THE UNIVERSITY OF CHICAGO | THE COMMITTEE ON COMPUTATIONAL AND APPLIED MATHEMATICS

Dissertation Defense:

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"Understanding Neural Variability: Mechanistic and Computational Models of Population Activity"

Monday, February 2, 2026, at 10:00 AM
Location: Tbd

ABSTRACT

Neural activity is stochastic in nature, with variable responses across trials under the same experimental conditions. It is also high-dimensional, with thousands of neurons in a network working in concert to fulfill a computational role. One classical approach to study population activity is mean-field theory, where the dimensionality of the system is reduced to allow for analytic tractability. However, this approach is incapable of capturing the complexities of the system needed to perform its functions and does not make full use of the rapidly growing scale of systems neuroscience datasets. In this talk, we present two mathematical models that produce theoretical insights without dimensionality reduction. The first part takes a bottom-up approach which constructs mechanistic models to examine how network dynamics give rise to neural variability structures. We prove in a recurrent circuit model that the more heterogeneous the firing rates of neurons in a population, the lower the effective dimension of their trial-to-trial covariability. We used operator-valued free probability theory to analyze the interaction between external inputs and recurrent dynamics, which are both modeled using random matrices. The second part takes a top-down approach which seeks the optimal neural representation for the task the animal performs. One long-standing question in neuroscience is how the neural code for a sensory, motor, or cognitive variable should be organized to optimize its discriminability. Here, we analytically minimize the average binary classification error of a circular variable in the function space of all population tuning curves for various noise models by solving a nonlocal variational problem. We obtained the solution by viewing the space of neural response distributions as a Riemannian manifold in the sense of information geometry and utilizing a result from knot energy theory. Both projects make nontrivial predictions that are verified in experimental data.