

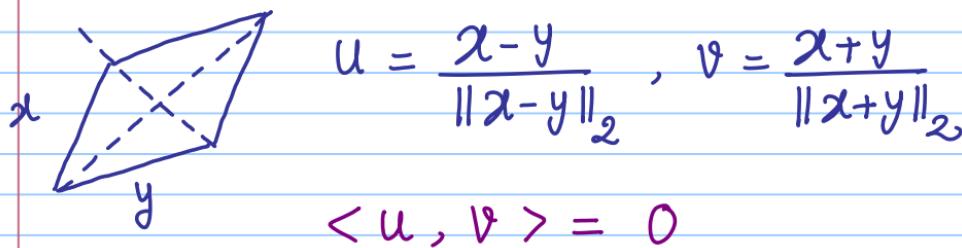
A :  $n \times n$  invertible matrix

Aim : To find an orthogonal matrix  $Q$  ( $Q^T Q = I$ ) and an upper triangular matrix  $R$  such that

$$A = QR$$

Let  $x, y \in \mathbb{R}^n$  be such that

$$x \neq y \text{ and } \|x\|_2 = \|y\|_2$$



$$x \neq y, \|x\|_2 = \|y\|_2$$

$$u = \frac{x-y}{\|x-y\|_2}, v = \frac{x+y}{\|x+y\|_2}$$

$$Q = I - 2uu^t$$

$$Qu = u - 2u\underbrace{u^tu}_1 = -u$$

$$Qv = v - 2u\underbrace{u^tv}_0 = v$$

$$x \neq y, \|x\|_2 = \|y\|_2$$

$$u = \frac{x-y}{\|x-y\|_2}, v = \frac{x+y}{\|x+y\|_2}$$

$$Q = I - 2uu^t$$

$$Qu = -u, Qv = v$$

$$\begin{aligned} Qx &= Q\left(\frac{x+y}{2} + \frac{x-y}{2}\right) = \frac{x+y}{2} - \frac{x-y}{2} \\ &= y \end{aligned}$$

$$x \neq y, \|x\|_2 = \|y\|_2$$

$$u = \frac{x-y}{\|x-y\|_2}$$

$$Q = I - 2uu^t$$

$$\boxed{Qx = y} \quad Q^t = Q$$

$$Q^2 = (I - 2uu^t)(I - 2uu^t)$$

$$= I - 2uu^t - 2uu^t + 4\underbrace{uu^tuu^t}_{=I}$$

$$= I$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & & & \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}$$

Let

$$x = \begin{bmatrix} a_{11} \\ a_{21} \\ \vdots \\ a_{n1} \end{bmatrix}, \quad \|x\|_2 = \sqrt{a_{11}^2 + \cdots + a_{n1}^2}$$

$$y = \begin{bmatrix} \sigma_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \Rightarrow \|y\|_2 = \|x\|_2$$

$$\begin{matrix} \alpha \\ \parallel \\ \left[ \begin{matrix} a_{11} \\ a_{21} \\ , \\ \vdots \\ a_{n1} \end{matrix} \right] \end{matrix} \rightarrow \begin{matrix} y \\ \parallel \\ \left[ \begin{matrix} \sigma_1 \\ 0 \\ \vdots \\ 0 \end{matrix} \right] \end{matrix}$$

$$\sigma_1 = \left( \sum_{i=1}^n a_{i1}^2 \right)^{1/2}$$

$$u = \frac{\alpha - y}{\|\alpha - y\|_2}$$

$$Q_1 = I - 2uu^t$$

$$\boxed{Q_1 \alpha = y}$$

$$x - y = \begin{bmatrix} a_{11} - g_1 \\ a_{21} \\ \vdots \\ a_{n1} \end{bmatrix}, \quad g_1^2 = \sum_{i=1}^n a_{i1}^2$$

$$\begin{aligned}\|x - y\|_2^2 &= \sum_{i=1}^n a_{i1}^2 - 2g_1 a_{11} + g_1^2 \\ &= 2g_1(g_1 - a_{11})\end{aligned}$$

$$\begin{aligned}Q_1 &= I - 2uu^t \\&= I - \frac{2(x-y)(x-y)^t}{\|x-y\|_2^2}\end{aligned}$$

$$G_1 = (\alpha_{11}^2 + \dots + \alpha_{n1}^2)^{1/2}$$

$$\|x-y\|_2^2 = 2G_1(G_1 - \alpha_{11})$$

$$Q_1 A = Q_1 [C_1 \ C_2 \ \dots \ C_n]$$

$$= [Q_1 C_1, \ Q_1 C_2, \ \dots, \ Q_1 C_n]$$

$$Q_1 = I - 2uu^t$$

$$\begin{aligned} Q_1 C_2 &= C_2 - 2uu^t C_2 \\ &= C_2 - 2 \langle C_2, u \rangle u \end{aligned}$$

$$Q_1 A = Q_1 [C_1 \ C_2 \ \cdots \ C_n]$$

$$= [Q_1 C_1, \ Q_1 C_2, \ \cdots, \ Q_1 C_n]$$

$$= \begin{bmatrix} G_1 & a_{12}^{(1)} & \cdots & a_{1n}^{(1)} \\ 0 & a_{22}^{(1)} & \ddots & a_{2n}^{(1)} \\ \vdots & \vdots & & \\ 0 & a_{n2}^{(1)} & \cdots & a_{nn}^{(1)} \end{bmatrix}$$

Find a  $(n-1) \times (n-1)$  matrix  $\tilde{Q}_2$

such that

$$\tilde{Q}_2 \begin{bmatrix} a_{22}^{(1)} \\ \vdots \\ a_{n2}^{(1)} \end{bmatrix} = \begin{bmatrix} \sigma_2 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

$$\sigma_2 = \left\{ \sum_{i=2}^n (a_{i2}^{(1)})^2 \right\}^{1/2}$$

Define  $Q_2 = \begin{bmatrix} 1 & \bar{0} \\ \bar{0} & \tilde{Q}_2 \end{bmatrix}_{n \times n}$

$$Q_2 Q_1 A = \begin{bmatrix} G_1 & a_{12}^{(1)} & a_{13}^{(2)} & \dots & a_{1n}^{(2)} \\ 0 & G_2 & a_{23}^{(2)} & \dots & a_{2n}^{(2)} \\ \vdots & 0 & \vdots & \ddots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & a_{n3}^{(2)} & \dots & a_{nn}^{(2)} \end{bmatrix}$$

$$Q_{n-1} Q_{n-2} \cdots Q_1 A = R$$

$$Q_i^t = Q_i, \quad Q_i^2 = I.$$

$$\begin{aligned} A &= Q_1 Q_2 \cdots Q_{n-1} R \\ &= QR. \end{aligned}$$

$$\begin{aligned} Q^t Q &= (Q_{n-1} \cdots Q_1) (Q_1 Q_2 \cdots Q_{n-1}) \\ &= I, \quad Q^t \neq Q. \end{aligned}$$

### Example

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 3 \end{bmatrix}$$

$$\alpha = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad \|\alpha\|_2 = \sqrt{2}, \quad y = \begin{bmatrix} \sqrt{2} \\ 0 \end{bmatrix}.$$

$$u = \frac{\alpha - y}{\|\alpha - y\|_2}, \quad Q = I - 2uu^t$$

$$x = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad y = \begin{bmatrix} \sqrt{2} \\ 0 \end{bmatrix}$$

$$\begin{aligned}(x-y)(x-y)^t &= \begin{bmatrix} 1-\sqrt{2} \\ 1 \end{bmatrix} \begin{bmatrix} 1-\sqrt{2} & 1 \end{bmatrix} \\ &= \begin{bmatrix} (1-\sqrt{2})^2 & 1-\sqrt{2} \\ 1-\sqrt{2} & 1 \end{bmatrix} \\ \|x-y\|_2^2 &= 4-2\sqrt{2}\end{aligned}$$

$$Q = I - \frac{2(x-y)(x-y)^t}{\|x-y\|_2^2}$$

$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \frac{2}{4-2\sqrt{2}} \begin{bmatrix} (1-\sqrt{2})^2 & 1-\sqrt{2} \\ 1-\sqrt{2} & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \frac{1}{\sqrt{2}} \begin{bmatrix} 1-\sqrt{2} & 1 \\ 1 & \frac{1}{1-\sqrt{2}} \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 3 \end{bmatrix}, Q = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

$$QA = \begin{bmatrix} \sqrt{2} & \frac{5}{\sqrt{2}} \\ 0 & -\frac{1}{\sqrt{2}} \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} 2 & 5 \\ 0 & -1 \end{bmatrix}$$

$$Q^t = Q^{-1}$$

$$A = QR$$

$$A = \begin{bmatrix} 1 & 2 \\ 1 & 3 \end{bmatrix}$$

$$= QR = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \quad \frac{1}{\sqrt{2}} \begin{bmatrix} 2 & 5 \\ 0 & -1 \end{bmatrix}$$

$$A = \hat{Q} \hat{R} = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \frac{1}{\sqrt{2}} \begin{bmatrix} 2 & 5 \\ 0 & 1 \end{bmatrix}$$

## Q R method

Write  $A = Q_0 R_0$

Define  $A_1 = R_0 Q_0$

Write  $A_1 = Q_1 R_1$ ,

Define  $A_2 = R_1 Q_1, \dots$

$A_m = Q_m R_m$ , Define

$A_{m+1} = R_m Q_m$

Theorem: Let  $A$  be a real  $n \times n$  matrix with eigenvalues  $\lambda_1, \dots, \lambda_n$  such that  $|\lambda_1| > |\lambda_2| > \dots > |\lambda_n| > 0$ .

Then  $A_m$  converge to an upper triangular matrix that contains  $\lambda_i$  in the diagonal position.

If  $A$  is symmetric, then  $A_m$  converge to a diagonal matrix.

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad \det(A - zI) = z^2 - 1 = 0$$

$\Rightarrow$  evs of  $A$ :  $\lambda_1 = -1, \lambda_2 = 1$

$$|\lambda_1| = |\lambda_2|$$

$$A^T = A, \quad A^2 = I : A \text{ orthogonal}$$

$$A = Q_0 R_0 \quad \text{with} \quad Q_0 = A, \quad R_0 = I$$

$$A_1 = R_0 Q = A \Rightarrow A_m = A \quad \text{for all } m$$

$A_m$  does not converge to a diagonal matrix

## Solution of a system of linear equations

$Ax = b$ ,  $A$  invertible

$A = QR$  :  $Q^T Q = I$ ,  $R$ : upper triangular

$QRx = b \Leftrightarrow Qy = b$  and  $Rx = y$ .

$$y = Q^T b$$

$Rx = y$  : back substitution

## Number of Computations

$$A = QR$$

$\frac{2n^3}{3}$  multiplications and

$\frac{2n^3}{3}$  additions

Twice expensive as compared  
to LU decomposition

## Polynomial Approximation

Bernstein Polynomials :

$$f \in C[0, 1]$$

$$(B_n f)(x) = \sum_{k=0}^n \frac{n!}{k!(n-k)!} x^k (1-x)^{n-k}$$

Slow Convergence, does not reproduce polynomials

## Best Approximation

$P_n$ : polynomials of degree  $\leq n$

Aim: To find  $p_n^* \in P_n$  such that

$$\| f - p_n^* \|_{\infty} = \min_{p \in P_n} \| f - p \|_{\infty}.$$

$\text{dist}_{\infty}(f, P_n)$

Second Algorithm of Remes

$f, g \in C[a, b]$

Inner Product

$$\langle f, g \rangle = \int_a^b f(x) g(x) dx$$

Induced norm

$$\|f\|_2 = \left( \int_a^b |f(x)|^2 dx \right)^{1/2}$$

## Least-Squares Approximation

$P_n$  : space of polynomials of degree  $\leq n$ .

Let  $f \in C[a, b]$

Aim: To find  $p_n^* \in P_n$  such that

$$\|f - p_n^*\|_2 = \min_{p_n \in P_n} \|f - p_n\|_2$$

$\{1, x, x^2, \dots\}$  linearly  
independent

Use Gram-Schmidt orthonormalization  
to obtain Legendre polynomials

$q_0, q_1, q_2, \dots$

$q_i$  : polynomial of degree  $i$

$$\langle q_i, q_j \rangle = \begin{cases} 1, & i=j \\ 0, & i \neq j \end{cases}$$

## Legendre Polynomials

$q_i$  : polynomial of degree  $i$

$$i = 0, 1, 2, \dots$$

$$\text{Span } \{q_0, q_1, \dots, q_n\} = P_n$$

$$\langle q_i, q_j \rangle = 0, i \neq j, \quad \langle q_i, q_i \rangle = 1$$

$$P_n \in P_n : P_n = \alpha_0 q_0 + \dots + \alpha_n q_n$$

To find  $p_n^* \in P_n$  such that

$$\|f - p_n^*\|_2 \leq \|f - p_n\|_2, \quad p_n \in P_n.$$

Claim:  $p_n^* = \sum_{j=0}^n \langle f, q_j \rangle q_j$

Note that  $\langle p_n^*, q_i \rangle = \sum_{j=0}^n \langle f, q_j \rangle \langle q_j, q_i \rangle$

$$\begin{aligned} \langle f - p_n^*, q_i \rangle &= 0, \\ i &= 0, 1, \dots, n \end{aligned}$$
$$= \langle f, q_i \rangle,$$
$$i = 0, 1, \dots, n$$

Let  $p_n = \alpha_0 q_0 + \cdots + \alpha_n q_n \in P_n$

and  $p_n^* = \sum_{j=0}^n \langle f, q_j \rangle q_j$

Since  $\langle f - p_n^*, q_i \rangle = 0$ ,  $i = 0, 1, \dots, n$ ,

it follows that

$$\langle f - p_n^*, p_n \rangle = 0 \quad \forall p_n \in P_n$$

$f \in C[a, b]$ ,  $p_n^* = \sum_{j=0}^n \langle f, q_j \rangle q_j$ ,  
 $\langle f - p_n^*, p_n \rangle = 0$  for  $p_n \in P_n$ .

Consider

$$\begin{aligned}\|f - p_n\|_2^2 &= \|\underbrace{f - p_n^*}_{\text{ }} + \underbrace{p_n^* - p_n}_{\text{ }}\|_2^2 \\ &= \|f - p_n^*\|_2^2 + \|p_n^* - p_n\|_2^2\end{aligned}$$

$$\Rightarrow \|f - p_n^*\|_2 \leq \|f - p_n\|_2, \quad p_n \in P_n$$

## Interpolating Polynomial

$$f \in C[a, b]$$

$x_0, x_1, \dots, x_n$  : distinct points  
in  $[a, b]$

$$p_n(x) = f(x_0) + f[x_0, x_1](x - x_0) + \dots + f[x_0, x_1, \dots, x_n](x - x_0) \dots (x - x_{n-1})$$

$$f(x) = p_n(x) + f[x_0, x_1, \dots, x_n, x] \\ (x - x_0) \dots (x - x_n)$$

## Numerical Integration

$$\int_a^b f(x) dx \simeq \int_a^b p_n(x) dx$$

$$p_n(x) = \sum_{i=0}^n f(x_i) l_i(x)$$

$$l_i(x) = \frac{1}{n} \frac{(x-x_j)}{(x_i-x_j)}$$

$$\int_a^b p_n(x) dx = \sum_{i=0}^n w_i f(x_i)$$

## Basic Rules

Midpoint Rule, Trapezoidal Rule,  
Simpson Rule, Newton-Cotes Rules

## Composite Rules

Gaussian Integration

## Numerical Differentiation

$$f : [a, b] \rightarrow \mathbb{R}$$

$p_n(x)$  : interpolating polynomial

$$f'(c) \simeq p_n'(c)$$

## Finite Difference Method

## System of linear equations

$Ax = b$  :  $A$  :  $n \times n$  invertible

Gauss elimination :  $A = LU$ ,

$L$  : unit lower triangular

$U$  : upper triangular

Gauss elimination with partial pivoting

$PA = LU$  :  $P$  : Permutation matrix

## Cholesky Decomposition

$A$  : positive-definite

$$A^t = A, \quad x \neq \vec{0} \Rightarrow \langle Ax, x \rangle > 0$$

$$A = G G^t : G : \text{lower triangular}$$

## Vector and Matrix Norms

$$x \in \mathbb{R}^n, \|x\|_1 = \sum_{j=1}^n |x(j)|,$$

$$\|x\|_2 = \left( \sum_{j=1}^n |x(j)|^2 \right)^{1/2}, \|x\|_\infty = \max_{1 \leq j \leq n} |x(j)|$$

$$\|A\| = \max_{x \neq 0} \frac{\|Ax\|}{\|x\|} : \text{Induced Matrix Norm}$$

## Perturbed Systems

$$A\alpha = b, \quad (A + \delta A)(\alpha + \delta \alpha) = b + \delta b$$

$\alpha$ : exact solution,  $\hat{\alpha} = \alpha + \delta \alpha$ :

Computed Solution

$$\text{Relative error: } \frac{\|\alpha - \hat{\alpha}\|}{\|\alpha\|}$$

$$\text{Condition Number: } \|A\| \|A^{-1}\|$$

## Iterative Methods

$$A\alpha = b$$

Jacobi and Gauss-Seidel  
Methods

## Solution of a non-linear equation

$$f(x) = 0$$

Fixed Point:  $g(c) = c$

Picard's fixed point iteration

Newton's and Secant Methods

## Initial Value Problem

$$y' = f(x, y), \quad y(a) = y_0$$

## Single Step Methods:

Euler and Runge-Kutta Methods

## Multi-Step Methods

Adams - Bashforth, Adams - Moulton

Methods

## Stability

## Boundary Value Problem

$$y''(x) + f(x)y'(x) + g(x)y(x) = r(x), \quad x \in [a, b]$$

$$y(a) = \alpha, \quad y(b) = \beta$$

$$y' = \frac{dy}{dx}, \quad y'' = \frac{d^2y}{dx^2}$$

$f, g, r$  : continuous.

## Finite Difference Method

## Eigenvalue Problem

localization results ,

Power Method and its extensions

Q.R method