

# Lecture 8

# Last time: Poisson regression

$y_i$  (a count variable  $\rightarrow$  values  $0, 1, 2, \dots$ )

$y_i \sim \text{Poisson}(\lambda_i)$  (random component)

$g(\lambda_i) = \beta^T X_i$  (systematic component)

(canonical link):  $g(\lambda_i) = \log(\lambda_i)$

$$f(y; \lambda) = \frac{e^{-\lambda} \lambda^y}{y!} = \frac{\exp\{y \log \lambda - \lambda\}}{y!}$$

$$= a(y, \emptyset) \exp\left\{ \frac{y\Theta - K(\Theta)}{\emptyset} \right\} \quad \underline{\text{EDM}}$$

$$a(y, \emptyset) = \frac{1}{y!} \quad \Theta = \log \lambda, K(\Theta) = \lambda, \emptyset = 1$$

# Exponential dispersion models

Bernoulli

$\gamma \sim \text{Bernoulli}(p)$

$$f(y, p) = p^y (1-p)^{1-y}$$

$$= \exp \left\{ \log(p^y (1-p)^{1-y}) \right\}$$

$$= \exp \left\{ \log(p^y) + \log((1-p)^{1-y}) \right\}$$

$$= \exp \left\{ y \log p + (1-y) \log(1-p) \right\}$$

$$= \exp \left\{ y(\log p - \log(1-p)) + \log(1-p) \right\}$$

$$= \exp \left\{ y \log \left( \frac{p}{1-p} \right) + \log(1-p) \right\}$$

$$a(y, \theta) \exp \left\{ \frac{y\theta - k(\theta)}{\theta} \right\}$$

$$\theta = \log \left( \frac{p}{1-p} \right)$$

$\theta$  is always a function of  $E[Y]$

$$\theta = 1 \quad a(y, \theta) = 1$$

$$k(\theta) = -\log(1-p)$$

$$= -\log \left( 1 - \frac{e^\theta}{1+e^\theta} \right)$$

# Examples of EDMs

EDM:  $f(y; \theta, \phi) = \underbrace{a(y, \phi)}_{\text{normalizing function}} \exp \left\{ \frac{y\theta - k(\theta)}{\phi} \right\}$

•  $\theta$  is a canonical parameter: function of  $E[Y]$

Say  $\mu = E[Y]$ , then  $\theta = g(\mu)$  ( $g$  is a monotonically increasing function)  
↑  
canonical link function

•  $\phi$  is a dispersion parameter is related to  $\text{Var}(Y)$

$$\text{Var}(Y) = \phi \cdot v(\mu)$$

Ex:  $N(\mu, \sigma^2)$   $\text{Var}(Y) = \sigma^2 \cdot 1 \stackrel{\phi}{\leftarrow} v(\mu)$

Bernoulli( $p$ ):  $\mu = p$   $\text{Var}(Y) = 1 \cdot p(1-p) = (\underbrace{\mu \cdot (1-\mu)}_{\phi}) \stackrel{\phi}{\rightarrow} v(\mu)$

Poisson( $\lambda$ ):  $\mu = \lambda$ ,  $\text{Var}(Y) = 1 \cdot \mu$   $v(\mu) = \mu$   $\phi \stackrel{\phi}{\rightarrow} v(\mu)$

# EDM components

$l_L(\theta)$  cumulant function

-derivatives of  $l_L(\theta)$  give mean & variance of  $\gamma$

MGF :  $m(t) = \mathbb{E}[e^{t\gamma}]$

$$\mathbb{E}[\gamma^r] = \left. \frac{\partial^r}{\partial t^r} m(t) \right|_{t=0}$$

Cumulant generating function (CGF) :

$$c(t) = \log m(t) = \log \mathbb{E}[e^{t\gamma}]$$

$$\left. \frac{\partial}{\partial t} c(t) \right|_{t=0} = \mathbb{E}[\gamma] \quad (\text{Hw})$$

$$\left. \frac{\partial^2}{\partial t^2} c(t) \right|_{t=0} = \text{Var}(\gamma) \quad (\text{Hw})$$

$$\text{For an EDM: } m(t) = \mathbb{E}[e^{tY}] = \int_y e^{ty} a(y, \theta) \exp\left\{\frac{y\theta - K(\theta)}{\phi}\right\} dy$$

$$= \int_y a(y, \theta) \exp\left\{\frac{y\theta - K(\theta) + ty\phi}{\phi}\right\} dy$$

Idea: try and get

$$\exp\left\{\frac{y\theta^* - K(\theta^*)}{\phi}\right\}$$

$$\theta^* = \theta + t\phi$$

$$\Rightarrow m(t) = \int_y a(y, \theta) \exp\left\{\frac{y\theta^* - K(\theta)}{\phi}\right\} dy$$

$$= \int_y a(y, \theta) \exp\left\{\frac{y\theta^* - K(\theta^*) + K(\theta^*) - K(\theta)}{\phi}\right\} dy$$

$$= \exp\left\{\frac{K(\theta^*) - K(\theta)}{\phi}\right\} \underbrace{\int_y a(y, \theta) \exp\left\{\frac{y\theta^* - K(\theta^*)}{\phi}\right\} dy}_{\text{brace}}$$

$$= \exp\left\{\frac{K(\theta^*) - K(\theta)}{\phi}\right\} = \exp\left\{\frac{1}{\frac{K(\theta + t\phi) - K(\theta)}{\phi}}\right\}$$

$$\Rightarrow C(t) = \frac{K(\theta + t\phi) - K(\theta)}{\phi}$$

$$C(t) = \frac{\kappa(\theta + t\phi) - \kappa(\theta)}{\phi}$$

Conclusion:  $\frac{\partial \kappa(\theta)}{\partial \theta} = \mu$   
 $\frac{\partial \mu}{\partial \theta} = v(\mu)$

$$\underbrace{\frac{\partial C(t)}{\partial t}}_{t=0} = \kappa'(\theta) = \frac{\partial \kappa(\theta)}{\partial \theta}$$

so  $\frac{\partial \kappa(\theta)}{\partial \theta} = E[Y] = \mu$

$$\underbrace{\frac{\partial^2 C(t)}{\partial t^2} C(t)}_{t=0} = \phi \cdot \frac{\partial^2 \kappa(\theta)}{\partial \theta^2}$$

$$= \text{var}(Y)$$

so  $\text{var}(Y) = \phi \cdot \frac{\partial^2 \kappa(\theta)}{\partial \theta^2} = \phi \cdot \frac{\partial}{\partial \theta} \left( \frac{\partial \kappa(\theta)}{\partial \theta} \right)$

$$= \phi \cdot \frac{\partial}{\partial \theta} \mu(\theta) = \phi \cdot v(\mu)$$

# Cumulants and the cumulant generating function

# Generalized linear models

