

Math 685.

Lecture 8.

Eigenvalue problems: $Ax = \lambda x$

Methods:

1) Power method: $x_{k+1} = Ax_k$

→ has to be scaled $\frac{x_k}{\|x_k\|}$ at every step to avoid possible overflow/underflow

→ linear convergence, dep. on $C = \left| \frac{\lambda_2}{\lambda_1} \right|$
 $\lambda_1 > \lambda_2 \geq \dots \geq \lambda_n$ $e_{n+1} \sim C \cdot e_n$

→ x_0 has to be chosen s.t.

$$x_0 = d_1 v_1 + \dots + d_n v_n \neq 0$$

→ can get complex eigenvalues, but has to have x_0 -complex in this case.

2) $x_{k+1} = (A - \sigma I) x_k \leftarrow$ shifted power iter.

$$x_k \rightarrow \text{max eigenvalue of } A - \sigma I = \lambda_{\max}(A) - \sigma$$

3) Inverse shifted:

$$x_k = (A - \sigma I) x_{k+1} \Rightarrow$$

converges to $\lambda_{\min}(A - \sigma I) = \min(\lambda_i - \sigma)$

where $\lambda_1, \dots, \lambda_n$ - eig. values of A

→ Have to solve a linear system of the form $(A - \sigma I) \underline{x} = \underline{b}$.

4) Rayleigh Quotient iteration

$$\lambda = \frac{x^T A x}{x^T x}$$

Step 1: $\sigma_k = \frac{x_{k-1}^T A x_{k-1}}{x_{k-1}^T x_{k-1}}$
↑
approximation to λ .

Step 2: $(A - \sigma_k I) y_{k+1} = x_k,$

$$\frac{y_{k+1}}{\|y_{k+1}\|} = x_{k+1}$$

⊕ at least quadratic convergence
 $e_{n+1} \sim C \cdot e_n^2$

⊖ recomputing σ_k , factoring $A - \sigma_k I$ at every step is time consuming, but may be worth it due to savings from convergence speed.

5) Deflation: $H A H^{-1} = \begin{bmatrix} \lambda_1 & B^T \\ 0 & B \end{bmatrix}$

reduces problem to

$\dim = n-1$ and repeat

Need to have: good estimate of λ_1 ,

⊖ forming H is costly.

6) Simultaneous iteration

$$X_{k+1} = A X_k$$

have to normalize (same as in power iter.)

9) QR with preliminary reduction.

Step 1. Converts A to Hessenberg form

Step 2 Do QR iteration on Hessenberg

$\Rightarrow O(n^2)$ operations

if A -symmetric \Rightarrow tridiagonal

$O(n)$ operations.

⊕ QR is very robust,
esp. if all eigenvalues need to be
computed.

⊖ Very expensive for large n

⊖ if only several $\lambda_i(A)$ are needed,
might be outperformed by other
methods.

⊖ ~~is~~ "fill-in" can occur for sparse A .

Krylov subspace methods,

Instead of working on the orthonormal
basis of \mathbb{R}^n , construct approximations
incrementally.

$$K_n = [\vec{x}_0 \quad A\vec{x}_0 \quad \dots \quad A^{k-1}\vec{x}_0]$$

Want: rotations transforming A
into a Hessenberg form though

$$K_n^{-1} A K_n = C_n \text{ (Companion matrix)}$$

Alternative:

Orthogonal iteration:

reduced QR-decomp. $\begin{cases} \hat{Q}_k R_k = X_{k-1} \\ X_k = A \hat{Q}_k \end{cases} \quad \begin{matrix} Q_k - n \times p \\ R_k = \begin{pmatrix} \times & & \\ & \times & \\ & & \times & \\ & & & \times & \\ & & & & \times & \\ & & & & & \times & \\ & & & & & & \times & \\ & & & & & & & \times & \\ & & & & & & & & \times & \\ & & & & & & & & & \times & \\ & & & & & & & & & & \times \end{pmatrix} \end{matrix}$

By Schur decomposition, there is a \hat{Q} s.t. $A\hat{Q} = \hat{Q}B$ where B is in triangular form.

7) QR iteration: $A_k = R_k \hat{Q}_k^H$, $A_{k-1} = \hat{Q}_k R_k$

$$A_k = \hat{Q}_k^H A_{k-1} \hat{Q}_k$$

↑ unitary similar to A

for general A $\begin{pmatrix} \times & & \\ & \times & \\ & & \times & \\ & & & \times & \\ & & & & \times & \\ & & & & & \times & \\ & & & & & & \times & \\ & & & & & & & \times & \\ & & & & & & & & \times & \\ & & & & & & & & & \times & \\ & & & & & & & & & & \times \end{pmatrix}$

In general, can be slow to converge.

for A-symm. $\begin{pmatrix} \times & & \\ & \times & \\ & & \times & \\ & & & \times & \\ & & & & \times & \\ & & & & & \times & \\ & & & & & & \times & \\ & & & & & & & \times & \\ & & & & & & & & \times & \\ & & & & & & & & & \times & \\ & & & & & & & & & & \times \end{pmatrix}$

8) QR with shift:

$$Q_k R_k = A_{k-1} - \sigma_k I \leftarrow \text{QR on shifted } A_{k-1}$$

$$A_k = R_k Q_k + \sigma_k I \leftarrow \text{recompute } A_k$$

⊕ speed up QR by using σ_k approximation

$$\sigma_k \approx a_{nn}^{(k-1)} \quad A_{k-1} = \begin{pmatrix} \times & & \\ & \times & \\ & & \times & \\ & & & \times & \\ & & & & \times & \\ & & & & & \times & \\ & & & & & & \times & \\ & & & & & & & \times & \\ & & & & & & & & \times & \\ & & & & & & & & & \times & \\ & & & & & & & & & & \times \end{pmatrix}$$

other shifts are possible

⊖ QR requires $O(n^3)$ operations.

$$K_n = Q_n R_n$$

$H \equiv Q_n^H A Q_n$ - Hessenberg form
↑ want to compute elements of H

Arnoldi
iter.

$$(1) A q_k = h_{1k} q_1 + \dots + h_{k+1,k} \underline{q_{k+1}}$$

$$(2) h_{jk} = q_j^H A q_k$$

By repeating this process: $A \rightsquigarrow H$

s.t. $\lambda(H) =$ Ritz values $\approx \lambda(A)$

$Q_k v(H) =$ Ritz vectors $\approx v(A)$

↑ eig. vectors of H

↑ eig. vec.
of A

In case A -symm. or Hermitian \Rightarrow

Arnoldi iteration can be made
more efficient by using Lanczos
iteration which converts A into
a tridiagonal form:

$$\begin{pmatrix} \circ & & \\ & \circ & \\ & & \circ \end{pmatrix}$$