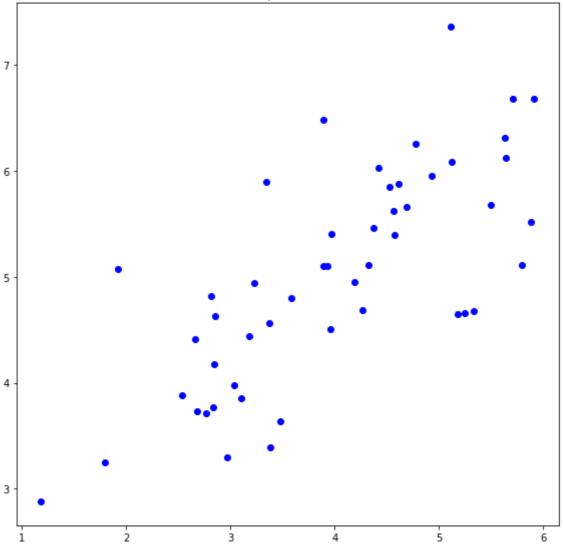
```
In []:
    plt.figure(figsize=(8,8))
    plt.title('input data')

    x0 = feature0[:,0]
    y0 = feature0[:,1]

    plt.scatter(x0, y0, color='blue')

    plt.tight_layout()
    plt.show()
```

input data



Normalization (Z-scoring)

• shape of feature = $n \times m$ where n is the number of data and m is the dimension of features

```
return feature_normalize
```

```
feature = normalize(feature0)

x = feature[:, 0]
y = feature[:, 1]

min_x = np.min(x)
min_y = np.min(y)

max_x = np.max(x)
max_y = np.max(y)
```

compute covariance matrix

• shape of feature = $n \times m$ where n is the number of data and m is the dimension of features

compute principal components

- np.linalg.eig
- argsort()
- return the eigenvalues and the eigenvectors in a decreasing order according to the eigenvalues

```
return (principal_component_1, principal_component_2)
```

compute the projection of point onto the axis

- np.matmul
- np.dot
- shape of feature = $n \times m$ where n is the number of data and m is the dimension of features
- shape of vector = $m \times 1$ where m is the dimension of features

compute the principal components and the projection of feature

functions for presenting the results

```
In []:
    def function_result_01():
        plt.figure(figsize=(8,8))
        plt.title('data normalized by z-scoring')
        plt.scatter(x, y, color='blue')

        plt.xlim(min_x - 0.5, max_x + 0.5)
        plt.ylim(min_y - 0.5, max_y + 0.5)

        plt.tight_layout()
        plt.show()
In []:

def function_result_02():
```

```
def function_result_02():
    plt.figure(figsize=(8,8))
```

```
plt.xlim(min_x - 0.5, max_x + 0.5)
plt.ylim(min_y - 0.5, max_y + 0.5)

plt.tight_layout()
plt.show()
```

```
In [ ]:
       def function_result_05():
           plt.figure(figsize=(8,8))
           plt.title('projection onto the first principle axis')
           # complete the blanks
           Sigma = compute_covariance(feature)
           S, U = np.linalg.eig(Sigma)
           plt.scatter(x, y, marker= 'o', color='blue')
           plt.plot([-5*U[0][0], 5*U[0][0]], [-5*U[1][0], 5*U[1][0]], color='red')
           plt.scatter(projection1[:,0], projection1[:,1], marker= 'o', c= "g")
           plt.xlim(min_x - 0.5, max_x + 0.5)
           plt.ylim(min_y - 0.5, max_y + 0.5)
           plt.tight_layout()
           plt.show()
```

```
In [ ]:
       def function_result_06():
           plt.figure(figsize=(8,8))
           plt.title('projection onto the second principle axis')
           # complete the blanks
           Sigma = compute_covariance(feature)
           S, U = np.linalg.eig(Sigma)
           plt.scatter(x, y, marker= 'o', color='blue')
           plt.plot([-5*U[0][1], 5*U[0][1]], [-5*U[1][1], 5*U[1][1]], color='red')
           plt.scatter(projection2[:,0], projection2[:,1], marker='o', c= "g")
           plt.xlim(min_x - 0.5, max_x + 0.5)
           plt.ylim(min_y - 0.5, max_y + 0.5)
           plt.tight_layout()
           plt.show()
```

```
In [ ]: def function_result_07():
```

```
plt.figure(figsize=(8,8))
plt.title('projection onto the first principle axis')
# +++++
# complete the blanks
Sigma = compute_covariance(feature)
S, U = np.linalg.eig(Sigma)
plt.scatter(x, y, marker= 'o', color='blue')
plt.plot([-5*U[0][0], 5*U[0][0]], [-5*U[1][0], 5*U[1][0]], color='red')
plt.scatter(projection1[:,0], projection1[:,1], marker = 'o', c= "g")
for i in range(number_data):
   plt.plot([feature[i,0], projection1[i,0]], [feature[i,1], projection1[i,1]], '-
plt.xlim(min_x - 0.5, max_x + 0.5)
plt.ylim(min_y - 0.5, max_y + 0.5)
plt.tight_layout()
plt.show()
```

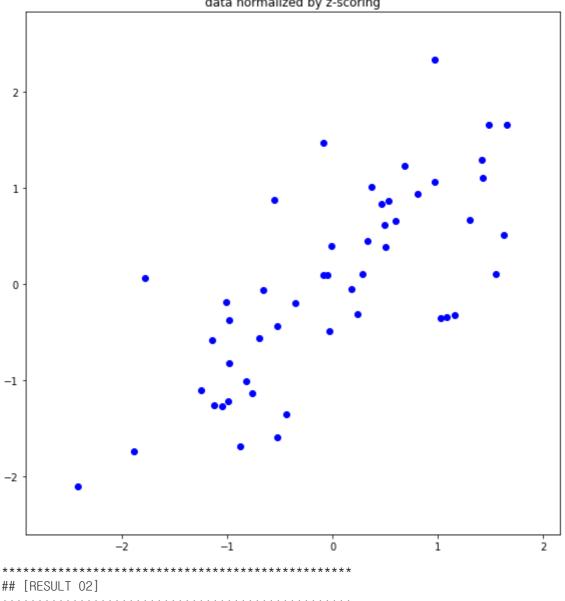
```
In [ ]:
        def function_result_08():
           plt.figure(figsize=(8,8))
           plt.title('projection to the second principle axis')
           # complete the blanks
           Sigma = compute_covariance(feature)
           S, U = np.linalg.eig(Sigma)
           plt.scatter(x, y, marker= 'o', color='blue')
           plt.plot([-5*U[0][1], 5*U[0][1]], [-5*U[1][1], 5*U[1][1]], color='red')
           plt.scatter(projection2[:,0], projection2[:,1], marker = 'o', c= "g")
           for i in range(number_data):
              plt.plot([feature[i,0], projection2[i,0]], [feature[i,1], projection2[i,1]], '-
           plt.xlim(min_x - 0.5, max_x + 0.5)
           plt.ylim(min_y - 0.5, max_y + 0.5)
           plt.tight_layout()
           plt.show()
```

results

```
In [ ]:
      number\_result = 8
      for i in range(number_result):
        title = '## [RESULT {:02d}]'.format(i+1)
        name_function = 'function_result_{:02d}()'.format(i+1)
        print(title)
        eval(name_function)
```

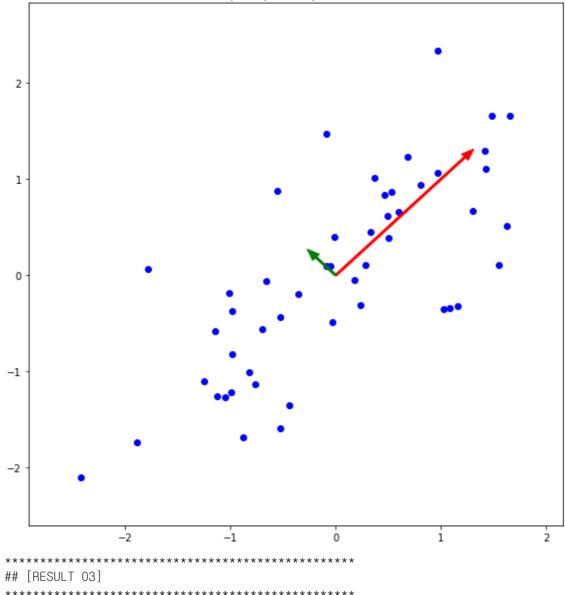
[RESULT 01]

data normalized by z-scoring

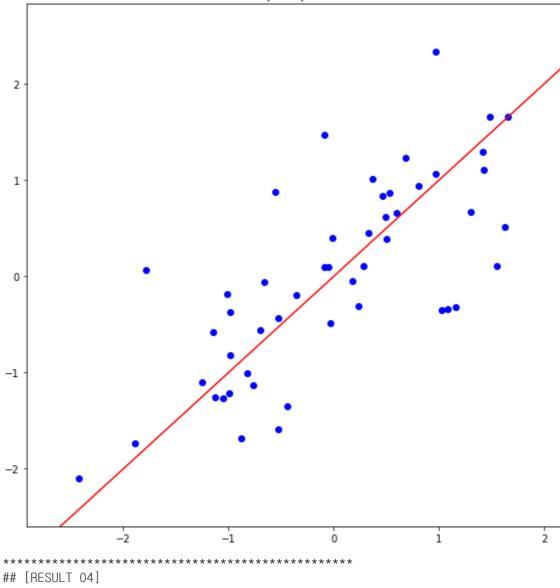


file:///C:/Users/eehaein/Desktop/devPROJECT/CAU/machine_learning/class/machine-learning-assignment/12/assignment_12.html



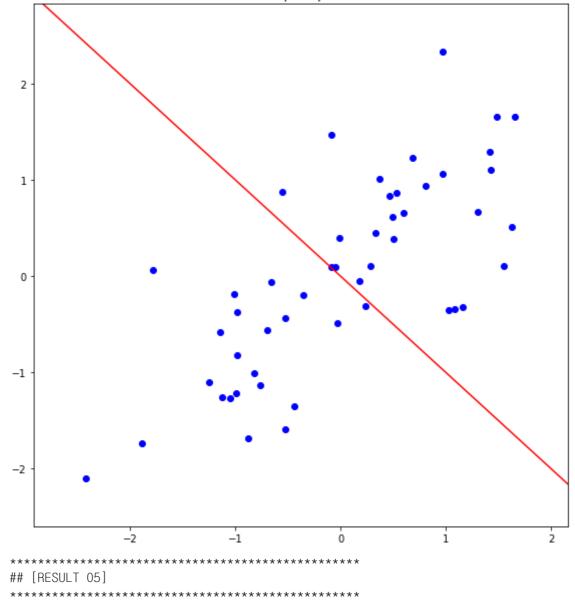




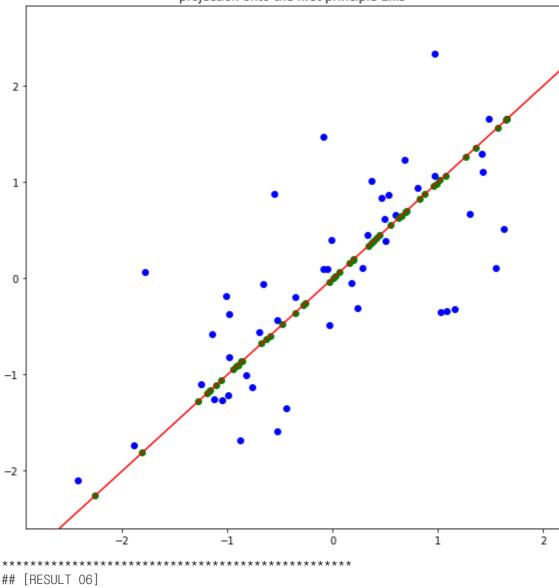


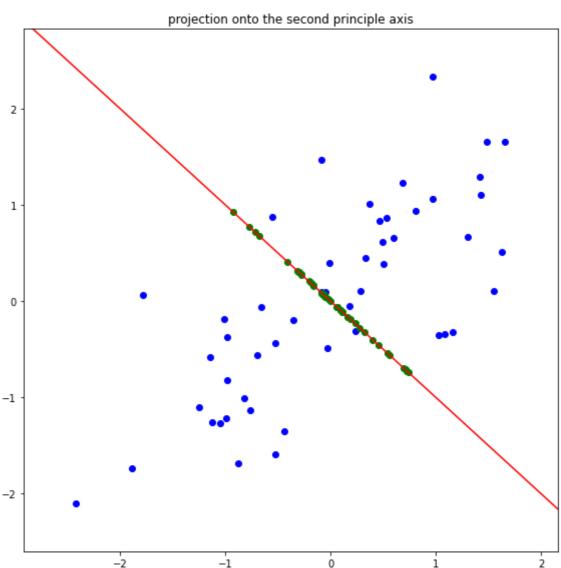
 $file: ///C:/Users/eehae in/Desktop/devPROJECT/CAU/machine_learning/class/machine-learning-assignment/12/assignment_12.html$





projection onto the first principle axis





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projection onto the first principle axis

