

LECTURE - 13 (03-28-16)

①

$$\theta | X, \sigma^2 \sim N\left(\frac{\bar{X} \frac{n}{\sigma^2} + \frac{\mu_0}{\tau^2}}{\frac{n}{\sigma^2} + \frac{1}{\tau^2}}, \frac{1}{\frac{n}{\sigma^2} + \frac{1}{\tau^2}}\right)$$

Likelihood Model

$$X | \theta, \sigma^2 \sim N(\theta, \sigma^2)$$

$$\theta \sim N(\mu_0, \tau^2)$$

over-dispersed Normal

$$X^* | X, \sigma^2 \sim N(\theta_p, \sigma_p^2 + \sigma^2)$$

→ convolution

$$P(\sigma^2 | X, \theta) \propto P(X | \sigma^2, \theta) P(\sigma^2 | \theta)$$

$$\propto \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(X_i - \theta)^2} p(\sigma^2 | \theta)$$

$$\propto (\sigma^2)^{-n/2} e^{-\frac{1}{2\sigma^2} \sum_{i=1}^n (X_i - \theta)^2} p(\sigma^2 | \theta)$$

$$\text{Let } \hat{\sigma}^2 := \frac{1}{n} \sum_{i=1}^n (X_i - \theta)^2$$

MLE for σ^2 when θ is known.

$$= (\sigma^2)^{-n/2} e^{-\frac{n\hat{\sigma}^2}{2\sigma^2}} p(\sigma^2 | \theta)$$

$$\text{Prior } p(\sigma^2 | \theta) \propto (\sigma^2)^a e^{-\frac{1}{2\sigma^2}}$$

$$Y \sim \text{Gamma}(d, \beta) := \frac{\beta^d}{\Gamma(d)} y^{d-1} e^{-\beta y}$$

'Change of variable'

$$W = \frac{1}{Y} = t(Y) \sim f_Y(t^{-1}(w)) \left| \frac{d}{dw} [t^{-1}(w)] \right|$$

$$t^{-1}(w) = \frac{1}{w} \quad = f_Y\left(\frac{1}{w}\right) \left| \frac{d}{dw} \left[\frac{1}{w}\right] \right|$$

②

$$\text{Then to Gamma} \propto \frac{\beta^d}{\Gamma(d)} w^{-(d+1)} e^{-\frac{\beta}{w}}$$

$$\text{Then it becomes } Y^{-1} \sim \text{Inv Gamma}(d, \beta)$$

$$:= \frac{\beta^d}{\Gamma(d)} w^{-(d+1)} e^{-\beta/w}$$

$$\sigma^2 | \theta = \sigma^2 \sim \text{Inv Gamma}(d, \beta)$$

$$E[W] = \frac{\beta}{d-1} \text{ if } d > 1$$

$$\text{Mode}[W] = \frac{\beta}{d+1}$$

$$SE[W] = \frac{\beta}{d-1} \frac{1}{\sqrt{d-2}} \text{ for } d > 2$$

$$p(\sigma^2 | \theta) \propto (\sigma^2)^{-n/2} e^{-\frac{n\hat{\sigma}^2}{2\sigma^2}} (\sigma^2)^{-(d+1)} e^{-\beta/\sigma^2}$$

$$= (\sigma^2)^{-(d+n/2+1)} e^{-\frac{(n\hat{\sigma}^2/2 + \beta)}{\sigma^2}}$$

$$\propto \text{Inv Gamma}\left(d + \frac{n}{2}, \beta + \frac{n\hat{\sigma}^2}{2}\right)$$

$$\text{let } d = \frac{\nu_0}{2} \quad \text{let } \beta = \frac{\nu_0 \sigma_0^2}{2} \quad d, \beta \in (0, \infty)$$

$$\propto \text{Inv Gamma}\left(\frac{\nu_0 + n}{2}, \frac{\nu_0 \sigma_0^2 + n\hat{\sigma}^2}{2}\right)$$

Inv Gamma (online) Inverse χ^2 (Chi-square)

$$\hat{\sigma}_{\text{unbiased}} = E[\sigma^2 | X, \theta] \quad E[\sigma^2] = \frac{\nu_0 \sigma_0^2 / \chi}{\nu_0 - 2 / \chi}$$

$$Y_1, \dots, Y_{N_0}, Y_{N_0+1}, \dots, Y_{N_0+N_1}$$

$$\sigma_0^2 := \frac{1}{N_0} \sum_{i=1}^{N_0} (X_i - \theta)^2$$

'prior' $n \rightarrow N_0$

$$= \frac{1}{N_0 - 2} \sum_{i=1}^{N_0} (X_i - \theta)^2$$

pseudo data [Beta, Gamma]

$$j(\sigma^2; X, \theta) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(X_i - \theta)^2} \quad (3)$$

$$\ln(\sigma^2; X, \theta) = -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{n\sigma^2}{2\sigma^2}$$

$$\ln'(\sigma^2; X, \theta) = -\frac{n}{2\sigma^2} + \frac{n\sigma^2}{2(\sigma^2)^2} \stackrel{x \neq 0}{=} 0 \Rightarrow \frac{x}{2\sigma^2} = \frac{n\sigma^2}{2(\sigma^2)^2}$$

$$\ln''(\sigma^2; X, \theta) = -\frac{n}{2(\sigma^2)^2} - \frac{n\sigma^2}{(\sigma^2)^3}$$

$$I(\theta) = E[-\ln''(\sigma^2; X, \theta)] = -\frac{n}{2(\sigma^2)^2} - \frac{nE[\frac{\sigma^2}{(\sigma^2)^3}]$$

$$\frac{1}{n} E\left[\sum_{i=1}^n (X_i - \theta)^2\right] \\ = \frac{1}{n} \sum_{i=1}^n E(X_i - \theta)^2$$

if frequentist
 $X_1, \dots, X_n \stackrel{iid}{\sim} N(\theta, \sigma^2)$
 $\frac{1}{n} \sum E(X_i - \theta)^2$
 $E[X^2 - 2\theta X + \theta^2]$
 $E[X^2] - 2\theta E[X] + \theta^2$
 $E[X^2] - \theta^2$
 $= \sigma^2 \{Var\}$

$$-\frac{n}{2(\sigma^2)^2} - \frac{n}{(\sigma^2)^2} = -\frac{n}{2(\sigma^2)^2}$$

$$j(\sigma^2) \propto \sqrt{I(\theta)}$$

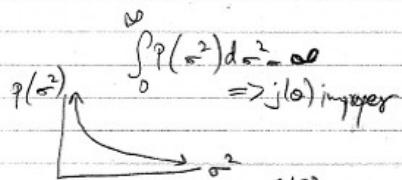
$$\sqrt{\frac{1}{2} \frac{1}{(\sigma^2)^2}}$$

$$\propto \frac{1}{\sigma^2}$$

$$\sigma^2 \in (0, \infty)$$

$$\propto (\sigma^2)^{-1} = \text{InvGamma}(0, 0)$$

(Heldau)



$$\int_0^\infty p(\sigma^2) d\sigma^2 = \infty \Rightarrow j(\theta) \text{ improper}$$

$$n_0 = 0$$

$$\sigma_0^2 = 0$$

$$\text{InvGamma}\left(\frac{n_0+n}{2}, \frac{n_0\sigma_0^2 + n\sigma^2}{2}\right)$$

under $j(\sigma^2)$

$$\propto \text{InvGamma}\left(\frac{n}{2}, \frac{n\sigma^2}{2}\right)$$

$$E[\sigma^2 | X, \theta] = \frac{\frac{n\sigma^2}{2}}{\frac{n}{2} - 1} = \frac{1}{n-2} \sum (X_i - \theta)^2 \sim \frac{1}{n-1} \sum (X_i - \bar{X})^2$$

$$\left[\frac{\theta}{\sigma^2}\right] \sim P(\theta, \sigma^2 | X) \propto P(X | \theta, \sigma^2) P(\theta, \sigma^2)$$

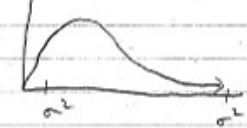
joint posterior joint prior

Assume

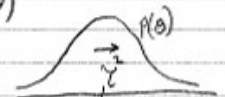
$$P(\theta, \sigma^2) = P(\theta) P(\sigma^2) \text{ jettrey's}$$

$$\propto (1) \left(\frac{1}{\sigma^2}\right)$$

$$= \frac{1}{\sigma^2}$$



$$\propto (\sigma^2)^{-\left(\frac{n}{2} + 1\right)} e^{-\frac{1}{2\sigma^2} \sum (X_i - \theta)^2}$$



$$\sum (X_i - \bar{X} + \bar{X} - \theta)^2$$

$$= \sum (X_i - \bar{X})^2 + \sum 2(X_i - \bar{X})(\bar{X} - \theta) + \sum (\bar{X} - \theta)^2$$

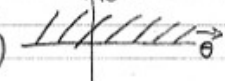
$$= 2 \sum X_i \bar{X} - \bar{X}^2 - X_i \theta + \bar{X} \theta$$

$$= 2(n\bar{X}^2 - n\bar{X}^2 - n\bar{X}\theta + n\bar{X}\theta)$$

$$s^2 := \frac{1}{n-1} \sum (X_i - \bar{X})^2$$

$$= (n-1)s^2 + n(\bar{X} - \theta)^2$$

InvGamma has one supp $\mathbb{R}^+ \times (0, \infty)$



EE]

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$$f(x, y) = f(x|y) f(y)$$

$$f(x, y|z) = f(x|y, z) f(y|z)$$

$$p(\theta, \sigma^2|x) = p(\theta|x, \sigma^2) p(\sigma^2|x)$$

$$p(\theta|x, \sigma^2) \propto e^{-\frac{1}{2\sigma^2}(\bar{x} - \theta)^2}$$

$$\propto N\left(\bar{x}, \frac{\sigma^2}{n}\right) \quad \text{posterior under jayfreys prior}$$

$$= (\sigma^2)^{-\left(\frac{n}{2}+1\right)} e^{-\frac{1}{2\sigma^2}((n-1)s^2 + n(\bar{x} - \theta)^2)}$$

$$\propto N\left(\bar{x}, \frac{\sigma^2}{n}\right) (\sigma^2)^{-\left(\frac{n}{2}+1\right)} e^{-\frac{(n-1)s^2}{2\sigma^2}}$$

$$\propto N\left(\bar{x}, \frac{\sigma^2}{n}\right)$$

$$\propto \text{Inv Gamma}\left(\frac{n}{2}, \frac{(n-1)s^2}{2}\right)$$

$$f(x) = \int f(x, y) dy$$

$$f(x|z) = \int_{\text{supp}[Y]} f(x, y|z) dy$$

$$\text{supp}[Y]$$

$$\underline{p(z|x)} = \int_{\text{supp}[\theta]} p(\theta, \sigma^2|x) d\theta$$