

# CS 450: Numerical Analysis

## Lecture 10

### Chapter 4 – Eigenvalue Problems

#### Theory of Eigenvalue Solvers

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# Perturbation Analysis of Eigenvalue Problems

- Suppose we seek eigenvalues  $D = X^{-1}AX$ , but find those of a slightly perturbed matrix  $D + \delta D = \hat{X}^{-1}(A + \delta A)\hat{X}$ :

$$D + \delta D = \hat{X}^{-1}A\hat{X} + \hat{X}^{-1}\delta A\hat{X}$$

$$= X^{-1}(A + \delta A)X = \underbrace{X^{-1}AX}_D + \underbrace{X^{-1}\delta AX}$$

$$\text{eig}(A + \delta A) = D + \delta D = \text{eig}\left(D + \underbrace{X^{-1}\delta AX}_D\right)$$

$$\begin{aligned} \|X^{-1}\delta AX\| &\leq \kappa(X)\|\delta A\| \\ &= \|X^{-1}\|\|X\|\|\delta A\| \end{aligned}$$

$D = A$  (matrix is diagonal)

$X = I$

for some perturbation (non-diagonal)  $\delta A$

$\text{eig}(A + \delta A) = D + \delta D$  differ from  $D$

$$D + \delta D = \hat{X}^{-1} (A + \delta A) \hat{X}$$

$$\hat{X} (D + \delta D) = (A + \delta A) \hat{X}$$

$$\begin{cases} \hat{X} = I + \delta X \\ \hat{X} \approx I - \delta X \end{cases}$$

$$\delta D \approx \hat{X}^{-1} \delta A \hat{X}$$

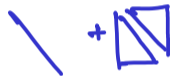
$$\|\delta D\| = \mathcal{O}(\|\delta A\|)$$

$$\underbrace{\delta X A + A \delta X}_{\delta X \delta D \sim \delta A}$$

# Gershgorin Theorem

- ▶ Another way to show that the eigenvalues of a matrix are insensitive to perturbation is via Gershgorin theorem, which states that

$$A = D + O$$



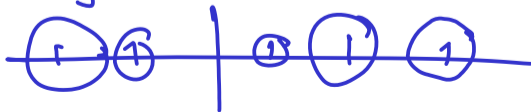
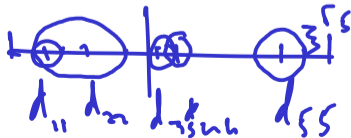
$$\lambda(A) \in \bigcup_i P(d_{ii}, r_i)$$

radius

↑  
d.i.v

↑  
center

$$r_i = \sum_{j=1}^n |O_{ij}|$$



# Conditioning of Particular Eigenpairs

- ▶ Consider the effect of a matrix perturbation on an eigenvalue  $\lambda$  associated with a right eigenvector  $x$  and a left eigenvector  $y^H$ ,  $\lambda = y^H A x / y^H x$

$$A = X^{-1} D X$$

$$\begin{bmatrix} | \\ \vdots \\ x \\ \vdots \\ | \end{bmatrix} \begin{bmatrix} \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \end{bmatrix} \begin{bmatrix} y \\ \vdots \\ \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

$$\frac{\langle y, Ax \rangle}{\langle y, x \rangle} = \frac{\langle y, \lambda x \rangle}{\langle y, x \rangle}$$

$$\langle y, (A + \delta A) x \rangle - \lambda \langle y, x \rangle = \frac{\langle y, \delta A x \rangle}{\langle y, x \rangle} \leq \frac{\| \delta A \| \| x \|}{\langle y, x \rangle}$$

- ▶ Connect the notion of the angle between left and right eigenvectors to the magnitude of off-diagonal entries in the Schur form

$$A = \begin{bmatrix} \text{orthogonal} \\ \vdots \\ Q^T \end{bmatrix} \begin{bmatrix} \text{off-diagonal entries must be small} \\ \vdots \\ \langle y, x \rangle = 2 \end{bmatrix} \begin{bmatrix} \vdots \\ \vdots \\ \vdots \end{bmatrix}$$

# Orthogonal Iteration via QR Iteration

hints for orthogonal iteration

► In orthogonal iteration  $\hat{Q}_{i+1} \hat{R}_{i+1} = A \hat{Q}_i$  QR iteration computes

$A_i = Q_i R_i$ ,  $A_{i+1} = R_i Q_i = \hat{Q}_{i+1}^T A \hat{Q}_{i+1}$  at iteration  $i$ :

$U = \text{l.m. } A_i = \text{l.m. } \hat{Q}_{i+1}^T A \hat{Q}_{i+1}$   
 $i \rightarrow \infty$   $i \rightarrow \infty$

true  $\rightarrow A_i = \hat{Q}_i^T A \hat{Q}_i$

induction  
 show  $\rightarrow \underline{A_{i+1}} = \hat{Q}_{i+1}^T A \hat{Q}_{i+1}$

$[\hat{Q}_{i+1}, \hat{R}_{i+1}] = \text{QR}(A \hat{Q}_i)$

$A \hat{Q}_i = \hat{Q}_{i+1} A_i = \hat{Q}_{i+1} Q_i R_i$

$\hat{Q}_{i+1} \hat{R}_{i+1} = \hat{Q}_{i+1} Q_i R_i$

$\hat{Q}_{i+1}^T A \hat{Q}_{i+1} = \hat{R}_{i+1} \hat{Q}_{i+1}^T \hat{Q}_{i+1}$

$= \hat{R}_{i+1} I$

$= \hat{R}_{i+1}$

## QR Iteration with Shift

- Describe QR iteration with shifting

$$[Q_i, R_i] = QR(A_i - \sigma_i I)$$

$$A_{i+1} = R_i Q_i + \sigma_i I$$

- Discuss how shift can be selected

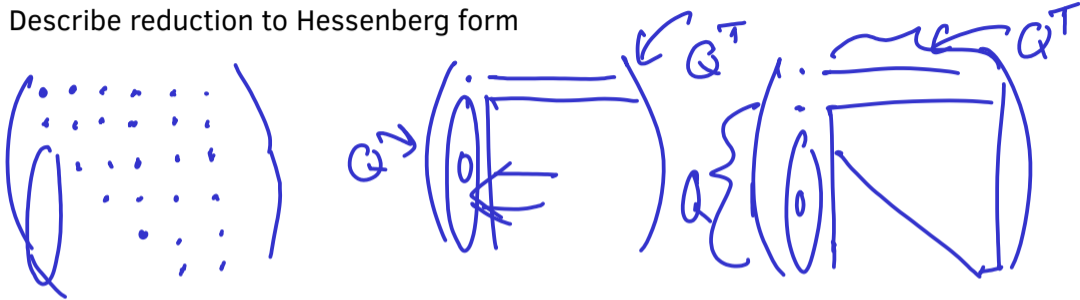
$$\sigma_i = (A_i)_{nn}$$

$$A_{i+1} = Q_i^+ (A_i - \sigma_i I) Q_i + \sigma_i I$$

$$A_i = \begin{pmatrix} \text{upper triangular} \\ \vdots \\ \text{lower triangular} \end{pmatrix} \begin{pmatrix} \text{upper triangular} \\ \vdots \\ \text{lower triangular} \end{pmatrix}$$

# Hessenberg and Tridiagonal Form

- ▶ Describe reduction to Hessenberg form



- ▶ Describe reduction to tridiagonal form in symmetric case

in symmetric case, similarity transformation introduces to rows and cols



## QR Iteration Complexity

- Compare complexity of QR iteration for various matrices

with tridiagonal form QR iteration

costs  $O(n)$  per iteration

Hessenberg form

$O(n^2)$  per iteration

General form

$O(n^3)$  per iteration



