Sufficient adjustment sets in DAGs

INFO/STSCI/ILRST 3900: Causal Inference

19 Sep 2023

Learning goals for today

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

1. Identify a sufficient adjustment set for 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
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- 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

Big picture

- Find a set of variables L that blocks all non-causal paths from A and Y
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Backdoor criterion

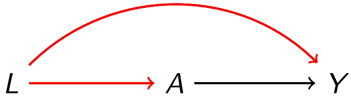
$$\begin{tikzcd} L \arrow[r] \arrow[rr, bend left] & A \arrow[r] & Y \end{tikzcd}$$

Backdoor criterion

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

Backdoor path starts with an edge pointing in to A and ends at Y

Backdoor criterion



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A set of variables satisfies the backdoor criterion if

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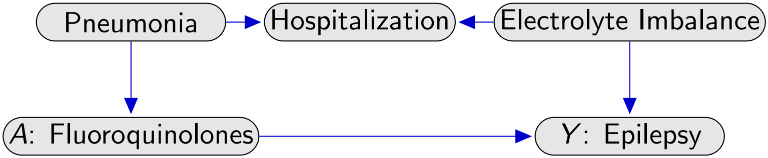
Sets that satisfy the backdoor criterion are sufficient adjustment sets!

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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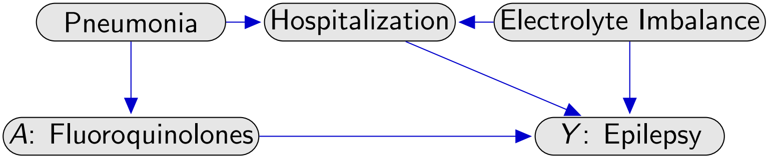

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[2]Example from "Using Causal Diagrams to Improve the Design and Interpretation of Medical Research" (Etminan et. al. 2020, Chest)

Exercise

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

$$
\begin{tikzcd}
 & \text{Obesity} \arrow[r] \arrow[ddl] \arrow[ddr] & \text{Hypertension} \arrow[dd] \\
 & \text{Age} \arrow[dl] \arrow[dr] & \\
\text{Diabetes} \arrow[rr] & & \text{Cardiac ischemia}
\end{tikzcd}
$$

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

[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"

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

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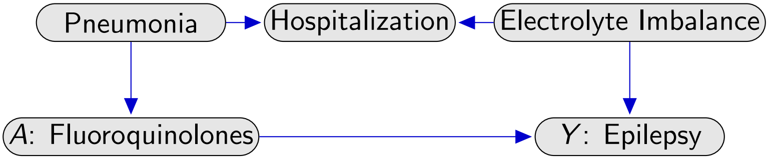

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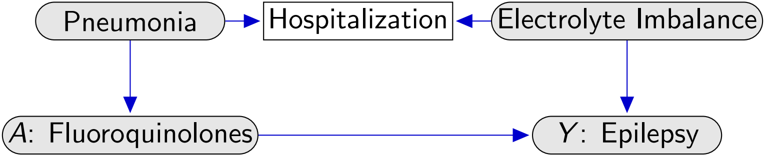

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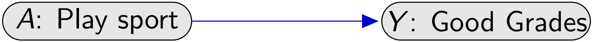

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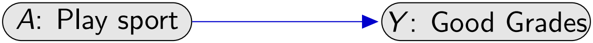

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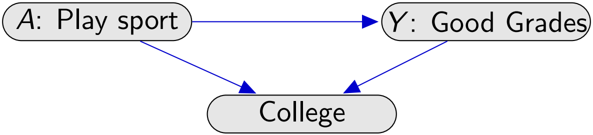

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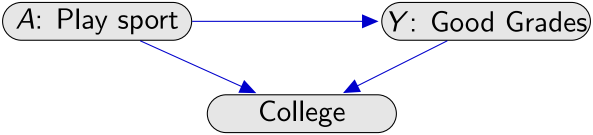
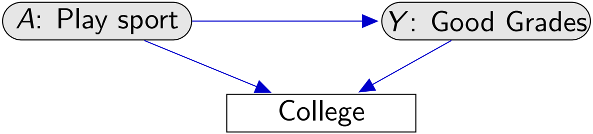


$$A \perp\!\!\!\perp Y^a$$

Selection Bias



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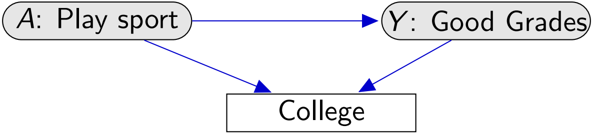

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- May open non-causal paths

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- Causal claims come from assumptions + data

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