

- 1) parameter p based on a Bernoulli(p) sample of size n

Given:

$D = \{x_1, x_2, \dots, x_n\}$, where m heads(1), $n-m$ tails(0)

$$\text{prob}(D|p) = \prod_{i=1}^n \text{prob}(x_i|p) = \prod_{i=1}^n p^{x_i} (1-p)^{(1-x_i)}$$

$$\ln \text{prob}(D|p) = \sum_{i=1}^n \ln p(x_i|p) = \sum_{i=1}^n \{x_i \ln p + (1-x_i) \ln(1-p)\}$$

$$p_{ML} = (1/n) \sum_{i=1}^n x_i$$

$$p_{ML} = m/n$$

- 2) parameter p based on a Binomial (N, p) sample of size n . Compute your estimators if the observed sample is (3, 6, 2, 0, 0, 3) and $N = 10$.

$D = \{x_1, x_2, \dots, x_n\}$

$$f(x_1, x_2, \dots, x_n) = \prod_{i=1}^n \binom{N}{x_i} p^{x_i} (1-p)^{N-x_i}$$

$$\ln f(x_1, x_2, \dots, x_n) = \sum_{i=1}^n \left[\ln \binom{N}{x_i} + x_i \ln p + (N-x_i) \ln(1-p) \right]$$

$$\frac{\partial}{\partial p} (\ln f(x_1, \dots, x_n)) = \sum_{i=1}^n \frac{x_i}{p} - \sum_{i=1}^n \frac{(N-x_i)}{(1-p)}$$

$$= (nX)/p - (nN - nX)/(1-p) = 0 \quad (X \text{ is the mean of input data } (x_1, x_2, \dots, x_n))$$

Solving this equation,

$$(1-p)X = p(N-X) \Rightarrow p = X/N$$

For given data and N

$$X = (3+6+2+0+0+3)/6 = 14/6$$

$$p_{ML} = (14/6)/10$$

$$p_{ML} = 7/30$$

- 3) parameters a and b based on a Uniform (a, b) sample of size n .

$$f(x_1, x_2, \dots, x_n) = \left\{ \frac{1}{(b-a)} \right\}^n \text{ if } a \leq x_1 \leq x_n \leq b$$

Function is increasing in a and decreasing in b . It is maximized at the largest value of a and the smallest value of b where this density is not 0. These are

$$a_{ML} = \min(x_i) \quad b_{ML} = \max(x_i)$$

- 4) parameter μ based on a $\text{Normal}(\mu, \sigma^2)$ sample of size n with known variance σ^2 and unknown mean μ .

Joint density function is

$$f(X_1, \dots, X_n) = \prod_{i=1}^n \frac{1}{(\sigma\sqrt{2\pi})} \exp \left\{ -\frac{(X_i - \mu)^2}{2\sigma^2} \right\}$$

taking log

$$\begin{aligned} \ln f(X_1, \dots, X_n) &= -n \ln(\sigma\sqrt{2\pi}) - \sum_{i=1}^n \frac{(X_i - \mu)^2}{2\sigma^2} \\ &= -n \ln(\sigma\sqrt{2\pi}) - \frac{n\mu^2 - 2\sum X_i \mu + \sum X_i^2}{2\sigma^2} \end{aligned}$$

Is parabola in terms of μ and is max at **ML $\mu = \sum X_i/n$**

- 5) parameter σ based on a $\text{Normal}(\mu, \sigma^2)$ sample of size n with known mean μ and unknown variance σ^2 .

Joint density function is

$$f(X_1, \dots, X_n) = \prod_{i=1}^n \frac{1}{(\sigma\sqrt{2\pi})} \exp \left\{ -\frac{(X_i - \mu)^2}{2\sigma^2} \right\}$$

partial differentiation with respect to σ

$$\begin{aligned} \text{Partial d } (\ln f(x_1, \dots, x_n)) &= -n/\sigma + \sum (X_i - \mu)^2 / \sigma^3 = 0 \\ \text{--} \\ \text{dp} \end{aligned}$$

On taking root, we will get maximize the density so that

$$\text{ML } \sigma = \sqrt{\sum (X_i - \mu)^2 / n}$$

- 6) parameters (μ, σ^2) based on a $\text{Normal}(\mu, \sigma^2)$ sample of size n with unknown mean μ and variance σ^2

Joint density function is

$$f(X_1, \dots, X_n) = \prod_{i=1}^n \frac{1}{(\sigma\sqrt{2\pi})} \exp \left\{ -\frac{(X_i - \mu)^2}{2\sigma^2} \right\}$$

maximizing the function from 4th question, ML $\mu = \sum X_i/n$ for all the values of σ

Then, substitute the obtained maximizer into $\ln f(X_1, \dots, X_n)$ for the unknown value of μ and maximize the resulting function in terms of σ

$$\text{ML } \sigma = \sqrt{(\sum (x_i - \bar{x})^2) / n}$$