A Series of Lectures for Causality:
How We Discover How the World Works

Course Outline

We all have a yearning to find order and meaning. This 5-sessioncourse examines how this yearning shapes our representation of the causal world. The course explains the challenge that causal learning poses for any intelligent system, and briefly reviews the psychological causal-learning literature with respect to rationality. Rational causal learning has specific implications for category formation, for rational statistics for testing causal hypotheses, and for analytic knowledge of mathematical functions expressing causal invariance in humans and perhaps other species. The course will consider these and other implications as outlined belowunder the framework of model-dependent realism.

Lecturer: Patricia Cheng, Professor of UCLA
Time and Place: 1/19~1/23, 2015, 2:00~5:00 p.m.
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Schedule of Topics

1) What is causation? Why causation?

- Causation is unobservable – inferred based on association (Hume, 1739), yet not limited by association:
  - Overview (Cheng &Buehner, 2012)
  - Contingency and blocking: watershed findings (Hollis, 1997)
    - Classical conditioning results hold across diverse species: honey bees, pigeons, rats, etc.
- Noncausal associations (e.g., rooster's crowing and sunrise) do not predict consequences of actions. Why not?
  - Problem of underdeterminacy
  - Why do principles of experimental design, such as "no confounding", enable causal inference? Cheng (1997)
    - E.g., preventive ceiling effect is never taught but is honored in rats and humans
- Assumptions are needed to avoid paralysis

2)What is the goal of causal learning?

- When is knowledge useful? Only when it can generalize from the learning context to the application context (Hume, 1777; Liljeholm& Cheng, 2007)
- The need for generalization raises the question:
  - Is the goal to accurately represent causal relations for given variables (Lucas & Griffiths, 2010), or …
  - to represent causal relations that are generalizable across contexts?

- “Nature is always simple and uniform” (Isaac Newton, 1687). Nature may or may not be simple and uniform – it’s Newton’s assumption that it is.
    - Why simplicity and uniformity/invariance are essential to a generalizable representation of causality
- Six ways to misunderstand causal invariance

3)Understanding causal invariance

- Causal invariance as aspiration
    - as exit condition in the hypothesis-testing WHILE loop
- Causal inference in the context of model-dependent realism (Hawking &Mlodinow, 2010)
    - theories in the history of science (Kuhn, 1970)
- causal-invariance functions
    - differ for continuous and discrete variables (Buehner et al., 2003; Beckers et al., 2006)
    - are not inducible by experience
- Categories are what obey causal laws (Lien & Cheng, 2000)

4)Implications of causal invariance for:

- rationalcausal statistics for binary outcome variables (Cheng, Liljeholm&Sandhofer, 2013)
- basic level categories
- analytic knowledge of causal-invariance functions in humans (McGillivray, Park& Cheng, under review) and nonhumans
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5)More implications and general discussion

- aesthetics, parsimony, and causal explanations
    - applying causal learning to mathematics learning (Walker, Cheng, Stigler, 2014)

References

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Walker JM, Cheng PW & Stigler JW (2014) Equations are effects: Using causal contrasts to support algebra learning. In *Proceedings of the 36th Annual Conferenceof the Cognitive Science Society*. Austin, TX: Cognitive Science Society.

ptional readings:

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