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The Causal Revolution

Jungle Program - Machine Learning & Data Science Community Meetup

Amric Trudel - OCTO Technology

June 29th, 2021

Outline

OCTO Technology

Towards a Causal Model

Causation

Inference Engines

The Tools of Science and 03 **Statistics**

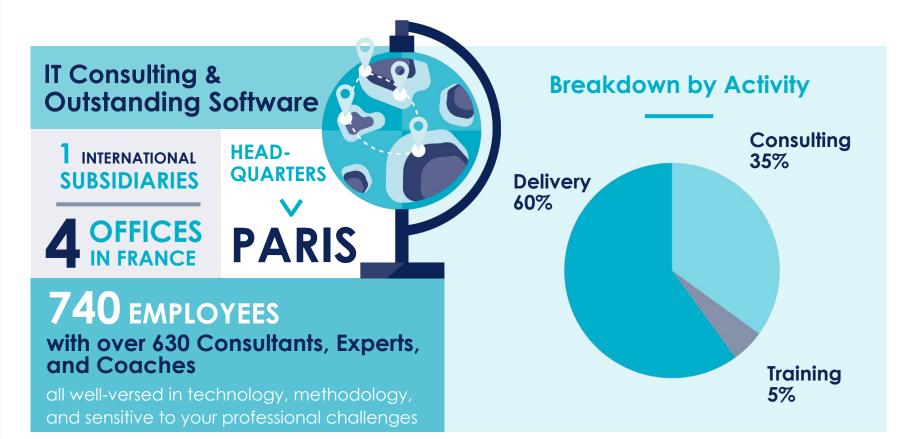
Conclusion

Le paradoxe de Simpson 04



OCTO Technology

OCTO in Numbers





OCTO - Digital Transformation Accelerator

USER CENTRIC

Rely on relevant technologies to **build** User Experience that can answer any need: ATAWAD "any time, anywhere, any device".

TECH TRENDS

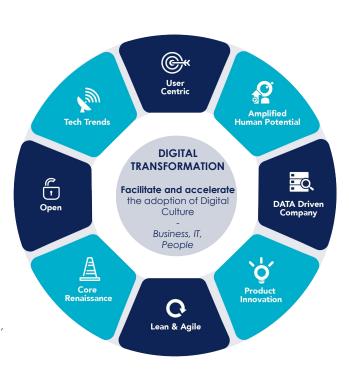
Provide expertise on the potential of technology to boost your business models and economic assets.

OPEN

Open your information system and **secure** access to your services to share, monetize, and benefit from the key drivers of Open Innovation.

CORE RENAISSANCE

Redesign the core of your information systems to meet digital's high standards, reduce TTM, and refocus on essential features.



AMPLIFIED HUMAN POTENTIAL

Share the codes of digital by establishing collaborative practices and boost potential and expertise within your teams.

DATA-DRIVEN COMPANY

Build data architecture that can drive your activities and make the most of opportunities provided by Big Data, Data Science, and Machine Learning.

PRODUCT INNOVATION

Structure and **Ensure** effective deployment of the Product Innovation approach (Design Thinking and Lean startup) to firmly plant it in your organization and processes (portfolio).

LEAN & AGILE

Coach your teams to take ownership of the best practices on the market: autonomous and multidisciplinary teams, short cycles, Test & Learn culture, industrialization of software procedures, DevOps, Software Craftsmanship.

Our Ecosystem

We provide support to all industries





TRAVEL



AEROSPACE



UTILITIES





BANKING





RETAIL



CONSUMER

GOODS



SERVICE PROVIDERS









HEALTHCARE

INSURANCE



















ENTERTAINMENT







INTERNET MEDIA

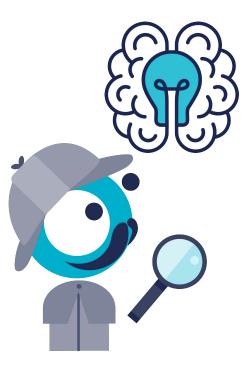


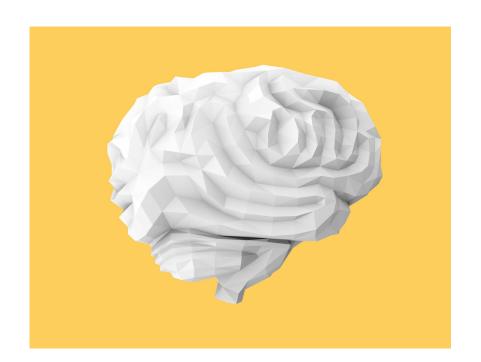
Causation

Why Study Causation?



Humans Think With Causation



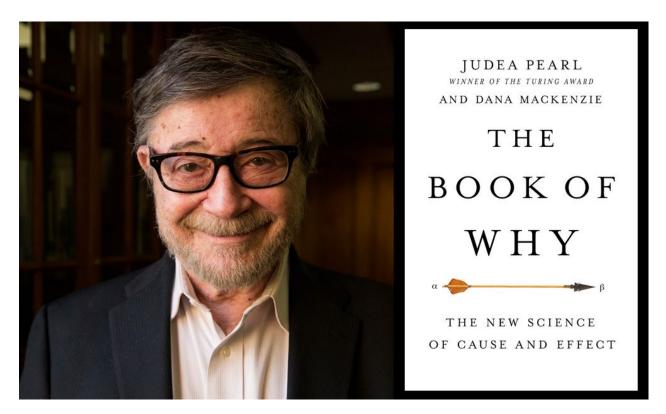


A Few Questions That Entail Causation

- 1. Why are some neighborhoods poorer than others?
- 2. Was it the new tax regulation or our advertising campaign that made our sales go up?
- 3. What is the efficacy of the AstraZeneca vaccine against coronavirus infection?
- 4. Should the European Medicines Agency approve the Sputnik V vaccine?
- 5. I'm about to switch careers to become a Data Scientist. Should I?

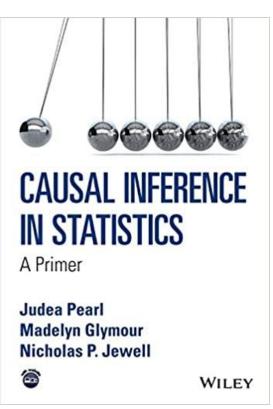
Judea Pearl

pioneer of the field of Causal Inference



Judea Pearl

To get started with causal calculus

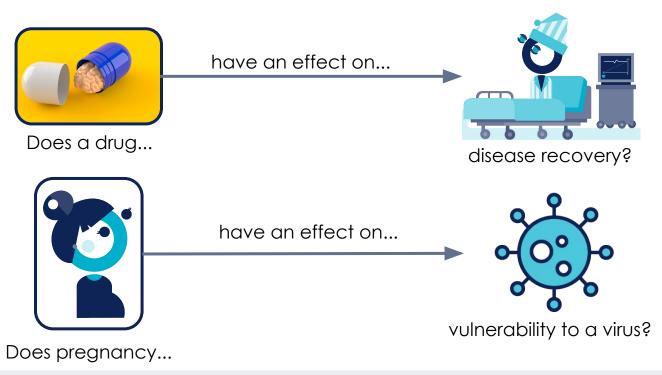








How Can We Find a Cause and its Effect?



How Can We Find a Cause and its Effect?

Research Methods

Randomized Controlled Trial (RCT)

- The Gold standard in causal research
- Individuals are randomly assigned to a treatment condition that corresponds to a possible value of the controlled variable.







Randomness guarantees that we find a causal relationship.

Observational Study

- Data is simply collected without intervention on the studied environment.
- Causation can't be distinguished from correlation

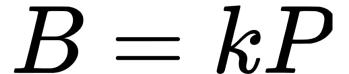


03

The Tools of Science and Statistics

Mathematical equations cannot express causal relationships

- B: Barometer reading
- P: Atmospheric Pressure
- **k**: constant of proportionality



The Tools of Science

$$B = kP$$

$$P = \frac{R}{k}$$

$$k = \frac{B}{P}$$

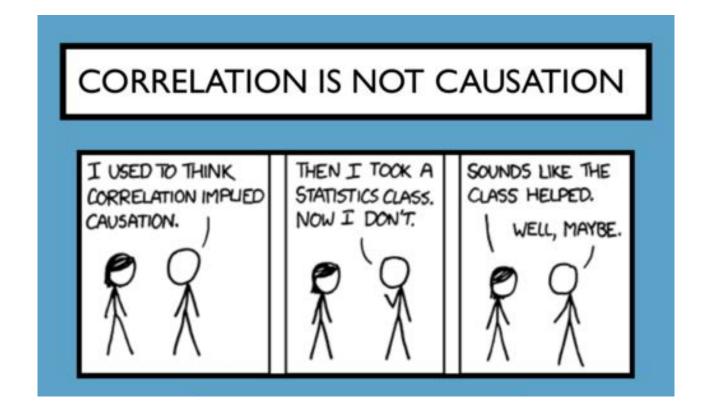
$$B - kP = 0$$

The Tools of Science

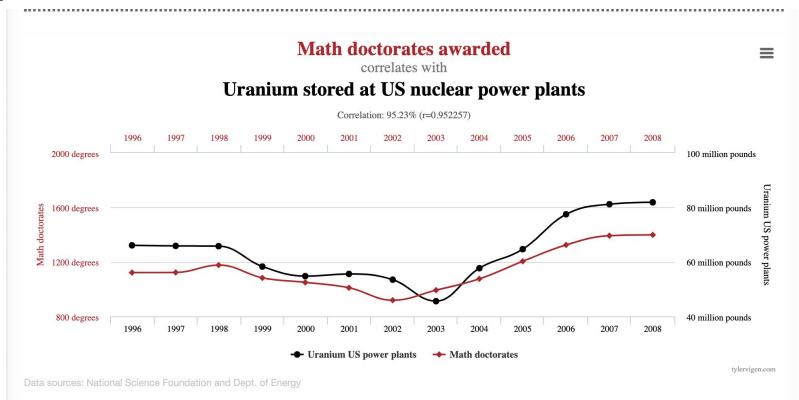
Probability



$$P(S|P=101kPa)$$



Spurious Correlations



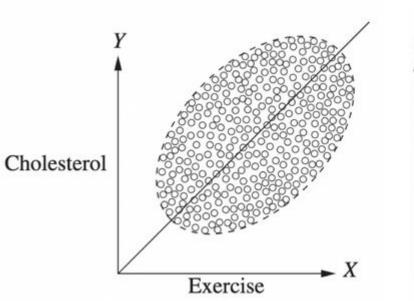
https://www.tylervigen.com/spurious-correlations

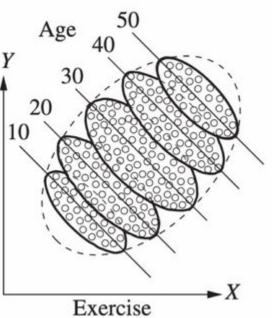


Simpson's Paradox

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Simpson's Paradox





Simpson's Paradox: Fictitious Example

Recovery Rate of a Drug



Drug taking (it's a choice)

Recovery

Simpson's Paradox: Fictitious Data as an Example

	Drug	No drug
Men	81 out of 87 recovered (93%)	234 out of 270 recovered (87%)
Women	192 out of 263 recovered (73%)	55 out of 80 recovered (69%)
Combined data	273 out of 350 recovered (78%)	289 out of 350 recovered (83%)

Counter-intuitive Mathematics

$$\frac{\frac{a}{b} + \frac{c}{d}}{\frac{e}{f} + \frac{g}{h}}$$

$$\frac{a+c}{b+d} > \frac{e+g}{f+h}$$

Statistics, an "Objective" Field

Modern statistics' objective is to <u>summarize</u> data.

- Contingency tables alone cannot tell the story of the mechanism that generated the data.
- So far, causation has been handled by the scientists' intuition.

New tools are needed to manipulate causal links easily.

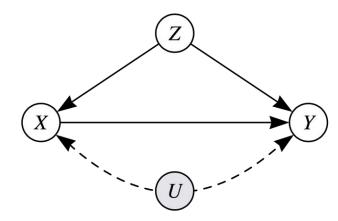
05

Towards a Causal Model

Causal Calculus

Two Components

Causal Diagram



To express what we know

Symbolic Language

$$P(Y \mid do(X))$$

To express what we want to know

Causal Calculus

The do() operator

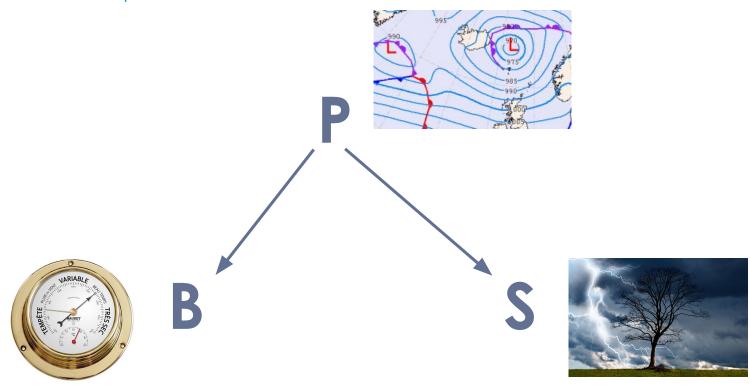
$$P(S \mid B)$$
 vs. $P(S \mid do(B))$





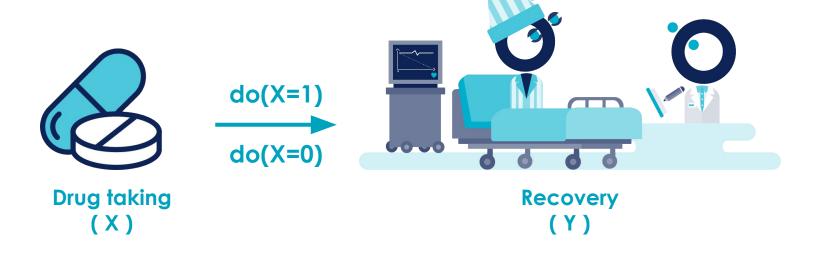
Causal Calculus

Causal Relationships Matter



Back to our Drug Example

We want to know the effect of the drug on recovery.

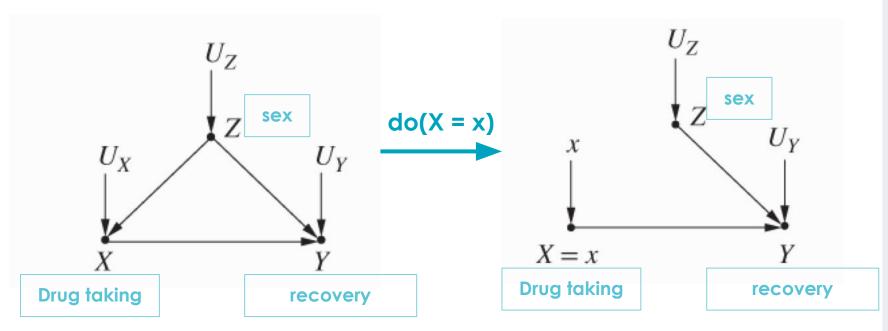


Calulate the Causal Effect

$$ACE = P(Y = 1|do(X = 1)) - P(Y = 1|do(X = 0))$$

ACE = Average Causal Effect

Do-calculus



The Adjustment Formula

$$P(Y = \bigcirc |do(X = \bigcirc)) =$$

$$P(Y = \bigcirc | X = \bigcirc, Z = \bigcirc)P(Z = \bigcirc)^{s}$$

$$+ P(Y = | X = , Z =)P(Z =)$$

The Adjustment Formula

$$P(Y=y|do(X=x)) = \sum P(Y=y|X=x,Z=z)P(Z=z)$$
 g

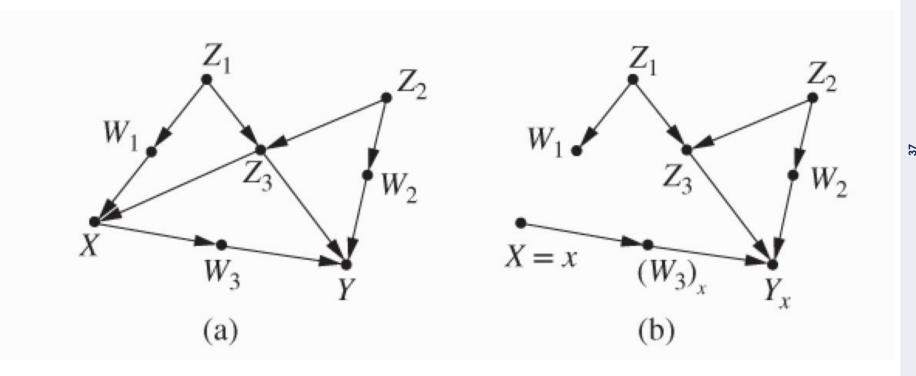
Back to the Original Data

	Drug	No drug
Men (51%)	81 out of 87 recovered (93%)	234 out of 270 recovered (87%)
Women (49%)	192 out of 263 recovered (73%)	55 out of 80 recovered (69%)
Combined data	273 out of 350 recovered (78%)	289 out of 350 recovered (83%)

83%

78%

Graphs Can Get More Complex

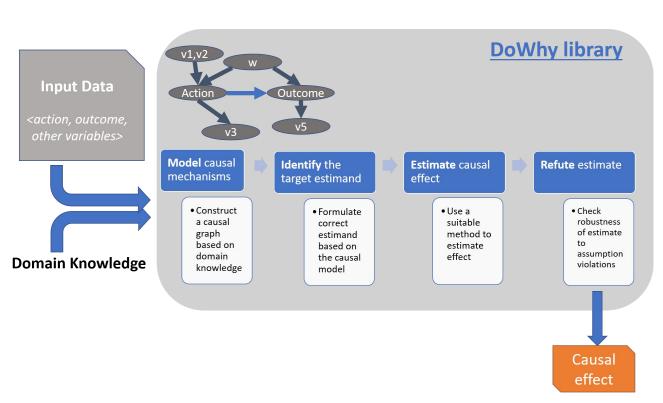


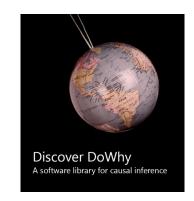


Inference Engines

The DoWhy Library

by Microsoft

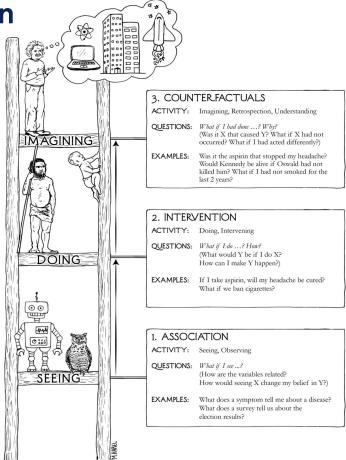






Conclusion

The Ladder of Causation





The Potential of Causal Inference

How could we use it in our Data Science projects?

Strengths

- Precise modelling of causal links
- Libraries can handle **complex** interactions.
- Transparent and interpretable model.
- Leverages domain expertise.



Difficulties

- MUST leverage domain expertise.
- Forces the consultant to look beyond the data themselves.
- Causal diagrams can be **tedious** to build.
- Any other ideas?

