Nick Chater and Mike Oaksford, eds.
The Probabilistic Mind: Prospects for Bayesian Cognitive Science.
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Comprised of twenty two papers, this volume follows the 2006 conference at University College London, entitled 'The Probabilistic Mind: Prospects for Rational Models of Cognition'. The conference and the resulting book are a follow-up on the seminal *Rational Models of Cognition* (Oxford University Press 1998), which developed out of a similar meeting held at Warwick University in 1996. The volume is meant to evaluate the considerable progress in the past decade in applying probabilistic methods to a range of central cognitive processes. This non-committal goal becomes more challenging in light of the editors' view that the mind is probabilistic only if the central cognitive processes, processes conducted by the general rather than specialized purpose cognitive mechanisms, have probabilistic character. This explains the book's focus on such areas of cognition as inference, decision-making, categorization, and causal reasoning, at the expense of such specialized cognitive modules as motor-control, perception, and language.

The first section, 'Foundations', starts with an introductory paper by editors Charter and Oaksford. This discusses the Bayesian approach to cognition in the context of the subjectivist and the frequentist interpretation of probability. It is followed by a technical introduction to Bayesian methods by Tom Griffiths and Alan Yuille, highlighting the ease with which the combination of structural representations and statistical methods lend themselves to the investigation of human cognition. The last paper of this section, 'Rational Analyses, Instrumentalism, and Implementations', by David Danks, addresses the role of rational analysis in the explanation of cognition. Pointing out the failure of the current instrumentalist use of rational analysis to connect to an account of implementation, Danks argues that optimality-based explanations of behavior require not only the mathematical demonstration that some behavior is optimal but also a developmental story showing that the behavior is implemented due to its optimality.

The section 'Inference and Argumentation' opens with two papers that re-examine the normative implications of traditional logic for day-to-day argumentation, from a pragmatic and probabilistic perspective. Discussing framing effects, Shlomi Sher and Craig McKenzie argue that, depending on communicative situation, logically equivalent descriptions might leak different normatively relevant information. The speaker's choice of descriptive frame often depends on salience of the attribute relative to some reference point (e.g. the glass is 'half empty' if the reference point is a full glass), and because listeners are sensitive to such regularities, the speaker's choice of frame is informative. The scrutiny of normative requirements from the pragmatic and probabilistic perspective is continued in another paper by Oaksford and Chater. They explain, from the Bayesian and pragmatic perspective, the asymmetry in people's acceptance of modus ponens and modus tollens and their relatively frequent endorsement of the conditional fallacies. They argue that understanding the pragmatic inferences that can be drawn from what is said is fundamentally important, and such inferences, which are subject to highly conventionalized regularities, are normatively defensible.

In 'Towards a Rational Theory of Human Information Acquisition', Jonathan Nelson examines a number of Bayesian approaches to quantifying the utility of data to the hypothesis under consideration, and he argues that some of the better theoretically motivated models fit our intuitions and provide better normative and descriptive models of human behavior. Denying that human information acquisition relies on suboptimal heuristic strategies, Nelson argues that it fits the rational optimal experimental design (OED) principles. Taking a different view of heuristics, Klaus Fiedler examines the pseudocontingency (PC) illusion in 'Pseudocontingencies—A Key Paradigm for Understanding Adaptive Cognition'. Calling PC a category mistake and a cognitive analogue of ecology bias, where the inferences about contingencies are based not on joint frequencies but on marginal base-rate distributions, nevertheless Fiedler argues that PC is a functional and economic heuristic that can lead to optimal decisions and long-term adaptive behavior. The section also contains an interesting paper by Ulrike Hahn and Mike Oaksford, which gives a Bayesian analysis of arguments from ignorance and applies the results to the problem of the absence of explicit negative evidence in grammar acquisition.

The section 'Judgement and Decision-Making' highlights the disagreements among the contributors on whether the proper framework for human cognition should be Bayesian theory, heuristics, or naive statistics, and it considers the assessment of the normative implications of these alternatives. In 'Bayesian Brains and Cognitive Mechanisms: Harmony or Dissonance?', Henry Brighton and Gerd Gigerenzer doubt the utility of rational analysis in deriving algorithmic level hypotheses about actual implementation of cognitive mechanisms. Rejecting the metaphor of the probabilistic mind in favor of the metaphor of the mind as an adaptive toolbox of simple heuristics, they propose the notion of ecological rationality. Rooted in the algorithmic level of description, it views a cognitive system as adapted to its environment insofar as it furnished good enough, rather than optimal, solutions, given limited resources, time, and processing capacities. Sample mean heuristic is also the explanation that authors Ralph Hertwig and Timothy Pleskac provide for the fact that in decisions from experience respondents give less weight to small-probability events than they do in decisions from descriptions. Because such decisions rely on small samples, there is less probability that a frugal searcher will come across the distribution's rare event. At some cost to optimality and accuracy, the use of such a heuristic makes the choices between alternatives simpler and faster by amplifying the differences between average earnings associated with the payoff distribution.

In 'The Neurodynamics of Choice, Value-Based Decisions, and Preference Reversals', Marius Usher, Anat Elhalal, and James McClelland reject the heuristic approach in explaining normative deviations (e.g. loss-aversion or contextual preference reversal effects) in value-based decision-making; and they propose, instead, a model that combines statistical normative principles with neural level implementation. Although the leaky competing accumulator (LCA) model is capable of optimal performance, experimental evidence points to various biases (e.g. recency bias), which might have adaptive value. Authors Neil Stewart and Keith Simpson develop a related choice model, in which the construction of attribute values depends on comparisons within a set of attribute values sampled from the decision context and long-term memory. Patrick Hansson, Peter Juslin, and Anders Winman, on the other hand, suggest that the mind is neither a Bayesian optimizer nor a cognitive miser: it is a naive intuitive statistician. Although constrained by the short-term memory capacity for sample size, judgments are accurate expressions of stored frequencies. Errors are due to people's naiveté with regards to estimators and input biases, which leads them to assume that sample properties are representative of population properties.

The section 'Categorization and Memory' demonstrates greater consensus on the utility of Bayesian methods and rational analysis. In 'Categorization as Nonparametric Bayesian Density Estimation', Thomas Griffiths et al. present a unifying model of category learning, which, drawing on rational models of categorization, provides a rational solution to the question when people's category representation should switch between prototype (parametric) and exemplar (nonparametric) models in learning tasks. In the paper that follows, Mark Steyvers and Thomas Griffiths rely on the rational analysis approach to suggest that because electronic information retrieval systems and human memory systems face similar computational problems, they can be mutually illuminating. The authors analyze the PageRank algorithm in the Google search engine to gain insight into the Bayesian underpinnings of human linguistic categorization and information retrieval from memory. Arguing that Bayesian models can have direct neural implementations, David Huber, in 'Causality and Time: Explaining Away the Future and the Past', relies on rational analysis and graph theory to construct a causal model which explains priming and provides insight into perception and inference over time. In 'Compositionality in Rational Analysis: Grammar-based Induction for Concept Learning', Noah Goodman, Joshua Tenenbaum, Thomas Griffiths, and Jacob Feldman argue that Bayesian methods and rational analysis are compatible with the formal compositional representational systems. Relying on (mentalese) concept language and its grammar, the authors harness the compositionality of the representational systems to develop a richer model of concept learning.

The volume concludes with a section entitled 'Learning about Contingency and Causality', which re-examines the associative/mechanistic models of causal learning from a probabilistic perspective. With papers ranging from optimism to skepticism about the explanatory value of rational analysis and Bayesian methods in causal learning, the section, and the volume, concludes with the editors' reflections on the prospects of Bayesian cognitive science.

While some of the papers in this volume contain minor typos, others make more significant mistakes: one stated that any conditional with a false consequent is true (clearly a typo), while another, for reasons known perhaps only to statisticians, referenced Wikipedia. Nevertheless, this volume is an excellent source of material for philosophers who are interested in more recent work in the application of probability to cognitive science and who have a solid grasp of probability theory and statistics. It highlights the fruitfulness of combining rigorous, empirically testable probabilistic models with neural connectionist hypotheses and the analysis of ecological conditions. Although this triangulating approach to cognition is promising, the prospects of the Bayesian, or even probabilistic, mind are less clear. The discussion of inference and judgment is not always couched in Bayesian terms, and the disagreement on whether central cognitive processes rely on rational optimization, adapted fast and frugal heuristics, or suboptimal, biased statistical solutions is philosophically profound. This disagreement is much less evident in the discussion of categorization and memory, where the circumscribed nature of the task seems to constrain functional and implementation-level theorizing. Although the prospects are bright, the answer to whether the mind is probabilistic will require a tighter link with the analysis of ecological conditions, biological functions, and neural implementation.

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