Acknowledgement

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Overview

- “Mobility” is a complex and ongoing issue in education settings

Overview

School Level

Student Level

Teacher Level
Overview

- Common modeling procedures to handle mobility in education:
  - Multiple membership random effects model (MMREM; Browne, Goldstein, & Rasbash, 2001)
  - Use observed student mobility as a predictor or outcome in regression
  - Ignore it!
Overview

• We propose an alternative approach—multilevel network analysis

• Our findings, in brief:
  • Network models are capable of handling the complex dependencies among schools
  • Real data may contain few cluster-level observations and few nodes within clusters, which is problematic for estimation
Outline

• Introduction to mobility
• Social network modeling methods
• Results from the real data illustration
• Where do we go from here?
Patterns of Mobility

Students are mobile...but in a particular way

(Kerbow, 1996; Kerbow, Azcoitia, & Buell, 2003)
Patterns of Mobility

Students are mobile...but in a particular way
Patterns of Mobility

Students are mobile...but in a particular way
Patterns of Mobility

Students are mobile...but in a particular way

- Current “best practices” recommendations in education indicate the use of MMREMs
- MMREMs are problematic because they don’t account for complex relations among schools
Multiple Membership Model

\[ \omega \sim N(\mathbf{Z}_w \cdot \beta, \tau_{00}) \]

\[ y \sim N(\omega + X \cdot \gamma, \sigma^2) \]

- Weights are often assigned (not estimated) as \(1/H\), where \(H\) is the number of schools attended by student \(i\)

- A naive, first-school approach is a special case of this model where the first school is given a weight of 1 and subsequent school weights are set at 0

- \(\mathbf{Z}_w\) is constructed as \(w_{i,1} \cdot z_{p,1} + \ldots + w_{i,H} \cdot z_{p,H}\) - assumes 0 correlation between schools
### Correlations Among School Residuals (J=266)

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<td>1. First School Attended</td>
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<td></td>
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<tr>
<td>2. Second School Attended</td>
<td>0.479</td>
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<tr>
<td>3. Third School Attended</td>
<td>0.396</td>
<td>0.392</td>
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### What do real data tell us? (HS Algebra)

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<tr>
<td>2. Second School Attended</td>
<td>0.432</td>
<td>—</td>
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</tr>
<tr>
<td>3. Third School Attended</td>
<td>0.359</td>
<td>0.375</td>
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What do simulations tell us?

Where do MMREMs fail?

- High Correlation (all)
- Gets worse with increasing ICC
What do simulations tell us?

Where do MMREMs fail?

- High Correlations (0.25, 0.50)
- Gets worse with increasing ICC
Goals of the Current Study

• Demonstrate the need for more appropriate methodological approaches to student mobility

• Illustrate the use of network analyses in this context using statewide longitudinal data

• Provide guidelines for future methodological studies
What is a Social Network?

- A social network is a set of relations or ties among individuals or entities.
  - Online relationships – e.g. Facebook (Lewis et al., 2008)
  - Friendships and personal relationships (Ennett and Bauman, 1993)
  - Workplace relationships (Krackhardt and Porter, 1986; Spillane et al., 2012)
  - Political alliances (Smith and White, 1992)
Social Network Analyses

Social Selection

Network as outcome variable
Estimate the impact of covariates on network ties

Social Influence

Network as a “predictor”
Estimate the impact of network ties on some outcome of interest
Constructing Mobility Networks

• Utilize statewide longitudinal data from the Maryland Longitudinal Data System

• Advantages: provides census-level information on students and professionals living and working in Maryland
Maryland High School Facts

- Maryland is a state with 24 counties

- In 2014, there were 174 schools in MD classified as public high schools serving students grades 9 - 12 (excluding Charter, Vocational, K through 12, and other alternative schools).

- The total Grade 9 enrollment for these schools in 2014 was 201945.

- Among students in Grade 9 alone, the mobility rate in 2014 was approximately 47%, with about 16.5% coming from mid-year entries and about 30.5% coming from mid-year exits.
A toy example:
A toy example:

Sch. A (get) — Sch. B (get) — Sch. A (get) — Sch. B (get)

Sch. A (send) — Sch. B (send)

2 0 3 0

23
Maryland School Networks
Visualization by Covariates
Descriptives: Node-level disruption

Out-degree: the number of ties sent by a node

In-degree: the number of ties received by a node
Predicting a Network

To predict binary (ordinal) network ties, we could use logistic (ordinal/probit) regression.

Standard GLMs assume independent observations.

Network ties are NOT independent.
Latent Space Model (for binary ties)

\[
\text{logit} \, P[Y_{ij} = 1] = \beta X_{ij} - |Z_i - Z_j|
\]

- \(Y_{ij}\) is the value of the tie from node \(i\) to node \(j\)
- \(X_{ij}\) is a set of covariates
- \(Z_i\) is the latent space position for node \(i\)

We assume ties are independent conditional on the latent space positions.
Latent Space Positions
Hierarchical Latent Space Models

\[ P(Y|X, \Theta) = \prod_{k=1}^{K} \text{LSM for } Y_k \]

\[ (\Theta_1, \ldots, \Theta_K) \sim F, \]

Implementation of the HLSM

• Aggregated student-level, school-level information, and county-level information assessed
  • Aggregated student-level
    • FARMS, suspensions, assessment performance, attendance
  • School-level
    • Previous year graduation and college enrollment rates
  • County-level
    • Previous-year average county wages, expenditures per student
Selected trace plots for the full HLSM
Examples of parameter non-convergence

County-Level Expenditures Per Student (Sender)

County-Level Expenditures Per Student (Receiver)
County-Level Expenditures Per Student

(Sender)

(Receiver)
Percent of FARMS Eligible Students

(Sender)

(Receiver)
Results summary

- County-level expenditures have an important school sender/receiver effects above and beyond aggregated student characteristics (more $$ = more students received)

- Measures of student poverty remained important predictors of network ties for many counties (higher poverty rates increased the likelihood of observing a tie for both sender & receiver schools)
Where do we go from here?

- Future methodological work needed to investigate the following issues
  - Small cluster-level sample sizes and within-network sample sizes are problematic for estimation
  - Social selection models do not fully place mobility networks in their causal systems
- Explore use of multilevel social influence modeling against MMREMs


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