

CS 450: Numerical Analysis

Lecture 3

Chapter 2 – Linear Systems Matrix Norms and Conditioning

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Vector Norms

- ▶ Properties of vector norms

$$\|x\| = 0 \quad \text{if and only if} \quad x = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\|\alpha x\| = |\alpha| \cdot \|x\|$$

$$\|x\| \geq 0, \quad \|x+y\| \leq \|x\| + \|y\|$$

- ▶ A norm is uniquely defined by its unit sphere:

$$V \subset \mathbb{R}^n, \quad x \in V, \quad \|x\| = 1$$

n-dim space
n=3



- ▶ *p*-norms

$$\|x\|_1 = \sum_i |x_i|$$

$$\|x\|_2 = \sqrt{\sum_i x_i^2}$$

$$\|x\|_p = \left(\sum_i |x_i|^p \right)^{1/p}$$

$$\|x\|_\infty = \max_i (|x_i|)$$

Inner-Product Spaces

- **Properties of inner-product spaces:** Inner products $\langle x, y \rangle$ must satisfy

e.g.

$$\langle x, y \rangle = x^T y$$

$$\langle x, x \rangle \geq 0$$

$$\langle x, x \rangle = 0 \Leftrightarrow x = 0$$

$$\langle x, y \rangle = \langle y, x \rangle$$

$$\langle x, y + z \rangle = \langle x, y \rangle + \langle x, z \rangle$$

$$\langle \alpha x, y \rangle = \alpha \langle x, y \rangle$$

- **Inner-product-based vector norms**

$$\|x\|_2 = \sqrt{x^T x}$$

more generally, for any $\langle x, y \rangle \Rightarrow x^T A y \Rightarrow$ new norm

$$\text{Cauchy-Schwarz inequality} \Rightarrow |x^T y| \leq \|x\|_2 \|y\|_2$$
$$|\langle x, y \rangle| \leq \sqrt{\langle x, x \rangle \langle y, y \rangle} \Rightarrow \|x\|_2 \|y\|_2$$

$$x^T A x$$
$$\langle x, x \rangle$$

Matrix Norms

- ▶ Properties of matrix norms:

$$A \in \mathbb{R}^{m \times n}$$

$$\|A\| \geq 0$$

$$\|A\| = 0 \Leftrightarrow A = 0$$

$$\|\alpha A\| = |\alpha| \cdot \|A\|$$

$$\|A + B\| \leq \|A\| + \|B\| \quad (\text{triangle inequality})$$

sometimes have submultiplicativity

$$\|A\| \|B\| \geq \|AB\|$$

- ▶ Frobenius norm:

$$\|A\|_F = \sqrt{\sum_i \sum_j a_{ij}^2} = \|\text{vec}(A)\|_2$$

stack cols of A into vector

- ▶ Operator/induced/subordinate matrix norms:

↳ from vector p-norm

$$\|A\|_p = \max_{\|x\|_p=1} \|Ax\|_p = \max_{x \neq 0} \frac{\|Ax\|_p}{\|x\|_p}$$

Induced Matrix Norms

- ▶ Interpreting induced matrix norms:

maximum amplification of any vectors

$$y = Ax \Rightarrow \|y\| \leq \|A\| \cdot \|x\|$$

$$A^{-1}y = x \Rightarrow \|x\| \leq \|A^{-1}\| \cdot \|y\|$$

$$\|y\| \geq \|x\| / \|A^{-1}\|$$

- ▶ General induced matrix norms:

$$\|A\|_{pq} = \max_{\|x\|_p=1} \|Ax\|_q$$

Matrix Condition Number

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

► **Definition:** $\kappa(A) = \|A\| \cdot \|A^{-1}\|$ is the ratio between the shortest/longest distances from the unit-ball center to any point on the surface.

► **Intuitive derivation:**

$$\kappa(A) = \lim_{\|\delta x\| \rightarrow 0} \max_{\text{inputs}} \max_{\text{perturbations in input}} \left| \frac{\text{relative perturbation in output}}{\text{relative perturbation in input}} \right|$$

$\|A\|$
 $1/\|A^{-1}\|$

since a matrix is a linear operator, we can decouple its action on the input x and the perturbation δx since $A(x + \delta x) = Ax + A\delta x$, so

$$\kappa(A) = \left| \frac{\overbrace{\max_{\text{perturbations in input}} \text{relative perturbation growth}}^{\|A\|}}{\underbrace{\max_{\text{inputs}} \text{relative input reduction}}_{1/\|A^{-1}\|}} \right|$$



$$\frac{\|A\|}{\|A^{-1}\|} = \kappa(A)$$

