

温兆和 10205501432. 数学基础作业 9.

$$1. \text{解: (1). } L(X, \theta) = \frac{1}{\theta^n} \exp \left\{ -\frac{\sum_{i=1}^n |x_i - c|}{\theta} \right\} I\{x_i \geq c\} \\ = \frac{1}{\theta^n} \exp \left\{ -\frac{\sum_{i=1}^n |x_i - c|}{\theta} \right\} I\{x_1 \geq c\}$$

欲使 L 最大化, 以便 c 尽可能大, 但 $c \leq x_1$.

$$\text{故 } \hat{c} = x_1.$$

$$\text{又: } \ln L = -n \ln \theta - \frac{\sum_{i=1}^n |x_i - c|}{\theta}$$

$$\frac{d \ln L}{d \theta} = -\frac{1}{\theta} + \frac{\sum_{i=1}^n |x_i - c|}{\theta^2}$$

$$\text{令 } \frac{d \ln L}{d \theta} = 0 \text{ 得: } \theta n = \sum_{i=1}^n |x_i - c|$$

$$\text{故 } \theta = \frac{\sum_{i=1}^n |x_i - c|}{n} = \bar{x} - c.$$

由最大似然估计的不变性, $\hat{\theta} = \bar{x} - \hat{c} = \bar{x} - x_1$.

$$(2). E(X) = \int_c^{+\infty} \frac{c-t}{\theta} e^{\frac{c-t}{\theta}} dt \\ = -t e^{\frac{c-t}{\theta}} \Big|_c^{+\infty} + \int_c^{+\infty} e^{\frac{c-t}{\theta}} dt \\ = c + \theta.$$

$$E(X^2) = \int_c^{+\infty} \frac{t^2}{\theta} e^{\frac{c-t}{\theta}} dt \\ = -t^2 e^{\frac{c-t}{\theta}} \Big|_c^{+\infty} + \int_c^{+\infty} 2t e^{\frac{c-t}{\theta}} dt \\ = c^2 + 2\theta(c + \theta) \\ = c^2 + 2c\theta + 2\theta^2 \\ = (c + \theta)^2 + \theta^2.$$

$$\text{由: } E(X^2) = (E(X))^2 + \theta^2,$$

$$\text{得 } \theta = \sqrt{E(X^2) - (E(X))^2} = \sqrt{\text{Var}(X)}$$

$$c = E(X) - \sqrt{\text{Var}(X)}.$$

用样本参数代替总体参数得:

$$\hat{\theta} = \sqrt{s^2} = s, \quad \hat{c} = \bar{x} - s$$

其中 \bar{x} 为样本均值, s 为样本标准差

2. 证: (1), $L(X; \theta) = \frac{1}{\theta^n} \left(\prod_{i=1}^n x_i \right)^{\frac{1}{\theta}-1}$

$$\frac{dL}{d\theta} = -n\theta^{-n-1} \left(\prod_{i=1}^n x_i \right)^{\frac{1}{\theta}-1} - \frac{1}{\theta} \left(\prod_{i=1}^n x_i \right)^{\frac{1}{\theta}-1} \ln \left(\prod_{i=1}^n x_i \right) \frac{1}{\theta^2}$$

令 $\frac{dL}{d\theta} = 0$, 得: $\hat{\theta} = -\frac{1}{n} \frac{1}{\ln \left(\prod_{i=1}^n x_i \right)}$

$$= -\frac{1}{n} \sum_{i=1}^n \ln x_i$$

(2) 证: $E(\hat{\theta}) = -\frac{1}{n} \sum_{i=1}^n E(\ln x_i)$

$$E(\ln x) = \int_0^1 \frac{\ln x}{\theta} x^{\frac{1}{\theta}-1} dx$$

$$= x^{\frac{1}{\theta}} \ln x \Big|_0^1 - \int_0^1 x^{\frac{1}{\theta}-1} dx$$

$$= \theta x^{\frac{1}{\theta}} \Big|_0^1 = -\theta$$

故 $E(\hat{\theta}) = -\frac{1}{n} \sum_{i=1}^n E(\ln x_i)$

$$= -\frac{1}{n} \cdot (-n\theta) = \theta$$

故 $\hat{\theta}$ 是 θ 的无偏估计

2. 证: $p(x|\mu) = \frac{1}{(\sqrt{2\pi}\sigma)^n} \exp \left\{ -\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2} \right\}$

$$h(X, \mu) = p(X|\mu) \pi(\mu)$$

$$= \frac{1}{(\sqrt{2\pi}\sigma)^n \sqrt{2\pi}\sigma_\mu} \exp \left\{ -\frac{\sum_{i=1}^n (x_i - \mu)^2}{2\sigma^2} - \frac{(\mu - \mu_0)^2}{2\sigma_\mu^2} \right\}$$

$$= \frac{1}{(\sqrt{2\pi}\sigma)^n \sqrt{2\pi}\sigma_\mu} \exp \left\{ -\left(\frac{\sigma_\mu^2 \sum_{i=1}^n (x_i - \mu)^2 + \sigma^2 (\mu - \mu_0)^2}{2\sigma^2 \sigma_\mu^2} \right) \right\}$$

$$= \frac{1}{(\sqrt{2\pi}\sigma)^n \sqrt{2\pi}\sigma_\mu} \exp \left\{ - \frac{\left(\mu - \frac{\sigma^2 \mu_0 + \sigma_\mu^2 \bar{x}_i}{\sigma^2 + n\sigma_\mu^2} \right)^2}{\frac{2\sigma^2 \sigma_\mu^2}{\sigma^2 + n\sigma_\mu^2}} \right\}$$

$$\text{令 } \mu' = \frac{\mu_0 \sigma^2 + \sigma_\mu^2 \bar{x}_i}{\sigma^2 + n\sigma_\mu^2} \quad \sigma'^2 = \frac{2\sigma^2 \sigma_\mu^2}{\sigma^2 + n\sigma_\mu^2}$$

$$\text{则: } \pi(\mu|x) = \frac{h(x, \mu)}{\int_{-\infty}^{+\infty} h(x, \mu) d\mu}$$

$$= \frac{\exp \left\{ - \frac{(\mu - \mu')^2}{2\sigma'^2} \right\}}{\int_{-\infty}^{+\infty} \exp \left\{ - \frac{(\mu - \mu')^2}{2\sigma'^2} \right\} d\mu}$$

$$= \frac{1}{\sqrt{2\pi}\sigma'^2} \exp \left\{ - \frac{(\mu - \mu')^2}{2\sigma'^2} \right\}$$

$$= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma'^2} \exp \left\{ - \frac{(\mu - \mu')^2}{2\sigma'^2} \right\} d\mu$$

$$= \frac{1}{\sqrt{2\pi}\sigma'^2} \exp \left\{ - \frac{(\mu - \mu')^2}{2\sigma'^2} \right\}$$

故: μ 的 Bayes 估计量为: $N \left(\frac{\mu_0 \sigma^2 + \sigma_\mu^2 \bar{x}_i}{\sigma^2 + n\sigma_\mu^2}, \frac{\sigma^2 \sigma_\mu^2}{\sigma^2 + n\sigma_\mu^2} \right)$

$$\text{4. 证: } P(x|\lambda) = \frac{\lambda^{\sum x_i}}{n! x_i!} e^{-n\lambda}$$

$$h(x, \lambda) = P(x|\lambda) \pi(\lambda)$$

$$= \frac{\lambda^{\sum x_i}}{n! x_i!} e^{-n\lambda} \frac{\beta^\alpha}{\Gamma(\alpha)} \lambda^{\alpha-1} e^{-\beta\lambda}$$

$$= \frac{\beta^\alpha}{n! x_i! \Gamma(\alpha)} \lambda^{\alpha + \sum x_i - 1} e^{-(n+\beta)\lambda}$$

$$\begin{aligned}
 \text{故 } \pi(\lambda|x) &= \frac{h(x|\lambda)}{\int_0^{+\infty} h(x|\lambda) d\lambda} \\
 &= \frac{(n+\beta)^{\alpha+\sum x_i} / \Gamma(\alpha+\sum x_i) \cdot h(x|\lambda)}{(n+\beta)^{\alpha+\sum x_i} / \Gamma(\alpha+\sum x_i) \int_0^{+\infty} h(x|\lambda) d\lambda} \\
 &= \frac{(n+\beta)}{\Gamma(\alpha+\sum x_i)} \lambda^{\alpha+\sum x_i-1} e^{-(n+\beta)\lambda}
 \end{aligned}$$

故 $\pi(\lambda|x)$ 为 $\text{Ga}(\alpha + \sum x_i, n+\beta)$
 其期望为 $\frac{\alpha + \sum x_i}{n+\beta}$

$$\text{故 } \hat{\lambda} = \frac{\alpha + \sum x_i}{n+\beta}$$