Causal Inference in Educational Systems

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Objectives

Our research targets the use of quasi-experimental and observational studies with emphasis on graphical and causal DAGs.
We propose to model the educational system as time-varying treatment and confounder feedback and claim that if a sufficient number of confounders are measured, the joint causal effect of interventions on the outcome can be estimated accurately Our method requires small changes in measurements that vastly simplify the computations while allowing more Hypotheses to be studied

Motivation

- Prior studies on education have mostly followed the model of the cross -sectional study, namely, examining the pretest, posttest and single intervention.
- Analyzing longitudinal data reveal useful information about the system that cannot be captured by cross-sectional studies.
- Large volume of educational data demand more complex and more intelligent inference algorithms.
- Learning is inherently a sequential process but existing techniques only handle a single intervention

Prior Work

- Hidden Markov Model (HMM) to analyze the student trajectory throughout an educational game.
- Bayesian knowledge tracing (BKT): a two state HMM where the probability of forgetting a concept is zero.
- Intelligent Tutoring system (ITS)

Limitation

- No control for the confounders.
- No account for modeling the feedback to students.
- No account for the loss-to-follow up.

O_1 X O_2

(a) Design without a control group

O_1 X O_2
O_1 O_2

(b) Design with a control group

Background

Potential Outcome (PO) Model:

- Y^a or Y_a is the outcome that would be observed if the treatment was set to A=a.

Background

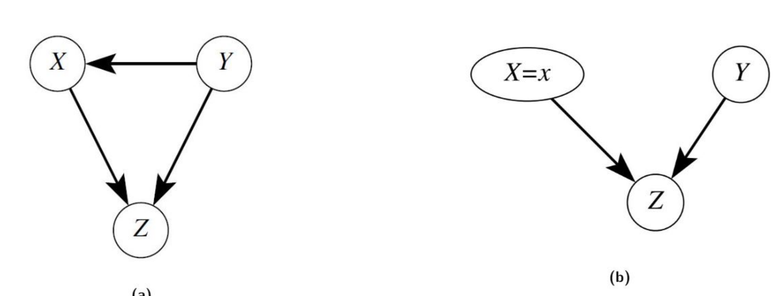
Counterfactual:Outcome would have been observed had the treatment been different, namely the unobserved outcome.

Graphical Model

Level (Symbol)	Typical Activity	Typical Questions
1. Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in$Y$?
2. Intervention $P(y\|do(x), z)$	Doing Intervening	What if? What if I do X?
3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?

Figure: Hierarchy of Causal Models

- Pre-intervention DAG
- Post-intervention DAG



- Structural Causal Model (SCM)

$$Y = f_Y(U_Y) \qquad Y = f_Y(U_Y)$$
$$X = f_X(Y, U_X) \qquad X = x$$
$$Z = f_Z(X, Y, U_Z) \qquad Z = f_Z(x, Y, U_Z)$$
$$U_X \perp\!\!\!\perp U_Y \perp\!\!\!\perp U_Z$$

Observational Study in Education

Problem Formulation

- $X_1, X_2, \ldots, X_T$ are time varying treatments, such as:
  - Reading chapter of book.
  - Solving some problems.
- $L_1, L_2, \ldots, L_T$ are observed and $U_1, U_2, \ldots, U_T$ are unobserved time varying confounders, such as:
  - Prior knowledge of subject.
  - Psychological/stress problems.
- O is the outcome. such as an exam score.
- $C_1, C_2, \ldots, C_T$ are time varying censoring variables. C = 1 (censored) and C = 0 (uncensored).

Objective Find the causal effect of joint interventions $X_1, X_2, \ldots, X_T$ on O.

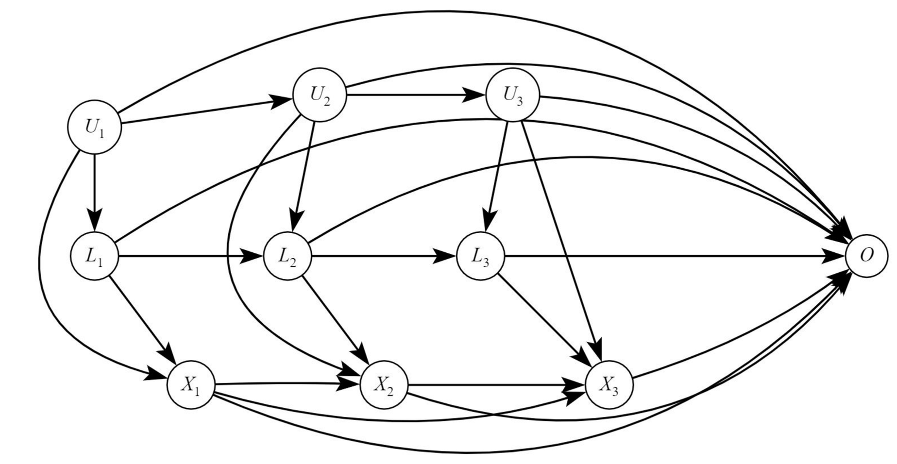


Figure: Time Varying Treatment and Confounder

Observational Study in Education

What happens if there is a treatment-confounder feedback:

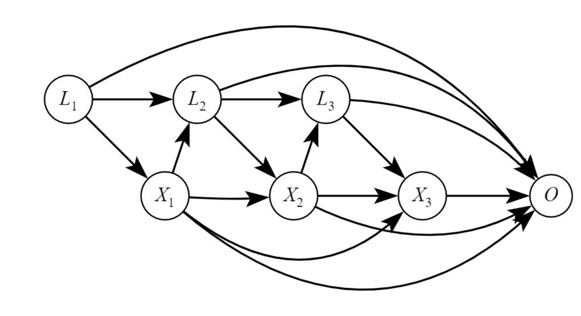


Figure: Treatment-Confounder Feedback

- Traditional methods such as regression would fail.
- Problem can be solved efficiently using Inverse Probability of Treatment Weighting (IPTW).
- Weight elements by the inverse of the probability of treatment received.
- Results in pseudo-population, where confounders and treatments are not connected.

Results

Experimental Setup: All treatments and confounders: X_1, X_2, X_3, L_1, L_2 and L_3 are Bernoulli random variables. The outcome (O) is normally distributed.

No unmeasured confounders

Coefficient	True	Estimate
Intercept	0.2	0.21
X_1	2	1.88
X_2	5	5.02
X_3	6	5.91
X_1X_2	1	0.97
X_1X_3	1	1.19
X_2X_3	1	0.99

With unmeasured confounders

Coefficient	True	Estimate
Intercept	0.2	1.2
X_1	2	3.68
X_2	5	5.42
X_3	6	6.45
X_1X_2	1	-0.92
X_1X_3	1	-0.51
X_2X_3	1	0.74

Treatment-Confounder Feedback

Coefficient	True	Regression Estimate	IPTW
Intercept	2.13	5.09	2.67
X_1	-2.42	4.12	-2.31
X_2	2.3	5.02	2.27
X_3	6	5.93	6.16

Conclusion

- A single intervention is not sufficient and does not provide enough feedback to students.
- Model the education system as time varying treatment-confounder feedback.
- Measure and account for sufficient set of confounders to close as many backdoor paths as possible.
- Can be done with simple means:
  - Include questions on potential confounders in diagnostic test.
  - Instruct TA's to inquire during office hours.