Mplus Short Courses
Day 5B

Multilevel Modeling With Latent Variables Using Mplus

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Mplus Background

- Inefficient dissemination of statistical methods:
  - Many good methods contributions from biostatistics, psychometrics, etc are underutilized in practice
- Fragmented presentation of methods:
  - Technical descriptions in many different journals
  - Many different pieces of limited software
- Mplus: Integration of methods in one framework
  - Easy to use: Simple, non-technical language, graphics
  - Powerful: General modeling capabilities
- Mplus versions
  - V1: November 1998
  - V2: February 2001
  - V3: March 2004
  - V4: February 2006
- Mplus team: Linda & Bengt Muthén, Thuy Nguyen, Tihomir Asparouhov, Michelle Conn

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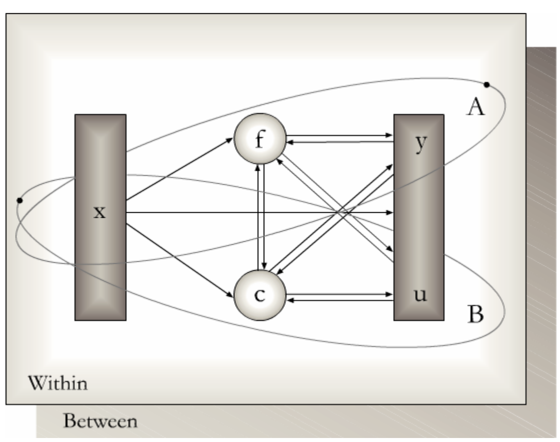
General Latent Variable Modeling Framework



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Mplus

Several programs in one

- Structural equation modeling
- Item response theory analysis
- Latent class analysis
- Latent transition analysis
- Survival analysis
- Multilevel analysis
- Complex survey data analysis
- Monte Carlo simulation

Fully integrated in the general latent variable framework

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Overview

Single-Level Analysis

	Cross-Sectional	Longitudinal
Continuous Observed And Latent Variables	***Day 1*** Regression Analysis Path Analysis Exploratory Factor Analysis Confirmatory Factor Analysis Structural Equation Modeling	***Day 2*** Growth Analysis
Adding Categorical Observed And Latent Variables	***Day 3*** Regression Analysis Path Analysis Exploratory Factor Analysis Confirmatory Factor Analysis Structural Equation Modeling Latent Class Analysis Factor Mixture Analysis Structural Equation Mixture Modeling	***Day 4*** Latent Transition Analysis Latent Class Growth Analysis Growth Analysis Growth Mixture Modeling Discrete-Time Survival Mixture Analysis Missing Data Analysis

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Overview (Continued)

Multilevel Analysis

	Cross-Sectional	Longitudinal
Continuous Observed And Latent Variables	***Day 5*** Regression Analysis Path Analysis Exploratory Factor Analysis Confirmatory Factor Analysis Structural Equation Modeling	***Day 5*** Growth Analysis
Adding Categorical Observed And Latent Variables	***Day 5*** Latent Class Analysis Factor Mixture Analysis	***Day 5*** Growth Mixture Modeling

Regression Mixture Analysis

Two-Level Data

- Education studies of students within schools
  - LSAY (3,000 students in 54 schools, grades 7-12)
  - NELS (14,000 students in 900 schools, grades 8-12),
  - ECLS (22,000 students in 1,000 schools, K- grade 8)
- Public health studies of patients within hospitals, individuals within counties

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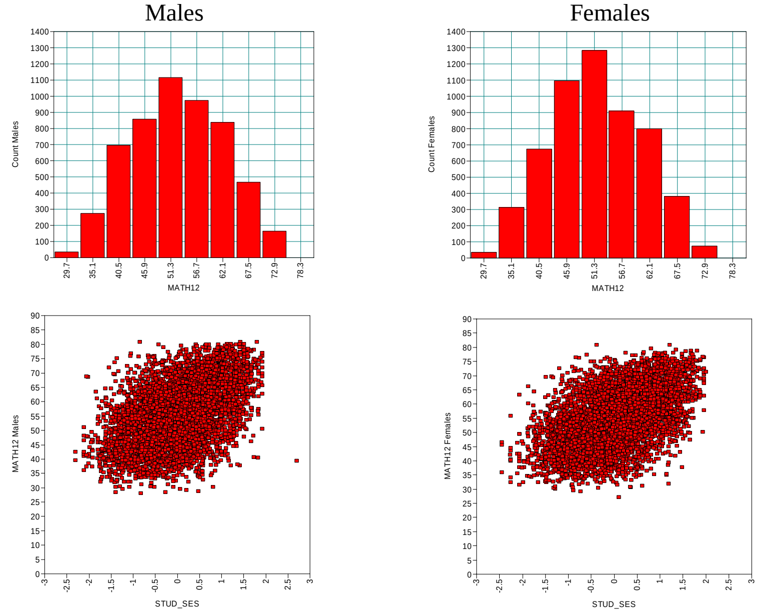
NELS Data: Grade 12 Math Related To Gender And SES

Males | Females



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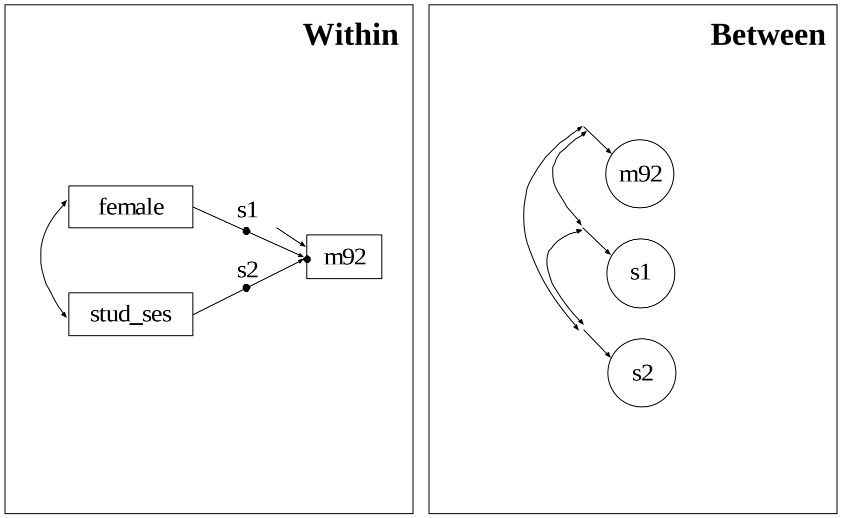
NELS Two-Level Math Achievement Regression



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Output Excerpts NELS Two-Level Regression

	Estimates	S.E.	Est./S.E.
Between Level			
Means			
M92	55.279	0.174	317.706
S_FEMALE	-0.850	0.188	-4.507
S_SES	5.450	0.132	41.228
Variances			
M92	11.814	1.197	9.870
S_FEMALE	5.762	1.426	4.041
S_SES	0.905	0.538	1.682
S_FEMALE WITH			
M92	-4.936	1.071	-4.610
S_SES	0.068	0.635	0.107
S_SES WITH			
M92	1.314	0.541	2.431

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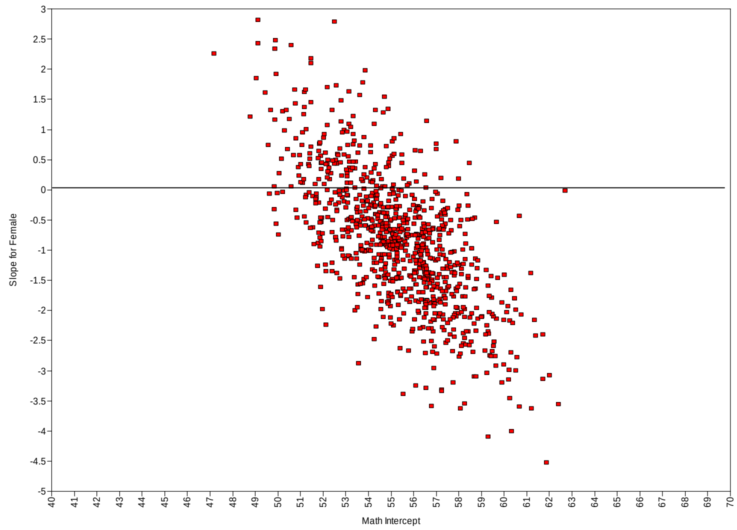
Random Effect Estimates For Each School: Slopes For Female Versus Intercepts For Math



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Is The Conventional Two-Level Regression Model Sufficient?

- Conventional Two-Level Regression of Math Score Related to Gender and Student SES
  - Loglikelihood = -39,512, number of parameters = 10, BIC = 79,117
- New Model
  - Loglikelihood = -39,368, number of parameters = 12, BIC = 78,848

- Which model would you choose?

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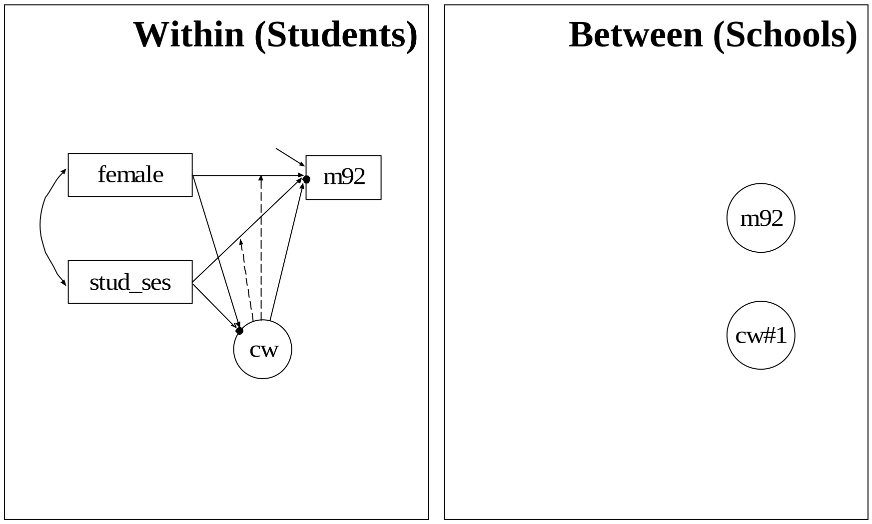
Two-Level Regression With Latent Classes For Students



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Model Results For NELS Two-Level Regression Of Math Score Related To Gender And Student SES

Model	Loglikelihood	# parameters	BIC
(1) Conventional 2-level regression with random intercepts and random slopes	-39,512	10	79,117
(2) Two-level regression mixture, 2 latent classes for students	-39,368	12	78,848
(3) Two-level regression mixture, 3 latent classes for students	**-39,280**	**19**	**78,736**

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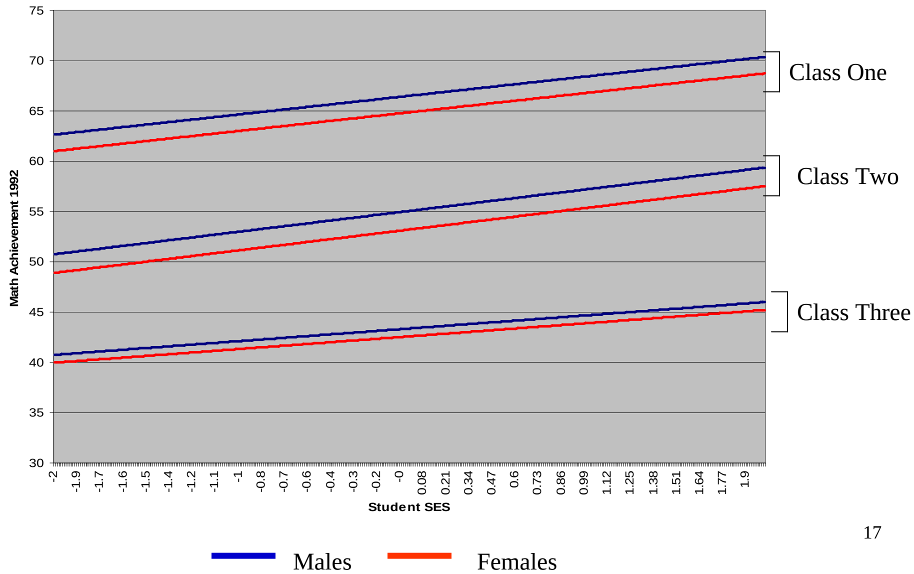
NELS: Estimated Three-Class Model



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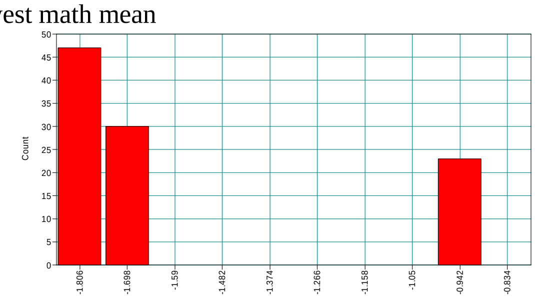
Estimated Two-Level Regression Mixture With 3 Latent Classes For Students

- Estimated Female slope means for the 3 latent classes for students do not include positive values.
- The class with the least Female disadvantage (right-most bar) has the lowest math mean



- Significant between-level variation in cw (the random mean of the latent class variable for students): Schools have a significant effect on latent class membership for students

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Input For Two-Level Regression With Latent Classes For Students

```
TITLE:     NELS 2-level regression
DATA:      FILE = comp.dat;
           FORMAT = 2f7.0 f11.4 13f5.2 79f8.2 f11.7;
VARIABLE:
           NAMES = school m92 female stud_ses;
           CLUSTER = school;
           USEV = m92 female stud_ses;
           WITHIN = female stud_ses;
           CENTERING = GRANDMEAN(stud_ses);
           CLASSES = cw(3);
ANALYSIS:
           TYPE = TWOLEVEL MIXTURE MISSING;
           PROCESS = 2;
           INTERACTIVE = control.dat;
           !STARTS = 1000 100;
           STARTS = 0;
```

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Input For Two-Level Regression With Latent Classes For Students (Continued)

```
MODEL:
           %WITHIN%
           %OVERALL%
           m92 ON female stud_ses;
           cw#1-cw#2 ON female stud_ses;
   ! [m92] class-varying by default
           %cw#1%
           m92 ON female stud_ses;
           %cw#2%
           m92 ON female stud_ses;
           %cw#3%
           m92 ON female stud_ses;
           %BETWEEN%
           %OVERALL%
           f BY cw#1 cw#2;
```

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Cluster-Randomized Trials And NonCompliance

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Randomized Trials With NonCompliance

- Tx group (compliance status observed)
  - Compliers
  - Noncompliers
- Control group (compliance status unobserved)
  - Compliers
  - NonCompliers

Compliers and Noncompliers are typically not randomly equivalent subgroups.

Four approaches to estimating treatment effects:

1. Tx versus Control (Intent-To-Treat; ITT)
2. Tx Compliers versus Control (Per Protocol)
3. Tx Compliers versus Tx NonCompliers + Control (As-Treated)
4. Mixture analysis (Complier Average Causal Effect; CACE):
   - Tx Compliers versus Control Compliers
   - Tx NonCompliers versus Control NonCompliers

CACE: Little & Yau (1998) in Psychological Methods

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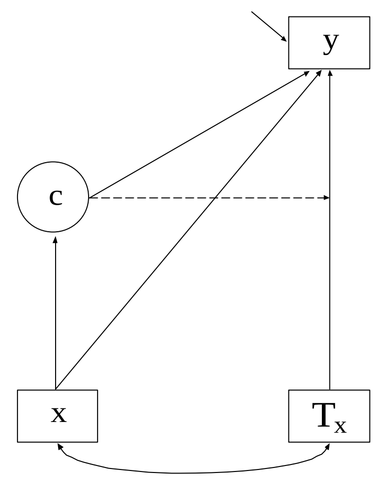
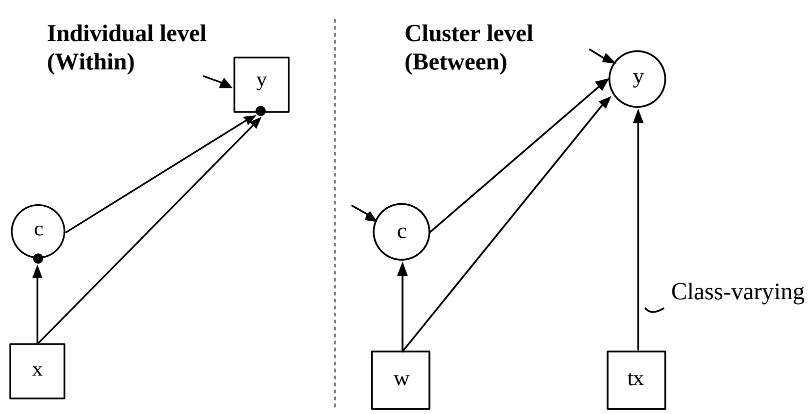
Randomized Trials with NonCompliance: Complier Average Causal Effect (CACE) Estimation

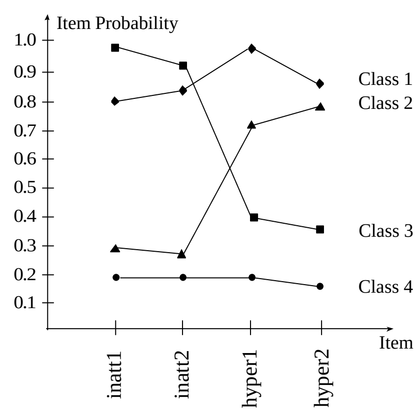


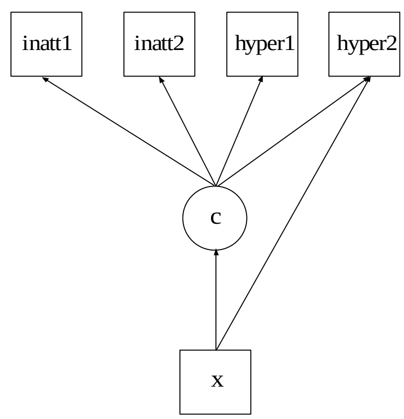
Two-Level Regression Mixture Modeling: Cluster-Randomized CACE



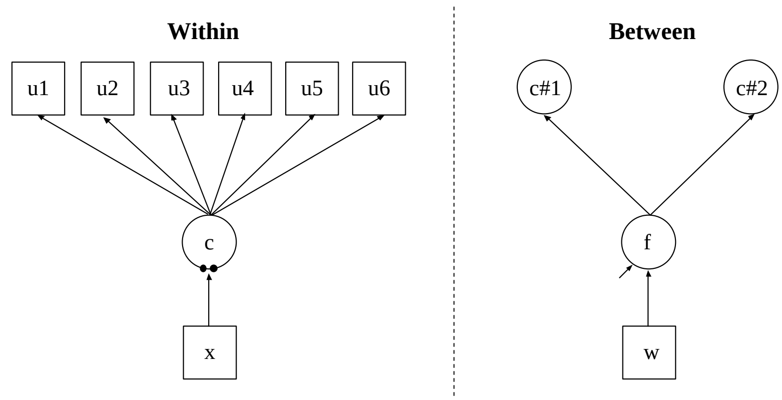
Latent Class Analysis

Latent Class Analysis





Two-Level Latent Class Analysis



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Input For Two-Level Latent Class Analysis

```
TITLE:     this is an example of a two-level LCA with
           categorical latent class indicators
DATA:      FILE IS ex10.3.dat;
VARIABLE:  NAMES ARE u1-u6 x w c clus;
           USEVARIABLES = u1-u6 x w;
           CATEGORICAL = u1-u6;
           CLASSES = c (3);
           WITHIN = x;
           BETWEEN = w;
           CLUSTER = clus;
ANALYSIS:  TYPE = TWOLEVEL MIXTURE;
```

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Input For Two-Level Latent Class Analysis (Continued)

```
MODEL:      %WITHIN%
            %OVERALL%
            c#1 c#2 ON x;

            %BETWEEN%
            %OVERALL%
            f BY c#1 c#2;
            f ON w;
OUTPUT:     TECH1 TECH8;
```


Latent Transition Analysis