

Lista 6 - MCI

Exercício 1

b) $Y_i | X_i, \theta \sim \text{Pois}(\theta X_i)$, X_i conhecido.

$$l(\theta | Y, X) = \log[L(\theta | Y, X)] = \sum_{i=1}^m l(\theta | y_i, x_i)$$

$$= \sum_{i=1}^m \{-\theta x_i + y_i [\log(\theta) + \log(x_i)] - \log(y_i!)\}$$

$$\frac{d l(\theta | Y, X)}{d\theta} = \sum_{i=1}^m \left[-x_i + \frac{y_i}{\theta} \right]$$

Tradicionalmente, o EMV é obtido ao igualar o escore a 0.

$$\frac{dl}{d\theta} = 0 \Rightarrow -m\bar{x} + \frac{m\bar{y}}{\theta} = 0 \Rightarrow \hat{\theta} = \frac{\bar{y}}{\bar{x}}$$

Portanto, o método escore de Fisher tende a $\frac{\bar{y}}{\bar{x}}$.

$$I(\theta) = -E \left[\frac{d^2 l}{d\theta^2} \right] = \sum_{i=1}^m \frac{E[y_i]}{\theta^2} = \sum_{i=1}^m \frac{\theta x_i}{\theta^2} = \frac{m\bar{x}}{\theta}$$

Exercício 2

$$\begin{aligned} \text{c) } P(Z_i=1 | X_i=x_i, \theta) &= \frac{\overbrace{f_{x_i}(x_i | Z_i=1, \theta)}^{\text{não depende de } \theta} \cdot \overbrace{P(Z_i=1 | \theta)}^{\text{não depende de } \theta}}{\sum_{j=0}^1 f_{x_i}(x_i | Z_i=j, \theta) \cdot P(Z_i=j | \theta)} \\ &= \frac{p \cdot \exp\left\{-\frac{1}{2\sigma^2} (x_i - \theta_1)^2\right\}}{(1-p) \exp\left\{-\frac{1}{2\sigma^2} (x_i - \theta_0)^2\right\} + p \cdot \exp\left\{-\frac{1}{2\sigma^2} (x_i - \theta_1)^2\right\}} \\ &= \frac{1}{\frac{(1-p)}{p} \exp\left\{-\frac{1}{2\sigma^2} [(x_i - \theta_0)^2 - (x_i - \theta_1)^2]\right\} + 1} \end{aligned}$$

Para $\sigma \rightarrow 0$, i) Se $|x_i - \theta_1| < |x_i - \theta_0|$, $P(Z_i=1 | X_i, \theta) = 1$

ii) Se $|x_i - \theta_1| > |x_i - \theta_0|$, $P(Z_i=1 | X_i, \theta) = 0$

$$\begin{aligned}\log[f(x, z|\theta)] &= \sum_{i=1}^m \log f(x_i, z_i|\theta) \\ &= -\frac{n}{2} \log(2\pi\sigma^2) + \\ &\quad \sum_{i=1}^m \left\{ z_i \left[\log p - \frac{1}{2\sigma^2} (x_i - \theta_1)^2 \right] + \right. \\ &\quad \left. + (1-z_i) \left[\log(1-p) - \frac{1}{2\sigma^2} (x_i - \theta_0)^2 \right] \right\}\end{aligned}$$

$$\begin{aligned}E_{\tilde{z}|x,\theta} \left\{ \log[f(x, z|\theta)] \right\} &= -\frac{n}{2} \log(2\pi\sigma^2) + \\ &+ \sum_{i=1}^m \left\{ \underbrace{P(z_i=1|x_i, \theta^{(t)})}_{p_{1i}} \cdot \left[\log p - \frac{1}{2\sigma^2} (x_i - \theta_1)^2 \right] + \right. \\ &\quad \left. + \underbrace{P(z_i=0|x_i, \theta^{(t)})}_{p_{0i}} \cdot \left[\log(1-p) - \frac{1}{2\sigma^2} (x_i - \theta_0)^2 \right] \right\}\end{aligned}$$

$$\frac{dE}{d\theta_0} = \sum_{i=1}^m \frac{p_{0i}^{(t)} (x_i - \theta_0)}{\sigma^2} = 0 \Rightarrow \theta_0^{(t+1)} = \frac{\sum_{i=1}^m p_{0i}^{(t)} x_i}{\sum_{i=1}^m p_{0i}^{(t)}}$$

$$\frac{dE}{d\theta_1} = \sum_{i=1}^m \frac{p_{1i}^{(t)} (x_i - \theta_1)}{\sigma^2} = 0 \Rightarrow \theta_1^{(t+1)} = \frac{\sum_{i=1}^m p_{1i}^{(t)} x_i}{\sum_{i=1}^m p_{1i}^{(t)}}$$

$$\text{Quando } \sigma \rightarrow 0, \theta_k^{(t+1)} = \frac{\sum_{i=1}^m \mathbb{I}[z_i^{(t)} = k] x_i}{\sum_{i=1}^m \mathbb{I}[z_i^{(t)} = k]}$$

Exercício 3

$$\begin{aligned}P(z_i=1|x_i, \theta) &= \frac{f_{x_i}(x_i|\theta_1) p}{f_{x_i}(x_i|\theta_0) \cdot (1-p) + f_{x_i}(x_i|\theta_1) \cdot p} \\ &= \frac{p \theta_1 \exp\{-\theta_1 x_i\}}{(1-p) \theta_0 \exp\{-\theta_0 x_i\} + p \theta_1 \exp\{-\theta_1 x_i\}} \\ &= \frac{1}{\frac{(1-p)\theta_0}{p\theta_1} \exp\{-(\theta_0 - \theta_1)x_i\} + 1} = p_{1i}\end{aligned}$$

$$\log[f(\underline{x}, \underline{z} | \underline{\theta})] = \sum_{i=1}^n \log f(x_i, z_i | \underline{\theta})$$

$$= \sum_{i=1}^n \left\{ z_i \cdot [\log(p) + \log(\theta_1) - \theta_1 x_i] + \right. \\ \left. + (1 - z_i) \cdot [\log(1-p) + \log(\theta_0) - \theta_0 x_i] \right\}$$

$$E[l] = \sum_{i=1}^n \left\{ p_{1i}^{(t)} \cdot [\log(p) + \log(\theta_1) - \theta_1 x_i] + p_{0i}^{(t)} \cdot [\log(1-p) + \log(\theta_0) - \theta_0 x_i] \right\}$$

$$\frac{dE}{d\theta_0} = \sum_{i=1}^n p_{0i}^{(t)} \cdot \left[\frac{1}{\theta_0} - x_i \right] = 0 \Rightarrow \theta_0^{(t+1)} = \frac{\sum_{i=1}^n p_{0i}^{(t)}}{\sum_{i=1}^n p_{0i}^{(t)} x_i}$$

$$\frac{dE}{d\theta_1} = 0 \Rightarrow \theta_1^{(t+1)} = \frac{\sum_{i=1}^n p_{1i}^{(t)}}{\sum_{i=1}^n p_{1i}^{(t)} x_i}$$