STA 702: Random Effects

Merlise Clyde

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Building Hierarchical Models

- Models for Gaussian Data with no Covariates

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- structure?

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- Put constraints on parameters
  - $\alpha = 0$
  - $\beta_d = 0$
  - $\sum \beta_j = 0$

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- post-processing of output

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- May want inference about the larger population and say things about future blocks!
- fixed effects do not allow us to say anything about blocks not in our sample!
- how to address this?

Random Effects

$$y_{ij} = \alpha + \beta_i + \epsilon_{ij}, \qquad \epsilon_{ij} \overset{iid}{\sim} N(0, \sigma^2)$$
$$\beta_i \overset{iid}{\sim} N(0, \tau^2)$$

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- Random effect distributions should be viewed as part of the model specification
- We've specified the likelihood in a hierarchical manner to induce desirable structure
- unknown parameters are population parameters α, τ and σ^2
- Bayesians put prior distributions on α, τ and σ^2; frequentists don't!

Equivalent Model

$$y_i = (y_{i1}, y_{i2}, \ldots, y_{in_i})$$

$$y_i \stackrel{ind}{\sim} N_{n_i}\left(\alpha 1_{n_i}, \begin{pmatrix} \sigma^2+\tau & \tau & \ldots & \tau \\ \tau & \ddots & & \tau \\ \vdots & & \ddots & \vdots \\ \tau & \ldots & \tau & \sigma^2+\tau \end{pmatrix}\right)$$

within-block correlation

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- algorithmically we can use either the latent variable model or the collapsed (marginal) model for inferences;
- often latent variable is easier to work with!

Simple Gibbs Sampler

$$\theta = (\alpha, \tau, \sigma^2, \beta_1, \ldots, \beta_n)$$

$$\begin{aligned}
\alpha &\sim N(\alpha_0, V_0) \\
\tau^{-1} &\sim \text{Gamma}(a_\tau/2, b_\tau/2) \\
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Full Conditionals:

$$\alpha \mid \tau, \sigma^2, \beta_1, \ldots \beta_n \sim N(\hat{\alpha}, \hat{V}_n)$$

$$\hat{V}_n = \left(\frac{1}{V_0} + \sum_i \frac{n_i}{\sigma^2} \right)^{-1}$$

$$\hat{\alpha} = \frac{\frac{\alpha_0}{V_0} + \frac{\sum_i n_i \bar{y}_i^*}{\sigma^2}}{\hat{V}_n^{-1}}$$

$$y_{ij}^* \equiv y_{ij} - \beta_i \qquad \bar{y}_i^* \equiv \frac{\sum_j (y_{ij} - \beta_i)}{n_i}$$

Full Conditional Continued

$$\sigma^{-2} \mid \alpha, \tau, \beta_1, \ldots, \beta_n \sim \textsf{Gamma}\left(\frac{a_\sigma + \sum_i n_i}{2}, \frac{b_\sigma + \sum_i \sum_j (y_{ij} - \alpha - \beta_i)^2}{2}\right)$$

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$$\beta_j \mid \alpha, \tau, \sigma^2 \overset{ind}{\sim} N(\hat{b}_i, \hat{V}_{\beta_i})$$

$$\hat{V}_{\beta_i} = \left(\frac{1}{\tau} + \frac{n_i}{\sigma^2}\right)^{-1}$$

$$\hat{b}_i = \frac{\frac{0}{\tau} + \frac{n_i \bar{y}_i^*}{\sigma^2}}{\hat{V}_{\beta_i}^{-1}}$$

$$y_{ij}^{**} \equiv y_{ij} - \alpha \qquad \bar{y}_i^{**} \equiv \frac{\sum_j (y_{ij} - \alpha)}{n_i}$$

Complications Relative to Usual Regression

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- Early recommendation after Gibbs Sampler introduced non-informative priors

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\begin{aligned}
\pi(\alpha) &\propto 1 & & \\
\pi(\sigma^{-2}) &\sim \textsf{Gamma}(\epsilon/2, \epsilon/2) & \qquad \pi(\sigma^{-2}) &\propto 1/\sigma^{-2} \text{ as } \epsilon \to 0 \\
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- Is joint posterior proper ?

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- may not notice it!

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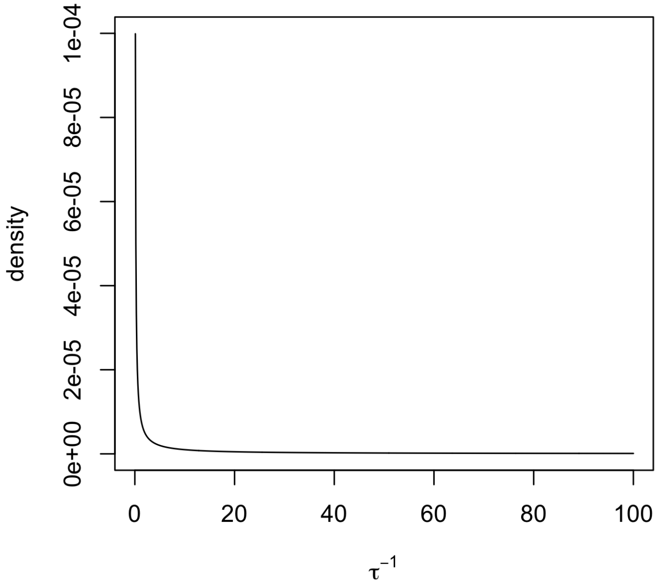

Alternative Priors

- Choose a flat or heavy tailed prior for random effect standard deviation $\tau^{1/2}$

$$\begin{aligned} y_{ij} &= \alpha + \beta_i + \epsilon_{ij} \\ \beta_i &\overset{iid}{\sim} N(0, \tau) \end{aligned} \quad \Leftrightarrow \quad \begin{aligned} y_{ij} &= \alpha + \lambda \eta_i + \epsilon_{ij} \\ \eta_i &\overset{iid}{\sim} N(0, 1) \end{aligned}$$

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- $\pi(\lambda) \propto 1(\lambda > 0) N(0, 1/\psi) \qquad \psi \sim \textsf{Gamma}(\nu/2, \nu/2)$ folded t or half t

Proper Posterior

Work with

$$\pi(\mu, \tau, \sigma^2 \mid y) \propto \pi(\mu, \tau, \sigma^2) \prod_{i=1}^{n} N\left(y_i ; \alpha 1_{n_i}, \begin{pmatrix} \sigma^2 + \tau & \tau & \dots & \tau \\ \tau & \ddots & & \tau \\ \vdots & & \ddots & \vdots \\ \tau & \dots & \tau & \sigma^2 + \tau \end{pmatrix} \right)$$

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- Show joint posterior is proper !
- See Gelman 2005 discussion of Draper paper in Bayesian Analysis

Propriety

- need expression for likelihood; requires determinant and inverse of intra-class correlation matrix! Write covariance as $\sigma^2 I_{n_i} + \tau n_1 P_1$ and find spectral decomposition to provide determinant and inverse!
- integrate out α (messy)
- determine if integrals are finite (what happens at 0 and infinity ?)
- look at special case when n_i are all equal.

Bayes Estimates of Variances

- Avoids issues when estimate of variance is on the boundary of the parmaeter space
- Do not have to use asymptotics to construct CI!

Linear Mixed Effects

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- students w/in schools; patients w/in hospitals
- As before not inherently Bayesian! It's just a model/likelihood specification!

Linear Mixed Effects

$$y_{ij} = X_{ij}^T B + z_{ij}^T \beta_i + \epsilon_{ij}$$

- Fixed effects $X_{ij}^T B$
- Random effects $z_{ij}^T \beta_i$ with $\beta_i \overset{iid}{\sim} N(0, \Psi)$
- Designed to accomodate correlated data due to nested/hierarchical structure/repeated measurements
- students w/in schools; patients w/in hospitals
- As before not inherently Bayesian! It's just a model/likelihood specification!
- If θ is population parameters, $\theta = (B, \Psi, \sigma^2)$, find the marginal distribution for y_i given θ!