(2) Cramér-Rao lower bound

Let X_1, \ldots, X_n be a random sample with the pdf $f(x|\theta) = \theta x^{\theta-1}$, where 0 < x < 1 and $\theta > 0$ is unknown. Is there a function of θ , say $g(\theta)$, for which there exists an unibiased estimator whose variance attains the Cramér-Rao lower bound? If there is, find it. If not, show why not.

$$\ell_{n}(\theta) = \sum_{i=1}^{n} \left(\log(\theta) + (\theta - 1) \log(x_{i}) \right)$$

$$\ell_{n}'(\theta) = \sum_{i=1}^{n} \left(\frac{1}{\theta} + \log(x_{i}) \right) = \frac{n}{\theta} + \sum_{i=1}^{n} \log(x_{i})$$

$$\ell_{n}''(\theta) = -\frac{n}{\theta^{2}} < 0$$

Since the MLE is the most efficient unbiased estimation, we want

$$0 = \ell_n'(\hat{\theta}) = \frac{n}{\theta} + \sum_{i=1}^n \log(x_i) \in g(\theta) := \frac{1}{\theta} = -\frac{1}{n} \sum_{i=1}^n \log(x_i) =: h(x)$$

$$\mathbb{E}(h(X)) = -\frac{1}{n} \sum_{i=1}^{n} \mathbb{E}(\log(X_i)) = -\frac{1}{n} \sum_{i=1}^{n} \int_{0}^{1} \log(x_i) \theta x_i^{\theta-1} dx_i$$

$$= -\frac{1}{n} \sum_{i=1}^{n} \left(\log(x_i) x_i^{\theta} \Big|_{x_i=0}^{1} - \int_{0}^{1} x_i^{\theta} dx_i^{\eta}\right) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{\theta} = \frac{1}{\theta} = g(\theta)$$

We have

$$\int_{0}^{2} \int_{0}^{2} \log(x_{i}) \log(x_{j}) \theta^{2} \times_{i}^{\theta-1} \times_{j}^{\theta-1} dx_{i} dx_{j} = \left(-\frac{1}{\theta}\right)^{2} = \frac{1}{\theta^{2}}$$

$$\int_{0}^{2} \left(\log(x_{i})\right)^{2} \theta \times_{i}^{\theta-1} dx_{i} = \left(\log(x_{i})\right)^{2} \times_{i}^{\theta} \Big|_{x_{i}=0}^{1} - 2 \int_{0}^{2} \log(x_{i}) \times_{i}^{\theta-1} dx_{i}$$

$$= -\frac{2}{\theta} \int_{0}^{2} \log(x_{i}) \theta \times_{i}^{\theta-1} dx_{i} = \frac{2}{\theta^{2}} = \frac{1}{\theta^{2}} + \frac{1}{\theta^{2}}$$

Thus,

$$\mathbb{E}((h(X))^{2}) = \frac{1}{n^{2}} \sum_{i=1}^{n} \sum_{j=1}^{n} \mathbb{E}(l_{G}(X_{i}) l_{GG}(X_{j})) = \frac{1}{n^{2}} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{1}{\theta^{2}} + \frac{1}{n^{2}} \sum_{i=1}^{n} \frac{1}{\theta^{2}}$$

$$= \frac{1}{\theta^{2}} + \frac{1}{n \theta^{2}}$$
Hence, $Van(h(X)) = \frac{1}{n \theta^{2}}$

$$V:=\frac{1}{\Theta}, \quad \ell_{n}(\gamma)=\sum_{i=1}^{n}\left(-\log\left(\gamma\right)+\left(\gamma^{-1}-1\right)\log\left(\times i\right)\right)$$

$$\ell_{n}'(\gamma)=\sum_{i=1}^{n}\left(-\gamma^{-1}-\gamma^{-2}\log\left(\times i\right)\right)$$

$$\ell_{n}''(\gamma)=\sum_{i=1}^{n}\left(\gamma^{-2}+2\gamma^{-3}\log\left(\times i\right)\right)$$

$$\mathbb{E}(L_{n}''(\gamma)) = \frac{n}{\gamma^{2}} + 2\gamma^{-3} \sum_{i=1}^{n} \mathbb{E}(\log(k_{i})) = \frac{n}{\gamma^{2}} - 2\gamma^{-3} n \gamma = \frac{-n}{\gamma^{2}} = n \theta^{2} = \ln(\theta)$$

$$=) \text{ Wan}(h(k)) = -\frac{1}{I_{n}(\theta)}$$