

Summary QR-algorithm

A tridiagonal [through Householder & Givens]

$$A^{(0)} = A_1 \text{ for } k=0, 1, 2, \dots$$

$$A^{(k)} - \mu^k I = Q^{(k)} R^{(k)} \quad \text{QR factorization}$$

$$A^{(k+1)} = R^{(k)} Q^{(k)} + \mu^k I \quad \text{mult. in reverse order}$$

end

[Shifted version, $\mu^k \in \mathbb{R}$ approx
to eigenvalue]

$$A^{(k+1)} = Q^{(k)} A^{(k)} Q^{(k)}$$

$$\Rightarrow \underbrace{Q^{(0)T} \cdots Q^{(k-1)T}}_{\bar{Q}^{(0)T}} \underbrace{A}_{Q^{(k)}} \underbrace{Q^{(0)} \cdots Q^{(k)}}_{\bar{Q}^{(k)}} \xrightarrow{k \rightarrow \infty} \text{diagonal matrix}$$

→ we find the eigenvalues, how about eigenvectors?

Start with $B \in \mathbb{R}^{n \times n}$, $B^T = B$

$$\xrightarrow{\text{Step 1}} P_n^T B P_n = A \quad \text{tridiagonal} \quad \text{flops: } \sim n^3$$

$$\xrightarrow{\text{Step 2}} \underbrace{Q^{(0)T} \cdots Q^{(k-1)T}}_{\text{orthogonal, products of Householder (or Givens) matrices}} A \underbrace{Q^{(0)} \cdots Q^{(k)}}_{\text{diagonal}} \rightarrow D \quad \text{flops: } \sim n^2 \text{ per QR iteration}$$

$$\xrightarrow{\text{Combining}} Q^{(0)T} P_n^T B P_n Q^{(0)} = D \quad (\text{or } \sim n^2)$$

$$\rightarrow B P_n \bar{Q}^{(0)} = P_n \bar{Q}^{(0)} D$$

$$B \cdot \begin{bmatrix} | \\ | \\ | \end{bmatrix} = \begin{bmatrix} | \\ | \\ | \end{bmatrix} \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ 0 & & 0 \end{bmatrix}$$

$$\Rightarrow B v_i = \lambda_i v_i, \text{ where } v_i \text{ is the } i\text{-th column of } P_n \bar{Q}^{(0)}$$

How expensive is one step of QR-algo?

$$A^{(k)} = \begin{bmatrix} x & x & \\ x & x & x & 0 \\ \vdots & \ddots & \ddots & \\ 0 & x & x & x \end{bmatrix} = \underbrace{\text{prod. of Givens-rotations}}_{\text{Givens } Q^{(k)} G_2} \quad \begin{array}{l} Q^{(k)} \\ G_2 \end{array}$$

$R^{(k)}$ fill-in entries

upper triangular

$$A^{(k+1)} = Q^{(k)^T} A^{(k)} Q^{(k)} = R^{(k)} D^{(k)} =$$

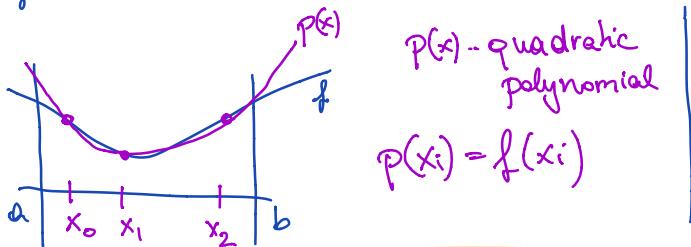
$$\begin{array}{c} \text{diag.} \\ \text{with } x \end{array} = \begin{array}{c} \text{triangular} \\ \text{with } x \dots x \end{array}$$

Since $A^{(k+1)}$ is symmetric, $x \dots x$ must vanish and $A^{(k+1)}$ is tridiagonal.

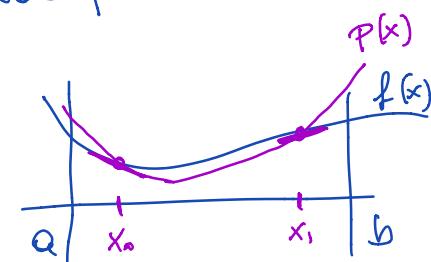
Each QR iteration is cheap since we are only working with tridiagonal matrices!

§ 6.2 Polynomial Interpolation

Approximate functions using polynomials that coincide with the function values (and/or derivatives) at node points.



Lagrange interpolation
(only function values)



$p(x) - 3^{\text{rd}}$ order polynomial

$p(x_i) = f(x_i) \quad i=0,1$

$p'(x_i) = f'(x_i) \quad i=0,1$

Hermite interpolation
(function values and derivatives)

Interpolation problem:

$n \geq 1$, x_0, \dots, x_n distinct ($x_i \neq x_j$ for $i \neq j$)

$y_0, \dots, y_n \in \mathbb{R}$; Find $P_n \in P_n$ such that $p_n(x_i) = y_i$: $i=0, \dots, n$

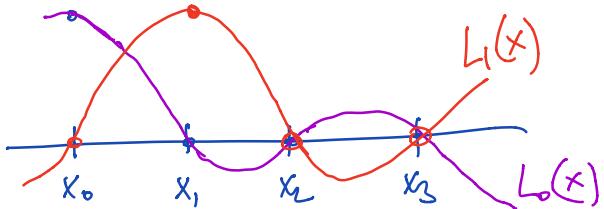
P_n ... space of polynomials of degree $\leq n$, i.e.

$$P_n = \left\{ a_n x^n + \dots + a_1 x + a_0 \mid a_n, \dots, a_0 \in \mathbb{R} \right\}$$

Lemma: $n \geq 1$, There exist polynomials $L_k \in P_n$ $k=0, \dots, n$ such

that $L_k(x_i) = \begin{cases} 1 & \text{if } i=k \\ 0 & \text{if } i \neq k \end{cases}$ (Lagrange polynomials)

Moreover, $P_n(x) = \sum_{k=0}^n L_k(x) y_k$ is the interpolating polynomial



Proof: $L_k(x) = C_k \prod_{\substack{i=0 \\ i \neq k}}^m (x - x_i)$, since $L_k(x_k) \stackrel{!}{=} 1$

$$\Rightarrow C_k = \frac{1}{\prod_{\substack{i=0 \\ i \neq k}}^m (x_k - x_i)} \Rightarrow L_k(x) = \frac{\prod_{i \neq k} (x - x_i)}{\prod_{i \neq k} (x_k - x_i)}$$

$$= 1 \text{ if } i=k \text{ and } 0 \text{ else}$$

interpolating polynomial. \square