

457.646 Topics in Structural Reliability

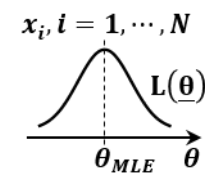
In-Class Material: Class 21

◎ Likelihood function $L(\theta)$ for distribution (statistical) parameters θ_f (e.g. $\mu, \sigma, \lambda, \xi, \dots$)

- ① Measured value are available, $\mathbf{x}_i, i = 1, \dots, N$

Assuming the observations are s.i.

$$\begin{aligned} L(\theta_f) &\propto P\left(\bigcap_{i=1}^N \mathbf{X} = \mathbf{x}_i \mid \theta_f = \theta_f\right) \\ &= \prod_{i=1}^N P(\mathbf{X} = \mathbf{x}_i \mid \theta_f = \theta_f) \quad (\because \text{s.i.}) \\ &\propto \prod_{i=1}^N f_{\mathbf{x}}(\mathbf{x}_i \mid \theta_f) \end{aligned}$$



e.g. $\mathbf{x} = \{x\}$ uni-variate normal $N(\mu, \sigma^2)$

Two samples observed: 12.3 ($\leftarrow x_1$), 13.5 ($\leftarrow x_2$) $f(\theta) = cL(\theta) \cdot P(\theta)$

$$L(\theta_f) \propto \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2}\left(\frac{12.3 - \mu}{\sigma}\right)^2\right) \times \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{1}{2}\left(\frac{13.5 - \mu}{\sigma}\right)^2\right)$$

$$\begin{aligned} \ast L(\theta) \begin{cases} \text{MLE} & \theta_{\text{MLE}} = \arg \max L(\theta) \\ \text{Bayesian Parameter Estimation} \end{cases} \begin{cases} \frac{\partial L}{\partial \theta} = 0 \\ \text{prefer } \frac{\partial \ln L}{\partial \theta} = 0 \end{cases} \end{aligned}$$

$$f(\theta) = c \cdot L(\theta) \cdot p(\theta)$$

- ② No direct measurement $\mathbf{x}$ of available, but a set of events that involve $\mathbf{x}$ are available

e.g. no measurement for compressive strength of concrete f'_c ($\leftarrow \mu, \sigma, \lambda, \dots$)

available but spalling observed under a certain condition

Inequality events : $h_i(\mathbf{x}) \leq 0, i = 1, \dots, N$

Equality events : $h_i(\mathbf{x}) = 0$

a) Inequality

e.g. $h_i(\mathbf{x}) = -C(\mathbf{x}) + D(\mathbf{x}) \leq 0$ no failure observed

$h_i(\mathbf{x}) = C(\mathbf{x}) - D(\mathbf{x}) \leq 0$ failure observed

$$L(\boldsymbol{\theta}_f) \propto \prod_{i=1}^N P(h_i(\mathbf{x}) \leq 0 | \boldsymbol{\theta}_f)$$

$$= \prod_{i=1}^N \int_{h_i(\mathbf{x}) \leq 0} f_{\mathbf{x}}(\mathbf{x}; \boldsymbol{\theta}_f) d\mathbf{x} \Rightarrow \text{structural reliability analysis}$$

b) Equality

e.g. $h_i(\mathbf{x}) = a(\mathbf{x}) - a_o = 0$

$a(\mathbf{x})$: fatigue crack growth model, e.g. Paris law

a_o : measured crack size

$$L(\boldsymbol{\theta}_f) \propto \prod_{i=1}^N \lim_{\delta \rightarrow 0} P[0 < h_i(\mathbf{x}) \leq \delta]$$

$$= \prod_{i=1}^N \frac{\partial}{\partial \delta} P[h_i(\mathbf{x}) - \delta \leq 0] \Big|_{\delta=0}$$

Proof

$$\lim_{\Delta\delta \rightarrow 0} \frac{P[h_i(\mathbf{x}) - \delta - \Delta\delta \leq 0] - P[h_i(\mathbf{x}) - \delta \leq 0]}{\Delta\delta} \Big|_{\delta=0}$$

$$= \lim_{\Delta\delta \rightarrow 0} \frac{P[h_i(\mathbf{x}) - \Delta\delta \leq 0] - P[h_i(\mathbf{x}) \leq 0]}{\Delta\delta}$$

$$\propto \lim_{\Delta\delta \rightarrow 0} P[0 \leq h_i(\mathbf{x}) \leq \Delta\delta]$$

$\nabla_{\delta} P_f \Big|_{\delta=0}$: can be considered as parameter sensitivity of P_f w.r.t δ (model parameter)

- FORM-based (Madsen, 1987)
- Good review & new development (Straub, 2011)

↘ a trick to transform equality constraint to _____ constraint

◎ Likelihood function for limit-state model parameters, $L(\boldsymbol{\theta}_g)$

e.g. $g(\mathbf{x}; \boldsymbol{\theta}_g) = \underline{V_c(\mathbf{x}; \boldsymbol{\theta}_g)} - V_d(\mathbf{x}; \boldsymbol{\theta}_g) \leq 0$

$$\frac{1}{6} \sqrt{f'_c} b_w d \quad (\text{ACI 11-3})$$

① Statistical model (using original deterministic model)

$y = \underline{\hat{g}(\mathbf{x}; \boldsymbol{\theta}_g)} + \sigma \varepsilon \sim \text{submodel or limit state function}$

e.g. $\theta_1 f_c^{\theta_2} b_w d \quad (\text{ACI 11-3}) \quad \boldsymbol{\theta}_g = \{\theta_1, \dots, \theta_n, \sigma\}$

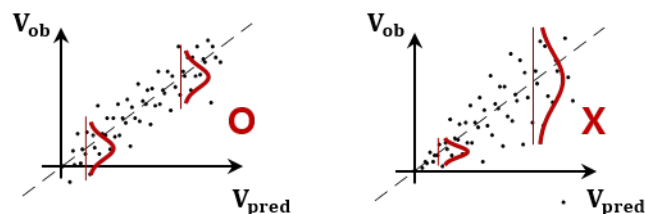
$\mathbf{x}$: observable input parameters ($f'_c, b_w, d, \dots$)

$\mathbf{y}$: observable output parameters (V_c)

$\boldsymbol{\theta}_g$: uncertain model parameters ($\theta_1, \theta_2 \dots$)

$\sigma\epsilon$: uncertainty due to missing variables and/or inexact mathematical form

- ϵ : std. normal r.v “ ” assumption
- σ : magnitude of model error (uncertain parameter)
→ constant over $\mathbf{x}$ “ ” assumption
- $\mu_\epsilon = 0$: unbiased model



May achieve H_____ by a proper nonlinear transformation

e.g. $\ln y = \ln \hat{g}(\mathbf{x}, \boldsymbol{\theta}_g) + \sigma\epsilon$

①' Statistical model (based on deterministic model, Gardoni et al. 2002)

$$y = \hat{g}(\mathbf{x}) + \gamma(\mathbf{x}; \boldsymbol{\theta}_g) + \sigma\epsilon$$

$\hat{g}(\mathbf{x})$: original deterministic model (e.g. $\frac{1}{6} \sqrt{f'_c b_w d}$)

$\gamma(\mathbf{x}; \boldsymbol{\theta}_g)$: corrects the bias

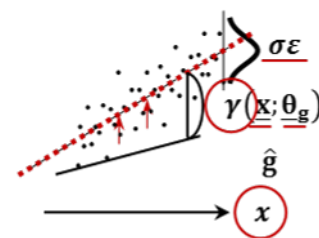
$\sigma\epsilon$: remaining scatter

e.g. RC beam w/o stirrups shear capacity
(Song et al. 2010, Structural Eng & Mechanics)

$$\ln V = \ln \hat{v}(\mathbf{x}) + \sum \theta_g \ln h_i(\mathbf{x}) + \sigma\epsilon$$

$\hat{v}(\mathbf{x})$: 8 models from codes & papers

$h_i(\mathbf{x})$: explanatory terms from the shear transfer mechanism



Find $\underline{\mathbf{M}}_{\boldsymbol{\theta}}, \quad \frac{\sigma_{\theta}}{\mu_{\theta}} = \delta_{\theta}$
 $\underline{\boldsymbol{\Sigma}}_{\boldsymbol{\theta}\boldsymbol{\theta}}$
 $\rho_{\theta_i \theta_j}$

using
(Bayesian
Parameter
Estimation

② Likelihood function $L(\theta_g)$?

Observed event Equality: $y = y_i, i = 1, \dots, m$ know v_c when failed

$$\text{Inequality: } \begin{cases} y > a_i & i = m+1, \dots, m+n \\ y > b_i & i = m+1, \dots, m+n+N \end{cases} \quad \begin{array}{l} \text{No failure up to } V_c \\ \text{Failed but do not know when} \end{array}$$

$$\text{Model } Y = \hat{g} + \gamma + \sigma \varepsilon$$

$$\text{a) } P(Y = y_i) = P(\sigma \varepsilon = y_i - \hat{g}(\mathbf{x}) - \gamma(\mathbf{x}, \theta_g))$$

$$P(Y = y_i) \propto f_Y(y_i)$$

$$= f_Q(q_i) \cdot \frac{dq}{dy}$$

$$= f_\varepsilon(\varepsilon_i) \cdot \frac{d\varepsilon}{dq}$$

$$= \frac{1}{\sigma} \varphi\left(\frac{y_i - \hat{g} - \gamma}{\sigma}\right)$$

$$f_Y(y_i) = f_Q(q) \cdot \frac{dq}{dy_i}$$

$$f_Q(q) = f_\varepsilon(\varepsilon) \cdot \frac{d\varepsilon}{dq}$$

$$q = \sigma \cdot \varepsilon$$

$$\text{b) } P(Y > a_i) = P(\hat{g} + \gamma + \sigma \varepsilon > a_i)$$

$$= P(\sigma \varepsilon > a_i - \hat{g} - \gamma)$$

$$= \Phi\left(-\frac{a_i - \hat{g} - \gamma}{\sigma}\right)$$

$$\text{c) } P(Y < b_i) = P(\hat{g} + \gamma + \sigma \varepsilon < b_i)$$

$$= P(\sigma \varepsilon < b_i - g - \gamma)$$

$$= \Phi\left(\frac{b_i - g - \gamma}{\sigma}\right)$$

$$\therefore L(\theta_g) = \prod_{i=1}^m \frac{1}{\sigma} \varphi\left(\frac{y_i - \hat{g} - \gamma}{\sigma}\right) \times \prod_{i=m+1}^{m+n} \Phi\left(-\frac{a_i - \hat{g} - \gamma}{\sigma}\right) \times \prod_{i=m+n+1}^{m+n+N} \Phi\left(\frac{b_i - \hat{g} - \gamma}{\sigma}\right)$$

※ Matlab codes for “Model Development by Bayesian method”

→ MDB (by Prof. S.Y. Ok at Hankyung univ. for educational purpose)