Causal Inference

Confounder → affects **both** treatment and outcome

Instrument → variable that affects treatment but not outcome (except its effect on treatment)
used when randomising treatment not possible.
Eg: can't control which plots get fertiliser, but can control which farmers get free fertiliser

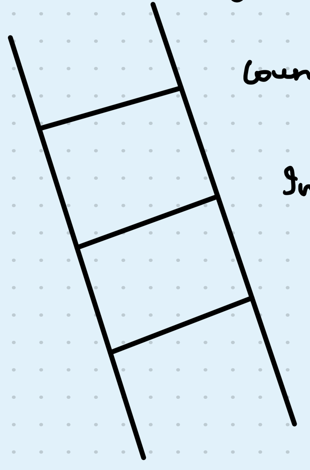
Process of causal inference

1. Hypothetical modeling: propose relationships, define treatment, outcome etc.
2. Causal effect: determine if causal effect is identifiable, whether its possible to separate from confounding influence
3. Parameter estimation: apply statistical techniques to quantify causal effect

Simpson's Paradox

Trend seen in subgroups reverses / disappears when they are combined, usually because a hidden variable changes weighting of data.

Judea Pearl's Ladder of Causation



Counterfactuals: If I had done X, what would Y be?
structural causal models, counterfactual models

Intervention: What happens to Y if I do X?
randomised experiments, structural models

Association: Observing X to see change in Y
correlation, statistical analysis, regression

Notation

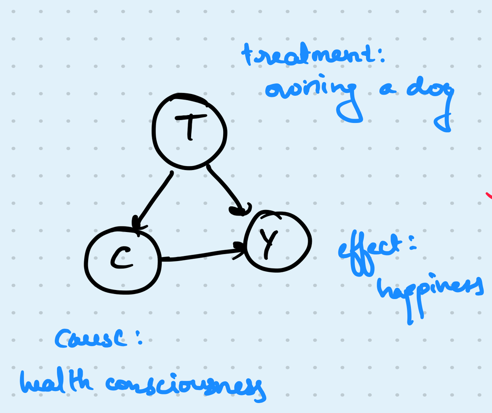
T → treatment Y → outcome X → covariates (may / may not be confounding)

$Y(t)$ → outcome for specific treatment t

Potential Outcomes

what would happen to $Y(t)$ for different values of t?

For individual, locked on to one value of t → other potential outcomes become counterfactuals.



confounder: backdoor path to Y
$T \to C \to Y$
⇒ $T \to Y$ is not causal

Individual Treatment Effect

Causal effect = outcome with treatment − outcome without treatment

$$\boxed{ITE_i = Y_i(1) - Y_i(0)}$$

Varies from individual to individual

Fundamental Problem of Causal Inference

You never know the counterfactual. You cannot observe the true change in applying the treatment to an individual, because you can't do both $Y(0)$ and $Y(1)$.

$\boxed{\text{You can never observe all potential outcomes for a given individual}}$

Average Treatment Effect

Measures avg. treatment effect (duh) over an entire population

$$\boxed{\tau = ATE = E[Y(1) - Y(0)]}$$

Allows you to substitute counterfactual by taking an average.

$E[Y(0)]$ → all individuals who got $t=0$
$E[Y(1)]$ → 〃 〃 〃 〃 $t=1$

We assume that these two groups are individually representative of the population and similar to each other.

IDEALLY: ATE = avg causal change we would see if we applied treatment to entire population, went back in time, applied control and then calculated avg change

Associational Difference

Associational difference = $E[Y(1)] - E[Y(0)]$

- Does not take causality into account, only correlation.
- AD = ATE if no confounders

For ATE, we have different ways of estimating avgs.

Experimental Studies: A/B Testing, Random Control Trials

Population → group A: treated
Population → group B: control

Key: Randomisation

- Removes all possible confounders
- Treatment assignment is independent of outcome or covariates
- Thus you are able to purely view treatment effect b/w A and B

⇓

you can use ATE = AD here

RCT: Trial that does A/B testing essentially
Allows direct comparison b/w A, B.
Solves fundamental problem.

Blinding
Single: patient unaware of treatment
Double: patient & medical staff unaware
Isolates treatment effect

Conditional exchangeability

w/o randomisation → conditioning on some covariate X → T assignment still independent
↓
conditional exchangeability ← you can still find causal affects

Requires all confounders to be measured

$$\boxed{\{Y(0), Y(1)\} \perp A \mid X}$$

→ participants may not follow treatment
→ blinding not always feasible
→ whole thing not feasible at scale
→ cannot assign harmful treatments
→ trial ≠ real world population
→ small effect can require large dataset

→ may not be able to find $X \to Y$ or $Y \to X$

Interventions

- Actively manipulate a variable to study causal effects
- RCT is a type of intervention

Structural (hard) intervention
- Breaks all causal edges
- Independent of everything
  Eg: ideal randomisation in RCT

Parametric (soft) intervention
- Do not cut causal links
- Modify distribution instead
- Eg: change the income of households by sampling from a known distribution for the increase instead of increasing by a set amount

Intervention beyond RCT:
- Causal discovery, not just effect estimate
- Intervening on multiple variables simultaneously → reveal structure

How many variables to intervene on:
- Single var: N−1
- Multiple var ∝ $\log(N)+1$
- Parametric: even one could be enough