

Question 1 (15 points): The Galenshore distribution (Hoff 3.9).

An unknown quantity Y has a Galenshore(a, θ) distribution if its density is given by

$$p(y) = \frac{2}{\Gamma(a)} \theta^{2a} y^{2a-1} e^{-\theta^2 y^2}$$

for $y > 0, \theta > 0$ and $a > 0$. Assume for now that a is known. For this density,

$$\mathbb{E}[Y] = \frac{\Gamma(a + \frac{1}{2})}{\theta \Gamma(a)}, \quad \mathbb{E}[Y^2] = \frac{a}{\theta^2}$$

- Identify a class of conjugate prior densities for θ . Plot a few (e.g. 4 or 6) members of this class of densities.
- Let $Y_1, \dots, Y_n \mid \theta \stackrel{iid}{\sim} \text{Galenshore}(a, \theta)$. Find the posterior distribution of θ given $Y_{1:n} = y_{1:n}$, using a prior from your conjugate class.
- Write down $\frac{p(\theta_a | y_{1:n})}{p(\theta_b | y_{1:n})}$ and simplify. Identify a sufficient statistic.
- Determine $\mathbb{E}[\theta \mid y_{1:n}]$.
- Determine the form of the posterior predictive density $p(y_{n+1} \mid y_{1:n})$.

a) $y \sim \text{Gal}(a, \theta)$ has a density in the exponential family indeed

$$p(y \mid \theta) = \frac{2}{\Gamma(a)} \cdot \theta^{2a} y^{2a-1} e^{-\theta^2 y^2} \mathbb{1}_{y>0} (= p_{\text{Gal}}(a, \theta)(y)) \quad , \theta > 0, a > 0$$

$\downarrow \phi := \theta^2$ maybe prove it (in T of the very end).

$$p(y \mid \phi) = h(y) \cdot c(\phi) \cdot e^{\phi \cdot t(y)} \quad \text{with } h(y) = \frac{2 y^{2a-1}}{\Gamma(a)} \mathbb{1}_{y>0}, c(\phi) = (\phi)^{-a} \text{ and } t(y) = -y^2.$$

\Rightarrow we know that a class of conj. prior for a distr. in the exponential family is

$$p(\phi) \propto c(\phi)^{n_0} \cdot e^{\phi \cdot n_0 t_0} = \phi^{a n_0} \cdot e^{\phi \cdot n_0 t_0} \quad (\leftarrow \text{use } n_0 = c_1, n_0 t_0 = c_2 \text{ as initial param., then change them (1)})$$

If $\tilde{\phi} \sim p(\phi)$ and we want to obtain the distr. of $\Theta^2 = \tilde{\phi} \Rightarrow \Theta = \sqrt{\tilde{\phi}} = \varphi(\tilde{\phi}) \quad \varphi: \mathbb{R}^+ \rightarrow \mathbb{R}^+$

$$\Rightarrow p_{\Theta}(\theta) \propto p_{\tilde{\phi}}(\varphi^{-1}(\theta)) \cdot \left(\det \left(\frac{d\varphi^{-1}}{d\theta}(\theta) \right) \right) = p(\theta^2) \cdot 2\theta = \frac{2}{\Gamma(a)} \theta^{2a} e^{-\theta^2 n_0 t_0} \cdot 2\theta = \frac{2}{\Gamma(a)} \theta^{2a+1} e^{-\theta^2 n_0 t_0}$$

one betw. n_0 and $t_0 = 0$. $\sqrt{-n_0 t_0}$ will be the parameter c of the distribution: it'll appear as an $(\sqrt{-n_0 t_0})^2$ for a 1st param

$$2a n_0 + 1 = 2k - 1$$

$$\text{recalling } \theta > 0 \text{ by hp. } k = (2a n_0 + 1) / 2 = a n_0 + \frac{1}{2}$$

$$\Rightarrow = 2(a n_0 + \frac{1}{2}) - 1$$

$$\Rightarrow p_{\Theta}(\theta) = \frac{2}{\Gamma(a n_0 + \frac{1}{2})} \cdot (-n_0 t_0)^{a n_0 + \frac{1}{2}} \theta^{2(a n_0 + \frac{1}{2}) - 1} e^{-\theta^2 n_0 t_0} \mathbb{1}_{\theta>0} (= p_{\text{Gal}}(\theta, a n_0 + \frac{1}{2}, \sqrt{-n_0 t_0}))$$

(remark: $a n_0 + \frac{1}{2} > 0$, $-n_0 t_0 > 0$ by construction indeed $a > 0$ by hp.; $n_0 > 0$ because it represent the "prior sample size", the prior has the same kernel of the likelihood based on n_0 observations $(p(\tilde{y}_{1:n} \mid \phi))$; $t_0 > 0$ because it is the "prior guess" for $t(y) = -y^2/2 < 0 \forall y$.)

Let's plot a few of this densities $\text{Gal}(a n_0 + \frac{1}{2}, \sqrt{-n_0 t_0})$

$$- n_0 = 1, t_0 = -1, a = 1 \Rightarrow \text{Gal}(2, 1)$$

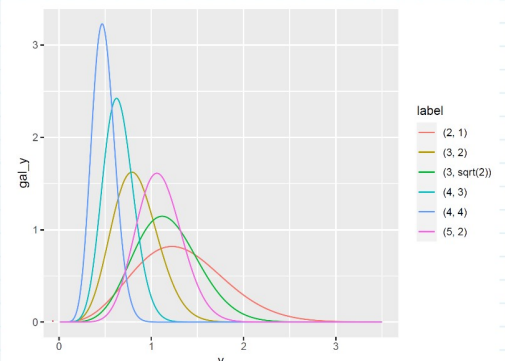
$$- n_0 = 1, t_0 = -1, a = 1 \Rightarrow \text{Gal}(3, \sqrt{2})$$

$$- n_0 = 2, t_0 = -2, a = 1 \Rightarrow \text{Gal}(3, 2)$$

$$- n_0 = 2, t_0 = -2, a = 2 \Rightarrow \text{Gal}(5, 2)$$

$$- n_0 = 3, t_0 = -3, a = 1 \Rightarrow \text{Gal}(4, 3)$$

$$- n_0 = 4, t_0 = -4, a = 1 \Rightarrow \text{Gal}(4, 4)$$



$$y \sim \mathcal{G}_d(a, \theta)$$

$$\theta \sim \mathcal{G}_d(b, c) \quad \rightarrow \quad \propto e^{-\theta^T y_i^*} \cdot \theta^{2d}$$

$$\begin{aligned} b) \quad p(\theta | y_{1:n}) &\propto p(\theta) \cdot p(y_{1:n} | \theta) = \\ &\propto (\theta^{2b-1} \cdot e^{-c^T \theta}) \cdot \theta^{2d \cdot n} \cdot e^{-\theta^T (\sum_{i=1}^n y_i^*)} \\ &\propto \theta^{2b-1+2dn} \exp \left\{ -\theta^T \left(c^T + \sum_{i=1}^n y_i^* \right) \right\} \\ \Rightarrow p(\theta | y_{1:n}) &\sim \mathcal{G}_d \left(dn + b, \sqrt{c^T + \sum_{i=1}^n y_i^*} \right) \quad \text{SS} := \sum_{i=1}^n y_i^* \end{aligned}$$

$$c) \quad p(\theta_a | y_{1:n}) / p(\theta_b | y_{1:n}) = \left(\frac{\theta_a}{\theta_b} \right)^{2(dn+b)-1} \exp \left\{ -(\theta_a^T - \theta_b^T) \left(c^T + \sum_{i=1}^n y_i^* \right) \right\}$$

does not dep. on θ_a, θ_b
 \Rightarrow let question: $\sqrt{\sum y_{1:n}}$
 minimal sufficient w.r.t. what?

$$d) \quad \mathbb{E}[\theta | y_{1:n}] = \frac{\Gamma(dn + b + 1/2)}{\Gamma(dn + b)} \cdot \frac{1}{(c^T + \sum y_i^*)}$$

$$\mathbb{E}[Y] = \frac{\Gamma(a + \frac{1}{2})}{\theta \Gamma(a)}, \quad (y \sim \mathcal{G}_d(a, \theta))$$

$$\begin{aligned} e) \quad p(y_{n+1} | y_{1:n}) &= \int_0^\infty p(y_{n+1} | \theta) \cdot p(\theta | y_{1:n}) d\theta = \leftarrow p(y) = \frac{2}{\Gamma(a)} \theta^{2a} y^{2a-1} e^{-\theta^2 y^2} \\ &= \int_0^\infty \frac{2}{\Gamma(a)} \cdot \theta^{2a} y_{n+1}^{2a-1} \cdot \exp \left\{ -\theta^T y_{n+1}^* \right\} \cdot \frac{\Gamma(dn + b)}{(c^T + \text{SS})^{dn+b}} \cdot \theta^{2(dn+b)-1} \cdot \exp \left\{ -(\theta^T + \text{SS}) \theta^T \right\} d\theta \\ &= \frac{2}{\Gamma(a) \Gamma(dn + b)} y_{n+1}^{2a-1} (c^T + \text{SS})^{dn+b} \int_0^\infty \theta^{2(dn+b)-1} \cdot \exp \left\{ -\theta^T \left(\sum_{i=1}^{n+1} y_i^* + c^T \right) \right\} d\theta = \end{aligned}$$

\uparrow
SS_{n+1}

kernel of $\mathcal{G}_d(d + dn + b, \sqrt{\text{SS}_{n+1} + c^T})$

$$= \frac{\Gamma(d + dn + b)}{2} \cdot \left(\frac{1}{c^T + \text{SS}_{n+1}} \right)^{d+dn+b}$$

$$= 2 \cdot \frac{\Gamma(a) + (dn + b)}{\Gamma(a) \Gamma(dn + b)} y_{n+1}^{2a-1} \cdot \frac{1}{y_{n+1}} \cdot (c^T + \text{SS})^{dn+b} \cdot \frac{1}{(c^T + \text{SS}_{n+1})^a} \cdot \frac{1}{(c^T + \text{SS}_{n+1})^{b+dn}} =$$

$$= \frac{2}{y_{n+1}} \cdot \left(\frac{1}{\text{Beta}(d, b + dn)} \left(\frac{(y_{n+1})^2}{c^T + \text{SS} + y_{n+1}^*} \right)^d \cdot \left(\frac{c^T + \text{SS}}{c^T + \text{SS} + y_{n+1}^*} \right)^{b+dn} \right) =$$

$$= \frac{2}{y_{n+1}} \cdot \frac{y_{n+1}^2 (c^T + \text{SS})}{(c^T + \text{SS} + y_{n+1}^*)^2} \cdot \left(\frac{1}{\text{Beta}(d, b + dn)} \left(\frac{(y_{n+1})^2}{c^T + \text{SS} + y_{n+1}^*} \right)^{d-1} \cdot \left(1 - \frac{(y_{n+1})^2}{c^T + \text{SS} + y_{n+1}^*} \right)^{b+dn} \right) =$$

$$= \frac{2 (c^T + \text{SS}) y_{n+1}}{(c^T + \text{SS} + y_{n+1}^*)^2} \cdot p_X \left(\frac{(y_{n+1})^2}{c^T + \text{SS} + y_{n+1}^*} \right)$$

\hookrightarrow pdf of $X \sim \text{Beta}(d, dn + b)$ evaluated on $(y_{n+1})^2 / (c^T + \text{SS} + y_{n+1}^*)$

$$= \det \left(\frac{d}{dy_{n+1}} \varphi^{-1}(y_{n+1}) \right) \cdot p_X \left(\varphi^{-1}(y_{n+1}) \right) = p_{\varphi(X)}(y_{n+1})$$

where $\left| \frac{d}{dy_{n+1}} \varphi^{-1}(y_{n+1}) \right| = \frac{2 (c^T + \text{SS}) y_{n+1}}{(c^T + \text{SS} + y_{n+1}^*)^2}$

$$\hookrightarrow \frac{d}{dy_{n+1}} \left(\frac{(y_{n+1})^2}{c^T + \text{SS} + y_{n+1}^*} \right) = \frac{2 y_{n+1} \cdot (c^T + \text{SS} - y_{n+1}^*) - (y_{n+1})^2 \cdot (2 y_{n+1})}{(c^T + \text{SS} + y_{n+1}^*)^2} = \frac{2 (c^T + \text{SS}) y_{n+1}}{(c^T + \text{SS} + y_{n+1}^*)^2}$$

$$\Rightarrow p_{y_{n+1} | y_{1:n}}(y_{n+1}) = p_{\varphi(X)}(y_{n+1}), \quad X \sim \text{Beta}(d, dn + b), \quad \varphi: \mathbb{R}^+ \rightarrow \mathbb{R}^+ \text{ s.t. } \varphi^{-1}(x) = \frac{x^2}{(c^T + \text{SS} + x^*)}$$

$$= 1 - \frac{c^T + \text{SS}}{c^T + \text{SS} + x^*}$$

$$\Rightarrow 1 - x = \frac{c^T + \text{SS}}{c^T + \text{SS} + \varphi(x)}$$

$$\Rightarrow \frac{\varphi(x)}{c^T + \text{SS}} + 1 = \frac{1}{1 - x}$$

$$\Rightarrow \varphi(x) = \frac{x \cdot (c^T + \text{SS})}{1 - x}$$

$$\Rightarrow y_{n+1} | y_{1:n} \sim \varphi(\text{Beta}(d, dn + b)), \quad \varphi(x) = \frac{x}{1-x} \cdot (c^T + \text{SS})$$

To do: test ex 2.