

## 1)

由最小二乘解的几何意义知

$r = b - Ax$ 是与 $\text{span}(A)$ 垂直的向量

所以 $r$ 具有唯一性, 即 $Ax_1 = Ax_2$

## 2)

$$\sum \|Ax - b_i\|_2^2 = \sum (Ax - b_i) \cdot (Ax - b_i) = \sum_j \sum_i ((Ax)_i - b_{ji})^2 = \sum_i \sum_j ((Ax)_i - b_{ji})^2$$

由于 $(Ax)_i$ 各自独立, 要使其最小, 则 $\sum_j ((Ax)_i - b_{ji})^2$ 最小

$$\text{所以 } (Ax)_i = \frac{1}{r} \sum_j b_{ji}$$

$$\text{得 } Ax = \frac{1}{r} \sum_i b_i$$

## 3)

$$\because \alpha = (X^T X)^{-1} X^T Y$$

$\therefore$  此时最小二乘解具有唯一性

而Lagrange插值在这种情况下的平方和为0, 是最小二乘解

由唯一性, 得证

## 4)

利用python进行编程计算

```
import numpy as np
x = np.array([-3, -2, -1, 0, 1, 2, 3])
y = np.array([4, 2, 3, 0, -1, -2, -5])
Y = np.array([y]).T
x0 = np.zeros(7, int) + 1
x2 = x**2
A = np.array([x0, x, x2])
A = A.T
print(np.linalg.inv(A.T.dot(A)).dot(A.T).dot(Y))
'''
Out:
[[ 0.66666667]
 [-1.39285714]
 [-0.13095238]]
'''
```

所以 $a_0 = 0.667, a_1 = -1.393, a_2 = -0.131$

## 5)

利用python进行编程计算

```
import numpy as np
x = np.array([1.02, 0.95, 0.87, 0.77, 0.67, 0.56, 0.44, 0.3, 0.16, 0.01])
y = np.array([0.39, 0.32, 0.27, 0.22, 0.18, 0.15, 0.13, 0.12, 0.13, 0.15])
Z = np.array([x**2]).T
x1 = y**2
x2 = x*y
x3 = x
x4 = y
x5 = np.zeros(10, int) + 1
A = np.array([x1, x2, x3, x4, x5]).T
print(np.linalg.inv(A.T.dot(A)).dot(A.T).dot(Z))
'''
Out:
[[-2.63562548]
 [ 0.14364618]
 [ 0.55144696]
 [ 3.22294034]
 [-0.43289427]]
'''
```

所以 $a = -2.636$ ,  $b = 0.144$ ,  $c = 0.551$ ,  $d = 3.223$ ,  $e = -0.433$