

$$\hat{x} = (A^T \Sigma_y^{-1} A + \Sigma_x^{-1})^{-1} (A^T \Sigma_y^{-1} y + \Sigma_x^{-1} \mu_0)$$

$$\Sigma_y$$

$1 \text{ mm} \rightarrow 6 = 3 \text{ mm}$   
 $G = \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1}$   
 $\hat{x} = (A^T \Sigma_y^{-1} A + \Sigma_x^{-1})^{-1} (A^T \Sigma_y^{-1} y + \Sigma_x^{-1} \mu_0)$   
 $\hat{\sigma}^2 = \frac{e^T e}{m-n}$   
 $p = \hat{\sigma}^2 \Sigma_y^{-1}$   
 $\hat{\sigma}^2 = 1 \Rightarrow p = \hat{\sigma}^2 \Sigma_y^{-1}$   
 $Q_x = (A^T p A)^{-1}$   
 $\hat{Q}_x = \hat{\sigma}^2 Q_x$

⑥

Conjugate Priors

A density such as  $\pi(\theta)$  is a conjugate prior, if it leads after being multiplied by the likelihood to a posterior density function which belongs to the same family of distributions

$\pi(\theta) \propto \text{likelihood} \times \text{posterior}$

Normal  
Normal-Gamma

Normal-Gamma Distribution

$x$  be an  $m \times 1$  random vector  
 $\tau$  a random variable

let the conditional density function  $p(x|\mu, \tau, V)$  be known  $\rightarrow$  Normal distribution

$N(\mu, \tau^{-1} V)$  shape

$\tau \sim G(b, P)$  an inverse scale parameter

$p(\tau|b, P) \sim G(b, P)$

The joint density function  $p(x, \tau|\mu, V, b, P)$

$$p(x, \tau|\mu, V, b, P) = (2\pi)^{-m/2} (\det V)^{-1/2} b^P \Gamma(P)^{-1} \tau^{P+1/2} \exp \left\{ -\frac{\tau}{2} [2b + (x-\mu)^T V^{-1} (x-\mu)] \right\}$$

$b > 0, P > 0, 0 < \tau < \infty, -\infty < x_i < \infty$

$$\Gamma(1) = (1-1)! = 1$$

$$\Gamma(p+1) = \frac{2p-1}{2} \Gamma(p) = \frac{2p-1}{2} \cdot \frac{2p-3}{2} \Gamma(p-1) = \dots = 1 \cdot 3 \cdot 5 \cdot \dots \cdot (2p-1) \Gamma(1)$$

marginal distribution for  $x$

$$p(x) \sim N(\mu, bV/P)$$

marginal distribution  $\tau$

$$p(\tau) = G(b, P) = \frac{b^P}{\Gamma(P)} \tau^{P-1} \exp\{-b\tau\} \quad b > 0, P > 0, \tau < \infty$$

$$E(\tau) = P/b$$

$$D(\tau) = P/b^2$$

$$\sigma_B = \tau^{-1}$$

$$y = Ax + e$$

$$\Sigma_x$$

$$x \sim N(\mu_0, \Sigma_x)$$

$$p(y|x, \Sigma_y) \sim N(Ax, \Sigma_y)$$

$$p(y|\mu, \Sigma_y) = \frac{1}{(2\pi)^{n/2} (\det \Sigma_y)^{1/2}} e^{-1/2 \{ (y-\mu)^T \Sigma_y^{-1} (y-\mu) \}}$$

$$\det(cJ) = c^n \det(J)$$

for  $N \times N$   $J$  matrix

$$\tau = \frac{1}{\sigma_B^2}$$

likelihood

$$p(y|\mu, \tau) = (2\pi)^{-n/2} (\det \Sigma_y^{-1})^{1/2} \tau^{n/2} \exp \left[ -\frac{\tau}{2} (y - Ax)^T \Sigma_y^{-1} (y - Ax) \right]$$

prior

$$p(x, \tau) \sim N(\mu_0, \Sigma_x, b, P)$$

posterior

$$\sigma_B = ?$$