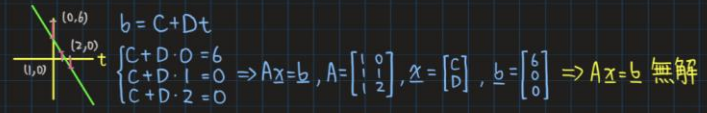


Least square solution

◦ $Ax \neq b$ $b - Ax = e$ The length of e or $\|e\|^2$ 越小越好

ex: Find the closest line to the points



The best fit is \hat{x} such that $p = A\hat{x}$ is the projection of b onto $C(A)$.

$$A^T(b - A\hat{x}) = 0 \Rightarrow A^T A \hat{x} = A^T b \Rightarrow \begin{bmatrix} 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} 1 & 1 & 2 \end{bmatrix} \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \begin{bmatrix} 3 & 3 \\ 3 & 3 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} 6 \\ 0 \end{bmatrix} \Rightarrow \hat{x} = \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} 5 \\ -3 \end{bmatrix}$$

Best line: $b = 5 - 3t$

◦ By linear algebra, $b = \underset{C(A)}{p} + \underset{N(A)}{e}$ We know that $Ax = b = p + e$ 無解 and $A\hat{x} = p$ 有解

$$\|Ax - b\|^2 = \|Ax - p - e\|^2 = (Ax - p - e)^T (Ax - p - e) = \|Ax - p\|^2 + \|e\|^2$$

$\langle (Ax - p)^T e = 0 \text{ since } Ax - p \in C(A) \text{ and } e \in N(A) \rangle \Rightarrow \|Ax - b\|^2$ is minimized when $x = \hat{x} (A\hat{x} = p)$

i.e. $\min_x \|Ax - b\|^2 = \|A\hat{x} - b\|^2 = \|A\hat{x} - p\|^2 + \|e\|^2 = \|e\|^2$ where $A^T A \hat{x} = A^T b$ and $p = A\hat{x}$

◦ By calculus, $E = \|Ax - b\|^2 = (C + D \cdot 0 - 6)^2 + (C + D \cdot 1)^2 + (C + D \cdot 2)^2$

$$\frac{\partial E}{\partial C} = 2(C + D \cdot 0 - 6) + 2(C + D \cdot 1) + 2(C + D \cdot 2) = 0$$

$$\frac{\partial E}{\partial D} = 2(C + D \cdot 1) + 4(C + D \cdot 2) = 0$$

$$\begin{cases} 6C + 6D = 12 \\ 6C + 10D = 0 \end{cases} \Rightarrow D = -3, C = 5 \Rightarrow b = 5 - 3t$$

The partial derivatives of $\|Ax - b\|^2$ are 0 when $A^T A \hat{x} = A^T b$, $\min_x \|Ax - b\|^2 = \|e\|^2$

◦ When $Ax = b$ 無解, the least square solution \hat{x} satisfies $A^T A \hat{x} = A^T b$



Curve Fitting

- Fitting a Straight Line : Fit height b_i at t_i by $C+Dt$

solution:
$$\begin{matrix} C+Dt_1=b_1 \\ \vdots \\ C+Dt_m=b_m \end{matrix} \Rightarrow \begin{bmatrix} 1 & t_1 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \quad (Ax=b \text{ 無解})$$

best fit:
$$A^T A = \begin{bmatrix} 1 & \dots & 1 \\ t_1 & \dots & t_m \end{bmatrix} \begin{bmatrix} 1 & t_1 \\ \vdots & \vdots \\ 1 & t_m \end{bmatrix} = \begin{bmatrix} m & \sum t_i \\ \sum t_i & \sum t_i^2 \end{bmatrix} \quad A^T b = \begin{bmatrix} 1 & \dots & 1 \\ t_1 & \dots & t_m \end{bmatrix} \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} = \begin{bmatrix} \sum b_i \\ \sum t_i b_i \end{bmatrix}$$

Solve
$$\begin{bmatrix} m & \sum t_i \\ \sum t_i & \sum t_i^2 \end{bmatrix} \begin{bmatrix} C \\ D \end{bmatrix} = \begin{bmatrix} \sum b_i \\ \sum t_i b_i \end{bmatrix}$$

The best $\hat{x}=(C,D)$ minimizes $\|Ax-b\|^2 = \|e\|^2 = \sum_{i=1}^m (C+Dt_i-b_i)^2$

- Fitting a Parabola : Fit heights b_i at t_i by $C+Dt+Et^2$

solution:
$$\begin{matrix} C+Dt_1+Et_1^2=b_1 \\ \vdots \\ C+Dt_m+Et_m^2=b_m \end{matrix} \Rightarrow \begin{bmatrix} 1 & t_1 & t_1^2 \\ \vdots & \vdots & \vdots \\ 1 & t_m & t_m^2 \end{bmatrix} \begin{bmatrix} C \\ D \\ E \end{bmatrix} = \begin{bmatrix} b_1 \\ \vdots \\ b_m \end{bmatrix} \quad (Ax=b \text{ 無解}) \Rightarrow \text{Solve } A^T A \hat{x} = A^T b \text{ for } \hat{x}$$

Orthogonal Bases and Gram-Schmidt

Def: The vectors $q_1 \dots q_n$ are orthogonal if $q_i^T q_j = 0$ whenever $i \neq j$

Claim: If nonzero vector $q_1 \dots q_n$ are orthogonal, then they are L.I.

pf: Consider $x_1 q_1 + \dots + x_n q_n = 0$, then $x_1 q_1^T q_1 + \dots + x_n q_1^T q_n = q_1^T 0 = 0 \Rightarrow x_1 \|q_1\|^2 = 0$
 $\Rightarrow x_1 = 0$, similarly, $x_2 = \dots = x_n = 0 \Rightarrow q_1 \dots q_n$ are L.I.

Def: The vectors $q_1 \dots q_n$ are orthonormal if $q_i^T q_j = \delta_{ij}$

- A matrix Q with orthonormal columns satisfies
$$Q^T Q = \begin{bmatrix} q_1^T \\ \vdots \\ q_n^T \end{bmatrix} \begin{bmatrix} q_1 & \dots & q_n \end{bmatrix} = I$$

 $n \times m$ $m \times n$ $n \times n$

When Q is 方阵, $Q^T Q = I \Rightarrow Q^T = Q^{-1}$. In this case, Q is called an orthogonal matrix.

ex: Rotation: $Q = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$ Reflection: $Q = I - 2u u^T$, u : any unit vector