

Vector and Matrix Norms

Def: Let  $\vec{u}, \vec{v}, \vec{x} \in \mathbb{R}^n$ .  $\|\cdot\|$  is a norm on  $\mathbb{R}^n$  if

(1)  $\|\vec{x}\| \geq 0$ ,  $\|\vec{x}\| = 0$  if and only if  $\vec{x} = \vec{0}$ .

(2)  $\|\alpha \vec{x}\| = |\alpha| \|\vec{x}\|$  for  $\alpha \in \mathbb{C}$

(3)  $\|\vec{u} + \vec{v}\| \leq \|\vec{u}\| + \|\vec{v}\|$  (triangle inequality)

Think about norms as distances, for example:

$$\|\vec{u}\|_2 = \sqrt{\vec{u} \cdot \vec{u}} = \sqrt{\sum_{i=1}^n |u_i|^2} \leftarrow l_2 \text{ norm,}$$

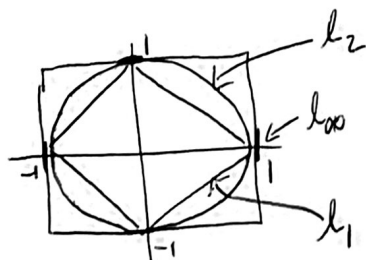
Other norms commonly used

$l_\infty$  norm:  $\|\vec{u}\|_\infty = \max_i |u_i|$

$l_1$  norm:  $\|\vec{u}\|_1 = \sum_i |u_i|$

$l_p$  norm:  $\|\vec{u}\|_p = \left( \sum_i |u_i|^p \right)^{1/p}$

Ex: Unit circles in  $l_1$ ,  $l_\infty$ , and  $l_2$ -norms:



Only the  $l_2$  norm comes from an inner product

Similarly, matrix norms must satisfy similar conditions:

Def For  $A, B \in \mathbb{C}^{m \times n}$ ,  $\|\cdot\|$  is a matrix norm if

$$(1) \quad \|A\| \geq 0, \quad \|A\| = 0 \text{ iff } A = 0$$

$$(2) \quad \|\alpha A\| = |\alpha| \|A\| \quad \text{for } \alpha \in \mathbb{C}$$

$$(3) \quad \|A+B\| \leq \|A\| + \|B\|$$

$$\left[ (4) \quad \|AB\| \leq \|A\| \cdot \|B\|, \text{ sometimes useful} \right]$$

If  $\|\cdot\|$  is any vector norm, then the induced matrix norm is

$$\|A\| = \max_{\|\vec{u}\|=1} \|A\vec{u}\| = \max_{\vec{u} \neq 0} \frac{\|A\vec{u}\|}{\|\vec{u}\|}$$

$$\Rightarrow \text{For any } \|\vec{u}\|, \quad \|A\vec{u}\| \leq \|A\| \cdot \|\vec{u}\|$$

Thm If  $\|\vec{u}\| = \|\vec{u}\|_1 = \sum |u_i|$ , then the induced matrix norm on  $A \in \mathbb{C}^{m \times n}$  is:

$$\|A\|_1 = \max_{j=1, \dots, n} \sum_{i=1}^m |a_{ij}|$$

Proof:  $\|A\vec{u}\|_1 = \left\| \sum_j u_j \vec{a}_j \right\|_1 \leq \sum_j |u_j| \|\vec{a}_j\|_1 \leq \max_j \|\vec{a}_j\|_1 \cdot \sum |u_i|$   
 $= \max_j \|\vec{a}_j\|_1 \cdot \|\vec{u}\|_1$   
 $= \|\vec{u}\|_1 \cdot \max_j \sum_i |a_{ij}|$

where  $A = (\vec{a}_1 \vec{a}_2 \dots \vec{a}_n)$

$$\text{So } \frac{\|A\vec{u}\|}{\|\vec{u}\|} \leq \max_j \sum_i |a_{ij}|$$

$$\text{But } \vec{u} = \begin{pmatrix} 0 \\ \vdots \\ 1 \\ \vdots \\ 0 \end{pmatrix} \leftarrow j^{\text{th}} \Rightarrow \|A\vec{u}\| \geq \|\vec{a}_j\|$$

$$\text{and therefore } \frac{\|A\vec{u}\|}{\|\vec{u}\|} = \max_j \sum_i |a_{ij}|$$

Similarly, we have

$$\text{Thm } \|A\|_\infty = \max_{i=1, \dots, m} \sum_{j=1}^n |a_{ij}|$$

Proof Nearly identical to previous theorem.

Lastly, the most commonly used matrix norm:

$$\text{Thm } \|A\|_2 = \sqrt{\max_j \lambda_j} \quad \text{where } \lambda_j \text{ is eigenvalue of } A^T A$$

with  $A \in \mathbb{R}^{m \times n}$  (or  $A^* A$  if  $A \in \mathbb{C}^{m \times n}$ ).

$$\text{Proof: } \|A\vec{u}\|_2^2 = (A\vec{u}, A\vec{u}) = \vec{u}^T \underbrace{A^T A}_{\substack{\uparrow \text{symmetric positive semi-definite} \\ \text{matrix}}} \vec{u}$$

$$\Rightarrow A^T A = P D P^{-1}, \quad D \text{ diagonal}$$

$P$  orthogonal,  $P^{-1} = P^T$

$$\Rightarrow \max_{\|\vec{u}\|=1} \|A\vec{u}\|_2^2 = \max_{\|\vec{u}\|=1} \|\vec{u}^T P D P^T \vec{u}\|_2^2$$

$$= \max_{\|\vec{y}\|=1} \|\vec{y}^T D \vec{y}\|_2^2 = \text{largest eigenvalue of } A^T A.$$

$\uparrow$  homework exercise.

## Condition number of a problem

$\Rightarrow$  The sensitivity of the "problem" ~~to~~ at the solution.

Ex: For a function  $y = f(x)$ , how sensitive is

$y$  to  $x$ ? ~~smaller estimate is the better~~

(The "problem" is computing  $f(x)$ .)

① In an absolute sense:

$$|y - y'| \approx \underbrace{C(x)}_{\text{absolute condition number}} |x - x'|$$

absolute condition number.

$$\Rightarrow C(x) \approx \frac{|y - y'|}{|x - x'|}$$

$$= \frac{|f(x) - f(x')|}{|x - x'|}$$

for  $x'$  close to  $x$ ,

$$C(x) \approx |f'(x)|.$$

② In a relative sense:

$$\frac{|x - x'|}{|x|} = \text{relative error}$$

$$\frac{|y' - y|}{|y|} \approx K(x) \left| \frac{x' - x}{x} \right|$$

$$\Rightarrow K(x) \approx \left| \frac{y' - y}{y} \right| \left| \frac{x}{x' - x} \right|$$

$$= \left| \frac{f'(x') - f(x)}{x' - x} \right| \left| \frac{x}{y} \right| = \left| \frac{x f'(x)}{f(x)} \right|$$

Ex: Let  $y = x^{\frac{1}{3}} = f'(x)$

$$C(x) = \frac{1}{3} x^{-\frac{2}{3}}$$

$$K(x) = \frac{x f'(x)}{f(x)} = \frac{x \cdot \frac{1}{3} \cdot x^{-\frac{2}{3}}}{x^{\frac{1}{3}}} = \frac{\frac{1}{3} x^{\frac{1}{3}}}{x^{\frac{1}{3}}} = \frac{1}{3}$$

$$C(x) = \frac{1}{3} \frac{1}{x^{\frac{2}{3}}} < \infty \text{ for } x \text{ away from } 0$$



$K(x)$  is small everywhere

~~$f(x)$~~   $f(x+\epsilon) \approx f(x) + f'(x)\epsilon$

$$\approx f(x) + \frac{1}{3} x^{-\frac{2}{3}} \epsilon$$

$$\Rightarrow |f(x+\epsilon) - f(x)| \approx \frac{1}{3} x^{-\frac{2}{3}} \epsilon$$

large for  $x$  near 0.