Evaluating Bayesian Transition Diagnostic Classification Models for Reporting Within-Year Progress

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Importance of Reporting Within-Year Progress

- Supplements performance results by providing additional information to students and parents
- Provides feedback to educators and administrators
- Supports the theory of action for assessments when it involves making progress

Diagnostic Modeling

- Diagnostic classification models (DCMs) assume discrete latent constructs (i.e., attributes)
  - For DCMs, the attributes are frequently binary and labeled as masters and nonmasters
- DCMs estimate the probability that each examinee is a member of each latent class
  - Outputs attribute mastery profiles

Log-Linear Cognitive Diagnosis Models (LCDMs)

- One of the more prevalent DCMs
- Uses an approach similar to ANOVA
  - Measurement model sums the log-odds for the mastered attributes

Transition Diagnostic Classification Models (TDCMs)

- The longitudinal extension of the LCDM
  - The TDCM uses the LCDM measurement model with latent transition analysis
- Models changes in attribute mastery statuses over time
- Item invariance is assumed across assessment points
  - E.g., items are just as difficult at Time 2 as at Time 1

Objectives

- Compare TDCM-based estimates of within-year progress to LCDM-based estimates of within-year progress in a simulation study
  - TDCM
  - Full-year LCDM (separately scoring data from each window)
  - Window-specific LCDMs

Simulation Factors

Factor/Level	Description
Transition from mastery to nonmastery	
Unconstrained	U[0.00, 1.00]
Moderate constraint	U[0.00, 0.50]
Large constraint	U[0.00, 0.15]

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Data Structures

- We simulated the data based on data collected from an operational alternate assessment from 2016—2017 to 2021—2022
  - Assessment is intended to be scaled with a DCM
  - Skills are individually modeled using single-attribute LCDMs
    - Produces TDCMs with 4 possible transitions

Simulated Parameters

- We based the item parameters and base rate of mastery in each repetition on randomly selected models from the alternate assessment's operational calibration
  - Produces operationally realistic parameter values
- The items in the alternate assessment are assumed to be fungible

Example Transition Matrix

Fall	Spring	
	Nonmaster	Master
Nonmaster	.30	.15
Master	.20	.35

Data Simulation

- Simulate number of examinees and items based on data structure
- Establish true parameter values
- Assign true transitions to students
- Simulate item responses based on true transition and parameter values

Model Evaluation

- Classification accuracy
  - Defined as the percent correct
- Measured at two levels
  - Overall classification accuracy (student-level transitions)
  - Marginal classification accuracy (student-level mastery in the fall and spring)

Model Estimation Results

- 900 estimated TDCMs
- 2,566 estimated LCDMs
  - 872 (97%) full-year LCDMs
  - 1,694 (94%) window-specific LCDMs
- All 134 LCDMs that did not complete took longer than 12 hours to estimate

Classification Accuracy

Type of classification accuracy	Transition constraint	TDCM	Full-year LCDM	Window-specific LCDM
Overall	Unconstrained	.80	.60	.66
	Moderate	.78	.58	.61
	Large	.78	.63	.65
Marginal – Fall	Unconstrained	.88	.74	.77
	Moderate	.87	.70	.72
	Large	.86	.70	.72
Marginal – Spring	Unconstrained	.89	.78	.82
	Moderate	.88	.77	.79
	Large	.88	.81	.83

Summary of Results

- The TDCM showed higher classification accuracy than the LCDM-based approaches
- Classification accuracies were consistent across the transition constraint

Discussion

- LCDM-based approaches appeared to miss significant aspects of within-year progress
- Full-year LCDM aggregates data across windows
  - Changes in attribute mastery may be obscured
- Window-specific LCDM did not assume item invariance
  - Progress as evidenced by improved performance may be interpreted as easier items

Thank you!

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