

## Conditioning and Stability

- Conditioning pertains to sensitivity of a mathematical problem to perturbations in inputs.
- Stability pertains to perturbation behavior of an algorithm used to solve the mathematical problem on a computer.

### (\*) Conditioning of a Problem

Solving a problem is like evaluating a function

$$y = f(x)$$

Here  $x$  represents input to the problem (the data),  $f$  represents problem itself and  $y$  represents its solution

\* What happens to  $y$  when given  $x$  is perturbed slightly?

If small changes in  $\underline{x}$  leads to large changes in  $\underline{y}$ , we say the problem is ill-conditioned and usually we are interested in solving well-conditioned problem.

\* Absolute condition number:-

If a small perturbation of  $\underline{x}$  is denoted by  $\delta \underline{x}$ , then let the resulting perturbation in the solution be represented as  $\delta f$   
i.e  $\delta f = f(\underline{x} + \delta \underline{x}) - f(\underline{x})$

then the absolute condition number

$\hat{\kappa} = \kappa(\underline{x})$  of the problem  $f$  at  $\underline{x}$  is

$$\text{given by } \kappa(\underline{x}) = \max_{\delta \underline{x}} \left( \frac{\|\delta f\|}{\|\delta \underline{x}\|} \right) - \textcircled{1}$$

for infinitesimally small  $\delta f$  and  $\delta \underline{x}$

If  $f$  has a derivative, we can evaluate

$$\text{the Jacobian matrix } J(\underline{x}) \text{ as } J_{ij} = \frac{\partial f_i}{\partial x_j}$$

We have  $\underline{\delta f} \approx J(x) \underline{\delta x}$  with

equality as  $\|\underline{\delta x}\| \rightarrow 0$

$$K(x) = \max_{\underline{\delta x}} \frac{\|J(x) \underline{\delta x}\|}{\|\underline{\delta x}\|}$$

$$\hat{K} = K(x) = \|J(x)\|$$

Relative condition number :-

Assume  $\underline{\delta f}$  and  $\underline{\delta x}$  are infinitesimal

$$\hat{K}^R = \max_{\underline{\delta x}} \left[ \frac{\|\underline{\delta f}\|}{\|f(x)\|} \right] \cdot \left[ \frac{\|\underline{\delta x}\|}{\|x\|} \right]$$

$$= \max_{\underline{\delta x}} \left( \frac{\|\underline{\delta f}\|}{\|\underline{\delta x}\|} \cdot \frac{\|\underline{\delta x}\|}{\|f(x)\|} \cdot \frac{\|x\|}{\|\underline{\delta x}\|} \right)$$

$$\boxed{\hat{K}^R = \frac{\|J(x)\|}{\|f(x)\| / \|x\|}}$$



A problem is well-conditioned if  $\hat{K}$  is small (eg:  $1, 10, 10^2$ ). and ill-conditioned if  $\hat{K}$  is large (eg:  $10^6, 10^{16}, \dots$ )

We talk about relative condition number below and drop the superscript R in  $\hat{K}^R$  below!

Examples :-

$$(1) \quad f(x) = \frac{x}{2} \quad x \in \mathbb{R}$$

Input:  $x$        $J = \frac{df}{dx} = \frac{1}{2}$   
 Output:  $\frac{x}{2}$

$$\hat{K} = \frac{\|J\|_1}{\frac{\|f(x)\|}{\|x\|}} = \frac{\frac{1}{2}}{\frac{|x|^2}{x}} = 1$$

well conditioned problem.

$$(2) \quad f(x) = x_1 - x_2 \text{ where } x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$J = \begin{bmatrix} \frac{\partial f}{\partial x_1} & \frac{\partial f}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 1 & -1 \end{bmatrix}_{1 \times 2}$$

$$\hat{K} = \frac{\|J\|_1^\infty}{\|f(x)\|_\infty / \|x\|_\infty}$$

$\|J\|_\infty$  is max row sum = 2

$$\hat{K} = \frac{2}{\frac{|x_1 - x_2|}{\max\{|x_1|, |x_2|\}}}$$

$$= \frac{2 \max\{|x_1|, |x_2|\}^2}{|x_1 - x_2|}$$

If  $|x_1 - x_2|$  is small  $\approx 0$ ,  $K$  is large  
and is not well conditioned  
when you are subtracting two  
numbers which are very close by.

$$\hat{K} = \frac{\|J\|_1}{\frac{\|f(x)\|_1}{\|x\|_2}} = \frac{1}{\frac{|x_1 - x_2|}{(|x_1| + |x_2|)}} = \frac{(|x_1| + |x_2|)}{|x_1 - x_2|}$$

Root finding of quadratic equation :-

$$x^2 - 2xp + 1 = 0$$

$$x_1 = p - \sqrt{p^2 - 1}$$

$$x_2 = p + \sqrt{p^2 - 1}$$

Input :- value of  $p$

Output :-  $x_1, x_2$  which are the roots of  
quadratic equation.

Examine sensitivity of  $x_2$  w.r.t  $p$

$$\hat{K} = K(p) = \frac{\|J\|_1}{\frac{\|f(p)\|_1}{\|p\|_1}} ; \quad J = \frac{dx_2}{dp}$$

$$K(p) = \left| \frac{dx_2}{dp} \right| \times \frac{|p|}{|x_2|}$$

$$= \left| 1 + \frac{p}{\sqrt{p^2 - 1}} \right| \times \frac{|p|}{|p + \sqrt{p^2 - 1}|}$$

$$\begin{aligned}
 &= \left| \frac{p + \sqrt{p^2 - 1}}{\sqrt{p^2 - 1}} \right| \times \frac{|p|}{|p + \sqrt{p^2 - 1}|} \\
 &= \frac{|p|}{\sqrt{p^2 - 1}}
 \end{aligned}$$

The root  $x_2$  is sensitive for  $|p|$  close to 1 with  $K(p) \rightarrow \infty$  and insensitive for large  $p$  with  $K \approx 1$

Eigenvalues of matrix :-

$$A \underline{x} = \lambda \underline{x}$$

$$\det(A - \lambda I) = 0$$

Input :-  $A$

Output : eigenvalues  $\lambda$

$$A = \begin{pmatrix} 1 & 1000 \\ 0 & 1 \end{pmatrix} \quad \text{eigenvalues of } A = \{1, 1\}$$

$$\tilde{A} = \begin{pmatrix} 1 & 1000 \\ 0.001 & 1 \end{pmatrix} \quad \text{eigenvalues of } \tilde{A} \text{ of 1st perturbation } \{0, 2\}$$

Consider a symmetric matrix  $\tilde{A} = A^T$

$\lambda$  and  $\lambda + \delta\lambda$  are corresponding eigenvalues

$$A \text{ and } \tilde{A} + \delta\tilde{A}, \text{ then } \underbrace{|\delta\lambda| \leq \|\delta A\|_2}_{-\textcircled{1}}$$

$$\text{Relative condition number} = \frac{|\delta\lambda|}{|\lambda|}$$

$$\max_{\|\delta A\|_2} \frac{\|\delta A\|_2}{\|A\|_2}$$

use ① →

$$\text{Relative condition number } \hat{k} = \frac{\|A\|_2}{|\lambda|}$$

Conditioning of matrix-vector multiplication :-

Fixed A

Input :-  $\underline{x}$

Output :-  $A\underline{x}$

Consider the problem of computing  $A\underline{x}$  for fixed  $A$  and input  $\underline{x}$

$$\hat{k} = \max_{\delta \underline{x}} \frac{\|A(\underline{x} + \delta \underline{x}) - A\underline{x}\|_2}{\|\delta \underline{x}\|_2}$$

$$\hat{k} = \max_{\delta \underline{x}} \frac{\|A(\underline{x} + \delta \underline{x}) - A\underline{x}\|_2}{\|\delta \underline{x}\|_2}$$

$$= \max_{\delta \underline{x}} \frac{\|A\delta \underline{x}\|_2}{\|\delta \underline{x}\|_2} = \left( \max_{\delta \underline{x}} \frac{\|A\delta \underline{x}\|_2}{\|\delta \underline{x}\|_2} \right) \times \frac{\|\underline{x}\|_2}{\|A\underline{x}\|_2}$$

$$\hat{k} = \frac{\|A\|_2 \|\underline{x}\|_2}{\|A\underline{x}\|_2} - ②$$

$\hat{k}$  for a given  $A$  and at  $\underline{x}$

To loosen above equality to get a bound  
of  $\underline{x}$ , let us assume  $A$  is square  
and non-singular

$$\underline{x} = \underline{A}^{-1} \underline{A} \underline{x}$$

$$\|\underline{x}\| = \|\underline{A}^{-1} \underline{A} \underline{x}\| \leq \|\underline{A}^{-1}\| \|\underline{A} \underline{x}\|$$

$$\frac{\|\underline{x}\|}{\|\underline{A} \underline{x}\|} \leq \|\underline{A}^{-1}\| \quad - (3)$$

From eqn(2)  $\hat{K} = \frac{\|A\| \|\underline{x}\|}{\|A \underline{x}\|} \quad \checkmark$

using (3)  $\hat{K} \leq \|A\| \|\underline{A}^{-1}\| \quad - (4)$

What about for a give  $A \rightarrow$  if you want  
to compute  $\underline{A}^{-1} b$  from a given input  $b$ ?

Input :-  $b$       Fixed  $A, A^{-1}$

Output :-  $\underline{A}^{-1} b = \underline{x} \quad \hat{K} = \frac{\|\underline{A}^{-1}\| \|b\|}{\|\underline{A}^{-1} b\|}$

$$\hat{K} = \frac{\|\underline{A}^{-1}\| \|b\|}{\|\underline{x}\|}$$

using (4), even for  
the problem of  $\underline{A}^{-1} b$

$$\hat{K} \leq \|\underline{A}^{-1}\| \|A\|$$

Result:-

Let  $A \in \mathbb{R}^{m \times m}$  be non-singular and consider the equation  $A\bar{x} = \bar{b}$ , the problem of computing  $\bar{x}$  given  $\bar{b}$  has condition number

$$\hat{\kappa} = \frac{\|A\| \|\bar{x}\|}{\|\bar{b}\|} \leq \|A\| \|A^{-1}\|$$

with respect to perturbations of  $\bar{x}$ .

The problem of computing  $\bar{x}$  given  $\bar{b}$  has condition number

$$\hat{\kappa} = \frac{\|A^{-1}\| \|\bar{b}\|}{\|\bar{x}\|} \leq \|A\| \|A^{-1}\|$$

Condition number of a matrix :-

The condition number of  $A$  (relative to norm  $\|\cdot\|$ )

$$\text{denoted by } \kappa(A) = \|A\| \|A^{-1}\|$$

If  $\kappa(A)$  is small,  $A$  is said to be well-conditioned

if  $\kappa(A)$  is large,  $A$  is said to be ill-conditioned.

If  $A$  is singular,  $\kappa(A) \rightarrow \infty$   
or close to singular

In the 2-norm

$$\hat{K}(A) = \|A\|_2 \|A^{-1}\|_2$$

$\sigma_1 \rightarrow$  max singular value of  $A$

$(1/\sigma_m) \rightarrow$  max singular value of  $A^{-1}$

$\sigma_m \rightarrow$  min singular of  $A$

$$\hat{K}(A) = \frac{\sigma_1}{\sigma_m}$$

~~non zero singular values are square roots of non-zero eigenvalues of  $A^T A$  or  $A A^T$~~

$$K(A) = \sqrt{\frac{\lambda_{\max}(A^T A)}{\lambda_{\min}(A^T A)}}$$

If  $A$  is symmetric  
 $K(A)$  is ratio of max of absolute value of eigenvalues of  $A$  and min of absolute value of eigenvalues of  $A$ .

If  $A \in \mathbb{R}^{m \times n}$  ( $m > n$ ),  $K(A)$  is defined in terms of pseudoinverse  $A^+$ .

$$K(A) = \|A\|_2 \|A^+\|_1$$

$$A^+ = (A^T A)^{-1} A^T$$

Conditioning of system of equations:-

So far we fixed  $A$  and perturbed  $x$  or  $b$

Non-zero singular values are

Square roots of non-zero eigenvalues of  $\underline{A}^T \underline{A}$  or  $\underline{A} \underline{A}^T$

$$K(\underline{A}) = \sqrt{\frac{\lambda_{\max}(\underline{A}^T \underline{A})}{\lambda_{\min}(\underline{A}^T \underline{A})}}$$

If  $\underline{A}$  is symmetric  $K(\underline{A}) = \frac{|\lambda_{\max}(\underline{A})|}{|\lambda_{\min}(\underline{A})|}$

If  $\underline{A} \in \mathbb{R}^{m \times n}$ ,  $K(\underline{A})$  is defined in terms of pseudoinverse  $\underline{A}^+$ .

$$K(\underline{A}) = \|\underline{A}\| \|\underline{A}^+\|$$
$$\underline{A}^+ = (\underline{A}^T \underline{A})^{-1} \underline{A}^T$$

Conditioning of system of equations:-

So far we fixed  $\underline{A}$  and perturbed  $\underline{b}$  or

→ What about if we perturb  $\underline{A}$ ?

Fix  $\underline{b}$  and consider  $f: \underline{A} \rightarrow \underline{x} = \underline{A}^{-1} \underline{b}$

inputs :-  $\underline{A}$

output :-  $\underline{x}$

$\underline{A}$  is perturbed by  $\underline{\delta A}$   
and let  $\underline{\tilde{x}}$ , the output  
be perturbed by  $\underline{\delta x}$

$$(\underline{A} + \underline{\delta A})(\underline{x} + \underline{\delta x}) = \underline{b} \quad - \textcircled{1}$$

$$\underline{A}\underline{x} = \underline{b} \quad - \textcircled{2}$$

using  $\textcircled{1}$  and  $\textcircled{2}$  above, we have

$$(\underline{\delta A})\underline{x} + \underline{A}(\underline{\delta x}) = 0$$

$$\begin{aligned} \underline{\delta x} &= -\underline{A}^{-1}(\underline{\delta A})\underline{x} \\ \|\underline{\delta x}\| &= \|\underline{A}^{-1}(\underline{\delta A})\underline{x}\| \\ &\leq \|\underline{A}^{-1}\| \|\underline{\delta A}\| \|\underline{x}\| \\ &\leq \|\underline{A}^{-1}\| \|\underline{\delta A}\| \|\underline{x}\| \quad - \textcircled{3} \end{aligned}$$

$$\hat{K} = \max_{\underline{\delta A}} \frac{\|\underline{\delta x}\|}{\frac{\|\underline{x}\|}{\frac{\|\underline{\delta A}\|}{\|\underline{A}\|}}}$$

using  $\textcircled{3}$

$$\left( \frac{\|\underline{\delta x}\|}{\|\underline{x}\|} \right) \leq \|\underline{A}^{-1}\| \|\underline{A}\|$$

If perturbation  $\underline{\delta}A$  exists which makes the above inequality an equality

then

$\hat{K}$  of solving system of equations

$$\hat{K} = \max_{\underline{\delta}A} \left( \frac{\|\underline{\delta}x\|}{\|\underline{x}\|} \right) = K(\underline{A})$$

Result :-

For a fixed  $b$ , Input  $\rightarrow \underline{A}$ , output  $\underline{x} = \underline{A}^{-1}b$

Condition number of this problem with respect to perturbations in  $\underline{A}$  is

$$\hat{K} = \|\underline{A}\| \|\underline{A}^{-1}\| = K(\underline{A})$$

eg:-

$$K(\underline{A}) = 10^6$$

$$\frac{\|\underline{\delta}x\|}{\|\underline{x}\|} \leq 10^6 \times \frac{\|\underline{\delta}A\|}{\|\underline{A}\|} \quad \epsilon_m \approx 10^{-8}$$

$$\leq 10^6 \times 10^{-8} \\ \approx O(10^{-2})$$

$$\frac{\|\underline{\delta}A\|}{\|\underline{A}\|} \leq O(\epsilon_m)$$