

‘Tough Love’ Interventions

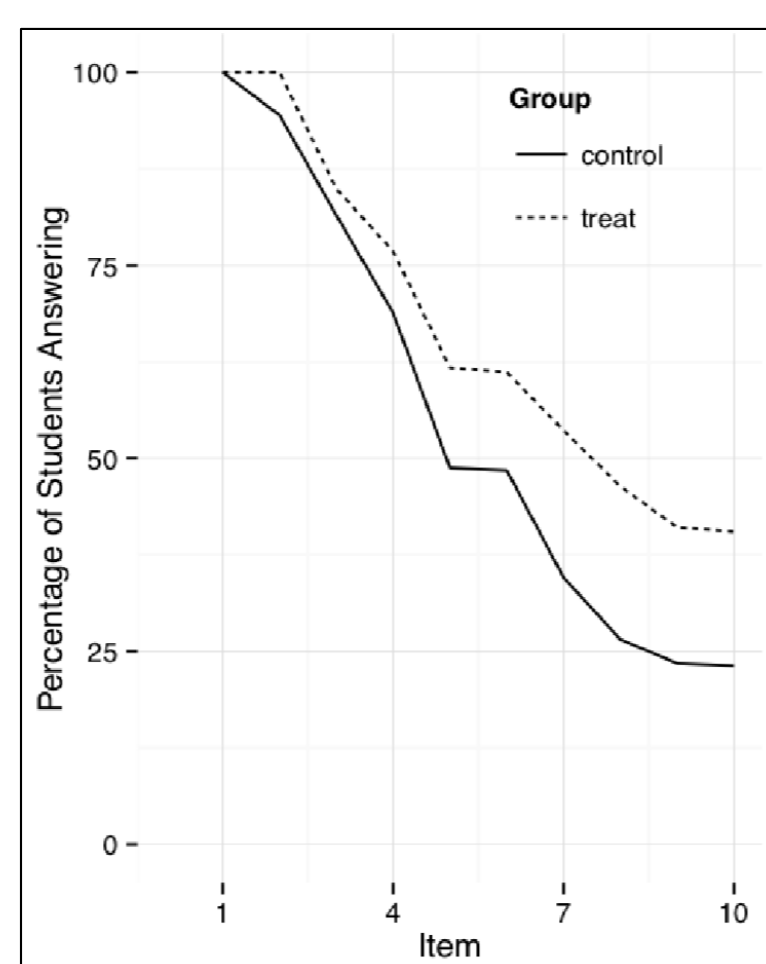
- A ‘tough love’ intervention (TLI) has a large effect but also increases the propensity of students to stop out of their work
- Such interventions are difficult to identify due to the selection bias caused by students who do not finish assignments
- Our goal here is to introduce Principal Stratification as a method of comparing student performance in the presence of differential attrition

Principal Stratification

- Principal Stratification is a statistical method used here to restrict analysis to the “stratum” of students who always complete their work
- It uses counterfactual analysis to identify students who would never stop out, regardless of condition

Case Study

- We use an existing study run in ASSISTments that asked students about their confidence before completing certain problems
- The study exhibited differential attrition making it difficult to fairly compare student performance



The figure on the right depicts the variable attrition between experimental and control groups in the case study

The Attrition Model

- Principal Stratification uses two models: the Attrition Model and Outcome Model
- The Attrition Model predicts if students in one condition would have attrited in the opposing condition

		Behavior in Control Condition	
		Attrits	Completes
Behavior in Treatment Condition	Attrits	AA (Always Attriters)	AC
	Completes	CA	CC (Never Attriters)

The four strata of students, based on whether they would complete the assignment depending on their condition

Attrition Model

$$\text{logit}(Pr(\text{completes}_{i,ctrl} = 1)) = \alpha_{ctrl} + \beta_{ctrl} * acc_i$$

$$\text{logit}(Pr(\text{completes}_{i,treat} = 1)) = \alpha_{treat} + \beta_{treat} * acc_i$$

Outcome Model

$$\text{masteryspeed}_i = \beta_{0s} + \beta_{1s} * acc_i + \beta_2 * cond_i + \sigma_i$$

The equation for the Attrition Model (top) to predict if each student would complete in the opposing condition and Outcome Model (bottom) observing performance of those students who never attrite

- With the known attrition value and the inferred counterfactual, students are ‘stratified’ into one of four categories
- Analysis can then be performed on just the stratum of interest, the Never Attriters

The Outcome Model

- The models are fit using Markov Chain Monte Carlo (MCMC) with four chains run over 16000 iterations (the first 8000 are used as a burn-in period to allow convergence)
- The outcome model observes ‘mastery speed’ as the performance metric – the number of problems needed to reach a sufficient threshold of understanding (the threshold in this study was 3 consecutive correct responses)
- For those students who would finish in either condition, no significant effect of the treatment is found
- The results (bottom) are compared to a traditional OLS analysis (top) yielding vastly different coefficient estimates
- A simulation study was then run to determine how well Principal Stratification is able to identify a ‘tough love’ intervention when it does exist

	mean	sd	0.95 CI	Rhat
Constant	1.78	0.13	(1.52,2.04)	1
Prior_Percent_Correct	-0.14	0.18	(-0.49,0.21)	1
Treatment	0.02	0.05	(-0.08,0.11)	1

	mean	sd	0.95 CI	Rhat
Constant	2.95	0.31	(2.34,3.55)	1
Prior_Percent_Correct	-1.33	0.39	(-2.09,-0.56)	1
Treatment	0.02	0.06	(-0.1,0.14)	1

Coefficients for the outcome model that predicts mastery speed based on condition and prior accuracy without using Principal Stratification (top) versus those using Principal Stratification (bottom)

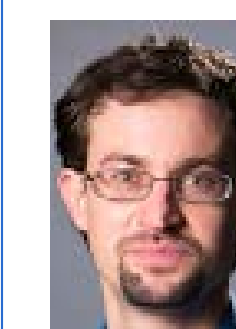
Simulation Study

- To further test the effectiveness of Principal Stratification to find ‘tough love’ interventions, 500 datasets were simulated to exhibit TLI treatments
- Traditional OLS confidence intervals included the average treatment effect 62% of the time while the Principal Stratification method included the treatment effect 91% of the time

Discussion

- A ‘tough love’ intervention was NOT found in our case study, but Principal Stratification provided the means to fairly measure the effects of treatment
- Identifying TLI’s is just one example of Principal Stratification, but differential attrition poses a wide-range of challenges to analyzing experiments in online learning platforms such as MOOCs

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