## University of Technology Sydney School of Mathematical and Physical Sciences

## Mathematical Statistics (37262) – Tutorial 11 SOLUTIONS

- 1. i)  $L(x_1, x_2, ..., x_n | \lambda) = (\lambda e^{-\lambda x_1})(\lambda e^{-\lambda x_2})...(\lambda e^{-\lambda x_n}) = \lambda^n e^{-\lambda (x_1 + ... + x_n)}$ 
  - ii) A conjugate prior is one such that, when combined with the likelihood function, gives a posterior distribution of the same form/family, albeit with different parameter values.

iii) 
$$L(x_1, x_2, ..., x_n | \lambda) = \lambda^n e^{-\lambda(x_1 + ... + x_n)} \cdot f(\lambda) = \frac{2^4 \lambda^3 e^{-2\lambda}}{\Gamma(4)} \cdot \Gamma(4)$$
The posterior is proportional to the prior multiplied by the likelihood hence  $f(\lambda | x_1, x_2, ..., x_n) \propto \lambda^n e^{-\lambda(x_1 + ... + x_n)} \times \frac{2^4 \lambda^3 e^{-2\lambda}}{\Gamma(4)} \cdot f(\lambda | x_1, x_2, ..., x_n) \propto \lambda^{n+3} e^{-\lambda(2 + x_1 + ... + x_n)}$  hence  $\lambda \sim Gamma(4 + n, 2 + x_1 + ... + x_n) \cdot Here, \ \lambda \sim Gamma(14, 7)$ 

iv) The prior mean was 2 and variance 1. The additional observations seemed to confirm the prior belief, keeping the posterior mean at 2 but shrinking the posterior variance to  $\frac{2}{7}$ , suggesting increased belief that the rate is close to 2.

Let a set of observations be  $\boldsymbol{\Theta} = (\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, ... \boldsymbol{\theta}_n)$ .

The likelihood function is then  $L(\boldsymbol{\Theta} \mid \boldsymbol{\omega}) = \frac{\omega m^{\omega}}{\theta_1^{\omega+1}} \frac{\omega m^{\omega}}{\theta_2^{\omega+1}} \dots \frac{\omega m^{\omega}}{\theta_n^{\omega+1}}$  (assuming all  $\boldsymbol{\theta}_i \geq \boldsymbol{m}$ , else the likelihood is zero.)

$$\begin{split} L(\boldsymbol{\Theta} \mid \boldsymbol{\omega}) &= \frac{\boldsymbol{\omega}^{n} \boldsymbol{m}^{n \boldsymbol{\omega}}}{\prod_{i=1}^{n} \boldsymbol{\theta}_{i}}. \text{Combined with the prior density} \\ f(\boldsymbol{\omega}) &= \begin{cases} \frac{\boldsymbol{\beta}^{\alpha} \boldsymbol{\omega}^{\alpha-1} \boldsymbol{e}^{-\boldsymbol{\beta} \boldsymbol{\omega}}}{\boldsymbol{\Gamma}(\alpha)} & \boldsymbol{\omega} \in [0,\infty) \\ 0 & \text{otherwise} \end{cases}, \text{ we obtain a posterior density of} \end{split}$$

$$f(\omega \mid \boldsymbol{\Theta}) = L(\boldsymbol{\Theta} \mid \omega)f(\omega) = \frac{\omega^{n}m^{n\omega}}{\prod_{i=1}^{n}\theta_{i}} \frac{\beta^{\alpha}\omega^{\alpha-1}e^{-\beta\omega}}{\boldsymbol{\Gamma}(\alpha)} \propto \omega^{\alpha+n-1}e^{-\beta\omega} \frac{m^{n\omega}}{\prod_{i=1}^{n}\theta_{i}}$$

$$\propto \omega^{\alpha+n-1} e^{-\beta\omega} e^{n\omega\ln(m)} e^{-(\omega+1)\sum_{i=1}^{n}\ln(\theta_i)} \propto \omega^{\alpha+n-1} e^{-\omega(\beta-n\ln(m)+\sum_{i=1}^{n}\ln(\theta_i))} e^{-\sum_{i=1}^{n}\ln(\theta_i))}$$

Note now that the term  $e^{-\sum_{i=1}^{ln(\theta_i)}}$  can be considered constant with respect to  $\omega$  hence

$$f(\boldsymbol{\omega} \mid \boldsymbol{\Theta}) \propto \boldsymbol{\omega}^{\alpha+n-1} \boldsymbol{e}^{-\boldsymbol{\omega}(\beta-n\ln(m)+\sum_{i=1}^{n}\ln(\theta_i))}$$
  
This tells us that

$$f(\omega \mid \boldsymbol{\Theta}) = L(\boldsymbol{\Theta} \mid \omega)f(\omega) \propto \omega^{\alpha+n-1} \exp\left(-\omega\left(\beta + \sum_{i=-1}^{n} \ln\left(\theta_{i}\right) - n \ln(m)\right)\right) \text{ or,}$$

simplifying this,

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$$f(\boldsymbol{\omega} \mid \boldsymbol{\Theta}) \propto \boldsymbol{\omega}^{\alpha+n-1} \exp\left(-\boldsymbol{\omega}\left(\boldsymbol{\beta} + \sum_{i=-1}^{n} \ln\left(\frac{\boldsymbol{\theta}_{i}}{m}\right)\right)\right)$$

This gives that the posterior density is a Gamma variable

$$Gamma\left(\alpha+n,\beta+\sum_{i=-1}^{n}\ln\left(\frac{\theta_{i}}{m}\right)\right).$$

i) 
$$X \sim U[0,\theta]$$
 therefore  $f(x) = \begin{cases} \frac{1}{\theta} & x \in [0,\theta] \\ 0 & \text{otherwise} \end{cases}$ 

ii) 
$$L(x_1, x_2, ..., x_n | \theta) = \begin{cases} \begin{bmatrix} \frac{1}{\theta} \end{bmatrix} \begin{bmatrix} \frac{1}{\theta} \end{bmatrix} ... \begin{bmatrix} \frac{1}{\theta} \end{bmatrix} = \frac{1}{\theta^n} \quad x_1, x_2, ..., x_n \le \theta \\ 0 \quad \text{otherwise} \end{cases}$$

$$L(\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n | \boldsymbol{\theta}) = \begin{cases} \frac{1}{\boldsymbol{\theta}^n} & \boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n \leq \boldsymbol{\theta} \\ 0 & \text{otherwise} \end{cases}$$

iii) 
$$f(\theta | x_1, x_2, ..., x_n) \propto L(x_1, x_2, ..., x_n | \theta) f(\theta) \text{ so}$$
$$f(\theta | x_1, x_2, ..., x_n) \propto \left[\frac{1}{\theta^n}\right] \left[\frac{\alpha m^{\alpha}}{\theta^{\alpha+1}}\right] \propto \frac{1}{\theta^{n+\alpha+1}} \text{ for } x_1, x_2, ..., x_n, m \le \theta.$$

Since we need all  $x_i$  to be no greater than  $\theta$  and also need m to be no greater than  $\theta$ , we have that  $M = \max\{x_1, x_2, ..., x_n, m\}$  is the lower bound on  $\theta$ .

This gives that the posterior distribution for  $\theta$  is a *Pareto*( $M, \alpha + n$ ) variable where  $M = \max\{x_1, x_2, ..., x_n, m\}$ .

iv) Yes. If the prior and posterior distributions are the same type of variable (in this case, both Pareto distributed) then the prior distribution is a conjugate prior for the likelihood function.

3.