Introduction to Multilevel Modeling Using HLM 6

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Multilevel data structure

- Students nested within schools
- Children nested within families
- Respondents nested within interviewers
- Repeated measures nested within individuals longitudinal data, growth curve modeling

In the example of student nested within schools:

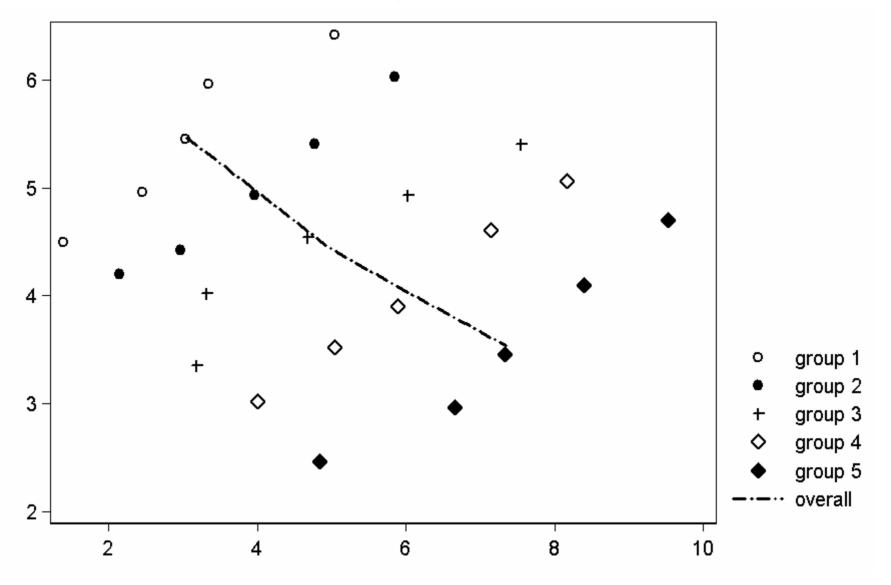
- Level-1 variables, such as student's gender and age
- Level-2 variables, such as school type and size

schid	minority	female	ses	mathach	size	schtype	meanses
1224	0	0	878	10.557	842	0	428
1224	0	0	938	.868	842	0	428
1224	0	0	548	8.296	842	0	428
1224	1	0	.142	-1.688	842	0	428
1224	0	1	.972	2.059	842	0	428
1224	0	0	.372	6.714	842	0	428
1224	1	0	-1.658	.122	842	0	428
1224	0	1	-1.068	2.381	842	0	428
1224	0	1	248	16.336	842	0	428
1224	0	1	-1.398	6.134	842	0	428
1224	0	1	.752	23.584	842	0	428
1224	0	1	.012	14.053	842	0	428
1224	0	1	418	2.183	842	0	428
1288	0	1	788	7.857	1855	0	.128
1288	1	0	328	10.171	1855	0	.128
1288	0	0	.472	15.699	1855	0	.128
1288	0	1	.352	22.919	1855	0	.128
1288	1	1	-1.468	10.664	1855	0	.128
1288	0	1	.202	13.543	1855	0	.128
1288	0	0	518	18.207	1855	0	.128
1288	1	0	158	5.552	1855	0	.128
1288	0	0	.042	7.416	1855	0	.128
1288	0	0	.682	18.792	1855	0	.128
1288	0	0	1.262	1.575	1855	0	.128
1288	0	1	.152	3.534	1855	0	.128
1288	0	1	678	20.173	1855	0	.128
1288	0	1	.332	10.772	1855	0	.128

How would we analyze such multilevel data?

- OLS regression
- OLS regression with robust standard error
- Aggregation
- Disaggregation
- Ecological fallacy interpreting analyses on aggregated data at the individual level

Ecological Fallacy



See figure 3.1, on page 14 from *Multilevel Analysis* by Snijders and Bosker

Hierarchical linear model

Random Intercept model

Yij = $\beta 0j + rij$ $\beta 0j = \gamma 00 + u0j$

• Written in mixed model format:

 $Yij = \gamma 00 + u0j + rij$

- i is for individuals and j is for schools
- $\beta 0j$ is the mean of Yij for school j
- $\gamma 00$ is the average of all the $\beta 0j$'s, therefore the grand
- rij and u0j are normally distributed
- rij and u0j are independent of each other
- Parameters to be estimated include regression coefficients and variance components: γ00, var(rij) and var(u0j)

• Random Intercept and random slope model

Yij = $\beta 0j + \beta 1jX + rij$ $\beta 0j = \gamma 00 + u0j$ $\beta 1j = \gamma 10 + u1j$

• Written in mixed model format:

 $Yij = \gamma 00 + \gamma 10X + u0j + u1jX + rij$

- β 0j is the mean of Yij for school j when X is zero
- β 1j is the slope of X for school j (or the effect of X for school j)
- rij, u0j and u1j are normally distributed
- u0j and u1j are assumed to be correlated
- cross-level error terms are assumed to be independent
- parameters: γ00, γ10, var(u0j), var(u1j), cov(u0j, u1j) and var(rij)

- Random Intercept and random slope model
- Level-2 variable(s) to predict intercept and/or slope $Yij = \beta 0j + \beta 1jX + rij$ $\beta 0j = \gamma 00 + \gamma 01W + u0j$
 - $\beta 1j = \gamma 10 + \gamma 11W + u1j$
- Written in mixed model format:

 $Yij = \gamma 00 + \gamma 01W + \gamma 10X + \gamma 11W^*X + u0j + u1j^*X + rij$

- β 0j is the mean of Yij for school j when X is zero
- β1j is the slope of X for school j (or the effect of X for school j)
- γ00 is the average intercept
- $\gamma 11$ is the coefficient for the cross-level interaction term
- rij, u0j and u1j are normally distributed
- u0j and u1j are assumed to be correlated
- Cross-level error terms are assumed to be independent
- parameters to be estimated: γ00, γ01, γ10, γ11, var(u0j), var(u1j), cov(u0j, u1j) and var(rij)

Comparing the assumptions for hierarchical linear models with OLS models

OLS Assumptions

- Linearity: function form is linear
- Normality: residuals are normally distributed
- Homoscedasticity: residual variance is constant
- Independence: observations are independent of each other

HLM assumptions

- Linearity: function forms are linear at each level
- Normality: level-1 residuals are normally distributed and level-2 random effects u's have a multivariate normal distribution
- Homoscedasticity: level-1
 residual variance is constant
- Independence: level-1 residuals and level-2 residuals are uncorrelated
- Independence: observations at highest level are independent of each other

Estimation Methods: REML vs. ML

- Reading: Section 4.6 Parameter Estimation from Snijder and Bosker
- REML and ML produce similar regression coefficients
- REML and ML differ in terms of estimating the variance components
- If the number of level-2 units is small, then ML variance estimates will be smaller than REML, leading to artificially short confidence interval and biased significant tests.
- REML is the default estimation method for HLM
- Likelihood ratio test for nested models
 - When fixed effects are the same, model has fewer random effects, then both REML or ML may be used
 - When one model has fewer fixed effects and possibly fewer random effects, then ML may be used

Issues with Centering

- Reading: Section 5.2 *The effects of centering* from Kreft and De Leeuw
- In OLS centering is to change the interpretation of the intercept
- Centering in HLM is not a simple issue
- Grand-mean centering

"The raw score model and the grand mean centered model are equivalent linear models."

- Group-mean centering Most of the times, the group mean centered model and the raw score model are neither equivalent in the fixed part nor in the random part.
- Combining substantive and statistical reasons in choosing
 - raw score
 - group-centering with reintroducing the means
 - group-centering without reintroducing the means

An Example

- The dataset is a subsample from the 1982 High School and Beyond Survey and is used extensively in *Hierarchical Linear Models* by Raudenbush and Bryk.
- It consists of 7185 students nested in 160 schools.
- The outcome variable of interest is the student-level math achievement score, **mathach**.
- Predictor variables
 - Level-1 (student level) predictor variables:
 - **ses**: social-economic-status of a student
 - **female** 0 = male and 1 = female
 - Level-2 (school level) predictor variables:
 - meanses: mean ses at school level, aggregated from student level
 - schtype: type of school: 0 = public and 1 = private, there are 90 public and 70 private schools
 - size: size of a school

Model Building

- Reading: Section 6.4 Model specification from Snijder and Bosker
- Unconditional model:

```
mathachij = \beta 0j + rij
\beta 0j = \gamma 00 + u0j
```

• Random intercept model with level-2 predictor(s):

```
mathachij = \beta 0j + rij
\beta 0j = \gamma 00 + \gamma 01(meanses) + u0j
```

• Random intercept and random slope model:

```
mathachij = \beta 0j + \beta 1j(ses) + rij
\beta 0j = \gamma 00 + u0j
\beta 1j = \gamma 10 + u1j
```

• Full model:

```
mathachij = \beta 0j + \beta 1j(\text{group}_mean\_centered\_ses) + rij
\beta 0j = \gamma 00 + \gamma 01(\text{schtype}) + \gamma 02(\text{meanses}) + u0j
\beta 1j = \gamma 10 + \gamma 11(\text{schtype}) + \gamma 12(\text{meanses}) + u1j
```

Model 1: Unconditional Means Model

```
mathachij = \beta 0j + rij \beta 0j = \gamma 00 + u0j

\gamma 00 = 12.636972

var(rij) = 39.14831 var(u0j) = 8.61431

Rho = var(u0j)/(var(u0j) + var(rij))

= 8.61431/(8.61431+39.14831) = .18035673
```

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	đĩ	Chi-square	P-value
INTRCPT1, level-1,	UO R	2.93501 6.25686	8.61431 39.14831	159	1660.23259	0.000

Final model

mathachij =
$$\beta 0$$
j + $\beta 1$ j(group_mean_centered_ses) + rij
 $\beta 0$ j = $\gamma 00$ + $\gamma 01$ (schtype) + $\gamma 02$ (meanses) + $u 0$ j
 $\beta 1$ j = $\gamma 10$ + $\gamma 11$ (schtype) + $\gamma 12$ (meanses) + $u 1$ j

Tau

INTRCPT1,B0	2.37996	0.19058
SES,B1	0.19058	0.14892

Final estimation of fixed effects

(with robust standard errors)

Fixed Effect	Coefficient	Standard Error	T-ratio	Approx. d.f.	P-value
For INTRCPT1, B0 INTRCPT2, G00 SCHTYPE, G01 MEANSES, G02 For SES slope, B1	12.096006 1.226384 5.333056	0.173699 0.308484 0.334600	69.638 3.976 15.939	157 157 157	$0.000 \\ 0.000 \\ 0.000 \\ 0.000$
INTRCPT2, G10 SCHTYPE, G11 MEANSES, G12	2.937981 -1.640954 1.034427	0.147620 0.237401 0.332785	19.902 -6.912 3.108	157 157 157	0.000 0.000 0.003

Final estimation of variance components:

Random Effect		Standard Deviation	Variance Component	df	Chi-square	P-value
INTRCPT1, SES slope, level-1,	UO U1 R	1.54271 0.38590 6.05831	2.37996 0.14892 36.70313	157 157	605.29503 162.30867	0.000 0.369

Final Model (continued)

mathachij = $\beta 0j + \beta 1j(group_mean_centered_ses) + rij$ $\beta 0j = \gamma 00 + \gamma 01(schtype) + \gamma 02(meanses) + u0j$ $\beta 1j = \gamma 10 + \gamma 11(schtype) + \gamma 12(meanses) + u1j$

 $\gamma 00 = 12.096$: the intercept for public schools with meanses =0 (average ses)

 γ 01 = 1.226: the change in intercept from a public school to a private school

- the intercept for private school with meanses = 0 is 12.096+1.226 = 13.322
- $\gamma 02 = 5.333$: the change in intercept for a one-unit change in meanses
 - the intercept for public school with meanses = 1 is 12.096 + 5.333 = 17.429
- $\gamma 10 = 2.94$: the slope of gcses for public schools with meanses = 0.
 - the effect of gcses for public schools with meanses = 0 is 2.94
- γ 11 = -1.641: the change in slope from a public school to a private school
 - the effect of gcses for private schools with meanses = 0 is 2.94 1.641 = 1.299
- γ 12 = 1.034: the change in slope for a one-unit change in meanses
 - the effect of gcses for public schools with meanses = 0 is 2.94
 - the effect of gcses for public schools with meanses = 1 is 2.94 + 1.034 = 3.974

For	INTRCPT1,	в0						
	INTRCPT2, G00		12.096006	0.173699	69.638	157	0.000	
	SCHTYPE, G01		1.226384	0.308484	3.976	157	0.000	
	MEANSES, G02		5.333056	0.334600	15.939	157	0.000	
For	SES slope,	В1						
	INTRCPT2, G10		2.937981	0.147620	19.902	157	0.000	
	SCHTYPE, G11		-1.640954	0.237401	-6.912	157	0.000	
	MEANSES, G12		1.034427	0.332785	3.108	157	0.003	

What's new in HLM 6

The following paragraph is based on:

http://www.ssicentral.com/hlm/new.html

HLM 6 greatly broadens the range of hierarchical models that can be estimated. It also offers greater convenience of use than previous versions. Here is a quick overview of key new features and options:

- All new graphical displays of data.
- Greater expanded graphics for fitted models.
- Model equations displayed in hierarchical or mixed-model format with or without subscripts easy to save for publication. Distribution assumptions and link functions are presented in detail.
- Slightly different and easier way for specifying random effects.
- <u>Cross-classified random effects models for linear models and non-linear link functions with convenient Windows interface.</u>
- High-order Laplace approximation with EM algorithm for stable convergence and accurate estimation in two-level hierarchical generalized linear models (HGLM).
- <u>Multinomial and ordinal models for three-level data. Also see the types of models.</u>
- New flexible and accurate sample design weighting for two- and three-level HLMs and HGLMs.
- Easier automated input from a wide variety of software packages, including the current versions of SAS, SPSS, and STATA.
- Residual files can be saved directly as SPSS (*.sav) or STATA (*.dta) files.
- Analyses are based on MDM files, replacing the older less flexible SSM format.

Getting ready for using HLM software for multilevel data analysis

- Creating MDM file
 - separate level-1 and level2 files for HLM2, or a single file
 - original file can be in different format, such as SPSS, Stata and SAS
 - linking variable can be either numeric or character
 - variables in the analyses have to be numeric
 - mdm file: binary file used for analyses and graphics
 - mdmt file: template file in text format for creating mdm file
 - hlm2mdm.sts: text file containing the summary statistics
- Data management
 - HLM does not have data management capability
 - One has to use other stat package(s) to clean the data and to create variables, such as dummy variables and within-level interaction terms
 - HLM handles cross-level interactions nicely

Choosing preferences and other settings

	Preferences						
Basic Model Specifications - HLM2 Distribution of Outcome Variable Normal (Continuous)	 type of non-ASCII data SAS SPSS Stata SYSTAT other non-ASCII 	Colors Choose foreground color Choose background color Choose background color Show Mixed Model ✓ Use level subscripts					
C Bernoulli (0 or 1)							
C Poisson (constant exposure) C Binomial (number of trials)	Est	Estimation Settings - HLM2					
C Poisson (variable exposure)	None	Type of Likelihood Restricted maximum likelihood C Full maximum likelihood					
C Multinomial Number of categories							
C Ordinal	, l [Le Diese Heartien Control					
Cver dispersion		LaPlace Iteration Control					
Level-1 Residual File Level-2	Residual File						
Title no title		Constraint of fixed effects Heterogeneous sigma*2 Plausible values Multiple imputation					
Output file name D:\work\test\hlm2.t)	dt 🔰	Level-1 Deletion Variables Weighting Latent Variable Regression					
Graph file name		Fix sigma^2 to specific value computed					
Cancel	ок	(Set to "computed" if you want sigma^2 random or if over-dispersion is desired)					

Demo on using HLM

- Input Data and Creating the "MDM" file
 - from a single SPSS file
- data-based graphs
 - box-plot
 - scatter plot
- Model Building
 - unconditional means model
 - regression with means-as-outcomes
 - random-coefficient model
 - intercepts and slopes-as-outcomes model
- Hypothesis Testing, Model Fit
 - Multivariate hypothesis tests on fixed effects
 - Multivariate Tests of variance-covariance components specification
 - Model-based graphs
- Other Issues
 - Modeling Heterogeneity of Level-1 Variances
 - Models Without a Level-1 Intercept
 - Constraints on Fixed Effects

References

- <u>Multilevel Analysis: An Introduction to Basic and</u> <u>Advanced Multilevel Modeling</u> by Tom Snijders and Roel Bosker
- Introduction to Multilevel Modeling by Ita Kreft and Jan de Leeuw
- <u>Multilevel Analysis: Techniques and Applications</u>
 by Joop Hox
- Hierarchical Linear Models, Second Edition by Stephen Raudenbush and Anthony Bryk
- HLM 6 Hierarchical Linear and Nonlinear Modeling by Raudenbush et al.