Causal Reasoning: Understanding Why Things Happen

Introduction to Logic

Brendan Shea, PhD

Causal Reasoning: Understanding Why Things Happen

- **Causal reasoning** is the process of identifying relationships where one event or condition brings about another.
- We use causal thinking every day when we ask "why" questions: Why did my car break down? Why did I get sick?
- Understanding causation helps us predict future events and make better decisions in our personal and professional lives.
- Today we'll learn systematic methods to distinguish genuine causes from mere coincidences.

Key Question

How can we reliably determine what causes what in a complex world?

From Correlation to Causation: Today's Journey

- **Correlation** means two things tend to occur together, but this doesn't necessarily mean one causes the other.
- The famous phrase "correlation does not imply causation" warns us against jumping to conclusions about cause and effect.
- We'll explore scientific methods that help us move beyond correlation to establish genuine causal relationships.
- By the end of this lecture, you'll have tools to critically evaluate causal claims in media, research, and everyday life.

Warning

Many false beliefs arise from mistaking correlation for causation!

Why Causal Thinking Matters in Logic and Life

- Causal reasoning connects to our previous studies of deductive, inductive, and abductive reasoning.
- In science, establishing causation is essential for developing effective treatments, policies, and technologies.
- Understanding causation helps us avoid superstitious thinking and make rational decisions based on evidence.
- Causal literacy is crucial for being an informed citizen who can evaluate claims about health, economics, and social issues.

Example (Real-World Applications)

- Does this medication actually cure the disease?
- Will this economic policy reduce unemployment?
- Does violent media cause aggressive behavior?

Defining Causation: The Interventionist Approach

- The **interventionist approach** defines causation in terms of what would happen if we actively changed something.
- X causes Y if intervening to change X would lead to a change in Y, all else being equal.
- This approach emphasizes that causes are things we can manipulate or that could be manipulated in principle.
- The key insight is that causation is about what happens when we "wiggle" one variable and observe effects on another.

Formal Definition

X causes Y if and only if there exists an intervention on X that would change Y (holding all else constant).

”If I Do X, Then Y Happens”: Intervention in Action

- **Intervention** means actively changing a variable rather than just observing it naturally occur.
- When we flip a light switch (intervention on X), the light turns on (change in Y) - this suggests a causal relationship.
- The intervention must be ”surgical” - it changes only the target variable without affecting other factors directly.
- This approach helps us distinguish causation from mere association or correlation in data.

$$\boxed{\text{Flip Switch}} \xrightarrow{\text{causes}} \boxed{\text{Light On/Off}}$$

Counterfactual Thinking: "What If Things Were Different?"

- **Counterfactual reasoning** asks what would have happened if circumstances had been different.
- "The rock caused the window to break" means: if the rock hadn't been thrown, the window wouldn't have broken.
- This approach defines causation by comparing the actual world with hypothetical alternative worlds.
- Counterfactuals help us think about causation even when we can't perform real interventions.

Example (Counterfactual Analysis)

- Actual world: I studied hard and passed the exam
- Counterfactual world: If I hadn't studied hard, I would have failed
- Conclusion: Studying hard caused me to pass

Example: Why Did Wile E. Coyote Fall? (Interventionist View)

- In the cartoon, Wile E. Coyote runs off a cliff but doesn't fall until he looks down and realizes there's no ground.
- **Interventionist analysis**: If we intervened to prevent him from looking down, would he still fall?
- In reality, gravity causes the fall regardless of awareness - looking down is not the true cause.
- This example illustrates how the interventionist approach helps us identify genuine causes versus coincidental timing.

Cartoon vs. Reality

In cartoons: Looking down $\rightarrow$ Falling (not real causation!)
In reality: Running off cliff $\rightarrow$ Falling (true causation)

Example: Would Batman Still Fight Crime Without His Parents' Death? (Counterfactual)

- Batman's origin story claims his parents' murder caused him to become a crime fighter.
- **Counterfactual analysis**: In a world where his parents lived, would Bruce Wayne still become Batman?
- Most interpretations suggest no - he would likely have become a philanthropist or businessman instead.
- This example shows how counterfactuals help us evaluate causal claims in complex narratives where we can't intervene.

Counterfactual Worlds

Actual World	**Counterfactual World**
Parents murdered	Parents survive
Becomes Batman	Remains civilian
Fights crime	Runs Wayne Enterprises

Everyday Causation: Coffee and Alertness

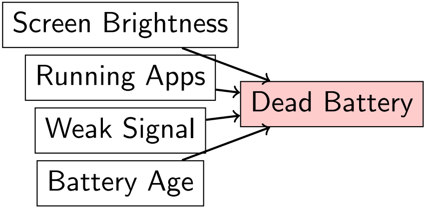
- We often claim "coffee makes me alert," but how can we verify this causal relationship?
- **Intervention test**: When I drink coffee (intervention), I become more alert within 20-30 minutes.
- **Counterfactual test**: On days I skip coffee, I remain drowsy longer than on days I drink it.
- However, other factors like placebo effects, sleep quality, and time of day might also influence alertness.

Example (Personal Experiment)

Try alternating coffee and decaf for a week while tracking alertness levels - this creates your own mini-intervention study!

Multiple Causes: Why Your Phone Battery Dies

- Real-world events often have **multiple causes** working together rather than a single cause.
- Your phone battery dies because of: screen brightness, running apps, cellular signal strength, and battery age.
- Each factor contributes causally - intervening on any one of them would affect battery life.
- Understanding multiple causation helps us see why simple "X causes Y" statements often oversimplify reality.



The Correlation Trap: When Association Isn't Causation

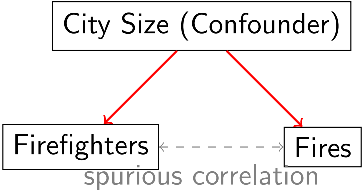
- **The correlation trap** occurs when we mistake statistical association for causal relationship.
- Just because two things occur together frequently doesn't mean one causes the other.
- Classic example: Ice cream sales and drowning deaths both increase in summer, but ice cream doesn't cause drowning!
- The trap is especially dangerous when correlation confirms our existing beliefs or desires.

Remember

Correlation is evidence that might suggest causation, but it's not proof! Always look for alternative explanations.

Confounding Variables: Hidden Factors at Play

- A **confounding variable** is a hidden factor that influences both the supposed cause and effect.
- Confounders create the illusion of causation where none exists by making two things appear related.
- Example: Cities with more firefighters have more fires, but firefighters don't cause fires - large city size causes both!
- Identifying and controlling for confounders is crucial for accurate causal inference.



Example: Ice Cream Sales and Drowning Deaths

- Data shows that when ice cream sales increase, drowning deaths also increase - but ice cream doesn't cause drowning!
- The hidden **confounding variable** is temperature/season: hot weather causes both more ice cream consumption and more swimming.
- This example perfectly illustrates why "correlation does not imply causation" is such an important principle.
- Without considering confounders like weather, we might implement useless policies like banning ice cream to prevent drowning.

The Real Causal Structure

Hot Weather → More Ice Cream Sales
Hot Weather → More Swimming → More Drowning Risk
(No direct causal link between ice cream and drowning!)

Simpson's Paradox: When Data Misleads

- **Simpson's Paradox** occurs when a trend appears in different groups of data but disappears or reverses when groups are combined.
- Example: A treatment might appear harmful overall but actually be beneficial within each patient subgroup.
- This paradox shows how aggregating data can hide true causal relationships and lead to wrong conclusions.
- The paradox typically arises when we ignore an important variable that affects both treatment assignment and outcomes.

Example (University Admissions)

Women have higher admission rates in each department but lower overall!

Department	Male Admit Rate	Female Admit Rate
Engineering	30%	35%
Liberal Arts	60%	65%
Overall	45%	40%

Fictional Example: Did Spider-Man's Powers Cause His Problems?

- Peter Parker gains powers and then experiences many personal tragedies - did the powers cause his problems?
- Alternative explanation: His decision to become a hero (not the powers themselves) puts him in dangerous situations.
- Another factor: "Parker Luck" suggests he was already prone to misfortune before gaining powers.
- This example shows how even in fiction, identifying true causes requires careful analysis of competing explanations.

Causal Analysis

Powers → Hero Choice → Dangerous Situations → Problems
(The powers are only an indirect cause through Peter's choices!)

Selection Bias: Why Your Sample Matters

- **Selection bias** occurs when the sample we study isn't representative of the population we want to understand.
- Example: Studying only gym members to determine if exercise improves health ignores that healthier people might choose to join gyms.
- This bias can make us think we've found a causal relationship when we've actually just selected a special group.
- Selection bias is especially tricky because it can be invisible - we don't see the data we didn't collect.

Example (Survivor Bias in WWII)

Engineers wanted to add armor where returning planes had bullet holes, but statistician Abraham Wald realized they should armor where the holes *weren't* - those planes didn't return!

The Gold Standard: Randomized Controlled Trials

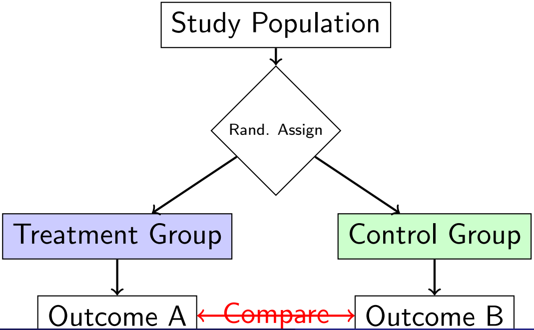
- **Randomized Controlled Trials (RCTs)** are considered the gold standard for establishing causation.
- In an RCT, participants are randomly assigned to either receive a treatment or be in a control group.
- Random assignment ensures that confounding variables are distributed equally between groups on average.
- By comparing outcomes between treatment and control groups, we can isolate the causal effect of the treatment.

Why RCTs Work

Randomization breaks the link between confounders and treatment assignment, allowing us to measure true causal effects.

Key Components: Treatment, Control, and Randomization

- **Treatment group** receives the intervention we're testing (new drug, teaching method, therapy, etc.).
- **Control group** receives either no treatment, a placebo, or the standard existing treatment.
- **Randomization** uses chance (like flipping a coin) to assign participants to groups, eliminating selection bias.
- These three components work together to create a fair comparison that reveals causal effects.



Example: Testing Popeye's Spinach Hypothesis

- Popeye claims spinach causes super strength - how would we test this claim with an RCT?
- **Design**: Randomly assign 100 sailors to eat either spinach (treatment) or lettuce (control) daily for one month.
- **Measurement**: Test grip strength, lifting capacity, and endurance before and after the trial.
- **Result**: If the spinach group shows significantly greater strength gains, we have evidence for causation.

Example (RCT Design for Popeye)

1. Recruit 100 sailors of similar baseline strength
2. Randomly assign: 50 to spinach, 50 to lettuce
3. Both groups eat identical diets except for the vegetable
4. Measure strength changes after 30 days
5. Compare average improvements between groups

The Placebo Effect: Mind Over Matter

- The **placebo effect** occurs when people improve simply because they believe they're receiving treatment.
- This psychological phenomenon can create false impressions of causation if not properly controlled.
- That's why control groups often receive a placebo (fake treatment) that looks identical to the real treatment.
- By comparing real treatment to placebo, we can separate the actual causal effect from psychological expectations.

Example: Sugar Pills

In drug trials, the control group receives sugar pills that look identical to the real medication. Any improvement in the control group is due to placebo effect, not the drug's chemistry.

Real Example: The Salk Polio Vaccine Trial

- In 1954, Jonas Salk's polio vaccine was tested in one of the largest RCTs in history.
- Over 400,000 children were randomly assigned to receive either the vaccine or a placebo injection.
- The trial was "double-blind" - neither children nor doctors knew who received which treatment.
- Results showed the vaccine was 80-90% effective at preventing paralytic polio, leading to widespread vaccination.

Example (Trial Statistics)

Group	Size	Polio Cases
Vaccine	200,745	33
Placebo	201,229	115

Blinding: Keeping Bias at Bay

- **Blinding** prevents knowledge of treatment assignment from influencing outcomes or measurements.
- **Single-blind**: Participants don't know their group assignment, preventing placebo effects from contaminating results.
- **Double-blind**: Neither participants nor researchers know assignments, preventing unconscious bias in measurement.
- Blinding is crucial because humans unconsciously behave differently when they know they're being treated or observed.

Why Double-Blind?

A doctor who knows a patient received the real drug might unconsciously look harder for improvements, biasing the results. Double-blinding prevents this!

Example: Would Superman's Powers Work Without Yellow Sun? (Experimental Design)

- Superman claims Earth's yellow sun causes his powers - how would we design an experiment to test this?
- **Treatment**: Exposure to yellow sun radiation in a controlled environment.
- **Control**: Exposure to red sun radiation (matching Superman's home planet Krypton).
- **Challenge**: We can't randomize Superman himself, and we have no other Kryptonians for a proper sample!

Example (Proposed Design)

1. Build chambers with different sun radiation types
2. Randomly assign Superman to chambers on different days
3. Measure strength, speed, and flight ability in each
4. Compare average abilities under yellow vs. red sun
5. Problem: Only n=1 subject, so results may not generalize!

Sample Size: How Many Test Subjects Do We Need?

- **Sample size** refers to the number of participants needed to detect a real causal effect reliably.
- Larger samples provide more statistical power to distinguish true effects from random chance.
- Too small a sample might miss real effects (false negative) or find effects that aren't real (false positive).
- The required sample size depends on how large the causal effect is and how much natural variation exists.

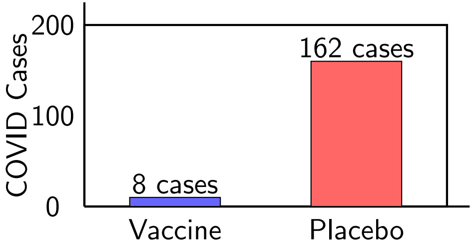
Rule of Thumb

Larger effect = Smaller sample needed
Smaller effect = Larger sample needed

Example: Detecting if a coin is two-headed requires few flips.
Detecting if a coin is slightly biased (51% heads) requires thousands!

Real Example: Clinical Trials for COVID-19 Vaccines

- COVID-19 vaccine trials in 2020 used RCTs with tens of thousands of participants.
- Pfizer's trial randomly assigned about 44,000 people to receive either the vaccine or a saline placebo.
- The large sample size was necessary because COVID infection rates were relatively low in the population.
- Results showed 95% efficacy: 8 COVID cases in vaccine group versus 162 in placebo group.



Ethical Considerations in Human Experiments

- **Ethical constraints** limit what experiments we can perform on humans, even if they would provide clear causal evidence.
- We cannot randomly assign people to harmful conditions like smoking, poverty, or dangerous occupations.
- All participants must give **informed consent**, understanding the risks and benefits of participation.
- Institutional Review Boards (IRBs) review all human experiments to ensure they meet ethical standards.

The Ethical Dilemma

We might want to know if smoking causes cancer through an RCT, but we cannot ethically randomize people to smoke! This is why we often rely on observational studies for harmful exposures.

Limitations: When Controlled Experiments Aren't Possible

- Some causal questions cannot be answered with RCTs due to practical, ethical, or logical constraints.
- **Practical**: We can't randomly assign countries to different economic systems or planets to different orbits.
- **Ethical**: We can't randomly assign children to different parents or people to natural disasters.
- **Logical**: We can't randomize unchangeable characteristics like biological sex at birth or historical events.

Example (Questions RCTs Cannot Answer)

- Does democracy cause economic growth?
- Do traumatic childhoods cause mental illness?
- Did the asteroid impact cause dinosaur extinction?
- Does gender affect career advancement?

For these questions, we need other methods like natural experiments!

Natural Experiments: When Nature Does the Randomization

- A **natural experiment** occurs when circumstances naturally create treatment and control groups without researcher intervention.
- These "experiments" arise from policy changes, natural disasters, arbitrary boundaries, or other external events.
- While not truly random, natural experiments can approximate randomization when assignment is unrelated to outcomes.
- Natural experiments help us study causal questions that would be impossible or unethical to test with RCTs.

Key Advantage

Natural experiments allow us to study real-world causation at scales and in contexts where controlled experiments are impossible.

Example: The Oregon Health Insurance Experiment

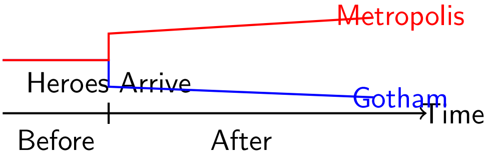
- In 2008, Oregon used a lottery to allocate limited Medicaid slots among 90,000 low-income adults.
- This created a natural experiment: lottery winners (treatment) versus lottery losers (control).
- The random lottery approximated the randomization of an RCT without researchers controlling assignment.
- Studies found Medicaid coverage increased healthcare use, reduced financial strain, and improved mental health.

Example (Natural Randomization)

Group	**Assignment**	**Outcome Studied**
Treatment	Won lottery	Health with Medicaid
Control	Lost lottery	Health without Medicaid

Fictional Example: Comparing Gotham and Metropolis Crime Rates

- Gotham has Batman while Metropolis has Superman - do different types of heroes cause different crime rates?
- This is a natural experiment: cities weren't randomly assigned heroes, but we can still compare outcomes.
- **Challenge**: Cities might differ in other ways (population, economy, corruption) that affect crime.
- To make causal claims, we'd need to show the cities were similar before the heroes arrived.



Real Example: London Cholera Outbreak of 1854

- John Snow used a natural experiment to prove cholera was waterborne, not airborne as believed.
- Different London neighborhoods received water from different companies, creating natural treatment groups.
- One company's water came from sewage-contaminated Thames; the other's came from cleaner upstream sources.
- Deaths clustered in areas served by the contaminated water company, proving water caused cholera transmission.

Snow's Innovation

By mapping deaths and water sources, Snow showed that water supply (not "bad air") caused cholera - revolutionizing public health and establishing epidemiology as a field.

Strengths and Weaknesses of Natural Experiments

- **Strengths**: Natural experiments study real-world settings, include entire populations, and examine effects over long time periods.
- **Weaknesses**: Assignment isn't truly random, confounding variables may still exist, and we can't control timing or implementation.
- Natural experiments require careful analysis to ensure the "natural" assignment process is truly unrelated to outcomes.
- They provide valuable evidence when RCTs are impossible, but generally offer weaker causal evidence than true experiments.

Comparison with RCTs

Feature	RCT	Natural Experiment
Control	High	Low
External validity	Lower	Higher
Ethical constraints	More	Fewer
Causal certainty	Highest	Moderate

Deductive Reasoning Meets Causal Inference

- **Deductive reasoning** moves from general principles to specific conclusions with logical certainty.
- In causal inference, we can deduce: "If A causes B, and B causes C, then A indirectly causes C."
- However, most causal claims require empirical evidence, not just logical deduction from premises.
- Deduction helps us understand the logical structure of causal chains but can't establish whether causes exist.

Example (Deductive Causal Chain)

1. Premise 1: Smoking causes lung damage (empirical claim)
2. Premise 2: Lung damage causes breathing problems (empirical claim)
3. Conclusion: Therefore, smoking causes breathing problems (deductive inference)

The logic is valid, but the premises require empirical support!

Inductive Reasoning: From Specific Cases to Causal Laws

- **Inductive reasoning** generalizes from specific observations to broader causal principles.
- We observe that aspirin relieves headaches in many cases, then inductively infer aspirin causes pain relief generally.
- Controlled experiments are essentially systematic inductive reasoning: from sample results to population effects.
- The problem of induction applies: we can never be certain our causal laws will hold in all future cases.

Trial 1: Drug works

Trial 2: Drug works $\xrightarrow{\text{Induction}}$ Drug causes recovery

Trial 3: Drug works

Abductive Reasoning: Best Causal Explanations

- **Abductive reasoning** infers the best causal explanation for observed phenomena.
- When we see wet streets, we abductively infer rain as the most likely cause (though sprinklers are possible).
- Natural experiments often rely on abduction: we observe patterns and infer the most plausible causal story.
- Good abductive causal reasoning considers multiple explanations and chooses the simplest one fitting all evidence.

Inference to Best Explanation

Observation: Students who sit in front get better grades
Possible causes:

- Sitting in front causes better learning (causal)
- Motivated students choose front seats (selection)
- Teachers favor front-row students (bias)

Experiments help determine which explanation is best!

Causal Reasoning: Your New Logical Superpower

- You now have tools to critically evaluate causal claims in science, media, and everyday life.
- Remember: correlation isn't causation, confounders lurk everywhere, and good experiments isolate causal effects.
- When RCTs aren't possible, natural experiments and careful reasoning can still provide causal insights.
- Combine causal thinking with deductive, inductive, and abductive reasoning for comprehensive logical analysis.

Your Causal Reasoning Toolkit

✓ Identify potential confounders
✓ Recognize selection bias
✓ Design controlled experiments
✓ Spot natural experiments
✓ Think counterfactually
✓ Integrate with other logical methods