

Handout 5a: Nuisance parameters ^a

The Normal model and the Normal linear regression with unknown variance

Lecturer: Georgios Karagiannis

georgios.karagiannis@durham.ac.uk

^a Author: Georgios P. Karagiannis.

Nuisance parameters

<concept

Definition 1. Assume observable quantities $y = (y_1, \dots, y_n)$. Assume that the sampling distribution is $dF(y|\theta)$ labeled by an unknown parameter $\theta \in \Theta$. Let $\theta = (\phi, \lambda)^\top$ with $\phi \in \Phi$ and $\lambda \in \Lambda$. Assume You are interested in learning parameter $\phi \in \Phi$, and You are not interested in learning the unknown parameter $\lambda \in \Lambda$; but both ϕ, λ are parts of the statistical model parameterisation. The unknown quantity $\lambda \in \Lambda$ is called nuisance parameter. We can call $\phi \in \Phi$ parameter of interest.

Note 2. In Bayesian Stats, learning (or quantifying uncertainty about) parameter of interest ϕ under the presence of a nuisance parameter $\lambda \in \Lambda$ is performed according to the Bayesian paradigm as usual: You specify a prior $d\Pi(\phi, \lambda)$ with PDF/PMF $\pi(\phi, \lambda) = \pi(\phi|\lambda)\pi(\lambda)$ on the joint space of ALL Your unknown parameters $\theta = (\phi, \lambda)^\top$; you compute the joint posterior distribution $d\Pi(\theta|y)$ of $\theta = (\phi, \lambda)^\top$ via the Bayesian theorem. Reasonably, Your posterior degree of belief about the parameter of interest ϕ given the data $y = (y_1, \dots, y_n)$ is given through the marginal posterior distribution $d\Pi(\phi|y)$.

Note 3. To summarize; Specify the Bayesian model as:

<sum-up

$$\begin{cases} \overbrace{y|\phi, \lambda}^{=\theta} \sim dF(\overbrace{y|\phi, \lambda}^{=\theta}) & , \text{ the statistical model} \\ \underbrace{(\phi, \lambda)}_{=\theta} \sim d\Pi(\underbrace{\phi, \lambda}_{=\theta}) & , \text{ the prior model} \end{cases}$$

The joint posterior of θ given y is $d\Pi(\theta|y) = d\Pi(\lambda|y, \phi)d\Pi(\phi|y)$ is with PDF/PMF

$$\pi(\overbrace{\phi, \lambda}^{=\theta}|y) = \frac{f(y|\overbrace{\phi, \lambda}^{=\theta})\pi(\overbrace{\phi, \lambda}^{=\theta})}{f(y)} = \underbrace{\frac{f(y|\phi, \lambda)\pi(\lambda|\phi)}{f(y|\phi)}}_{=\pi(\lambda|y, \phi)} \underbrace{\frac{f(y|\phi)\pi(\phi)}{f(y)}}_{=\pi(\phi|y)} = \pi(\lambda|y, \phi)\pi(\phi|y)$$

The (marginal) likelihood $f(y|\phi)$ of y given ϕ is

$$f(y|\phi) = \underbrace{\int_{\Lambda} f(y|\overbrace{\phi, \lambda}^{=\theta})d\Pi(\lambda|\phi)}_{=E_{\Pi(\lambda|\phi)}(f(y|\phi, \lambda)|\phi)} = \begin{cases} \int_{\Lambda} f(y|\phi, \lambda)\pi(\lambda|\phi)d\lambda & , \text{ if } \lambda \text{ cont} \\ \sum_{\forall \lambda \in \Lambda} f(y|\phi, \lambda)\pi(\lambda|\phi) & , \text{ if } \lambda \text{ discr} \end{cases}$$

The PDF/PMF $\pi(\phi|y)$ of marginal posterior $d\Pi(\phi|y)$ of ϕ is

$$\pi(\phi|y) = \underbrace{\int_{\Lambda} \pi(\overbrace{\phi, \lambda}^{=\theta}|y)d\lambda}_{=E_{\Pi(\lambda|y)}(\pi(\phi|y, \lambda))} \quad \text{or equivalently} \quad \pi(\phi|y) = \frac{f(y|\phi)\pi(\phi)}{f(y)}$$

The predictive distribution $dG(z|y)$ of the next outcome $z = (y_{n+1}, \dots, y_{n+m})$ given y has pdf/pmf

$$g(z|y) = \int f(y|\underbrace{\phi, \lambda}_{=\theta}) d\Pi(\underbrace{\phi, \lambda}_{=\theta}|y)$$

and the marginal likelihood $f(y)$ is

$$f(y) = \int f(y|\underbrace{\phi, \lambda}_{=\theta}) \pi(\underbrace{\phi, \lambda}_{=\theta}) d\phi d\lambda$$

Practice in challenging problems

Exercise 4. (★★)(Nuisance parameters are involved)

<-story

Assume observable quantities $y = (y_1, \dots, y_n)$ forming the available data set of size n . Assume that the observations are drawn i.i.d. from a sampling distribution which is judged to be in the Normal parametric family of distributions $N(\mu, \sigma^2)$ with unknown mean μ and variance σ^2 . We are interested in learning μ and the next outcome $z = y_{n+1}$. We do not care about σ^2 .

Assume You specify a Bayesian model

<-set-up

$$\begin{cases} y_i | \mu, \sigma^2 \sim N(\mu, \sigma^2), \text{ for all } i = 1, \dots, n & \text{, Statistical model} \\ \mu | \sigma^2 \sim N(\mu_0, \sigma^2 \frac{1}{\tau_0}) & \text{, prior} \\ \sigma^2 \sim \text{IG}(a_0, k_0) & \text{, prior} \end{cases}$$

1. Show that the joint posterior distribution $\Pi(\mu, \sigma^2|y)$ is such as

$$\begin{aligned} \mu | y, \sigma^2 &\sim N(\mu_n, \sigma^2 \frac{1}{\tau_n}) \\ \sigma^2 | y &\sim \text{IG}(a_n, k_n) \end{aligned}$$

with

$$\mu_n = \frac{n\bar{y} + \tau_0\mu_0}{n + \tau_0}; \quad \tau_n = n + \tau_0; \quad a_n = a_0 + n$$

$$k_n = k_0 + \frac{1}{2} \frac{(n\bar{y} + \tau_0\mu_0)^2}{n + \tau_0} - \frac{1}{2} (n\bar{y}^2 + \tau_0\mu_0^2)$$

Hint: 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

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

2. Show that the marginal posterior distribution $\Pi(\mu|y)$ is such as

$$\mu | y \sim T_1 \left(\mu_n, \frac{k_n}{a_n} \frac{1}{\tau_n}, 2a_n \right)$$

Hint-1: If $x \sim \text{IG}(a, b)$, $y = cx$, then $y \sim \text{IG}(a, cb)$.

Hint-2: The definition of Student T is considered as known

3. Show that the predictive distribution $\Pi(z|y)$ is Student T such as

$$z|y \sim T_1 \left(\mu_n, \frac{k_n}{a_n} \left(\frac{1}{\tau_n} + 1 \right), 2a_n \right)$$

Hint-1: Consider that

$$N(x|\mu_1, \sigma_1^2) N(x|\mu_2, \sigma_2^2) = N(x|m, v^2) N(\mu_1|\mu_2, \sigma_1^2 + \sigma_2^2)$$

where

$$v^2 = \left(\frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} \right)^{-1}; \quad m = v^2 \left(\frac{\mu_1}{\sigma_1^2} + \frac{\mu_2}{\sigma_2^2} \right)$$

Hint-2: The definition of Student T is considered as known

General practice

Exercise 5. (**) Consider the Bayesian model

$$\begin{cases} x_i|\theta & \stackrel{\text{iid}}{\sim} \text{Ex}(\theta), \forall i = 1, \dots, n \\ \theta & \sim \text{Ga}(a, b) \end{cases}$$

Hint-1: The PDF of $x \sim G(a, b)$ is $\text{Ga}(x|a, b) = \frac{b^a}{\Gamma(a)} x^{a-1} \exp(-bx) \mathbf{1}_{(0, +\infty)}(x)$

Hint-2: The PDF of $x \sim \text{Ex}(\theta)$ is $\text{Ex}(x|\theta) = \text{Ga}(x|1, \theta)$

1. Show that the parametric model is member of the Exponential family, and the sufficient statistic for a sample of observables $x = (x_1, \dots, x_n)$.
2. Show that the posterior distribution θ given x is Gamma and compute its parameters.
3. Show that the predictive distribution $G(z|x)$ of a future z given $x = (x_1, \dots, x_n)$, has PDF

$$g(z|x) = \frac{a^* (b^*)^{a^*}}{(z + b^*)^{a^*+1}} \mathbf{1}(z \geq 0)$$

Exercise 6. (**) Consider the Bayesian model

$$\begin{cases} x_i|\theta & \stackrel{\text{iid}}{\sim} \text{Mu}_k(\theta) \\ \theta & \sim \text{Di}_k(a) \end{cases}$$

where $\theta \in \Theta$, with $\Theta = \{\theta \in (0, 1)^k \mid \sum_{j=1}^k \theta_j = 1\}$ and $\mathcal{X}_k = \{x \in \{0, \dots, n\}^k \mid \sum_{j=1}^k x_j = 1\}$.

Hint-1: Mu_k denotes the Multinomial probability distribution with PMF

$$\text{Mu}_k(x|\theta) = \begin{cases} \prod_{j=1}^k \theta_j^{x_j} & , \text{ if } x \in \mathcal{X}_k \\ 0 & , \text{ otherwise} \end{cases} \quad (1)$$

Hint-2: $\text{Di}_k(a)$ denotes the Dirichlet distribution with PDF

$$\text{Di}_k(\theta|a) = \begin{cases} \frac{\Gamma(\sum_{j=1}^k a_j)}{\prod_{j=1}^k \Gamma(a_j)} \prod_{j=1}^k \theta_j^{a_j-1} & , \text{ if } \theta \in \Theta \\ 0 & , \text{ otherwise} \end{cases}$$

1. Show that the parametric model (1) is a member of the $k - 1$ exponential family.
2. Compute the likelihood $f(x_{1:n}|\theta)$, and find the sufficient statistic $t_n := t_n(x_{1:n})$.
3. Compute the posterior distribution. State the name of the distribution, and express its parameters with respect to the observations and the hyper-parameters of the prior. Justify your answer.
4. Compute the probability mass function of the predictive distribution for a future observation $y = x_{n+1}$ in closed form.

Hint $\Gamma(x) = (x - 1)\Gamma(x - 1)$.
