Unsupervised online learning of complex sequences in spiking neuronal networks

Younes Bouhadjar[1,*,†], Melissa Lober[2,3,*], Emre Neftci[1,3],
Markus Diesmann[2,4], Tom Tetzlaff[2]

[1] Neuromorphic Software Ecosystems (PGI-15), Jülich Research Centre, Jülich, Germany
[2] Institute for Advanced Simulation (IAS-6) and JARA Brain Institute I (INM-10), Jülich Research Centre, Jülich, Germany
[3] RWTH Aachen University, Aachen, Germany
[4] Department of Physics, Faculty 1, & Department of Psychiatry, Psychotherapy, and Psychosomatics, Medical School, RWTH Aachen University, Aachen, Germany

∗ shared first authors, † y.bouhadjar@fz-juelich.de

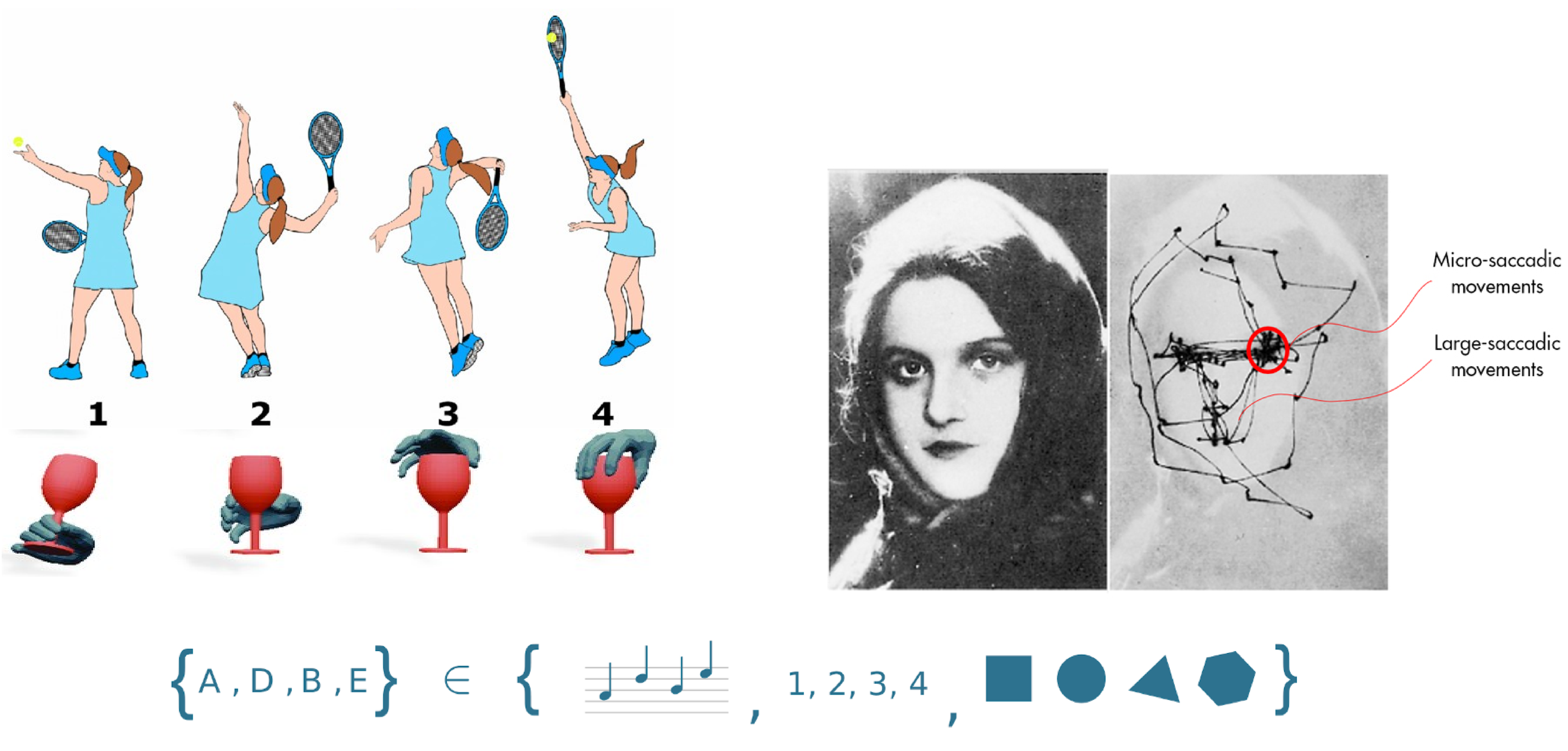
Motivation

Data processed by the brain is typically sequential:

- Sensory inputs (visual, auditory, somatosensory, . . .)
- Motor activity
- Language comprehension and production
- High-level cognitive processes such as planning, math, problem solving, . . .

Sequence processing:

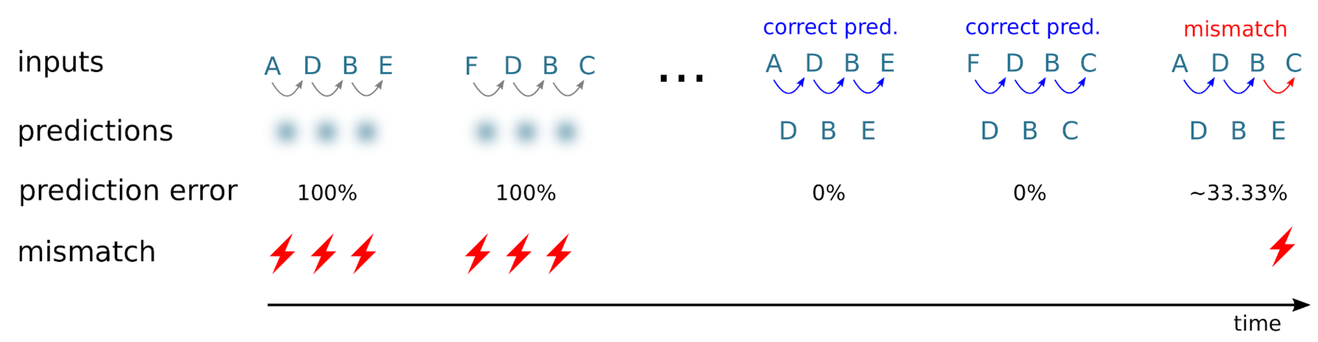
- **Prediction** of upcoming events in a context-dependent manner
- **Anomaly detection**
- **Replay** of sequences in response to a cue signal (pattern completion)
- Chunking, merging, classification, etc.



Whiteside et al. (2013); Zhou et al. (2022); wikipedia: Fixation [visual]; Bouhadjar et al. (2022) [1]

Network model

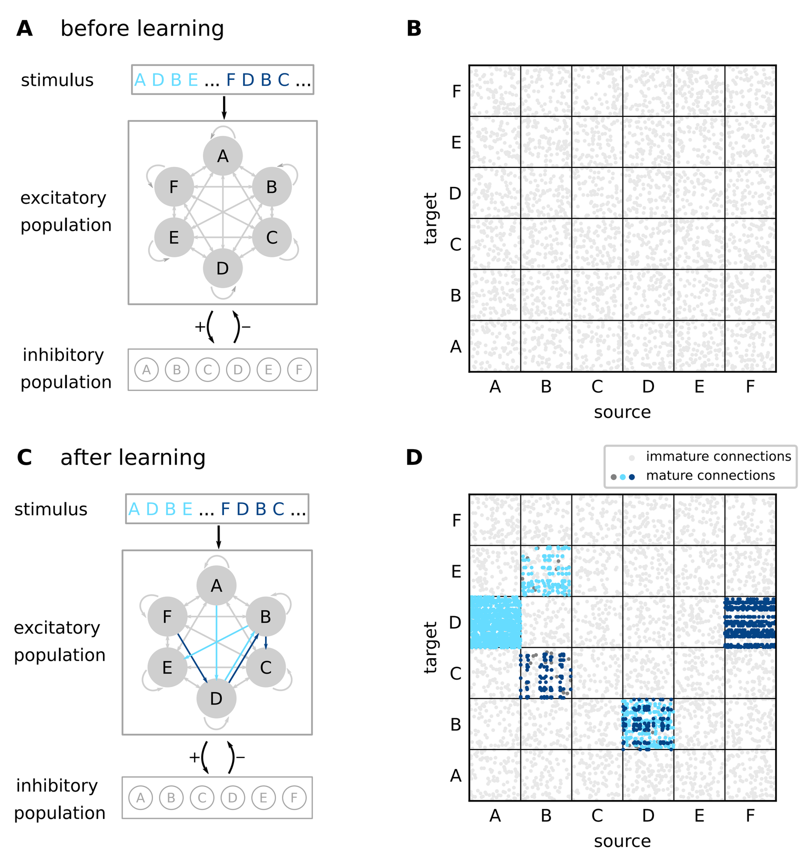
Task



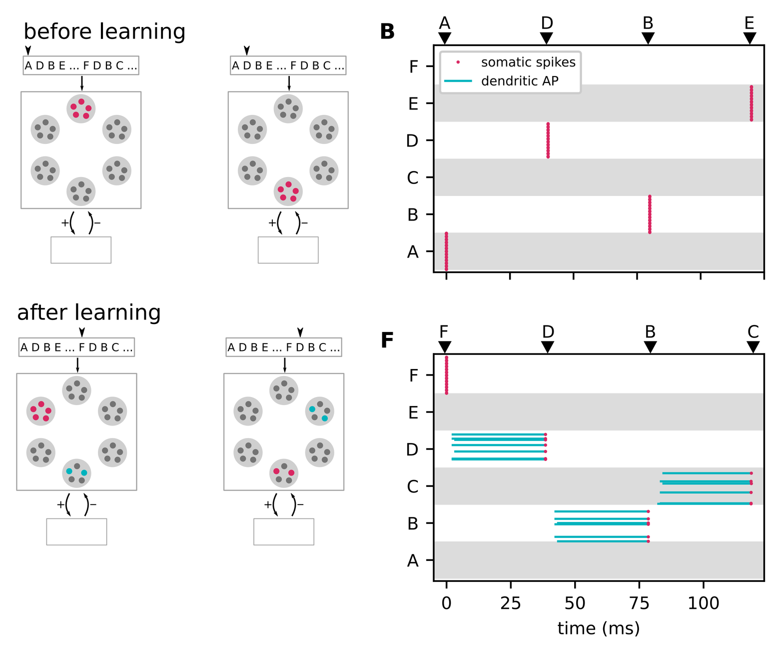
Bouhadjar et al. (2022) [1]

Network model

- Sparsely, randomly connected network of excitatory and inhibitory leaky integrate-and-fire neurons
- Stimulation of excitatory neurons according to stimulus preference
- Nonlinear integration of synaptic inputs in excitatory neurons (dendritic action potentials)
- Unsupervised learning of sequences by structural spike-time dependent plasticity
- Formation of sequence-specific subnetworks



Sequence prediction



- No predictions yet → Non-sparse activation
- Predictions → Sparse activation
- Context specificity

Neuromorphic hardware implementations

- Memristive hardware [2, 3]: robustness and energy efficiency
- BrainScales [4]: robustness and exploitation of substrate heterogeneity

References

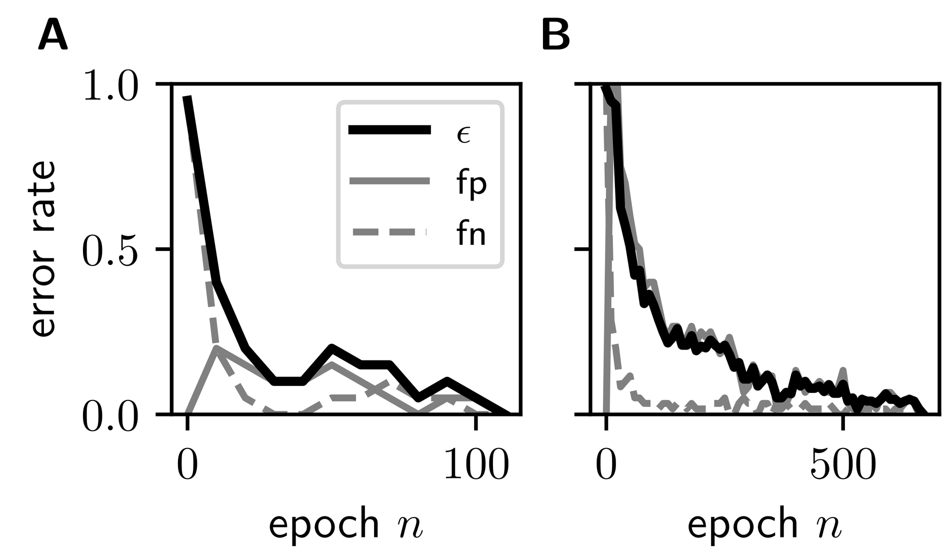
[1] Bouhadjar, Y. et al., (2022). PLOS Computational Biology 18(6):e1010233
[2] Siegel, S. et al., (2023). Neuromorph. Comput. Eng. 3 024002
[3] Bouhadjar, Y. et al (2023). Neuromorph. Comput. Eng. 3 034014
[4] Dietrich, R. et. al. (2025). Machine Learning, Optimization, and Data Science. Lecture Notes in Computer Science, vol 15510.

Acknowledgments

This project was supported by the Federal Ministry of Education and Research (NeuroSys grant no. 03ZU1106CB, 03ZU2106CB; NEUROTEC-II grant no. 16ME0398K, 16ME0399), the German Research Foundation grant no. 368482240/GRK2416 and the Joint Lab "Supercomputing and Modeling for the Human Brain" (SMHB).

Results

Learning Dynamics



Learning progress for sequences of length $C = 20$ (A) and $C = 60$ (B). Hyperparameters optimized for $C_{\mathrm{opt}} = 40$.

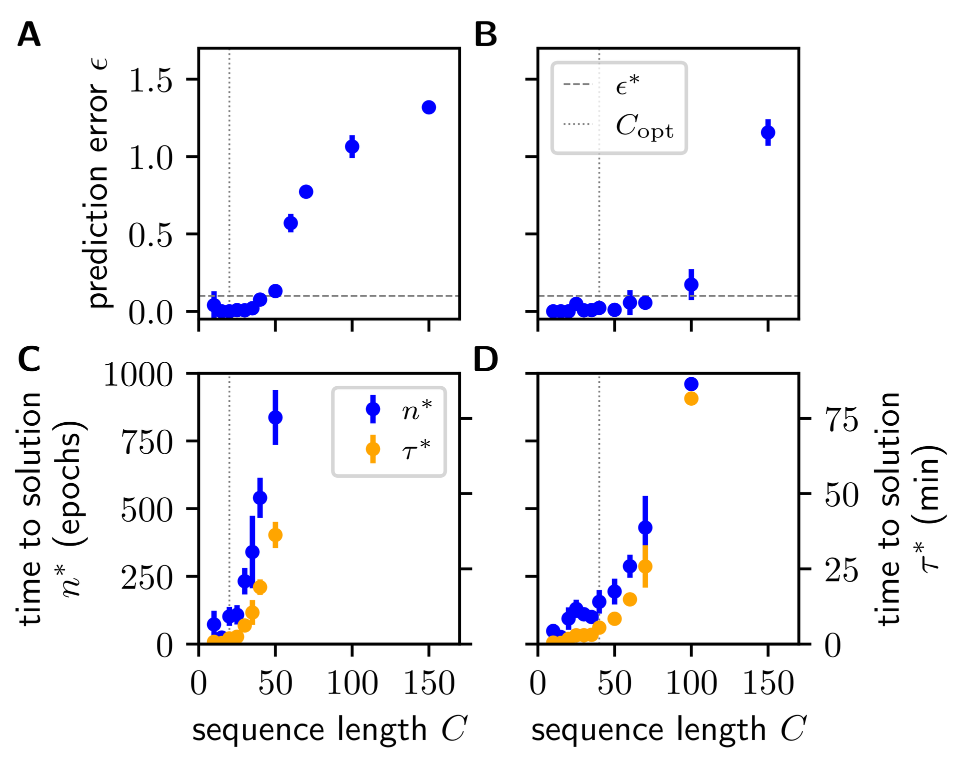
Phases of learning:

1. All connections are immature, no predictions
2. First sparse activations, not yet coordinated across network
   - Alternating sparse and non-sparse activity
3. Coordinated, sparse and context-specific activity

▶ *Forming accurate, context-sensitive sequence representations requires multiple phases of refinement*

▶ *Most time spent on reducing false predictions*

Prediction performance and learning speed



Prediction performance (A, B) and learning speed (C, D) over sequence length. Plasticity parameters optimized for sequence lengths 20 (A, C) and 40 (B, D).

▶ *Successful learning of sequences with tens of elements*

▶ *Hyperparameter transfer*

▶ *High performance for sequences with $C < C_{\mathrm{opt}}$*

▶ *Supralinear increase of time to solution with sequence length*

Outlook

How can we speed up the learning process?

- Accelerated neuromorphic hardware (e.g., BrainScales [4])
- Exploiting structure in training data through hierarchical computation
- Insight into learning dynamics and revision of plasticity rules

Further goals: memory consolidation; multi-modality