

Least-Square Approximation

Orthonormality

m equations $>$ n no. of variables \Rightarrow over-determined system

\bullet $x = A^{-1}b$ can't give any solution, A^{-1} is not invertible as its not a square matrix

- $A = m \times n$ matrix

- solution (approx.) of over-determined system is L.S.A.

$$\begin{matrix} (m \times n) & (n \times 1) & = & (m \times 1) \\ A & x & = & b \end{matrix}$$

- $A = (q_1 \quad q_2 \quad \dots \quad q_n)$ each $m \times 1$ matrix

Theorem :

Let A be $m \times n$ matrix. The columns of A form an orthonormal set iff $A^T A = I_n$

* Orthogonality :

Let \bar{x} & \bar{y} are 2 vectors in n -dimensional Euclidean vector space \mathbb{R}^n . $\bar{x}, \bar{y} \in \mathbb{R}^n$ ($n \times 1$ column matrix)

$$\bar{x} \cdot \bar{y} = x^T y = \sum_{i=1}^n x_i y_i \quad (\text{scalar / dot product in 3D})$$

(number)

- inner product with itself $= \|\cdot\|_2$ norm = norm of vector

$$|\bar{x}| = \sqrt{x^T x} = \text{absolute value} = \text{magnitude in 3D}$$

- for angle θ between any 2 vectors,

$$x^T y = |\bar{x}| |\bar{y}| \cos \theta$$

$$= xy \cos \theta$$

- \bar{x} & \bar{y} are orthogonal iff $\boxed{x^T y = 0} \Rightarrow \theta = 90^\circ$

(perpendicular to each other)

- a set of n vectors in \mathbb{R}^n , $S = \{x_1, x_2, \dots, x_n\}$. S is called orthogonal set if $x_i^T x_j = 0 \quad \forall \quad i, j = 1, 2, \dots, n$ with $i \neq j$ (any pair)

- $\boxed{x_i^T x_i = 1}$ for each $i = 1, 2, \dots, n \Rightarrow$ vectors x_i has norm unity
(all unit vectors)

* Orthonormal set :

The set of vectors in which every pair of vectors are orthogonal & each vector has norm one.

$$S = \{x_i \mid x_i \in \mathbb{R}^n, x_i^T x_j = \delta_{ij}, i, j = 1, 2, \dots, n\}$$



Kronecker delta

$$\delta_{ij} = \begin{cases} 1 & i=j \text{ (norm-1)} \\ 0 & i \neq j \text{ (orthogonal)} \end{cases}$$

(2) orthonormal $S = \left\{ \frac{1}{\sqrt{5}} (2, 1)^T, \frac{1}{\sqrt{5}} (1, -2)^T \right\}$. prove it.

⇒ Let $u = \frac{1}{\sqrt{5}} (2, 1)^T$, $v = \frac{1}{\sqrt{5}} (1, -2)^T$

$$\bar{u} \cdot \bar{u} = u^T u = \frac{1}{5} (2 \ 1) \begin{pmatrix} 2 \\ 1 \end{pmatrix} = \frac{1}{5} (2^2 + 1^2) = 1$$

$$\bar{v} \cdot \bar{v} = v^T v = \frac{1}{5} (1 \ -2) \begin{pmatrix} 1 \\ -2 \end{pmatrix} = 1$$

$$\bar{u} \cdot \bar{v} = u^T v = \frac{1}{5} (2 \ 1) \begin{pmatrix} 1 \\ -2 \end{pmatrix} = \frac{1}{5} (2 \times 1 + 1 \times (-2)) = 0$$

∴ S is orthonormal set in \mathbb{R}^2 and hence form a basis in 2D vector space.

Polynomial data fitting

- Normal equation:

$$\underbrace{(A^T A)}_{\substack{n \times n \text{ matrix} \\ \text{(square)}}} \underbrace{x}_{n \times 1 \text{ matrix}} = \underbrace{A^T b}_{n \times 1 \text{ matrix}} \quad \left([n \times m] [m \times 1] = [n \times 1] \right)$$

• If $\det(A^T A) \neq 0$, $A^T A$ is invertible

□ Theorem:

The matrix $A^T A$ is invertible iff the columns of A are linearly independent, in which case $\Downarrow Ax = b$ has a unique least-squares solution $x = (A^T A)^{-1} A^T b$

(*)

$$p_n(x_0) = a_0 + a_1 x_0 + \dots + a_n x_0^n = f(x_0)$$

$$p_n(x_1) = a_0 + a_1 x_1 + \dots + a_n x_1^n = f(x_1)$$

$(m > n)$

$$p_n(x_m) = a_0 + a_1 x_m + \dots + a_n x_m^n = f(x_m)$$

\Downarrow

$$\begin{bmatrix} 1 & x_0 & \dots & x_0^n \\ 1 & x_1 & \dots & x_1^n \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_m & \dots & x_m^n \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix} = \begin{bmatrix} f(x_0) \\ f(x_1) \\ \vdots \\ f(x_m) \end{bmatrix}$$

$(m \times n)$ $(n \times 1)$ $(m \times 1)$

(?) Fit a L.S. straight line to the data : $f(-3) = f(0) = 0$ and $f(6) = 2$

⇒ straight line, so $n=1$

$$\therefore p_1(x) = a_0 + a_1 x$$

3 nodes, $x_0 = -3$, $x_1 = 0$, $x_2 = 6$

$$\therefore m=2$$

$$\therefore p_1(x_0) = a_0 + a_1 x_0 = f(x_0)$$

$$p_1(x_1) = a_0 + a_1 x_1 = f(x_1)$$

$$p_1(x_2) = a_0 + a_1 x_2 = f(x_2)$$

↓

$$\begin{bmatrix} 1 & x_0 \\ 1 & x_1 \\ 1 & x_2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} f(x_0) \\ f(x_1) \\ f(x_2) \end{bmatrix}$$

A x b

$$\Rightarrow \begin{bmatrix} 1 & -3 \\ 1 & 0 \\ 1 & 6 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 1 & 1 & 1 \\ -3 & 0 & 6 \end{bmatrix} \begin{bmatrix} 1 & -3 \\ 1 & 0 \\ 1 & 6 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ -3 & 0 & 6 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} 3 & 3 \\ 3 & 45 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 2 \\ 12 \end{bmatrix}$$

 $A^T A$ $A^T b$

$$\det(A^T A) = 135 - 9 = 126 \neq 0$$

$$\therefore x = (A^T A)^{-1} A^T b$$

$$= \frac{1}{126} \begin{bmatrix} 45 & -3 \\ -3 & 3 \end{bmatrix} \begin{bmatrix} 2 \\ 12 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 3/7 \\ 5/21 \end{bmatrix}$$

$$\therefore p_1(x) = 3/7 + 5/21 x$$

\downarrow \downarrow
 intercept slope

QR Decomposition

□ Theorem :

Any real $m \times n$ matrix A , with $m \geq n$, can be written in the form $A = QR$, where Q is an $m \times n$ matrix with orthonormal columns & R is an upper triangular $n \times n$ matrix.

$$\therefore A_{m \times n} = Q_{m \times n} R_{n \times n} \quad \text{where } Q = \{q_1, q_2, \dots, q_n\}$$

* Gram-Schmidt orthogonalization process :

Mathematical process to obtain an orthonormal basis or set from a set of linearly independent vectors.
($m \times 1$ column matrix)

$$A = \begin{bmatrix} v_1 & v_2 & \dots & v_n \\ u_{11} & u_{12} & \dots & u_{1n} \\ u_{21} & u_{22} & \dots & u_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ u_{m1} & u_{m2} & \dots & u_{mn} \end{bmatrix}$$

; u_i for $i = 1, 2, \dots, n$

- linearly independent

$$u_i = (u_{1i} \quad u_{2i} \quad \dots \quad u_{mi})^T$$

= $n \times 1$ column matrix

- Let $\{q_1, q_2, \dots, q_n\}$ be the set of orthonormal vectors constructed from set $A = \{u_1, u_2, \dots, u_n\}$ which is a set of n vectors in \mathbb{R}^m .

Gram-Schmidt process yields that,

$$p_k = u_k - \sum_{i=1}^{k-1} (u_k^T q_i) q_i \quad \&$$

$$q_k = \frac{p_k}{|p_k|}$$

where $k=1, 2, \dots, n$ & norm $|p_k| = \sqrt{(p_k^T, p_k)}$

• each p_k is constructed from u_k by subtracting projections of u_k on each of previous q_i for $i < k$

(?) $u_1 = (3, 6, 0)^T$, $u_2 = (1, 2, 2)^T$. Find orthonormal vectors.

\Rightarrow

$$p_1 = u_1 = \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}, \quad |p_1| = \sqrt{p_1^T p_1} = \sqrt{3^2 + 6^2 + 0} = \sqrt{45}$$

$$\therefore q_1 = \frac{1}{\sqrt{45}} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$k=1$

$i=0$

$$k=2$$

$$i=1$$

$$p_2 = u_2 - (u_2^T q_1) q_1$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \left(\begin{bmatrix} 1 & 2 & 2 \end{bmatrix} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix} \frac{1}{\sqrt{45}} \right) \frac{1}{\sqrt{45}} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \frac{15}{\sqrt{45}} \cdot \frac{1}{\sqrt{45}} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \frac{1}{3} \begin{bmatrix} 3 \\ 6 \\ 0 \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 1 \\ 2 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$$\therefore |p_2| = \sqrt{2^2} = 2$$

$$\therefore q_2 = \frac{1}{2} \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

$$u_k = |p_k| q_k + \sum_{i=1}^{k-1} (u_k^T q_i) q_i$$

$$\Rightarrow u_k \cdot q_k = |p_k| \underbrace{q_k \cdot q_k}_1 + \sum_{i=1}^{k-1} (u_k^T q_i) \underbrace{q_i \cdot q_k}_0$$

$$= |p_k|$$

$$\therefore u_k = (u_k \cdot q_k) q_k + \sum_{i=1}^{k-1} (u_k^T q_i) q_i$$

$$= \sum_{i=1}^k (u_k^T q_i) q_i \quad ; k=1, 2, \dots, m$$

$$u_1 = (q_1) (u_1^T q_1)$$

$$u_2 = (q_1 \quad q_2) \begin{pmatrix} u_2^T q_1 \\ u_2^T q_2 \end{pmatrix}$$

$$u_3 = (q_1 \quad q_2 \quad q_3) \begin{pmatrix} u_3^T q_1 \\ u_3^T q_2 \\ u_3^T q_3 \end{pmatrix}$$

u_p to 3rd term,

$$(u_1 \quad u_2 \quad u_3) = (q_1 \quad q_2 \quad q_3) \begin{pmatrix} u_1^T q_1 & u_2^T q_1 & u_3^T q_1 \\ 0 & u_2^T q_2 & u_3^T q_2 \\ 0 & 0 & u_3^T q_3 \end{pmatrix}$$

Up to n^{th} term,

$$\underbrace{(u_1 | u_2 | \dots | u_n)}_{A_{m \times n}} = \underbrace{(q_1 | q_2 | \dots | q_n)}_{Q_{m \times n}}$$

$$\begin{pmatrix} u_1^T q_1 & u_2^T q_1 & \dots & u_n^T q_1 \\ 0 & u_2^T q_2 & \dots & u_n^T q_2 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & u_n^T q_n \end{pmatrix}$$

 $R_{n \times n}$

$$A^T A x = A^T b$$

$$\Rightarrow (QR)^T (QR) x = (QR)^T b$$

$$\Rightarrow R^T (Q^T Q) R x = R^T Q^T b$$

$$\Rightarrow R x = Q^T b$$

$$\Rightarrow x = R^{-1} Q^T b$$

$$[Q^T Q = I]$$

(?) Least-square, ^{straight} line fitting to the data : $f(-3) = f(0) = 0$, $f(6) = 2$

\Rightarrow $n=1$ (straight line)

$m=3$ (3 data point)

$$P_1 = a_0 + a_1 x$$

$$\begin{bmatrix} 1 & x_0 \\ 1 & x_1 \\ 1 & x_2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} f(x_0) \\ f(x_1) \\ f(x_2) \end{bmatrix}$$

$$= \begin{bmatrix} 1 & -3 \\ 1 & 0 \\ 1 & 6 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$A \quad x \quad b$

linearly independent columns of A ,

$$u_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \quad u_2 = \begin{bmatrix} -3 \\ 0 \\ 6 \end{bmatrix}$$

Using Gram-Schmidt,

$$p_1 = u_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$\therefore |p_1| = \sqrt{p_1^T p_1}$$

$$= \sqrt{1^2 + 1^2 + 1^2} = \sqrt{3}$$

$$\therefore q_1 = \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$p_2 = u_2 - (u_2^T q_1) q_1$$

$$= \begin{bmatrix} -3 \\ 0 \\ 6 \end{bmatrix} - \left(\begin{bmatrix} -3 & 0 & 6 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \frac{1}{\sqrt{3}} \right) \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} -3 \\ 0 \\ 6 \end{bmatrix} - \frac{3}{\sqrt{3}} \cdot \frac{1}{\sqrt{3}} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} -4 \\ -1 \\ 5 \end{bmatrix}$$

$$\therefore |p_2| = \sqrt{p_2^T p_2} = \sqrt{4^2 + 1^2 + 5^2} = \sqrt{42}$$

$$\therefore q_2 = \frac{1}{\sqrt{42}} \begin{bmatrix} -4 \\ -1 \\ 5 \end{bmatrix}$$

$$\therefore Q = \begin{bmatrix} \frac{1}{\sqrt{3}} & -\frac{4}{\sqrt{42}} \\ \frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{42}} \\ \frac{1}{\sqrt{3}} & \frac{5}{\sqrt{42}} \end{bmatrix}$$

$$R = \begin{bmatrix} u_1^T q_1 & u_2^T q_1 \\ 0 & u_2^T q_2 \end{bmatrix} = \begin{bmatrix} \sqrt{3} & \sqrt{3} \\ 0 & \sqrt{42} \end{bmatrix}$$

$$\therefore R_2 \quad Rx = A^T b$$

$$\Rightarrow \begin{bmatrix} \sqrt{3} & \sqrt{3} \\ 0 & \sqrt{42} \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 1/\sqrt{3} & 1/\sqrt{3} & 1/\sqrt{3} \\ -4/\sqrt{42} & -1/\sqrt{42} & 5/\sqrt{42} \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 2 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} \sqrt{3} a_0 + \sqrt{3} a_1 \\ \sqrt{42} a_1 \end{bmatrix} = \begin{bmatrix} 2/\sqrt{3} \\ 10/\sqrt{42} \end{bmatrix}$$

$$\therefore a_1 = \frac{10/\sqrt{42}}{\sqrt{42}} \times \frac{1}{\sqrt{42}} = \frac{10}{42} = \frac{5}{21}$$

$$\therefore \sqrt{3} a_0 = -\sqrt{3} \cdot \frac{5}{21} + \frac{2}{\sqrt{3}}$$

$$\Rightarrow a_0 = \cancel{\frac{5\sqrt{3}}{21}} \times \cancel{\frac{1}{\sqrt{3}}} - \frac{3\sqrt{3}}{7} \times \frac{1}{\sqrt{3}} = \frac{3}{7}$$

$$\therefore \begin{bmatrix} a_0 \\ a_1 \end{bmatrix} = \begin{bmatrix} 3/7 \\ 5/21 \end{bmatrix}$$