Computational Models of Historical Scientific Discoveries

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The discovery of scientific knowledge is one of the most challenging tasks that confront humans, yet cognitive science has made considerable progress toward explaining this activity in terms of familiar cognitive processes like heuristic search (e.g., Langley et al., 1987). A main research theme relies on selecting historical discoveries from some discipline, identifying data and knowledge available at the time, and implementing a computer program that models the processes that led to the scientists' insights. The literature on computational scientific discovery includes many examples of such studies, but initial work in this tradition had some significant drawbacks, which we address in this symposium.

One such limitation was that early research in law discovery ignored the influence of domain knowledge in guiding search. For example, Gordon et al. (1994) noted that attempts to fit data from solution chemistry in the late 1700s took into account informal qualitative models like polymerization and dissociation. They have developed Hume, a discovery system that draws on such qualitative knowledge to direct its search for numeric laws. Hume utilizes this knowledge not only to rediscover laws found early in the history of solution chemistry, but also to explain, at an abstract level, the origins of other relations that scientists proposed and later rejected.

Early discovery research also downplayed the role of diagrams, which occupy a central place in many aspects of science. For example, Huygens' and Wren's first presentations of momentum conservation took the form of diagrams, suggesting they may have been instrumental in the discovery process. In response, Cheng and Simon (1992) have developed Huygens, a computational model for inductive discovery of this law that uses a psychologically plausible diagrammatic approach. The system replicates the discovery by manipulating geometric diagrams that encode particle collisions and searching for patterns common to those diagrams. The quantitative data given to the system are equivalent to those available at the time of the original discovery.

Another challenge concerns the computational modeling of extended periods in the history of science, rather than isolated events. To this end, Kocabas and Langley (1995) have developed BR4, an account of theory revision in particle physics that checks if the current theory is consistent (explains observed reactions) and complete (forbids unobserved reactions), revises quantum values and posits new particles to maintain consistency, and introduces new properties to maintain completeness. BR-4 models, in abstract terms, major developments in particle physics over two decades, including the proposal of baryon and lepton numbers, postulation of the neutrino, and prediction of numerous reactions. Background knowledge about symmetry and conservation combine with data to constrain the search for an improved theory in a manner consistent with the incremental nature of historical discovery.

We hope this symposium will encourage additional research that extends our ability to model historical scientific discoveries in computational terms.

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Symposium: When Cognition Shapes its Own Environment

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Introduction

Cognitive mechanisms are shaped by their environments, both through evolutionary selection across generations and through learning and development within lifetimes. But by making decisions that guide actions which in turn alter the surrounding world, cognitive mechanisms can also shape their environments in turn. This mutual shaping interaction between cognitive structure and environment structure can even result in coevolution between the two over extended periods of time. In this symposium, we explore how simple decision heuristics can exploit the information structure of the environment to make good decisions, how simple language-learning mechanisms can capitalize on the structure of the ”spoken” environment to develop useful grammars, and how both sorts of cognitive mechanisms can actually help build the very environment structure that they rely on to perform well.

Programme

There will be three talks, as follows:

1. Peter Todd, “Simple Heuristics that exploit environment structure”,

   Traditional views of rational decision making assume that individuals gather, evaluate, and combine all the available evidence to come up with the best choice possible. But given that human and animal minds are designed to work in environments where information is often costly and difficult to obtain, we should instead expect many decisions to be made with simple ”fast and frugal” heuristics that limit information use. In our study of ecological rationality, we have been exploring just how well such simple decision-making heuristics can do when they are able to exploit the structure of information in specific environments. This talk will outline the research program pursued by the Center for Adaptive Behavior and Cognition as developed in the book, *Simple Heuristics That Make Us Smart* (Oxford, 1999), and highlight how the match between cognitive mechanism structure and environment structure allows the Recognition heuristic and Take The Best heuristic to perform on par with traditionally rational decision mechanisms.

2. Simon Kirby, “The Iterated Learning Model of Language Evolution”,

   The past decade has seen a shift in the focus of research on language evolution away from approaches that rely solely on natural selection as an explanatory mechanism. Instead, there has been a growing appreciation of languages (as opposed to the language acquisition device) as complex adaptive systems in their own right. In this talk we will present an approach that explores the relationship between biologically given language learning biases and the cultural evolution of language. We introduce a computationally implemented model of the transmission of linguistic behaviour over time: the Iterated Learning Model (ILM). In this model there is no biological evolution, natural selection, nor any measurement of the success of communication. Nonetheless, there is significant evolution. We show that fully syntactic languages emerge from primitive communication systems in the ILM under two conditions specific to Hominids: (i) a complex meaning space structure, and (ii) the poverty of the stimulus.

3. Peter Todd, Simon Kirby and Jim Hurford, “Putting the Models Together: how the environment is shaped by the action of the recognition heuristic”,

   To explore how cognitive mechanisms can exert a shaping force on their environment and thus affect their own performance, we begin by considering the actions of a very simple cognitive mechanism, the recognition heuristic for making choices. This heuristic specifies that when choosing between two options, one of which is recognized and one not, the recognized option should be selected. The recognition heuristic makes good choices, in environments where recognition is correlated with the choice criterion. Many natural environments have this structure, but such structure can also be “built”: By using the recognition heuristic, agents can create an environment in which some objects are much more often and “talked about” and recognized than others. An agent-based simulation is used to show what behavioral factors affect the emergence of this environmental structure.

The Cognitive Basis of Science: The View from Science

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The issue of the nature of the processes or "mechanisms" that underlie scientific cognition is a fundamental problem for cognitive science. A rich and nuanced understanding of scientific knowledge and practice must take into account how human cognitive abilities and limitations afford and constrain the practices and products of the scientific enterprise. Reflexively, investigating scientific cognition opens the possibility that aspects of cognition previously not observed or considered will emerge and require enriching or even altering significantly current understandings of cognitive processes.

The Baby in the Lab Coat: Why child development is an inadequate model for understanding the development of science

Stephen P. Stich, Department of Philosophy, Rutgers University

In two recent books and a number of articles, Alison Gopnik and her collaborators have proposed a bold and intriguing hypothesis about the relationship between scientific cognition and cognitive development in childhood. According to this view, the processes underlying cognitive development infants and children and the processes underlying scientific cognition are identical. One of the attractions of the hypothesis is that, if it is correct, it will unify two fields of investigation – the study of early cognitive development and the study of scientific cognition – that have hitherto been thought quite distinct, with the result that advances in either domain will further our understanding of the other. In this talk we argue that Gopnik's bold hypothesis is untenable. More specifically, we will argue that if Gopnik and her collaborators are right about cognitive development in early childhood then they are wrong about science. The minds of normal adults and of older children, we will argue, are more complex than the minds of young children, as Gopnik portrays them. And some of the mechanisms that play no role in Gopnik's account of cognitive development in childhood play an essential role in scientific cognition.

Scientific Cognition as Distributed Cognition

Ronald N. Giere, Center for Philosophy of Science, University of Minnesota

I argue that most important cases of cognition in contemporary science are best understood as examples of distributed cognition. Here I focus exclusively on the acquisition of new knowledge as the paradigm of scientific cognition. Scientific cognition, then, does not reduce to mere distributed computation. The simplest case is that in which two people cooperate in acquiring some knowledge that is not directly acquired by either one alone. It is even possible that neither person could physically perform the task alone. This is an example of what has been called "socially shared cognition" (Resnick) or "collective cognition" (Knorr). The most elaborate example is the case of experimental high-energy physics at CERN, as described by the sociologist, Karin Knorr in her recent book, *Epistemic Cultures*. I go beyond Knorr's analysis to include the particle accelerator and related equipment as part of a distributed cognitive system. So here the cognition is distributed both among both people and artifacts. Such artifacts as diagrams and graphics and even abstract mathematical constructions are also included as components of distributed cognitive systems. This makes it possible to understand the increasing power of science since the seventeenth century as in large measure due to the creation of increasing powerful cognitive systems, both instrumental and representational.

The Cognitive Basis of Model-based Reasoning in Science

Nancy J. Nersessian, Program in Cognitive Science, Georgia Institute of Technology

Although scientific practice is inherently "socially shared cognition," the nature of individual cognitive abilities and how these constrain and facilitate practices still needs to be figured into the account of scientific cognition. This presentation will focus on the issue of the cognitive basis of the model-based reasoning practices employed in creative reasoning leading to conceptual change across the sciences. I will first locate the analysis of model-based reasoning within the mental modeling framework in cognitive science and then discuss the roles of analogy, visual representation, and thought experimenting in constructing new conceptual structures. A brief indication of the lines along which a fuller account of how the cognitive, social, and material are fused in the scientist's representations of the world will be developed. That the account needs to be rooted in the interplay between the individual and the communal in the model-based reasoning that takes place in concept formation and change. Modeling is a principal means through which a scientist transports conceptual resources drawn from her wider cultural milieu into science and transmits novel representations through her community. Scientific modeling always takes place in a material environment that includes the natural world, socio-cultural artifacts (stemming from both outside of science and within it), and instruments devised by scientists and communities to probe and represent that world.

Symposium Discussant: Dedre Gentner, Department of Psychology, Northwestern

The Interaction of Explicit and Implicit Learning

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The Focus of the Symposium

The role of implicit learning in skill acquisition and the distinction between implicit and explicit learning have been widely recognized in recent years (see, e.g., Reber 1989, Stanley et al 1989, Willingham et al 1989, Anderson 1993), Although implicit learning has been actively investigated, the complex and multifaceted interaction between the implicit and the explicit and the importance of this interaction have not been universally recognized; to a large extent, such interaction has been downplayed or ignored, with only a few notable exceptions. [1] Research has been focused on showing the *lack* of explicit learning in various learning settings (see especially Lewicki et al 1987) and on the controversies stemming from such claims. Similar oversight is also evident in computational simulation models of implicit learning (with few exceptions such as Cleeremans 1994 and Sun et al 2000).

Despite the lack of studies of interaction, it has been gaining recognition that it is difficult, if not impossible, to find a situation in which only one type of learning is engaged (Reber 1989, Seger 1994, but see Lewicki et al 1987). Our review of existing data has indicated that, while one can manipulate conditions to emphasize one or the other type, in most situations, both types of learning are involved, with varying amounts of contributions from each (see, e.g., Sun et al 2000; see also Stanley et al 1989, Willingham et al 1989).

Likewise, in the development of cognitive architectures (e.g., Rosenbloom et al 1993, Anderson 1993), the distinction between procedural and declarative knowledge has been proposed for a long time, and advocated or adopted by many in the field (see especially Anderson 1993). The distinction maps roughly onto the distinction between the explicit and implicit knowledge, because procedural knowledge is generally inaccessible while declarative knowledge is generally accessible and thus explicit. However, in work on cognitive architectures, focus has been almost exclusively on "top-down" models (that is, learning first explicit knowledge and then implicit knowledge on the basis of the former), the bottom-up direction (that is, learning first implicit knowledge and then explicit knowledge, or learning both in parallel) has been largely ignored, paralleling and reflecting the related neglect of the interaction of explicit and implicit processes in the skill learning literature. However, there are a few scattered pieces of work that did demonstrate the parallel development of the two types of knowledge or the extraction of explicit knowledge from implicit knowledge (e.g, Willingham et al 1989, Stanley et al 1989, Sun et al 2000), contrary to usual top-down approaches in developing cognitive architectures.

Many issues arise with regard to the interaction between implicit and explicit processes, which we need to look into if we want to better understand this interaction:

- How can we best capture implicit processes computationally? How can we best capture explicit processes computationally?
- How do the two types of knowledge develop along side each other and influence each other's development?
- Is bottom-up learning (or parallel learning) possible, besides top-down learning? How can they (bottom-up learning, top-down learning, and parallel learning) be realized computationally?
- How do the two types of acquired knowledge interact during skilled performance? What is the impact of that interaction on performance? How do we capture such impact computationally?

Titles of the Talks

Axel Cleeremans: "Behavioral, neural, and computational correlates of implicit and explicit learning"

Zoltan Dienes: "The effect of prior knowledge on implicit learning"

Bob Mathews: "Finding the optimal mix of implicit and explicit learning"

Ron Sun: "The synergy of the implciit and the explicit"

[1] By the explicit, we mean processes involving some form of generalized (or generalizable) knowledge that is consciously accessible.