

# CS5321 Numerical Optimization Homework 1

Due Oct 28

1. (30%) For a single variable unimodal function  $f \in [0, 1]$ , we want to find its minimum. We have introduced the binary search algorithm in the class. But in each iteration, we need two function evaluations,  $f(x_k)$  and  $f(x_k + \epsilon)$ . Here is another type of algorithms, called ternary search. Figure 1 illustrates the idea. The initial triplet of  $x$  values is  $\{x_1, x_2, x_3\}$ .

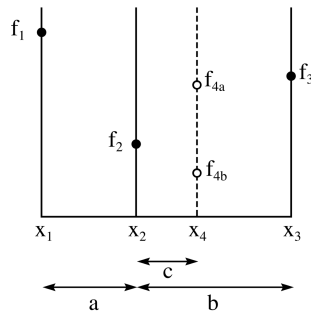


Figure 1: The idea of ternary search.

[Answers are put here.](#)

[也可以使用中文回答](#)

- (a) (10%) For the search direction, show that to find the minimum point, if  $f(x_4) = f_{4a}$ , the triplet  $\{x_1, x_2, x_4\}$  is chosen for the next iteration. If  $f(x_4) = f_{4b}$ , the triplet  $\{x_2, x_4, x_3\}$  is chosen. (Hint: use the property of unimodal.)

由unimodal可知極值在 $[x_1, x_3]$ 之間，且由任何點往極點靠近都會是單調遞增(若極值為最大值)或單調遞減(若極值為最小值)，而我們在 $[x_1, x_3]$ 之間取兩個端點 $x_2$ 和 $x_4$ ，將區間分成3份。

這題要求函數最小值，因此我們可以去判斷 $x_2$ 和 $x_4$ 的函數值，它們的函數值和距離極值點有關係的。距離極值點越近，函數值越小(也可能越大視函數而定)。若 $f(x_4) = f_{4a}$ ，可以判斷出 $f_{4a} > f_2$ ， $x_2$ 離極點較近，而我們需要縮小區間範圍，因此我們拋棄 $[x_4, x_3]$ 區間，故下一次的iteration會選擇triplet  $\{x_1, x_2, x_4\}$

若 $f(x_4) = f_{4b}$ ，可以判斷出 $f_{4b} < f_2$ ， $x_4$ 離極點較近，而我們需要縮小區間範圍，因此我們拋棄 $[x_1, x_2]$ 區間，故下一次的iteration會選擇triplet  $\{x_2, x_4, x_3\}$

三分搜索主要方法就是，每次通過比較兩個值的大小，縮小三分之一的區間，直到最後區間範圍小於我們設定的閾值為止。

- (b) (10%) For either case, we want these three points keep the same ratio, which means

$$\frac{a}{b} = \frac{c}{a} = \frac{c}{b-c}.$$

Show that under this condition, the ratio of  $b/a = (\sqrt{5}+1)/2$ , which is the golden ratio  $\phi$ . (So this algorithm is called the *Golden-section search*).

假設 $a \neq 0$ 或 $b \neq 0$ 或 $c \neq 0$ 下，由左邊兩個等式中可以推導出

$$\frac{a}{b} = \frac{c}{a}$$

$$\rightarrow c = \frac{a^2}{b} \quad (1)$$

由右邊兩個等式中可以整理推導出

$$\frac{c}{a} = \frac{c}{b-c}$$

$$\rightarrow a = b - c \quad (2)$$

公式(1)帶入公式(2)替換 $c$ 並且同時乘 $\frac{b}{a^2}$ 可以得到

$$\frac{b}{a} = \frac{b^2}{a^2} - 1$$

$$\rightarrow \left(\frac{b}{a}\right)^2 - \frac{b}{a} - 1 = 0 \quad (3)$$

公式(3)使用公式解解出兩個值

$$\frac{b}{a} = \frac{1 \pm \sqrt{5}}{2}$$

另外因為 $a$ 和 $b$ 是長度，所以 $a$ 和 $b \geq 0$ ，因此 $\frac{b}{a} \geq 0$ ，所以不可能是負值，最後得到

$$\frac{b}{a} = \frac{1 + \sqrt{5}}{2}$$

得證。

- (c) (10%) If we let each iteration of the algorithm has two function evaluations, show the convergence rate of the Golden-section search is  $\phi^{-2}$ . (This means it is faster than the binary search algorithm under the same number of function evaluations.)

binary search每次都要帶2個點才能進行1次收斂，但ternary search每次收斂都只需要1個點，所以假設ternary search在每次也都帶2個點，等於收斂兩次。

$$\frac{b}{a+b} = \frac{\frac{b}{a}}{1 + \frac{b}{a}} \quad (4)$$

而原先每次收斂的長度都如式(4)，將 $b/a = (\sqrt{5} + 1)/2$ 值帶入後化整理得到

$$\frac{b}{a+b} = (\sqrt{5} - 1)/2$$

因此可知每帶一次點可以收斂 $\phi^{-1}$ ，所以帶二次點可以收斂兩次 $\phi^{-2}$ ，得證。

2. (15%) Show that Newton's method for single variables is equivalent to build a quadratic model

$$q(x) = f(x_k) + f'(x_k)(x - x_k) + \frac{f''(x_k)}{2}(x - x_k)^2$$

at the point  $x_k$  and use the minimum point of  $q(x)$  as the next point. (Hint: to show the next point  $x_{k+1} = x_k - f'(x_k)/f''(x_k)$ )

將題目中的多項式以降幂重新排列後

$$q(x) = \frac{f''(x_k)}{2}x^2 + [f'(x_k) - f''(x_k)x_k]x + [f(x_k) - f'(x_k)x_k + \frac{f''(x_k)}{2}x_k^2]$$

利用配方法求極值，公式(5)中 $C$ 為某一常數使等式成立

$$\rightarrow q(x) = \frac{f''(x_k)}{2}\left(x - \left[x_k - \frac{f'(x_k)}{f''(x_k)}\right]\right)^2 + C \quad (5)$$

$$\arg \min_x q(x) = x_k - \frac{f'(x_k)}{f''(x_k)} \quad (6)$$

根據Newton's method

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)} = \arg \min_x q(x)$$

得證

3. (15%) Matrix  $A$  is an  $n \times n$  symmetric matrix. Show that all  $A$ 's eigenvalues are positive if and only if  $A$  is positive definite.

當 $A$ 為實對稱矩陣時， $A$ 是可以正交對角化的，所以存在一個正交矩陣 $Q$ 讓 $Q^T A Q = D$ ， $D$ 為對角矩陣，其中 $\lambda_i$ 為 $A$ 的eigenvalues，其值都為正， $\lambda_i > 0$

$$D = \begin{bmatrix} \lambda_1 & 0 & \dots & \dots & \dots & 0 \\ 0 & \lambda_2 & 0 & \dots & \dots & 0 \\ 0 & 0 & \lambda_3 & 0 & \dots & 0 \\ \vdots & \dots & \dots & \ddots & \dots & \vdots \\ \vdots & \dots & \dots & \dots & \ddots & \vdots \\ 0 & \dots & \dots & \dots & 0 & \lambda_n \end{bmatrix}_{n \times n}$$

假設 $x$ 為任意nonzero vector，又 $A = Q D Q^T$ (因 $Q^{-1} = Q^T$ )，等是兩邊同時左乘 $x^T$ ，而右乘 $x$ ，可以得到

$$x^T A x = x^T Q D Q^T x \quad (7)$$

另 $y = Q^T x$  替換公式(7)可以得到

$$x^T A x = y^T D y \quad (8)$$

而

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}_{n \times 1}$$

把公式(8)乘開得到

$$\begin{aligned} x^T A x = y^T D y &= \begin{bmatrix} y_1 & y_2 & y_3 & \dots & \dots & y_n \end{bmatrix} \begin{bmatrix} \lambda_1 & 0 & \dots & \dots & \dots & 0 \\ 0 & \lambda_2 & 0 & \dots & \dots & 0 \\ 0 & 0 & \lambda_3 & 0 & \dots & 0 \\ \vdots & \dots & \dots & \ddots & \dots & \vdots \\ \vdots & \dots & \dots & \dots & \ddots & \vdots \\ 0 & \dots & \dots & \dots & 0 & \lambda_n \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ \vdots \\ y_n \end{bmatrix} \\ &= \lambda_1 y_1^2 + \lambda_2 y_2^2 + \dots + \lambda_n y_n^2 \end{aligned} \quad (9)$$

假設 $\lambda_i$ 都是正的eigenvalues，又因為 $x$ 為任意的nonzero vector且 $Q$ 為可逆矩陣，所以 $y = Q^T x$ 是nonzero vector，因此 $x^T A x > 0$ ，滿足正定矩陣定義，因此 $A$ 為正定矩陣。

$A$ 為實對稱矩陣， $\lambda$ 為 $A$ 的eigenvalue， $x$ 為其相應的eigenvector

$$A x = \lambda x \quad (10)$$

同時左乘 $x^T$

$$\begin{aligned} x^T A x &= \lambda x^T x \\ &= \lambda \|x\|^2 \end{aligned} \quad (11)$$

當 $A$ 為positive definite且 $x$ 為nonzero vector的eigenvector， $x^T A x > 0$ ，又 $\|x\|^2$ 為 $x$ 的長度平方必為正，故其eigenvalue  $\lambda$ 皆必為正

A's eigenvalues are positive  $\iff$  A is positive definite

4. (50%) Consider a function  $f(x_1, x_2) = (x_1 - x_2)^3 + 2(x_1 - 1)^2$ .

(a) Suppose  $\vec{x}_0 = (1, 2)$ . Compute  $\vec{x}_1$  using the steepest descent step with the optimal step length.

$$\frac{\partial f(x_1, x_2)}{\partial x_1} = 3(x_1 - x_2)^2 + 4(x_1 - 1)$$

$$\frac{\partial f(x_1, x_2)}{\partial x_2} = -3(x_1 - x_2)^2$$

$$\Rightarrow \nabla f(x_1, x_2) = \begin{bmatrix} 3(x_1 - x_2)^2 + 4(x_1 - 1) \\ -3(x_1 - x_2)^2 \end{bmatrix}$$

$$\frac{\partial^2 f(x_1, x_2)}{\partial x_1^2} = 6(x_1 - x_2) + 4$$

$$\frac{\partial^2 f(x_1, x_2)}{\partial x_1 \partial x_2} = -6(x_1 - x_2)$$

$$\begin{aligned}
\frac{\partial^2 f(x_1, x_2)}{\partial x_2 \partial x_1} &= -6(x_1 - x_2) \\
\frac{\partial^2 f(x_1, x_2)}{\partial x_2^2} &= 6(x_1 - x_2) \\
\Rightarrow H(x_1, x_2) &= \begin{bmatrix} 3(x_1 - x_2)^2 + 4(x_1 - 1) & -6(x_1 - x_2) \\ -6(x_1 - x_2) & -3(x_1 - x_2)^2 \end{bmatrix} \\
\vec{g}_0 &= \nabla f(1, 2) \begin{bmatrix} 3 \\ -3 \end{bmatrix} \\
\vec{p}_0 &= -\nabla f(1, 2) \begin{bmatrix} -3 \\ 3 \end{bmatrix} \\
H(1, 2) &= \begin{bmatrix} -2 & 6 \\ 6 & -6 \end{bmatrix} \\
\alpha &= \frac{-\vec{g}_0^T \vec{p}_0}{\vec{p}_0^T H \vec{p}_0} = \frac{-18}{-180} = -\frac{1}{10} \\
\vec{x}_1 &= \begin{bmatrix} 1 \\ 2 \end{bmatrix} - \frac{1}{10} \begin{bmatrix} -3 \\ 3 \end{bmatrix} = \begin{bmatrix} 1.3 \\ 1.7 \end{bmatrix}
\end{aligned}$$

- (b) What is the Newton's direction of  $f$  at  $(x_1, x_2) = (1, 2)$ ? Is it a descent direction?

$$\vec{p}_k = -H_k^{-1} \vec{g}_k = \begin{bmatrix} \frac{1}{4} & \frac{1}{12} \\ \frac{1}{4} & \frac{1}{12} \end{bmatrix} \begin{bmatrix} -3 \\ 3 \end{bmatrix} = \begin{bmatrix} 0 \\ \frac{1}{2} \end{bmatrix}$$

由於  $H^{-1}$  並不是正定義矩陣，因為它的特徵值中有負值，所以  $\vec{p}_k$  不是 descent direction。

- (c) Compute the LDL decomposition of the Hessian of  $f$  at  $(x_1, x_2) = (1, 2)$ . (No pivoting)

$$\begin{aligned}
H(1, 2) &= \begin{bmatrix} -2 & 6 \\ 6 & -6 \end{bmatrix} \xrightarrow{r_{12}(3)} \begin{bmatrix} -2 & 6 \\ 0 & 12 \end{bmatrix} \xrightarrow{c_{12}(3)} \begin{bmatrix} -2 & 0 \\ 0 & 12 \end{bmatrix} \\
&= \begin{bmatrix} 1 & 0 \\ -3 & 1 \end{bmatrix} \begin{bmatrix} -2 & 0 \\ 0 & 12 \end{bmatrix} \begin{bmatrix} 1 & -3 \\ 0 & 1 \end{bmatrix} = LDL^T
\end{aligned}$$

- (d) Compute the modified Newton step using LDL modification.

$$\begin{aligned}
\hat{D} \text{ 取代 } D, \text{ 把 } -2 \text{ 替換成 } 1 & \begin{bmatrix} -2 & 0 \\ 0 & 12 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 \\ 0 & 12 \end{bmatrix} \\
\hat{H}_0 = L \hat{D} L^T &= \begin{bmatrix} 1 & 0 \\ -3 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 12 \end{bmatrix} \begin{bmatrix} 1 & -3 \\ 0 & 1 \end{bmatrix} \\
\hat{H}_0^{-1} = (L^T)^{-1} \hat{D}^{-1} (L)^{-1} &= \begin{bmatrix} 1 & 3 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & \frac{1}{12} \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 3 & 1 \end{bmatrix} \\
\vec{p}_0 = -\hat{H}_0^{-1} \vec{g}_0 &= -\begin{bmatrix} \frac{7}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{12} \end{bmatrix} \begin{bmatrix} 3 \\ -3 \end{bmatrix} = \begin{bmatrix} -\frac{9}{2} \\ -\frac{1}{2} \end{bmatrix}
\end{aligned}$$

- (e) Suppose  $\vec{x}_0 = (1, 1)$  and  $\vec{x}_1 = (1, 2)$ , and the  $B_0 = I$ . Compute the quasi Newton direction  $p_1$  using BFGS.

$$\begin{aligned}
\vec{s}_0 &= \vec{x}_1 - \vec{x}_0 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \\
B_0 &= I \\
\vec{y}_0 &= \nabla f(1, 2) - \nabla f(1, 1) = \begin{bmatrix} 3 \\ -3 \end{bmatrix} \\
\text{因為 } B_1 &= B_0 - \frac{B_0 \vec{s}_0 \vec{s}_0^T B_0}{\vec{s}_0^T B_0 \vec{s}_0} + \frac{\vec{y}_0 \vec{y}_0^T}{\vec{y}_0^T \vec{s}_0} \\
B_1 &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \frac{\begin{bmatrix} 0 \\ 1 \end{bmatrix} \begin{bmatrix} 0 & 1 \end{bmatrix}}{\begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}} + \frac{\begin{bmatrix} 3 \\ -3 \end{bmatrix} \begin{bmatrix} 3 & -3 \end{bmatrix}}{\begin{bmatrix} 3 & -3 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}} = \begin{bmatrix} -2 & 3 \\ 3 & -3 \end{bmatrix}
\end{aligned}$$

$$\vec{p}_1 = -B_1^{-1} \vec{g}_1 = -B_1^{-1} \nabla f(\vec{x}_1) = - \begin{bmatrix} 1 & 1 \\ 1 & \frac{2}{3} \end{bmatrix} \begin{bmatrix} 3 \\ -3 \end{bmatrix} = \begin{bmatrix} 0 \\ -1 \end{bmatrix}$$