

# BAYESIAN STATISTICS

## Chapter 9

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## 9. Population Variance Estimation

### 9.1. Introduction

In this new chapter, we continue to consider normal distribution. Contrast to the last chapter where  $\mu$  is the parameter of interest and  $\sigma^2$  is known, this chapter considers the inference on  $\sigma^2$  with the known  $\mu$ .

It is not common in practice that  $\mu$  is known and  $\sigma^2$  is not known. With this simplification, however, the Bayesian inference on  $\sigma^2$  only is easy to derive and this will be a warm-start for the case for the unknown  $\mu$  and unknown  $\sigma^2$ .

## 9.2. Bayes estimation for $\sigma^2$

Instead of using  $\sigma^2$ , we consider  $p_{rec} = \frac{1}{\sigma^2}$ . Suppose, thus, that

$$X \sim N(\mu = m, \sigma^2) = N\left(m, \frac{1}{p_{rec}}\right).$$

Then, the likelihood is going to be

$$\ell(x|m, p_{rec}) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(x-m)^2}{2\sigma^2}\right\} = \frac{p_{rec}^{1/2}}{\sqrt{2\pi}} \exp\left\{-\frac{p_{rec}(x-m)^2}{2}\right\}.$$

The conjugate prior for  $p_{rec}$  is gamma distribution,  $\text{Gamma}(\alpha, \beta)$  for positive  $\alpha$  and  $\beta$ . Thus, the posterior is obtained as following:

- prior:  $g(p_{rec}) = \frac{1}{\Gamma(\alpha)\beta^\alpha} p_{rec}^{\alpha-1} e^{-p_{rec}/\beta}$

- likelihood:

$$\ell(x_1, \dots, x_n | p_{rec}) = \prod_{i=1}^n f(x_i | p_{rec}) = (2\pi)^{-n/2} p_{rec}^{n/2} \exp \left\{ -p_{rec} \frac{\sum_{i=1}^n (x_i - m)^2}{2} \right\}$$

- posterior:

$$\begin{aligned} h(p_{rec} | x_1, \dots, x_n) &\propto p_{rec}^{\alpha-1} e^{-p_{rec}/\beta} \times p_{rec}^{n/2} \exp \left\{ -p_{rec} \frac{\sum_{i=1}^n (x_i - m)^2}{2} \right\} \\ &\propto p_{rec}^{n/2 + \alpha - 1} \exp \left\{ -p_{rec} \left( \frac{\sum_{i=1}^n (x_i - m)^2}{2} + \frac{1}{\beta} \right) \right\} \\ &\sim \text{Gamma} \left( \frac{n}{2} + \alpha, \left\{ \frac{\sum_{i=1}^n (x_i - m)^2}{2} + \frac{1}{\beta} \right\}^{-1} \right) \end{aligned}$$

Thus, the Bayes estimate is

$$\hat{p}_{rec,B} = \frac{n/2 + \alpha}{ns^2/2 + 1/\beta}$$

with  $s^2 = \sum_{i=1}^n (x_i - m)^2 / n$ . This becomes  $1/s^2$  when  $n$  gets large.

The posterior variance is given as

$$\frac{n/2 + \alpha}{(ns^2/2 + 1/\beta)^2}$$

and, so, it is going to be close to zero when  $n$  gets large.

### 9.3. No prior information on $\sigma^2$

Suppose we consider the prior distribution for  $p_{rec} = 1/\sigma^2$  as gamma distribution  $\text{Gamma}(\alpha, \beta)$  as we did previously.

Note that no information on  $p_{rec}$  implies that there is no preference on any value of  $p_{rec} > 0$ . This can be interpreted as that the prior must “spread out” and be “flat”.

$\beta$  is the scale parameter. The larger  $\beta$ , the more the gamma distribution spreads out. So the natural choice is  $\beta \rightarrow \infty$ .

$\alpha$  is the shape parameter. The gamma distribution becomes symmetric when  $\alpha$  gets larger. If  $\alpha = 0$  (this makes the prior improper, anyway), then the gamma distribution becomes flat. Thus, the natural choice for  $\alpha$  is 0.

Thus the vague, and improper, prior for  $p_{rec}$  is

$$g(p_{rec}) = \frac{1}{p_{rec}}, \quad p_{rec} > 0$$

and the associated posterior is

$$\text{Gamma}\left(\frac{n}{2} + \alpha, \left(\frac{ns^2}{2} + \frac{1}{\beta}\right)^{-1}\right) \xrightarrow{\alpha \rightarrow 0, \beta \rightarrow \infty} \text{Gamma}\left(\frac{n}{2}, \left(\frac{ns^2}{2}\right)^{-1}\right).$$

Note that

$$\frac{ns^2}{\sigma^2} \left| (X_1, X_2, \dots, X_n) \sim \chi^2(n). \quad (\text{prove it!}) \right.$$

## 9.5. Credible interval for $\sigma^2$ with the vague prior

From the fact that  $\frac{ns^2}{\sigma^2} | (X_1, X_2, \dots, X_n) \sim \chi^2(n)$ ,

$$\begin{aligned} & \Pr \left( \chi_{n,\alpha/2}^2 \leq \frac{ns^2}{\sigma^2} \leq \chi_{n,1-\alpha/2}^2 \middle| X_1, \dots, X_n \right) \\ &= \Pr \left( \frac{ns^2}{\chi_{n,1-\alpha/2}^2} \leq \sigma^2 \leq \frac{ns^2}{\chi_{n,\alpha/2}^2} \middle| X_1, \dots, X_n \right) \\ &= 1 - \alpha. \end{aligned}$$

Thus, 95% EPD credible interval for  $\sigma^2$  is

$$\left( \frac{ns^2}{\chi_{n,1-\alpha/2}^2}, \frac{ns^2}{\chi_{n,\alpha/2}^2} \right).$$

In the same manner, 95% EPD credible interval for  $p_{rec}$  is

$$\left( \frac{\chi_{n,\alpha/2}^2}{ns^2}, \frac{\chi_{n,1-\alpha/2}^2}{ns^2} \right).$$

## Example (9-1)

Suppose we obtained 12 samples from normal distribution with mean  $m = 6$  and the unknown  $\sigma^2$  as follow:

7.12   5.62   4.31   8.22   6.39   5.91   6.55   5.25   7.02   4.99   6.02   7.00

If there is no prior information on  $\sigma^2$ , find the posterior for  $\sigma^2$  and the corresponding 95% EPD credible interval.

**(solution)** The posterior distribution with the vague prior is

$$p_{rec}|X_1, \dots, X_n \sim \text{Gamma}(n/2, ns^2/2).$$

From the data, we get  $s^2 = 1.1058$  and  $n = 12$ . Thus, the posterior of  $p_{rec}$  is  $\text{Gamma}(6, 6.6348)$ . The 95% EPD credible interval for  $p_{rec}$  is

$$\left( \frac{\chi_{n, \alpha/2}^2}{ns^2}, \frac{\chi_{n, 1-\alpha/2}^2}{ns^2} \right) = (0.3316, 1.7353)$$

and the 95% EPD credible interval for  $\sigma^2$  is

$$\left( \frac{ns^2}{\chi_{n, 1-\alpha/2}^2}, \frac{ns^2}{\chi_{n, \alpha/2}^2} \right) = (0.5762, 3.0157).$$