University of Montpellier M2 IDIL - HAX918X 2024 - 2025

## Partial examination - October 2, 2024 Duration 1 hour - Documents not allowed

**Exercise 1 (5 pts)** The number x of arrivals in a queue follows a negative binomial distribution with parameter  $(k, \theta)$  for  $x \in \mathbb{N}$ 

$$f(x|k,\theta) = C_x^{k+x-1}\theta^k(1-\theta)^x$$

with  $\theta \in ]0,1[$ . We assume k is fixed and wish to estimate  $\theta$ . We consider the Bayesian paradigm. What is the family of conjugate distributions for the parameter  $\theta$ ?

**Solution** The conjugate prior for  $\theta$  is the Beta distribution

$$\theta \sim \text{Beta}(\alpha, \beta)$$
.

**Exercise 2 (7 pts)** The lifetime x of an electrical component follows a lognormal distribution with parameter  $(\theta, 1)$  for  $x \in \mathbb{R}^*_+$ 

$$f(x|\theta, 1) = \frac{1}{x\sqrt{2\pi}} \exp\left(-\frac{1}{2}[\log(x) - \theta]^2\right)$$

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

We have a *n*-sample  $x_1, \ldots, x_n$  of lifetimes. We consider the Bayesian paradigm and assume that  $\theta$  is distributed according to a standard Gaussian distribution. Calculate the Bayesian estimator associated with the quadratic loss function.

**Solution** The lifetime follows a lognormal distribution, and we aim to find the Bayesian estimator for  $\theta$  under the quadratic loss function.

The likelihood function for a single observation  $x_i$  is given by the lognormal distribution:

$$f(x_i|\theta) = \frac{1}{x_i\sqrt{2\pi}} \exp\left(-\frac{1}{2}[\log(x_i) - \theta]^2\right)$$

For an *n*-sample of lifetimes,  $x_1, x_2, \ldots, x_n$ , the likelihood function is the product of the individual likelihoods

$$L(\theta|x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{x_i \sqrt{2\pi}} \exp\left(-\frac{1}{2} [\log(x_i) - \theta]^2\right)$$
$$L(\theta|x_1, \dots, x_n) \propto \exp\left(-\frac{1}{2} \left[n\theta^2 - 2\theta \sum_{i=1}^n \log(x_i)\right]\right).$$

We assume a standard normal prior for  $\theta$ 

$$\theta \sim \mathcal{N}(0,1)$$
.

We get

$$\pi(\theta) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\theta^2}{2}\right) \,,$$

and using Bayes' theorem, the posterior distribution is such that

$$\pi(\theta|x_1, \dots, x_n) \propto L(\theta|x_1, \dots, x_n)\pi(\theta),$$
  
$$\pi(\theta|x_1, \dots, x_n) \propto \exp\left(-\frac{1}{2}\left[(n+1)\theta^2 - 2\theta\sum_{i=1}^n \log(x_i)\right]\right).$$

This is a quadratic form in  $\theta$ , so the posterior distribution is Gaussian

$$\theta|x_1,\ldots,x_n \sim \mathcal{N}\left(\frac{\sum_{i=1}^n \log(x_i)}{n+1},\frac{1}{n+1}\right)$$

This is the Bayesian estimate of  $\theta$  under the quadratic loss function is

$$\hat{\theta} = \frac{\sum_{i=1}^{n} \log(x_i)}{n+1}.$$

**Exercise 3 (8 pts)** The waiting time t between two telephone calls in a call centre follows an exponential distribution with parameter  $\lambda > 0$ . We have an n-sample  $t_1, \ldots, t_n$  of waiting times. We consider the Bayesian paradigm.

1) (4 pts) Give the Jeffreys prior distribution for the parameter  $\lambda$ . Is it a proper prior distribution?

**Solution** For the exponential distribution, the Fisher information is

$$I(\lambda) = \frac{1}{\lambda^2}.$$

The Jeffreys prior is proportional to the square root of the Fisher information

$$\pi(\lambda) \propto \left(\frac{1}{\lambda}\right) \mathbf{1}_{\lambda>0} \,.$$

This is an improper prior, as it does not integrate to 1 over the positive real line. However, it can still be used in Bayesian analysis.

2) (4 pts) For the Jeffreys prior, calculate the Bayesian estimator of  $\lambda$  associated with the quadratic loss function.

Solution The likelihood function for the exponential distribution is

$$f(t|\lambda) = \lambda \exp(-\lambda t)$$
.

For a sample  $t_1, t_2, \ldots, t_n$ , the likelihood is

$$L(\lambda|t_1,\ldots,t_n) = \lambda^n \exp\left(-\lambda \sum_{i=1}^n t_i\right).$$

Multiplying this by the Jeffreys prior gives the posterior distribution

$$\pi(\lambda|t_1,\ldots,t_n) \propto \lambda^{n-1} \exp\left(-\lambda \sum_{i=1}^n t_i\right) \mathbf{1}_{\lambda>0}.$$

This is a Gamma distribution

$$\lambda | t_1, \dots, t_n \sim \operatorname{Gamma}\left(n, \sum_{i=1}^n t_i\right)$$

This is the Bayesian estimate of  $\lambda$  under the quadratic loss function is

$$\hat{\lambda} = \frac{n}{\sum_{i=1}^{n} t_i} \,.$$