

1. MISSPECIFIED POISSON REGRESSION

ASSUMED MODEL:

$$Y_i | C_i \sim \text{Poi}(\underbrace{\exp\{\beta_0 + \beta_1 C_i\}}_{\lambda(\underline{\beta}, \underline{X}_i)})$$

$\uparrow$ COUNT $\uparrow$ CONCENTRATION

DENOTE: $\underline{X}_i = \begin{pmatrix} 1 \\ C_i \end{pmatrix}$, $\underline{\beta} = \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}$

$$f(y, \underline{x}; \underline{\beta}) = \underbrace{f_{Y|X}(y | \underline{x}; \underline{\beta})}_{\text{Poisson}} \cdot f_{\underline{X}}(\underline{x})$$
$$\underline{P}_{\underline{\beta}}(Y=y | \underline{X}=\underline{x}) = \frac{[\lambda(\underline{\beta}; \underline{x})]^y}{y!} e^{-\lambda(\underline{\beta}; \underline{x})}$$

$$\rightarrow \rho(y, \underline{x}; \underline{b}) = -\log f(y, \underline{x}; \underline{b}) =$$

$$= -y \log \lambda(\underline{b}; \underline{x}) - \lambda(\underline{b}; \underline{x})$$

$$= -y \underline{x}^T \underline{b} + \exp\{\underline{x}^T \underline{b}\} + c$$

$$\hat{\underline{\beta}}_n = \underset{\underline{b} \in \mathbb{R}^2}{\text{argmax}} \quad \frac{1}{n} \sum_{i=1}^n (-Y_i \underline{X}_i^T \underline{b} + \exp\{\underline{X}_i^T \underline{b}\})$$

OK, if $\mathbb{E}[Y_i | \underline{X}_i] = \exp\{\underline{X}_i^T \underline{\beta}_x\}$

$$\rightarrow \underline{\psi}(y, \underline{x}; \underline{b}) = \frac{\partial \rho(y, \underline{x}; \underline{b})}{\partial \underline{b}} = -y \underline{x} + \exp\{\underline{x}^T \underline{b}\} \underline{x}$$
$$= -\underline{x} (y - \exp\{\underline{x}^T \underline{b}\})$$

$$\mathbb{E}(\underline{\beta}_x) = \text{var}(\underline{\psi}(Y_i, \underline{X}_i, \underline{\beta}_x)) =$$
$$= \mathbb{E}[\underline{X}_i \underline{X}_i^T (Y_i - \exp\{\underline{X}_i^T \underline{\beta}_x\})^2]$$

$$\hat{\mathcal{I}}_n = \frac{1}{n} \sum_{i=1}^n \underline{X}_i \underline{X}_i^T (Y_i - \underline{X}_i^T \hat{\underline{\beta}}_n)^2$$

$$\text{D}\eta(\underline{y}, \underline{x}; \underline{b}) = \frac{\partial \eta(\underline{y}, \underline{x}; \underline{b})}{\partial \underline{b}} = \underline{x} \underline{x}^T \exp\{\underline{x}^T \underline{b}\}$$

$$\rightarrow \Pi(\underline{\beta}_x) = \mathbb{E} \underline{X}_1 \underline{X}_1^T \exp\{\underline{X}_1^T \underline{\beta}_x\}$$

$$\rightarrow \hat{\Pi}_n = \frac{1}{n} \sum_{i=1}^n \underline{X}_i \underline{X}_i^T \exp\{\underline{X}_i^T \hat{\underline{\beta}}_n\}$$

↑
WHEN WE BELIEVE THAT $\eta(Y_i | X_i) \sim \text{Poi}(\lambda(\underline{x}, X_i))$,

THEN $\hat{\Pi}_n$ IS USUALLY USED AS THE

ESTIMATE OF FIM $\Pi(\underline{\beta}_x) \rightarrow \text{"VCOR(FIT.GLN)"}$
 $\widehat{\text{avar}}(\hat{\underline{\beta}}_n) = \frac{1}{n} \hat{\Pi}_n^{-1} \hat{\mathcal{I}}_n \hat{\Pi}_n^{-1} \leftarrow \text{"SANDWICH"}$

SIMULATION EXPERIMENT

$$\underline{X}_i = \begin{pmatrix} 1 \\ C_i \end{pmatrix}, \quad C_i \sim \text{DISCR. UNIF}(\{0; \frac{1}{2}; \dots; 4\})$$

$$Y_i | \underline{X}_i \sim \exp\{\underline{\beta}^T \underline{X}_i\} \cdot \varepsilon_i, \quad \underline{\beta} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$\text{where } \varepsilon_i \sim \frac{\text{Bin}(20, \frac{1}{2})}{20}, \quad \mathbb{E} \varepsilon_i = 1$$

$$\varepsilon_i \perp C_i$$

NOTE THAT: $\mathbb{E}[Y_i | \underline{X}_i] = \exp\{\underline{\beta}^T \underline{X}_i\} \mathbb{E} \varepsilon_i = \exp\{\underline{\beta}^T \underline{X}_i\}$

2. WHITE ESTIMATOR OF ASYMPT. VARIANCE IN A LINEAR MODEL

CASE STUDY: $Y_i = \beta_0 + \beta_1 X_i + \sigma(X_i) \varepsilon_i$

$$X_i \sim U(0, 2), \quad \varepsilon_i \sim \text{Exp}(1) - 1 \quad \mathbb{E}\varepsilon_i = 0$$

$$X_i \perp \varepsilon_i, \quad \sigma(X_i) = e^{X_i}$$

$$\rho(y, x; \underline{b}) = \frac{1}{2}(y - \underline{x}^T \underline{b})^2$$

$$\underline{x} = \begin{pmatrix} 1 \\ x \end{pmatrix}$$

$$\psi(y, x; \underline{b}) = -(y - \underline{x}^T \underline{b}) \underline{x}$$

$$\text{ID}_\psi(y, x; \underline{b}) = \underline{x} \underline{x}^T$$

$$\underline{X}_i = \begin{pmatrix} 1 \\ X_i \end{pmatrix}$$

$$\hat{\Pi}_n = \frac{1}{n} \sum_{i=1}^n \underline{X}_i \underline{X}_i^T$$

$$\hat{\Sigma}_n = \frac{1}{n} \sum_{i=1}^n \underline{X}_i \underline{X}_i^T (Y_i - \underline{X}_i^T \hat{\beta}_n)^2$$

STANDARD HOMOSC. ASYMPT. VARIANCE

$$\text{avar}(\hat{\beta}_n) = \frac{1}{n} \left(\mathbb{E} \underline{X}_i \underline{X}_i^T \right)^{-1} \text{var}(\varepsilon_i)$$

$$\leadsto \text{avar}(\hat{\beta}_n) = \frac{1}{n} \hat{\Pi}_n^{-1} \frac{1}{n-2} \sum_{i=1}^n (Y_i - \underline{X}_i^T \hat{\beta}_n)^2$$

HETEROSCEDASTICITY

$$\text{avar}(\hat{\beta}_n) = \frac{1}{n} \left(\mathbb{E} \underline{X}_i \underline{X}_i^T \right)^{-1} \left(\mathbb{E} \underline{X}_i \underline{X}_i^T (Y_i - \underline{X}_i^T \beta_x)^2 \right) \cdot \left(\mathbb{E} \underline{X}_i \underline{X}_i^T \right)^{-1}$$

$$\widehat{\text{avar}}(\hat{\beta}_n) = \frac{1}{n} \hat{\Pi}_n^{-1} \hat{\Sigma}_n \hat{\Pi}_n^{-1}$$

$$\text{"HCS - version"} - \hat{\Sigma}_n^{(\text{HCS})} = \frac{1}{n} \sum_{i=1}^n \underline{\underline{x_i}} \underline{\underline{x_i}}^T \left(\frac{y_i - \underline{\underline{x_i}}^T \hat{\beta}_n}{1 - h_{ii}} \right)^2$$