

## S.5 QR-algorithm

Let  $A$  be an  $n \times n$  (possibly complex) matrix. We want to find eigenvalues.

- Schur's Thm:  $A$  is unitarily similar to a triangular matrix.

$$\begin{array}{ccc} U A U^* = T & & \\ \uparrow & & \uparrow \\ \text{unitary} & & \text{triangular} \end{array}$$

## QR-algorithm

$$A_1 = A$$

$$A_k = Q_k R_k$$

$$A_{k+1} = R_k Q_k$$

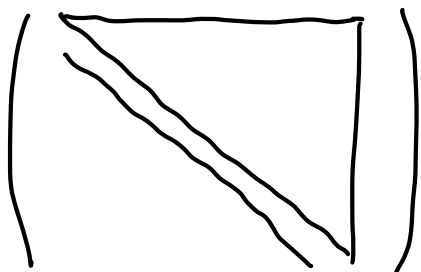
$$\begin{array}{ccc} \uparrow & & \uparrow \\ \text{unitary} & & \text{upper-triangular} \\ & & \text{w/ } (R_k)_{ii} \geq 0 \end{array}$$

$$A_{k+1} = Q_k^* A_k Q_k$$

- Direct calculation of  $Q_k R_k$  costs  $O(n^3)$  in one iteration.  
Too expensive!

## Reduction to upper Hessenberg form

Def An  $n \times n$  matrix  $H$  is upper Hessenberg if  $H_{ij} = 0 \ \forall \ i > j+1$



- QR-factorization for an upper Hessenberg matrix costs  $O(n^2)$

$$U^{(1)} H^{(1)} = H^{(2)}$$

$$\begin{pmatrix} I_2 - 2\vec{v}^{(1)}\vec{v}^{(1)\top} & \\ & I_{n-2} \end{pmatrix} \begin{pmatrix} \text{Upper Hessenberg matrix} \end{pmatrix} = \begin{pmatrix} * & * & \dots & * \\ 0 & \boxed{\text{Upper Hessenberg matrix}} & & * \end{pmatrix}$$

$$U^{(2)} = \begin{pmatrix} I_1 & & \\ & I_2 - 2\vec{v}^{(2)}\vec{v}^{(2)\top} & \\ & & I_{n-3} \end{pmatrix}$$

...

Calculation of RQ also costs  $O(n^2)$

RQ is also upper Hessenberg

$$Q = U^{(1)} \dots U^{(n-1)}$$

$$\begin{pmatrix} \text{Upper Hessenberg matrix} \end{pmatrix} \begin{pmatrix} I_2 - 2\vec{v}^{(1)}\vec{v}^{(1)\top} & \\ & I_{n-2} \end{pmatrix} = \begin{pmatrix} * & \text{Upper Hessenberg matrix} \end{pmatrix}$$

$R \qquad U^{(1)}$

$$\begin{pmatrix} \text{Upper Hessenberg matrix} \end{pmatrix} \begin{pmatrix} I_1 & & \\ & I_2 - 2\vec{v}^{(2)}\vec{v}^{(2)\top} & \\ & & I_{n-3} \end{pmatrix} = \begin{pmatrix} * & \text{Upper Hessenberg matrix} \end{pmatrix}$$

$R U^{(1)} \qquad U^{(2)}$

- Starting from a general  $A$ , we want to unitarily transform it into upper Hessenberg form. (cost  $O(n^3)$ )

Step 1:

$$A = A^{(1)} = \left( \begin{array}{c|ccc} \hline & & & \\ \hline \color{red}{\vdots} & | & | & \dots & | \\ \hline & & & & \end{array} \right)$$

↪ Apply Householder

$$U^{(1)} = \left( \begin{array}{c} I_1 \\ \hline I_{n-1} - 2 \vec{v}^{(1)} \vec{v}^{(1)*} \end{array} \right)$$

$$U^{(1)} A^{(1)} = \left( \begin{array}{c|ccc} \hline * & & & \\ \hline 0 & | & | & \dots & | \\ \hline \vdots & & & & \\ 0 & & & & \end{array} \right)$$

$$A^{(2)} = U^{(1)} A^{(1)} \quad U^{(1)} = \left( \begin{array}{c|ccc} \hline * & \color{blue}{\boxed{\dots}} & & \\ \hline 0 & | & | & \dots & | \\ \hline \vdots & & & & \\ 0 & \color{blue}{\boxed{\dots}} & & & \end{array} \right) \left( \begin{array}{c} I_1 \\ \hline I_{n-1} - 2 \vec{v}^{(1)} \vec{v}^{(1)*} \end{array} \right)$$

↑  
=  $U^{(1)*}$

$$= \left( \begin{array}{c|ccc} \hline * & \color{red}{\boxed{\dots}} & & \\ \hline 0 & | & | & \dots & | \\ \hline \vdots & & & & \\ 0 & & & & \end{array} \right)$$

Step 2: ...

A heuristic proof of convergence of QR-algorithm

$$\begin{aligned} A_{k+1} &= Q_k^* A_k Q_k = Q_k^* Q_{k-1}^* A_{k-1} Q_{k-1} Q_k \\ &= \dots = Q_k^* \dots Q_1^* A \underbrace{Q_1 \dots Q_k}_{P_k} = P_k^* A P_k \end{aligned}$$

Denote  $T_k = R_k \dots R_1$  (upper-triangular)

Then  $P_k T_k = Q_1 \dots Q_k R_k \dots R_1$

$$= Q_1 \cdots Q_{k-1} A_k R_{k-1} \cdots R_1$$

$$= P_{k-1} A_k T_{k-1}$$

$$A_k = P_{k-1}^* A P_{k-1} \Rightarrow P_{k-1} A_k = A P_{k-1}$$

Substitute into previous, we get

$$P_k T_k = A P_{k-1} T_{k-1} = \cdots = A^{k-1} P_1 T_1 = A^k$$

Suppose  $A$  can be diagonalized as  $A = X D X^{-1}$  w/  $D$  invertible

Let  $X = Q R$  and  $X^{-1} = L U$  Then

$\begin{matrix} \uparrow & \uparrow & \uparrow & \uparrow \\ \text{unitary} & \text{upper-triangular} & \text{lower-triangular} & \text{upper-triangular} \end{matrix}$

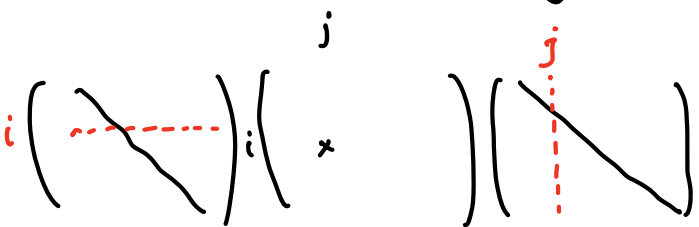
diagonal entries = 1

$$A^k = X D^k X^{-1} = Q R D^k L U = Q R (D^k L D^{-k}) D^k U$$

Lemma If  $D = \text{diag}\{\lambda_1, \dots, \lambda_n\}$  satisfies  $|\lambda_1| > \dots > |\lambda_n|$ , then

$$\lim_{k \rightarrow \infty} D^k L D^{-k} = I$$

Proof  $(D^k L D^{-k})_{ij} = L_{ij} \lambda_i^k \lambda_j^{-k} = L_{ij} \left(\frac{\lambda_i}{\lambda_j}\right)^k$



$$\left| \frac{\lambda_i}{\lambda_j} \right| \begin{cases} = 1 & i = j \\ < 1 & i > j \end{cases}$$

✓

Then  $P_k T_k = A^k \approx Q R D^k U$

$\begin{matrix} \uparrow & \uparrow & \uparrow \\ \text{unitary} & \text{unitary} & \text{upper-triangular} \end{matrix}$

upper-triangular

$$\Rightarrow P_k \approx Q$$

“Uniqueness”  
of QR-factor.

Then, since  $A = X D X^{-1} = Q R D R^{-1} Q^* \approx P_k R D R^{-1} P_k^*$

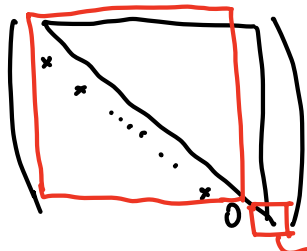
$$A_{k+1} = P_k^* A P_k \approx R D R^{-1} \text{ upper-triangular.}$$

### Shifted QR algorithm

$$A_k - z_k I = Q_k R_k, \quad A_{k+1} = R_k Q_k + z_k I$$

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

- If  $z_k$  is exactly an eigenvalue of  $A_k$ , then  $(A_{k+1})_{n,n-1} = 0$



get an eigenvalue, take out (deflation)

Generally, if  $A = \begin{pmatrix} B_1 & B_2 \\ 0 & B_3 \end{pmatrix}$  w/ square  $B_1, B_3$

$$\text{then } \text{eig}(A) = \text{eig}(B_1) \cup \text{eig}(B_3)$$

$\Rightarrow$  Choose  $z_k$  as an approximation of an eigenvalue of  $A$ .

Raleigh quotient shift:  $z_k = (A_k)_{n,n}$

Wilkinson shift:  $z_k = \text{eigenvalue of } \begin{pmatrix} (A_k)_{n-1,n-1} & (A_k)_{n-1,n} \\ (A_k)_{n,n-1} & (A_k)_{n,n} \end{pmatrix}$

that is closer to  $(A_k)_{n,n}$ .

When  $|(A_k)_{n,n-1}| < \text{TOL}$ , do deflation