When People Move: Using Cross-Classified and Multiple Membership Growth Curve Modeling in Non-Hierarchical Multilevel Data Structures

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Mobility

- Evaluations often look at change *over time*
- Family, employee, and student mobility is the norm in the U.S. today
- So how do you analyze data?

BACKGROUND

Terms and Definitions

Multilevel Data

- Units "nested" within units
- Examples:
  - Students in classrooms
  - Employees in job sites
  - Measurement occasions in students in schools
- Outcomes within groups are likely correlated, so use multilevel modeling, not regression

Unconditional HLM Growth Models

The reading score at time *t* for student *i* who attended school *j*:

At Level 1 (measurement time):

Year has to start at 0

$$Rdg_{tij} = \pi_{0ij} + \pi_{1ij} Yr_{tij} + e_{tij}$$

Intercept (Starting Point)

Slope (Annual Growth)

Unconditional HLM Growth Models

The reading score at time *t* for student *i* who attended school *j*:

At Level 2 (student):

Intercept: $\pi_{0ij} = \beta_{00j} + r_{0ij}$

Slope: $\pi_{1ij} = \beta_{10j} + r_{1ij}$

Unconditional HLM Growth Models

The reading score at time *t* for student *i* who attended school *j*:

At Level 3 (school):

Intercept:

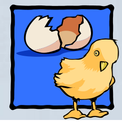
$$\beta_{00j} = \gamma_{000} + u_{00j}$$

Slope:

$$\beta_{10j} = \gamma_{100} + u_{10j}$$

Hierarchical

- Usually multilevel = hierarchical
- Each unit belongs to one (and only one) higher-level unit
- When this isn't true, we have non-hierarchical multilevel data



Cross-Classification

- Lower-level units belong to more than 1 higher-level *classification*
- Examples:
  - Students may attend the same school but live in different neighborhoods (e.g., Scotland Neighbourhood Study, Garner & Raudenbush, 1991)

Cross-Classification

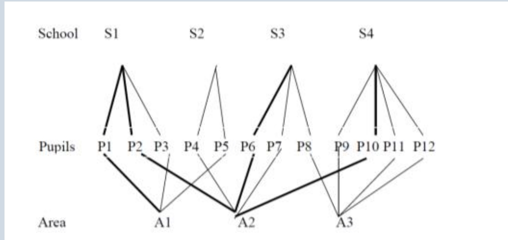
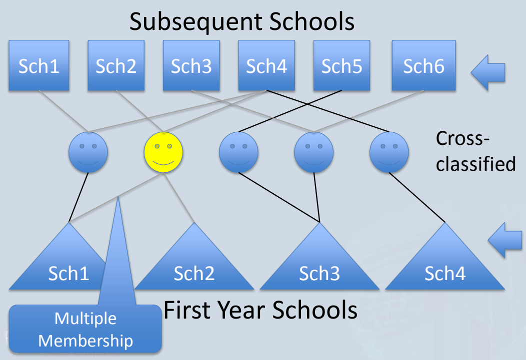


Figure 7: Twelve Students at Level 1 Nested Within an Area and School Cross-Classification at Level 2

(Fielding & Goldstein, 2006)

Multiple Membership

- Lower-level units belong to more than 1 higher-level *unit within the same classification*
- Examples:
  - Patients served by multiple nurses
  - Doctors practicing in multiple hospitals
  - Students taking multiple classes
  - Students attending more than one high school



Growth Models With Mobility

The reading score at time *t* for student *i* who attended (the set of) school(s) j_1 in the first year and (the set of) school(s) j_2 in subsequent years:

Year has to start at 0

At Level 1 (measurement time):

$$Rdg_{ti(\{j_1\},\{j_2\})} = \pi_{0i(\{j_1\},\{j_2\})} + \pi_{1i(\{j_1\},\{j_2\})} Yr_{ti(\{j_1\},\{j_2\})} + e_{ti(\{j_1\},\{j_2\})}$$

Intercept (Starting Point)

Slope (Annual Growth)

(Adapted from Grady & Beretvas, 2010, pp. 405-407)

Growth Models With Mobility

The reading score at time *t* for student *i* who attended (the set of) school(s) j_1 in the first year and (the set of) school(s) j_2 in subsequent years:

At Level 2 (student):

Intercept: $\pi_{0i(\{j_1\},\{j_2\})} = \beta_{00(\{j_1\},\{j_2\})} + r_{0i(\{j_1\},\{j_2\})}$

Slope: $\pi_{1i(\{j_1\},\{j_2\})} = \beta_{10(\{j_1\},\{j_2\})} + r_{1i(\{j_1\},\{j_2\})}$

(Adapted from Grady & Beretvas, 2010, pp. 405-407)

Growth Models With Mobility

At Level 3 (school):

Starting point takes into account all first-year schools

Intercept:

$$\beta_{00(\{j_1\},\{j_2\})} = \gamma_{0000} + \Sigma_{h\in\{j_1\}} w_{tih} u_{00h0}$$

Slope:

$$\beta_{10(\{j_1\},\{j_2\})} = \gamma_{1000} + \Sigma_{h\in\{j_1\}} w_{tih} u_{10h0} + \Sigma_{h\in\{j_2\}} w_{tih} u_{100h}$$

Growth curve also takes into account all subsequent schools

(Adapted from Grady & Beretvas, 2010, pp. 405-407)

Can ignoring mobility change your study's findings?

YES

Goldstein, Burgess, & McConnell (2007)
Chung (2009)
Grady & Beretvas (2010)
Luo & Kwok (2012)

SETTING UP THE DATA

Growth Models or Repeated Measures

Data for MLwiN

- Prepare your data file in another stats program
- Single data file (unlike HLM)
- Each row is a measurement occasion
- Student and school info repeated within student
- Student and school IDs must start at 1
- Some data manipulation can be done in MLwiN (sort, rename, select cases)

Data for MLwiN

- Columns:
  - Measurement Occasion or Time (Level 1)
  - Year (for growth model, starts at 0)
  - ID (Level 2)
  - Rdg (Dependent Var or Outcome)
  - First_School_1, First_School_2, etc and weights
  - Subsequent_School_1, Subs_Sch_2, etc and weights
  - Student covars
- Let’s look at the data!

T	Yr	id	Rdg	FS 1	FS 2	FS 1 wt	FS 2 wt	Sub Sch 1	Sub Sch 2	Sub Sch 3	SS1 wt	SS2 wt	SS3 wt
4	3	1	1.04	25	0	1	0	25	20	0	.5	.5	0
7	6	1	1.04	25	0	1	0	25	20	0	.5	.5	0
2	1	2	0.80	15	0	1	0	15	20	0	.5	.5	0
7	6	2	1.84	15	0	1	0	15	20	0	.5	.5	0
4	3	81	1.84	68	153	.33	.33	68	65	62	.33	.33	.33
6	5	81	0.28	68	153	.33	.33	68	65	62	.33	.33	.33
7	6	81	0.25	68	153	.33	.33	68	65	62	.33	.33	.33

USING MLWIN TO MODEL STUDENT GROWTH WITH MOBILITY

Growth Models or Repeated Measures

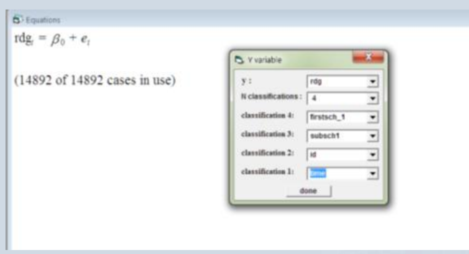
Setting Up Models in MLwiN

- Sort by:
  - First_Sch_1
  - Subsequent_Sch_1
  - Student
  - Time

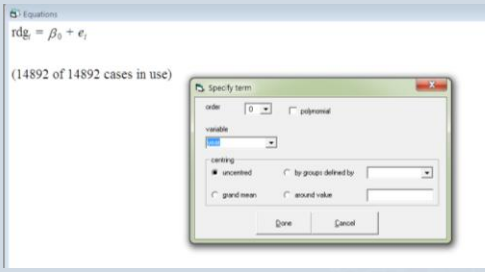
Setting Up Models in MLwiN

- Run “naïve” model using hierarchical nesting:
  - First_Sch_1 (Level 4)
  - Subsequent_Sch_1 (Level 3)
  - Student (Level 2)
  - Time (Level 1)
- This gives starting values for actual modeling using Monte Carlo

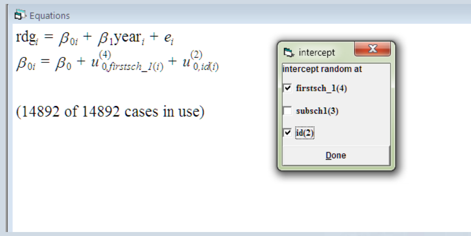
Setting Up Naïve Model



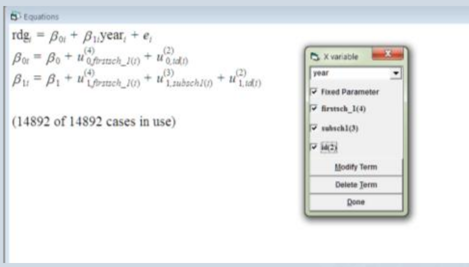
Add Year for Growth Model



Set Intercept Random at Levels 2 & 4

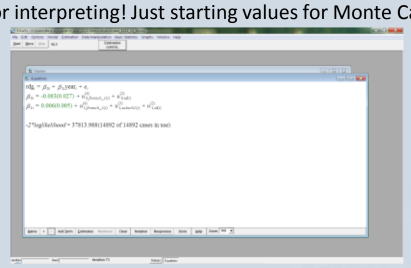


Set Year Random at All Levels



Run Naïve Model

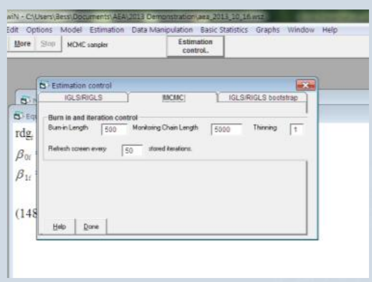
Not for interpreting! Just starting values for Monte Carlo.



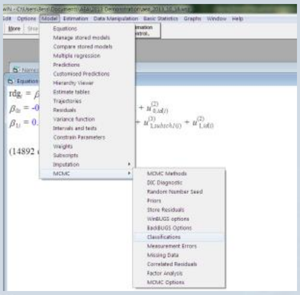
Adding Cross-Classification & Multiple Membership to the Model

- The "real" model using CCMM:
  - First_Sch_1 – First_Sch_4 (CC Level 3 – MM)
  - Subs_Sch_1 – Subs_Sch_12 (CC Level 3 – MM)
  - Student (Level 2)
  - Time (Level 1)
- First switch to Monte Carlo
- Then set cross-classifications and multiple memberships

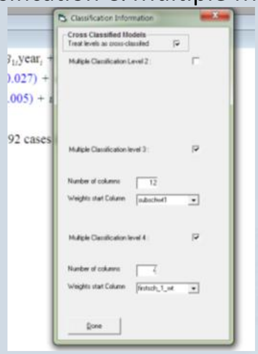
Estimation Control - MCMC



MCMC - Classifications



Cross-Classification & Multiple Membership



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CCMM Model

Equations

$$\text{rdg}_i = \beta_{0i} + \beta_{1i}\text{year}_i + e_i$$
$$\beta_{0i} = \beta_0 + \textstyle\sum_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u^{(4)}_{0j} + u^{(2)}_{0,id(i)}$$
$$\beta_{1i} = \beta_1 + \textstyle\sum_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u^{(4)}_{1j} + \textstyle\sum_{j\in subsch1(i)} w^{(3)}_{i,j} u^{(3)}_{1j} + u^{(2)}_{1,id(i)}$$

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Monte Carlo Results

Equations

$$\text{rdg}_i = \beta_{0i} + \beta_{1i}\text{year}_i + e_i$$
$$\beta_{0i} = -0.093(0.028) + \textstyle\sum_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u^{(4)}_{0j} + u^{(2)}_{0,id(i)}$$
$$\beta_{1i} = -0.001(0.007) + \textstyle\sum_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u^{(4)}_{1j} + \textstyle\sum_{j\in subsch1(i)} w^{(3)}_{i,j} u^{(3)}_{1j} + u^{(2)}_{1,id(i)}$$

Deviance(MCMC) = 28726.614(14892 of 14892 cases in use)

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Variance Components

Equations

$$\text{rdg}_i = \beta_{0i} + \beta_{1i}\text{year}_i + e_i$$
$$\beta_{0i} = -0.093(0.028) + \textstyle\sum_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u$$
$$\beta_{1i} = -0.001(0.007) + \textstyle\sum_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u$$

$$\begin{bmatrix} u^{(4)}_{0,firstsch\_1(i)} \\ u^{(4)}_{1,firstsch\_1(i)} \end{bmatrix} \sim \text{N}(0,\ \Omega^{(4)}_u)\ :\ \Omega^{(4)}_u = \begin{bmatrix} 0.212(0.027) & \\ -0.032(0.005) & 0.005(0.001) \end{bmatrix}$$

$$u^{(3)}_{1,subsch1(i)} \sim \text{N}(0,\ \Omega^{(3)}_{u1,1})\quad \Omega^{(3)}_{u1,1} = 0.016(0.001)$$
$$\begin{bmatrix} u^{(2)}_{0,id(i)} \\ u^{(2)}_{1,id(i)} \end{bmatrix} \sim \text{N}(0,\ \Omega^{(2)}_u)\ :\ \Omega^{(2)}_u = \begin{bmatrix} 0.534(0.034) & \\ -0.032(0.006) & 0.004(0.001) \end{bmatrix}$$

$$e_i \sim \text{N}(0,\ \Omega_{e0,0})\quad \Omega_{e0,0} = 0.403(0.007)$$

Deviance(MCMC) = 28726.614(14892 of 14892 cases in use)

Variance in intercept among 1st-year schools

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Variance Components

Equations

$$\text{rdg}_i = \beta_{0i} + \beta_{1i}\text{year}_i + e_i$$
$$\beta_{0i} = -0.093(0.028) + \textstyle\sum_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u^{(4)}_{0j} + u^{(2)}_{0,id(i)}$$
$$\beta_{1i} = -0.001(0.007) + \textstyle\sum \ldots w^{(3)}_{i,j} u^{(3)}_{1j} + u^{(2)}_{1,id(i)}$$

$$\begin{bmatrix} u^{(4)}_{0,firstsch\_1(i)} \\ u^{(4)}_{1,firstsch\_1(i)} \end{bmatrix} \sim \text{N}(0 \ldots 005(0.001)$$

$$u^{(3)}_{1,subsch1(i)} \sim \text{N}(0,\ \Omega^{(3)}_{u1,1})\quad \Omega^{(3)}_{u1,1} \ldots 16(0.001)$$
$$\begin{bmatrix} u^{(2)}_{0,id(i)} \\ u^{(2)}_{1,id(i)} \end{bmatrix} \sim \text{N}(0,\ \Omega^{(2)}_u)\ :\ \Omega^{(2)}_u = \begin{bmatrix} 0.534(0.034) & \\ -0.032(0.006) & 0.004(0.001) \end{bmatrix}$$

$$e_i \sim \text{N}(0,\ \Omega_{e0,0})\quad \Omega_{e0,0} = 0.403(0.007)$$

Deviance(MCMC) = 28726.614(14892 of 14892 cases in use)

Variance in intercept among students

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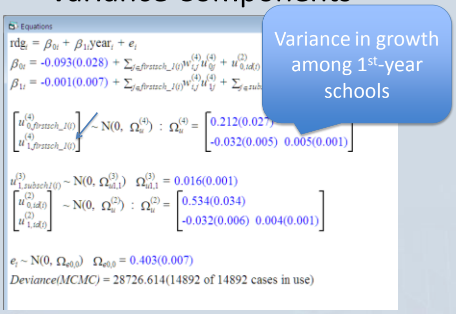
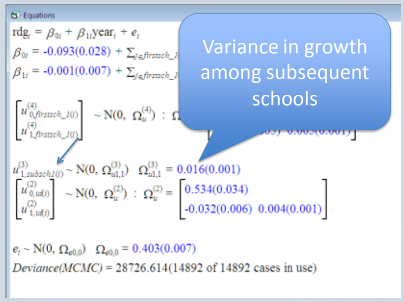
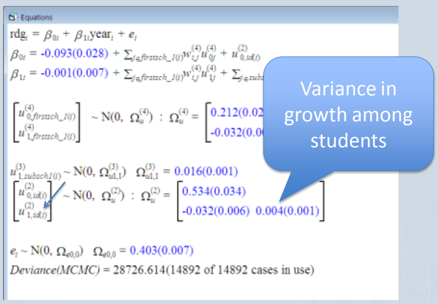
Variance Components



Variance Components



Variance Components



Added Covars

$$\mathrm{rdg}_i = \beta_{0i} + \beta_{1i}\mathrm{year}_i + -0.334(0.026)\mathrm{frpl}_i + -0.288(0.025)\mathrm{minority}_i + 0.181(0.019)\mathrm{female}_i + e_i$$

$$\beta_{0i} = 0.049(0.031) + \Sigma_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u^{(4)}_{0j} + u^{(2)}_{0,sid(i)}$$

$$\beta_{1i} = -0.001(0.006) + \Sigma_{j\in firstsch\_1(i)} w^{(4)}_{i,j} u^{(4)}_{1j} + \Sigma_{j\in subsch1(i)} w^{(3)}_{i,j} u^{(3)}_{1j} + u^{(2)}_{1,sid(i)}$$

$$\begin{bmatrix} u^{(4)}_{0,firstsch\_1(i)} \\ u^{(4)}_{1,firstsch\_1(i)} \end{bmatrix} \sim \mathrm{N}(0,\ \Omega^{(4)}_u) \ : \ \Omega^{(4)}_u = \begin{bmatrix} 0.135(0.023) & \\ -0.022(0.004) & 0.004(0.001) \end{bmatrix}$$

$$u^{(3)}_{1,subsch1(i)} \sim \mathrm{N}(0,\ \Omega^{(3)}_{u1,1}) \quad \Omega^{(3)}_{u1,1} = 0.012(0.001)$$

$$\begin{bmatrix} u^{(2)}_{0,sid(i)} \\ u^{(2)}_{1,sid(i)} \end{bmatrix} \sim \mathrm{N}(0,\ \Omega^{(2)}_u) \ : \ \Omega^{(2)}_u = \begin{bmatrix} 0.479(0.029) & \\ -0.025(0.005) & 0.003(0.001) \end{bmatrix}$$

$$e_i \sim \mathrm{N}(0,\ \Omega_{e0,0}) \quad \Omega_{e0,0} = 0.405(0.007)$$

Deviance(MCMC) = 28778.174(14892 of 14892 cases in use)

Variance Components

	Intercept Estimate (SE)	Growth Estimate (SE)
Students	.479 (.029)	.003 (.001)
First schools	.135 (.023)	.004 (.001)
Subsequent schools	N/A	.012 (.001)

- Most of the variation in initial reading scores is due to variation among students
- Students' growth is due largely to influence of schools, not students
- Small estimates of growth likely due to use of standardized *z* scores

Required Reading:

MLwiN online course at Center for Multilevel Modelling www.bristol.ac.uk/cmm/

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- Fielding & Goldstein (2006): Cross-classified and Multiple Membership Structures in Multilevel Models http://www.education.gov.uk/publications/eorderingdownload/rr791.pdf
- Grady & Beretvas (2010): Incorporating student mobility in achievement growth modeling: A cross-classified multiple membership growth curve model *Multivariate Behavioral Research*
- Leckie & Bell (2013): MLwiN Practical on Cross-Classified Multilevel Models (MLwiN course)
- Leckie & Owen (2013): MLwiN Practical on Multiple Membership Multilevel Models (MLwiN course)

References

Browne, W. J. (2012). MCMC estimation in MLwiN version 2.26. Centre for Multilevel Modelling, University of Bristol.

Bryk, A. S., Sebring, P. B., Allensworth, E., Luppescu, S., & Easton, J. Q. (2010). *Organizing schools for improvement: Lessons from Chicago*. Chicago: The University of Chicago Press.

Chung, H. (2009). The Impact of Ignoring Multiple-Membership Data Structures. Dissertation. The University of Texas at Austin.

Fielding, A. & Goldstein, H. (2006). Cross-classified and Multiple Membership Structures in Multilevel Models: An Introduction and Review. Research Report No. 791. Department for Education and Skills.

References

Goldstein, H. (2003). *Multilevel Statistical Models*, 3rd ed. London: Arnold.

Goldstein, H., Burgess, S., & McConnell, B. (2007). Modelling the effect of pupil mobility on school differences in educational achievement. *Journal of the Royal Statistical Society, 170*, 941-954.

Grady, M. W., & Beretvas, S. N. (2010). Incorporating student mobility in achievement growth modeling: A cross-classified multiple membership growth curve model. *Multivariate Behavioral Research, 45*, 393-419.

References

Leckie, G., & Bell, A. (2013). Cross-Classified Multilevel Models – MLwiN Practical. LEMMA VLE Module 12, 1-60. http://www.bristol.ac.uk/cmm/learning/course.html

Leckie, G., & Owen, D. (2013). Multiple Membership Multilevel Models – MLwiN Practical. LEMMA VLE Module 13, 1-48. http://www.bristol.ac.uk/cmm/learning/course.html

Luo, W., & Kwok, O. (2012). The consequences of ignoring individuals' mobility in multilevel growth models: A Monte Carlo study. *Journal of Educational and Behavioral Statistics, 37*, 31-56.

References

Rasbash, J., Browne, W. J., Healy, M., Cameron, B., & Charlton, C. (2013). MLwiN Version 2.27. Centre for Multilevel Modelling, University of Bristol.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*, 2nd ed. Thousand Oaks, CA: SAGE.

Rumberger, R. W. (2002). Student mobility. In *Encyclopedia of Education* (2nd ed., Vol. 7, pp. 2381-2385). New York: Macmillan Reference USA.