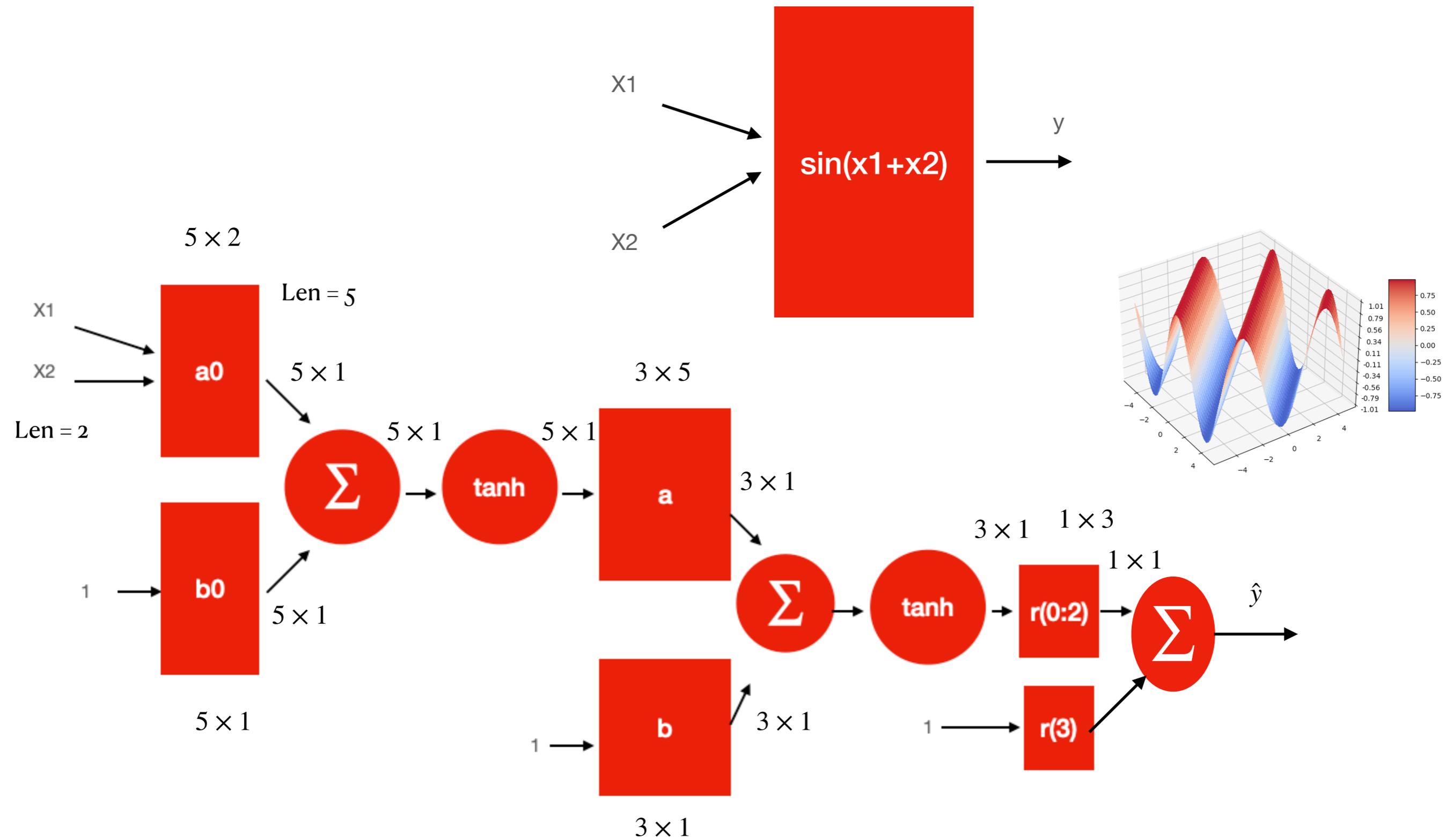
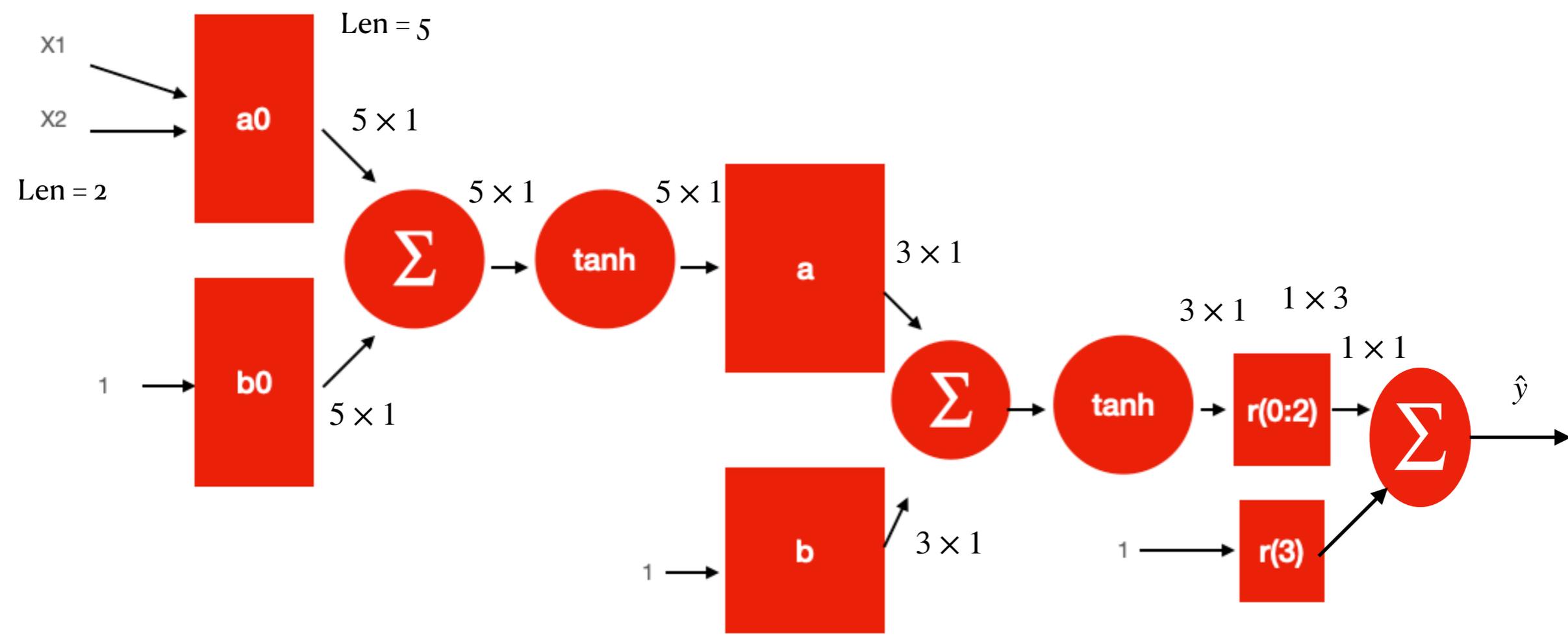
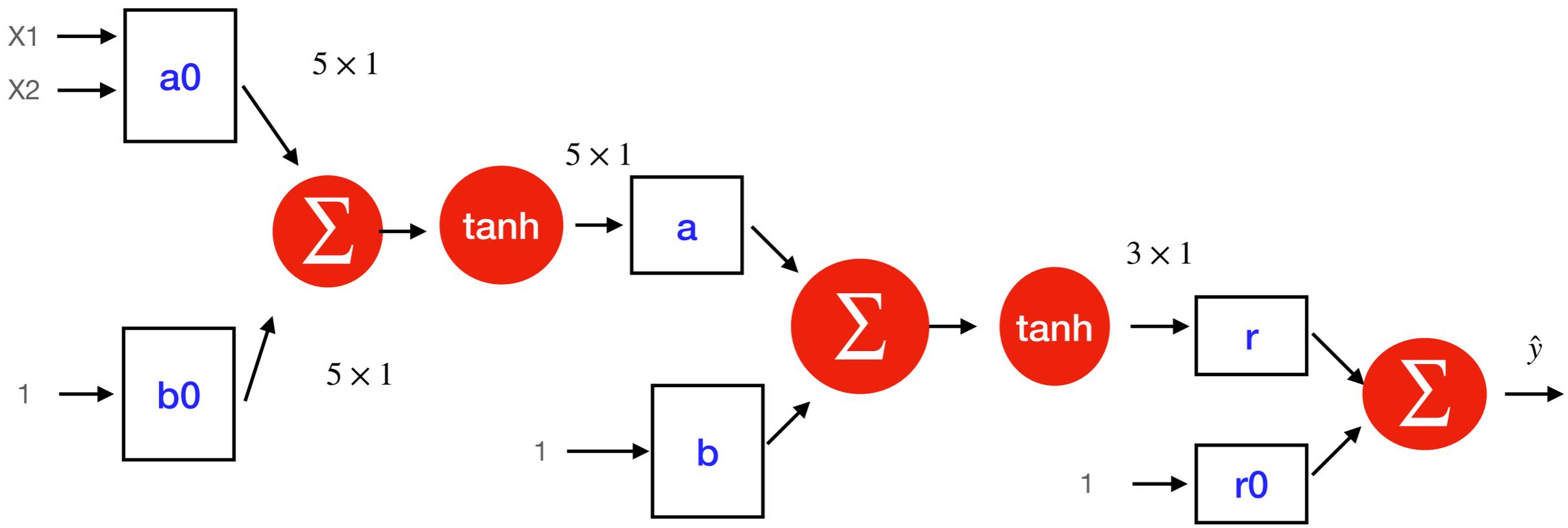


# 反矩陣的資料分析應用

給定不共線的多個點求一直線

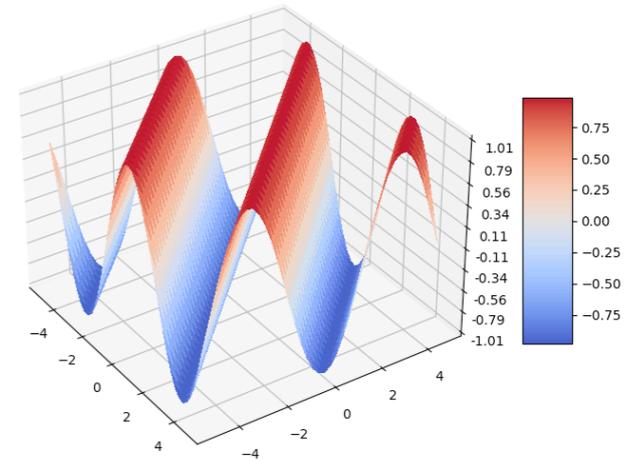
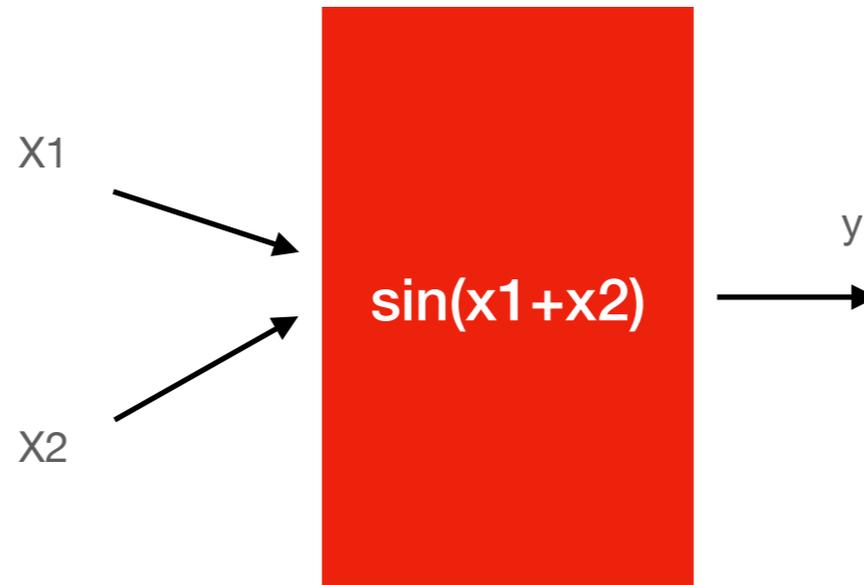




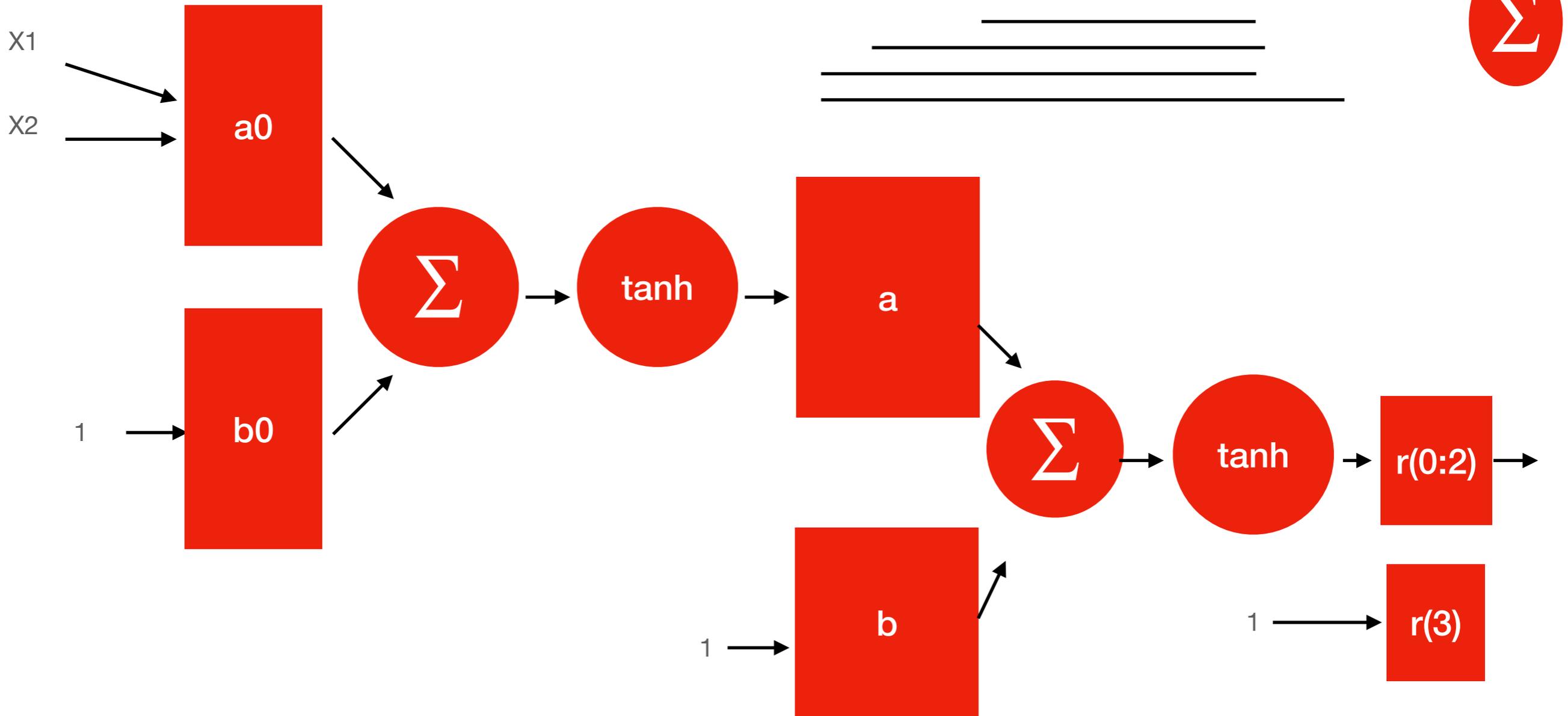


Mean square error  $10^{-6}$

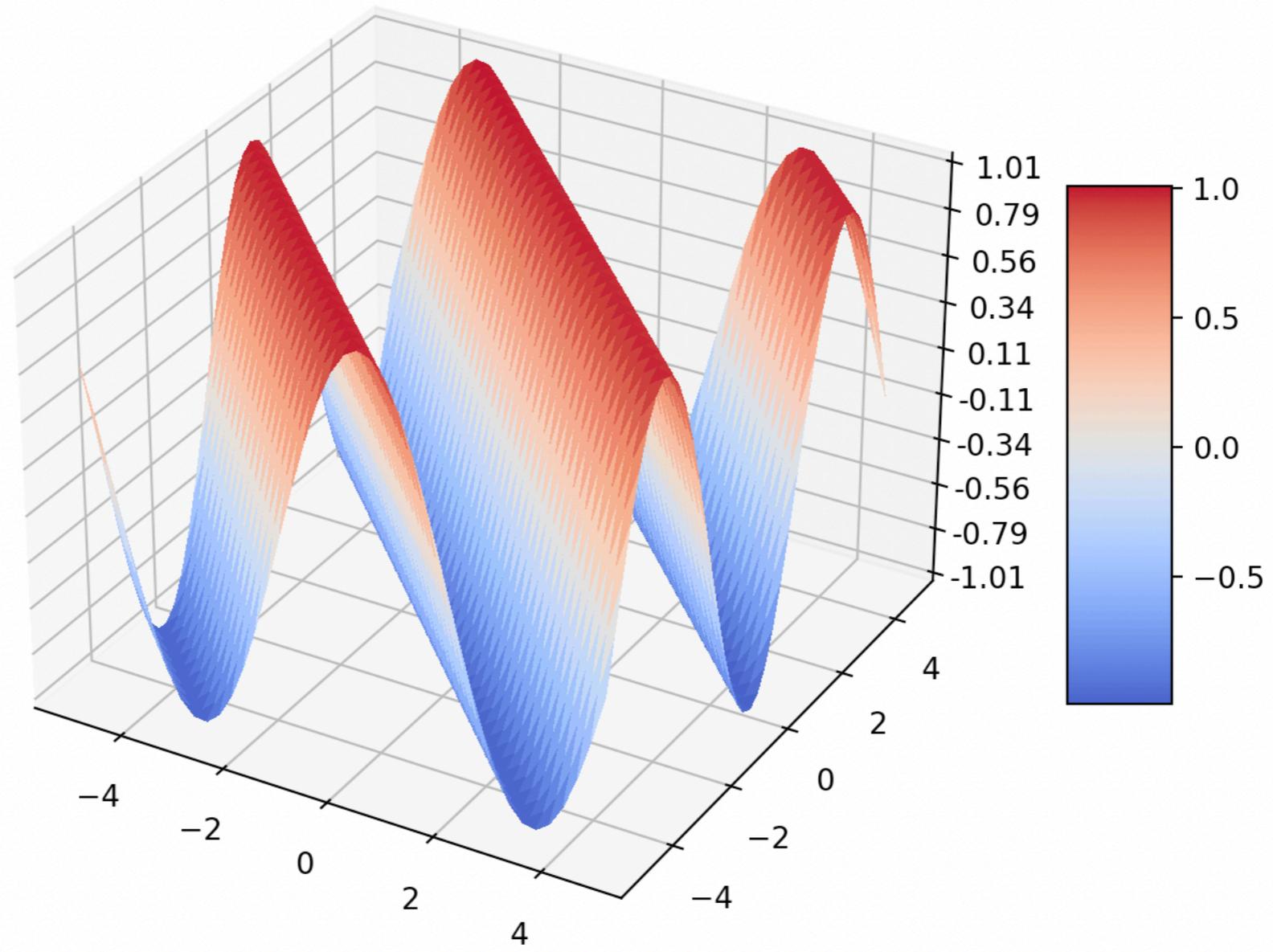
$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$



$$y\_hat = r(1:3)*\tanh(a*\tanh(a0*x(1,:)'+b0)+b)+r(4)$$



```
def mySin(x):
    a0 = np.array([[[-0.3918, -0.3918], [-0.0975, -0.0975],
                    [-0.3304, -0.3303], [-0.2186, -0.2185],
                    [-0.3472, -0.3472]])
    b0 = np.array(
        [[-3.5903], [0.1043], [1.9609], [1.1944], [-1.0927]])
    a = np.array([[[-0.6988, -0.1312, 0.5554, -2.1678, -0.1380],
                    [-0.2736, -4.3798, 0.7643, 5.0048, -2.2072],
                    [0.4992, -3.2731, -0.8272, 2.2502, 0.5677]])
    b = np.array([[0.6347], [-0.3891], [-0.1289]])
    r = np.array([-16.7872, 7.2905, 36.4077, 7.4048])
    z = a0 @ x[0, :]
    h0 = np.reshape(z, np.shape(b0)) + b0
    v = np.tanh(h0)
    h1 = a @ v + b
    v2 = np.tanh(h1)
    y_hat = r[0:3] @ v2 + r[3]
    return y_hat
```



```

9 # Make data.
10 X = np.arange(-5, 5, 0.25)
11 Y = np.arange(-5, 5, 0.25)
12 X, Y = np.meshgrid(*xi: X, Y)
13 Z = np.sin(X+Y)
14
15 # Plot the surface.
16 surf = ax.plot_surface(X, Y, Z, cmap=cm.coolwarm,
17                          linewidth=0, antialiased=False)

```

Figure4

Shape of X+Y  
(40,40)

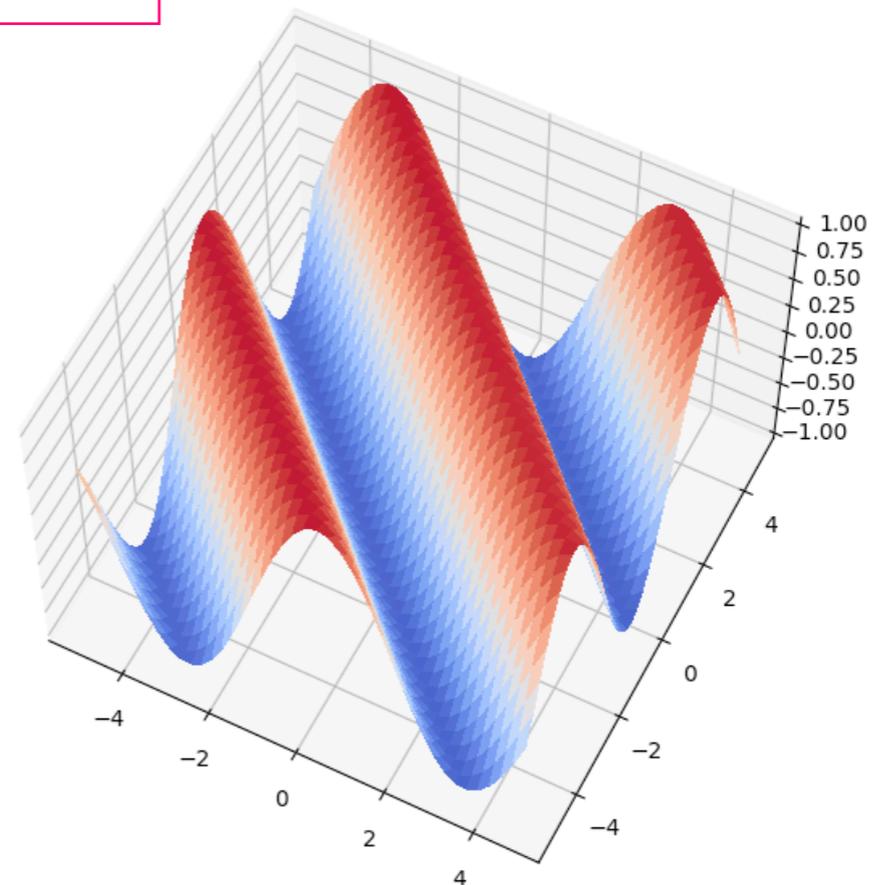
```

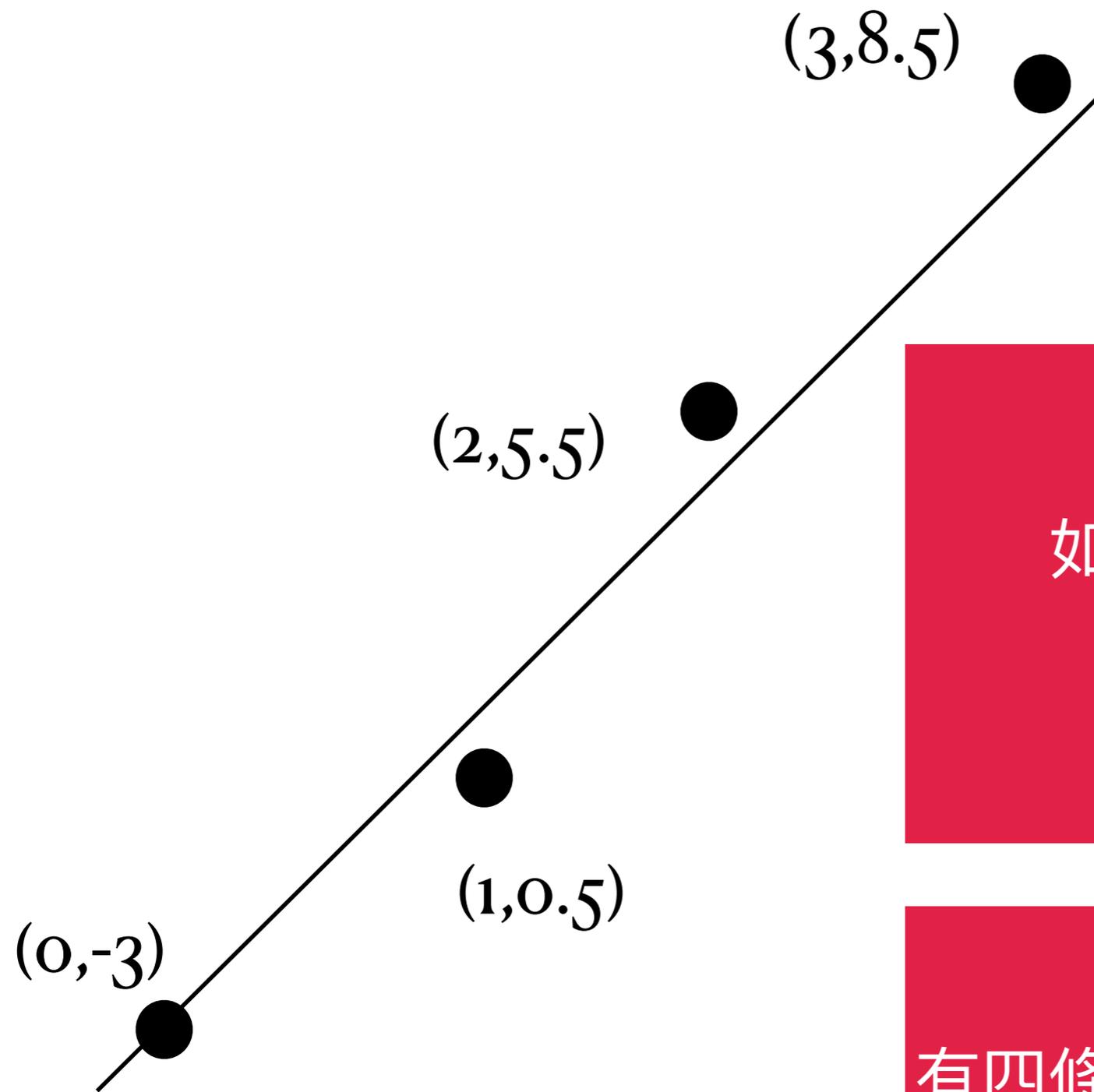
25 x = np.random.rand(1, 2) * 4 * np.pi - 2 * np.pi
26 y = np.sin(x[0, 0] + x[0, 1])
27 ● y_hat = mySin(x)
28 print((y - y_hat[0]) ** 2)

```

Shape of x  
(1, 2)

```
28 X = np.arange(-5, 5, 0.25)
29 Y = np.arange(-5, 5, 0.25)
30 X, Y = np.meshgrid(*xi: X, Y)
31 shapeX = np.shape(X)
32 Z = np.zeros((shapeX[0], shapeX[1]))
33 v = np.random.rand(1, 2)
34 for i in range(shapeX[0]):
35     for j in range(shapeX[1]):
36         v[0, 0] = X[i, j]
37         v[0, 1] = Y[i, j]
38         Z[i, j] = mysin(v)
```





四點不共線  
如何求出最好的一條線，  
描述這四點呢？

線性系統是長方形的  
有四條方程式，但是只有兩個未知  
數

步驟一：匯入  
套裝

```
import numpy as np
from numpy.linalg import inv
```

步驟二：將資料以  
矩陣A向量b表示

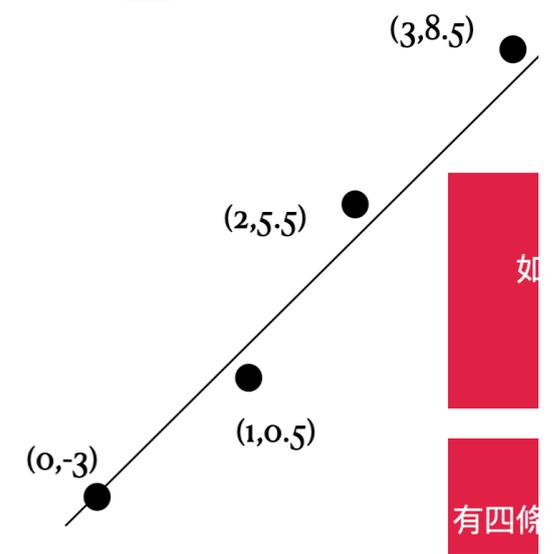
```
A = np.matrix([[2, 1], [1, 1], [3, 1], [0, 1]])
b = np.matrix([[5.5], [0.5], [8.5], [-3]])
```

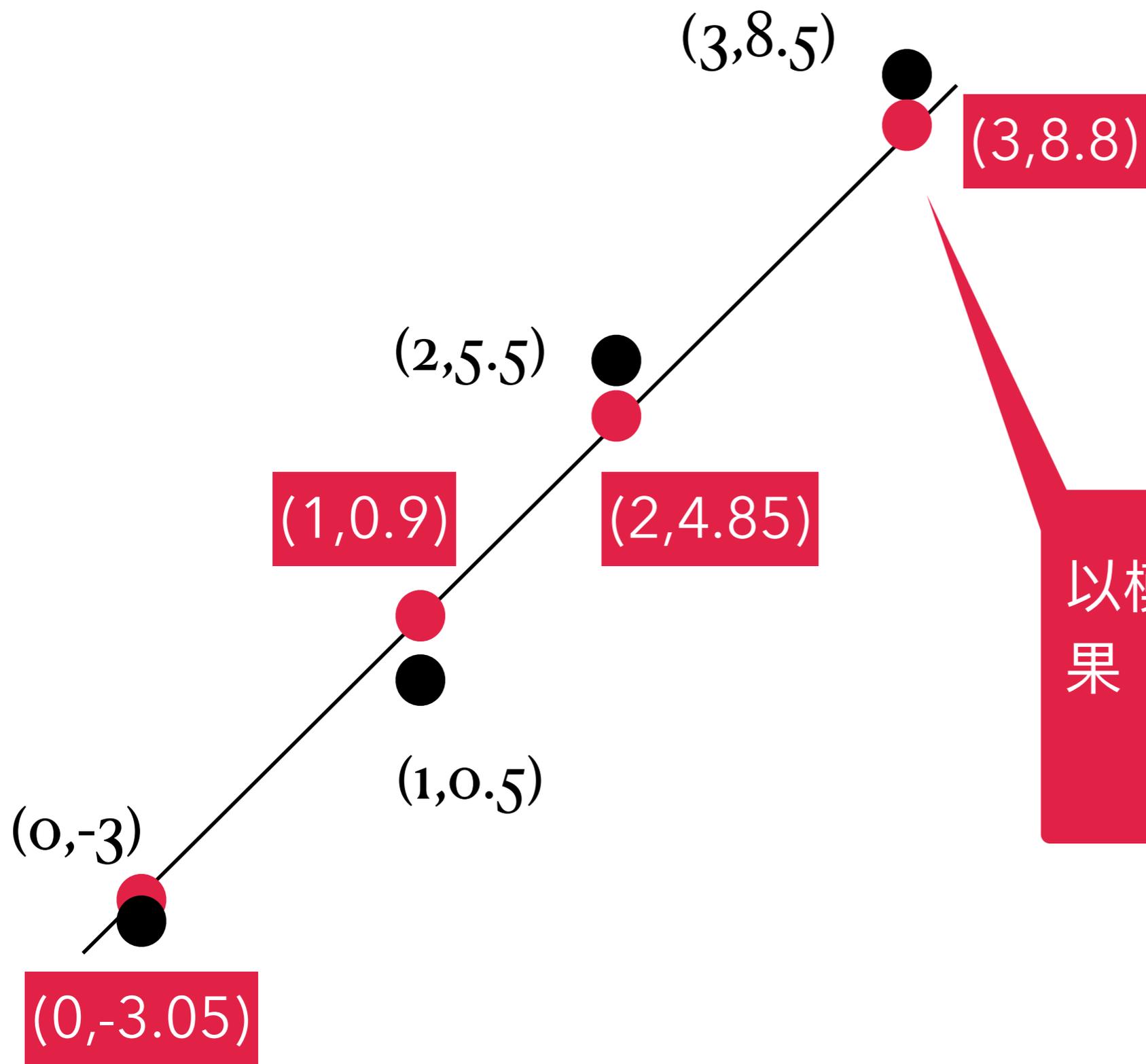
步驟三：求轉置矩陣

```
AT = np.matrix. (A)
```

步驟四：求最佳參數

```
B = A.T * A
invB = inv(B)
ans = invB * A.T * b
```





以模型校正或近似的結果，讓我們對實驗資料有進一步的認識

```
import numpy as np  
from numpy.linalg import inv
```

# Matrix

```
A = np.matrix([range(1,5)])
```

```
matrix([[1, 2, 3, 4]])
```

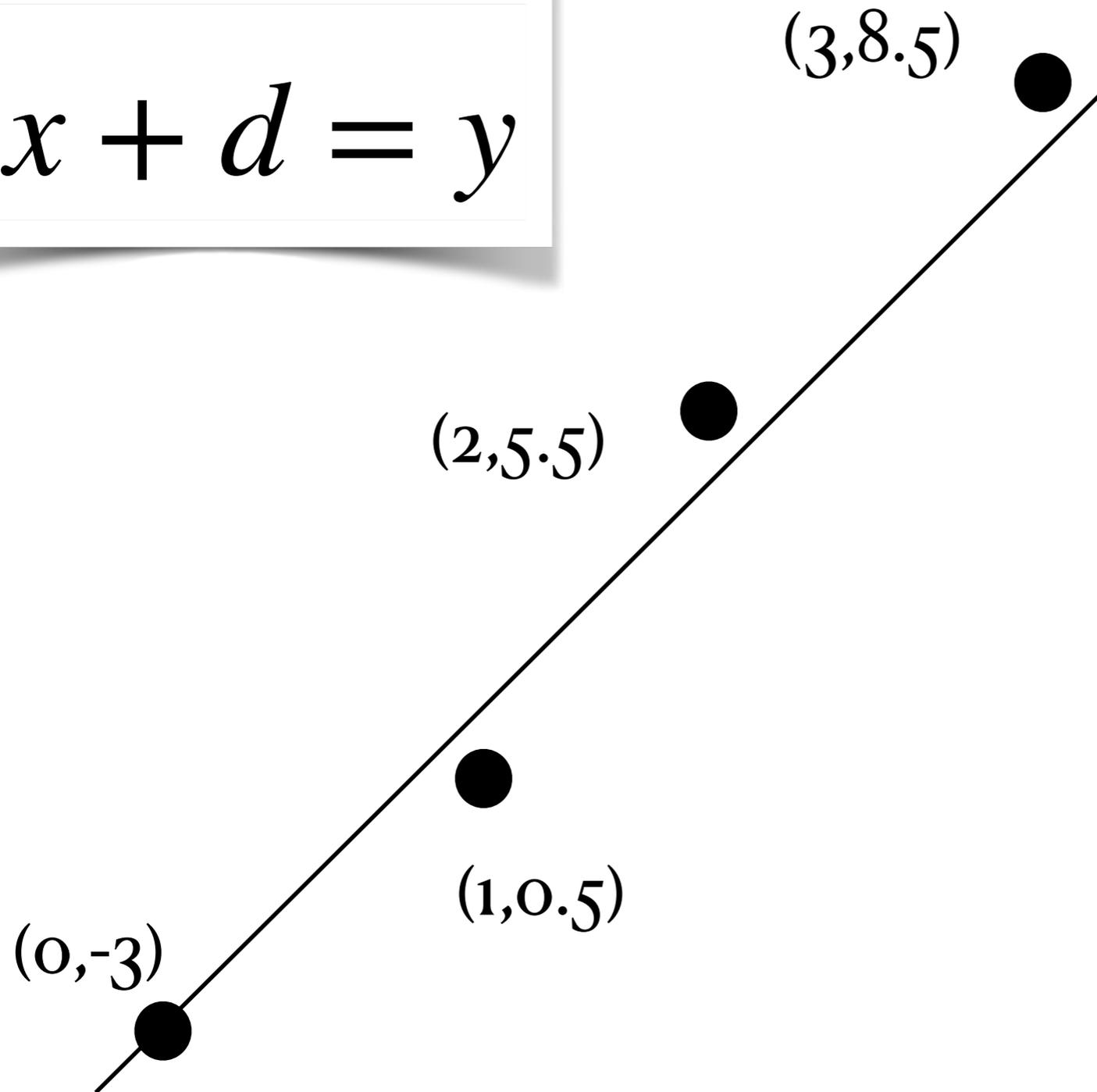
# 轉置矩陣

# Matrix 轉置

```
A = np.matrix([range(1,5)])  
np.matrix.transpose(A)
```

```
>>> np.matrix.transpose(A)  
matrix([[1],  
        [2],  
        [3],  
        [4]])
```

$$ax + d = y$$



$$\begin{bmatrix} x & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = y$$

$$\begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = 5.5$$

$$\begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = 0.5$$

$$\begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = -3$$

$$\begin{bmatrix} 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = 8.5$$

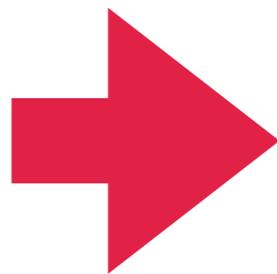
$$ax + d = y$$

(0,-3)

(1,0.5)

(2,5.5)

(3,8.5)



$$[2 \ 1] \begin{bmatrix} a \\ d \end{bmatrix} = 5.5$$

$$[1 \ 1] \begin{bmatrix} a \\ d \end{bmatrix} = 0.5$$

$$[0 \ 1] \begin{bmatrix} a \\ d \end{bmatrix} = -3$$

$$[3 \ 1] \begin{bmatrix} a \\ d \end{bmatrix} = 8.5$$

$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 0 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

# 長方形的系統

$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 0 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

矩陣A

$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 0 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

向量b

```
A = np.matrix([[2, 1], [1, 1], [3, 1], [0, 1]])  
b = np.matrix([[5.5], [0.5], [8.5], [-3]])
```

```
>>> A  
matrix([[2, 1],  
        [1, 1],  
        [3, 1],  
        [0, 1]])
```

```
>>> b  
matrix([[ 5.5],  
        [ 0.5],  
        [ 8.5],  
        [-3. ]])
```

```
A = np.matrix([[2, 1], [1, 1], [3, 1], [0, 1]])  
b = np.matrix([[5.5], [0.5], [8.5], [-3]])
```

可以求A的反矩陣嗎？

反矩陣一定是正方形的矩陣才有反矩陣

使用轉置矩陣  
讓等號左邊變成  
正方形矩陣

$2 \times 4$  $A^t$  $4 \times 2$  $A$  $2 \times 4$  $A^t$  $4 \times 1$  $b$ 

$$\begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 0 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

$$\begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 0 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

```
A = np.matrix([[2, 1], [1, 1], [3, 1], [0, 1]])  
b = np.matrix([[5.5], [0.5], [8.5], [-3]])  
AT = np.transpose(A)  
AT @ A
```

```
>>> print(AT@A)  
[[14  6]  
 [ 6  4]]
```

```
>>> AT @ b  
matrix([[37. ],  
        [11.5]])
```

$$\begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 0 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

```
>>> print(AT@A)
[[14  6]
 [ 6  4]]
```

```
>>> AT @ b
matrix([[37. ],
        [11.5]])
```

$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

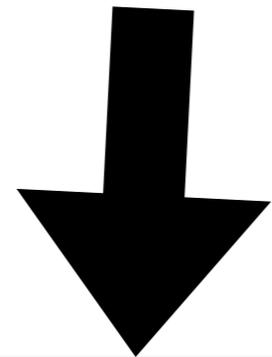
$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

可以使用反矩陣嗎？

等號左邊已經是正方形矩陣  
那就可能有反矩陣

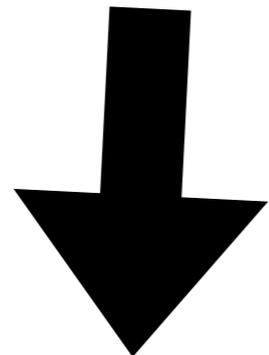
觀察：向量元素不同

討論： $d$ 不是只代表截距  
那代表什麼呢？



$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

$d$ 代表截距+雜訊  
因為點不在直線上



$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

$$ax + d = y$$

在上方，是正  
雜訊

在下方，是負  
雜訊

近似的概念：  
容忍雜訊  
直接求解

$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

# 最小（平方）近似誤差 提供近似概念

可以求最小（平方）近似誤差的直線

近似的概念：

忽略雜訊，直接求解

$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

$$\begin{bmatrix} a \\ d \end{bmatrix} = \mathit{inv}\left( \begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \right) \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

```
B = np.matrix([[14,6],[6,4]])  
invB = inv(B)  
ans = invB @ np.matrix([[37],[11.5]])
```

```
>>> A  
matrix([[14, 6],  
        [ 6, 4]])
```

```
>>> invA  
matrix([[ 0.2, -0.3],  
        [-0.3,  0.7]])
```

$$\text{inv}\left(\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix}\right) \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$

```
>>> ans  
matrix([[ 3.95],  
        [-3.05]])
```

```
A = np.matrix([[2, 1], [1, 1], [3, 1], [0, 1]])  
b = np.matrix([[5.5], [0.5], [8.5], [-3]])  
AT = np.transpose(A)
```

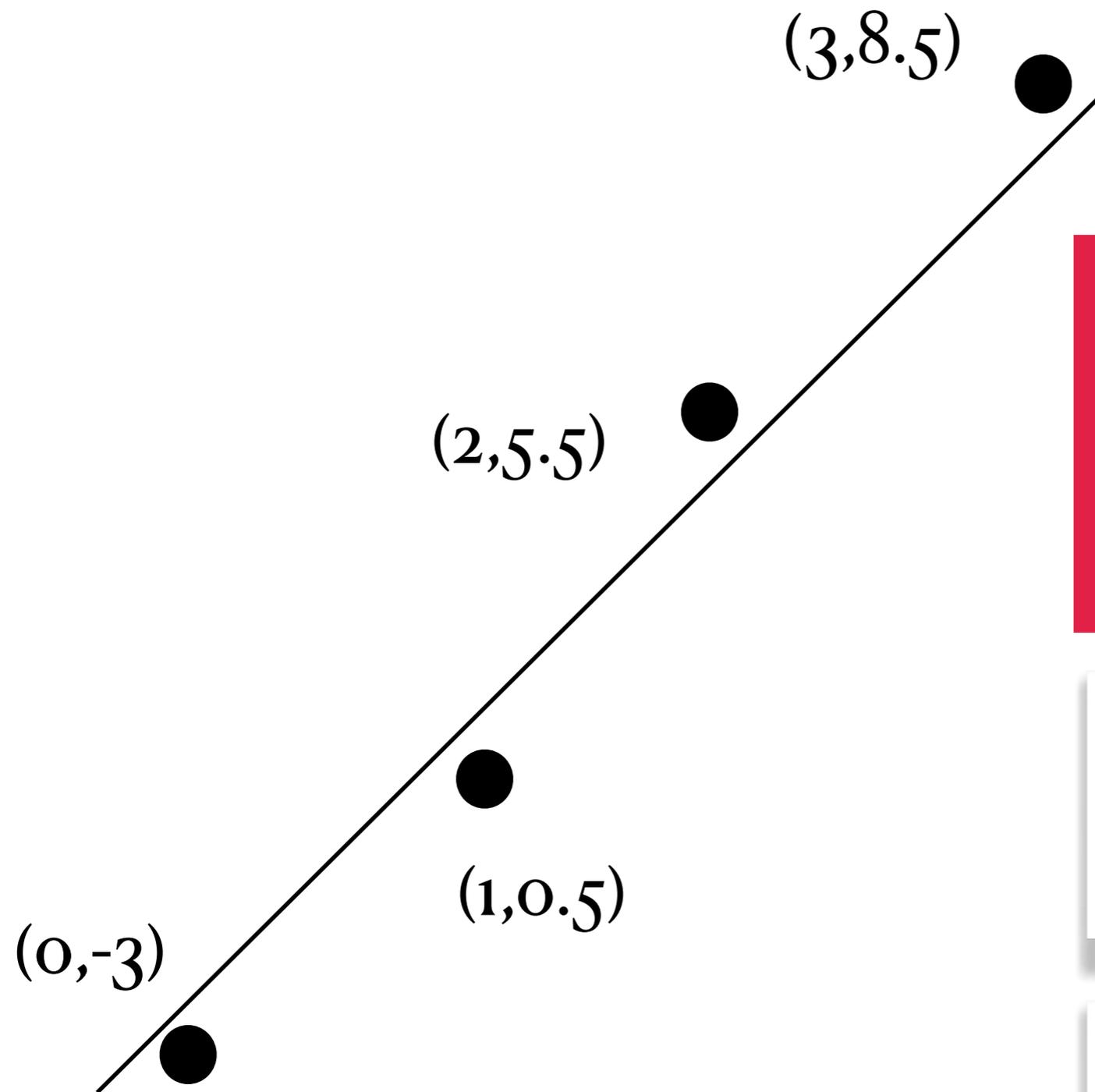
```
B = AT @ A  
invB = inv(B)  
ans = invB @ AT @ b
```

$$ax + d = y$$

$$a = 3.95, \quad d = -3.05$$

```
>>> ans  
matrix([[ 3.95],  
        [-3.05]])
```

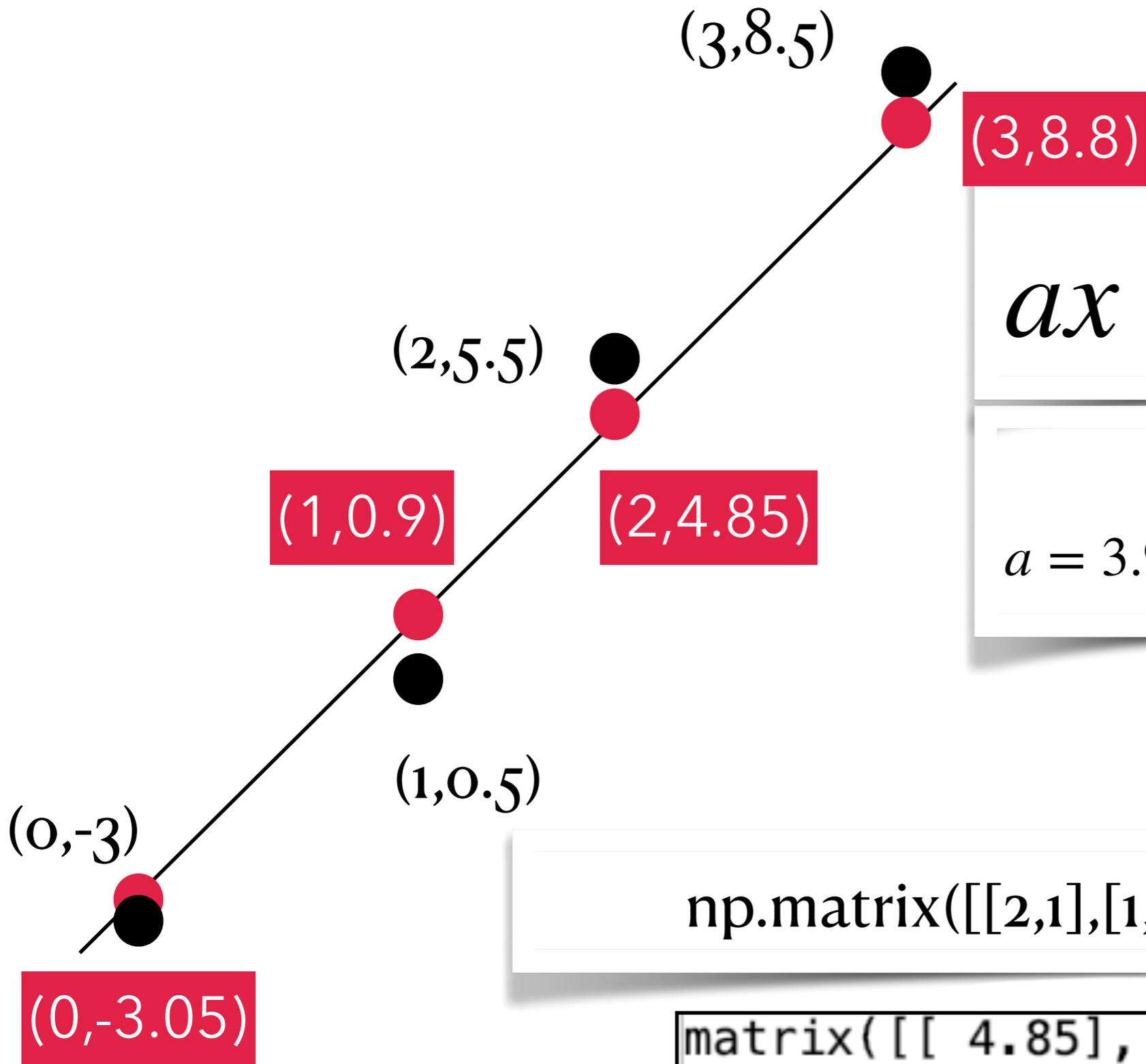
$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 37 \\ 11.5 \end{bmatrix}$$



四點不共線  
如何求出最好的一條線，  
描述這四點呢？

$$ax + d = y$$

$$a = 3.95, \quad d = -3.05$$

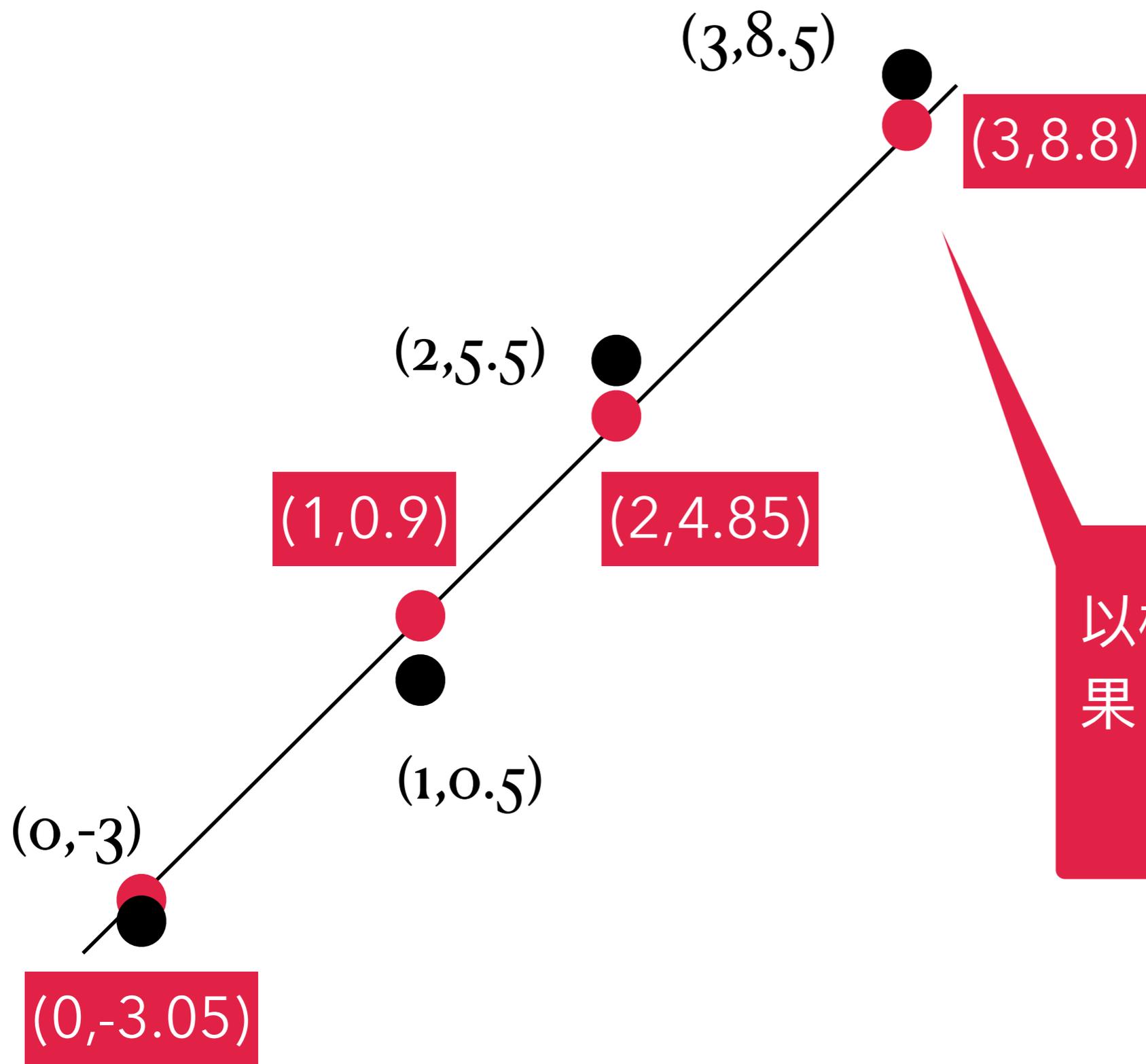


$$ax + d = y$$

$$a = 3.95, \quad d = -3.05$$

```
np.matrix([[2,1],[1,1],[0,1],[3,1]]) @ ans
```

```
matrix([[ 4.85],  
        [ 0.9 ],  
        [-3.05],  
        [ 8.8 ]])
```



以模型校正或近似的結果，讓我們對實驗資料有進一步的認識

# 方法

$A^t$  $A$  $A^t$  $b$ 

$$\begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 1 \\ 0 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

$$B = A^t A$$

$$A^t$$

$$b$$

$$\begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} a \\ d \end{bmatrix} = \begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

$B^{-1}$  $A^t$  $b$ 

$$\begin{bmatrix} a \\ d \end{bmatrix} = \text{inv}\left( \begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \right) \begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

$B^{-1}$  $A^t$  $b$ 

$$\begin{bmatrix} a \\ d \end{bmatrix} = \text{inv}\left( \begin{bmatrix} 14 & 6 \\ 6 & 4 \end{bmatrix} \right) \begin{bmatrix} 2 & 1 & 0 & 3 \\ 1 & 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} 5.5 \\ 0.5 \\ -3 \\ 8.5 \end{bmatrix}$$

$B = AT @ A$

$\text{inv}B = \text{inv}(B)$

$\text{ans} = \text{inv}B @ AT @ b$

步驟一：匯入  
套裝

```
import numpy as np  
from numpy.linalg import inv
```

步驟二：將資料以  
矩陣A向量b表示

```
A = np.matrix([[2, 1], [1, 1], [3, 1], [0, 1]])  
b = np.matrix([[5.5], [0.5], [8.5], [-3]])
```

步驟三：求轉置矩陣

```
AT = np.transpose(A)
```

步驟四：求最佳參數

```
B = AT @ A  
invB = inv(B)  
ans = invB @ AT @ b
```

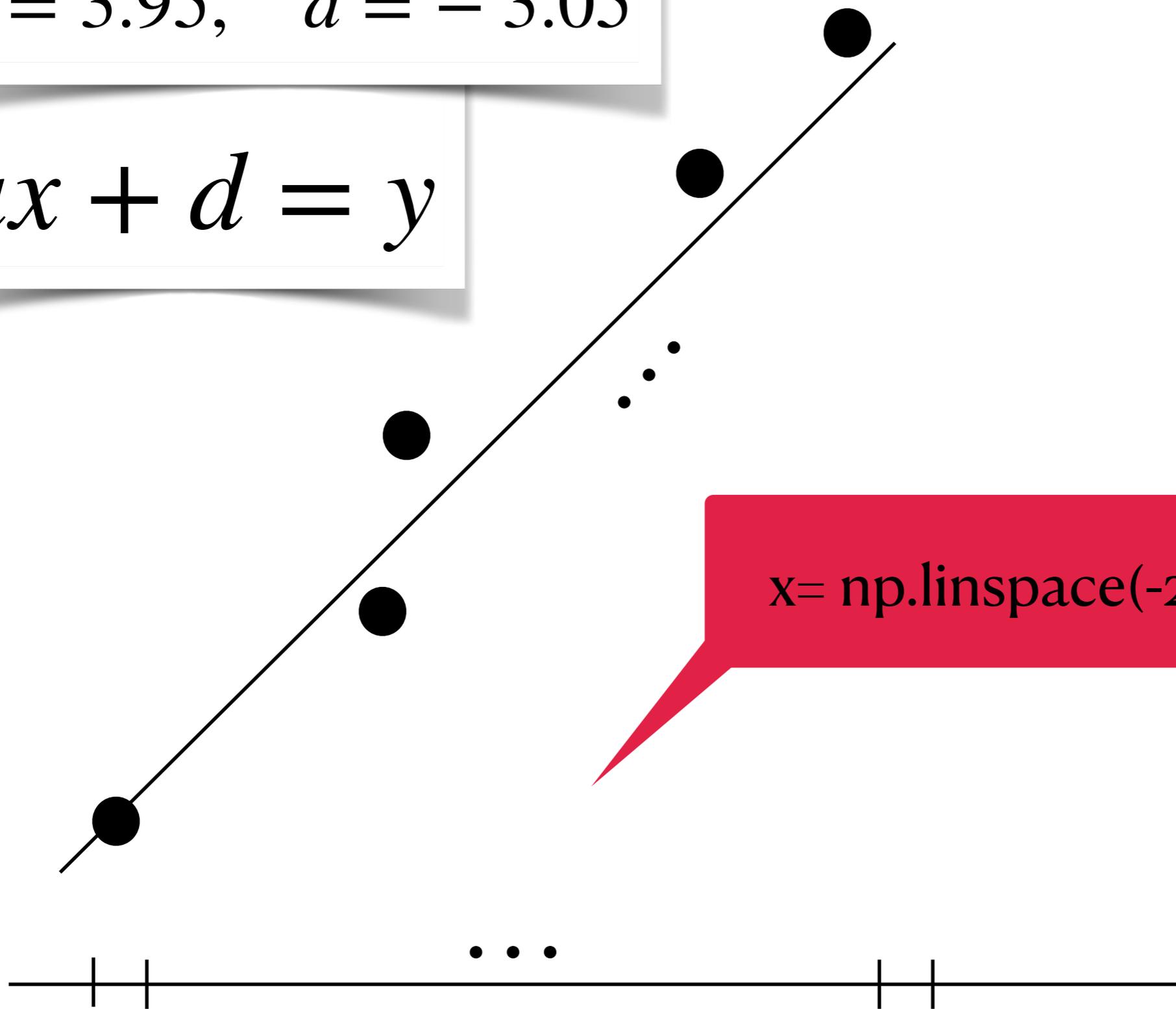
# 製作模擬的實驗資料

可以擴充到更多點？

在 $[-2\pi, 2\pi]$ 的區間取50點  
對應到直線上，取值加雜訊

$$a = 3.95, \quad d = -3.05$$

$$ax + d = y$$

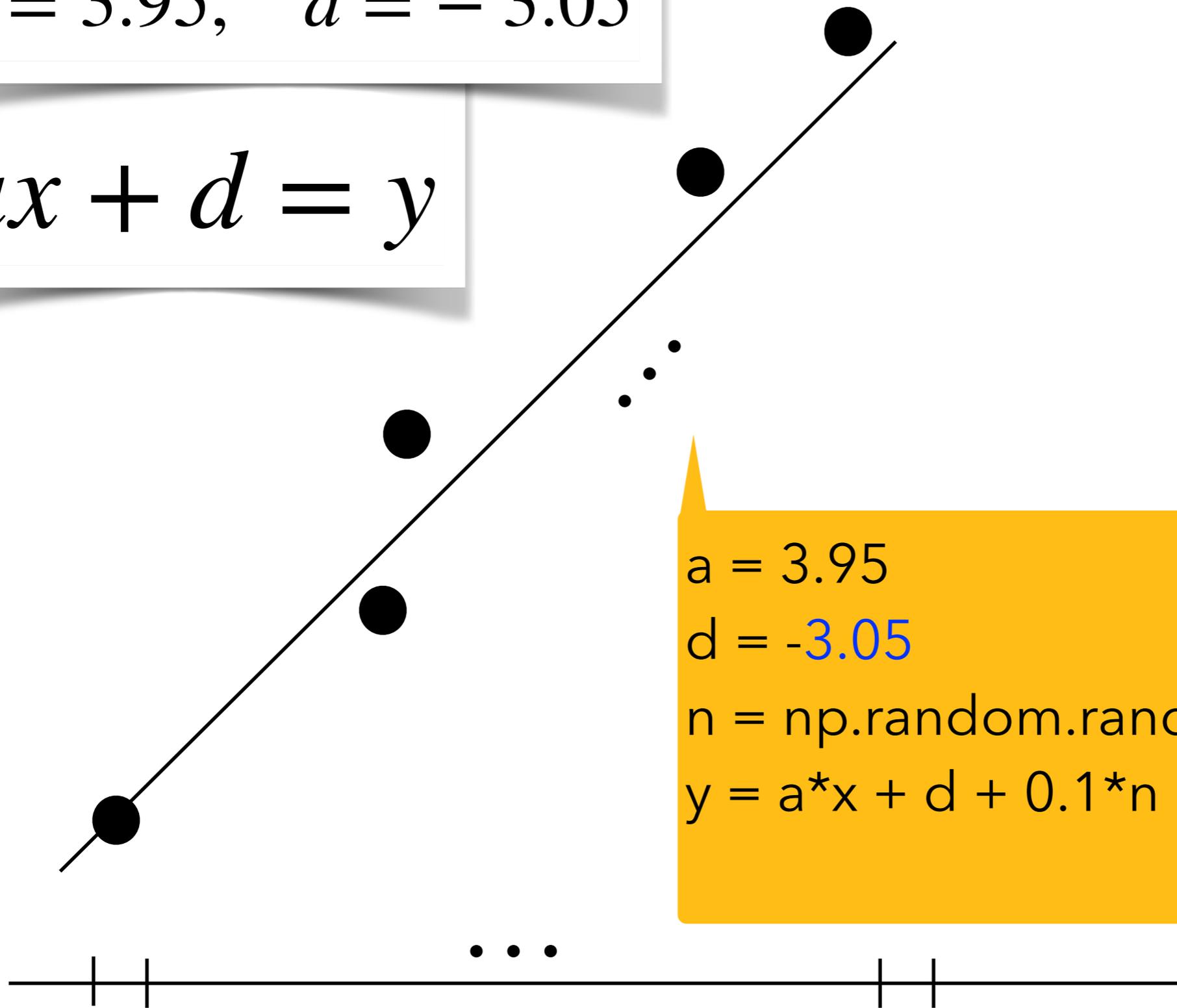


```
x = np.linspace(-2*np.pi, 2*np.pi)
```

$[-2\pi, 2\pi]$

$$a = 3.95, \quad d = -3.05$$

$$ax + d = y$$



$$a = 3.95$$

$$d = -3.05$$

$$n = \text{np.random.rand}(1,50)-0.5$$

$$y = a*x + d + 0.1*n$$

$$[-2\pi, 2\pi]$$

```
x = np.linspace(-2*np.pi, 2*np.pi)
```

```
a = 3.95
```

```
d = -3.05
```

```
n = np.random.rand(1, 50) - 0.5
```

```
x = np.linspace(-2*np.pi, 2*np.pi)
```

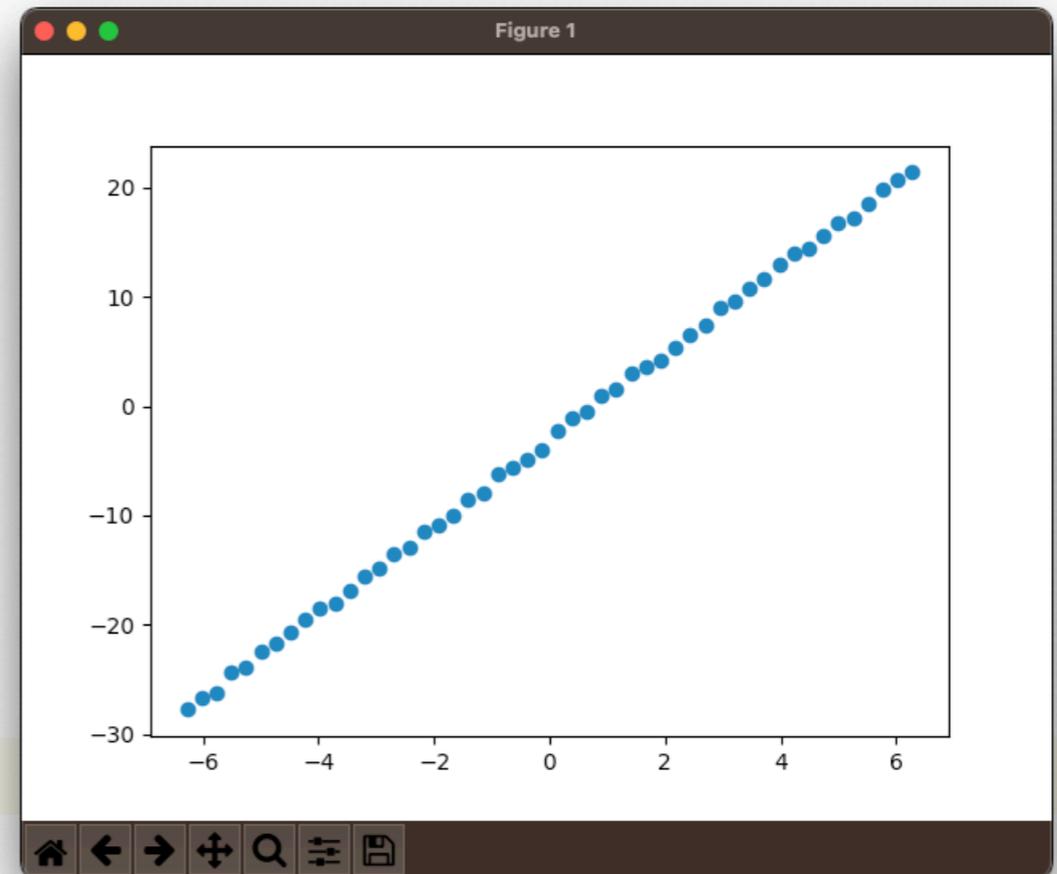
```
y = a*x + d + 0.1 * n
```

```
vx = np.matrix(x)
vy = np.matrix(y)
```

```
A = np.hstack((np.transpose(vx), np.ones((50, 1))))
b = np.transpose(vy)
```

如何使用步驟三、步驟四  
求直線參數？

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3
4 a = 3.95
5 d = -3.05
6 x = np.linspace(-2*np.pi, 2*np.pi)
7 print(np.shape(x))
8 n = np.random.rand(1, 50) - 0.5
9 y = a * x + d + n
10
11 plt.figure()
12 plt.scatter(x, y, marker='o')
13 plt.show()
14
15
```



```
AT = np.transpose(A)
B = AT @ A
invB = inv(B)
ans = invB @ (AT @ b)
```

# A plane with seven parameters

## Sampling data

- $y = ax_1 + bx_2 + cx_3 + dx_4 + ex_5 + fx_6 + g$

```
import numpy as np
from numpy.linalg import inv
a = 3.95
b = 1.2
c = -2.5
d = -3.05
e = 2
f = -1
g = -1.5
dim = 5
dataSize = 500
x = np.random.rand(6, 500)
print(x.shape)
y = np.array([[a,b,c,d,e,f]]) @ x + g
print(y.shape)
```

$A$  $y$ 

$$\begin{bmatrix} x_1[1] & x_2[1] & x_3[1] & x_4[1] & x_5[1] & 1 \\ x_1[2] & x_2[2] & x_3[2] & x_4[1] & x_5[2] & 1 \\ \dots & & & & & \\ x_1[500] & x_2[500] & x_3[500] & x_4[500] & x_5[500] & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \\ g \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_{500} \end{bmatrix}$$

 $A^t$  $A$  $\begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \\ g \end{bmatrix}$  $=$  $A^t y$

$$A^t A \begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \\ g \end{bmatrix} = A^t y$$

$$\begin{bmatrix} a \\ b \\ c \\ d \\ e \\ f \\ g \end{bmatrix} = (A^t A)^{-1} A^t y$$

# Solve by matrix inversion

$$A = \begin{bmatrix} x_1[1] & x_2[1] & x_3[1] & x_4[1] & x_5[1] & 1 \\ x_1[2] & x_2[2] & x_3[2] & x_4[1] & x_5[2] & 1 \\ \dots & & & & & \\ x_1[500] & x_2[500] & x_3[500] & x_4[500] & x_5[500] & 1 \end{bmatrix}$$

```
A = np.hstack((np.transpose(x), np.ones((dataSize, 1))*g))
print(A.shape)
AT = np.transpose(A)
ans = inv(AT @ A) @ ( AT @ np.transpose(y) )
print(ans)
```

$$(A^t A)^{-1} A^t y$$

```
16 A = np.hstack((np.transpose(x), np.ones((dataSize, 1))*g))
17 print(A.shape)
18 AT = np.transpose(A)
19 ans = inv(AT @ A) @ (AT @ np.transpose(y))
20 print(ans)
```

thon Console x

```
[[ 3.95]
 [ 1.2 ]
 [-2.5 ]
 [-3.05]
 [ 2.  ]
 [-1.  ]
 [ 1.  ]]
```

# Solve by conjugate gradient method

```
import numpy as np
def conjgrad(A, b, x0, tol):
    r = b - A @ x0
    p = r
    rsold = np.transpose(r) @ r
    x = x0
    count = 0
    while np.sqrt(rsold) > tol:
        Ap = A @ p
        alpha = rsold / (np.transpose(p) @ Ap)
        x = x + alpha * p
        r = r - alpha * Ap
        rsnew = np.transpose(r) @ r
        p = r + (rsnew/rsold) * p
        rsold = rsnew
        count += 1
        if count % 2000 == 0:
            print('loop ', count)
            break
    return x
```



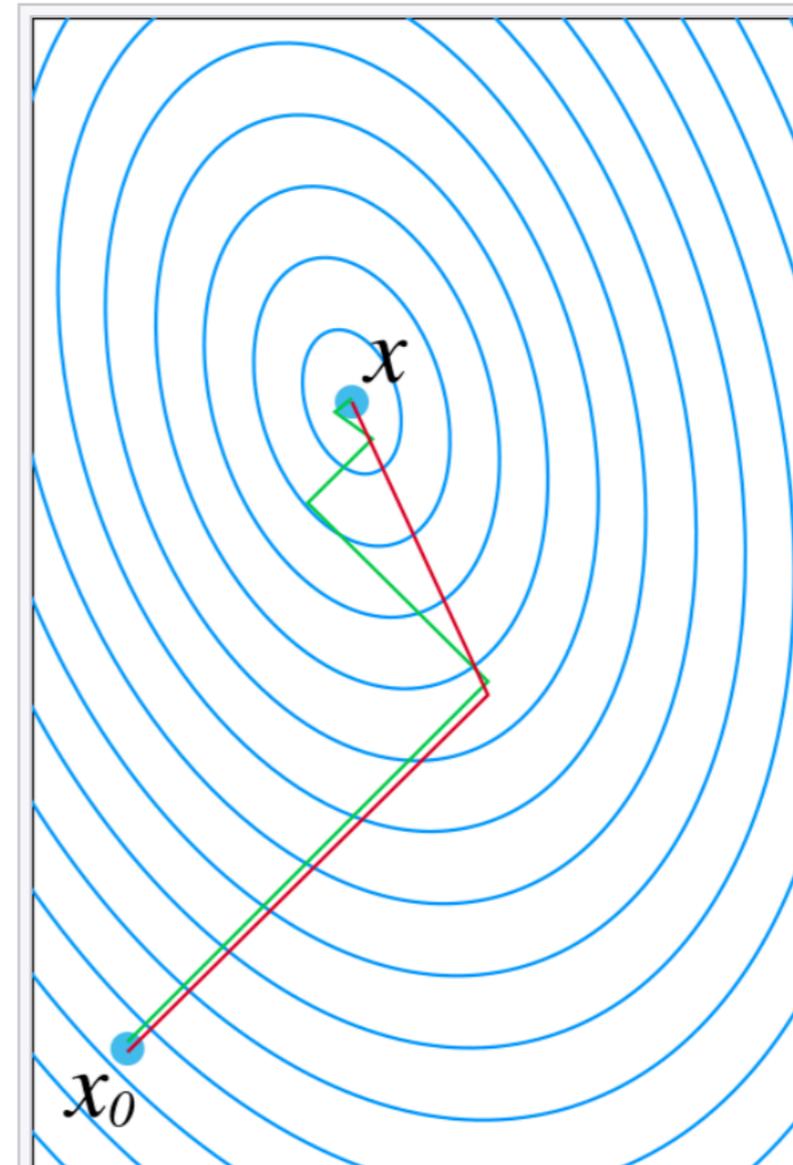
conjgrad.py

# Conjugate gradient method

Article [Talk](#)

From Wikipedia, the free encyclopedia

In [mathematics](#), the **conjugate gradient method** is an [algorithm](#) for the [numerical solution](#) of particular [systems of linear equations](#), namely those whose matrix is [positive-semidefinite](#). The conjugate gradient method is often implemented as an [iterative algorithm](#), applicable to [sparse systems](#) that are too large to be handled by a direct implementation or other direct methods such as the [Cholesky decomposition](#). Large sparse systems often arise when numerically solving [partial differential equations](#) or optimization problems.



A comparison of the convergence of [gradient descent](#) with optimal step size (in green) and conjugate vector (in red) for minimizing a quadratic function associated with a given linear system. Conjugate gradient, assuming exact arithmetic, converges in at most  $n$  steps, where  $n$  is the size of the matrix of the system (here  $n = 2$ ).

```
from conjgrad import *  
b = np.transpose(y)  
ans = conjgrad(AT @ A, AT @ np.transpose(y), np.zeros((7,1)), 10**-8)  
print(ans)
```

```
[[ 3.95]  
 [ 1.2 ]  
 [-2.5 ]  
 [-3.05]  
 [ 2.  ]  
 [-1.  ]  
 [ 1.  ]]
```

```
from conjgrad import *
import time
n = 10000
m = 30
AA = np.random.randn(n,m)
A = AA @ np.transpose(AA) + np.eye(n)
x = np.random.rand(n,1)
b = A@x
t = time.time()
ans = conjgrad(A,b,np.zeros((n,1)),10**-8)
tt = t = time.time() - t
print('mean abs error : ', np.mean(abs(A @ ans - b)))
print('execution time :', tt)
```

A is symmetric  
A : 10000x10000

conjgrad is accurate and  
fast

```
mean abs error : 1.5202749636955558e-11
execution time : 0.7015669345855713
```

```
from conjgrad import *
import time
n = 10000
m = 30
AA = np.random.randn(n,m)
A = AA @ np.transpose(AA) + np.eye(n)
x = np.random.rand(n,1)
b = A@x
t = time.time()
ans = inv(A)*b
tt = t = time.time() - t
print('mean abs error : ', np.mean(abs(A @ ans - b)))
print('execution time :', tt)
```

A is symmetric  
A : 10000x10000

inv is slow

execution time : 26.37588119506836