

# Lecture 20 MATH 3A1/6A1

New def:  $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Poisson}(\theta) := \frac{\theta^x e^{-\theta}}{x!} \mathbb{1}_{x \in \mathbb{N}_0}$ ,  $\theta \in (0, \infty)$

prior & posterior counting

$$f(\theta | \vec{x}) = \frac{p(\vec{x} | \theta) f(\theta)}{p(\vec{x})} \propto p(\vec{x} | \theta) f(\theta) = \left( \prod_{i=1}^n \frac{\theta^{x_i} e^{-\theta}}{x_i!} \right) f(\theta)$$

$$= \frac{\theta^{\sum x_i} e^{-n\theta}}{\prod x_i!} f(\theta)$$

$\propto \theta^{\sum x_i} e^{-n\theta} k(\theta)$  What does the conjugate kernel look like?

$$\propto (\theta^{\sum x_i} e^{-n\theta}) (\theta^{\alpha-1} e^{-\beta\theta}) \Rightarrow f(\theta) = \text{Gamma}(\alpha, \beta), \text{ s.t. } \alpha, \beta > 0$$

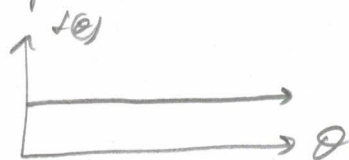
$$= \theta^{\alpha + \sum x_i - 1} e^{-(\beta + n)\theta} \propto \text{Gamma}(\alpha + \sum x_i, \beta + n)$$

Pseudocount interpretation? Look at counts!!

$\alpha = \# \text{ pseudocounts}$

$\beta = n_0 = \# \text{ pseudocounts}$

Laplace Prior?



No way to have a flat prior on  $\theta \in (0, \infty)$ .

Trick: let  $f(\theta) \propto 1$ . If so...

$$f(\theta | \vec{x}) \propto \theta^{\sum x_i} e^{-n\theta} (1) \propto \text{Gamma}(1 + \sum x_i, n) \Rightarrow f(\theta) = \text{Gamma}(1, 0)$$

improper  
since  $\beta \neq 0$ !

Haldane Prior? Total ignorance

$$\# \text{ pseudocounts} = 0 \Rightarrow \alpha = 0$$

$$n_0 = 0 \Rightarrow \beta = 0$$

$$\Rightarrow f(\theta) = \text{Gamma}(0, 0) \text{ improper!}$$

Jeffreys Prior  $\propto 1/\theta$

Also Improper

$$f_J(\theta) \propto \sqrt{I(\theta)} = \sqrt{\frac{n}{\theta}} \propto \theta^{-\frac{1}{2}} = \theta^{\frac{1}{2}-1} \propto \text{gamma}(\frac{1}{2}, 0)$$

Point Estimates?

$$\hat{\theta}_{\text{MMSE}} = \frac{\alpha + \sum x_i}{\beta + n}$$

$$\hat{\theta}_{\text{MMSE}} = \text{gamma}(0.5, \alpha + \sum x_i, \beta + n) \quad \text{Not available in closed form}$$

$$X \sim \text{gamma}(\alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-\beta x}$$

$$\text{Mode}(X) = ? \quad \text{symm}\{f_X(x)\} = \text{symm}\{x^{\alpha-1} e^{-\beta x}\}$$

$$\Rightarrow (x^{\alpha-1})(-\beta e^{-\beta x}) + (\alpha-1)x^{\alpha-2}e^{-\beta x} \stackrel{!}{=} 0$$

$$\Rightarrow x^{\alpha-2} e^{-\beta x} (-\beta x + \alpha - 1) = 0$$

$$\Rightarrow (\alpha-1) = \beta x \quad x = \frac{\alpha-1}{\beta} \quad \text{only 1 mode if } \alpha > 1, \text{ otherwise } 0$$

$$\Rightarrow \hat{\theta}_{\text{MAP}} = \frac{\alpha + \sum x_i - 1}{\beta + n} \quad \text{for } \alpha + \sum x_i - 1 > 1, \text{ otherwise } 0$$

$$\hat{\theta}_{\text{MLE}} \stackrel{\text{Under Laplace i.e. } \alpha=1, \beta=0}{=} \hat{\theta}_{\text{MAP}} = \frac{\sum x_i}{n} = \bar{x} \quad \text{if } \sum x_i > 0, \text{ otherwise } 0$$

(13)

2-sided  
Credible Region

$$CR_{\theta, 1-\alpha_0} = \left[ \text{pgamma}\left(\frac{\chi^2_0}{2}, \alpha + \varepsilon_{\alpha}, \beta + \gamma\right), \text{pgamma}\left(1 - \frac{\chi^2_0}{2}, \alpha + \varepsilon_{\alpha}, \beta + \gamma\right) \right]$$

Hypothesis Tests at level  $\alpha_0$

$$H_a: \theta > \theta_0 \Rightarrow H_0: \theta \leq \theta_0$$

$$p_{\text{val}} = \text{pgamma}(\theta_0, \alpha + \varepsilon_{\alpha}, \beta + \gamma) \quad \text{Reject if } p_{\text{val}} \geq \alpha_0$$

$$H_a: \theta < \theta_0 \Rightarrow H_0: \theta \geq \theta_0$$

$$p_{\text{val}} = 1 - \text{pgamma}(\theta_0, \alpha + \varepsilon_{\alpha}, \beta + \gamma) \quad \text{Reject if } p_{\text{val}} \geq \alpha_0$$

$$H_a: \theta \neq \theta_0 \Rightarrow H_0: \theta = \theta_0$$

Using margin of equivalence  $S$

$$\Rightarrow H_a: \theta \notin [\theta_0 \pm S] \Rightarrow H_0: \theta \in [\theta_0 \pm S]$$

$$p_{\text{val}} = \text{pgamma}(\theta_0 + S, \alpha + \varepsilon_{\alpha}, \beta + \gamma) - \text{pgamma}(\theta_0 - S, \alpha + \varepsilon_{\alpha}, \beta + \gamma)$$

Using CR method

Reject if  $p_{\text{val}} \geq \alpha_0$

Reject  $H_0$  if  $\theta_0 \in CR_{\theta, 1-\alpha_0}$

## Poisson Predictive Distribution

observe  $X_1, \dots, X_n$ . What is dist of  $X_{n+1}$ , the future observation

Note: we only do the case of  $\eta_i = 1$  otherwise very complicated.

$$P(X_{n+1}) = \int_{\mathbb{R}} \underbrace{P(X_i | \theta)}_{\text{Poisson}(\theta)} \underbrace{f(\theta | \mathbf{x})}_{\text{Gamma}(\alpha + \sum x_i, \beta + n)} d\theta \quad \begin{array}{l} \text{by Mark 390 Lec 19} \\ \downarrow \end{array} = \text{ExpNegBin}(\alpha + \sum x_i, \frac{\beta + n}{\beta + n + 1})$$

Shrinkage...

$$\begin{aligned} \hat{g}_{\text{marg}} &= \frac{\alpha + \sum x_i}{\beta + n} = \frac{\alpha}{\beta + n} \cdot \frac{\beta}{\beta} + \frac{\sum x_i}{\beta + n} \cdot \frac{n}{n} \\ &= \underbrace{\frac{\beta}{\beta + n}}_p \underbrace{\frac{\alpha}{\beta}}_{E(\theta)} + \underbrace{\frac{n}{\beta + n}}_{(1-p)} \underbrace{\bar{x}}_{\hat{g}_{\text{marg}}} \end{aligned}$$

Done!

New Model!

likelihood and prior pred. distr cons.

DBP:  $X_1, \dots, X_n \stackrel{iid}{\sim} N(\theta, \sigma^2)$  where  $\sigma^2$  known

$$\theta \in \mathbb{R}$$

prior and posterior continuous

$$f(\theta | \vec{x}, \sigma^2) = \frac{f(\vec{x} | \theta, \sigma^2) f(\theta | \sigma^2)}{f(\vec{x} | \sigma^2)}$$

$$\propto f(\vec{x} | \theta, \sigma^2) f(\theta | \sigma^2)$$

$$\propto \left( \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x_i - \theta)^2} \right) k(\theta | \sigma^2)$$

$$\propto e^{-\frac{1}{2\sigma^2} \sum (x_i - \theta)^2} k(\theta | \sigma^2)$$

$$= e^{-\frac{1}{2\sigma^2} (\sum x_i^2 - 2\theta \sum x_i + n\theta^2)} k(\theta | \sigma^2)$$

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

$$\propto e^{\frac{n\bar{x}}{\sigma^2} \theta - \frac{n}{2\sigma^2} \theta^2} k(\theta | \sigma^2)$$

What's the conjugate prior?

$$= e^{(a_0 + \frac{n\bar{x}}{\sigma^2})\theta - (b_0 + \frac{n}{2\sigma^2})\theta^2} \propto e^{a_0\theta - b_0\theta^2}$$

$$\propto N\left(\frac{a_0 + \frac{n\bar{x}}{\sigma^2}}{2b_0 + \frac{n}{\sigma^2}}, \frac{1}{2b_0 + \frac{n}{\sigma^2}}\right)$$

$$f(\theta | \sigma^2) = N\left(\frac{a_0}{2b_0}, \frac{1}{2b_0}\right) = N(\mu_0, \tau^2)$$

$$= N\left(\frac{\frac{\mu_0}{\tau^2} + \frac{n\bar{x}}{\sigma^2}}{\frac{1}{\tau^2} + \frac{n}{\sigma^2}}, \frac{1}{\frac{1}{\tau^2} + \frac{n}{\sigma^2}}\right)$$

Let  $b_0 = \frac{1}{2\tau^2}$ ,  $a_0 = \frac{\mu_0}{\tau^2}$

## Point Estimation

$$\hat{\theta}_{\text{MMSE}} = \hat{\theta}_{\text{MLE}} = \hat{\theta}_{\text{MAP}} = \theta_p = \frac{\frac{\mu_0}{\tau^2} + \frac{y}{\sigma^2}}{\frac{1}{\tau^2} + \frac{1}{\sigma^2}}$$

## Credible Region

$$CR_{\theta, 1-\alpha} = \left[ q_{\text{norm}}\left(\frac{\alpha}{2}, \theta_p, \sigma_p^2\right), q_{\text{norm}}\left(1-\frac{\alpha}{2}, \theta_p, \sigma_p^2\right) \right]$$

## Hypothesis Tests

$$H_0: \theta \leq \theta_0, H_1: \theta > \theta_0$$

$$p_{\text{val}} = P(H_0 | \vec{x}) = P(\theta \leq \theta_0 | \vec{x}) = \text{pnorm}(\theta_0, \theta_p, \sigma_p^2)$$

$$H_0: \theta \geq \theta_0, H_1: \theta < \theta_0$$

$$p_{\text{val}} = P(H_0 | \vec{x}) = P(\theta \geq \theta_0 | \vec{x}) = 1 - \text{pnorm}(\theta_0, \theta_p, \sigma_p^2)$$