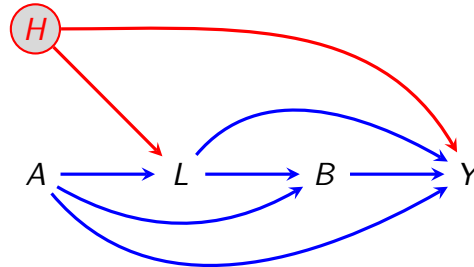


# Post-Module Exercises

## Part 4: Sequential Treatment and the g-formula

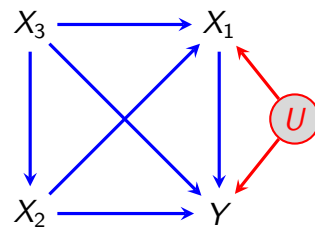
Consider the sequential treatment DAG  $\mathcal{G}$  shown below.



The variable  $H$  is unobserved,  $A$  and  $B$  represent treatments, and  $L$  and  $Y$  an intermediate and final outcome respectively.

- Form the SWIG  $\mathcal{G}[a, b]$ .
- Using d-separation, show that  $A \perp\!\!\!\perp L(a)$  under distributions Markov with respect to  $\mathcal{G}[a, b]$ . Then, via consistency and the independence provide a formula to compute  $P(L(a) = \ell)$  using only  $P(A = a, L = \ell)$ .
- Show that  $Y(a, b)$  is d-separated from  $\{A, B(a)\}$  given  $L(a)$  in  $\mathcal{G}[a, b]$ .
- Use the fact proved in c) to find a simple identifying expression for  $P(Y(a, b) = y \mid L(a) = \ell)$  in terms of a conditional probability that can be computed from the observed distribution  $P(A = a, L = \ell, B = b, Y = y)$ .
- Use your answers to b) and d) to derive an identifying expression for  $P(L(a) = \ell, Y(a, b) = y)$ , and hence obtain one for  $P(Y(a, b) = y)$ . *[Hint: don't overthink this!]*

## Part 4: Causal DAGs and multiple regression



Assume the simplistic causal DAG above is correctly specified, where  $Y$  = (a measure of) infant health,  $X_1$  = birth weight,  $X_2$  = maternal smoking during pregnancy,  $X_3$  = maternal education,  $U$  = unmeasured genetic predisposition.

Further consider the following (linear) regressions and assume for simplicity these models are correctly specified. Explain whether the coefficients of  $X_1$ ,  $X_2$ , and/or  $X_3$  have an interpretation as a causal effect, and if so state what type of effect it is.

- Regress  $Y$  on  $X_1$ .
- Regress  $Y$  on  $X_2$ .
- Regress  $Y$  on  $X_3$ .
- Regress  $Y$  on  $X_1$  and  $X_2$  jointly.
- Regress  $Y$  on  $X_1$  and  $X_3$  jointly.
- Regress  $Y$  on  $X_2$  and  $X_3$  jointly.
- Regress  $Y$  on  $X_1$ ,  $X_2$  and  $X_3$  jointly.
- What other sensible analyses might you suggest?

## Part 5: Instrumental Variables

Consider the standard IV set-up with instrument  $G$ , exposure  $X$ , outcome  $Y$ , unobserved confounder  $U$ , and assume that the IV conditions are satisfied.

(a) Assume all observable variables  $G, X, Y$  are binary.

(i) Use a SWIG to show that  $Y(x) \perp\!\!\!\perp G$ .

(ii) Show that  $E(Y(1) - Y(0)|X = 1, G = g) = \psi$  is equivalent to

$$E(Y|X = x, G = g) - E(Y(0)|X = x, G = g) = \psi x.$$

(iii) Use (i) and (ii) to show that

$$\psi = \frac{E(Y|G = 1) - E(Y|G = 0)}{E(X|G = 1) - E(X|G = 0)}.$$

Trick: take expectation over  $X$  given  $G = g$ .

(b) Now, for continuous  $Y$ , assuming

$$E(Y|X = x, U = u) = \mu_Y + \beta x + h(u),$$

show that

$$\beta = \frac{\text{Cov}(Y, G)}{\text{Cov}(X, G)}.$$

State clearly what IV assumptions you use.

Trick: define  $\tilde{G} = G - E(G)$  and work out  $E(Y\tilde{G})$ .

(c) Typical data, where IVs might be useful, are obtained from case-control studies: this means that 50% of the observations were sampled from known ‘cases’  $Y = 1$  and the other 50% from known ‘controls’  $Y = 0$ .

(i) Draw a DAG that includes a sampling indicator  $S$  to represent this situation.

(ii) Give arguments for or against the validity of IV-based inference regarding (I) testing the null-hypothesis of no  $X \rightarrow Y$  edge; (II) estimating the causal effect of  $X$  on  $Y$  using  $G$  with a standard IV-method.