

First: Recap the Tuesday online lecture.

Quadratic Model Problem (QMP):

$$f(\underline{x}) = c + \langle \underline{a}, \underline{x} \rangle + \frac{1}{2} \langle \underline{x}, B \underline{x} \rangle,$$

where B is a symmetric positive-definite matrix.

Steepest Descent:

$$\begin{aligned} \underline{x}_{k+1} &= \underline{x}_k + \alpha_k \underline{p}_k \\ &= \underline{x}_k - \alpha_k \nabla f(\underline{x}_k) \end{aligned}$$

The α_k is obtained from the 1D subproblem:

$$\alpha_k = \arg \min_{\alpha > 0} f(\underline{x}_k - \alpha \nabla f_k)$$

Exact step (QMP):

$$\alpha_k = \frac{\langle \nabla f_k, \nabla f_k \rangle}{\langle \nabla f_k, B \nabla f_k \rangle}$$

Minimizer (QMP):

$$\begin{aligned} B \underline{x}_* &= -\underline{a} \quad \dots \quad \nabla f(\underline{x}_*) = 0 \\ \Rightarrow \underline{x}_* &= -B^{-1} \underline{a} \end{aligned}$$

B -norm:

$$\|\underline{v}\|_B^2 = \langle \underline{v}, B \underline{v} \rangle \quad \forall \underline{v} \in \mathbb{R}^n$$

Distance to the minimizer:

$$\|\underline{x}_k - \underline{x}_*\|_B$$

Key result in Tuesday lecture:

$$\|\underline{x}_{k+1} - \underline{x}_*\|_B \leq \left(1 - \frac{\lambda_{\min}}{\lambda_{\max}}\right)^{1/2} \|\underline{x}_k - \underline{x}_*\|_B$$

OR :

$$\|x_{k+1} - x^*\|_B \leq \left(1 - \frac{1}{\kappa(B)}\right)^{1/2} \|x_k - x^*\|_B$$

If $\kappa(B) \gg 1$, then

$$1 - \frac{1}{\kappa(B)} \approx 1$$

Then,

$$\frac{\|x_{k+1} - x^*\|_B}{\|x_k - x^*\|_B} \approx 1 \Rightarrow \text{Slow convergence.}$$

Remark : When $\lambda_{\min} = \lambda_{\max}$, then

$$\|x_{k+1} - x^*\|_B \leq 0 \cdot \|x_k - x^*\|_B$$

Then, the steepest-descent method converges in one iteration.

$$\text{When } \lambda_{\min} = \lambda_{\max}, \quad B = \lambda \underline{I}.$$

Theorem : When $B = \lambda \underline{I}$, the SD method converges in at most one step. \square

Moving on, we will extend this analysis to Newton and Quasi-Newton methods:

Theorem 6.3 : Suppose that f is twice differentiable and the Hessian Matrix $B(x)$ is Lipschitz in a neighbourhood of the minimiser x^* at which sufficient conditions for optimality hold ($\nabla f(x^*) = 0$, $B(x^*)$ is

positive-definite). Suppose that the starting-point \underline{x}_0 is sufficiently close to the minimizer \underline{x}^* and consider the iterates

$$\underline{x}_{k+1} = \underline{x}_k + P_k^N.$$

Then:

1. The iterates converge to \underline{x}^* as $k \rightarrow \infty$.

2. The rate of convergence is quadratic:

$$\|\underline{x}_{k+1} - \underline{x}^*\|_2 \leq C \|\underline{x}_k - \underline{x}^*\|_2^2, \text{ some } C.$$

Remark: By $B(\underline{x})$ Lipschitz in a neighbourhood N of \underline{x}^* , we mean that there exists a positive constant K such that:

$$\|B(y_2) - B(y_1)\|_2 \leq K \|y_2 - y_1\|_2$$

for all y_1 and y_2 in the neighbourhood N .

Remark: As you go through the different steps in the proof, we get down to:

$$\frac{\|\underline{x}_1 - \underline{x}^*\|_2}{\|\underline{x}_0 - \underline{x}^*\|_2} \leq \underbrace{C \|\underline{x}_0 - \underline{x}^*\|_2}_{\leq 1/2}, \text{ for}$$

some constant C . "Sufficiently close" means the RHS should be $\leq 1/2$.

One last remark: A similar result holds for quasi-Newton methods such as BFGS:

$$\|x_{k+1} - x^*\|_2 \leq C \|x_k - x^*\|_2^{1+\epsilon}, \quad \epsilon > 0.$$

i.e. super-linear convergence.

Exercises #2

Question 1 Newton Method, with

$$\|x_{k+1} - x^*\|_2 \leq C \|x_k - x^*\|_2^2 \quad \text{some } C, \quad (1)$$

whenever $\|x_k - x^*\|_2 < \delta$.

Choose a starting-value x_0 such that:

$$\|x_0 - x^*\|_2 < \delta \quad \text{AND} \quad \|x_0 - x^*\|_2 < \frac{1}{2C}.$$

i.e. $\|x_0 - x^*\|_2 < \min(\delta, \frac{1}{2C})$.

Aim: We want to show:

$$\|x_k - x^*\|_2 \leq \frac{1}{2^{2^k - 1}} \|x_0 - x^*\|_2$$

a) Take Eqⁿ (1) with $k=0$:

$$\begin{aligned} \|x_1 - x^*\|_2 &\leq C \underbrace{\|x_0 - x^*\|_2}_{< \frac{1}{2C}} \|x_0 - x^*\|_2 \\ &< C \cdot \frac{1}{2C} \|x_0 - x^*\|_2 \end{aligned}$$

$$\Rightarrow \|x_1 - x^*\|_2 < \frac{1}{2} \|x_0 - x^*\|_2 < \frac{1}{2} \min(\delta, \frac{1}{2C})$$

Apply Eqⁿ (1) with $k=1$:

$$\|x_2 - x^*\|_2 \leq C \underbrace{\|x_1 - x^*\|_2} \|x_1 - x^*\|_2$$

$$\begin{aligned}
 &< \frac{1}{2} \underbrace{C \|x_0 - x_*\|_2}_{< \frac{1}{2C}} \cdot \frac{1}{2} \|x_0 - x_*\|_2 \\
 &< \frac{1}{2^3} \|x_0 - x_*\|_2
 \end{aligned}$$

Apply Eqⁿ (1) with $k=2$:

$$\|x_3 - x_*\|_2 \leq C \underbrace{\|x_2 - x_*\|_2}_{< \frac{1}{2^3}} \|x_2 - x_*\|_2$$

$$\begin{aligned}
 &< \frac{1}{2^3} \underbrace{C \|x_0 - x_*\|_2}_{< \frac{1}{2C}} \cdot \frac{1}{2^3} \|x_0 - x_*\|_2 \\
 &< C \cdot \frac{1}{2^6}
 \end{aligned}$$

$$< \frac{1}{2^3} \cdot \frac{1}{2^3} \cdot \frac{1}{2} \|x_0 - x_*\|_2$$

$$= \frac{1}{2^7} \|x_0 - x_*\|_2$$

Part b): $\|x_k - x_*\|_2 \leq \frac{1}{2^{p_k}} \|x_0 - x_*\|_2$

$$k=1, \quad p_k = 1$$

$$k=2, \quad p_k = 3$$

$$k=3, \quad p_k = 7$$

Guess:
$$\begin{cases} p_k = 2p_{k-1} + 1 & , \quad k = 2, 3, \dots \\ p_k = 1 & k = 1 \end{cases} \quad (2)$$

Part c)

$$p_k = B \cdot \lambda^k + A$$

Sub in to (2) :

$$B \cdot \lambda^k + A = 2(B \lambda^{k-1} + A) + 1$$

$$\Rightarrow \begin{array}{l} B \cdot \lambda^k \\ + A \end{array} = \begin{array}{l} 2B \lambda^{k-1} \\ + 2A + 1 \end{array}$$

$$\text{Equate: } \begin{cases} \cancel{B} \lambda^k = 2\cancel{B} \lambda^{k-1} \Rightarrow 1 = 2 \cdot \lambda^{-1} \Rightarrow \lambda = 2 \\ A = 2A + 1 \Rightarrow 0 = A + 1 \Rightarrow A = -1 \end{cases}$$

$$p_k = B \cdot 2^k - 1$$

$$\text{But } p_1 = 1$$

$$\Rightarrow B \cdot 2 - 1 = 1$$

$$\Rightarrow B = 1.$$

$$\text{Hence: } p_k = 2^k - 1$$

$$\begin{aligned} \text{a) } \|x_k - x_{k+1}\|_2 &\leq \frac{1}{2^{p_k}} \|x_0 - x_{k+1}\|_2 \\ &= \frac{1}{2^{2^k - 1}} \|x_0 - x_{k+1}\|_2 \end{aligned}$$

Hence:

$$\lim_{k \rightarrow \infty} \|x_k - x_{k+1}\|_2 = 0 \quad \square$$

Question 2 : Show that if $0 < c_2 < c_1 < 1$
then there may be no step lengths satisfying

then there may be no step lengths satisfying the SWCS.

Hint: $\phi(\alpha) = a + b\alpha + c\alpha^2$

where $b < 0$, $c > 0$

Solution: $\phi(0) = a$, $\phi'(0) = b$, $b < 0$.

SWC1: $\phi(\alpha) \leq \phi(0) + c_1 \alpha \phi'(0)$.

$\Rightarrow \cancel{a} + b\alpha + c\alpha^2 \leq \cancel{a} + c_1 \alpha b$

Solve for α : $\alpha = 0$, OR

$$b + c\alpha \leq c_1 b$$

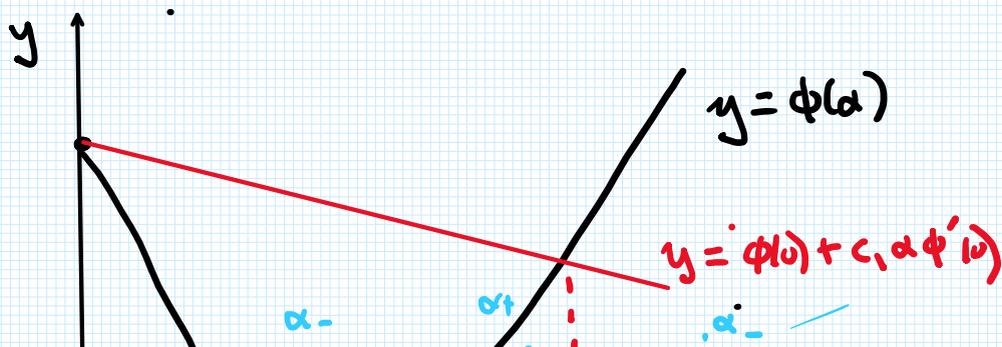
$$\Rightarrow c\alpha \leq -b + c_1 b$$

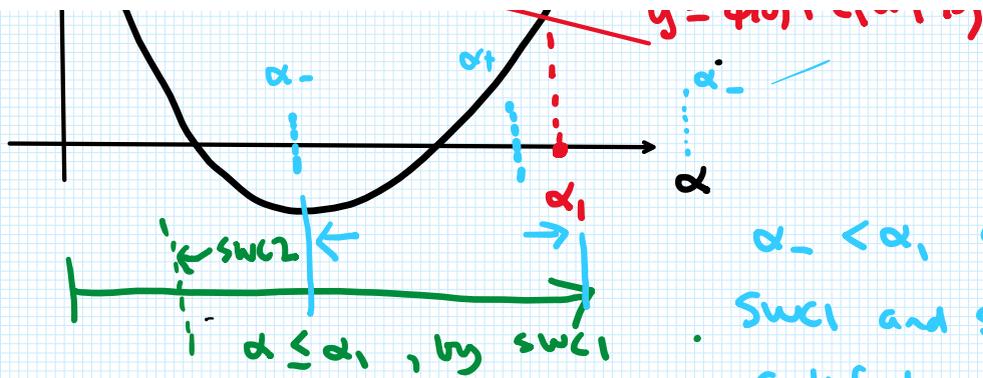
$$\Rightarrow c\alpha \leq -b(1 - c_1)$$

$$\Rightarrow c\alpha \leq |b| \underbrace{(1 - c_1)}_{\text{pos}}$$

$$\Rightarrow \alpha \leq \frac{|b| (1 - c_1)}{c}$$

Take: $\alpha_1 = \frac{|b| (1 - c_1)}{c}$





$\alpha_- < \alpha_+$, OK
 SWC1 and SWC2
 Satisfied simultaneously.

$\alpha_- > \alpha_+$, BAD
 SWC1 and SWC2 not
 satisfied simultan....

SWC2: We require

$$|\phi'(\alpha)| \leq c_2 |\phi'(0)|$$

$$\Rightarrow |b + 2c\alpha| \leq c_2 |b|$$

$$b^2 + 4bc\alpha + 4c^2\alpha^2 \leq c_2^2 b^2$$

$$\Rightarrow 4c^2\alpha^2 + 4bc\alpha + b^2(1-c_2^2) \leq 0.$$

Critical points, where equality holds:

$$4c^2\alpha^2 + 4bc\alpha + b^2(1-c_2^2) = 0.$$

$$\alpha = \frac{-4bc \pm \sqrt{16b^2c^2 - 16b^2c^2(1-c_2^2)}}{8c^2} \quad \sqrt{b^2} = |b|$$

$$= \frac{-4bc \pm 4|b|c c_2}{8c^2}$$

$$= \frac{4|b|c \cdot (1 \pm c_2)}{8 \cdot c \cdot c}$$

$$\Rightarrow \alpha_{\pm} = \frac{|b|}{2c} (1 \pm c_2)$$

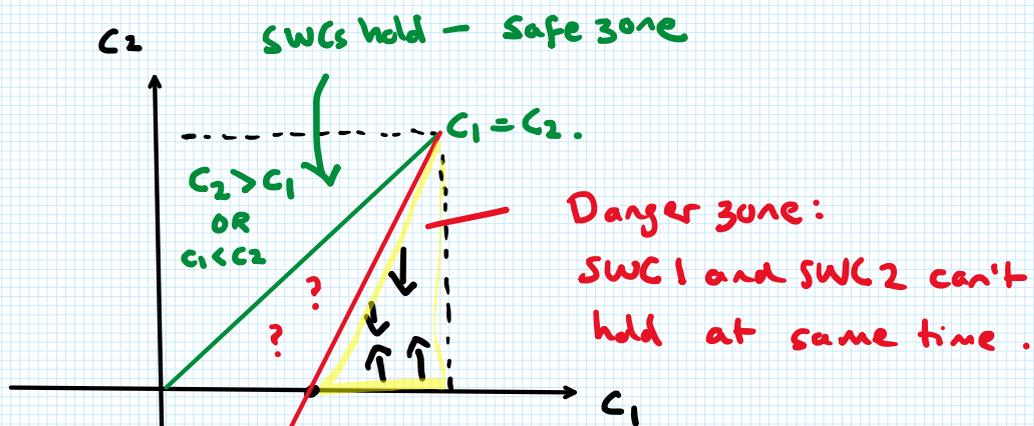
Referring to the figure, we attempt to make $\alpha_- > \alpha_+$.

$$\frac{\cancel{1b}}{\cancel{2c}} (1-c_2) > \frac{\cancel{1b}}{\cancel{c}} (1-c_1)$$

$$\Rightarrow 1-c_2 > 2-2c_1$$

$$\Rightarrow \boxed{2c_1 > c_2 + 1} \quad \text{BAD.}$$

Plot in c_1 - c_2 space:



Danger zone: $2c_1 > c_2 + 1$
 $2x > y + 1$

Margin: $2x = y + 1$

$$\left\{ \begin{array}{l} x=0, y=-1. \\ y=0, x=1/2 \\ x=1, y=1 \end{array} \right.$$

Hence, to stay out of danger, we should take

$$\boxed{c_1 < c_2}$$

On the other hand, if $c_1 > c_2$, we cannot rule out being in the danger zone in the figure, where SWCs 1 and 2 can't hold simultaneously. \square

We look at another question, which will help us to understand Q5.

Q4, ACM40990 Midterm Exam, 2025.

Consider the Steepest-Descent method with exact line search applied to the quadratic cost function

$$f(x) = c + \langle a, x \rangle + \frac{1}{2} \langle x, Bx \rangle, \quad (2) \quad \text{QMP}$$

where $c \in \mathbb{R}$, $a \in \mathbb{R}^n$ and $B \in \mathbb{R}^{n \times n}$ are constant. Take as given that B is symmetric positive-definite.

Question 4(b)

(b) Consider again the cost function in Equation (2). Take $n = 2$ and

$$B = \begin{pmatrix} 2 \times 10^8 & 10^4 \\ 10^4 & 1 \end{pmatrix}.$$

Comment on the convergence of the Steepest-Descent algorithm applied to this problem. [5 marks]

Solution: We calculate the condition number of B .

Since B is symmetric,

$$\kappa(B) = \|B\|_2 \|B^{-1}\|_2 = \frac{\max_i |\lambda_i|}{\min_i |\lambda_i|}$$

So we compute the eigenvalues of B :

$$\begin{vmatrix} 2 \times 10^8 - \lambda & 10^4 \\ 10^4 & 1 - \lambda \end{vmatrix} = 0$$

$$(2 \times 10^8 - \lambda)(1 - \lambda) - 10^8 = 0$$

$$\text{Let } \rho = 10^8$$

$$(1 - \lambda)(2\rho - \lambda) - \rho = 0$$

$$\Rightarrow (\lambda - 2\rho)(\lambda - 1) - \rho = 0$$

$$\Rightarrow \lambda^2 - \lambda - 2\rho\lambda + \rho = 0$$

$$\Rightarrow \lambda^2 - \lambda(1 + 2\rho) + \rho = 0$$

$$\Rightarrow \lambda = \frac{(1 + 2\rho) \pm \sqrt{(1 + 2\rho)^2 - 4\rho}}{2}$$

$$\Rightarrow \lambda = \frac{(1 + 2\rho) \pm \sqrt{1 + 4\rho + 4\rho^2 - 4\rho}}{2}$$

Since $\rho = 10^8$ is large:

$$\lambda = \begin{cases} \frac{(1 + 2\rho) + \sqrt{1 + 4\rho^2}}{2} \approx \frac{1 + 2\rho + 2\rho}{2} \approx 2\rho \\ \frac{1 + 2\rho - \sqrt{1 + 4\rho^2}}{2} \approx \frac{1 + 2\rho - 2\rho}{2} = \frac{1}{2} \end{cases}$$

Or, more accurately,

$$\lambda = \begin{cases} 2\rho + O(\rho^0) \\ \frac{1}{2} + O(\rho^{-1}) \end{cases}$$

$$\left(\frac{1}{2} + O(p^{-1}) \right)$$

$$\max_{i=1,2} |\lambda_i| = 2p + O(p^0)$$

$$\min_{i=1,2} |\lambda_i| = \frac{1}{2} + O(p^{-1})$$

$$\kappa(B) = \frac{2p + O(p^0)}{\frac{1}{2} + O(p^{-1})}$$

$$= 4p + O(p^0).$$

$$\text{But } p = 10^8.$$

$$\Rightarrow \kappa(B) = O(10^8).$$

Remark: It suffices to estimate the order of magnitude of the condition number.

$$\|x_{k+1} - x_k\|_2 \leq \underbrace{\left(1 - \frac{1}{\kappa(B)} \right)^{1/2}}_{\text{prefactor}} \|x_k - x^*\|_2$$

Prefactor close to 1, convergence of SD algorithm is very slow.

Question 5 : Coding question

- SD is very slow

- Newton is fast.

Check $\kappa(B)$, $\kappa(B) \gg 1$, so the SD is slow.

One last remark about condition numbers:

For a symmetric matrix,

$$\kappa(B) = \frac{\max_i |\lambda_i|}{\min_i |\lambda_i|}$$

If the denominator is small, then $\kappa(B)$ is large. Then one of the eigenvalues is close to zero. Then, there exists a perturbation of small size:

$$B + \overset{\text{small}}{\epsilon} \in B_1$$

such that $B + \epsilon \in B_1$ is a singular matrix

If $\epsilon = O(10^{-k})$ then the matrix is effectively singular, in double precision.

Moral: Be very careful about inverting (numerically)

a matrix with a large condition number.

