

Recitation: DAGs and data analysis

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Recall we are interested in causal questions

What is the impact of D (your independent variable, the treatment) on Y (the outcome of interest or dependent variable)?

or...

Does D (your independent variable, the treatment) cause Y (the outcome of interest or dependent variable)?

Directed Acyclic Graphs (DAGs)

- Arrows connect the elements of your design.
 - Treatment and outcome.
 - Observable variables.
 - Unobservable variables.
- There should not be circularities (thus acyclic).
- If you can construct your DAG you can:
 - Identify problems of selection.
 - Define what is a confounder (pre-treatment).
 - Define what is a control but not a confounder (pre-treatment).
 - Define what is post-treatment (mechanism).

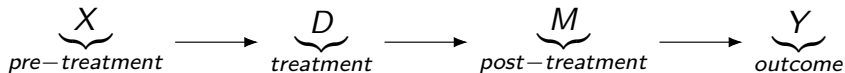
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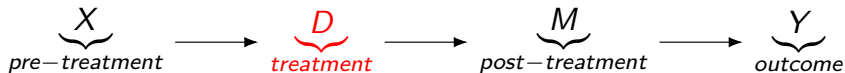
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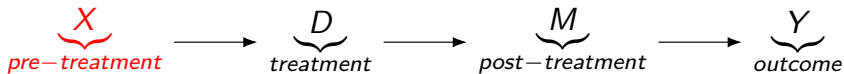
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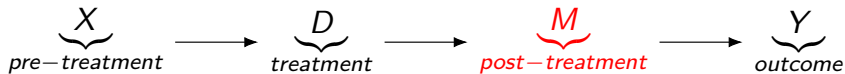
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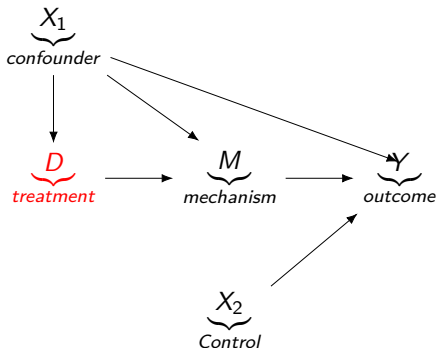
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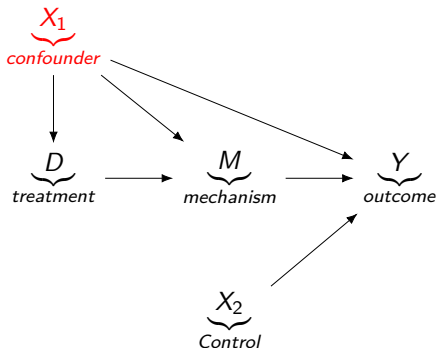


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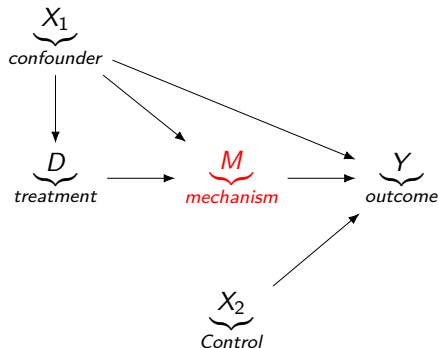
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- Control and confounder: affects treatment and outcome.
- Mechanism: it is a consequence of the treatment.
- Control but not confounder: affects only the outcome.

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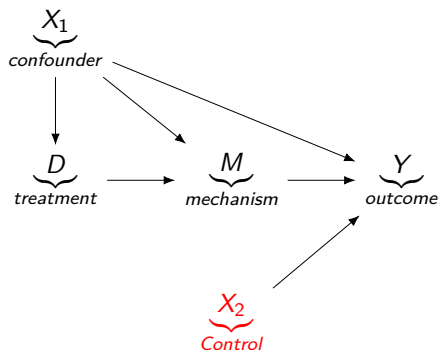
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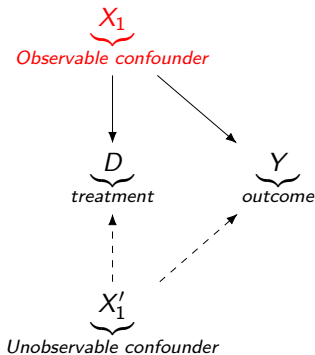
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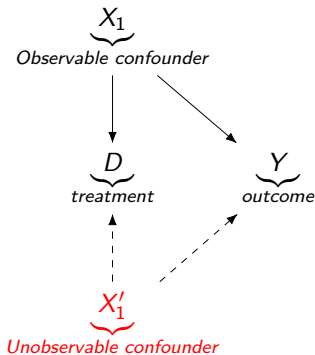
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- Controls that are confounders (X_1) are problematic!
 - Particularly if they are unobservable (X'_1) !



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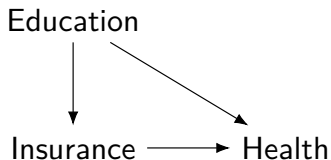


Example 1: Health insurance and health outcomes

Insurance \longrightarrow Health

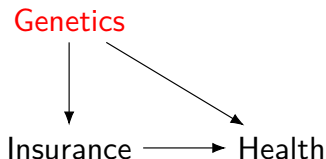
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- But education affects both.

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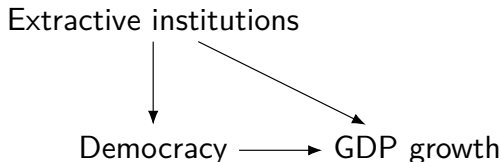
- We ask whether insurance causes health status.
- But education affects both.
- Genetics can also affect both—but hard to measure.

Example 2: Democracy and economic growth

Democracy \longrightarrow GDP growth

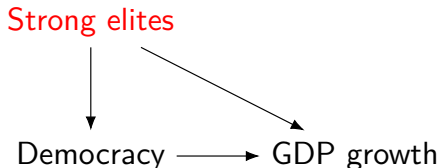
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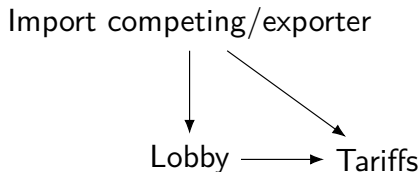
- We ask whether democracy causes growth.
- But extractive institutions from colonial legacies affect both.
- ... having strong elites is hard to measure.

Example 3: Tariffs on chinese imports and export competition

Lobby \longrightarrow Tariffs

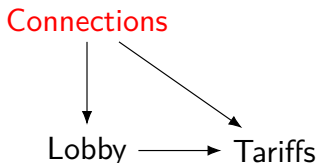
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- We ask whether lobbying increases tariffs on imports.
- Import competing (export) sectors has incentives to protect (liberalize).
- Political connections in Washington is hard to measure.

- A DAG for your question will provide clarity.
- Identify the observable confounders (measurable; data exists).
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