

1. X_1, \dots, X_n is a random variable having the bernoulli distribution with the parameter θ .
 - (a) **(2 mark)** Let $S = \sum_{i=1}^n X_i$, find the distribution of S .
 - (b) **(2 marks)** Find the maximum likelihood estimate of $\theta(1 - \theta)$.
 - (c) **(2 marks)** Is it unbiased estimator? No mark will be given if the answer is “Yes” or “No”.
 - (d) **(2 marks)** Find the Cramer-Rao Lower Bound for the variance of an unbiased estimator for $\theta(1 - \theta)$.
 - (e) **(2 mark)** Does the variance of any unbiased estimator for $\theta(1 - \theta)$ achieve this bound? Why? Explain in details.
 - (f) **(3 marks)** Find the limiting distribution of the maximum likelihood estimate for $\theta(1 - \theta)$ by Central Limit Theorem and Delta method. What phenomenon do you observe?

Solutions:

- (a) Since $X_i \stackrel{\text{i.i.d.}}{\sim} \text{Bernoulli}(\theta)$, we have

$$\begin{aligned} M_{X_i}(t) &= (1 - \theta) + \theta e^t \\ M_S(t) &= M_{\sum_{i=1}^n X_i}(t) = \Pi_{i=1}^n M_{X_i}(t) = ((1 - \theta) + \theta e^t)^n \end{aligned}$$

Therefore, $S = \sum_{i=1}^n X_i \sim \text{Bin}(n, \theta)$.

- (b)

$$\begin{aligned} f_{\mathbf{X}}(\mathbf{x}) &= \theta^{\sum_{i=1}^n x_i} (1 - \theta)^{n - \sum_{i=1}^n x_i} \\ l(\theta) &= \log f_{\mathbf{X}}(\mathbf{x}) = \left(\sum_{i=1}^n x_i \right) \log \theta + \left(n - \sum_{i=1}^n x_i \right) \log(1 - \theta) \\ l'(\theta) &= \frac{\sum_{i=1}^n x_i}{\theta} + \frac{n - \sum_{i=1}^n x_i}{\theta - 1} \end{aligned}$$

Taking $l'(\theta) = 0$, we have $\theta = \bar{x}$ and $l''(\theta) < 0$ at $\theta = \bar{x}$. Therefore, we get the MLE for θ , which is $\hat{\theta} = \bar{X}$. Then by the invariance property of MLE, we get the MLE of $\theta(1 - \theta)$ is $\hat{\theta}(1 - \hat{\theta}) = \bar{X}(1 - \bar{X})$.

- (c) By part (a), we have

$$\begin{aligned} E(S) &= n\theta \\ \text{Var}(S) &= n\theta(1 - \theta) \\ E(S^2) &= n\theta(1 - \theta + n\theta) \end{aligned}$$

Since $\hat{\theta} = \bar{X} = \frac{1}{n}S$, we have

$$\begin{aligned} E(\hat{\theta}) &= \frac{1}{n}E(S) = \theta \\ E(\hat{\theta}^2) &= \frac{1}{n^2}E(S^2) = \frac{\theta(1 - \theta + n\theta)}{n} \\ E(\hat{\theta}(1 - \hat{\theta})) &= \theta - \frac{\theta(1 - \theta + n\theta)}{n} = \frac{n - 1}{n}\theta(1 - \theta) \neq \theta(1 - \theta) \end{aligned}$$

Therefore, it is not unbiased.

- (d) By part(c), take $T = \frac{n}{n-1}\bar{X}(1 - \bar{X})$ and $E(T) = \theta(1 - \theta)$, so T is an unbiased estimator of $g(\theta) = \theta(1 - \theta)$.

$$\begin{aligned}
 \log f_{X_i}(x_i; \theta) &= x_i \log \theta + (1 - x_i) \log(1 - \theta) \\
 \frac{\partial^2}{\partial \theta^2} \log f_{X_i}(x_i; \theta) &= -\frac{x_i}{\theta^2} - \frac{1 - x_i}{(1 - \theta)^2} \\
 E\left(\frac{\partial^2}{\partial \theta^2} \log f_{X_i}(x_i; \theta)\right) &= -\frac{1}{\theta} - \frac{1}{1 - \theta} = -\frac{1}{\theta(1 - \theta)} \\
 g'(\theta) &= 1 - 2\theta \\
 \text{CR Lower Bound} &= -\frac{g'(\theta)^2}{nE\left(\frac{\partial^2}{\partial \theta^2} \log f_{X_i}(x_i; \theta)\right)} \\
 &= \frac{(1 - 2\theta)^2}{\frac{n}{\theta(1 - \theta)}}
 \end{aligned}$$

(e)

$$\frac{\partial}{\partial \theta} \log f_{\mathbf{X}}(\mathbf{x}; \theta) = \frac{\sum_{i=1}^n x_i}{\theta} - \frac{n - \sum_{i=1}^n x_i}{1 - \theta} = \frac{\sum_{i=1}^n x_i - n\theta}{\theta(1 - \theta)} = \frac{n}{\theta(1 - \theta)} \left(\frac{\sum_{i=1}^n x_i}{n} - \theta \right)$$

There is no function $A(n, \theta)$ s.t. $\frac{\partial}{\partial \theta} \log f_{\mathbf{X}}(\mathbf{x}; \theta) = A(n, \theta)[h(\mathbf{x}) - g(\theta)]$, where $g(\theta) = \theta(1 - \theta)$ and $h(\mathbf{x})$ is an unbiased estimator of $g(\theta)$. Therefore, no unbiased estimator of $g(\theta)$ achieve the CR lower bound.

- (f) By C.L.T., we have $\hat{\theta} \rightarrow N\left(\theta, \frac{\theta(1-\theta)}{n}\right)$. Then by Delta Method, we have $g(\hat{\theta}) \rightarrow N\left(g(\theta), \frac{g'(\theta)^2 \theta(1-\theta)}{n}\right) = N\left(\theta(1 - \theta), \frac{(1-2\theta)^2 \theta(1-\theta)}{n}\right)$. So the limiting variance of MLE can achieve the CR lower bound.

2. X_1, X_2, \dots, X_n are observations of a random sample of size n from the geometric distribution with probability distribution $f(x, \theta) = \theta(1 - \theta)^x$

- (a) **(2 marks)** Find the distribution of $\sum_{i=1}^n X_i$.
- (b) **(2 mark)** Find the estimator from the method of moment.
- (c) **(2 mark)** Find the estimator from the method of maximum likelihood.
- (d) **(2 marks)** Find the maximum likelihood estimator for $E(X)$.
- (e) **(2 marks)** Is the maximum likelihood estimator for $E(X)$ unbiased? If yes, find its variance. If no, find its mean squared error.
- (f) **(2 marks)** Is the variance of any unbiased estimator for $E(X)$ equal to the Cramer-Rao Lower Bound? No need to find the Cramer-Rao Lower Bound.

Solutions:

(a) Since $X_i \stackrel{\text{i.i.d.}}{\sim} \text{Geometric}(\theta)$, we have

$$\begin{aligned} M_{X_i}(t) &= \frac{\theta}{1 - (1 - \theta)e^t} \\ M_S(t) &= M_{\sum_{i=1}^n X_i}(t) = \Pi_{i=1}^n M_{X_i}(t) = \left(\frac{\theta}{1 - (1 - \theta)e^t} \right)^n \end{aligned}$$

Therefore, $S = \sum_{i=1}^n X_i \sim \text{NB}(n, \theta)$.

(b) For MME:

$$\begin{aligned} M'_1 &= \widetilde{E(X)} \\ \frac{1}{n} \sum_{i=1}^n x_i &= \frac{\widetilde{1 - \theta}}{\theta} \\ \hat{\theta} &= \frac{1}{1 + \bar{X}} \end{aligned}$$

(c)

$$\begin{aligned} f_{\mathbf{X}}(\mathbf{x}) &= \theta^n (1 - \theta)^{\sum_{i=1}^n x_i} \\ l(\theta) &= \log f_{\mathbf{X}}(\mathbf{x}) = n \log \theta + \left(\sum_{i=1}^n x_i \right) \log(1 - \theta) \\ l'(\theta) &= \frac{n}{\theta} + \frac{\sum_{i=1}^n x_i}{\theta - 1} \end{aligned}$$

Taking $l'(\theta) = 0$, we have $\theta = \frac{1}{1 + \bar{x}}$ and $l''(\theta) < 0$ at $\theta = \frac{1}{1 + \bar{x}}$. Therefore, we get the MLE for θ , which is $\hat{\theta} = \frac{1}{1 + \bar{X}}$.

(d) $EX = \frac{1 - \theta}{\theta}$. Therefore, by the invariant property of MLE, we have the MLE of EX is $\frac{1 - \hat{\theta}}{\hat{\theta}} = \bar{X}$

(e)

$$E(\bar{X}) = \frac{1}{n} \sum_{i=1}^n E(X_i) = \frac{1 - \theta}{\theta}$$

Therefore, the MLE of EX is unbiased.

$$\text{Var}(\bar{X}) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{1 - \theta}{n\theta^2}$$

(f)

$$\begin{aligned} \frac{\partial}{\partial \theta} \log f_{\mathbf{X}}(\mathbf{x}; \theta) &= \frac{n}{\theta} - \frac{\sum_{i=1}^n x_i}{1 - \theta} = \frac{n(1 - \theta) - \sum_{i=1}^n x_i \theta}{\theta(1 - \theta)} \\ &= \frac{-n}{1 - \theta} \left(\bar{x} - \frac{1 - \theta}{\theta} \right) \end{aligned}$$

Therefore, the variance of the unbiased estimator \bar{X} is equal to the CR lower bound.

3. Let X_1, \dots, X_n are independently uniformly distributed on $(\theta, 2\theta)$.