

4/19/21

Lec 18

Jeffrey's  $P(\sigma^2 | \theta) \propto \sqrt{I(\sigma^2; \theta)}$ 

$$J'(\sigma^2; X, \theta) = -\frac{n}{2\sigma^2} - \frac{\sum (x_i - \theta)^2}{2(\sigma^2)^2}$$

$$J''(\sigma^2; X, \theta) = \frac{1}{2(\sigma^2)^2} + \frac{\sum (x_i - \theta)^2}{(\sigma^2)^3}$$

$$I(\sigma^2; \theta) = E_X[-J''] = + E_X \left[ \frac{n}{2(\sigma^2)^2} + \frac{\sum (x_i - \theta)^2}{(\sigma^2)^3} \right] \quad \begin{array}{l} \text{Defn of} \\ \text{Var}[X] = \sigma^2 \\ \uparrow \\ X \sim N(\theta, \sigma^2) \end{array}$$

$$= + \left( \frac{n}{2(\sigma^2)^2} + \frac{\sum E[(x_i - \theta)^2]}{(\sigma^2)^3} \right)$$

$$= + \left( \frac{n}{2(\sigma^2)^2} + \frac{\sum \sigma^2}{(\sigma^2)^3} \right)$$

$$= -\frac{n}{2(\sigma^2)^2} + \frac{n}{(\sigma^2)^2} = \frac{n}{(\sigma^2)^2} \left( -\frac{1}{2} + 1 \right) = \frac{n}{2(\sigma^2)^2}$$

$$P_J(\sigma^2 | \theta) \propto \sqrt{\frac{n}{2(\sigma^2)^2}} \propto \sqrt{\frac{1}{(\sigma^2)^2}} = (\sigma^2)^{-1} \propto \text{InvGamma}(\theta, 0) \\ = \text{Haldane}$$

Jeffrey's and Haldane are equivalent principled objective priors and they're the default for this model.

$$\text{Shrinkage } P(\sigma^2 | \theta) = \text{InvGamma}\left(\frac{n_0}{2}, \frac{n_0 \sigma_0^2}{2}\right) \Rightarrow E[\sigma^2 | \theta] \\ = \frac{n_0 \sigma_0^2}{n_0 - 2} \quad (\text{valid for } n_0 > 2)$$

$$\hat{\sigma}_{\text{MMSE}}^2 = \frac{n \hat{\sigma}_{\text{MLE}}^2 + n_0 \sigma_0^2}{n + n_0 - 2} = \frac{n \hat{\sigma}_{\text{MLE}}^2}{n + n_0 - 2} + \frac{n_0 \sigma_0^2}{n + n_0 - 2} \cdot \frac{n_0 - 2}{n_0 - 2} \\ = \underbrace{\frac{n}{n + n_0 - 2}}_{1 - \rho} \hat{\sigma}_{\text{MLE}}^2 + \underbrace{\frac{n_0 - 2}{n + n_0 - 2}}_{\rho} E[\sigma^2 | \theta]$$

Posterior Predictive distribution

$$P(X_* | X, \theta) = \int_0^\infty \underbrace{P(X_* | \theta, \sigma^2)}_{N(\theta, \sigma^2)} \underbrace{P(\sigma^2 | X, \theta)}_{\text{InvGamma}\left(\frac{n+n_0}{2}, \frac{n \hat{\sigma}_{\text{MLE}}^2 + n_0 \sigma_0^2}{2}\right)} d\sigma^2$$



$$= \int_0^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_* - \theta)^2} \cdot \frac{\beta^{\alpha}}{\Gamma(\alpha)} (\sigma^2)^{-\alpha-1} e^{-\frac{\beta}{\sigma^2}} d\sigma^2$$

$$\propto \int_0^{\infty} (\sigma^2)^{-\frac{1}{2}} e^{-\frac{(x_* - \theta)^2}{2\sigma^2}} (\sigma^2)^{-\alpha-1} e^{-\frac{\beta}{\sigma^2}} d\sigma^2$$

$$= \int_0^{\infty} (\sigma^2)^{-(\alpha+\frac{1}{2})-1} e^{-\frac{(x_* - \theta)^2/2 + \beta}{\sigma^2}} d\sigma^2$$

U-Subst  $\frac{\Gamma(\alpha')}{\beta^{\alpha'}}$

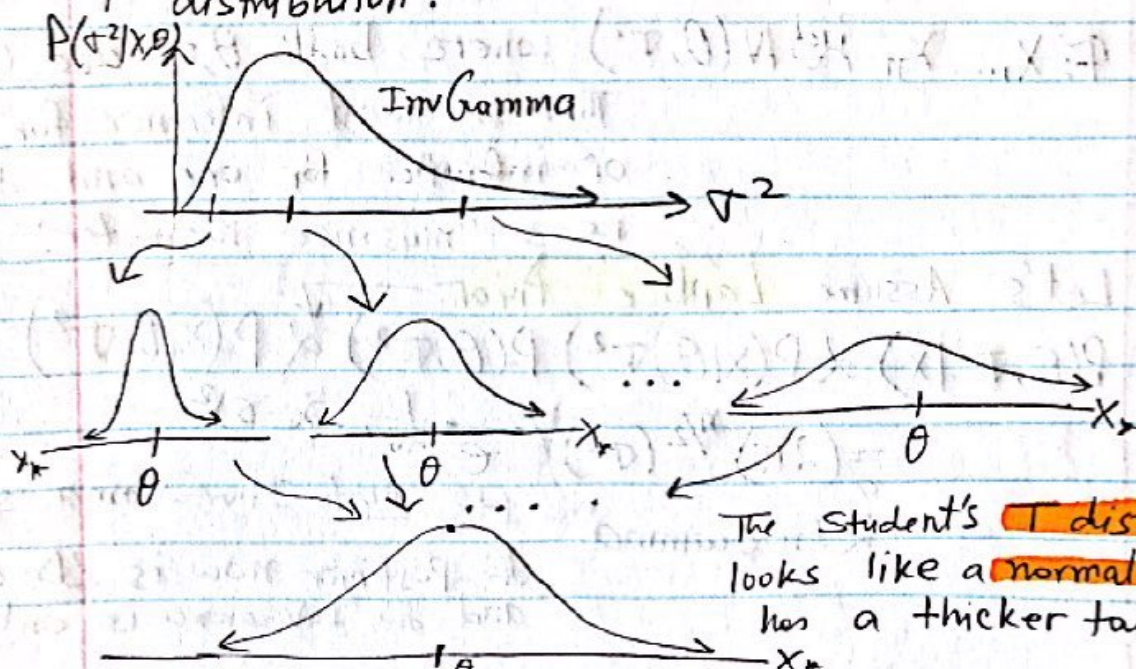
$$P(x_* | x, \theta) \propto \Gamma\left(\frac{n+n_0+1}{2}\right) \left( \frac{(x_* - \theta)^2 + \frac{n\hat{\sigma}_{MLE}^2 + n_0\sigma_0^2}{2}}{2} \right)^{-\frac{n+1}{2}} \left(\frac{2}{a}\right)^{-\frac{n+1}{2}} \left(\frac{2}{a}\right)^{\frac{n+1}{2}}$$

$$= \left( \frac{(x_* - \theta)^2}{a} + 1 \right)^{-\frac{n+1}{2}} \left(\frac{2}{a}\right)^{\frac{n+1}{2}}$$

$$= \left( 1 + \frac{1}{n} \frac{(x_* - \theta)^2}{\frac{a}{n}} \right)^{-\frac{n+1}{2}} \left(\frac{2}{a}\right)^{\frac{n+1}{2}}$$

$$\propto \left( 1 + \frac{1}{n} \frac{(x_* - \theta)^2}{\frac{a}{n}} \right)^{-\frac{n+1}{2}} \propto T_{n+n_0}\left(\theta, \frac{n\hat{\sigma}_{MLE}^2 + n_0\sigma_0^2}{n+n_0}\right)$$

This distribution is "non-standard Student's T distribution" or "shifted and scaled Student's T distribution".





$$T_{n+n_0}(\theta, \frac{n\hat{\sigma}_{MLE}^2 + n_0\sigma_0^2}{n+n_0}) \stackrel{n+n_0 > 20}{\approx} N(\theta, \frac{n\hat{\sigma}_{MLE}^2 + n_0\sigma_0^2}{n+n_0})$$

if  $n$  is large  
 $\Rightarrow \hat{\sigma}_{MLE}^2 \rightarrow \sigma^2$

$$\approx N(\theta, \sigma^2)$$

$\theta = 5$   
 $n = 12$ ,  $\hat{\sigma}_{MLE}^2 = 0.387$ , Jeffreys Prior  $\Rightarrow n_0 = \sigma_0^2 = 0$

$$P(X_* > 8 | X, \theta) = 1 - P(X_* \leq 8 | X, \theta)$$

$$= 1 - P(\text{t. scaled}) \left[ \underset{\hat{x}_*}{8}, \underset{\hat{v}}{12}, \underset{\theta}{5}, \underset{\sqrt{\text{scale}}}{\sqrt{\frac{12(0.387)}{12}}} \right]$$

**Predictive Intervals (PI)**

$$PI_{X_*, 1-\alpha_0} = [Q[X_* | X, \frac{\alpha_0}{2}], Q[X_* | X, 1 - \frac{\alpha_0}{2}]]$$

$$P(X_* \in PI_{X_*, 1-\alpha_0} | X) = 1 - \alpha_0$$

$\sigma^2 = 1.1$ ,  $\bar{x} = 1.89$ ,  $n = 13$ , Jeffreys Prior  $\Rightarrow P(X_* | X, \sigma^2) = N(\bar{x}, \sigma^2)$

$$PI_{X_*, 95\%} = [qnorm(0.025, 1.89, \sqrt{1.1}), qnorm(0.975, 1.89, \sqrt{1.1})]$$

**\* End of Mid II Materials ↑ \***

**\* Start of final Exam Materials ↓ \***

$\mathcal{F}: X_1, \dots, X_n \text{ iid } N(\theta, \sigma^2)$  where both  $\theta, \sigma^2$  are Unknown.

Thus we want inference for both, or inference for one and the other is a "nuisance Parameter."

Let's Assume **Laplace Prior**

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

$$= (2\pi)^{-n/2} (\sigma^2)^{-n/2} e^{-\frac{1}{2\sigma^2} \sum (x_i - \theta)^2}$$

$\propto$  Invgamma

It's Not Invgamma since

the Posterior now is 2D dist. and the Invgamma is only 1D.



What we have is a known distribution but to get it into Canonical form, we need to do algebra.

$$\sum (x_i - \theta)^2 = \sum ((x_i - \bar{x}) + (\bar{x} - \theta))^2 = \sum (x_i - \bar{x})^2 + 2\sum (x_i - \bar{x})(\bar{x} - \theta) + \sum (\bar{x} - \theta)^2$$

$$S^2 := \frac{1}{n-1} \sum (x_i - \bar{x})^2 \text{ the sample variance formula}$$

↙

from MATH 241

$$\bar{x} = \frac{1}{n} \sum x_i \Rightarrow \sum x_i = n\bar{x}$$

$$= (n-1)S^2 + 2\sum (x_i\bar{x} - \bar{x}^2 - x_i\theta + \bar{x}\theta) + n(\bar{x} - \theta)^2$$

$$= (n-1)S^2 + n(\bar{x} - \theta)^2 + 2(n\bar{x}^2 - n\bar{x}^2 - n\bar{x}\theta + n\bar{x}\theta)$$

↓

$$\rightarrow P(\theta, \sigma^2 | x) \propto (\sigma^2)^{-\frac{n}{2}} e^{-\frac{1}{2\sigma^2} ((n-1)S^2 + n(\bar{x} - \theta)^2)}$$

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

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

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

$$\propto \text{Normal-InvGamma}\left(\mu = \bar{x}, \eta = n, \alpha = \frac{n+2}{2}, \beta = \frac{(n-1)S^2}{2}\right)$$

This is the "normal-inverse-gamma" distribution with four parameters!