

Orthogonality

Orthogonality (review (on. alg.))

A matrix, A^* hermitian transpose. : $(A^*)_{ij} = \overline{A_{ji}}$ ← c.c.

$A = A^*$ Symm?

Ex. prove $(AB)^* = B^*A^*$, $(A^{-1})^* = (A^*)^{-1}$

x col. vec, x^* row vec.

$x, y \in \mathbb{C}^m$, $x^*y = ?$ inner prod $\begin{bmatrix} x^* \\ \vdots \end{bmatrix} \begin{bmatrix} y \\ \vdots \end{bmatrix} = \sum_{i=1}^m \overline{x_i} y_i$

2-norm $\|x\|_2 := \sqrt{x^*x}$
↑
write always write.

Defn of a norm?

- i) $\|\alpha x\| = |\alpha| \|x\|$ α scalar
- ii) $\|x\| = 0 \Rightarrow x = 0$ ← vector.
- iii) $\|x+y\| \leq \|x\| + \|y\|$ tri

2-norm also has. $|x^*y| \leq \|x\| \|y\|$ Cauchy-Schwarz

$x^*y = 0$? x, y orthog.

Thm: mutually orthog. set of vectors are (n. indep. (pf: Ex).

\Rightarrow n orthog. vecs in \mathbb{C}^n form basis; if unit length, o.n.b.

Say $\vec{q}_1, \dots, \vec{q}_n \in \mathbb{C}^n$ o.n.b., can stack into cols. of Q , then $(Q^*Q)_{ij} = \vec{q}_i^* \vec{q}_j = \delta_{ij}$
so $Q^*Q = I$ i.e. $Q^{-1} = Q^*$ [cols o.n.b. \Leftrightarrow unitary]

so Q^*b is coeffs of expansion of b in o.n.b. $\{q_i\}$

$\|Qx\| = \sqrt{(Qx)^*Qx} = \sqrt{x^*Q^*Qx} = \|x\|$ preserves lengths. (rotation, poss w/ reflect)

Matrix 2-norm: $\|A\|$ smallest $\# c$ st. $\|Ax\| \leq c \|x\| \forall x \in \mathbb{C}^n$
← implied "max growth factor"

or $\|A\| := \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|} = \sup_{\|x\|=1} \|Ax\|$

Eg i) 2-norm of diag matrix? Its largest-magnitude entry.

ii) 2-norm of $A = uv^*$? (rank-1). $\|uv^*x\|_{\text{scalar}} = |v^*x| \|u\| \leq \|v\| \|x\| \|u\| = \|A\| \|x\|$
← c.s. ←

2-norm submultiplicative: $\|ABx\| \leq \|A\| \|Bx\| \leq \|A\| \|B\| \|x\|$
why?

Ex. show QA & AQ have same 2-norm as A . So $\|AB\| \leq \|A\| \|B\|$. (Thm 3-1)

Singular Value Decomposition (SVD) — as important as spectral decomp.

Geom fact: every $A \in \mathbb{C}^{m \times n}$ maps unit ball into hyperellipsoid

$S \subset \mathbb{R}^n$ $AS \subset \mathbb{R}^m$
 $(\mathbb{C}^n \text{ harder to plot!})$

full case $m \geq n$ & full rank. ($=n$): left sing. vecs u_1, \dots, u_n unit orthog. sh. ellip. m. 2x2 case.
 sing. vals. $\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n > 0$ semiaxes.
 so what is $\|A\|$? = σ_1
 right sing. vecs $v_j, j=1, \dots, n$, also orthog. amazingly! \Rightarrow o.n.b. for \mathbb{C}^n .
 precursors of $\sigma_j u_j$

rank $r < n$ then $\sigma_1, \dots, \sigma_r > 0$ while $\sigma_{r+1} = \dots = \sigma_n = 0$.

So $Av_j = \sigma_j u_j, j=1, \dots, n$.

$$A \begin{bmatrix} | & & | \\ v_1 & & v_n \\ | & & | \end{bmatrix} = \begin{bmatrix} | & & | \\ u_1 & & u_n \\ | & & | \end{bmatrix} \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{bmatrix}$$

$\underbrace{\hspace{10em}}_V \quad \underbrace{\hspace{10em}}_U \quad \underbrace{\hspace{10em}}_\Sigma$

(postmult by V^*)
 so $A = U \Sigma V^*$
 reduced SVD.

May complete \hat{U} to U o.n.b. for \mathbb{C}^m .
 & pad $\hat{\Sigma}$ to Σ if $m < n$

Thm (4.1 in NLA): every $A \in \mathbb{C}^{m \times n}$ has SVD, $\{\sigma_j\}$ unique, & if $\sigma_j > 0$, u_j & v_j unique up to phase.

Then $A = \begin{matrix} m & & n \\ \boxed{} & \boxed{} & \boxed{} \\ U & \Sigma & V \end{matrix}$ (analogous if $m < n$)

Every matrix is rotation (w/ refl.) \rightarrow stretch \rightarrow rot. (w/ refl.) — even nonsymm or nonsquare ones. (cf. spectral decomp may not exist.)

or: every matrix is drag in correct basis for \mathbb{C}^n & \mathbb{C}^m . (V^* projects to cells of orb)

If A square invertible, $A^{-1} = (U \Sigma V^*)^{-1} = V \Sigma^{-1} U^*$ is the SVD of A^{-1} (if reorder Σ^{-1} !)
 What is $\|A^{-1}\|$? largest sing val of A^{-1} = $\frac{1}{\sigma_n}$ (smallest sing val of A)

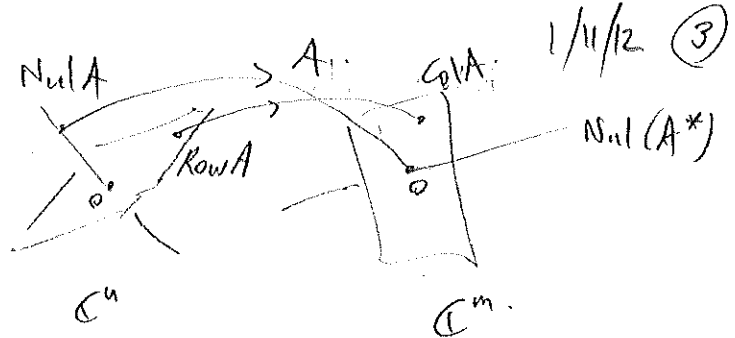
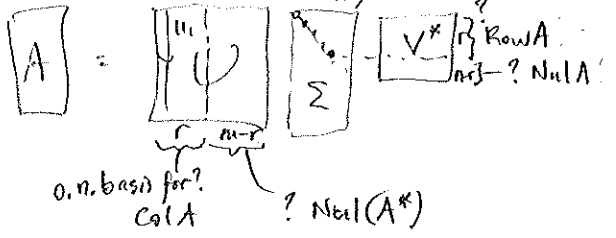
\rightarrow WS (PTO) —

back

needed for WS.

Notes on SVD: existence pf either by induction (NLA ch. 4 — beautiful proof: grad students read) or A^*A has eivals $\{\sigma_j^2\}$ & complete eigvecs v_j o.n.b. why? A^*A symm.
 AA^* " " " " u_j " " "
 eivals $\lambda_j \geq 0$ & then define $\sigma_j = \sqrt{\lambda_j}$.

Anatomy: SVD & spaces:



1/11/2 (3)

rank $r := \#\{j : \sigma_j > 0\}$

numerical rank $r_\epsilon := \#\{j : \sigma_j > \epsilon\}$

$\epsilon \sim \sigma_i$ (machine precision!) $\sim 10^{-16}$

Qu: what do think σ_j 's of Vandermonde did? shut down to ϵ when $m \sim 40$.

Conditioning (§12 NLA)

: property of a math problem (vs. Stability: property of alg. used to solve it).

problem is map $f: X \rightarrow Y$
 input space X space of solns. Y

eg. $f(x)$ could return $\begin{cases} \cdot 2x & \text{"the easy" "double prob."} \\ \cdot \text{vector of roots of poly} & \text{given } x = \text{vec. of poly coeffs.} \end{cases}$

f well-cond if infinitesimal pert δx causes 'small' pert δf .
 one symbol! $\delta f := f(x + \delta x) - f(x)$ in soln.

Abs. cond. # $\tilde{\kappa} = \tilde{\kappa}(x) := \lim_{\delta \rightarrow 0} \sup_{\|\delta x\| \leq \delta} \frac{\|\delta f\|}{\|\delta x\|} = \sup_{\delta x} \frac{\|\delta f\|}{\|\delta x\|}$
 abbrev. \uparrow 2-norms

if x, f vectors, $\frac{\partial f_i}{\partial x_j} = J_{ij}(x)$ is Jacobian matrix $J \in \mathbb{C}^{m \times n}$

As $\|\delta x\| \rightarrow 0$ have $\delta f \approx J(x) \delta x$ so $\tilde{\kappa}(x) = \|J(x)\|$ matrix 2-norm.

more useful is:

Rel. cond # $\kappa := \sup_{\delta x} \frac{\|\delta f\| / \|f\|}{\|\delta x\| / \|x\|} = \frac{\|J(x)\|_2}{\|f\| / \|x\|}$

important since compute brings in relative errors.

$\kappa < 10^3$ well cond
 $\gg 10^3$ ill-cond

Basic ops:

- $f(x) = x/2$ ($m=n=1$) $J = f' = 1/2$ so $\kappa = \frac{|1/2|}{1/2} = 1$
- $f(x) = x^x$ $J = f' = x^{x-1}$ $\kappa = \frac{|x \cdot x^{x-1}|}{x^x/x} = |x| \ll 10^3$ well-cond for reasonable powers.
- $f(x_1, x_2) = x_1 - x_2$ subtraction ($n=2, m=1$). $J = [1 \ -1]$ $\|J\| = \sqrt{2}$
 $\kappa = \frac{\sqrt{2} \sqrt{x_1^2 + x_2^2}}{|x_1 - x_2|} \rightarrow \infty$ as $x_1 \rightarrow x_2 \neq 0$. can be ill-cond.
- $f(x) = \sin x$, for $x \approx 10^{100}$ say: $\|J\| \leq 1$ but $\kappa = \frac{\|J\| \|x\|}{|\sin x|} \gg |x| = \text{huge}$.
 (but abs cond # ≤ 1)
- finding poly roots ill-cond
- eigenls of nonsymm matrices: eg $A = \begin{bmatrix} 1 & 10^3 \\ & 1 \end{bmatrix}$ vs $\begin{bmatrix} 1 & 10^3 \\ 10^{-3} & 1 \end{bmatrix}$
 $\lambda = 0, 1$ vs $\lambda = 10^3, 1$
 $\| \delta x \| = 10^{-3}$
 $\| \delta f \| \sim 1$
 $\tilde{\kappa} \sim 10^3, \kappa \sim 10^6$

but symm, $\tilde{\kappa} \approx 1$.