学 位 論 文 内 容 の 要 旨

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学 位 論 文 題 名

Nonequilibrium Dynamics in Sparse Neural Activity: Insights from State-Space Kinetic Ising Model
(スパースな神経活動における非平衡ダイナミクス：状態空間キネティック・イジングモデルに基づく知見)

Neuronal population activity exhibits nonequilibrium dynamics accompanied by broken time-reversal symmetry, and the resulting irreversibility is linked to entropy dissipation. However, directly evaluating time asymmetry from spike trains is challenging because firing rates and couplings vary over time, i.e., the signals are nonstationary. This dissertation extends the kinetic Ising framework for causal spike dynamics into a state-space model and combines sequential Bayesian estimation with a mean-field approximation to construct a new framework that estimates entropy flow that changes over time. The goal is to clarify how task engagement reorganizes neural couplings and entropy flow, and to demonstrate their relationship to behavioral performance.

The dissertation has two chapters. Chapter 1 formalizes a method that integrates an observation model—binary spiking with causal dependence on the immediately preceding bin—with a state model in which time-varying parameters for external drive and couplings evolve smoothly. Using sequential Bayesian filtering/smoothing with a Laplace approximation and the EM algorithm, the method identifies parameter means and uncertainties along the time series, and it derives a mean-field estimator for entropy flow that accounts for temporal variation and scales to large datasets without sampling. Simulations show accurate recovery of ground-truth time-varying parameters in small systems and practical convergence for datasets with 80 neurons and 550 trials. At the same time, the analysis examines assumptions—such as the omission of higher-order interactions and the synchronous update of all neurons—that simplify real neural circuits, thereby clarifying that the framework should be interpreted as a statistical summary of causal structure.

Chapter 2 applies the method to the Allen Institute Visual Behavior Neuropixels dataset (37 mice), comparing mouse V1 spike trains for the same natural images under two conditions: active task engagement and passive replay. The analysis used 10-ms bins within a 750-ms post-onset window, focusing on the top 80 simultaneously recorded neurons per animal. In the active condition, mean firing rates decreased and the distribution became sparser, while the variance and asymmetry of couplings increased. Trial-shuffled controls confirmed that these changes reflect genuine variations in inter-neuronal couplings rather than estimation noise. Entropy flow showed transient increases immediately after stimulus onset and offset, coinciding with periods of declining mean activity. Although the total entropy flow, defined as the sum over all bins, was smaller in the active condition, the shuffle difference (the component attributable to couplings) was positive in both conditions, suggesting that variations in couplings elevate dissipation. Furthermore, a perturbation analysis that uniformly rescales all model parameters revealed an interaction-driven difference in irreversibility that becomes apparent in a low-gain regime and is stronger during active engagement. With respect to behavior (d′), animals with higher entropy flow per spike (from the shuffle difference) performed better in the active condition, and this relationship provided explanatory power independent of sparsification indices. These findings suggest that efficient computation (information representation) during task performance is supported by time-asymmetric causal activity.

In summary, the proposed method estimates time-dependent entropy flow from nonstationary, nonequilibrium spike activity and elucidates how task engagement reorganizes coupling dynamics in ways that relate to behavioral outcomes. While acknowledging limitations—such as the omission of higher-order interactions and the assumption of synchronous updates—it offers a practical tool for testing the thermodynamic underpinnings of neural computation using real data.