

ETC3580: Advanced Statistical Modelling

Week 8: Mixed Effect Models for non-Gaussian Responses

Generalized Linear Mixed Models

- Combine GLMs with random effects
- \blacksquare y_i from exponential family distribution $f(y_i, \theta_i, \phi)$
- \blacksquare E(y_i) = μ_i
- Link function $g: g(\mu_i) = \mathbf{x}_i'\beta + \mathbf{z}_i'\gamma$
- lacksquare eta are fixed effects; γ are random effects.
- lacksquare $\gamma \sim N(\mathbf{0}, \mathbf{D})$ with density $h(\gamma | \mathbf{D})$

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Likelihood

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

Can only solve integrals if f and h both normal

Numerical integration of likelihood

Likelihood

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

- 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:

$$\tilde{\mathbf{y}}_{i}^{j} = \hat{\eta}_{i}^{j} + (\mathbf{y}_{i} - \hat{\mu}_{i}^{j}) \frac{d\eta}{d\mu}\Big|_{\hat{\eta}_{i}^{j}}$$

where *j* is iteration in optimization algorithm

- Find $Var(\tilde{y}_i|\gamma)$
- Use weighted linear mixed effects models

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- Find $Var(\tilde{y}_i|\gamma)$
- Use weighted linear mixed effects models
 - fast
 - approximate inference
 - biased estimates, esp. for binary data or low counts
 - even worse inference than regular LMM

Bayesian methods

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