STAT 201B Homework 4

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1. (a) $f(\lambda | x^n) \propto f(x^n|\lambda) f(\lambda)$

$$= \left(\frac{1}{\lambda}\right)^n e^{-\frac{1}{\lambda}\sum_{i=1}^n x_i} \frac{b^a}{\Gamma(a)} \lambda^{-a-1} e^{-b/\lambda}$$

$$\propto \lambda^{-n} e^{-\frac{1}{\lambda}\sum_{i=1}^n x_i} \lambda^{-a-1} e^{-b/\lambda}$$

$$= \lambda^{-(n+a)-1} e^{-\frac{1}{\lambda}(\sum_{i=1}^n x_i + b)}$$

$\therefore$ $f(\lambda | x^n)$ also satisfies Inverse Gamma distribution (a', b') where $a' = n+a$ $b' = \sum_{i=1}^n x_i + b$

(b) Now the prior mean is $\frac{b}{a-1}$

$$\frac{\partial}{\partial\lambda} \log(\lambda^{-n} e^{-\frac{\sum x_i}{\lambda}}) = \frac{\partial}{\partial\lambda}\left[(-n)\log\lambda - \frac{\sum_{i=1}^n x_i}{\lambda}\right] = -n \times \frac{1}{\lambda} + \frac{\sum_{i=1}^n x_i}{\lambda^2} = 0$$

$$\lambda = \frac{1}{n}\sum_{i=1}^n x_i = \bar{X}_n$$

Check the $\frac{\partial^2}{\partial\lambda^2}\log(\lambda^{-n} e^{-\frac{\sum_{i=1}^n x_i}{\lambda}}) = \frac{n}{\lambda^2} - \frac{2\sum_{i=1}^n x_i}{\lambda^3}$

When $\lambda = \bar{X}_n$ $\frac{\partial^2}{\partial\lambda^2}\log(\lambda^{-n} e^{-\frac{\sum_{i=1}^n x_i}{\lambda}}) = \frac{n^3}{(\sum_{i=1}^n x_i)^2} - \frac{2n^3}{(\sum_{i=1}^n x_i)^2} = -\frac{n^3}{(\sum_{i=1}^n x_i)^2} < 0$

$\therefore$ $\hat{\lambda} = \bar{X}_n$ is the MLE of λ.

The posterior mean is $\frac{b'}{a'-1} = \frac{\sum_{i=1}^n x_i + b}{n+a-1} = \left(\frac{a-1}{n+a-1}\right)\frac{b}{a-1} + \left(\frac{n}{n+a-1}\right)\bar{X}_n$

$\because$ When $n \to \infty$, $\frac{a-1}{n+a-1} \to 0$ $\frac{n}{n+a-1} \to 1$

$\therefore$ $\frac{b'}{a'+1} \longrightarrow \bar{X}_n$

$\therefore$ When $n \to \infty$ the posterior mean will be close to $\bar{X}_n$.

2. (a) $m = \frac{b}{a-1}$ $V = \frac{b^2}{(a-1)^2(a-2)}$

$$(m(a-1))^2 = V(a-1)^2(a-2)$$

$$m^2(a-1)^2 = V(a-1)^2(a-2)$$

$\because a > 2$ $\therefore$ $m^2 = V(a-2)$ $a-2 = \frac{m^2}{V}$ $a = \frac{m^2+2V}{V}$

$\therefore$ $b = (a-1)m = \left(\frac{m^2+V}{V}\right)m = \frac{m^3+mV}{V}$ $\therefore \begin{cases} a = \frac{m^2+2V}{V} \\ b = \frac{m^3+mV}{V} \end{cases}$

(b) Based on my current knowledge, I have lived in Berkeley for 15 month now and I have felt two earthquakes. The time difference between these two is about 1 year. So I would guess m to be 365. But I completely have no knowledge about the prior variance v, So I guess this variance to be $v = 1000$

(c) The R code and the plot of the prior and posterior PDF are on the last page.

From the plot I can see that the mean λ value is a little smaller then my knowledge which is about 310 days. the variance is smaller than my guess too.

3. According to the definition of rejection sampling, the probability of the acceptance of θ^{cand} is:

$$P\left(u \le \frac{f(x^n | \theta^{cand})}{f(x^n | \hat{\theta}_n)}\right) = \frac{f(x^n | \theta^{cand})}{\underbrace{f(x^n | \hat{\theta}_n)}_{\hat{\theta}_n \to \text{MLE of } \theta} \Rightarrow M}$$ (Because $u \sim Unif(0,1)$)

$\because M = f(x^n | \hat{\theta}_n) = \sup_{\theta} f(x^n | \theta^{cand})$

$\therefore$ If $M < f(x^n | \hat{\theta}_n)$

then $\frac{f(x^n | \theta^{cand})}{M}$ may > 1

$\therefore$ the probability of the acceptance of θ^{cand} will be $\min\left\{1, \frac{f(x^n | \theta^{cand})}{M}\right\}$

Then when $M < f(x^n | \hat{\theta}_n)$

This probability may not be $\frac{f(x^n | \theta^{cand})}{M}$

$\because f(\theta^{accep}) \propto f(\theta^{cand}) P(\text{acceptance of } \theta^{cand})$

$$= f(\theta^{cand}) \min\left\{1, \frac{f(x^n | \theta^{cand})}{M}\right\}$$

Then $f(\theta^{accep})$ may not $\propto f(\theta^{cand}) \times \frac{f(x^n | \theta^{cand})}{M}$

may not $\propto f(\theta^{cand}) f(x^n | \theta^{cand})$

may not $\propto f(\theta^{cand} | x^n)$

$\therefore$ When $M < f(x^n | \theta^{cand})$, θ^{accep} may not satisfy the posterior distribution

4. (a) Obviously $f(x | \lambda)$ belongs to exponential family.

$$f(\lambda) \propto I(\lambda)^{\frac{1}{2}} = \left[\frac{I_n(\lambda)}{n}\right]^{\frac{1}{2}} = \left[-\frac{E_\lambda\left(\frac{\partial^2}{\partial \lambda^2} \log\left[\left(\frac{1}{\lambda} e^{-\frac{x_1}{\lambda}}\right)\left(\frac{1}{\lambda} e^{-\frac{x_2}{\lambda}}\right) \cdots \left(\frac{1}{\lambda} e^{-\frac{x_n}{\lambda}}\right)\right]\right.}{n}\right]^{\frac{1}{2}}$$

$$= \left[\frac{-E_\lambda \left(\frac{\partial^2}{\partial \lambda^2} \log (\lambda^{-n} e^{-\frac{\sum_{i=1}^n X_i}{\lambda}}) \right)}{n} \right]^{\frac{1}{2}} = \left[- \frac{E_\lambda \left(\frac{n}{\lambda^2} - \frac{2\sum_{i=1}^n X_i}{\lambda^3} \right)}{n} \right]^{\frac{1}{2}}$$

$$= \left[-E_\lambda \left(\frac{1}{\lambda^2} - \frac{2\bar{X}_n}{\lambda^3} \right) \right]^{\frac{1}{2}}$$

$\because X_1 \cdots X_n$ are i.i.d $\therefore$ $E_\lambda \bar{X}_n = E_\lambda X_1 = \int_0^{+\infty} \frac{1}{\lambda} e^{-\frac{X_1}{\lambda}} dx_1$

$= -x_1 e^{-\frac{X_1}{\lambda}} \Big|_0^{+\infty} - \int_0^{+\infty} (-e^{-\frac{X_1}{\lambda}}) dx_1 = 0 - (-\lambda) = \lambda$

$\therefore f(\lambda) \propto \left[-\frac{1}{\lambda^2} + \frac{2\lambda}{\lambda^3} \right]^{\frac{1}{2}} = \left[\frac{1}{\lambda^2} \right]^{\frac{1}{2}}$

$\because f(X|\lambda) \geq 0 \quad \therefore \lambda > 0$

$\therefore f(\lambda) \propto \frac{1}{\lambda}$

(b) This Jefferey's Prior is not proper.

$\because \int_0^{+\infty} \frac{1}{\lambda} d\lambda = \log \lambda \Big|_0^{+\infty} = +\infty$

$\therefore$ This Jefferey's Prior is not proper

5. (a) $f(x, y | H_1) = \int f(x, y, P_1, P_2 | H_1) \, dP_1 dP_2$

$= \int f(x, y | P_1, P_2, H_1) f(P_1, P_2 | H_1) \, dP_1 P_2$

$\because P_1$ and P_2 are independent, x and y are independent

$\therefore = \int_0^1 f(x|P_1) f(y|P_2) \cdot 1 \cdot 1 \cdot dP_1 \, dP_2$

$= \int_0^1 \binom{n}{x} P_1^x (1-P_1)^{n-x} \binom{m}{y} P_2^y (1-P_2)^{m-y} \, dP_1 dP_2$

$= \binom{n}{x} \left(\int_0^1 P_1^x (1-P_1)^{n-x} dP_1 \right) \binom{m}{y} \left(\int_0^1 P_2^y (1-P_2)^{m-y} dP_2 \right)$

$= \binom{n}{x} B(x+1, n-x+1) \binom{m}{y} B(y+1, m-y+1)$

$= \frac{1}{(n+1)(m+1)}$

(b) $f(x, y | H_0)$ $\quad \because$ Under H_0 $P_1 = P_2 \sim Unif(0, 1)$, X and Y are independent

$\therefore = \int_0^1 \binom{n}{x} P_1^x (1-P_1)^{n-x} \binom{m}{y} P_1^y (1-P_1)^{m-y} \, dP_1$

$= \int_0^1 \binom{n}{x} \binom{m}{y} P_1^{x+y} (1-P_1)^{m+n-x-y} \, dP_1 = \binom{n}{x} \binom{m}{y} B(x+y+1, m+n-x-y+1)$

$$= \binom{n}{x}\binom{m}{y}\frac{\Gamma(x+y+1)\,\Gamma(m+n-x-y+1)}{\Gamma(m+n+2)}$$

$$= \frac{n!}{x!\,(n-x)!}\;\frac{m!}{y!\,(m-y)!}\;\frac{(x+y)!\,(m+n-x-y)!}{(m+n+1)!}$$

$$= \frac{(x+y)!}{x!\;y!}\;\frac{(m+n-x-y)!}{(n-x)!\,(m-y)!}\;\frac{m!\,n!}{(m+n+1)!}$$

$$= \binom{x+y}{x}\binom{m+n-x-y}{n-x}\frac{1}{(m+n+1)\binom{m+n}{n}}$$

(c) $$BF_{10} = \frac{f(x,y\mid H_1)}{f(x,y\mid H_0)}$$

$$= \frac{\dfrac{1}{(m+1)(n+1)}}{\binom{x+y}{x}\binom{m+n-x-y}{n-x}\dfrac{1}{(m+n+1)\binom{m+n}{n}}}$$

$$= \frac{1}{(m+1)(n+1)} \times \frac{(m+n+1)\binom{m+n}{n}}{\binom{x+y}{x}\binom{m+n-x-y}{n-x}}$$

$$= \frac{1}{m+n+2}\;\frac{(m+n+2)(m+n+1)(m+n)!\,/\,(m+1)\,m!\,(n+1)\,n!}{\binom{x+y}{x}\binom{m+n-x-y}{n-x}}$$

$$= \frac{1}{m+n+2}\;\frac{\binom{m+n+2}{m+1}}{\binom{x+y}{x}\binom{m+n-x-y}{n-x}}$$

(d) Pujols : 5146 at bats , 1717 hits (n, x)

Suzuki : 6099 at bats , 2030 hits (m, y)

$$\therefore BF_{10} = \frac{1}{5146+6099+2}\;\frac{\binom{5146+6099+2}{6099+1}}{\binom{1717+2030}{1717}\binom{5146+6099-1717-2030}{5146-1717}} \approx 0.022 < 1$$

$\therefore$ The evidence against H_0 and favor H_1 is weak

So it favors H_0