

Q5 Derivation

Given:  $y = \phi x + \eta$

$$\phi \in \mathbb{R}^{m \times n} \quad y \in \mathbb{R}^m \quad x \in \mathbb{R}^n \quad \text{a}$$

$$\eta \sim N(0, \sigma^2 I_{m \times m})$$

$$\Rightarrow \eta \sim N(0, \sigma^2 I_{m \times m}) = N(0, \Sigma_{\sigma^2})$$

Where  $\Sigma_{\sigma^2} = \begin{bmatrix} \sigma^2 & 0 & 0 & \dots \\ 0 & \sigma^2 & 0 & \dots \\ 0 & 0 & \sigma^2 & \dots \\ \vdots & \vdots & \vdots & \ddots \\ 0 & \dots & \dots & \sigma^2 \end{bmatrix}_{m \times m}$

$\Rightarrow$  We know that  $x$  is drawn from zero-mean Gaussian with known  $\Sigma_x$

$$\therefore x \sim N(0, \Sigma_x)$$

$$\therefore p(x) = \underbrace{\frac{1}{(2\pi)^{n/2} |\Sigma_x|^{1/2}}}_{C_2} \exp\left(-\frac{1}{2} x^T \Sigma_x^{-1} x\right)$$

$$\therefore p(y|x, \phi) = \frac{1}{(2\pi)^{1/2} \sigma} \exp\left(-\frac{\|y - \phi x\|^2}{2 \sigma^2}\right)$$

$$= \underbrace{\frac{1}{(2\pi)^{1/2} |\Sigma_{\sigma^2}|^{1/2}}}_{C_1} \exp\left(-\frac{1}{2} (y - \phi x)^T \Sigma_{\sigma^2}^{-1} (y - \phi x)\right)$$

→ map estimate.

$$\hat{x} = \arg \max_x P(x|y)$$

$$= \arg \max_x \left\{ \frac{P(y|x) P(x)}{P(y)} \right\}$$

$$= \arg \max_x P(y|x) P(x) \quad (\text{as } P(y) \text{ is independent of } x)$$

$$= \arg \max_x C_1 \exp\left(-\frac{1}{2} (y - \phi(x))^T \Sigma_{\sigma}^{-1} (y - \phi(x))\right) \\ C_2 \exp\left(-\frac{1}{2} x^T \Sigma_x^{-1} x\right)$$

$$(i) \quad = \arg \max_x C_1 \cdot C_2 \exp\left(-\frac{1}{2} \left[ (y - \phi(x))^T \Sigma_{\sigma}^{-1} (y - \phi(x)) + x^T \Sigma_x^{-1} x \right]\right)$$

∴ we can write eq. (i) as

$$= \arg \max_x C_1 \cdot C_2 \exp\left(-\frac{1}{2} (x - \hat{u})^T \hat{\Sigma}^{-1} (x - \hat{u})\right)$$

for some  $\hat{u} \in \hat{\Sigma}^{-1}$   
or as

$$(ii) \quad = \arg \max_x C_1 \cdot C_2 \exp\left(-\frac{1}{2} (\hat{u} - x)^T \hat{\Sigma}^{-1} (\hat{u} - x)\right)$$

$$\boxed{\hat{x} = \hat{u}}$$

∴ so we have find value of  $\hat{u}$



Binding value of  $\hat{x}$  i.e.  $\hat{\mu}$

→ • Comparing eq (i) & (ii)

i.e. eq (i)

$$\exp\left(-\frac{1}{2}\left((Y-\Phi X)^T \Sigma_{\epsilon}^{-1}(Y-\Phi X) + X^T \Sigma_x^{-1} X\right)\right)$$

$$= \exp\left(-\frac{1}{2}\left((Y-\Phi X)^T (\Sigma_{\epsilon}^{-1} Y - \Sigma_{\epsilon}^{-1} \Phi X) + X^T \Sigma_x^{-1} X\right)\right)$$

$$= \exp\left(-\frac{1}{2}\left(Y^T \Sigma_{\epsilon}^{-1} Y - \underbrace{X^T \Phi^T \Sigma_{\epsilon}^{-1} Y}_{(a)} - Y^T \Sigma_{\epsilon}^{-1} \Phi X + \underbrace{X^T \Phi^T \Sigma_{\epsilon}^{-1} \Phi X + X^T \Sigma_x^{-1} X}_{\text{merging}}\right)\right)$$

$$= \exp\left(-\frac{1}{2}\left(Y^T \Sigma_{\epsilon}^{-1} Y - \underbrace{X^T (\Phi^T \Sigma_{\epsilon}^{-1} \Phi + \Sigma_x^{-1}) X}_{(b)}\right)\right)$$

eq (ii) expanding

$$= \exp\left(-\frac{1}{2}(\hat{\mu} - X)^T \hat{\Sigma}^{-1}(\hat{\mu} - X)\right)$$

$$= \exp\left(-\frac{1}{2}(\hat{\mu} - X)^T (\hat{\Sigma}^{-1} \hat{\mu} - \hat{\Sigma}^{-1} X)\right)$$

$$= \exp\left(-\frac{1}{2}\left(\hat{\mu}^T \hat{\Sigma}^{-1} \hat{\mu} - \underbrace{X^T \hat{\Sigma}^{-1} \hat{\mu}}_{(c)} - \hat{\mu}^T \hat{\Sigma}^{-1} X + \underbrace{X^T \hat{\Sigma}^{-1} X}_{(d)}\right)\right)$$

As

$$eq(i) = eq(ii)$$

which means by similarity of eq.

$$(a) = (c) \quad \& \quad (b) = (d)$$

$$\Rightarrow (b) = (d) \text{ i.e.}$$

$$x^T (\Phi^T \Sigma_{\sigma^2}^{-1} \Phi + \Sigma_x^{-1}) x = x^T \hat{\Sigma}^{-1} x$$

$$\therefore \text{we get } \hat{\Sigma}^{-1} = \Phi^T (\Sigma_{\sigma^2}^{-1} \Phi + \Sigma_x^{-1})$$

$$\Rightarrow \text{as } (a) = (c) \text{ i.e.}$$

(iii)

$$x^T \Phi^T \Sigma_{\sigma^2}^{-1} y = x^T \hat{\Sigma}^{-1} \hat{u}$$

$$\therefore \Phi^T \Sigma_{\sigma^2}^{-1} y = \hat{\Sigma}^{-1} \hat{u}$$

by eq (iii) we get

$$\hat{u} = (\Phi^T \Sigma_{\sigma^2}^{-1} \Phi + \Sigma_x^{-1})^{-1} \Phi^T \Sigma_{\sigma^2}^{-1} y$$

$$\therefore x = (\Phi^T \Sigma_{\sigma^2}^{-1} \Phi + \Sigma_x^{-1})^{-1} \Phi^T \Sigma_{\sigma^2}^{-1} y$$

(ans)

on. if we use  $\Sigma_{\sigma^2} = \sigma^2 I_{m \times m}$

$$\therefore \Sigma_{\sigma^2}^{-1} = \frac{1}{\sigma^2} I_{m \times m}$$

we get

$$x = \left( \frac{1}{\sigma^2} \Phi^T I \Phi + \Sigma_x^{-1} \right)^{-1} \cdot \frac{1}{\sigma^2} \Phi^T I y$$

$$x = (\Phi^T \Phi + \sigma^2 \Sigma_x^{-1})^{-1} \Phi^T y$$

(ans)