

STAT347: Generalized Linear Models

Lecture 13

Today's topics: Chapters 9.4, 9.5, 9.7

- Two examples for linear mixed effect models
- GLMM: generalized linear mixed effect model
 - Binomial response: logistic-normal models
 - Poisson GLMM
 - Marginal likelihood MLE for GLMM: Gauss-Hermite Quadrature (Chapters 9.5.1, 9.5.2)
- Example: modeling correlated survey responses

1 Two examples for LMM

1.1 Multilevel model for smoking prevention and cessation study (Chapter 9.2.3)

1600 students are collected from 135 classrooms in 28 schools. We want to understand the effect of SC (exposure to a school-based curriculum or not), TV (exposure to a television-based prevention program or not) and previous THK scale on the current THK scale. We have 1600 samples, but some share the same school and some share the same classroom.

The multilevel model:

$$y_{ics} = \beta_0 + \beta_1 \text{P}THK_{ics} + \beta_2 \text{SC}_{ics} + \beta_3 \text{TV}_{ics} + u_s + v_{cs} + \epsilon_{ics}$$

R example in class

1.2 Multi-subject, multi-group example

We try to understand the relationship between a student's GPA on his/her test scores.

- Each student has a GPA x_i
- For $j = 1, 2, \dots, p$ th type of exam, student i has a test score y_{ij}

Here are a few related modeling ideas from different perspectives

- Assume that y_{ij} are i.i.d. across students for each exam j

$$y_{ij} = \beta_{0j} + \beta_{1j}x_i + \epsilon_{ij}$$

- To consider the fact that each student can have different ability/background, that affects scores across all of his/her exams, there are two perspectives
 - Each student has a student-specific baseline score:

$$y_{ij} = (\beta_{0j} + u_i) + \beta_{1j}x_i + \epsilon_{ij}$$

which shows that the model has a student-specific intercept (baseline). Here this is both a student indicator and an exam type indicator.

- scores are correlated within each student by sharing a latent variable u_i

$$y_{ij} = \beta_{0j} + \beta_{1j}x_i + u_i + \epsilon_{ij}$$

where $u_i \stackrel{i.i.d.}{\sim} N(0, \sigma_u^2)$

- The above two ideas are very similar, the only difference is that u_i are fixed p different parameters for the first model, while u_i are random and information can be borrowed across students.
- Comparing with the general LMM form: $E(y_i | u_i) = X_i\beta + Z_iu_i$, the LMM in this example has

$$y_i = \begin{pmatrix} y_{i1} \\ \vdots \\ y_{ip} \end{pmatrix}, \quad X_i = (I_{p \times p} \quad x_i I_{p \times p}), \quad \beta = \begin{pmatrix} \beta_{01} \\ \vdots \\ \beta_{0p} \\ \beta_{11} \\ \vdots \\ \beta_{1p} \end{pmatrix}, \quad Z_i = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}_p$$

2 Generalized linear mixed effect models

For LMM, the form is

$$y_{is} = X_{is}^T\beta + Z_{is}^T u_i + \epsilon_{is}$$

with u_i and ϵ_{is} random. With the typical assumption that $E(u_i) = E(\epsilon_{is}) = 0$, we would also have marginally

$$E(y_{is}) = X_{is}^T\beta$$

However, for GLMM, the model is

$$g[E(y_{is} | u_i)] = X_{is}^T\beta + Z_{is}^T u_i$$

when the link function g is non-linear, we would have

$$g[E(y_{is})] = g(\mu_{is}) \neq X_{is}^T\beta$$

2.1 Binomial response

- Logistic-normal model:

$$\text{logit}[P(y_{is} = 1 | u_i)] = X_{is}^T\beta + Z_{is}^T u_i$$

- Item response models: y_{ij} the yes/no (correct/incorrect) response of subject i on question j

$$\text{logit}[P(y_{ij} | u_i)] = \beta_0 + \beta_j + u_i$$

- latent variable threshold model with random effects:

Remember for binary GLM, we can also write down the link as the form

$$P(y_{is} = 1) = F(X_{is}^T\beta)$$

With random effects, we can extend to the assumption:

$$P(y_{is} = 1 | u_i) = F(X_{is}^T\beta + Z_{is}^T u_i)$$

In other words, from the latent variable threshold modeling perspective, we assume there is a latent y_{is}^* where

$$y_{is}^* = X_{is}^T\beta + Z_{is}^T u_i + \epsilon_{is}$$

where ϵ_{is} are i.i.d. following some distribution (normal, logistic, ...) and we have

$$y_{is} = \begin{cases} 1 & \text{if } y_{is}^* \geq 0 \\ 0 & \text{else} \end{cases}$$

Here are some properties:

- Conditional independence:

$$P(y_{i1} = a_1, \dots, y_{id_i} = a_{d_i} \mid u_i = u_*) = P(y_{i1} = a_1 \mid u_i = u_*) \cdots P(y_{id_i} = a_{d_i} \mid u_i = u_*)$$

- Marginal correlation:

$$\begin{aligned} \text{cov}(y_{is}, y_{ik}) &= E[\text{cov}(y_{is}, y_{ik} \mid u_i)] + \text{cov}[E(y_{is} \mid u_i), E(y_{ik} \mid u_i)] \\ &= 0 + \text{cov}[F(X_{is}^T \beta + Z_{is}^T u_i), F(X_{ik}^T \beta + Z_{ik}^T u_i)] \end{aligned}$$

where F is the cdf of $-\epsilon_{is}$. If $Z_{is} = 1$ (the random intercept model), then $\text{cov}(y_{is}, y_{ik}) > 0$.

Marginally,

$$P(y_{is} = 1) \neq F(X_{is}^T \beta)$$

After some calculations to integrate out the random variable u_i (see page 308), we have

- For the probit link random-intercept model $P[y_{is} = 1 \mid u_i] = \Phi(X_{is}^T \beta + u_i)$,

$$P(y_{is} = 1) = \Phi\left(\frac{X_{is}^T \beta}{\sqrt{1 + \sigma_u^2}}\right)$$

- For the logistic-normal model:

$$P(y_{is} = 1) \approx \Phi\left(\frac{X_{is}^T \beta}{\sqrt{1 + \sigma_u^2/c^2}}\right)$$

where $c \approx 1.7$

- Why does the β in the random effect model typically larger than the marginal relationship between x and y ? Figure 9.2

2.2 Poisson GLMM

$$\log[E(y_{is} \mid u_i)] = X_{is}^T \beta + Z_{is}^T u_i$$

Equivalently,

$$E[y_{is} \mid u_i] = e^{Z_{is}^T u_i} e^{X_{is}^T \beta}$$

For the random-intercept model where $Z_{is} = 1$ and $u_i \sim N(0, \sigma_u^2)$, we have

$$E(y_{is}) = e^{X_{is}^T \beta + \sigma_u^2/2}$$

The coefficients β does not change except for the intercept.

2.3 Fitting GLMM with Gauss-Hermite Quadrature methods

Fitting GLMM is more complicated than fitting LMM as the marginal distribution of the observations $\{y_{is}\}$ do not have a closed form. You may learn other methods like MCMC and EM in the future. Here we very briefly discuss how to approximate the marginal likelihood numerically.

The marginal likelihood

$$l(\beta, \Sigma_u; y) = f(y; \beta, \Sigma_u) = \int f(y | u, \beta) f(u; \Sigma_u) du$$

This typically do not have a closed form

Gauss-Hermite Quadrature methods: approximate the integral by a weighted sum

$$\int h(u) \exp(-u^2) du \approx \sum_{k=1}^q c_k h(s_k)$$

the tabulated weights $\{c_k\}$ and quadrature points $\{s_k\}$ are the roots of Hermite polynomials. The approximation is more more accurate with larger q . For more details, read chapter 9.5.2.

3 Example: modeling correlated survey responses

Chapter 9.7