

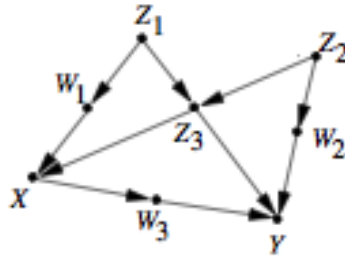
Fundamental structural causal modeling (SCM) questions

For concreteness, consider two models for discussion (but without specifying their content). The models are nonparametric, structural models with endogenous variables $Y, X, Z_1, Z_2, Z_3, W_1, W_2, W_3$, mutually independent, unobserved exogenous variables $U, U', U_1, U_1', U_2, U_2', U_3, U_3'$, and arbitrary, unknown functions $f, f_1, f_2, f_3, g, g_1, g_2, g_3$.

Model 1

$$\begin{aligned} Y &= f(W_3, Z_3, W_2, U) & X &= g(W_1, Z_3, U') \\ W_3 &= g_3(X, U_3') & W_1 &= g_1(Z_1, U_1') \\ Z_3 &= f_3(Z_1, Z_2, U_3) & Z_1 &= f_1(U_1) \\ W_2 &= g_2(Z_2, U_2') & Z_2 &= f_2(U_2) \end{aligned}$$

The DAG below is equivalent to the algebraic representation.



Model 1b is the same except the direction between X and Z_3 is reversed, $X \rightarrow Z_3$. In the familiar, special linear model case, we have Model 2

$$\begin{aligned} Y &= aW_2 + bZ_3 + cW_3 + U & X &= t_1W_1 + t_2Z_3 + U' \\ W_3 &= c_3X + U_3' & W_1 &= a_1Z_1 + U_1' \\ Z_3 &= a_3Z_1 + b_3Z_2 + U_3 & Z_1 &= U_1 \\ W_2 &= c_2Z_2 + U_2' & Z_2 &= U_2 \end{aligned}$$

The orthogonality conditions render these equations regressional. However, if some of the endogenous variables are not measurable, then we can illustrate non-regressional models. We explore the following 8 fundamental questions.

1. Testable implication (misspecification tests)
 - a. What are the testable implications of assumptions embedded in model 1?
 - b. Assume only X, Y, Z_3 , and W_3 are measured, are there any testable implications?
 - c. The same as (b), except only X, Y , and Z_3 are measured?

- d. The same as (b), except all but Z_3 are measured?
- e. What statistical tests distinguish between models 1 and 1b?
- f. Identify the regression coefficient for the test devised in e.

2. Equivalent models

The conditions for edge replacement are (i) Rule 1: An arrow $X \rightarrow Y$ can be replaced by a bidirected arrow $X \leftrightarrow Y$ only if every neighbor or parent of X is inseparable from Y . (By neighbor we mean any node connected to X by a bidirected arrow). (ii) Rule 2: An arrow $X \rightarrow Y$ can be reversed by $X \leftarrow Y$ only if every neighbor or parent of Y (excluding X) is inseparable from X every neighbor or parent of X is inseparable from Y . Further, in a Markovian model (a *DAG* with jointly independent errors) arrows are reversible if and only if every parent of X is also a parent of Y .

- a. Which arrows in the DAG can be reversed without being detected by any statistical test?
- b. Is there an equivalent model (statistically indistinguishable) in which variable Z_3 can be made a mediator between X and Y (arrow $Z_3 \rightarrow X$ is reversed)?

3. Identification

- a. Suppose we wish to identify the average causal effect of X on Y

$$ACE = \Pr[Y \mid do(X = 1)] - \Pr[Y \mid do(X = 0)]$$

Which subsets of variables need to be adjusted to obtain an unbiased estimate of ACE ?

- b. Is there a single variable, if adjusted would allow an unbiased estimate of ACE ?
- c. If there is a choice between subsets of variables $\{Z_3, Z_1\}$ or $\{Z_3, Z_2\}$, which would be preferred?

4. Instrumental variables

Definition 1 (Instrument) *A variable Z is an instrument for the $X \rightarrow Y$ relationship if there exists a set of measurement $S = s$, unaffected by X , such that the following graphical criteria holds. (i) $(Z \perp\!\!\!\perp Y \mid S)_{G_{\bar{X}}}$ and (ii) $(Z \not\perp\!\!\!\perp X \mid S)_G$ where $\perp\!\!\!\perp$ is read not independent.*

Definition 2 (linear-IV estimand)

$$b \equiv \frac{\partial}{\partial x} E[Y | \hat{x}] = \frac{E[Y | z, s]}{E[X | z, s]} = \frac{r_{YZ.S}}{r_{XZ.S}}$$

where $r_{AB.C}$ is the regression coefficient for A regressed on B conditional on C .

Definition 3 (Generalized conditional instrument) Z is an instrument for the parameter c in the $X \rightarrow Y$ relationship conditional on variable set W if the following conditions are satisfied: (1) W contains only non-descendants of Y ; (2) W d -separates Z from Y in the subgraph G_c , obtained by removing edge $X \rightarrow Y$ from G ; (3) W does not d -separate Z from X in G_c .

Definition 4 (Generalized conditional IV estimand)

$$c \equiv \frac{\text{Cov}[Y, Z | w]}{\text{Cov}[X, Z | w]} = \frac{r_{YZ.W}}{r_{XZ.W}}$$

where $r_{AB.C}$ is the regression coefficient for A regressed on B conditional on C .

a. Is there an instrumental variable for the $Z_3 \rightarrow Y$ relationship? If so, what is the (linear) IV estimand for parameter b in model 2?

b. Is there an instrumental variable for the $X \rightarrow Y$ relationship? If so, what is the (linear) IV estimand for the product c_3c in model 2?

5. Mediation

The total effect of $X \rightarrow Y$ is $\Pr(Y | \hat{x})$. The average (natural or pure) total effect can be decomposed into average direct and indirect effects. The direct effect is the sensitivity of Y to changes in X holding all other factors constant. For the example, this implies there is no direct effect for $X \rightarrow Y$ as it is mediated by W_3 and holding W_3 constant disconnects X from Y .

Indirect effects are only defined for averages. The average direct effect is

$$DE_{x,x'}(Y) = E[Y(x', Z(x)) - E[Y(x)]]$$

where Z represents all parents of Y excluding X and $Y(x', Z(x))$ represents the value Y would take under action $X = x'$ and simultaneously setting Z to the value obtained when setting $X = x$. The average indirect effect is

$$IE_{x,x'}(Y) = E[Y(x, Z(x')) - E[Y(x)]]$$

and is interpreted as the value Y would obtain holding X constant at x while changing the value of Z to whatever it would obtain if X is set to x' . Their sum is the average total effect

$$\begin{aligned} TE_{x,x'}(Y) &= DE_{x,x'}(Y) + IE_{x,x'}(Y) \\ &= E[Y(x') - Y(x)] \end{aligned}$$

In the simple case of unconfounded mediators, the natural direct and indirect effects are estimable via two regressions called the mediation formula.

$$\begin{aligned}
DE_{x,x'}(Y) &= \sum_z \{E[Y | x', z] - E[Y | x, z]\} P(z | x) \\
IE_{x,x'}(Y) &= \sum_z E[Y | x, z] \{P(z | x') - P(z | x)\}
\end{aligned}$$

a. What variables must be measured if we wish to estimate the direct effect of Z_3 on Y ?

Graphically, the expected natural direct effect is identified if there exists four set of variables, W_0, W_1, W_2, W_3 such that

- (i) $(Y \perp\!\!\!\perp Z | W_0)_{G_{XZ}}$
- (ii) $(Y \perp\!\!\!\perp X | W_0, W_1)_{G_{X\bar{Z}}}$
- (iii) $(Y \perp\!\!\!\perp Z | X, W_0, W_1, W_2)_{G_{\underline{Z}}}$
- (iv) $(Z \perp\!\!\!\perp X | W_0, W_3)_{G_{\underline{X}}}$
- (v) W_0, W_1, W_3 contain no descendant of X and W_2 contains no descendant of Z

and its estimand for $X \rightarrow Y$ in Markovian models is

$$\begin{aligned}
&NDE(x, x^*; Y) \\
&= \sum_s \sum_z \{E[Y | x, z] - E[Y | x^*, z]\} \Pr(z | x^*, s) \Pr(s)
\end{aligned}$$

b. What variables must be measured if we wish to estimate the indirect effect of Z_3 on Y , mediated by X ?

The expected natural indirect effect is identified analogously to the expected natural direct effect but with x and x^* reversed. That is, the average natural indirect effect is identified if there exists a set W , nondescendants of X or Z , such that

$$Y_{x^*z} \perp\!\!\!\perp Z_x | W \quad \text{for all } z, x$$

and its estimand is

$$\begin{aligned}
&NIE(x, x^*; Y) \\
&= \sum_w \sum_z E[Y_{x^*z} | w] \{\Pr(Z_x = z | w) - \Pr(Z_{x^*} = z | w)\} \Pr(w)
\end{aligned}$$

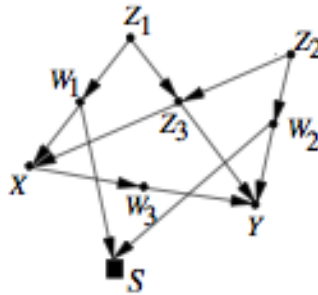
c. What is the estimand for the indirect effect in (b), if all variables are binary?

6. Sampling selection bias

Suppose we wish to estimate the conditional expectation $E[Y | x = x]$ and samples are preferentially selected to the data set depending on a set V_s of variables.¹

a. Let $V_s = \{W_1, W_2\}$, what set, T , of variables need be measured to correct for selection bias? (Assuming we can estimate $\Pr(T = t)$ from external sources e.g., census data.)

Consider the augmented graph G_S below where node or variable $S = 1$ for inclusion in the sample and 0 for exclusion.



b. In general, for which sets, V_s , would selection bias be correctable.

c. Repeat (a) and (b) assuming that our aim is to estimate the causal effect of X on Y .

7. Linear digressions (consider the linear model, Model 2)

a. Name three testable implications of this model

b. Suppose X, Y , and W_3 are the only variables that can be observed. Which parameters can be identified from the data?

c. If we regress Z_1 on all other variables in the model, which regression coefficient will be zero?

d. If we regress Z_1 on all the other variables in the model and then remove Z_3 from the regressor set, which coefficient will not change?

¹For a more complete discussion see Pearl, 2012, "A solution to a class of selection-bias problems."

e. (“Robustness” – a more general version of d.) Model 2 implies that certain regression coefficients will remain invariant when an additional variable is added as a regressor. Identify five such coefficients with their added regressors.

8. Counterfactual reasoning

The back-door condition leads to conditional independence. For the causal effect $X \rightarrow Y$, the back-door condition involves identifying a conditioning set Z such that

1. we block all spurious paths from X to Y ,
2. we leave all directed paths unperturbed,
3. we create no new spurious paths.

a. Find a set S of endogenous variables such that X would be independent of the counterfactual Y_x conditioned on S .

b. Determine if X is independent of the counterfactual Y_x conditioned on all the other endogenous variables.

c. Determine if X is independent of the counterfactual $W_{3,x}$ conditioned on all the other endogenous variables.

d. Determine if the counterfactual relationship $\Pr(Y_x|X = x)$ is identifiable, assuming that only X, Y , and W_3 are observed.