# Simulated Tempering in Biologically Inspired Neural Networks

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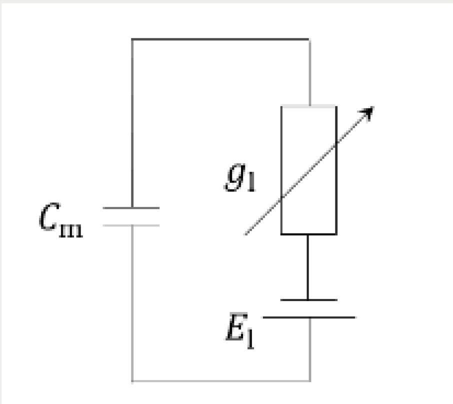
## 1 Modelling Neurons in the Brain

The brain consists of neurons that process information and synapses that transmit these information. Communication happens in discrete events, so called action potentials or spikes. Modelling neurons in their full complexity is way to difficult, hence we use abstract models of information processing.




**Cell membrane modelled** as an electric circuit. Taken from [1].

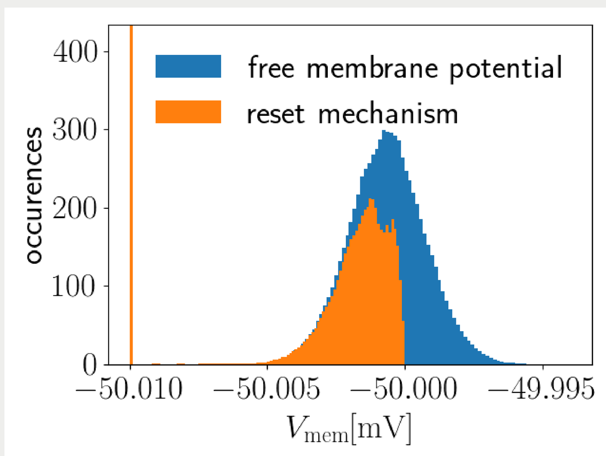
The leaky integrate-and-fire model is tractable and derives from modelling the axon membrane as an electric circuit. Connected ensembles of these model neurons form networks, with which biological phenomena can be simulated. This study focuses on a phenomenon called neural oscillations that range from 0.2 Hz ($\delta$ oscillation) to 100 Hz ($\gamma$).

## 2 Spiking Neuron Dynamics

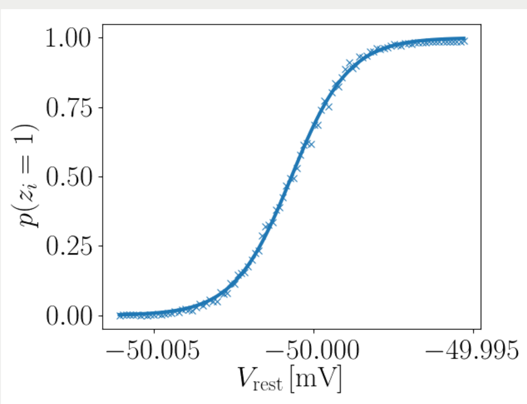
Inspired by neural structures in the brain, artificial neural networks are widely used in machine learning and have been applied to hard problems such as classification and generation of images and sound. Usually, these networks are rate-based, i.e. not suitable for sampling or they consist of abstract stochastic units. Here, the biologically more plausible leaky integrate-and-fire (LIF) neuron is used. The freely evolving membrane $V_m$ potential is described by the first order ordinary differential equation:

$$C_m \frac{dV_m}{dt} = g_l \left( V_{rest} - V_m \right) - I_{syn}.$$

Moreover, if the membrane potential crosses the threshold a spike is elicited and the potential reset.




**Membrane potential distribution** with and without reset mechanism.

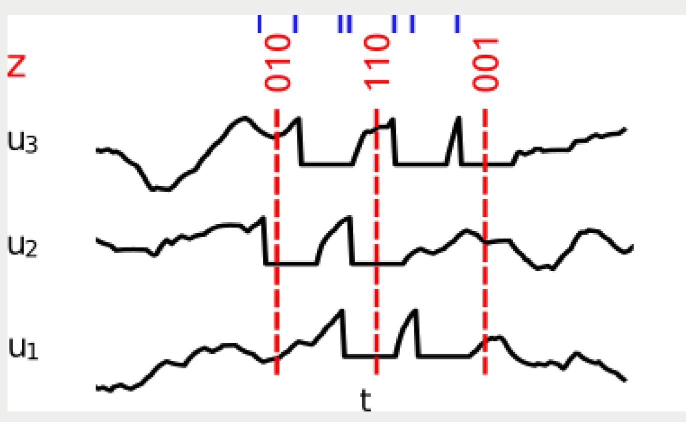



**Activation function** describes the probability of the neuron to spike in dependence of the rest potential.

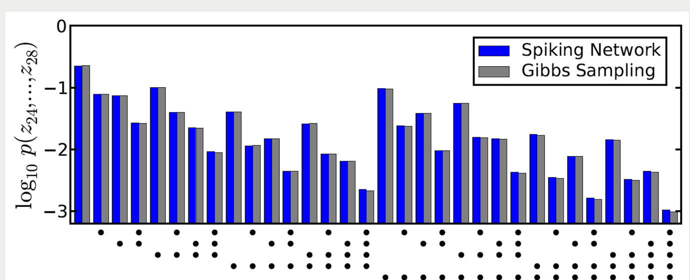
For inference tasks, Poisson noise is employed as background stimulus of the network to approximate the required stochastic dynamics. The LIF networks are simulated with the two open-source softwares NEST [3] with the Python-based frontend PyNN [2] and the Python-package SbS [4].

## 3 Sampling with Spiking Neurons

Biological in vivo observations indicate that the brain performs Bayesian inference to process sensory stimuli while in vitro experiments evidence deterministic functioning of neurons. Regarding the First Passage Time of the membrane potential from reset to threshold a single neuron's activation function is analytically derivable [1]. Spiking LIF neurons embedded in a noisy environment feature the firing statistics necessary to implement Markov Chain Monte Carlo sampling from a well-defined target distribution - like the Boltzmann distribution [1].



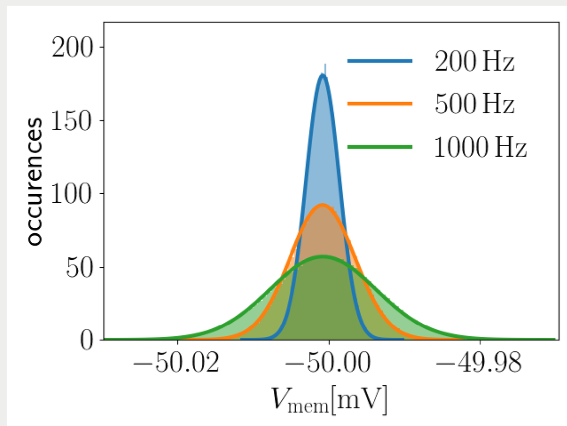

**Membrane potential traces converted to binary states**: Refractory neurons are in state 1.



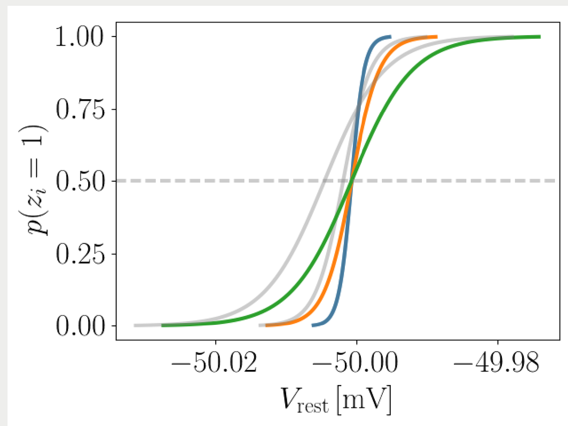

**Gibbs- compared to LIF-sampling :** Matching probability distributions [1].

## 4 Background Noise Analogous to Temperature

The membrane potential values of a LIF neuron fed with high-frequency Poisson noise approximately accumulate to a Gaussian distribution. Setting excitatory and inhibitory noise inputs to the same rate and weight (balanced), eliminates the rate-dependence of the expectation value of the effective membrane potential but not of the variance. Elevating the rates hence shifts and tilts the activation function.The activation function's slope is controlled by the temperature in the algorithm for abstract model neurons described in [5] - giving rise to the idea of mapping the temperature to Poisson noise rate in LIF networks.



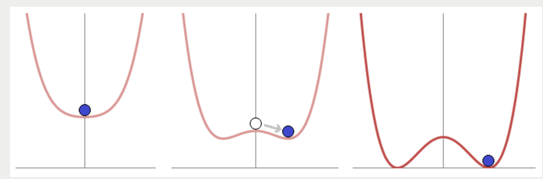

**Membrane potential distribution under increasing noise input:** broadens with unchanged mean at $E_l$.




**Activation function under increasing noise input:** Balanced rates in grey versus shift-compensating rates in colours.

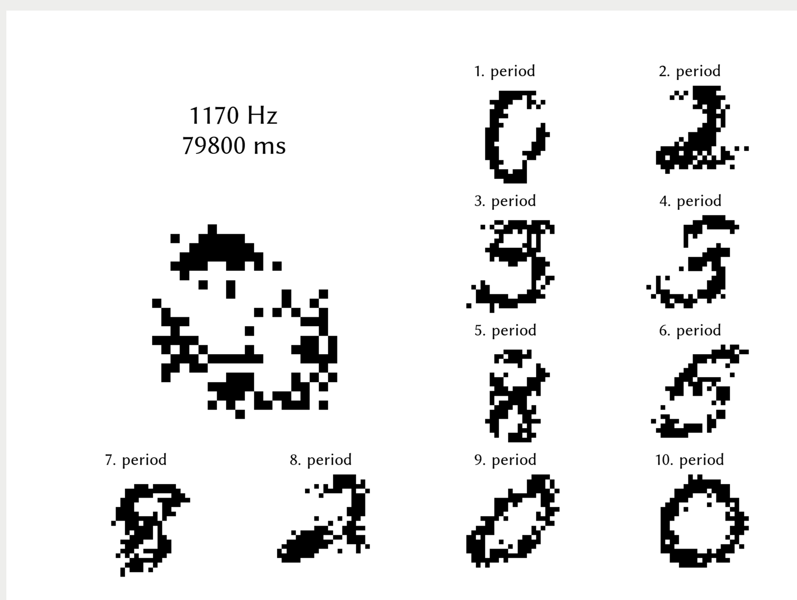
## 5 Application in Generative Tasks

An LIF-based, restricted Boltzmann machine is first trained on the MNIST handwritten digit data set [6] and then its performance tested on generating digits similar to the training examples.



**Potential minima in the energy landscape**

Due to the multimodal energy landscape created during training on this high-dimensional data, conventional algorithms such as Gibbs sampling are prone to get trapped in local minima which leads to the mixing problem. An appropriate modulation of the background noise leads to a rescaling of the energy landscape that is analogous to simulated tempering. An algorithm based on this principle facilitates the network to jump out of local minima and mix fast between different modes. We thereby suggest a functional role of the macroscopic neural oscillations observed in the cortex with potential applications for artificial generative neural networks.




**MNIST Digits exposed to sinusoidal noise input**: The network forms digits in the "ground" states of lowest Poisson noise/temperature from 10 sine periods and blurry images (large picture) in the high peaks of the sine wave.

## References

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