Bayesian Statistics III/IV (MATH3361/4071)

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## Problem class 2

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Exercise 1.  $(\star\star)$ Consider the Bayesian model

$$\begin{cases} x_i | \theta & \stackrel{\text{iid}}{\sim} \text{Ga}(\alpha, \beta), \ \forall i = 1, ..., n \\ (\alpha, \beta) & \sim \Pi(\alpha, \beta) \end{cases}$$

where  $Ga(a, \beta)$  is the Gamma distribution with expected value  $\alpha/\beta$ . Specify a Jeffrey's prior for  $\theta = (\alpha, \beta)$ .

**Hint-1:** Gamma distr.:  $x \sim \operatorname{Ga}(a,b)$  has pdf  $f(x) = \frac{b^a}{\Gamma(a)} x^{a-1} \exp(-bx) 1_{(0,+\infty)}(x)$ , and Expected value  $\operatorname{E}_{\operatorname{Ga}}(x|a,b) = \frac{a}{b}$ 

**Hint-2:** You may also need that the second derivative of the logarithm of a Gamma function is the 'polygamma function of order 1'. Ie,

- $F^{(0)}(\alpha) = \frac{\mathrm{d}}{\mathrm{d}\alpha} \log(\Gamma(a))$
- $F^{(1)}(\alpha) = \frac{\mathrm{d}^2}{\mathrm{d}\alpha^2} \log(\Gamma(a))$

**Hint-3:** You may leave your answer in terms of function  $F^{(1)}(\alpha)$ .

**Exercise 2.**  $(\star\star)$ Consider observables  $x=(x_1,...,x_n)$ . Consider the Bayesian model

$$\begin{cases} x_i | \theta & \stackrel{\text{IID}}{\sim} N(\theta, 1), \quad i = 1, ..., n \\ \theta & \sim \Pi(\theta) \end{cases}$$

where  $\pi(\theta) \propto 1$  and that we have only one observable. Consider the LINEX loss function

$$\ell(\theta, \delta) = \exp(c(\theta - \delta)) - c(\theta - \delta) - 1$$

- 1. Show that  $\ell(\theta, \delta) \geq 0$
- 2. Find the Bayes estimator  $\hat{\delta}$  under LINEX loss function and under the given Bayesian model.

**Hint-1:** Random variable B follows a log-normal distribution  $B \sim \text{LN}(\mu_A, \sigma_A^2)$  with parameters  $\mu_A, \sigma_A^2$  if  $B = \exp(A)$  where  $A \sim \text{N}(\mu_A, \sigma_A^2)$ .

**Hint-2:** If  $B \sim \text{LN}(\mu_A, \sigma_A^2)$  then  $E_{\text{LN}(\mu_A, \sigma_A^2)}(B) = \exp(\mu_A + \frac{\sigma_A^2}{2})$ .

Hint-3: It is

$$-\frac{1}{2}\frac{(\mu-\mu_1)^2}{v_1^2} - \frac{1}{2}\frac{(\mu-\mu_2)^2}{v_2^2} \dots - \frac{1}{2}\frac{(\mu-\mu_n)^2}{v_n^2} = -\frac{1}{2}\frac{(\mu-\hat{\mu})^2}{\hat{v}^2} + C$$

where

$$\hat{v}^2 = \left(\sum_{i=1}^n \frac{1}{v_i^2}\right)^{-1}; \quad \hat{\mu} = \hat{v}^2 \left(\sum_{i=1}^n \frac{\mu_i}{v_i^2}\right); \quad C = \frac{1}{2} \frac{\hat{\mu}^2}{\hat{v}^2} - \frac{1}{2} \sum_{i=1}^n \frac{\mu_i^2}{v_i^2}$$

Exercise 3.  $(\star\star)$ Suppose we wish to estimate the values of a collection of discrete random variables  $\vec{X}=X_1,\ldots,X_n$ . We have a posterior joint probability mass function for these variables,  $p\left(\vec{x}|y\right)=p\left(x_1,\ldots,x_n|y\right)$  based on some

data y. We decide to use the following loss function:

$$\ell(\hat{\vec{x}}, \vec{x}) = \sum_{i=1}^{n} (1 - \delta(\hat{x}_i, x_i))$$
 (1)

where  $\delta(a, b) = 1$  if a = b and zero otherwise.

- 1. Derive an expression for the estimated values, found by minimizing the expectation of the loss function. [Hint: use linearity of expectation.]
- 2. When the probability distribution is a posterior distribution in some problem, this type of estimate is sometimes called 'maximum posterior marginal' (MPM) estimate. Explain why this name is appropriate.
- 3. Explain in words what the loss function is measuring. Compare with the loss function for MAP estimation.

## Exercise 4. (Example from the Lecture's handout) Consider a Bayesian model

$$\begin{cases} y_i | \mu & \stackrel{\text{iid}}{\sim} \mathbf{N}_d(\mu, \Sigma), & i = 1, ..., n \\ \mu & \sim \mathbf{N}_d(\mu_0, \Sigma_0) \end{cases}$$

where uncertain  $\mu \in \mathbb{R}^d$ ,  $d \ge 1$ , and known  $\Sigma$ ,  $\mu_0$ ,  $\Sigma_0$ . Find the  $C_a$  parametric HPD credible set for  $\mu$ .

**Hint-1:** If 
$$z = (z_1, ..., z_d)^{\top}$$
 such as  $z_j \stackrel{\text{iid}}{\sim} \text{N}(0, 1)$  for  $j = 1, ..., d$ , and  $\xi = z^{\top}z = \sum_{j=1}^d z_j^2$ , then  $\xi \sim \chi_d^2$ 

## Hint-2: It is

$$\begin{split} -\frac{1}{2} \sum_{i=1}^{n} (x - \mu_{i})^{\top} \Sigma_{i}^{-1} (x - \mu_{i})) &= -\frac{1}{2} (x - \hat{\mu})^{\top} \hat{\Sigma}^{-1} (x - \hat{\mu})) + C(\hat{\mu}, \hat{\Sigma}) \quad ; \\ \hat{\Sigma} &= (\sum_{i=1}^{n} \Sigma_{i}^{-1})^{-1}; \quad \hat{\mu} = \hat{\Sigma} (\sum_{i=1}^{n} \Sigma_{i}^{-1} \mu_{i}); \\ C(\hat{\mu}, \hat{\Sigma}) &= \underbrace{\frac{1}{2} (\sum_{i=1}^{n} \Sigma_{i}^{-1} \mu_{i})^{\top} (\sum_{i=1}^{n} \Sigma_{i}^{-1})^{-1} (\sum_{i=1}^{n} \Sigma_{i}^{-1} \mu_{i}) - \frac{1}{2} \sum_{i=1}^{n} \mu_{i}^{\top} \Sigma_{i}^{-1} \mu_{i}}_{= \text{independent of } x} \end{split}$$