Modeling Growth of SAT Reading Performance using Repeated Measures Data

Annual Meeting of National Council on Measurement in Education

New York, NY

March 27, 2008

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The College Board

Background

- Each year, over a million high school students take the SAT. Nearly one-half of them take the test more than once.
- SAT score change analyses have focused on tracking average score differences of student cohorts from year to year.
- It is also important to examine growth trajectories of students' performance using repeated measures data.

Growth Models

Two types of the models have gained prominent use:

<u>The multilevel growth models</u>

- Assume a single population growth model
- Allow variation across individuals in the growth parameters

<u>The growth mixture models</u>

- Allow for different subpopulation growth trajectories
- Estimate random effects for within-class variation
- A more flexible analysis framework.

Purpose of the Study

- The study aimed to explore the growth trajectory of SAT Reading scores, examine the amount of variation across students, and the influence of demographics on the growth parameters.
- In addition, the study aimed to explore whether there exists latent classes of growth that can be described by different growth trajectories.

Data (1)

- A sample of 3000 students from the 2007 college bound seniors who took SAT at least three times.
- Stratified sampling using target proportions of gender and ethnic groups based on the cohort.
- 84.4% of students in the sample took the test 3 times, 12% took the test 4 times, and 3.6% took the test 5 to 10 times. The ages of students taking each test ranged from 14.6 to 20.8 years old.
- The students had varying number of test scores and varying spacing of test occasions.

Data (2)

- Computed each student's actual age (to the nearest month) when taking the test each time, as temporal indicator for each test score.
- Gender and several ethnic characteristics were dummy coded and used as covariates in modeling growth:
  - Gender (1=Male, 0=Female)
  - White (1=White, 0=not White)
  - Black (1=Black, 0=not Black)
  - Asian (1=Asian, 0=not Asian)
  - Hispanic (1=Hispanic, 0=not Hispanic)

Analyses (1)

Unconditional linear growth model:

Level-1:

$$Y_{ij} = \alpha_{0j} + \alpha_{1j}(TIME)_{ij} + r_{ij}$$

Level-2:

$$\alpha_{0j} = \beta_{00} + u_{0j}$$

$$\alpha_{1j} = \beta_{10} + u_{1j}$$

Analyses (2)

Conditional linear growth model:

Level-1:

$$Y_{ij} = \alpha_{0j} + \alpha_{1j}(TIME)_{ij} + r_{ij}$$

Level-2:

$$\alpha_{0j} = \beta_{00} + \beta_{01}x_{1j} + \beta_{02}x_{2j} + \ldots + \beta_{0\mathrm{n}}x_{\mathrm{n}j} + u_{0j}$$

$$\alpha_{1j} = \beta_{10} + \beta_{11}x_{1j} + \beta_{12}x_{2j} + \ldots + \beta_{1\mathrm{n}}x_{\mathrm{n}j} + u_{1j}$$

Analyses (3)

The Growth Mixture Model (GMM):

$$Y_{ij|(C_j=c)} = \alpha_{0cj} + \alpha_{1cj}(TIME)_{ij} + r_{icj}$$

$$\alpha_{c0j} = \beta_{c00} + \beta_{c01}x_{1j} + \beta_{c02}x_{2j} + \ldots + \beta_{c0\mathrm{n}}x_{\mathrm{n}j} + u_{c0j}$$

$$\alpha_{c1j} = \beta_{c10} + \beta_{c11}x_{1j} + \beta_{c12}x_{2j} + \ldots + \beta_{c1\mathrm{n}}x_{\mathrm{n}j} + u_{c1j}$$

Parameter estimates for the traditional growth models

	Model-1			Model-2			Model-3		
Random Variar	**Estimate**	**SE**	**Pr**	**Estimate**	**SE**	**Pr**	**Estimate**	**SE**	**Pr**
Intercept	8066.60	542.14	<.0001	8051.07	310.61	<.0001	7621.38	299.05	<.0001
time	176.29	54.90	0.0007	174.87	30.33	<.0001	156.82	29.20	<.0001
Residual	1220.22	23.08	<.0001	1220.19	21.94	<.0001	1216.77	21.84	<.0001
Fixed Effects									
Intercept	430.59	3.06	<.0001	433.70	4.23	<.0001	408.39	7.52	<.0001
time	28.77	0.99	<.0001	29.66	1.39	<.0001	32.15	2.48	<.0001
gender				-7.08	6.13	0.2483			
time*gender				-1.75	1.99	0.3788			
black							-11.27	11.95	0.3457
white							43.27	8.57	<.0001
asian							1.26	12.29	0.9185
hispanic							4.00	12.46	0.7482
time*black							-13.19	3.90	0.0007
time*white							-5.25	2.82	0.0624
time*asian							9.97	3.99	0.0126
time*hispanic							-3.83	4.08	0.3480

Comparison of class formation for the Growth Mixture Model

	Loglikelihood	df	AIC	BIC
1 class	-41402.392	16	82836.8	82930.172
2 class	-41374.677	25	82799.4	82945.272
3 class	-41409.322	34	82886.6	83085.094

Logistic regression odds ratio for Class 1 on covariates

Covariate	Odds ratio
Gender	1.4
White	32.4
Black	0.1
Asian	3.6
Hispanic	0.1

Frequency and percentage of students in each latent class by ethnic group

		Class 1			Class 2		
Ethnic Group		**N**	**% against class**	**% against group**	**N**	**% against class**	**% against group**
White	**1**	1414	78%	100%	6	1%	0%
	0	396	22%	36%	716	99%	64%
Black	**1**	7	0%	3%	250	35%	97%
	0	1803	100%	79%	472	65%	21%
Asian	**1**	207	11%	86%	35	5%	14%
	0	1603	89%	70%	687	95%	30%
Hispanic	**1**	7	0%	2%	288	40%	98%
	0	1803	100%	81%	434	60%	19%

Parameter estimates from the 2-class Growth Mixture Model

		Estimate	P-Value
Class 1			
	Intercept	503.0	0.000
	Slope	35.8	0.000
	Residual vriances		
	Intercept	6709.6	0.000
Class 2			
	Intercept	394.3	0.000
	Slope	23.0	0.000
	Residual vriances		
	Intercept	6509.2	0.000
Covariate effects			
Intercept			
	Gender	16.8	0.527
	White	-27.7	0.019
	Black	-1.5	0.929
	Asian	45.0	0.004
	Hispanic	19.3	0.168
Slope			
	Gender	-0.6	0.952
	White	-11.4	0.000
	Black	-4.9	0.000
	Asian	-6.3	0.000
	Hispanic	4.1	0.000

Summary of results

- Large variability in intercept and slope parameters among students.
- Gender did not account for much variation in growth parameters.
- Ethnicity accounted for a portion of variation in intercept and slope. There was significant intercept effect for White and significant slope effect for Black.
- Growth Mixture Modeling revealed 2 latent subpopulations of different growth trajectories. Class 1 primarily consists of White and Asian, with higher average intercept and higher slope than Class 2 which primarily consists of Black and Hispanic students.
- The GMM results identified a significant intercept effect for Asian, and significant slope effects for White, Black, Asian, and Hispanic.

Discussion

- Results and interpretations were conditioned on the 2007 cohort data. Need cross-validation with data form other cohort year.
- The modeling approach and selection of covariates were exploratory in nature. More in-depth examinations are needed.
- Future studies need to include other predictors, especially variables related to student academic background. Variables at school level can also be explored.
- Future studies can explore a outcome variable (e.g., the first year GPA in college) in the growth mixture model.