

Welcome back to Ma221! Lecture 28, Oct 27

Making QR Iteration Practical

1) Reduce cost of 1 iteration from $O(n^3) \rightarrow O(n^2)$

2) How to converge to Real Schur form:
shift by $\lambda, \bar{\lambda}$ in one step
all imaginary parts cancel

3) Detect convergence:

set any $|H(i+1, i)| \leq O(\epsilon) \cdot \|A\|$ to 0



solve H_{11}, H_{22}
independently

4) Reduce communication

no known alg to reach lower bound

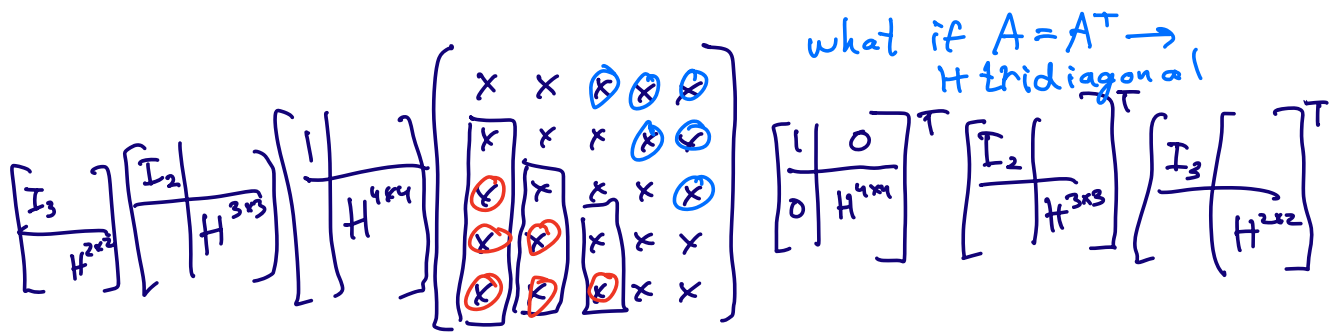
$O\left(\frac{n^3}{\sqrt{\text{cache size}}}\right)$ that is deterministic,

just randomized, Srivastava (2022)

More detail on Hessenberg QR 

How to reduce $A = QHQ^T$, H Hessenberg

Analogous to QR decomposition,
use Householder transforms to
zero out columns of A

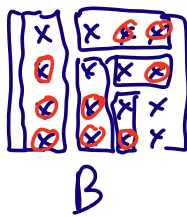


↑
upper Hessenberg, can use BLAS3

Cost: $\frac{16}{3} n^3 + O(n^2)$ just for H
or $\frac{14}{3} n^3 + O(n^2)$ for Q too

much more than LU or QR, already
(next step more expensive)

SVD similar



$$QAV = B$$

bidiagonal

QR iteration on upper Hessenberg H in $O(n^2)$
flops

Lemma: upper Hessenberg preserved by QR iteration

pf: A upper Hess $\rightarrow A - \sigma I$ upper Hess

$\Rightarrow A - \sigma I = QR$, Q upper Hess, because
col $_i$ of Q = linear comb of first i cols
of $A - \sigma I$

\Rightarrow 0's at bottom, rows $i+2:n$, stay 0

$RQ = \begin{bmatrix} \square & & \\ & \square & \\ & & \square \end{bmatrix}$ still upper Hess

How to do one step of QR iteration in $O(n^2)$

Def: Assume H "unreduced" i.e. $H(i+1, i) \neq 0$ for all i ^{flops}

Implicit Q Theorem: suppose $Q^T A Q$ upper Hess and unreduced, then cols 2:n of Q uniquely determined by col 1 (proof later)

Step 1 of QR in $O(n^2)$ flops

$A - \sigma I = QR$ first col of $A - \sigma I = \begin{bmatrix} A(1,1) - \sigma \\ A(2,1) \\ \vdots \\ 0 \\ \vdots \\ 0 \end{bmatrix}$
 upper Hess \Rightarrow know first col of Q

Let Q_1 be Givens rotation s.t

$$\begin{bmatrix} c_1 & & & & \\ s_1 & & & & \\ & \ddots & & & \\ & & 1 & & \\ & & & \ddots & \\ & & & & 1 \end{bmatrix} \begin{bmatrix} A(1,1) - \sigma \\ A(2,1) \\ \vdots \\ 0 \\ \vdots \\ 0 \end{bmatrix} = \begin{bmatrix} x \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Q_1^T

$Q_4^T Q_3^T Q_2^T Q_1^T \begin{bmatrix} x & x & x & x & x \\ \otimes & x & x & x & x \\ \oplus & x & x & x & x \\ & \oplus & x & x & x \\ & & \oplus & x & x \end{bmatrix}$

first col of Q same as Q_1
 $Q_1 Q_2 Q_3 Q_4$
 Q
 cost = $O(n^2)$

"bulge chasing"

Proof of Implicit Q Theorem

let q_i be col i of Q

$$Q^T A Q = H \Rightarrow A Q = Q H$$

$$\text{Col 1: } (A Q)_1 = A q_1 = q_1 \cdot H(1,1) + q_2 \cdot H(2,1)$$

\Rightarrow determines $q_2, H(1,1)$ and $H(2,1)$ uniquely

$$\text{via QR } [q_1, A q_1] = [q_1, q_2] \cdot \begin{bmatrix} 1 & H(1,1) \\ 0 & H(2,1) \end{bmatrix}$$

Induction on column number i :

suppose we have q_1, \dots, q_i
and columns $1, \dots, i-1$ of H

Get next columns: $(A Q)_i = (Q H)_i$

$$q_i^T (A q_i = \sum_{j=1}^{i-1} q_j H(j,i))$$

$$q_j^T A q_i = H(j,i) \quad \text{for } j=1:i-1$$

$$A q_i - \sum_{j=1}^{i-1} q_j H(j,i) = q_{i+1} H(i+1,i)$$

gives us $q_{i+1}, H(i+1,i)$ QED

Used: in LAPACK xGEES (Schur)
 xGEEV (evec too)
 eig(A) Matlab

Symmetric Eigenproblem + SVD

Goals: Perturbation Theory

Algorithms

need Perturbation Theory to understand Algs too

Real Symmetric $A = A^T$ ← do this case

Complex Hermitian $A = A^{H}$

$$A = Q \Lambda Q^T$$

$$\Lambda = \text{diag}(d_1, \dots, d_n) \quad d_1 \geq d_2 \geq \dots \geq d_n$$

$$Q = [q_1, \dots, q_n]$$

Complex symmetric different

$$\begin{bmatrix} 1 & i \\ i & -1 \end{bmatrix} \quad i = \sqrt{-1} \quad \text{has 2 eivals at 0} \\ \text{not diagonalizable}$$

Most results apply to SVD

(Thm 3.3 part 4), want $\text{svd}(A)$

$$B = \left[\begin{array}{c|c} 0 & A \\ \hline A^T & 0 \end{array} \right] = B^T$$

eigencomp of B closely related

to $\text{svd}(A) \Rightarrow$ algs, perturbation theory for sym erg extend to SVD

Some open problems extending fastest symeig algs to SVD

Def: Rayleigh Quotient
$$p(u, A) = \frac{u^T A u}{u^T u} \quad u \neq 0$$

Properties: if $Au = \lambda u \Rightarrow p(u, A) = \lambda$

$$u = \sum_{i=1}^n b_i q_i = Q b \quad b = \begin{bmatrix} b_1 \\ \vdots \\ b_n \end{bmatrix}$$

$$p(u, A) = \frac{u^T A u}{u^T u} = \frac{(Qb)^T A (Qb)}{(Qb)^T (Qb)}$$

$$= \frac{b^T \overbrace{Q^T A Q}^L b}{b^T \underbrace{Q^T Q}_I b} = \frac{b^T L b}{b^T b} \quad A = Q L Q^T$$

$$= \frac{\sum_{i=1}^n \lambda_i b_i^2}{\sum_{i=1}^n b_i^2} = \text{convex combination of all evals}$$

$$\lambda_1 \geq p(u, A) \geq \lambda_n$$

all evals can be expressed using $p(u, A)$

Courant-Fischer Minimax Thm

$R^j = j$ -dimensional subspace of \mathbb{R}^n
 $S^{n-j+1} = n-j+1$ " " " "

$$\max_{R^j} \min_{\substack{r \in R^j \\ r \neq 0}} p(r, A) = \lambda_j = \min_{S^{n-j+1}} \max_{\substack{s \in S^{n-j+1} \\ s \neq 0}} p(s, A)$$

max over R^i attained by $\text{span}(q_1, \dots, q_i)$

min over $r \in R^i$ " " $r = q_i$

min over S^{n-j+1} " " $\text{span}(q_j, q_{j+1}, \dots, q_n)$

max over $s \in S^{n-j+1}$ " " $s = q_j$