

3. What is the MLE of  $\Pr[x_{10} = 1 \text{ or } 2]$

$$\begin{aligned} \arg \max_{\theta > 0} f(x_1, x_2, \dots, x_{10}) &= \arg \max_{\theta > 0} \log f(x_1, x_2, \dots, x_{10}) \\ \log f(x_1, x_2, \dots, x_{10}) &= \log \prod_{i=1}^{10} \frac{\theta^{x_i} e^{-\theta}}{x_i!} = \log \theta * \sum_{i=1}^{10} x_i - 10\theta - \sum_{i=1}^{10} \log x_i! \\ F.O.C. \quad \frac{\sum_{i=1}^{10} x_i}{\theta} - 10 &= 0 \Rightarrow \theta_{mle} = \frac{\sum_{i=1}^{10} x_i}{10} = \bar{x} \\ \Pr[x_{10} = 1 \text{ or } 2] &= \theta e^{-\theta} + \frac{\theta^2 e^{-\theta}}{2} \end{aligned}$$

By the invariant principle of MLE, the MLE of  $\Pr[x_{10} = 1 \text{ or } 2] = \bar{x}e^{-\bar{x}} + \frac{\bar{x}^2 e^{-\bar{x}}}{2}$ .

4.

$$\bar{X} = n^{-1} \sum_{i=1}^{10} X_i$$

Since  $X_1, X_2, \dots, X_n$  is an iid sample from  $Binomial(1, \pi)$ , we know that the variance of

$$\bar{X} = n^{-1} var(X_i) = \frac{\pi(1-\pi)}{n}.$$

$$\begin{aligned} \log \mathcal{L} &= \log f(x_1, x_2, \dots, x_n) \\ &= \log \prod_{i=1}^n \pi^{x_i} (1-\pi)^{1-x_i} \\ &= \log \pi * \sum_{i=1}^n x_i + \log(1-\pi) * (n - \sum_{i=1}^n x_i) \end{aligned}$$

$$\begin{aligned} \frac{\partial \log \mathcal{L}}{\partial \pi} &= \frac{\sum_{i=1}^n x_i}{\pi} - \frac{n - \sum_{i=1}^n x_i}{1-\pi} \\ \frac{\partial^2 \log \mathcal{L}}{\partial \pi^2} &= -\frac{\sum_{i=1}^n x_i}{\pi^2} - \frac{n - \sum_{i=1}^n x_i}{(1-\pi)^2} \end{aligned}$$

The Fisher Information  $I(\pi) = -E[\frac{\partial^2 \log \mathcal{L}}{\partial \pi^2}] = \frac{n\pi}{\pi^2} + \frac{n-n\pi}{(1-\pi)^2} = \frac{n}{\pi(1-\pi)}$

We know that for all unbiased estimator of  $\pi$ , say  $E[h(x)] = \pi$ ,  $var[h(x)] \geq I(\pi)^{-1} = \frac{\pi(1-\pi)}{n}$ , which is called the Cramer-Rao lower bound.

Hence,  $\bar{X} = n^{-1} \sum_{i=1}^{10} X_i$  has the minimum variance among all the unbiased estimators of  $\pi$ .