

Exponential dispersion models

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

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

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

$$a(y, \theta) = \frac{1}{y!}, \quad \theta = \log \lambda, \quad \kappa(\theta) = \lambda, \quad \theta = 1$$

Exponential dispersion model (EDM)

$$\mu = \beta^T x_i$$

Examples of EDMs

$$f(y; \theta, \phi) = a(y, \phi) \exp \left\{ \frac{y\theta - \kappa(\theta)}{\phi} \right\}$$

Normal: $y \sim N(\mu, \sigma^2)$ (σ^2 is known)

$$\begin{aligned} f(y; \mu, \sigma^2) &= \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{1}{2\sigma^2} (y-\mu)^2 \right\} \\ &= \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ \frac{y\mu - (\mu^2/2)}{\sigma^2} - \frac{y^2}{2\sigma^2} \right\} \end{aligned}$$

$$\phi = \sigma^2, \quad (\theta = \mu), \quad \kappa(\theta) = \frac{\mu^2}{2} = \frac{\phi^2}{2},$$

$$a(y, \phi) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left\{ -\frac{y^2}{2\sigma^2} \right\}$$

Bernoulli : $Y \sim \text{Bernoulli}(p)$

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

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

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

$$\phi = 1, \quad a(y, \phi) = 1, \quad \theta = \log \left(\frac{p}{1-p} \right), \quad k(\theta) = -\log(1-p)$$

θ is always a function of $E[Y]$

EDM components

$$\text{EDM} : \text{f}(y; \theta, \phi) = a(y, \theta) \exp \left\{ \frac{y\theta - h(\theta)}{\phi} \right\}$$

- $a(y, \theta)$ is a normalizing function
- θ (canonical parameter): function of $E[Y]$
Let $\mu = E[Y]$, $\theta = g(\mu)$ (g is a monotonically increasing function)
- ϕ dispersion parameter, related to the variance

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

Ex: $N(\mu, \sigma^2)$ $\text{var}(Y) = \underbrace{\sigma^2}_{\phi} \cdot \underbrace{1}_{v(\mu)}$

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

Poisson(λ): $\mu = \lambda$, $\text{var}(Y) = \underbrace{\lambda}_{\phi} \cdot \underbrace{\mu}_{v(\mu)}$

Cumulants and the cumulant generating function

$\kappa(\theta)$ cumulant function

- derivatives of $\kappa(\theta)$ give mean & variance of γ

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

$$\mathbb{E}[\gamma^r] = \frac{\partial^r}{\partial t^r} M(t) \Big|_{t=0}$$

Cumulant generating function (CGF) :

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

$$\frac{\partial}{\partial t} C(t) \Big|_{t=0} = \mathbb{E}[\gamma] \quad (\text{Hw})$$

$$\frac{\partial^2}{\partial t^2} C(t) \Big|_{t=0} = \text{Var}(\gamma) \quad (\text{Hw})$$

For an EDM:

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

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

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

$$C(t) = \underbrace{\kappa(\theta + t\phi)}_{\phi} - \mu(\theta)$$

$$\frac{\partial}{\partial t} C(t) = \kappa'(\theta + t\phi) \Rightarrow \left. \frac{\partial}{\partial t} C(t) \right|_{t=0} = \kappa'(\theta) = \frac{\partial \mu(\theta)}{\partial \theta}$$

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

$$\frac{\partial^2}{\partial t^2} C(t) \Big|_{t=0} = \phi \cdot \frac{\partial^2 \mu(\theta)}{\partial \theta^2}$$

$$\begin{aligned} \Rightarrow \text{Var}(Y) &= \phi \cdot \frac{\partial^2 \mu(\theta)}{\partial \theta^2} \\ &= \phi \cdot \frac{\partial}{\partial \theta} \left(\frac{\partial \mu(\theta)}{\partial \theta} \right) \\ &= \phi \cdot \underbrace{\frac{\partial}{\partial \theta} \mu}_{\text{v}(\mu)} \end{aligned}$$

Ex: $\gamma \sim \text{Poisson}(\lambda)$

$$\mu = \lambda \quad \text{Var}(\gamma) = \underbrace{\lambda}_{\phi} \cdot \underbrace{\mu}_{\sqrt{\mu}}$$

$$\theta = \log \lambda \Rightarrow \mu = e^\theta$$

$$\sqrt{\mu} = \frac{\partial \mu}{\partial \theta} = e^\theta = \mu \Rightarrow \sqrt{\mu} = \mu \quad \checkmark$$

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

$$\mu = p \quad \text{Var}(\gamma) = \underbrace{\lambda}_{\phi} \cdot \underbrace{\mu(1-\mu)}_{\sqrt{\mu}}$$

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

$$\Rightarrow \mu = \frac{e^\theta}{1+e^\theta}$$

$$\sqrt{\mu} = \frac{\partial \mu}{\partial \theta} = \frac{(1+e^\theta)e^\theta - (e^\theta)^2}{(1+e^\theta)^2} = \frac{e^\theta}{(1+e^\theta)^2} = \mu(1-\mu) \quad \checkmark$$

Summarizing: $Y \sim EDM(\mu, \phi)$ $\mu = E[Y]$

$$\Rightarrow f(y; \theta, \phi) = a(y, \phi) = \exp \left\{ \frac{y\phi - k(\phi)}{\phi} \right\}$$

$$0) \quad \phi > 0$$

where:

$$1) \quad \frac{\partial \mu(\theta)}{\partial \theta} = \mu$$

$$2) \quad \text{Var}(Y) = \phi \frac{\partial^2 \mu(\theta)}{\partial \theta^2} = \phi \frac{\partial \mu}{\partial \theta} = \phi v(\mu)$$

$$\text{Var}(Y) > 0 \Rightarrow \frac{\partial \mu}{\partial \theta} > 0$$

$\Rightarrow \mu \nmid \theta$ are monotonic increasing functions of each other

3) $\theta = g(\mu)$, where $g(\mu)$ is monotonically increasing

GLM:

$y_i \sim EDM(\mu_i, \phi)$

$$h(\mu_i) = \beta^T x_i$$

canonical link:

$$h(\mu_i) = g(\mu_i) = \theta_i$$

(canonical parameter)

Generalized linear models