Sufficient adjustment sets in DAGs

INFO/STSCI/ILRST 3900: Causal Inference

21 Sep 2023

Learning goals for today

At the end of class, you will be able to:

1. Identify a sufficient adjustment set using the backdoor criterion
2. Assess whether selection bias may hold in a gathered sample

Logistics

- Ch 7.1 - 7.4 in Hernan and Robins
- Homework posted today, due Sep 28

Open or blocked?

How to check if a path is open or blocked:

1. Traverse the path node by node (don't need to check the endpoints)
2. If any node is blocked, the entire path is blocked
3. If all nodes are open, then entire path is open

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How to check if a node is open or blocked:

- If non-collider:
  - Open if it is not in the conditioning set
  - Blocked if it is in the conditioning set
- If collider:
  - Open if it or any of its descendants are in the conditioning set
  - Otherwise it is blocked

Clarifications

Whether a node is a collider or non-collider depends on the specific path we are considering

$$\begin{tikzcd} & & H \arrow[dl] \arrow[dr] & \\ A \arrow[r] & Z \arrow[rr] & & Y \end{tikzcd}$$

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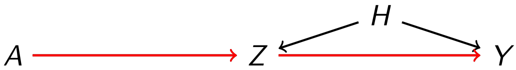

Z is a non-collider

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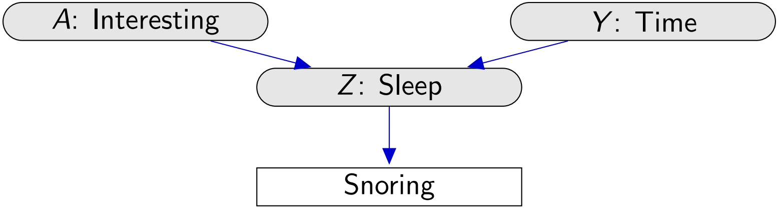
Z is a collider

Clarifications

Conditioning on the descendant of a collider opens the collider, even when it is not on the path we are considering



Clarifications

- A path is a causal path if all edges point from the treatment to the outcome
- Remains causal or non-causal regardless of whether it is open or blocked
- Can determine if path is causal or non-causal without considering what is being conditioned on

Big picture

- Conditional Exchangeability holds if **all** unblocked paths (given L) from A to Y are causal paths
- The only association we observe between A and Y is due to causation

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- Find a set of variables L that blocks all non-causal paths from A and Y
- L is called **sufficient adjustment set**
- **If** the DAG is true, this means $Y^a \perp\!\!\!\perp A \mid L$
- Use standardization (Lecture 2-3) or inverse probability weighting (Lecture 2-4) to estimate average causal effect

$$ACE = \mathrm{E}(Y^{a=1}) - \mathrm{E}(Y^{a=0})$$

Backdoor criterion

$$\begin{tikzcd} L \arrow[r] \arrow[rr, bend left] & A \arrow[r] & Y \end{tikzcd}$$

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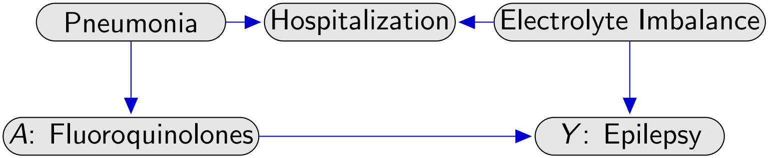
Sets that satisfy the backdoor criterion are sufficient adjustment sets!

Exercise

Researchers may be interested in the effect of fluoroquinolones, a class of antibiotics, on epilepsy[1]



- Does a sufficient adjustment set exist? If so, what is it?

[1] Example from "Using Causal Diagrams to Improve the Design and Interpretation of Medical Research" (Etminan et. al. 2020, Chest)

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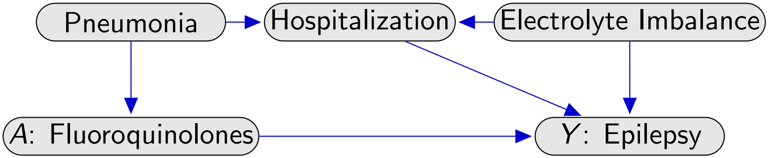

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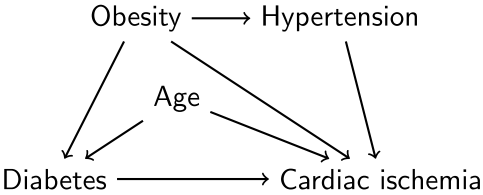
Exercise

Researchers may be interested in the effect of diabetes on cardiac Ischemia[3]



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[3]Example from "Using Causal Diagrams for Biomedical Research" (Kyriacou et. al. 2023, Annals of Emergency Medicine)

Selection Bias

- Sufficient adjustment set to close backdoor paths

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- Does not always mean conditioning on more things

$$\begin{tikzcd}
Z_1 \arrow[dr] \arrow[dd] & & Z_3 \arrow[dl] \arrow[dd] \\
& Z_2 & \\
A \arrow[rr] & & Y
\end{tikzcd}$$

Selection Bias

In some settings, certain variables may already be "conditioned on"

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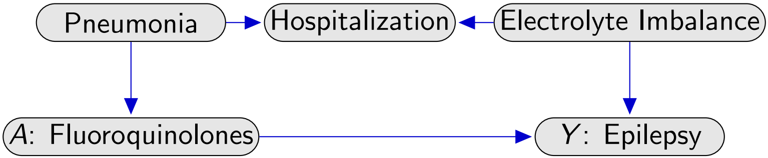

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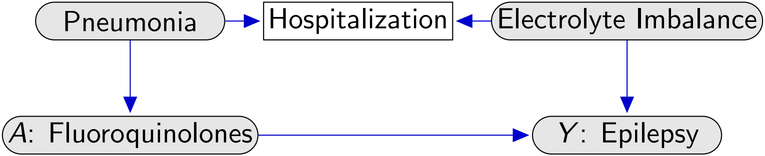

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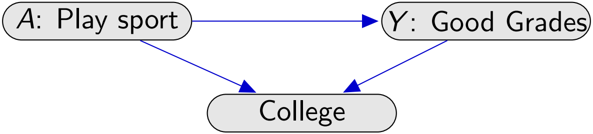
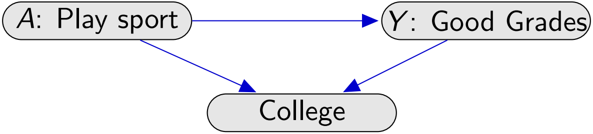
$$A\text{: Play sport} \longrightarrow Y\text{: Good Grades}$$

Selection Bias

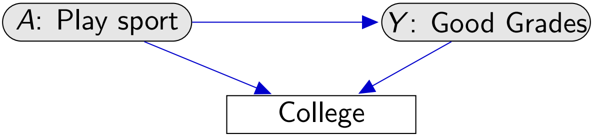


Selection Bias



$$A \perp\!\!\!\perp Y^a$$

Selection Bias



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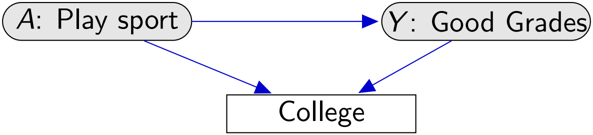

$$A \not\perp\!\!\!\perp Y^a \mid \text{College}$$

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- This may implicitly condition on a variable
- May open non-causal paths

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  - If it exists, use standardization or IPW to estimate causal effect
  - If it does not exist, consider gathering more variables
- Carefully consider the data gathering process

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- Causal claims come from assumptions + data

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