Solution 1

(a) In this case

$$k(\varphi) = \log \int_0^1 e^{\varphi y} dy = \log \left(\frac{e^{\varphi} - 1}{\varphi} \right), \quad \varphi \in \mathcal{N} = \mathbb{R},$$

with k(0) = 0 defined by continuity as $\varphi \to 0$. Hence the resulting exponential family is

$$f(y;\varphi) = e^{\varphi y - k(\varphi)} = \frac{\varphi e^{\varphi y}}{e^{\varphi} - 1}, \quad y \in \mathcal{Y}, \varphi \in \mathbb{R}.$$

(b) In this case

$$k(\varphi) = \log \int_0^1 e^{\varphi_1 \log y + \varphi_2 \log(1-y)} dy = \log \int_0^1 y^{\varphi_1} (1-y)^{\varphi_2} dy$$

and we recognise this as a beta integral, defined for $\varphi_1, \varphi_2 > -1$, and then equal to $\Gamma(1 + \varphi_1)\Gamma(1 + \varphi_2)/\Gamma(2 + \varphi_1 + \varphi_2)$. The resulting density is therefore

$$f(y;\varphi) = \frac{\Gamma(2+\varphi_1+\varphi_2)}{\Gamma(1+\varphi_1)\Gamma(1+\varphi_2)} y^{\varphi_1} (1-y)^{\varphi_2}, \quad y \in \mathcal{Y}, \varphi = (\varphi_1,\varphi_2) \in (-1,\infty)^2,$$

which is just a rewriting of the beta density, for which $\alpha = \varphi_1 + 1$ and $\beta = \varphi_2 + 1$, and $\alpha, \beta > 0$, in the usual notation.

Solution 2 Using the results on linear combinations of normal variables, $\overline{X} \stackrel{\text{D}}{=} \mu + \sigma n^{-1/2} Z$, where $Z \sim \mathcal{N}(0,1)$. Hence $Y \stackrel{\text{D}}{=} 1/(\mu + \sigma n^{-1/2} Z)$.

If we apply the delta method with g(u) = 1/u, we have $g'(u) = -1/u^2$, provided $u \neq 0$. If $\mu \neq 0$ and as $n \to \infty$, therefore,

$$Y = g(\overline{X}) \stackrel{\mathrm{D}}{=} g(\mu + \sigma n^{-1/2} Z) \doteq g(\mu) + \sigma n^{-1/2} Z g'(\mu) \stackrel{\cdot}{\sim} \mathcal{N} \left\{ g(\mu), g'(\mu)^2 \times \sigma^2/n \right\} = \mathcal{N} \{ 1/\mu, \sigma^2/(n\mu^4) \}.$$

Note that if X has units of length (say), then its mean and its variance have units of length and length², so 1/X has units of 1/length and its variance has units of $1/\text{length}^2$, agreeing with the distribution here. If $\mu = 0$, then for any n,

$$P(\overline{X} < 0) = P(\overline{X} > 0) = P(\mu + \sigma n^{-1/2}Z > 0) = P(Z > 0) = 1/2,$$

and if y > 0 we can write

$$\begin{split} \mathrm{P}(Y>y\mid \overline{X}>0) &=& \mathrm{P}\{1/(\mu+\sigma n^{-1/2}Z)>y\mid Z>0\}\\ &=& \mathrm{P}\{Z< n^{1/2}/(\sigma y)\mid Z>0\}\\ &=& 2\left[\Phi\left\{n^{1/2}/(y\sigma)\right\}-1/2\right]\\ &\to& 1, \quad n\to\infty, \end{split}$$

so as this is true for any positive y, the distribution of Y will concentrate at $\pm \infty$ with equal probabilities.

Solution 3

(a) Clearly $\tau = 0$ is one possible solution for any $R_0 > 0$. The slopes of $1 - \tau$ and $e^{-R_0\tau}$ at $\tau = 0$ are respectively -1 and $-R_0$, and it is clear from a plot of these two functions against τ that there is a second, positive, solution to the equation within the interval $\tau \in (0,1)$ if $R_0 > 1$. The intuition is that if $R_0 \leq 1$, then the epidemic is certain to be of negligible size, but that if $R_0 > 1$ then it may be of negligible size (if by chance it dies out immediately) but otherwise will affect a positive fraction of the population.

(b) The equation $1 - \tau = e^{-R_0 \tau}$ gives $R_0 = -\tau^{-1} \log(1 - \tau) = g(\tau)$, say, which is a smooth function of τ for $\tau \in (0,1)$. Hence the delta method applies, and $\widehat{R}_0 = g(\widehat{\tau})$ is asymptotically normal with mean $g(\tau) = R_0$ and with variance given using

$$g'(\tau) = \log(1-\tau)/\tau^2 + 1/\{\tau(1-\tau)\} = -R_0/\tau + 1/\{\tau(1-\tau)\} = \{1 - R_0(1-\tau)\}/\{\tau(1-\tau)\};$$

the delta method variance formula $\sigma_R^2 = g'(\tau)^2 \sigma^2$ gives the required result.

(c) The variance of a constant is zero, so if the constant itself is non-zero, $c^2 = 0/T = 0$. If $T \sim U(0, d)$ then E(T) = d/2 and $var(T) = d^2/12$, leading to $c^2 = 1/3$. An exponential variable with mean μ has variance μ^2 , giving $c^2 = 1$. The exponential distribution has high coefficient of variation (for example, the gamma distribution has $c = \alpha^{-1/2}$, where α is the shape parameter, and taking $\alpha > 1$ gives a unimodal distribution that seems potentially suitable for T), so taking c = 1 should give an upper bound for σ^2 and hence for σ_R^2 .

Solution 4

(a) The density is

$$f(y) = \frac{\alpha \theta^{\alpha}}{(\theta + y)^{\alpha + 1}} = \exp\left\{-(\alpha + 1)\log(\theta + y) + \log\alpha + \alpha\log\theta\right\}, \quad y > 0, \quad \alpha, \theta > 0.$$

This is not of exponential family form, because no term in the log density can be written as $s(y)^{\mathrm{T}}\varphi(\theta)$ for some function s(y) that depends only on y.

(b) The method-of-moments estimator satisfies $\overline{Y} = \tilde{\theta}/(\alpha - 1)$, i.e., $\tilde{\theta} = (\alpha - 1)\overline{Y}$, and this is easily checked to be unbiased using the given formula for E(Y) and the fact that $E(\overline{Y}) = E(Y)$.

Moreover $var(\overline{Y}) = var(Y)/n$, so

$$\operatorname{var}(\tilde{\theta}) = (\alpha - 1)^2 \operatorname{var}(\overline{Y}) = \frac{(\alpha - 1)^2}{n} \operatorname{var}(Y) = \frac{\theta^2 \alpha}{n(\alpha - 2)}.$$

(c) The bias of of $\tilde{\theta}_c$ is

$$b(\tilde{\theta}_c; \theta) = E(\tilde{\theta}_c) - \theta = c \frac{\theta}{\alpha - 1} - \theta = \frac{(\alpha - 1 - c)\theta}{\alpha - 1},$$

and $\operatorname{var}(\tilde{\theta}_c) = c^2 \operatorname{var}(\overline{Y})$, so (after a little algebra) the mean squared error of $\tilde{\theta}_c$ is

$$b(\tilde{\theta}_c; \theta)^2 + c^2 \operatorname{var}(\overline{Y}) = \frac{\theta^2}{n(\alpha - 1)^2 (\alpha - 2)} \left\{ n(\alpha - 2)(\alpha - 1 - c)^2 + c^2 \alpha \right\}.$$

This is minimised by differentiating the expression $\{\cdot\}$ here with respect to c, giving

$$\frac{\mathrm{d}\{\cdot\}}{\mathrm{d}c} = -2n(\alpha - 2)(\alpha - 1 - c) + 2c\alpha = 0,$$

which results in

$$c = \frac{n(\alpha - 1)(\alpha - 2)}{n(\alpha - 2) + \alpha} \to \alpha - 1, \quad n \to \infty.$$

Note that for any finite n the estimator is biased, but it is asymptotically unbiased, and that the second derivative $d^2\{\cdot\}/dc^2 = 2n(\alpha - 1)(\alpha - 2) + 2\alpha$ is positive — which is obvious because the MSE is a sum of positive quadratic expressions in c.