Shaping Low-Rank Recurrent Neural Networks with Biological Learning Rules

Extensive experimental evidence shows that task-relevant neural population dynamics often evolve along trajectories constrained to low-dimensional subspaces. However, how these low-dimensional task representations emerge through learning, and how the neural activity interacts with synaptic plasticity is still an unresolved question. The recent theoretical framework of low-rank recurrent neural networks (lrRNNs) provides a method for formulating analytically the relationship between connectivity and dynamics by relating structured patterns embedded in the network connectivity to the resulting low-dimensional dynamics.

We expand upon this framework by applying various plasticity rules, such as Hebb and BCM, to lrRNNs, analyzing how these rules shape the network's connectivity and resulting dynamics in spontaneous and input-driven regimes. We study whether, in the more general polynomial class of functions over firing rates, one can find rules, which offer a more flexible and general solution for learning context-dependent, low-dimensional trajectories within a single recurrent network.

This approach promises to offer insights into the potential mechanisms through which neural circuits may develop and structure the computations underlying diverse cognitive abilities.