→ In a DAG, causality runs in one direction, $X \to Y$, forward in time.

→ No Cycles in a DAG

Reverse causality ≠ Simultaneity (Eg. Mathew Effect)

↓ Only Y causes behaviour change

↓ Variables on both sides of a model equation impact one another at the same time

9 criteria that determine ~~Reverse~~ causality.

— Bradford Hill Criteria (1965)

1. Strength.
   - Causal relationships have strong connections (Correlation coefficient)

2. Consistency
   - Causal relations are usually consistent across different populations

3. Specificity
   (sometimes) — Causation occurs under specific conditions when no other explanation is likely.
   1–1 relationship b/w exposure & outcome.

4. Temporal sequence

   Effect → cause ⇒ Reverse Causality

5. Gradient

Greater exposure should lead to greater effect.
(Adapted from bio-science)

6. Plausibility - Reasonable Explanation.

7. Coherence - Consistent & Logical

8. Experiment

9. Analogy

— DAGs explain causality in terms of counterfactuals.

Causal Effects

Direct

$D \rightarrow Y$

Mediated

$D \rightarrow X \rightarrow Y$

"A DAG is meant to describe all causal relations relevant to the effect of D on Y"

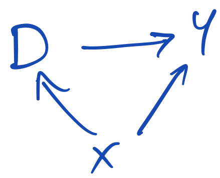
<u>Complete DAG</u>

↳ All direct causal effects
↳ All common causes of a pair of variables.

Lack of an arrow ⇒ You think there is no relationship in the data.

Strongest beliefs

DAG



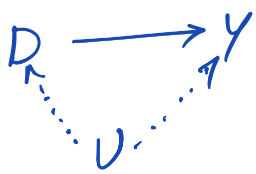
D → Y (direct path) → causal

D ← X → Y (backdoor path) → non-causal

Backdoor path – is a process that creates spurious correlations b/w D & Y that are driven solely by fluctuations in X Random Variable.

– Leaving a backdoor open creates a bias.

– X is a confounder, confounds the ability to discern the effect of D on Y in näive comparisons.



D → Y

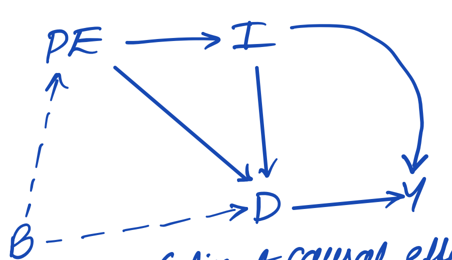
D ← U → Y

U → unobserved confounder

– non-collider

Backdoor is always open.

Use panel data to close backdoor if possible.



PE = Parental Education

I = Family Income

B = Unobserved background factors (genetics, family env. & mental ability.

D = College education

Y = Earnings.

1. D → Y (direct causal effect)
2. D ← I → Y (Backdoor 1)
3. D ← PE → I → Y (Backdoor 2)
4. D ← B → PE → I → Y. (Backdoor 3)

Open Backdoors create systematic & independent correlations b/w D & Y. $\Rightarrow$ **Bias**

Colliding

$$\begin{tikzcd} D \arrow[rr] \arrow[dr] & & Y \arrow[dl] \\ & X & \end{tikzcd}$$

A collider – when left alone
– closes the backdoor path.

1. $D \rightarrow Y$ (causal effect)
2. $D \rightarrow X \leftarrow Y$ (Backdoor)

Closing Backdoors

Confounder $\rightarrow$ Conditioning on confounder

Conditioning = Holding the variable fixed using
- subclassification
- matching
- regression. etc.

"Control" for the confounder

All backdoors closed $\Rightarrow$ Satisfied backdoor criterion.

Under what conditions is it ok to condition on a collider? (Chapter 3 Scott Cunningham)
Section 3.1.5

[<u>Megan Fox example</u>

Is there a negative correlation between beauty & talent?

When you take the entire sample of actors, there is no correlation. When you take top 15% a frontier appears that seems negatively correlated. → Spurious. It is not <u>caused</u> by anything

$$
\begin{tikzcd}
 & \text{Movie Star} & \\
\text{Talent} \arrow[ur] & & \text{Beauty.} \arrow[ul]
\end{tikzcd}
$$

This is what happens when you condition on the collider, in this case, the "star" i.e. top 15%ile.

Unobserved confounders can lead to conditioning on colliders leading to spurious correlations.

Eg. Scott Cunningham Book.

3.1.7 Police use of force.