

1. If A is upper triangular,

let $Z = A^{-1}$, then

$$I = AZ$$

$$d[j][c] = \sum_{i=1}^m \underbrace{a[j][i]}_{\substack{0 \text{ for } i < j \\ \neq 0 \text{ for } i \geq j}} z[i][j] = \begin{cases} 1 & c=j \\ 0 & c \neq j \end{cases}$$

0 for $i < j$

$\neq 0$ for $i \geq j$

so for $j=0$

$$d[0][c] \quad [1 \ 0 \ 0 \ 0 \ \dots] = \begin{matrix} \text{A row 0} \\ [a_1 \ a_2 \ \dots \ a_m] \\ \text{all nonzero} \end{matrix} \begin{matrix} \text{Z col 0} \\ \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix} \end{matrix}$$

$$\text{so } a_1 z_1 = 1 \quad \text{if } z_1 \neq 0$$

$$\left. \begin{matrix} a_2 z_2 = 0 \\ \vdots \\ a_m z_m = 0 \end{matrix} \right\} \text{for these to be 0, } z_2 \dots z_m = 0$$

$$\text{more generally, since } a[j][i] = \begin{cases} 0 & i < j \\ \neq 0 & i \geq j \end{cases} \quad z[i][j] = \begin{cases} \text{nonzero} & i \leq j \\ 0 & i > j \end{cases}$$

so the columns of Z are nonzero for $i \leq j$

thus, if A is upper triangular $\rightarrow Z = A^{-1}$ is upper triangular. Pt 1. \blacksquare

Since A is unitary, $A^* = A^{-1}$, so A^* is upper triangular by Pt 1.

A and A^* are both upper triangular iff A is diagonal

// If A is lower triangular, then for Pt 1 above,

$$d[0][c] = [1 \ 0 \ \dots \ 0] = \begin{matrix} \text{all nonzero,} \\ [a_1 \ a_2 \ a_3 \ \dots \ a_m] \\ \text{nonzero} \quad \quad \quad 0 \end{matrix} \begin{matrix} \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_m \end{bmatrix} \\ a[j][i] = \begin{cases} \neq 0 & i \leq j \\ 0 & i > j \end{cases} \\ z[i][j] = \begin{cases} 0 & i < j \\ \neq 0 & i \geq j \end{cases} \end{matrix}$$

So if A lower tri., $Z = A^{-1}$ is lower tri., and if A is unitary,

A^* is also lower triangular, so A^* and A are lower triangular iff A is diagonal

2. a. If λ is eigenvalue of A ,

by def $Av = \lambda v$ \longrightarrow $A^{-1}Av = A^{-1}\lambda v$
 $= \lambda A^{-1}v$

if A is invertible, $A^{-1}Av = v$

$$\lambda A^{-1}v = v$$

$$\text{iff } A^{-1}v = \frac{1}{\lambda}v$$

also, $\frac{1}{\lambda}$ is eigenvalue of A^{-1}

b. If λ is eigenvalue of AB ,

so by def $\lambda v = ABv$

let $y = Bv$, then $BAy = BABv$
 $= B\lambda v$
 $= \lambda Bv$

$BAy = \lambda y$

so λ is eigenvalue of BA

2c. Eigenvalues are solutions to

~~$$\det(A - \lambda I) = 0$$~~

$$(A - \lambda I)^t = A^t - \lambda I^t = A^t - \lambda I$$

and since $\det(M) = \det(M^t)$

$$\det(A - \lambda I) = \det(A^t - \lambda I)$$

$\downarrow \qquad \qquad \qquad \downarrow$
 $\text{solutions to } f(x) = 0 = \text{solutions to } f(x) = 0$

$\hookrightarrow A, A^t$ have same eigenvalues

3	4
---	---

$$Ax = \lambda x$$

$$\begin{aligned}\bar{x}^T(Ax) &= \bar{x}^T \lambda x \\ &= \lambda \bar{x}^T x\end{aligned}$$

$$\bar{x}^T(Ax) = \lambda \|x\|$$

take complex conjugate both sides

$$x^T A^{-T} x = \bar{\lambda} \|x\|$$

$$A^T = A, \text{ so } \bar{x}^T A^T x = \bar{x}^T A x$$

$$= \bar{x}^T \lambda x$$

$$= \lambda \|x\|$$

$$\lambda \|x\| = \bar{\lambda} \|x\|$$

$$\lambda = \bar{\lambda}$$

so λ is real

b. $\lambda_1 x = Ax \quad \lambda_1 \neq \lambda_2$
 $\lambda_2 y = Ay$

$$Ax \cdot y = x \cdot A^T y$$

$$= x \cdot Ay$$

$$\lambda_1 x \cdot y = x \cdot \lambda_2 y$$

$$\lambda_1 x \cdot y = \lambda_2 x \cdot y$$

$$(\lambda_1 - \lambda_2)(x \cdot y) = 0$$

$\neq 0$

so $(x \cdot y) = 0 \Rightarrow$ they are orthogonal.

4. If A had $\lambda = 0$, then there will be $Ax = 0x = 0$,

$x^T Ax = 0$ for some eigenvector x . Contradiction.

If A had $\lambda < 0$, then \exists eigenvector x st $Ax = \lambda x$

$$x^T Ax = x^T \lambda x = \lambda x^T x = \lambda \|x\|^2 < 0, \text{ since } \|x\| > 0.$$

contradiction

So A must have strictly positive eigenvalues.

5. a. by def, if A is unitary, $AA^* = I$

$$Ax = \lambda x$$

$$A^*Ax = A^*\lambda x = Ix$$

since eigenvalues of transpose are the same (Question 2c),

$$A^*\lambda x = \lambda \lambda x = Ix$$

$$\|\lambda\|^2 = 1$$

$$|\lambda| = 1$$

b.

$$\begin{aligned}\|A\|_F &= \sqrt{\text{trace}(A^*A)} = \sqrt{\text{trace}(I_n)} \\ &= \sqrt{n} \neq 1\end{aligned}$$

6. a. Following the proof in 3a.

$$\bar{x}^T \bar{A}^T x = \bar{\lambda} \|x\|$$

↓

$$\bar{A}^T = -A, \text{ so}$$

$$\bar{x}^T -Ax = \bar{\lambda} \|x\|$$

~~for~~

$$\bar{x}^T(-\lambda)x = \bar{\lambda} \|x\|$$

$$-\lambda \|x\| = \bar{\lambda} \|x\|$$

$$-\lambda = \bar{\lambda} \Rightarrow \lambda \text{ is } \overset{\text{pure}}{\text{imaginary}}$$

b. If $I-A$ is singular,

$$\exists x \text{ s.t. } (I-A)x = 0$$

$$\Rightarrow x = Ax$$

$$\Rightarrow A \text{ has eigenvalue } 1$$

from a.), this is not possible, contradiction.

so $I-A$ is not singular.

7.) let λ be the eigenvalue, x be nonzero eigenvector.

$$Ax = \lambda x \quad \text{then let } X = \{x_1 | x_2 | x_3 \dots\}$$

all eigenvectors.

so $AX = \lambda X$

so $|\lambda| \|X\| = \|\lambda X\| = \|AX\| \leq \|A\| \|X\|$

so $|\lambda| \leq \|A\|$

so $\rho(A) \leq |\lambda| \leq \|A\|$

$$\rho(A) \leq \|A\|$$

8. $\|A\|_2 = \sqrt{\rho(A^*A)}$

a.

$$= \sqrt{\rho(uv^*vu^*)}$$

$$= \sqrt{\rho(uu^*v^*v)}$$

$$= \sqrt{\rho(uu^*)} \sqrt{\rho(v^*v)}$$

$$= \sqrt{\rho(uu^*)} \sqrt{\rho(vv^*)}$$

$$= \|u\|_2 \|v\|_2$$

b. $\|A\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n (u_{ij})^2}$

$$= \sqrt{\sum_{i=1}^m (u_i)^2 \sum_{j=1}^n (v_j)^2}$$

$$= \sqrt{\sum_{i=1}^m (u_i)^2} \sqrt{\sum_{j=1}^n (v_j)^2}$$

$$= \|u\|_2 \|v\|_2$$

$$= \|u\|_F \|v\|_F$$

$$a) \quad \|AQ\|_2 = \sup_{\substack{x \neq 0 \\ x \in \mathbb{C}^n}} \frac{\|AQx\|_2}{\|x\|_2}$$

~~Since $AQ = B$, then~~

let $AQ = B$ then

$$= \sup \frac{\|AQx\|_2}{\|x\|_2} = \sup \frac{\|Bx\|_2}{\|x\|_2} = \|B\|_2$$

and since $\|AQ\|_2 = \|A\|_2 = \|B\|_2$,

$$\underline{\|AQ\|_2 = \|A\|_2}$$

$$b) \quad \|AQ\|_F = \sqrt{\text{Tr}[(AQ)^* \underset{AQ}{AA}] } = \sqrt{\text{Tr}[Q^* A^* \underset{AQ}{AA} Q]}$$

$$= \sqrt{\text{Tr}(AQ^*QA)} \quad \leftarrow \quad \text{[scribbled out]}$$

$$= \sqrt{\text{Tr}(A^*A)}$$

$$= \underline{\|A\|_F}$$

$$= \sqrt{\text{Tr}(A^*Q^*QA)}$$

$$= \sqrt{\text{Tr}[(QA)^*QA]}$$

$$= \underline{\|QA\|_F}$$

10 a $\|A\|_F = \|QBQ^*\|_F$

then by proofs in 9), $RHS = \|BQ^*\|_F = \|B\|_F$

so $\|A\|_F = \|B\|_F$

and since Frobenius norm is L_2 norm of singular values,

A and B have the same L_2 of singular values

$$\sqrt{\sum_i \sigma_i^2} \text{ of } A = \sqrt{\sum_i \sigma_i^2} \text{ of } B$$

$$\text{so } A's \sum_i \sigma_i^2 = B's \sum_i \sigma_i^2$$

and since every matrix has unique singular values

this is only possible if $A's \sigma \text{ values} = B's \sigma \text{ values}$

//

$$A = QBQ^*$$

$$= Q(U \Sigma_B V^*) Q^*$$

$$= \underbrace{QU}_{\uparrow} \underbrace{\Sigma_B V^* Q^*}_{\leftarrow}$$

still a singular value form,

$$= U' \Sigma_A V^*$$

thus $A's \Sigma = B's \Sigma$

10b.

Let $\Sigma_A = \Sigma_B$, so singular values are equal

Let $A = (QU + E \text{ for nonzero } E) \Sigma_A (QU + F \text{ for nonzero } F)^*$
for $B = U \Sigma_B V^*$

then there exists A, B with same Σ s.t.

$A - QBQ^* \neq 0$ aka not ~~unitarily~~ equivalent.
Unitarity

11.a $f(x_1, x_2) = x_1 + x_2$

$$J = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \right) = (1, 1)$$

$$\|J\|_\infty = 2$$

$$k(x_1, x_2) = \frac{\|J\|_\infty \|x\|_\infty}{\|f(x_1, x_2)\|_\infty} = \frac{2 \max\{|x_1|, |x_2|\}}{|x_1 + x_2|}$$

if $|x_1 + x_2| \approx 0$, ill-conditioned.
 $x_1 \approx -x_2$

b. $f(x_1, x_2) = x_1 x_2$

$$J = \left(\frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \right) = (x_2, x_1)$$

$$\|J\|_\infty = |x_1| + |x_2|$$

$$k(x_1, x_2) = \frac{(|x_1| + |x_2|) \cdot \max\{|x_1|, |x_2|\}}{|x_1 x_2|}$$

if $|x_1| > |x_2|$ \uparrow
 $k = \frac{(|x_1| + |x_2|) |x_1|}{|x_1 x_2|} = \left| \frac{x_1}{x_2} \right| + 1$

if $|x_2| > |x_1|$ \rightarrow ill conditioned if $|x_2| \gg |x_1|$
 $k = \left| \frac{x_2}{x_1} \right| + 1$

11c. $f(x) = (x-2)^9$

$$J = \frac{df}{dx} = 9(x-2)^8$$

From the Ex 12.5 in the book the $g(x)$ Jacobian is infinite and it is ill-conditioned.

or by def $k = \left| \frac{dx_j}{x_j} \right| / \left| \frac{da_i}{a_i} \right| = \left| \frac{a_i x_j^{i-1}}{p'(x_j)} \right|$

~~well-conditioned~~
 $J_{x=2} = 0$, so
 well-conditioned at $x=2$

So for the $g(x)$ expression / expansion of $f(x)$,

$$k \text{ of } x_j=0 \text{ wrt } a_{i=1} = \left| \frac{a_1 x_j^0}{p'(x_j)} \right| = \left| \frac{5/2}{x_j'} \right|$$

*

etc.

these k values can be very large, i.e. ill-conditioned

$$k \text{ of } x_j \text{ wrt } a_6 = \left| \frac{a_6 x_j^5}{g'(x_j)} \right| = \left| \frac{2016 x_j^5}{g'(x_j)} \right| \quad x_j=2, \text{ so near } x=2$$

$$\left| \frac{2016 \times 2}{9(x-2)^8} \right|$$

can be very large.