

# ST308 Bayesian Inference

Kostas Kalogeropoulos (Office B610)

## Week 1: Exercises

1. Let  $x = (x_1, \dots, x_n)$  be a random sample from an  $\text{Exponential}(\lambda)$  distribution. Set the prior for  $\lambda$  to be a  $\text{Gamma}(\alpha, \beta)$  and derive its posterior distribution.

*Answer:* The likelihood can be written as

$$f(x|\lambda) = f(x_1, \dots, x_n|\lambda) = \prod_{i=1}^n \lambda \exp(-\lambda x_i) = \lambda^n \exp\left(-\lambda \sum_{i=1}^n x_i\right)$$

The prior is set to a  $\text{Gamma}(\alpha, \beta)$ , so we can write

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

The posterior is then proportional to

$$\begin{aligned} \pi(\lambda|x) &\propto f(x|\lambda)\pi(\lambda) \propto \lambda^n \exp\left(-\lambda \sum_{i=1}^n x_i\right) \lambda^{\alpha-1} \exp(-\beta\lambda) \\ &= \lambda^{n+\alpha-1} \exp\left[-\lambda \left(\beta + \sum_{i=1}^n x_i\right)\right] \\ &\stackrel{\mathcal{D}}{=} \text{Gamma}\left(n + \alpha, \beta + \sum_{i=1}^n x_i\right) \end{aligned}$$

2. Let  $x = (x_1, \dots, x_n)$  be a random sample from a  $N(\theta, \sigma^2)$  distribution with  $\sigma^2$  known.

(a) Show that the likelihood is proportional to

$$f(x|\theta) \propto \exp\left(-\frac{n(\bar{x} - \theta)^2 + (n-1)S^2}{2\sigma^2}\right).$$

where  $\bar{x}$  is the sample mean and  $S^2$  is the sample variance

$$S^2 = \frac{1}{n-1} \sum_{i=1}^n (x_i - \bar{x})^2.$$

Hence the likelihood simplifies to

$$f(x|\theta) \propto \exp\left(-\frac{(\theta - \bar{x})^2}{2\frac{\sigma^2}{n}}\right)$$

- (b) Set the prior for  $\theta$  to be  $N(\mu, \tau^2)$  and derive its posterior distribution. (You can use the above result)

*Answer:*

- 2 (a) The joint density of the sample  $x$  is

$$\begin{aligned} f(x|\theta, \sigma^2) &= f(x_1, \dots, x_n|\theta, \sigma^2) = \prod_{i=1}^n (2\pi\sigma^2)^{-1/2} \exp\left(-\frac{(x_i - \theta)^2}{2\sigma^2}\right) \\ &= (2\pi\sigma^2)^{-n/2} \exp\left(-\frac{\sum_{i=1}^n (x_i - \theta)^2}{2\sigma^2}\right) \end{aligned}$$

Hence, it suffices to show that

$$\sum_{i=1}^n (x_i - \theta)^2 = n(\bar{x} - \theta)^2 + \sum_{i=1}^n (x_i - \bar{x})^2.$$

Note that

$$\begin{aligned} \sum_{i=1}^n (x_i - \theta)^2 &= \sum_{i=1}^n (x_i^2 - 2\theta x_i + \theta^2) = \sum_{i=1}^n x_i^2 - 2\theta n\bar{x} + n\theta^2 \\ \sum_{i=1}^n (x_i - \bar{x})^2 &= \sum_{i=1}^n (x_i^2 - 2\bar{x}x_i + \bar{x}^2) = \sum_{i=1}^n x_i^2 - 2n\bar{x}^2 + n\bar{x}^2 = \sum_{i=1}^n x_i^2 - n\bar{x}^2 \end{aligned}$$

Subtracting the second of these equations from the first yields

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

Since  $\sigma^2$  is known, we are interested in  $f(x|\theta)$  which is proportional to

$$\begin{aligned} f(x|\theta) &= (2\pi\sigma^2)^{-n/2} \exp\left(-\frac{n(\bar{x} - \theta)^2 + (n-1)S^2}{2\sigma^2}\right) \\ &\propto \exp\left(-\frac{n(\bar{x} - \theta)^2}{2\sigma^2}\right) \exp\left(-\frac{(n-1)S^2}{2\sigma^2}\right) \\ &\propto \exp\left(-\frac{(\theta - \bar{x})^2}{2\frac{\sigma^2}{n}}\right) \end{aligned}$$

2 (b) The prior for  $\theta$  is set to be  $N(\mu, \tau^2)$ . Hence we can write

$$\pi(\theta) \propto \exp\left(-\frac{(\theta - \mu)^2}{2\tau^2}\right).$$

Using the result of part (i), the posterior is then proportional to

$$\begin{aligned}\pi(\theta|x) &\propto f(x|\theta)\pi(\theta) \propto \exp\left(-\frac{(\theta - \bar{x})^2}{2\frac{\sigma^2}{n}}\right) \exp\left(-\frac{(\theta - \mu)^2}{2\tau^2}\right) \\ &= \exp\left(-\frac{\theta^2 + 2\theta\bar{x}}{2\frac{\sigma^2}{n}} - \frac{\theta^2 - 2\theta\mu}{2\tau^2}\right) \exp\left(-\frac{\bar{x}^2}{2\frac{\sigma^2}{n}}\right) \exp\left(-\frac{\mu^2}{2\tau^2}\right) \\ &\propto \exp\left(-\frac{\theta^2 + 2\theta\bar{x}}{2\frac{\sigma^2}{n}} - \frac{\theta^2 - 2\theta\mu}{2\tau^2}\right) \\ &= \exp\left(-\frac{\tau^2\theta^2 - 2\theta\bar{x}\tau^2 + \frac{\sigma^2}{n}\theta^2 - 2\theta\mu\frac{\sigma^2}{n}}{2\frac{\sigma^2}{n}\tau^2}\right) \\ &= \exp\left(-\frac{(\frac{\sigma^2}{n} + \tau^2)\theta^2 - 2\theta(\bar{x}\tau^2 + \mu\frac{\sigma^2}{n})}{2\frac{\sigma^2}{n}\tau^2}\right) \\ &= \exp\left(-\frac{\theta^2 - 2\theta\frac{\bar{x}\tau^2 + \mu\frac{\sigma^2}{n}}{(\frac{\sigma^2}{n} + \tau^2)}}{2\frac{\frac{\sigma^2}{n}\tau^2}{(\frac{\sigma^2}{n} + \tau^2)}}\right) \stackrel{\mathcal{D}}{=} N\left(\frac{\frac{\sigma^2}{n}\mu + \tau^2\bar{x}}{\tau^2 + \frac{\sigma^2}{n}}, \frac{\tau^2\frac{\sigma^2}{n}}{\tau^2 + \frac{\sigma^2}{n}}\right)\end{aligned}$$

3. Let  $x = (x_1, \dots, x_n)$  be a random sample from a  $N(0, \sigma^2)$  distribution. Set the prior for  $\sigma^2$  to be  $\text{IGamma}(\alpha, \beta)$  and derive its posterior distribution.

*Answer:*

$$\begin{aligned}f(x|\sigma^2) &= f(x_1, \dots, x_n|\sigma^2) = \prod_{i=1}^n (2\pi)^{-1/2} (\sigma^2)^{-1/2} \exp\left(-\frac{x_i^2}{2\sigma^2}\right) \\ &\propto (\sigma^2)^{-n/2} \exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2}\right)\end{aligned}$$

The prior is set to a  $\text{IGamma}(\alpha, \beta)$ , so we can write

$$\pi(\sigma^2) \propto (\sigma^2)^{-\alpha-1} \exp\left(-\frac{\beta}{\sigma^2}\right)$$

The posterior is then proportional to

$$\begin{aligned}
\pi(\sigma^2|x) &\propto f(x|\theta)\pi(\theta) \propto (\sigma^2)^{-n/2} \exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2}\right) (\sigma^2)^{-\alpha-1} \exp\left(-\frac{\beta}{\sigma^2}\right) \\
&= (\sigma^2)^{-(n/2+\alpha)-1} \exp\left[-\frac{\beta + \frac{1}{2}\sum_{i=1}^n x_i^2}{\sigma^2}\right] \\
&\stackrel{\mathcal{D}}{=} \text{IGamma}\left(n/2 + \alpha, \beta + \frac{1}{2}\sum_{i=1}^n x_i^2\right)
\end{aligned}$$