

Summary : QR algorithm

A tridiagonal [through Householder or Givens]

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

$$A^{(k)} \overset{\mu^k \mathbf{I}}{=} Q^{(k)} R^{(k)}$$

QR factorization

$$A^{(k+1)} = R^{(k)} Q^{(k)} \overset{\mu^k \mathbf{I}}{+}$$

multiply in reverse order

end

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

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

so, $A^{(k)}$ and $A^{(k+1)}$ have same eigenvalues since $Q^{(k)}$ orthogonal.

$$= \underbrace{Q^{(k)T} Q^{(k-1)T} \dots Q^{(1)T}}_{\overline{Q^{(k)T}}} A \underbrace{Q^{(1)} Q^{(2)} \dots Q^{(k)}}_{\overline{Q^{(k)}}} \xrightarrow{k \rightarrow \infty} \text{diagonal matrix}$$

→ we find the eigenvalues. How about the eigenvectors?

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

skip 1
Householder

$$P_n^T B P_n = A$$

orthogonal tridiagonal

skip 2
QR-algo

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

diagonal

putting
together

$$\overline{Q^{(k)T}} P_n^T B P_n \overline{Q^{(k)}} = D$$

$$\Rightarrow \mathcal{B}(P_n \bar{Q}^{(k)}) = (P_n \bar{Q}^{(k)}) \mathcal{D}$$

$$\mathcal{B} \cdot \begin{bmatrix} | & \dots & | \end{bmatrix} = \begin{bmatrix} | & \dots & | \end{bmatrix} \begin{bmatrix} \times & \dots & \times \end{bmatrix}$$

↑ eigenvectors are columns of $P_n \bar{Q}^{(k)}$!

Remark: QR algorithm always only works with tridiagonal matrices:

$$A = \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \diagdown \end{bmatrix} \text{ tridiagonal}$$

QR algo:

$$A^{(k)} = \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \diagdown \end{bmatrix}$$

$$= \begin{matrix} Q & R \end{matrix}$$

↑ Gives solutions

$$= \begin{matrix} \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \diagdown \end{bmatrix} \cdot \begin{bmatrix} \times & & \\ & \times & \\ & & \times \end{bmatrix} \end{matrix}$$

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

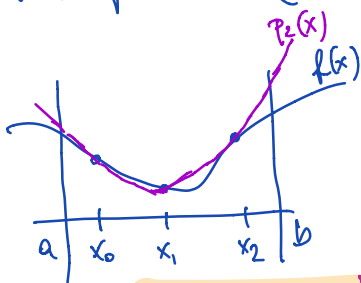
$$\begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \diagdown \end{bmatrix} \begin{bmatrix} \diagdown & & \\ & \diagdown & \\ & & \diagdown \end{bmatrix} =$$

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

Since $A^{(k+1)}$ is symmetric, \times must be zero, and thus $A^{(k+1)}$ is tridiagonal.

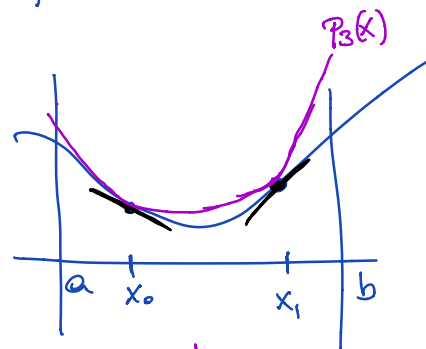
§ 6.2 Polynomial Interpolation

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



$P_2(x)$... quadratic
 $P_2(x_i) = f(x_i) \quad i=0,1,2$

Lagrange interpolation
 (only uses function values)



$P_3(x)$... 3rd order polynomial
 $P_3(x_i) = f(x_i) \quad i=0,1$
 $P_3'(x_i) = f'(x_i) \quad i=0,1$

Hermite interpolation
 (function values + derivatives)

Interpolation problem:

$n \geq 1$, x_0, \dots, x_n distinct (i.e. $x_i \neq x_j$ for $i \neq j$) $y_0, \dots, y_n \in \mathbb{R}$

Find polynomial $p_n \in \mathcal{P}_n$ such that $p_n(x_i) = y_i \quad i=0, \dots, n$

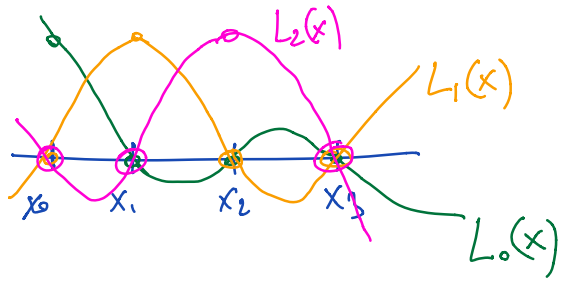
\mathcal{P}_n ... space of polynomials of degree $\leq n$, i.e.

$$\mathcal{P}_n = \{ a_n x^n + a_{n-1} x^{n-1} + \dots + a_1 x + a_0 \mid a_n, \dots, a_0 \in \mathbb{R} \}$$

Lemma: $n \geq 1$. There exist polynomials $L_k \in \mathcal{P}_n \quad k=0,1,\dots,n$ such that

$$L_k(x_i) = \begin{cases} 1 & i=k \\ 0 & i \neq k \end{cases} \quad \text{for all } i,k$$

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



Proof:

$$L_k(x) = C_k \prod_{\substack{i=0 \\ i \neq k}}^n (x - x_i)$$

$$C_k \in \mathbb{R}$$

$$L_k(x_k) = C_k \prod_{\substack{i=0 \\ i \neq k}}^n (x_k - x_i) \stackrel{!}{=} 1$$

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

satisfies the condition.

$$P_n(x_i) = \sum_{k=0}^n L_k(x_i) y_k = y_i \quad i=0, 1, \dots, n.$$

interpolating polynomial \square