

- HW length
- Please tag your forum posts.
- Ask Ques @ 12:30 after class
- Examlet 1 : book your times
- HW3
- HW sol : show up after it winds

$$\|A\|_2 = \max_{\|x\|=1} \|Ax\|_2$$

Properties of Matrix Norms

Matrix norms inherit the vector norm properties:

- ▶ $\|A\| > 0 \Leftrightarrow A \neq 0$. *definiteness*
- ▶ $\|\gamma A\| = |\gamma| \|A\|$ for all scalars γ . *semilik*
- ▶ Obeys triangle inequality $\|A + B\| \leq \|A\| + \|B\|$ Δ -ineq.

But also some more properties that stem from our definition:

$$\|A x\| \leq \|A\| \|x\|$$
$$\|A B\| \leq \|A\| \|B\|$$

submultiplicativity

$$A \Delta x = \Delta b \quad | \quad A^{-1}$$
$$\Delta x = A^{-1} \Delta b$$

Conditioning

What is the condition number of solving a linear system $Ax = b$?

Input: \vec{b} with error $\Delta \vec{b}$

Output: \vec{x} with error $\Delta \vec{x}$

$$A(\vec{x} + \Delta \vec{x}) = \vec{b} + \Delta \vec{b} \Rightarrow A \Delta \vec{x} = \Delta \vec{b}$$

$$\frac{\text{rel. error in output}}{\text{rel. error in input}} = \frac{\|\Delta \vec{x}\| / \|\vec{x}\|}{\|\Delta \vec{b}\| / \|\vec{b}\|} = \frac{\|\Delta \vec{x}\| \|\vec{b}\|}{\|\Delta \vec{b}\| \|\vec{x}\|}$$

$$= \frac{\|\Delta^{-1} \Delta \vec{b}\| \|\vec{Ax}\|}{\|\Delta \vec{b}\| \|\vec{x}\|}$$

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

Conditioning of Linear Systems: Observations

Showed $\kappa(\text{Solve } \mathbf{Ax} = \mathbf{b}) \leq \|A^{-1}\| \|A\|$.

I.e. found an *upper bound* on the condition number. With a little bit of fiddling, it's not too hard to find examples that achieve this bound, i.e. that it is *sharp*. ✓ (see HW)

So we've found the *condition number of linear system solving*, also called the **condition number of the matrix A** :

$$\text{cond}(A) = \kappa(A) = \|A\| \|A^{-1}\|.$$

↪ rel. to the (matrix) norm.

$$\kappa_2(A) = \|A\|_2 \|A^{-1}\|_2$$

Conditioning of Linear Systems: More properties

- ▶ cond is relative to a given norm. So, to be precise, use

cond_2 or cond_∞ .

- ▶ If A^{-1} does not exist: $\text{cond}(A) = \infty$ by convention.

What is $\kappa(A^{-1})$?

recall: square

$\kappa(A)$

What is the condition number of matrix-vector multiplication?

solve: $Ax = b$ matvec: $A\vec{x} = \vec{b} \Leftrightarrow A^{-1}\vec{b} = \vec{x}$

Demo: Condition number visualized [cleared]

Demo: Conditioning of 2x2 Matrices [cleared]

equiv. solving lh. system

Residual Vector

What is the **residual vector** of solving the linear system

$$\mathbf{b} = A\mathbf{x}?$$

$$\vec{r} = \vec{b} - A\vec{x}$$

↑
computable!

Residual and Error: Relationship

How do the (norms of the) residual vector \mathbf{r} and the error $\Delta \mathbf{x} = \mathbf{x} - \hat{\mathbf{x}}$ relate to one another?

$$\|\Delta \hat{\mathbf{x}}\| = \|\hat{\mathbf{x}} - \hat{\mathbf{x}}^{\dagger}\| = \|A^{-1}(b - A\hat{\mathbf{x}})\| = \|A^{-1}\mathbf{r}\| \quad \text{computable!}$$

$$\underbrace{\frac{\|\Delta \hat{\mathbf{x}}\|}{\|\hat{\mathbf{x}}\|}}_{\text{"rel. error"}} = \frac{\|A^{-1}\mathbf{r}\|}{\|\hat{\mathbf{x}}\|} \leq \frac{\|A^{-1}\|\|\mathbf{r}\|}{\|\hat{\mathbf{x}}\|} = \underbrace{\frac{\|A\|}{\|A\|}}_{\text{cond}(A)} \frac{\|\mathbf{r}\|}{\|A\hat{\mathbf{x}}\|} \leq \text{cond}(A) \underbrace{\frac{\|\mathbf{r}\|}{\|A\hat{\mathbf{x}}\|}}_{\text{rel. resid}}$$

\uparrow A
 \uparrow

$$\text{"rel. error"} \leq \text{cond}(A) \cdot \text{rel. resid}$$

$$\|A\| \|\hat{\mathbf{x}}\| \geq \|A\hat{\mathbf{x}}\|$$

Changing the Matrix

So far, only discussed changing the RHS, i.e. $Ax = b \rightarrow A\hat{x} = \hat{b}$.
The matrix consists of FP numbers, too—it, too, is approximate. I.e.

$$Ax = b \rightarrow \hat{A}\hat{x} = b.$$

What can we say about the error due to an approximate matrix?

$$\Delta x = \hat{x} - x = A^{-1}(A\hat{x} - b) = A^{-1}(A\hat{x} - \hat{A}\hat{x}) = A^{-1}\Delta A \hat{x}$$

$$\|\Delta x\| \leq \|A^{-1}\| \|\Delta A\| \|\hat{x}\| \cdot \frac{\|A\|}{\|A\|}$$

$$\frac{\|\Delta x\|}{\|\hat{x}\|} \leq \text{cond}(A) \cdot \frac{\|\Delta A\|}{\|A\|}$$

"rel. error"

Changing Condition Numbers

Once we have a matrix A in a linear system $A\mathbf{x} = \mathbf{b}$, are we stuck with its condition number? Or could we improve it?



What is this called as a general concept?



In-Class Activity: Matrix Norms and Conditioning

In-class activity: Matrix Norms and Conditioning

Singular Value Decomposition (SVD)

What is the *Singular Value Decomposition* of an $m \times n$ matrix?

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

$$A = U \Sigma V^T$$

col U = left. sig. vect. U : orthogonal $\in m \times m$

singular values Σ : diagonal, has nonneg. entries $m \times n$

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0$$

$$\Sigma = \text{diag}(\sigma_1, \dots, \sigma_n)$$

col V = right. sig. vect. V : orthogonal $\in n \times n$

Computing the 2-Norm

Using the SVD of A , identify the 2-norm.

$$\begin{aligned} \text{Let } Q \text{ be orthogonal: } \|Q\vec{x}\|_2 &= \|\vec{x}\|_2 \\ &\begin{array}{c} \text{orth} \\ \downarrow \end{array} \quad \begin{array}{c} \text{orth.} \\ \downarrow \end{array} \\ \|A\|_2 &= \|U \Sigma V^T\|_2 = \|\Sigma\|_2 = \sigma_1 \end{aligned} \Rightarrow \|QB\|_2 = \|B\|_2 \leftarrow$$

Express the matrix condition number $\text{cond}_2(A)$ in terms of the SVD:

$$\text{cond}_2(A) = \sigma_1 / \sigma_n$$

Not a matrix norm: Frobenius

The 2-norm is very costly to compute. Can we make something simpler?

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What about its properties?

