

第七次作业 6.38, 6.39

6.38 设 $\xi_1, \xi_2, \dots, \xi_n$ 是取自正态母体 $N(\mu, \sigma^2)$ 的一个子样, 其中 μ 已知. 证明:

i) $S_n^2 = \frac{1}{n} \sum_{i=1}^n (\xi_i - \mu)^2$ 是 σ^2 的相合估计. (例题)

ii) $\hat{\sigma} = \frac{1}{n} \sqrt{\frac{\pi}{2}} \sum_{i=1}^n |\xi_i - \mu|$ 是 σ 的无偏估计, 并求其有效率.

解: i) 因为 $\frac{nS_n^2}{\sigma^2} = \sum_{i=1}^n \left(\frac{\xi_i - \mu}{\sigma}\right)^2 \sim \chi^2(n)$, 所以

$$E\left(\frac{nS_n^2}{\sigma^2}\right) = n, \quad D\left(\frac{nS_n^2}{\sigma^2}\right) = 2n.$$

即

$$ES_n^2 = \sigma^2, \quad DS_n^2 = \frac{2\sigma^4}{n}.$$

母体的概率函数为: $f(x; \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2\sigma^2}(x - \mu)^2\right\}$,

$$\ln f(x; \sigma^2) = -\frac{1}{2} \ln 2\pi - \frac{1}{2} \ln \sigma^2 - \frac{1}{2\sigma^2}(x - \mu)^2,$$

$$\frac{\partial \ln f(x; \sigma^2)}{\partial \sigma^2} = -\frac{1}{2\sigma^2} + \frac{1}{2\sigma^4}(x - \mu)^2,$$

$$\frac{\partial^2 \ln f(x; \sigma^2)}{\partial (\sigma^2)^2} = \frac{1}{2\sigma^4} - \frac{1}{\sigma^6}(x - \mu)^2,$$

$$I(\sigma^2) = -E\left(\frac{\partial^2 \ln f(\xi; \sigma^2)}{\partial (\sigma^2)^2}\right) = -\frac{1}{2\sigma^4} + \frac{1}{\sigma^6}E(\xi - \mu)^2 = -\frac{1}{2\sigma^4} + \frac{1}{\sigma^4} = \frac{1}{2\sigma^4}.$$

因为 $\frac{1}{nI(\sigma^2)} = \frac{2\sigma^4}{n} = D(S_n^2)$, 所以 S_n^2 是 σ^2 的有效估计.

ii) 因为 $\frac{\xi_i - \mu}{\sigma} \sim N(0, 1)$, 所以

$$\begin{aligned} E\frac{|\xi_i - \mu|}{\sigma} &= \int_{-\infty}^{\infty} |x| \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx \\ &= 2 \int_0^{\infty} x \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} dx \\ &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-\frac{1}{2}x^2} d\frac{x^2}{2} \\ &= \sqrt{\frac{2}{\pi}}. \end{aligned}$$

所以

$$E|\xi_i - \mu| = \sqrt{\frac{2}{\pi}}\sigma, i = 1, 2, \dots, n.$$

$$E\hat{\sigma} = \frac{1}{n} \sqrt{\frac{\pi}{2}} \sum_{i=1}^n E|\xi_i - \mu| = \frac{1}{n} \sqrt{\frac{\pi}{2}} \sum_{i=1}^n \sqrt{\frac{2}{\pi}} \sigma = \sigma,$$

即 $\hat{\sigma}$ 是 σ 的无偏估计.

下面计算 $D(|\xi_i - \mu|)$.

$$\begin{aligned} D(|\xi_i - \mu|) &= E(|\xi_i - \mu|)^2 - (E|\xi_i - \mu|)^2 = E(\xi_i - \mu)^2 - \left(\sqrt{\frac{2}{\pi}}\sigma\right)^2 \\ &= D\xi_i - 2\sigma^2/\pi = \sigma^2 - 2\sigma^2/\pi = \frac{\pi-2}{\pi}\sigma^2. \end{aligned}$$

所以

$$D\hat{\sigma} = \frac{\pi}{2n^2} \sum_{i=1}^n D|\xi_i - \mu| = \frac{\pi-2}{2n}\sigma^2.$$

由于 $\sigma = \sqrt{\sigma^2} \triangleq g(\sigma^2)$, 故由上可知 $\hat{\sigma}$ 是 $g(\sigma^2)$ 的无偏估计. 而 $g'(\sigma^2) = \frac{1}{2\sqrt{\sigma^2}} = \frac{1}{2\sigma}$. 因此

$$\frac{[g'(\sigma^2)]^2}{nI(\sigma^2)} = \frac{[1/(2\sigma)]^2}{n \frac{1}{2\sigma^4}} = \frac{\sigma^2}{2n} < \frac{\pi-2}{2n}\sigma^2 = D\hat{\sigma}.$$

所以 $\hat{\sigma}$ 不是 σ 的有效估计. $\hat{\sigma}$ 的有效率为

$$\frac{\sigma^2}{2n} / \frac{(\pi-2)\sigma^2}{2n} = \frac{1}{\pi-2}.$$

6.39 设 $\xi_1, \xi_2, \dots, \xi_n$ 是取自具有下列指数分布的一个子样.

$$f(x) = \begin{cases} \frac{1}{\theta} e^{-\frac{x}{\theta}}, & x \geq 0 \\ 0, & \text{else.} \end{cases}$$

证明: $\bar{\xi} = \frac{1}{n} \sum_{i=1}^n \xi_i$ 是 θ 的无偏、相合、有效估计.

证明: 用 ξ 表示母体, 那么

$$E\xi = \theta, D\xi = \theta^2.$$

由此可知(定理5.1):

$$E\bar{\xi} = E\xi = \theta.$$

$$D\bar{\xi} = D\xi/n = \theta^2/n.$$

所以 $\bar{\xi}$ 是 θ 的无偏估计.

因为 $E\xi_i = E\xi = \theta$, 且 $\xi_1, \xi_2, \dots, \xi_n, \dots$ 是独立同分布的随机变量序列, 故由辛钦大数定律可知:

$$\frac{1}{n} \sum_{i=1}^n \xi_i \xrightarrow{P} \theta.$$

即 $\bar{\xi} = \sum_{i=1}^n \xi_i$ 是 θ 的相合估计.

又

$$\begin{aligned} \ln f(x; \theta) &= -\ln \theta - \frac{x}{\theta}, \\ \frac{\partial \ln f(x; \theta)}{\partial \theta} &= -\frac{1}{\theta} + \frac{x}{\theta^2}, \\ \frac{\partial^2 \ln f(x; \theta)}{\partial \theta^2} &= \frac{1}{\theta^2} - \frac{2x}{\theta^3}. \end{aligned}$$

因为

$$I(\theta) = -E\left(\frac{\partial^2 \ln f(\xi; \theta)}{\partial \theta^2}\right) = -\frac{1}{\theta^2} + \frac{2}{\theta^3} E\xi = -\frac{1}{\theta^2} + \frac{2}{\theta^3} \theta = \frac{1}{\theta^2}.$$

故

$$\frac{1}{nI(\theta)} = \frac{\theta^2}{n} = D\bar{\xi},$$

所以 $\bar{\xi}$ 是 θ 的有效估计.