

## Least square

$$\hat{x} = \arg \min_z E[\|x - z\|_2^2 | y]$$

Given two random vectors  $x$  and  $y$ , what is the best estimation of  $x$  given  $y$ ?

For any distribution:  $\hat{x} = E(x|y)$

For Gaussian distribution:

- Estimation error of  $\hat{x} = E(x|y)$   $\tilde{x} = x - \hat{x}$  is uncorrelated with  $y$ .
- $E(x|y, z) = E(x|y) + E(\tilde{x}|y|z)$  when  $y, z$  uncorrelated
- $E(x|y, z) = E(x|y) + E(\tilde{x}|y|\tilde{z}|y)$  when  $y, z$  are correlated
- $m_{x|y} = m_x + \Sigma_{xy} \Sigma_{yy}^{-1} (y - m_y)$
- $\Sigma_{x|y} = \Sigma_{xx} - \Sigma_{xy} \Sigma_{yy}^{-1} \Sigma_{yx} = \text{Var}(\tilde{x})$ .
- $\text{Var}(\hat{x}) = \Sigma_{xy} \Sigma_{yy}^{-1} \Sigma_{yx}$

Example:  $T_A = T + v_A$   $T \sim \mathcal{N}(T_0, X_0)$

$T_B = T + v_B$   $v_A \sim \mathcal{N}(0, V_A)$

$v_B \sim \mathcal{N}(0, V_B)$

$T$  is uncorrelated with  $A$  &  $B$ ,  $A$  &  $B$  uncorrelated.

Calculate  $\hat{T} = E(T | T_A, T_B)$

① Recursive Approach

$$\hat{T} = E(T | T_A, T_B) = E(T | T_A) + E(\tilde{T} | T_A | \tilde{T}_B | T_A)$$

$$E(T | T_A) = E(T) + \Sigma_{TTA} \Sigma_{TATA}^{-1} (T_A - m_{TA})$$

$$\boxed{m_{TA} = E(T + v_A) = T_0}$$

$$\boxed{\Sigma_{TATA} = X_0 + V_A \quad \Sigma_{TTA} = X_0}$$

$$E(T | T_A) = T_0 + \frac{X_0}{X_0 + V_A} (T_A - T_0)$$

$$\begin{aligned} E(\tilde{T} | T_A | \tilde{T}_B | T_A) &= E(\tilde{T} | T_A) + \Sigma_{\tilde{T}T_A \tilde{T}_B | T_A} \Sigma_{\tilde{T}_B | T_A}^{-1} (\tilde{T}_B | T_A - E(\tilde{T}_B | T_A)) \\ &= \Sigma_{\tilde{T} | T_A} \Sigma_{\tilde{T}_B | T_A} \Sigma_{\tilde{T}_B | T_A}^{-1} (T_B - E(T_B | T_A)) \end{aligned}$$

$$\begin{aligned} \tilde{T}_B | T_A &= T_B - (E(T_B) - \Sigma_{TBTA} \Sigma_{TATA}^{-1} (T_A - m_{TA})) \\ &= T_B - (E(T_B) - X_0 / (X_0 + V_A) \cdot (T_A - T_0)) \end{aligned}$$

$$\begin{aligned} \Sigma_{\tilde{T} | T_A \tilde{T}_B | T_A} &= E[(\tilde{T} | T_A) \cdot \tilde{T}_B | T_A] \\ &= E\left[\left((T - T_0) + \frac{X_0}{X_0 + V_A} (T_A - T_0)\right) \left((T_B - T_0) + \frac{X_0}{X_0 + V_A} (T_A - T_0)\right)\right] \\ &= \frac{X_0 V_A}{X_0 + V_A} \end{aligned}$$

$$\Sigma \tilde{T}_{B|A} \tilde{T}_{B|A}$$

$$= \Sigma T_B T_B - \Sigma T_B T_A \Sigma_{T_A T_A}^{-1} \Sigma T_B T_A$$

$$= (X_0 + V_B) X_0 \frac{1}{X_0 + V_A} X_0 = \frac{\cancel{X_0^2} + (V_A + V_B) X_0 + V_B V_A - \cancel{X_0^2}}{X_0 + V_A}$$

$$\hat{T} = T_0 + \frac{X_0}{X_0(V_A + V_B) + V_A V_B} [V_B (T_A - T_0) + V_A (T_B - T_0)]$$

Batch Approach

$$T_c = \begin{bmatrix} T_A \\ T_B \end{bmatrix}$$

$$T_c \sim N\left(\begin{bmatrix} T_0 \\ T_0 \end{bmatrix}, \begin{bmatrix} X_0 + V_A & X_0 \\ X_0 & X_0 + V_B \end{bmatrix}\right)$$

$$\begin{aligned} E[(T | \begin{bmatrix} T_A \\ T_B \end{bmatrix})] &= E[T] + \Sigma_{T \begin{bmatrix} T_A \\ T_B \end{bmatrix}} \Sigma_{\begin{bmatrix} T_A \\ T_B \end{bmatrix} \begin{bmatrix} T_A \\ T_B \end{bmatrix}}^{-1} (\begin{bmatrix} T_A \\ T_B \end{bmatrix} - \begin{bmatrix} T_0 \\ T_0 \end{bmatrix}) \\ &= T_0 + \begin{bmatrix} X_0 & X_0 \end{bmatrix} \begin{bmatrix} X_0 + V_A & X_0 \\ X_0 & X_0 + V_B \end{bmatrix}^{-1} \begin{bmatrix} T_A - T_0 \\ T_B - T_0 \end{bmatrix} \end{aligned}$$