

1. 求  $P(\lambda=1.5 | X=3)$

$$P(\lambda=1.8 | X=3)$$

$$P(X=3) = P(X=3 | \lambda=1.5) \times P(\lambda=1.5) + P(X=3 | \lambda=1.8) \times P(\lambda=1.8)$$

$$= \frac{1.5^3}{3!} e^{-1.5} \times 0.45 + \frac{1.8^3}{3!} e^{-1.8} \times 0.55$$

$$= \frac{\frac{243}{160} e^{-1.5}}{6} + \frac{\frac{8019}{2500} e^{-1.8}}{6}$$

$$P(\lambda=1.5 | X=3) = \frac{P(X=3 | \lambda=1.5) \times P(\lambda=1.5)}{P(X=3)} = \frac{\frac{243}{160} e^{-1.5}}{P(X=3)}$$

$$= 0.38992$$

$$P(\lambda=1.8 | X=3) = \frac{P(X=3 | \lambda=1.8) \times P(\lambda=1.8)}{P(X=3)} = \frac{\frac{8019}{2500} e^{-1.8}}{P(X=3)} = 0.610077$$

2.  $N(\mu, \sigma^2)$  证  $\frac{1}{\sigma^2}$  的分布

$\sigma^2 \sim$  伽玛分布  $\frac{1}{\sigma^2} \sim$  伽玛分布  $G_a(\alpha, \lambda)$

Y.V. 函数的分布

$$P\left(\frac{1}{\sigma^2}\right) = \frac{\lambda^\alpha}{\Gamma(\alpha)} \left(\frac{1}{\sigma^2}\right)^{\alpha-1} \cdot e^{-\frac{\lambda}{\sigma^2}} \quad \frac{1}{\sigma^2} \geq 0 \quad \frac{1}{\sigma^2} \sim G_a(\alpha, \lambda)$$

$$\pi(\sigma^2) = \frac{\lambda^\alpha}{\Gamma(\alpha)} \left(\frac{1}{\sigma^2}\right)^{\alpha-1} e^{-\frac{\lambda}{\sigma^2}} \quad \sigma^2 \geq 0 \quad \sigma^2 \sim IG(\alpha, \lambda)$$

$$\pi(\sigma^2 | x_1, \dots, x_n) = \frac{P(x_1, \dots, x_n | \sigma^2) \pi(\sigma^2)}{\int_0^{+\infty} P(x_1, \dots, x_n | \sigma^2) \pi(\sigma^2) d\sigma^2}$$

$$P(x_1, \dots, x_n | \sigma^2) \quad x_1, \dots, x_n \stackrel{i.i.d.}{\sim} N(\mu, \sigma^2)$$

$$= (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}\right\}$$

$$(2\pi\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}\right\} \frac{\lambda^\alpha}{\Gamma(\alpha)} \left(\frac{1}{\sigma^2}\right)^{\alpha-1} e^{-\frac{\lambda}{\sigma^2}}$$

$$\int_0^{+\infty} (2\pi\sigma^2)^{-\frac{n}{2}} \exp\left\{-\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2}\right\} \frac{\lambda^\alpha}{\Gamma(\alpha)} \left(\frac{1}{\sigma^2}\right)^{\alpha-1} e^{-\frac{\lambda}{\sigma^2}} d\sigma^2$$



$$= \frac{(\sigma^2)^{-\frac{n}{2}} \exp \left\{ -\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2} \right\} (\sigma^2)^{1-d} e^{-\frac{\lambda}{\sigma^2}}}{\int_0^{+\infty} (\sigma^2)^{-\frac{n}{2}} \exp \left\{ -\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2} \right\} (\sigma^2)^{1-d} e^{-\frac{\lambda}{\sigma^2}} d\sigma^2}$$

$$= \frac{(\sigma^2)^{-\frac{n}{2}-1-d} \exp \left\{ -\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 + 2\lambda \right] \right\}}{\int_0^{+\infty} (\sigma^2)^{-\frac{n}{2}-1-d} \exp \left\{ -\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 + 2\lambda \right] \right\} d\sigma^2}$$

欲证  $\pi(\sigma^2 | x_1, \dots, x_n)$  是倒伽玛分布

$$= \frac{(\sigma^2)^{-\frac{n}{2}-d-1} \exp \left\{ -\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 + 2\lambda \right] \right\}}{\int_0^{+\infty} (\sigma^2)^{-\frac{n}{2}-1-d} \exp \left\{ -\frac{1}{2\sigma^2} \left[ \sum_{i=1}^n (x_i - \mu)^2 + 2\lambda \right] \right\} d\sigma^2}$$

$$\downarrow \quad \frac{1}{\sigma^2} = x \quad \sigma^2 = \frac{1}{x} \quad d\sigma^2 = -\frac{1}{x^2} dx$$

$$\begin{aligned} & \int_0^{+\infty} x^{\frac{n}{2}+1+d} \exp \left\{ -\frac{1}{2} \left[ \sum_{i=1}^n (x_i - \mu)^2 + 2\lambda \right] x \right\} \cdot \frac{1}{x^2} dx \\ &= \int_0^{+\infty} x^{\frac{n}{2}+d-1} \exp \left\{ -\left[ \frac{\sum_{i=1}^n (x_i - \mu)^2}{2} + \lambda \right] x \right\} dx \end{aligned}$$

$$= \frac{P(\frac{n}{2}+d)}{\left[ \frac{\sum_{i=1}^n (x_i - \mu)^2}{2} + \lambda \right]^{\frac{n}{2}+d}} \int_0^{+\infty} \frac{\left[ \frac{\sum_{i=1}^n (x_i - \mu)^2}{2} + \lambda \right]^{\frac{n}{2}+d}}{P(\frac{n}{2}+d)} x^{\frac{n}{2}+d-1} \exp \left\{ -\left[ \frac{\sum_{i=1}^n (x_i - \mu)^2}{2} + \lambda \right] x \right\} dx$$

$$\therefore \pi(\sigma^2 | x_1, \dots, x_n) = \frac{\left[ \frac{\sum_{i=1}^n (x_i - \mu)^2}{2} + \lambda \right]^{\frac{n}{2}+d}}{P(\frac{n}{2}+d)} (\sigma^2)^{-\frac{n}{2}-d-1} \exp \left\{ -\frac{1}{2\sigma^2} \left[ \frac{\sum_{i=1}^n (x_i - \mu)^2}{2} + \lambda \right] \right\}$$

$$\sigma^2 | x_1, \dots, x_n \sim IG\left(\frac{n}{2}+d, \lambda + \frac{\sum_{i=1}^n (x_i - \mu)^2}{2}\right)$$

$\therefore \sigma^2$  的共轭先验分布是倒伽玛分布



3. (c) 已知

(a)  $\theta \sim$  帕雷托分布

$$\pi(\theta) = \frac{k\theta_{\min}^k}{\theta^{k+1}} I\{\theta > \theta_{\min}\}$$

$$\begin{aligned} P(\theta | x_1, \dots, x_n) &= \frac{P(x_1, \dots, x_n | \theta) \pi(\theta)}{\int_{\theta_{\min}}^{+\infty} P(x_1, \dots, x_n | \theta) \pi(\theta) d\theta} = \frac{c^n \left(\prod_{i=1}^n x_i\right)^{c-1} \theta^{-nc} I\{x_{(n)} \leq \theta\} \frac{k\theta_{\min}^k}{\theta^{k+1}} I\{\theta > \theta_{\min}\}}{c^n \left(\prod_{i=1}^n x_i\right)^{c-1} \int_{\theta_{\min}}^{+\infty} \theta^{-nc} I\{x_{(n)} \leq \theta\} \frac{k\theta_{\min}^k}{\theta^{k+1}} I\{\theta > \theta_{\min}\} d\theta} \\ &= \frac{\theta^{-nc} I\{x_{(n)} \leq \theta\} \frac{k\theta_{\min}^k}{\theta^{k+1}} I\{\theta > \theta_{\min}\}}{\int_{\theta_{\min}}^{+\infty} \theta^{-nc} I\{x_{(n)} \leq \theta\} \frac{k\theta_{\min}^k}{\theta^{k+1}} I\{\theta > \theta_{\min}\} d\theta} = \frac{\theta^{-nc} I\{x_{(n)} \leq \theta \text{ 且 } \theta > \theta_{\min}\} \theta^{-k-1}}{\int_{\mu}^{+\infty} \theta^{-nc} \theta^{-k-1} d\theta} \\ & \quad \mu = \max\{\theta_{\min}, x_{(n)}\} \\ &= \frac{\theta^{-nc-k-1} I\{\theta \geq \mu\} (nc+k) \mu^{nc+k}}{(nc+k) \mu^{nc+k} I\{\theta \geq \mu\}} = \frac{(nc+k) \mu^{nc+k} I\{\theta \geq \mu\}}{\theta^{nc+k+1}} \end{aligned}$$

$\therefore P(\theta | x_1, \dots, x_n)$  也属于帕雷托分布  $\therefore \theta$  的共轭先验分布为帕雷托分布

(b)  $c \sim \text{Ga}(d, \lambda)$

$$\pi(c) = \frac{\lambda^d}{\Gamma(d)} c^{d-1} e^{-\lambda c}, \quad c \geq 0$$

$$\begin{aligned} P(c | x_1, \dots, x_n) &= \frac{P(x_1, \dots, x_n | c) \pi(c)}{\int_0^{+\infty} P(x_1, \dots, x_n | c) \pi(c) dc} = \frac{c^n \left(\prod_{i=1}^n x_i\right)^{c-1} \theta^{-nc} I\{0 \leq x_{(n)} \leq \theta\} \frac{\lambda^d}{\Gamma(d)} c^{d-1} e^{-\lambda c}}{\int_0^{+\infty} c^n \left(\prod_{i=1}^n x_i\right)^{c-1} \theta^{-nc} I\{0 \leq x_{(n)} \leq \theta\} \frac{\lambda^d}{\Gamma(d)} c^{d-1} e^{-\lambda c} dc} \\ &= \frac{c^{n+d-1} \left(\prod_{i=1}^n x_i\right)^{c-1} \theta^{-nc} e^{-\lambda c}}{\int_0^{+\infty} c^{n+d-1} \left(\prod_{i=1}^n x_i\right)^{c-1} \theta^{-nc} e^{-\lambda c} dc} = \frac{c^{n+d-1} \left(\prod_{i=1}^n \frac{x_i}{\theta}\right)^c e^{-\lambda c}}{\int_0^{+\infty} c^{n+d-1} \left(\prod_{i=1}^n \frac{x_i}{\theta}\right)^c e^{-\lambda c} dc} \\ & \quad \left(\prod_{i=1}^n \frac{x_i}{\theta}\right)^c = e^{c \left[\sum_{i=1}^n \ln x_i - n \ln \theta\right]} \\ &= \frac{c^{n+d-1} e^{-c \left[\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)\right]}}{\int_0^{+\infty} c^{n+d-1} e^{-c \left[\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)\right]} dc} \quad \text{凑 Ga 分布} \\ &= \frac{\frac{c^{n+d-1}}{\Gamma(n+d)} \left(\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)\right)^{n+d} e^{-c \left[\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)\right]}}{\int_0^{+\infty} \frac{c^{n+d-1}}{\Gamma(n+d)} \left(\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)\right)^{n+d} e^{-c \left[\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)\right]} dc} \end{aligned}$$



$$= \frac{(\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i))^{n+d}}{\Gamma(n+d)} C^{n+d-1} e^{-C[\lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)]}$$

$$\therefore C | x_1, \dots, x_n \sim \text{Ga}(n+d, \lambda + \sum_{i=1}^n (\ln \theta - \ln x_i)^{n+d})$$

$\therefore C$  的共轭先验分布为伽玛分布

$$4. \pi(\lambda) = \frac{\beta^d}{\Gamma(d)} \lambda^{d-1} e^{-\beta\lambda} \quad \lambda \geq 0$$

$$P(x_1, \dots, x_n | \lambda) = \frac{\lambda^{\sum_{i=1}^n x_i} e^{-n\lambda}}{\prod_{i=1}^n x_i!}$$

$$P(\lambda | x_1, \dots, x_n) = \frac{\lambda^{\sum_{i=1}^n x_i} e^{-n\lambda}}{\prod_{i=1}^n x_i!} \frac{\beta^d}{\Gamma(d)} \lambda^{d-1} e^{-\beta\lambda} = \frac{\lambda^{\sum_{i=1}^n x_i + d - 1} e^{-\lambda(n+\beta)}}{\int_0^{+\infty} \frac{\lambda^{\sum_{i=1}^n x_i} e^{-n\lambda}}{\prod_{i=1}^n x_i!} \frac{\beta^d}{\Gamma(d)} \lambda^{d-1} e^{-\beta\lambda} d\lambda} = \frac{\lambda^{\sum_{i=1}^n x_i + d - 1} e^{-\lambda(n+\beta)}}{\int_0^{+\infty} \lambda^{\sum_{i=1}^n x_i + d - 1} e^{-\lambda(n+\beta)} d\lambda}$$

$$\begin{aligned} & \text{凑伽玛} \\ &= \frac{(n+\beta) \lambda^{\sum_{i=1}^n x_i + d}}{\Gamma(\sum_{i=1}^n x_i + d)} \lambda^{\sum_{i=1}^n x_i + d - 1} e^{-\lambda(n+\beta)} \\ &= \frac{\int_0^{+\infty} (n+\beta) \lambda^{\sum_{i=1}^n x_i + d} \lambda^{\sum_{i=1}^n x_i + d - 1} e^{-\lambda(n+\beta)} d\lambda}{\Gamma(\sum_{i=1}^n x_i + d)} \end{aligned} \quad \therefore \lambda | x_1, \dots, x_n \sim \text{Ga}(\sum_{i=1}^n x_i + d, n+\beta)$$

$\therefore \lambda$  的后验分布为  $\text{Ga}(\sum_{i=1}^n x_i + d, \beta+n)$

$$(b) \quad \hat{\lambda}_1 = \frac{\sum_{i=1}^n x_i + d}{\beta+n} \quad (\text{后验分布求期望})$$

$$(c) \quad P(x_1, \dots, x_n) = \frac{\lambda^{\sum_{i=1}^n x_i} e^{-n\lambda}}{\prod_{i=1}^n x_i!} \alpha(\lambda)$$

$$L(\lambda) = \lambda^{\sum_{i=1}^n x_i} e^{-n\lambda} \quad (\text{与 } \lambda \text{ 无关})$$

$$\ln L(\lambda) = -n\lambda + \sum_{i=1}^n x_i \ln \lambda$$

$$\frac{d \ln L(\lambda)}{d\lambda} = -n + \frac{\sum_{i=1}^n x_i}{\lambda} = 0$$

$$\hat{\lambda}_2 = \frac{\sum_{i=1}^n x_i}{n} = \frac{n\bar{x}}{n} = \bar{x}$$



$$(5) \quad p \sim \text{Be}(a, b)$$

$$\pi(p) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1}, \quad 0 < p < 1$$

$$p(X_1, \dots, X_n | p) = \prod_{i=1}^n \binom{x_i-1}{k-1} p^{nk} (1-p)^{\sum_{i=1}^n x_i - nk}$$

$$p(p | X_1, \dots, X_n) = \frac{\prod_{i=1}^n \binom{x_i-1}{k-1} p^{nk} (1-p)^{\sum_{i=1}^n x_i - nk} \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1}}{\int_0^1 \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} p^{a-1} (1-p)^{b-1} \prod_{i=1}^n \binom{x_i-1}{k-1} p^{nk} (1-p)^{\sum_{i=1}^n x_i - nk} dp}$$

$$= \frac{p^{nk+a-1} (1-p)^{\sum_{i=1}^n x_i - nk + b-1}}{\int_0^1 p^{nk+a-1} (1-p)^{\sum_{i=1}^n x_i - nk + b-1} dp}$$

$$= \frac{\Gamma(nk+a + \sum_{i=1}^n x_i - nk + b)}{\Gamma(nk+a) \Gamma(\sum_{i=1}^n x_i - nk + b)} p^{nk+a-1} (1-p)^{\sum_{i=1}^n x_i - nk + b-1}$$

凑 Be  $\int_0^1 \frac{\Gamma(nk+a + \sum_{i=1}^n x_i - nk + b)}{\Gamma(nk+a) \Gamma(\sum_{i=1}^n x_i - nk + b)} p^{nk+a-1} (1-p)^{\sum_{i=1}^n x_i - nk + b-1} dp$

1

$$\therefore p | X_1, \dots, X_n \sim \text{Be}(nk+a, \sum_{i=1}^n x_i - nk + b)$$

$$\therefore p \text{ 的后验分布为 } \text{Be}(nk+a, \sum_{i=1}^n x_i - nk + b)$$

$$\therefore p \text{ 的先验分布族为 Be 分布族}$$



$$1. \left[ \bar{X} - z_{0.975} \cdot \frac{3}{\sqrt{10}}, \bar{X} + z_{0.975} \frac{3}{\sqrt{10}} \right]$$

$$2. \left[ \bar{X} - z_{0.955} \cdot \frac{3}{\sqrt{30}}, \bar{X} + z_{0.955} \frac{3}{\sqrt{30}} \right]$$

$$3. \left[ \bar{X} - t_{0.975(9)} \frac{s}{\sqrt{10}}, \bar{X} + t_{0.975(9)} \frac{s}{\sqrt{10}} \right]$$

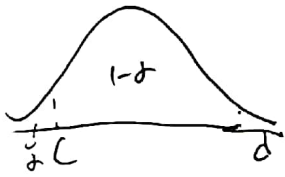
$$4. \left[ \bar{X} - t_{0.975(9)} \frac{s}{\sqrt{30}}, \bar{X} + t_{0.975(9)} \frac{s}{\sqrt{30}} \right]$$



2.

$$u = \frac{\bar{X} - \mu}{\sqrt{\frac{\sigma^2}{n}}} \sim N(0, 1)$$

$$P\left(c \leq \frac{\bar{X} - \mu}{\sqrt{\frac{\sigma^2}{n}}} \leq d\right) = 0.95$$



$$c = z_{\frac{\alpha}{2}} \quad d = z_{1-\frac{\alpha}{2}}$$

$$z_{\frac{\alpha}{2}} \leq \frac{\bar{X} - \mu}{\sqrt{\frac{\sigma^2}{n}}} \leq z_{1-\frac{\alpha}{2}}$$

$$\frac{\sigma z_{\frac{\alpha}{2}}}{\sqrt{n}} \leq \bar{X} - \mu \leq \frac{\sigma z_{1-\frac{\alpha}{2}}}{\sqrt{n}}$$

$$\bar{X} - \frac{\sigma z_{1-\frac{\alpha}{2}}}{\sqrt{n}} \leq \mu \leq \bar{X} - \frac{\sigma z_{\frac{\alpha}{2}}}{\sqrt{n}}$$

$$-\frac{\sigma z_{\frac{\alpha}{2}}}{\sqrt{n}} + \frac{\sigma z_{1-\frac{\alpha}{2}}}{\sqrt{n}} \leq 1c$$

$$\cancel{z_{1-\frac{\alpha}{2}}} \leq \frac{\sqrt{n} 1c}{\sigma z_{\frac{\alpha}{2}}}$$

$$\frac{\sqrt{n} 1c}{2\sigma} \geq z_{0.975} = 1.96$$

$$\therefore n \geq \frac{(1.96)^2 4\sigma^2}{1c^2} = 15.3664 \left(\frac{\sigma}{1c}\right)^2$$

3.

$$\begin{array}{lll} n_1 = 10 & \bar{X} = 1.64 & S_X = 0.2 \\ (a) & & \\ n_2 = 10 & \bar{Y} = 1.62 & S_Y = 0.1 \end{array}$$

$$\left[ \frac{S_X^2}{S_Y^2} \cdot \frac{1}{F_{1-\frac{\alpha}{2}}(n_1-1, n_2-1)}, \frac{S_X^2}{S_Y^2} \cdot \frac{1}{F_{\frac{\alpha}{2}}(n_1-1, n_2-1)} \right]$$

$$\left[ \frac{4}{F_{0.975}(9, 9)}, 4 \cdot \frac{1}{F_{0.025}(9, 9)} \right]$$

$$\left[ \frac{4}{4.03}, \frac{4 \times 4.03}{1} \right] = [0.9926, 16.12]$$



(b)

对  $\sigma_1^2$  和  $\sigma_2^2$  无信息

$$S_0^2 = \frac{S_x^2}{10} + \frac{S_y^2}{10} = \frac{1}{200}$$

$$S_0 = \frac{\sqrt{2}}{20}$$

$$l = \frac{(\frac{1}{200})^2}{\frac{(0.2)^4}{10^2 \times 9} + \frac{(0.1)^4}{10^2 \times 9}} = \frac{225}{17}$$

$$t_{0.975}(13.2353) = 2.1565$$

$$\left[ \bar{x} - \bar{y} - \frac{\sqrt{2}}{20} \times 2.1565, \bar{x} - \bar{y} + \frac{\sqrt{2}}{20} \times 2.1565 \right]$$

$$= \left[ 1.64 - 1.62 - \frac{\sqrt{2}}{20} \times 2.1565, 1.64 - 1.62 + \frac{\sqrt{2}}{20} \times 2.1565 \right]$$

$$= [-0.1325, 0.1725]$$





$$(a) P_1(x) = \frac{n!}{(n-1)!} (1-F(x))^{n-1} p(x) = n (e^{-(x+\theta)})^{n-1} e^{-(x+\theta)} \quad x > \theta$$

$$Y = X_{(n)} - \theta$$

$$P(y) = n (e^{-y})^{n-1} e^{-y} \cdot 1 = n e^{-y(n-1)} e^{-y} = n e^{-yn} \quad y > 0$$

$\therefore Y$  的分布与  $\theta$  无关, 即  $X_{(n)} - \theta$  分布与  $\theta$  无关

$$Y = X_{(n)} - \theta \sim \text{Exp}(n)$$

(b)

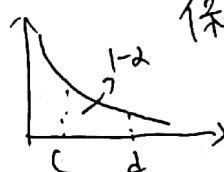
$G = X_{(n)} - \theta$  分布已知, 未知  $\theta$  有  $\theta$ , 与样本  $X_{(n)}$  有关

$$P(c \leq X_{(n)} - \theta \leq d) = 1 - \alpha = \int_c^d n e^{-yn} dy$$



$$-\int_c^d e^{-yn} dny = -e^{-yn} \Big|_c^d = -(e^{-dn} - e^{-cn}) = e^{-cn} - e^{-dn}$$

$$e^{-cn} - e^{-dn} = 1 - \alpha \quad (\text{根据密度函数图可以看出, 向右移, 为})$$



保证  $F(d) - F(c) = 1 - \alpha$ ,  $c, d$  之间距离会增加)

$$\therefore \text{取 } c=0 \quad X_{(n)} - e^{-dn} = 1 - \alpha$$

$$e^{-dn} = \alpha$$

$$-dn = \ln \alpha$$

$$d = \frac{\ln \alpha}{-n}$$

$$Y \quad \left[ 0, \frac{\ln \alpha}{-n} \right] \Rightarrow 0 \leq X_{(n)} - \theta \leq \frac{\ln \alpha}{-n}$$

$$\therefore -\frac{\ln \alpha}{-n} + X_{(n)} \leq \theta \leq X_{(n)}$$

$$X_{(n)} + \frac{\ln \alpha}{n} \leq \theta \leq X_{(n)}$$

$$\therefore \text{区间 } \left[ X_{(n)} + \frac{\ln \alpha}{n}, X_{(n)} \right]$$



$$5. \quad (a) \quad \bar{Y} = \frac{\ln 0.5 + \ln 1.25 + \ln 0.8 + \ln 2}{4} = 0$$

$$\bar{Y} \sim N(\mu, \frac{1}{4})$$

$$\frac{\bar{Y} - \mu}{\sqrt{\frac{1}{4}}} \sim N(0, 1)$$

$$P\left(c \leq \frac{\bar{Y} - \mu}{\frac{1}{2}} \leq d\right) = 0.95$$

$$c = z_{0.025} \quad d = z_{1-0.025} = z_{0.975} = 1.96$$

$$-1.96 \leq -2\mu \leq 1.96$$

$$-0.98 \leq \mu \leq 0.98$$

$$[-0.98, 0.98]$$

(b)

$$Y = \ln X \sim N(\mu, 1)$$

$$X \sim \text{lognormal} \quad p(x) = \frac{1}{x\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(\ln x - \mu)^2}{2\sigma^2}\right\}$$

$$E(X) = e^{\mu + \frac{1}{2}} \quad \uparrow \text{ as } \mu \uparrow$$

$$-0.98 \leq \mu \leq 0.98$$

$$e^{-0.98 + \frac{1}{2}} \leq e^{\mu + \frac{1}{2}} \leq e^{0.98 + \frac{1}{2}}$$

$$0.6188 \leq E(X) \leq 4.3929$$

$$[0.6188, 4.3929]$$

