An Overview of Causal Reasoning

Tom Coyne

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Agenda

- Why we engage in causal reasoning
- Causal reasoning challenges
- Basic concepts and tools
- Simplified Example
- Causal Reasoning in Practice

Typical Goal Directed Reasoning Process

- We observe evidence that the actual situation is not the desired situation
  - The desired situation can be formulated as a specific goal, or it can be a more generally described state
- We then formulate a causal model to explain the observed variance between the actual and desired state
  - Causal reasoning is obviously critical here, but up to now it has not been extensively studied by researchers
- Having formulated a causal/explanatory model, we then use it to predict the results of different possible actions we could take to close the gap between the actual and desired states

Causal Reasoning Challenges

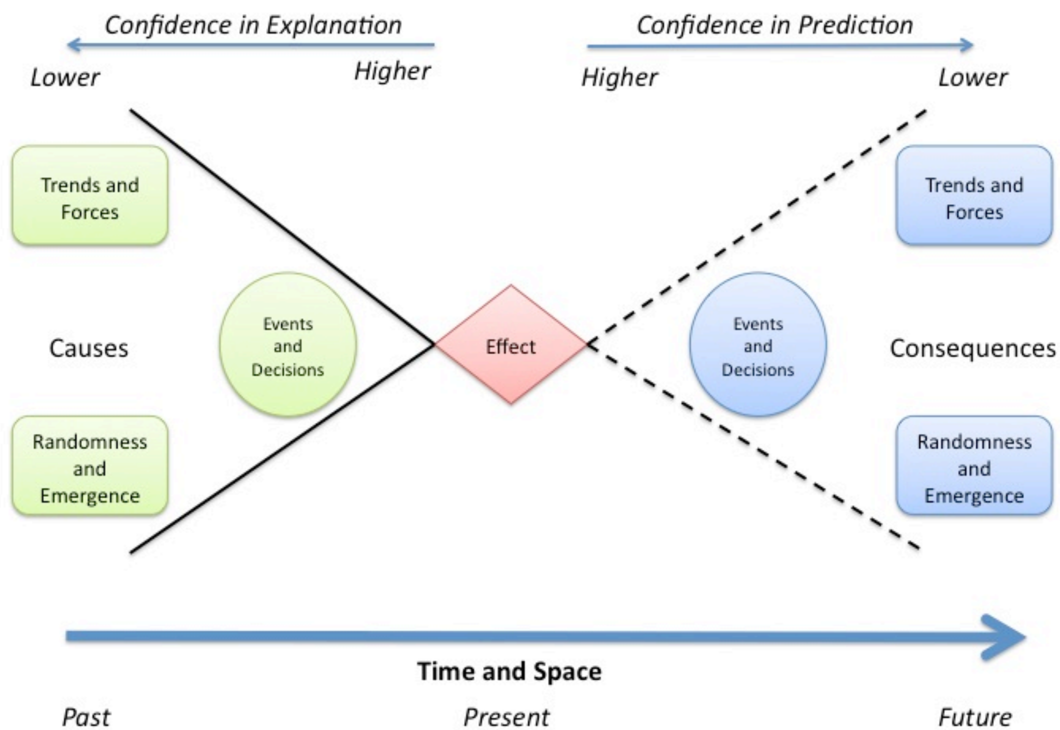
- Most of what we are taught about causation comes from the physical sciences, where:
  - Observed effects usually have relatively few causes
    - Weather and climate change are exceptions, as they are complex systems
  - Cause and effect are usually related by unchanging natural laws
  - Experiments can be repeated to test and confirm hypotheses
- However, many of the causal reasoning situations we encounter involve "complex adaptive systems", where:
  - Effects often have multiple causes, and causal relationships are often non-linear (i.e., characterized by positive feedback loops) and time-delayed,
  - This produces effects that are "emergent" rather than the result of intentional causation
  - Causal relationships also change over time, as the agents (e.g., people) involved in the system adapt their behavior and relationships
  - Experiments are usually difficult, and hard to repeat
    - Though agent based modeling and computer simulations of complex adaptive systems now enable researchers to develop more insights into the behavior of complex adaptive systems
  - Examples: a financial market, an economy, international relations, military conflicts
- Causal reasoning about complex adaptive systems will inevitably be imperfect
  - The best we can hope for is a "coarse grained" understanding that will have an irreducible level of uncertainty

Patterns of Causation in Complex Adaptive Systems

- In agent based models (ABM), agents follow a few simple rules; however, these rules, along with the information available to agents (from the media and each other) and the pattern of interactions between them (which is driven by the number of connections between agents) combine to produce "emergent" effects that cannot be predicted from knowledge of the agent rules alone
- Note that complex adaptive systems typically produce a power law (exponential) distribution of effects – i.e., many small ones, and a few very big ones
  - Power law distributions also characterize the number of connections between agents – i.e., most have only a few connections, but some agents that are central to a network have many
- Complex adaptive systems are often characterized by three different behavioral regimes (phases) – one is very stable, one is very unstable, and one in the middle maximizes system resilience and adaptability
  - Because of the power law distribution of changes in a CAS, a large change will usually be preceded by a number of smaller events of lesser magnitude, that hint at the pressure for change that is building in the system
  - Rapid change often occurs once one or more system "control parameters" have passed a critical threshold, or "tipping point" (e.g., the amount of leverage in a financial system)
  - This process creates the familiar "S-shaped" pattern of change in many domains
- Non-linear behavior results when positive feedback loops are more powerful than negative feedback loops
  - Try to identify key feedback loops in the system, and understand how their relative power is changing
- Complex adaptive systems typically have both flow and stock parameters. Flows tend to make the news, but it is accumulating stocks that often cause tipping points and crises
  - E.g., the annual government deficit is a flow; the amount of government debt outstanding is a stock

In Addition to Complexity, Time also Creates Causal Reasoning Challenges

- The further back in time we go, the harder it is to identify specific causes; instead we have to focus on broad trends and forces



Evolution has also Made Causal Reasoning Hard

- Eons ago, when we were trying to survive on the East African Savannah, some basic rules of causation served us well
  - The timeline of events implies a causal relationship, with the earlier event causing the later result
  - Events that happen at the same time are causally related (e.g., either one causes they other, or they have a common cause)
- Today we recognize that this instinctive reasoning can lead to fallacious conclusions about causation
  - "post hoc ergo propter hoc" – temporal succession does not always imply causation; however, often it does
  - "cum hoc ergo propter hoc" – correlation does not always imply causation; again, often it does
  - As always, our initial intuitions need to be tested with analysis

Some Basic Causal Concepts

- Necessary versus Sufficient Cause
  - A necessary cause must be present in order for an effect to occur (however, the effect may requires other conditions to also be present)
    - E.g., in order to be charged with a DWAI or DUI, it is necessary to have been ingesting alcohol
  - A sufficient cause is a condition that in an of itself can cause an effect to occur
    - E.g., if you are over 21, a blood alcohol level of .05% or greater is sufficient for you to be charged with DWAI, and a level of .08% or greater is sufficient for you to be charged with DUI
  - Counterfactual reasoning can help us identify necessary and sufficient causes
    - Would the effect have occurred if the conjectured cause did not occur?
- Axiom vs. Conjecture vs. Hypothesis vs. Theory
  - Axioms are self-evident premises that can can be accepted as true without argument; i.e., they are possible starting point for reasoning
  - Conjectures are unproved propositions assumed to be true that may be testable
  - Hypotheses are testable conjectures
  - Theories are frameworks for explaining and predicting multiple related effects, that are based on hypotheses that have been tested and not falsified, sometimes combined with axioms and conjectures

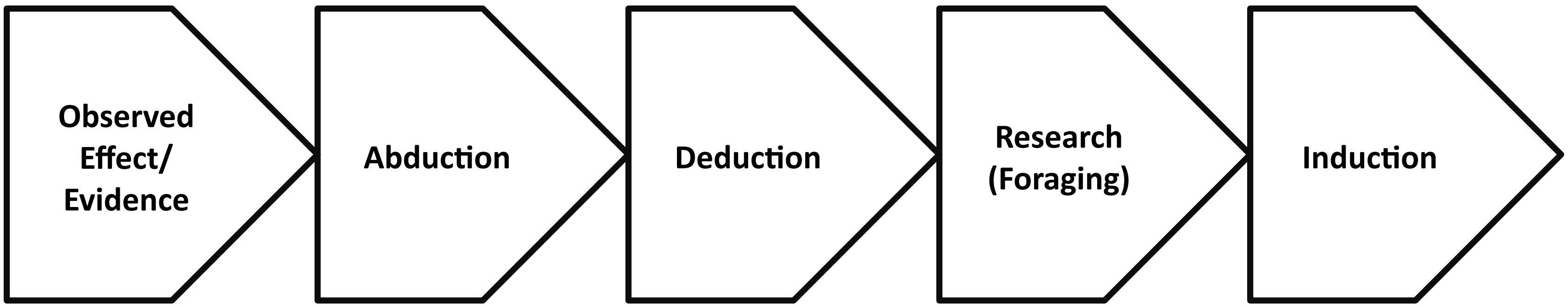
Three Types of Reasoning

- Abductive (inference to plausible possible explanation)
  - Socrates is mortal (Observed Result/Effect)
  - All humans are mortal (General Rule/Axiom/Theory)
  - Therefore, Socrates possibly is human (Inferred Causal Conjecture or Case Hypothesis)
- Deductive (inference to true conclusion, provided premises are true)
  - All humans are mortal (General Rule/Axiom/Theory/Major Premise)
  - Socrates is human (Specific Case Truth/Minor Premise)
  - Therefore Socrates must be mortal (Logically True Conclusion/Effect)
- Inductive (inference to a general rule)
  - Socrates is mortal (Observed Result/Effect)
  - Socrates is human (Tested Case Hypothesis)
  - Therefore, all humans probably are mortal (Inferred General Rule or Theory)

Three Types of Reasoning: Summary

Abduction	Deduction	Induction
Effect (Evidence, Observation)	General Rule	Effect (Evidence, Observations)
General Rule	True Case Fact	Tested Case Hypothesis
Inferred Case Conjecture	Logically True Conclusion	Inferred General Rule

A Simplified Causal Reasoning Process



Observed Effect/ Evidence	Abduction	Deduction	Research (Foraging)	Induction
E.g. performance shortfalls, anomalous data, near misses, large or rapid change	*Generate insights about possible explanations*	*If a possible explanation is true, what other evidence should we observe or not observe?*	*For each possible explanation, search for additional evidence with highest diagnostic value*	*Use collected evidence to test possible explanations and reach conclusions about their respective probabilities*

Abduction is the most difficult step

- The range of explanations that come to mind is limited by our knowledge and experience (hence, it pays to be curious)
- It can also be constrained by our judgment about what constitutes a "plausible" (hence, it pays to be imaginative)
- Organizational limits on "acceptable" explanations can also inhibit causal reasoning (e.g., if I say this, will I offend my boss, challenge important organizational assumptions, etc.)

Abduction: Helpful Hints

- Our minds work on two levels – System 1 operates rapidly, focuses on critical cues and patterns, and subconsciously, producing "gut feelings", "intuition", and physiological reactions (e.g., fight or flight response)
  - Long ago, evolution equipped us with System 1 to protect us from danger on the East African Savannah
- System 2 operates more slowly, and analytically, producing conscious reasoning and explicit thoughts
  - In abduction, it pays to listen to your intuition, and try to reconcile them with your analysis; let intuition generate initial insights, but then use analysis to test and expand them
- It is also very helpful to focus on the evidence that is not explained by a conjecture, their potential importance given the situation you are facing
  - Anomalous data has the highest information value, and we assume it away (e.g., "don't worry about the outliers") at our peril

Abduction: Different Frames that can be Used to Generate Causal Conjectures

- Temporal order of events and decisions
- Covariation/Correlation/Co-occurrence of events and decisions
- Necessary, Sufficient, and Counterfactual events and decisions
- Cumulative impact of trends, forces, and/or stocks, leading to thresholds, tipping points, and regime changes (e.g., the increasingly complexity over time of economic systems, which makes their effective governance increasingly difficult, thus increasing the probability that a crisis and sharp change will occur)
- Gradual changes in the balance of positive and negative feedback loops, and/or control parameters, again leading to a regime change
- Organizations that will not or cannot change, despite evolving circumstances (change is surprisingly hard for organizations, which is why so few survive for longer periods of time)
- Integrated stories, that link forces and trends to events, decisions, and results

Another Causal Reasoning Tool: Bayes' Rule

- In the early 19th century, Pierre Laplace (in France) and Thomas Bayes (in England) both struggled with the same issue: how much to adjust a prior probability estimate in light of new evidence
- They discovered this formula:

$$\text{New ("Posterior") Probability of Hypothesis given New Evidence} = P(H|E) = \frac{\text{Probability of Evidence given Hypothesis } P(E|H) \text{ times Prior Probability of Hypothesis } P(H)}{\text{Probability of Observing the New Evidence } P(E)}$$

Bayes' Rule Helps Us Reason About the Value of Evidence, and Plan Our Research Strategy

- The "Likelihood Ratio" measures the probability of observing a piece of evidence if a hypothesis is true, relative to the probability of observing it a hypothesis if false
  - You can also substitute "not observing" for "observing" – i.e., Sherlock Holme's "dog that didn't bark"
  - The potential value of a piece of evidence – also known as its "inferential power" or "diagnosticity"-- increases with the likelihood ratio
- The value of evidence is also sometimes expressed as a "Relevance Ratio" – the probability of observing a piece of evidence if a hypothesis is true (or false) relative to the overall probability of observing the evidence, regardless of the hypothesis
- In testing possible explanations generated through abduction, you should focus on finding evidence that has a high likelihood ratio for your hypotheses

A Simple Example

- You return home, and observe that your driveway is wet. You wonder why
- Abduction → Possible Explanations
  - Children had squirt gun fight
  - Neighbor's dog visited
  - Sprinkler went on
  - It rained
- Deduction → High Value Evidence for Each Explanation
  - Squirt gun fight: children's direct testimony; witness reports
    - Negative
  - Neighbor's dog: smell and composition of wet spot; witness reports
    - Negative
  - Sprinkler: Area of driveway wetness (e.g., garden but not lower part of driveway is wet); setting on sprinkler timer; witness reports
    - Positive
  - Rainstorm: Area of driveway wetness (e.g., all driveway plus lawn are wet); weather records; witness reports
    - Negative
- Induction → Compare High Value Evidence and Hypotheses
  - Wetness most likely caused by sprinkler

In Practice, Causal Reasoning is Often an Iterative Process with Separate Sensemaking and Foraging Loops

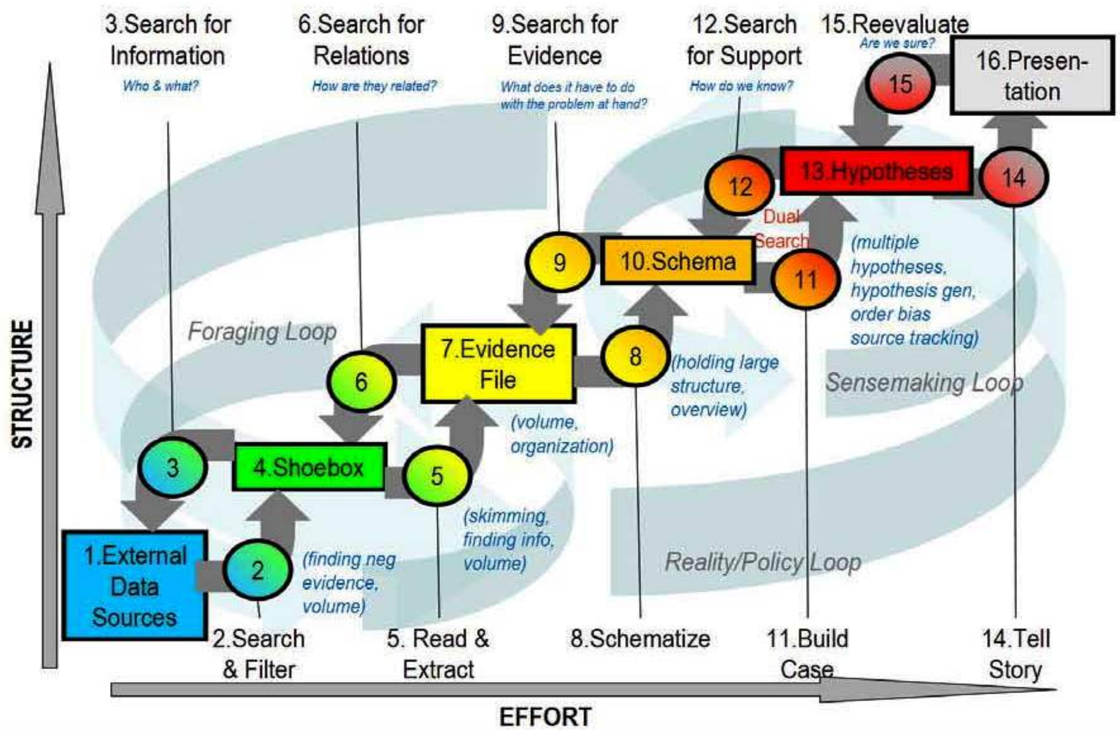


Figure 2. Notional model of sensemaking loop for intelligence analysis derived from CTA.

*From *"The Sensemaking Process and Leverage Points for Analyst Technology as Identified Through Cognitive Task Analysis"* by Pirolli and Card