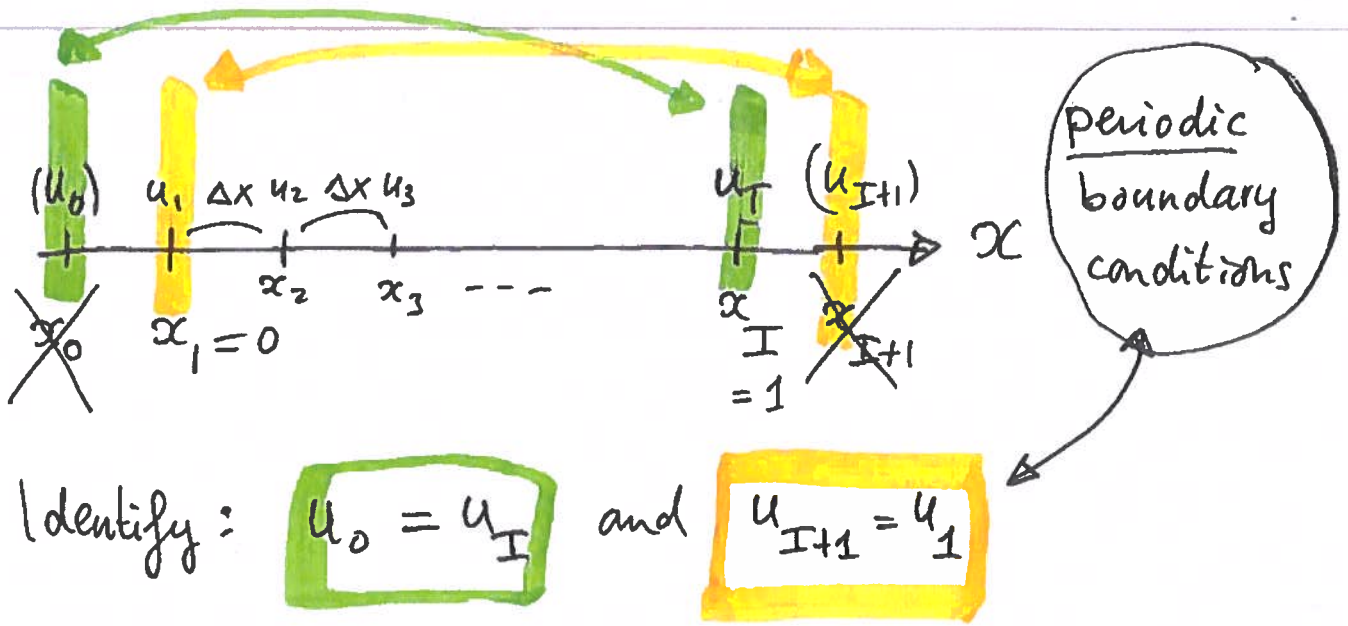


Finite Difference Matrices (FD)



A central approximation for $\frac{\partial u}{\partial x}$ at $x = x_i$:

$$\frac{u_{i+1} - u_{i-1}}{2\Delta x}$$

$i = 2, 3, \dots, I-1$

$i=1 \rightarrow u_0 \times$

$i=I \rightarrow u_{I+1} \times$

Define the solution vector:

$$\vec{u} = \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_{I-1} \\ u_I \end{pmatrix} \quad \text{length } I$$

$$\Rightarrow \text{matrix } D_{IC} = \frac{1}{2\Delta x}$$

$$\begin{pmatrix} 0 & 1 & & & \\ -1 & 0 & 1 & & \\ & -1 & 0 & 1 & \\ \ominus & & & & \ominus \\ & & & \ddots & \\ & & & -1 & 0 & 1 \\ & & & & -1 & 0 \\ & & & & & -1 & 0 \end{pmatrix}$$

$I \times I$ matrix

$(A^T = A)$
symm.

$(A^T = -A)$ skew-symmetric $\Rightarrow$ eigenvalues $\lambda \in i\mathbb{R} \subset \mathbb{C}$
property

$$D_{1c} = \frac{1}{2} (D_{1+} + D_{1-}) = \frac{1}{2\Delta x} \left\{ \begin{pmatrix} -1 & 1 & 0 & \dots \\ \theta & -1 & 1 & \dots \\ \vdots & \vdots & \vdots & \ddots \\ 1 & \theta & -1 & 1 \end{pmatrix} + \begin{pmatrix} 1 & -1 & 0 & \dots \\ -1 & 1 & -1 & \dots \\ \vdots & \vdots & \vdots & \ddots \\ 0 & -1 & 1 & -1 \end{pmatrix} \right\}$$

"upwind" $\frac{u_{i+1} - u_i}{\Delta x} \sim \frac{\partial u}{\partial x} \Big|_{x=x_i}$

"downwind" $\frac{u_i - u_{i-1}}{\Delta x} \sim \frac{\partial u}{\partial x} \Big|_{x=x_i}$

periodic boundary condition (s)

matrix $D_2 = D_{1+} D_{1-}$

$$= \frac{1}{(\Delta x)^2} \begin{pmatrix} 1 & -2 & 1 & \dots \\ \theta & \theta & \theta & \dots \\ \vdots & \vdots & \vdots & \ddots \\ \theta & \theta & \theta & \dots \\ 1 & -2 & 1 & \dots \end{pmatrix}$$

CHECK!

eigenvalues $\lambda \in \mathbb{R} \subset \mathbb{C}$

$\sim \frac{\partial^2 u}{\partial x^2}$ at $x=x_i$

matrix $D_3 = D_2 D_{1c} = D_{1+} D_{1-} D_{1c} = \frac{1}{(\Delta x)^3} \begin{pmatrix} \dots \\ \dots \\ \dots \end{pmatrix}$

$\sim \frac{\partial^3 u}{\partial x^3}$ at $x=x_i$

eigenvalues $\lambda \in i\mathbb{R} \subset \mathbb{C}$

check! (exercise/Matlab)

matrix $D_4 = D_2^2 = D_{1+} D_{1-} D_{1+} D_{1-} = \frac{1}{(\Delta x)^4} \begin{pmatrix} \dots \\ \dots \\ \dots \end{pmatrix}$

$\sim \frac{\partial^4 u}{\partial x^4}$ at $x=x_i$

eigenvalues $\lambda \in \mathbb{R}^+ \subset \mathbb{C}$

etcetera !!!

Square roots of matrices

Definition:

matrix A , $B = \sqrt{A}$ if $B \cdot B = \sqrt{A} \sqrt{A} = A$

A matrix can have several (many) square roots

Example¹⁾ $A = I = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ (identity matrix)

has infinitely many square roots:

$$\begin{pmatrix} 1 & 0 \\ 0 & \pm 1 \end{pmatrix}, \begin{pmatrix} -1 & 0 \\ 0 & \pm 1 \end{pmatrix}, \frac{1}{c} \begin{pmatrix} b & a \\ a & -b \end{pmatrix}, \frac{1}{c} \begin{pmatrix} b & -a \\ -a & -b \end{pmatrix},$$

$$\frac{1}{c} \begin{pmatrix} -b & a \\ a & b \end{pmatrix}, \frac{1}{c} \begin{pmatrix} -b & -a \\ -a & b \end{pmatrix}$$

$$\text{with } a^2 + b^2 = c^2$$

2) a positive semi-definite matrix (eigenvalues $\lambda \geq 0$)
has only one positive semi-definite square root:
"principal square root"

3) a 2×2 matrix with eigenvalues $\lambda_1 \neq 0, \lambda_2 \neq 0$
and $\lambda_1 \neq \lambda_2$
has four square roots

4) a general $n \times n$ matrix with $\lambda_1 \neq \lambda_2 \neq \dots \neq \lambda_n \neq 0$
has 2^n square roots

5) $\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix}$ has no square roots --- ETCETERA!

Matrix - Newton

remember: $x^2 - a = 0 \rightarrow \begin{cases} x_0 = a \\ x_{k+1} = \frac{1}{2} \left(x_k + \frac{a}{x_k} \right), k=0,1,2,\dots \\ = \frac{1}{2} (x_k + x_k^{-1} a) \end{cases}$

check $\rightarrow x_k - \frac{x_k^2 - a}{2x_k}$

Newton-Raphson to find $\pm\sqrt{a}$

matrix variant of this iteration method:

$X^2 - A = O \rightarrow \begin{cases} X_0 = A \\ X_{k+1} = \frac{1}{2} (X_k + X_k^{-1} A) \end{cases}$

$k=0,1,2,\dots$

"matrix-Newton" for square roots of matrices.

$\begin{pmatrix} 0 & \dots & 0 \\ \vdots & \Theta & \vdots \\ 0 & \dots & 0 \end{pmatrix}$

Theorem: if $\frac{1}{2} \left| 1 - \left(\frac{\lambda_j}{\lambda_i} \right)^{1/2} \right| \leq 1 \quad \forall i,j$ ($\frac{n \times n}{\text{matrix}}$)

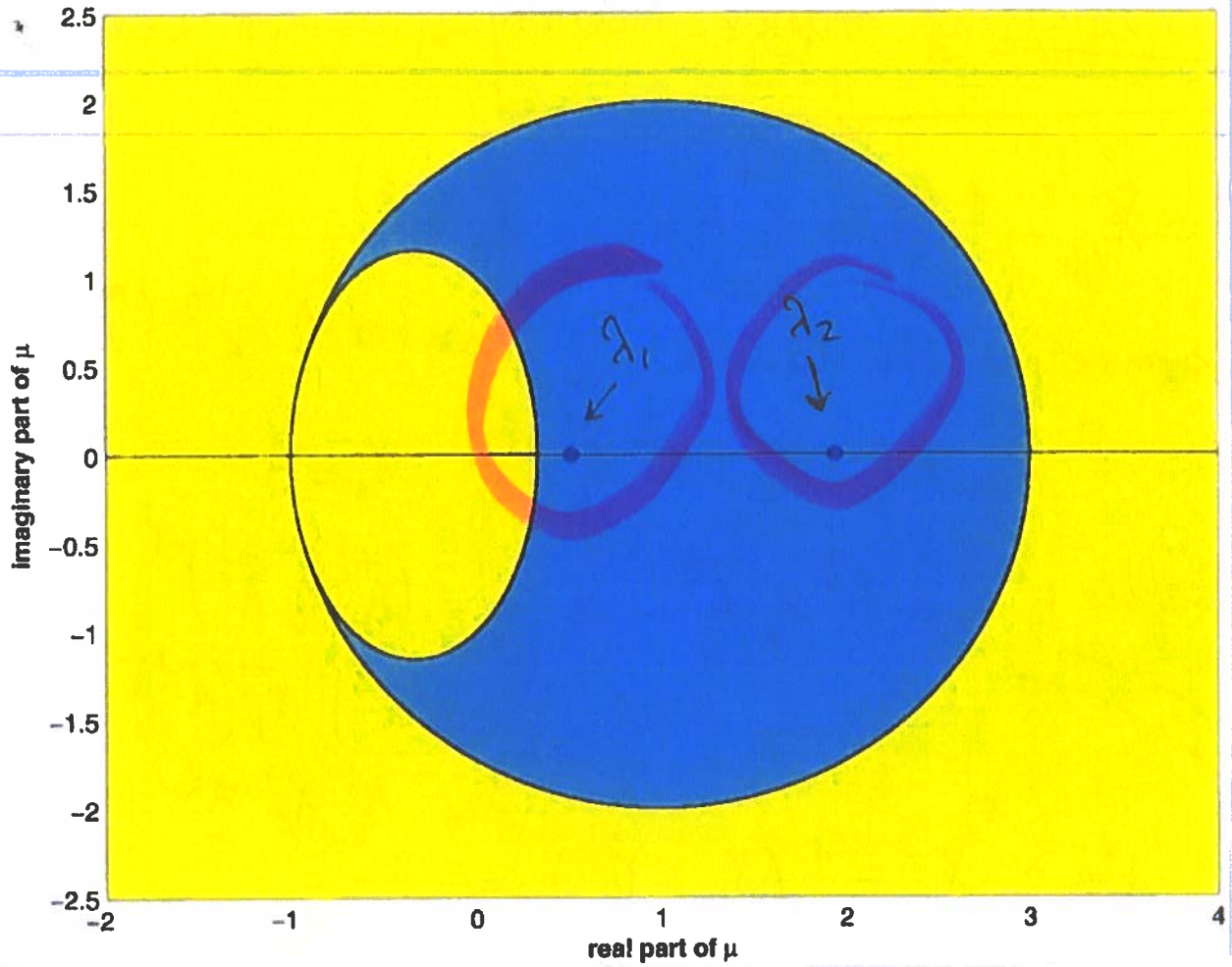
(Higham, 1986)

then matrix-Newton is stable
(small roundoff errors won't be amplified)

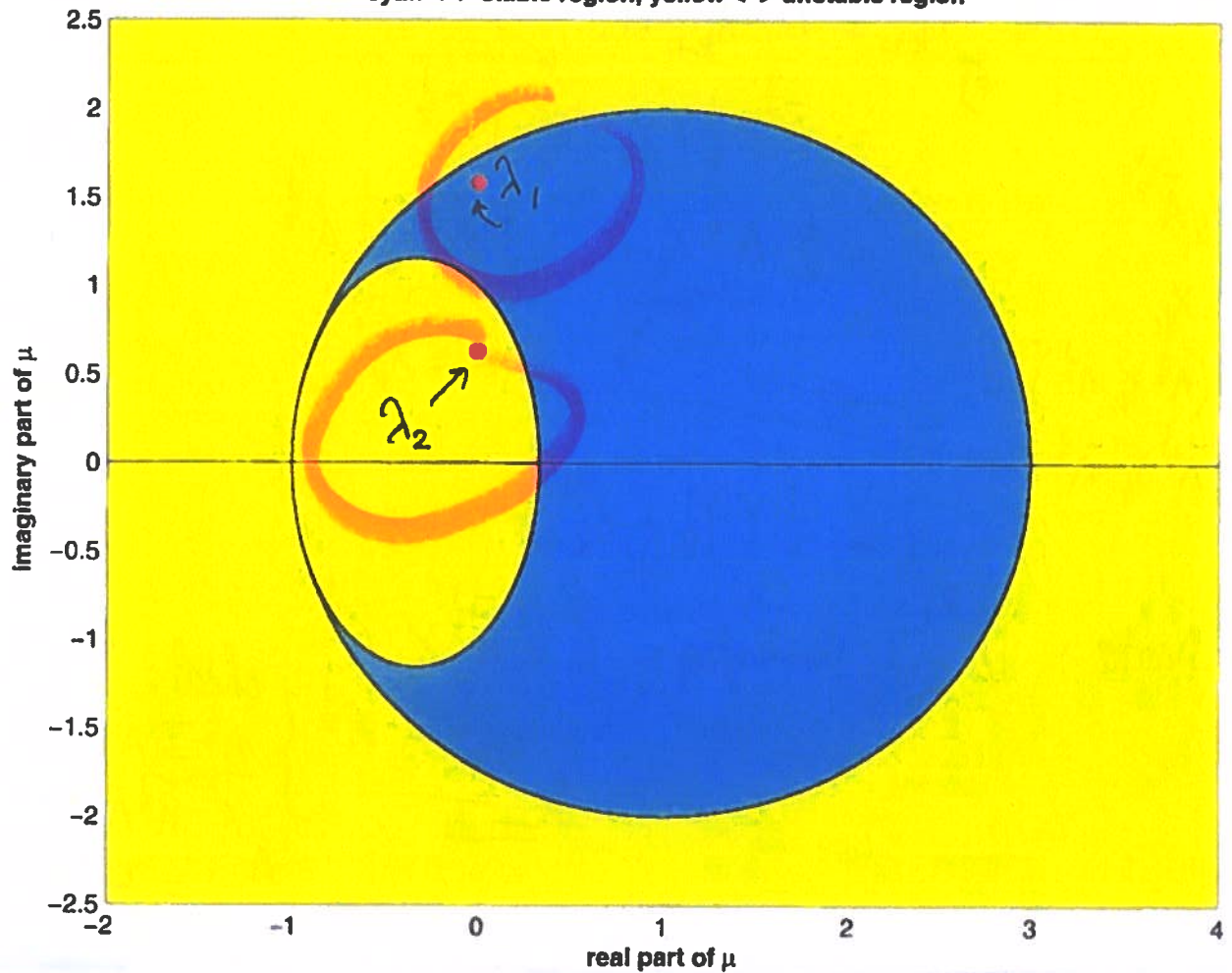
λ 's are eigenvalues of A (otherwise, it may be unstable)

for a 2×2 matrix this condition can be visualized:

cyan $\leftrightarrow$ stable region, yellow $\leftrightarrow$ unstable region



cyan $\leftrightarrow$ stable region, yellow $\leftrightarrow$ unstable region



Stabilizing matrix - Newton

→ "Denman-Beaver"

$$X_{k+1} = \frac{1}{2} (X_k + \bar{X}_k^{-1} A), \quad X_0 = A$$

"symmetrize" the iteration: $\downarrow$ $\rightarrow$? or $A \bar{X}_k^{-1}$? (may be different!)

$$1) \quad X_{k+1} = \frac{1}{2} (X_k + A^{\frac{1}{2}} \bar{X}_k^{-1} A^{\frac{1}{2}}), \quad X_0 = A$$

Define: $2) \quad Y_k = A^{\frac{1}{2}} X_k A^{\frac{1}{2}} \Rightarrow Y_k^{-1} = (A^{\frac{1}{2}} X_k A^{\frac{1}{2}})^{-1}$ 3)

$$= (A^{\frac{1}{2}})^{-1} X_k^{-1} (A^{\frac{1}{2}})^{-1} = A^{-\frac{1}{2}} X_k^{-1} A^{-\frac{1}{2}}$$

then: $5) \quad X_{k+1} = \frac{1}{2} (X_k + Y_k^{-1})$

and $6) \quad Y_{k+1} = A^{\frac{1}{2}} X_{k+1} A^{\frac{1}{2}}$

$$= A^{\frac{1}{2}} \cdot \frac{1}{2} (X_k + Y_k^{-1}) A^{\frac{1}{2}}$$

$$= \frac{1}{2} \underbrace{A^{\frac{1}{2}} X_k A^{\frac{1}{2}}}_{= Y_k} + \frac{1}{2} \underbrace{A^{\frac{1}{2}} Y_k^{-1} A^{\frac{1}{2}}}_{= Y_k^{-1}}$$

$$7) \quad = \frac{1}{2} (Y_k + Y_k^{-1})$$

Note: $8) \quad Y_0 = I$ satisfies:

$$Y_0 = A^{\frac{1}{2}} X_0 A^{\frac{1}{2}} = A^{\frac{1}{2}} A A^{\frac{1}{2}} = I$$

check: $10) \quad A^{\frac{1}{2}} I A^{\frac{1}{2}} = A^{\frac{1}{2}} A^{\frac{1}{2}} A A^{\frac{1}{2}} = I A I = A$

$$1) \quad A^{\frac{1}{2}} Y_k = X_k A^{\frac{1}{2}}$$

$$A^{\frac{1}{2}} Y_k A^{\frac{1}{2}} = X_k$$

$$\Rightarrow X_k^{-1} = (A^{\frac{1}{2}} Y_k A^{\frac{1}{2}})^{-1} = A^{-\frac{1}{2}} Y_k^{-1} A^{-\frac{1}{2}}$$

⇒ Denman-Beaver, 1976
(stable iterations, but twice as expensive)

$$\begin{cases} X_{k+1} = \frac{1}{2}(X_k + Y_k^{-1}), & X_0 = A \\ Y_{k+1} = \frac{1}{2}(Y_k + X_k^{-1}), & Y_0 = I \end{cases}$$

$k=0, 1, 2, \dots$

For checking the convergence, one could use the Frobenius-norm of a matrix: $\|A\|_F = \sqrt{\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2}$

(in Matlab: norm(A, 'fro'))

and check $\|X_{k+1} - X_k\|_F$, for example.

[Matlab $\sqrt{A}$: sqrtm.m $\rightsquigarrow$ sqrt(A)].