

(1) 联合密度函数 $f(x_1, \dots, x_n, \theta, \mu) = \frac{1}{\theta^n} \exp\left(-\frac{\sum_{i=1}^n x_i - n\mu}{\theta}\right) I_{\mu < \theta} \frac{1}{\theta} \exp\left(-\frac{n\mu - n\mu}{\theta}\right) I_{\mu > \theta} g(\bar{x}, \theta, \mu) \cdot h(x_1, \dots, x_n)$
 其中 $h(x_1, \dots, x_n) = 1$. 由因子分解定理得: (\bar{x}, λ_n) 为 (θ, μ) 的充分统计量

$$I_{\mu > \theta} = \begin{cases} 1 & \mu > \theta \\ 0 & \mu \leq \theta \end{cases}$$

(2) $f(x_1, \dots, x_n) = \frac{\lambda^n}{[\Gamma(\lambda)]^n} \prod_{i=1}^n x_i^{\lambda-1} \exp(-\lambda \sum_{i=1}^n x_i)$
 设 $T = (t_1, t_2)$ $\left[\begin{matrix} t_1 = \sum_{i=1}^n x_i & t_2 = \sum_{i=1}^n x_i^2 \end{matrix} \right]$
 则 $f(x_1, \dots, x_n) = \frac{\lambda^n}{[\Gamma(\lambda)]^n} t_1^{\lambda-1} \exp(-\lambda t_1) = g(t_1, t_2, \lambda) h(x_1, \dots, x_n)$
 其中 $h(x_1, \dots, x_n) = 1$. 由因子分解定理得 (t_1, t_2) 为 (λ, λ) 的充分统计量

(3) (a) $E(\bar{x}) = \frac{1}{\lambda} = \frac{1}{\lambda}$, 故 \bar{x} 为 λ 的无偏估计
 (b) $E(\frac{1}{\bar{x}}) = E(\frac{n}{\sum_{i=1}^n x_i})$ 由伽玛分布的可加性: $(Z = X+Y \sim \text{Ga}(\lambda_1 + \lambda_2, \lambda))$:

$$\sum_{i=1}^n (\frac{x_i}{n}) \sim \text{Ga}(1, \lambda) = \text{Exp}(\lambda) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

$\therefore E(\frac{n}{\sum_{i=1}^n x_i}) = \int_0^{+\infty} \frac{n}{x} \lambda e^{-\lambda x} dx = \infty \neq \frac{1}{\lambda}$, 故 $\frac{1}{\bar{x}}$ 不是 λ 的无偏估计

(c) 构造 $T = \frac{1}{2}(x_{(n)} + x_{(1)})$. $(x_{(n)}, x_{(1)})$ 的联合密度函数为 $n(n-1)\lambda^2(e^{-\lambda y} - e^{-\lambda x})^{n-2} e^{-\lambda y - \lambda x}$
 故: $E(x_{(n)} + x_{(1)}) = \int_0^{+\infty} \int_0^y (x+y) n(n-1)\lambda^2 (e^{-\lambda y} - e^{-\lambda x})^{n-2} e^{-\lambda y - \lambda x} dx dy$

$$= \int_0^{+\infty} -\frac{\lambda e^{-2y}}{4n} (4(y+1) - e^{2(y+1)}) dy$$

$$= 2\lambda \quad E(\frac{x_{(n)} + x_{(1)}}{2}) = \lambda$$

(4) (a) $P(x) = 1$. $F(x) = \frac{x - \theta + \frac{1}{2}}{n!}$
 $\therefore P_{(n)}(x, y) = \frac{n!}{0!(n-2)!(n-n)!} (y - \theta + \frac{1}{2})^0 (z - y)^{n-1-1} (\frac{1}{2} + \theta - z)^0 \cdot 1 \cdot 1 = n(n-1) (z - y)^{n-2}$
 $\therefore E(\frac{x_{(n)} + x_{(1)}}{2}) = \int_{\theta-\frac{1}{2}}^{\theta+\frac{1}{2}} \int_{\theta-\frac{1}{2}}^y (y+z) n(n-1) (z-y)^{n-2} dz dy = \left[-\frac{n}{2} (y+z) (z-y)^{n-1} - \frac{1}{2} (z-y)^n \right] \Big|_{\theta-\frac{1}{2}}^{\theta+\frac{1}{2}} \Big|_{\theta-\frac{1}{2}}^{\theta+\frac{1}{2}}$
 $E(\bar{x}) = E(U(\theta - \frac{1}{2}, \theta + \frac{1}{2})) = \theta$. 故 \bar{x} 与 $\frac{1}{2}(x_{(n)} + x_{(1)})$ 均为参数为 θ 的无偏估计

(b) $\text{Var}(\bar{x}) = \frac{\sigma^2}{n} = \frac{1}{12n}$

$$\text{Var}(\frac{x_{(n)} + x_{(1)}}{2}) = \int_{\theta-\frac{1}{2}}^{\theta+\frac{1}{2}} \int_{\theta-\frac{1}{2}}^y \frac{1}{4} (y+z)^2 (n-1)n (z-y)^{n-2} dz dy - [E(\frac{x_{(n)} + x_{(1)}}{2})]^2$$

$$= \int_{\theta-\frac{1}{2}}^{\theta+\frac{1}{2}} \left[-\frac{n}{4} (y+z)^2 (z-y)^{n-1} - \frac{1}{2} (y+z) (z-y)^n - \frac{1}{2(n+1)} (z-y)^{n+1} \right] \Big|_{\theta-\frac{1}{2}}^{\theta+\frac{1}{2}} dy - \theta^2$$

$$= \left[-\frac{(z-y)^n (n^2(y+z)^2 + n(y^2 + 6yz + 3z^2) + 6z^2)}{4(n+1)(n+2)} + \frac{(z-y)^{n+1} [(n+1)y + (n+2)z]}{2(n+1)(n+2)} + \frac{(z-y)^{n+2}}{2(n+1)(n+2)} \right] \Big|_{\theta-\frac{1}{2}}^{\theta+\frac{1}{2}} - \theta^2$$

$$= \frac{4n^2 + 12n + 8}{4(n+1)(n+2)} \left[(2\theta+1)^2 - (2\theta-1)^2 \right] + \frac{(2n+4)(\theta+\frac{1}{2} - (\theta-\frac{1}{2}))}{2(n+1)(n+2)} + \frac{0}{2(n+1)(n+2)} - \theta^2$$

$$= -\frac{1}{4} - 4\theta + \frac{1}{n+1} - \theta^2$$

\bar{x} 比 $\frac{x_{(n)} + x_{(1)}}{2}$ 更有效, 它包含了所有样品的信息, 方差更小

(5) $E(z) = E(a s_1^2 + b s_2^2) = a E(s_1^2) + b E(s_2^2) = (a+b) \sigma^2 = \sigma^2 \therefore a s_1^2 + b s_2^2$ 为 σ^2 的无偏估计

(b) s_1^2 与 s_2^2 相互独立, $\therefore \text{Var}(z) = a^2 \text{Var}(s_1^2) + b^2 \text{Var}(s_2^2) = 0$

~~s_1^2 为 σ^2 的相合估计, s_2^2 为 σ^2 的相合估计~~

\therefore ~~$a s_1^2 + b s_2^2$~~ $a s_1^2 + b s_2^2$ 为

$\frac{(n_1-1)s_1^2}{\sigma^2} \sim \chi^2(n_1-1) \quad \frac{(n_2-1)s_2^2}{\sigma^2} \sim \chi^2(n_2-1)$

$\therefore \text{Var}(s_1^2) = \frac{2n_1}{(n_1-1)^2} \sigma^4 \quad \text{Var}(s_2^2) = \frac{2n_2}{(n_2-1)^2} \sigma^4$

$\therefore \text{Var}(z) = 2\sigma^4 \left(\frac{n_1}{(n_1-1)^2} a^2 + \frac{n_2}{(n_2-1)^2} b^2 \right) = 2\sigma^4 (A a^2 + B b^2)$

又 $a+b=1$, 故 $\begin{cases} a = \frac{B}{A+B} = \frac{n_2(n_1-1)^2}{n_1(n_1-1)^2 + n_2(n_1-1)^2} \text{ 时, } z \text{ 方差最小} \\ b = \frac{n_1(n_2-1)^2}{n_1(n_2-1)^2 + n_2(n_1-1)^2} \end{cases}$

(6) 二项分布: $E(X) = mp \quad \text{Var}(X) = mp(1-p)$

$\Rightarrow m = \frac{E(X) - \text{Var}(X)}{E(X)}, \quad p = \frac{E^2(X)}{E(X) - \text{Var}(X)}$

\Rightarrow 估计 $\hat{m} = \frac{\bar{x} - s^2}{\bar{x}}, \quad \hat{p} = \frac{\bar{x}^2}{\bar{x} - s^2}$

(7) (a) $E(X) = \int_0^\theta \frac{2x}{\theta^2} (1-x) d\theta = \frac{\theta}{3} \quad \text{Var}(X) = \int_0^\theta \frac{2x^2}{\theta^2} (1-x) d\theta = \frac{2}{3} \theta^2 - 2\theta^2 = \frac{1}{6} \theta^2$

$\therefore \text{Var}(X) = E(X^2) - E^2(X) = \frac{1}{6} \theta^2$

$\Rightarrow \hat{\theta} = 3\bar{x}$ 或 $\hat{\theta} = \sqrt{18} s$

(b) $E(X) = \int_{-\infty}^{\infty} \frac{x}{\theta} \exp\left(-\frac{x-u}{\theta}\right) d\theta = \frac{\theta(1+u)}{\theta} = 1+u, \quad E(X^2) = \int_{-\infty}^{\infty} \frac{x^2}{\theta} \exp\left(-\frac{x-u}{\theta}\right) d\theta = 2\theta^2 + u^2 + 2\theta u$

$\therefore \text{Var}(X) = E(X^2) - E^2(X) = 2\theta^2 + u^2 + 2\theta u - (1+u)^2 = \theta^2$

$\therefore \hat{\theta} = s, \quad \hat{u} = \bar{x} - s$

(8) $\text{Var}\left(\frac{2jx_j}{n(n+1)}\right) = \frac{4j^2}{n^4(n+1)^2} \text{Var}(X) \quad \therefore \frac{1}{n^2} \text{Var}\left(\frac{2}{(n+1)n} \sum_{j=1}^n jx_j\right) = \frac{4}{n^5} \frac{4}{n^4(n+1)^2} \text{Var}(X) \frac{n(n+1)(2n+1)}{6}$
 $= \frac{4(2n+1)}{n^3(n+1)} \text{Var}(X) \rightarrow 0 \quad (n \rightarrow \infty)$

由马尔可夫大数定律, 可为 H 的相合统计量

$E(\hat{H}) = E\left(\frac{2}{n(n+1)} \sum_{j=1}^n jx_j\right) = E(x_j) = H$

$\frac{1^2 + 2^2 + \dots + n^2}{n(n+1)(2n+1)/6}$