Spike-frequency adaptation contributes long short-term memory to networks of spiking neurons

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Outline

Integration and manipulation of information from the recent past into current computation is crucial for solving cognitive tasks. This is a challenge for artificial spiking networks.

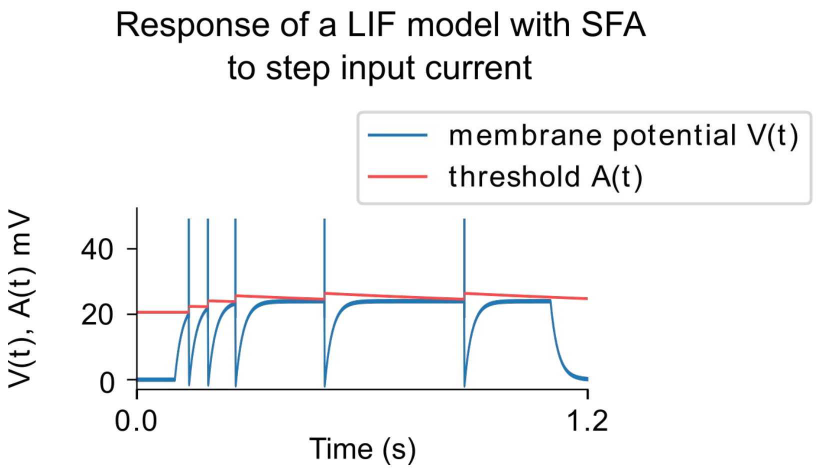
We compare different mechanisms that could enhance network computations on the time scale of seconds in such networks.

We find that models of spiking networks benefit most by including Spike-Frequency Adaptation (SFA).

We test the limits of such models and find that neural codes emerge spontaneously after training a generic recurrent spiking neural network.

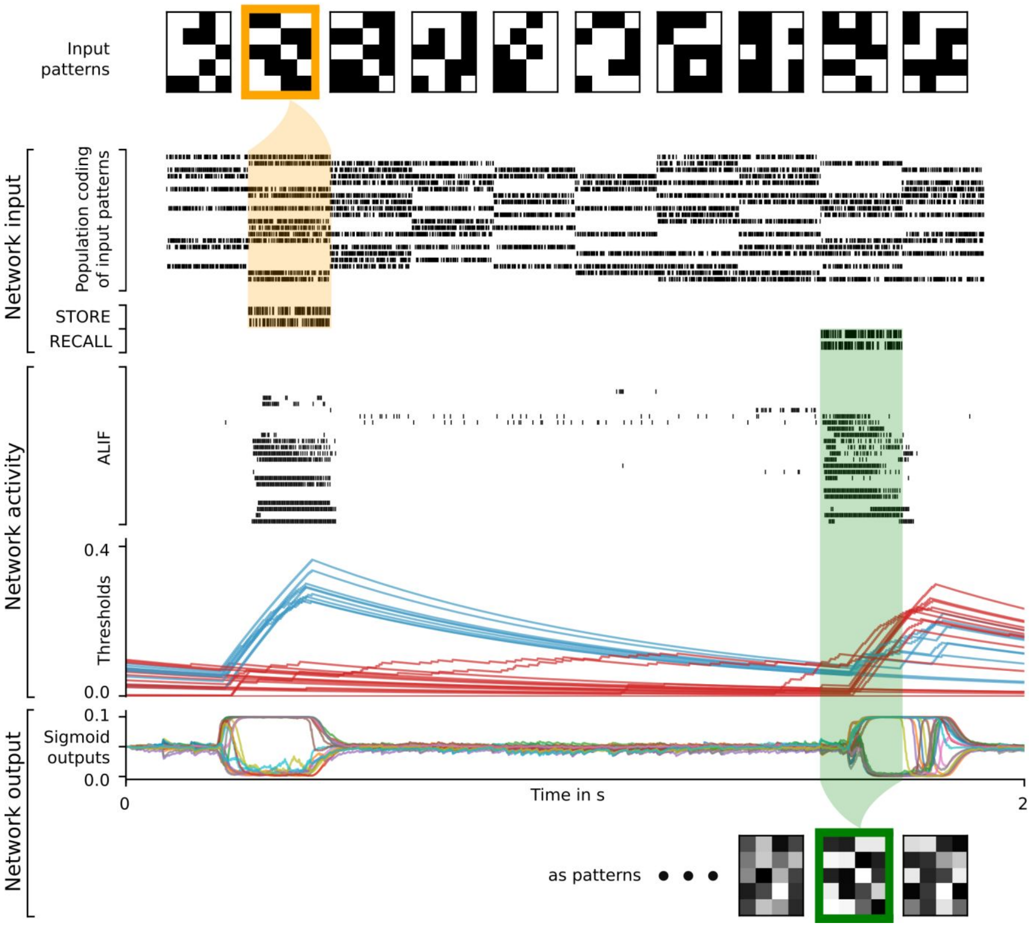
See [1] for more details.

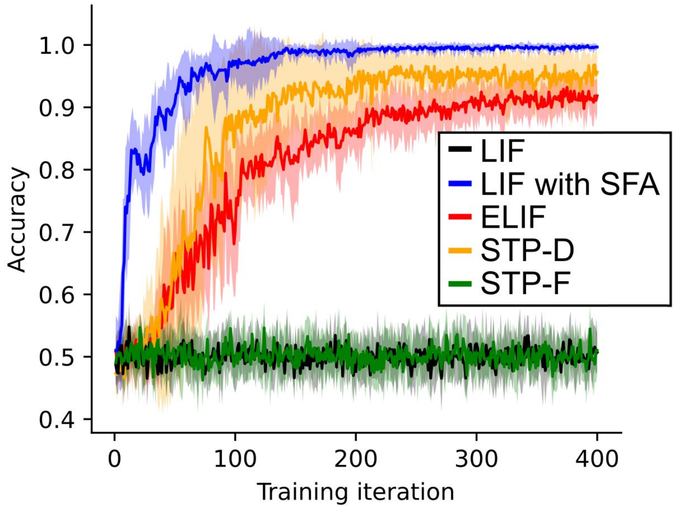
Introduction



Spike-Frequency Adaptation (SFA) reduces the excitability of a neuron in response to its firing.
According to Allen Institute [2], this is relevant for many cognitive tasks.

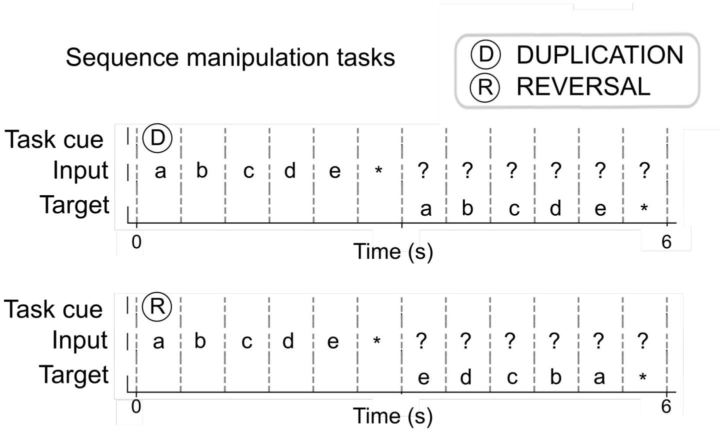
Evaluating mechanism for temporal computing: Storing and Recalling information



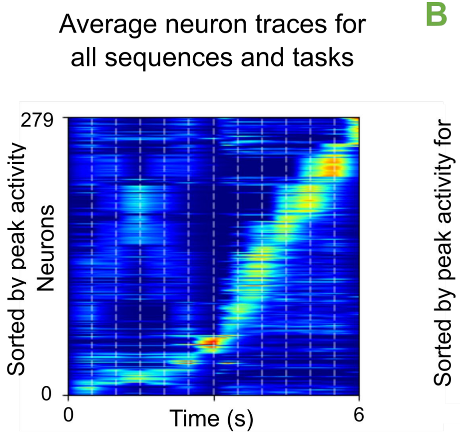


Other experiments, such as Delayed XOR task, sequential MNIST (sMNIST), Google Speech Commands, show that networks with SFA can integrate and manipulate memory content over time.

SFA supports brain-like operations on sequences



A



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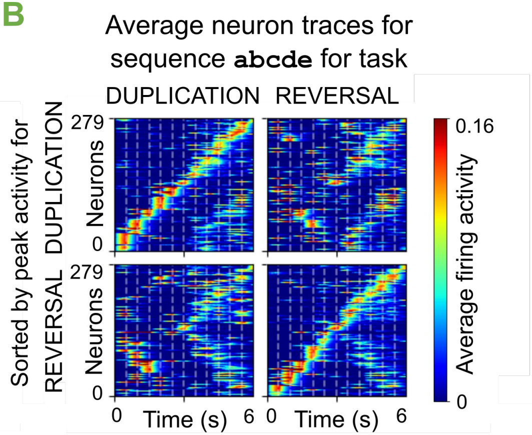

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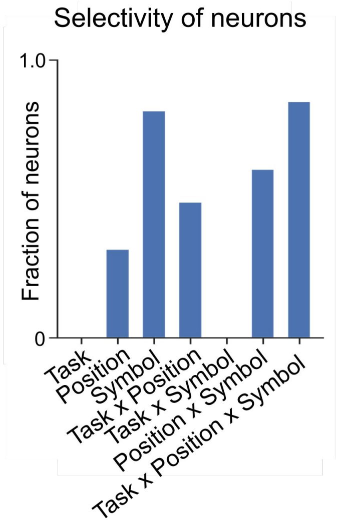

Fig. A, B: Temporal sequences of activation emerge through training.
Sorting of neurons: time of peak activity. Averaged over 1000 episodes.

Fig. A, C: About 1/3rd of neurons specialize for timing. (Timing “=” Position).

Fig. B: Neurons change their preference depending on the task, as early as during the loading of the input sequence.

Fig. C: A large proportion of neurons are mixed-selective.
Results of 3-way ANOVA, neurons belong to more than one category.

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Conclusion

SFA enables SNNs to integrate working memory from the recent past seamlessly into ongoing network computations

Provides a biologically plausible alternative to ANNs/LSTMs with comparable performance

Biologically realistic models allow comparisons with detailed experimental data from neurophysiology on the level of neurons and synapses

Neural codes comparable to the recordings from neurons in the neocortex emerge after training a generic recurrent network of spiking neurons

Our results are consistent with findings in neuroscience:

- Data on presence of neurons with spike-frequency adaptation in the neocortex [2]
- Persistent activity is more prominent if the memory content has to be manipulated rather than just maintained [4]
- Negative imprinting hypothesis [5]
- Mixed selectivity and serial position encoding in temporal sequences of activation [3, 6]

Also of interest from the perspective of novel computing hardware like neuromorphic technologies.

Acknowledgements
This research was partially supported by the Human Brain Project (Grant Agreement number 785907) and the SYNCH project (Grant Agreement number 824162) of the European Union. We gratefully acknowledge the support of NVIDIA Corporation with the donation of the Quadro P6000 GPU used for this research.

References

[1] Salaj, D., Subramoney, A., Kraisnikovic, C., Bellec, G., Legenstein, R., and Maass, W. (2020). Spike-frequency adaptation provides a long short-term memory to networks of spiking neurons. bioRxiv:10.1101/2020.05.11.081513.
[2] Allen Institute. Allen Cell Types Database Technical white paper: GLIF models Technical report, October 2017. v4.
[3] Y. Liu, R. J. Dolan, Z. Kurth-Nelson, and T. E. Behrens. Cell, 178(3):640–652, 2019.
[4] N. Y. Masse, G. R. Yang, H. F. Song, X.-J. Wang, and D. J. Freedman. Nature Neuroscience, page 1, 2019.
[5] M. J. Wolff, J. Jochim, E. G. Akyurek, and M. G. Stokes. Nature Neuroscience, 20(6):864, 2017.
[6] A. F. Carpenter, G. Baud-Bovy, A. P. Georgopoulos, and G. Pellizzer. Journal of Neuroscience, 38(21):4912–4933, 2018.