Late breaking news:
Distributed Neural State Machines on Loihi 2

April 24 I Alpha Renner I NICE Conference 2024

New preprint

Cotteret, Madison, Hugh Greatorex, Alpha Renner, Junren Chen, Emre Neftci, Huaqiang Wu, Giacomo Indiveri, Martin Ziegler, and Elisabetta Chicca. "Distributed Representations Enable Robust Multi-Timescale Computation in Neuromorphic Hardware." arXiv preprint arXiv:2405.01305 (2024).

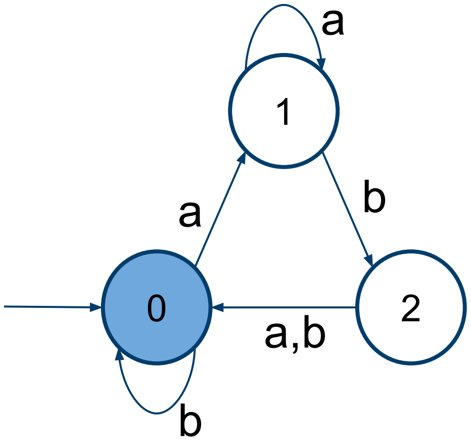
https://arxiv.org/abs/2405.01305

Motivation for stable attractors in RSNN

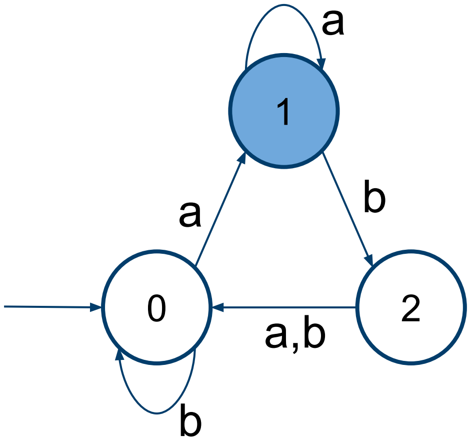
- Robust state transitions for decision making
- Context dependent routing and control flow
- Motor planning and execution

→ Training RSNNs to achieve stable dynamics on arbitrary time-scales is non-trivial

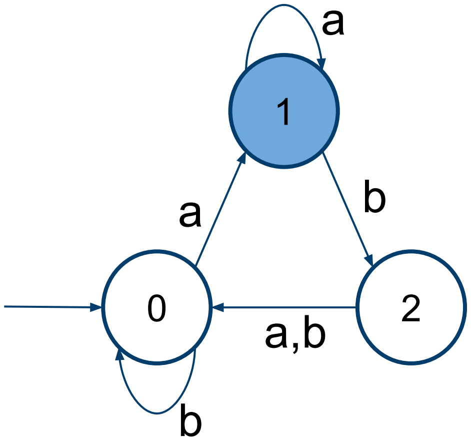
Intuition: State machine



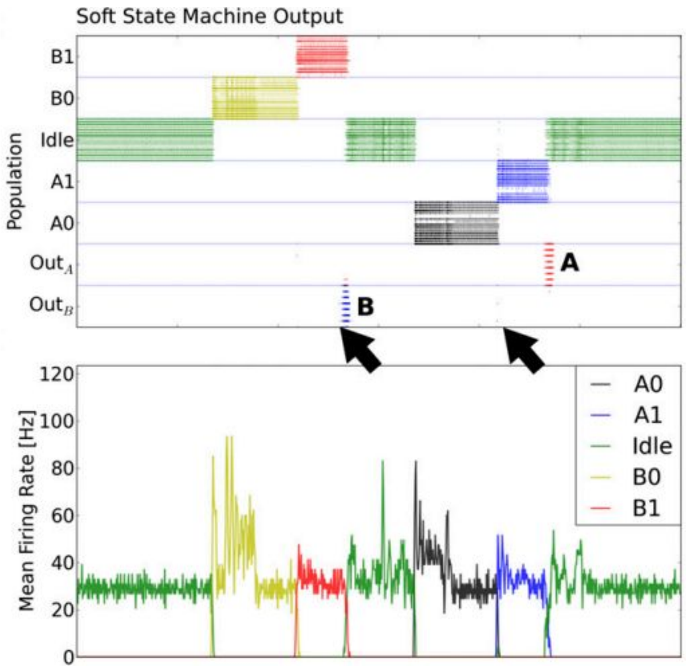
Input:
"a"

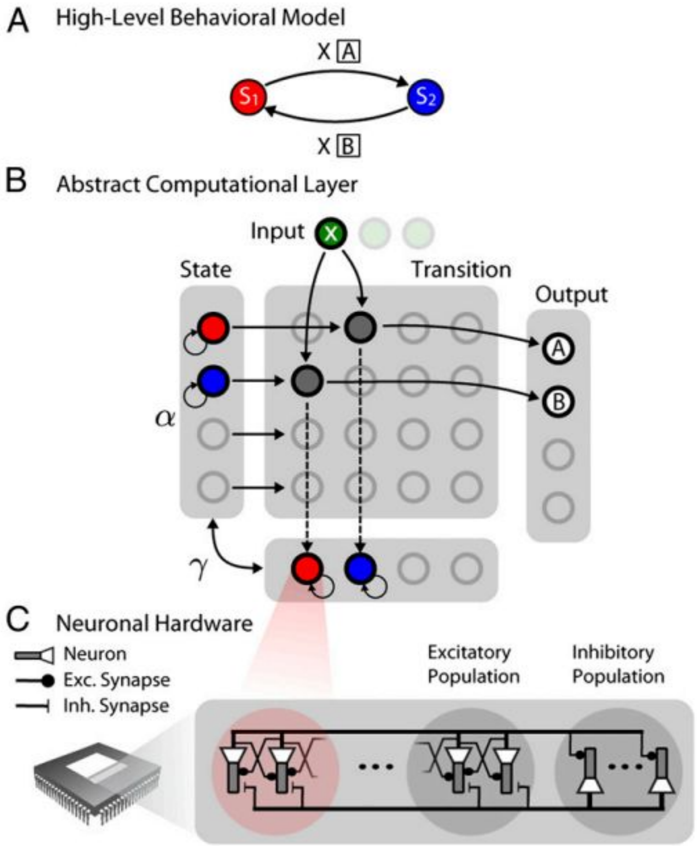


Input:
"a"



Neural state machines on hardware





Neftci, E., Binas, J., Rutishauser, U., Chicca, E., Indiveri, G., & Douglas, R. J. (2013). Synthesizing cognition in neuromorphic electronic systems. Proceedings of the National Academy of Sciences.

Distributed neural state machines

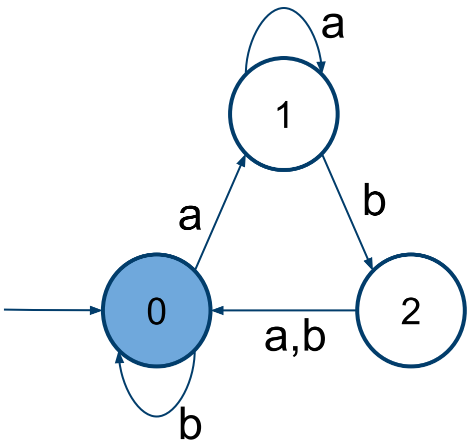
More **robust**, **flexible** and **scalable**

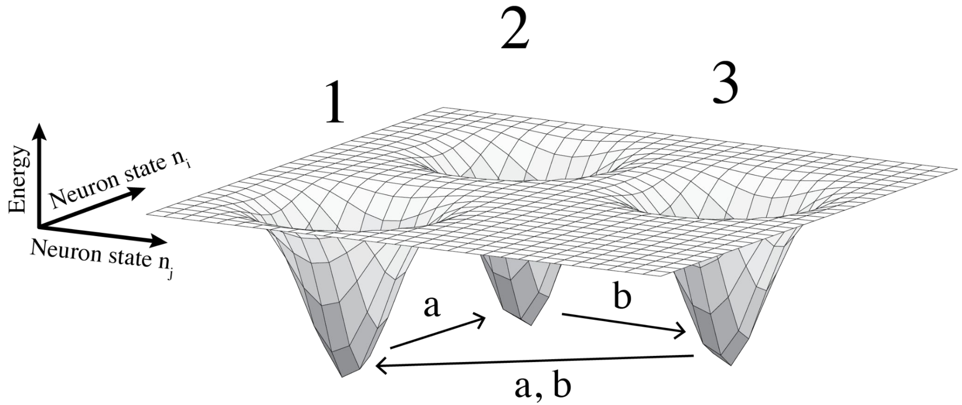
Store nodes and transitions in an associative memory rather than using distinct populations.

→ Connection terms are programmed in a Hebbian way

→ Nodes are auto-associative, state transitions are hetero-associative

→ Transitions are “protected” and only activated when an inhibitory input acts on the network





Distributed neural state machines inspired by HDC

Encoding and connectivity is inspired by Hyperdimensional Computing (HDC).

HDC was proposed as a framework for computation on neuromorphic hardware.

→ Provides an abstraction layer or “instruction set” of a few operations that allows universal computation.

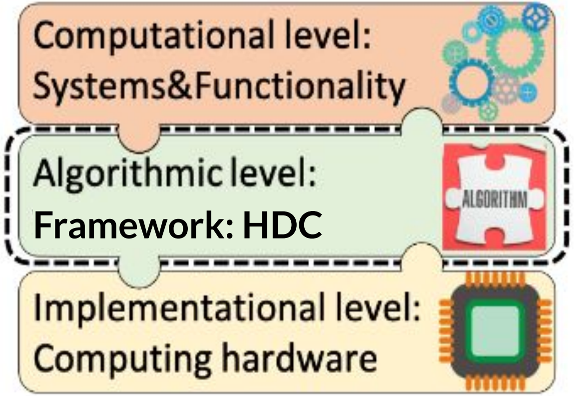
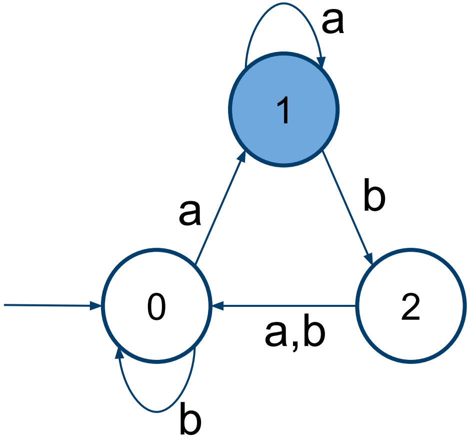


Figure modified from: Kleyko, D., Davies, M., Frady, E.P., Kanerva, P., Kent, S.J., Olshausen, B.A., Osipov, E., Rabaey, J.M., Rachkovskij, D.A., Rahimi, A. and Sommer, F.T., 2021. Vector symbolic architectures as a computing framework for nanoscale hardware. *arXiv:2106.05268*.

Intuition:
State encoding

Nodes/states are encoded as sparse activation patterns in a block-structured vector

$$\vec{x}_\nu = \begin{bmatrix}0\\0\\1\\0\\1\\0\\0\\0\\\vdots\end{bmatrix} \begin{matrix}\left.\vphantom{\begin{matrix}0\\0\\1\\0\end{matrix}}\right\}\text{Block 1}\\ \left.\vphantom{\begin{matrix}1\\0\\0\\0\end{matrix}}\right\}\text{Block 2}\\ \vphantom{\vdots}\end{matrix}$$



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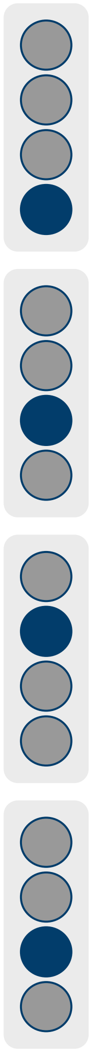
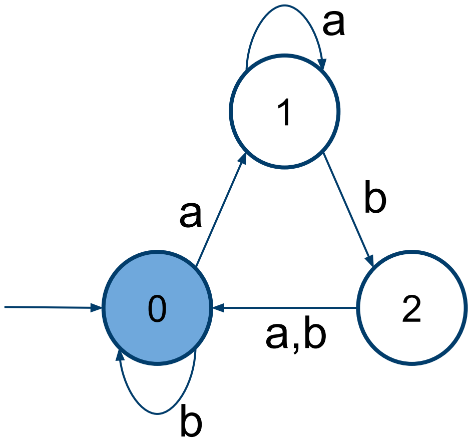
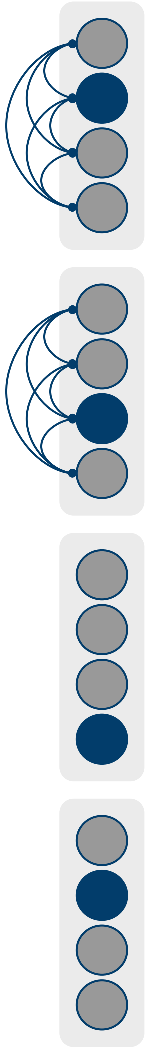




Intuition: Connectivity

Each block only allows one active neuron (WTA)

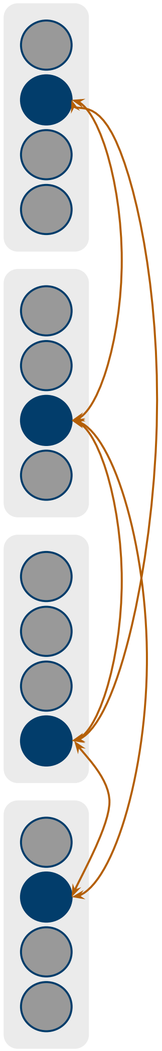


Intuition: Connectivity

Each state is a stable fixed point attractor.

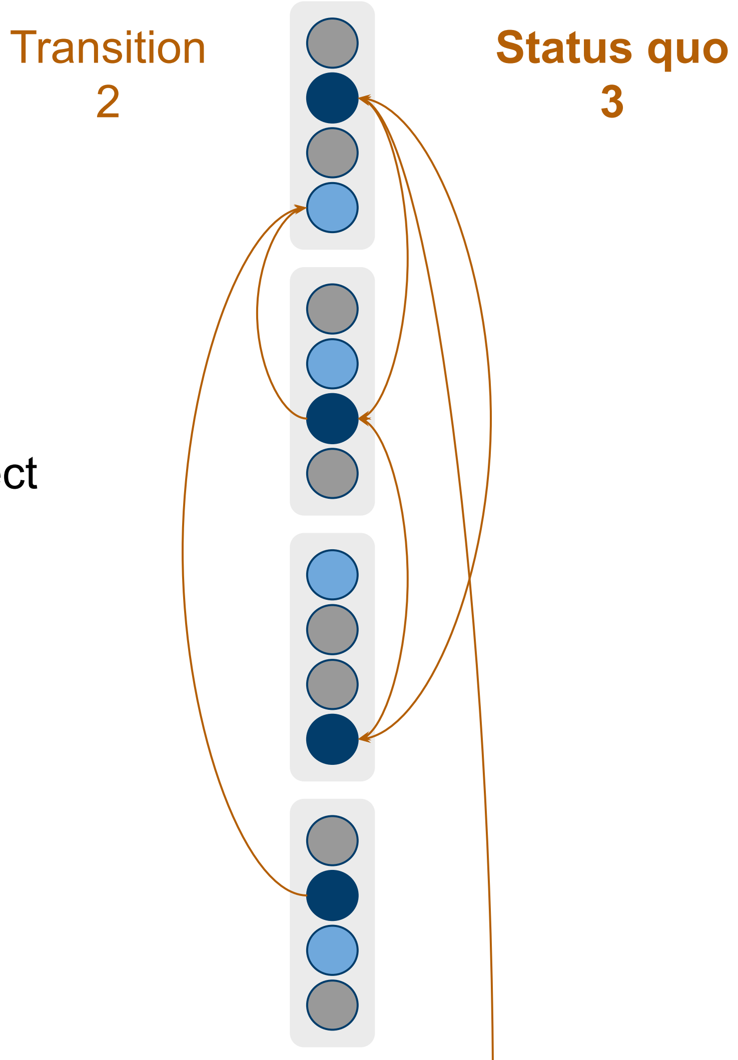
→ Hopfield-like auto-associative connectivity

Hebbian outer-product weights: "Neurons that fire together wire together"



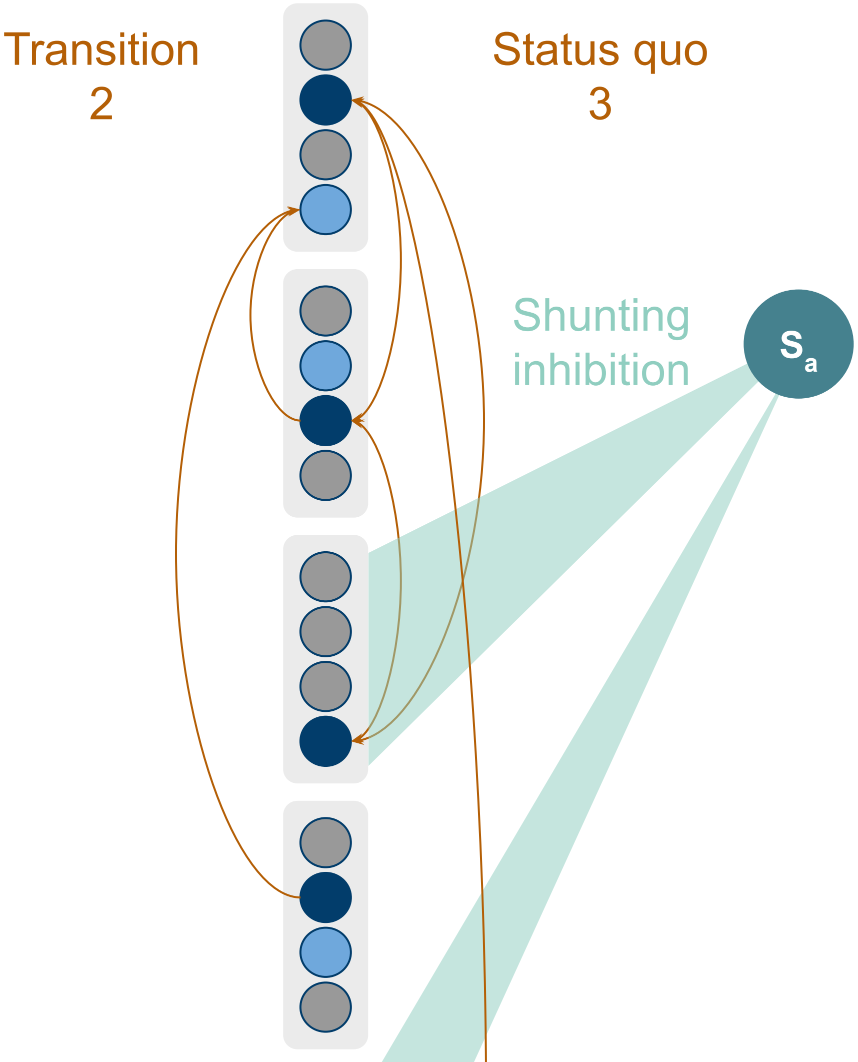
Intuition: Connectivity

Asymmetric connections for state transitions are present, but have no effect due to the WTA.



Intuition: Connectivity

Block-wise masking removes the effect of a subset of connections that favor the status quo.



Intuition: Connectivity

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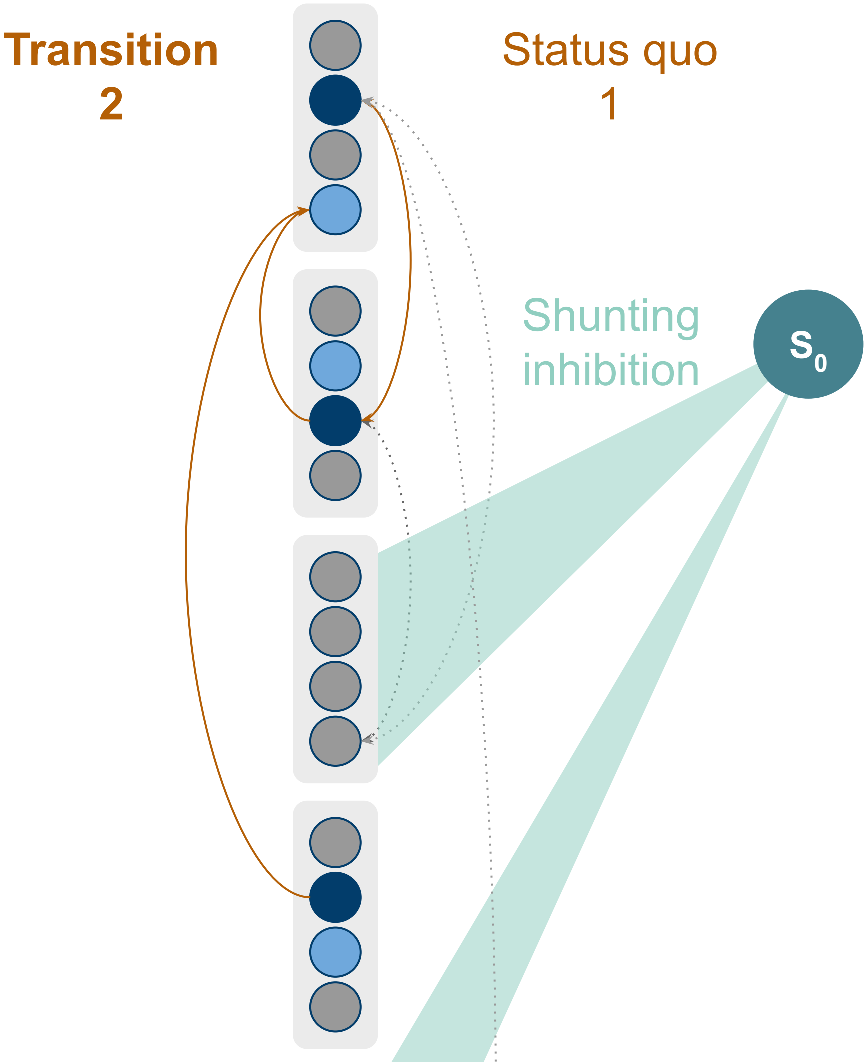
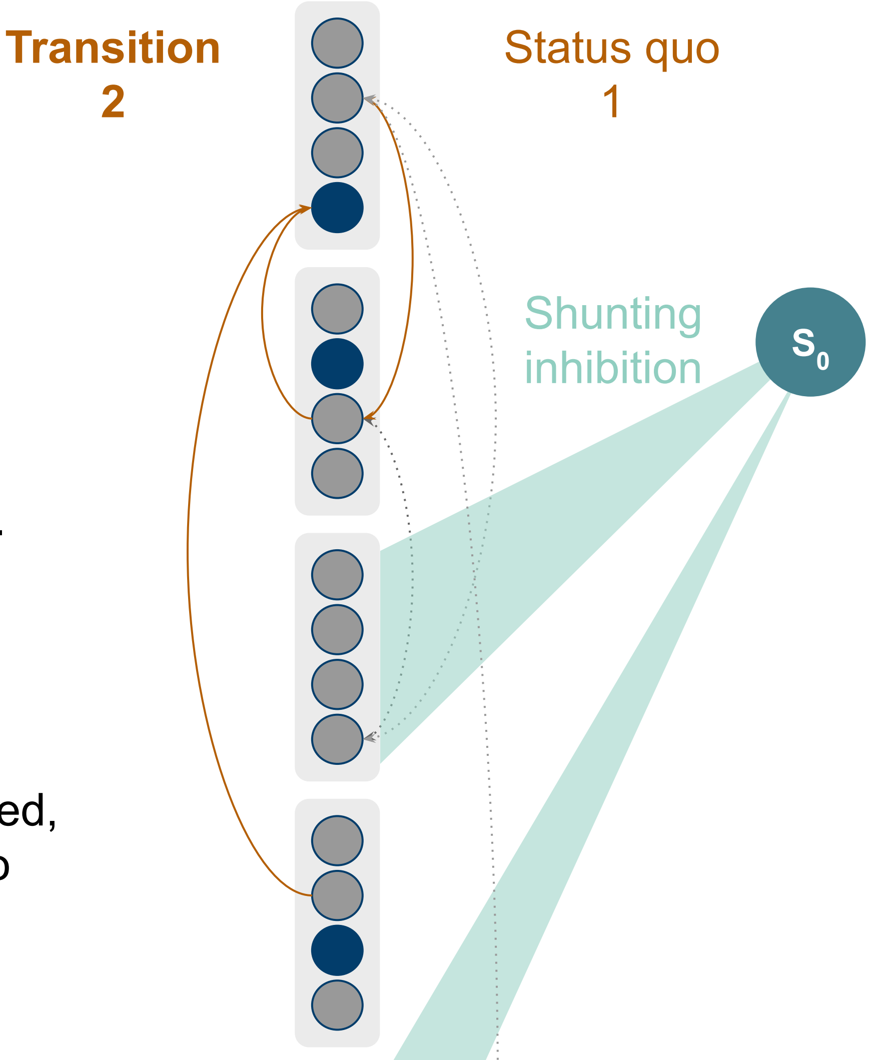


Intuition: Connectivity

Block-wise masking removes the effect of a subset of connections that favor the status quo.

→ Network transitions to transitory “bridge” state

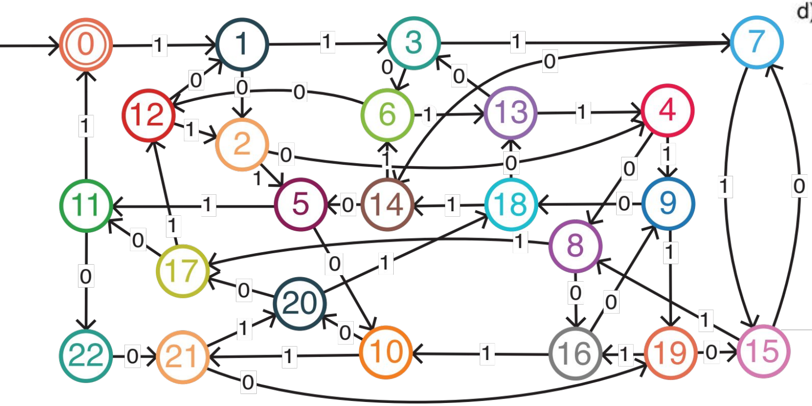
When the input is removed, the network transitions to the stable state.

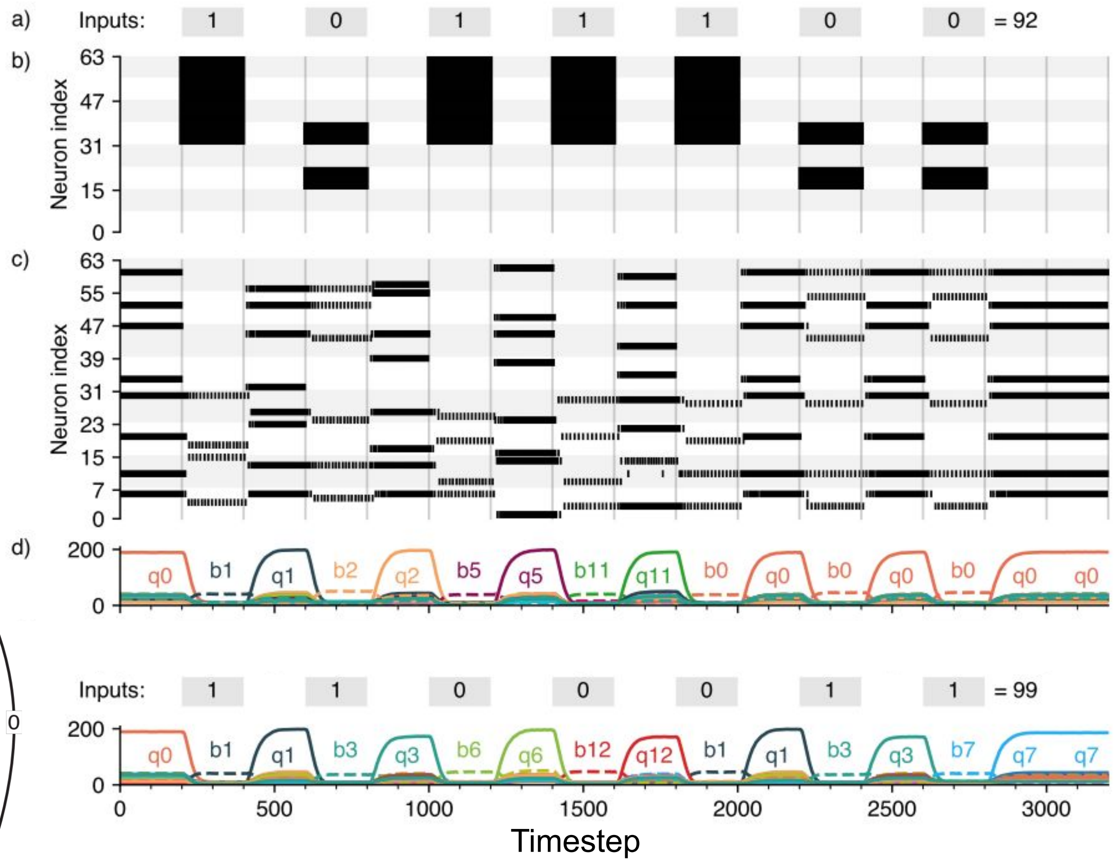


Results on Loihi 2

State machine with 23 states
Computes “x mod 23”
1024 neurons, 8 neurons per block

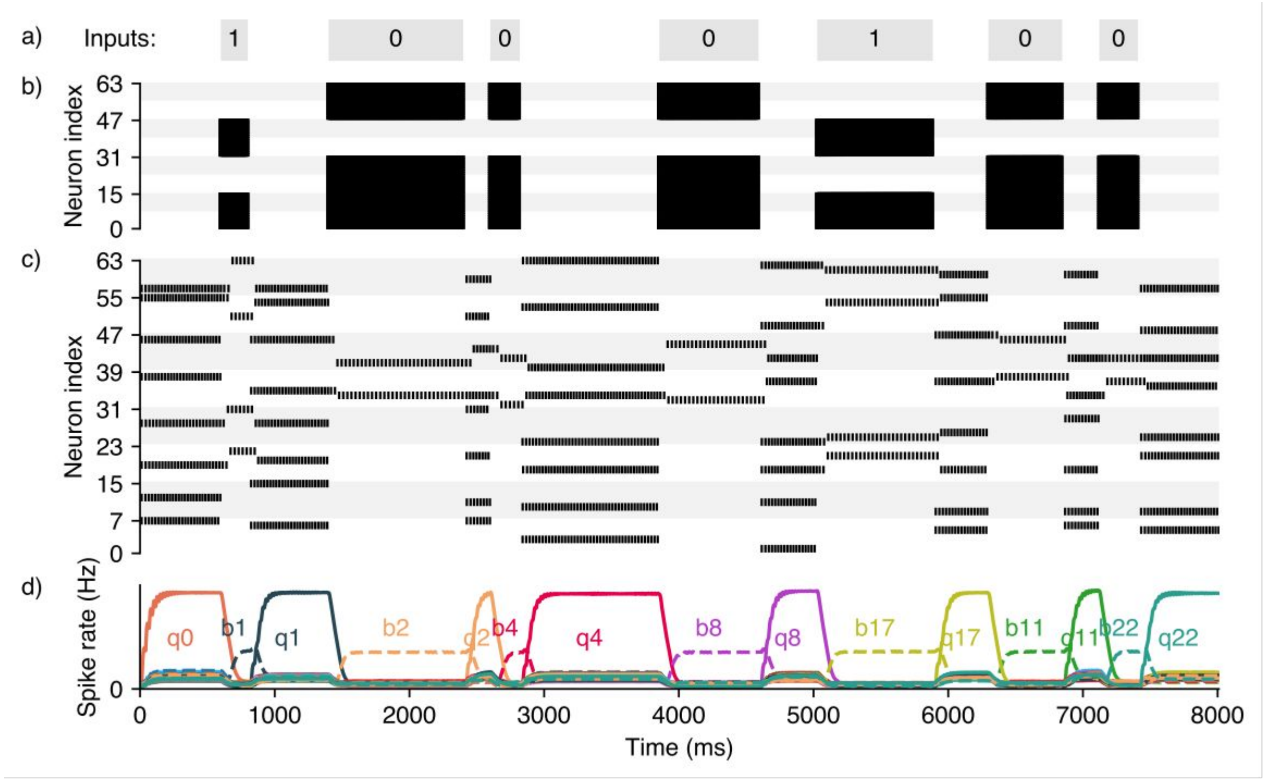
Using Loihi2’s custom neuron microcode.





100% reliable if the network is large enough

Arbitrary timing and length of input signals



Discussion and future work

- Robust to mismatch, noise and neuron failures

  → suitable for implementation on analog and memristive hardware
  (shown in simulation and on RRAM device in the preprint)

- States and transitions are added in a Hebbian way, no need to add neurons or restructure the network

- Can be used to coordinate information flow in complex neuromorphic algorithms

- Can be generalized to other than fixed point attractors → continuous manifolds

Thank you!

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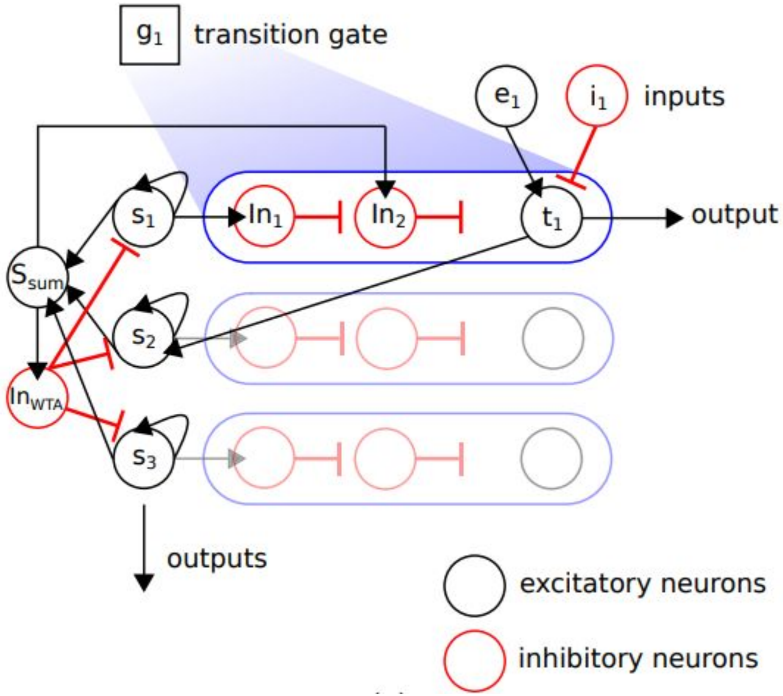
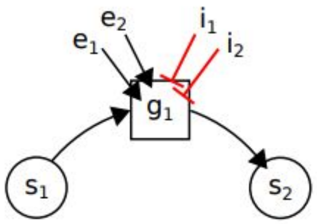
Neural state machines on hardware





Liang, D., & Indiveri, G. (2017). Robust state-dependent computation in neuromorphic electronic systems. In *2017 IEEE Biomedical Circuits and Systems Conference (BioCAS)*

Papers

Cotteret, Madison, Hugh Greatorex, Alpha Renner, Junren Chen, Emre Neftci, Huaqiang Wu, Giacomo Indiveri, Martin Ziegler, and Elisabetta Chicca. "Distributed Representations Enable Robust Multi-Timescale Computation in Neuromorphic Hardware." arXiv preprint arXiv:2405.01305 (2024).

https://arxiv.org/abs/2405.01305

Cotteret, Madison, Hugh Greatorex, Martin Ziegler, and Elisabetta Chicca. "Vector symbolic finite state machines in attractor neural networks." Neural Computation 36, no. 4 (2024): 549-595.

https://doi.org/10.1162/neco_a_01638