## Statistical Modeling 2 Exercise 1

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## 1 Bayesian inference in simple conjugate families

 $\mathbf{A}$ 

$$p(w \mid x_1, \dots, x_N) \propto p(x_1, \dots, x_N \mid w) p(w)$$
 (Bayes rule)  

$$\propto \prod_{i=1}^N p(x_i \mid w) w^{a-1} (1-w)^{b-1}$$
 (indepence)  

$$\propto w^s (1-w)^{N-s} w^{a-1} (1-w)^{b-1}$$
 (let  $s = \sum_{i=1}^N x_i$ )  

$$= w^{s+a-1} (1-w)^{N-s+b-1}$$
  

$$\propto \operatorname{Beta}(s+a, N-s+b)$$

 $\mathbf{B}$ 

Let 
$$f(x_1, x_2) = (y_1, y_2) = (x_1/(x_1 + x_2), x_1 + x_2)$$
, we have:  

$$f^{-1}(y_1, y_2) = (x_1, x_2) = (y_1y_2, y_2 - y_1y_2)$$

We then calculate the Jacobian of  $f^{-1}$ :

$$\begin{split} \partial x_1/\partial y_1 &= y_2 \\ \partial x_1/\partial y_2 &= y_1 \\ \partial x_2/\partial y_1 &= -y_2 \\ \partial x_2/\partial y_2 &= 1 - y_1 \end{split}$$

Therefore,

$$|J(f^{-1})| = \begin{vmatrix} y_2 & y_1 \\ -y_2 & 1 - y_1 \end{vmatrix}$$
$$= y_2(1 - y_1) + y_1y_2$$
$$= y_2$$

Let  $p_X$  be the joint density of  $(x_1, x_2)$ . We have the joint density of  $y_1$  and  $y_2$ :

$$\begin{split} p(y_1, y_2) &= p_X(f^{-1}(y_1, y_2))|J(f^{-1}(y_1, y_2))| \\ &= \operatorname{Ga}(y_1 y_2; a_1, 1)\operatorname{Ga}(y_2 - y_1 y_2; a_2, 1)y_2 \\ &= \frac{(y_1 y_2)^{a_1 - 1} \exp(-y_1 y_2)}{\Gamma(a_1)} \frac{((1 - y_1) y_2)^{a_2 - 1} \exp(y_1 y_2 - y_2)}{\Gamma(a_2)} y_2 \\ &= \frac{y_1^{a_1 - 1} y_2^{a_1 + a_2 - 1} (1 - y_1)^{a_2 - 1} \exp(-y_2)}{\Gamma(a_1)\Gamma(a_2)} \end{split}$$

The marginals are:

$$p(y_1) = \int_0^\infty p(y_1, y_2) dy_2$$

$$= \frac{y_1^{a_1 - 1} (1 - y_1)^{a_2 - 1}}{\Gamma(a_1) \Gamma(a_2)} \int_0^\infty y_2^{a_1 + a_2 - 1} \exp(-y_2) dy_2$$

$$= \frac{y_1^{a_1 - 1} (1 - y_1)^{a_2 - 1} \Gamma(a_1 + a_2)}{\Gamma(a_1) \Gamma(a_2)}$$

and

$$p(y_2) = \int_0^\infty p(y_1, y_2) dy_1$$

$$= \frac{y_2^{a_1 + a_2 - 1} \exp(-y_2)}{\Gamma(a_1)\Gamma(a_2)} \int_0^\infty y_1^{a_1 - 1} (1 - y_1)^{a_2 - 1}$$

$$= \frac{y_2^{a_1 + a_2 - 1} \exp(-y_2)}{\Gamma(a_1)\Gamma(a_2)} \text{Beta}(a_1, a_2)$$

 $\mathbf{C}$ 

The posterior is:

$$p(\theta|x_1, \dots, x_N) \propto p(x_1, \dots, x_N|\theta)p(\theta)$$

$$= \prod_{i=1}^N \mathcal{N}(x_i; \theta, \sigma^2) \mathcal{N}(\theta; m, v)$$

$$\propto \prod_{i=1}^N \exp\left(-\frac{(x_i - \theta)^2}{2\sigma^2}\right) \exp\left(-\frac{(\theta - m)^2}{2v}\right)$$

$$= \prod_{i=1}^N \exp\left(-\frac{x_i^2 - 2x_i\theta + \theta^2}{2\sigma^2}\right) \exp\left(-\frac{\theta^2 - 2\theta m + m^2}{2v}\right)$$

$$= \exp\left(-\frac{\sum_i x_i^2 + 2\sum_i x_i\theta - N\theta^2}{2\sigma^2}\right) \exp\left(-\frac{\theta^2 + 2\theta m - m^2}{2v}\right)$$

$$= \exp\left(-\theta^2 \left(\frac{N}{2\sigma^2} + \frac{1}{2v}\right) + \theta\left(\frac{\sum_i x_i}{\sigma^2} + \frac{m}{v}\right) - \frac{\sum_i x_i^2}{2\sigma^2} - \frac{m^2}{2v}\right)$$

We then complete the square:

 $\mathbf{D}$ 

$$p(\omega \mid x_1, \dots, x_N) \propto \prod_{i=1}^N p(x_i \mid \theta, \omega) p(\omega)$$

$$\propto \prod_{i=1}^N \omega^{1/2} \exp\left[-\frac{\omega}{2} (x_i - \theta)^2\right] \frac{b^a}{\Gamma(a)} \omega^{a-1} \exp(-b\omega)$$

$$\propto \omega^{N/2 + a - 1} \exp\left[-\omega \left(b + \frac{\sum_i (x_i - \theta)^2}{2}\right)\right]$$

$$\propto \operatorname{Ga}\left(a + \frac{N}{2}, b + \frac{\sum_i (x_i - \theta)^2}{2}\right)$$

We have the posterior of the variance:

$$p(\sigma^2 \mid x_1, ..., x_N) = IG\left(a + \frac{N}{2}, b + \frac{\sum_i (x_i - \theta)^2}{2}\right)$$

 $\mathbf{E}$ 

 $\mathbf{F}$ 

$$\begin{split} p(x) &= \int_0^\infty p(x \mid \sigma^2) p(\sigma^2) d\sigma^2 \\ &= \int_0^\infty p(x \mid \omega) p(\omega) d\omega \\ &= \int_0^\infty \left(\frac{\omega}{2\pi}\right)^{1/2} \exp\left(-\frac{\omega}{2}x^2\right) \frac{b^a}{\Gamma(a)} \omega^{a-1} \exp(-b\omega) d\omega \\ &\propto \int_0^\infty \omega^{1/2+a-1} \exp\left(-\omega \left(\frac{x^2}{2} + b\right)\right) d\omega \\ &= \frac{\Gamma(a+1/2)}{(b+x^2/2)^{a+1/2}} \\ &\propto \frac{\Gamma(\frac{2a+1}{2})}{(1+\frac{x^2/2}{b})^{a+1/2}} \end{split}$$