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$$y_i = (\alpha + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + u_i)$$

MLE

likelihood function

$$L = f(\dots)$$

FOC
SOC

$$\frac{\partial L}{\partial \theta_1}, \frac{\partial L}{\partial \theta_2}$$

$$L(\theta) = \prod f(x_i, \theta)$$

MLE same for all distributions

$$n \quad (x_1, x_2, \dots, x_n)$$

$P_{\mu}(\mu)$

$$L(\mu) = \prod_{i=1}^n \frac{e^{-\mu} \cdot \mu^{x_i}}{x_i!} = \text{const} \times e^{-n\mu} \cdot \mu^{\sum x_i}$$

$$\ln L(\mu) = \text{const} - n\mu + \sum x_i \ln \mu$$

$$\frac{d}{d\mu} \ln L(\mu) = -n + \frac{\sum x_i}{\mu} = 0$$

$$\hat{\mu} = \frac{\sum x_i}{n} = \bar{x}$$

$$d^2 \ln L(\mu) = -\frac{\sum x_i}{\mu^2} < 0 = \boxed{\text{max}}$$

1 Parameter

$$\frac{d^2}{d\mu^2} \ln L(\mu) = -\frac{\sum x_i^2}{\mu^2} < 0 = \boxed{\text{max}}$$

estimate as \bar{X} ←

2 Parameter Case

MLE of (μ, σ)

$$L(\mu, \sigma) = \prod \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x_i - \mu}{\sigma}\right)^2\right] \\ = \sigma^{-n} \exp\left[-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2\right] \times \text{const}$$

$$\ln L(\mu, \sigma) = -n \ln \sigma - \frac{1}{2\sigma^2} \sum (x_i - \mu)^2 + \text{const}$$

$$\frac{\partial}{\partial \mu} \ln L = -\frac{1}{2\sigma^2} \sum 2(x_i - \mu) = \frac{1}{\sigma^2} \left[\sum x_i - n\mu \right]$$

$$\frac{\partial}{\partial \mu} \ln L = -\frac{n}{\sigma} \exp\left[-\frac{1}{2}\left(\frac{x_i - \mu}{\sigma}\right)^2\right] \\ = \frac{1}{\sigma} \left[\frac{1}{\sigma^2} \sum (x_i - \mu)^2 - n \right] = 0$$

$$\bar{\mu} = \frac{1}{n} \sum x_i = \bar{x}$$

$$\sigma^2 = \frac{n-1}{n} s^2$$

Exponential
mean θ 2θ 3θ

MLE of θ

$$X \sim \exp\left(\frac{1}{\theta}\right) \quad Y \sim \exp\left(\frac{1}{2\theta}\right) \quad Z \sim \exp\left(\frac{1}{3\theta}\right)$$

$$\dots \times \frac{1}{\theta} e^{-\frac{1}{\theta} x} \times \frac{1}{2\theta} e^{-\frac{1}{2\theta} y} \times \frac{1}{3\theta} e^{-\frac{1}{3\theta} z}$$

$$L(\theta) = \frac{1}{\theta} e^{-\frac{x}{\theta}} \cdot \frac{1}{\theta} e^{-\frac{y}{\theta}} \times \frac{1}{\theta} e^{-\frac{z}{\theta}}$$

$$= \frac{1}{\theta^3} e^{-\frac{1}{\theta}(x+y+z)}$$

$$\ln L(\theta) = -3 \ln \theta - \frac{1}{\theta}(x+y+z)$$

$$\frac{d}{d\theta} \ln L(\theta) = -\frac{3}{\theta} + \frac{1}{\theta^2}(x+y+z)$$

$$\hat{\theta} = \frac{1}{3}(x+y+z)$$

ISS 2WS

$$x_1 = -2, x_2 = 1, x_3 = 3, x_4 = -4$$

PDF $f(x|\theta) = \frac{\theta^{-x}}{e^\theta - e^{-\theta}}$

$-\theta < x < \theta$
 $\theta > 0$

then MLE of θ = ??

$$f(x|\theta) = \frac{e^{-x}}{e^\theta - e^{-\theta}} \quad -\theta \leq x \leq \theta$$

$\theta > 0$

$0 < |x| < \theta$

$$L(\theta) = \prod_{i=1}^4 \frac{e^{-x_i}}{e^\theta - e^{-\theta}}$$

$\hat{\theta} = \max(|x_i|, i=1,2,\dots,n) = \max(2, 1, 3, 4) = 4$

~~##~~ $f(x|\theta, \sigma) = \frac{1}{\sigma} e^{-\frac{(x_i - \theta)}{\sigma}}$ $x > \theta$, $-\infty < \theta < \infty$, $\sigma > 0$

- (i) moment method
- (ii) MLE

$= 0$, only
 $L(\theta) = \prod_{i=1}^n \frac{1}{\sigma} e^{-\frac{1}{\sigma}(x_i - \hat{\theta})}$

Rang $\rightarrow \theta < x_1 < x_2 \dots < x_n < \infty$
 \rightarrow min terms
 $\frac{d}{dn} n \rightarrow \infty$

Ex 1)
Ex 2)

$\therefore \hat{\theta} = \min(x_1, x_2, \dots, x_n) = X_{(1)}$

$L(\hat{\theta}) = \prod_{i=1}^n \frac{1}{\sigma} e^{-\frac{1}{\sigma}(x_i - \hat{\theta})}$

$L(\sigma) = \frac{1}{\sigma^n} \cdot e^{-\frac{1}{\sigma} \sum (x_i - x_1)}$

$\ln L(\sigma) = -n \ln \sigma - \frac{1}{\sigma} \sum (x_i - x_1)$

$\frac{d}{d\sigma} \ln L(\sigma) = -\frac{n}{\sigma} + \frac{1}{\sigma^2} \sum (x_i - x_1)$

So, $\frac{1}{\sigma} \left[-n + \frac{1}{\sigma} \sum (x_i - x_1) \right] = 0$
 $\hat{\sigma} = \frac{1}{n} \sum (x_i - x_1) = \bar{X} - X_{(1)}$

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$$f(x|\theta) = \theta e^{-\theta x} \quad \theta > 0$$

$\Rightarrow 0$, volume

if $\theta > 0$, then obtain MLE of $P(X > 10)$.

~~f(x|\theta)~~

$$L(\theta) = \prod \theta e^{-\theta x_i}$$

$$= \theta^n \cdot e^{-\theta \sum x_i}$$

(unfused)

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Scanned

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X_1, X_2, \dots, X_n be a random sample

Exp dist \rightarrow mean = $\frac{1}{\lambda}$

MLE of median ??

$$X_i \sim \text{Exp}(\lambda) \quad \forall i=1, 2, \dots, n$$

$$\text{Median} = \text{mean} \ln 2 = \frac{1}{\lambda} \ln 2 \quad \text{--- (1)}$$

$$L(\lambda) = \prod \lambda e^{-\lambda x_i}$$

$$= \lambda^n e^{-\lambda \sum x_i}$$

$$\ln L(\lambda) = n \ln \lambda - \lambda \sum x_i$$

$$\frac{d}{d\lambda} \ln L(\lambda) = 0 \Rightarrow \lambda = \frac{n}{\sum x_i} = \frac{1}{\bar{x}}$$

In which $\frac{1}{\lambda} = \bar{x} \Rightarrow \lambda = \frac{1}{\bar{x}}$

Observed value & parameter case

we \rightarrow $N(0, 1)$

if parameter space is $\Theta = \{0, 1, 2, 3\}$

find $MLE(\theta) = ??$

$$L(\theta) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x_i - \theta)^2}$$

$$= \left(\frac{1}{\sqrt{2\pi}}\right)^n e^{-\frac{1}{2} \sum (x_i - \theta)^2}$$

we estimate $\theta \rightarrow$ when the square error is min

$$\sum (x_i - \theta)^2 = \sum (x_i - \bar{x} + \bar{x} - \theta)^2$$

$$\Rightarrow \sum (x_i - \bar{x})^2 + \sum (\bar{x} - \theta)^2 + 2 \sum (x_i - \bar{x})(\bar{x} - \theta)$$

$$\Rightarrow \sum (x_i - \bar{x})^2 + n(\bar{x} - 0)^2 + 2(\bar{x} - 0) \sum (x_i - \bar{x})$$

$$\Rightarrow \sum (x_i - \bar{x})^2 + n(\bar{x} - 0)^2 + 2(\bar{x} - 0) \underline{(n\bar{x} - n\bar{x})}$$

$$\Rightarrow \sum (x_i - 2.3)^2 + n(2.3 - 0)^2$$

the quadratic loss or error is min.

$$(2.3 - 0)^2 = \text{ @ } \underline{2.3}$$

$$X \rightarrow \text{Bin}(1, p)$$

$$p \in \left[\frac{1}{5}, \frac{4}{5} \right]$$

if the observed value of X is 0

then using $p = ?$

$$f(x) = p^x (1-p)^{1-x}$$

$$L(p) = P(X=0)$$

$$= p^0 (1-p)^{1-0}$$

$$= p^0 (1-p)^1$$

$L(p)$ attains its max

$$= (1-p) \text{ when } \frac{1}{5} \leq p \leq \frac{4}{5}$$

$$\text{at } p = \underline{\frac{1}{5}}$$

~~#~~
$$f(x) = \frac{2x^2}{x^3} \quad x > 0$$

$$f'(x) = 0 \quad \text{value of } x$$

Here we can't find value by cancel method.

Order Statistics \rightarrow Concept of

$$\text{Let } L(x) = 2^n \cdot \frac{1}{\prod_{i=1}^n x_i^3}$$

Here, value of x subset the Range $\{x_1, x_2, \dots, x_n < \infty\}$

$$\therefore \hat{x} = \min \{x_1, x_2, \dots, x_n\} = \underline{x_{(1)}}$$