Research Statement

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My research applies computational and simulation-based models and develops computational methods for estimating, validating, and optimizing these often nonlinear economic models. I focus on settings where standard analytical approaches break down due to learning dynamics, strategic interaction, network structure, or bounded rationality, and where computational tools are required to support credible inference and policy analysis. While many of my applications are motivated by behavioral and experimental economics, my primary contribution in many cases is methodological, building tools that allow complex models to be taken seriously as objects of empirical and experimental analysis. Increasingly, this work draws on ideas from machine learning and optimization, particularly in environments characterized by high-dimensional state spaces and adaptive behavior.

A central theme of my research is the use of computational models, especially agent-based and learning models, as complements to theory and experiments. I treat these models not as black-box simulators, but as estimable objects whose identification, stability, and performance depend critically on model structure, data availability, and implementation choices. Across projects, I use simulation to diagnose identifiability, guide experimental design, and evaluate the robustness of policy conclusions in environments characterized by strategic interaction and adaptation.

My job market paper, **Monte-Carlo Tests for Identification and Validation of Agent-Based Models** (with Nency Dhameja, Yixin Ren, and Andreas Pape), develops a simulation-based framework for inference in nonlinear computational models. We argue that reliable estimation of agent-based and other stochastic models requires explicit assessment of parameter identifiability given the model's internal dynamics, the available data, and the researcher's estimation design. We introduce a novel Monte Carlo testing procedure that decomposes estimation uncertainty into components driven by intrinsic model stochasticity and numerical search versus sampling variation in the data. Applying these diagnostics to a repeated prisoner's dilemma with learning agents and a network diffusion model, we show that estimator performance can be highly sensitive to seemingly innocuous implementation choices. This work provides practical guidance for applied researchers using computational models and highlights the importance of simulation-based diagnostics as a standard component of model validation.

A related methodological line of my research studies how information is preserved or degraded in complex networked systems, with direct applications to learning and optimization in both economic models and machine learning architectures. In **On the Preservation of Input/Output Directed Graph Informativeness under Crossover** (with Andreas Pape, J. David Schaffer, and Hiroki Sayama, conditionally accepted at *Complexity*), we develop a general theoretical framework for evolutionary crossover on input/output directed graphs, which represent systems mapping inputs to outputs, including neural networks, circuits, and institutional or decision-making pipelines. We formalize *informativeness*, defined as the degree to which inputs influence outputs, and its complement, *actionability*, and analyze how these properties behave under crossover operations.

We show that even fully informative parent graphs can generate non-informative offspring, revealing an instability in evolutionary search over network architectures. At the same time, we identify conditions under which partial or very high informativeness is preserved. These results are directly relevant to machine learning and deep learning, particularly for recurrent architectures such as feedback networks and spiking neural networks, where information must propagate through time as well as across layers. More broadly, this contribution provides a key component which opens the door for applying the Genetic Algorithm, a powerful and fairly robust evolutionary method for optimizing complex problems, to evolve recurrent networks by operating on the topology of the network directly.

Building on these methodological tools, a second stream of my research applies computational and simulation-based methods to study learning and institutional design in strategic environments. In **Evolving Sustainable Institutions in Agent-Based Simulations with Learning** (with Andreas Pape, Todd Guilfoos, and Peter DiCola, accepted at the *Journal of Economic Behavior & Organization*), we develop a behavioral game-theoretic model in which policy and agent behavior jointly evolve through reinforcement learning in a common-pool resource setting. Using variations of the model, we study why effective policies take the form they do in adaptive environments and how the shape of optimal policy depends on features of learning and institutional constraints.

We compare the emergent policies generated by the model to the successful governance practices documented by Ostrom across hundreds of empirical case studies. This comparison allows us to interpret Ostrom's design principles through the lens of adaptive optimization. More broadly, the results clarify how policies that perform well in practice can emerge from the interaction of learning agents and constrained policy spaces.

In my working paper **A Case for Simulated Self-Play in Decision Models with Learning**, I propose *Simulated Self-Play* as a principled method for generating initial beliefs in learning models. Many applied learning models rely on ad hoc assumptions about priors despite their importance for short-run dynamics and empirical fit. Simulated self-play allows agents to form expectations through simulated interaction prior to observed play, providing a psychologically plausible and internally consistent alternative. Using laboratory data from Beauty Contest games, I show that models with simulated self-play generated priors perform as well or better than standard specifications in out-of-sample prediction. More broadly, this project illustrates how computational pre-play can be used as a design tool in experimental and structural modeling.

A complementary project explores the use of large language models as computational agents in social simulations. In **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 demonstrate how language-mediated reasoning can be incorporated into agent-based models to study contextual effects that are difficult to parameterize directly. By varying social framing while holding economic incentives fixed, we show how model outcomes depend critically on informational context. This work highlights the potential of large language models as flexible computational components in simulation-based research rather than as predictive black boxes.

Across these projects, my research treats computational modeling as an infrastructure for economic analysis rather than an end in itself. My goal is to develop transparent, reproducible methods that allow complex models to be estimated, stress-tested, and meaningfully compared to data and experiments. Looking forward, I aim to further integrate simulation-based inference, machine learning methods, and laboratory experimentation, contributing tools that support credible empirical work in environments characterized by learning, strategic interaction, and institutional complexity.