

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 δf
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 δf and $\delta \underline{x}$

If f has a derivative, we can evaluate the Jacobian matrix $J(\underline{x})$ as

$$J_{ij} = \frac{\partial f_i}{\partial x_j}$$

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

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

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

$$R = K(x) = \|\underline{J(x)}\|$$

Relative condition number :-

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

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

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

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



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

Examples :-

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

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

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

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

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

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

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

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

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 :-

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

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

Input : A

Output : eigenvalues λ

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

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

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

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

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

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

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

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}

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

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

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

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

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

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

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

Input :- b Fixed A, \underline{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

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

$\sigma_1 \rightarrow$ max singular value of \underline{A}

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

$\sigma_m \rightarrow$ min singular of \underline{A}

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

For a square matrix, non zero singular values are square roots of non-zero eigenvalues of $\underline{A}^T \underline{A}$ or $\underline{A} \underline{A}^T$.

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

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

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

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

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

Conditioning of system of equations:-

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

→ 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{x} , the output
be perturbed by $\underline{\delta x}$

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

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

using ① and ② above, we have

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

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

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

using 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:-

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

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

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

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