Causal Inference

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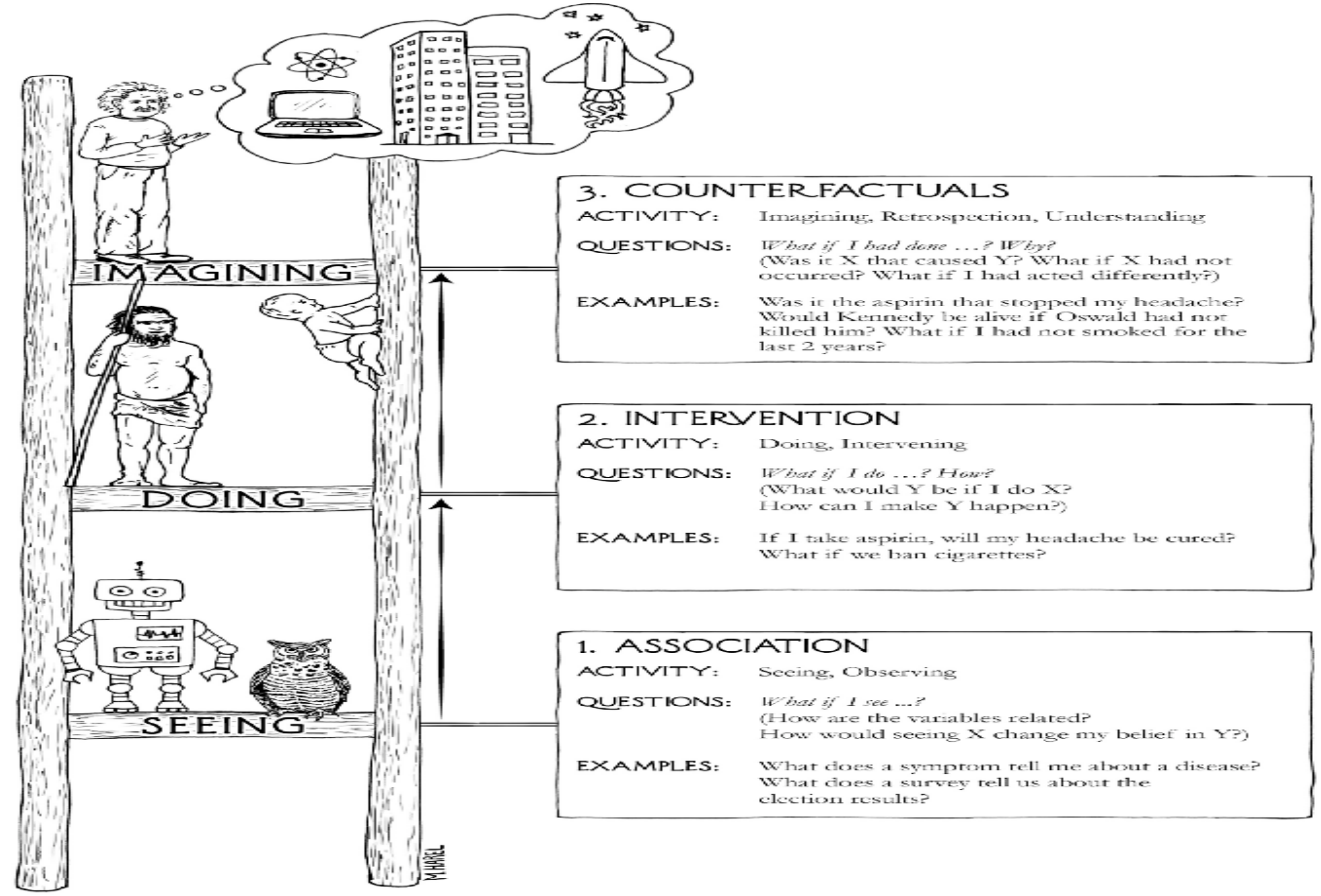
Ladder of Causation



Level (Symbol)	Typical Activity	Typical Questions	Examples
1. Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in$Y$?	What does a symptom tell me about a disease? What does a survey tell us about the election results?
2. Intervention $P(y\|do(x), z)$	Doing	What if? What if I do X?	What if I take aspirin, will my headache be cured? What if we ban cigarettes?
3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?	Was it the aspirin that stopped my headache? Would Kennedy be alive had Oswald not shot him? What if I had not been smoking the past 2 years?

Strong AI

- Counterfactual AI
- Self-driving car: “if I had slowed down, I could have avoided the accident”
- Free will: accountable for killing a pedestrian

Models of Reality

- Data science is only as much of a science as it facilitates the interpretation of data (Judea Pearl, 2018)

- Babylonian astronomers (Model-blind) were masters of black-box prediction, far surpassing their Greek (Model-based) rivals in accuracy and consistency (Toulmin, 1961)

- Today’s Data Science and Machine Learning are Babylonian (Think of Neural Networks)

Ethics and Law

- Epistemology: Explanation & Prediction
- Data Science Ethics: Transparency and Fairness
- EU GDPR – Explanations of ML Results

Counterfactual

- We may define a cause to be *an object followed by another, and where all the objects, similar to the first, are followed by objects similar to the second*. Or, in other words, *where, if the first object had not been, the second never had existed*. (Hume, 1748)

- Rooster crows and Sun rises: satisfies first definition but not the second

Statistics

- Observational Data with Joint Distribution P(X,Y,Z)
- Correlations are not causations
- Algebra is agnostic to causal relations:

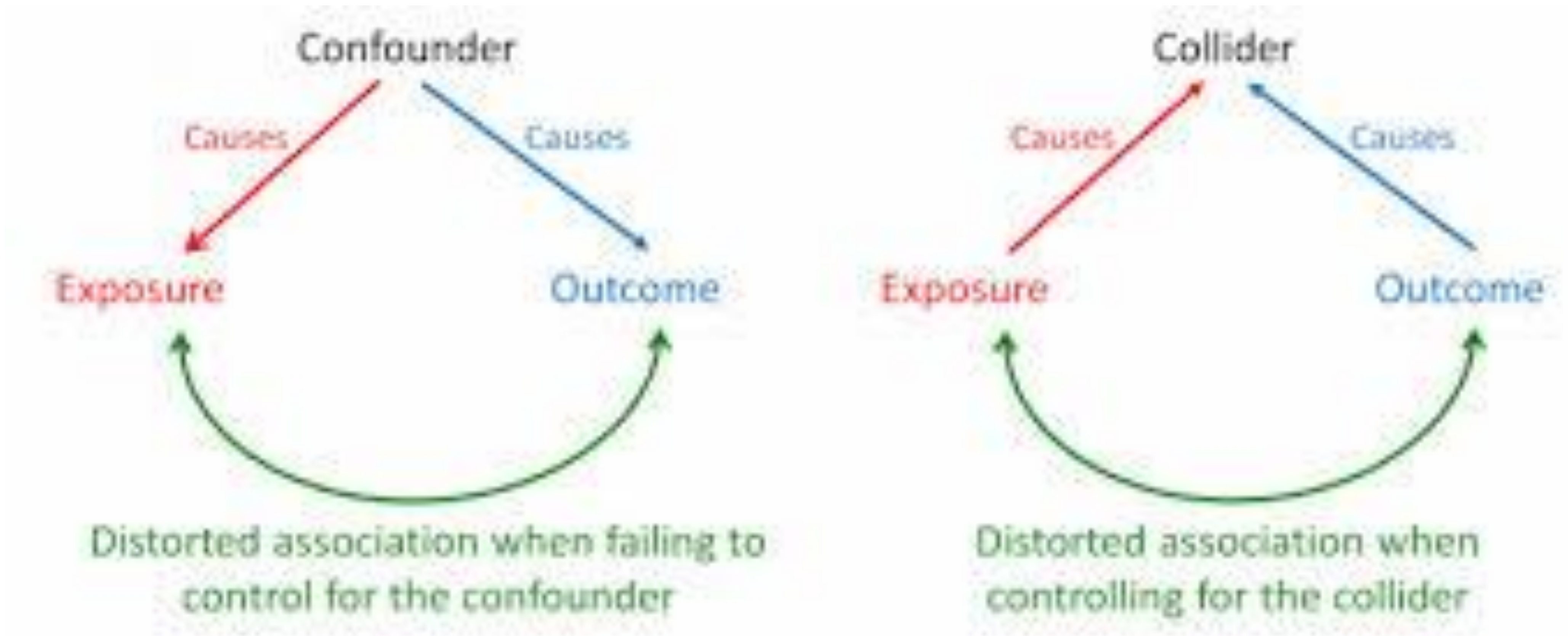
  $$y = 3x \leftrightarrow x = y/3$$

Observation vs Intervention

- See vs Do
- X = ice cream sale, Y = crime rate
- $P(Y|X)$ and $P(Y|do(x))$
- Need for causal graphs

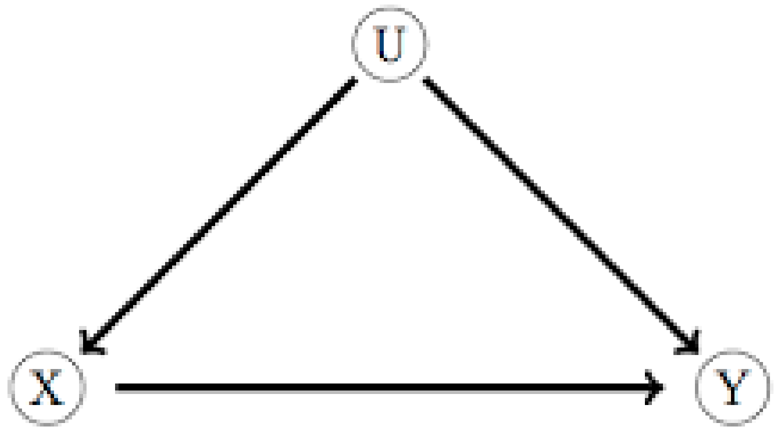
Causal Graphs

- Forks, mediators, and colliders


Confounder
Causes
Causes
Exposure
Outcome
Distorted association when failing to control for the confounder
Collider
Causes
Causes
Exposure
Outcome
Distorted association when controlling for the collider

Simpson's Paradox

- U = Gender
- X = Department
- Y = Admission



Linear Regression

- Regression coefficients as causal impact
- R code, Python code

Identification

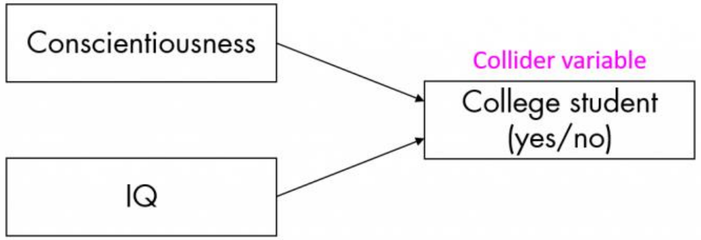
- Is Causality identifiable from observational data: example smoking cancer

Discovery

- Can a causal graph be discovered from observational data?
- Conditional probability as necessary but not sufficient
- $P(y|x,z) = P(y|z)$: is z a fork or a mediator?
- The d-separation criterion

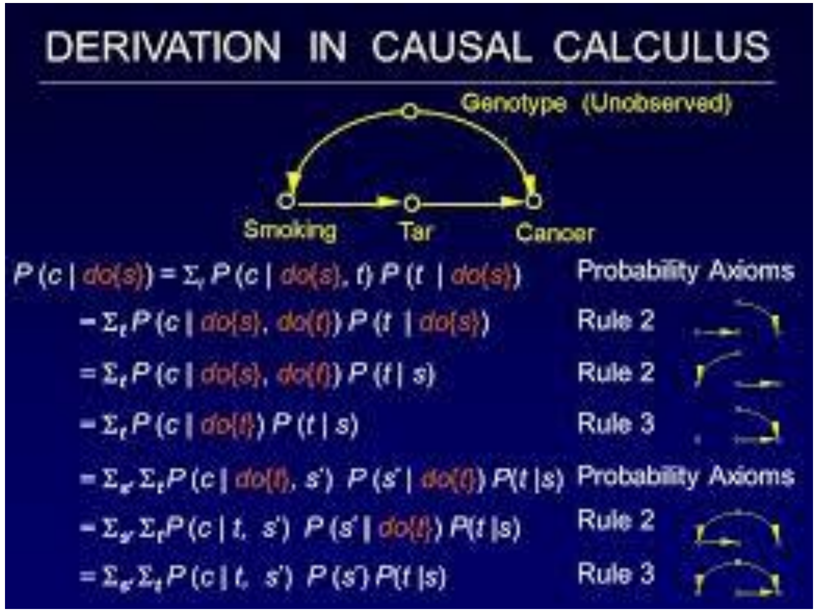
Packages

- Python: Dowhy
- R: CausalImpact



Colliders

- *Talent→Celebrity←Beauty*



Causality from Observational Data

- Domain Expertise of Humans to create Causal Graphs
- Costs of Experiments and Ethics

Causal Impact for Time-Series

- R Package CausalImpact for Time-Series

(Inferring causal impact using Bayesian structural time-series models, *Annals of Applied Statistics*, vol. 9 (2015), pp. 247-274

- Example: VW emission scandal and its stock price

https://rpubs.com/rinaldif/volkswagen-causal-impact

DaGitty

- Birth Weight Paradox