Spiking networks and their rate-based equivalents: does it make sense to use Siegert neurons?

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Neuronal simulations fall in two broad classes: ones that use spiking neurons and ones that don’t. While spiking models match biology better than rate-based systems, computationally they can be quite expensive. The literature offers some attempts to find and use rate-based neuron models that capture important properties of spiking units. One of the most rigorous approaches [1] approximates the output rate of leaky integrate-and-fire neurons (LIF) for Poisson input trains by analyzing the subthreshold activity of the neuron [2]. This approach, the Siegert neuron, is shown in Fig. 1.

To this day it is not clear for which conditions networks of Siegert neurons and LIF neurons show similar dynamics. Using both of these neuron models, we systematically compare simulations of (i) single neurons, (ii) feedforward inhibition networks (FFI), and (iii) recurrent networks (RN).

While the match for single neurons is very good, the activity of individual Siegert neurons in RNs can deviate significantly from the equivalent LIF simulation. However, we find that important qualitative features of FFIs and RNs remain unchanged. This complements and extends previous findings [3]. Therefore, switching between spiking and rate-based versions of the same network can be feasible for certain applications. In such cases a Siegert network may be that can later be implemented using spiking units.

Beyond mere comparisons, we show that Siegert neurons are a potent alternative to other rate-based neuron models such as linear threshold units with linear or sigmoidal activation functions. In particular we demonstrate that networks of Siegert neurons can be used to learn soft winner-take-all networks [4] that can further be utilized to learn simple relations without supervision.

Fig. 1: A Siegert neuron receiving excitatory and inhibitory rates \( \lambda_e \) and \( \lambda_i \) and corresponding input weights \( \bar{w}_e \) and \( \bar{w}_i \).

Fig. 2: Setups to compare Siegert neurons and LIF neurons. (a) single cells, (b) FFI networks, and (c) Recurrent networks.

REFERENCES


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