

# 02-712 Biological Modeling and Simulations: Homework 2

Thomas Zhang

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## Question 1

a)

$$\begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ c_{n+1,1} & c_{n+1,2} & \cdots & c_{n+1,n} & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \\ g_0 \end{bmatrix} = \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_n \\ g_{n+1} \end{bmatrix}$$

$c_{i,j}$  is the  $j'$ th condition during the  $i'$ th experiment.  $x_i$  is the contribution that environment condition  $c_i$  contributes to the overall growth rate.  $g_i$  is the growth rate of the  $i'$ th experiment. The system is full rank since there are  $n + 1$  weights to learn and there are  $n + 1$  equations. Since the matrix is full rank, an iterative solving algorithm like Krylov-Subspace can be used.

b)

$$\begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ c_{2n,1} & c_{2n,2} & \cdots & c_{2n,n} & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \\ g_0 \end{bmatrix} = \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_n \\ g_{2n} \end{bmatrix}$$

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c)

$$\begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} & c_{1,1}c_{1,1} & c_{1,1}c_{1,2} & \cdots & c_{1,n-1}c_{1,n} & c_{1,n}c_{1,n} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ c_{2n,1} & c_{2n,2} & \cdots & c_{2n,n} & c_{2n,1}c_{2n,1} & c_{2n,1}c_{2n,2} & \cdots & c_{2n,n-1}c_{2n,n} & c_{2n,n}c_{2n,n} & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{\frac{n^2-3n}{2}} \\ g_0 \end{bmatrix} = \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_n \\ g_{2n} \end{bmatrix}$$

$c_{i,j}$  is the  $j'$ th condition during the  $i'$ th experiment.  $x_i$  is the contribution that environment condition  $c_i$  contributes to the overall growth rate.  $g_i$  is the growth rate of the  $i'$ th experiment. The system is under determined since there are  $1 + \frac{n^2-3n}{2}$  weights to learn and there are  $2n$  equations. Since the system is under determined there are infinite solutions. So one approach that we can use to solve for  $x$  is to find the pseudo-inverse of  $A$ , which is denoted as  $\bar{A}$  and then calculate  $\bar{A}b = x$ . The pseudo inverse of  $A$  is  $Q_2 \bar{\Sigma} Q_1^T$  where  $\bar{\Sigma}$  the negative transpose of the singular value matrix  $\Sigma$  of  $A$ ,  $Q_1$  is the left singular matrix of  $A$  and  $Q_2$  is the right singular matrix of  $A$  ( $A = Q_1 \Sigma Q_2^T$ ).

c)

$$\begin{bmatrix} c_{1,1} & c_{1,2} & \cdots & c_{1,n} & c_{1,1}c_{1,1} & c_{1,1}c_{1,2} & \cdots & c_{1,n-1}c_{1,n} & c_{1,n}c_{1,n} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ c_{n^2,1} & c_{n^2,2} & \cdots & c_{n^2,n} & c_{n^2,1}c_{n^2,1} & c_{n^2,1}c_{n^2,2} & \cdots & c_{n^2,n-1}c_{n^2,n} & c_{n^2,n}c_{n^2,n} & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{\frac{n^2-3n}{2}} \\ g_0 \end{bmatrix} = \begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_n \\ g_{n^2} \end{bmatrix}$$

$c_{i,j}$  is the  $j'$ th condition during the  $i'$ th experiment.  $x_i$  is the contribution that environment condition  $c_i$  contributes to the overall growth rate.  $g_i$  is the growth rate of the  $i'$ th experiment. The system is over determined since there are  $1 + \frac{n^2-3n}{2}$  weights to learn and there are  $n^2$  equations and  $n^2 > 1 + \frac{n^2-3n}{2}$ . Since the system is over determined, there are multiple solutions, so we can use least squares regression to find a solution that minimizes  $\sum_i a_i x - g_i$  where  $a_i$  is one row of the matrix of conditions  $[c_{1,1}, c_{1,2}, \dots]$ . This can be solved by solving the solution for  $A^T A x = A^T g$ .

## Question 2

$$f(x) = \frac{4}{x^7} - \frac{3}{x^2} + 0.1$$

a)

$$\begin{aligned} f(x_{max}) &= f(1) = \frac{4}{1^7} - \frac{3}{1^2} + 0.1 = 1.1 \\ f(x_{mid}) &= f(2) = \frac{4}{2^7} - \frac{3}{2^2} + 0.1 = -0.61875 \\ f(x_{min}) &= f(3) = \frac{4}{3^7} - \frac{3}{3^2} + 0.1 = -0.23150434385 \end{aligned} \quad (1)$$

$$\begin{aligned} f(x_{max}) &= f(1) = \frac{4}{1^7} - \frac{3}{1^2} + 0.1 = 1.1 \\ f(x_{mid}) &= f(1.5) = \frac{4}{1.5^7} - \frac{3}{1.5^2} + 0.1 = -0.99922267947 \\ f(x_{min}) &= f(2) = \frac{4}{2^7} - \frac{3}{2^2} + 0.1 = -0.61875 \end{aligned} \quad (2)$$

$$\begin{aligned} f(x_{max}) &= f(1) = \frac{4}{1^7} - \frac{3}{1^2} + 0.1 = 1.1 \\ f(x_{mid}) &= f(1.25) = \frac{4}{1.25^7} - \frac{3}{1.25^2} + 0.1 = -0.9811392 \\ f(x_{min}) &= f(1.5) = \frac{4}{1.5^7} - \frac{3}{1.5^2} + 0.1 = -0.99922267947 \end{aligned} \quad (3)$$

The backwards error is 0.5 and the forwards error is 0.9811392 after the  $3^{rd}$  bisection.

b)

$$\begin{aligned} f(x_{max}) &= f(1) = \frac{4}{1^7} - \frac{3}{1^2} + 0.1 = 1.1 \\ f(x_{mid}) &= f(2.65226648352) = \frac{4}{2^7} - \frac{3}{2^2} + 0.1 = -0.322135968884 \\ f(x_{min}) &= f(3) = \frac{4}{3^7} - \frac{3}{3^2} + 0.1 = -0.23150434385 \end{aligned} \quad (4)$$

$$\begin{aligned} f(x_{max}) &= f(1) = \frac{4}{1^7} - \frac{3}{1^2} + 0.1 = 1.1 \\ f(x_{mid}) &= f(2.2780023652) = \frac{4}{1.5^7} - \frac{3}{1.5^2} + 0.1 = -0.465547707306 \\ f(x_{min}) &= f(2.65226648352) = \frac{4}{2^7} - \frac{3}{2^2} + 0.1 = -0.322135968884 \end{aligned} \quad (5)$$

$$\begin{aligned} f(x_{max}) &= f(1) = \frac{4}{1^7} - \frac{3}{1^2} + 0.1 = 1.1 \\ f(x_{mid}) &= f(1.89796216057) = \frac{4}{1.25^7} - \frac{3}{1.25^2} + 0.1 = -0.687723865076 \\ f(x_{min}) &= f(2.2780023652) = \frac{4}{1.5^7} - \frac{3}{1.5^2} + 0.1 = -0.465547707306 \end{aligned} \quad (6)$$

The backwards error is 2.2780023652 and the forwards error is 0.687723865076

c)

$$f'(x) = -7\left(\frac{4}{x^8}\right) + 2\left(\frac{3}{x^3}\right) + 0 = \frac{21}{x^8} + \frac{6}{x^3}$$

$$f(1) = \frac{4}{1^7} - \frac{3}{1^2} + 0.1 = 1.1 \quad (7)$$

$$f(1.05) = \frac{4}{1.05^7} - \frac{3}{1.05^2} + 0.1 = 0.221636885146 \quad (8)$$

$$f(1.06609) = \frac{4}{1.06609^7} - \frac{3}{1.06609^2} + 0.1 = 0.0159992621509 \quad (9)$$

$$f(1.06745) = \frac{4}{1.06745^7} - \frac{3}{1.06745^2} + 0.1 = 0.000102031079136 \quad (10)$$

The estimate of backward error is  $1.06609 - 1.06754 = 0.00145$  and the forward error is 0.000102

### Question 3

a)

$$2a + b + 3c \leq 10$$

$$a + b + 2c \leq 7$$

$$3a + b + c \leq 12$$

$$a \geq 0$$

$$b \geq 0$$

$$c \geq 0$$

$$\operatorname{argmax}_{a,b,c} f(a,b,c) = a + 2b + 5c$$

b)

$$2a + b + 3c + k_1 = 10$$

$$a + b + 2c + k_2 = 7$$

$$3a + b + c + k_3 = 12$$

$$a \geq 0$$

$$b \geq 0$$

$$c \geq 0$$

$$k_1 \geq 0$$

$$k_2 \geq 0$$

$$k_3 \geq 0$$

$$\operatorname{argmin}_{a,b,c} g(a,b,c,k_1,k_2,k_3) = -f(a,b,c) = -a - 2b - 5c$$

c) Let  $a = b = c = 0$

$$k_1 = 10 \quad k_2 = 7 \quad k_3 = 12 \quad g(a,b,c,k_1,k_2,k_3) = 0$$

Increase  $c$  since it causes  $g(a,b,c)$  to drop the fastest.

$$k_1 = 10 - 3c$$

$$k_2 = 7 - 2c$$

$$k_3 = 12 - c$$

Set LHS to 0 for each of the constraints to find how much  $c$  can be increased before some other variable gets set to 0.

$$\begin{array}{ll} 0 = 10 - 3c & c = \frac{10}{3} \\ 0 = 7 - 2c & c = \frac{7}{2} \\ 0 = 12 - c & c = 12 \end{array}$$

$c = \frac{10}{3}$  is the minimum value of  $c$  before some other variable becomes 0, so we set  $c = \frac{10}{3}$  which makes  $k_1 = 0$ . Next we rearrange the constraint with  $k_1$  so that  $c$  is expressed in terms of variables that have been set to 0 and substitute the expression into the other constraints where there is a  $c$ .

$$\begin{aligned} c &= \frac{1}{3}(10 - 2a - b - k_1) \\ k_2 &= 7 - \frac{2}{3}(10 - 2a - b - k_1) - a - b \\ &= \frac{1}{3} + \frac{1}{3}a - \frac{1}{3}b = \frac{1}{3} \\ k_3 &= 12 - \frac{1}{3}(10 - 2a - b - k_1) - 3a - b \\ &= \frac{26}{3} - \frac{7}{3}a - \frac{2}{3}b = \frac{26}{3} \\ g(a,b,c,k_1,k_2,k_3) &= -a - 2b - \frac{5}{3}(10 - 2a - b - k_1) \\ &= \frac{7}{3}a - \frac{1}{3}b + \frac{5}{3}k_1 - \frac{50}{3} = -\frac{50}{3} \end{aligned}$$

$g$  decreases fastest with  $b$  so  $b$  is the next variable to be increased. As before find the minimum amount  $b$  can be increased before some other parameter becomes 0.

$$\begin{aligned} 0 &= \frac{1}{3}(10 - 2a - b - k_1) & b &= 10 - 2a - k_1 = 10 \\ 0 &= \frac{1}{3} + \frac{1}{3}a - \frac{1}{3}b & b &= 1 + a = 1 \\ 0 &= \frac{26}{3} - \frac{7}{3}a - \frac{2}{3}b & b &= \frac{1}{2}(26 - 7a) = 13 \end{aligned}$$

$b = 1$  is the minimum. So we set  $b = 1$  which makes  $k_2 = 0$ .

$$\begin{aligned} b &= 1 + a - 3k_2 \\ c &= \frac{1}{3}(10 - 2a - (1 + a - 3k_2) - k_1) \\ &= \frac{1}{3}(9 - 3a - k_1 + 3k_2) = 3 \\ k_3 &= \frac{26}{3} - \frac{7}{3}a - \frac{2}{3}(1 + a - 3k_2) \\ &= 8 - 3a + 2k_2 = 8 \\ g(a, b, c, k_1, k_2, k_3) &= \frac{7}{3}a - \frac{1}{3}(1 + a - 3k_2) + \frac{5}{3}k_1 - \frac{50}{3} \\ &= 2a + \frac{5}{3}k_1 + k_2 - 17 = -17 \end{aligned}$$

Now no variable can decrease  $g$  so the solution is:

$$a = 0 \quad b = 1 \quad c = 3 \quad k_1 = 0 \quad k_2 = 0 \quad k_3 = 8$$

- d) The optimal solution is to perform single-cell RNA-seq 0 times,  $a = 0$ , perform bulk RNA-seq once,  $b = 1$ , and perform spatial RNA-seq 3 times  $c = 3$ . The utility of this solution is 17
- e) This solution would use \$10,000, take 7 days of time, and require 4 grams of tissue.

## Question 4

a)

$$\begin{bmatrix} \frac{f(A, T, x+dx, y) - f(A, T, x-dx, y)}{2dx} \\ \frac{f(A, T, x, y+dy) - f(A, T, x, y-dy)}{2dy} \end{bmatrix}$$

b)

$$\begin{bmatrix} \frac{d^2 f}{dx^2} & \frac{d^2 f}{dx dy} \\ \frac{d^2 f}{dy dx} & \frac{d^2 f}{dy^2} \end{bmatrix}$$

$$\begin{aligned} \frac{df}{dx^2} &= \frac{f(A, T, x + 2dx, y) - 2f(A, T, x, y) + f(A, T, x - 2dx, y)}{4dx^2} \\ \frac{df}{dx dy} &= \frac{f(A, T, x + dx, y + dy) - f(A, T, x - dx, y + dy) - f(A, T, x + dx, y - dy) + f(A, T, x - dx, y - dy)}{4dx dy} \\ \frac{df}{dy dx} &= \frac{f(A, T, x + dx, y + dy) - f(A, T, x - dx, y + dy) - f(A, T, x + dx, y - dy) + f(A, T, x - dx, y - dy)}{4dx dy} \\ \frac{df}{dy^2} &= \frac{f(A, T, x, y + 2dy) - 2f(A, T, x, y) + f(A, T, x, y - 2dy)}{4dy^2} \end{aligned}$$

c) Newton Rathson Algorithm

**Data:**  $\Delta x, \Delta y$  = increment size of 'finer' grid;  $dx, dy$  = step size for finite derivatives  
 $M, N \leftarrow \text{SHAPE}(A)$   
 $m, n \leftarrow \text{SHAPE}(T)$   
 $\text{best\_score} \leftarrow \infty$   
 $\text{best\_x}, \text{best\_y} \leftarrow 0, 0$   
**for**  $i \leftarrow 0$  **to**  $(N - n)\Delta x$  **do**  
    **for**  $j \leftarrow 0$  **to**  $(M - m)\Delta y$  **do**  
         $x \leftarrow i \times dx$   
         $y \leftarrow j \times dy$   
        **for**  $k \leftarrow 0$  **to** 10 **do**  
             $\text{Grad} \leftarrow \text{GRADIENT}(A, T, x, y, dx, dy)$   
             $\text{Hess} \leftarrow \text{HESSIAN}(A, T, x, y, dx, dy)$   
             $x \leftarrow x + \text{Hess}^{-1} \text{Grad}[0]$   
             $y \leftarrow y + \text{Hess}^{-1} \text{Grad}[1]$   
        **end**  
        **if**  $\text{SCORE}(A, T, x, y) < \text{best\_score}$  **then**  
             $\text{best\_score} \leftarrow \text{SCORE}(A, T, x, y)$   
             $\text{best\_x} \leftarrow x$   
             $\text{best\_y} \leftarrow y$   
        **end**  
    **end**  
**end**  
**return**( $\text{best\_x}, \text{best\_y}$ )

d, e) For test case 1 the best coordinates were (4.499997017072263, 3.5) For test case 2 the best coordinates were (4.876557112637574, 0.3019367812834329)

## Question 5

a)

$$a_i \vec{x} - b_i = c_i - d_i \quad \forall i \in \{1, 2, \dots, m\}$$

$$\begin{aligned} \underset{x}{\operatorname{argmin}} \quad & f(c, d) = \sum_i c_i + d_i \\ & c_i \geq 0 \quad \forall i \in \{1, 2, \dots, m\} \\ & d_i \geq 0 \quad \forall i \in \{1, 2, \dots, m\} \end{aligned}$$

$m$  is the number of rows of the matrix  $A$ .  $a_i$  is the  $i$ 'th row of the matrix  $A$ .  $b_i$  is the  $i$ 'th element in vector  $b$ . An algorithm that can be used to solve this linear program is an iterative algorithm like Krylov-Subspace if the program is full rank. If the matrix is over determined then we can use least-squares optimization. Lastly if the matrix is under determined we can just solve for the pseudo-inverse and calculate  $\bar{A}b$ .

b)

$$\begin{aligned} x_i &= c_i - d_i \quad \forall i \in \{1, 2, \dots, m\} \\ \underset{x}{\operatorname{argmin}} \quad & f(x, c, d) = \sum_i (a_i \vec{x}_i - b_i)^2 + \lambda(c_i + d_i) \\ & c_i \geq 0 \quad \forall i \in \{1, 2, \dots, m\} \\ & d_i \geq 0 \quad \forall i \in \{1, 2, \dots, m\} \end{aligned}$$

$m$  is the number of rows of the matrix  $A$ .  $a_i$  is the  $i$ 'th row of the matrix  $A$ .  $b_i$  is the  $i$ 'th element in vector  $b$ . One algorithm that we can use to solve for  $\vec{x}$  is the conjugate gradient algorithm which generally works with non-linear programs.

c) The least squares regressions optimization equation is  $\|A\vec{x} - \vec{b}\|_2^2$ . This is a convex function. The L1 regularization term is an absolute value, which is also a convex function. The objective function for part b, is the sum of two convex functions, and the sum of two convex functions is also convex. Thus the objective function for b which is:

$$f(x, c, d) = \sum_i (a_i \vec{x}_i - b_i)^2 + \lambda(c_i + d_i)$$

is also convex.