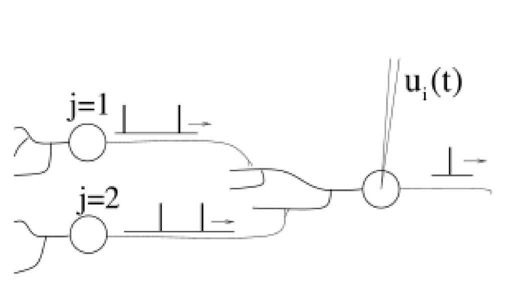
Magnetic Phenomena in Spiking Neural Networks

A. Baumbach, A. F. Kungl, M. A. Petrovici, J. Schemmel, K. Meier

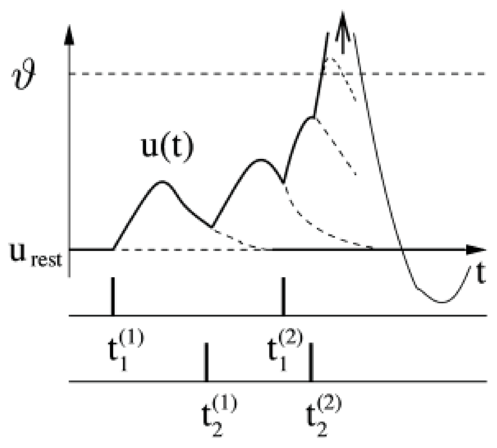
Heidelberg University, Kirchhoff-Institute for Physics

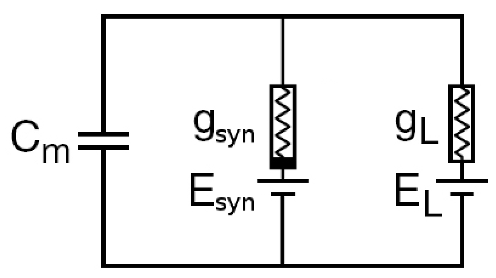
The Manfred Stärk Foundation

Modeling Biology



Figures taken from [Neuronal Dynamics, Gerstner, 2014]





LIF circuit

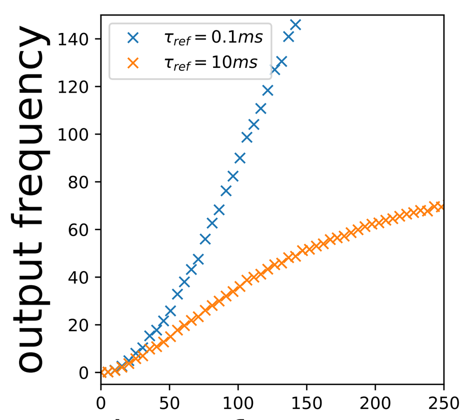
In the leaky-integrate-and-fire (LIF) model the neuron's soma *integrates* synaptic input and constantly *leaks* charge. It *fires* when its voltage crosses the threshold value v_{thresh}. Whenever a neuron emits a spike the exponentially decaying synaptic conductance g_{syn} is increased by the synaptic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

$$C_{\text{m}} \frac{du}{dt} = g_{\text{l}} \left(E_{\text{l}} - u \right) + \sum_{\text{syn}} g_{\text{syn}}(t) \left(E_{\text{syn}}^{\text{rev}} - u \right)$$

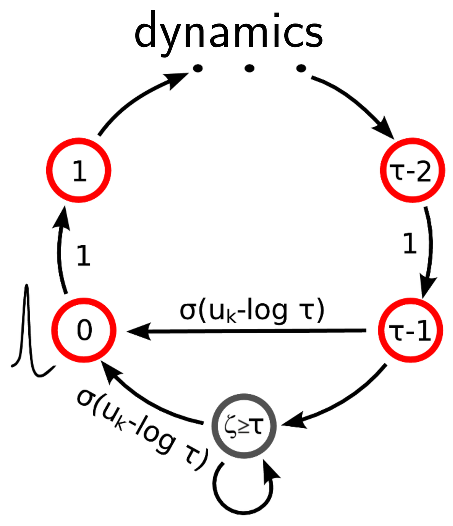
$$\frac{dg_{\text{syn}}}{dt} = -\frac{g_{\text{syn}}}{\tau_{\text{syn}}} + w \sum_{\text{spk}} \delta \left(t - t_{\text{spk}} \right)$$

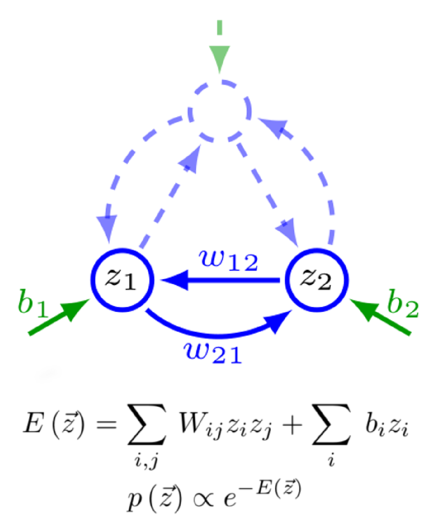
After a spike the membrane is clamped to a reset potential v_{reset} for a fixed period of time τ_{ref}. In the limit $\tau_{\text{ref}} \to 0$ the transfer function of the neuron is close to linear. Finite τ_{ref} limit the output. Adding Poisson noise softens the onset of the activation, furthermore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

LIF transfer function



Neural sampling dynamics

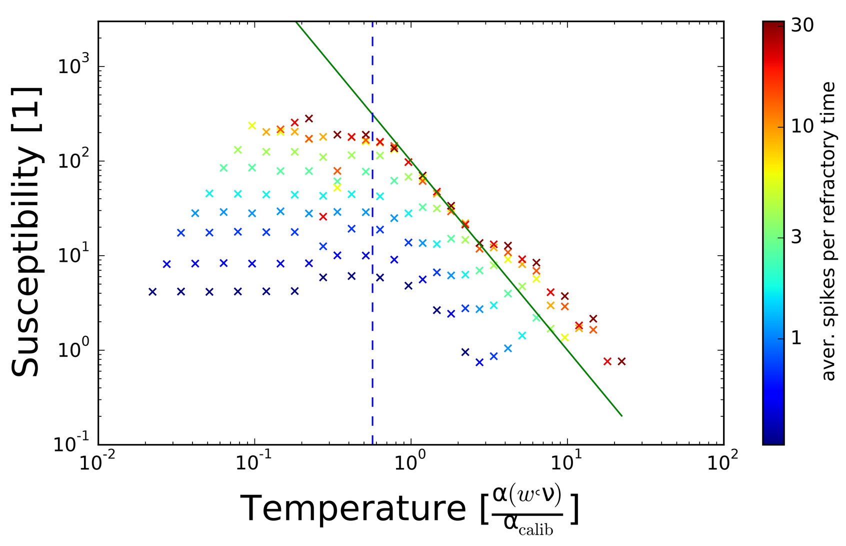


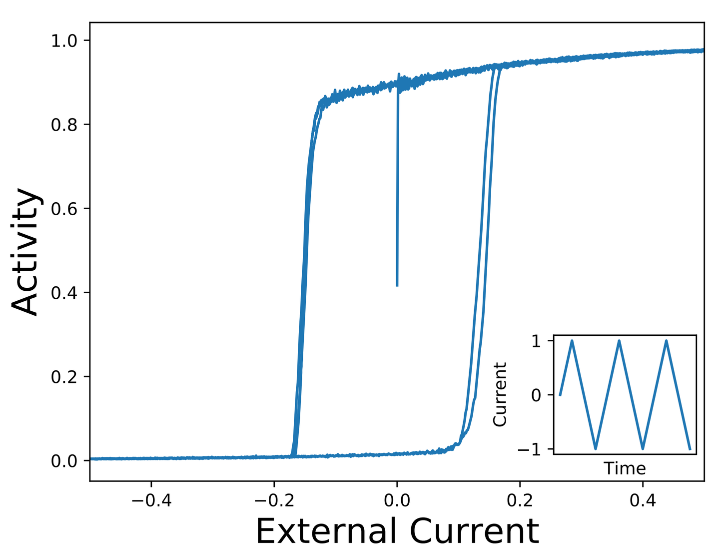


The neural sampling framework [2] provides a link to Glauber dynamics for neurons with finite refractory times. By using non-rectangular interaction kernels we obtain a stochastic model resembling biological neural networks.

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.

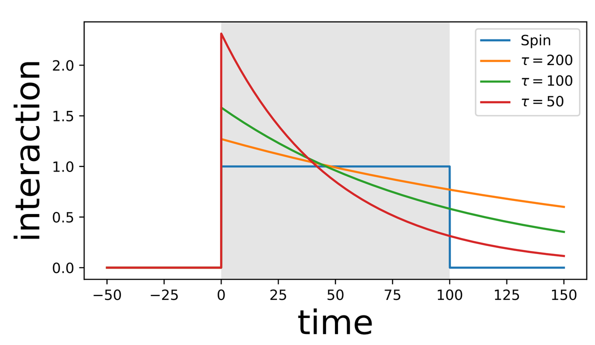




To translate between different interaction shapes we match the mean interaction strength within the refractory time (shaded area).

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

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

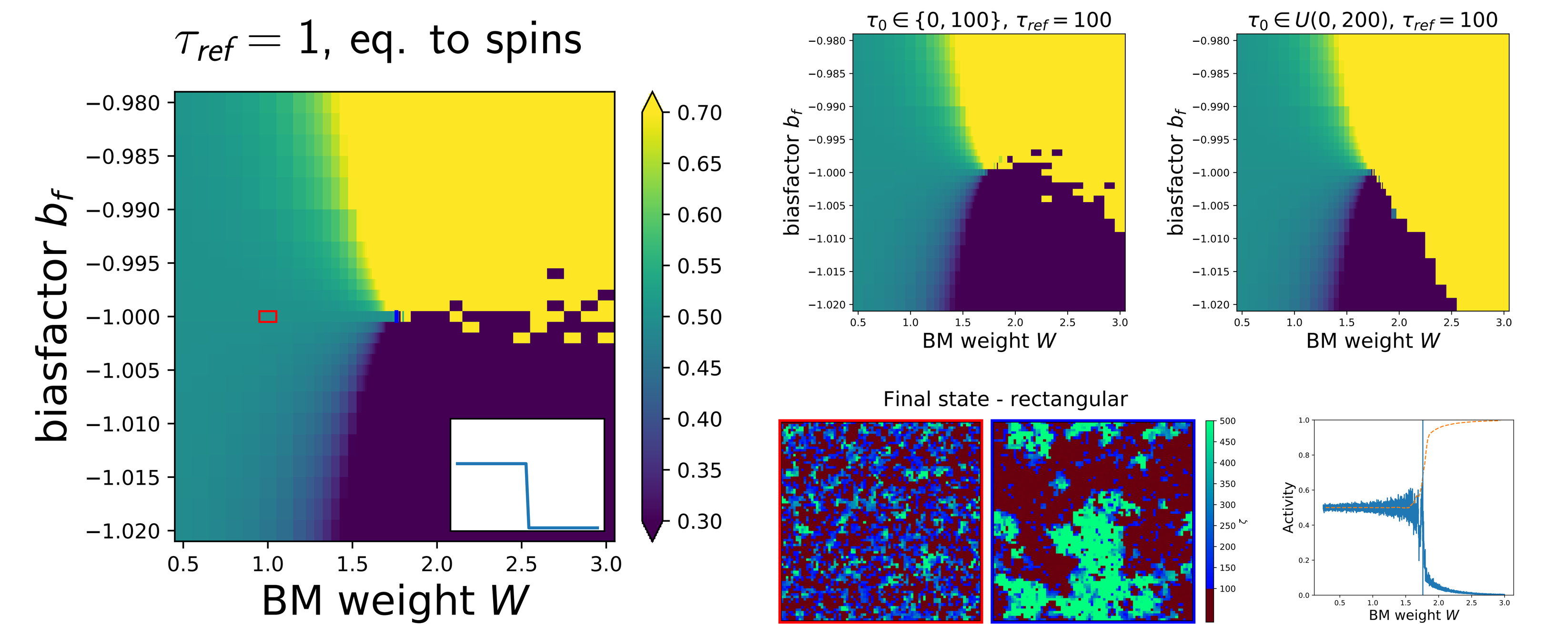


	States	External field	Coupling	Mean Activity
Spin glass	$-1, 1$	h	J	$\langle m \rangle = 0$
Boltzmann machine	$0, 1$	b	W	$\langle A \rangle = 0.5$

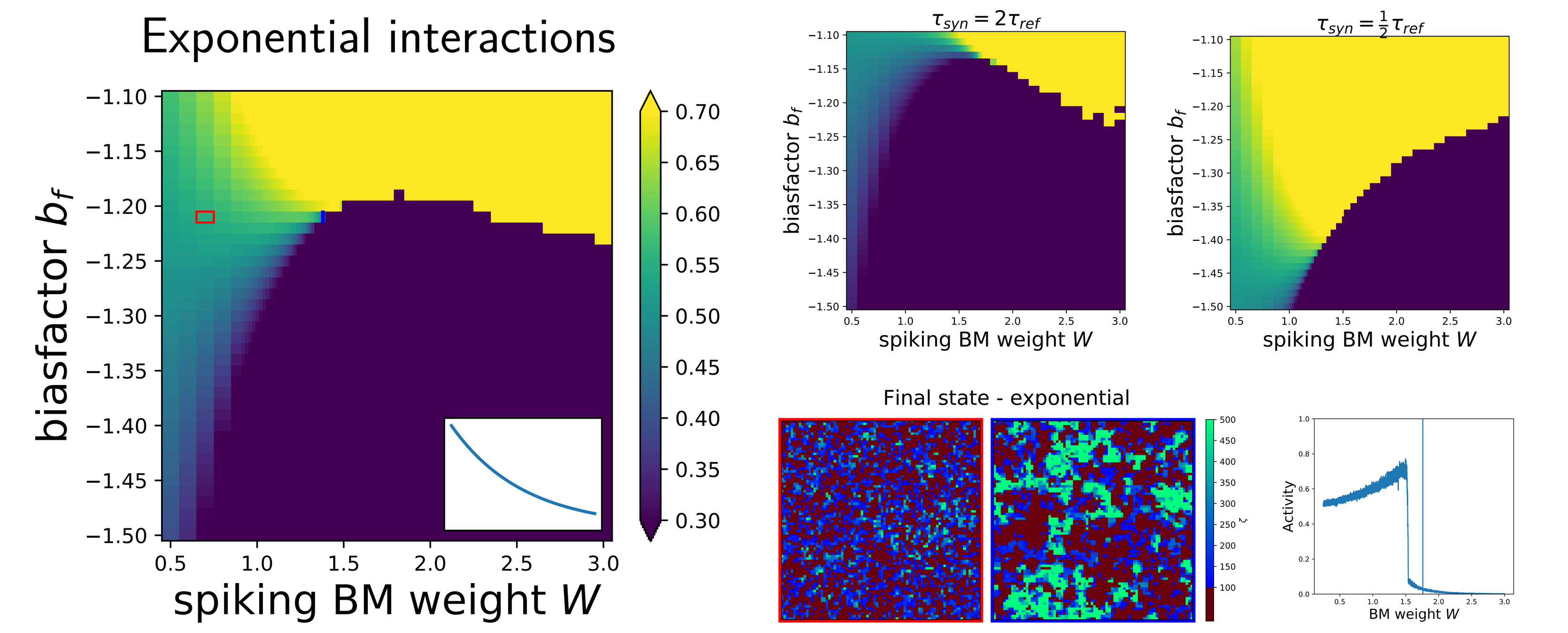
The BM system, unlike the spin system, is not symmetric around zero, meaning the point $h = 0$ requires fine tuning of the parameters. This makes most of the physical effects much harder to measure.

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 $T \to T_c$ 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.



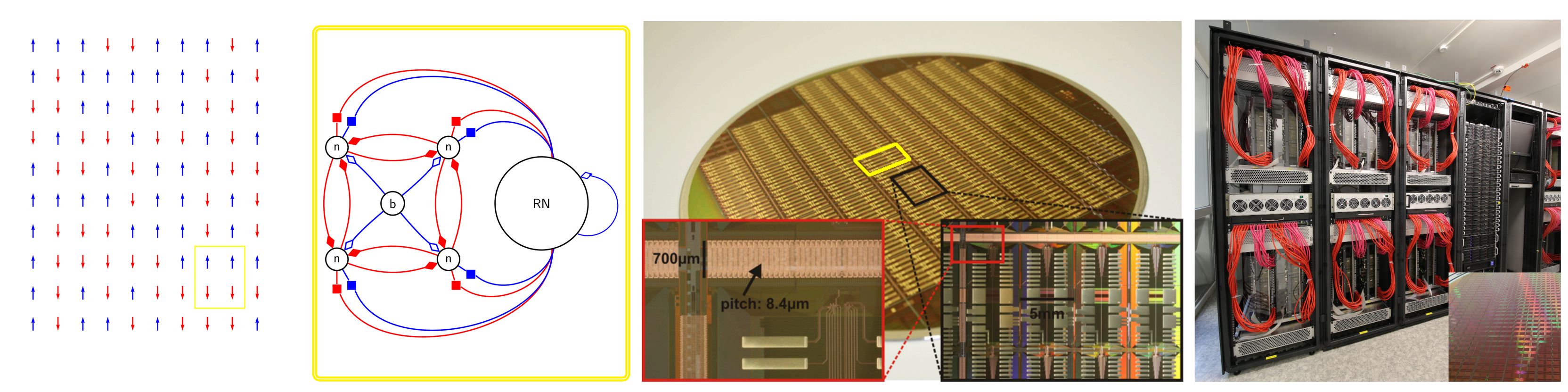
At low temperature, we observe an unusually strong dependence of the ensemble behavior on the initial topology. More importantly however, depending on the interaction shape, we observe a large diversity of the resulting state diagrams. Taking into account the additive nature of PSPs from the same presynaptic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

Network and future hardware implementation

Implementation on the BrainScaleS 1 system uses the 2D topology of the Ising network. We segment the "magnet" into smallish slices which can be handled by a single chip. Each slice consists of it's "heat bath", an "external field" neuron and the network. This implementation restricts chip-to-chip communication to nearest neighbors.



Each BSS1 wafer should be able to support more than 10 000 network neurons. The heat bath is implemented as a network of randomly inhibitory connected neurons with leak-over-threshold, in order to reduce the IO requirement. External fields will be emulated by providing two (inhibitory and excitatory) external spike sources that project on to all network neurons.

References

This work has received funding from the European Union 7th Framework Programme under grant agreement 604102 (HBP), the Horizon 2020 Framework Programme under grant agreement 720270 (HBP) and the Manfred Staerk Foundation.

[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] 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.

[4] T. Pfeil *et al.*, "Six networks on a universal neuromorphic computing substrate.," *Frontiers in neuroscience*, vol. 7, pp. 11–11, 2012.

andreas.baumbach@kip.uni-heidelberg.de