

# Spike-based symbolic computations on symbol sequences

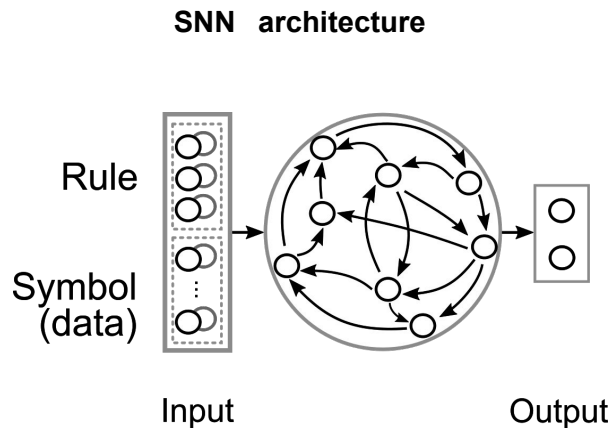
Ceca Krašniković, Wolfgang Maass, Robert Legenstein

Institute of Theoretical Computer Science, Graz University of Technology, Inffeldgasse 16b, Graz, Austria

## Outline

The brain uses symbols and rules on how to process and manipulate them when solving higher-cognitive tasks. Performing such symbolic computations is rather a challenge for models of Spiking Neural Networks (SNNs).

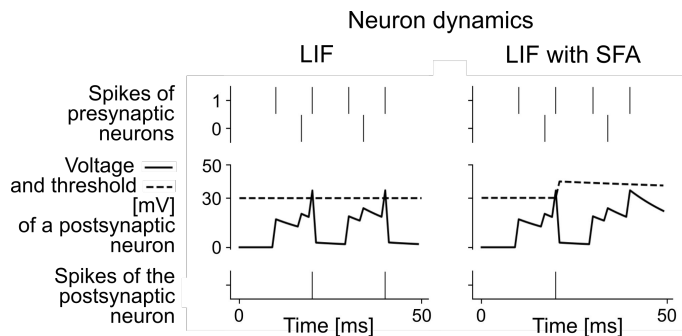
In our work, models of spiking networks *learn* to perform *symbolic computations*. They learn to solve tasks in which both rules and sequences of symbols appear in the input stream, and perform on the level of humans.



See [1] for more details.

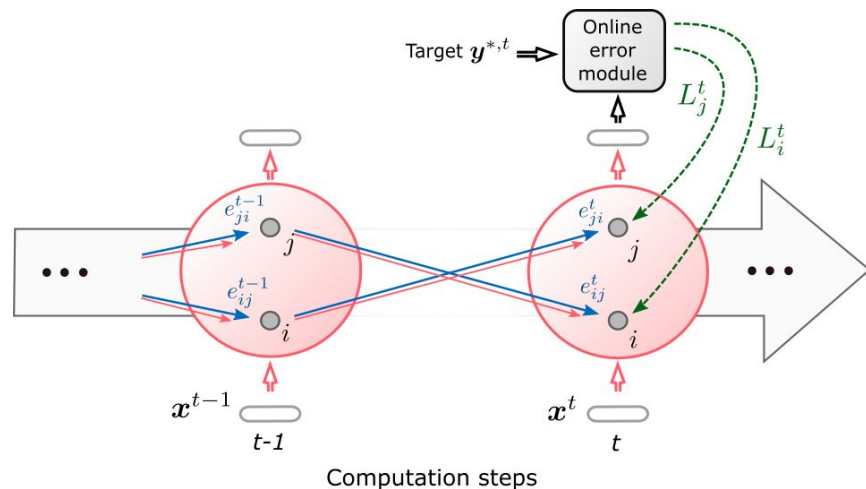
## Neuron model

- LIF (leaky integrate and fire)
- LIF with Spike Frequency Adaptation (SFA) [2]:  
by increasing the firing threshold of a neuron, the neuron's state is protected for a longer period → manipulation of temporally dispersed information on time scales of seconds



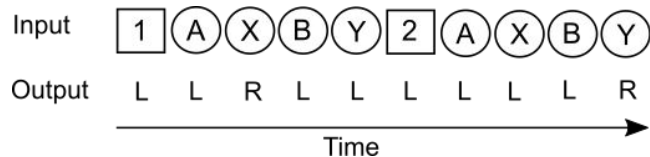
## Training method: e-prop [3]

- A biologically plausible learning rule for training recurrent SNNs
- Update of synaptic weights: information locally available to each synapse (eligibility trace  $e_{ji}$ ), and a global learning signal ( $L_j$ ) distributed to each neuron



# 12AX task

Simple version:



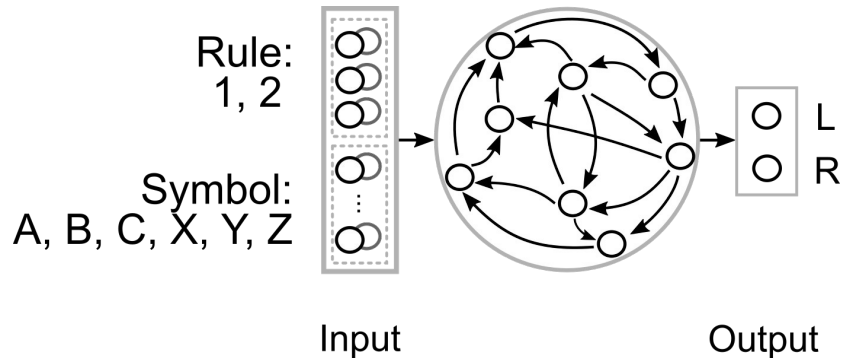
Under the context of:

- rule 1, observe if A is followed by X.
- rule 2, observe if B is followed by Y.

Process symbols sequentially. When the sequence 1-A-X or 2-B-Y is detected, press R (right button), otherwise L (left button).

The difficulty of the task is increased by adding distractor symbols C and Z between relevant symbols.

SNN architecture

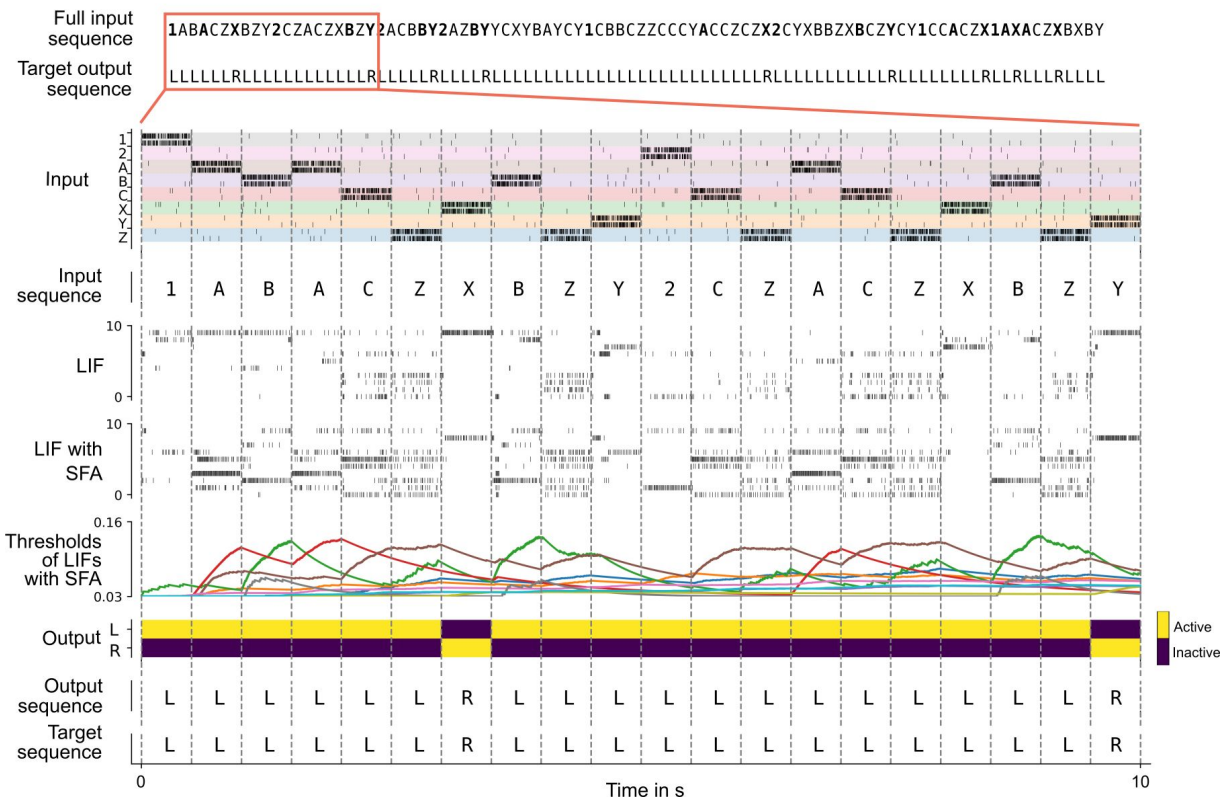


## 12AX task

An SNN can learn the task.

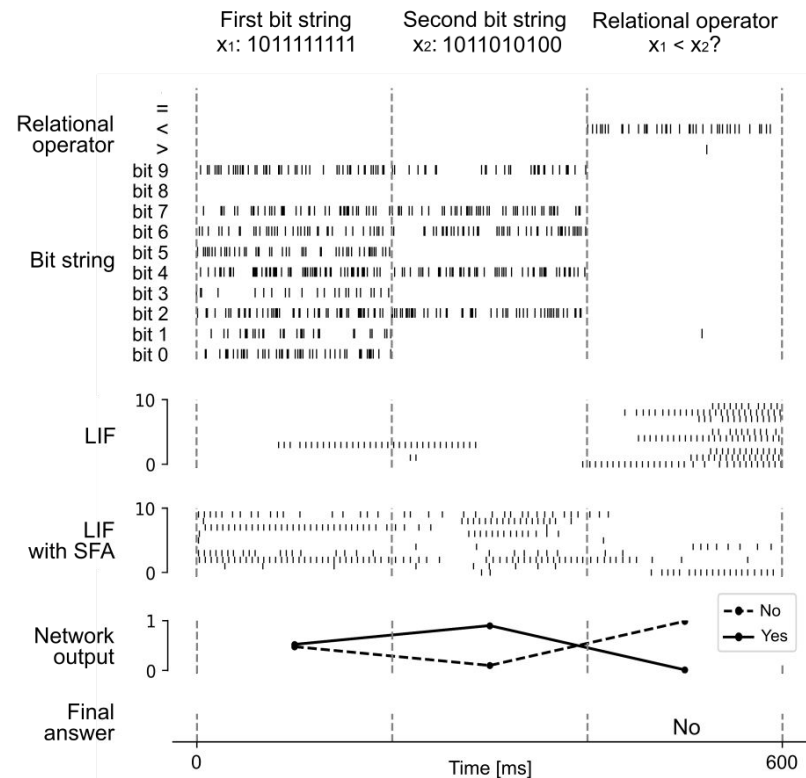
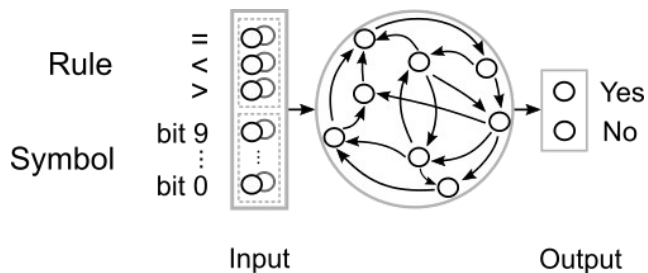
### Performance:

**97.79%** of trials with all correct outputs L and R



# Comparison of (binary encoded) numbers

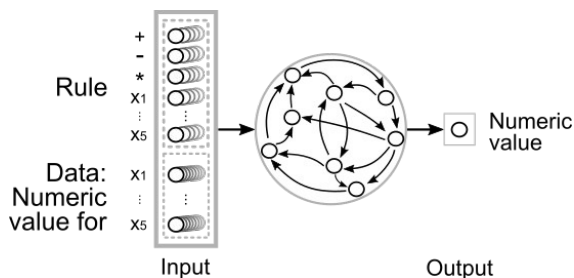
- The network learns to answer the questions:  
*"Is  $x_1 = x_2$ ?"*,  
*"Is  $x_1 < x_2$ ?"*,  
*"Is  $x_1 > x_2$ ?"*.



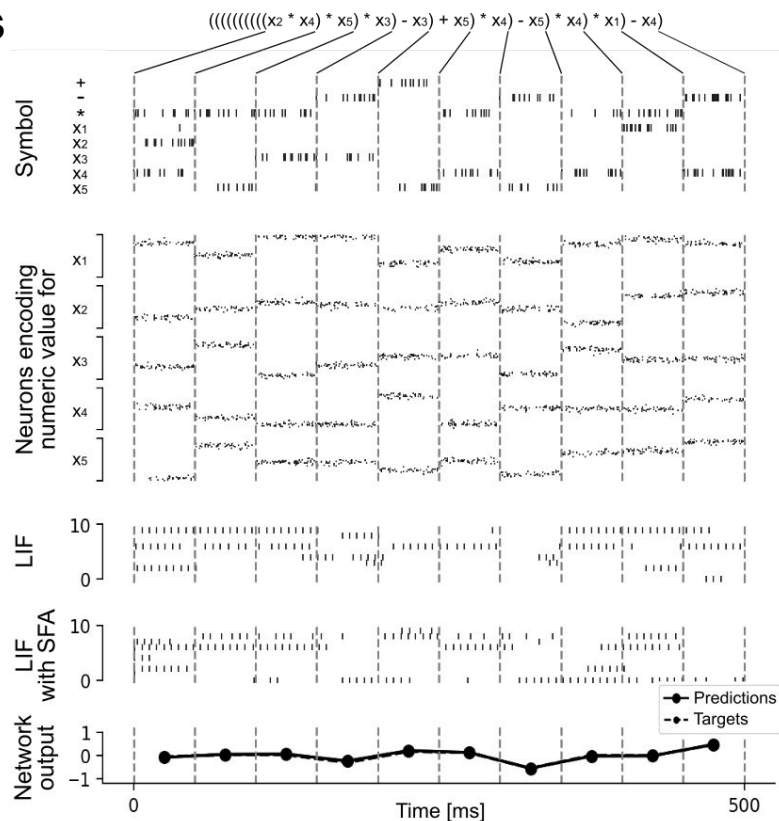
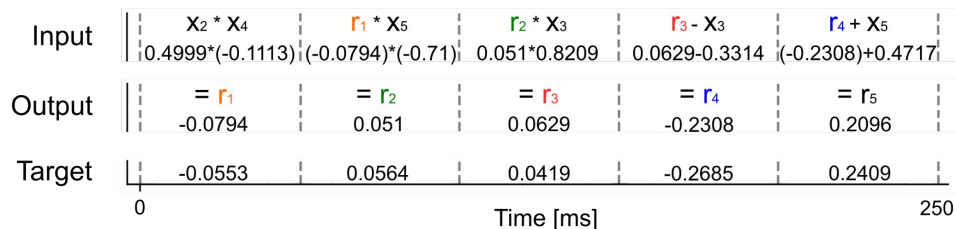
Accuracy:  $0.8723 \pm 0.0235$  (mean  $\pm$  std)

# Evaluation of nested arithmetic expressions

- Variables and numbers encoded into spiking activity
- The network learns the binding “variable - concrete values”, and evaluates given expressions in real time



An example trial:  $(((((x_2 * x_4) * x_5) * x_3) - x_3) + x_5)$



MSE: 0.0341, MAE: 0.1307

# Spike-based symbolic computations on symbol sequences

## Conclusions

Models of spiking neural networks can provide brain-like computational capabilities.

Our experiments show that cognitively demanding tasks in which symbols are manipulated (e.g., arithmetics, number comparison) that brains are able to solve can be reproduced by simple models.

Crucial for that was the inclusion of the Spike Frequency Adaptation (SFA) mechanism. With SFA, implemented in our models as reduced excitability of neurons (i.e., increased firing threshold), the hidden state of the neuron is better protected against perturbations by ongoing network activity.

Our models are trained by a biologically plausible learning rule *e-prop*. This is of 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 945539), the SYNCH project (Grant Agreement number 824162) of the EU, and under partial support by the Austrian Science Fund (FWF) within the ERA-NET CHIST-ERA programme (project SMALL, I 4670-N).

## References

- [1] Krašniković, C., Maass, W., & Legenstein, R. (2021). Spike-based symbolic computations on bit strings and numbers. *bioRxiv*.
- [2] Salaj, D., Subramoney, A., Krašniković, C., Bellec, G., Legenstein, R., & Maass, W. (2021). Spike frequency adaptation supports network computations on temporally dispersed information. *Elife*, 10, e65459.
- [3] Bellec, G., Scherr, F., Subramoney, A., Hajek, E., Salaj, D., Legenstein, R., & Maass, W. (2020). A solution to the learning dilemma for recurrent networks of spiking neurons. *Nature communications*, 11(1), 1-15.