

$$\begin{aligned}
 (1) \quad (a) \quad L_{\pi}(1|1) &= \frac{1}{2}, & L(2|1) &= \frac{1}{3} \\
 L_{\pi}(1|2) &= \frac{1}{3}, & L(2|2) &= \frac{4}{5} \\
 L_{\pi}(1|3) &= \frac{1}{2}, & L(2|3) &= \frac{1}{6}
 \end{aligned}$$

and any positive multiple of these gives all possible profile likelihoods.

$$\begin{aligned}
 (b) \quad C_{1/2}(1) &= \{ \mu : L_{\pi}(\mu|1) \geq \frac{1}{2} \sup_{\mu} L(\mu|1) \} \\
 &= \{ \mu : L_{\pi}(\mu|1) = 1/4 \} = \{1, 2\}
 \end{aligned}$$

$$C_{1/2}(2) = \{ \mu : L_{\pi}(\mu|2) \geq \frac{2}{5} \} = \{2\}$$

$$C_{1/2}(3) = \{ \mu : L_{\pi}(\mu|3) \geq \frac{1}{4} \} = \{1\}$$

$$(2) (a) L(\mu, \sigma^2 | x) = (\sigma^2)^{-\frac{n}{2}} \exp \left\{ -\frac{n}{2\sigma^2} (\bar{x} - \mu)^2 - \frac{(n-1)s_x^2}{2\sigma^2} \right\}$$

$$\text{and } L(\mu, \sigma^2 | x) = (\sigma^2)^{-\frac{n}{2}} \exp \left\{ -\frac{n}{2\sigma^2} (\bar{x} - \frac{\sigma}{\mu})^2 - \frac{(n-1)s_x^2}{2\sigma^2} \right\}$$

and note that  $\mu \in \mathbb{R} \setminus 0$ ,  $\sigma^2 > 0$  are unconstrained so  $L_{\pi}(\mu|x) = \sup_{\sigma^2 > 0} L(\mu, \sigma^2 | x)$  and we need to maximize  $L(\mu, \sigma^2 | x)$  as a function of  $\sigma^2$ .

(b) Taking the log of the likelihood we obtain

$$\ell(\mu, \sigma^2 | x) = -\frac{n}{2} \log \sigma^2 - \frac{n}{2\sigma^2} (\bar{x} - \frac{\sigma}{\mu})^2 - \frac{(n-1)s_x^2}{2\sigma^2} \text{ and}$$

(2)

$$\frac{\partial \ell(\tau, \sigma^2 | x)}{\partial \sigma^2} = -\frac{n}{2\sigma^2} + \frac{n}{2\sigma^4} (\bar{x} - \frac{\sigma^2}{\tau})^2 + \frac{n}{2\sigma^2} 2(\bar{x} - \frac{\sigma^2}{\tau}) \frac{1}{\tau} \frac{(\sigma^2)^{\frac{1}{2}}}{\tau} + \frac{(n+1)s_x^2}{2\sigma^4}$$

Then setting this equal to 0 and multiplying through by  $-2\sigma^5/n$  we get

$$\begin{aligned} \sigma^3 - \sigma(\bar{x}^2 - 2\bar{x}\sigma/\tau + \sigma^2/\tau^2) - \sigma^3(\bar{x} - \sigma/\tau)\frac{1}{\tau} - \frac{n+1}{2} s_x^2 \sigma \\ = \sigma^3 - \bar{x}^2 \sigma + \frac{2\bar{x}}{\tau} \sigma^2 - \frac{\sigma^3}{\tau^2} - \frac{\bar{x}}{\tau} \sigma^2 + \frac{\sigma^3}{\tau^2} - \frac{n+1}{2} s_x^2 \sigma \\ = \sigma^3 + \frac{\bar{x}}{\tau} \sigma^2 - (\bar{x}^2 + \frac{n+1}{2} s_x^2) \sigma = 0 \end{aligned}$$

$$\text{or } \sigma^2 + \frac{\bar{x}}{\tau} \sigma - (\bar{x}^2 + \frac{n+1}{2} s_x^2) = 0$$

$$\text{so } \sigma = \frac{-\frac{\bar{x}}{\tau} \pm \sqrt{\left(\frac{\bar{x}}{\tau}\right)^2 + 4(\bar{x}^2 + \frac{n+1}{2} s_x^2)}}{2}$$

$$= \frac{1}{2} \left( \frac{\bar{x}}{\tau} + \sqrt{\left(\frac{\bar{x}}{\tau}\right)^2 + 4\bar{x}^2 + 2(n+1)s_x^2} \right) \text{ since } \bar{x}^2 + \frac{n+1}{2} s_x^2 = \frac{1}{2} \left( \frac{\bar{x}}{\tau} \right)^2 + 2\bar{x}^2 + (n+1)s_x^2$$

and since  $\sigma$  is not negative the root must be

$$\sigma(\tau) = \frac{1}{2} \left( -\frac{\bar{x}}{\tau} + \sqrt{\left(\frac{\bar{x}}{\tau}\right)^2 + 4\bar{x}^2 + 2(n+1)s_x^2} \right)$$

Then the profile likelihood  $f_n$  is

$$L_{\Pi}(\tau | x) = (\sigma^2(\tau))^{-\frac{n}{2}} \exp \left\{ -\frac{n}{2\sigma^2(\tau)} \left( \bar{x} - \frac{\sigma(\tau)}{\tau} \right)^2 - \frac{(n+1)s_x^2}{\sigma^2(\tau)} \right\}.$$



③ 6.2.20 The likelihood function for  $\mu$  is given by

$$L(\mu|x) = c \exp\left\{-\frac{n}{2}(\bar{x}-\mu)^2\right\}$$

and  $\Phi(\mu) = \Phi(1-\mu)$ . Now  $d\Phi(\mu)/d\mu = \phi(1-\mu) = -\frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(1-\mu)^2} > 0$  and so  $\Phi$  is a strictly decreasing function of  $\mu$  which implies it is 1-1. Now  $\mu = \Phi^{-1}(\frac{1}{2}) = 1 - \Phi^{-1}(\frac{1}{2})$  and so the likelihood  $f_n$  is

$$L(\theta|x) = c \exp\left\{-\frac{n}{2}(\bar{x} - 1 + \Phi^{-1}(\frac{1}{2}))^2\right\}.$$

The MLE of  $\mu$  is  $\bar{x}$  and so the MLE of  $\theta$  is  $\Phi(1-\bar{x})$ .

④ 6.3.25 We have that  $\bar{x} \sim N(\mu, \sigma_0^2/n)$  so

$$P_\mu\left(\mu \leq \bar{x} + k \frac{\sigma_0}{\sqrt{n}}\right) = P_\mu\left(-k \leq \frac{\bar{x} - \mu}{\sigma_0/\sqrt{n}}\right)$$

$$= 1 - P_\mu\left(\frac{\bar{x} - \mu}{\sigma_0/\sqrt{n}} \leq +k\right) = 1 - \Phi(k) = \delta$$

$$\text{and so } k = -\Phi^{-1}(1-\delta) = -z_{1-\delta} = z_\delta$$

a  $\delta$ -confidence interval for  $\mu$ .

(4)

(5) (6.3.26) We have that

$$\max_{\mu \leq \mu_0} P_{\mu}(\bar{X} > \bar{x}) = \max_{\mu \leq \mu_0} P_{\mu}\left(\frac{\bar{X} - \mu}{\sigma_0/\sqrt{n}} > \frac{\bar{x} - \mu}{\sigma_0/\sqrt{n}}\right)$$

$$= \max_{\mu \leq \mu_0} \left(1 - \Phi\left(\frac{\bar{x} - \mu}{\sigma_0/\sqrt{n}}\right)\right)$$

$$= 1 - \min_{\mu \leq \mu_0} \Phi\left(\frac{\bar{x} - \mu}{\sigma_0/\sqrt{n}}\right) = 1 - \Phi\left(\frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}}\right)$$

since  $\Phi\left(\frac{\bar{x} - \mu}{\sigma_0/\sqrt{n}}\right)$  decreases as  $\mu$  increases,

(6) (6.3.27) The p-value

$$1 - \Phi\left(\frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}}\right) \leq \alpha \quad \text{iff} \quad \frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \geq \Phi^{-1}(1 - \alpha) = z_{1-\alpha}$$

The power function is then given by

$$\beta(\mu) = P_{\mu}\left(\frac{\bar{x} - \mu_0}{\sigma_0/\sqrt{n}} \geq z_{1-\alpha}\right)$$

$$= P_{\mu}\left(\frac{\bar{x} - \mu}{\sigma_0/\sqrt{n}} \geq \frac{\mu_0 - \mu}{\sigma_0/\sqrt{n}} + z_{1-\alpha}\right)$$

$$= 1 - \Phi\left(\frac{\mu_0 - \mu}{\sigma_0/\sqrt{n}} + z_{1-\alpha}\right)$$