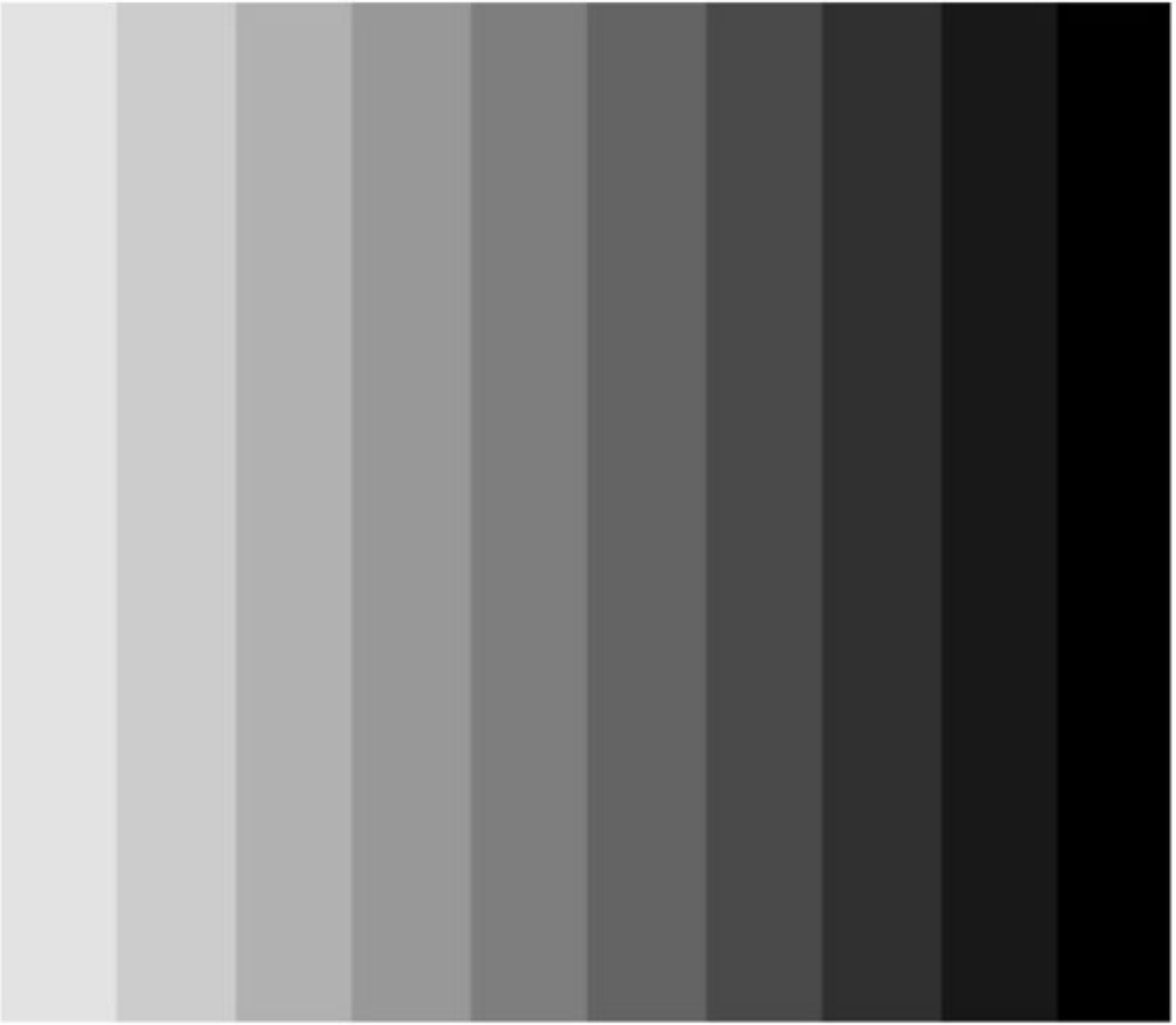
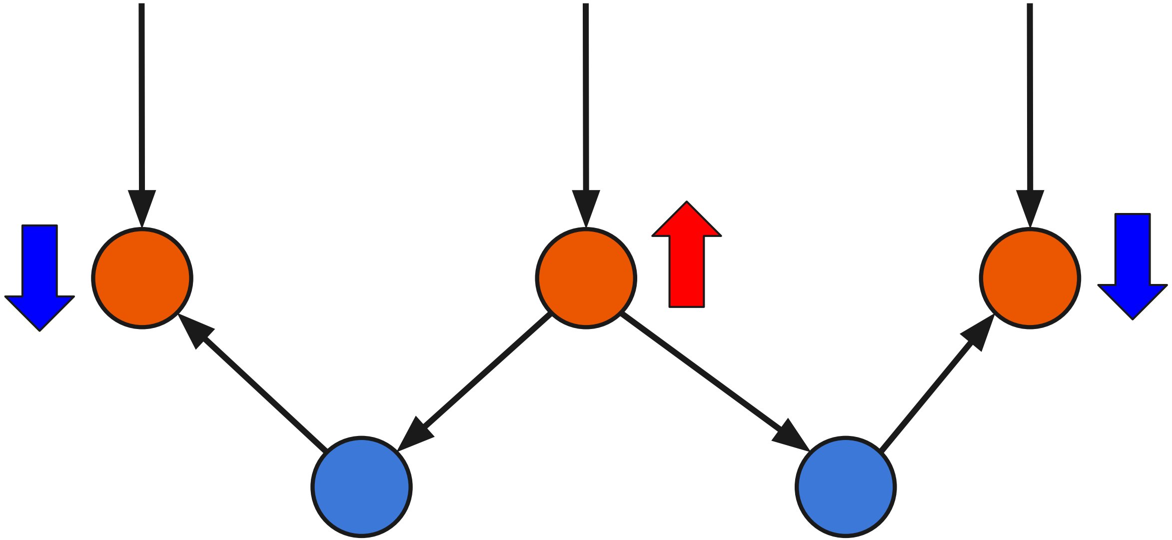
Inhibitory selectivity in recurrent networks

Project for the Spiking networks Hackathon 2025



Mach band effect

Lateral Inhibition



Representation Learning

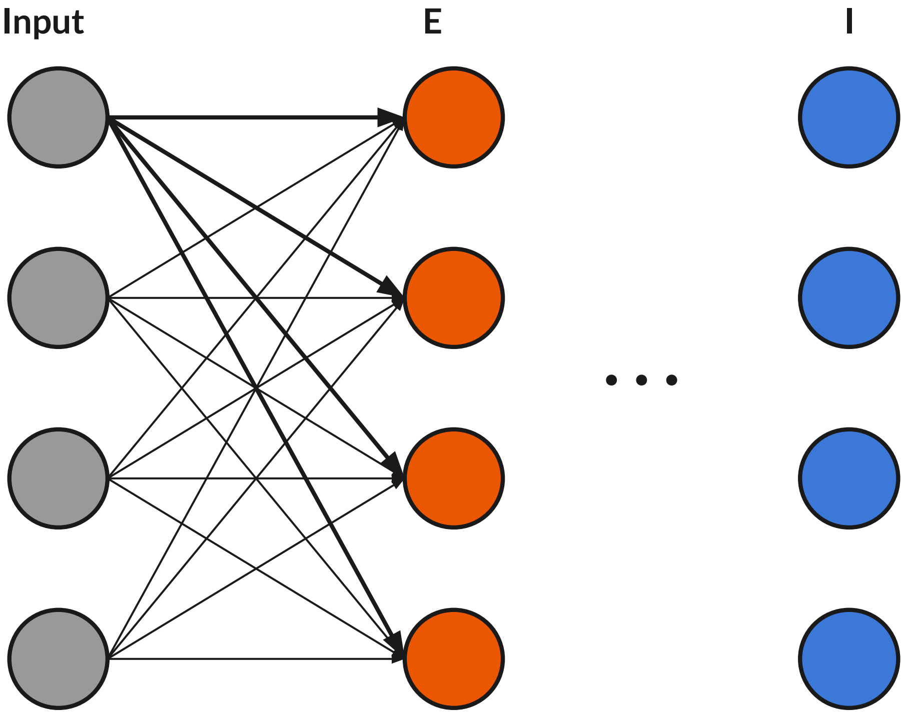
= "learning representations of the data that make it easier to extract useful information [...]."

(Bengio et al., 2013, p. 1798)

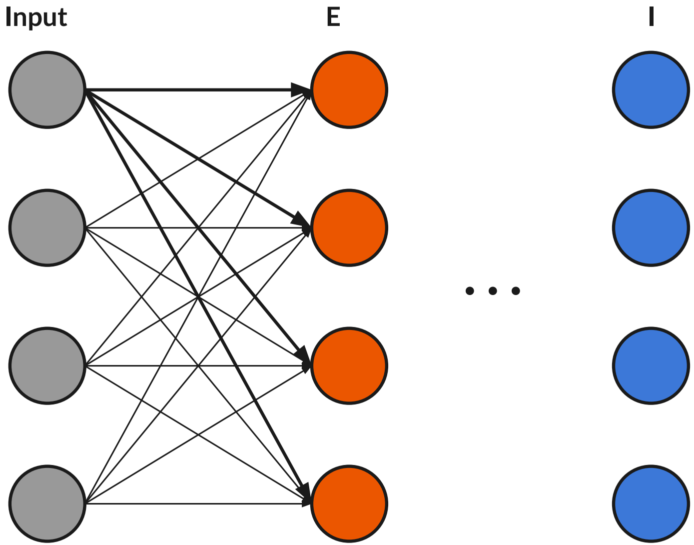
Research Question

How can inhibitory wiring motifs change the learned representations of the excitatory layer?

Experimental Setup



Experimental Setup

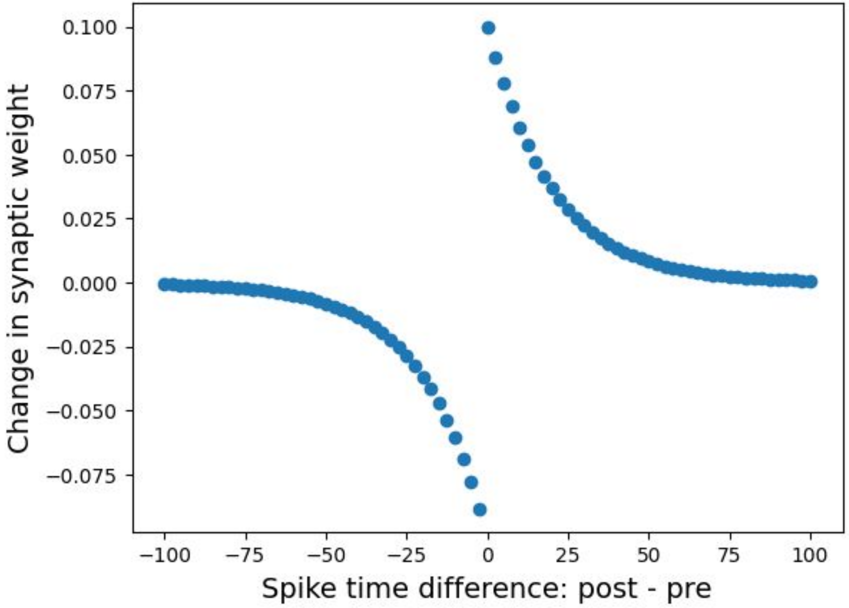


- complies with Dale’s law (separate excitatory and inhibitory population)

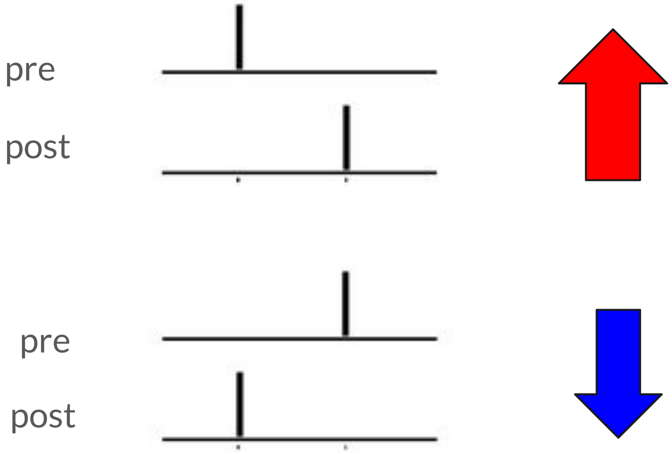
- E-Layer: DiehlAndCookNodes()
- I-Layer: LIFNodes()

- fixed E⟶I, E⟵I connections
- train E-Layer with STDP

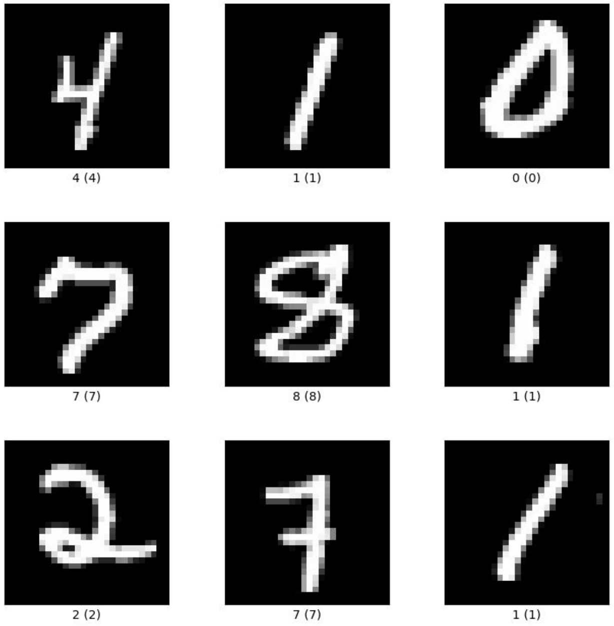
Spike-Timing Dependent Plasticity (STDP)



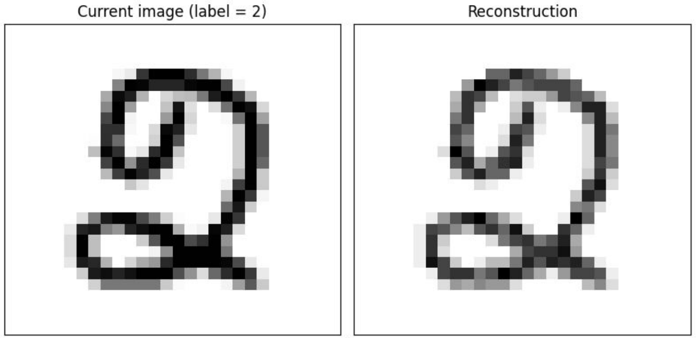
- introduced by Song et al. (2000)



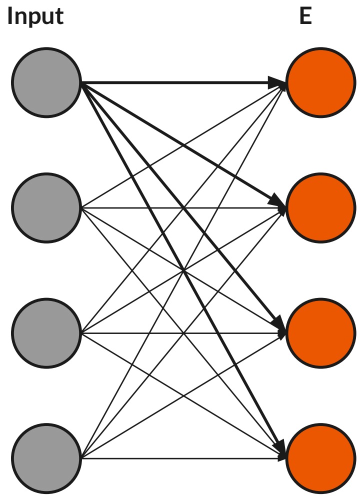
Data: MNIST

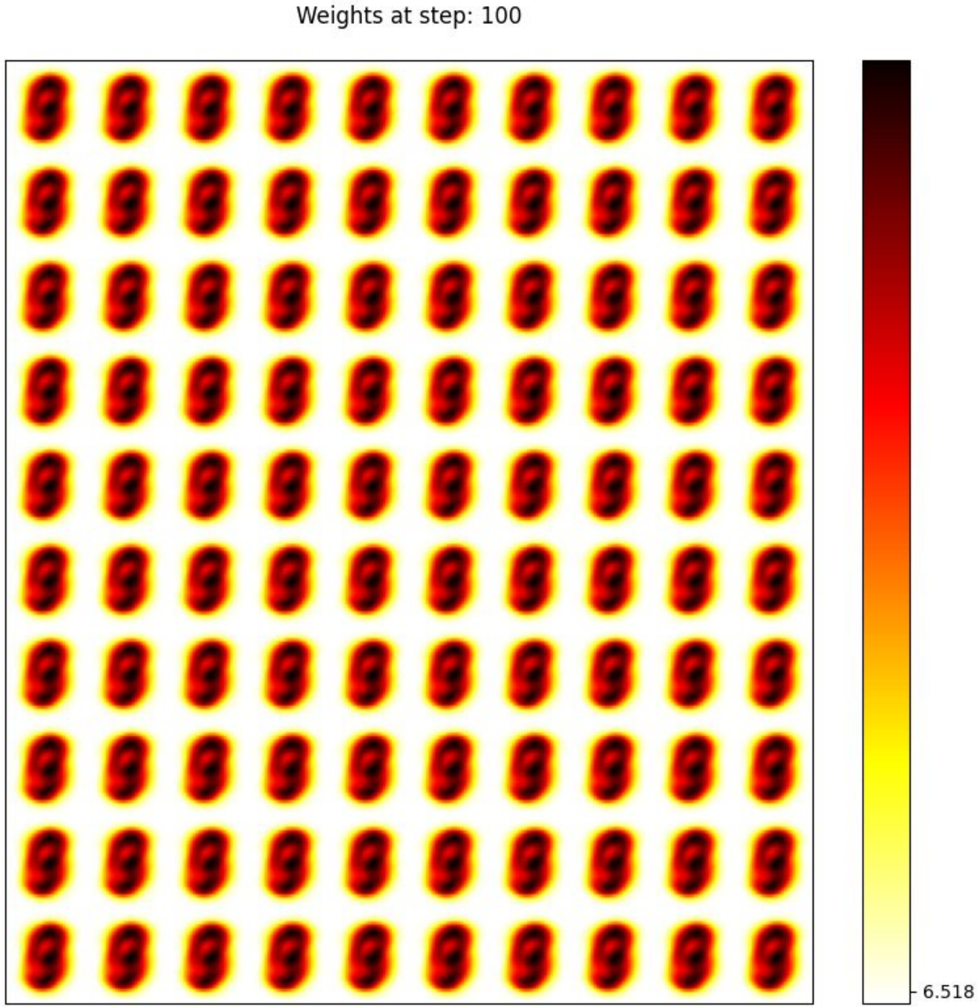


- dataset of handwritten digits
- 60.000 samples for training and 10.000 samples for testing
- images are 28x28 pixel
- encoded with PoissonEncoder():



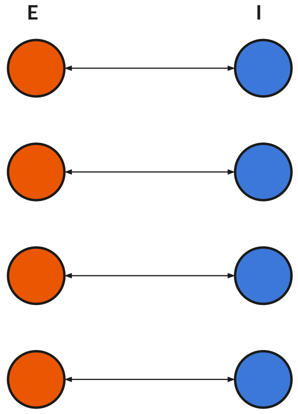
“Control” Setup



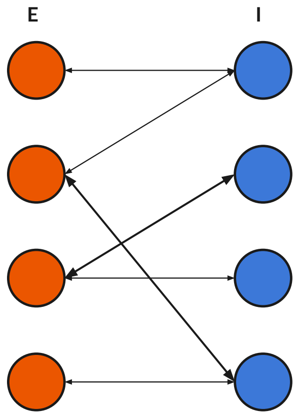


Co-selective wiring motif

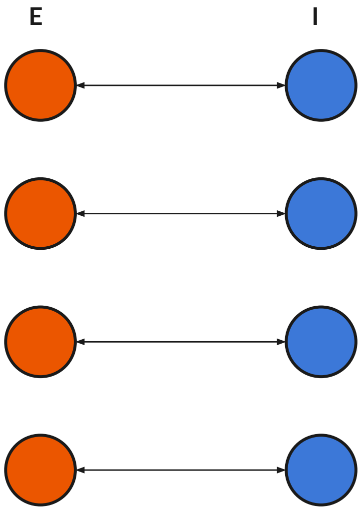
one to one

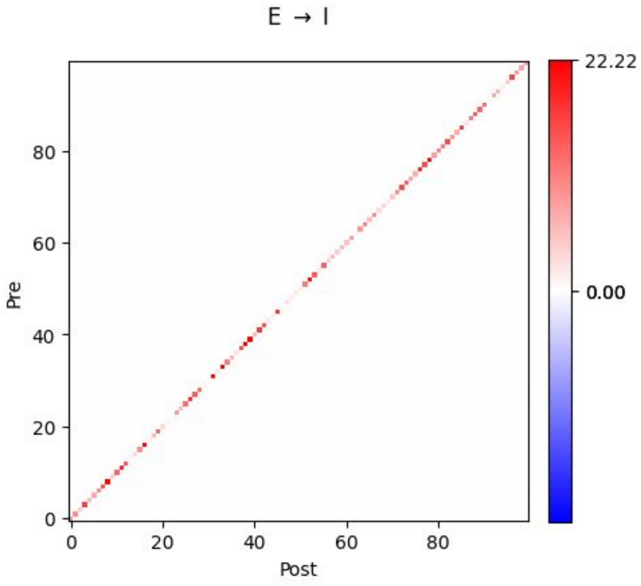


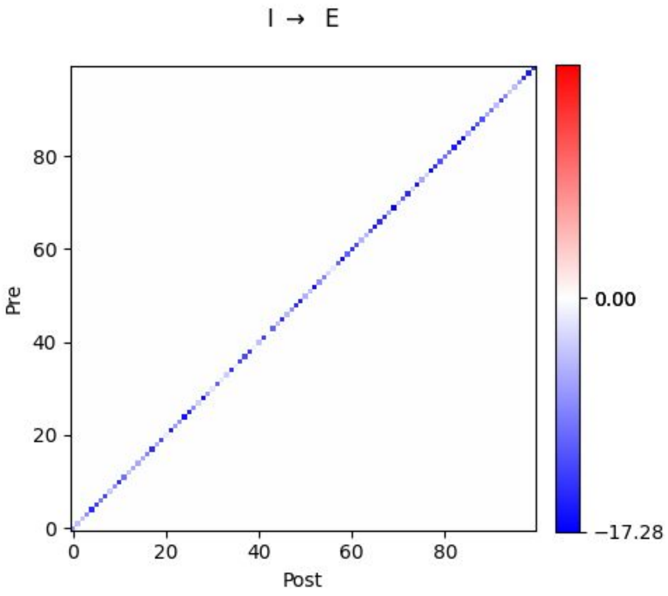
random (symmetrical)



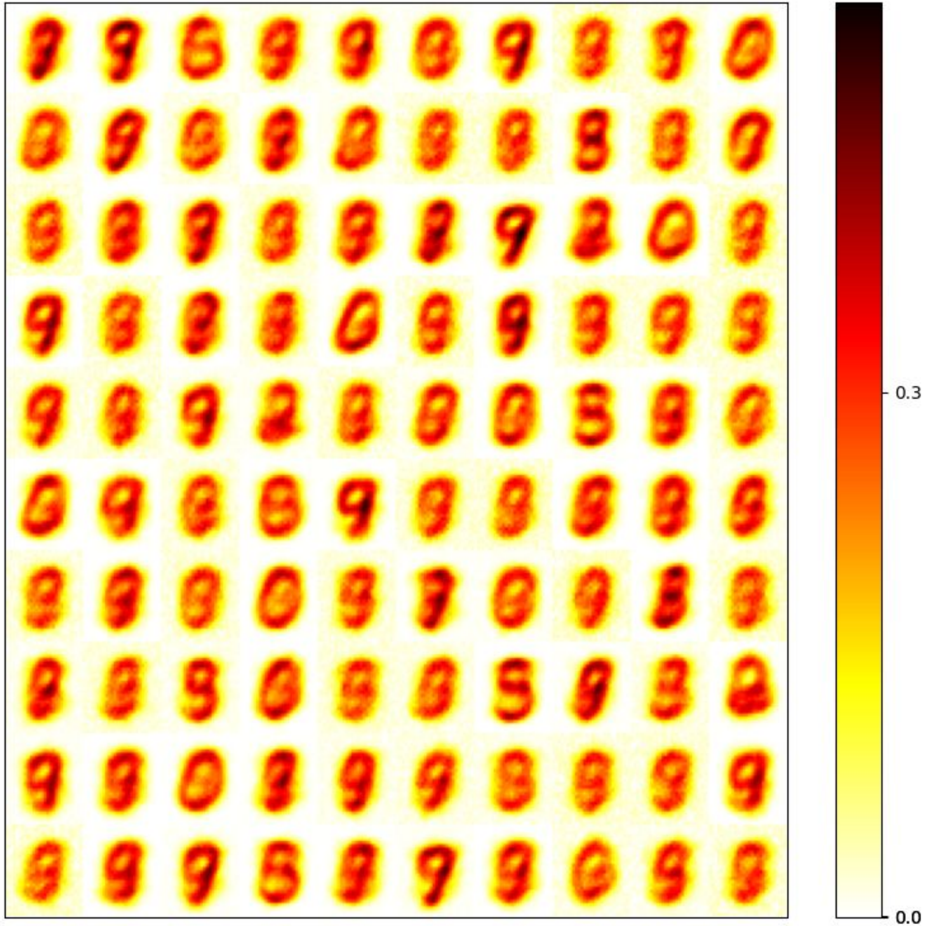
Wiring Motif: one to one



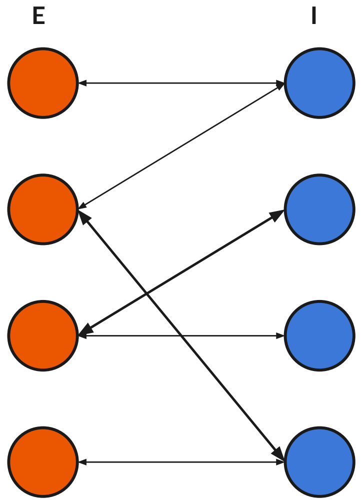


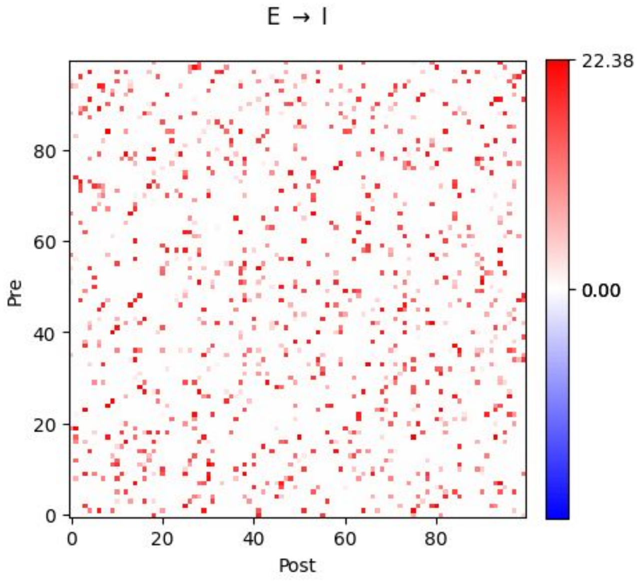


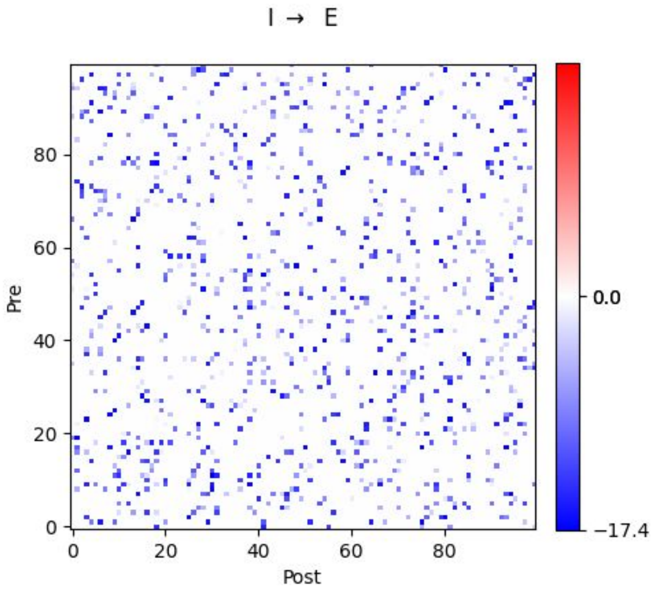
Weights at step: 100



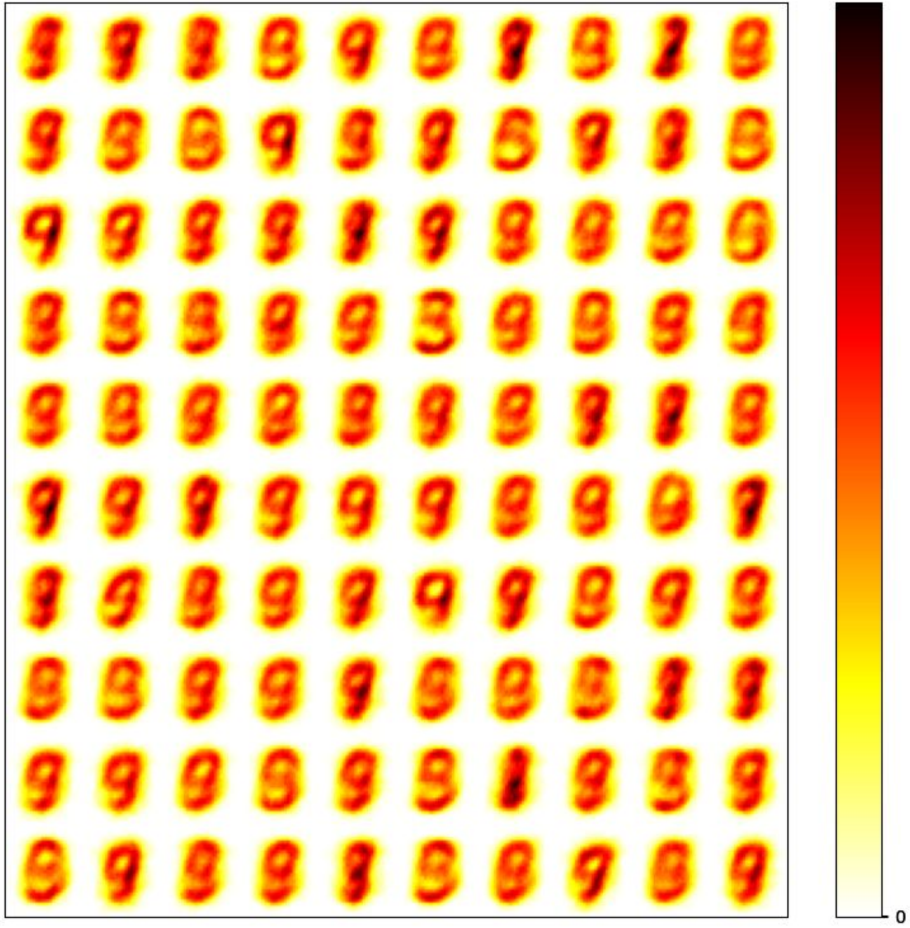
Wiring Motif: random (symmetrical)



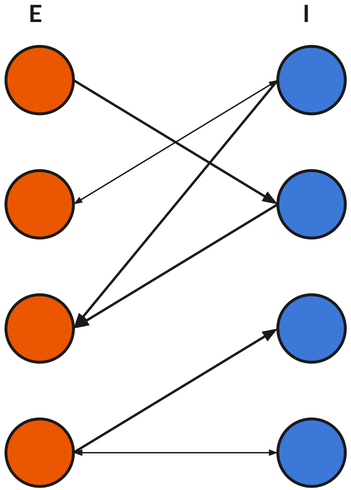


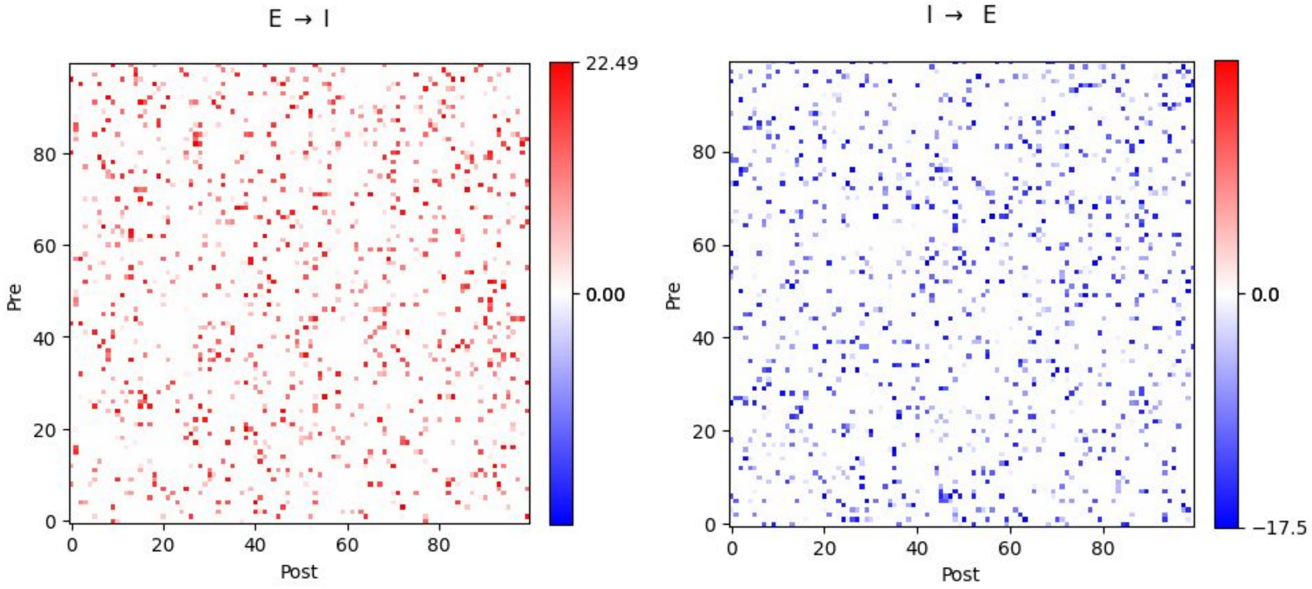


Weights at step: 100

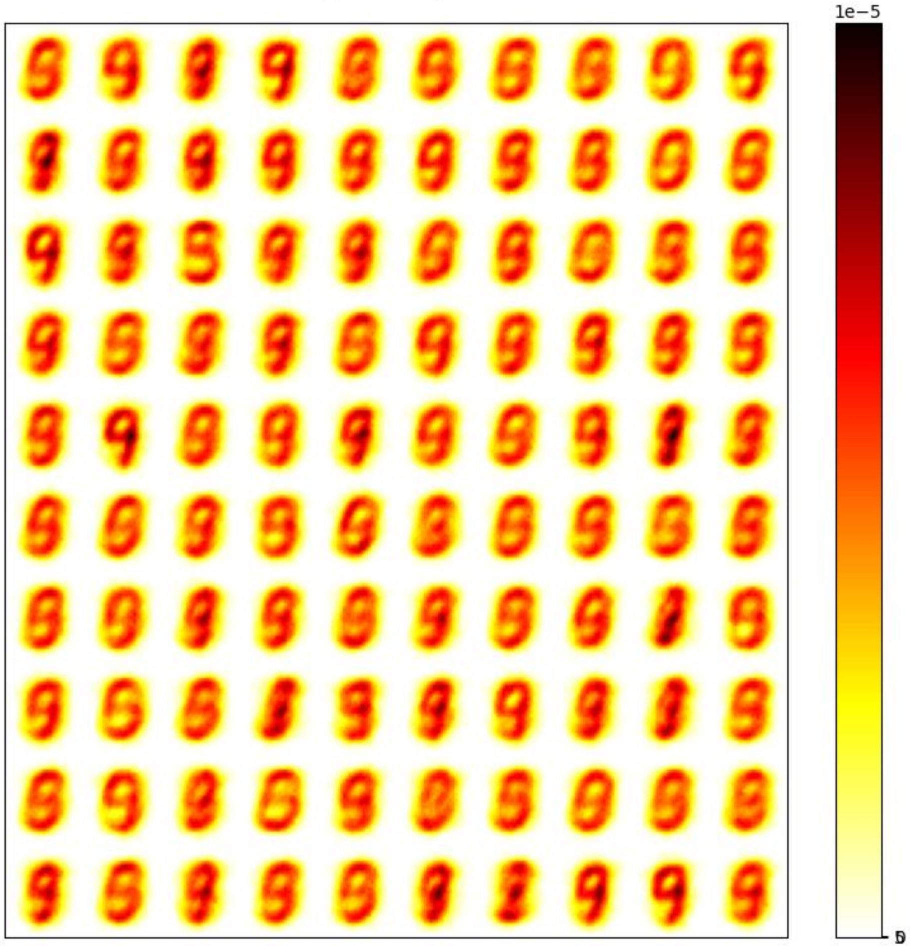


Wiring Motif: random



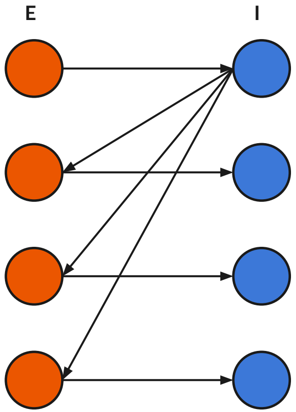


Weights at step: 100

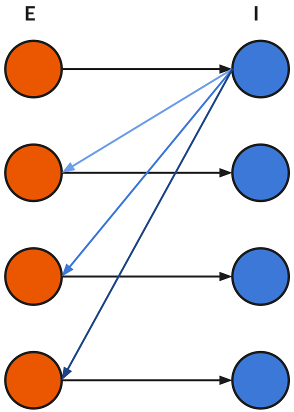


Counter-selective wiring motif

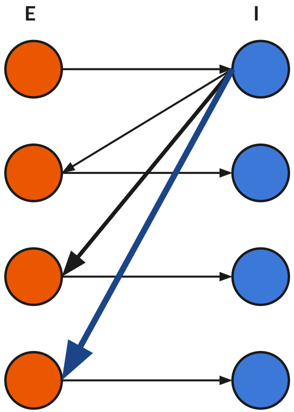
Diehl & Cook, 2015



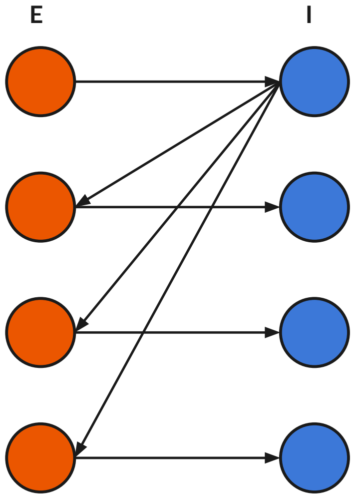
local & random

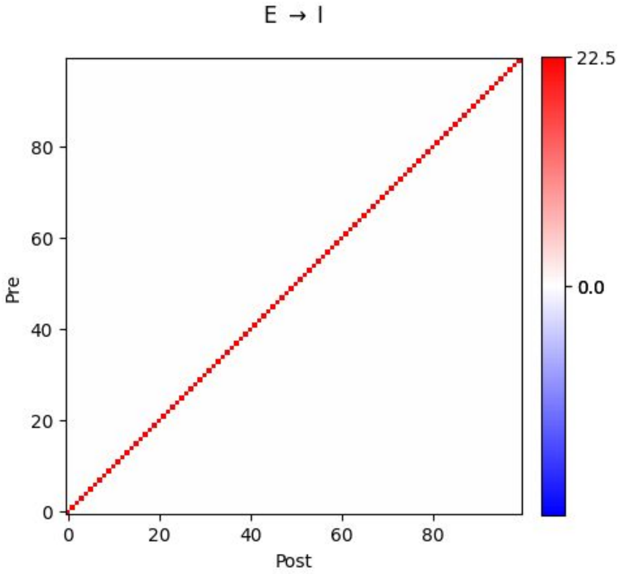


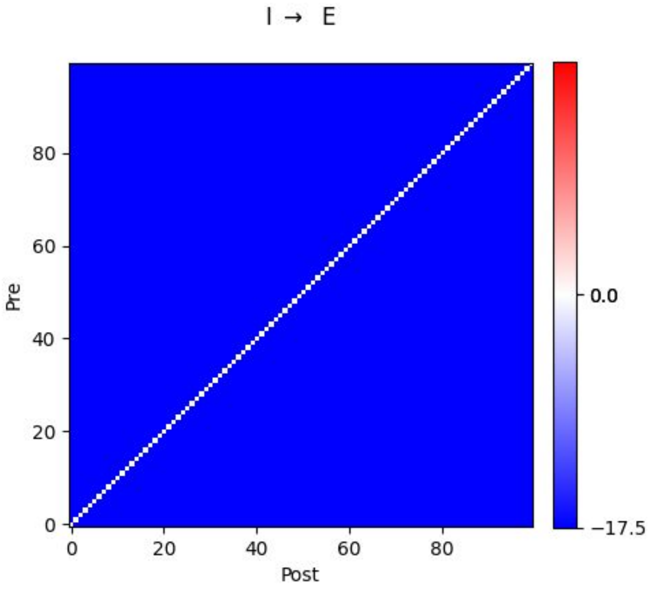
Hazan et al., 2018

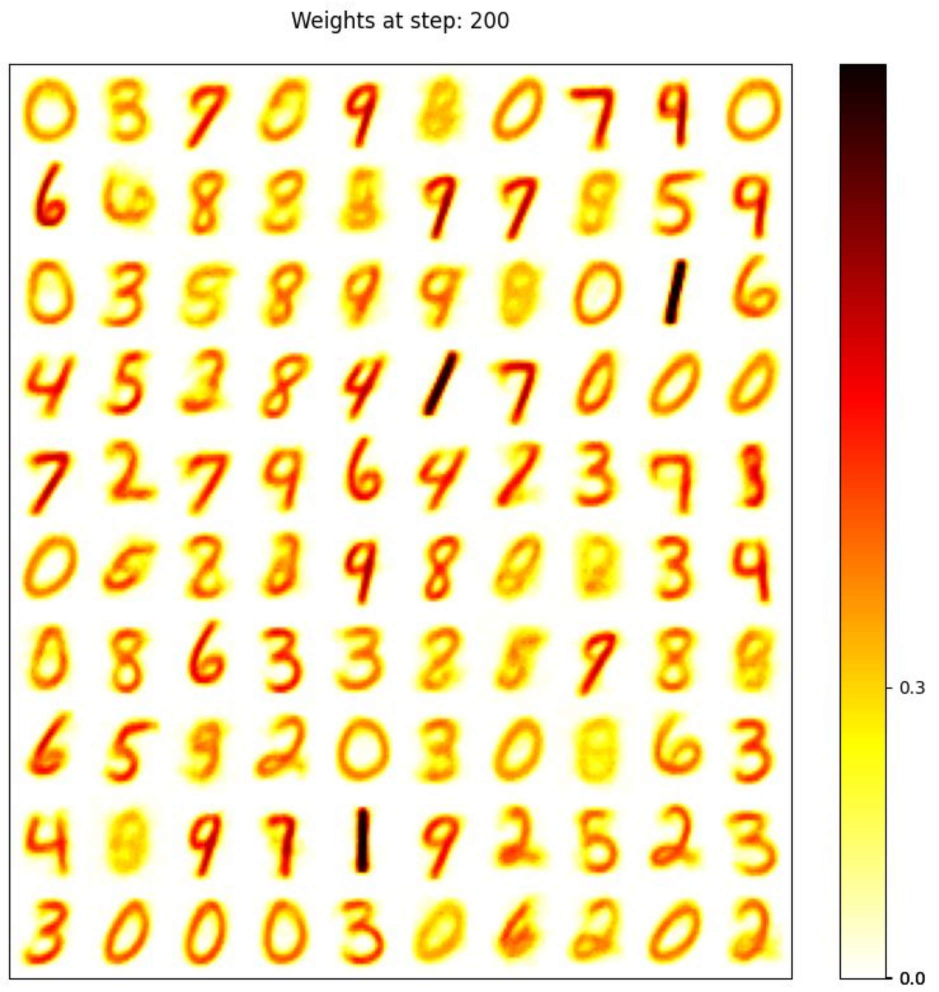


Wiring Motif: Diehl & Cook, 2015

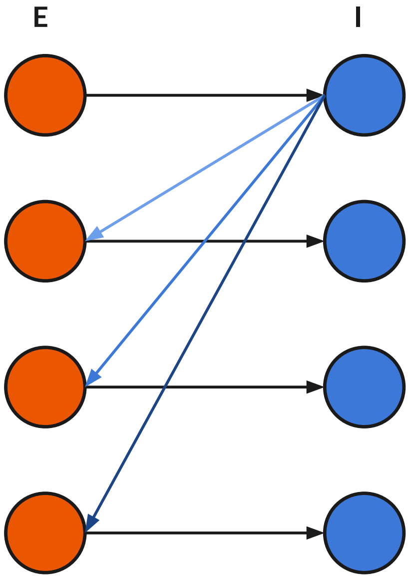


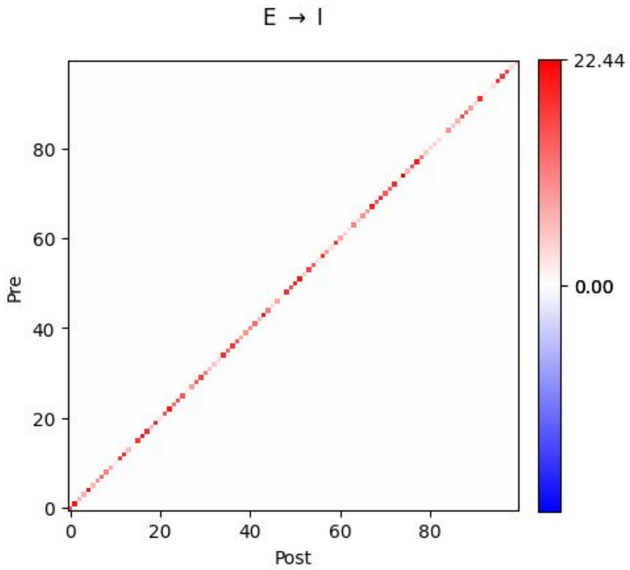


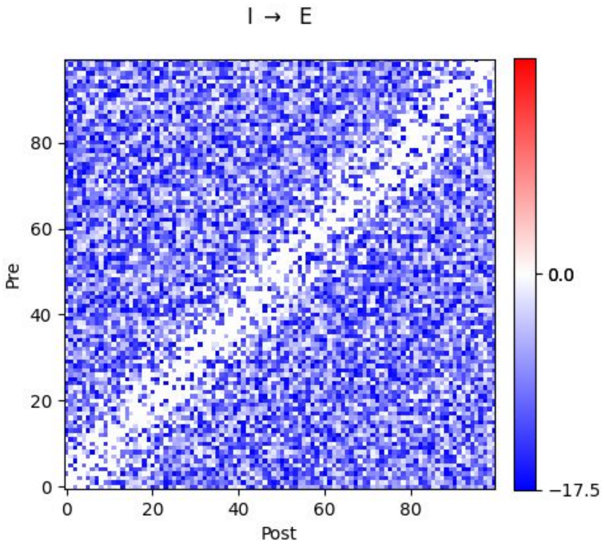



Weights at step: 200
0.3
0.0

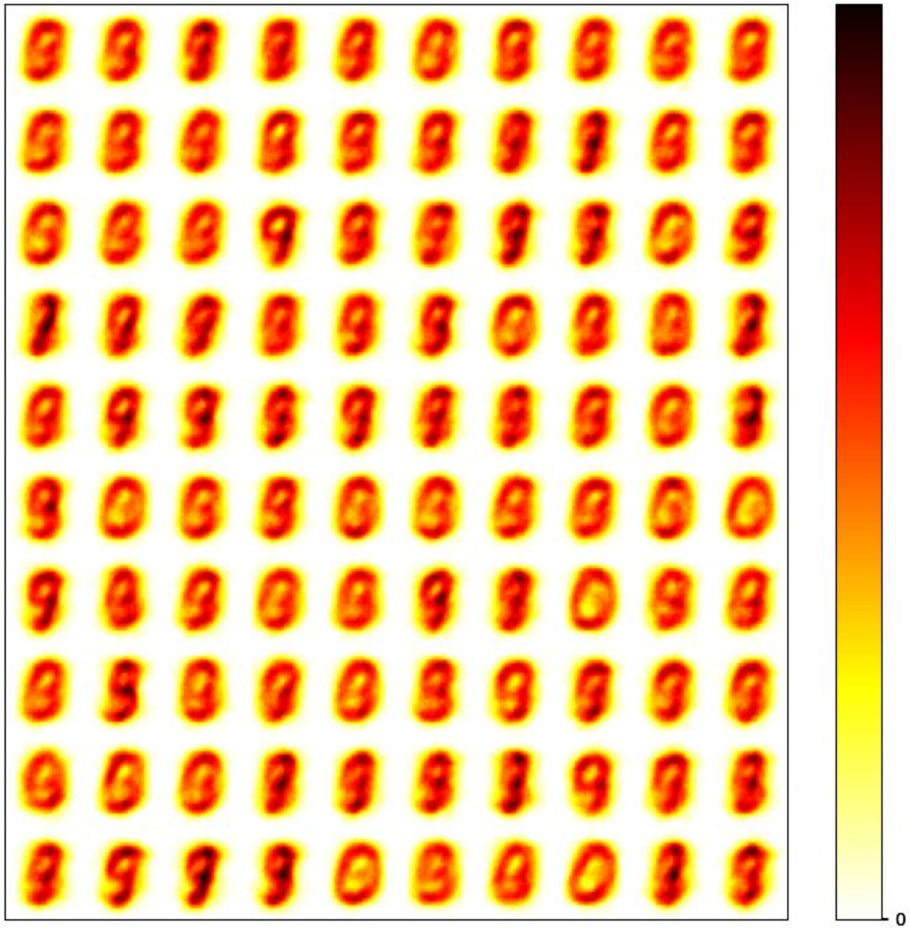
Wiring Motif: local & random



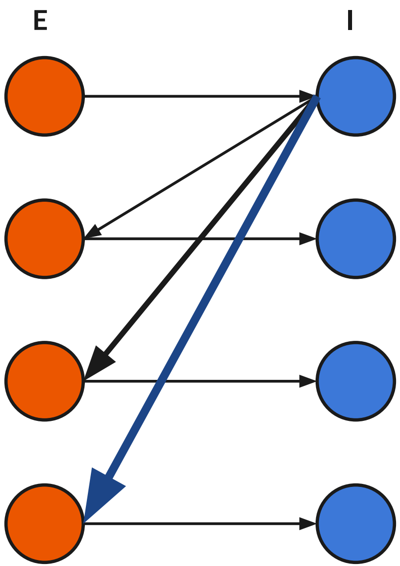


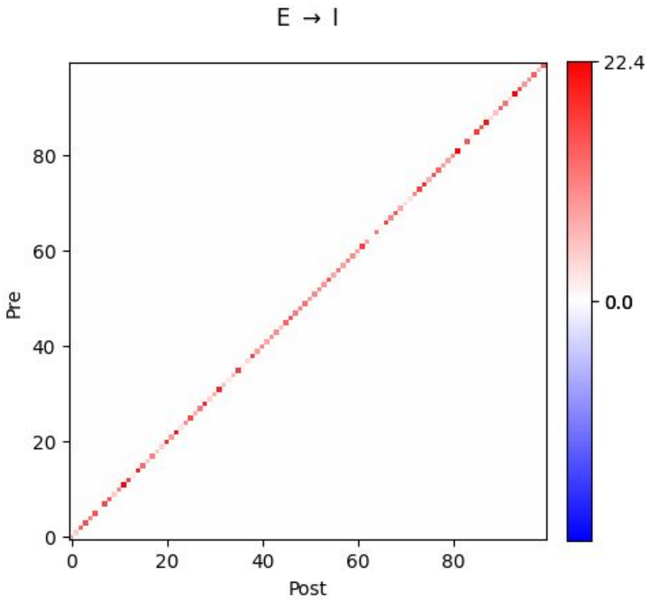


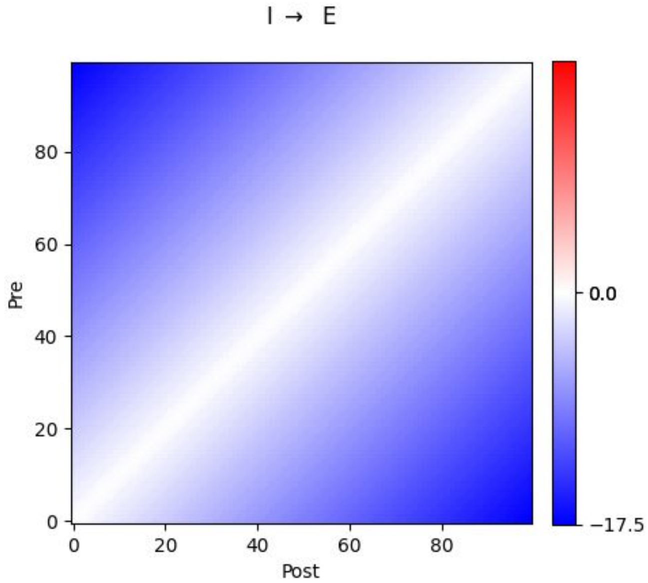
Weights at step: 100



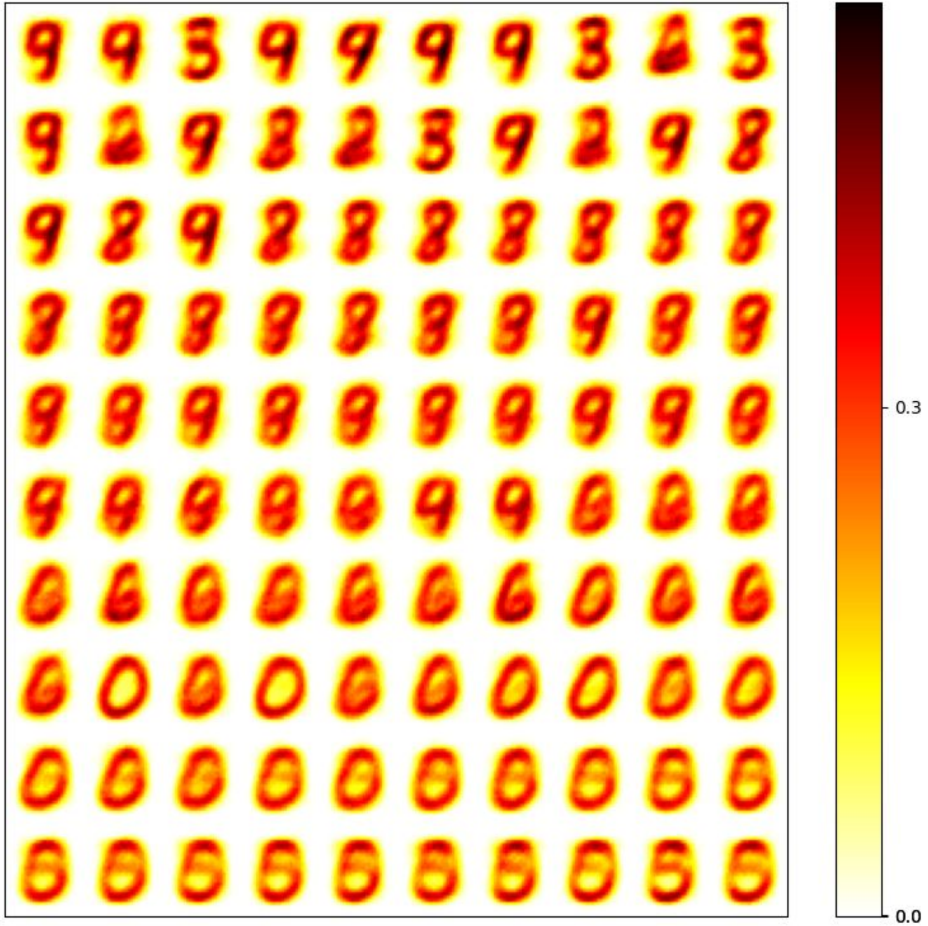
Wiring Motif: Hazan et al., 2018







Weights at step: 300



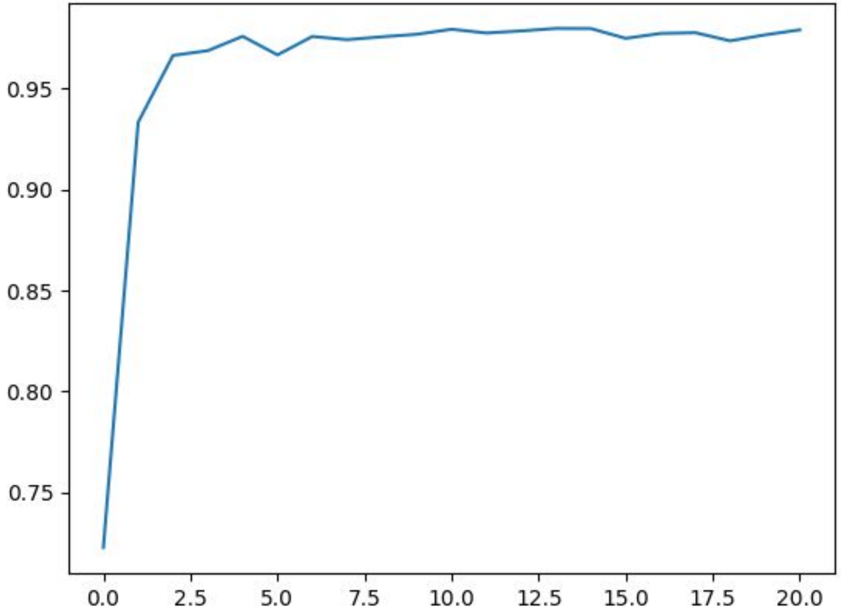
Input Selectivity

$$Sel_d(N) = 1 - \frac{\text{mean response of N with respect to d}}{\text{max response of N with respect to d}}$$

firing rate: $$\nu_k = \frac{n_k^{\mathrm{sp}}}{T}$$

Input Selectivity

Diehl & Cook, 2015

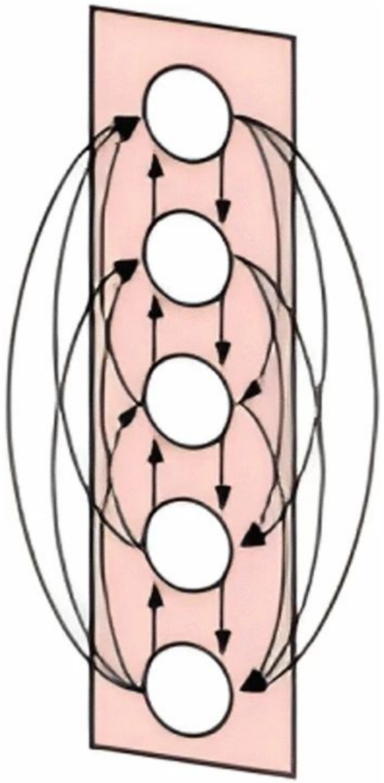


How can inhibitory wiring motifs change the learned representations of the excitatory layer?

- less redundancy
- increased sparsity
- push representations into clusters

Future Work

- Compare with self-connections among excitatory neurons →(Liu, 2024)
- Compare with WTA algorithms
- try continual learning tasks
- test learned representation with adversarial attacks



(Liu, 2024)

Thank you!

Sources (in order)

Mach band effect picture - https://www.numerade.com/ask/question/q3-3-points-consider-the-following-mach-band-visual-illusion-below-the-mach-bands-appear-as-though-there-is-a-gradient-on-either-side-of-the-boundary-between-the-bands-in-reality-each-band-i-48345/

Song, S., Miller, K. D., & Abbott, L. F. (2000). Competitive Hebbian learning through spike-timing-dependent synaptic plasticity. *Nature neuroscience*, *3*(9), 919-926.

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Bengio, Y., Courville, A., & Vincent, P. (2013). Representation learning: A review and new perspectives. *IEEE transactions on pattern analysis and machine intelligence*, *35*(8), 1798-1828.

Hazan, H., Saunders, D., Sanghavi, D. T., Siegelmann, H., & Kozma, R. (2018, July). Unsupervised learning with self-organizing spiking neural networks. In *2018 International Joint Conference on Neural Networks (IJCNN)* (pp. 1-6). IEEE.

Liu, X. (2024). Inhibition SNN: unveiling the efficacy of various lateral inhibition learning in image pattern recognition. *Discover Applied Sciences*, *6*(11), 611.