

Last time: "plain" QR iteration \Leftrightarrow block power iteration

$$A_0 = A$$

for $k = 1, 2, \dots$

$$\begin{cases} Q_k, R_k = \text{qr}(A_k) \\ A_{k+1} = R_k Q_k \end{cases}$$

Why is it slow?

- ① QR = $O(n^3)$ cost per QR factorization \rightarrow Upper Hessenberg
- ② Can require many iterations \rightarrow shifts.

① Upper Hessenberg form: pre-factorize A ($O(n^3)$ cost)
 $\Rightarrow A = U H U^T$ via Householder reflectors
w/ $H_{ij} = 0$ if $i > j+1$

$$H = \begin{bmatrix} \times & \times & \times & \times \\ \times & \times & \times & \times \\ \times & \times & \times & \times \\ \times & \times & \times & \times \end{bmatrix}$$

Construction via Householder reflectors.

QR(H) \rightarrow using Householder structure or Givens rotations (for matrices w/ sparsity)
 $\rightarrow O(n)$ cost for QR

Recall Householder reflectors for QR:

$$Q_1 A = \left[\begin{array}{c|cccc} x & xxx & & & \\ 0 & xxx & & & \\ \hline & xxx & & & \\ & xxx & & & \end{array} \right]$$

Want $\underline{Q_1 A Q_1^*} = \left[\begin{array}{c|c} x & x \\ \hline 0 & X \end{array} \right] Q_1^*$

$$= \left(Q_1 \left[\begin{array}{c|c} x & 0 \\ \hline x & X \end{array} \right] \right)^* \neq$$

< dense matrix < useless

Define Q_1 via Householder: $A = \left[\begin{array}{c} -a_1 \\ \hline A_1 \end{array} \right]$

Let $\tilde{Q}_1 A_1 = \left[\begin{array}{c|cccc} x & xxx & & & \\ 0 & xxx & & & \\ \hline & xxx & & & \end{array} \right]$

$$\underbrace{\left[\begin{array}{c|cccc} 1 & & & & \\ \hline & \tilde{Q}_1 & & & \end{array} \right]}_{Q_1} A = \left[\begin{array}{cccc|c} xxx & xxx & & & \\ x & xxx & x & & \\ \hline 0 & xxx & xxx & & \\ & xxx & xxx & & \end{array} \right]$$

$$Q_1 A Q_1^* = \underbrace{\left[\begin{array}{cccc|c} xxx & xxx & & & \\ x & xxx & x & & \\ \hline 0 & xxx & xxx & & \\ & xxx & xxx & & \end{array} \right]}_{Q_1 A} \left[\begin{array}{c|c} 1 & \\ \hline & \tilde{Q}_1 \end{array} \right]$$

$$Q_1 A Q_1^* = \left[\begin{array}{c|cccc} x & xxx & & & \\ x & xxx & x & & \\ \hline 0 & xxx & xxx & & \\ \vdots & xxx & xxx & & \\ 0 & xxx & xxx & & \end{array} \right]$$

$$\text{Repeat} \Rightarrow Q_2 Q_1 A Q_1^* Q_2^* = \begin{bmatrix} x & x & x & x & x \\ x & x & x & x & x \\ 0 & x & x & x & x \\ 0 & 0 & x & x & x \\ 0 & 0 & 0 & x & x & x \end{bmatrix}$$

$$\Rightarrow \underbrace{Q_{n-2} \dots Q_1}_{U^*} A \underbrace{Q_1^* Q_2^* \dots Q_{n-2}^*}_{U} = \begin{bmatrix} x & x & x & x & x \\ x & x & x & x & x \\ & x & x & x & x \\ 0 & & x & x & x \\ & & & x & x \\ & & & & x \end{bmatrix}$$

$$U^* A U = H \Rightarrow A = U H U^*$$

$$\text{QR}(H) = O(n^2)$$

$$\Rightarrow \text{cost of QR} = O(n^2) \times \text{number of iters}$$

Practical QR algorithm:

$$H_0 = U^* A U$$

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

$$\begin{cases} Q_k R_k = \text{qr}(H_k - \mu_k I) \\ H_{k+1} = R_k Q_k + \mu_k I \end{cases}$$

Note $R_k Q_k =$ retains upper Hessenberg form (see homework)
 $Q_k =$ upper Hessenberg.

Practical QR \Leftrightarrow shifted inverse iter.

① Practical QR \Leftrightarrow inverse iteration w/out shifts.

QR iter: constructs $A^k = \tilde{Q}_k \tilde{R}_k$

where

$$\tilde{Q}_k = Q_1 \dots Q_k$$

$$\tilde{R}_k = R_1 \dots R_k$$

(Q_i, R_i from QR iter)

QR iter also factorizes A^{-k} implicitly!

Assume $A = A^T$ for simplicity

$$A^{-k} = \tilde{R}_k^{-1} \tilde{Q}_k^{-T}$$

Since $A = A^T$,

$$(A^{-k})^T = \tilde{Q}_k \tilde{R}_k^{-T}$$

Note \tilde{R}_k^{-T} = lower tri. matrix

$$P = \begin{bmatrix} & & & 1 \\ & & & & 1 \\ & & & & & 1 \\ & & & & & & 1 \\ 1 & & & & & & & \end{bmatrix} = \text{reverses order}$$

Since R^{-1} = upper triangular

Note $P^2 = I$.

$$(A^{-k})^T P = \underbrace{\tilde{Q}_k P}_{\text{still orthonormal}} \underbrace{P \tilde{R}_k^{-T} P}_{\text{upper tr.}}$$

still orthonormal

$$= P \begin{bmatrix} \times & & & \\ & \times & & \\ & & \times & \\ & & & \times \end{bmatrix} P$$

$$= \begin{bmatrix} \times & \times & \times \\ & \times & \\ & & \times \end{bmatrix} P$$

$$P \tilde{R}_k^{-T} P = \begin{bmatrix} \times & \times & \times \\ & \times & \\ & & \times \end{bmatrix} \text{ upper tr.}$$

\Rightarrow QR iter also constructing a "permuted" QR factorization of A^{-k}

Shifts:

$$Q_k R_k = A_{k-1} - \mu_k I$$

$$A_k = R_k Q_k + \mu_k I$$

$$R_k = Q_k^* A_{k-1} - \mu_k Q_k^*$$

$$A_k = (Q_k^* A_{k-1} - \mu_k Q_k^*) Q_k + \mu_k I$$

$$= Q_k^* A_{k-1} Q_k - \mu_k \underbrace{Q_k^* Q_k}_I + \mu_k I$$

$$\Rightarrow A_k = Q_k^* A_{k-1} Q_k$$

Turns out shifts change $A^k = \tilde{Q}_k \tilde{R}_k$ to

$$\tilde{Q}_k \tilde{R}_k = (A - \mu_k I)(A - \mu_{k-1} I) \cdots (A - \mu_1 I)$$

By relation to inverse iteration,

$$(\tilde{Q}_k P)(P \tilde{R}_k P) = \prod_{j=1}^k (A - \mu_j I)^{-1}$$

Recall RQI: shifted inverse iter. with

$$\mu_k = \frac{v_k^* A v_k}{v_{k-1}^* v_{k-1}}, \quad v_k \rightarrow \text{eigen vector as } k \rightarrow \infty$$

How to mimic w/ QR^2 Recall \tilde{Q}_k columns will converge to eigenvectors for $A=A^T$

same $\tilde{Q}_k = Q_1 \cdots Q_k$

and $A_k = \tilde{Q}_k^* A \tilde{Q}_k$. If $A_k \rightarrow \text{diagonal}$

$$\Rightarrow A_k = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix} = \tilde{Q}_k^* A \tilde{Q}_k$$

$$\Rightarrow Q_k (\leftarrow) Q_k^* = A$$

Consider $q_m = m^{\text{th}}$ col. of \tilde{Q}_k ,

$$\text{Want } g_m^* A g_m = \mu_k$$

$$\text{But } (A_k)_{mm} = (\tilde{Q}_k^* A \tilde{Q}_k)_{mm}$$

$$e_m = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \vdots \\ 0 \end{bmatrix} \leftarrow \begin{array}{l} \text{mth} \\ \text{entry} \end{array} = e_m^* \tilde{Q}_k^* A \tilde{Q}_k e_m = g_m^* A g_m$$

\Rightarrow Pick a diag entry of A_k as the shift.