

1. Exact Methods
 2. Asymptotic methods
- ↪ approximate

Example. $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Exp}(\theta)$. $E(X) = \theta$

$$\hat{\theta} = \frac{T}{n} \quad T = \sum_{i=1}^n X_i \quad 100 \times (1-\alpha)\% \text{ CI of } \theta.$$

• Exact $100 \times (1-\alpha)\%$ CI of θ $[\hat{\theta}_L, \hat{\theta}_U]$ $P(\hat{\theta}_L \leq \theta \leq \hat{\theta}_U) = 1-\alpha$

$$T \sim \text{Gamma}(n, \theta)$$

$$\frac{2T}{\theta} \sim \text{Gamma}(n, 2) = \chi_{2n}^2$$

$$\chi_{2n, 1-\frac{\alpha}{2}}^2 \leq \frac{2T}{\theta} \leq \chi_{2n, \frac{\alpha}{2}}^2$$

$$\left[\frac{2n\hat{\theta}}{\chi_{2n, \frac{\alpha}{2}}^2}, \frac{2n\hat{\theta}}{\chi_{2n, 1-\frac{\alpha}{2}}^2} \right]$$

• Approximated $100 \times (1-\alpha)\%$ CI for θ :

$$\hat{\theta} \sim AN\left(\theta, \frac{\theta^2}{n}\right)$$

CLT: $\frac{\sqrt{n}(\hat{\theta} - \theta)}{\theta} \xrightarrow{d} N(0, 1)$

$$-z_{\alpha/2} \leq \frac{\sqrt{n}(\hat{\theta} - \theta)}{\theta} \leq z_{\alpha/2}$$

$$\left[\frac{\sqrt{n}\hat{\theta}}{\sqrt{n} + z_{\alpha/2}}, \frac{\sqrt{n}\hat{\theta}}{\sqrt{n} - z_{\alpha/2}} \right]$$

Data $\underline{Y} = (Y_1, \dots, Y_n)^T$ $f(\underline{y}; \underline{\theta})$ is joint density of \underline{Y}
 \downarrow
 $\underline{\theta} = (\theta_1, \dots, \theta_b)^T$

Likelihood function is just $f(\underline{Y}; \underline{\theta}) = L(\underline{\theta} | \underline{Y})$

iid : $L(\underline{\theta} | \underline{Y}) = \prod_{i=1}^n f(Y_i; \underline{\theta})$

independent $Y_i \sim f_i(y; \theta)$

$$L(\underline{\theta} | \underline{Y}) = \prod_{i=1}^n f_i(Y_i; \theta)$$

Important: In all situations, the likelihood is the joint density of the **observed data** to be analyzed

1. Interpretation
2. Is the density appropriate for data
3. observed data?

(Interpretation)

$Y_i, i=1, \dots, n$ iid Discrete r.v. with Prob. mass function $f(y; \underline{\theta})$

$$\Pr(Y = y; \underline{\theta})$$

$$L(\underline{\theta} | \underline{Y}) = \prod_{i=1}^n f(Y_i; \theta) = \prod_{i=1}^n \Pr(Y_i^* = Y_i; \theta)$$

where $Y_i^*, i=1, \dots, n$ are iid from $f(y; \theta)$ and are mutually independent of Y_1, \dots, Y_n

Continuous

$$\begin{aligned} f(Y_i; \theta) &= \lim_{h \rightarrow 0^+} \frac{1}{2h} (F(Y_i + h; \theta) - F(Y_i - h; \theta)) \\ &= \lim_{h \rightarrow 0^+} \frac{\Pr(Y_i - h \leq Y_i^* \leq Y_i + h)}{2h} \end{aligned}$$

$$L(\underline{\theta} | \underline{Y}) = \lim_{h \rightarrow 0^+} \left(\frac{1}{2h} \right)^n \prod_{i=1}^n \Pr(Y_i - h \leq Y_i^* \leq Y_i + h)$$

(Is ^{the} density appropriate?)

Example. 2.1 counts of movements in five-second intervals of one fetal Lamb.

No of Movements. 0 1 2 3 4 5 6 7

counts 182 41 12 2 2 0 0 1 (260)

Starting with Poisson $f(y; \theta) = \frac{\theta^y e^{-\theta}}{y!}$ $y=0, 1, 2, \dots$

$$\prod_{i=1}^n \frac{\theta^{y_i} e^{-\theta}}{y_i!} \xrightarrow{MLE} \hat{\theta} = \bar{Y}_n \text{ (sample mean)}$$

$X_1, \dots, X_n \stackrel{iid}{\sim} f_X(x; \theta)$

$$\hat{\theta}_{MLE}^{(X)} = \underset{\theta}{\operatorname{argmax}} \mathcal{L}(\theta | \underline{X})$$

$$\mathcal{L}(\theta | \underline{X}) = \prod_{i=1}^n f_X(x_i; \theta)$$

Suppose. g is a one-to-one transformation. $Y_i = g(X_i)$

$$\hat{\theta}_{MLE}^{(Y)} = \underset{\theta}{\operatorname{argmax}} \mathcal{L}(\theta | \underline{Y})$$

$$f_Y(y; \theta) = f_X(g^{-1}(y); \theta) \times |g^{-1}(y)'|$$

$$\hat{\theta} \quad \mathcal{L}(\theta | \underline{Y}) = \prod_{i=1}^n f_X(g^{-1}(Y_i); \theta) \times |g^{-1}(Y_i)'|$$

$$= \mathcal{L}(\theta | \underline{X}) \times \text{constant}$$

$$\hat{\theta}_{MLE}^{(Y)} = \hat{\theta}(Y_1, \dots, Y_n)$$

$$\hat{\theta}_{MLE}^{(X)} = \hat{\theta}(X_1, \dots, X_n)$$

$X_1, \dots, X_n \stackrel{iid}{\sim} N(\mu, \sigma)$ $\hat{\theta}_{MLE}^{(\mu)} = \bar{X}_n = \frac{\sum X_i}{n}$

$Y_i = \exp(X_i)$ $\hat{\theta}_{MLE}^{(\sigma^2)} = \frac{\sum \ln(Y_i)}{n}$

Empirical Estimator of F

suppose $Y_1, \dots, Y_n \stackrel{iid}{\sim} f(y)$ with cdf $F(y)$

- nonnegative, non-decreasing, right-continuous.
- $\lim_{y \rightarrow -\infty} F(y) = 0$
- $\lim_{y \rightarrow \infty} F(y) = 1$

$$\underline{P(Y = Y_i)} \approx \underbrace{\{F(Y_i+h) - F(Y_i-h)\}}_{P_{ih}}$$

$$L(F|\underline{Y}) \approx \prod_{i=1}^n P_{ih}$$

$$0 < P_{ih} < 1 \quad \sum_{i=1}^n P_{ih} = 1$$

Estimate P_{1h}, \dots, P_{nh} by maximizing $\left(\prod_{i=1}^n P_{ih}\right)$ w.r.t. $\left\{ \begin{array}{l} 0 < P_{ih} < 1 \\ \sum_{i=1}^n P_{ih} = 1 \end{array} \right.$

method of Lagrange Multipliers. find the stationary points of

$$g(P_{1h}, \dots, P_{nh}, \lambda) = \sum_{i=1}^n \log(P_{ih}) + \lambda \left(\sum_{i=1}^n P_{ih} - 1 \right)$$

$$\frac{\partial g}{\partial P_{ih}} = \frac{1}{P_{ih}} + \lambda = 0 \quad i=1, \dots, n$$

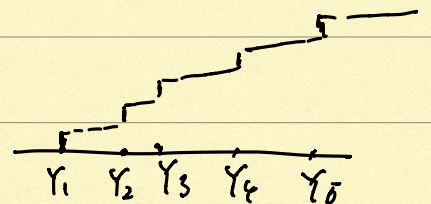
$$\frac{\partial g}{\partial \lambda} = \sum_{i=1}^n P_{ih} - 1 = 0$$

$$-\frac{n}{\lambda} - 1 = 0 \Rightarrow \lambda = -n$$

$$P_{ih} = \frac{1}{n}$$

$$\hat{P}_{ih} = \frac{1}{n} \quad \text{for } i=1, \dots, n$$

$$= F(Y_i+h) - F(Y_i-h)$$



$$\hat{F}_{MLE}(y) = \frac{1}{n} \sum_{i=1}^n I(Y_i \leq y)$$

• Censoring:

$$X_1, \dots, X_n \sim f(x; \theta)$$

$$Y_i = \min(X_i, R_i)$$

$$S_i = I(X_i \leq R_i) \begin{cases} = 1, & X_i \text{ before } R_i \\ = 0, & \text{censored. } X_i > R_i \end{cases}$$

Example.

pieces of equipment that are started at different times and late regularly checked for failure.

Y:	2	72	51	60	33	27	14	24	4	21
S:	1	0	1	0	1	1	1	1	1	0

suppose. ~~$X_1, \dots, X_{10} \stackrel{iid}{\sim} \exp(\theta)$~~ How to estimate θ ?

$$(Y_i, S_i)$$

$$P(Y_i \leq y, S_i = 1) = P(Y_i \leq y, Y_i = X_i) = P(X_i \leq y)$$

If $S_i = 1$. $Y_i \sim f_X(y; \theta)$

If $S_i = 0$ $X_i > R_i$ $P(X_i > R_i) = 1 - F(R_i; \theta)$

$$L(\theta | \underline{Y}) = \prod_{i=1}^n [f_X(Y_i; \theta)]^{S_i} [1 - F(Y_i; \theta)]^{1 - S_i}$$

$$f_X(x; \theta) = \frac{1}{\theta} \exp\left(-\frac{x}{\theta}\right) \quad \theta > 0 \quad F_X(x; \theta) = 1 - \exp\left(-\frac{x}{\theta}\right)$$

$$L(\theta | \underline{Y}) = \prod_{i=1}^n \left[\frac{1}{\theta} \exp\left(-\frac{Y_i}{\theta}\right) \right]^{S_i} \left[\exp\left(-\frac{Y_i}{\theta}\right) \right]^{1 - S_i}$$

$$= \left(\frac{1}{\theta}\right)^{\sum \delta_i} \prod_{i=1}^n \exp\left(\frac{\delta_i Y_i}{\theta} + \frac{(1-\delta_i) Y_i}{\theta}\right)$$

$$= \left(\frac{1}{\theta}\right)^{\sum \delta_i} \prod_{i=1}^n \exp\left(\frac{Y_i}{\theta}\right)$$

$$l(\theta | \underline{Y}) = \log L(\theta | \underline{Y}) = -\sum \delta_i \log \theta + \frac{\sum Y_i}{\theta}$$

$$\hat{\theta} = \frac{\sum Y_i}{\sum \delta_i}$$

random

right censoring

$X_1, \dots, X_n \stackrel{iid}{\sim} f_X(x; \theta)$ } independent
 random censoring times $R_1, \dots, R_n \stackrel{iid}{\sim} G(r)$ }

observed data $\left\{ \begin{array}{l} Y_i = \min(X_i, R_i) \\ \delta_i = I(X_i \leq R_i) \end{array} \right.$

$\delta_i = 1 \Rightarrow Y_i = X_i$
 $\Rightarrow X_i \leq R_i$

random random
 ↓ ↓

$$\frac{P(Y_i \in (y-h, y+h), \delta_i = 1)}{2h} = \frac{P(X_i \in (y-h, y+h), X_i \leq R_i)}{2h}$$

$$= \frac{1}{2h} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} I(y-h < x < y+h, x < r) \times \underbrace{f(x; \theta) g(r)}_{X \text{ and } R \text{ are independent}} dx dr$$

$$f(x, r) = f(x; \theta) \times g(r)$$

$$= \frac{1}{2h} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} I(y-h < x < y+h) \times I(x < r) f(x; \theta) g(r) dx dr$$

$$= \frac{1}{2h} \int_{-\infty}^{+\infty} I(y-h < x < y+h) f(x; \theta) \left[\int I(x < r) g(r) dr \right] dx$$

$$= \frac{1}{2h} \int_{y-h}^{y+h} f(x; \theta) \times \left[\int_x^{+\infty} g(r) dr \right] dx$$

$$= \frac{1}{2h} \int_{y-h}^{y+h} f(x; \theta) [1 - G(x)] dx$$

$h \rightarrow 0 \rightarrow (1 - G(y)) \cdot f(y; \theta)$ $\delta_i = 0 \Rightarrow \begin{cases} Y_i = R_i \\ X_i > R_i \end{cases}$

Similarly

$$\frac{P(Y_i \in (y-h, y+h), \delta_i=0)}{2h} \rightarrow [1 - F(y; \theta)] g(y)$$

$$\begin{aligned} L(\theta | \underline{y}, \underline{\delta}) &= \prod_{i=1}^n \left[[1 - G(y_i)] \times f(y_i; \theta) \right]^{\delta_i} \times \left[[1 - F(y_i; \theta)] g(y_i) \right]^{1-\delta_i} \\ &= \prod_{i=1}^n \left[f(y_i; \theta) \right]^{\delta_i} \left\{ [1 - F(y_i; \theta)] \right\}^{1-\delta_i} \\ &\quad \times \prod_{i=1}^n \left\{ [1 - G(y_i)] \right\}^{\delta_i} \left\{ g(y_i) \right\}^{1-\delta_i} \end{aligned}$$

(Y_i, X_i) $Y_i \sim X_i$ $Y_i = X_i \beta + \epsilon_i$

$\downarrow \downarrow$
 \uparrow

$$\left\{ \begin{aligned} L(\theta | Y_i, X_i) &= \prod_{i=1}^n f_{y,x}(y_i, x_i) \\ &= \prod_{i=1}^n f_{y|x}(y_i | x_i) f_x(x_i) \\ &= \left(\prod_{i=1}^n f_{y|x}(y_i | x_i; \theta) \right) \times f_x(x_i) \end{aligned} \right.$$

\uparrow
 β, θ^2, \dots

$(Y_i, X_i) \quad i = 1, \dots, N$

$\downarrow \downarrow \dots$

1st group $(Y_{11}, X_{11}) \dots (Y_{1c}, X_{1c})$

J group $(Y_{j1}, X_{j1}) \dots (Y_{jc}, X_{jc})$

$$Y_i = \beta_0 + X_i \beta_1 + \epsilon_i$$

$$\begin{aligned} \bar{Y}_1 &= \frac{1}{c} \sum_{i=1}^c Y_{1i} & \bar{X}_1 &= \frac{1}{c} \sum_{i=1}^c X_{1i} \\ & \vdots & & \vdots \\ \bar{Y}_j & & \bar{X}_j & \end{aligned}$$

$$\bar{Y}_j = \beta_0 + \bar{X}_j \beta_1 + \frac{1}{c} \sum_{i=1}^c \epsilon_i$$

$\underbrace{\hspace{10em}}_{\epsilon_j}$

$$\log Y_{ij} = \beta_0 + X_{ij}\beta_1 + \varepsilon_{ij}$$

like

→ (\bar{Y}_j, \bar{X}_j) ? \nearrow estimate.

$$\log \bar{Y}_j \neq \beta_0 + \bar{X}_j \beta_1 + \bar{\varepsilon}_j$$

$f(y_{ij}, x_{ij})$

Example. The annual maximum sea levels in Venice 1951-1981

$$Y_i = X_i \beta + \varepsilon_i \quad \varepsilon_i \sim N(0, \sigma^2)$$

$$Y_i = X_i \beta + \varepsilon_i \quad \varepsilon_i \sim f_e(\varepsilon, \sigma)$$

$$\underline{f_e(\varepsilon) = \frac{\exp(-\varepsilon) \exp\{-\exp(-\varepsilon)\}}{\sigma}} \quad \varepsilon > 0$$

extreme value density

$$\frac{Y_i - X_i \beta}{\sigma} \sim f_e(\varepsilon)$$