

①

Bayes Regression

$$y = x\beta + \epsilon \quad \epsilon \sim N(0, \sigma^2 I)$$

Assume we know σ .

$$p(\beta) \sim N(\bar{\beta}, A^{-1})$$

$$p(\beta) = (2\pi)^{-\frac{p}{2}} |A|^{-\frac{1}{2}} \exp\left[-\frac{1}{2} (\beta - \bar{\beta})^T A (\beta - \bar{\beta})\right]$$

$$(\beta - \bar{\beta})^T A (\beta - \bar{\beta})$$

$$= \beta^T A \beta - 2\beta^T A \bar{\beta} + \bar{\beta}^T A \bar{\beta}$$

$$L(\beta) \propto \exp\left[-\frac{1}{2\sigma^2} (y - x\beta)^T (y - x\beta)\right]$$

Need:

(*)

$$\frac{(y - X\beta)^T (y - X\beta)}{\sigma^2} + (\beta - \bar{\beta})^T A (\beta - \bar{\beta})$$

In the form

$$(\beta - \bar{\beta})^T V^{-1} (\beta - \bar{\beta})$$

$$\frac{(y - X\beta)^T (y - X\beta)}{\sigma^2}$$

$$= \frac{1}{\sigma^2} (y^T y - 2\beta^T X^T y + \beta^T X^T X \beta)$$

(*) =

$$\beta^T \frac{X^T X}{\sigma^2} \beta - 2\beta^T \frac{X^T y}{\sigma^2}$$

$$+ \beta^T A \beta - 2\beta^T A \bar{\beta}$$

$$+ c$$

3

(*) =

$$\beta^T \left[\frac{X^T X}{\sigma^2} + A \right] \beta$$

$$- 2\beta \left[\frac{X^T y}{\sigma^2} + A\beta \right] + c$$

$$V \equiv \left[\frac{X^T X}{\sigma^2} + A \right]^{-1}$$

(*) =

$$\beta^T V^{-1} \beta - 2\beta V^{-1} \left[\frac{X^T y}{\sigma^2} + A\beta \right]$$

+ c

$$\beta | \sigma, y \sim N \left(\left[\frac{X^T X}{\sigma^2} + A \right]^{-1} \left(\frac{X^T y}{\sigma^2} + A\beta \right) \right)$$

$$\left(\frac{X^T X}{\sigma^2} + A \right)^{-1}$$

4

Note

"flat prior" $\Rightarrow A \approx 0$

$$\sim \beta | \sigma, y \sim$$

$$N \left((X^T X)^{-1} X^T y, \sigma^2 (X^T X)^{-1} \right)$$

plug-in $\hat{\beta}$

$$\beta_i \sim N(b_i, s_{b_i}^2)$$

b_i : least square

s_{b_i} : usual $SE(b_i)$.

5

Nota

$$Y_i \sim N(\mu, \sigma^2) \quad \text{i.i.d.}$$

$$Y_i = \mu + \varepsilon_i \quad \varepsilon_i \sim N(0, \sigma^2)$$

$$Y = \mathbf{1}\mu + \varepsilon$$

$$\mathbf{1} = (\mathbf{1}, \mathbf{1}, \dots, \mathbf{1})^T, \quad \varepsilon \sim N(0, \sigma^2 \mathbf{I})$$

$$X^T X = n$$

$$X^T Y = n\bar{y}$$

$$\mu \sim N(\bar{y}, \frac{\sigma^2}{n}) \Leftrightarrow \begin{matrix} \beta = \mu \\ \Gamma = \frac{\sigma^2}{n} \end{matrix}$$

$$\left(\frac{X^T X}{\sigma^2} + \Gamma \right)^{-1} \left(\frac{X^T Y}{\sigma^2} + \Gamma \beta \right)$$

$$= \frac{\frac{1}{\sigma^2} \mathbf{1}\mathbf{1}^T + \frac{1}{\sigma^2} n}{\frac{1}{\sigma^2} \mathbf{1}\mathbf{1}^T + \frac{1}{\sigma^2} n}$$

⑥

Gibbs Sampler for Bayesian Regression

$$Y = X\beta + \epsilon \quad \epsilon \sim N(0, \sigma^2 I)$$

$$\beta \sim N(\bar{\beta}, A^{-1})$$

$$\sigma^2 \sim \frac{\nu \lambda}{\chi^2_\nu}$$

independent

Gibbs

$$\beta \mid \sigma, y$$

$$\sigma \mid \beta, y$$

$$\sigma \mid \beta, y: \quad \epsilon = y - X\beta \sim N(0, \sigma^2) \text{ i.i.d.}$$