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Personal Information
Date of birth: May 14, 1990
Citizenship: USA

Undergraduate Studies
S.B. in Economics, Massachusetts Institute of Technology, 2011
S.B. in Mathematics, Massachusetts Institute of Technology, 2011

Graduate Studies
Harvard University, 2011 to present
Ph.D. Candidate in Economics
Thesis Title: *Economic Theory and Statistical Learning*
Expected Completion Date: June, 2016

References:

Professor Drew Fudenberg
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Professor Jerry Green
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Professor David Laibson
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Professor Sendhil Mullainathan
Littauer Center M-18
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Teaching and Research Fields
Primary Field: Theory
Secondary Fields: Behavioral Economics, Machine Learning

Teaching Experience

Fall 2012-2013	2010a Economic Theory (graduate) Teaching Fellow for Eric Maskin
Spring 2013-2014	2030 Psychology and Economics (graduate) Teaching Fellow for David Laibson, Sendhil Mullainathan, and Andrei Shleifer
Fall 2014 – 2015	2010a Economic Theory (graduate) Teaching Fellow for Jerry Green
Spring 2014-2015	2030 Psychology and Economics (graduate) Teaching Fellow for David Laibson and Andrei Shleifer

Research Experience and Other Employment

Summer 2011 Research assistant for Jerry Green

Professional Activities

Referee: *Quarterly Journal of Economics*

Other: Workshop on Complexity and Simplicity in Economics (2015), Jerusalem School in Economic Theory (2013), Russell Sage Foundation Summer Institute in Behavioral Economics (2012)

Honors, Scholarships, and Fellowships

2015-2016	Roger L. Martin Cornerstone Graduate Student Fellowship Fund
2015-2016	Dissertation Completion Fellowship, Harvard University
2013	LEAP Research Grant, Harvard University
2013	Simon Kuznets Travel & Research Grant, Harvard University
2011-present	Harvard University Graduate Research Fellowship

Job Market Paper

"Games of Incomplete Information Played by Statisticians"

The common prior assumption is a convenient restriction on beliefs in games of incomplete information, but stands in conflict to evidence that agents publicly disagree in many economic environments. This paper proposes a foundation for heterogeneous beliefs in games, in which disagreement arises not from different information, but from different interpretations of common information. I model players as statisticians who use models to infer unknown payoffs from data. Players know that they may use different models (and, therefore, may disagree about the distribution of payoffs), but the set of possible models is common knowledge. Using this framework, I study the robustness of solutions to the common prior assumption. My main results characterize which rationalizable actions and which Bayesian Nash equilibria persist given finite quantities of data, and at what rate agents learn these solutions. I suggest a new criterion for equilibrium selection based on statistical complexity—solutions that are "hard to learn" are selected away.

<u>Other Papers</u>

"*The Theory is Predictive, but is it Complete? An Application to Human Perception of Randomness,*" with Jon Kleinberg and Sendhil Mullainathan.

When we test a theory using data, it is common to focus on *correctness*: do the predictions of the theory match what we see in the data? But we also care about *completeness*: how much of the predictable variation in the data is captured by the theory? This question is difficult to answer, because in general we do not know how much "predictable variation" there is in the problem. In this paper, we propose the use of machine learning algorithms as a means of constructing a benchmark level for the best attainable level of prediction. We illustrate this approach on the task of prediction of human-generated random sequences. Relative to an atheoretical machine learning algorithm benchmark, we find that existing behavioral models explain roughly 10 to 15 % of the predictable variation in this problem. This fraction is robust across several datasets, including experimental data from Mechanical Turk and field data on loan officer approvals (Chen et al., 2015). These results suggest that (1) there is a significant amount of structure in this problem that our models have yet to capture and (2) machine learning may provide a generally viable approach to testing completeness.

"*Interpretation of Inconsistent Choice Data: How Many Context-Dependent Preferences are There?*" (Submitted.)

Inconsistencies in choice data may emerge either from context dependencies in preference or from stochastic choice error. These inconsistencies are quite different, and have distinct implications for welfare assessment and prediction. How can the analyst separate the two in data? This paper provides a tool for identifying the number of context-dependent preferences in noisy choice data. Using the technique of statistical regularization, I define a *best multiple-ordering rationalization* as one that maximizes fit to the data subject to a penalty on the number of orderings used. I show that although recovery of the orderings themselves is an ill-posed problem, exact recovery of the number of context-dependent orderings is feasible with probability exponentially close to 1 (in quantity of data) using the proposed approach.