# GLM Resum I

### Densitat de la distribució exponencial dels mlg

$$f_{Y_i|(\theta_i,\Phi)}(y) \sim e^{\frac{y_i\theta_i-b(\theta_i)}{\Phi}+c(y,\phi)}$$

$$b'(\theta_i) = E[Y_i]$$
  $b''(\theta_i) \Phi = Var(Y_i)$ 

#### Paràmetre de dispersió



 $\sqrt{\Phi}$  també s'anomena paràmetre d'escala.

# GLM Resum II

#### Predictor lineal

$$\eta_i = X_i \beta$$

#### Funció d'enllaç: link function

$$\eta_i = g(\mu_i)$$

#### inversa de la funció link

$$\mu_i = \mathsf{g}^{-1}\left(\eta_i\right)$$

## Inversa de $b'(\theta_i) = \mu_i$ : q function

$$\theta_i = q(\mu_i)$$

# GLM Resum III

### Variance function

$$V\left(\mu_{i}\right)$$
 :  $Var\left(y_{i}\right) = \Phi V\left(\mu_{i}\right)$ 

$$V(\mu_i) = b''(\theta_i)$$

# Deviància i Estadístic de Pearson generalitzat l

#### Deviància escalada: scaled deviance

$$D^{s} = -2\log\left(\frac{\mathcal{L}(\textit{fitted})}{\mathcal{L}(\textit{saturated})}\right)$$

$$D^{s} = 2\log\left(\mathcal{L}\left(\textit{saturated}\right)\right) - 2\log\left(\mathcal{L}\left(\textit{fitted}\right)\right)$$
fitted  $\longrightarrow \ell\left(\hat{\theta}, \Phi | y\right) = \sum_{i=1}^{n} \frac{y_{i}\hat{\theta}_{i} - b\left(\hat{\theta}_{i}\right)}{\Phi} + c\left(y_{i}, \phi\right)$ 
saturated  $\longrightarrow \ell\left(\tilde{\theta}, \Phi | y\right) = \sum_{i=1}^{n} \frac{y_{i}\tilde{\theta}_{i} - b\left(\tilde{\theta}_{i}\right)}{\Phi} + c\left(y_{i}, \phi\right)$ 
on  $\tilde{\eta}_{i} = y_{i} \Rightarrow \tilde{\mu}_{i} = g^{-1}\left(y_{i}\right) \Rightarrow \tilde{\theta}_{i} = q\left(g^{-1}\left(y_{i}\right)\right)$ 

$$D^{s} = 2\sum_{i=1}^{n} \frac{y_{i}\left(\tilde{\theta}_{i} - \hat{\theta}_{i}\right) - \left(b\left(\tilde{\theta}_{i}\right) - b\left(\hat{\theta}_{i}\right)\right)}{\Phi} \sim \chi_{n-k}^{2}$$

# Deviància i Estadístic de Pearson generalitzat II

#### Deviància, o deviància no escalada: unscaled deviance

$$D =_{\Phi D^s} = 2 \sum_{i=1}^{n} \left( y_i \left( \tilde{\theta}_i - \hat{\theta}_i \right) - \left( b \left( \tilde{\theta}_i \right) - b \left( \hat{\theta}_i \right) \right) \right) \sim \Phi \chi_{n-k}^2$$

### Estadístic de Pearson generalitzat

$$\chi^{2} = \sum_{i=1}^{n} \left( \frac{y_{i} - \hat{\mu}}{V(\hat{\mu}_{i})} \right) = \Phi \sum_{i=1}^{n} \left( \frac{y_{i} - \hat{\mu}}{Var(y_{i})} \right) \sim \Phi \chi_{n-k}^{2}$$

# Paràmetre de dispersion & Residuals I

## Φ a partir de la deviància

$$D \sim \Phi \chi_{n-k}^2 \Rightarrow E[D] = \Phi(n-k)$$

$$\hat{\Phi}_{deviance} = \frac{D}{n-k}$$

### Φ a partir de Pearson (per defecte a R)

$$\chi^2 \sim \Phi \chi^2_{n-k} \Rightarrow E[\chi^2] = \Phi(n-k)$$

$$\hat{\Phi}_{pearson} = \frac{\chi^2}{n-k}$$

# Paràmetre de dispersion & Residuals II

#### Residuals

• Deviance (per defecte a R)

$$r_{D,i} = sign\left(y_i - \hat{\mu}_i\right)\sqrt{d_i}$$

on 
$$d_i = 2\left(y_i\left(\tilde{\theta}_i - \hat{\theta}_i\right) - \left(b\left(\tilde{\theta}_i\right) - b\left(\hat{\theta}_i\right)\right)\right)$$

Nota: 
$$D(y; \mu) = \sum_{i=1}^{n} r_{D,i}^2$$

Pearson

$$r_{P,i} = \frac{y_i - \hat{\mu}_i}{\sqrt{V(\hat{\mu}_i)}}$$

Nota: 
$$\chi^2 = \sum_{i=1}^n r_{D,i}^2$$

# Quasiversemblança

## Funció de quasiversemblança

$$Q(\mu, \Phi; y) = \frac{1}{\Phi} \int \frac{y - \mu}{V(\mu)} d\mu$$

## Funció *U* "score de la quasiversemblança"

$$U(\mu, \Phi; y) = \frac{1}{\Phi} \frac{y - \mu}{V(\mu)}$$

#### Quasi-deviance

$$\int_{\mu}^{y} \frac{y-s}{V\left(s\right)} \mathrm{d}s = \Phi\left(Q\left(y,\Phi;y\right) - Q\left(\mu,\Phi;y\right)\right)$$