

## Uncertainty Propagation (Chapter 13)

- Once we have  $\vec{\theta} \in \mathbb{R}^p$  + information about  $\vec{\theta}$  (e.g., estimate from OLS, maybe upper & lower bounds, or  $\pi(\vec{\theta}|\vec{y})$ ).
- How do we quantify the uncertainty in  $f(\vec{x}; \vec{\theta})$ ?
- E.g., if  $f(\vec{x}; \vec{\theta}) = \vec{y} \in \mathbb{R}^{N_y}$ .

E.g.) Once we have  $\vec{\theta}$ , what's

$$E[f(\vec{x}; \vec{\theta})] = \int_{\mathbb{R}^p} f(\vec{x}; \vec{\theta}) \rho(\vec{\theta}) d\vec{\theta}, \quad \rho(\vec{\theta}) \text{ is a density}$$

$$\text{Var}[f(\vec{x}; \vec{\theta})] = \int_{\mathbb{R}^p} [f(\vec{x}; \vec{\theta}) - E[f(\vec{x}; \vec{\theta})]]^2 \rho(\vec{\theta}) d\vec{\theta}$$

## Linear Models in Frequentist Perspective

- Consider

$$\vec{y} = \underset{\sim}{X} \vec{\theta} + \vec{\epsilon}, \quad \epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon^2), \quad \underset{\sim}{X} \in \mathbb{R}^{N_x \times p}$$

- Given  $\vec{\theta}$  s.t.  $E[\vec{\theta}] = \vec{\theta}^*$

$$\begin{aligned} \Rightarrow E[\vec{y}] &= E[\underset{\sim}{X} \vec{\theta} + \vec{\epsilon}] = \underset{\sim}{X} E[\vec{\theta}] + \vec{0} \\ &= \underset{\sim}{X} \vec{\theta}^* \end{aligned}$$

$$\Rightarrow \text{Cov}[\underset{\sim}{X} \vec{\theta}] = \underset{\sim}{X} \text{Cov}(\vec{\theta}) \underset{\sim}{X}^T = \underset{\sim}{X} \underset{\sim}{V}_\theta \underset{\sim}{X}^T, \quad \underset{\sim}{V}_\theta = \text{Cov}(\vec{\theta})$$

$$\Rightarrow \text{Cov}[\tilde{X}\tilde{\theta}] = \tilde{X} \text{Cov}(\tilde{\theta}) \tilde{X}^T = \tilde{X} \tilde{\Sigma}_{\theta} \tilde{X}^T$$

$$\Rightarrow \text{Cov}[\tilde{y}] = \text{Cov}[\tilde{X}\tilde{\theta} + \tilde{e}] = \text{Cov}[\tilde{X}\tilde{\theta}] + \text{Cov}[\tilde{e}]$$

$$\Rightarrow \text{Cov}[\tilde{y}] = \tilde{X} \tilde{V}_{\theta} \tilde{X}^T + \tilde{V}_{\text{obs}}, \quad \text{if } \tilde{e}_i \stackrel{\text{iid}}{\sim} N(0, \sigma_e^2) \\ \Rightarrow \tilde{V}_{\text{obs}} = \sigma_e^2 \tilde{I}_{N_x}$$

- If each  $\theta_i$  is independent

$$\Rightarrow \tilde{V}_{\theta} = \text{diag}[\text{var}(\theta_1), \text{var}(\theta_2), \dots, \text{var}(\theta_p)]$$

$$\Rightarrow \begin{aligned} \tilde{X}\tilde{\theta} &\sim N(\tilde{X}\tilde{\theta}^*, \tilde{X} \tilde{V}_{\theta} \tilde{X}^T) \\ \tilde{y} &\sim N(\tilde{X}\tilde{\theta}^*, \tilde{X} \tilde{V}_{\theta} \tilde{X}^T + \tilde{V}_{\text{obs}}) \end{aligned}$$

- Hence, a confidence interval on  $\tilde{y}$  with significance  $\alpha$ , is

$$CI \equiv \left[ \tilde{y} \pm t_{N_y-P}^{1-\alpha/2} \sqrt{\sigma_e^2 (\tilde{X}^T \tilde{X})^{-1}} \right], \quad \text{since } \text{Cov}(\tilde{\theta}) = \sigma_e^2 (\tilde{X}^T \tilde{X})^{-1}$$

- The prediction interval is

$$PI \equiv \left[ \tilde{y} \pm t_{N_y-P}^{1-\alpha/2} \sqrt{\sigma_e^2 + \sigma_e^2 (\tilde{X}^T \tilde{X})^{-1}} \right]$$

### Nonlinear Models under Frequentist Assumption

- Assume that  $f(\mathbf{z}; \tilde{\theta})$  can be accurately represented by a first order Taylor expansion.

$$\Rightarrow f(\mathbf{z}; \tilde{\theta}) \approx f(\mathbf{z}; \tilde{\theta}^*) + \sum_{j=1}^p \left. \frac{\partial f}{\partial \theta_j} \right|_{\tilde{\theta}^*} \cdot \Delta \theta_j, \quad \Delta \theta_j = \theta_j - \theta_j^*$$

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$$\Rightarrow f(\mathbf{x}_j; \tilde{\theta}) \approx f(\tilde{\theta}) \quad j=1 \dots P$$

$$= \bar{f} + \sum_{j=1}^P \tilde{S}_j \Delta \theta_j$$

$$\begin{aligned} \Rightarrow E[f(\mathbf{x}_j; \tilde{\theta})] &\approx E\left[\bar{f} + \sum_{j=1}^P \tilde{S}_j \Delta \theta_j\right] = E[\bar{f}] + E\left[\sum_{j=1}^P \tilde{S}_j \Delta \theta_j\right] \\ &= \int_{\mathbb{R}^p} \bar{f} \cdot p(\tilde{\theta}) d\tilde{\theta} + \int_{\mathbb{R}^p} \sum_{j=1}^P \tilde{S}_j \cdot (\theta_j - \theta_j^*) p(\tilde{\theta}) d\tilde{\theta} \\ &= \bar{f} + \sum_{j=1}^P \tilde{S}_j \int_{\mathbb{R}^p} (\theta_j - \theta_j^*) p(\tilde{\theta}) d\tilde{\theta} \end{aligned}$$

- Let's assume that  $p(\tilde{\theta})$  is symmetric (e.g., uniform, Gaussian)

$$\Rightarrow \int_{\mathbb{R}^p} (\theta_j - \theta_j^*) p(\tilde{\theta}) d\tilde{\theta} = 0$$

$$\Rightarrow E[f(\mathbf{x}_j; \tilde{\theta})] = \bar{f} + 0$$

- Now for Variance

$$\text{Var}[f(\mathbf{x}_j; \tilde{\theta})] = E\left[\left(\bar{f} + \sum_{j=1}^P \tilde{S}_j \Delta \theta_j - \bar{f}\right)^2\right]$$

$$= E\left[\left(\sum_{j=1}^P \tilde{S}_j \Delta \theta_j\right)^2\right]$$

$$= E\left[\sum_{j=1}^P \tilde{S}_j^2 \Delta \theta_j^2 + \sum_{j=1}^P \sum_{\substack{l=1 \\ l \neq j}}^P \tilde{S}_j \tilde{S}_l \Delta \theta_j \Delta \theta_l\right]$$

$$= E\left[\sum_{j=1}^P \tilde{S}_j^2 \Delta \theta_j^2\right] + E\left[\sum_{j=1}^P \sum_{\substack{l=1 \\ l \neq j}}^P \tilde{S}_j \tilde{S}_l \Delta \theta_j \Delta \theta_l\right]$$

$$= \sum_{j=1}^P \tilde{S}_j^2 \int_{\mathbb{R}^p} (\theta_j - \theta_j^*)^2 p(\tilde{\theta}) d\tilde{\theta} + \sum_{j=1}^P \sum_{\substack{l=1 \\ l \neq j}}^P \tilde{S}_j \tilde{S}_l \int_{\mathbb{R}^p} (\theta_j - \theta_j^*) (\theta_l - \theta_l^*) p(\tilde{\theta}) d\tilde{\theta}$$

Var( $\tilde{\theta}$ )

$$= \sum_{j=1}^p \bar{S}_j^2 \text{Var}(\theta_j) + \sum_{j=1}^p \sum_{q=1, q \neq j}^p \bar{S}_j \bar{S}_q \text{Cov}(\theta_j, \theta_q)$$

$$= \underline{S} \underline{V}_{\theta} \underline{S}^T$$

$$\Rightarrow \text{Var}[f(\underline{\theta}; \underline{\theta})] \approx \underline{S} \underline{V}_{\theta} \underline{S}^T$$

$$\Rightarrow f \approx N(\bar{f}, \underline{S} \underline{V}_{\theta} \underline{S}^T), \text{ where } \underline{S} = \left[ \frac{\partial f}{\partial \theta_j} \right]_{j=1, \dots, p}$$

$$\Rightarrow \text{PI} \equiv \left[ \bar{Y}_{\underline{\theta}} \pm t_{N_{Y-P}}^{1-\alpha/2} \sqrt{\sigma_{\epsilon}^2 + \sigma_{\epsilon}^2 \underline{S}^* (\underline{S}^T \underline{S})^{-1} \underline{S}^{*T}} \right]$$

$$\text{where } \underline{S}^* = \left. \frac{\partial f}{\partial \theta_j} \right|_{\underline{\theta}^*, \bar{Y}}$$