Longitudinal Data Analysis with the Multilevel Model for Change

Overview

The longitudinal dataset

- Structure
- Example we will use

The multilevel model

- Formula
- description

Example in R

- Model
- Plot

The Longitudinal dataset

Person-Period structure is considered optimal

Can have time varying and time invariant variables

Important features to model change

- 3 or more waves
- An outcome whose values change systematically over time (time varying)
- Sensible metric for clocking time

```
id age coa male age_14
                              alcuse
        14
                          0 1.732051 1.2649111
                           2.000000 1.2649111
                           0.000000 0.8944272 -0.1235728
                          1 0.000000 0.8944272 -0.1235728
                          2 1.000000 0.8944272
                          0 1.000000 0.8944272 -0.1235728
                          1 2.000000 0.8944272 -0.1235728
11
12
        16
                          2 1.732051 1.7888544
13
14
                          1 0.000000 0.8944272 -0.1235728
                          0 3.000000 1.5491934
                          1 3.000000 1.5491934
                          0 1.732051 1.5491934
20
                          1 2.449490 1.5491934
21
                           1.000000 1.5491934
                          0 0.000000 0.0000000 -1.0180000 0.549
                          1 0.000000 0.0000000 -1.0180000 0.549
                          2 0.000000 0.0000000 -1.0180000 0.549
```

The Longitudinal dataset

Changes in adolescent alcohol use

- 3 waves of 82 adolescents each year beginning at age 14
- COA = child of alcoholic parent
- PEER = measure of alcohol use among the adolescent's peers
- ALCUSE = measure of an adolescent's alcohol use
- Age_14 is the time variable used (age 14)

How does COA and PEER affect ALCUSE over time?

```
id age coa male age_14
                              alcuse
        14
                         0 1.732051 1.2649111
                         1 2.000000 1.2649111
                         2 2.000000 1.2649111
                           0.000000 0.8944272 -0.1235728
                         1 0.000000 0.8944272 -0.1235728 0.549
                         0 1.000000 0.8944272 -0.1235728 0.549
                         1 2.000000 0.8944272 -0.1235728 0.549
                         2 3.316625 0.8944272 -0.1235728 0.549
                         0 0.000000 1.7888544
11
                         1 2.000000 1.7888544
                         2 1.732051 1.7888544
13
                         0 0.000000 0.8944272 -0.1235728 0.549
                         0 3.000000 1.5491934
17
                         1 3.000000 1.5491934
                         0 1.732051 1.5491934
20
                         1 2.449490 1.5491934
21
                         2 1.000000 1.5491934
22
                         0 0.000000 0.0000000 -1.0180000 0.549
        15
                         1 0.000000 0.0000000 -1.0180000 0.549
                         2 0.000000 0.0000000 -1.0180000 0.549
```

The Multilevel model for change

Level 1 model – individual growth

$$\circ Y_{ij} = \beta_{0i} + \beta_{1i} TIM E_{ij} + \varepsilon_{ij}$$

Level 2 sub model – fixed effects/interindividual change

$$\circ \ \beta_{0i} = \ \gamma_{00} + \gamma_{01}COA_i + \gamma_{02}PEER_i + \zeta_{0i}$$

•
$$\beta_{1i} = \gamma_{10} + \gamma_{12} PEER_i + \zeta_{1i}$$

The Multilevel model – in words

Level 1 model

• intercept and slope for individual *i* in population

Level 2 model

- Fixed effects (gamma)
 - $^{\circ}$ γ_{00} is population average intercept for non-COA and non-PEER
 - $^{\circ}$ γ_{01} and γ_{02} are the differences in population average intercepts for COA and PEER
 - \circ γ_{10} and γ_{12} are the population average slope and difference in PEER slope

Benefit of the multilevel approach

Provides an efficient way to show how different predictors affect individual intercept and slope

Modeling in R

library(nlme)

Linear and nonlinear mixed effects models

Ime() function

- Ime(alcuse ~ coa+peer*age_14 , data=alcohol1, random= ~ age_14 | id, method="ML")
- Ime(model with fixed effects, data, random effects | grouping, method is maximum likelihood)

nlme()

• Nonlinear – maybe in another presentation...

Modeling in R

Recommended way to visualize change is to plot prototypical values for predictors

- COA = 0 or 1
- $^{\circ}$ Prototypical values for PEER can be generated by taking \pm .5 standard deviation of sample mean
 - .655 (low) and 1.381 (high)
- Plot fixed effects with these values

```
Linear mixed-effects model fit by maximum likelihood
  Data: alcohol1
       AIC
               BIC
  606.7033 638.2513 -294.3516
Random effects:
 Formula: ~age_14 | id
 Structure: General positive-definite, Log-Cholesky parametrization
            StdDev Corr
(Intercept) 0.490839 (Intr)
age_14
            0.373038 -0.034
Residual
           0.580769
Fixed effects: alcuse ~ coa + peer * age_14
                 Value Std.Error DF t-value p-value
(Intercept) -0.3138215 0.14762324 162 -2.125827 0.0350
             0.5711970 0.14773614 79 3.866332 0.0002
            0.6951827 0.11240370 79 6.184696 0.0000
peer
            0.4246867 0.10667944 162 3.980961 0.0001
peer:age_14 -0.1513771 0.08538522 162 -1.772873 0.0781
 Correlation:
            (Intr) coa
                          peer
                                age_14
coa
            -0.338
            -0.709 -0.146
peer
age_14
            -0.410 0.000 0.351
peer:age_14  0.334  0.000 -0.431 -0.814
Standardized Within-Group Residuals:
                    Q1
                                            Q3
-2.59554447 -0.40414054 -0.08351858 0.45549533 2.29975194
Number of Observations: 246
Number of Groups: 82
```

Modeling in R

How does COA and PEER affect ALCUSE over time?

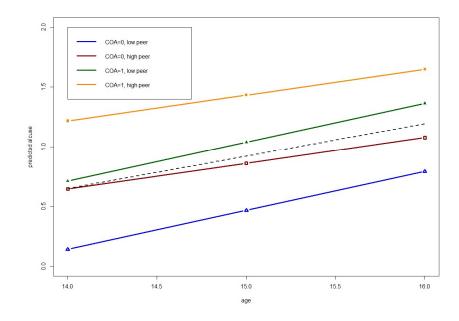
PEER	COA	Intercept eta_{0i}	Slope eta_{1i}
Low	No	.142	.326
Low	Yes	.713	.326
High	No	.646	.216
High	Yes	1.217	.216

-.314 + .571(1) + .695(1.381)

$$\beta_{0i} = \gamma_{00} + \gamma_{01}COA_i + \gamma_{02}PEER_i$$

.425 - .151(1.381)

$$\beta_{1i} = \gamma_{10} + \gamma_{12} PEER_i$$



References

Applied Longitudinal Data Analysis by Singer and Willett

Applied Longitudinal Data Analysis, Chapter 4 | R Textbook Examples (ucla.edu)

nlme: Linear and Nonlinear Mixed Effects Models (r-project.org)