Psych 434 Quiz 1- Key Concepts and Causal Diagrams

March 25 2024

Answer by circling 'True' or 'False' (1pt $\times$ 10)

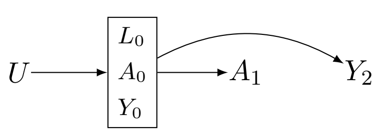
1. Association can never be causation: **TRUE / FALSE**.

   Answer: FALSE. When the assumptions satisfied for causal inference are met, then association consistently estimates causation.

2. Measurement error in the exposure variable will always threaten to bias a causal effect estimate, even if the outcome is measured without error: **TRUE / FALSE**

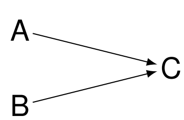
   Answer: True. Measurement error in either the exposure, the outcome, or the confounders will always threaten to bias a causal effect estimate.

3. According to this causal diagram, any association between A_1 on Y_2 would be an unbiased causal effect estimate: **TRUE / FALSE**

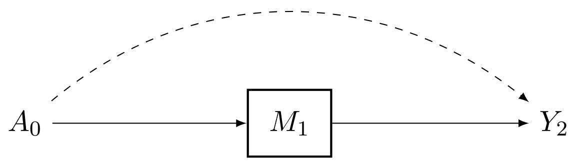
   Answer: True, because on this causal diagramme there are no open backdoor paths.

4. According to this causal diagram, $A \coprod B|C$: **TRUE / FALSE**

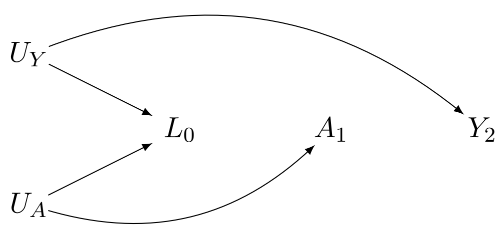
   Answer: False, C is a collider of A and B. Thus, if we were to condition on C, A and B would become associated. Put another way, $A \coprod B$, but $A \not\coprod B|C$

5. According to this causal diagram, if we were to condition on $\boxed{M_1}$, the total effect of $A_0 \to Y_2$ is guaranteed to be equal to the direct effect of $A_0 \to Y_2$: **TRUE / FALSE**



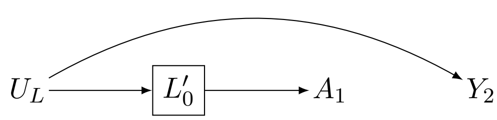
Answer: False. Conditioning on M_1 introduces mediator bias. If we condition on a mediator, there is no guarantee that the direct effect that we estimate corresponds to the total effect.

6. According to this causal diagram, there is no way to avoid bias when estimating the causal effect of A_1 on Y_2: **TRUE / FALSE**



False. According to this causal diagram, there are no open backdoor paths between A and Y. However, if we were to condition on L we would open a backdoor path. This bias is called M-bias, and it is an example of over-conditioning bias.

7. According to this causal diagram, if we were to condition on $\boxed{L'_0}$ then we would block all backdoor paths between A_1 and Y_2: **TRUE / FALSE**



Answer: True. Conditioning on $\boxed{L'_0}$, a descendant of U_L (which we assume is unmeasured), would block the back door path between A_1 and Y_2.

8. If the sample at baseline differs from the target population, and no further adjustment is made, we say the study lacks external validity: **TRUE / FALSE**

Answer: True. When the sample population differs from the target population a study lacks external validity.

9. If a study lacks internal validity, then it will also lack external validity, but if a study lacks

external validity, it will not necessarily lack internal validity **TRUE / FALSE**

Answer: True. For example, a randomised controlled experiment may be internally valid but lack external validity.

10. According to the rules of d-separation, if a variable L' is a descendant of an immediate parent variable L, then L' functions as a proxy for L such that conditioning on $\boxed{L'}$ is akin to conditioning on $\boxed{L}$: **TRUE / FALSE**

    Answer: True. Conditioning on an immediate descendant of a parent variable amounts to conditioning on the parent by proxy.

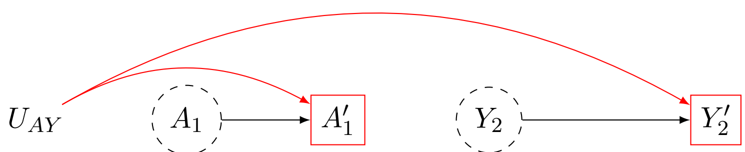
Answer *only three* of the five following questions (5 pt each). Attempt *two* short paragraphs for each answer. For each graph, assume that that we are interested in estimating the causal effect of A_1 on Y_2. (5pts $\times$ 3)

1. Briefly explain why we cannot estimate a causal effect of Y_1 on A_2 if the following causal diagram describes our data; give an example.

$Y_{\text{time 0}} \longrightarrow A_{\text{time 1}}$

Answer: The graph describes reverse causation. Y causes A. Association is causation, but not for the effect we seek. For example, suppose that we are interested in the effect of marriage (A) on happiness (Y). Suppose further that marriage does not affect happiness but that happy people tend to get married. In this example, the association between marriage and happiness would not reflect the causal effect of marriage on happiness.

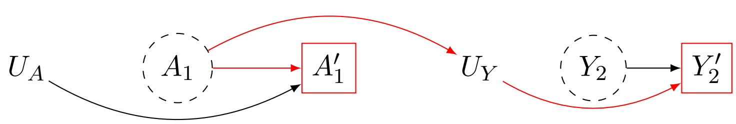
2. Briefly explain the threat of Measurement Error Bias in this causal graph; give an example.



Answer: The graph describes a setting in which the measurement error of the treatment and the outcome are correlated and there are no further biases.

For example, suppose that some participants want to appear socially desirable to researchers. Suppose further that attendance at religious service and charitable giving are socially desirable in the culture we are studying. This may lead to systematic reporting bias so that there is an inflation in both (reported) attendance at religious services and charity.

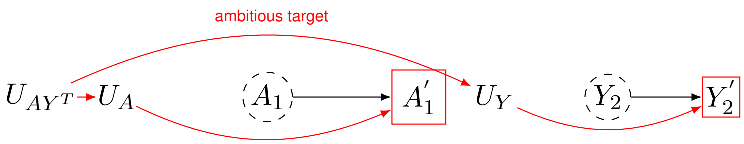
3. Briefly explain the threat of Measurement Error Bias in this causal graph; give an example.



This graph presents a bias of directed measurement error. Here, the treatment affects the error in measuring the outcome. There are no further biases. This may lead to an association in the absence of causation.

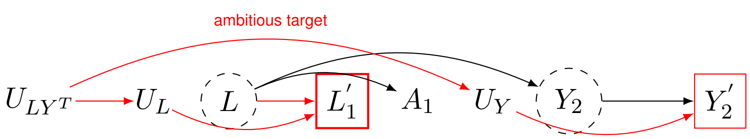
Answer: Return to the previous example. This time, suppose that social desirability bias does not lead people to report more attendance at religious services. However, imagine that attending religious service tends to increase social desirability bias (U_Y). In the setting described, we confront directed measurement error, which may lead to an association between the treatment and outcome without any causal effect.

4. Briefly explain the threat of External Validity in this causal graph; give an example.



Answer: The mis-measured exposure is a collider. It is caused by the true exposure and the unmeasured perturbation of the true exposure U_A. There is furthermore an unmeasured cause of U_A, called U_{AY^T}, that affects the measurement error of the outcome. This opens a path between the exposure and outcome, denoted by the red line, leading to bias in causal effect estimation.

5. Briefly explain the threat of External Validity in this causal graph; give an example.



Answer: Bias in the common cause of the measurement error of a confounder L_1', opens a path from the exposure to the outcome, indicated in red. This biasing path is through the measurement error of the confounder U_L and a common cause of this error and the measurement error of the outcome U_{LY^T} (Note the path from L $\to A_1$ should be coloured red.)

Extra Credit **(+1 point): which path in the causal diagram in Question 5 should be coloured red but is not. State the path and briefly explain.**

See previous answer.