1 The Bayesian brain

The noisy behavior of cortical neurons might be a hallmark of an underlying stochastic computation scheme. Such a scheme would enable the brain to cope with ambiguous inputs and offers an explanation for behavioral effects like bistable images (duck/rabbit) as sampling from different modes of a posterior distribution. The neural sampling hypothesis [1] proposes that some cortical areas implement sampling-based Bayesian inference.

These models are of particular interest for physical model systems, which face similar challenges as the brain. We review two works [2, 3], in which we deployed stochastic spiking networks as robust and flexible models on analog neuromorphic hardware.

2 Sampling with spikes

For applications on spiking hardware, we require models that explicitly treat and use spiking neural networks.

In the LIF sampling framework [6] a single neuron describes a binary random variable based on its spiking behavior (Fig-A-B). Immediately after a spike the neuron is in the on-state and otherwise in the off-state. The network approximately samples from a Boltzmann distribution over binary random variables \( z \):

\[
\rho(z) \sim \frac{1}{Z} \exp \left( \frac{1}{2} \sum_i w_{i} z_{i} + \sum \beta_{i} z_{i} \right).
\]  

This framework establishes an important connection to Boltzmann machines. For practical applications we use a hierarchical sampling network (Fig-C) inspired by restricted Boltzmann machines [5].

3 Deterministic sampling

In most models of cortical networks, temporal variability is introduced using explicit white noise sources. This is, however, problematic because i) the background activity of other brain areas is not necessarily white noise and ii) a neuromorphic implementation would require dedicated, uncorrelated noise sources for every neuron.

We found [2] that an ensemble of dynamically fully deterministic, but functionally probabilistic networks can learn a connectivity pattern that enables probabilistic computation with a degree of precision that matches the one attainable with idealized, perfectly stochastic components (Fig-left). The key element of this construction is self-consistency, i.e., all input activity seen by a neuron is the result of output activity of other neurons that fulfill a functional role in their respective subnetworks (Fig-right).

4 The BrainScaleS system

On a single module of the BrainScaleS [6] analog neuromorphic hardware (Fig-A) the physical model of 200k neurons and 40 million synapses is implemented using CMOS technology. The system follows the principle of physical modeling: it uses the dynamics of the underlying substrate to implement computation.

As such it can emulate networks of spiking neurons with \(10^6\)-fold speed-up compared to biological real-time, but suffers from considerable variability of neuron parameters (Fig-B-C). Hence, we require robust network dynamics and learning rules.

5 Use-case on neuromorphic hardware

Using the LIF sampling framework we implemented a restricted Boltzmann machine (RBM) [5] on the BrainScaleS system [3]. We evaluate the model on a reduced version of the MNIST dataset. The original pictures were binarized, reduced to \(12 \times 12\) pixels and the digits 0, 1, 4 and 7 were selected (Fig-A).

We map an RBM that was pretrained on a computer to BrainScaleS and perform in-the-loop training to compensate for the model and substrate imperfections. The classification rate recovers software level performance after \(O(10)\) training steps (Fig-B). The implemented model is able to completely occluded images while predicting the label correctly (Fig-C-F). Finally, it is able to generate recognizable images if the respective label is clipped (Fig-G).

References


http://www.kip.uni-heidelberg.de/ vision/publications/