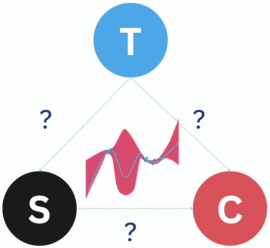

NormaSTIC Symposium on Causal Inference and Uncertainty Quantification

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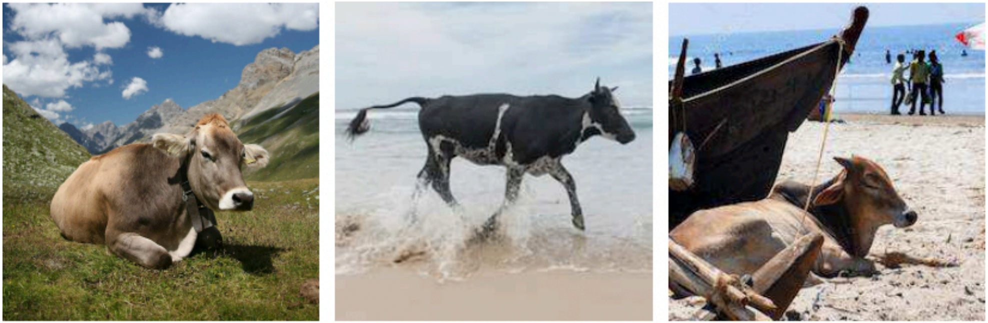
Caen, June 25, 2025


WELCOME

Predicting in terra incognita



(A) **Cow: 0.99**, Pasture: 0.99, Grass: 0.99, No Person: 0.98, Mammal: 0.98

(B) No Person: 0.99, Water: 0.98, Beach: 0.97, Outdoors: 0.97, Seashore: 0.97

(C) No Person: 0.97, **Mammal: 0.96**, Water: 0.94, Beach: 0.94, Two: 0.94

[Beery, Van Horn, and Perona 2018]

Figure 1: Cow and grass are spuriously correlated

- Is the label ‘cow’ really due to the presence of the cow, or just the grass?
- Spurious correlations in ML models may lead to unreliable predictions in unseen environments.

Most real-world questions are causal

- What does it mean for **something to be causal**?
- When people say **"X causes Y"**, what do they really mean?
- Many questions we care about are fundamentally **causal**:
  - Do **minimum wage increases** reduce poverty?
  - Did the **medicine** make patients recover faster?
  - Did the **interest rate cut** cause the recession?
- Causal inquiry begins with observed **associations**:
  - **Lung cancer** is more common among **smokers**.
  - **Sickness** is more common in **hospitals**.

☞ **Causality** provides tools for action, recommendation, and "what if" reasoning.

Causality: an interventionist interpretation

- **Definition**: **X** is a cause of **Y** *iff*
  changing **X** leads to a change in **Y**,
  keeping everything else constant.

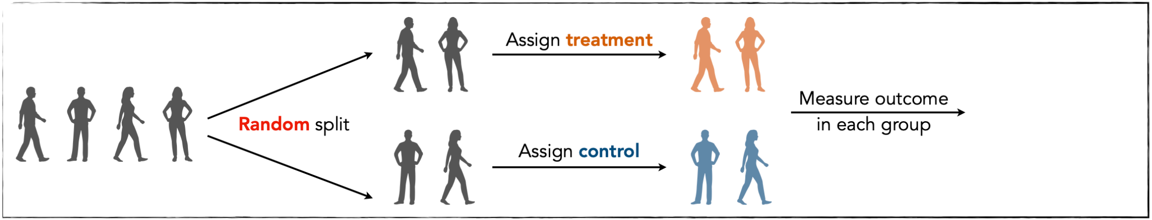
$$P(Y \mid \mathbf{do}(X = x)) \neq P(Y \mid \mathbf{do}(X = x'))$$

- **Example**:
  C: Cancer, **S**: Smoking, **G**: Genetic factors

$$P(C \mid \mathbf{do}(S = 0, G = 0)) \neq P(C \mid \mathbf{do}(S = 1, G = 0))$$

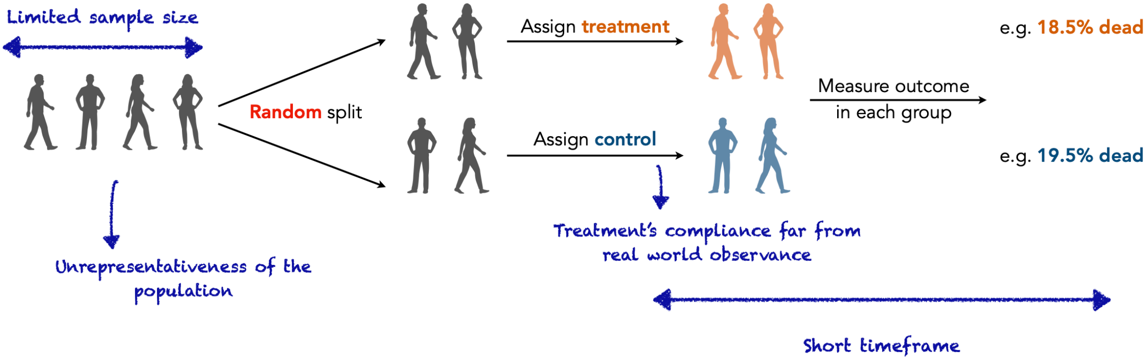
Estimating a causal effect

Principle



Credit: Bénédicte Colnet, 2023

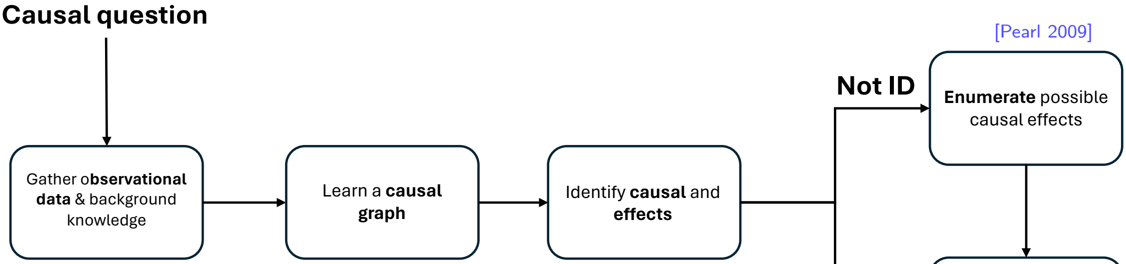
Estimating a causal effect

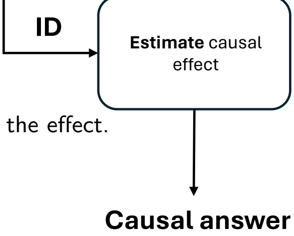


"'*External validity*' asks the question of generalizability: to what populations, settings, treatment variables, and measurement variables can this effect be generalized?" — Campbell and Stanley (1963), p. 5

Credit: Bénédicte Colnet, 2023

Estimating causal effect from observational data





Assumptions:

- Access to **observational data** and some **domain knowledge**.
- We know (or assume) all relevant variables that **confound** or **moderate** the effect.
- The full structure of dependencies may be **unknown**.

Key Questions:

1. Can the **causal effect** be uniquely identified?
2. How **strong** is the causal relationship?
3. What **estimator** is optimal under **uncertainty**?

Why does uncertainty quantification matter?

- Data is often **incomplete**, **noisy**, or **biased**.
- Even perfect models carry **uncertainty** about their predictions and causal claims.
- To support decisions, we need to ask:
  - How confident are we in our estimate?
  - How would our conclusions change with new data?

☞ Uncertainty quantification is essential for **robust**, **trustworthy**, and **actionable** causal analysis.

Types of uncertainty in causal analysis

- **Aleatoric uncertainty**: randomness in the data (e.g., outcomes vary even under same treatment).
- **Epistemic uncertainty**: due to **limited knowledge**, such as:
  - Model misspecification
  - Unmeasured confounders
  - Limited sample size
- **Structural uncertainty**: lack of clarity in the causal graph or data-generating process.

☞ Distinguishing and quantifying these is key for **causal discovery** and **policy evaluation**.

Quantifying and leveraging uncertainty

- **Bayesian methods**: posterior distributions over causal effects.
- **Sensitivity analysis**: explore how conclusions change under assumption violations.
- **Bootstrap/Jackknife**: empirical uncertainty via resampling.
- **Bounds and intervals**: partial identification and worst/best-case scenarios.
- **Conformal prediction**:
  - Provides **distribution-free** prediction intervals with **valid coverage**, even under weak assumptions
  - Can be adapted for use in **counterfactual inference** and **individual-level treatment effect estimation**.

☞ **Goal**: inform decision-making under **ambiguity and doubt**, not just in idealized settings.

- Highlight **novel methods** for **causal inference** and **uncertainty quantification**.
- Understand how these tools apply to **machine learning**, policy, and science.
- Promote rich **cross-disciplinary insights**.

☞ Foster new collaborations via ANR projects, PhD theses, and internships.

Welcome

- Welcome to this NormaSTIC symposium on **causal inference** and **uncertainty quantification**.
- We are delighted to host a diverse group of **speakers** who will share their latest research and perspectives.
- We thank all the **administrative staff**: Caroline Pilate and Sophie Rastello for their support in organizing this event.
- We gratefully acknowledge the support of the **NormaSTIC Federation**, which made this symposium possible.

Agenda

09:00	Arrival and welcome coffee
09:30	Opening remarks
09:45	`Tutorial`: **MAPIE – Model Agnostic Prediction Interval Estimator** **Speakers**: Vincent Blot (Capgemini, CNRS, LISN, Université Paris-Saclay) & Valentin Laurent (Capgemini, Paris)
11:00	Coffee break
11:15	`Tutorial`: **Khiops Uplift – A Library for Causal Inference** **Speaker**: Nicolas Voisine (Orange Labs)
12:30	Lunch break
13:45	`Talk`: **Large-scale causal structure learning: challenges and new methods** **Speaker**: Shuyu Dong (L2S, CentraleSupélec, CNRS, Université Paris-Saclay)
14:15	`Talk`: **Causal Inference and Large Language Models: opportunities, methods & challenges** **Speaker**: Louis Hernandez (LITIS, INSA Rouen, Craft AI)
14:45	`Talk`: **Managing Uncertainty in Regression Neural Networks: From Prediction Intervals to Adaptive Sampling** **Speaker**: Giorgio Morales (GREYC, Université de Caen Normandie)
15:15	`Talk`: **Uncertainty Quantification in Deep Evidential Fusion for Medical Imaging Applications** **Speaker**: Su Ruan (AIMS, Université de Rouen Normandi)
15:45	Coffee break
16:00	Closing discussion

"Thank you all for contributing to this collaborative scientific exchange."