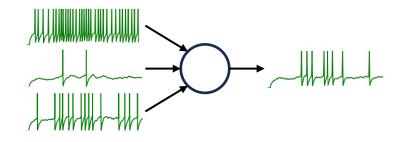


Addressing the speed-accuracy simulation trade-off for adaptive spiking neurons

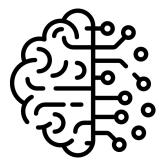
Luke Taylor, Andrew J King, Nicol S Harper Department of Physiology, Anatomy and Genetics University of Oxford



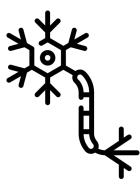
Overview: spiking neural networks



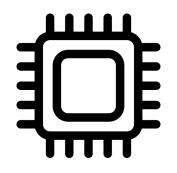
Build biologically plausible models of the brain



Fit neural data and gain insights



Applications in energy efficient machine learning

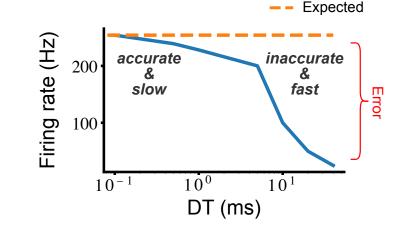


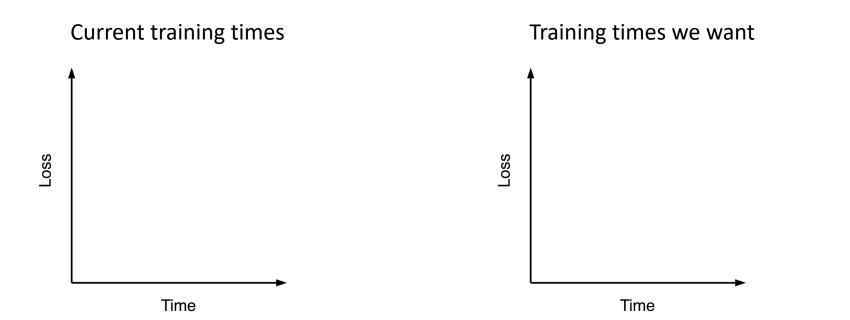


Spiking model: LIF and ALIF (continuous-time models)

Problem: slow simulation/training due to sequential and autoregressive nature

Our goal: to accelerate the inference and training of spiking LIF and ALIF neurons without sacrificing simulation accuracy.

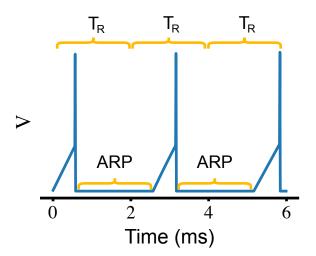






Idea: LIF/ALIF dynamics can be computed in constant time over some simulation length when at most a single spike is emitted (i.e. over sim length T_R = absolute refractory period length).

Contribution: algorithmically reframed the LIF/ALIF to simulate in blocks of times, instead of individual time steps.



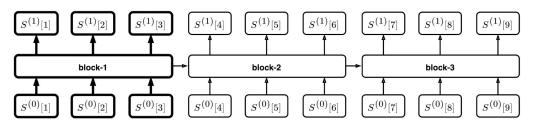
Current simulation method

t=1

$ \begin{array}{c} S^{(1)}[1] \\ \hline \mathbf{f} \\ $
$ \begin{array}{c} \mathbf{L} \\ V^{(1)}[1] \\ \mathbf{L} \\ $
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$

Our simulation method

t=[1,3]

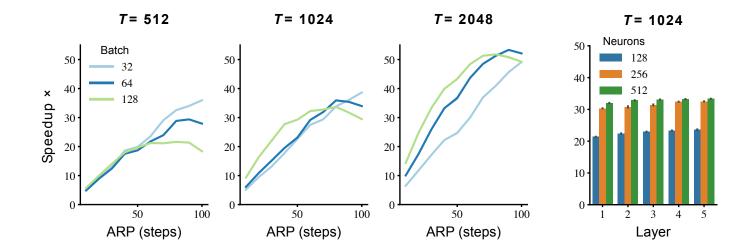




Theoretical speedup: longer ARP -> Faster simulation

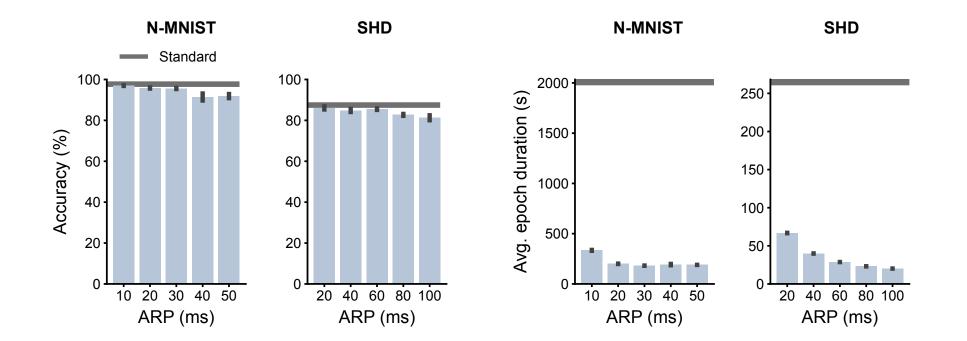
Method	Computational Complexity	Sequential Operations
Standard	$O(N^{ ext{in}} \cdot N^{ ext{out}} \cdot T)$	O(T)
Blocks	$O(N^{ ext{in}} \cdot N^{ ext{out}} \cdot T^2_R \cdot N)$	$O(T/T_R)$

Training speedup scales close to linear with respect to the ARP length (over different simulation times, batch sizes and number of layers).





Similar accuracy to the standard method on ML benchmarks, but in a fraction of the training time!





Can fit electrophysiological recordings a lot quicker (without sacrificing accuracy)!

DT=0.1ms ARP=2ms

