Inference & Causality
Week 2
Session 4

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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 2
Session 4

- Unit 1 quiz
- Introduction to Causality
- Correlation vs causation
- Granger causality
- Directed Acyclic Graphs (DAG)
- Elements of causal graphs

Let’s check what we remember from unit 1

You have 15min.

Why Causality?

- Humans always seek causal stories
- Let’s have a few random draws from:
  - https://tylervigen.com/spurious-correlations
  - Share your best with the class!

Correlation vs Causation

What Correlation Means

In statistics, correlation describes how two variables change together, whether or not one causes the other.

Note: Correlation ≠ Direction ≠ Mechanism.

Pearson Correlation Coefficient

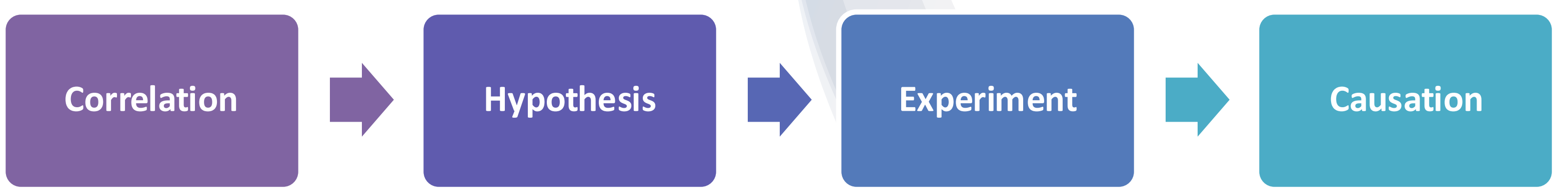
- Quantifies the of a **linear relationship** between two continuous variables.
- Values range from −1 to +1:
- +1 : perfect positive linear relationship
- 0 : no linear relationship
- −1 : perfect negative linear relationship
- Computed as:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

Let’s play this game:
If you get a **higher than 5 streaks**, you get some bonus points for the course:
https://www.guessthecorrelation.com/

How to Approach Causality?

Domain knowledge + experiments + causal models



Causal Models: Framing the Question

Causal models describe how and why variables influence each other.

They go beyond observing co-movement, they encode mechanisms and predict interventions (“what if X changes?”).

Example:

Correlation: “Ice cream sales and drowning increase together.”

Causal model: “Hot weather causes both ice cream sales and swimming frequency, which affects drowning risk.”

Causality in Time

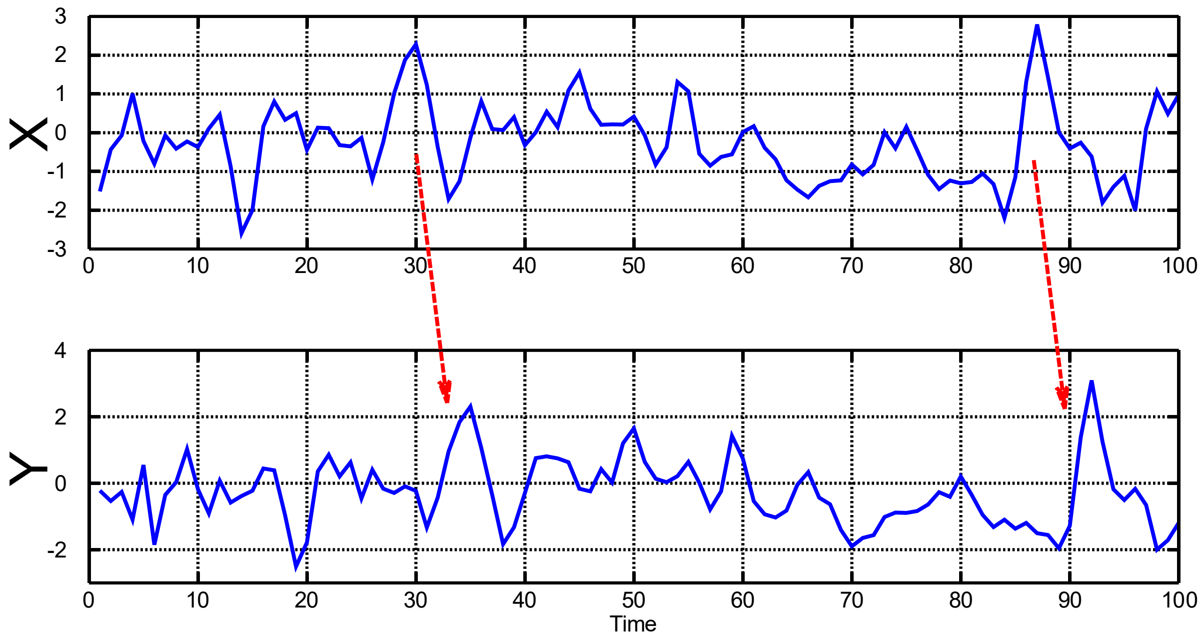
- In time series, we often ask:

  "Does knowing the past of X help us predict Y?"

- This idea leads to **Granger** causality, which tests whether one variable's history adds predictive power for another.

- Important: It captures temporal predictiveness, <u>not necessarily true causal mechanism</u>.

Granger Causality



Source: Wikimedia Commons. "**Granger Causality Illustration**." From the article *Granger causality*, Wikipedia, https://en.wikipedia.org/wiki/Granger_causality.

$$Y_t = a_0 + \sum_{i=1}^{p} a_i Y_{t-i} + \sum_{i=1}^{p} b_i X_{t-i} + \varepsilon_t'$$

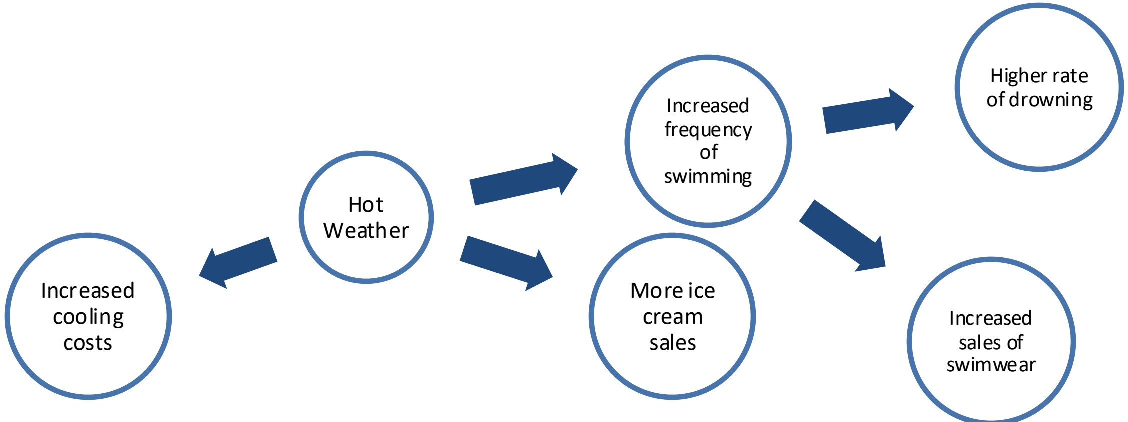
Let’s check out our notebook 5.

From Predictive to Structural Causality

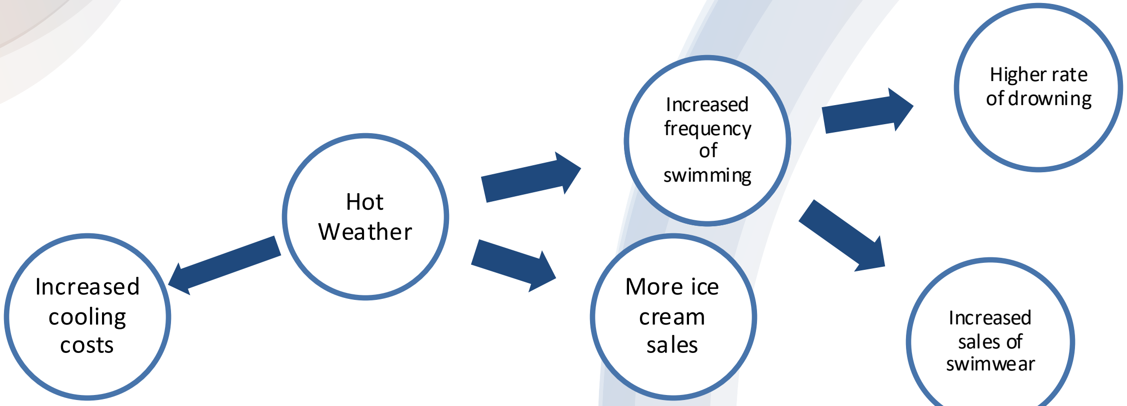
Directed Acyclic Graphs (DAGs)

- Granger causality helps identify predictive direction in time series.
- But prediction ≠ explanation: It doesn’t tell us the full causal mechanism.

- DAGs extend this idea: they represent structural causal relationships between variables.
- With DAGs, we can **model systems, test assumptions**, and **reason about interventions**.
- **Each arrow in a DAG represents a causal relationship.**



Causal DAGs



- DAGS:
  - Directed: Links have directions
  - Acyclic: There in no loop! Why?

Causal DAGs

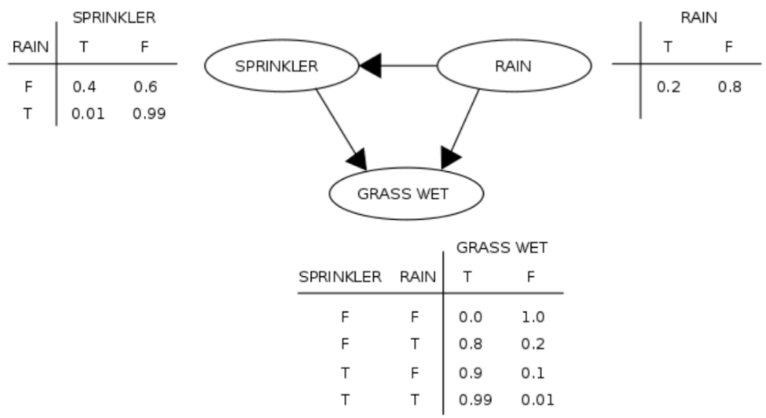


Image source: chegg.com

- Reminder:
- Every **Bayesian Network** (BN) is a DAG (but not every DAG is a BN), a BN also includes probability distributions.
- Each node in a BN has a conditional probability distribution (CPD) that specifies how it depends on its parents.

Elements of Causal Graphs

Pattern	Structure	Example	Effect
Chain	A → B → C	Smoking → Tar → Cancer	**Mediator B** transmits effect
Fork	A ← B → C	Genetics → Smoking & Cancer	**Confounder B** creates spurious link
Collider	A → B ← C	Smoking & Pollution → Hospitalization	Conditioning on B introduces bias

Have a look at notebook 6 of this week!

D-Separation/Connection

- Goal: To check whether two variables X and Y are conditionally independent given some set of variables Z.
- How: Look at the causal graph and check the paths between X and Y.

Result	Meaning	Interpretation
X and Y are d-separated (given Z)	All paths between X and Y are blocked	X and Y are **conditionally independent given Z**. No information flows
X and Y are d-connected (given Z)	At least one path between X and Y is open	X and Y are **conditionally dependent given Z.** Some information flows (this may be a true causal link **or** a spurious correlation, e.g. from a collider)

Reminder of what “elements of DAG” do to path

Type	Example	Without conditioning	After conditioning	Why
Chain	A → B → C	Open	**Blocked** if you condition on B	B passes information from A to C
Fork (confounder)	A ← B → C	Open	**Blocked** if you condition on B	B creates a shared cause link
Collider	A → B ← C	**Blocked**	**Opened** if you condition on B	Conditioning creates spurious correlation

Session Summary

- Correlation vs Causation
- Pearson Correlation
- Causality and Causal Models
- Granger Causality
- Directed Acyclic Graphs (DAGs)
- Elements of Causal Graphs
- D-separation and connection

Congratulations!
We finished unit 2 of this course.

Don’t forget to read unit one of your course book for more detailed understanding of this unit.

Let’s check what we learnt in unit 2

You have 15min.

Homework

- Exercise: Fill out the exercises on notebooks 1 and 2 and 4 for this week, commit your answers and submit .