Fast sampling with neuromorphic hardware

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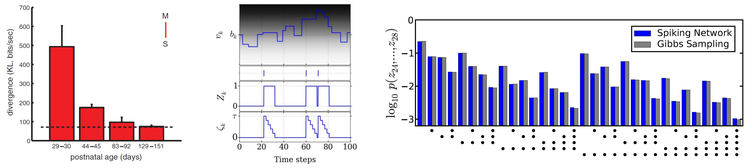
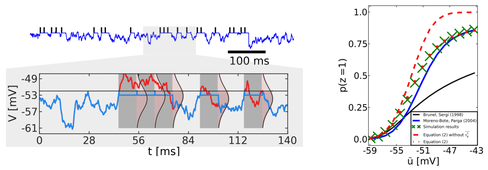
Stochastic inference with deterministic spiking neurons



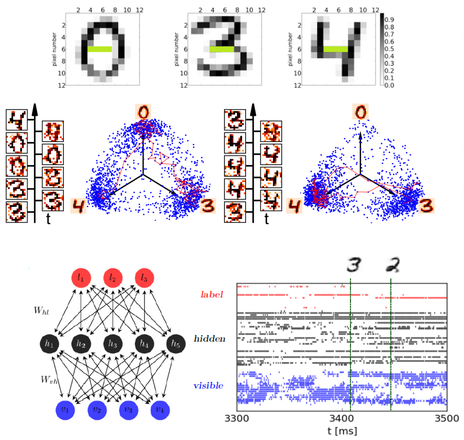
Left: Spontaneous activity in V1 of awake ferrets in darkness increasingly matches the evoked activity when viewing natural-scene movies [1]. Middle: Sketch of the abstract neural sampling model proposed in [2]. Right: Comparison to Gibbs sampling [2].

$$\bar{u}_k = \ln\frac{p(z_k=1|z_{\setminus k})}{p(z_k=0|z_{\setminus k})}$$

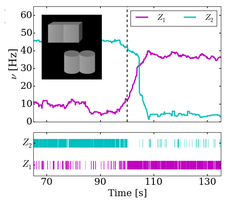
$$\nu_k = \frac{\sum_n n P_n \tau^{\mathrm{ref}}}{\sum_n P_n\left(n\tau^{\mathrm{ref}} + \sum_{k=1}^{n-1}\tau_k^b + T_n\right)}$$



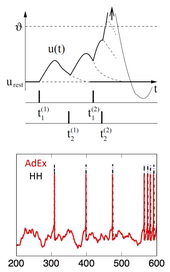
Left: Neural computability condition for neural sampling [2] vs. activation function of LIF neurons in the high-conductance state [4]. Middle: Membrane dynamics in the high-conductance state [3]. Right: Prediction and symmetrization of the LIF activation function [4].



Left: Simple inference scenario (pattern completion) [3]. Bottom left: Deep spiking networks as simultaneous discriminative and generative models of MNIST handwritten digits [9]. Bottom right: Beyond Boltzmann distributions – LIF sampling from arbitrary discrete probability spaces (explaining away effect in the Knill-Kersten illusion) [5].



From single neuromorphic chips to wafer-scale integration



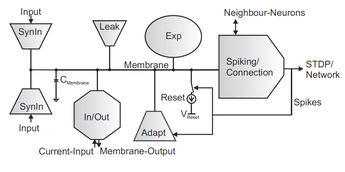
$$C_m\dot{u} = g_L(u-E_L) + g_{\mathrm{syn}}(u-E_{\mathrm{syn}}) + g_{\mathrm{K}}\,n^4(u-E_{\mathrm{K}}) + g_{\mathrm{Na}}\,m^3h(u-E_{\mathrm{Na}})$$

$$\dot{x} = \alpha_x(u)(1-x) - \beta_x(u)\,, x \in \{m,n,h\}$$

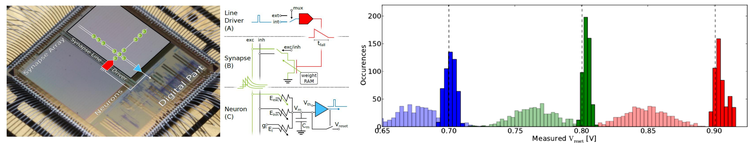
$$C_m\dot{u} = g_L(u-E_L) + g_{\mathrm{syn}}(u-E_{\mathrm{syn}}) + g_L\Delta_T\exp\left(\frac{V-V_T}{\Delta_T}\right) - w$$

$$\tau_w\dot{w} = a(V-E_L) - w$$

$$\text{if } u = u_{\mathrm{thresh}} \rightarrow \begin{cases} u \rightarrow E_r \\ w \rightarrow w + b \end{cases}$$



Left: Subthreshold and spiking dynamics of neuronal membranes. Middle: abstract models – Hodgkin-Huxley versus Adaptive Exponential Integrate-and-Fire (AdEx). Right: Embedding of model equations into VLSI circuits (schematic) [10].

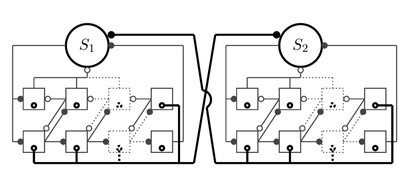


Left: Mixed-signal neuromorphic “Spikey” chip with highlighted communication infrastructure (384 neurons, 100k synapses) [8]. Right: Characterization and calibration of neuromorphic circuits (here, for the neuronal reset potential) [6,7].

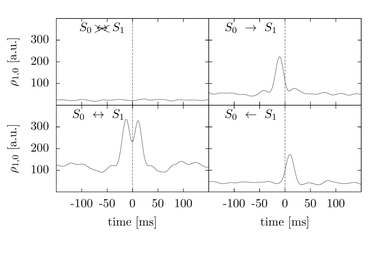
Left: Wafer-scale integration of 200k neurons and 50M synapses [10]. Right: Hybrid modeling facility.

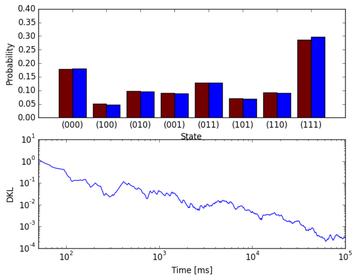
http://electronicvisions.github.io/hbp-sp9-guidebook/

Fast & robust emulation of functional spiking networks

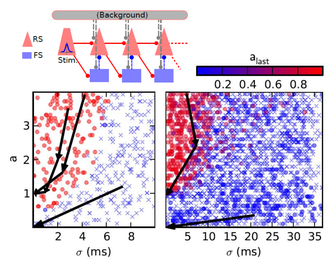


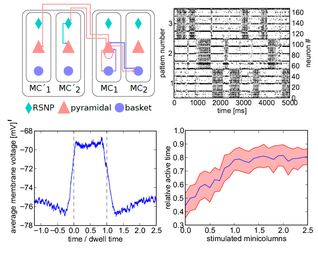
Left: Replacing individual neurons by sampling network modules increases the robustness of sampling towards hardware-inherent effects such as parameter noise and signal transmission delays. Right: Characteristic network activity.





Left: Functional configuration of the lateral interaction between the sampling modules. Right: Sampling from a target distribution over 3 binary random variables on the Spikey chip. The entire experiment, with a duration of 100 s in biological time, takes only 10 ms on Spikey.





The configurability of the Spikey chip makes it a versatile general-purpose emulation device for spiking neural networks [8]. Left: Synfire chain network with feed-forward inhibition. Right: Cortical L2/3 attractor memory model.

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