

Math 3A1 4/2/19 Lecture

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$$P(x^* | x, \sigma^2) \propto e^{-\frac{x^{*2}}{2\sigma^2}} \sqrt{\frac{\pi}{b}} e^{\frac{q^2}{4b}} \propto e^{-\frac{x^{*2}}{2\sigma^2} + \frac{q^2}{4b}} = e^{-\frac{x^{*2}}{2\sigma^2} + \frac{x^{*2}}{4b\sigma_p^2} + \frac{2x^*\sigma_p}{4b\sigma_p^2\sigma^2} + \frac{\sigma_p^2}{(4b\sigma_p^2\sigma^2)^2}} e^{\frac{\sigma_p^2}{(4b\sigma_p^2\sigma^2)^2}}$$

$$q^2 = \left(\frac{x^*}{\sigma^2} + \frac{\sigma_p}{\sigma_p^2}\right)^2 = \frac{x^{*2}}{(\sigma^2)^2} + \frac{2x^*\sigma_p}{\sigma^2\sigma_p^2} + \frac{\sigma_p^2}{(\sigma_p^2)^2}$$

$$b = \frac{1}{2\sigma^2} + \frac{1}{2\sigma_p^2}$$

$$\propto e^{\left(\frac{2\sigma_p}{4b\sigma_p^2\sigma^2} - \frac{1}{2\sigma^2}\right)x^* - \left(-\frac{1}{4b\sigma_p^2\sigma^2}\right)x^{*2}}$$

$$\propto N\left(\frac{c}{2d}, \frac{1}{2d}\right)$$

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

$$\frac{1}{2d} =$$

$$2\left(-\frac{1}{4b\sigma_p^2\sigma^2}\right) = -2b\sigma_p^2\sigma^2 = -2\left(\frac{1}{2\sigma^2} + \frac{1}{2\sigma_p^2}\right)\sigma_p^2\sigma^2 = \sigma_p^2 + \sigma^2$$

$$\frac{c}{2d} = c\left(\frac{1}{2d}\right) = \left(\frac{\sigma_p}{2b\sigma_p^2\sigma^2} - \frac{1}{2\sigma^2}\right)(\sigma_p^2 + \sigma^2) = \left(\frac{\sigma_p}{\sigma_p^2 + \sigma^2} - \frac{1}{2\sigma^2}\right)(\sigma_p^2 + \sigma^2) = \sigma_p - \frac{\sigma^2}{2\sigma^2}$$

$$2b\sigma_p^2\sigma^2 = 2\left(\frac{1}{2\sigma^2} + \frac{1}{2\sigma_p^2}\right)\sigma_p^2\sigma^2 = \sigma_p^2 + \sigma^2$$

$$4b(\sigma^2)^2 = 4\left(\frac{1}{2\sigma^2} + \frac{1}{2\sigma_p^2}\right)(\sigma^2)^2 = 2\left(\sigma^2 + \frac{(\sigma^2)^2}{\sigma_p^2}\right)$$

$$\propto e^{\frac{\sigma_p}{2b\sigma_p^2\sigma^2}x^* - \left(\frac{1}{2\sigma^2} - \frac{1}{4b(\sigma^2)^2}\right)x^{*2}} \propto N\left(\frac{c}{2d}, \frac{1}{2d}\right) = N(\sigma_p, \sigma^2 + \sigma_p^2)!!$$

$$\frac{1}{2d} = \frac{1}{2\left(\frac{1}{2\sigma^2} + \frac{1}{4b(\sigma^2)^2}\right)} = \frac{1}{\sigma^2 - \frac{1}{2b(\sigma^2)^2}} = \frac{1}{\frac{2b(\sigma^2)^2 - \sigma^2}{2b(\sigma^2)^2}} = \frac{2b(\sigma^2)^2}{2b(\sigma^2)^2 - \sigma^2} = \frac{2b(\sigma^2)^2}{2b\sigma^2 - 1} = \frac{2\left(\frac{1}{2\sigma^2} + \frac{1}{2\sigma_p^2}\right)(\sigma^2)^2}{2\left(\frac{1}{2\sigma^2} + \frac{1}{2\sigma_p^2}\right)\sigma^2 - 1}$$

$$= \frac{\sigma^2 + \frac{(\sigma^2)^2}{\sigma_p^2}}{1 + \frac{\sigma^2}{\sigma_p^2} - 1} = \frac{\sigma^2\sigma_p^2 + (\sigma^2)^2}{\sigma^2} = \sigma_p^2 + \sigma^2$$

$$\frac{c}{2d} = c\left(\frac{1}{2d}\right) = \frac{\sigma_p}{(2b\sigma_p^2\sigma^2)\sigma_p^2}(\sigma_p^2 + \sigma^2) = \frac{\sigma_p}{(1 + \frac{\sigma^2}{\sigma_p^2})\sigma_p^2}(\sigma_p^2 + \sigma^2) = \frac{\sigma_p}{\sigma_p^2 + \sigma^2}(\sigma_p^2 + \sigma^2) = \sigma_p$$



$$\sigma_p^2 \xrightarrow{h \rightarrow \infty} 0 \quad P(x^* | x, \sigma^2) \xrightarrow{h \rightarrow \infty} P(x^* | \sigma, \sigma^2)$$

we are done with inferring  $\theta$  when  $\sigma^2$  known. Now we do the opposite: inferring  $\sigma^2$  when  $\theta$  known.

$$F: \underbrace{X_1, \dots, X_n}_x | \theta, \sigma^2 \sim N(\theta, \sigma^2)$$

$$P(x | \theta, \sigma^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_i - \theta)^2} = (2\pi\sigma^2)^{-n/2} e^{-\frac{1}{2\sigma^2} \sum (x_i - \theta)^2}$$

Let's find  $\hat{\sigma}_{MLE}^2$  first.

$$l(\sigma^2; x, \theta) = -\frac{n}{2} \ln(2\pi) - \frac{n}{2} \ln(\sigma^2) - \frac{1}{2\sigma^2} \sum (x_i - \theta)^2$$

$$l'(\sigma^2; x, \theta) = -\frac{n}{2} \frac{1}{\sigma^2} + \frac{1}{2(\sigma^2)^2} \sum (x_i - \theta)^2 \stackrel{\text{constant!}}{=} 0$$

$$\Rightarrow -n + \frac{\sum (x_i - \theta)^2}{\sigma^2} = 0 \Rightarrow \hat{\sigma}_{MLE}^2 = \frac{1}{n} \sum (x_i - \theta)^2$$

make sure?

Aug. 2nd derivation for mean!!

$$P(\sigma^2 | x, \theta) \propto (\sigma^2)^{-n/2} e^{-\frac{n \hat{\sigma}_{MLE}^2 / 2}{\sigma^2}} = (\sigma^2)^{-n} e^{-\frac{n}{2\sigma^2}}$$

Back to prob. theory... 6.2) suff...

$$\text{Let's say } P(y) \propto y^{-a} e^{-\frac{b}{y}}$$

Let us try to solve for the normalization constant

$$\frac{1}{C} = \int_0^{\infty} u^{-a} e^{-b/u} du$$

a kernel we have seen!

$$\text{let } t = \frac{b}{y} \Rightarrow u = \frac{b}{t} \Rightarrow \frac{du}{dt} = -b t^{-2} \Rightarrow du = -b t^{-2} dt$$

$$u=0 \Rightarrow t=\infty, u=\infty \Rightarrow t=0$$

$$\Rightarrow \frac{1}{c} = \int_0^{\infty} \left(\frac{b}{t}\right)^{-q} e^{-t} (-b t^{-2}) dt = \int_0^{\infty} b^{-q} t^q e^{-t} b t^{-2} dt$$

$$= \int_0^{\infty} b^{-q+1} t^{q-2} e^{-t} dt = b^{-q+1} \int_0^{\infty} t^{(q-1)-1} e^{-t} dt = b^{-q+1} \Gamma(q-1)$$

$$\Rightarrow c = \frac{b^{q-1}}{\Gamma(q-1)}$$

Inversion conjugate prior  
for likelihood model

$$\Rightarrow P(y) = \frac{b^{q-1}}{\Gamma(q-1)} y^{-q} e^{-\frac{b}{y}} = \text{Inv Gamma}(q+1, b) \quad \alpha \leq 1 \Rightarrow \text{no mean!!}$$

In general ...  $P(y) = \text{Inv Gamma}(\alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} y^{-\alpha-1} e^{-\frac{\beta}{y}}$

why called inverse gamma?

$$P(U) = \text{Gamma}(\alpha, \beta)$$

$$V = t(U) = \frac{1}{U} \sim ?$$

$$u = t^{-1}(v) = \frac{1}{v}$$

$$f_V(v) = f_U(t^{-1}(v)) \left| \frac{d}{dv} [t^{-1}(v)] \right| = f_U\left(\frac{1}{v}\right) \left| \frac{d}{dv} \left[\frac{1}{v}\right] \right|$$

$$= \left( \frac{\beta^\alpha}{\Gamma(\alpha)} \left(\frac{1}{v}\right)^{\alpha-1} e^{-\beta \frac{1}{v}} \right) \left| -\frac{1}{v^2} \right| = \frac{\beta^\alpha}{\Gamma(\alpha)} v^{-\alpha+1-2} e^{-\frac{\beta}{v}}$$

$$= \frac{\beta^\alpha}{\Gamma(\alpha)} v^{-\alpha-1} e^{-\frac{\beta}{v}}$$

$F: X_1, \dots, X_n | \theta, \sigma^2 \sim N(\theta, \sigma^2)$  with  $\theta$  known

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

$$\Rightarrow P(\theta, \sigma^2 | x, \theta) \propto \underbrace{(\sigma^2)^{-n/2} e^{-\frac{\sum_{i=1}^n (x_i - \theta)^2}{2\sigma^2}}}_{K(x|\theta)} \underbrace{(\sigma^2)^{-\alpha-1} e^{-\frac{\beta}{\sigma^2}}}_{K(\sigma^2|\theta)} = \underbrace{(\sigma^2)^{-\left(\frac{n}{2} + \alpha\right) - 1} e^{-\frac{\frac{\sum_{i=1}^n (x_i - \theta)^2}{2} + \beta}{\sigma^2}}}_{K(\sigma^2|x, \theta)}$$

$$\propto \text{InvGamma} \left( \frac{n}{2} + \alpha, \frac{n\hat{\sigma}_{MLE}^2}{2} + \beta \right)$$

units don't  
really line up so no easy pseudo-count interpretation

Let's parameterize the prior differently.

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

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

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

Pseudocount Interpretation:

$n_0$ : # pseudobservers (strength)

$\sigma_0^2$ : variance of the pseudobservers

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

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

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

CR 3 & Hypothesis Tests... same!!

Uninformative Priors

① Laplace  $P(\theta | \theta) \propto 1$

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

only proper if  $n \geq 3$

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

Shrinkage

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