

1. To estimate the proportion  $p$  of butterflies that have a special marking on their wings. Consider two approaches:
  - (a) Capture butterflies one at a time until five with the special marking have been collected. A total of 43 butterflies are required to collect the five. what is the M.L.E. of  $p$ ?
  - (b) Collect butterflies all day and count those with the special mark. 58 are captured. Three have the Mark. What is the M.L.E. of  $p$ ?

$$(a) \quad \hat{p} = \frac{5}{43}$$

$$(b) \quad \hat{p} = \frac{3}{58}$$

2. Consider a random sample  $X_1, \dots, X_n \sim \text{Uniform}(0, \theta)$ ,  $\theta$  unknown. Show that the sequence of MLE's of  $\theta$  is a consistent sequence.

$$X_1, \dots, X_n \sim U(0, \theta)$$

$$f(x) = \frac{1}{\theta}$$

$$\begin{aligned} L(\theta, X_1, \dots, X_n) &= f(x_1) \dots f(x_n) = \frac{1}{\theta^n} = \theta^{-n}, \quad \theta \geq \max(X_n) \\ &= -n \log(\theta) \end{aligned}$$

$$\frac{dL}{d\theta} = -\frac{n}{\theta}$$

The sequence of MLE of  $\theta$  is a function with no  $x$ , therefore it's a constant sequence.

3. Consider a random sample  $X_1, \dots, X_n \sim N(\mu, \sigma^2)$ ,  $\mu, \sigma$  unknown. Find the MLE of the 0.95 quantile.

$X_1, \dots, X_n \sim N(\mu, \sigma^2)$ .  $\mu$  is known.  $\sigma^2$  is unknown

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$L(\mu, \sigma; x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{\sigma\sqrt{2\pi}} e^{(-\frac{1}{2}(\frac{x_i-\mu}{\sigma})^2)}$$

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

$$\frac{dL(\mu, \sigma; x_1, \dots, x_n)}{d\sigma} = -\frac{n}{\sigma} + \sigma^{-3} \sum_{i=1}^n (x_i - \mu)^2 = 0$$

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

$$95\% \text{ MLE} = \hat{\mu} + 1.64 \hat{\sigma}$$

$$= \bar{X} + 1.64 \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{X})^2}$$

4. Consider again a random sample  $X_1, \dots, X_n \sim N(\mu, \sigma^2)$ ,  $\mu, \sigma$  unknown. Find the MLE of  $v = P(X > 2)$ .

$$X_1, \dots, X_n \sim N(\mu, \sigma^2)$$

$$\text{MLE of } v = P(X > 2)$$

$$v = P(Z > \frac{2-\mu}{\sigma})$$

$$= 1 - \Phi \frac{2-\mu}{\sigma}$$

5. Find the MLE estimator for  $\theta$  in the Cauchy distribution given the sample  $X = (-22.33, -10.29, -1.35, -1.73, 6.91, -0.52, 0.43, -0.00, -8.66, -7.16, 1.15, 1.15, -3.75, 2.54, 7.31, 0.65, 6.66, 5.52, 2.02, -1.48)$ .

$$X \sim \text{Cauchy}(\theta, 1)$$

$$f(x) = \frac{1}{\pi (1+(x-\theta)^2)}$$

$$L(\theta, 1; X) = \frac{1}{\pi^n \prod_{i=1}^n (1+(x_i-\theta)^2)}$$

$$= \frac{1}{\pi^n} \cdot \frac{1}{(1+(x-\theta)^2)^n}$$

$$\ell = -n \log(\pi) - \sum_{i=1}^n \log(1+(x_i-\theta)^2)$$

$$\frac{d\ell}{d\theta} = \sum_{i=1}^n \frac{2(x_i-\theta)}{1+(x_i-\theta)^2} = 0$$

$$2\theta(\theta^2 + (1-x^2)) = 0$$

$$\hat{\theta} = \pm \sqrt{x^2 - 1}$$

Given  $\bar{x} = -1.15$

$$\hat{\theta} = \pm \sqrt{0.3225} \approx \pm 0.57$$

6. Consider a random sample of 21 observations from  $\text{exponential}(\lambda)$ . Mean ( $\mu > 0$ ). 20 of the observations are collected without incident and have a mean of 6. The 21st observation was not measured exactly except that it is greater than 15.

Find the MLE of  $\mu$ .

$$X_1, \dots, X_n \sim \text{EXP}(\lambda)$$

$$f(x) = \lambda e^{-\lambda x}$$

$$F(x) = 1 - e^{-\lambda x}$$

$$P(X > 15) = e^{-15\lambda}$$

$$L(\mu, x_n) = \frac{1}{\mu^{20}} \exp\left(\frac{\sum x_i}{\mu}\right) \exp\left(\frac{-15}{\mu}\right)$$

$$= \frac{1}{\mu^{20}} \exp\left(\frac{-135}{\mu}\right)$$

$$\log 20 \log(\mu) - 135/\mu$$

$$\frac{dL}{d\mu} = \frac{20}{\mu} - 135 = 0$$

$$\hat{\mu} = 6.75$$

7.  $X_1, \dots, X_n$  form a random sample from a Poisson distribution for which the mean is unknown. Determine the MLE of the standard deviation of the distribution.

$$X_1, \dots, X_n \sim \text{Poisson}(\lambda)$$

$$f(x) = \frac{e^{-\lambda} \lambda^x}{x!}$$

$$L(\lambda; x_1, \dots, x_n) = e^{-n\lambda} \lambda^{\sum x_i} \left(\prod_{i=1}^n \frac{1}{x_i!}\right)$$

$$\log -n\lambda + \sum_{i=1}^n x_i \log(\lambda) + \log\left(\prod_{i=1}^n \frac{1}{x_i!}\right)$$

$$\frac{dL}{d\lambda} = -n + \frac{\sum x_i}{\lambda} = 0$$

$$\hat{\lambda} = \frac{\sum x_i}{n} = \bar{x} \Rightarrow \hat{\sigma} = \sqrt{\lambda} = \sqrt{\bar{x}}$$

8. Consider a random sample  $X_1, \dots, X_n \sim \exp(\beta)$ ,  $\beta$  is unknown. Determine the MLE of the median of the distribution.

$$X_1, \dots, X_n \sim \exp(\beta)$$

$$f(x) = \lambda e^{-\lambda x}$$

$$L(\beta, X_1, \dots, X_n) = \lambda^n e^{-\sum_{i=1}^n X_i \lambda}$$

$$\log L(\beta, X_1, \dots, X_n) = n \log(\lambda) - \lambda \sum_{i=1}^n X_i$$

$$\frac{dL}{d\lambda} = \frac{n}{\lambda} - \sum_{i=1}^n X_i = 0$$

$$\hat{\lambda} = \frac{n}{\sum_{i=1}^n X_i} = \frac{1}{\bar{X}} = \frac{1}{\bar{X}}$$

$$\text{median} = \lambda^{-1}(\log(2)) = \bar{X}(\log(2))$$

## Sufficiency Statistics

For each of these distributions show that the specified statistic  $T$  is sufficient for the parameter.

1. The Bernoulli distribution with parameter  $p$ .  
( $0 < p < 1$ ),  $T = \sum_{i=1}^n X_i$ .

$$\begin{aligned} f(p, x_1, \dots, x_n) &= p^{\sum x_i} (1-p)^{n - \sum x_i} \\ U(x_1, \dots, x_n) &= 1, \quad V(T, p) = p^T (1-p)^{n-T} \\ f(p, x_1, \dots, x_n) &= U(x_1, \dots, x_n) \cdot V(T, p) \\ T = \sum x_i &\text{ is sufficient} \end{aligned}$$

2. The geometric distribution with parameter  $p$ .  
( $0 < p < 1$ ),  $T = \sum_{i=1}^n X_i$ .

$$\begin{aligned} f(p, x_1, \dots, x_n) &= p^n (1-p)^{\sum x_i} \\ U(x_1, \dots, x_n) &= 1, \quad V(T, p) = p^n (1-p)^T \\ T = \sum x_i &\text{ is sufficient.} \end{aligned}$$

3. The negative binomial distribution with parameters  $r$  and  $p$ .  
 $r$  is known. ( $0 < p < 1$ ),  $T = \sum_{i=1}^n X_i$ .

$$\begin{aligned} f(r, p, x_1, \dots, x_n) &= \prod_{i=1}^n \binom{x_i-1}{r-1} p^r (1-p)^{x_i-r} \\ &= \prod_{i=1}^n \binom{x_i-1}{r-1} p^{nr} (1-p)^{\sum x_i - nr} \\ U(x_1, \dots, x_n) &= \prod_{i=1}^n \binom{x_i-1}{r-1}, \quad V(T, p) = p^{nr} (1-p)^{\sum x_i - nr} \\ T = \sum x_i &\text{ is sufficient} \end{aligned}$$

4. The gamma distribution with parameters  $\alpha$  and  $\beta$ .  $\alpha$  is known.  
 $(\beta > 0)$ ,  $T = \sum_{i=1}^n X_i$ .

$$\begin{aligned}
 f(\alpha, \beta, x_1, \dots, x_n) &= \prod_{i=1}^n \frac{\beta^\alpha}{\Gamma(\alpha)} x_i^{\alpha-1} e^{-\beta x_i} \\
 &= \frac{\beta^{n\alpha}}{\Gamma(\alpha)^n} \left( \prod_{i=1}^n x_i^{\alpha-1} \right) e^{-\beta \sum x_i} \\
 U(x_1, \dots, x_n) &= \prod_{i=1}^n x_i^{\alpha-1}, \quad V(T, \beta) = \frac{\beta^{n\alpha}}{\Gamma(\alpha)^n} e^{-\beta T} \\
 T = \sum x_i &\text{ is sufficient}
 \end{aligned}$$

5. The gamma distribution with parameters  $\alpha$  and  $\beta$ .  $\beta$  is known.  
 $(\alpha > 0)$ ,  $T = \prod_{i=1}^n X_i$ .

$$\begin{aligned}
 f(\alpha, \beta, x_1, \dots, x_n) &= \prod_{i=1}^n \frac{\beta^\alpha}{\Gamma(\alpha)} x_i^{\alpha-1} e^{-\beta x_i} \\
 &= \frac{\beta^{n\alpha}}{\Gamma(\alpha)^n} \left( \prod_{i=1}^n x_i^{\alpha-1} \right) e^{-\beta \sum x_i} \\
 &= \frac{\beta^{n\alpha}}{\Gamma(\alpha)^n} \exp(\alpha-1) \sum_{i=1}^n \ln(x_i) e^{-\beta \sum x_i} \\
 U(x_1, \dots, x_n) &= e^{\beta \sum x_i}, \quad V(T, \alpha) = \frac{\beta^{n\alpha}}{\Gamma(\alpha)^n} \exp(\alpha-1) \sum_{i=1}^n \ln(T) \\
 T = \sum x_i &\text{ is sufficient.}
 \end{aligned}$$