

L21 Least square solutions to $AXB = D$

1. Least square solutions

(1) Least square solutions

For equation $AXB = D$, $\hat{X}$ is a least square solution (LSS) if

$$\|D - A\hat{X}B\|^2 \leq \|D - AXB\|^2 \text{ for all } X \in C^{p \times q}.$$

(2) Relation to ordinary solutions

If $AXB = D$ is consistent, then

$$\hat{X} \text{ is a LSS} \iff \hat{X} \text{ is an ordinary solution.}$$

Proof If $AXB = D$ is consistent, then there exists X_0 such that $\|AX_0B - D\|^2 = 0$.

So $\hat{X}$ is a LSS if and only if $\|A\hat{X}B - D\|^2 \leq 0$, i.e., $\hat{X}$ is an ordinary solution.

(3) Collection of all LSSs

The collection of all LSSs to $AXB = D$ is $A^+DB^+ + \mathcal{N}(A, B)$.

Proof

$\hat{X}$ is a LSS to $AXB = D$

$$\iff \|D - A\hat{X}B\|^2 \leq \|D - AXB\|^2 \text{ for all } X \in C^{p \times q}$$

$$\iff A\hat{X}B = \pi(D|\mathcal{R}(A, B)) = AA^+DB^+B$$

$$\iff A(\hat{X} - A^+DB^+)B = 0 \iff \hat{X} - A^+DB^+ \in \mathcal{N}(A, B)$$

$$\iff \hat{X} \in A^+DB^+ + \mathcal{N}(A, B).$$

Ex1: For vector equation $Ax = b$,

$$\hat{x} \text{ is a LSS to } Ax = b \iff \hat{x} \text{ is a LSS to } Ax1 = b$$

$$\iff \hat{x} \in A^+b1^+ + \mathcal{N}(A, 1) = A^+b + \mathcal{N}(A).$$

Ex2: $A^+XB^+ = D$ is consistent. Find the collection of all its solutions.

The collection of all its solutions is

$$(A^+)^+D(B^+)^+ + \mathcal{N}(A^+, B^+) = ADB + \mathcal{N}(A^*, B^*).$$

2. Minimum norm LSS

(1) A^+DB^+ is minimum norm LSS to $AXB = D$

Proof $A^+DB^+ = A^+DB^+ + 0 \in A^+DB^+ + \mathcal{N}(A, B)$. So A^+DB^+ is a LSS.

But $A^+DB^+ \in \mathcal{R}(A^+, B^+) = \mathcal{R}(A^*, B^*) = \mathcal{N}^\perp(A, B)$.

So for LSS $\hat{X} = A^+DB^+ + Z$ where $Z \in \mathcal{N}(A, B)$, $A^+DB^+ \perp Z$. Hence

$$\|\hat{X}\|^2 = \|A^+DB^+ + Z\|^2 = \|A^+DB^+\|^2 + \|Z\|^2 \geq \|A^+DB^+\|^2.$$

So A^+DB^+ is the minimum norm LSS.

(2) Lemma

If X_0 is a LSS to $AXB = D$, then the collection of all LSSs is $X_0 + \mathcal{N}(A, B)$.

Proof X_0 as a LSS by (3) of 1 satisfies $AX_0B = AA^+DB^+B$. We show

$$X_0 + \mathcal{N}(A, B) = A^+DB^+ + \mathcal{N}(A, B).$$

⊂: If $\hat{X} \in X_0 + \mathcal{N}(A, B)$, then $\hat{X} = X_0 + Z_1$ where $Z_1 \in \mathcal{N}(A, B)$.

So $\hat{X} = A^+DB^+ + (X_0 - A^+DB^+ + Z_1)$.

But $A(X_0 - A^+DB^+ + Z_1)B = 0$.

Hence $\hat{X} \in A^+DB^+ + \mathcal{N}(A, B)$.

⊃: If $\hat{X} \in A^+DB^+ + \mathcal{N}(A, B)$, then $\hat{X} = A^+DB^+ + Z_2$ where $Z_2 \in \mathcal{N}(A, B)$.

So $\hat{X} = X_0 + (A^+DB^+ - X_0 + Z_2)$.

But $A(A^+DB^+ - X_0 + Z_2)B = 0$.

Hence $\hat{X} \in X_0 + \mathcal{N}(A, B)$.

Comment: In terms of expressing the collection of all LSSs, the role of A^+DB^+ can be replaced by any LSS X_0 .

Every matrix X in $\mathcal{N}(A, B)$ is moved along X_0 to form $X_0 + \mathcal{N}(A, B)$. But only when $X_0 = A^+DB^+$ the moving direction is perpendicular to $\mathcal{N}(A, B)$.

Ex3: $\pi(A^+DB^+ | \mathcal{N}(A, B)) = (A^+DB^+) - (A^+A)(A^+DB^+)(BB^+) = 0$.

3. An application in Statistics

(1) A linear model for random matrix

For random $Y \in R^{m \times n}$ the model

$$Y = A\Theta B + \mathcal{E} \text{ with } E(\mathcal{E}) = 0$$

is a linear model since the linear transformation $E(Y) = A\Theta B$ specifies $E(Y)$ in linear space $\mathcal{R}(A, B)$.

(2) Least square estimators

For parameter matrix $\Theta \in R^{p \times q}$, $\hat{\Theta}$ is called a least square estimator (LSE) if

$$\|Y - A\hat{\Theta}B\|^2 \leq \|Y - A\Theta B\|^2 \text{ for all } \Theta \in R^{p \times q}.$$

Clearly by the definition

$$\begin{aligned} \hat{\Theta} \text{ is a LSE for } \Theta &\iff \hat{\Theta} \text{ is LSS to } A\Theta B = Y \\ &\iff A\hat{\Theta}B = \pi(Y | \mathcal{R}(A, B)) \\ &\iff \hat{\Theta} \in A^+YB^+ + \mathcal{N}(A, B). \end{aligned}$$