Lab 2: DAGs

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January 26th, 2021

Introductory meme

When your code is a mess but it somehow still works.

Why use DAGs?

A short history

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- You’ll see there are different types
- And your empirical strategy depends on the type

Anatomy of a DAG

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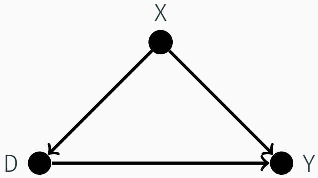

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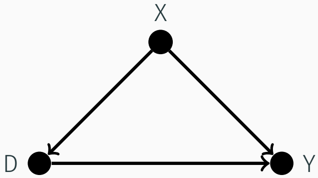

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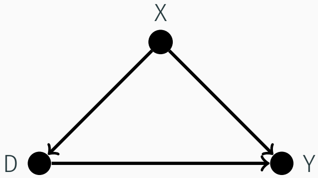

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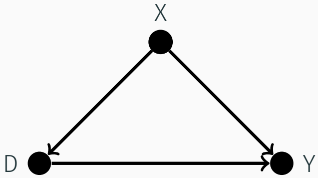

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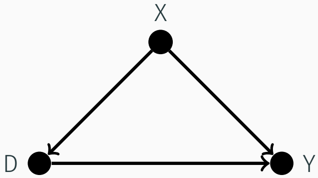

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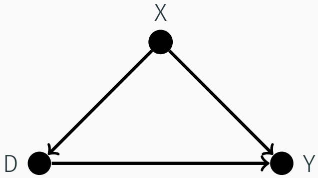

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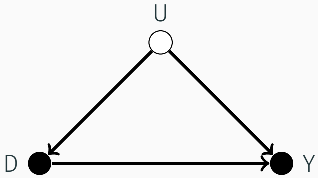
- What does that mean? What do we need to do?

Types of third variables

Confounder



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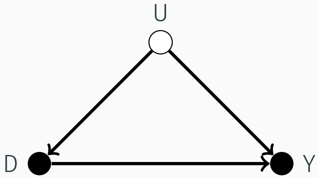

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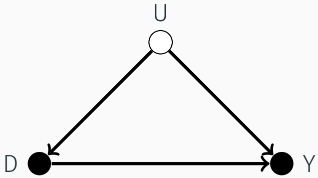

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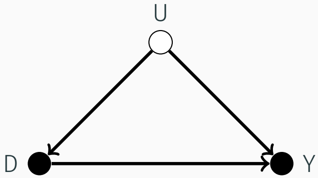

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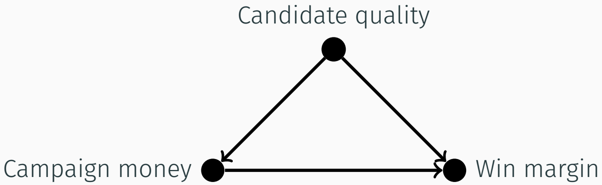
- Is the causal effect of D on Y identified?

Simple example

From Andrew Heiss:



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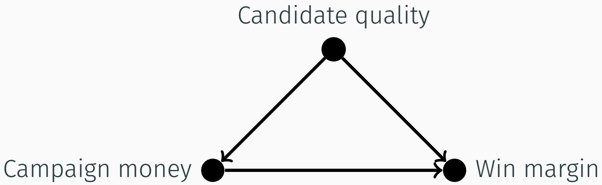

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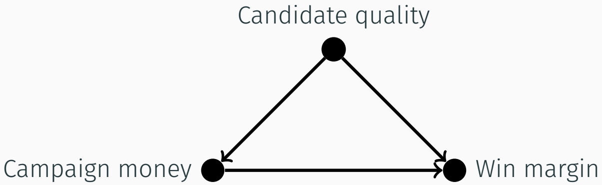

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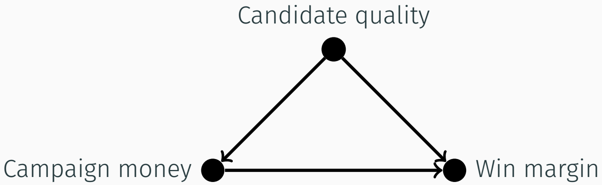

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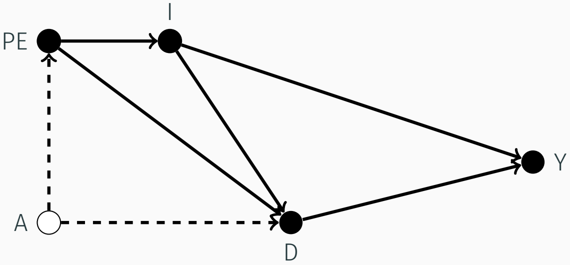
- To retrive the causal effect Money →Margin, I need to adjust/condition/control for Candidate Quality
- In other words: to block the backdoor path
- Matching, regression...

A more complex example

Drawn from the *Causal Inference Mixtape*:



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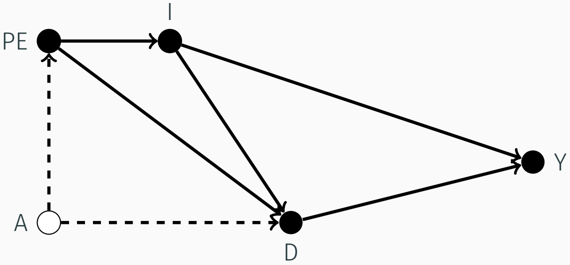


D: education

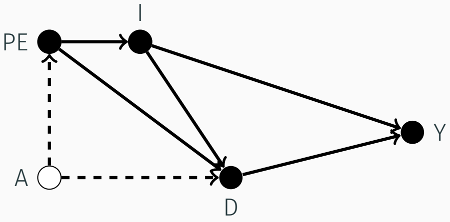
Y: wages

I: Parental income

PE: Parental education

A: (unobserved) ability

Paths in this DAG



We need to list all direct and indirect (backdoor) paths between D and Y

$D \rightarrow Y$ (causal effect of education on wages)

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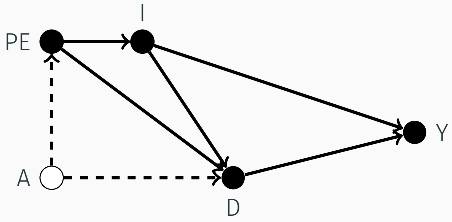

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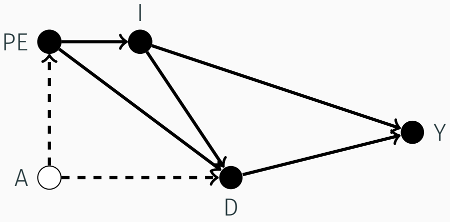

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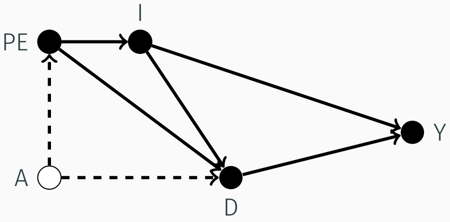

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We can identify the causal effect of interest!

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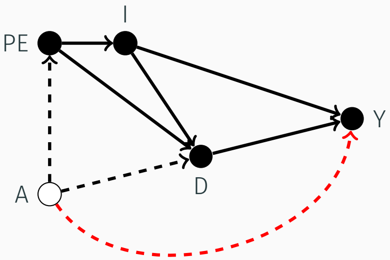
But what if ability has a direct effect on wages? And not only through education?



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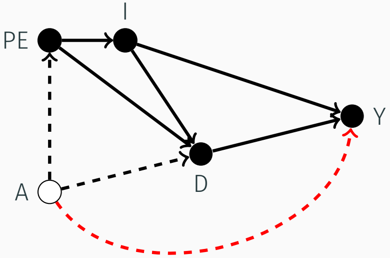

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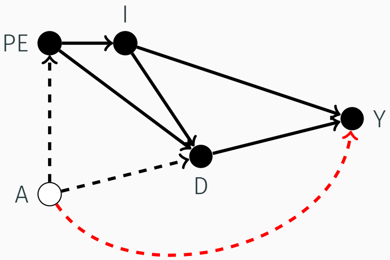

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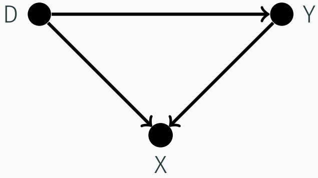
- Any solutions?

2nd type: Colliders

We've seen confounders, but we also need to be careful with colliders:



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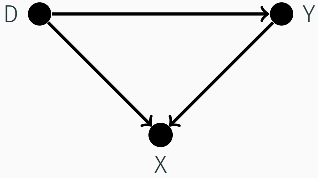

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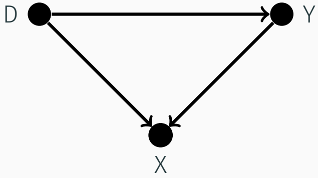

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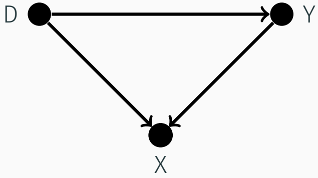

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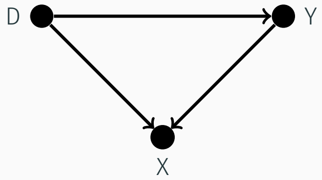

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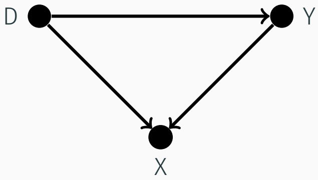

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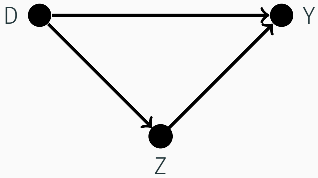
- But if you condition on the collider, **you open the backdoor path**

Causation between D and Z

What's going on here? Should I condition on Z?



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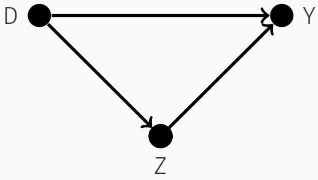

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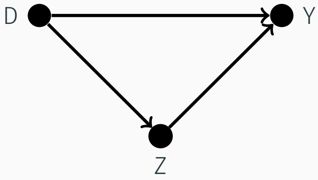

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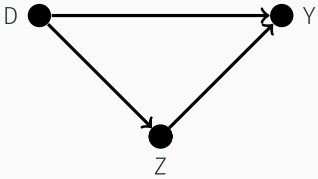

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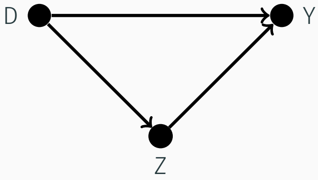

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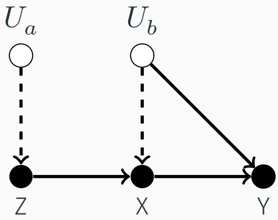
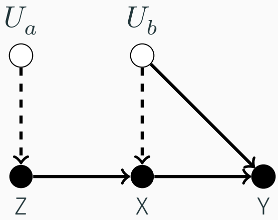
- Advanced topics: Mediation analysis for estimation of direct effect vs total effect

Some exercises





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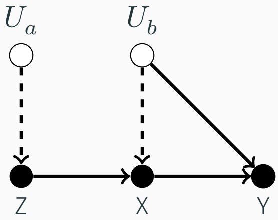

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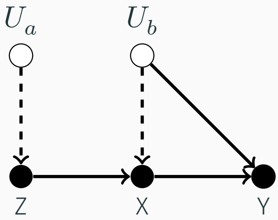

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2. List all directed edges
3. Is the relationship between X and Y identified? Why?

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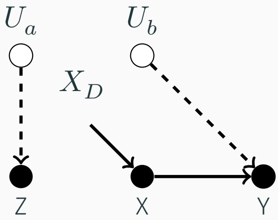

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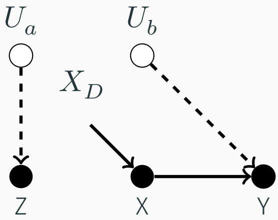

1. What is X_D?
2. Is the relationship between X and Y identified?

How do I draw these things?

- *ggdag* in R

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- This website

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- *ggdag* in R
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- tikz in Latex:

```
\begin{center}
  \begin{tikzpicture}[scale=0.8]
    \node[shape = circle, fill = black, label=west:D] (D) at (0, 0) {};
    \node[shape = circle, fill = black, label=east:Y] (Y) at (4, 0) {};
    \node[shape = circle, fill = white, draw = black, label=north:U] (X) at (2, 2) {};

    \path[->] (D) edge[draw=black,very thick] node {} (Y);
    \path[->] (X) edge[draw=black,very thick] node {} (D);
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  \end{tikzpicture}
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