

# Best Linear Unbiased Estimator

Wednesday, April 5, 2017 9:43 AM

$$y = Ax_0 + e \quad \text{where } e \in \mathbb{R}^M \text{ is random}$$

statistical  $E\{e\} = \underline{0}$ ,  $E\{ee^T\} = R$

What is the best estimate of  $x_0$ ?

1) Linearity  $\rightarrow$  for some matrix  $L$ . ( $L \in \mathbb{R}^{N \times M}$ )

$$\hat{x} = Ly$$

2) Unbiased  $\rightarrow E\{\hat{x}\} = x_0$

$$E\{\hat{x} - x_0\} = \underline{0}$$

3) "best" implies  $E\{\|\hat{x} - x_0\|_2^2\}$  is minimized

$$\hat{x} = Ly = L(Ax_0 + e) = LAx_0 + Le$$

unbiased  $\rightarrow E\{\hat{x} - x_0\} = LAx_0 - E\{Le\} - x_0 = 0$

$$LAx_0 = x_0$$

$L$  is the left inverse of  $A \Rightarrow LA = I$

"best"  $\rightarrow E\{\|x_0 - \hat{x}\|_2^2\} = E\{\|x_0 - LAx_0 - Le\|_2^2\}$

$$= E\{\|Le\|_2^2\} \quad \leftarrow \text{find } L \text{ to minimize this}$$

we want

$$\min_{\substack{L: N \times M \\ LA=I}} E\{\|Le\|_2^2\} = \min_{\substack{L: N \times M \\ LA=I}} \text{trace}(LRL^T)$$

The solution is

$$L_0 = (A^T R^{-1} A)^{-1} A^T R^{-1}$$

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$\leftarrow$  let's check this

The solution is  $L_0 = (A^T R^{-1} A)^{-1} A^T R^{-1}$  ← let's check this

$$L_0 A = (A^T R^{-1} A)^{-1} (A^T R^{-1} A) = I \quad \checkmark$$

we will show that for any other  $L$

$$\text{trace}(L R L^T) \geq \text{trace}(L_0 R L_0^T)$$

$$\text{let } L = L_0 + (L - L_0)$$

$$\begin{aligned} \text{trace}(L R L^T) &= \text{trace}(L_0 R L_0^T) + \text{trace}(L_0 R (L - L_0)^T) \\ &\quad + \text{trace}((L - L_0)^T R L_0^T) + \text{trace}((L - L_0) R (L - L_0)^T) \end{aligned}$$

$$R L_0^T = R R^{-1} A (A^T R^{-1} A)^{-1} = A (A^T R^{-1} A)^{-1}$$

$$\begin{aligned} (L - L_0) R L_0^T &= (L - L_0) A (A^T R^{-1} A)^{-1} \\ &= (I - I) (A^T R^{-1} A)^{-1} = 0 \end{aligned}$$

$$\text{trace}(L R L^T) = \text{trace}(L_0 R L_0^T) + \text{trace}((L - L_0) R (L - L_0)^T)$$

$$\text{trace}(L R L^T) \geq \text{trace}(L_0 R L_0^T)$$

for any  $L$  satisfying

$$L A = I$$

$R$  is positive semi-def.  
so this term  $\geq 0$

Best Linear Unbiased Estimator (BLUE)

$$y = A x_0 + e \quad E\{e e^T\} = R \quad E\{e\} = 0$$

$$\hat{x}_{\text{blue}} = (A^T R^{-1} A)^{-1} A^T R^{-1} y$$

$$L_0 R L_0^T = (A^T R^{-1} A)^{-1}$$

$$E \left\{ \|x_0 - \hat{x}_{\text{blue}}\|_2^2 \right\} = \text{trace} \left( (A^T R^{-1} A)^{-1} \right) \\ = \text{sum of eigenvalues of } (A^T R^{-1} A)^{-1}$$


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example

$$y = Ax_0 + e \quad A = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad y = \begin{bmatrix} 0 \\ 5 \end{bmatrix} \quad R = \begin{bmatrix} 3 & -1 \\ -1 & 2 \end{bmatrix}$$

$$R^{-1} = \frac{1}{5} \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix}$$

$$\hat{x}_{\text{blue}} = \left( (1 \ 1) \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \cdot \frac{1}{5} \right)^{-1} (1 \ 1) \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix} \cdot \frac{1}{5} \cdot \begin{pmatrix} 0 \\ 5 \end{pmatrix}$$

$$= \left( (3 \ 4) \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right)^{-1} (3 \ 4) \begin{pmatrix} 0 \\ 5 \end{pmatrix}$$

$$= \frac{1}{7} \cdot 20 = \frac{20}{7} \quad \text{— our best estimate of } x_0$$

$$E \left\{ \|x_0 - \hat{x}_{\text{blue}}\|_2^2 \right\} = \frac{1}{7}$$

# Weighted Least Squares

Wednesday, April 5, 2017 10:21 AM

what if some measurements that are more reliable than others?

↳ BLUE can deal with this  
but another way of solving is ...

let  $r = y - Ax$   $\rightsquigarrow$  residual

minimize  $\|W_r\|_2^2 = \|W_y - WAx\|_2^2$   
weighting matrix  
(it is usually diagonal)

$$\hat{x}_{wls} = (WA)^+ W_y$$