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Learning, Inference, and Replay of Hidden State Sequences in Recurrent Spiking Neural Networks

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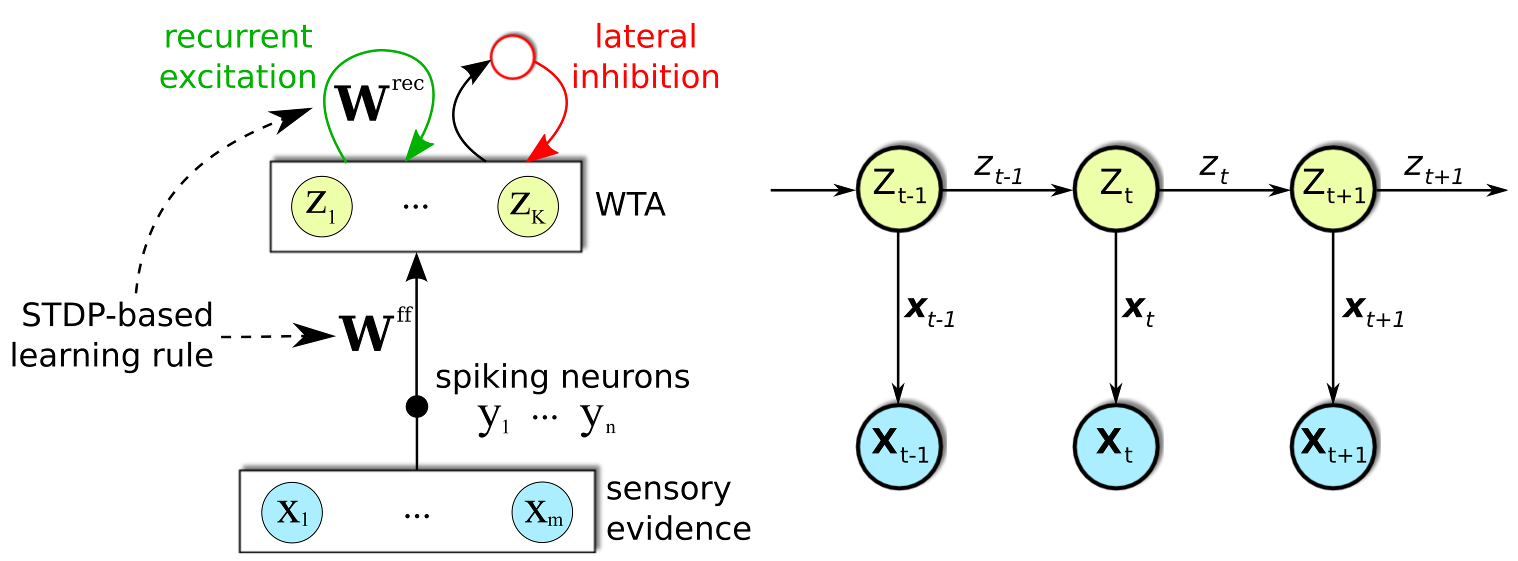
Abstract

Learning to recognize, predict, and generate spatio–temporal patterns and sequences of spikes is a key feature of nervous systems, and essential for solving basic tasks like localization and navigation. How this can be done by a spiking network, however, remains an open question. Here we present a STDP-based framework extending a previous model [1], that can simultaneously learn to abstract hidden states from sensory inputs and learn transition probabilities [2] between these states in recurrent connection weights.

Network Structure



Each output neuron z_k encodes a hidden cause over the input, where

$$p(z_k \text{ fires at time t}) \propto \exp(u_k(t) - I(t))$$

$$u_k(t) = \sum_{i=1}^{N} w^{\text{ff}}_{ki} \cdot \tilde{y}_i(t) + \sum_{k'=1}^{K} w^{\text{rec}}_{kk'} \cdot \tilde{z}_{k'}(t)$$

$$w^{\text{ff}}_{ki} = \log p(\tilde{y}_i = 1 | z_k = 1, \text{w})$$

$$w^{\text{rec}}_{kk'} = \log p(z_k = 1 | \tilde{z}_{k'} = 1, \text{w}).$$

Trained on input generated by a Hidden Markov Model, the activity of the Winner-Take-All (WTA) network evolves as a single–sample (unitary) particle filter [3].

Recurrent Learning Rule

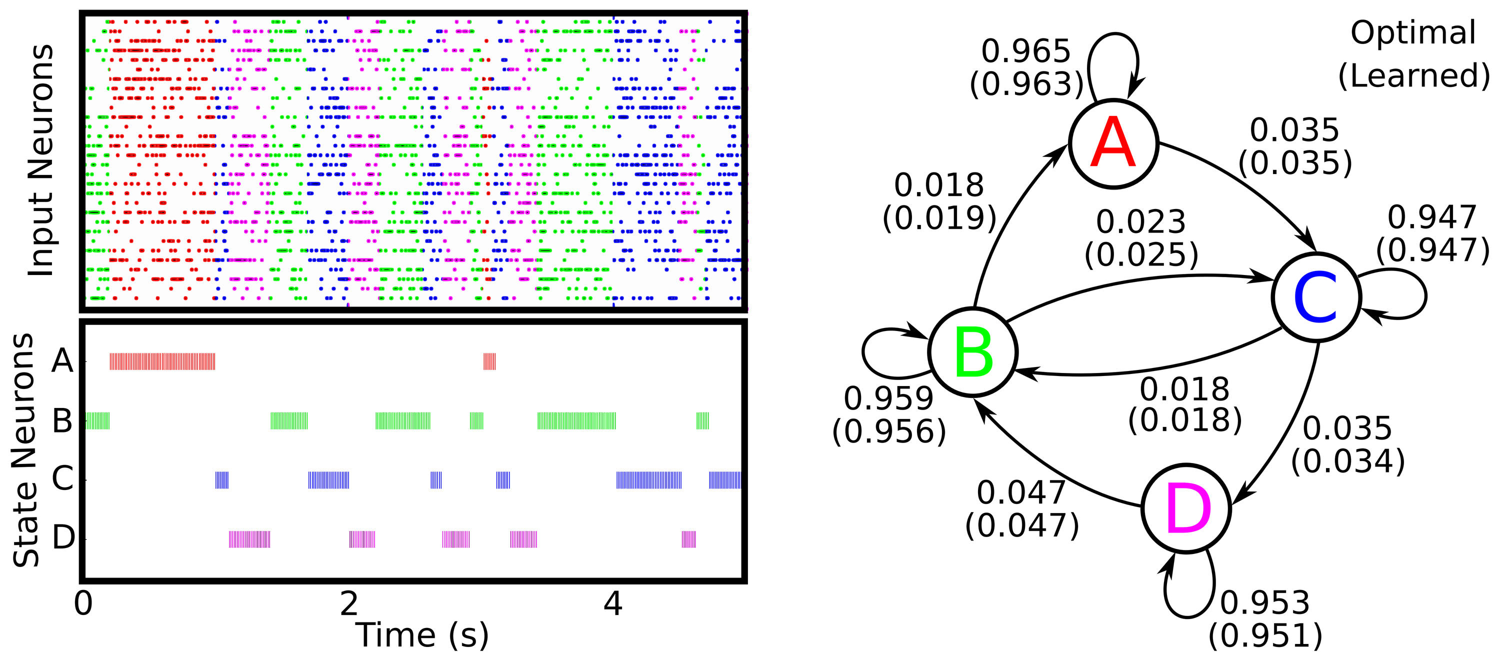
Depression on every presynaptic spike; weight– and time– dependent potentiation if postsynaptic neuron fires within a time window.

$$\Delta w^{\text{rec}}_{kk'} \propto \begin{cases} -1 & \text{after presynaptic spike, and} \\ e^{-w_{kk'} \cdot \tilde{z}_{k'}(t)} & \text{after pre–post pair} \end{cases}$$

$$E[\Delta w^{\text{rec}}_{kk'}] = 0 \Leftrightarrow w^{\text{rec}}_{kk'} = \log p(z_k = 1 | \tilde{z}_{k'} = 1, \text{w})$$

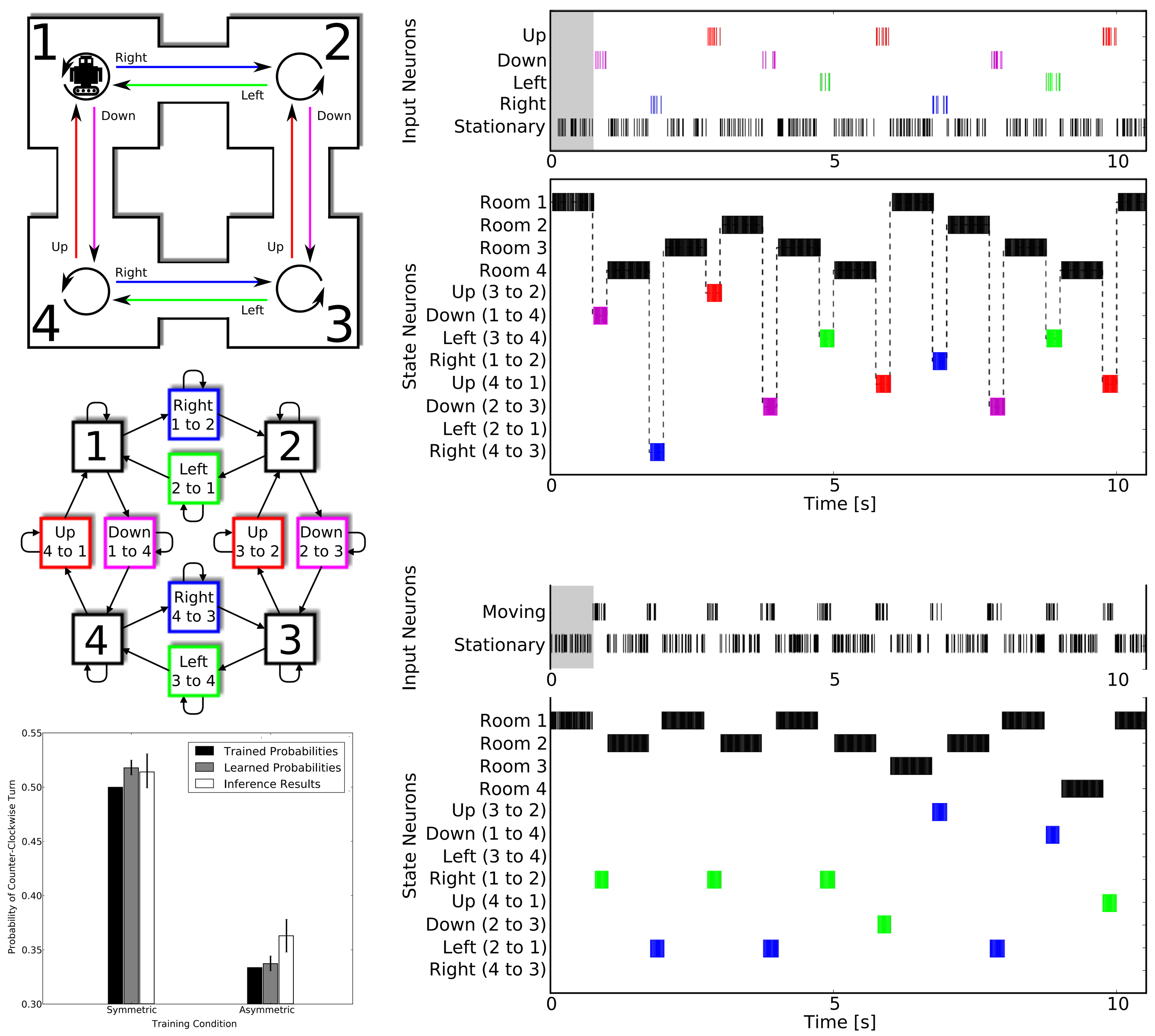
Learning a Hidden Markov Model

A four–state HMM was presented to the network, with states defined by differing Poisson firing statistics over 225 input neurons.



State–dependent Inference

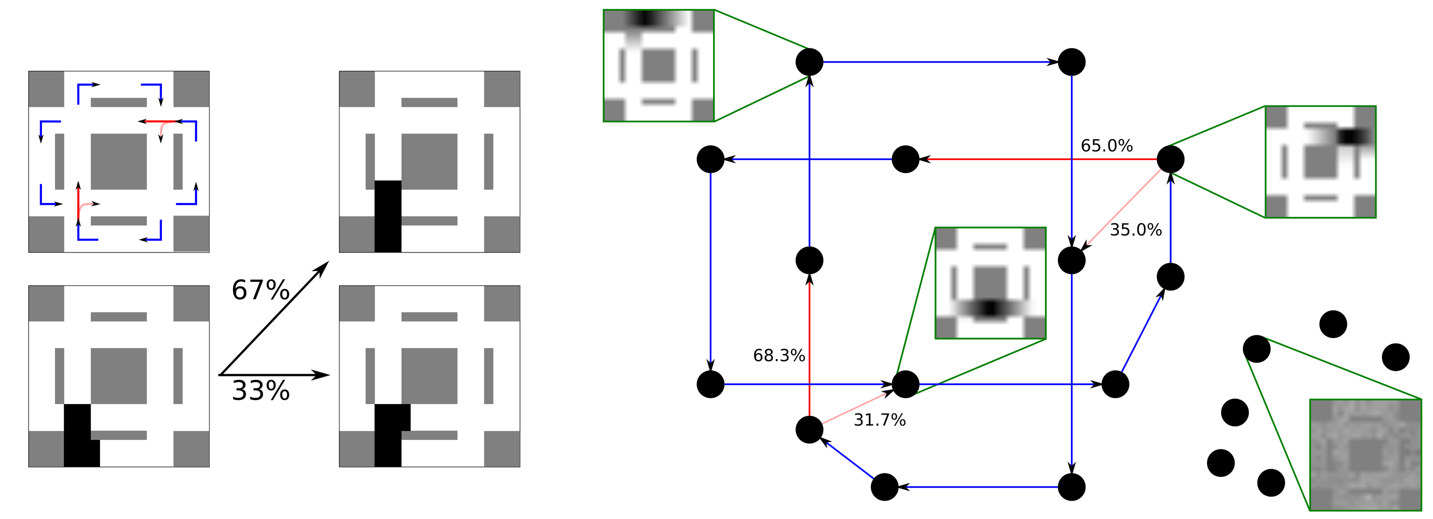
A network model with additional transition neurons for encoding and learning Finite State Machines (FSMs) was trained on observations from a four–state maze traversal task. After training, the network resolved the current state given only transition symbols.



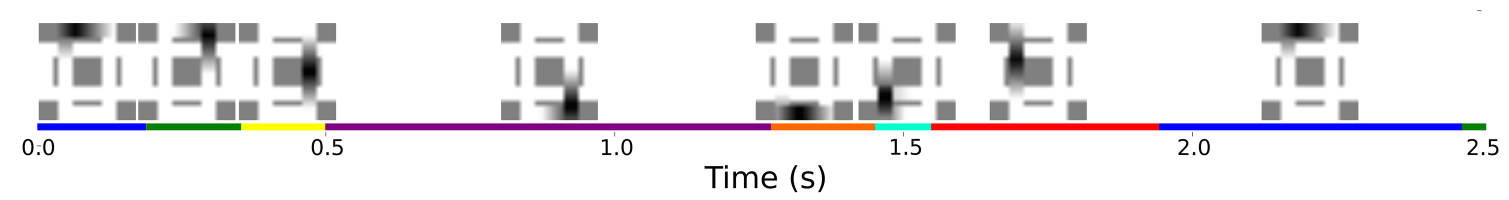
Temporal Replay

The network was trained on input defined by a spatio–temporal pattern with two stochastically branching trajectories.

- Input neurons indicated the current color (black or white) of the pixels
- Network learned both the spatial attributes (feedforward weights) and the temporal progression (recurrent weights) of the input pattern



After training, the network produced samples of states corresponding to a stochastic "replay" of observed trajectories.



Conclusions

We have presented a recurrent spiking neural network architecture, which can be trained to perform dynamical Bayesian inference of hidden states. The same network can be used to generate random sample trajectories through the state space by spontaneous activity in the WTA (using the recurrent connections as a generative Bayesian model) or can be used as a probabilistic FSM in which transitions are actively triggered by movement signals.

References

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