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Self-sustained probabilistic computing on spike-based neuromorphic systems

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The massively parallel nature of biological information processing plays an important role for its superiority to human-engineered computing devices. In particular, it may hold the key to overcoming the von Neumann bottleneck that limits contemporary computer architectures. Physical-model neuromorphic devices seek to replicate not only this inherent parallelism, but also aspects of its microscopic dynamics in analog circuits emulating neurons and synapses. However, these machines require network models that are not only adept at solving particular tasks, but that can also cope with the inherent imperfections of analog substrates. The mammalian brain has to cope with similar challenges, and it has recently been suggested that some cortical areas implement sampling-based probabilistic inference as a robust computing scheme capable of dealing with noise and ambiguities [1,4].

Inspired by the brain, we implemented sampling with leaky integrate-and-fire (LIF) neurons on the BrainScaleS system in a setup where stochastic background activity is provided by a random inhibitory decorrelation network [3]. In this spike-based sampling framework [5], the spike dynamics of the network realizes approximate sampling from an underlying Boltzmann distribution. We extended this approach by showing, both in computer simulations and on the BrainScaleS system, that decorrelation networks can be replaced by other stochastic spiking networks -- effectively eliminating dedicated noise sources on the substrate. Thus, an ensemble of functional networks can provide itself with sufficient stochasticity while each network fullfils its own functional role [2], leading to a parsimonious and self-consistent implementation of spike-based sampling.

Our work contributes to the effort of searching for new computational paradigms in the field of physical model systems by closing a gap between the abstract models and the biology of functionally Bayesian spiking networks, effectively reducing the architectural constraints imposed on physical neural substrates required to perform probabilistic computing, be they biological or artificial.

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