



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>





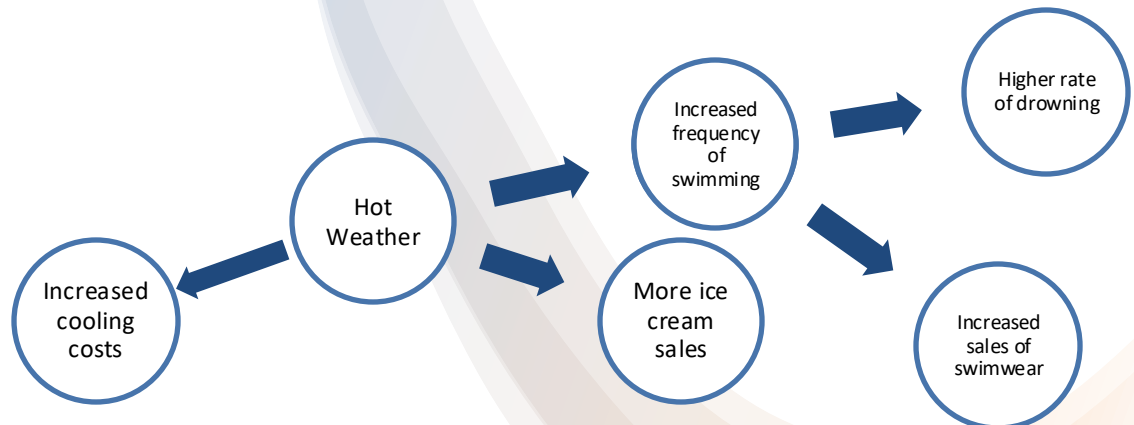
Outline of Week 3

Session 5

- Observation vs Intervention
- Conditional independence

Review: Elements of Causal Graphs

Pattern	Structure	Effect
Chain	$A \rightarrow B \rightarrow C$	Mediator B transmits effect
Fork	$A \leftarrow B \rightarrow C$	Confounder B creates spurious link
Collider	$A \rightarrow B \leftarrow C$	Conditioning on B introduces bias

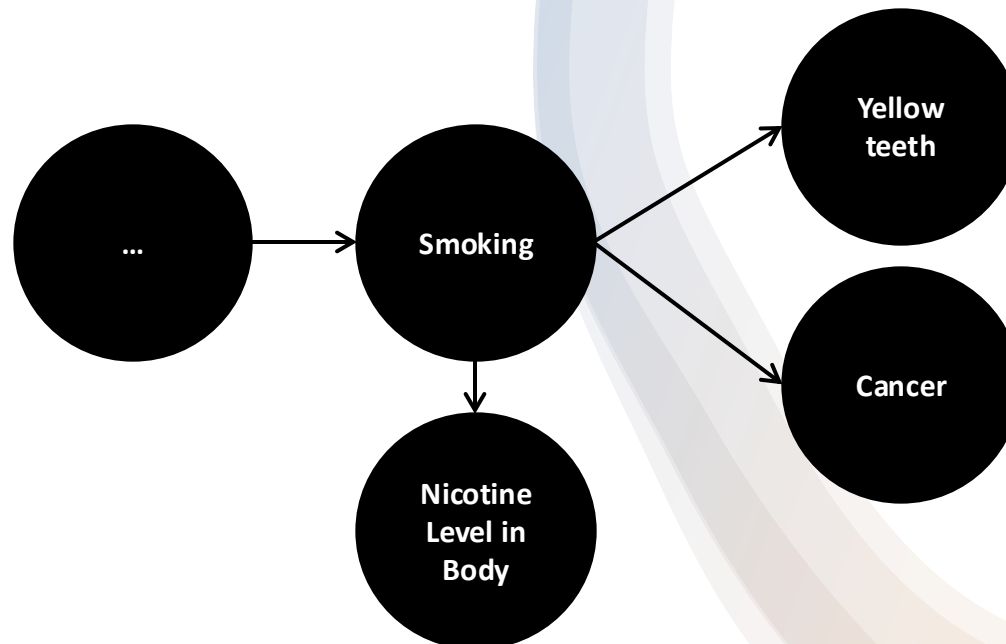


An Addition to our Vocabulary

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.

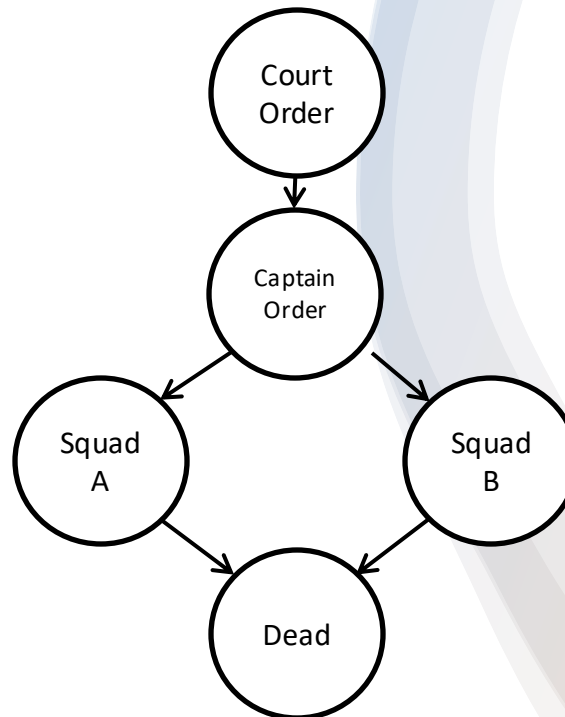
Counterfactuals:

What would have happened if we were doing something different.

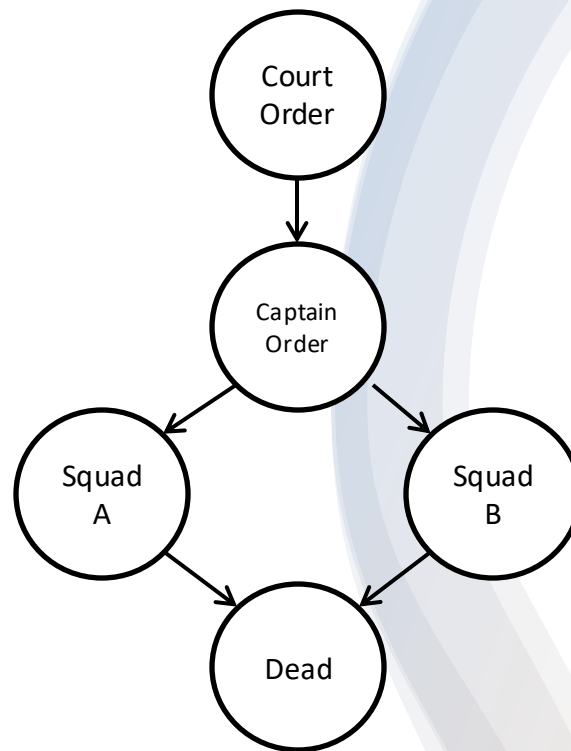
Intervention vs Conditioning

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.

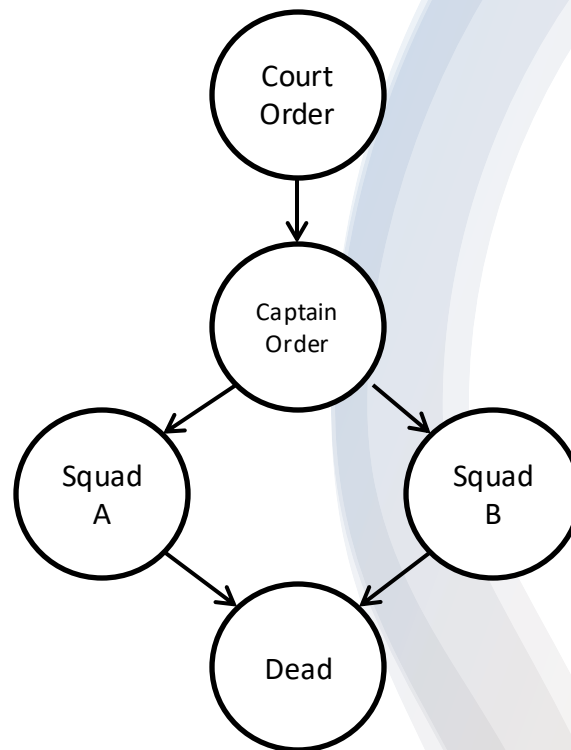
Hospitals & Death

- 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 intervene and ask squad A to always fire?



Conditioning vs Intervening Notations

For conditioning we already had:

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

For intervention we use:

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



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.

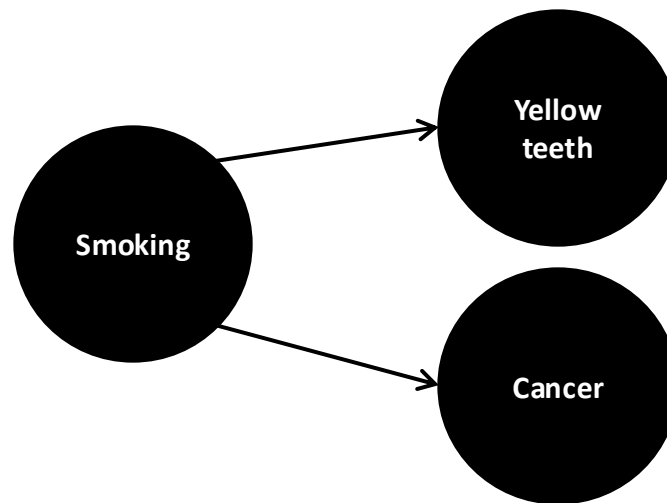
Confounding in Do Language

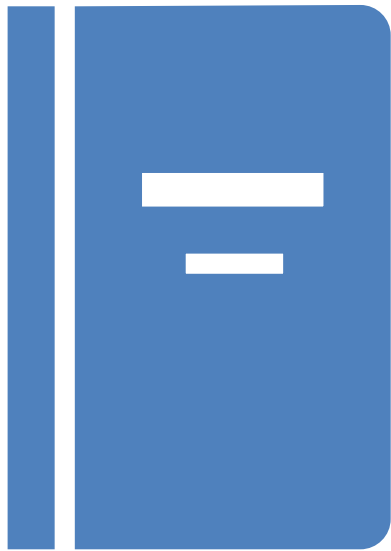
Confounding is whenever:

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

Is not equal to:

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





**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.

