Correlated Excitatory & Inhibitory Noise Mitigates Hebbian Synaptic Drift

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Strongly interconnected neuronal populations are thought to be a substrate for memory in the brain. Dynamic connectivity relies on plasticity rules to adjust synapses, enabling learning and neural circuit formation. Networks with only excitatory synaptic plasticity can become unstable due to runaway excitation, compromising a circuit's ability to store memories. To counter this, homeostatic synaptic plasticity of inhibitory connections provide a matched negative feedback that stabilizes neural activity and any associated learning. In this study, we outline the conditions under which recurrent Excitatory (E) and Inhibitory (I) circuits with E $\to$ E and I $\to$ E plasticity produce stable dynamics. In a firing rate (FR) model, E and I plasticity produce a line attractor on which the firing rates remain fixed and learning is stable. However, in spiking networks with stochastic dynamics, these stable dynamics do not occur - we rather find a deterministic drift of synaptic weights that reflects a failure of homeostasis. We derive a self consistent mean field theory of the dynamics for an EI model of Hawkes process neurons with an Spike-Time Dependent Plasticity. By including spike correlations in the theory, we understand this drift in the plasticity rule as being induced by shared correlations in the spiking activity. This theory further shows how drift can be mitigated by shared correlations among the E and I populations, effectively reducing correlated activity between synaptic fluctuations by pushing the network into the asynchronous regime. Our work illustrates how correlations between pairs of spikes in the evolution of synaptic weights can lead to unexpected behavior during learning in recurrent networks.