

# Generalized Linear Models

Lecture 9: Mixed Effect Models for non-Gaussian Responses



## **Generalized Linear Mixed Models**

- Combine GLMs with random effects
- **y**<sub>i</sub> from exponential family distribution  $f(y_i, \theta_i, \phi)$
- E(y<sub>i</sub>) = μ<sub>i</sub>
- Link function  $g: g(\mu_i) = \mathbf{x}'_i \beta + \mathbf{z}'_i \gamma$
- $\beta$  are fixed effects;  $\gamma$  are random effects.
- **a**  $\boldsymbol{\gamma} \sim \textit{N}(\mathbf{0}, \mathbf{D})$  with density  $h(\boldsymbol{\gamma} | \mathbf{D})$

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#### Likelihood

$$L(\boldsymbol{\beta}, \boldsymbol{\phi}, \mathbf{D}) = \prod_{i=1}^{n} \int f(\boldsymbol{y}_{i} | \boldsymbol{\beta}, \boldsymbol{\phi}, \boldsymbol{\gamma}) h(\boldsymbol{\gamma} | \mathbf{D})$$

Can only solve integrals if f and h both normal

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- Use numerical integration to approximate integrals
- More accurate than PQL
- Can be slow or impossible for complex models
- Inference will be problematic, as for MLE with LMMs

## **Penalized Quasi Likelihood**

Transform fitted values:

$$\eta_i = g(\mu_i) = \mathbf{x}'_i \boldsymbol{\beta} + \mathbf{z}'_i \boldsymbol{\gamma}$$

2 Create pseudo-responses:

$$ilde{\mathsf{y}}_{\mathsf{i}}^{\mathsf{j}} = \hat{\eta}_{\mathsf{i}}^{\mathsf{j}} + (\mathsf{y}_{\mathsf{i}} - \hat{\mu}_{\mathsf{i}}^{\mathsf{j}}) \left. rac{\mathsf{d}\eta}{\mathsf{d}\mu} \right|_{\hat{\eta}_{\mathsf{i}}}$$

where *j* is iteration in optimization algorithm Find  $V(\tilde{y}_i | \gamma)$ 

4 Use weighted linear mixed effects models

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## fast

- approximate inference
- biased estimates, esp. for binary data or low counts
- even worse inference than regular LMM

- Much more accurate inference
- Allow for prior information and flexibility
- Usually take more computation
- Inferential form different
- Require additional software (either INLA or STAN).