From Efficient Coding to Information Gain: Information-Theoretic Principles in Models of Human Decision Making

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Keywords: cognitive modeling; perceptual choice; hypothesis testing; decision making under risk; entropy; information theory; efficient coding

Introduction

Soon after the publication of Shannon's (1948) seminal paper on information theory, the formalization of entropy and efficient coding systems saw applications in a wide range of disciplines ranging from biology and economics to fundamental physics (Shannon, 1956). In mathematical psychology, notions borrowed from information theory were successfully applied to pattern perception (Garner, 1962), proportion estimation (Attneave, 1953), choice reaction times (Hick, 1952), perceptual judgment (Miller, 1956), and data analysis (McGill, 1954). Within a couple of decades, however, these applications decreased, partially due to difficulties in quantifying perceptions of uncertainty and in connecting uncertainty with the psychological valence of associated outcomes (Luce, 2003).

In recent years, theories and methods based on the information-theoretic notion of uncertainty have re-emerged in different areas of cognitive modeling, both in information-theory-based tools for data processing (e.g., Rissanen, 2007; Williams & Beer, 2010) and as assumptions of the goals and mechanisms of the human cognitive system (Feldman, 2016, and Friston, 2010).

In studies of decision making under uncertainty, measures of entropy have been applied in models of information acquisition (Oaksford & Chater, 1994; Crupi et al., 2018; Coenen, Nelson, & Gureckis, 2019), neural valuation of information (Filimon et al., in press), active learning (Parpart et al., 2017), economic choice (Luce, Marley, & Ng, 2009; Yang & Qui, 2014), and probability distortion (Zhang, Ren, & Maloney, 2019; Akrenius, 2020), whereas approaches based on efficient coding have been used to explain preference reversals (Summerfield & Tsetsos, 2015), decisions by sampling (Bhui & Gershman, 2018), and biased number perception (Prat-Carrabin & Woodford, 2020).

Even though these frameworks differ strongly in their domain and theoretical postulates, they share the general assumption that a perceived (or neurally coded) reduction in uncertainty carries psychological utility, and that this reduction can be quantified using information entropy. This has inspired theoretical frameworks that aim to describe performance in different kinds of choice tasks under a unified formal theory (Ortega & Braun, 2013) and has been interpreted to suggest that cognitive function and adaptive behavior could be governed by a single principle (Friston, 2010). However, given the diverse array of models that the notion of reducing entropy is embedded in, it appears likely that this conclusion is too simplified or needs to be refined.

Goal and Scope

The purpose of the proposed workshop is to bring together cognitive scientists, cognitive psychologists, physicists, neuroscientists, economists, philosophers, and computational biologists to (1) establish information-theoretic principles that extend across tasks and disciplines and can be modeled using similar or analogous notions, and (2) diagnose limiting cases in which these principles break or carry fundamentally different meanings. The invited speakers consist of experts in subfields of decision making that relate to the foundational processes underlying adaptive and intelligent behavior.

Structure and Tentative Schedule

This will be a full day workshop with three sessions of 20-minute presentations, a 45-minute panel discussion, 5-minute flash talks, and opportunities for (virtual) mingling and conversation. The full program, along with a platform for participants to submit flash talks, will be published on the workshop website.

Morning Session 1: Rationality and Optimal Encoding
Nick Chater: *Overview of the field*
Christopher Summerfield: *Optimal irrationality*
Rahul Bhui: *Context-dependent preferences and efficient neural coding*
Daniel Ortega: *Information-theoretic bounded rationality models for sensorimotor learning and decision making*

Morning Session 2: Value and Uncertainty
Laurence Maloney: *The value of information: if you want to know the subtitle it will cost you $5*
Mikaela Akrenius: *Information theory meets expected utility*
Flavia Filimon: *Ventral striatum dissociates information expectation, reward anticipation, and reward receipt*

Afternoon Session 1: Evidence and Accuracy

Eric Schulz: *Beyond uncertainty and information bonuses: Exploration as fun and empowerment*

Paula Parpart: *Active information sampling, information gain, and decision heuristics*

Vincenzo Crupi: *Towards an accuracy-based approach to information search*

Todd Gureckis: *Asking the right questions about the psychology of human inquiry*

Afternoon Session 2: Panel discussion

Organizers and Presenters

Mikaela Akrenius is a PhD student in Cognitive Science at Indiana University Bloomington. Her current work focuses on the psychological roots of non-expected utility theories and the applicability of the notion of entropy in models of risky choice.

Rahul Bhui is a postdoctoral fellow in Psychology and Economics at Harvard University, and incoming Assistant Professor at the MIT Sloan School of Management. His research combines cognitive science, computational neuroscience, and behavioral economics to understand the unifying principles that capture both rationality and irrationality.

Daniel Braun is a Professor at the Institute of Neural Information Processing at Ulm University. His background spans physics, biology, and philosophy and his current research interests lie in the intersection of cognitive modeling, decision making and bounded rationality, sensorimotor learning, and information processing.

Nick Chater is Professor of Behavioural Science at Warwick Business School. He researches rationality and cognition using both experimental and modeling approaches.

Vincenzo Crupi is a Professor of Philosophy of Science and director of the Center for Logic, Language, and Cognition at the University of Turin. His interests are in formal epistemology, the psychology of reasoning, and medical decision making.

Flavia Filimon is a cognitive neuroscientist interested in perceptual and cognitive decision making and the neural bases of the value of information.

Todd Gureckis is an Associate Professor at the Department of Psychology at New York University. His research centers on models of memory, learning, and decision making.

Laurence Maloney is a Professor at New York University. His work concerns Bayesian decision theoretic models of perception, cognition, and action.

Jonathan Nelson researches the psychology of uncertainty and information in cognition and perception.

Paula Parpart is a postdoc at the University of Oxford in the Human Information Processing Group. Her current research focuses on the role of robust decision strategies in human cognition and artificial neural networks.

Eric Schulz leads the Computational Principles of Intelligence lab at the Max Planck Institute for Biological Cybernetics. He researches learning and decision making from a computational and cognitive perspective.

Christopher Summerfield is a Professor of Cognitive Neuroscience at the University of Oxford and Research Scientist at Deepmind. His work is concerned with understanding the neural and computational mechanisms that underlie human perception and cognition.

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