

# MATH43515: Multilevel Modelling

## Lecture 8: Generalized Linear Mixed Models

Module Convenor / Tutor: Andy Golightly

This lecture does not follow any particular book, but makes use of some aspects of

**Aitkin, M., Francis, B., Hinde, J., and Darnell, R.**  
Statistical Modelling in R (2009).



... also available via the library.

- Combining multilevel models and generalized linear models
- Example: The betablocker data (logistic mixed model)
- Software considerations

- We know, for Gaussian response models ("linear models"), how to account for data with hierarchical (multilevel) structure
- We know, for one-level models, how to account for data with non-Gaussian response.

**Gap:** Data with multilevel structure **and** non-Gaussian response.

Models which do this job are referred to as **generalized linear mixed models**, a combination of mixed models ( $\equiv$  multilevel models) and generalized linear models.

Recall the earlier defined random-intercept-and-slope model (Lecture 4), for two levels ( $i$ =lower,  $j$ =upper):

$$y_{ij} = a + bx_{ij} + u_j + v_jx_{ij} + \epsilon_{ij}$$

We worked out that

$$E(y_{ij}|x_{ij}) = a + bx_{ij}$$

The more relevant quantity for the current context is

$$E(y_{ij}|x_{ij}, u_j, v_j) = a + bx_{ij} + u_j + v_jx_{ij} \quad (1)$$

Thinking now of a situation with  $p$  predictor variables, we would have observations  $x_{ij1}, \dots, x_{ijp}$ , yielding  $\mathbf{x}_{ij} = (1, x_{ij1}, \dots, x_{ijp})^T$ , and a corresponding upper-level vector of random effects  $\mathbf{z}_j = (u_j, v_{j1}, \dots, v_{jp})^T$ .

Hence, equation (1) can be written as

$$E(y_{ij}|\mathbf{x}_{ij}, \mathbf{z}_j) = \mathbf{x}_{ij}^T \boldsymbol{\beta} + \mathbf{x}_{ij}^T \mathbf{z}_j$$

which makes the **mixed model** character of the multilevel model explicit.

Recall also the **generalized linear model** (at one level), with

$$E(y_i|\mathbf{x}_i) = h(\mathbf{x}_i^T \boldsymbol{\beta}).$$

From this, we define a model of type

$$E(y_{ij}|\mathbf{x}_{ij}, \mathbf{z}_j) = h(\mathbf{x}_{ij}^T \boldsymbol{\beta} + \mathbf{x}_{ij}^T \mathbf{z}_j)$$

for some response function  $h$  (link function  $g = h^{-1}$ ). The result is a **generalized linear mixed model (GLMM)**.

Large multi-centre study ([meta-analysis](#) of several clinical trials) to check the effectiveness of beta-blockers in reducing mortality after myocardial infarction (beta-blockers "block" the release of certain hormones, to reduce blood pressure).

Our data set has 44 rows: One for each of treatment and control, for each of 22 centres.

For each centre and treatment,  $x$  patients died out of  $n$  treated.

## Betablocker data

```
betablok <-  
  read.table('https://andygolightly.github.io/teaching/MATH43515/betablok.dat')
```

Add trial and centre information:

```
names(betablok) <- c('r', 'n')  
betablok$treat <- factor(gl(2,1), labels=c(0,1))  
betablok$center <- gl(22,2)
```



## Betablocker data (cont'd)

```
head(betablok)
```

```
##      r    n treat center
## 1   3   39     0       1
## 2   3   38     1       1
## 3  14  116     0       2
## 4   7  114     1       2
## 5  11   93     0       3
## 6   5   69     1       3
```

```
dim(betablok)
```

```
## [1] 44  4
```

## Betablocker data: logistic model

Firstly, ignore two-level structure and fit a GLM, with Binomial response and logit link:

```
betablok.glm <- glm(cbind(r,(n-r))~treat, data=betablok, family=binomial)
summary(betablok.glm)

##
## Call:
## glm(formula = cbind(r, (n - r)) ~ treat, family = binomial, data = betablok)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -5.3160  -1.4916  -0.1341   1.7067   5.8564
##
## Coefficients:
```

## Betablocker data: logistic model

```
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.19711    0.03359 -65.417  < 2e-16 ***
## treat1      -0.25737    0.04942  -5.207 1.91e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 332.99  on 43  degrees of freedom
## Residual deviance: 305.76  on 42  degrees of freedom
## AIC: 527.19
##
## Number of Fisher Scoring iterations: 4
```

## Betablocker data: logistic mixed model

Now, recognize the two-level structure, with centers in the upper level:

```
require(lme4)
betablok.glmer <- glmer(cbind(r,(n-r)) ~ treat + (1|center),
  data=betablok, family=binomial)
summary(betablok.glmer)

## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##   Family: binomial   ( logit )
## Formula: cbind(r, (n - r)) ~ treat + (1 | center)
##      Data: betablok
##
##            AIC          BIC    logLik deviance df.resid
##      324.4       329.8   -159.2    318.4         41
##
## Scaled residuals:
```

## Betablocker data: logistic mixed model

```
##      Min      1Q  Median      3Q      Max
## -1.8876 -0.5129  0.0605  0.4969  1.8623
##
## Random effects:
##   Groups Name      Variance Std.Dev.
##   center (Intercept) 0.2362   0.486
## Number of obs: 44, groups:  center, 22
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.19618     0.11292 -19.450  < 2e-16 ***
## treat1      -0.26091     0.04982  -5.237 1.63e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr)
## treat1 -0.205
```

We have seen that, in this particular case, accounting for the multilevel structure did not make much difference – but it could have!

The treatment of myocardial infarction patients with beta-blockers reduces the log-odds of patient death by the value 0.26. That is, after treatment, the odds of dying against not dying have reduced by the factor  $\exp(-0.26) = 0.77$ , i.e. 77% of the untreated value.

Generalized linear mixed models are in principle simple to apply: Just use `glmer` (or `glmmTMB`) with the respective `family` argument.

We have seen the R package **lme4** (functions `lmer` and `glmer`). Other R packages for random effect modelling in R include

- **nlme** (for non-linear models)
- **npmlreg** (for non-Gaussian random effect distributions),
- **gamlss** (very general modelling framework, incl. smoothing).