Research Statement

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I study topics in behavioral game theory and complex systems. My work focuses on developing and applying computational models to understand behavior in strategic environments. Such models serve as powerful tools for bridging gaps between theory and the real world by relaxing the tractability assumptions required in conventional mathematical approaches. They can be used both as theory-generating devices (by exploring the implications of altering particular assumptions) and as structural models that can be directly estimated with data. Current projects either employ learning-based models with non-trivially interacting agents or address practical challenges that arise when fitting computational models to data in applied settings.

A central line of my research seeks methodological foundations for inference using computational models such as agent-based models for structural estimation. In my job market paper, **Monte-Carlo Tests for Identification and Validation of Agent-Based Models** (with Nency Dhameja, Yixin Ren, and Andreas Pape), we argue that reliable estimation of ABMs requires systematic assessment of whether parameters are *identifiable* given model properties, sample size, and estimation design choices. We demonstrate how Monte Carlo simulations (MCS) can be used to evaluate whether estimators recover true parameters in controlled environments and how accuracy depends on hyper-parameters such as search algorithm specification and number of simulated runs. We further introduce a novel Monte Carlo test that decomposes imprecision into two sources: randomness inherent to the model and parameter search process versus sampling variation in the data. Applying these diagnostics to two canonical settings, a repeated prisoner's dilemma with learning agents and a network diffusion model, we show that in both cases, although parameters can in principle be recovered, estimator performance is highly sensitive to seemingly innocuous implementation choices. This work provides practical guidance for researchers using ABMs in applied empirical contexts and underscores the need for MCS-based robustness checks before drawing substantive conclusions from estimated parameters. A sequel project currently under development, **A Guide for Estimating Agent-Based Model Parameters, their Confidence Intervals, and Establishing Estimator Properties using AgentCarlo**, extends this agenda by translating the proposed diagnostics into a practical software toolkit while providing an accessible guide for its application. The accompanying Python package, AgentCarlo (in development), implements a range of estimation routines and Monte Carlo–based tests for low-cost application, lowering the barrier for applied researchers to conduct principled inference with ABMs and other computational models.

A complementary line of my research examines the theoretical properties of evolutionary operations performed on networks, with the aim of advancing our understanding of their uses and limitations for network topology optimization. In **On the Preservation of Input/Output Directed Graph Informativeness under Crossover** (with Andreas Pape, J. David Schaffer, and Hiroki Sayama - now in revise & resubmit status at Complexity, a top journal in interdisciplinary complex systems research), we study a broad class of directed graphs that map inputs to outputs which allow for dynamics and recurrent loops. Such graphs can be used to represent chemical reaction networks, electrical circuits, municipal water systems, and neural networks. We define a crossover operator on these Input/Output Directed (IOD) graphs by identifying subgraphs with matching in- and out-link structures and "swapping" them, enabling evolutionary computation over graph topologies. We then analyze how informativeness is preserved (or lost) under crossover. We also introduce a general framework for analyzing *informativeness* (and its complement *actionability*) which characterizes the degree to which information flows from inputs to outputs. We show that even two fully informative parent graphs may produce a non-informative child, highlighting a potential instability in evolutionary search over network architectures. However, we also identify conditions under which informativeness is retained: crossover-compatible, partially informative parents yield partially informative offspring, and very-informative input parents paired with partially-informative output parents produce very informative children. Analogous results hold for actionability. These findings provide theoretical guidance for designing evolutionary algorithms over a very general class of functional network structures and offer insight into when recombination preserves meaningful input-output relationships.

A second stream of my research more aligned with behavioral game theory investigates how learning and institutional structure jointly shape collective outcomes. In **Evolving Sustainable Institutions in Agent-Based Simulations with Learning** (with Andreas Pape, Todd Guilfoos, and Peter DiCola - now in revise & resubmit status at JEBO, a leading journal in the behavioral economics subfield), we develop a game-theoretic computational model in which agents decide how much to extract from a common-pool resource under three institutional regimes: private provision, centralized control by a benevolent social planner, and competitive direct democracy over Pigouvian fine schedules. Both consumption and voting behavior are governed by a unified learning process based on reinforcement with similarity in action space. This framework allows institutions to *co-evolve* with behavioral adaptation, producing rich panel data of fine vectors across regimes. We show that centralized enforcement significantly improves welfare over uncoordinated private action, but, perhaps surprisingly, competitive democratic institutions learn to implement fine structures which perform nearly as well. Moreover, incorporating learning alters the normative benchmark itself: the fine vector discovered by the adaptive social planner both differs from and outperforms the analytically optimal solution derived under full rationality when applied to our model of learnign agents. Relating these findings to Elinor Ostrom's design principles, we see "graduated sanctions" emerge endogenously *only* when agents generalize across similar actions. We also see draconian sanctions dominate when fine revenue is redistributed without cost. These results highlight how institutional robustness depends not just on formal rules but on assumptions about human cognition.

In another working paper of mine which explores behavior using a computational model, **A Case for Simulated Self-Play in Decision Models with Learning**, I introduce the concept of *Simulated Self-Play* (SSP), in which agents engage in simulated pre-play against themselves to form expectations about the strategic environment prior to the observed game. While decision theories with learning have a long history of application to laboratory data, they typically rely on unrealistic assumptions about what players know before the first round of play. Although self-play has been highly successful in artificial intelligence applications, most notably in systems such as AlphaZero for Chess and Go, it has rarely been explored as a cognitive parameter when modeling human decision-making. First, I demonstrate that SSP improves theoretical coherence relative to commonly used alternatives, including uniform or uninformative priors, fitted priors, and so-called "burned-in" priors. I argue that each of these approaches faces conceptual challenges when interpreted as a realistic account of players' beliefs, whereas SSP provides a psychologically plausible and parsimonious alternative. I then evaluate its empirical value by estimating a learning model with SSP-generated priors and comparing its out-of-sample predictive accuracy against models using the standard priors listed above. Using lab data of variations of the Beauty Contest game, I find that SSP performs as well or better than all competing specifications. This work demonstrates that allowing agents to "practice" before play is not only natural from a cognitive perspective but also yields meaningful improvements in predictive power.

Finally, in a recent project titled **Social Context Matters: How Large Language Model Agents Reproduce Real-World Segregation Patterns in the Schelling Model** (with Mohammed Mahinur Alam, Nency Dhameja, Srikanth Iyer, Carl Lipo, and Andreas Pape), we extend the classic Schelling segregation model by replacing its traditional rule-based agents with Large Language Model (LLM) agents that make residential decisions through natural language reasoning informed by social context. We then compare LLM agent behavior across five social contexts: neutral (red/blue teams), racial (White/Black), ethnic (Asian/Hispanic), economic (high/low income), and political (liberal/conservative). Our findings reveal striking differences in segregation patterns driven purely by social framing, underscoring that LLMs can capture nuanced, context-dependent information often abstracted away in conventional models. This highlights their potential as tools for modeling social phenomena and exploring the implications of policy interventions.

Computational modeling is not just one tool among many in my work; it is the organizing lens through which I approach questions of behavior and strategic interaction. Across the projects described above, I have used such models both to generate new theoretical insights and to develop methods that make these tools more accessible and empirically grounded. Moving forward, I aim to continue expanding the methodological foundations of both learning-based and simulation-based models while lowering the barrier to their adoption in applied research. My goal is not only to advance these techniques, but to help shape a broader shift in how we study complex systems. This shift should take seriously the richness of real-world behavior without sacrificing analytical rigor.