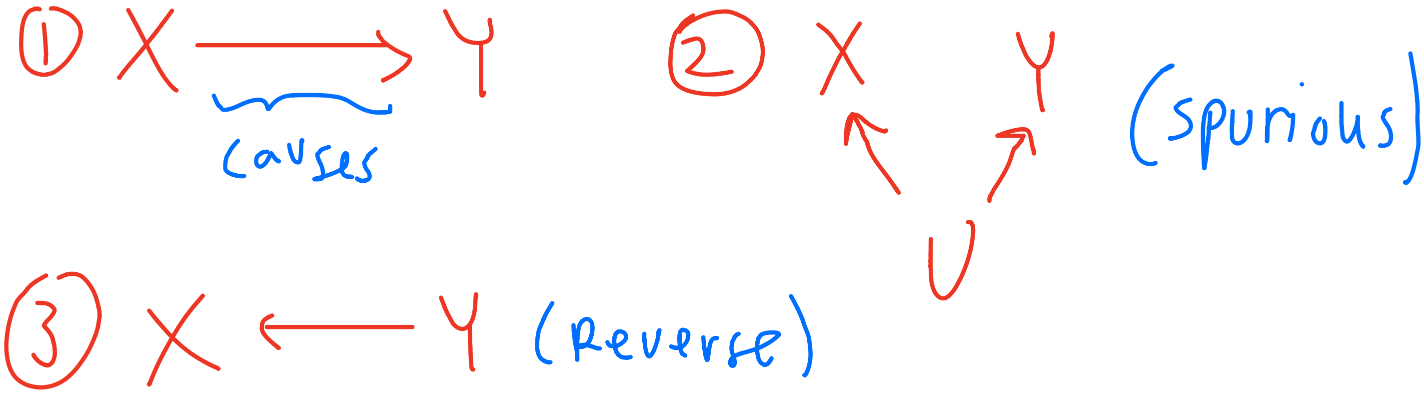
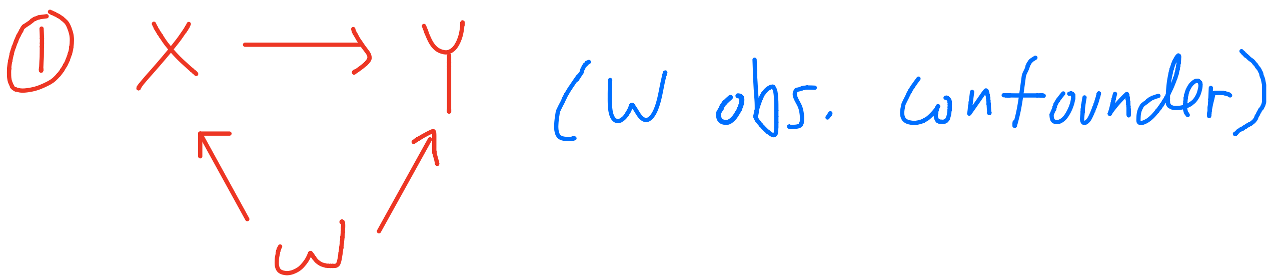
Potential Outcome and Directed Acyclic Graph Approaches to Causality: Relevance for Empirical Practice in Economics, July 2019, By Guido W. Imbens (Summary by Hammad Shaikh)

Introduction

- *Reverse* causal inference questions interested in addressing why an outcome occurred, and *forward* causal inference is about determining the impact of some intervention.



- Given joint distribution between (X,Y) we can determine associations between variables. However associations can occur due to multiple reasons (as shown in examples above), and we need a causal model to determine that X causes Y.



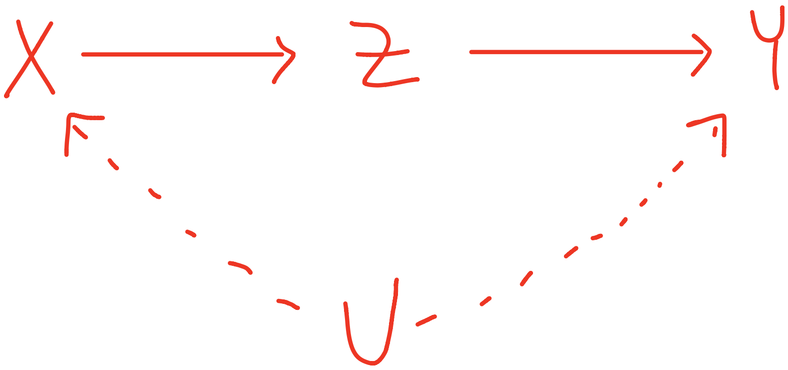
- A *collider* is a variable caused by two different variables (the treatment and outcome for example).
- Directed paths are paths that go in the same direction, a path that is not directed must have at least one collider in it.
- P(Y|do(X)) manipulates the distribution of Y for different values of X. Can be used to make causal inferences.
- When the impact of X on Y is identified, then P(Y|X) = P(Y|do(X))

Back-door Criterion

- Provides systematic method of controlling for variables such that identification is achieved.
- The causal effect of X on Y is identified if all backdoor paths from X to Y are blocked by conditioning on some set of variables.

Front-door Criterion

- Does not require blocking all back door paths to identify causal effect of X on Y.
- Assumption is that effect of X on Y is entirely mediated by Z (along path from X to Y), similar to exclusion restriction of IV.
- Another assumption is that U is not correlated with Z but still related to X and Y.
- The idea is that total effect of X on Y decomposed into X on Z and Z on Y. The effect Z on Y can be identified by controlling of X (closes Z <-- X <-- U --> Y). The effect of X on Z can be directly estimated as there are not confounders. Taking the product of the two effects results in the total effect from X on Y.
- Not used in economics yet, might be difficult to justify this environment.



possible to identify

$X \longrightarrow Y$

① $X \longrightarrow Z$ identified $\Rightarrow P(Z|X) = P(Z|do(X))$

② $Z \longrightarrow Y$ identified controlling for X

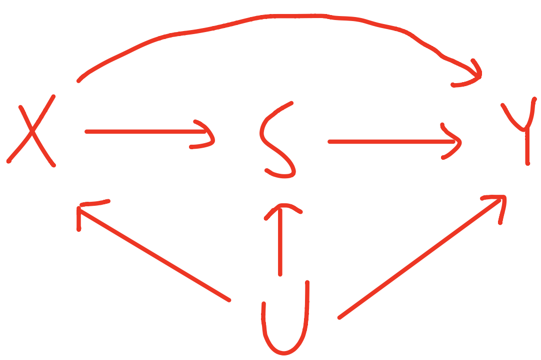
$\Rightarrow P(Y|Z,X) = Pr(Y|do(Z),X)$

$$P(Y|do(X)) = \sum_{x'} \sum_{z} P(Y|z,x)\, P(x')\, P(z|X)$$

Mediation and Surrogates

- Mediation is about understand causal paths from some treatment to the outcome of interest.

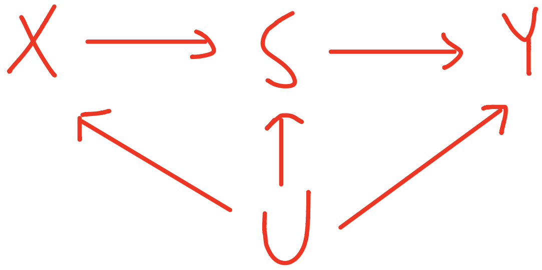
<u>Mediation</u>



S = mediator

- If no unobserved in above DAG, the DAG is insightful about estimating 1) X on Y (directly since no confounders), 2) S on Y (control for X), and 3) X on S (the difference between first two).
- Surrogate is environment with no direct effect from treatment to the outcome.

Surrogate



- DAG not insightful about estimation in surrogate scenario.
- In the surrogate setting goal is estimate impact of treatment on outcome without observing them both at the same time, but the surrogate is observed.

Potential Outcome Model

$$\text{POM: } Y_{obs} = \sum_{x} Y(x)\, I(X=x)$$

- Components of POM are 1) Treatment, 2) Multiple units, and 3) Assignment mechanism,
- **Assignment Mechanism:** How does the assignment to treatment depend on the pre-treatment variables and potential outcomes.
  - In a experiment we know the assignment mechanism does not depend on potential outcomes since the treatment is randomly assigned.

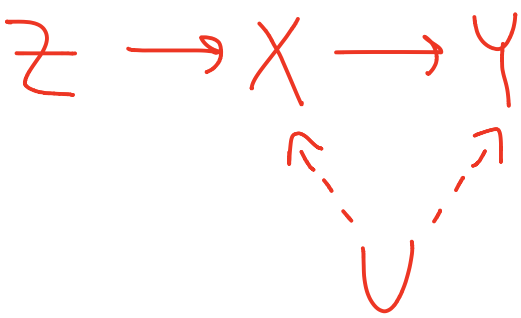
Graphical Models, Potential Outcomes and Empirical Practice in Economics

- DAGs not good for identifying subpopulations for which causal effects be measured. Also not good for formulation assumptions such as monotonicity.
- DAG issues: 1) importance of manipulability in RCT, 2) IV and shape restrictions, 3) simultaneity in economics, 4) unconfoundedness, 5) counterfactuals, and 6) returns to education.
- Gender is not a causal variable is it cannot be manipulated.
- Imbens perspective is that do(obesity = x) doesn't make sense if obesity is indirectly changed by exercise or diet and not directly manipulated.

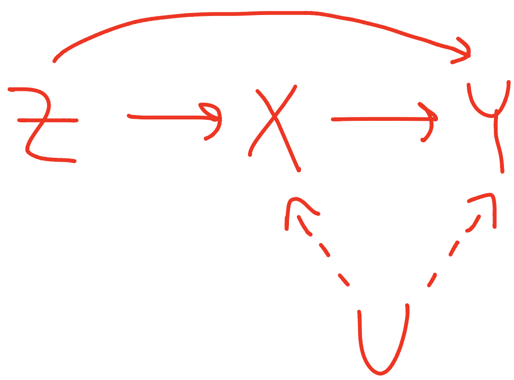
Instrumental variables and Compliers

- Some key assumptions of IV not captured in DAG but are represented in POM.
- Identification of LATE is not easily derived from DAG.
- Key IV assumptions 1) Z doesn't directly effect Y (*exclusion*) and 2) No unobserved confounders correlated with Z and X or Y (*exogeneity)*

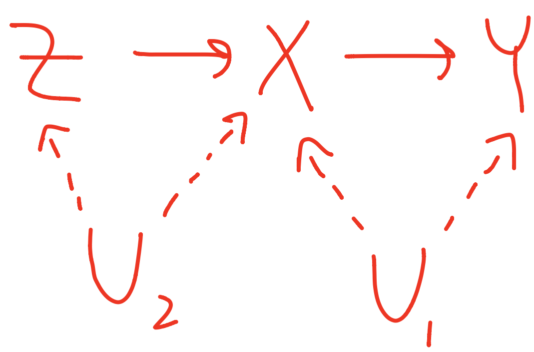
IV



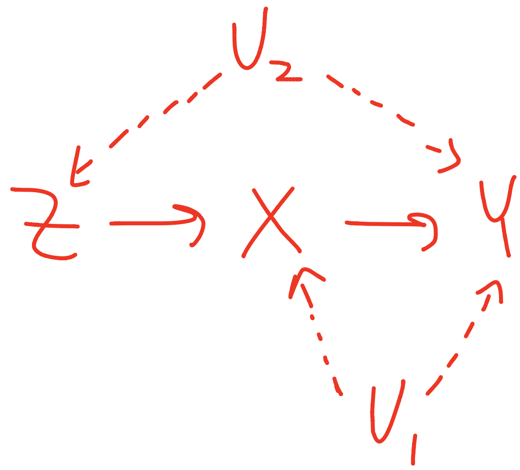
Exclusion Violation



Exog. Violation



Exog. Violation



IV assumption POM

1) **Exclusion:** $Y_i(z_i, X_i) = Y_i(z_i', X_i), \forall z_i \neq z_i'$

2) **Unconfoundedness:** $Z_i \perp \{\{Y_i(z_i, X_i)\}, \{X_i(z_i)\}\}$

3) **Monotonicity:** $X_i(1) \geq X_i(0)$

- Let Z = randomly given scholarship in high school, X = I(attend college), Y = adult earnings
- *Exclusion* says potential outcomes are not directly impacted by value of IV. That is the receiving high school scholarship itself doesn't effect your adult earnings.
- *Unconfoundedness* says instrument is independent of potential outcomes and also potential treatment status. That is adult earnings are independent of whether a individual is a high or low earner. Similarly students being assigned the scholarship is not related to how it affects their decision to attend college.
- *Monotonicity* says that their are no defiers in the population.

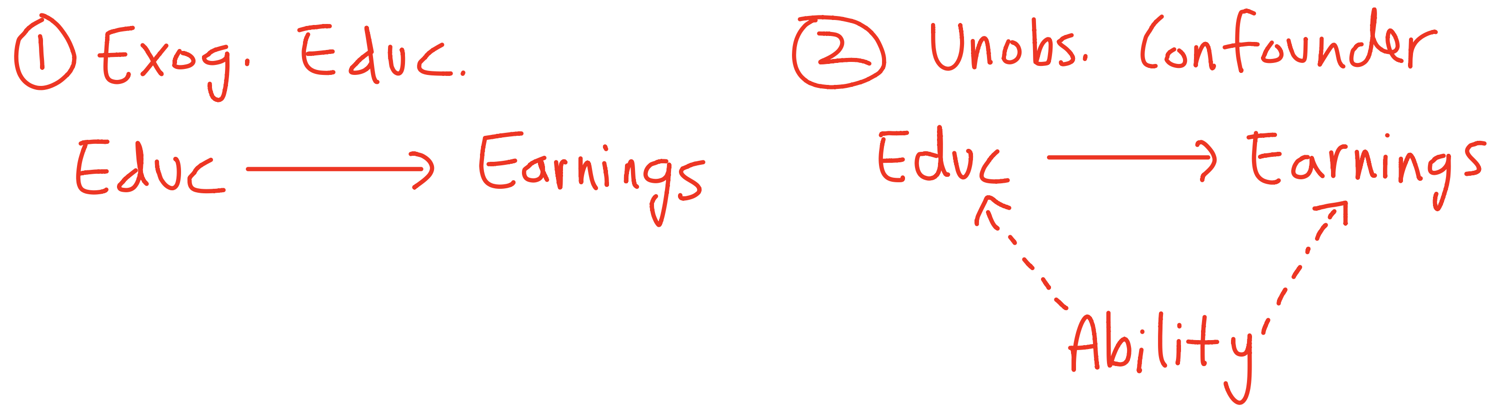
Regression discontinuity
- Note DAGs not useful for articulating regression discontinuity designs.
- Graphs with running variable on x-axis and outcome or density on y-axis are informative about RDD approach.

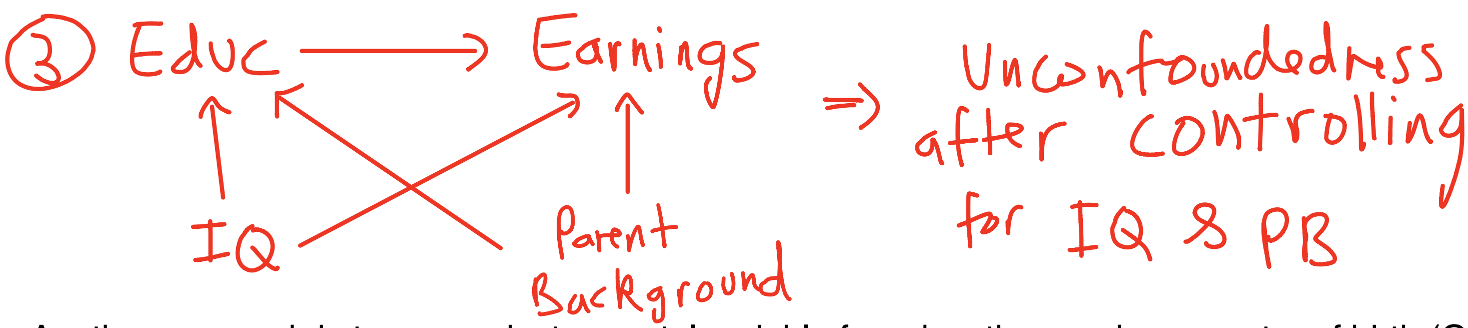
Simultaneity
- Cannot clearly represent supply and demand using DAG framework.

Unconfoundedness
- Potential outcome literature generally suggests to control for all pre-treatment variables. One exception to this rule is if the pre-treatment variable is an instrument.
- It is possible to construct DAG where conditioning for pre-treatment variable introduces collider bias, but these may be very unlikely in practice.

Returns to Education Application

- A first pass to estimating returns to education is regress log earnings on years of education.
  - Identifies returns to education if education levels are randomly assigned in population.
- Since ability is correlated with potential outcomes (e.g. earning potential increases ability and is correlated with education), simple regression estimates will be biased.
  - Upwards bias returns to education is ability is positively correlated with education.
- One identification approach is to measure ability through IQ scores of parental background and control for it when estimation impacts of education and earnings.





- Another approach is to use an instrumental variable for education, such as quarter of birth (QOB) or distance to college.
- Another strategy is to associate difference in sibling/twin earnings with the corresponding differences in the sibling/twin education levels. This implicitly controls for family and genetic background.
  - More difficult to represent all the assumptions behind the fixed sibling fixed effects strategy in DAG framework.