Probability And Mathmatical Statistics Homework 10

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解得

矩估计

使用样本矩代替标准矩,得

$$\begin{cases} \bar{X} &= e^{\mu + \frac{\sigma^2}{2}} \\ \frac{1}{n} \sum_{i=1}^n X_i^2 &= e^{2\mu + 2\sigma^2} \end{cases}$$

$$\hat{\mu} = \frac{4ln\bar{X} - ln\frac{\sum_{i=1}^{n} X_{i}^{2}}{n}}{2}$$

$$\hat{\sigma^{2}} = ln\frac{\sum_{i=1}^{n} X_{i}^{2}}{n} - 2ln\bar{X}$$

极大似然估计

似然函数为

$$\begin{split} L(\mu,\sigma^2) &= \Pi_{i=1}^n (2\pi\sigma^2)^{-\frac{1}{2}} X_i^{-1} e^{-\frac{(\ln X_i - \mu)^2}{2\sigma^2}} \\ &= (2\pi\sigma^2)^{-\frac{n}{2}} \frac{1}{\prod_{i=1}^n X_i} e^{-\frac{\sum_{i=1}^n (\ln X_i - \mu)^2}{2\sigma^2}} \\ lnL(\mu,\sigma^2) &= -\frac{n}{2} ln(2\pi\sigma^2) + ln\frac{1}{\prod_{i=1}^n X_i} \\ &- \frac{\sum_{i=1}^n (\ln X_i - \mu)^2}{2\sigma^2} \end{split}$$

$$\begin{cases} \frac{\partial lnL}{\partial \sigma^2} &= -\frac{n}{2} \frac{2\pi}{2\pi\sigma^2} + \frac{\sum_{i=1}^n (lnX_i - \mu)^2}{2(\sigma^2)^2} = 0\\ \frac{\partial lnL}{\partial \mu} &= -\frac{\sum_{i=1}^n 2(\mu - lnX_i)}{2\sigma^2} = 0 \end{cases}$$

解得

$$\hat{\mu} = \frac{\sum_{i=1}^{n} lnX_i}{n}$$

$$\hat{\sigma^2} = \frac{\sum_{i=1}^{n} \left[lnX_i - \sum_{j=1}^{n} \frac{lnX_j}{n} \right]}{n}$$

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$$p(y; \mu, \theta) = \begin{cases} \frac{1}{\theta} e^{-\frac{y}{\theta}}, y \ge 0\\ 0 & O.W. \end{cases}$$

則
$$Y \sim E(\theta), EY = \theta, EY^2 = 2\theta^2.$$

$$EX = E(Y + \mu) = \theta + \mu$$

$$EX^2 = E(Y + \mu)^2 = 2\theta^2 + 2\mu\theta + \mu^2$$

$$\vdots$$

$$\hat{\mu} = \bar{X} - S_n$$

$$\hat{\theta} = \sqrt{EX^2 - (EX)^2}$$

$$= \sqrt{\frac{1}{n} \sum X_i^2 - \bar{X}^2}$$

极大似然估计

 $=S_n$

$$\begin{split} L(\mu,\theta) &= \Pi_{i=1}^n \frac{1}{\theta} e^{-\frac{X_i - \mu}{\theta}} \\ &= \frac{1}{\theta^n} e^{\sum_{i=1}^n - \frac{X_i - \mu}{\theta}} \\ lnL(\mu,\theta) &= ln \frac{1}{\theta^n} + \sum_{i=1}^n - \frac{X_i - \mu}{\theta} \\ \frac{\partial lnL(\mu,\theta)}{\partial \mu} &= \frac{n}{\theta} > 0 \\ \frac{\partial lnL(\mu,\theta)}{\partial \theta} &= -\frac{n}{\theta} + \sum_{i=1}^n \frac{X_i - \mu}{\theta^2} \\ &= -\frac{n}{\theta} + \frac{\sum_{i=1}^n X_i - n\mu}{\theta^2} \ . \end{split}$$

由于似然函数随 μ 递增而递增, μ 最大为 $\min_i X_i$. 所以

$$\hat{\mu} = \min_{i} X_i$$

此时

$$\hat{\theta} = \frac{\sum_{i=1}^{n} X_i - n\hat{\mu}}{n} = \bar{X} - \min_{i} X_i$$

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无偏估计意味着 $E[.] = \sigma^2$.

$$E[.] = c \sum_{i=1}^{n-1} E(X_{i+1} - X_i)^2$$

$$= c \sum_{i=1}^{n-1} \left[D(X_{i+1} - X_i) + (E(X_{i+1} - X_i))^2 \right]$$

$$= c(n-1)2\sigma^2$$

$$= \sigma^2$$

$$\therefore c = \frac{1}{2(n-1)}$$

$$L(\sigma^{2}) = \prod_{i=1}^{n} \frac{1}{\sqrt{2\pi\sigma^{2}}} e^{-\frac{(X_{i}-\mu)^{2}}{2\sigma^{2}}}$$

$$lnL(\sigma^{2}) = \sum_{i=1}^{n} -\frac{(X_{i}-\mu)^{2}}{2\sigma^{2}} + ln\frac{1}{\sqrt{2\pi\sigma^{2}}}$$

$$\frac{dlnL(\sigma^{2})}{d\sigma^{2}} = \sum_{i=1}^{n} \frac{(x-\mu)^{2}}{2\sigma^{4}} + \sqrt{2\pi\sigma^{2}} (-\frac{1}{2\pi\sigma^{2}}) \frac{\sqrt{2\pi}}{2\sqrt{\sigma^{2}}}$$

$$= \sum_{i=1}^{n} \frac{(x-\mu)^{2}}{2\sigma^{4}} - \frac{1}{2\sigma^{2}}$$

$$\frac{dlnL(\sigma^{2})}{d\sigma^{2}} = 0$$

$$\frac{\sum_{i=1}^{n} (X_{i}-\mu)}{2\sigma^{2}} = \frac{n}{2\sigma^{2}}$$

$$\hat{\sigma^{2}} = \frac{1}{n} \sum_{i=1}^{n} (X_{i}-\mu)^{2}$$

所以极大似然估计为 $\hat{\sigma^2} = \frac{1}{n} \sum_{i=1}^n (X_i - \mu)^2$. 标准正态分布的 k 阶原点矩为

$$\begin{cases} (k-1)!! & \text{ 当 k 为偶} \\ 0 & \text{ 当 k 为奇数} \end{cases}$$

$$E\hat{\sigma^2} = E(X_i - \mu)^2$$
$$= \sigma^2 E(\frac{X_i - \mu}{\sigma})^2$$
$$= \sigma^2$$

$$M(\hat{\sigma^2}, \sigma^2) = D(\hat{\sigma^2}) + (E\hat{\sigma^2} - \sigma^2)^2$$

$$= \frac{1}{n^2} \sum_{i=1}^n D(X_i - \mu)^2$$

$$= \frac{1}{n} \left[E(X_i - \mu)^4 - (E(X_i - \mu)^2)^2 \right]$$

$$= \frac{1}{n} \sigma^4 \left[E(\frac{X_i - \mu}{\sigma})^4 - (E(\frac{X_i - \mu}{\sigma})^2)^2 \right]$$

$$= \frac{2\sigma^4}{n}$$

$$ES^{2} = \frac{1}{n-1} \sum_{i=1}^{n} E(X_{i} - \bar{X})^{2}$$

$$= \frac{1}{n-1} \sum_{i=1}^{n} D(X_{i} - \bar{X})$$

$$= \frac{1}{n-1} \sum_{i=1}^{n} D(-\frac{1}{n}X_{1}, \dots, + \frac{n-1}{n}X_{i} - \frac{1}{n}X_{i+1} - \dots - \frac{1}{n}X_{n})$$

$$= \frac{1}{n-1} \sum_{i=1}^{n} D(-\frac{1}{n}X_{1}, \dots, + \frac{n-1}{n}X_{i} - \frac{1}{n}X_{i+1} - \dots - \frac{1}{n}X_{n})$$

$$= \frac{1}{n-1} \sum_{i=1}^{n} \frac{n-1}{n} \sigma^{2}$$

$$= \sigma^{2}$$

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$$= \frac{1}{n-1} \sum_{i=1}^{n} \frac{n-1}{n} \sigma^{2}$$

$$= \frac{2u_{\frac{n}{2}}\sigma}{\sqrt{n}} \leq L$$

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$$= \frac{4u_{\frac{n}{2}}\sigma}{\sqrt{n}} \leq L$$

$$= \frac{4$$

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大样本法, 当 n 足够大时, 根据中心极限定理,

有

$$\frac{\sum_{i=1}^{n} X_i - n\mu}{\sqrt{n}\sigma} \rightarrow N(0,1)$$

$$\frac{n\bar{X} - n\lambda}{\sqrt{n}\sqrt{\lambda}} \to N(0, 1)$$

$$\bar{X} \to \lambda \text{ when } n \to \infty$$

$$\frac{\bar{X} - \lambda}{\sqrt{\frac{\bar{X}}{n}}} \to N(0, 1)$$

$$P(X_1 \le \frac{\bar{X} - \lambda}{\sqrt{\frac{\bar{X}}{n}}} \le X_2) = 1 - \alpha$$

$$-u_{\frac{\alpha}{2}} \le \frac{\bar{X} - \lambda}{\sqrt{\frac{\bar{X}}{n}}} \le u_{\frac{\alpha}{2}}$$

$$\bar{X} - u_{\frac{\alpha}{2}}\sqrt{\frac{\bar{X}}{n}} \le \lambda \le \bar{X} + u_{\frac{\alpha}{2}}\sqrt{\frac{\bar{X}}{n}}$$