

Stat 461-561: Exercises 5

Remarks: Exercises 8.10 & 8.11 in C&B make implicit use of the incomplete Gamma function. No such question will be given at the exam.

Exercise C&B 8.53.

(a). We have

$$\begin{aligned}\pi(\theta) &= \pi(H_0)\pi(\theta|H_0) + \pi(H_1)\pi(\theta|H_1) \\ &= \frac{1}{2}\delta_0(\theta) + \frac{1}{2}\mathcal{N}(\theta; 0, \tau^2)\end{aligned}$$

so it is by construction a proper prior distribution.

(b) We have

$$\begin{aligned}\pi(H_0|x_{1:n}) &= \frac{\pi(x_{1:n}|H_0)\pi(H_0)}{\pi(x_{1:n}|H_0)\pi(H_0) + \pi(x_{1:n}|H_1)\pi(H_1)} \\ &= \frac{\pi(x_{1:n}|H_0)}{\pi(x_{1:n}|H_0) + \pi(x_{1:n}|H_1)}\end{aligned}$$

where

$$\pi(x_{1:n}|H_0) = \prod_{i=1}^n f(x_i|\theta=0) = \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2}\right)$$

and

$$\begin{aligned}\pi(x_{1:n}|H_1) &= \frac{1}{(2\pi\sigma^2)^{n/2}} \frac{1}{(2\pi)^{1/2} \tau} \\ &\quad \times \int \exp\left(-\frac{\sum_{i=1}^n (x_i - \theta)^2}{2\sigma^2}\right) \exp\left(-\frac{\theta^2}{2\tau^2}\right) d\theta.\end{aligned}$$

We have

$$\begin{aligned}&\frac{\sum_{i=1}^n (x_i - \theta)^2}{\sigma^2} + \frac{\theta^2}{\tau^2} \\ &= \theta^2 \left(\frac{1}{\tau^2} + \frac{n}{\sigma^2}\right) - 2 \left(\frac{\sum_{i=1}^n x_i}{\sigma^2}\right) \theta + \frac{\sum_{i=1}^n x_i^2}{\sigma^2} \\ &= \frac{(\theta - m)^2}{v^2} + \frac{\sum_{i=1}^n x_i^2}{\sigma^2} - \frac{m^2}{v^2}\end{aligned}$$

where $v^2 = \left(\frac{1}{\tau^2} + \frac{n}{\sigma^2}\right)^{-1}$ and $m = v^2 \left(\frac{\sum_{i=1}^n x_i}{\sigma^2}\right)$. So integrating out θ , we obtain

$$\pi(x_{1:n}|H_1) = \frac{v}{(2\pi\sigma^2)^{n/2} \tau} \exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2} + \frac{m^2}{2v^2}\right).$$

So

$$\begin{aligned}
 \pi(H_0 | x_{1:n}) &= \frac{\pi(x_{1:n} | H_0)}{\pi(x_{1:n} | H_0) + \pi(x_{1:n} | H_1)} \\
 &= \frac{\exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2}\right)}{\exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2}\right) + \frac{v}{\tau} \exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2} + \frac{m^2}{2v^2}\right)} \\
 &= \frac{1}{1 + \frac{v}{\tau} \exp\left(\frac{m^2}{v^2}\right)}
 \end{aligned}$$

(c) For the p-value, we take $P_{\theta_0}(|\bar{X}| \geq |\bar{x}|)$ where under H_0 we have $\bar{X} \sim \mathcal{N}\left(0, \frac{\sigma^2}{n}\right)$. So

$$P_{\theta_0}(|\bar{X}| \geq |\bar{x}|) = 2P\left(Z \geq \frac{\sqrt{n}}{\sigma} \bar{x}\right).$$

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

(d) (i) Graph omitted.

(ii). If $\bar{x} = \frac{\sigma z_{\alpha/2}}{\sqrt{n}}$ then

$$P_{\theta_0}(|\bar{X}| \geq |\bar{x}|) = 2P(Z \geq z_{\alpha/2}) = \alpha.$$

For the posterior probability, we have that

$$\pi(H_0 | x_{1:n}) = \frac{1}{1 + \frac{v}{\tau} \exp\left(\frac{m^2}{v^2}\right)}$$

where

$$\begin{aligned}
 \frac{m^2}{v^2} &\sim \frac{\bar{x}^2}{\sigma^2/n} = \frac{n\bar{x}^2}{\sigma^2} \\
 &= z_{\alpha/2}^2
 \end{aligned}$$

whereas $\frac{v}{\tau} = \frac{\sigma}{n\tau} \rightarrow 0$ so

$$\lim_{n \rightarrow \infty} \pi(H_0 | x_{1:n}) = 1.$$

Exercise C&B 8.54

(a) For $\pi(\theta) = \mathcal{N}(\theta; 0, \tau^2)$, we have shown (implicitly) in 8.53 (c) that

$$\pi(\theta | x_{1:n}) = \mathcal{N}(\theta; m, v^2)$$

where $v^2 = \left(\frac{1}{\tau^2} + \frac{n}{\sigma^2}\right)^{-1}$ and $m = v^2 \left(\frac{\sum_{i=1}^n x_i}{\sigma^2}\right)$. So

$$\begin{aligned}
 P(\theta \leq 0 | x_{1:n}) &= \int_{-\infty}^0 \mathcal{N}(\theta; m, v^2) d\theta. \\
 &= P\left(Z \leq -\frac{m}{v}\right)
 \end{aligned}$$

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

(b) For the p-value, we take $\sup_{\theta \leq 0} P_{\theta}(\bar{X} \geq \bar{x})$. In this case, the sup is reached in $\theta = 0$ where $\bar{X} \sim \mathcal{N}\left(0, \frac{\sigma^2}{n}\right)$. So the p-value is given by

$$P_{\theta=0}(\bar{X} \geq \bar{x}) = P\left(Z \geq \frac{\sqrt{n}}{\sigma} \bar{x}\right) = P\left(Z \leq -\frac{\sqrt{n}}{\sigma} \bar{x}\right).$$

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

(c) For $\sigma^2 = \tau^2 = 1$, we have $v^2 = \frac{1}{n+1}$, $m = \frac{n\bar{x}}{n+1}$ and

$$P(\theta \leq 0 | x_{1:n}) = P\left(Z \leq -\frac{m}{v}\right) = P\left(Z \leq -\frac{n\bar{x}}{(n+1)^{1/2}}\right)$$

whereas

$$P_{\theta=0}(\bar{X} \geq \bar{x}) = P(Z \leq -\sqrt{n}\bar{x}).$$

We have

$$\frac{n}{(n+1)^{1/2}} \leq \sqrt{n}$$

so

$$P(\theta \leq 0 | x_{1:n}) \geq P_{\theta=0}(\bar{X} \geq \bar{x}).$$

(d) As $\tau^2 \rightarrow \infty$, we have

$$v^2 \rightarrow \frac{1}{n}, \quad m \rightarrow \bar{x}$$

and thus

$$\lim_{\tau^2 \rightarrow \infty} P(\theta \leq 0 | x_{1:n}) = \text{p-value}.$$

Exercise 6. Let $X_i \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(\theta, \sigma^2)$ with σ^2 known. We have

$$p(x_{1:n} | H_0) = \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{\sum_{i=1}^n x_i^2}{2\sigma^2}\right)$$

and

$$p(x_{1:n} | H_1) = \int \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{\sum_{i=1}^n (x_i - \theta)^2}{2\sigma^2}\right) \frac{1}{(2\pi\tau^2)^{1/2}} \exp\left(-\frac{(\theta - \mu)^2}{2\tau^2}\right) d\theta.$$

We have for any k

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

where $m = (n\bar{x} + k\mu) / (n + k)$. Thus

$$\begin{aligned} & \frac{\sum_{i=1}^n (x_i - \theta)^2}{\sigma^2} + \frac{(\theta - \mu)^2}{\tau^2} \\ = & \frac{(n\tau^2 + \sigma^2)}{\sigma^2\tau^2} (\theta - m)^2 + \frac{n}{n\tau^2 + \sigma^2} (\bar{x} - \mu)^2 + \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2. \end{aligned}$$

Also we have

$$\int \exp \left(-\frac{(n\tau^2 + \sigma^2)}{2\sigma^2\tau^2} (\theta - m)^2 \right) d\theta = \left(\frac{2\pi\sigma^2\tau^2}{n\tau^2 + \sigma^2} \right)^{1/2}.$$

Hence it follows that

$$\begin{aligned} p(x_{1:n} | H_1) &= \frac{1}{(2\pi\sigma^2)^{n/2}} \left(\frac{\sigma^2}{n\tau^2 + \sigma^2} \right)^{1/2} \\ &\quad \times \exp \left(-\frac{1}{2} \left(\frac{n}{n\tau^2 + \sigma^2} (\bar{x} - \mu)^2 + \frac{1}{\sigma^2} \sum_{i=1}^n (x_i - \bar{x})^2 \right) \right) \end{aligned}$$

and so

$$\frac{p(x_{1:n} | H_0)}{p(x_{1:n} | H_1)} = \left(1 + \frac{n\tau^2}{\sigma^2} \right)^{1/2} \exp \left(-\frac{1}{2} \left(\frac{n\bar{x}^2}{\sigma^2} - \frac{n}{n\tau^2 + \sigma^2} (\bar{x} - \mu)^2 \right) \right).$$

Exercise 7

We have

$$\begin{aligned} B_{01} &= \frac{\binom{n}{x} \theta_0^x (1 - \theta_0)^{n-x}}{\int_0^1 \binom{n}{x} \theta_0^x (1 - \theta_0)^{n-x} d\theta} \\ &= \frac{\theta_0^x (1 - \theta_0)^{n-x}}{\int_0^1 \theta_0^{x+1-1} (1 - \theta_0)^{n+1-x-1} d\theta} \\ &= \frac{\Gamma(n+2) \theta_0^x (1 - \theta_0)^{n-x}}{\Gamma(x+1) \Gamma(n+1-x)} \\ &= \frac{(n+1)!}{x! (n-x)!} \theta_0^x (1 - \theta_0)^{n-x}. \end{aligned}$$

Now we could use Stirling's approximation and further approximations to establish this approximation (see Exercise 8). Alternatively a much simpler solution consists of realising that B_{01} has the form of a Binomial distribution of parameter θ_0 up to a constant; i.e.

$$B_{01} = (n+1) \text{Bin}(\theta_0; x, n).$$

We know that for large n , we can approximate $\text{Bin}(\theta_0; x, n)$ by a Gaussian of mean $n\theta_0$ and variance $n\theta_0(1 - \theta_0)$ so

$$\begin{aligned} B_{01} &\approx (n+1) \frac{1}{\sqrt{2\pi n\theta_0(1-\theta_0)}} \exp\left(-\frac{(x-n\theta_0)^2}{2n\theta_0(1-\theta_0)}\right) \\ &\approx \left(\frac{n}{2\pi\theta_0(1-\theta_0)}\right)^{1/2} \exp\left(-\frac{(x-n\theta_0)^2}{2n\theta_0(1-\theta_0)}\right). \end{aligned}$$

Exercise 8

(a) Under H_0 , we have

$$\begin{aligned} \mathbb{E}[S_n] &= \mathbb{E}[X_1] = 1, \\ \mathbb{V}[S_n] &= n\mathbb{V}[X_1] = n \end{aligned}$$

so, using the CLT, we know that asymptotically

$$S_n - n \sim \mathcal{N}(0, n)$$

and the result follows.

(b) We have

$$\pi(x_{1:n}|H_0) = \prod_{i=1}^n \exp(-x_i) = \exp(-s_n),$$

and

$$\begin{aligned} \pi(x_{1:n}|H_1) &= \int \theta^n \exp\left(-\theta \sum_{i=1}^n x_i\right) \frac{b^a \theta^{a-1} e^{-b\theta}}{\Gamma(a)} d\theta \\ &= \frac{b^a}{\Gamma(a)} \int \theta^{n+a-1} \exp\left(-\theta \left(\sum_{i=1}^n x_i + b\right)\right) d\theta \\ &= \frac{b^a}{\Gamma(a)} \frac{\Gamma(n+a)}{(s_n + b)^{n+a}}. \end{aligned}$$

So the result follows and

$$B_{01} = \frac{\pi(x_{1:n}|H_0)}{\pi(x_{1:n}|H_1)} = \frac{\Gamma(a)}{\Gamma(a+n)} \frac{(b+s_n)^{a+n}}{b^a} \exp(-s_n)$$

(c) If $a = b = 1$ then

$$\begin{aligned} B_{01} &= \frac{\Gamma(1)}{\Gamma(1+n)} (1+s_n)^{1+n} \exp(-s_n) \\ &= \frac{(1+s_n)^{1+n}}{n!} \exp(-s_n). \end{aligned}$$

We have

$$(1+s_n)^{1+n} = \exp((1+n) \log(1+s_n))$$

where

$$\begin{aligned}\log(1 + s_n) &= \log(1 + n + \sqrt{n}z_n) \\ &= \log(1 + n) + \log\left(1 + \frac{\sqrt{n}z_n}{1 + n}\right) \\ &\approx \log(1 + n) + \frac{\sqrt{n}z_n}{1 + n} - \frac{nz_n^2}{2(1 + n)^2}\end{aligned}$$

It follows that

$$\begin{aligned}&(1 + n)\log(1 + s_n) - s_n \\ &\approx (1 + n)\log(1 + n) + \sqrt{n}z_n - \frac{nz_n^2}{2(1 + n)} - n - \sqrt{n}z_n \\ &\approx (1 + n)\log(1 + n) - n - \frac{z_n^2}{2}.\end{aligned}$$

So

$$B_{01} \approx \frac{(n + 1)^{n+1} \exp(-n)}{n!} \exp\left(-\frac{z_n^2}{2}\right).$$

Now using Stirling's approximation, we have

$$n! \approx n^n \exp(-n) \sqrt{2\pi n}$$

so

$$B_{01} \approx \frac{(n + 1)^{n+1}}{n^n \sqrt{2\pi n}} \exp\left(-\frac{z_n^2}{2}\right).$$

Now

$$\begin{aligned}\frac{(n + 1)^{n+1}}{n^n} &= (n + 1) \left(1 + \frac{1}{n}\right)^{n+1} \\ &\approx (n + 1) \exp(1)\end{aligned}$$

so

$$B_{01} \approx \sqrt{\frac{n}{2\pi}} \exp\left(1 - \frac{z_n^2}{2}\right).$$

(d) For s_n as defined above, H_0 will be rejected (it is just on the borderline) whereas we have

$$B_{01} \approx \sqrt{\frac{n}{2\pi}} \exp\left(1 - \frac{z_\alpha^2}{2}\right) \rightarrow \infty.$$