APPLICATION OF GROWTH MIXTURE MODELS FOR EARLY DETECTION

Christy K. Boscardin, Ph.D. CAPS Methods Core Seminar October 30, 2009  Boscardin, C., Muthén, B., Francis, D. & Baker, E. (2008). Early identification of reading difficulties using heterogeneous developmental trajectories. Journal of Educational Psychology, 100, 192-208.



# **Advantages of Growth Mixture**

- Provide more flexibility of assumptions about the population
- Used to identify heterogeneous subgroups in the population
- Used to identify & cluster individuals with similar developmental profiles/trajectories
- Useful for determining the appropriate intervention based on the factors associated with each subgroup

### **Overview**

- Reading Development
- Longitudinal Data Analysis
- Introduction to Growth Mixture Modeling
- Early Reading Assessment Study

## **Background on Reading**

- Reading Disability accounts for 80% of Learning Disability
- Term Learning Disability Coined by Kirk & Bateman (1962)
  - Unexpected Difficulties in Language, Learning, Reading
- Until recently IQ discrepancy method used for diagnosis
- Discrepancy between ability (as measured by IQ) and reading achievement (as measured by standardized state test)

### **Problems with IQ Discrepancy Method**

- 2 measures involved: IQ and standardized achievement test
- Problems with IQ test:
  - IQ includes linguistic components
  - Validity of IQ tests have been questioned
- Students with reading disability diagnosed in 2<sup>nd</sup> grade
  - No standardized achievement scores available
  - Require oral assessment rather than traditional testing format
  - Unnecessarily delay identification

## **Background on Reading Cont.**

- NICHD study: approximately 75% of children will continue to have reading difficulties in later grades diagnosed after 2<sup>nd</sup> grade
- Early intervention is key to successful remediation
- Studies with intervention starting in kindergarten shown success
- Intervention most effective prior to overt manifestation

#### **Current Reading Development Movement**

- Focus shifted to early identification of student at-risk
- Require examination of predictors & precursors
- Limited empirical studies on reading development over time
- Hypothesis: Reading development may include subtypes rather than one normative trajectory
- Longitudinal analysis helps identify best time to intervene

### **Research Questions**

- Are there distinct subtypes of reading developmental trajectories?
- Are students at-risk for reading difficulties look qualitatively different compared to students with normal reading development?
- What are the factors related to being at-risk?

## **Growth Modeling**

- Typical approach for looking at development over time: Conventional Growth Modeling
- Describes changes in pattern over time using repeated measures
- Typical questions:
- Are there individual differences in reading development over time?
- Do boys and girls develop differently?

#### **Growth Modeling (Latent Variable Framework)**

With individual repeated measures, you can estimate underlying developmental trajectory:

$$\mathbf{Y}_{ijt} = \eta_{ij1} + (t - T) \eta_{ij2} + \varepsilon_{ijt}; t = 1, 2, ..., T.$$

Where for example

 $Y_{ijt} = j$ th reading skill for *i*th individual at time *t*  $\eta_{ij1} =$  initial status of reading ability  $\eta_{ij2} =$  rate of improvement or change in reading ability  $\varepsilon_{iit} =$  error associated with the model

#### Individual growth parameters are assumed to come from a single population: one normative slope & one normative intercept

# **Growth Mixture Modeling**

- Technical advantages over conventional growth modeling
- Allow more flexibility in model specifications
- Allows for heterogeneity of subgroups more than one population for individual specific parameters
- Advantages
  - More precise estimate of growth trajectory
  - Identify variations in developmental profiles
  - Vary the effect of covariates (factors) depending on the developmental profile
- Reading development suggest subgroups
  - Student with no response to instruction may be etiologically different from students who do respond to instruction



## **Growth Mixture Modeling**

- Here's the difference:
- Allowing for heterogeneity of subgroups with latent categorical variable
- Individuals are allowed to be in one of K latent classes (characteristically distinct developmental profiles)
- Covariates are used to both estimate growth but also to help predict class membership

## **Growth Mixture Modeling**

$$\mathbf{Y}_{ik} = \mathbf{v}_k + \Lambda_k \,\eta_{ik} + \mathbf{K}_k \,\mathbf{x}_{ik} + \varepsilon_{ik}, \\ \eta_{ik} = \alpha_k + \mathbf{B}_k \,\eta_{ik} + \Gamma_k \,\mathbf{x}_{ik} + \zeta_{ik},$$

#### Where

 $\mathbf{Y}_{ik}$  represents the repeated measures over fixed time points.  $\eta_{ik}$  random effects

 $\Lambda_k$  represent the shape of the growth curves.

 $\mathbf{K}_k$  represents the effects of time-varying covariates,

 $\Gamma_k$  represents the effects of time-invariant covariates.

 $\alpha_k$  represents the intercepts for  $\eta$  for latent class k.

The residual vectors,  $\varepsilon_{ik}$  and  $\zeta_{ik}$ , are assumed to have covariance matrices  $\Theta_k$  and  $\Psi_k$ , respectively.

# **Class Membership**

The multinomial logistic regression for predicting class membership with a covariate :

P (c<sub>*ik*</sub> = 1|x<sub>*i*</sub>) = exp(
$$\beta_{0k} + \beta_{1k}x_i$$
)/ $\sum_{c=1}^{K} exp(\beta_{0c} + \beta_{1c}x_i)$ 

Estimated posterior probabilities for each individual's class membership are derived as follows:

 $p_{ik} = P(\mathbf{c}_{ik} = 1 | \mathbf{y}_i, \mathbf{x}_i) \propto P(\mathbf{c}_{ik} = 1 | \mathbf{x}_i) f(\mathbf{Y}_{ik} | \mathbf{x}_i)$ latent class membership indicators,  $\mathbf{c}_{ik}$ , to be 1 if individual *i* belongs to class *k*, and 0 otherwise

## **Technical Details: Model Selection**

- Identifying Number of Classes: Model Selection
  - Bayesian Information Criterion (BIC): non-nested models
    - smaller value
  - Entropy: precision in estimated posterior probability
- Comparison of individual estimated mean trajectories and observed mean trajectories

### Early Assessment of Reading Skills (EARS) DATA

#### Purpose:

- Identify Students Most At-Risk for Reading Difficulties
- Factors related to at-risk for reading difficulties
- Earlier identification using precursor measures instead of waiting until 2<sup>nd</sup> grade

#### Sample:

- Subset of 411 from 945 with complete data in kindergarten
  - No significant differences in measures between the subset and total population
- **50%** boys
- 55% White, 17% African American, 16% Hispanic, 11% Asian, and 1% other
- White & Asian (Non-Minority) vs. African American, Hispanic, & Other (Minority)

#### Kindergarten: Phonological Awareness

- Deficits in Phonological awareness related to reading difficulties later
- Ability to manipulate phonemes
  cake & camp, pan & can, /s/pill & pill
- At entry to formal schooling, know 6,000 words & basic phonological awareness
- Signs of trouble in kindergarten: difficulty in learning to name letters and attach phonemes to letters.
- Instrument: 7 subtests including: a) phoneme segmentation, b) phoneme elision, c) sound categorization, d) first sound comparison,
   e) blending onset and rime, f) blending phonemes into words, and
   g) blending phonemes into non-words.
- Internal consistency estimates for the subtests ranged from 0.85 to 0.95
- Score based on IRT estimate
- Measured 4 times during the year: Oct, Dec, Feb, April

### First & Second Grade: Word Recognition

- Central to reading acquisition
- Fluency and efficiency of word recognition highly correlated with reading skills in later grades
- Signs of trouble in 1st grade: can't recognize single words out of sentence context
- Instrument: 50 isolated words (index cards) included 36 single-syllable, 11 two-syllable, and 3 threesyllable real words.
  - 16 words in common across the two grades
  - internal consistency estimates exceeded 0.90
  - Score based on IRT estimate
  - Measured 4 times in each grade (total of 8 times)

### Covariate: Letter Identification/Rapid Naming

- Accuracy and Fluency of Letter Identification shown to be highly correlated with reading
- Not considered a precursor skill
- Instrument: The correct number of letter naming within 60 seconds was recorded.
  - Measured at the end of kindergarten





	First and Second Grade				
Kindergarten	WR1	WR2	WR3	WR4	WR5
PA1	Class 1 45 (11%)				
PA2		Class 2 63 (15%)	Class 3 77 (19%)		
PA3		Class 4 8 (2%)	Class 5 56 (14%)	Class 6 36 (9%)	
PA4			Class 7 20 (5%)	Class 8 8 (14%)	Class 9 30 (7%)
PA5					Class 10 18 (4%)









#### Reading Achievement Predicted by Class membership



# **Summary of Findings**

- 5 Distinct Developmental Profiles in Each Grade
- 10 Distinct Developmental Profiles (including transitional groups) across 3 years
- Class 1 students: no Phonological Awareness development – no Word Recognition Development
- Rapid naming is strong predictor of class membership
- As early as kindergarten we can start to identify students who are potentially at-risk for reading difficulties
- Significantly higher proportion of minority students in class 1 compared to other classes.

#### **Applications of Growth Mixture Modeling**

- Greenbaum, P.E., Del Boca, F.K., Darkes, J., Wang, C. & Goldman, M.S. (2005). Variation in the drinking trajectories of freshman college students. Journal of Consulting and Clinical Psychology, 73, 229-238
  - Investigated whether a single growth curve adequately characterizes the variability in individual drinking trajectories. Identified 5 trajectories.
- Chen L, Eaton WW, Gallo JJ, Nestadt G: Understanding the heterogeneity of depression through the triad of symptoms, course and risk factors: A longitudinal, population-based study. J Affect Disord 2000; 59:1-11
  - There is an ongoing research effort to test if depression is a homogeneous clinical syndrome and to identify valid and useful subtypes based on the number and nature of depressive symptoms.
- Croudace, T.J., Jarvelin, M.R., Wadsworth, M.E. & Jones, P.B. (2003). Developmental typology of trajectories to nighttime bladder control: Epidemiologic application of longitudinal latent class analysis. American Journal of Epidemiology, May 1;157(9):834-42.
- Muthén, B., Brown, C.H., Masyn, K., Jo, B., Khoo, S.T., Yang, C.C., Wang, C.P., Kellam, S., Carlin, J., & Liao, J. (2002). General growth mixture modeling for randomized preventive interventions. Biostatistics, 3, 459-475.

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