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 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
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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}
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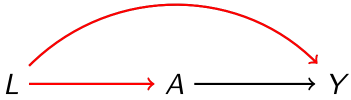
Backdoor criterion



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

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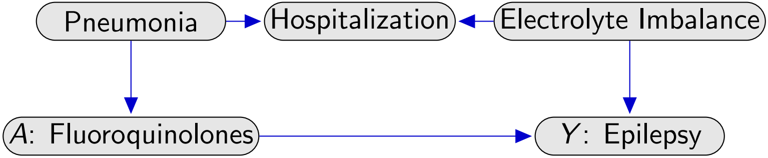
Sets that satisfy the backdoor criterion are sufficient adjustment sets!

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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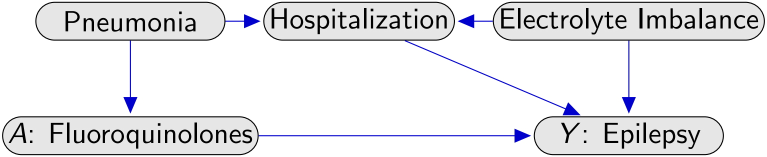

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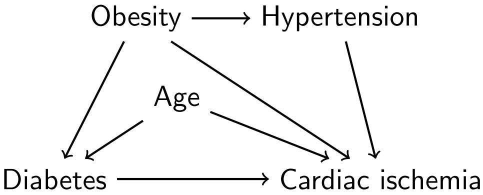
Exercise

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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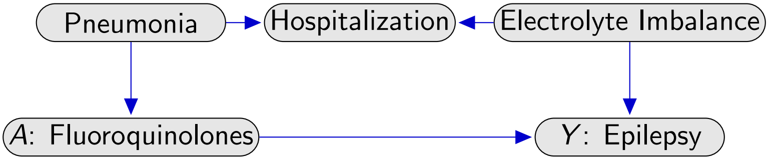

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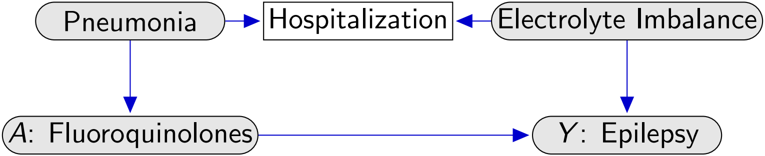

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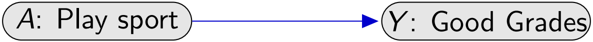

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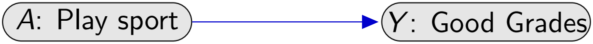

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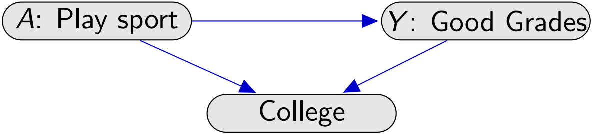

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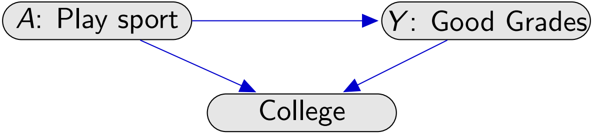

$$A \perp\!\!\!\perp Y^a$$

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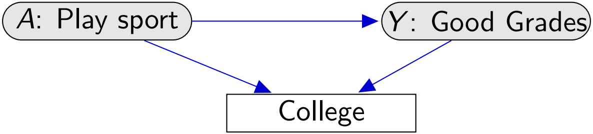

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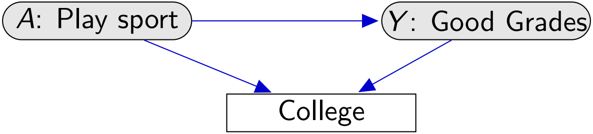

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- May open non-causal paths

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- Causal claims come from assumptions + data

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