

MA - 473

Date: 28/9/24

Bsp discuss

MA - 483

Date: 29/9/24

"non-singular" only reserved for 39 matrices

D)

A full rank $\text{rank}(A) = m$

$$\begin{bmatrix} R_1 \\ 0 \end{bmatrix} x_0 = \begin{bmatrix} I_m & 0 \\ 0 & 0 \end{bmatrix}_{n \times n} c$$

$$\begin{bmatrix} R_1 x_0 \\ 0 \end{bmatrix} = \begin{bmatrix} I_m c_1 + 0.c_2 \\ 0.c_1 + 0.c_2 \end{bmatrix}, \quad C = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}_{\frac{n}{m} \times m}$$

$$R_1 x_0 = c_1$$

we can make any assumption on $\text{rank}(A)$ position.

Rank revealing QR decomst

$$\text{rank}(A) = r (\leq m)$$

$$A_{n \times m} = Q_1 A P_1 \dots P_r = \begin{bmatrix} R_1 & R_2 \\ 0 & 0 \end{bmatrix}$$

Or

$$Q^T A P = R$$

$$AP = QR$$

$$\text{rank}(\tilde{A}) \text{? } \begin{bmatrix} R_1 & R_2 \\ 0 & R_3 \end{bmatrix}$$

$Q R_3$ has very small abs values

we can zero out R_3 st $\text{rank}(\tilde{A}) = \infty$ (numerical rank of \tilde{A})

Case 2

$$\text{rank}(A) = r < m$$

$(AP)e_1 \quad (AP)e_2$
 linear ind why?

$$AP = Q \Sigma = \begin{bmatrix} I_r & 0_{r \times (m-r)} \\ 0_{(m-r) \times r} & 0_{(m-r) \times (m-r)} \end{bmatrix} \begin{bmatrix} \Sigma_r & 0_{r \times (m-r)} \\ 0_{(m-r) \times r} & 0_{(m-r) \times (m-r)} \end{bmatrix}$$

$$= \begin{bmatrix} Q_1 R_1 & 0_{r \times (m-r)} \\ 0 & 0 \end{bmatrix}$$

$Q_1 R_1$ will preserve range of R_1 $\&$ ($\because Q_1$ is orthogonal)

$$\begin{bmatrix} (AP)_1 & \dots & (AP)_r \\ \vdots & \ddots & \vdots \end{bmatrix} = \begin{bmatrix} R_1 & 0 \\ 0 & 0 \end{bmatrix}$$

orthogonal matrix
preserves rank of A
matrix on output

(in our context
chaos in
existing hierarchical
structure)

25/9/24
HSS-217

Kaliyuga :

chaos /
lawless news

MA-473 26/9/24
for non singular matrix A ,
 $Ax = b$

$$x = A^{-1}b \rightarrow \cos \theta b$$

$$\lim_{n \rightarrow \infty} x^{(n)} \xrightarrow{\sim} \tilde{x}$$

MA-423

$$Q = [Q_1 \ Q_2]$$

$$A \times_Q = Q_1 Q_1^T b$$

$$= Q_1 e_1$$

$$e_1] [e_1 \ e_2]^T Q_1^T b$$

$$Q^T \neq \begin{bmatrix} Q_1^T \\ Q_2^T \end{bmatrix}$$

$$b_* = b_1 + b_2$$

$$b_1 = Q_1 Q_1^T b$$

$$I - Q_1 Q_1^T = Q_2 Q_2^T$$

$$\begin{aligned} b_2 &= (I - Q_1 Q_1^T)^T b \\ &= Q_2 Q_2^T b = \lambda \end{aligned}$$

$$Q Q^T = I_n$$

$$Q_1 Q_1^T + Q_2 Q_2^T = I_n$$

$$\|z_1\| = \|Q_2 Q_2^T b\|_2 = \|Q_2^T b\|_2 = \|c_2\|$$

$$c = Q^T b = [Q_1 \ Q_2]^T b = \begin{bmatrix} Q_1^T b \\ Q_2^T b \end{bmatrix}^T$$

Matrix value Decomposition:

Singular value Decompsn is implicitly
rank revealing decomp. too.

$$A = U \Sigma V = [u_1 \ \dots \ u_m] \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_m \end{bmatrix} [v_1 \ \dots \ v_m]$$

$$v_2 [v_1 \ \dots \ v_m]$$

$$A\vartheta_i = \Delta V e_i \quad 1 \leq i \leq m$$

up to the 3rd prob.

$$= U \Sigma V^* V e_i$$

$$= U \Sigma e_i$$

$$= U \begin{bmatrix} 0 \\ a_i \\ 0 \end{bmatrix} = [U_1 \dots U_r \ U_{r+1} \dots U_m] \begin{bmatrix} 0 \\ a_i \\ 0 \end{bmatrix}$$

$$= \alpha_i u_i$$

$$A^* = (U \Sigma V^*)^* = V \Sigma^* U^*$$

Thm: Every matrix has a singular value decom.

Properties of SVD

$$\text{i) } A = \sum_{i=1}^r \alpha_i u_i v_i^*$$

$$\text{ii) } A = V \Sigma^* U^*$$

$$\text{iii) } R(A) = \text{span}(u_1, \dots, u_r)$$

$$R(A^*) = \text{span}(v_1, \dots, v_r)$$

$$N(A) = \text{span}\{v_{r+1}, \dots, v_m\}$$

$$N(A^*) = \text{span}\{u_{r+1}, \dots, u_m\}$$

$$A\vartheta_i = \alpha_i u_i \quad (\vartheta_i \in \mathbb{C}^m)$$

$$\alpha_i \neq 0 \Rightarrow u_i \text{ spans colspace}(A)$$

$$\text{iv) } \|A\|_2 = \alpha_1 \quad \|A\|_2 = \|\Sigma\|_2$$

$$= \|\Sigma^*\|_2$$

$$= \|V \Sigma^* U^*\|_2$$

$$= \|\Sigma^*\|_2 = \alpha_1$$

$$\alpha_1 = \|A\|_2 = \max_{\mathbf{x} \neq 0} \frac{\|\mathbf{Ax}\|_2}{\|\mathbf{x}\|_2} = \max_{\mathbf{x} \neq 0} (\mathbf{x}^T A \mathbf{x})$$

~~Suppose A is square and full rank~~

~~Suppose A is square and full rank~~

$\Rightarrow \text{rank}(A) < m \Rightarrow \text{Null}(A) \neq \{0\}$
 $\min_{\mathbf{x} \neq 0} (\mathbf{x}^T A \mathbf{x}) < 0, \text{ Null}(A) \neq \{0\}$

~~Suppose A is broad, $n < m$~~

$$\text{rank}(A) \leq n < m$$

$$= \infty$$

$$\Rightarrow \text{Null}(A) \neq \{0\} \Rightarrow \min_{\mathbf{x} \neq 0} (\mathbf{x}^T A \mathbf{x}) = 0$$

for $k(A)$ consider $k(A^T)$ if A is broad.

$$P = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \rightarrow \text{flip matrix}$$

- A is sq. & non singular.

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

$$= (V^T)^T \Sigma^T U^T$$

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

$$= V F F^T \Sigma^T U^T = (V F^2) \Sigma^T (U F^T)$$

$$k(A^T) = \frac{a_1}{a_n}$$

$$\|A\|_2 = \sqrt{a_1}$$

or then $a_1 \gg a_n$

\Rightarrow singular matrix

α

MA-428 Date: 26/4/23

$$\|U_i v_i\|_2 = \|x_i v_i\|_2 \quad \text{if } A v_i \neq 0$$
$$\|U_i v_i\|_2 = \|U_i\|_2 \|v_i\|_2 - 2$$

A

$$A v_i = \underbrace{\alpha_i v_i}_{} v_i = u_i$$

$$A v = u_i v_i \theta = 0 \quad \forall \theta \perp v_i$$

θ is v_i, v_{i+} or $\gamma \in \text{ONB of } F^r$

$$x = \sum_{i=1}^m v_i \quad \max_{x \neq 0} \frac{\|Ax\|_2}{\|x\|_2} = ?$$

$$g_i^\top g_j = 0 \quad i \neq j$$

~~(1)~~

Full rank, full row rank $A_{n \times m}$ $\text{rank}(A) = n$

$$A^\top v_i = \underbrace{\alpha_i v_i}_{} \quad \alpha_i \neq 0$$
$$A^\top A v_i = \alpha_i A^\top v_i = \alpha_i^\top v_i$$

$\alpha_i \neq 0$

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

Every singular media is surrounded by non singular matrix
 hence it is numerically difficult to find rank - deficient matrix
 & vice versa

$$A = U \begin{bmatrix} a_1 & & \\ & \ddots & \\ & & a_n \end{bmatrix} V^* \quad r < n \quad \epsilon > 0$$

$$\text{Consume } B = U \begin{bmatrix} a_1 & & \\ & a_2 & \\ & & \epsilon_2 - \epsilon_2 \end{bmatrix} V^* \quad \text{rank } B = n$$

$$\|A - B\|_2 = \|U \left(\begin{bmatrix} a_1 & a_2 & 0 \\ & \ddots & \ddots \\ & & 0 \end{bmatrix} - \begin{bmatrix} a_1 & a_2 & \epsilon_2 & \epsilon_2 \\ & \ddots & \ddots & \ddots \\ & & \epsilon_2 & \epsilon_2 \end{bmatrix} \right) V^*\|_2$$

$$= \| \begin{bmatrix} 0 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0 \end{bmatrix} V^*\|_2$$

$$= \left\| \begin{bmatrix} 0 & \dots & -\epsilon_2 & -\epsilon_2 \\ \vdots & \ddots & \vdots & \vdots \\ 0 & \dots & -\epsilon_2 & -\epsilon_2 \end{bmatrix} \right\|_2 = \max_{1 \leq i \leq n} (\text{di})$$

$$= \frac{\epsilon}{2}$$

Condensed SVD

$$A = U \Sigma V = [U_1 \ U_n] \begin{bmatrix} \alpha_1 & & \\ & \alpha_2 & \\ & & \ddots & \\ & & & 0 \end{bmatrix} \begin{bmatrix} v_1^* \\ v_2^* \\ \vdots \\ v_m^* \end{bmatrix}$$

$$= [U_1 \ U_n] \left\{ \begin{bmatrix} \alpha_1 v_1^* & & \\ & \alpha_2 v_2^* & \\ & & \ddots & \\ & & & 0 \end{bmatrix} \right\}^* \}_{m \times n}$$

$$= \begin{bmatrix} \alpha_1 u_1 v_1^* & & \\ & \alpha_2 u_2 v_2^* & \\ & & \ddots & \\ & & & 0 \end{bmatrix}$$

$$= \sum_{i=1}^k \alpha_i u_i v_i^*$$

$$= [U_1 \dots U_k] \begin{bmatrix} \alpha_1 & & \\ & \alpha_2 & \\ & & \ddots & \\ & & & 0 \end{bmatrix} \begin{bmatrix} v_1^* \\ v_2^* \\ \vdots \\ v_k^* \end{bmatrix}$$

$$\underbrace{(A A^*)^*}_{P} = A A^*$$

$$A^* A A^* = A^* \Rightarrow A A^* A A^* = A A^* \Rightarrow P^* = P$$

$$P^* = P$$

$$B = \begin{bmatrix} 1 & 2 \end{bmatrix}$$

$$B \begin{bmatrix} x \\ y \end{bmatrix} \Rightarrow x + 2y = 1$$

$$B^+ \begin{bmatrix} 1 \end{bmatrix} = \begin{bmatrix} 1/5 \\ 2/5 \end{bmatrix} \rightarrow \text{closest to origin}$$

Date: 17/10/29 MA-973

Date: 18/10/29

MA-923

Transformation to upper Hessenberg Form:

~~recall midsem
in exam~~ $x, y \rightarrow n \times 1$ non zero vectors
 $\|x\|_2 = \|y\|_2$ & $x^* y \in \mathbb{R}$
 s.t. $x \neq y$

$$\begin{aligned} \langle x, y \rangle &= (x_1 - y_1) \\ &= x_1 y_1 - y_1 \\ &\quad - (y_2 + y_3) \end{aligned}$$

$$\begin{aligned} &\langle x+y, x-y \rangle \\ &= \|x\|^2 - \|y\|^2 - \underbrace{y^* x + x^* y}_{x^* y = y^* x} \quad \text{or} \quad (\because x^* y \in \mathbb{R}) \end{aligned}$$

$$= \|x\|^2 - \|y\|^2 = 0 \quad \text{show } Q \text{ is unique}$$

$$Q = I - \frac{2}{\|x-y\|^2} z z^* \quad (z = x-y)$$

$$Q = I - \frac{2}{\|x-y\|^2} \hat{u} \hat{u}^* \quad \hat{u} \neq 0 \quad \text{is another reflector}$$

Supp

$$s.t. \quad \hat{u} = y$$

$$\Rightarrow x - \frac{2}{\|\hat{u}\|^2} \hat{u} (\hat{u}^* x) = y$$

$$\Rightarrow x - \frac{2}{\|\hat{u}\|^2} \hat{u} (\hat{u}^* x) = x - y$$

$$\Rightarrow \frac{2}{\|\hat{u}\|^2} \hat{u} (\hat{u}^* x) = 0$$

$$x \neq y \Rightarrow \hat{u}^* x \neq 0$$

$$\hat{u}^* x = 0$$

$$\left\{ \frac{2(\hat{u}^* x)}{\|\hat{u}\|^2} \right\} = 0 \quad \Rightarrow \quad x = y$$

$$Q = I - \frac{2(x-y)(x-y)^*}{\|(x-y)\|^2} = I - \frac{2\hat{u}\hat{u}^*}{\|\hat{u}\|^2} = Q$$

$$\underline{\text{norm}(Q \& R - V)}$$

$$\text{norm}(Q' * Q - \underline{\text{eye}(m)}) \approx$$

$\text{mgs} \rightarrow \text{bilb}(13)$

\downarrow
quality of orth.

$$|\phi|_{\text{2nd}} = |\phi|_P \cdot 10^3$$

run 2 mins

2nd time will give
better orthonormal

MAA23 30/9/24 notes (class stopped)

MA-923 1/10/24

$$A = U \sum V^* \in \mathbb{F}^{n \times m}, \text{rank}(A) = r, A_k = U \sum_{k=1}^r V^*$$

$$\|A - A_k\|_2 = \min \{ \|A - B\|_2 : B \in \mathbb{F}^{n \times m}, \text{rank } B \leq k \}$$

$$\Sigma_k = \text{diag}(\alpha_1, \alpha_2, \dots, \alpha_k, 0, \dots, 0)$$

$\dim(V)$
 \uparrow
vector space
 $= \max \# \text{ linearly}$
 $\text{indep vectors in } S.$

$$B \in \mathbb{F}^{n \times m}, \text{rank } B \leq k \}$$

$$\text{rank } A_k = k \quad \&$$

$$= \alpha_k \alpha_k$$

$$\|A - A_k\|_2 = \alpha_{k+1},$$

$$\therefore \alpha_{k+1} \geq \min \{ \|A - B\|_2 : B \in \mathbb{F}^{n \times m}, \text{rank } B \leq k \}. \text{ Let } B \in \mathbb{F}^{n \times m}$$

such that $B \leq k$. Then $\dim \text{null } B \geq n-k$. Let $S = \text{span } \{v_1, \dots, v_{n-k}\}$

then $\dim(\text{null } B \cap S) \geq 1$.

$$\Downarrow \exists x_0 \in \text{null } B \cap S \text{ st } x_0 \in \mathbb{R}^m, x_0 \neq 0$$

$$(\because x_0 \in \text{null } B)$$

$$(A - B)x_0 = Ax_0$$

$$\sum_{j=1}^m \alpha_j v_j$$

$$\& \|x_0\|_2^2 =$$

$$\sum_{j=1}^m \|\alpha_j v_j\|_2^2$$

$$\therefore \text{Now, } x_0 \in S \Rightarrow x_0 = \sum_{j=1}^m \alpha_j v_j$$

$$= \sum_{j=1}^m \|\alpha_j v_j\|_2^2$$

$$\therefore \|x_0\|_2^2 = \sum_{j=1}^{kn} |\alpha_j|^2$$

$$\langle x_0, v_i \rangle = \left\langle \sum_{j=1}^{kn} \alpha_j v_j, v_i \right\rangle$$

$$(1 \leq i \leq k+1) = \sum_{j=1}^{kn} \alpha_j \langle v_j, v_i \rangle$$

$$\langle x_0, v_i \rangle = \alpha_i \quad (\text{if } j \leq k)$$

$$\begin{aligned} \| (A-B)x_0 \|_2^2 &= \| Ax_0 \|_2^2 = \| A \left(\sum_{j=1}^{kn} \alpha_j v_j \right) \|_2^2 \\ &= \| \sum_{j=1}^{kn} \alpha_j A v_j \|_2^2 \\ &= \| \sum_{j=1}^{kn} \alpha_j \underbrace{\alpha_j u_j}_{} \|_2^2 \end{aligned}$$

$$\begin{aligned} &= \sum_{j=1}^{kn} \alpha_j^2 \| \alpha_j \|^2 \\ &\geq \alpha_{kn}^2 \underbrace{\sum_{j=1}^{kn} \| \alpha_j \|^2}_{\| x_0 \|^2} \\ &= \alpha_{kn}^2 \| x_0 \|^2 \end{aligned}$$

$$\therefore \| (A-B)x_0 \|_2^2 \geq \alpha_{kn}^2 \| x_0 \|_2^2$$

$$\begin{aligned} &\therefore \| (A-B)x_0 \|_2 = \max_{x \neq 0} \frac{\| (A-B)x \|}{\| x \|} \\ &\geq \frac{\| (A-B)x_0 \|_2}{\| x_0 \|_2} \end{aligned}$$

$$\begin{aligned} &\therefore \min_{\text{rank } B \leq k} \| A - B \|_2 : \text{BCF}^{n \times m} \\ &\text{rank } B \leq k \geq \alpha_{kn} \quad \forall B, \\ &\text{rank } B \leq k \end{aligned}$$

Corollary: $A \in \mathbb{F}^{n \times n}$ be non-singular. Let $A = U \Sigma V^T$ be an SVD of A then,

$$\alpha_n = \min \{ \|A - B\|_2 : B \in \mathbb{F}^{n \times n} \text{ is singular}\}$$

\rightsquigarrow
dist of A from the closest sing. matrix.

$$\alpha_n = \min \{ \|A + \Delta A\| : A + \Delta A \text{ is sing}\}$$

Corollary

$$\frac{1}{k_2(A)} = \frac{\alpha_n}{\alpha_1}$$

$$\alpha_1 \pm = \|A\|_2,$$

$$\|\Delta A\| \leq \frac{1}{k(A)}$$

$A + \Delta A$ is non-singular.

ΔA st $A + \Delta A$ is sing
 $\Rightarrow A = \begin{bmatrix} \alpha_1 & \alpha_1 \\ \alpha_1 & 0 \end{bmatrix}$

$$A = U \begin{pmatrix} \alpha_1 & \alpha_n \end{pmatrix} V^T$$

$$A_{n+1} = U \begin{pmatrix} \alpha_1 & \alpha_1 \\ & 0 \end{pmatrix} V^T$$

$$A_{n+1} = A - U \underbrace{\begin{pmatrix} 0 & 0 \\ & \alpha_n \end{pmatrix}}_{\Delta A} V^T$$

$$\|\Delta A\|_2 = \alpha_n \leftarrow \text{nearest sing}$$

matrix to A

in $\|1\|_2$

$$\Rightarrow \|\Delta A\|_2 \leq \frac{1}{k(n)}$$

$$\Delta A = -\alpha_n U_n V_n^T$$

Numerical rank determination via SVD

A) Eckart-Young's theorem.

Δs_n^{rank} will be numerically close to rank = 4

prove it (ex)

- * Hilbert matrix are free definite, revealing exact rank of A but → point of $\text{rank}(A)$ to not ~~around~~ s_n ~~that~~ revealing exact rank of A but the close rank ~~rank~~ neighbor.

MA 473 Lab

$$\frac{y_m^{nn} - y^n}{\kappa} =$$

$$\frac{y_{mn}^{nn} - 2y_m^{nn} + y_{m+1}^{nn}}{h^2}$$

$$y_m^{nn} - y^n = \alpha y_{m+1}^{nn} - 2y_m^{nn} + \alpha y_{m-1}^{nn}$$

$$\alpha = \frac{k}{h^2}$$

$$\textcircled{B} \quad -\alpha y_{m+1}^{nn} + (1+2\alpha) y_m^{nn} - \alpha y_{m-1}^{nn} = y^n$$

$$\left[\begin{array}{cc} (1+2\alpha) & -\alpha \\ -\alpha & (1+2\alpha) \end{array} \right] \left[\begin{array}{c} y_{m+1}^{nn} \\ y_m^{nn} \\ y_{m-1}^{nn} \end{array} \right] = \left[\begin{array}{c} y^n \\ 0 \\ 0 \end{array} \right]$$

MA HSS-217

n=8

n=9

n=10

0.10 $\approx 1.1 \times 10^{-2}$

0.11 $\approx 1.1 \times 10^{-2}$

0.12 $\approx 1.1 \times 10^{-2}$

1.02

* Remember to answer
the quest & don't give
ans that doesn't ans the quest

8167211360 - term
paper
mentor.

Numerical method for Jam diffusion

MA-923
Stability &
Sensitivity

4/9/29
of LSP problems.

$$\frac{\|SA\|_2}{\|A\|_2} \leq k_1(v) [nu + O(u^2)]$$

$$\frac{\|E\|_2}{\|A\|_2} \leq n^\beta u + O(u^2) = O(u)$$

n is st
more over we are
assuming a very very
pessimistic upper bdd.
In reality we
don't reach n unless
we're considering very
very large systems.

$$f_L(QA) = f_L(Q(A+E))$$

$Q = \text{unitary/orthogonal}$

$k_2(A) \leq 1$, backward stable

$$\text{Corollary } f_L(QA) = f_L[(QA)^T]$$

$$= f_L(Q^TA^T) \cong f_L(CB)$$

$$R = Q_p - Q_1 A$$

$$\|E\|_2 = \|Q_p - Q_1 A\|_2 = \|Q_p - \underbrace{Q_1}_{=Q} (A + E)\|_2 \text{ where}$$

$$\frac{\|E\|_2}{\|(A+E)\|_2} \simeq O(\epsilon) \quad A+E = \underbrace{(Q_1 \quad Q_p)}_{=Q} \text{ s.t. } \epsilon$$

For Normal Ears

we cannot push back the error always we can do for our algo.

$$r = b - Ax_0 \\ Ax_0 = b_1$$

$$\cos \theta = \frac{|\langle b, y \rangle|}{\|b\|_2 \|y\|_2}$$

$$\cos \theta = \frac{|\langle y+r, y \rangle|}{\|b\|_2 \|y\|_2}$$

$b = y + r$ where
y and r are orthogonal.

$$= \frac{\|y\|_2^2 + \cancel{\langle r, y \rangle}}{\|b\|_2 \|y\|_2}$$

$$= \frac{\|y\|_2^2}{\|b\|_2 \|y\|_2}$$

$$\sin \theta = \frac{|\langle b, r \rangle|}{\|b\|_2 \|r\|_2}$$

Def - eqn

W.L.O.G.

$\pi_{\text{new}} = \pi_{\text{old}}$ except one class will be left
from other entity methods

Writing Every Value Function

Let A be a diagonal matrix & x diagonal

$$\begin{aligned} L(x) &= \sum_{i=1}^n s_i \left(\frac{x_i}{a_i} \right)^2 \\ &= \sum_{i=1}^n s_i \left(\frac{x_i}{x_i + b_i} \right)^2 \\ &= \sum_{i=1}^n s_i \end{aligned}$$

$L(x) = L(x_i)$ without loss of generality

$$L(x) = 0 \Rightarrow \sum s_i x_i = 0$$

Maximize

$L(x)$ is non-negative

Now consider $L(x)$ & $L(x')$

$L(x) = \sum s_i x_i^2 / (x_i + b_i)^2$

$$L(x') = \sum s_i x'^2 / (x'_i + b'_i)^2$$

$\Rightarrow L(x')$ is called the loss function

Date - 7/9/20

MA-923

go algo ~~vers~~ version taught in class will be diff
from other study materials.

Matrix Eigenvalue Problem

If diagonal matrix A is ~~diag~~ $n \times n$

$$A[\mathbf{v}_1 \quad \mathbf{v}_n] = [\mathbf{v}_1 \quad \mathbf{v}_n] \quad S = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}$$
$$A\mathbf{v}_i = \lambda_i \mathbf{v}_i \quad i=1, \dots, n$$

if $(\lambda_i \neq \lambda_j \text{ for } i \neq j)$ \rightarrow so that but not necessary

$$\therefore A S = S D \quad \Rightarrow \quad S^T A S = D$$

\downarrow
invertible

Ex: $\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$ is not diagonalizable.

Jordan Canonical form:

Given any matrix $A_{n \times n}$
 \exists an inv matrix X & block diagonal matrix $J = \text{diag}(J_{\lambda_1}, J_{\lambda_n})$

with $J_{\lambda_i} = \begin{bmatrix} \lambda_i & & \\ & \ddots & \\ & & \lambda_i \end{bmatrix} \quad i=1, \dots, p$

$A = X J X^{-1}$ is called the Jordan Canonical form of A .

Schur's theorem will reveal all eigen values of A

through unitary transformtn.

Schur's Thm: $\forall m \times n$
any $A \in \mathbb{C}^{n \times m}$ & an upper triangular matrix θ

$\exists A$ is Hermitian, $T^* = T$,

$$(A^* = A)$$

$\exists A$ is skew Hermitian $(A^* = -A)$, $T^* = -T$ normal matrix unitary

$\exists A A^* = A^* A$

$$\Downarrow$$

$$TT^* = T^* T$$

unitary mat $\theta^* = \theta$

$$\theta^* A \theta = \theta^* T$$

$\theta, T \rightarrow$ not unique,

Schur's theorem proof: $\forall v \neq 0 \in \mathbb{C}^n$ $\theta A v = \lambda v$ is trivially true
 $A \in \mathbb{C}^{n \times n}$, let $\lambda \in \mathbb{C}$ & the theorem holds for sizes $< n$

If $n=1$, then $A = [\lambda]$ & the statement holds for sizes $< n$

Suppose that the statement holds for sizes $< n$. Then $\|v\|_2 = 1$ & $A v = \lambda v$.

Let $q_1 = v/\|v\|_2$. Then q_1 is in the set in \mathbb{C}^n .

Consider let d_1, w_2, \dots, w_n be an QR decm of s

def $s = [q_1, w_2, \dots, w_n] = \tilde{\theta} R$ (be a QR decm of s)

Now $\tilde{\theta}^* A \tilde{\theta} = \begin{bmatrix} q_1^* \\ q_2^* \\ \vdots \\ q_n^* \end{bmatrix} A [q_1, q_n]$

$\tilde{\theta} = [q_1, q_2, \dots, q_n]$

orthonormal basis of \mathbb{C}^n

$$= \begin{bmatrix} q_1^* \\ q_2^* \\ \vdots \\ q_n^* \end{bmatrix} \begin{bmatrix} A q_1 & A q_n \end{bmatrix}$$

$$= \begin{bmatrix} q_1^* A q_1 & q_1^* A q_n \\ q_n^* A q_1 & q_n^* A q_n \end{bmatrix}$$

$$= \begin{bmatrix} \lambda q_1^* q_1 & * \\ * & \lambda q_n^* q_n \end{bmatrix}$$

$$\begin{bmatrix} x & * \\ 0 & \tilde{A} \end{bmatrix}$$

By inducⁿ hypothesis \tilde{A} is a unitary
 \tilde{A} is an upper triag. \tilde{T} st

$$\tilde{Q}_1^* A \tilde{Q}_2 = \tilde{T}$$

$$Q A \tilde{Q} = \begin{bmatrix} x & * \\ 0 & \tilde{A} \end{bmatrix}$$

$$\tilde{A} = \tilde{Q}, \tilde{T} \tilde{Q}^*$$

$$= \begin{bmatrix} x & * \\ 0 & \tilde{Q}, \tilde{T} \tilde{Q}^* \end{bmatrix}$$

$$= \begin{bmatrix} 1 & * \\ * & 0 \end{bmatrix} \begin{bmatrix} x & * \\ 0 & \tilde{T} \end{bmatrix} \begin{bmatrix} 1 & * \\ * & 0 \end{bmatrix}$$

$$\therefore \begin{bmatrix} 1 & * \\ * & 0 \end{bmatrix} Q^* \sim Q \begin{bmatrix} 1 & * \\ * & 0 \end{bmatrix} = T \text{ (upper triag)}$$

$$Q^* A Q = T \text{ for } n\text{-size}$$

$$Q^* A Q = T \text{ for } n\text{-size}$$

Corollary: λ value taken initially will decide $Q^* T$

- if A is Hermitian $\Rightarrow T$ is diagonal $\in \mathbb{R}$

- if A is Hermitian $\Rightarrow T$ is diagonal $\rightarrow T$ is Hermitian

- if T is real & diagonal $\rightarrow T$ is Hermitian
 $\Rightarrow A$ is Hermitian

Only Hermitian matrices can be turned
 into real diagonal matrices via unitary transform &

\Rightarrow Only un

$$Av = \lambda v$$

$$v^T Av = \lambda v^T v = \lambda \|v\|^2$$

$$\overline{v^T Av} = \bar{\lambda} \|v\|^2$$

$$v^T A^* v = \bar{\lambda} \|v\|^2$$

$$v^T A^* v = \bar{\lambda} \|v\|^2 \Rightarrow \bar{\lambda} = \lambda \Rightarrow \lambda \in \mathbb{R}$$

$$v^T A^* v = \bar{\lambda} \|v\|^2$$

Hermitian matrix \Leftrightarrow Real eigenvalues

\Rightarrow eigen vectors are also real

MA-973

$$\text{FEM} \quad r = (B - \Delta T(1-\theta)A)\omega^{(n)}$$

$$C = B + \Delta T \theta A$$

$$\text{if } \theta \geq g, \quad (\theta - \omega)^T(C\omega - \lambda) \geq 0 \quad \omega \geq g.$$



$$\text{FDM} : A = C, \quad b = g$$

$$(C\omega - g)^T(C\omega - g) \geq 0, \quad \omega \geq g$$

$$(C\omega - g)^T(\omega - g) = 0$$

$$Aw - b \geq 0, \quad \omega \geq g$$

$$(Aw - b)^T(\omega - g) = 0$$

topperidal



$$\phi_i = \begin{cases} \frac{2x_i x_{i+1} - x_i}{x_{i+1} - x_i} & x_i \leq x \leq x_{i+1} \\ \frac{x - x_{i+1}}{x_i - x_{i+1}} & x_{i+1} \leq x \leq x_i \end{cases}$$

$\delta - w$

$\text{rank}(A)$ should be 5

$\text{rank}(A) \rightarrow 5$
O/P: 5

$\text{Svd}(A)$

ans: $\begin{bmatrix} 1 \\ 5 \\ 6.0(4) \\ 7.0(0) \end{bmatrix}$

rank threshold:
 $\epsilon \times 9 \times \text{ans}(1)$
 $= 1.6639 \times 10^{-14}$

$\text{rank}(A, 10^{-16})$ changing?

ans: 7

Ex 4.2. 24

$\text{Svd}(A) \rightarrow$ able to detect correctly $\text{rank}(A)$

$\text{qr}(A) \rightarrow$ fails to detect num. $\text{rank}(A)$

$\text{svd}(A) \rightarrow$ able to detect more clearly
promising of numerical rank deficiency of A.

MA-423

Date: 8/10/24

from PPT there already exists an unitary matrix Q (possibly complex) s.t. $Q^T A Q = D \rightarrow$ real diagonal

if $A \in \mathbb{R}^{n \times n}$ is symm \Leftrightarrow & a real orthogonal matrix &

& a real diag matrix D s.t. $Q^T A Q = D$

Q: build similar to Schur's thm

$A \rightarrow$ real & symm $n \times n$. let $x \in \mathbb{R}^n$ & $v \in \mathbb{R}^n$ s.t. Then $Aq_1 = \lambda_1 q_1$

let $a_1 = v / \|v\|_2$

$Au = \lambda u$

$\|a_1\|_2 = 1$

① Build

an orth. matrix

$\tilde{Q} \in \mathbb{R}^{n \times n}$ s.t. $\tilde{Q} = [a_1 \dots a_n]$

$$\textcircled{2} \quad Q^T A \tilde{Q} = \left[\begin{array}{c|cc|c} \lambda_1 & 0 & \cdots & 0 \\ 0 & & \ddots & \\ \vdots & & & \tilde{A} \\ 0 & & & \end{array} \right] \quad [\because A^T = A \quad (Q^T A Q)^T = Q^T A Q]$$

\textcircled{3} Use the indⁿ hypothesis for \tilde{A} when

$$\boxed{\tilde{A}^T = \tilde{A}}$$

$$Q^T A Q = D \Rightarrow A Q = Q D \Rightarrow A q_i = \lambda_i q_i \quad i \leq n$$

Normal Matrix:

$A q_i, q_{n+1} \rightarrow$ orthonormal basis of eigen vectors of A .

$$\text{where } Q = [q_1 \dots q_n]$$

$$D = \begin{bmatrix} \lambda_1 & \\ & \lambda_n \end{bmatrix}$$

λ, λ^T need not be real

- If A has complex non-eigen values

Quasi-upper-triangular:

$$A = \left[\begin{array}{c|c|c|c} A_1 & * & * & * \\ 0 & A_2 & & \\ 0 & 0 & \ddots & \\ \hline 0 & 0 & & AP \end{array} \right]$$

$$\det(A - \lambda I) = \prod_{i=1}^p \det(A_i - \lambda I)_{\text{size } A_i}$$

~~If A_i is 2×2 matrix~~

~~If $\text{size}(A_i) \leq 2 \times 2$ & $i = 1 \dots p$~~

The A is quasi-upper

$$A = \left[\begin{array}{cc|c} 2 & 2 & 1 \\ 3 & 1 & -1 \\ \hline 0 & a & 5 \end{array} \right] \quad \begin{array}{l} \text{if } a=0, \text{ quasi-upper triangular} \\ \text{if } a \neq 0, \text{ not quasi-upp trng.} \end{array}$$

when $A \in \mathbb{R}^{n \times n}$ & has complex eigen values + will have
an quasi upper trng matrix

\rightarrow finding eigen values of matrix is eqv to finding
roots of polynomial.

Power Method & its Variants

$$x = c_1 v_1 + c_2 v_2 + \dots + c_n v_n \quad c_i \neq 0$$

$$\beta v_i = x_i v_i, \forall i \leq n$$

$$f(x_i) > |x_1|^2 \geq |x_2|^2 \geq \dots \geq |x_n|^2$$

$$Ax = c_1 x_1 v_1 + \dots + c_n x_n v_n$$

$$A^2 x = c_1 x_1^2 v_1 + \dots + c_n x_n^2 v_n$$

$$A^j x = A^j \left(\sum_{i=1}^n c_i v_i \right) = \sum_{i=1}^n c_i x_i^j v_i$$

$$c_1 v_1 + \sum_{i=2}^n \left(\frac{x_i}{x_1} \right)^j c_i v_i = c_1 v_1 + \sum_{i=2}^n \left(\frac{x_i}{x_1} \right)^j c_i v_i$$

$$\frac{A^j x}{x_1^j} = \sum_{i=2}^n c_i \left(\frac{x_i}{x_1} \right)^j v_i$$

$$\left\| \frac{A^j x}{x_1^j} - c_1 v_1 \right\| = \left\| \sum_{i=2}^n \left(\frac{x_i}{x_1} \right)^j c_i v_i \right\|$$

$$\leq \sum_{i=2}^n \left| \frac{x_i}{x_1} \right|^j \|c_i\| \|v_i\|$$

$$\lim_{j \rightarrow \infty} \left\| \frac{A^j x}{x_1^j} - c_1 v_1 \right\| \leq \lim_{j \rightarrow \infty} \sum_{i=2}^n \left| \frac{x_i}{x_1} \right|^j \|c_i\| \|v_i\|$$

$$\lim_{j \rightarrow \infty} \left\| \frac{A^j x}{x_1^j} - c_1 v_1 \right\| = \lim_{j \rightarrow \infty} \sum_{i=2}^n \left| \frac{x_i}{x_1} \right|^j \|c_i\| \|v_i\|$$

$$\left| \frac{x_i}{x_1} \right| < 1 \quad (x_1 > |x_2|)$$

$$\Rightarrow \lim_{j \rightarrow 0} \left\| \frac{A^n}{x_j} - c.v. \right\| = 0$$

we don't know x_2

HSS-217 Date: 9/10/29

- In the West, target consumers for sewing machines were women.
- Sales of sewing machines were done from door to door to women, it assumed.
- By attaching the gender in India for sewing machines.
- Early customers in India for sewing machines were Europeans (Anglo-Indians) sold to Europeans.
- Till 1950s sewing machines were only sold to Anglo-Indians.
- Patell was opposed to selling machines to Indians to advertise his new strategies.

* Power method needs dominant eigen vector

Shift & Invert Method \rightarrow (can find any eigen value of the matrix) by choosing $\rho \approx \lambda_i$

ρ must not be an eigen value.

$(A - \rho I)^{-1}$ eigen value

$$(A - \rho I)^{-1} v_i = (\lambda_i - \rho)^{-1} v_i$$

$$(A - \rho I)^{-1} v_i$$

$(A - \rho I)^{-1}$ \rightarrow dominant e.v

$$i = 1 \dots r$$

$$A v_i = \lambda_i v_i$$

$$(A - \rho I)^{-1} v_i = (\lambda_i - \rho)^{-1} v_i$$

$$v_i = \left(\frac{1}{\lambda_i - \rho} \right) (A - \rho I)^{-1} v_i$$

$$(A - \rho I)^{-1} v_i = \frac{1}{(\lambda_i - \rho)} v_i$$

→ use pow method to find the dominant e.v of $(A - \rho I)^{-1}$ set ρ to get the eig val corrpond to λ_i $(\lambda_B + \rho) = \lambda_i$

- invert & add the

shift back after convergence

if q is not an eigen vector then do $Mq = Aq$, there will not exist any m that solves the eqn, therefore overdekmnd sys.

Q.E.D.

$$q_M = \frac{Aq}{b} \rightarrow ①$$

$$\mu_0 = \frac{q^T A q}{q^T q}$$

\rightarrow SP of ①

μ_0 is Rayleigh quotient associated with A & q .

$$Av = \lambda v \quad \|(\lambda)v\|_2^2 = 1, \quad \rho = \sqrt{\lambda} \quad \|\rho\|_2^2 = 1$$

$$\begin{aligned}
 |\lambda - \rho| &= |v^* A v - \rho^* A v| \\
 &= |v^* A v - v^* A \rho + v^* A \rho - \rho^* A v| \\
 &\leq |v^* A(v - \rho)| + |(v - \rho)^* A v| \\
 &\leq |v^* A(v - \rho)| + |(v - \rho)^* A v| \\
 &= |v^* A(v - \rho)| + |(v - \rho)^* A(v - \rho)| \\
 &= |v^* A(v - \rho)| + |(v - \rho)^* A^* A(v - \rho)| \\
 &\stackrel{(C.S. \text{ inequality})}{\leq} \|v\|_2 \|A(v - \rho)\|_2 + \|\rho\|_2 \|A^* A(v - \rho)\|_2 \\
 &\leq \|A(v - \rho)\|_2 + \|A^* A(v - \rho)\|_2 \\
 &= \|A(v - \rho)\|_2 + \|A^* A(v - \rho)\|_2 \\
 &\leq \|A\|_2 \|v - \rho\|_2 + \|A^*\|_2 \|v - \rho\|_2 \\
 &= 2 \|A\|_2 \|\lambda - \rho\|_2
 \end{aligned}$$

can't ~~apply~~ A
Non-convergent iteration \Rightarrow wrong Hessenberg matrix

$$A = \begin{bmatrix} 0 & 1 \\ 2 & 0 \end{bmatrix}, \quad v = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = q_0$$

$$V_0 = v^* A v = 0$$

so that $(A - V_0) \hat{q}_1 = -q_0 \Rightarrow$

$$\hat{q}_1 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \in \mathbb{C}^2$$

$$V_1 = q_1^* A q_1 = 0,$$

$$\text{Solve } (A - \rho_1 I) \hat{\omega}_2 = \hat{\omega}_1$$

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \hat{\omega}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\hat{\omega}_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

keeps alt. b/w $e_1 \oplus e_2$
 reason: $\text{sgn}t = 0$ mid value b/w ev $1 \oplus -1$

$$w \cdot x = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \cdot \hat{\omega}_0 \quad P_0 = \frac{x^T A \hat{\omega}}{2} = 1 \text{ (e.v.)}$$

v : prv vector

$$\lim_{j \rightarrow \infty} \frac{\|\hat{\omega}_{j+1} - v\|_2}{\|\hat{\omega}_j - v\|_2} = C (\neq 0)$$

quad convg.

MA-ATB Lab.

$$(A^T A - b^T)(\omega - g) = w^T A \omega - w^T A g - b^T \omega$$

PSOR (A, b, ω):

$$\hat{b} = b - Ag, \quad v = u - g$$

$$\frac{\lambda}{2} \omega_{\text{min}, \sigma} + (1 - \frac{\lambda}{2}) \omega_{\text{var}} + \frac{\lambda}{2} \omega_{\text{var}, \sigma}$$



HSS-217

Date: 17/10/23

- Patel went door to door to sell adhesive/sell sewing machines for his company.
- His strategies were seen as unprofessional & were not accepted by his colleagues.
- Bishandas Basil made the first 1st India made sewing machine Usha.

Bicycles in Modern India

- cycle made it possible to be autonomous while travelling & gave more mobility & more convenient than other means of transport like horses, horse carriages & trains.
 - it was cheaper than other means of transport like motorcars, horse carriages
- (Autonomous in the sense that it didn't depend on other means of transport for travelling.)

Date: 18/10/23

MA-423

when

Date: 18/10/23

{ 1st pt written
is cut in (rotated) }

some pages
some

$$\begin{bmatrix} a_{11} \\ \vdots \\ a_{1n} \end{bmatrix} \rightarrow \begin{bmatrix} 1 \\ a_{12}/a_{11} \\ \vdots \\ a_{1n}/a_{11} \end{bmatrix} \text{ if } a_{11} \neq 0$$

$$Q_n = \begin{bmatrix} \pm \|x\|_2 e^{i\theta} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad q_{11} = (a_{11})e^{i\theta}$$

if $A_{n \times m} \quad n \geq m$ $A = Q_{nm} R_{mm}$ $R_{(1,1)} > 0 \quad \forall r=1, \dots, m$

Show R is unique

$A^* A$ is positive definite

$$R^* R$$

so unique

R has
pos diag
entries

$$\text{supp } A = Q_1 R_1 = Q_2 R_2, \quad Q_2^* Q_1 = R_2 R_1$$

$$(Q_2 Q_1)^* (Q_2^* Q_1) = Q_1 Q_2 Q_2^* Q_1$$

$$= I$$

$$A_{1/2} Q_1 = \left[(A_{1/2} Q_1)^T \right]^T = \left[Q_1^T A_{1/2}^T \right]^T = \left(\begin{bmatrix} 1 & 0 \\ 0 & \hat{Q}_1 \end{bmatrix} \begin{bmatrix} a_{11} & \pm \|b\|_2 0 \dots 0 \\ c & \hat{A}^T \hat{Q}_1 \end{bmatrix} \right)^T = \left[\begin{array}{c|cc} a_{11} & \pm \|b\|_2 0 \dots 0 \\ \hline \hat{Q}_1^T & \hat{Q}_1^T \hat{A}^T \hat{Q}_1 \end{array} \right]$$

$$\hat{Q}_1 [c \quad \hat{A}^T \hat{Q}_1]_{(n-1 \times n)}$$

stop count: $4n \times (n-1)$

$$-\tilde{g}_U (\hat{U}^\dagger \hat{A} \hat{U}) \hat{U}^\dagger = -\cancel{\tilde{g}_U \hat{A} \hat{U}} - \underbrace{\tilde{g}_U (-\hat{A} \hat{U})}_{\cancel{\hat{U}}} \hat{U}^\dagger$$

$$= \cancel{-\tilde{g}_U \hat{A}}$$

$$= \tilde{g}_U \hat{U}^\dagger \hat{U}$$

Date: MA-973

recap:

$$\frac{\partial U}{\partial t} = \frac{\partial U}{\partial x^n} + \frac{\partial U}{\partial y^n}$$

$$t_n \rightarrow t_{n+1/2} \rightarrow t_{nn}$$

$$\delta_x \tilde{U}_{ij}^n = \tilde{U}_{i+1,j} - 2\tilde{U}_{ij}^n + \tilde{U}_{i-1,j}$$

$$\delta_y \tilde{U}_{ij}^n = \tilde{U}_{i,j+1} - 2\tilde{U}_{ij}^n + \tilde{U}_{i,j-1}$$

$$\frac{\tilde{U}_{lm}^{n+1/2} - \tilde{U}_{lm}^n}{\Delta t/2} = \frac{1}{h^2} \left[\delta_x \tilde{U}_{lm}^{n+1/2} + \delta_y \tilde{U}_{lm}^n \right] \rightarrow ⑤$$

$$\frac{\tilde{U}_{lm}^{n+1/2} - \tilde{U}_{lm}^n}{\Delta t/2} = \frac{1}{h^2} \left[\delta_x \tilde{U}_{lm}^{n+1/2} + \delta_y \tilde{U}_{lm}^{n+1/2} \right] \rightarrow ⑥$$

δ \tilde{U}_{lm}

HSS-217

Bicycles, Race & Gender

- Bicycles were mainly used a sense of social norm by Europeans until many Indians started owing them.
- cycles were also genderised in associations & with men.
- cyclists → making someone feel feminine

MA-423 Date: 21/10/24

$$\hat{A} + vU^T + Uv^T + \underbrace{2\alpha vv^T}_{\alpha UU^T + \alpha vU^T}$$

$$\begin{aligned}
 & \det w = \theta + \alpha u \\
 &= \hat{A} + (\theta + \alpha u)U^T + U(\theta + \alpha u)^T \\
 &= \hat{A} + \omega U^T + UW^T \\
 &\quad \text{Cost of } \hat{A}, \quad \cancel{\text{if } U \neq I} = \\
 &\quad 9[n^2 + - - - + 2] = 2n(n+1) \\
 &\quad = 2n^2 + O(n)
 \end{aligned}$$

steps.

$$\text{Total cost in calculating } H = 4 \sum_{k=0}^n (n-k)^3 + O(n^2)$$

$$= \frac{4}{3} n^3 + O(n^2)$$

ϕ eigen vector of H^{-1}

$$Q\phi = 0_{n-2} \quad Q, \phi \rightarrow \text{e.vac of } A.$$

OK

$$\text{Correct } \phi \text{ if } x \in \Phi = \begin{bmatrix} n_1 \\ \vdots \\ n_n \end{bmatrix}$$

for
Householder
reflectors Φ

$$Qn = \begin{bmatrix} \pm \|n\|_2 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} \alpha \\ -\beta \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \alpha \neq 0 \quad \alpha = \|n\|_2$$

$$\alpha = x_1 / \|n_1\|$$

~~sign not~~

$$= \text{sign}(x_1)$$

$$u = n - \underbrace{\begin{bmatrix} x_1 + \gamma \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{bmatrix}}_{\text{row}} \rightarrow \begin{bmatrix} \gamma \\ x_2 / (x_1 + \gamma) \\ x_3 / (x_1 + \gamma) \\ \vdots \\ x_n / (x_1 + \gamma) \end{bmatrix}$$

$$\alpha_1 +$$

x_1 is real.

const ensure

QR Algorithm

Under suitable condⁿ, $\|A_j\|_F$ will converge to the Schur's form of A.

Reduce A to upper Hessenberg form before start
do ~~more~~ flop count for each step $O(n^2)$

$$[Q, H] = \text{hess}(A) \rightarrow O(n^3)$$

$$A_0 = I$$

Step 1 : Find reflectors

(a) Set

$$A_1 = R Q_1 \dots$$

A_1 upp Hessen?

$H \rightarrow$ upper Hessenberg $\not\Rightarrow$

$Q^T A Q$ is upp Hessenberg for unitary orthogonal Q arising in QR decomp of I.

$$A_0 = \begin{bmatrix} a_{11} & & a_{1n} \\ a_{21} & a_{22} & a_{2n} \\ & \ddots & a_{nn} \end{bmatrix}$$

$$Q_1 = \begin{bmatrix} \hat{Q}_1 \\ \vdash \\ I_{n-2} \end{bmatrix}$$

$$\hat{Q}_1 = \begin{bmatrix} a_{11} \\ a_{21} \end{bmatrix} = \begin{bmatrix} -z \\ 0 \end{bmatrix}$$

$$Q_2 = \begin{bmatrix} \vdash \\ \hat{Q}_2 \\ \vdash \\ B_{n-2} \end{bmatrix}_{n-3}$$

where

$$R_{O_1} = \begin{bmatrix} m_{11} & & \\ & \ddots & \\ & & m_{nn} \end{bmatrix} \left[\begin{array}{c|c} O_1 & \\ \hline & I_{n-2} \end{array} \right]$$

Applying this tech. on the i^{th} row we get ~~O_1~~ A_i as up Hess
 ~~O_1~~ A_i as up Hess. & so on every row matrix

MA-473 If we sample the underlying asset S_t time interval at discrete time intervals with equidistant we obtain $s_{t_1}, s_{t_2}, \dots, s_{t_n}$. Then we

we obtain arithmetic mean

can consider avg as the time

$$\frac{1}{n} \sum_{i=1}^n s_{t_i} = \frac{h}{T} \sum_{i=1}^n s_{t_i} = A \rightarrow ①$$

then

the avg will be

interval is cts instead of the arithmetic mean

$$\hat{s} = \frac{1}{T} \int_0^T s_t dt \rightarrow ②$$

for both discrete

$$\text{we can consider the geo. mean } (\prod_{t=1}^n s_{t_i})^{1/n} = \exp\left(\frac{1}{n} \log \prod_{t=1}^n s_{t_i}\right)$$

$$\& \text{OK. } (\prod_{t=1}^n s_{t_i})^{1/n} = \exp\left(\frac{1}{n} \sum_{t=1}^n \log s_{t_i}\right) \rightarrow ③$$

Discrete:

$$\text{GTS: } \hat{s} = \exp\left(\frac{1}{T} \int_0^T \log s_t dt\right) \rightarrow ④$$

Substituting in original eq

$$\frac{\partial H}{\partial t} + \frac{\sigma^2}{2} R \frac{\partial^2 H}{\partial R^2} + (1-\lambda R) \frac{\partial H}{\partial R} = 0$$

On the bddy condn $R \rightarrow \infty$ we obtain from the payoff $H(R, t) = (1 - \frac{1}{t} R_t)^+$

$$R_t \rightarrow \infty \quad H(R_t, t) = 0$$

$R_t = \frac{1}{t} \int_0^t S_0 d\theta$, the integral R_t is bdd

$$As S \rightarrow \infty, R \rightarrow \infty$$

This is the European call as $S \rightarrow 0$, we cannot exercise the European call $\Rightarrow HCR, D = 0, R \rightarrow \infty$

Date: 25/10/29

$$\Delta_0 = \Delta, \quad \Delta_0 = Q_0 R_0 \quad (R_0(i,i) > 0 \forall i=1, \dots, n) \quad \Delta_1 := R_0 Q_0 \\ = Q_1^T A_0 Q_0$$
$$\Delta_1 = Q_1 R_1 \quad (R_1(i,i) > 0) \quad \Delta_2 = R_1 Q_1 \\ = Q_2^T A_1 Q_1$$

converse
→ Schur form of P

A_1, A_2

$$A_0 = \tilde{O}_0 \tilde{R}_0$$

$$\tilde{A}_1 = \tilde{O}_0 A_0 \tilde{O}_1$$

$$\begin{pmatrix} 0 & 0 \\ 1 & -1 \\ \vdots & \vdots \\ -1 & 1 \end{pmatrix}$$

$$\begin{pmatrix} 0 & 0 \\ 1 & 0 \\ \vdots & \vdots \\ 0 & 1 \end{pmatrix}$$

$$\tilde{A}_1 = \tilde{O}_1 \tilde{R}_1$$

$$\tilde{A}_2 = \tilde{O}_1 A_1 \tilde{O}_2$$

$$\vdots \quad \tilde{O}_1, \tilde{R}_2$$

$$A_1 = O_1 A O_1, \quad A_2 = O_2 A O_2$$

$$A = O_1 R_1 = O_2 R_2$$

Then $A_1 = O_1 A_2 O_1$ where
 $D = \text{diag}(e^{i\theta_1}, \dots, e^{i\theta_n})$

If all the 1st subdiagonal entries of upp. Hessenberg
 or non zero its called proper or irreducible upp. Hessenberg
 matrix else its called improper or reducible
 upp. Hessenberg matrix.

Eg $A = \left[\begin{array}{ccc|cc} a_{11} & a_{12} & a_{13} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} & a_{32} & a_{33} \end{array} \right] \xrightarrow{\text{proper}}$

$$\left[\begin{array}{c|cc} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & 0 & a_{33} \end{array} \right]$$

- OR algo tries to hasten the deflom by zeroing out the ~~sub diag~~ sub diag entries & dividing the matrix processing into sub-Hessenberg matrices.

as $n \rightarrow \infty$

Note (imp)

$\lim_{n \rightarrow \infty} (a_{nn}) \rightarrow 0$

$$P_j = \frac{e^{i\theta_1} e^{i\theta_2} \dots e^{i\theta_n}}{e^{i\theta_m}}$$

HSS-217

- recording takes out sound out of its original context to listen to it anywhere & anywhere we want.

Date: 29/10/24

QR algo assumes im sing A so that QR 'decomp' is unique in each iteration
This ~~rec~~ is not a necessary cond'n as long as

QR imp with singular A,

$$A = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ a_{21} & & \\ \vdots & & a_{nn} \end{bmatrix} = QR - (*)$$

$a_{i1}, i = 1, \dots, n$
A is singular.

$$A_1 = RQ = \begin{bmatrix} q_{11}^{(1)} & & a_{1n}^{(1)} \\ q_{21}^{(1)} & \dots & a_{2n}^{(1)} \\ 0 & \dots & 0 \end{bmatrix}$$

1st n columns of A \Rightarrow proper basis $\Leftrightarrow \text{rank } A = n$.
are l.i set $\Rightarrow \text{rank } A = n$.

$$\text{rank}(R) = n-1.$$

$$QR = Q [R]$$

$$[R_1 \ R_n] = [A_1 \ A_n]$$

$$[A_1 \ A_n]$$

$$a) [QR_1 \ OR_n] = [A_1 \ A_n]$$

$$Q [R_1 \ R_n] = [A_1 \ A_n] \Leftarrow \text{l.i}$$

eig values of R will lie in its diag.

$$Q \underbrace{[R_1 \dots R_n]}_{\text{rank}} = Q \begin{pmatrix} q_{11} & q_{1n} \\ \vdots & \vdots \\ 0 & q_{n,n} \end{pmatrix} \} \text{rank} = \text{rank}([R_1 \dots R_n])$$

$$\Rightarrow q_{ii} \neq 0 \quad \forall i=1, \dots, n-1 \Rightarrow q_{n,n}=0$$

\Rightarrow entire last row of R is 0.

QR

To extract complex eig values of A

Double-shift: To extract complex eig values of A

while staying in real domain.

$$A - \rho I = Q_p^* R_p \xrightarrow{\textcircled{1}} R_p Q_p + \rho I = \hat{A} \Rightarrow \hat{A} = Q_p^* A Q_p \quad \textcircled{3}$$

$$A - z I = Q_z^* R_z \xrightarrow{\textcircled{2}} R_z Q_z + z I = \tilde{A} \Rightarrow \tilde{A} = Q_z^* A Q_z \quad \textcircled{4}$$

$$\textcircled{3} \& \textcircled{4}, \quad \tilde{A} = Q_z^* \hat{A} Q_z = Q_z^* Q_p^* A Q_p Q_z = Q^* A Q$$

$$Q = Q_p Q_z$$

$$Q_R = Q_p^* Q_2 R_2 R_{\bar{y}p} = Q_p (\hat{A} - \rho I)^R p \xrightarrow{\text{by } ②}$$

$$= Q_p [Q_p^* A Q_p - Z Q_p^* Q_p] R_p \xrightarrow{\text{by } ③}$$

$$= \underbrace{Q_p Q_p^*}_{J} [A - Z^T] Q_p R_p$$

$$= [A - Z^T] Q_p R_p$$

$$= (A - Z^T) (A - \rho I) \xrightarrow{\text{by } ①}$$

if $\rho \neq \bar{\rho}$ then $(A - \rho I)(A - \bar{\rho} I) = A^m - 1 + \rho^m I \in \mathbb{R}^{n \times n}$

$$(A - \rho I)(A - \bar{\rho} I) = \det(A - \rho I)$$

Supp' $(A - \rho I)(A - \bar{\rho} I) = Q_1 R_1$
 $R = \begin{bmatrix} e^{i\alpha_1} & \\ & e^{i\alpha_2} \end{bmatrix}$ if $\rho = Q D$ for

$(A - \rho I)(A - \bar{\rho} I) \xrightarrow{\text{using}}$

P2

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$$\Omega_1^* \Delta \Omega_1 = (\Omega D)^* \Delta (\Omega D)$$
$$= D^* \Omega^* \Delta \Omega D$$

Friend OR-den

$\rightarrow \Omega_1 R_1$

ours $\rightarrow \Omega_1 R_1$

Modulus remains same for jth en nos
 \rightarrow leads to ~~same~~ same schus form.