Research Statement

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I'm an Economics PhD student at Binghamton University studying topics in Decision Theory, Game Theory and Behavioral Economics. I focus on the use of learning algorithms (used either as decision rules or as methods of optimization) and the use of multi-agent simulation to investigate the sometimes delicate relationship between model features/decision rules and their outcomes. More specifically, my work has involved making progress on three separate but related fronts.

1. Formalizing aspects of bringing complex simulations (e.g. agent-based models) to data.
2. Evaluating the predictive or explanatory power of different learning process (and their variations) on play in existing lab data.
3. Building multi-agent simulations of learning agents playing games to investigate which, if any, model assumptions or components are pivotal in producing various (sometimes emergent) phenomenon and what happens when we relax those assumptions or change those components.

1 Formalizing Methods for Fitting Complex Models

Utilizing computational models can be desirable when the relaxation of a model assumption makes the model infeasible or very difficult to encode mathematically or solve closed-form. Can we build upon existing optimization techniques to develop new tools capable of solving particular types of problems / estimating parameters for certain types of models? What are best practices for bringing such models to data and how do we know if parameters in these models can even be identified? The first branch of my work explores these questions.

In "**On the Preservation of Input/Output Directed Graph Informativeness under Crossover**", a joint project with Andreas Pape, J. David Schaffer, and Hiroki Sayama (in review at Evolutionary Computation), we lay a theoretical foundation for applying part of a particular operation from the genetic algorithm, 'crossover', to a fairly general class of networks (Input Output Directed Graphs) which take Input and, after processing, returns some output. Such graphs can represent a broad class of decision making processes (in addition to many other systems e.g. municipal water systems, electrical circuits, etc.). With this contribution, we hope we are one step closer to establishing a fairly robust method for evolving IOD graphs which are capable of solving all sorts of complex problems.

While computational models are becoming increasingly popular across many disciplines, structured discussion on when and how to bring such models to data as structural models remains sparse. In "**A Guide and General Method for Estimating Parameters and their Confidence Intervals in Agent-Based Simulations with Stochasticity**", a joint project with Nency Dhameja, Yixin Ren, and Andreas Pape (draft - in progress), we are developing a user friendly guide for bringing agent-based models (or any computational model which unfolds over time) to panel data in a manner consistent with common econometric practices. Rather than focusing on a narrow class of models, we instead focus on how the use of some common tools and tests which can be fairly generally applied to fairly generally: block-bootstrapping confidence intervals and running Monte Carlo Simulations to establish if model parameters are reasonably identifiable. We also walk the reader through the earlier stages of getting a model estimation. These include summarizing and aggregating simulation output, choosing a fitness function and using an appropriate optimization technique.

A promising future avenue in this direction involves developing a public facing python library which encodes off the shelf functions for the methods discussed above (in **A Guide and General Method for Estimating Parameters and their Confidence Intervals in Agent-Based Simulations with Stochasticity**), lowering the barrier of entry for researchers looking to bring various computational models (from any discipline) to data.

2 On the Efficacy of Learning Algorithms as Models of Behavior

The development of models of decision making with learning has been of great interest to many scholars in Psychology and Artificial Intelligence communities. Such work, however, should be of great interest to Decision Theorists and Behavioral Economists. To what degree can such models serve as good, boundedly rational models of human behavior? Can learning models well explain/predict behavior in the lab? Does there exist features of decision making shared across a number of learning models that are particularly salient for capturing observed behavior? The second branch of my research explores these questions.

In "**The Problem with Empty-Headedness: Generalizing K-Level Beliefs to Simulate Priors in Models of Learning and Boundedly Rational Response**" (in progress), I investigate the problem of "empty-headedness", which is derived from the common assumption in learning models that agents have no information to go on before the first round of play. To solve this problem, I formalize a method of *simulated self-play* to generate priors using the features of the game themselves which can be applied to a large class of boundedly rational decision making processes. Next, I demonstrate that k-level reasoning exists as a very specific case of this process which utilizes a rational "best response" function and batched updating. Finally, I compare the empirical performance of out of sample prediction of two common learning models (with and without simulated priors) as well as K-level reasoning, utilizing lab data of players playing different versions of the Beauty Contest Game.

A number of promising future projects in this direction are also on the horizon. Extending our work in "**On the Preservation of Input/Output Directed Graph Informativeness under Crossover**" (mentioned above), we aim to evolve spiking neural networks (using the genetic algorithm to evolve the network structure) to make investment decisions (trained on stock market data) or a categorical learning problem.

3 Emergence in Simulations of Boundedly-Rational Agents

While traditional methods in behavioral economics (and psychology) are well suited for establishing alternative decision rules or measuring biases present in existing ones, agent-based simulation can sever as a digital laboratory for exploring the implications of such biases. How does game play and outcomes differ from theory when agents use simple learning rules to make decisions? Can small changes in those learning rules produce fairly different results? Can we isolate what features of decision making or the game are pivotal in giving rise to certain emergent phenomenon? The third branch of my research aims to answer some of these questions.

In "**Evolving Sustainable Institutions in Agent-Based Simulations with Learning**", a joint project with Andreas Pape, Todd Guilfoos, and Peter DiCola (Review & Resubmit at JEBO), we investigate the conditions which are sufficient to give rise to one of Ostrom's principles of sustainable governance (Ostrom, 1990) - graduated sanctions. We build a simulation of a simple coordination game where agents share some common resource and decide each round how much to harvest from it using a simple learning rule over a number of periods. We then explore the shape of implemented policies (in the form of fines), which emerges either via a top-down social planner who aims to find a social welfare maximizing policy or from the bottom up by agents voting for policies. We find the use of similarity in agent-level learning rules can give rise to graduated sanctions.

This avenue of research is extremely exciting as we look forward at next steps. For one, a number of Ostrom's other principles for sustainable governance can be explored through extensions of our existing models. In particular, we'd like to next focus on if monitoring can emerge, which we have some early work. We're also interested in further exploring how institutions and institutional constraints affect the communities ability to solve such sustainable practice problems.