Lecture 8: Causal Inference
CS486/686 Intro to Artificial Intelligence

2023-6-6

Pascal Poupart
David R. Cheriton School of Computer Science

UNIVERSITY OF
WATERLOO

Outline

- Models
  - Causal Bayesian Networks
  - Structural Causal Models
- Causal inference
  - Interventions
  - Counterfactuals

Causality

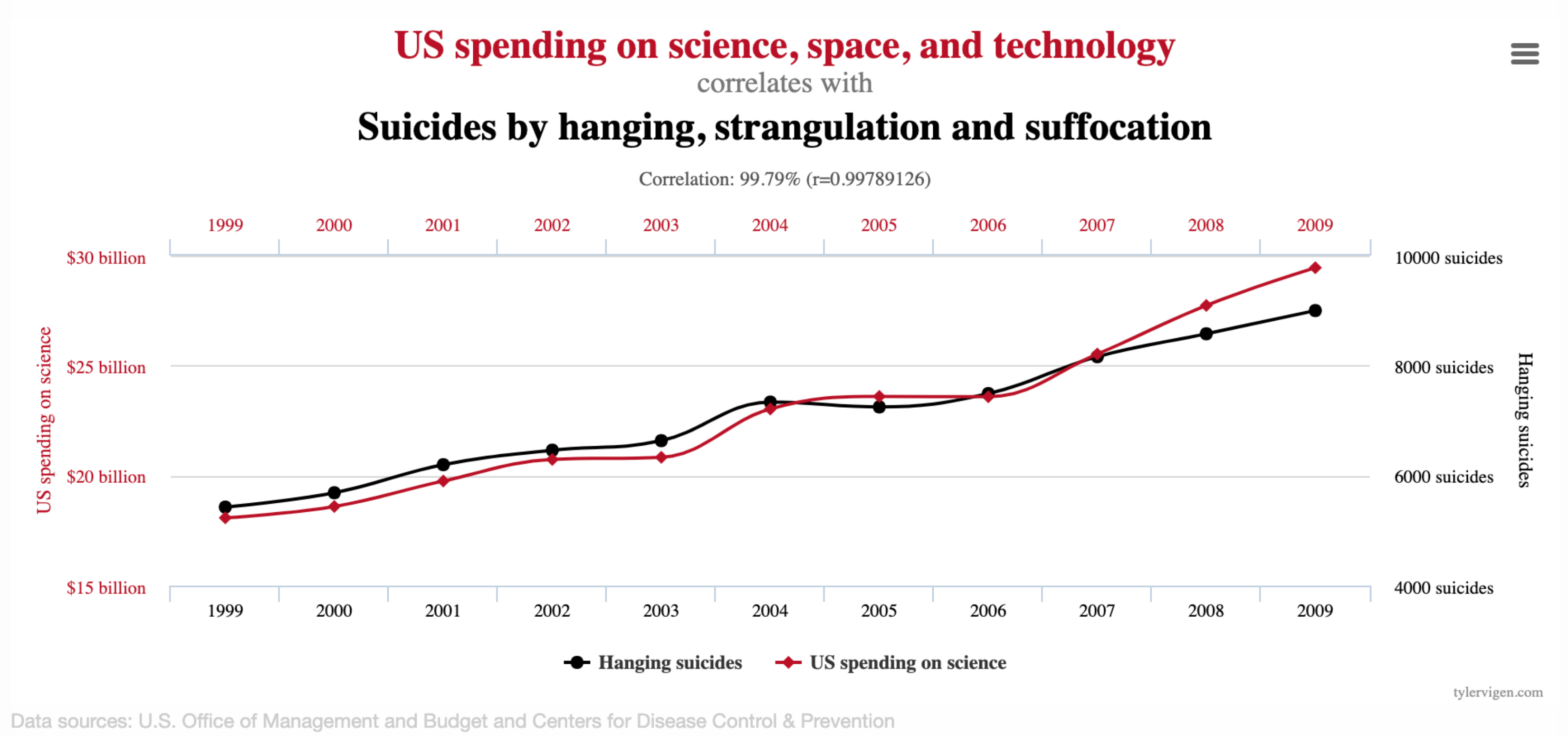
- **Causality** is the study of **how things influence one other**, **how causes lead to effects**.

- **Causal dependence**: X causes Y iff changes to X induce changes to Y
  - Example: Diseases cause symptoms, but symptoms do not cause diseases

Causal and Non-Causal Correlations

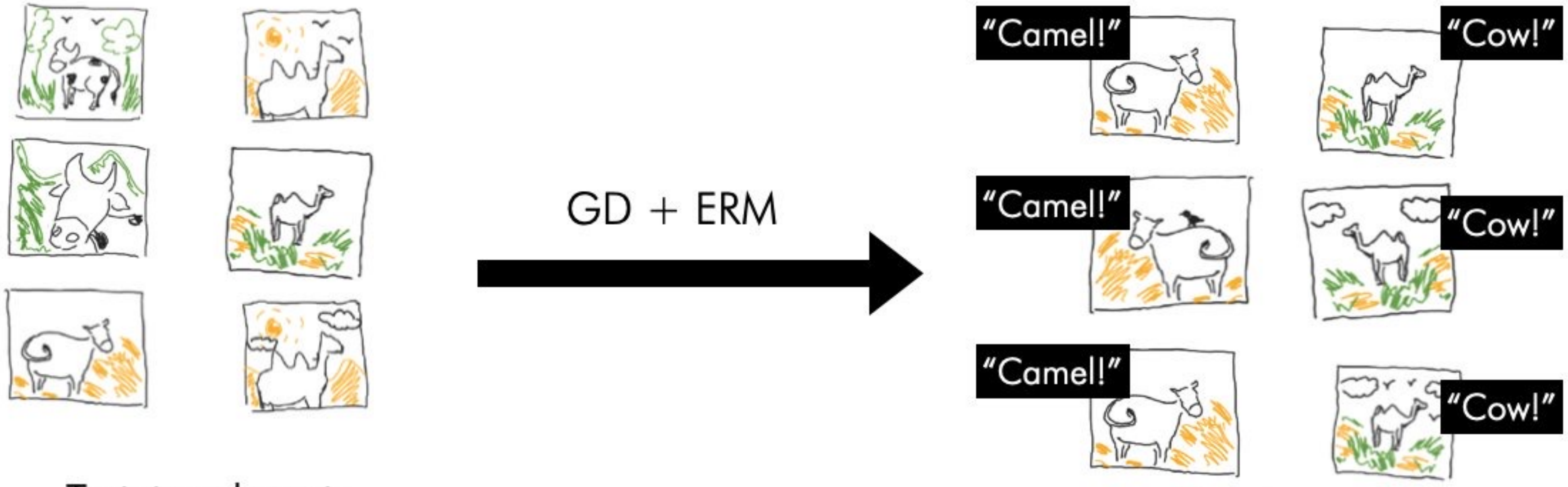
- A **joint distribution $P(X, Y)$ captures correlations** between X and Y, but does not indicate whether a causal relation exists between X and Y nor the direction of the causal relation when it exists.
- A **conditional distribution $P(Y|X)$ does not necessarily indicate X causes Y**
  - Recall Bayes' rule: $P(Y|X) = \frac{\Pr(X|Y)P(Y)}{P(X)}$
  - Since we can transform $P(X|Y)$ into $P(Y|X)$, conditional distributions do not always indicate causal dependences, otherwise Y would cause X and X would cause Y

Spurious Correlations



From https://www.tylervigen.com/spurious-correlations

Spurious Correlations



Training domain
Cows: 90% green background
Camels: 90% yellow background

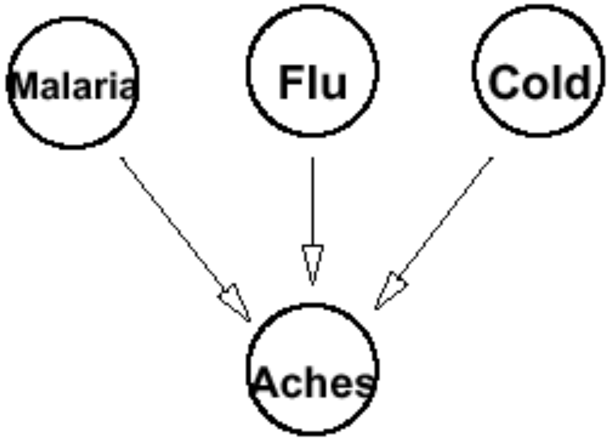
Test domain
Cows: 0% green background
Camels: 0% yellow background

Standard example (Beery et al., '18 Arjovsky et al., '19)

Causal Bayesian Network

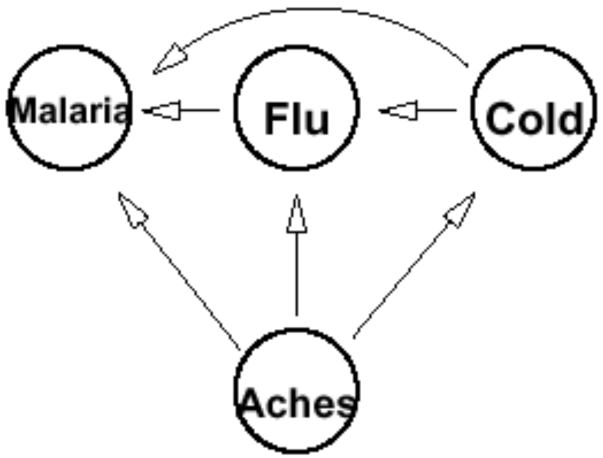
Definition: Bayesian network where all edges indicate direct causal effects.

Causal Bayes net



Probabilistic Inference
Causal Inference

Non-causal Bayes net



Probabilistic Inference

Causal Inference

Intervention: What is the effect of an action?

E.g., What is the effect of a treatment?

Causal networks can easily support intervention queries, but not non-causal networks do not.

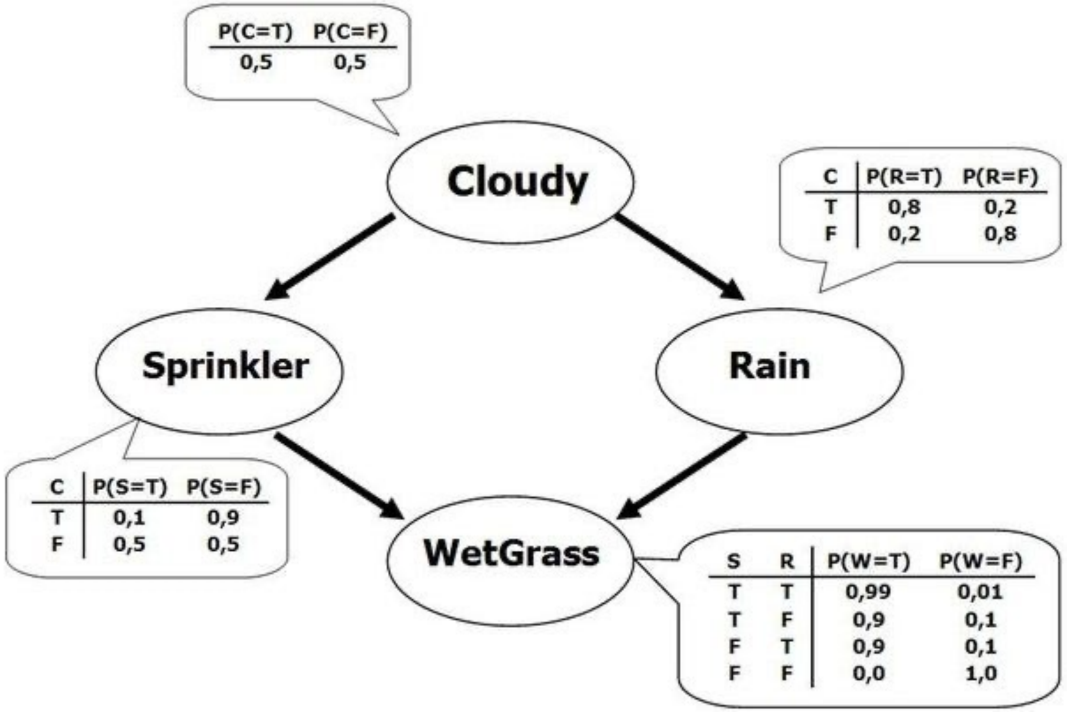
Observation versus Intervention

Observation: What is the likelihood that the grass is wet when the sprinkler is observed to be on?

$$P(WG|S = true)?$$

Intervention: How does turning on the sprinkler affect the grass?

$$P(WG|\boldsymbol{do}(S = true))?$$



Do Operator

Observational query:

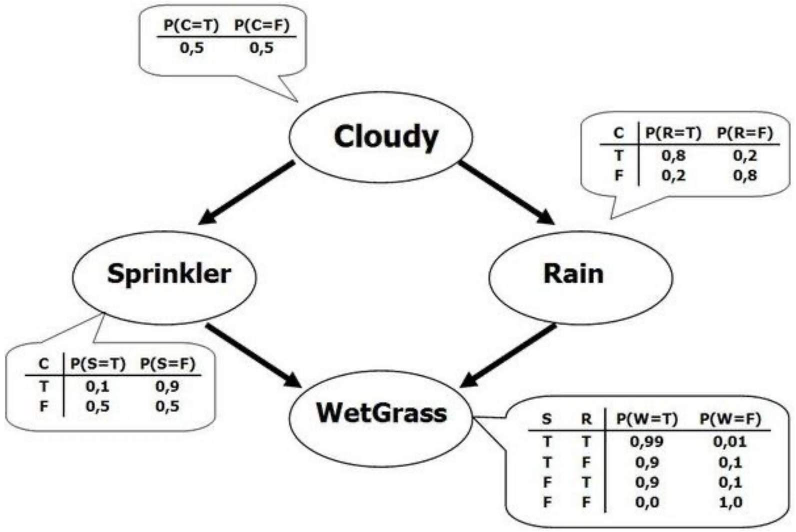
$P(WG|S = true)$?

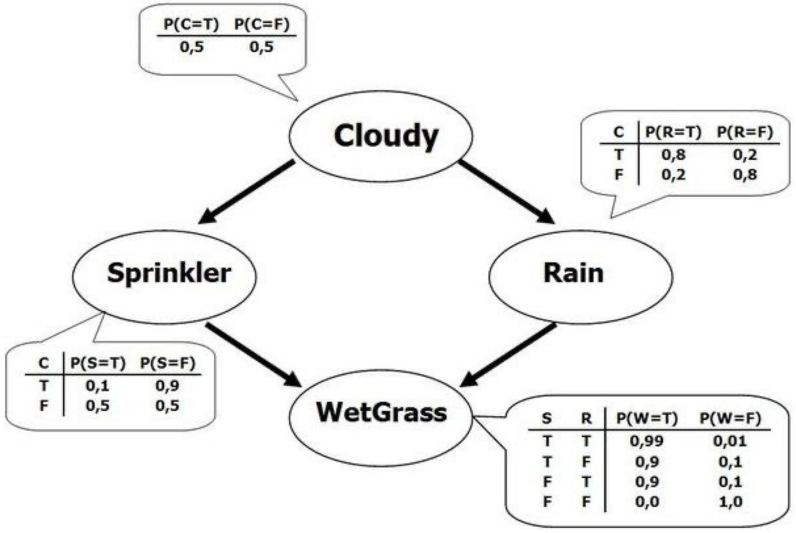
- Factors:
- Evidence:
- Eliminate:

Intervention query:

$P(WG|\boldsymbol{do}(S = true))$?

- Factors:
- Evidence:
- Eliminate:





Inference with Do Operator

$$P(X|do(Y = y), Z = z)$$

In a causal graph:

1) Remove edges pointing to Y and $P(Y|parents(Y))$
2) Perform variable elimination on remaining graph:
   a) Restrict factors to evidence: $Y = y$ and $Z = z$
   b) Eliminate variables
   c) Multiply remaining factors and normalize

Non-Causal Graph

Observational query:

$P(WG|S = true)?$

- Factors:
- Evidence:
- Eliminate:

Intervention query:

$P(WG|\boldsymbol{do}(S = true))?$

- Factors:
- Evidence:
- Eliminate:

UNIVERSITY OF WATERLOO

Counterfactual Analysis

Intervention: What is the effect of an action?

E.g., What is the effect of a treatment?

Counterfactual analysis (or counterfactual thinking): explores outcomes that did not actually occur, but which could have occurred under different conditions. It's a kind of what if? analysis and is a useful way for testing cause-and-effect relationships.

E.g., Would the patient have died if he was not treated?

E.g., Would a goal be scored had the player not tripped?

Counterfactual Analysis

How can we answer counterfactual questions with a causal Bayes net?

Treatment → Dead

Fact: patient was treated and then died

Counterfactual question: Had the patient not been treated, would the patient have survived?

Can't answer this question since we can't revive the patient to try no treatment…

UNIVERSITY OF WATERLOO

Structural Causal Models

Idea: separate causal relations from noise

Structural Causal Model contains:

- **X:** endogenous variables (domain variables)
- **U:** exogenous variables (noise)
- Only **deterministic** relations given by equations
  - $X_i = f(parents(X_i), U_i)$

Conversion

- Structural Causal Models (SCMs) can be converted into equivalent Causal Bayesian Network, but not the other way around

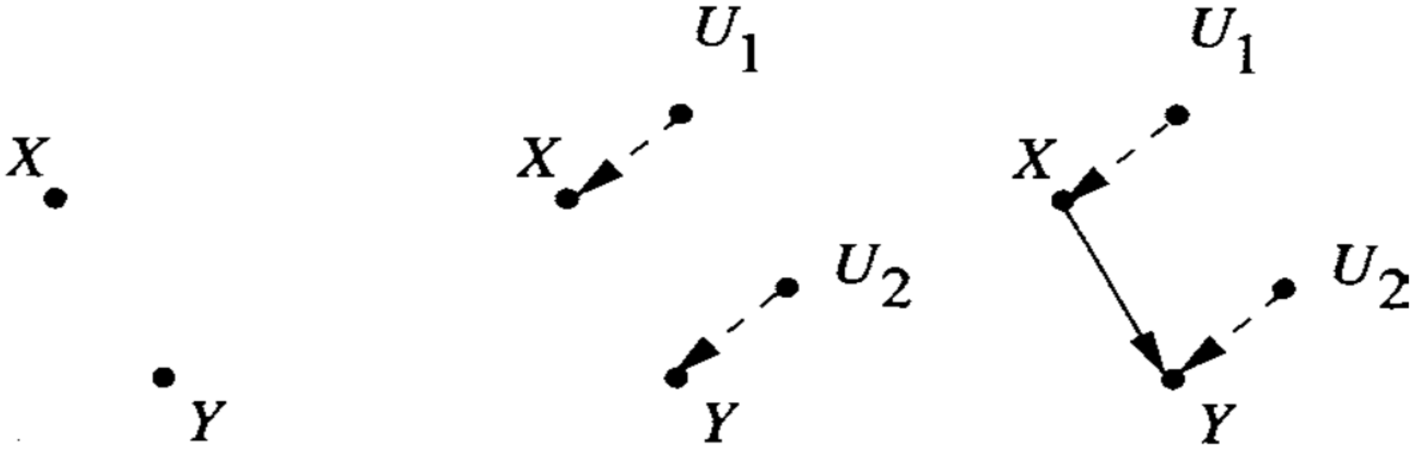
- SCMs separate causal relations from the noise and therefore provide more information

Example

Let $P(X, Y)$ be uniformly distributed i.e., $P(X = x, Y = y) = 0.25 \;\; \forall x, y$

X: treatment

Y: dead



(a) (b) (c)

Example

Model B	$u_2 = 0$		$u_2 = 1$		Marginal	
	$x = 1$	$x = 0$	$x = 1$	$x = 0$	$x = 1$	$x = 0$
$y = 1$ (death)	0	0	0.25	0.25	0.25	0.25
$y = 0$ (recovery)	0.25	0.25	0	0	0.25	0.25

Model C	$u_2 = 0$		$u_2 = 1$		Marginal	
	$x = 1$	$x = 0$	$x = 1$	$x = 0$	$x = 1$	$x = 0$
$y = 1$ (death)	0	0.25	0.25	0	0.25	0.25
$y = 0$ (recovery)	0.25	0	0	0.25	0.25	0.25

Counterfactual Analysis

These three steps can be generalized to any causal model M as follows. Given evidence e, to compute the probability of $Y = y$ under the hypothetical condition $X = x$ (where X is a subset of variables), apply the following three steps to M.

***Step 1* (*abduction*):** Update the probability $P(u)$ to obtain $P(u \mid e)$.

***Step 2* (*action*):** Replace the equations corresponding to variables in set X by the equations $X = x$.

***Step 3* (*prediction*):** Use the modified model to compute the probability of $Y = y$.

Example

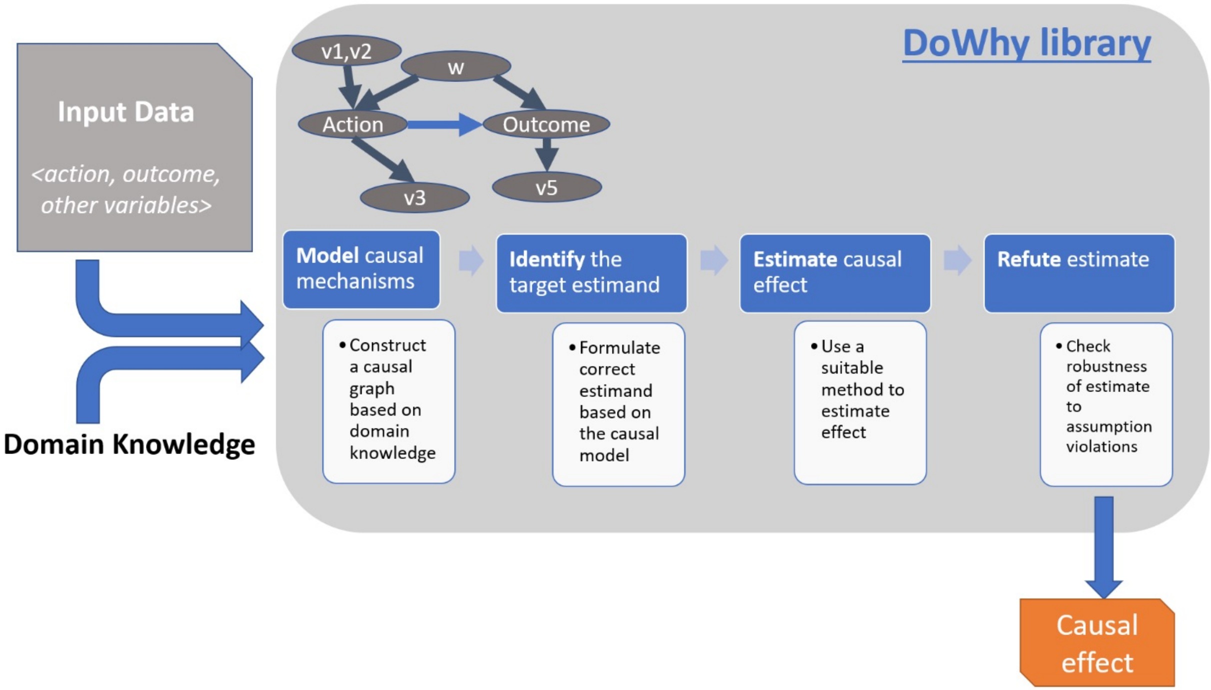
Model b:

Model c:

DoWhy Library (Microsoft)

- https://github.com/py-why/dowhy

Case Studies using DoWhy: Hotel booking cancellations | Effect of customer loyalty programs | Optimizing article headlines | Effect of home visits on infant health (IHDP) | Causes of customer churn/attrition



UNIVERSITY OF WATERLOO