Inference & Causality
Week 3
Session 5

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Course Overview

Reminder: Check the course hub on Notion for up-to-date information:

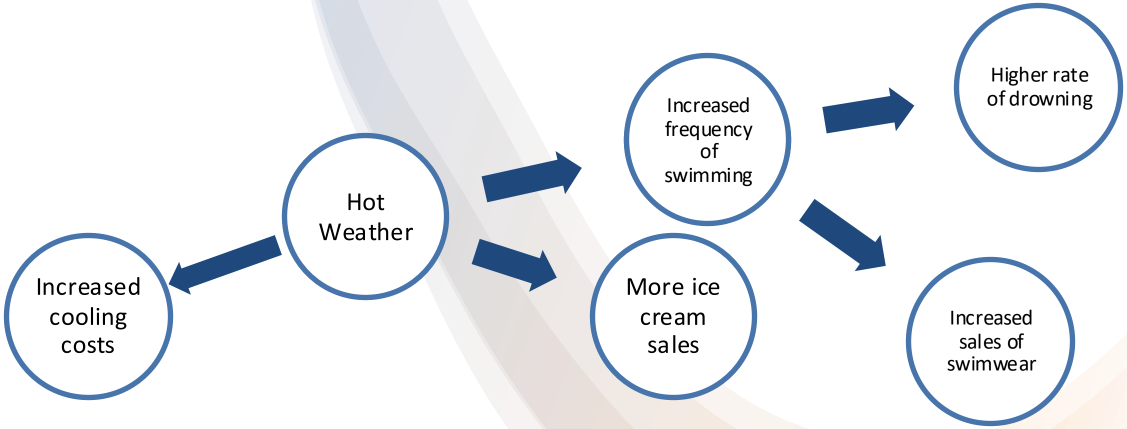
https://tinyurl.com/mrcjp79s

Outline of Week 3
Session 5

- Observation vs Intervention
- Conditional independence

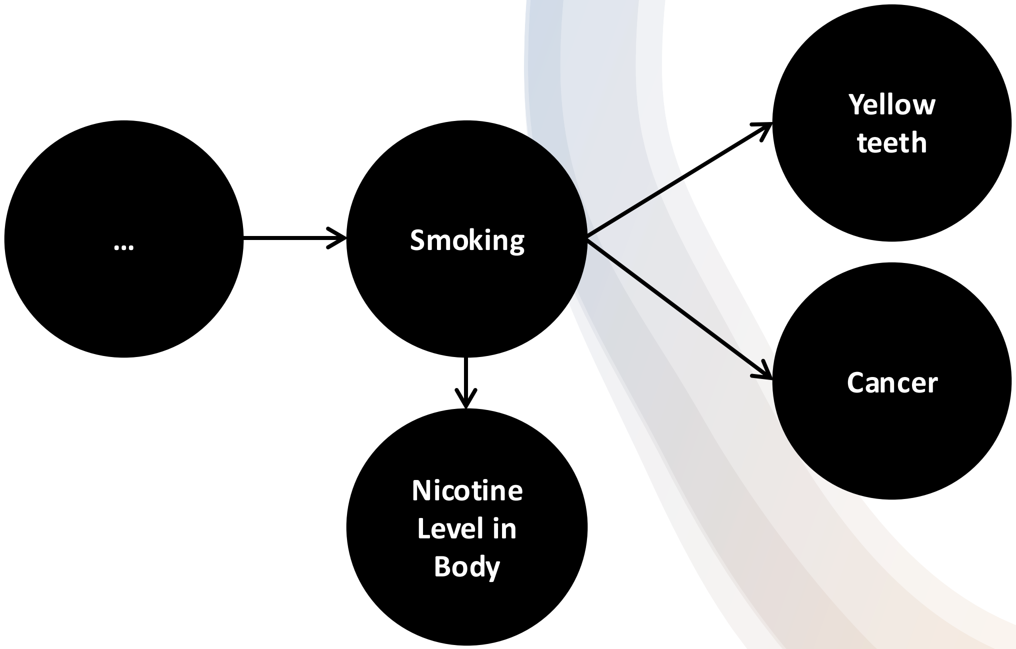
Review: Elements of Causal Graphs

Pattern	Structure	Effect
Chain	A → B → C	**Mediator B** transmits effect
Fork	A ← B → C	**Confounder B** creates spurious link
Collider	A → B ← C	Conditioning on B introduces bias



An Addition to our Vocabulary

A proxy:
A proxy is a variable that stands in for another variable that isn't observed (often a hidden cause).
An example DAG with Nicotin Level in Body as a proxy for Smoking.



Observation vs Intervention

Observations:
What happens…

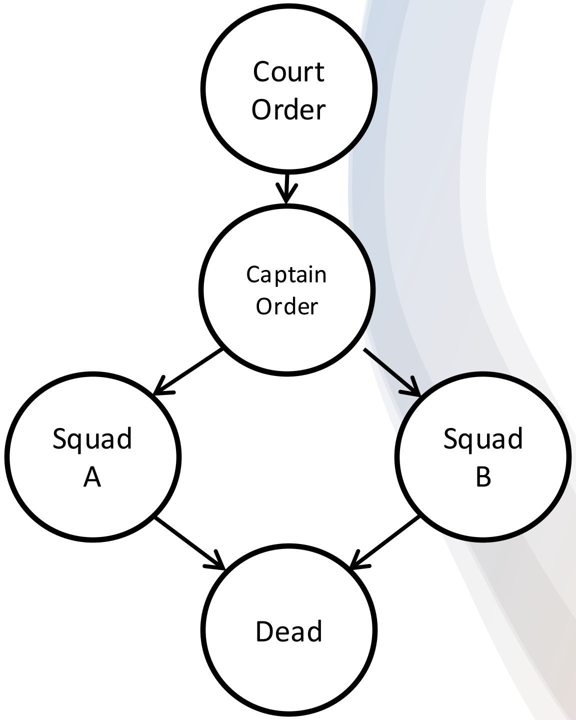
Interventions:
What happens if we DO something.

Counterfactuals:
What would have happened if we were doing something different.

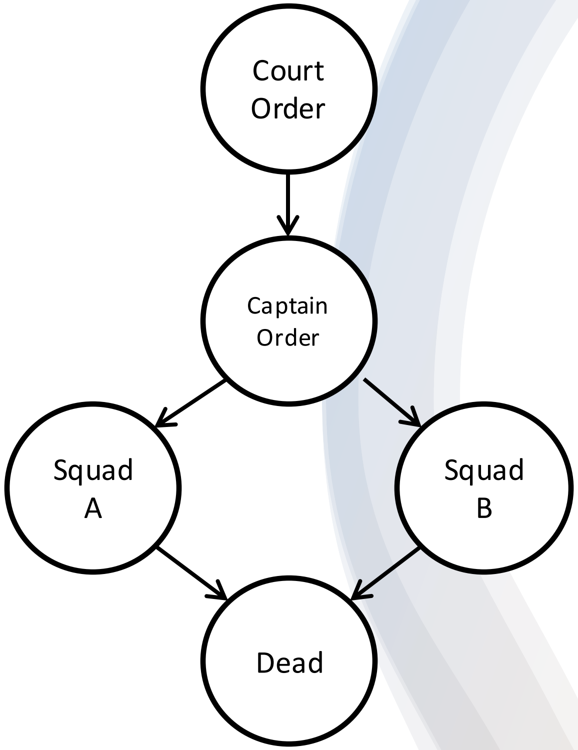
Intervention vs Conditioning

firing squad example (Pearl & Mackenzie, 2018)

- When we do **intervention**:
  We cut the parent nodes in the causal graph and fix the value.
- When we do **conditioning**:
  We limit the node to specific values without changing the causal graph.



Always all true or all false when observing.



Insufficiency of Observational Data

- Only observation, might bring us to false conclusions:

Some examples:

Police & Crime

- Observation: Neighborhoods with more police presence have higher crime rates.
- False conclusion: Police cause crime.

- Reality: Police are deployed to high-crime areas — an intervention effect.
  We cut the parent nodes in the causal graph and fix the value.

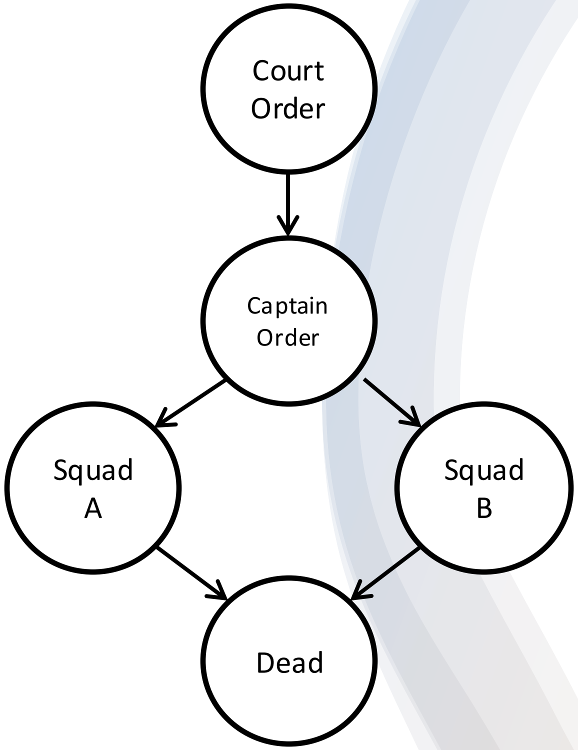
Hospitals & Death

- Observation: People in hospitals have higher mortality rates.
- False conclusion: Hospitals make people die.

- Reality: Severely ill people are more likely to go to hospitals — again, selection bias.

Here comes the role of INTERVENTIONS

What if we <u>intervene</u> and ask squad A to always fire?



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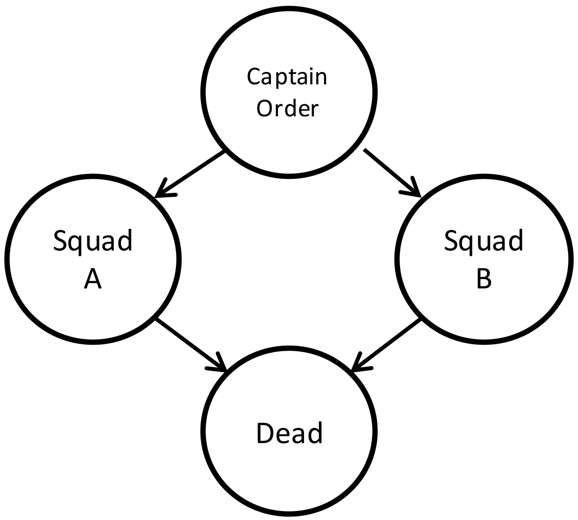


Conditioning vs Intervening Notations

For conditioning we already had:

$$P\ (\ Y{=}y \mid X{=}x\ )$$

For intervension we use:

$$P\ (\ Y{=}y \mid \mathbf{do}(X{=}x)\ )$$

Pearl et al., 2016

Do-Calculus

- Pearl’s Do-Calculus: Rules for Moving Between Observing and Intervening

A Little History:

Before the 1990s:
Statistics could describe associations but not interventions.
Concepts like “randomized control” and “adjustment” existed, but not a unified logic.

Judea Pearl (UCLA, 1990s):
Introduced causal diagrams (DAGs) and the do-operator,
giving a mathematical language to express causal mechanisms.

1995 – 2000:
Pearl formalized three algebraic rules [now called Do-Calculus] to manipulate expressions involving do() and to decide when causal effects can be identified from data.

Today:
Do-Calculus underlies modern causal tools:
back-door / front-door criteria, causal discovery, structural causal models (SCMs),
and software like DoWhy, Tetrad, CausalNex.

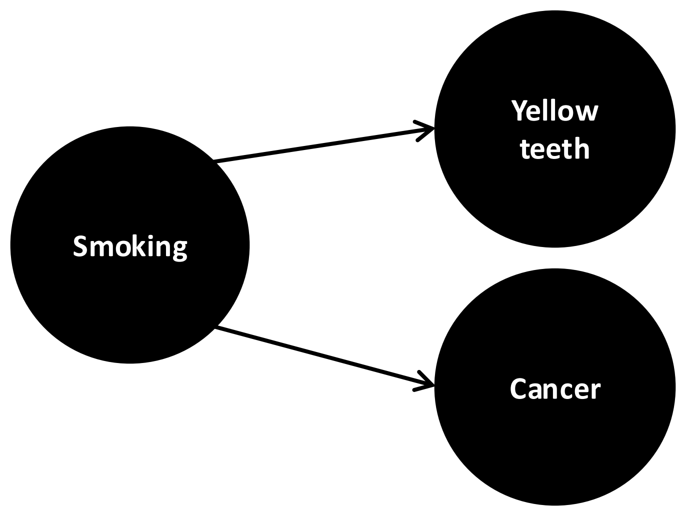
Confounding in Do Language

Confounding is whenever:

$$P\ (\ Y{=}y \mid X{=}x\ )$$

Is not equal to:

$$P\ (\ Y{=}y \mid \mathbf{do}(X{=}x)\ )$$



Pearl & Mackenzie, 2018 and Pearl, 2009

Let’s check out our notebooks.

Session Summary

- Observation vs Intervention
- Introduction to Do-Calculus.

Let’s check what we learnt in so far in unit 3
You have 15min.