



Magnetic Phenomena in Spiking Neural Networks

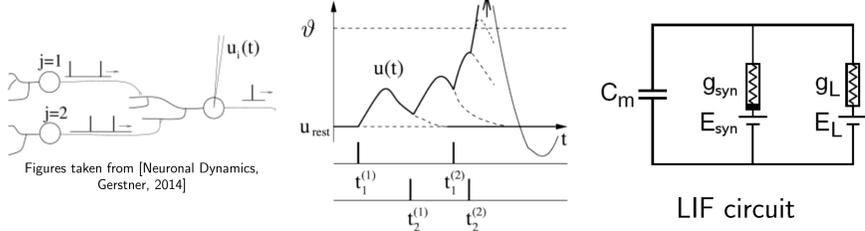
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Modeling Biology

Interactions between biological neurons are largely based on action potentials (AP) or *spikes* that are transmitted via synaptic connections with characteristic time courses.

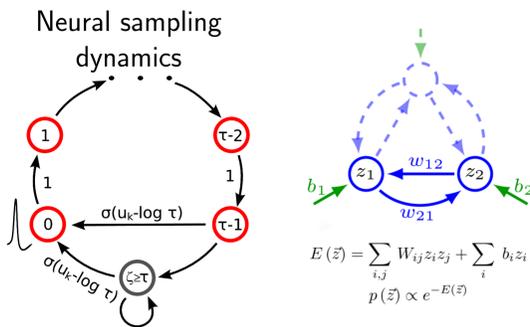
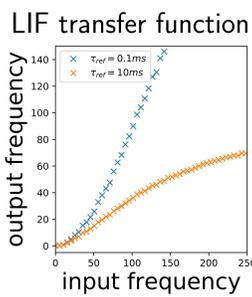


In the leaky-integrate-and-fire (LIF) model the neuron's soma is modeled as a capacitor which *integrates* synaptic input and constantly *leaks* charge. It emits a spike or *fires* when its voltage crosses the threshold value v_{thresh} . Whenever a neuron emits a spike the exponentially decaying synaptic conductance g_{syn} is increased by the synaptic strength w .

$$C_m \frac{du}{dt} = g_l (E_l - u) + \sum_{\text{syn}} g_{\text{syn}}(t) (E_{\text{syn}}^{\text{rev}} - u)$$

$$\frac{dg_{\text{syn}}}{dt} = -\frac{g_{\text{syn}}}{\tau_{\text{syn}}} + w \sum_{\text{spk}} \delta(t - t_{\text{spk}})$$

After a spike the membrane is clamped to a reset potential v_{reset} for a fixed period of time τ_{ref} . In the limit $\tau_{\text{ref}} \rightarrow 0$ the transfer function of the neuron is close to linear. Finite τ_{ref} limit the output. Adding Poisson noise softens the onset of the activation, furthermore this renders the neuron stochastic, enabling an ensemble to sample from a Boltzmann distribution [1].



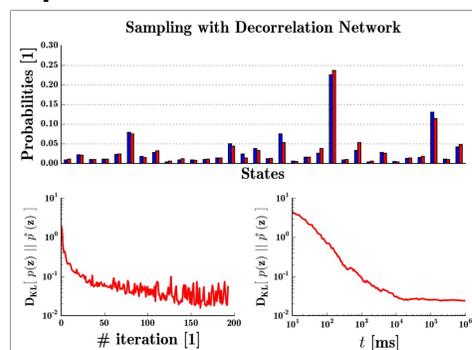
The neural sampling framework [2] provides a link to Glauber dynamics for neurons with finite refractory times. By using non-rectangular interaction kernels we obtain a stochastic model resembling biological neural networks.

Applications and Hardware

Current small-scale demonstrations on the BrainScaleS platform include pattern recognition and the emulation of generative models of high-dimensional data sets. The latter are based on hierarchical sampling networks, enabled by the neural sampling theory described above. A broad range of hardware-emulated models can be found in [3, 4].



BrainScaleS machine room



The BrainScaleS system consists of 20 wafer systems with up to 4 million configurable neurons and up to one billion synaptic connections. It runs with a constant speedup of 10 000 compared to biological real time.

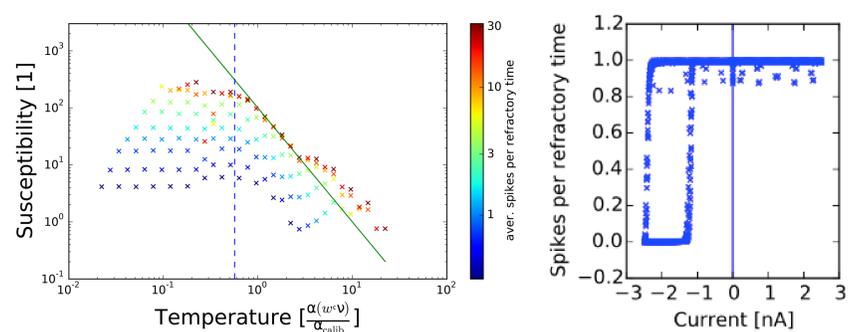
References

- [1] M. A. Petrovici, J. Bill, I. Bytschok, J. Schemmel, and K. Meier, "Stochastic inference with spiking neurons in the high-conductance state," *Physical Review E*, vol. 94, no. 4, p. 042312, 2016.
- [2] L. Buesing, J. Bill, B. Nessler, and W. Maass, "Neural dynamics as sampling: a model for stochastic computation in recurrent networks of spiking neurons," *PLoS Comput Biol*, vol. 7, no. 11, p. e1002211, 2011.
- [3] T. Pfeil et al., "Six networks on a universal neuromorphic computing substrate," *Frontiers in neuroscience*, vol. 7, pp. 11–11, 2012.
- [4] M. A. Petrovici, S. Schmitt, et al., "Pattern representation and recognition with accelerated analog neuromorphic systems," in *Circuits and Systems (ISCAS)*, 2017 IEEE International Symposium on, pp. 1–4, IEEE, 2017.



Relation to Spin Glasses

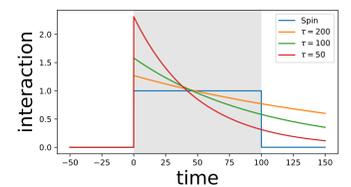
Boltzmann machines are mathematically equivalent to spin glasses. In networks of LIF neurons we can therefore observe known physical phenomena such as the Curie law and hysteresis.



To translate between different interaction shapes we match the mean interaction strength within the refractory time (shaded area).

$$W = 4J \quad J = \frac{1}{4}W$$

$$b = 2h - 2W \quad h = \frac{1}{2}b + W$$

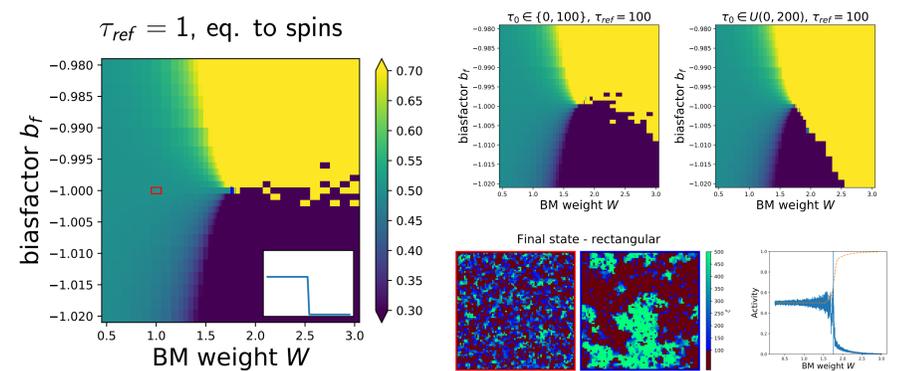


	States	External field	Coupling	Mean Activity
Spin glass	-1, 1	h	J	$\langle m \rangle = 0$
Boltzmann machine	0, 1	b	W	$\langle A \rangle = 0.5$

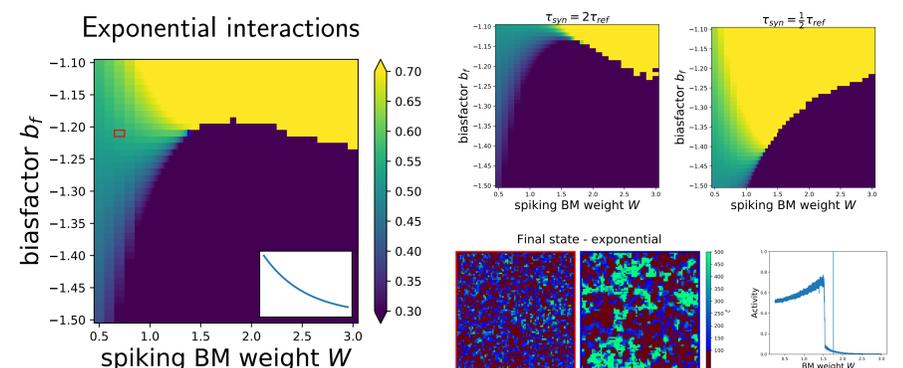
The BM system, unlike the spin system, is not symmetric around zero, meaning the point $h = 0$ requires fine tuning of the parameters. This makes most of the physical effects much harder to measure.

New Physics?

We parameterize the 2D Ising model as W, b_f with $b = -2Wb_f$ and scan the two parameters to simulate a changing temperature and external field. Glauber dynamics (left) show increasing susceptibility for $T \rightarrow T_c$ and a hard boundary at $h = 0 \Leftrightarrow b_f = 1$, independent of the spatial pattern of the initialization (with $A = 0.5$). For spiking neurons, the ensemble behavior can be fundamentally different.



At low temperature, we observe an unusually strong dependence of the ensemble behavior on the initial topology. More importantly however, depending on the interaction shape, we observe a large diversity of the resulting state diagrams. Taking into account the additive nature of PSPs from the same presynaptic neuron further complicates the picture.



These differences are so far without firm theoretical understanding, but they might turn out to be essential to understanding cortical computation, which is often hypothesized to occur at the edge of criticality.