Simplifying Causal Complexity: How Interactions between Modes of Causal Induction and Information Availability Lead to Heuristic Driven Reasoning

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Abstract

This paper considers a set of well-researched default assumptions that people make in reasoning about complex causality and argues that in part, they result from the forms of causal induction that we engage in and the type of information available in complex environments. It considers how information often falls outside our attentional frame such that co-variation falls short, mechanism knowledge can be non-obvious, and the testimony that others offer is typically subject to the same constraints as our own perceptions. It underscores the importance of multiple modes of causal induction used in support of one another when discerning and teaching about causal complexity. It considers the importance of higher-order reflection on the nature of causality that recognizes the challenging features of complex causality and how it interacts with human causal cognition.

Introduction

An expansive literature exists on how humans engage in causal induction. Laboratory and classroom research reveals fairly sophisticated reasoning in these confined contexts and offers models that effectively account for how people reason. However, engaging effectively in causal induction in a complex world is a vastly more complicated task and challenging to account for. Reasoning well about our world requires cognitive flexibility in perceiving and attending to the features and parameters of a problem space and in considering how patterns are structured. It necessitates looking beyond immediate constraints and events to reason about extended temporal and spatial frames and about processes and steady states. It involves detecting non-linear, indirect, and interactive relationships and considering agentive and non-agentive causes—including those that might be deemed passive and non-intentional. Human cognition appears to be heuristic driven in ways that may be adaptive in some instances and yet in others, can derail an ability to discern and understand these complex causal instances.

This paper reviews findings from disparate literatures on the types of assumptions that people typically make about the nature of causality, the heuristics that they engage, and how they constrain causal inference and limit causal searches. It considers the possibility that reasoning characterized by co-variance accounts, broadly speaking, and Causal Bayes Net (CBN) accounts specifically, may contribute to the robustness of these default assumptions when reasoning about particular forms of causal complexity. It examines how knowledge of mechanism and testimony may interact with co-variance accounts in instances when people are limited in their ability to draw inferences based upon the available information and constraints of everyday contexts. The paper argues that discerning causality in a complex world necessitates flexible reliance on multiple modes of causal induction contingent on the features of the information available in the environment.

Simplifying Complexity and Heuristic Driven Reasoning

The human tendency to simplify complexity has been well documented across multiple contexts. Historically, the most intensely studied areas are those having to do with judgments in the face of uncertainty conducted by Kahneman, Slovic and Tversky (1982) and their colleagues and more recently reviewed by Kahneman (2011). This work identified a well-defined set of biases or heuristics that people invoke to simplify complex calculations when attending to assessments of risk and benefit. For instance, *availability heuristic* refers to the tendency to search in our minds for available cases when determining the prevalence of an event (e.g. Tversky & Kahneman, 1982; Slovic, Fischhoff & Lichtenstein, 2000). The ease with which cases are generated interacts with one's assessment of prevalence, thereby introducing *probability neglect,* the tendency to focus on the salient cases even when they contradict the statistical likelihoods. Salient cases skew people's assessments towards thinking such events are more highly probable. Salience is impacted by how we feel about an event (introducing an *affect bias*) (e.g. Finucane, Alhakami, Slovic, & Johnson, 2000) and by how alarming it is (*alarmist bias*) (e.g. Slovic, 2000). As argued by Sunstein (2002), this work highlights the prevalence of emotion in facilitating the shortcuts that we take and is increasingly supported by research in neuroscience for how our brains work; the amygdala bypassing higher order processing to result in immediate actions (e.g. LeDoux, 2007; Damasio, 1994).

It may be easier to accept the idea that humans use shortcuts in reflexive, everyday causal reasoning than in reflective reasoning about the nature of causality but research suggests that simplifying assumptions exist across both forms (Dorner, 1989; Grotzer, 2012, Tenner, 1996). Reflexive causal reasoning refers to the actionable connections that people make on the fly in their everyday behavior, the type that Kahneman (2011) has written about as System One. These have a serviceable quality that functions in everyday contexts. The resulting observations also give rise to abstracted principles over time that people implicitly learn and use forward in their reasoning. In contrast, reflective reasoning about the nature of causality involves explicit reflection on the way that causality behaves. It may be reflectively abstracted from multiple everyday causal reasoning experiences; induced by the power of narrative by hearing about mistakes in complex causal reasoning such as the events at Chernobyl (Dorner, 1989); or abstracted from explicit metacognition, for instance, stepping back to evaluate causal archetypes (Senge, 1990) or through programs that engage learners in evaluating and construct new causal forms such as Star Logo (Resnick, 1996; Wilensky & Resnick, 1999), for a few examples.

What compels these shortcuts? A central question in why we engage in these heuristics relates to whether we have the ability to reason about complexity—it's features, dynamics, and the number of components we need to hold in mind in order to do so. The literature examining what novices in comparison to experts do in response to complexity offers some insights into what the human mind is able to do. However, even if we have the ability to reason about complexity, we may invoke heuristics for other reasons—the power of emotions, compelling narratives, or efficiency in the moment. As elaborated below, many well-documented cases reveal that experts do not perform to the levels that their expertise would suggest (Dorner, 1989). Understanding human performance in complex situations necessitates that we also consider issues of perception, attention, and motivation in the moment against a complex backdrop of environmental noise that competes for one's attention. How do we discern the patterns of complexity despite complicating features and noise that obscures the signals? Humans are inclined towards certain default assumptions that make it harder to perceive complex causal patterns; we argue that these assumptions can be predicted based on how the causal modes of induction that people engage in interact with the contextually available information.

We begin by reviewing the research on reasoning about complexity, systems-thinking, and complex causality. Next, we discuss three primary modes of causal induction, with an emphasis on covariance accounts, and consider the potential of each to account for causal complexity in ontologically messy problem spaces. We consider how these modes of induction interact with features of the environment such that people end up with lean information from which to make causal inferences. As examples, we examine four features of causal complexity inherent in ecosystems dynamics in terms of how each feature impacts the modes of causal induction that are possible. Finally, we consider some implications for education.

Reducing Complexity: Background Research

Research in Science Learning. The tendency to reduce complexity has received considerable attention in the research literature, historically and currently. Much of this research has focused on learning in science education. Driver, Guesne, and Tiberghien (1985) found that certain reasoning tendencies impeded learning, for instance, focusing on changes as opposed to steady states, subsequently failing to see a need to explain systems in equilibrium, or engaging in linear causal reasoning by looking only for sequential chains of causes and effects when systemic patterns are in play. Chi and colleagues (1997; Ferrari & Chi 1998) found that students often assigned the fundamental nature of what something is — its "ontological status" (Chi et al. 1994) — to the wrong categories. For instance, students thought of electrical current as matter instead of a process or treat processes such as those involved in diffusion and electricity as event-like (Chi et al. 2012). This impacts its salience and the assumptions that one makes about how it behaves in systems contexts (Grotzer, Kamarainen, Tutwiler, Metcalf & Dede, 2013; Sander et al. 2006). Brown (1995) identified core causal intuitions in how people attribute agency that led students astray when learning difficult science concepts. Andersson (1986) illustrated how students extend primitive notions of agency, such as "the nearer, the greater the effect," resulting in difficulties learning physics.

Feltovich, Spiro, and Coulson (1993) argued for a general "reductive bias" that learners engage in contexts involving inherent complexity that applies generally to reasoning about causality and systems. They argued that learners were likely to adopt concepts that were simpler and that misunderstandings leaning toward the simpler side of cognitive processing were likely to be stable and robust. They outlined dimensions of difficulty that were likely to result in a reductive response. These included instances when properties or processes are abstract (vs. concrete); non-linear (vs. linear); continuous (vs. discrete); dynamic (vs. static); simultaneous (vs. stepwise and sequential); holistic and organic (vs. mechanistic); characterized by relative interdependence (vs. independence); and conditional (rather than context dependent) in their application.

Building from the research of Feltovich and colleagues and the broader extant literature, Grotzer and colleagues (2004; 2012) identified a set of simplifying default assumptions specifically about the nature and features of causality. These includes assumptions of: 1) Simple linearity with direct connections as opposed to nonlinearity or linearity with indirect connections (e.g. Driver et al., 1994; Fischer & Bidell, 2006; Grotzer, 1993; Raia, 2008; Van Orden & Paap, 1997); 2) Event-based as opposed to process-like causality; 3) Unidirectionality as opposed to bidirectionality, mutuality or symbiotic relationships; 4) Sequentiality as opposed to simultaneity; 5) Obvious and perceptible as opposed to non-obvious and imperceptible causes and effects; 6) Agency-based: active or intentional agents as opposed to non-intentional or passive causes; 7) Deterministic—wherein effects must consistently follow “causes” or the “cause” is not considered to be the cause—as opposed to probabilistic causation or statistical patterns of correlation with supporting mechanisms; 8) Spatial and temporal contiguity between causes and effects as opposed to spatial gaps or temporal delays or triggering points for causal impact; and 9) Centralized causes with few agents—missing more complex interactions or emergent effects—as opposed to decentralized causes or distributed agency” (2009; p. 57-58). Substantial support for these tendencies exists in the research literature (e.g. Chi, 2000; Feltovich et al., 1993; Ferrari & Chi, 1998; Grotzer & Basca, 2003; Hmelo-Silver, Marathe & Liu, 2007; Houghton et al., 2000; Perkins & Grotzer, 2005; Wilensky & Resnick, 1999).

Perkins and Grotzer (2005) conducted a series of studies to consider how these assumptions interacted with students’ ability to learn concepts for which the scientifically accepted explanations required letting go of the simplifying assumptions and adopting more complex forms. A distinction between knowledge about the general nature of causality (for example, “causes tend to precede their effects”) and theories of causation, which refer to causal knowledge within a particular domain (for example, “flipping the switch causes an interruption in the flow of electricity”) made by Pazzani (1991) is useful in explaining the results. Across a number of concepts, theories of causality interacted with students’ understanding of the theories of causation in the scientifically accepted explanations. For instance, instruction that included an explicit focus on the patterns of causality underlying simple circuits resulted in significantly greater gains in understanding the underlying scientific model for fourth and eighth graders than students in a best practices control condition (Perkins et al., 2005). Similar findings were identified in understanding the relational nature of density (Houghton et al., 2000; Perkins et al, 2005) and ecosystems concepts (Grotzer et al., 2003). Raia (2008) found similar patterns in Earth Science education.

How simplifying assumptions interact with learning in the environmental sciences and in understanding ecological systems has been especially well-studied. The tendency to reduce ecosystems dynamics results in significant misunderstandings of key systems behaviors (e.g. Green, 1997; Grotzer et al., 2003; Grotzer et al., 2013; Hmelo-Silver et al., 2007; Hogan & Fishkeller, 1996; White, 1997). This research shows that students tend to focus on the visible components of an ecosystem and missing the behavioral and functional aspects (Hmelo-Silver et al., 2007); initially adopt a focus on events rather than considering events in the context of causal dynamics and processes and steady states over time (Grotzer et al., 2013) and struggle to think across levels when reasoning about ecosystems (Penner, 2000).

Contrasting Experts to Novices. Distinctions between novice and expert reasoning are well established and demonstrated in the broader literature on expertise as well with seminal studies by Chi and colleagues (e.g. Chi, Feltovich, & Glaser, 1981) showing that experts quickly discern the deeper, more meaningful patterns and structures in their categorization of physics problems. Similar reasoning has been demonstrated about the configuration of chess pieces on the board in relation to strategy and perceiving “higher-order chunks” (Chase & Simon, 1973).

A subset of the broader research on complexity contrasts novice and expert reasoning about how systems characteristics and dynamics are characterized. Jacobson (2001) identified the distinctions in terms of a novice “Clockwork Mental Model” and an expert “Complex Systems Mental Model.” Clockwork beliefs include the notion that phenomena are reductive, with centralized control and single causes; that the actions of agents are predictable with small actions leading to small effects and complex actions deriving only from complex rules. The focus is on static structures and events with teleology describing the relationship between purpose and outcome. The contrasting Complex Systems beliefs include non-reductive, decentralized notions with multiple causes, the possibility of big effects from small actions, that complex behavior can result from simple rules and that agent actions can be random and, in some respects, stochastic. The focus is on equilibration processes rather than events or static structures and the relationship between outcomes and causes is viewed as non-teleological. Hmelo-Silver et al. (2007) found that experts focused on the behavioral and functional dynamics. Jacobson and Wilensky (2006) have argued that understanding the learnability of such concepts is a critical challenge for 21st century science education.

However, while expertise is an important variable in how one detects systemic patterns, experts are not immune to the reductive heuristics employed by novices. Through a series of well-designed computer simulations, Dorner (1989) documented the choices that experts made working with dynamic systems and found that experts often fail to capture the causal dynamics of our complex, interconnected world. He chronicled the actions of the experts managing the routine test at Chernobyl and the series of reductive decisions made, for instance, they acted upon the system as a set of discrete events, rather than as a continuous, dynamic, and systematic set of patterns, a tendency identified by Feltovich and colleagues. Similarly, Eddy (1982) studied how doctors reasoned about probabilistic information from medical tests and found that they make major errors that impact the efficacy of their decisions. The finding that even experts who manage complex causal systems daily employ simplifying default assumptions suggests a resilient cognitive mechanism to their robustness. We turn our attention to possible cognitive mechanisms below as we consider modes of causal induction and how they may interact with environmental features to support reinforcing, reductive assumptions.

These reductive biases interact with learning across the curriculum, are compelling enough that even experts employ them in some instances, and clearly impact our ability to make sense of complex causal dynamics in the world. This underscores the importance of considering two closely related questions. First, what are the primary modes of human causal induction that people can engage in reasoning about complexity and what sources of information do they depend upon? Below we consider three bodies of literature have made strong contributions to our understanding of how humans derive information about causality in everyday reasoning. The primary focus is on covariance theories and the prevailing notions of Causal Bayes Net models. Then we consider two other sources of causal information: specific generative transmission notions of mechanism (e.g. Atran, 1995; Keil, 1994) and testimony from others (e.g. Harris, 2002; 2012). Secondly, how do the features and sources of environmentally available information and human cognition interact in ways that contribute to our reliance on heuristics and default assumptions that can sometimes derail our ability to reason about causal complexity? We examine features of complex causal phenomena that interact with humans' ability to use the modes of causal induction to discern the causal relationships. First, we step back to further elaborate the problem space of perceiving, attending to, and reasoning about complex causal dynamics.

The Ontological Problem and the Puzzles of Perception and Attention

One of the essential puzzles for any theory of how we make sense of our world is to explain the ontological problem—how we get from a messy, complex world to a set of meaningful variables to reason about. It asks, "how do we know what to attend to in the first place from the wealth of stimulation coming our way?" The ontological problem, poses quite a challenge.

The research on how initial, unconscious perception leads to attentional capture and then to focused perception makes clear how much information we miss—particularly that which does not fit with our current expectations (Mack & Rock, 1998; See Grotzer, Miller, & Lincoln, 2011 for a review.) Research on perception and attention argues that our attention is necessarily selective and that filtering impacts what crosses the gate (Lamme, 2003) between implicit perception and explicit perception—what gains attentional capture (Mack et al., 1998).

Attention and efficiency are in tension with one another impacting what we notice and where we draw boundaries. Selectivity and efficiency have perceptual and cognitive costs. While it isn't efficient in most instances to do an extended, unbounded search, efficiency can lead to constraining our view of the system parameters. In many cases, a workable heuristic can be substituted for an elegant or "most correct" solution without consequences. However, these filters privilege certain kinds of information over others; meaningfulness is particularly powerful in attentional capture, outweighing familiarity and recency effects (Mack et al., 1998; Treisman, 2009; Tutwiler & Grotzer, 2012).

As certain patterns become meaningful from our earliest days, we may prioritize those patterns, selectively attending to them to the possible exclusion of others. Our robust, early causal tendencies shape our prior knowledge and may shape the world that we perceive, what we consider relevant, and the problem parameters that we assume. The research on perception and attention suggests that the ontological problem can be framed in terms of the salience of variables in the environment. Salience can be thought of as the interaction between the physical properties of an object or event and the prior knowledge of the observer (Melloni, van Leeuwen, Alink, Muller, & 2012). And so, the more salient (or surprising) an object or event is, the more likely it is that an observer will attend to it. As we consider each mode of induction below, we consider what each means for the ontological problem in relation to what we perceive and ultimately attend to.

The ontological problem was largely bracketed in early research (e.g. Scheines, Easterday & Danks, 2007) as researchers pursued the structures that subjects discerned in lab contexts. More recent research includes attempts to address it. For instance, Wu, Gopnik, Richardson and Kirkham (2011) considered how infants figure out what to attend to in noisy, real world environments and found that while social cues provide important attentional guidance. The ontological problem takes on particular characteristics when the focus is on complex causality. As discussed below, the features make it difficult for all ages to discern the interacting variables.

Modes of Causal Induction

Covariance Modes of Causal Induction

Research on how people sum across multiple occurrences of an event in relation to other events to consider the possibility of a causal connection has a long and extensive history (e.g. Einhorn & Hogarth, 1986). It substantiates that even preschoolers use co-variation data in combination with spatial and temporal contiguity (e.g. Leslie, 1984; Leslie & Keeble, 1987; Oakes, 1993; Spelke, Phillips & Woodward, 1995; Van de Walle & Spelke, 1993) and information about plausible mechanisms in assessing causality (e.g. Bullock, 1979).

Causal Bayes Nets (CBNs) are considered to be a prevailing model of how humans connect across statistically probabilities that a cause and effect are linked. These theories, CBN models in particular (Pearl, 2000), argue that we sum across instances using association and intervene to screen off variables as needed to discern causal patterns, as our primary mode of induction (e.g. Gopnik & Schulz, 2007).

Features of Bayesian models of Human Causal Induction. Learning is time dependent. The entire corpus of human understanding, from the novel folk-theories, the collective discoveries of science and so forth, is invented as we explore our environments over the course of our lives. Over time, as learners observe and interact with the world around them, the more evidence or data they collect. In this process, they may let go of old ideas and embrace new ones. If their prior beliefs do not adequately explain the new, often more detailed and complex, material, then they are forced to either adapt their beliefs, or let go of them entirely in favor of a new explanatory model. In short, they learn.

In general, interaction between prior belief and new data is modeled by Bayes' Theorem, which postulates that posterior (new) beliefs are a product of prior beliefs and new data. This relationship can be seen in Equation 1, below:

$$P(H|D) = \frac{P(D|H)P(H)}{P(D)} \qquad \text{(Equation 1)}$$

Where:

p(H|D) is the posterior belief in a certain hypothesis, given observed data

p(H) is the prior belief in your hypothesis before observing any data

p(D|H) is the likelihood that the observed data fits your hypothesis

p(D) is the probability that the data is valid

Over the last half-century, techniques based on Bayes' Theorem have been developed to model ways in which incoming data affects systems in fields such as biostatistics (Neopolitan, 2009), law (Aitken & Taroni,2005), and machine learning (Bishop, 2006). Advances in this last field have had direct implications on models of human learning, which will be discussed later.

Some researchers have postulated that humans (and other animals) are explicitly "Bayesian Learners" (Tenenbaum, 1999). The degree to which Bayes' Theorem captures variability in human learning is a matter of debate, however. Studies across various fields have alternatively shown that humans are both strong (e.g. Sobel, Tenenbaum, & Gopnick, 2004) and weak (e.g. Zhang & Yu, 2013) Bayesian learners. Independent of this debate, however, is the argument that properties of Bayes' Theorem

As mentioned above, Bayes' Theorem elegantly models the relationship between incoming evidence and belief. In general, evidence overwhelms the prior, that is, ideally learners' use their prior beliefs (knowledge, understanding, etc.) as a lens through which they view incoming data, as shown by the product of p(H) and p(D|H) in Equation 1, above. In the field of economics, for example, researchers have shown that decision making is sensitive to data salience and frequency in ways that are consistent with Bayes' Theorem (Luca, 2011). Bayes' Theorem also models the summation of observations (or interventions) over time. The posterior, p(H|D), of an initial data collection event becomes the prior, p(H), of a new event, allowing researchers to model what the learning progression of a rational agent should be.

This assumption of rationality is inherent to Bayes' Theorem and all techniques derived from it. However, humans make irrational choices, often in the face of evidence to the contrary (e.g. Kahneman, 2011; Sunstein, 2002). Other times, people may simply choose to ignore new evidence, based on deeply held prior beliefs. This results in not being able to attend to or perceive new evidence, as discussed below. In either case, Bayes' Theorem is not equipped to handle such deviations. A model of human learning needs to be able to account for rational as well as irrational choices.

One application of Bayes' Theorem that has been of particular interest to psychologists is that of "Causal Bayes Nets" or the CBN. CBNs are graphical models that summarize the conditional relationship between variables. For example, examining Figure 1, below, we see that B and C are effects of a common cause, A, and D is the effect of cause C. The variables (A, B, C, D) are referred to as nodes, while the arrows are directed edges.

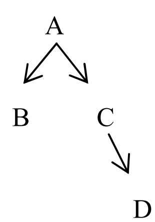

Figure 1. Example directed acyclic graph (DAG)

Figure 1 can then be parameterized into a conditional probability term, as in Equation 2, below.

$$P(A|B,C,D) = P(B|A)P(D|C)P(C|A)\,P(A)/[P(A)] \qquad \text{[Equation 2]}$$

Inspection of Figure 1 yields some observations that can be generalized to all CBNs. First, notice that all nodes are connected by directed edges in only one direction, and no child node has any edges that return to their parent or other ancestors. This classifies the graph as a Directed Acyclic Graph, or DAG, a necessary (but not sufficient) condition for it to be a CBN.

In addition, note that node D is independent of all other higher-order nodes (A, B), conditional on its parent (C). This independence is known as the Causal Markov Assumption (Pearl, 2000), and it flows directly in part from the fact that the graph is a DAG, as well as the fact that there are no hidden common causes. It is also important to assume that causes in the model will not exactly cancel each other out, thus confounding the ability to accurately measure the results of interventions. This is known as the Faithfulness Assumption (Sprites, Glymour, & Scheines, 1993).

Other researchers have proposed models of causal inference from stochastic data. These models include P (Jenkins & Ward, 1965) and Rescorla-Wagner (Rescorla-Wagner, 1972), based on contingency, and Cheng's (1997) Power PC theory, which assumes humans make causal inferences based on causal strength. These methods are all inter-related. The Rescorla-Wagner and P models are equivalent when learning is at asymptote (Danks, 2003), and P is the numerator of Cheng's Power PC theory.

CBNs were proposed as a possible normative model for human causal inference by Glymour (1998), who had previously outlined their utility in the field of artificial intelligence (Sprites et al., 1993; Glymour, 1997). Glymour recognized the importance of framing causal inference probabilistically (Cheng, 1997), and realized that Cheng's model was in fact a noisy-OR parameterizations of CBNs (Pearl, 1988). It should be noted that Glymour (1998) outlined a belief that any normative causal theory would likely only apply to simple causal connections.

A decade of research into the use of CBNs to model rapid, simple causal induction ensued. Some researchers (e.g. Tenenbaum & Griffiths, 2001; Griffiths &Tenenbaum, 2005; Tenenbaum, Griffiths, & Niyogi, 2007) further postulated that human causal inference was driven by a top-down approach, summing over CBNs in a theory space, while others focused on a more bottom-up approach, in which children (at least) construct CBNs from data (Gopnik et al., 2004, Schulz & Gopnik, 2004, Schulz et al., 2006). The work assumed that the subjects came into studies with either no, or uniformly uninformative, prior information, and thus used uniform priors in their models. An interesting alternative model was proposed by Lu, Yuille, Liljiholm, Cheng, and Holyoak (2007). They combined Cheng's (1997) initial Power PC model (which motivated the work of Glymour (1998) and Griffiths and Tenenbaum (2006)) with what they dubbed a "Necessary and Sufficient" (NS) prior. This NS Power model was an attempt to capture human preference for simple causal models and deterministic relationships, and found that their NS Power model outperformed a Bayesian model with uniform priors, and linear generating functions derived from the P rule (Jenkins & Ward, 1965).

How good we are at summing across instances of conditional probabilities is a key aspect of covariance approaches. Gopnik and colleagues (e.g. Gopnik et al., 2004; Gopnik, Sobel, Schulz, & Glymour, 2001; Kushnir & Gopnik, 2007) conducted research to suggest that even the youngest children follow Bayesian rules in summing across their experiences; overriding imperfect correlation and using different patterns of probability in contiguity to make accurate causal inferences. Earlier research had found that five-year-olds accepted less than perfect correlation in determining whether or not a causal relationship exists, presumably due to the cognitive load of tracking perfect correlation (Shultz & Mendelson, 1975; Siegler, 1976; Siegler & Liebert, 1974). However, they also found that eight and nine-year-olds were more sensitive to the lack of perfect covariation than the five-year-olds (Siegler et al., 1974) and were less likely to call imperfect relationships causal. It appeared that they held an expectation that cause-effect relationships should be reliable (e.g. Bullock, 1985; Bullock, Gelman, & Baillargeon, 1982; Shultz, 1982). However, Gopnik and colleagues (2004) showed that young children are able to use different patterns of probability in contiguity to make accurate causal inferences (Kushnir & Gopnik, 2007). This suggests that, at least in the lab, young children override imperfect correlation and that if the problem is one of tracking correlation, they are still able to produce statistically accurate results.

What students tend to do, decide to do, and are able to do are related but distinct questions. Schulz and Sommerville (2006) found that preschoolers prefer reliable causal relationships over probabilistic ones, at least in the instance of a machine-like toy box mechanism. Grotzer, Duhaylongsod, and Tutwiler (2011) found explicit expectations of determinism amongst kindergarteners, second, fourth, and sixth graders across four domains (social, biology, games, and machines) for most children with outliers at each age who were open to either possibility. This suggests that children may hold an explicit assumption of determinism even while they are able to use conditional probabilities to answer questions of causality with unreliable effects.

The CBN research suggests that people also intervene upon and partition off certain variables to assess their impact allowing us to readily detect causal structure by disambiguating causes (e.g. Gopnik et al., 2007; Gopnik et al, 2004; Sobel & Kushnir, 2003; Steyvers, Tenebaum, Wagenmakers, & Blum, 2003). Intervention can refer to one's own actions, those of others, and to changes wrought by nature (Meltzoff, 2007). Preschoolers are able to intervene to figure out the causal structure of problems with limited numbers of variables in deterministic (Gopnik et al., 2001; Schulz et al., 2004) and probabilistic contexts where the outcome often but not always followed the cause (Kushnir, Gopnik, & Schaefer, 2005; Schulz & Gopnik, 2004). Backwards blocking is the tendency to retrospectively determine that one of two variables is not causal when one witnesses an outcome when the two variables are present, but then one is removed and the outcome still occurs. Sobel and colleagues found that the ability to backwards-block was developmental; four year olds could do so, but three year olds could not (Sobel et al., 2004). Children made correct causal inferences given probabilistic data, but were more accurate when observations were spatially contiguous (Kushnir et al., 2007).

So, research over the last decade seems to indicate that humans learn simple causal connections intuitively, from sparse and stochastic data, in a way that can be modeled by Causal Bayes Nets. Griffiths and Tenenbaum (2005) and Lu et al., (2007) realized that certain conditions of human cognition might constrain the graph selection / graph building process: that humans generally seek to discover the existence of causal relationships, not the strength of said relationships, and that heuristics and biases might impact causal inferences. Questions remain about how assuming a CBN model for human causal inference might explain some of the reductive biases outlined in the sections above.

Complex Causality, Real World Contexts and CBN Models. Covariational theories may explain how we meet with success in simple causal induction, but when causality becomes complex, problems arise. The studies reviewed above were conducted in lab contexts without the attentional challenges and cognitive load of the complex forms of causality discussed in the first section of this paper. The real world involves many possible variables and possible interactions between them. Discerning these causal relationships involves: 1) significant cognitive load and 2) patterns than extend beyond the assumptions in CBN models. It also assumes: 3) effective intervention in contexts where it is typically not possible and; 4) fully specified and available data. The unaided human mind in every day contexts is unlikely to be able to effectively intervene and build effective causal models of such complexity.

Detecting complex causality through discerning co-variation can involve significant cognitive load. Using computers, researchers and engineers regularly use CBNs to infer complex causal structures. Those applications often occur under extreme computational loads, however, and are intractable by humans. In addition, even those models use heuristics to guide their searches (Bishop, 2006). CBNs seem to reflect the almost reflexive way in which humans make inferences about relatively simple causal relationships (containing few nodes that are spatio-temporally close). Complex causal reasoning, on the other hand, often requires the inference of cyclical models based on data that is noisy, often difficult to recognize, and spatio-temporally distant. As Lu et al. (2007) attempted to do, models of more complex inference need to take into account heuristics and biases common to more complex human causal inference, as outlined above.

Assumptions about the system under investigation might also help to lessen to cognitive load associated with CBN-like causal inference. For example, assuming sequential temporal contiguity and determinism amongst nodes in a CBN allows learners to relax the Faithfulness Assumption (Glymour, 1998). Knowing the order of events in a potential cause-and-effect relationship "considerably speeds up algorithmic search for structure" (Glymour, 1998, pg. 10) since the universe of possible graphs that do not represent the ordering can be discounted. Similarly, if certain relationships in a CBN are assumed to be deterministic, then calculations of joint probabilities can be ignored. .

A primary assumption of CBN theories is known as the Causal Markov Assumption. It assumes causal patterns that are acyclic and further, that the variables are independent except for their direct and indirect effects (Gopnik et al., 2007). This does not allow for non-linearity. The patterns of complex causality call for discerning cyclic causalities with feedback loops (e.g. Green, 2001; Grotzer et al., 2003); mutual causation (Perkins et al., 2005) perturbation and dissipation effects (White, 1997) and outcomes that emerge from massively parallel interactions such as those in distributed causality (e.g. Chi et al., 2012; Wilensky & Resnick, 1999) to name just a few complex causalities that violate the Causal Markov Assumption.

As researchers have increasingly tested whether people use Bayesian analyses (e.g. Glymour, 2001) to sum across their experiences to make causal connections in the world, some have questioned whether Bayesian networks are too limited to capture the complexity of higher-level intuitive theories. Tenenbaum, Griffiths, and Niyogi, (2007), however, suggest that these might give rise to causal grammars that function generatively as do grammars for natural languages. One of the questions this work raises is how (and whether) Bayesian networks can account for higher level causal models such as those described here.

Problems also arise in relation to intervention. Many of the patterns that we reason about are not so easily manipulated and come to us as observations, not personal experiences. Intervention doesn't just refer to our own actions, it can refer to those of others and to changes wrought by nature. Opportunistic "natural experiments" enable learning causal structure from observing interventions in the world, however, the sciences often rely upon models, Gedanken experiments, and other means of investigating outcomes that control aspects of the real world. The limits of this approach, even in science where the tension between efficiency and attention are set aside, are apparent. Ecosystems scientists are experimenting with micro-labs situated within lakes to closely simulate the complex real world variables due to the difficulty of interpreting lab results that strip away complexity (Gessner, 2012).

The CBN model assumes fully specified and accessible data. This requires that the ontological challenge is solved. CBN Researchers admit that it poses quite a challenge and thus, often assume that it is solved and give the variables to the subjects (Scheines, Easterday & Danks, 2007). CBN research also tends to focus on the strong case of when we know the value of the variables, for instance, when we can measure how much a certain substance is imbibed, the exact temperature of a room, and so on. Framed another way, this limitation to the utility of the current approaches is that all prior covariational research has assumed that learners make their decisions based on data that is fully informative.

In terms of Shannon's (1948) Information Theory, data about a system carries a degree of information or "surprise". In covariational learning models, such as CBNs, data which is more surprising (informative) is more likely to be integrated into the model and result in updated beliefs. The degree of information required for belief change to occur, then, is referred to as *information entropy*. Finally, the average additional information required for data to be understood, given that the learner's mental model of the causal system is different than the true complex causal system, is referred to as *relative entropy*. Learners in covariational studies were given tables of contingency data or shown a small number of well-defined trials, and asked to make causal judgments immediately after (e.g. Lu et al., 2006; Schulz et al., 2004). That is to say, they were given data that was highly informative and with low entropy. Also, because the causal models being inferred were simple, the relative entropy between the actual model being tested and learners' models was likely quite low on average. This allowed the subjects to accurately infer simple causal relationships with sparse data. However, data in authentic contexts is rarely ever so well defined or informative.

In everyday causal reasoning, we often do not have such information available to us and when we do, we are notoriously bad at incorporating it into evaluating interventions (Hagmayer, Sloman, Lagnado, & Waldmann, 2007). Even with considerable statistical information about the likelihood of an event, we tend to override it with other kinds of information—powerful images, personal experiences, and narratives that tap into our affect and impact reasoning (Tversky et al., 1982).

We argue that when addressing complex causality, the issue is more than whether or not one is able to construct higher-level grammars from Bayesian algorithms. Issues related to available information and its salience; learned heuristics and reductive reasoning patterns; and tendencies when dealing with the tension between efficiency and extended analysis lead to different patterns of engagement. While much of the research carried out in a lab exists in one attentional context, causal induction in a complex, noisy world involves reasoning across spatial scales, extended time frames, instances where non-obvious variables compete for salience with more obvious ones, and patterns where effects may not become noticeable until substantive accumulation has occurred. Covariational, data-driven reasoning may be a predominant part of our causal repertoire. If so, it may help to explain why we struggle so with causal complexity and rely on simplifying heuristics.

Other Information Sources for Causal Induction: Specific Generative Mechanisms and Testimony

Specific Generative Mechanisms. Humans rely on other forms of information in addition to co-variation when they make sense of the causal relationships in their world. One of these, specific generative mechanisms, relates to knowledge of types of mechanisms; that we amass considerable knowledge about types of causes, the causal force of particular mechanisms, and situation-specific details about where this information applies (e.g. Atran, 1995; Carey, 1995; Keil, 1994; Leslie, 1995; Shultz, 1982; Shultz, Fisher, Pratt, & Rulf, 1986; Sobel, 2004). Mechanisms may be physical, behavioral, or mental such as forces, mechanical devices, and intentions. Children learn about remote controls, telephones, and so on, and use this knowledge to reason about causality in particular instances.

What constitutes a plausible mechanism is a point of discussion in the research. One instantiation argues that causes are seen as particular types of domain-specific forces and this research focuses on what children understand about the nature of such mechanisms (e.g. Atran, 1995; Carey, 1995; Keil, 1994; Leslie, 1995). Children realize that mechanisms must exist based upon evidence that they, do not allow for causeless events (Bullock et al., 1982), even when they aren't able to specify the details. Further, they search for mechanism if one is not apparent (e.g. Bullock, 1979; Baillargeon et al, 1981; Bullock, 1984; 1985; Corrigan, 1995; Schulz et al., 2006). When told that two objects move together because of a hidden string, but no string is obvious, four- and five-year-olds respond in ways similar to adults; they looked for another cause or said it was a trick (Bullock, 1985). Even 3-year-olds were correct up to 78% of the time when asked to predict the effects of a series of relevant and irrelevant modifications to a wooden apparatus that eventually knocked a toy rabbit into a bed. Gopnik and colleagues (2004) found that most 4-year-olds posited an unobserved causal mechanism when asked why two puppets moved together and no causal mechanism was obvious.

By age four, children are developing a differentiated sense of mechanism (e.g. Springer & Keil, 1991; Goswami & Brown, 1989). However, other research argues that children are developing an understanding of "impersonal mechanistic causality" whether or not they have knowledge of a particular mechanism (e.g. Bullock, 1979, 1984, 1985; Shultz, 1982; Shultz & Kestenbaum, 1985; White, 1995). (See Grotzer, 2003 for an in-depth review.)

A difficulty in employing mechanism knowledge, particularly in complex causal phenomena, is that often mechanisms are difficult to detect. They may be non-obvious in that they are inferred (e.g. Frederiksen & White, 2000), microscopic (e.g. Hogan et al., 1996), or in a different attentional space (Grotzer & Solis, 2014). Research reveals that even young children search for causal mechanisms when they are non-obvious (Schulz et al., 2006). Problems can arise, however, when, there is no easily discernible outcome to initiate the search for a cause or when a plausible mechanism is readily available so one isn't inclined to question it or push beyond it to consider multiple possible causes (See Sedlak & Kurtz, 1981 for a review).

Testimony and the Power of Narrative. A third body of research focuses on how the testimony of others supports causal learning. Harris (2012) argues that there are many concepts that children would never learn from first-hand experience alone and that the testimony of trusted others is an important source of learning. Complex causality offers many examples. For instance, the connection between automobile usage and changes to polar bear habitats is unlikely to be discerned through co-variation relationships and or without deep and extensive knowledge of mechanisms that one would be unlikely to figure out on their own. Even the concepts of sunburn—that a distant object in the sky can result in a painful burning sensation on your skin over time and not necessarily when you are still in the sun but hours later is most likely to be learned from others. Harris argues that testimony is an important avenue to learning about mechanisms that we can't see—germs, oxygen, and so forth. Testimony also comes in the form of powerful narratives. Some research suggests that we often override statistical data using such narratives—powerful available cases referred to as the availability heuristic by Tversky and Kahneman (1982). The cognitive load of summing across many cases may explain why we override this information with narratives that are motivated by affect (Finucane, Alhakami, Slovic, & Johnson, 2000). It may well be adaptive to do so (Scheines, Easterday, & Danks, 2007).

Research suggests that even young children can be discerning about their informants and use subtle cues as to the reliability of the testimony that they hear. They attend to information about the informant: how much the informant is like them (Chen, Corriveau, & Harris, 2011); how much consensus exists in the opinions of different informants (e.g. Corriveau, Fusaro, & Harris, 2009); how familiar the informant is (Corriveau & Harris, 2009); and the perceived accuracy of the informant (e.g. Birch, Vauthier, & Bloom, 2008; Konig & Harris, 2005). This suggests that variables in how information is communicated and by whom should raise the salience of particular pieces of testimony.

A difficulty of relying on testimony to discern complex causal instances is that typically those who are trusted sources of information for learners, are constrained by the same lack of environmentally available information and employ the same reductive biases that learners are inclined towards. Even when scientists have carefully studied a phenomenon and present connections that extend beyond our default assumptions about the nature of causality, gaining public acceptance for the causal explanation may be difficult as in EPA attempts to link causes related to carbon emissions in the Southern US States and impacts on polar bear habitats (Grotzer, 2012).

Reductive Assumptions about Complex Causality as an Interaction Between Human Cognition and the Available Information

Next, we examine how modes of causal induction and the availability of information in the environment can interact to help explain the resilience of reductive tendencies. We consider four typical features of complex causality: non-linearity; spatial gaps; temporal delays; and non-obvious causes, and how they interact with discerning the causal dynamics of ecosystems as an example of a complex causal system. We discuss how each of the modes of causal induction may contribute to or constrain deep understanding of the concepts.

Discerning Non-Linear Patterns of Causal Interaction

Ecosystems hold many instances of causation that are complex, indirect, non-linear, and process-like. These include cyclic or spiraling forms in which there are causal loops as in escalation and homeostasis; relational causality in which a relationship of balance or differential between two variables, (such as lower and higher pressure) is responsible for an outcome (such as the movement of air resulting in wind). Mutual or bidirectional forms of causality, such as in symbiotic and parasitic relationships, are common in the environmental sciences. Walker and Salt (2006) stress interdependence in biological systems as a key aspect of resilience thinking.

The tendency to reduce complex causality to forms that are simple, event-like, direct, sequential, and non-extended forms has been well documented (e.g. Driver et al., 1985; Fischer et al., 2006; Grotzer, 1993; Raia, 2008) along with a tendency to not look beyond indirect causes except, perhaps, in the form of the simplest domino relationships (Grotzer, 1993; Perkins et al., 2005; Van Orden et al., 1997). Some research essentially defines causation as a unidirectional generative mechanism (see Bindra, Clarke, & Shultz, 1980 for a discussion). Students struggle with reciprocal causal interactions (Barman & Mayer, 1994). Fewer than 25% of third graders expressed mutually causal connections (and those who did made limited connections) within food webs (Grotzer et al., 2003). High schoolers were unable to detect the mutual effects of population changes (Barman et al, 1995; Barman et al., 1994). Only 16% of 20-year-olds gave two-way causal accounts of a predator-prey relationship when uncued (Green, 1997) (rising to 60% when cued). When presented with more complex problems, 40% used two-way causal models when explaining a two-level problem involving two species in which one or both of the populations changed over time, but more complex problems elicited fewer two-way causal models. Palmer (1996) found that 12- and 16-year-olds applied the ecological concept of interdependence with relatively low scientific consistency to the issue of preservation of species.

As discussed above, Causal Bayes Nets theories of induction only account for acyclic directed graphs, i.e., they assume linear descendent causality. Further, the descendency aspects of CBN models are also violated in non-linear interaction patterns that blur the distinction between what is an effect and what is a cause. Effects can in turn become causes (as in domino causality) or can simultaneously act as causes and effects (as in mutual causality). Mechanism knowledge could be helpful but it would require knowledge of particular kinds of mechanisms, for instance, those that work in pairs such as in the case of magnets. Some research suggests that learners attach notions of mechanism to causes and differentiate as suggested by whether an entity is a cause or an effect (e.g. diSessa, 1993; Leslie, 1995). It follows that reciprocal instances of causation would contradict both mechanism and co-variation knowledge. It is possible that with obvious and immediate outcomes that do not involve other forms of complexity such as tracing extended and spatially distant effects, as in ecosystems, children would learn that certain mechanisms involve bi-directional forms of causality. Solis and Grotzer (in review) found that kindergartners were able to demonstrate understanding of bi-directional causality through gesture and explanation when working with a pair of sound block toys. Whether this learning would enable them to override their assumptions of simple descendent effects is an empirical question. Cueing students to attend to the possibility that two-way effects exist does seem to have an impact (Green, 1997). This suggests that testimony alerting students to the value of attending to extended effects may have an impact upon reasoning about extended and non-linear effects.

The science education research on ecosystems understanding suggests that tracing co-variation patterns, even when effects are linearly descendent from the initial causes, is constrained by efficiency, lack of extended attention, and cognitive load. Students miss extended domino-like causal events (e.g. Griffiths & Grant, 1985; Grotzer, 1993; Grotzer et al., 2003; Webb & Boltt, 1990). High school students believed that a change in one population will not be passed along several different pathways of a food web and that a change in one population will only affect another population if the two are related in a predator-prey relationship (Barman et al, 1995; Griffiths et al., 1985). White (1997) found that students' ability to reason about causal connections involving perturbations in the food web decreased with increasing distance of the item from the target item in the problem– what he termed a 'dissipation effect.' Grotzer (1993) found that reducing the cognitive load and differential access to information by giving students concrete informational supports to reason from, resulted in improved reasoning about extended effects.

Discerning Instances of Causality Across Spatial Gaps and Distances.

Ecosystems involve many instances in which the spatial scales are large and involve distance between causes and effects. For instance, watersheds are often extensive and reservoirs can be impacted by actions very far away, volcanoes erupting in one part of the world can impact weather patterns across the planet, and climate change has local sources and global impacts. In each of these instances, cause and the effect fall within different attentional parameters. Grotzer and Solis (in review) refer to this as action at an attentional distance, differentiating it from the developmental literature on action at a distance where physical gaps exist but both causes and effects exist within the same attentional space. Action at an attentional distance makes co-variation relationships difficult to discern because the causes and effects exist in different attentional frames. Related to this, a set of reductive assumptions in the complex causality literature has to do with how spatial gaps are handled. Research with subjects at all ages reveals a tendency towards spatial contiguity in reasoning about cause and effect relationships with increasing ability of older learners and adults to override it as an expectation, but a tendency to be more likely to notice causes and effects that exist in the same spatial frame.

The developmental research literature suggests a strong tendency on behalf of infants and preschoolers towards expecting spatially contingent causality (e.g. Leslie, 1984; Leslie & Keeble, 1987; Oakes, 1993; Spelke et al., 1995; Van de Walle et al., 1993). Children show signs of surprise and discomfort in picking a spatially non-contingent cause when temporal priority strongly suggests it (Bullock & Gelman, 1979). Preschoolers choose inconsistent but spatially contiguous events over events consistent co-variation (Mendelson & Shultz, 1976) and can use conditional probabilities even when it involves action at a distance, but are more accurate when the causes are spatially contiguous (Kushnir et al., 2007). Even older children expect spatial contiguity (e.g. Wilde & Coker, 1978). Adults override spatial contiguity cues when specific information suggests the need to (Michotte, 1946/1963) and are more likely to have and therefore use information about the contingency relations between two events–how often they are likely to co-occur (e.g. Kelley, 1973; Nisbett & Ross, 1980). However in each of these cases, these cases both aspects of the co-variation information, cause and effect, are contained within one attentional space.

Research shows that in contexts where candidate causes for an effect can be local or distant, students tend to focus on causes that are spatially local to effects and that are in the same attentional frame. Grotzer, Tutwiler, Dede, Kamarainen, and Metcalf (2011) found that middle school students exploring a virtual ecosystem engaged in initial search behaviors that were consistent with this pattern. Student pretest responses fit the hypothesized patterns for spatially local as opposed to distant causes ($M = 3.45$, ($SD = 1.35$); $M = .59$, ($SD = .79$) respectively, mean difference = 2.89, $t(73) = 13.20$, $p < .0001$).

This tendency makes sense if one is relying upon co-variation cues to discern the relationship between cause and effect. Research on simple action at a distance, suggests that children use mechanism knowledge to help them make a connection between spatially separate instances of co-variation (e.g. Sobel & Buchanan, 2009) and that children can be taught related mechanism knowledge such as in a study carried out by Lesser (1977) in which first through fourth graders learned to reason about magnets and how they work across spatial gaps. All of these instances involve a less complex version of the inherent causality. In these cases, causes and effects are in the same attentional space. This makes it possible to observe the co-variation between causes and effects.

It appears that students use mechanism and prior knowledge to reason in instances involving action at an attentional distance. Grotzer and Solis (in review) found that second, fourth, and sixth graders were able to reason about causal relationships between candidate causes and their potential effects despite action at an attentional distance, when they used mechanism knowledge to make the connection. Bar, Zinn, and Rubin (1997) also found that students looked for some type of mechanism to support reasoning about causes and effects that are at a significant spatial distance but that their reasoning shifted with the salient perceptual features of different situations. This resonates with the difficulties of reasoning about non-obvious causes and the lack of sophisticated mechanism knowledge on behalf of students. In a study using a virtual world, middle school students were able to use obvious mechanisms such as the movement of water to connect environmental events with distances between them (Grotzer et al., 2013).

Students also used narratives to connect distant causes and effects. The middle school students (Grotzer et al., 2013) used domino-like narratives to make connections between human impacts at a distance from a pond in a virtual environment and the local pond environment. The second, fourth, and sixth graders in the Grotzer and Solis study (in review) used stories that they had heard to discern a mechanism for connecting the distal causes and effects. Narratives, a form of testimony, can provide a way to make connections when the necessary links from the stance of co-variation are not easily discerned and the mechanisms are unfamiliar. For example, despite not understanding the mechanisms involved, elementary students could realize that acid rain has impacts far away, tides result from the gravitational attraction between the moon and the earth, and polar bears are impacted by climate change.

Discerning Instances of Causation Across Time Delays

Understanding the complex causal dynamics of ecosystems also requires reasoning about extended time frames and processes that do not have an event-like character (Chi, 1997; Grotzer et al., 2013) that can be attention-grabbing. For instance, realizing that the introduction of certain predators to an ecosystem impacts the diversity and stability of that system, can take many years to notice. Often, no counterfactual exists for people to contrast to that would make the later results salient enough that one might reason backwards to discern the impact. Co-variation relationships that involve domino-like effects can be difficult enough to trace but when they stretch out over time, the attentional demands required to notice the patterns are quickly overwhelmed.

The cognitive science literature reveals reductive assumptions related to how causality is characterized in terms of time with a tendency to focus on temporal contiguity as opposed to delays. Seminal research showed that time delays between causes and effects make it difficult for all ages to recognize a causal relationship. Children are more likely to infer causation when an effect immediately follows a cause (even when it turns out to be merely correlational) (e.g. Michotte, 1946/1963; Schlottmann, Allen, Linderoth, & Hesketh, 2002; Siegler et al., 1974). Infants processed events with delays as non-causal. Introducing a five second delay, presumably making it more difficult to notice the covariation relationship, impacted preschoolers' ability to make a causal inference (Siegler, 1975; Siegler et al,. 1974). Five-year-olds denied causality to delayed events at the same level as adults. Adults typically treated all delayed events as noncausal (Michotte, 1946/1963). When mechanism knowledge is integrated with co-variation patterns, different tendencies are revealed. When the delay has an identifiable explanation (Mendelson & Shultz, 1976) with a mechanism that they grasp, such as disgust or contamination (Kalish, 1997) even five year olds can infer causality despite it. This demonstrates that humans learn that certain mechanisms act across time and in spite of time delays.

If the available environmental information is spread over time such that it takes a long time to collect enough instances of co-variation to realize the existence of a correlation between candidate causes and effects, the likelihood that people will recognize such a connection is vastly diminished. The possibility that the evidence for a connection will hold enough salience to be noticed is less likely, particularly when the data is observational in nature, not involving intervention. Add to this the difficulties of the cognitive load of recalling cases across space and time and the information required by a CBN model to induce the existence of a causal relationship would predict that people would encounter the difficulties making the connections across extended time frames. Once the attentional challenges are part of the equation in reasoning about long term effects, presumably testimony and narrative would be required to learn the relevant mechanism knowledge.

Discerning Instances of Causation Despite Nonobvious Causes

It is not always the case that the availability of co-variation information is what presents challenges to complex causal reasoning that can be solved by the existence of mechanism data. There are many instances where a mechanism is non-obvious or completely unknown and inferences would need to depend upon co-variation information and/or testimony. Non-obvious causes include inferred and unknown mechanisms. For instance, density is inferred by the relationship between mass and volume. Phosphates and nitrates can be the non-obvious causes of eutrophication in ponds and lakes. The Theory of Natural Selection, a co-variation pattern, actually predated knowledge of the mechanism of Mendelian genetics that gives rise to it.

People tend to focus on obvious causes when a salient one exists. Kushnir, Gopnik, Schulz, and Danks (2003) found that adults did not seek a non-obvious or hidden cause when an obvious one existed. A number of researchers have found that for young children, causality is dominated by perception (e.g. Cohen & Oakes, 1993; Leslie, 1988; Leslie & Keeble, 1987; Oakes & Cohen, 1990). However, considerable evidence suggests that by age four, preschoolers do not rely entirely on perceptual cues and features to reason about causal mechanisms and that they do have a grasp of the non-obvious (Wellman & Gelman, 1988). Young children invoke nonobvious causal mechanisms to explain biological processes and mechanisms, such as the internal parts of animals and artifacts, such as wind up mechanisms that cause movement (Gelman & Gottfried, 1996; Gelman & Kremer, 1991). They also believe, presumably based upon testimony from others such as parents (Harris, 2002) that things can be contaminated due to non-obvious and non-visible causal mechanisms (Au, Sidle, & Rollins, 1993; Kalish, 1996; Springer & Belk, 1994; Siegal & Share, 1990). Schulz and Sommerville (2006) found that when faced with an obvious cause that behaved stochastically, preschoolers inferred the existence of a non-obvious cause.

Schlottmann (1999) argues that while it appears that children's understanding of causality moves from one dominated by perception to one dominated by an appreciation for mechanism, this is not a smooth and continuous development. According to Shultz and colleagues (1986), one of the causal rules that children follow is that if the nature of the causal mechanism is sufficiently obvious to the observer, it will be used in making a causal attribution. When mechanism is not so obvious, five secondary principles come into play: fundamentality, salience, facility, plausibility, and discriminability.

The research on hidden or non-obvious causal mechanisms reveals an interesting contrast between situations when people are looking for a cause and cannot find an obvious one and when there is an obvious cause to draw our attention or no clear cause or effect to be detected. People tend to search for mechanisms, but something has to drive the search. The instances that have been studied are all ones in which there is an obvious effect that needs explaining and are a lacking obvious cause. Further, older research on multiple sufficient causes suggests that in the presence of a salient obvious cause, we are unlikely to search beyond it and even to explicitly discount the possibility of further, alternative causes (Karniol & Ross, 1976; Kelley, 1972; Kun & Weiner, 1973). While Erwin and Kuhn (1979) found a shift towards the ability to recognize multiple causal possibilities between fourth and eighth grades, the ontology of what variables exist and their salience levels influences the tendency to focus on the most obvious explanations.

These forms of reasoning are apparent in students' ideas about ecosystems and biology. In considering the causes of decomposition, when an obvious cause is available such as earthworms, students focus on it as the cause. In the absence of earthworms or obvious decomposers, students consider non-obvious causes that might also be responsible for decay (Grotzer et al., 2003; Hogan et al., 1996). Most students are unaware of the fundamental role that microbes play in life as recyclers of carbon, nitrogen, water, and minerals (Brinkman & Boschhuizen, 1989; Leach, Driver, Scott, & Wood-Robinson, 1992) and they have no reason to wonder about or engage in a causal search for such organisms. Ontologically speaking, nothing draws their attention to their existence.

Co-variation is an effective mode of causal induction in the case of non-obvious mechanisms when there is enough information on both sides of the causal equation to compel a search. Complex causation does not typically exist in an attentional frame that allows for such a search. Harris (2012) has persuasively argued that these are instances where testimony is needed.

Conclusions

The analysis of these complex causal features through the lens of the modes of causal induction suggests that in different instances, particular modes can offer either affordances or challenges depending upon the available information. The typical default patterns in relation to each causal feature are in some respects predictable assuming that co-variation is a primary means of discerning causal patterns in our everyday world, backed up by mechanism knowledge and testimony that we have heard from others. When both co-variation and mechanism do not afford enough information to discern relationships, only sustained study over space and time through a scientific lens is likely to enable us to detect relationships. The impact of climate change on polar bears is a good example; everyday causal reasoning is not equipped to reveal a causal relationship between the two.

Often the sustained engagement required to detect probabilistic co-variation patterns across space and time eludes us and we resort to powerful narratives of the type identified by Kahneman and colleagues (2011; 1982). This appears to be irrational behavior from the perspective of statistical probabilities. Whether or not it is adaptive given our attentional and cognitive limits may be a different question entirely.

A further implication of this analysis is that everyday causal reasoning alone is unlikely to lead to effective complex causal reasoning—expert complex causal reasoning requires a reflective, meta-stance. We don't argue that there is only one way to develop such a stance, just that we are unlikely to build such a stance from a purely co-variational accounting of causal induction. One perspective might be that explicit, reflective knowledge has the potential to inform our considered causal actions and optimistically, to revise the everyday heuristics that we employ. This makes it a promising target for instruction.

The argument here centers on the following key ideas related to the nature of the human mind and how it interacts with the cognitive and attentional load of summing across patterns. Allowing for statistical summing across of instances may enable us to discern broad patterns over time. However, what we attend to in the world is subject to the limits of attention—both in the sense of what we are able to attend to and what we are likely to attend to. Much of what we would need to notice to construct complex causal models falls beyond our attentional boundaries. This compels local explanation, both temporally and spatially.

Intervention is a critical component in CBN explanations of how we screen off and disambiguate causes. Complex systems, particularly natural systems, often do not offer opportunities for intervention and even if they did, there is typically no simple way to intervene which would not result in a cascade of unanticipated and unwelcome effects. Intervention also prioritizes causal models that involve agentive explanations. Research on the centrality of agency shows that it is learned early and that it creates compelling schemas for knowing the world (Andersson, 1986; Carey, 2009; Meltzoff, 2007). Generating from our own actions, it is also most salient to us. Agentive explanation in turn compels local and egocentric explanation because our own agency is within our attentional capacity—spatially and temporally proximal to our attention, i.e. we notice and attend to what we do.

So there is clearly much to be overcome in arriving at complex causal models from everyday causal reasoning, yet beyond this, there is a reinforcing quality to everyday causal reasoning. Research on perception, attention, and neuroscience suggests that we are likely to perceive and attend to patterns that we have perceived and attended to in the past. These increase in meaning and thus salience for individuals.

The analysis in this paper points to some important implications for education. It suggests the importance of multiple approaches to understanding causal explanations. A combination of exploring the co-variation patterns, and learning about possible mechanisms while given support for reasoning across extended attentional frames in terms of space and time would support deeper learning. Computer simulations for exploring ecosystems have been designed with these affordances in mind (e.g. Metcalf et al, 2011). Learning can be supported with powerful narratives and case-based reasoning that helps to draw attention to particular causal patterns. Further, higher order reflection on the nature of causality—its patterns and features (Grotzer, 2012)—in addition to opportunities to explore specific instances of causation can help to build a broader repertoire of causal models to bring to bear.

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