

3 condition numbers

Sunday, September 13, 2020 6:52 PM

Def. 8.9 For $A = (a_{ij}) \in \mathbb{C}^{n \times n}$, the norm $\|A\|_2$ is often called the spectral norm.

A few technical inequalities:

Prop. 8.8/8.11 Let $\|\cdot\|$ be any matrix norm, and let $B \in \mathbb{C}^{n \times n}$ s.t. $\|B\| < 1$.

(1) If $\|\cdot\|$ is a subordinate matrix norm, then $I+B$ is invertible and

$$\|(I+B)^{-1}\| \leq \frac{1}{1-\|B\|}.$$

(2) If a matrix of the form $I+B$ is singular, then $\|B\| \geq 1$ for every matrix norm.

proof. (1) If $(I+B)u = 0$, then $Bu = -u \Rightarrow \|u\| = \|Bu\|$.

But $\|Bu\| \leq \|B\|\|u\|$ for every subordinate norm.

Since $\|B\| < 1$, if $u \neq 0$, then $\|Bu\| < \|u\|$, a contradiction.


$\Rightarrow u = 0$ if $(I+B)u = 0$, so $I+B$ is invertible.

Then $I = (I+B)(I+B)^{-1} = (I+B)^{-1} + B(I+B)^{-1}$.

$$\Rightarrow (I+B)^{-1} = I - B(I+B)^{-1}$$

$$\Rightarrow \|(I+B)^{-1}\| \leq (1 + \|B\|) \|(I+B)^{-1}\|$$

$$\Rightarrow \|(I+B)^{-1}\| \leq \frac{1}{1-\|B\|}.$$

(2) If $I+B$ is singular, then -1 is an eigenvalue of B , and recall $\rho(B) \leq \|B\| \Rightarrow 1 \leq \rho(B) \leq \|B\|$. 

spectral radius

We will need the following to deal with convergence of sequences of matrix powers

Prop. 8.9/8.12 $\forall A \in \mathbb{C}^{n \times n}$, $\forall \epsilon > 0$, \exists a subordinate matrix norm $\|\cdot\|$

s.t. $\|A\| \leq \rho(A) + \epsilon$.

proof. Recall the Schur decomposition, starting that $A = U^* T U$ where U is a unitary matrix and T is upper triangular.

proof. Recall the Schur decomposition, starting that
 $A = UTU^{-1}$, where U is a unitary matrix and T is upper triangular.

Say $T = \begin{pmatrix} \lambda_1 & t_{12} & t_{13} & \dots & t_{1n} \\ & \lambda_2 & & & \vdots \\ & & \ddots & & \\ 0 & & & & t_{n-1,n} \\ & & & & \lambda_n \end{pmatrix}$, where $\lambda_1, \dots, \lambda_n$ are eigenvalues.

For every $\delta \neq 0$, define

$$D_\delta = \text{diag}(1, \delta, \delta^2, \dots, \delta^{n-1}).$$

Then $(UD_\delta)^{-1} A (UD_\delta) = D_\delta^{-1} T D_\delta = \begin{pmatrix} \lambda_1 & \delta t_{12} & \delta^2 t_{13} & \dots & \delta^{n-1} t_{1n} \\ & \lambda_2 & & & \vdots \\ & & \ddots & & \\ & & & & \delta t_{n-1,n} \\ & & & & \lambda_n \end{pmatrix}$

We now construct $\|\cdot\|: \mathbb{C}^{n \times n} \rightarrow \mathbb{R}$ by defining

$$\|B\| = \|(UD_\delta)^{-1} B (UD_\delta)\|_\infty,$$

which is the matrix norm subordinate to the vector norm

$$v \mapsto \|(UD_\delta)^{-1} v\|_\infty.$$

$$\forall \varepsilon > 0, \text{ pick } \delta \text{ s.t. } \sum_{j=i+1}^n |\delta^{j-i} t_{ij}| \leq \varepsilon, \quad 1 \leq i \leq n-1$$

$$\Rightarrow \|A\| \leq \rho(A) + \varepsilon. \quad \left(\begin{array}{l} \text{because } \|\cdot\|_\infty \text{ is the maximum over} \\ \text{e}^1\text{-norm of rows} \end{array} \right)$$



Aside: equality is generally not possible (e.g. $\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$).

Condition numbers of matrices

Def 8.10 For any subordinate matrix norm $\|\cdot\|$, for any invertible A ,

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

is called the condition number of A relative to $\|\cdot\|$.

Condition numbers measure the sensitivity of the linear system $Ax = b$ to variations in A and b .

Condition numbers measure the sensitivity of the solution to variations in A and b .

Prop. 8.10/8.13 Let A be an invertible matrix and let

$$Ax = b$$

$$A(x + \Delta x) = b + \Delta b.$$

If $b \neq 0$, then

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

Further, for a given A , $\exists b \neq 0$ and $\Delta b \neq 0$ for which equality holds

proof.

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

$$\Rightarrow \|\Delta x\| \leq \|A^{-1}\| \|\Delta b\|$$

$$\Rightarrow \|b\| \leq \|A\| \|x\|. \Rightarrow \|x\| \geq \frac{\|b\|}{\|A\|} \Rightarrow \frac{1}{\|x\|} \leq \frac{\|A\|}{\|b\|}$$

$$\Rightarrow \frac{\|\Delta x\|}{\|x\|} \leq \frac{\|A^{-1}\| \|\Delta b\|}{\frac{\|b\|}{\|A\|}} = (\|A\| \|A^{-1}\|) \cdot \frac{\|\Delta b\|}{\|b\|}.$$

$$= \text{cond}(A) \cdot \frac{\|\Delta b\|}{\|b\|}.$$

Now just need to exhibit $b \neq 0$ and $\Delta b \neq 0$ s.t. we get equality.

Because $\|\cdot\|$ is a subordinate matrix norm, $\exists x \neq 0$ and $\Delta b \neq 0$ s.t.

$$\|A^{-1} \Delta b\| = \|A^{-1}\| \|\Delta b\| \quad \text{and} \quad \|Ax\| = \|A\| \|x\|.$$

(since subordinate matrix norms can be defined as supremums over closed unit balls)

$$\text{Then } \frac{\|\Delta x\|}{\|x\|} = \frac{\|A\| \|\Delta x\|}{\|A\| \|x\|} = \frac{\|A\| \|A^{-1} \Delta b\|}{\|Ax\|} = \frac{\|A\| \|A^{-1}\| \|\Delta b\|}{\|b\|}.$$



Above, we have perturbed b . We can similarly perturb A .

Prop. 8.11/8.14 Let A be an invertible matrix, and let

$$Ax = b$$

$$(A + \Delta A)(x + \Delta x) = b.$$

$$\|x + \Delta x\| \leq \|x\| + \|\Delta x\|$$

$$(A + \Delta A)(x + \Delta x) = b.$$

If $b \neq 0$, then $\frac{\|\Delta x\|}{\|x + \Delta x\|} \leq \text{cond}(A) \cdot \frac{\|\Delta A\|}{\|A\|}$ holds and is the best possible.

Basically, the condition number tells us how sensitive the system $Ax = b$ is to perturbations under $\|\cdot\|$.

Def. 8.11 Given a complex $n \times n$ matrix A , a triple (U, V, Σ) such that $A = V \Sigma U^*$, where U and V are $n \times n$ unitary matrices and $\Sigma = \text{diag}(\sigma_1, \dots, \sigma_n)$ is a diagonal matrix of singular values $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n \geq 0$ is called a singular value decomposition (SVD) of A . If A is real, then U and V are orthogonal matrices.

Preview: Chapter 20: every real or complex rectangular matrix has an SVD. (Nice geometric interpretation that we will cover after adjoints and spectral theorems).

Note: $A = V \Sigma U^* \Rightarrow A^* A = U \Sigma^2 U^*$ and $A A^* = V \Sigma^2 V^*$
 $\Rightarrow \sigma_1^2, \dots, \sigma_n^2$ are eigenvalues of both $A^* A$ and $A A^*$.
 \Rightarrow cols of U are eigenvectors for $A^* A$.
 \Rightarrow cols of V are eigenvectors for $A A^*$.

$$\Rightarrow \sqrt{\rho(A^* A)} = \sqrt{\rho(A A^*)} = \sigma_1.$$

Corollary 8.3/8.15 $\|A\|_2 = \sigma_1$ (spectral norm is equal to largest sing. val.)
 $= \|(\sigma_1, \dots, \sigma_n)\|_\infty$.

Corollary 8.4/8.16 $\|A\|_F = \sqrt{\text{tr}(A^* A)} = \sqrt{\sigma_1^2 + \dots + \sigma_n^2} = \|(\sigma_1, \dots, \sigma_n)\|_2$.

Prop. 8.12/8.17 For any invertible $A \in \mathbb{C}^{n \times n}$,
 (because $1 = \|I\| \leq \|A\| \|A^{-1}\| = \text{cond}(A)$)

(1) $\text{cond}(A) \geq 1$

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

(1) cond \dots - ,
 $\text{cond}(A) = \text{cond}(A^{-1})$
 $\text{cond}(\alpha A) = \text{cond}(A) \quad \forall \alpha \in \mathbb{C} - \{0\}$.

(2) Let $\text{cond}_2(A)$ be the condition number of A w.r.t. the spectral norm.

Then $\text{cond}_2(A) = \frac{\sigma_2}{\sigma_n}$.

(3) If A is normal (i.e. $AA^* = A^*A$), then

$$\text{cond}_2(A) = \frac{|\lambda_1|}{|\lambda_n|},$$

where $\lambda_1, \dots, \lambda_n$ are the eigenvalues, sorted so that $|\lambda_1| \geq |\lambda_2| \geq \dots \geq |\lambda_n|$.

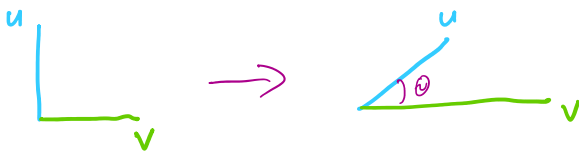
(4) If A is a unitary or orthogonal matrix, then $\text{cond}_2(A) = 1$.

(5) $\text{cond}_2(A) = \text{cond}_2(UA) = \text{cond}_2(AV) \quad \forall$ unitary U, V .

We very often care about unitary/orthogonal matrices since they are extremely well-conditioned for the spectral norm (indeed, they are "length-preserving").

Geometric interpretation

$\text{cond}_2(A) = \cot\left(\frac{\theta(A)}{2}\right)$, where $\theta(A)$ is the smallest angle between Au and Av , where u, v are orthonormal vectors



Caution: It's tempting to think of condition number cond_2 as related to eigenvalues. However, this is only true for normal matrices.

Consider $A = \begin{pmatrix} 1 & 2 & & 0 \\ & 1 & 2 & \\ & & \ddots & \ddots \\ 0 & & & 2 \\ & & & & 1 \end{pmatrix}$, with $\text{cond}_2(A) \geq 2^{n-1}$.

Or a Hilbert matrix $H_{ij}^{(n)} = \frac{1}{i+j-1}$, $\text{cond}_2(H^{(n)}) = O\left(\frac{(1+\sqrt{2})^{4n}}{\sqrt{n}}\right)$.