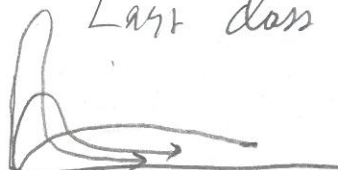


$F: X_1, \dots, X_n | \theta, \sigma^2 \stackrel{iid}{\sim} N(\theta, \sigma^2)$  with  $\theta$  known  
and we want inference for  $\sigma^2$

Last class we derived the conjugate prior as:  

 $\# \text{ pseudobs's (strength)}$   $\xrightarrow{\text{inspection of hyperparameters}}$   $\text{variance of pseudobs's.}$

$$P(\sigma^2) = \text{InvGamma}\left(\frac{n_0}{2}, \frac{n_0 \sigma_0^2}{2}\right) \propto (\sigma^2)^{-\frac{n_0}{2}-1} e^{-\frac{n_0 \sigma_0^2}{2\sigma^2}}$$

prior exp:  $E(\sigma^2) = \frac{\frac{n_0 \sigma_0^2}{2}}{\frac{n_0}{2}-1} = \frac{n_0}{n_0-2} \sigma_0^2$

$$\Rightarrow P(\sigma^2 | X, \theta) = \text{InvGamma}\left(\frac{n + n_0}{2}, \frac{n \hat{\sigma}_{MLE}^2 + n_0 \sigma_0^2}{2}\right) \quad \text{Pt. Est.}$$

Pseudocount Interpretation:

$n_0$ : # pseudobservations (strength)

$\sigma_0^2$ : variance of the pseudobservations

$$\Rightarrow \hat{\sigma}_{MLE}^2 = \frac{n \hat{\sigma}_{MLE}^2 + n_0 \sigma_0^2}{n + n_0 - 2}$$

$$\hat{\sigma}_{MAP}^2 = \frac{n \hat{\sigma}_{MLE}^2 + n_0 \sigma_0^2}{n + n_0 + 2}$$

$$\hat{\sigma}_{MLE}^2 = \text{InvGamma}(0.5, \frac{n + n_0}{2}, \frac{n \hat{\sigma}_{MLE}^2 + n_0 \sigma_0^2}{2})$$

CR's & Hypothesis Tests... same!!

Uninformative Priors

① Laplace  $P(\sigma^2 | \theta) \propto 1$

$$P(\sigma^2 | \theta, X) \propto P(X | \sigma^2, \theta) \propto (\sigma^2)^{-(n/2+1)} e^{-\frac{n \hat{\sigma}_{MLE}^2}{2\sigma^2}} \propto \text{InvGamma}\left(\frac{n+2}{2}, \frac{n \hat{\sigma}_{MLE}^2}{2}\right)$$

$$\Rightarrow P(\sigma^2 | \theta) = \text{InvGamma}(-1, 0) \propto \frac{1}{(\sigma^2)^2} \quad \text{ie. improper}$$

$\hat{\sigma}_{MLE}^2 = \frac{n \hat{\sigma}_{MLE}^2}{n + n_0 - 2} + \frac{n_0 \sigma_0^2}{n + n_0 - 2} \cdot \frac{n_0 - 2}{n_0 - 2}$   
 $= \frac{n}{n + n_0 - 2} \hat{\sigma}_{MLE}^2 + \frac{n_0 - 2}{n + n_0 - 2} E(\sigma^2)$   
 $\hat{\sigma}_{MLE}^2 = \frac{n \hat{\sigma}_{MLE}^2 + n_0 \sigma_0^2}{n + n_0 - 2}$   
 $\hat{\sigma}_{MAP}^2 = \frac{n \hat{\sigma}_{MLE}^2 + n_0 \sigma_0^2}{n + n_0 + 2}$   
 $\hat{\sigma}_{MLE}^2 = \text{InvGamma}(0.5, \frac{n + n_0}{2}, \frac{n \hat{\sigma}_{MLE}^2 + n_0 \sigma_0^2}{2})$   
 $\sigma_0^2 = 0$   
 $n_0 = -2$

## ② Haldane Prior

$$n_0 = 0 \Rightarrow P(\theta|0) = \text{Invariance}(0,0) \Rightarrow P(\sigma^2|0,X) = \text{Invariance}\left(\frac{4}{2}, \frac{4\sigma^2_{max}}{2}\right)$$

(proper)

proper only if  $n \geq 1$ . ~~OK?~~

$$\text{Aff } \gamma=1 \Rightarrow \hat{\sigma}^2_{max} = 0$$

## ③ Jeffreys Prior

$$l'(\sigma^2; X, \theta) = -\frac{4}{2} \frac{1}{\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum (X_i - \theta)^2$$

$$-l''(\sigma^2; X, \theta) = -\left(\frac{4}{2} \frac{1}{(\sigma^2)^2} + -2\left(\frac{1}{2}\right) \frac{1}{(\sigma^2)^3} \sum (X_i - \theta)^2\right)$$

$$= -\frac{4}{2(\sigma^2)^2} + \frac{\sum (X_i - \theta)^2}{(\sigma^2)^3}$$

$$J(\sigma^2) = E[-l''] = E\left[-\frac{4}{2(\sigma^2)^2} + \frac{\sum (X_i - \theta)^2}{(\sigma^2)^3}\right] = -\frac{4}{2(\sigma^2)^2} + \frac{4 E[(X_1 - \theta)^2]}{2(\sigma^2)^3} = 4 \left(-\frac{1}{2(\sigma^2)^2} + \frac{1}{2(\sigma^2)^2}\right) = \frac{4(\sigma^2)^{-2}}{2}$$

$$E[(X - \theta)^2] = E[X^2 + 2X\theta + \theta^2] = E[X^2] - 2\theta^2 + \theta^2 = \sigma^2 + \theta^2 - 2\theta^2 + \theta^2$$

$$\text{Var}(X) = E(X)^2 - E(X)^2 \Rightarrow E(X^2) = \sigma^2 + \theta^2$$

$$p_{\gamma}(\sigma^2) \propto \sqrt{J(\sigma^2)} = \sqrt{\frac{4(\sigma^2)^{-2}}{2}} \propto (\sigma^2)^{-1} = (\sigma^2)^{-0-1} \propto \text{Invariance}(0,0) \propto \frac{1}{\sigma^2}$$

Posterior Predictive Distr.

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

where  $\beta = \frac{4\sigma^2 + 4\theta^2}{2}$ ,  
 $\alpha = \frac{4+\gamma}{2}$

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

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

$$= \frac{\Gamma(\alpha')}{\beta^{\alpha'}} = \frac{\Gamma(\frac{n+n_0+1}{2})}{\left( \frac{n\sigma_0^2 + n_0\sigma_0^2 + (x^* - \theta)^2}{2} \right)^{-\frac{n+n_0+1}{2}}}$$

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

$$\propto \left( 1 + \frac{(x^* - \theta)^2}{n} \right)^{-\frac{n+1}{2}} = \left( 1 + \frac{1}{\frac{n}{2}} \frac{(x^* - \theta)^2}{2} \right)^{-\frac{n+1}{2}} \propto T_{\frac{n}{2}}\left(0, \frac{\sigma}{2}\right)$$

shifted & scaled student T

$$= T_{n+n_0}\left(0, \frac{n\sigma_0^2 + n_0\sigma_0^2}{n+n_0}\right)$$

known

we will derive this formally soon

Problem Review: class sheet

$F: X|\theta, n \sim \text{bin}(n, \theta)$ ,  $P(\theta) = \text{Beta}(\alpha, \beta)$   
 $\Rightarrow P(X^*|X, n) = \text{Beta}(\alpha + X^*, n - X^* + \beta)$

$F: X_1, \dots, X_n \in \text{Poisson}(\theta)$   
 Conj prior:  $\theta \sim \text{Gamma}(\alpha, \beta)$   
 Likelihood:  $\text{Gamma}(1, \theta)$   
 Holdout:  $\text{Gamma}(\theta, 0)$   
 Jeffreys:  $\text{Gamma}(\frac{1}{2}, 0)$

Posterior:  $P(\theta|x) = \text{Gamma}(Ex + \alpha, n + \beta)$

$\hat{\theta}_{MLE} = \frac{Ex + \alpha}{n + \beta}$ ,  $\hat{\theta}_{MAP} = \frac{Ex + \alpha - 1}{n + \beta}$ ,  $\hat{\theta}_{Bayes} = \text{EGamma}(0.5, Ex + \alpha, n + \beta)$ ,  $\hat{\theta}_{MLE} = \bar{X}$   
 CR's: use gamma approx! Hyp tests: use gamma approximations! Shrinkage:  $\phi = \frac{\beta}{n + \beta}$

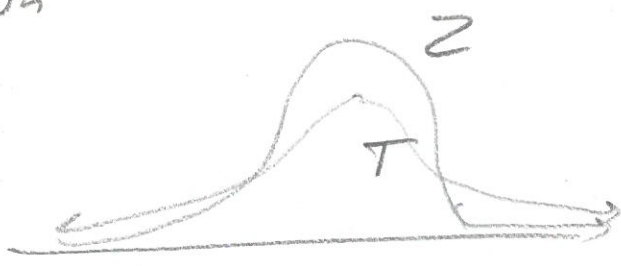
Post. pred:  $P(X^*|x) = \text{BetaBin}(Ex + \alpha, \frac{n + \beta}{n + \beta + 1})$

What is the T distr? Back to 291... Let  $X_1, \dots, X_n | \theta, \sigma^2 \sim N(\theta, \sigma^2)$

$\Rightarrow \frac{\bar{X} - \theta}{\frac{\sigma}{\sqrt{n}}} \sim N(0, 1)$  Basis for "z-test"

But what if  $\sigma$  unknown? We know  $S \approx \sigma$   $S = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2}$

$\frac{\bar{X} - \theta}{\frac{S}{\sqrt{n}}} \sim T_{n-1}(0, 1) = T_{n-1}$  ↓ Should be standard Student's T distr.



Looks like some bus lines stretch tails.

Recall if  $P(\theta) \propto 1$

$\Rightarrow P(\theta | x, \sigma^2) = N(\bar{x}, \frac{\sigma^2}{n})$  Now...

$P(\theta | x) = T_{n-1}(\bar{x}, \frac{S}{\sqrt{n}})$  Same thing with Student tails!

FVI

If  $V \sim T_n := \frac{\Gamma(\frac{n+1}{2})}{\sqrt{\pi n} \Gamma(\frac{n}{2})} \left(1 + \frac{v^2}{n}\right)^{-\frac{n+1}{2}} = T_n(0, 1) = T_n$  (standard T)  
(non-centered T)  
 $= T_n(\mu, \sigma)$

$W = \sigma V + \mu = t(w) \Rightarrow v = \frac{w - \mu}{\sigma} = t^{-1}(w)$

$f_w(w) = f_v(t^{-1}(w)) \left| \frac{d}{dw} t^{-1}(w) \right| = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{\pi n} \Gamma(\frac{n}{2})} \left(1 + \frac{(w - \mu)^2}{\sigma^2 n}\right)^{-\frac{n+1}{2}} \frac{1}{\sigma} = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{\pi n \sigma^2} \Gamma(\frac{n}{2})} \left(1 + \frac{1}{n} \frac{(w - \mu)^2}{\sigma^2}\right)^{-\frac{n+1}{2}}$