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Authors
Battaglia, Peter
Ullman, Tomer
Tenenbaum, Joshua
et al.

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Computational Models of Intuitive Physics

Peter Battaglia (pbatt@mit.edu)
Tomer Ullman (tomeru@mit.edu)
Joshua Tenenbaum (jbt@mit.edu; moderator)
MIT, BCS Dept.,77 Massachusetts Ave.
Cambridge, MA 02139 USA

Adam Sanborn (a.n.sanborn@warwick.ac.uk)
Dept. of Psychology, University of Warwick
Coventry, CV4 7AL UK

Kenneth Forbus (forbus@northwestern.edu)
Northwestern University, EECS Dept., 2133 Sheridan Rd
Evanston, IL 60208 USA

Tobias Gerstenberg (t.gerstenberg@ucl.ac.uk)
David Lagnado (d.lagado@ucl.ac.uk)
Cognitive, Perceptual, and Brain Sciences Dept., UCL,
26, Bedford Way, London WC1H 0AP, UK

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People have a powerful "physical intelligence" – an ability to infer physical properties of objects and predict future states in complex, dynamic scenes – which they use to interpret their surroundings, plan safe and effective actions, build and understand devices and machines, and communicate efficiently. For instance, you can choose where to place your coffee to prevent it from spilling, arrange books in a stable stack, judge the relative weights of objects after watching them collide, and construct systems of levers and pulleys to manipulate heavy objects. These behaviors suggest that the mind relies on a sophisticated physical reasoning system, and for decades cognitive scientists have been interested in the content of this knowledge, how it is used and how it is acquired. In the last few years, there has been exciting progress in answering these questions in formal computational terms, with the maturation of several different traditions of cognitive modeling that have independently come to take intuitive physics as a central object of study. The goals of this symposium are to: 1) highlight these recent computational developments, focusing chiefly on qualitative reasoning (QR) models and Bayesian perceptual and cognitive models; 2) begin a dialog between leading proponents of these different approaches, discussing a number of dimensions along which the approaches appear to differ and working towards bridging those differences; 3) enrich these models with perspectives from empirical work in cognitive science.

Background. The research to be discussed builds on several decades of prior work from multiple traditions in cognitive science. Cognitive psychologists since the 1970s have studied the role that human intuitive physics plays in development, perception, education, and reasoning. Behavioral research with adults focused on identifying errors and biases in people's general understanding and theories about physical rules (McCloskey, 1983), as well as psychophysical studies of how sensory cues drive specific judgments in dynamic displays (Todd & Warren, 1982). Early and ongoing developmental work has identified milestones in cognitive sensitivity and expectations about core physical principles (Baillargeon, 2007). Though these efforts have made significant progress, they did not frame their results as computational models with sufficient clarity and power to explain people's physical reasoning in complex and varied scenes.

Crucial computational progress has come from the fields of human and computer vision, artificial intelligence (AI), and machine learning. Human and machine vision researchers have recently developed computational models of natural scene understanding (Oliva & Torralba, 2007), but their focus has been on knowledge about the geometry and semantics of scene layouts, not the role of physical constraints and how physical properties are represented and exploited for prediction, reasoning and planning. AI researchers have been developing frameworks for qualitative reasoning (QR) and applying them to physical domains for over 30 years, and these approaches have now matured to the point that they can both solve challenging real-world inference problems and engage directly with behavioral experiments, giving state-of-the-art accounts of people's intuitive reasoning in a wide range of science and engineering domains (Forbus, 2011). The framework of Bayesian reasoning in probabilistic generative models has revolutionized AI and machine learning, and in the last decade has also come to provide a lingua franca for sophisticated reverse-engineering models of human perception, action and cognition (Chater et al, 2006; Tenenbaum et al, 2011). But only in the last few years have Bayesian models been applied to challenging physical reasoning problems, and been shown to give strong quantitative accounts of human physical judgments (Sanborn et al, 2009; Hamrick et al, 2011).

This symposium brings together leading researchers modeling intuitive physics from the QR, Bayesian cognition and perceptual modeling traditions, to discuss highlights of recent models and points of contact and contrast between different modeling approaches. The talks and discussion will explore several axes in the space of possible models, including the following: rational reverse-engineering vs. descriptive or heuristic accounts; qualitative vs. quantitative reasoning; probabilistic vs. deterministic inference; lower-level perceptual vs. higher-level cognitive inferences; implicit vs. explicit reasoning; analog simulation vs. symbolic rule-based representations; the role of memory-, experience- and learning-dependent reasoning; the role of causal, counterfactual and explanatory reasoning; reasoning about simple rigid bodies vs. complex physical entities and concepts, like non-rigid objects, non-solid substances, fluids, gasses, heat; simple scenarios with few objects moving in simple ways vs. compound scenes of many objects interacting and moving according to complex dynamics.

The speakers come from various avenues of artificial intelligence and cognitive science: Sanborn studies computational models of memory and cognition; Battaglia, computational perception and motor control; Forbus, AI and qualitative reasoning; Tenenbaum, learning and inference in humans and machines.

Sanborn: Reconciling intuitive and Newtonian mechanics for colliding objects

People have strong intuitions about the masses of objects and the causal forces that they exert upon one another when they collide. These intuitions appear to deviate from Newtonian physics, leading researchers to conclude that people use a set of heuristics to make judgments about collisions. We show that people's judgments about mass are indeed consistent with Newtonian physics, provided uncertainty about the velocities of the objects is taken into account. The resulting rational model of intuitive dynamics easily extends to accommodate other aspects of people's inferences about physical causation, such as judgments of whether one object caused another to move. We argue that intuition and physics need not be divorced, and that a simple psychological process - stochastically approximating Bayesian inference by recalling previous collisions - can bring them together.

Battaglia: Intuitive mechanics in physical reasoning

I will explore the idea that the brain has an "intuitive mechanics", a realistic model of physics that can estimate physical properties and predict probable futures. This intuitive mechanics is surprisingly faithful to the laws of classical mechanics, it captures statics, dynamics, forces, collisions, and friction. It is fundamentally probabilistic, it supports Bayesian inferences that robustly handle uncertainty, and, like people, its predictions can deviate from objective reality. And, it is resource-bounded, supporting only judgments that can be made based on a few low-precision, short-lived simulations. We conducted a series of psychophysical experiments in which participants made physical judgments about various complex, 3D scenes, and found that this formal model of intuitive mechanics well-predicts people's responses by accounting for their accuracy and several systematic biases. These results suggest that an approximate, probabilistic model of physics forms the basis of human physical reasoning. More generally, this principled computational approach provides a unifying framework for analyzing and understanding this crucial part of human cognition.

Forbus: Qualitative modeling: Capturing human reasoning about the physical world

There is ample evidence that qualitative representations of space, quantity, and causality capture important regularities of human reasoning about physical situations and systems (Forbus, 2011). Qualitative reasoning has been used to model intuitive phenomena, such as motion, liquids, and heat. It has also been used to model aspects of the reasoning of scientists and engineers, such as guiding the solution of quantitative problems and extracting insights about complex dynamical systems from visual data. Qualitative representations of space provide a bridge between perception and conceptual knowledge, and can be used to model visual problem solving. When combined with analogical reasoning, qualitative models can provide explanations for aspects of conceptual change (eg. Friedman & Forbus, 2010). This talk will summarize recent work on modeling conceptual change concerning intuitive notions of force, the human circulatory system, and how the seasons change. There is great potential for synthesis between qualitative and Bayesian modeling: Qualitative modeling provides formal languages for hypotheses, while statistical information (in our case, computed automatically via analogical generalization over examples) provides criteria for accepting hypotheses.

Tenenbaum: Integrative perspectives

I will discuss the prospects for building computational models of intuitive physical reasoning that integrate features of qualitative and probabilistic approaches introduced earlier in the symposium, and present preliminary results on several lines of work exploring this integration. Specific points will include (1) using qualitative reasoning to generate efficient proposals for Monte Carlo-based approximate inference in probabilistic models; (2) using dynamic probabilistic models as the basis for linguistic ascriptions of causal responsibility and explanatory reasoning (joint work with Gerstenberg and Langado); (3) modeling conceptual change in intuitive physics via hierarchical Bayesian inference over symbolic expressions for physical laws (joint work with Ullman).

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