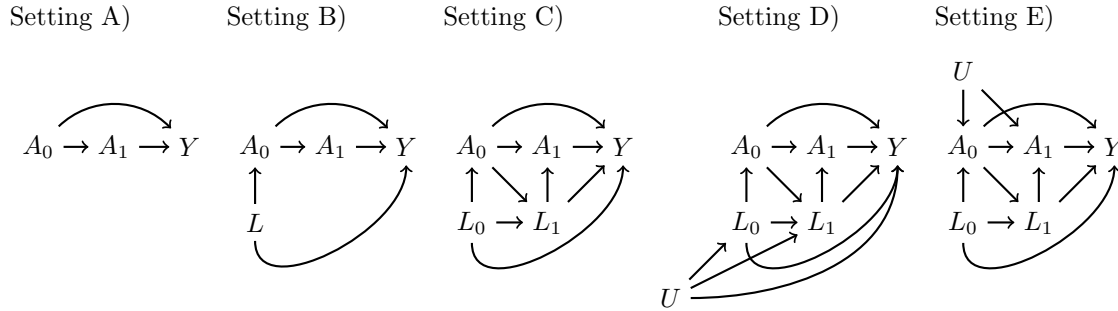


Submit a PDF. For Part 2, either embed your code in the PDF or include as an attachment.

## 1 Causal identification in dynamic settings (30 points)

In each DAG below, the researcher observes the outcome  $Y$  and the variables  $\{\vec{L}_t, A_t\}$  for every time period  $t$ . The researcher does not observe  $U$ .



The researcher wants to know the expected potential outcome  $E(Y^{a_0, a_1})$  under an intervention to set  $A_0 = a_0$  and  $A_1 = a_1$ . In which of settings A–E can this causal estimand be identified using

- 1.1. (10 points) The simple mean  $E(Y \mid A_0 = a_0, A_1 = a_1)$
- 1.2. (10 points) Inverse probability weights applied in a marginal structural model, adjusting at each period for the observed past

Now focus on Setting D.

- 1.3. (10 points) For Setting D, explain how  $L_1$  complicates the quest to jointly identify the causal effects of  $A_0$  and  $A_1$  using our usual adjustment strategies.

## 2 Causal estimation in a dynamic setting (20 points)

This problem is an extension of the class exercise from Tuesday. The goal is for you to practice estimating a marginal structural model in a dynamic setting designed to be as simple as possible.

Suppose a teacher observes students who are struggling academically ( $L_t = 1$ ) or not ( $L_t = 0$ ) in every time period  $t$ . The teacher can assign students to receive extra support ( $A_t = 1$ ) or not ( $A_t = 0$ ). The outcome  $Y$  is a subsequent measure of skills (e.g., can the student read a picture book to the teacher). The attached `pset8.csv` contains a simulated setting with  $n = 128$  students. It is not identical to the one from class, but as in class:

- Treatment  $A_t = 1$  is assigned with higher probabilities to students who are struggling  $L_t = 0$ .
- Students who are treated in one period  $A_0 = 1$  are never struggling in the next period  $L_1 = 0$ .

Assume the causal structure represented by Setting D above. Using these data,

- 2.1. (3 points) Fit a logistic regression for each  $A_t$ , including as predictors all pre-treatment variables entered without interactions.
- 2.2. (3 points) Predict the probability of  $A_t = 1$  at each time period for every unit. Remember that in R you will need the `type = "response"` option. For grading, what is the predicted value of  $A_0$  for the first unit in the sample?
- 2.3. (3 points) Define the generalized propensity score  $\pi_{it}$  at each time period  $t$  for each unit  $i$ . When  $A_{it} = 1$  this will be the number from 2.2. When  $A_{it} = 0$ , it will be  $1 - (\text{that number})$ .

- 2.4. (3 points) Define a weight for each unit:  $w_i = \frac{1}{\pi_{i0}} \frac{1}{\pi_{i1}}$ . For grading, what is the weight on the first unit in the sample?
- 2.5. (3 points) Estimate a marginal structural model of the form  $E(Y^{a_0, a_1}) = \alpha + \beta_0 a_0 + \beta_1 a_1$ . Report the coefficients.
- 2.6. (5 points) What does your model estimate for the average causal effect  $E(Y^{1,1} - Y^{0,0})$ ?