

Tutorial Problems 3
MATH3871/MATH5970
Bayesian Inference and Computation

1. Find Jeffreys' prior for θ in the geometric model

$$\mathbb{P}(X = x | \theta) = (1 - \theta)^{x-1}\theta; \quad x = 1, 2, \dots$$

for a random sample X_1, \dots, X_n .

2. Suppose that $X_1, \dots, X_n \sim \mathbf{N}(\mu, \tau^{-1})$ with a known μ , where $\tau = 1/\sigma^2$ is the precision parameter. If we specify the prior $\tau \sim \mathbf{Gamma}(\alpha, \beta)$, since $\tau = 1/\sigma^2$, then σ^2 is distributed as Inverse Gamma. Show that the Gamma distribution is conjugate for the posterior of τ , and that the Inverse Gamma distribution is the conjugate for the posterior of σ^2 .

Solutions

1. The likelihood for this model is

$$L(x|\theta) = (1 - \theta)^{\sum x_i - n} \theta^n.$$

Noting that $E(x) = 1/\theta$, then the information matrix is computed as

$$\begin{aligned} I(\theta) &= -E\left(\frac{\partial^2 \log L(x|\theta)}{\partial \theta^2}\right) \\ &= -E\left(\frac{\partial^2 ((\sum x_i - n) \log(1 - \theta) + n \log \theta)}{\partial \theta^2}\right) \\ &= -E\left(\frac{\partial [-\frac{\sum x_i - n}{1 - \theta} + \frac{n}{\theta}]}{\partial \theta}\right) \\ &= E\left(\frac{\sum x_i - n}{(1 - \theta)^2} + n/\theta^2\right) \\ &= \frac{nE(x_i) - n}{(1 - \theta)^2} + n/\theta^2 \\ &= n\left[\frac{1/\theta - 1}{(1 - \theta)^2} + 1/\theta^2\right] \\ &\propto \frac{1}{\theta^2(1 - \theta)} \end{aligned}$$

Hence Jeffreys' prior is proportional to $|I(\theta)|^{1/2} = \theta^{-1}(1 - \theta)^{-1/2}$.

2. The likelihood is

$$L(x|\tau^{-1}) = \prod_{i=1}^n \sqrt{\frac{\tau}{2\pi}} \exp(-\tau/2(x - \mu)^2)$$

and the prior is a Gamma distribution

$$\pi(\tau) \propto \tau^{\alpha-1} \exp(-\beta\tau).$$

Hence the posterior distribution is $(S_\mu^2 := \sum_{i=1}^n (x_i - \mu)^2/n)$

$$\begin{aligned} \pi(\tau|x) &\propto \tau^{n/2} \exp(-nS_\mu^2\tau/2) \times \tau^{\alpha-1} \exp(-\beta\tau) \\ &= \tau^{\alpha+n/2-1} \exp(-\tau[\beta + nS_\mu^2]) \\ \tau|x &\sim \text{Gamma}(n/2 + \alpha, \beta + 1/2nS_\mu^2). \end{aligned}$$

Similarly, if we use the σ^2 parameterisation, then

$$L(x|\sigma^2) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma^2}} \exp(-\frac{1}{2\sigma^2}(x - \mu)^2),$$

and the prior is an Inverse Gamma distribution

$$\pi(\sigma^2) \propto \sigma^{2(-\alpha-1)} \exp(-\beta/\sigma^2).$$

Hence the posterior distribution is

$$\begin{aligned} \pi(\sigma^2|x) &\propto \sigma^{-n/2} \exp\left(-\frac{nS_\mu^2}{2\sigma^2}\right) \times \sigma^{2(-\alpha-1)} \exp(-\beta/\sigma^2) \\ &= \sigma^{-n/2-\alpha-1} \exp\left(-\frac{1}{\sigma^2}[\beta + \frac{nS_\mu^2}{2}]\right) \\ \sigma^2|x &\sim \text{IGamma}(n/2 + \alpha, \beta + nS_\mu^2/2). \end{aligned}$$