

## QR- Algo (basic form)

1.  $A_0 := A$
2.  $A_{\ell} := Q_{\ell} R_{\ell} Q_{\ell}^T$  (QR-decomp.)
3.  $A_{\ell+1} := R_{\ell} Q_{\ell}$  ( $\rightarrow$  conv to upper tri. form)

~~efficiency~~ efficiency:

$O(n^3)$  for each  $\ell$

so  $O(n^4)$  in total  $\rightarrow$  combine w. shift parameter to make more efficient

## QR- Algo (~~basic~~ Hessenberg form)

if  $A$  has Hessenb. form

(A)

$\Rightarrow$  cost of QR:  $O(n^2)$

$\Rightarrow$  cost of multiplication with  $RQ$ :  $O(n^2)$

## QR- Algo (Deflation)

if  $A = \begin{pmatrix} x & x & \dots & x \\ x & & & \\ \vdots & & & \\ 0 & 0 & \dots & 0 \end{pmatrix} \mu$ ,  $x \neq 0$ ,  $\mu \dots \text{eval}(A)$

(B)

now one can look for  $\lambda_i$  on the submatrix

## QR- Algo (with shift)

(tries to accelerate  
Deflation)

(C)

1. init  $A_0 := A$
2. choose  $\mu^{(2)}$
3.  $A_{\ell} - \mu^{(2)} := Q \cdot R$
4.  $A_{\ell+1} := R \cdot Q + \mu^{(2)}$

$\mu^{(2)}$  can be chosen as  $A_{\ell}(n,n)$ .

The QR- Algo does implicitly an inverse iter. for a certain starting value.  
A good choice for  $\mu$  is therefore a Rayleigh-quotient  $\rightarrow A_{\ell}(n,n)$

## QR- Algo (combining (A)(B)(C))

1. make  $A$  Hessenberg,  $\mu^{(1)} := A_{\ell}(n,n)$
  2.  $A_{\ell} - \mu^{(1)} := Q \cdot R$
  3.  $A_{\ell+1} = R \cdot Q + \mu^{(1)}$
  4. recursion on submatrix  $A(1:n-1, 1:n-1)$
- } until  $A(n, n-1)$  is small

## 8) Conjugate Gradient Method

$$Ax^* = b \Leftrightarrow Ae_0 = r_0$$

goal: approx  $x^*$  by  $x_{\ell} = x_0 + e_{\ell}$

$\Rightarrow$  find  $x_{\ell} \in x_0 + K_{\ell}$  st.  $\|x^* - x_{\ell}\|_A \leq \|x^* - x\|_A \quad \forall x$

iterative sol for  $Ax^* = b$ ,  $A \dots$  SPD

rule: don't compute  $A^{-1}$ , only use  $x \mapsto A \cdot x$

Def.:  $\begin{cases} (x, y)_A := x^T A y \\ K_{\ell} := \{r_0, A r_0, \dots, A^{\ell-1} r_0\} \end{cases}$

From that  $\Rightarrow (x^* - x_e, v)_A = 0 \quad \forall v \in K_e$   
 $(r_e, v)_2 = 0 \quad \forall v \in K_e, \quad r_e := b - Ax_e$

One could solve  $2 \times 2$  linear system, better: find  $x_e$  as cheap update from  $x_{e-1}$

Algor. CG

$$\begin{cases} d_e = r_e - \beta_{e-1} d_{e-1} \\ r_e = r_{e-1} - \alpha_e A d_{e-1} \\ x_e = x_{e-1} + \alpha_e d_{e-1} \end{cases} \quad \begin{cases} \alpha_e = \frac{\|r_{e-1}\|_2^2}{\|d_{e-1}\|_A^2} \\ \beta_{e-1} = -\frac{\|r_{e-1}\|_2^2}{\|r_{e-1}\|_2^2} \end{cases}$$

Derivation: led. notes

It is very economical wrt. memory req.

After  $N$  steps: exact solution

Convergence:

$$\|x^* - x_e\|_A \leq 2 \left| \frac{\sqrt{K-1}}{\sqrt{K+1}} \right|^e \cdot \|e_0\|_A$$

$$K := \frac{\lambda_{\max}(A)}{\lambda_{\min}(A)}$$

GMRES iterative method for non-symm.  $A$

~~seek~~ seek  $x_e \in x_0 + K_e$  st.  $\|b - Ax_e\|_2 \leq \|b - Ax\|_2 \quad \forall x$

we know  $(b - Ax_e, v)_2 = 0 \quad \forall v$ ,  $x_e$  computed successively

Also exact after  $N$  steps!

How?

1. write  $x_e = x_0 + V y$ ,  $V$  orthonog. basis of  $K_e$ ,  $y \in \mathbb{R}^d$
2.  $(b - Ax_e, v)_2 = 0 \Rightarrow \dots \Rightarrow x_e = x_0 + V \underbrace{(W^T A V)^{-1} W^T r_0}_{\in \mathbb{R}^{d \times d}}$
3. by constructing orthonog.  $v_i$  ( $V = (v_1, v_2, \dots)$ )  
 $\Rightarrow \|b - Ax_e\|_2 = \min_y \|B e_1 - H e y\|_2$   
 $\uparrow$  Hessenberg
4. solve  $R e$  for  $y$  using QR in  $\mathcal{O}(n^2)$  and  $x_e = x_0 + V e y_e$

Remark: if  $H_e$  is not full rank: exact sol immediately

inpractise if memory is full  $\Rightarrow$  delete all and start with  $x_e$  as  $x_0$