

SMF SOLUTIONS 2. 16.5.2012

Q1. (i) $f(x) = p^x(1-p)^{1-x}$ (this takes the required values p at 1 and $1-p$ at 0). So

$$L = p^{\sum x_i} (1-p)^{n-\sum x_i} = p^{n\bar{x}} (1-p)^{n(1-\bar{x})}, \quad \ell = n\bar{x} \log p + n(1-\bar{x}) \log(1-p).$$

So

$$\ell' = \frac{n\bar{x}}{p} - \frac{n(1-\bar{x})}{1-p},$$

which is 0 iff

$$\frac{\bar{x}}{p} = \frac{1-\bar{x}}{1-p}, \quad \bar{x} - p\bar{x} = p - p\bar{x}, \quad p = \bar{x}.$$

This is indeed a maximum (as one can check), so \bar{x} is the MLE for p .

(ii)

$$\frac{L(x)}{L(y)} = \left(\frac{p}{1-p} \right)^{\sum x_i - \sum y_i}.$$

This is independent of p iff $\sum x_i = \sum y_i$, i.e. iff $\bar{x} = \bar{y}$. so by Lehmann-Scheffé, \bar{x} is minimal sufficient for p .

Q2. In an obvious notation,

$$\begin{aligned} \ell_x &= \text{const} - \frac{1}{2}n \log |\Sigma| - \frac{1}{2}n \text{trace}(VS_x) - (\bar{x} - \mu)^T V (\bar{x} - \mu) \\ &= \text{const} - \frac{1}{2}n \log |\Sigma| - \frac{1}{2}n \text{trace}(VS_x) - \bar{x}^T V \bar{x} - 2\mu^T V \bar{x} + \mu^T V \mu \end{aligned}$$

(the two cross-terms are scalars, so are their own transposes, so we can combine them), and similarly for ℓ_y . Subtract:

$$\ell_x - \ell_y = -\frac{1}{2}n \text{trace}[V(S_x - S_y)] - [\bar{x}^T V \bar{x} - \bar{y}^T V \bar{y}] - 2\mu^T V (\bar{x} - \bar{y}).$$

This is independent of the parameters μ and Σ (or V) iff

$$\bar{x} = \bar{y}, \quad S_x = S_y.$$

So by the Lehmann-Scheffé theorem, (\bar{x}, S_x) is minimal sufficient for (μ, Σ) .

Q3 *Rayleigh distribution.* (i) Putting $u := \frac{1}{2}x^2/v$, $du = (x/v)dx$, so

$$\int f(x)dx = \int_0^\infty e^{-u}du = 1,$$

so f is indeed a density.

(ii)

$$\begin{aligned} E[\tfrac{1}{2}X^2] &= \int_0^\infty \tfrac{1}{2}x^2 \cdot \exp\{-\tfrac{1}{2}x^2/v\} \cdot x dx / v = v \int_0^\infty (\tfrac{1}{2}x^2/v) \exp\{-\tfrac{1}{2}x^2/v\} d(\tfrac{1}{2}x^2/v) \\ &= v \int_0^\infty te^{-t}dt = v \end{aligned}$$

(integrating by parts, or by $\Gamma(2) = 1! = 1$). So the mean is v .

The same substitution gives

$$E[(\tfrac{1}{2}X^2)^2] = v^2 \int_0^\infty t^2 e^{-t} dt = 2v^2$$

(integrate by parts, or use $\Gamma(3) = 2! = 2$). So

$$\text{var}(\tfrac{1}{2}X^2) = E[(\tfrac{1}{2}X^2)^2] - (E[\tfrac{1}{2}X^2])^2 = 2v^2 - v^2 = v^2 :$$

$\tfrac{1}{2}X^2$ has variance v^2 .

(iii)

$$\ell = \log f = \log x - \log v - \tfrac{1}{2}x^2/v.$$

So the score function is

$$s = \ell' = -\frac{1}{v} + \frac{1}{2} \cdot \frac{x^2}{v^2} = \frac{x^2 - 2v}{2v^2}.$$

So the information per reading is

$$\begin{aligned} I = E[s^2] &= E\left[\left(\frac{x^2 - 2v}{2v^2}\right)^2\right] = \frac{1}{4v^4} [E(X^4) - 4vE(X^2) + 4v^2] \\ &= \frac{1}{4v^4} [8v^2 - 4v \cdot 2v + 4v^2] = \frac{4v^2}{4v^4} = 1/v^2. \end{aligned}$$

So the CR lower bound is v^2/n . But by (i) \hat{v} is unbiased for v , and by (ii) it attains the CR bound, so is efficient for v .

NHB