

Nonlinear Regression

- Consider

$$\hat{\theta} = \underset{\theta \in \Pi}{\operatorname{argmin}} \quad J(\theta) = \sum_{i=1}^{N_y} \left(y_i - f(x_i; \theta) \right)^2$$

given by OLS solution, i.e. $\varepsilon_i \stackrel{\text{iid}}{\sim} N(0, \sigma^2)$

Estimator Mean

- using gradients, we have

$$\begin{aligned} \nabla_{\theta} J(\theta) &= -2 \nabla_{\theta} f(x; \theta) (\bar{y} - f(x; \theta)) \\ &= -2 \sum (\bar{y} - f(x; \theta)), \quad \tilde{S} = \frac{\partial f}{\partial \theta} \end{aligned}$$

- If $\bar{\theta} \approx \bar{\theta}^0$, then

$$f(x; \bar{\theta}) \approx f(x; \bar{\theta}^0) + \left. \frac{\partial f}{\partial \theta} \right|_{\bar{\theta}^0} (\bar{\theta} - \bar{\theta}^0)$$

$$\Rightarrow \nabla_{\theta} J(\bar{\theta}) = \nabla_{\theta} \sum \left(y - f(x; \bar{\theta}^0) - \left. \tilde{S} \right|_{\bar{\theta}^0} (\bar{\theta} - \bar{\theta}^0) \right)^2$$

$\xrightarrow{\quad \quad \quad} \quad \quad \quad \bar{y} = f(x; \bar{\theta}^0) + \tilde{\varepsilon}$

$$\Rightarrow \nabla_{\theta} J(\bar{\theta}) \approx -2 \sum \left(y - f(x; \bar{\theta}^0) - \left. \tilde{S} \right|_{\bar{\theta}^0} (\bar{\theta} - \bar{\theta}^0) \right)$$

$$(y = f + \tilde{\varepsilon}) \quad \Rightarrow \nabla_{\theta} J(\bar{\theta}) \approx -2 \sum (\tilde{\varepsilon} - \left. \tilde{S} \right|_{\bar{\theta}^0} (\bar{\theta} - \bar{\theta}^0))$$

$$\Rightarrow (\tilde{S}^T \tilde{S})^{-1} \tilde{S}^T \tilde{\varepsilon} = \bar{\theta} - \bar{\theta}^0$$

$$\Rightarrow \hat{\theta} \approx \bar{\theta} + \dots$$

- If number of observations, $N_y \rightarrow \infty$, then estimator $\hat{\theta}$, gives

$$\hat{\theta} - \bar{\theta} \approx (S_{\hat{\theta}}^T S_{\hat{\theta}})^{-1} S_{\hat{\theta}}^T \bar{\epsilon}, \quad S_{\hat{\theta}} = \left. \frac{\partial f}{\partial \theta} \right|_{\bar{\theta}_0}$$

- Note:

$$\begin{aligned} E[\hat{\theta}] &= E[\bar{\theta}] + E[(S_{\hat{\theta}}^T S_{\hat{\theta}})^{-1} S_{\hat{\theta}}^T \bar{\epsilon}] \\ &= E[\bar{\theta}] + (S_{\hat{\theta}}^T S_{\hat{\theta}})^{-1} S_{\hat{\theta}}^T E[\bar{\epsilon}] \rightarrow 0 \\ &= E[\bar{\theta}] \end{aligned}$$

$$\text{Var}[\hat{\theta}] = E[(\hat{\theta} - \bar{\theta})(\hat{\theta} - \bar{\theta})^T] \approx \sigma_o^2 (S_{\hat{\theta}}^T S_{\hat{\theta}})^{-1}$$

$$\text{where } \sigma_o^2 \approx \frac{1}{N_y - P} (\bar{y} - f(\bar{x}; \hat{\theta}))^T (\bar{y} - f(\bar{x}; \hat{\theta}))$$

where P is the number of parameters.

- Recall for linear regression, $\hat{\theta}_{LR} \sim N(\bar{\theta}_{LR}^o, \sigma_o^2 (X_{\hat{\theta}}^T X_{\hat{\theta}})^{-1})$

- For nonlinear regression

$$\hat{\theta}_{NR} \sim N(\bar{\theta}_{NR}^o, \sigma_o^2 (S_{\hat{\theta}}^T S_{\hat{\theta}})^{-1})$$

Confidence intervals

$$\text{Let } v_{\theta} = (S_{\hat{\theta}}^T S_{\hat{\theta}})^{-1}$$

$$\Rightarrow CI(\hat{\theta}_{\theta}) = \left[\bar{\theta}_{\theta} \pm t_{N_y - P}^{1-\alpha/2} \sqrt{\sigma^2 v_{\theta}} \right]$$

$$\Rightarrow CI(\hat{\theta}_x) = \left[\hat{\theta}_x \pm t_{N_y-P}^{1-\alpha/2} \sqrt{\sigma^2 v_x} \right]$$

Uncertainty in Outputs

- Note that in linear regression, \vec{x}^* represented new values of the design matrix, i.e. $\vec{y}^* = \vec{x}^* \hat{\theta}$

• To linearize $f(x; \hat{\theta})$, we replace design matrix approach with

$$\vec{g}|_{x^*} = \frac{\partial f}{\partial \theta} \bigg|_{x^*}$$

$$\Rightarrow CI(\hat{y}^*) = \left[\vec{y} \pm t_{N_y-P}^{1-\alpha/2} \sqrt{\sigma^2 \vec{g}|_{x^*}^T (\hat{S}^T \hat{S})^{-1} \vec{g}|_{x^*}} \right]$$

$$\Rightarrow PI(\hat{y}^*) = \left[\vec{y} \pm t_{N_y-P}^{1-\alpha/2} \sqrt{\sigma^2 + \sigma^2 \vec{g}|_{x^*}^T (\hat{S}^T \hat{S})^{-1} \vec{g}|_{x^*}} \right]$$