Adaptive coding schemes in deterministic spiking networks

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Spiking neural networks are nature's solution for robust, energy-efficient information processing and can be effectively trained [1, 2]. While the theoretical understanding of artificial neural networks has advanced substantially, comparable frameworks for trained spiking neural networks remain underdeveloped. This gap limits the integration of neuroscience and machine learning, largely due to the discontinuous nature of spikes, nonlinear reset dynamics, and the temporal ordering of spike events. Inspired by the rapid information processing in the brain, we study transient processing dynamics in spiking networks on short timescales of tens of milliseconds. We generalize an established Bayesian learning approach for artificial neural networks to recurrent networks of deterministically spiking leaky integrate-and-fire neurons. This approach is general and independent of a specific learning rule; instead it quantifies the general capability of optimally trained networks. We combine the Bayesian approach with a dynamic mean-field theory to track the transient spike emission in large networks down to individual neurons to characterize two coding regimes in overparameterized trained networks: (1) rate coding, where information is carried by average firing rates with weak spike correlations across data samples; and (2) precise temporal coding, where distinct patterns are encoded by aligned spike sequences, transiently increasing pattern separability and yielding improved classification performance. Strikingly, we find that both coding schemes coexist in the same network, and that contextual inputs allow a flexible switch between these regimes. We validate the theory on the MNIST dataset and show how the precise coding regime employs microscopic chaos [3, 4] to enhance separability of stimuli that are represented by fine-tuned spike timings. Our framework provides a crucial step toward a principled understanding of trained spiking networks by embedding them into the Gaussian process framework [5, 6], which has brought fundamental insights into deep learning, opening the door to their integration into modern machine learning.

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