DevNCA

Co-Evolving Developmental Patterns and Plasticity Rules for Self-Organising Spiking Neural Networks

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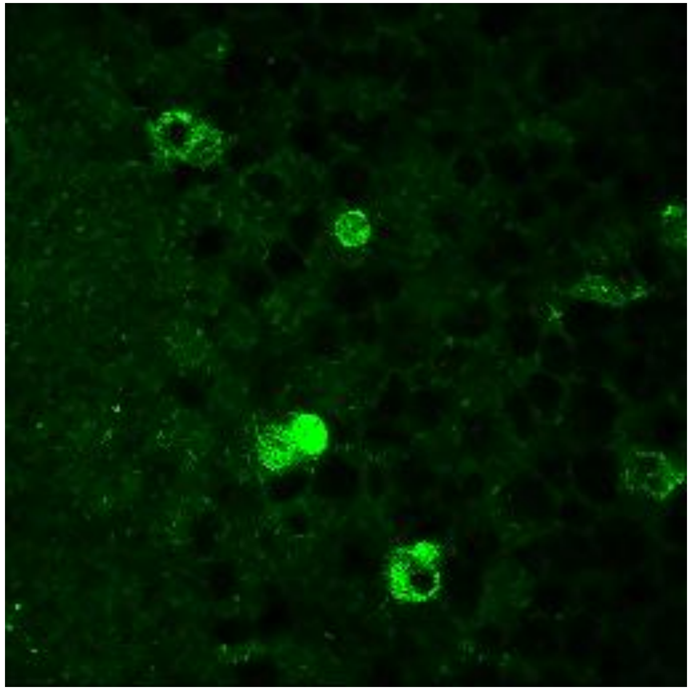

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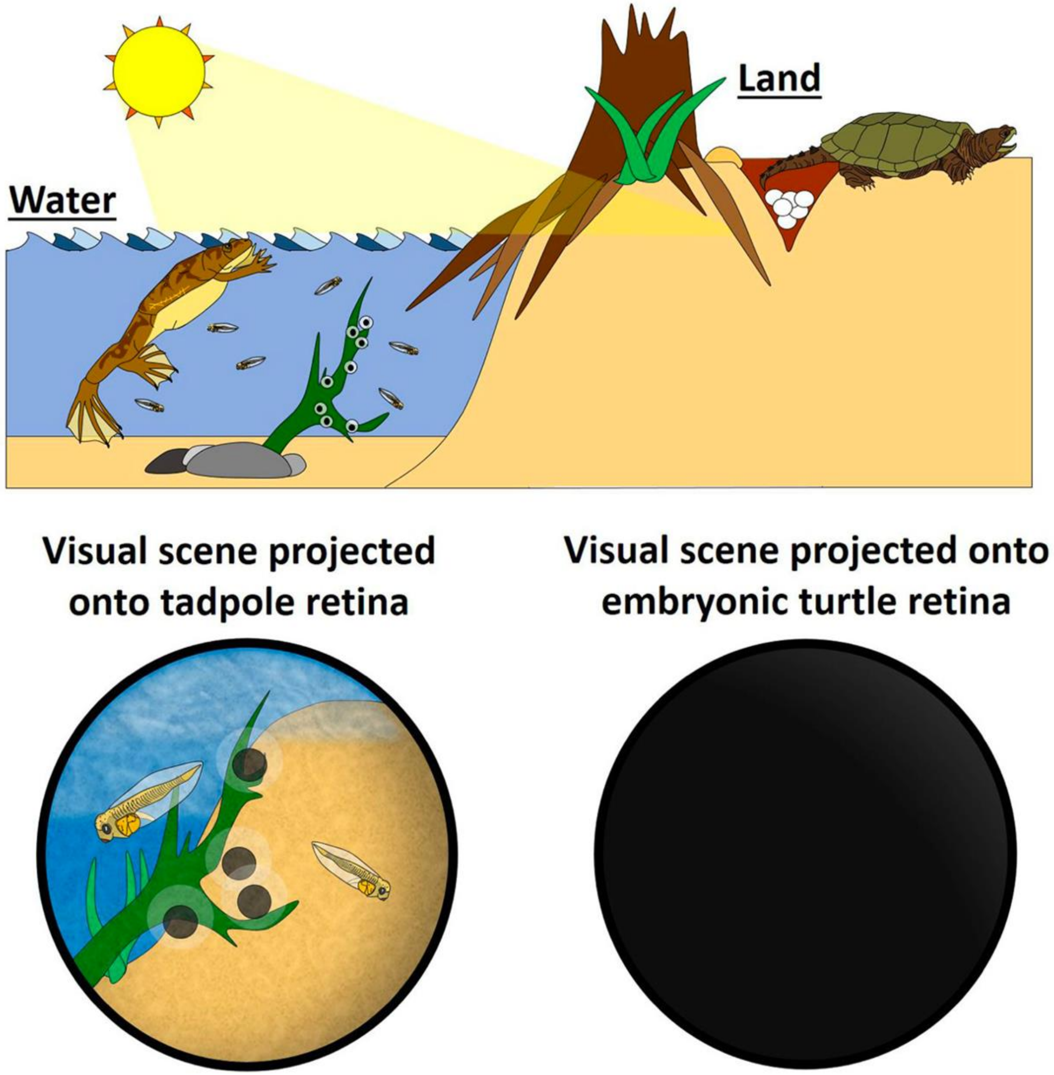
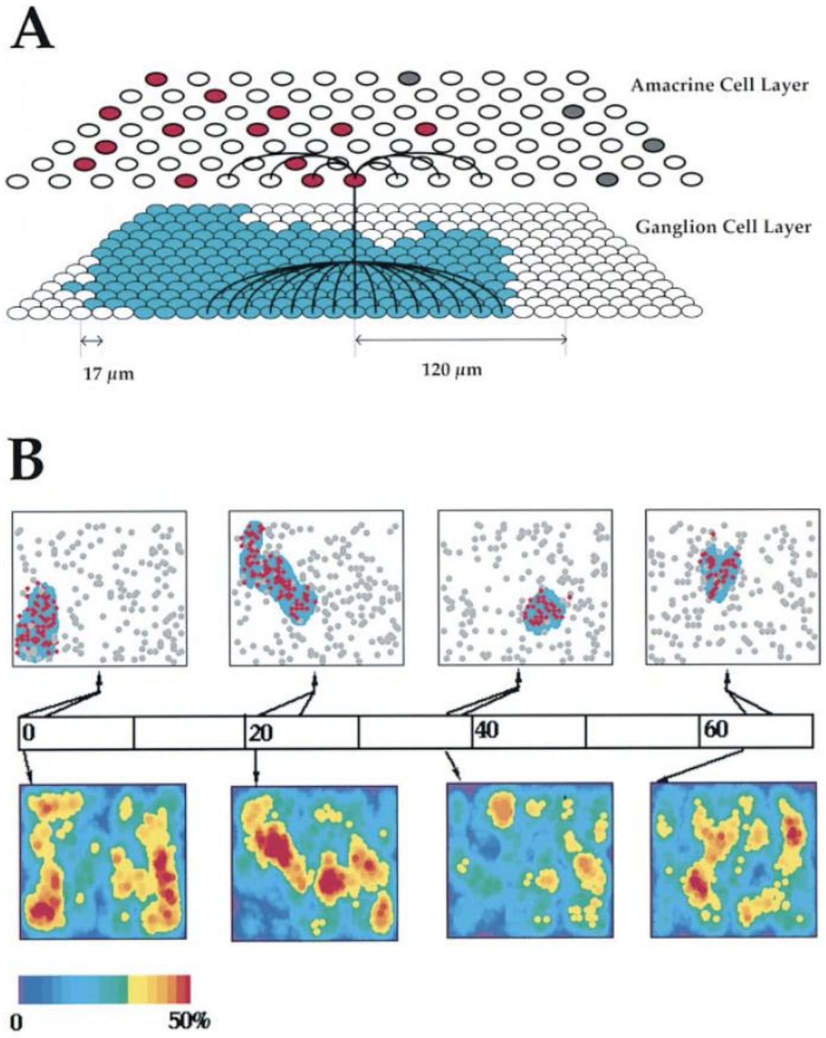
Background



Water
Land
Visual scene projected onto tadpole retina
Visual scene projected onto embryonic turtle retina

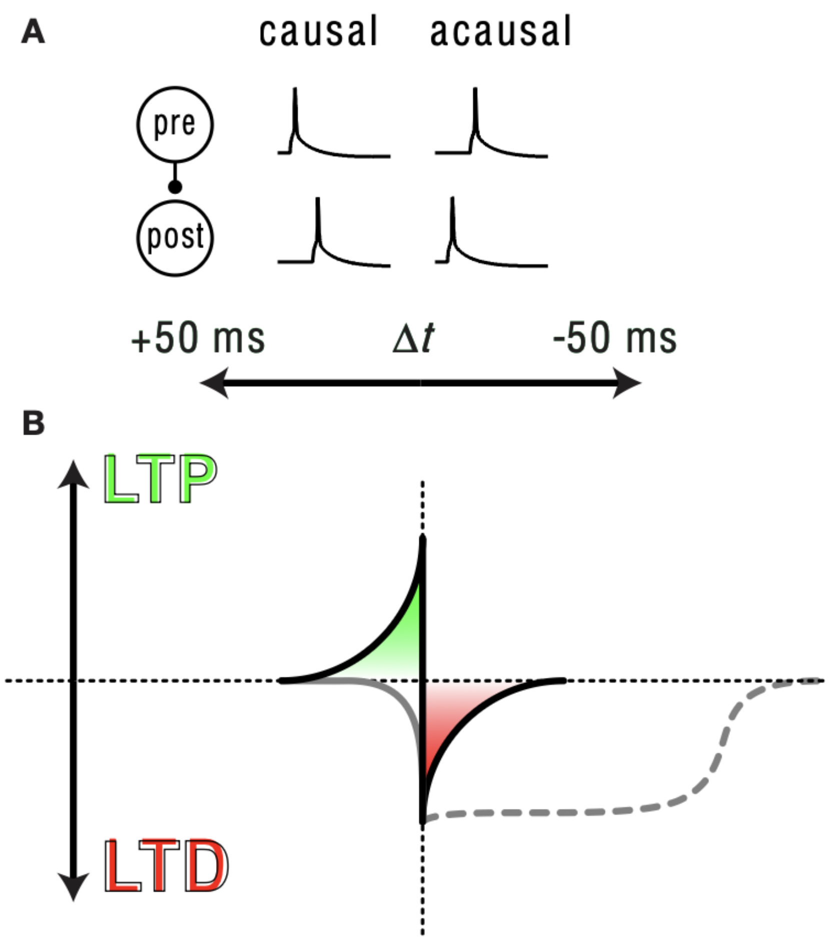
Spontaneous Retinal Waves



What is STDP?

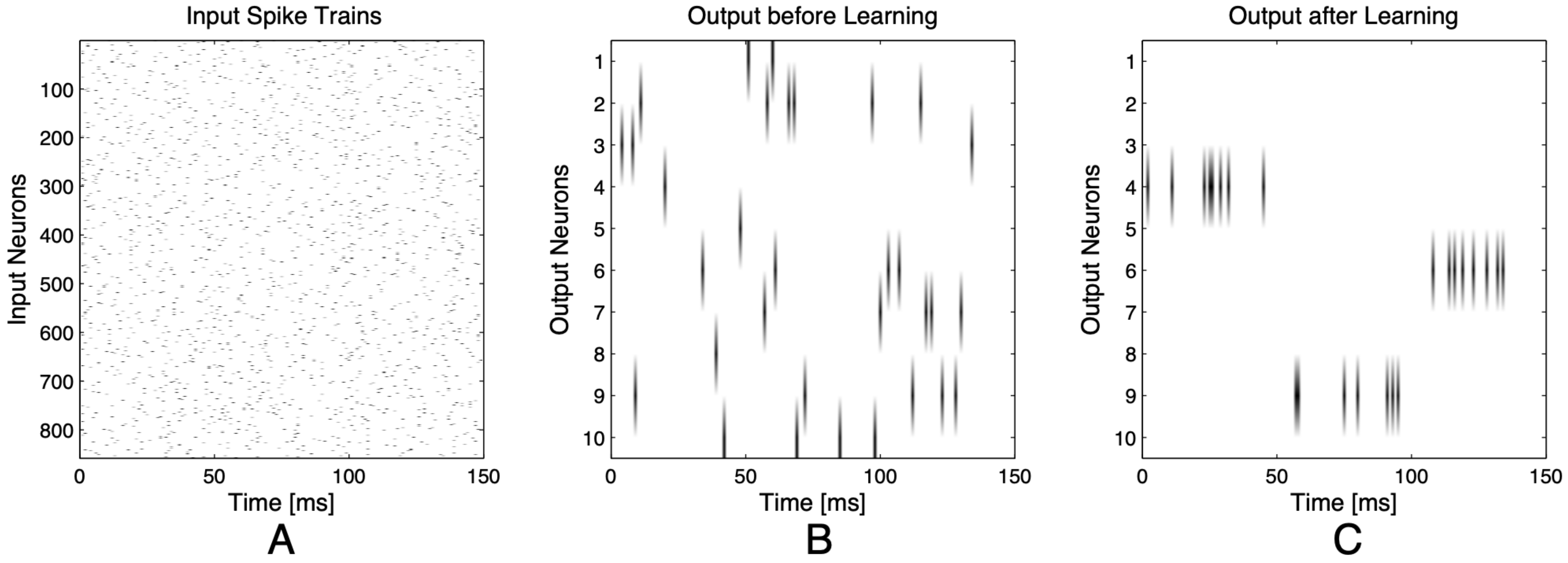
“When an axon of cell A is near enough to excite a cell B and repeatedly or persistently **takes part in firing it**, some growth process or metabolic change takes place in one or both cells such that **A’s efficiency, as one of the cells firing B, is increased**.”

—Donald Hebb (1949)



What is the function of STDP?

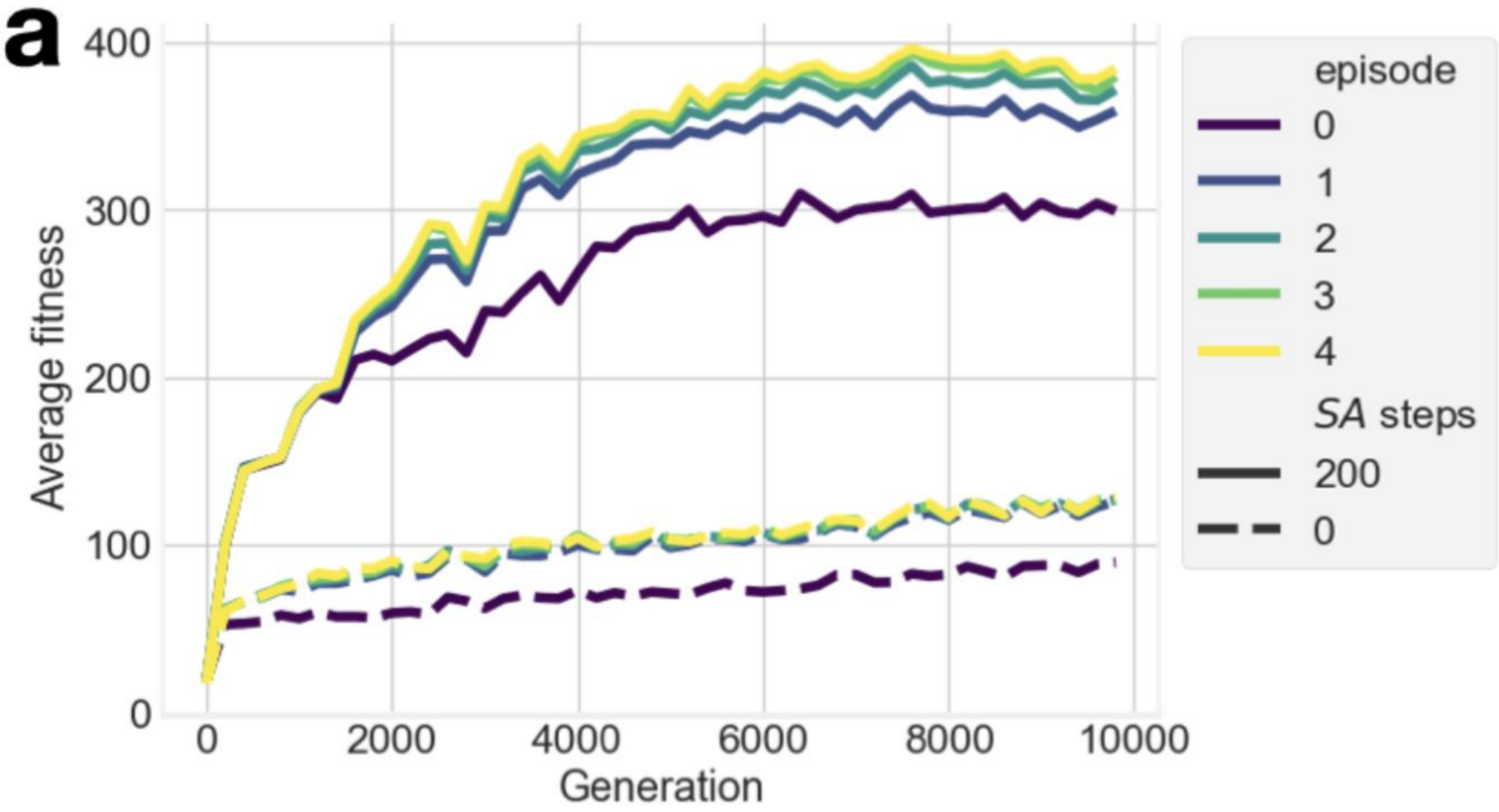
STDP enables spiking neurons to detect hidden causes of their inputs (Nessler et al., 2009)



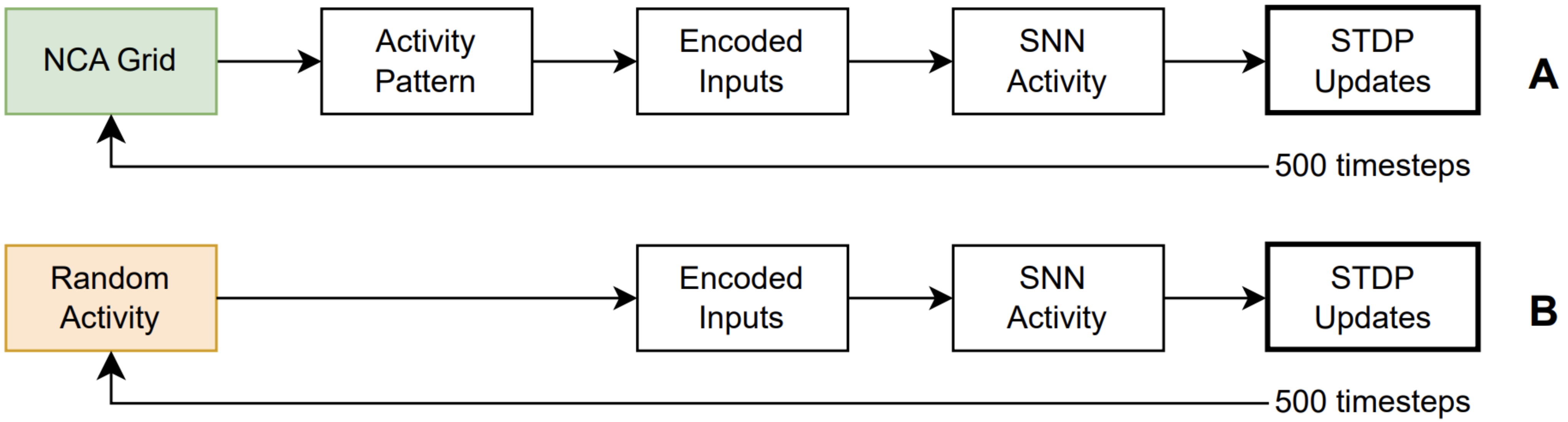
Methods

Spontaneous activity in self-organised control

Evolving Self-Assembling Neural Networks (Plantec et al., 2024)



Developmental Phase

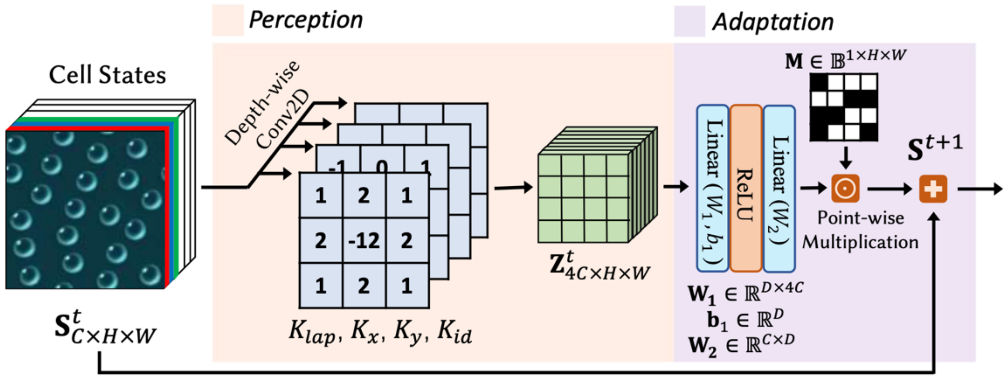


NCA Parameters

Emergent Dynamics in Neural Cellular Automata (Xu et al., 2024)

Xu et al. (2024): “We empirically find that the **number of hidden neurons** should be **larger than the number of channels** and that **their ratio should be at least greater than 2.0** for an NCA to display emergent dynamics.”

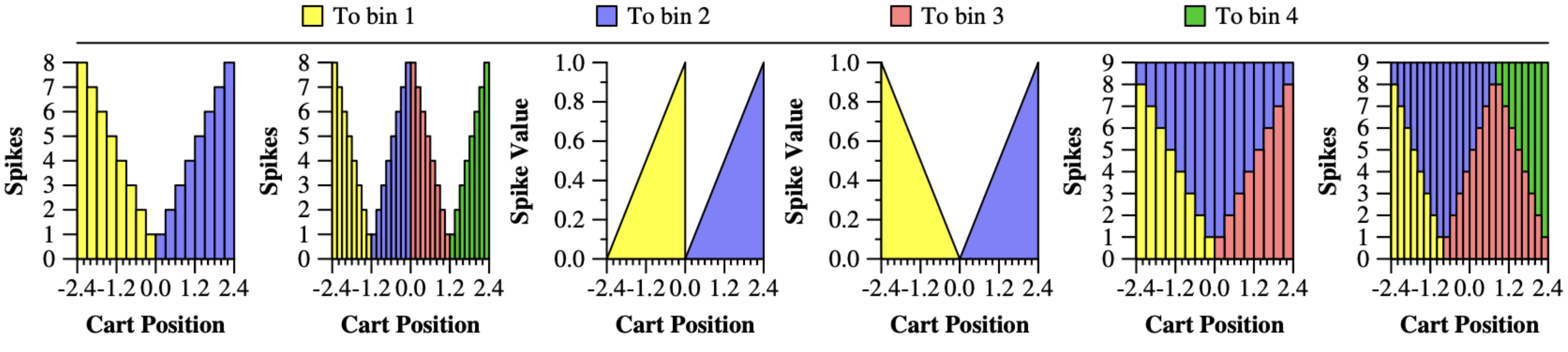
- **24 neurons**
- **8 channels**



Dynamic textures synthesized by NCA models with different Channels (C) and Hiddens (D). When D<2C, NCA struggles to be dynamic and gets stuck in local minima, where artifacts appear in the generated textures.

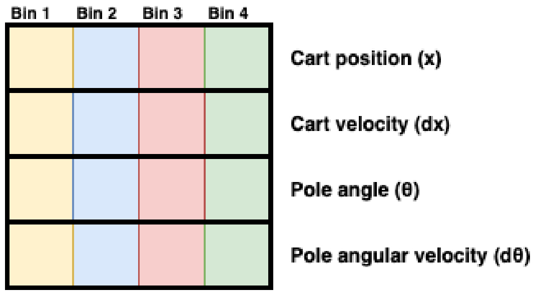
Encoding and Decoding

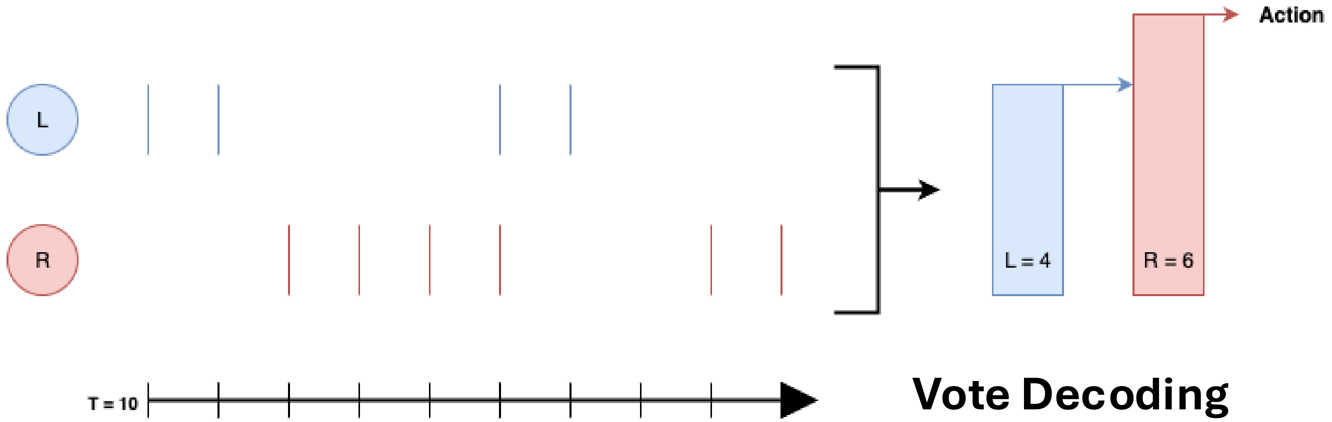
The Cart-Pole Application as a Benchmark for Neuromorphic Computing (Plank et al. 2025)



(a) Spike-FF-2 (b) Spike-FF-4 (c) Val-B-2 (d) Val-FF-2 (e) Argyle-3 (f) Argyle-4

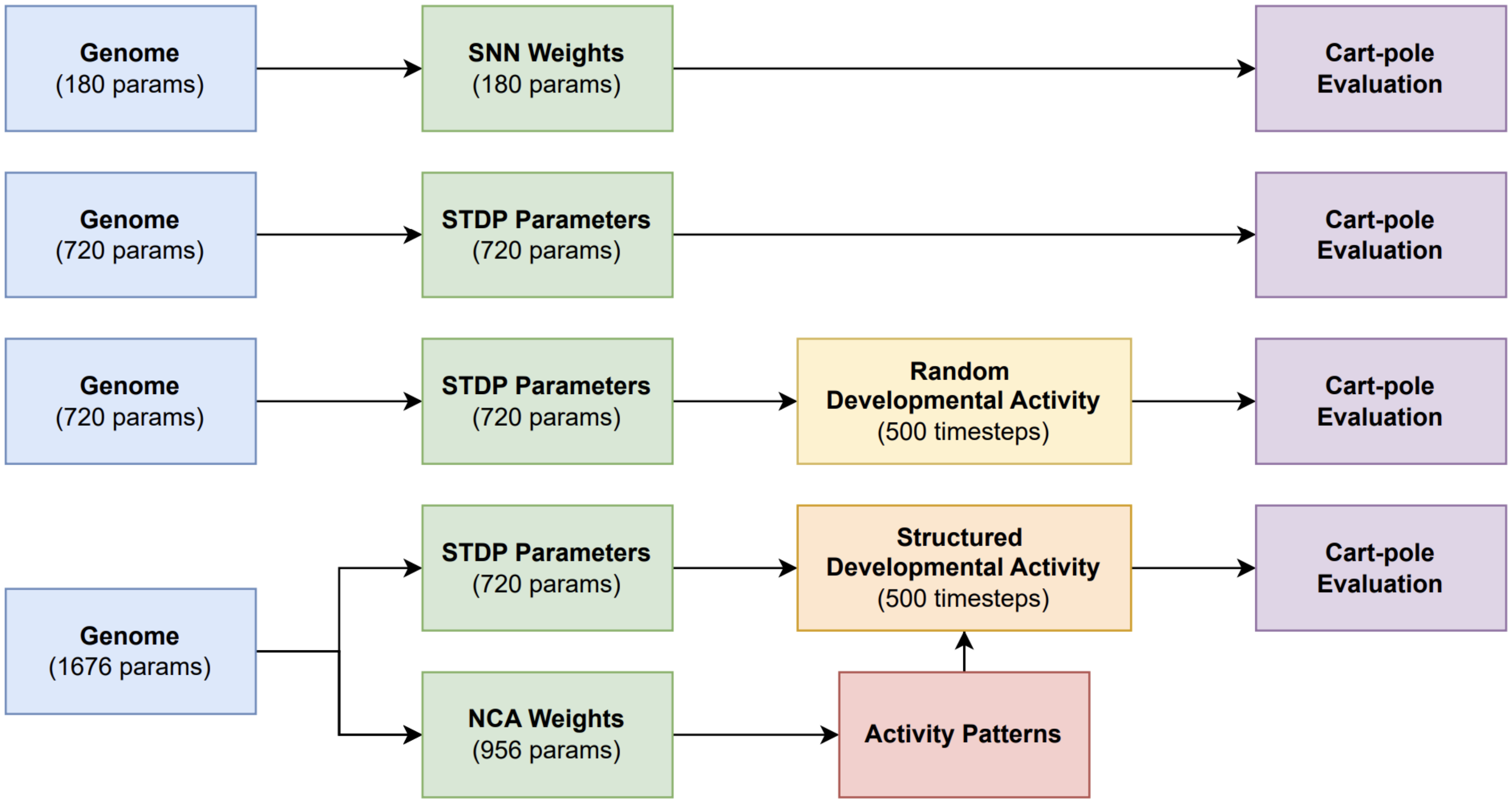
Spike FF-4 Encoding



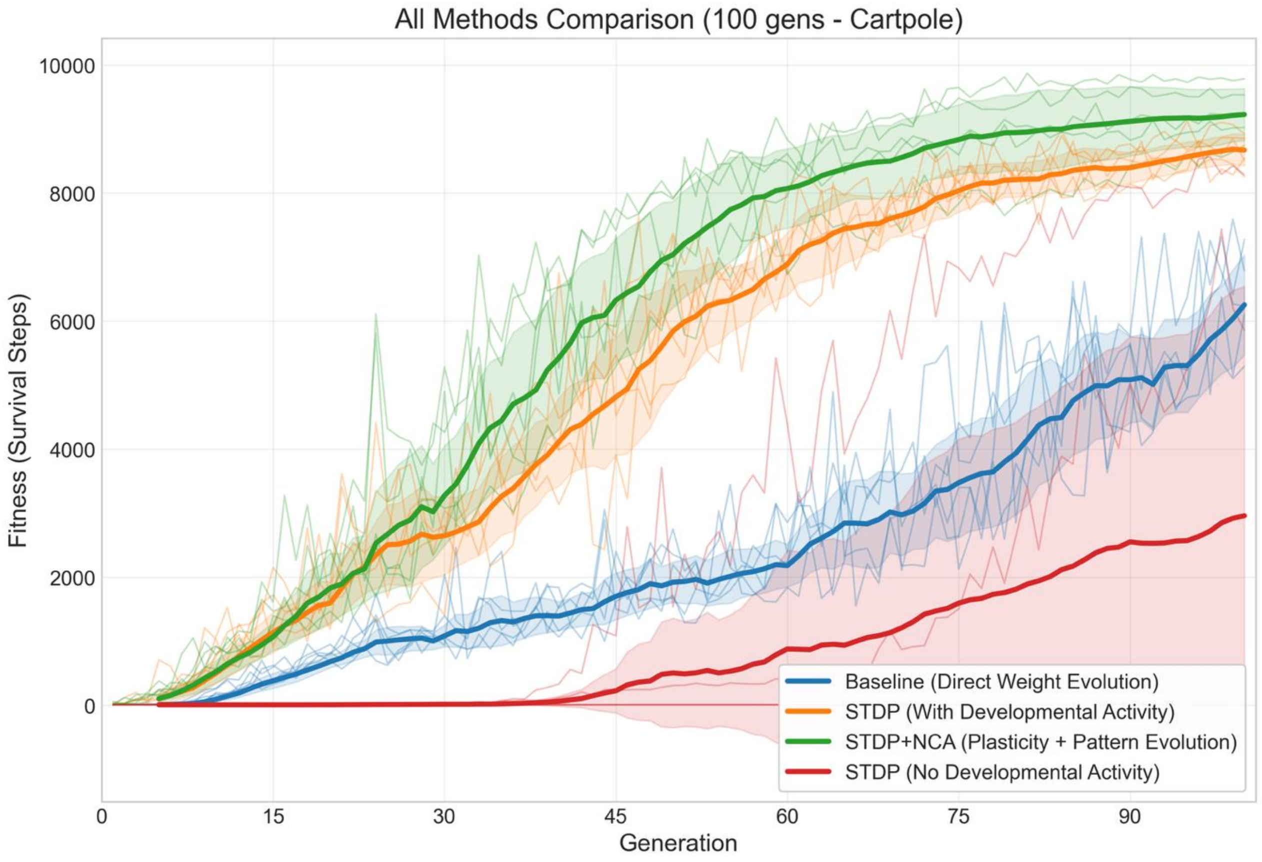


Vote Decoding

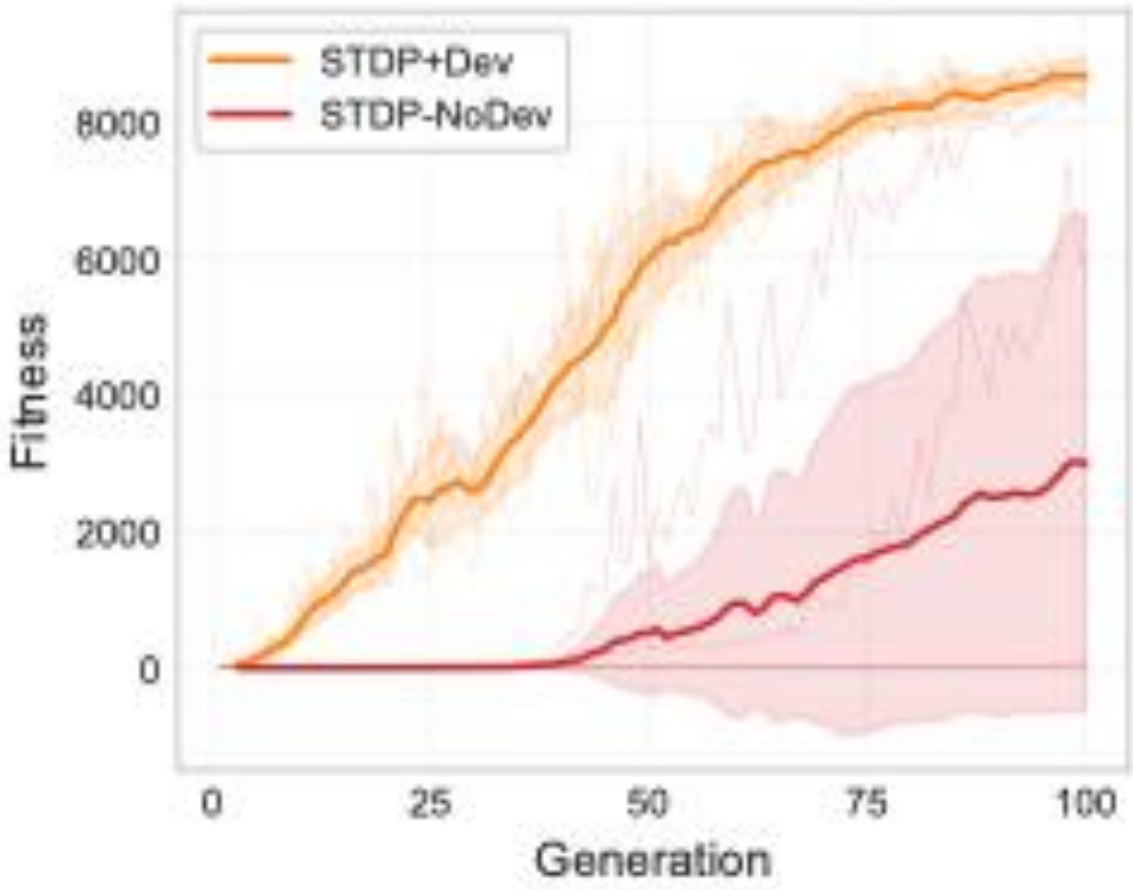
Experimental Conditions



Results

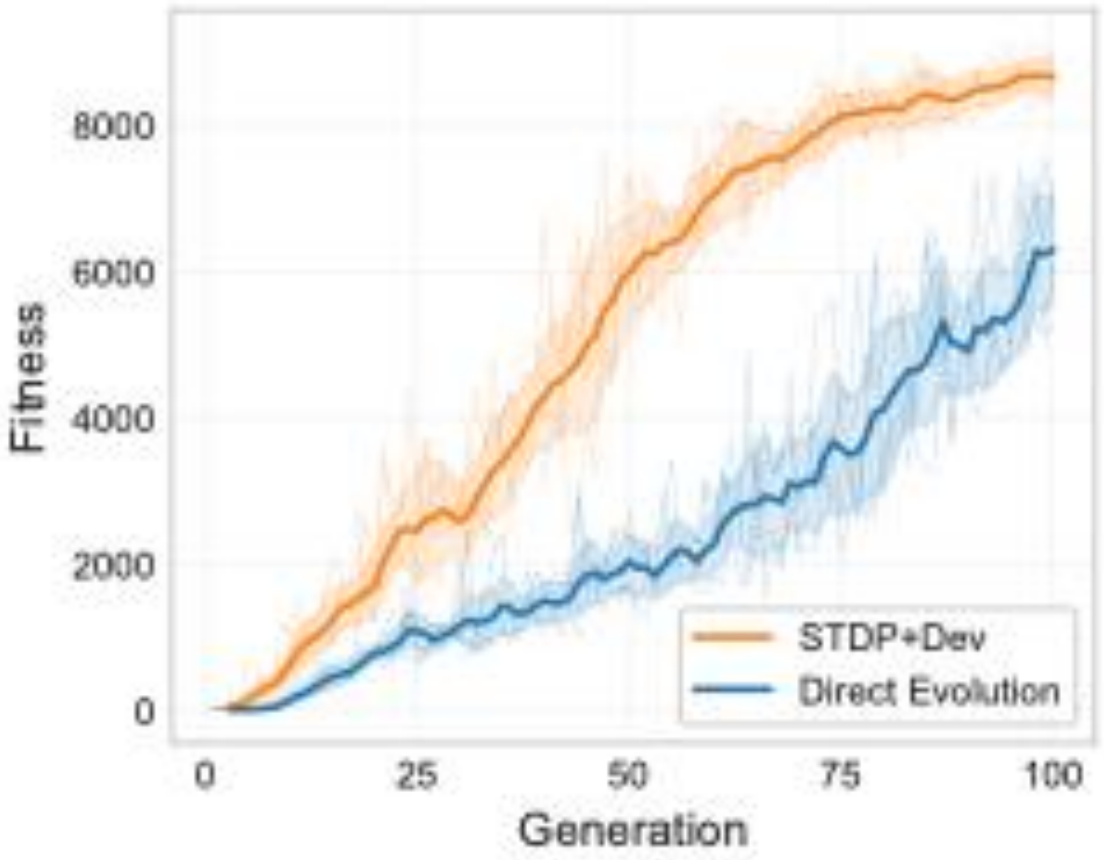

All Methods Comparison (100 gens - Cartpole)
Fitness (Survival Steps)
Generation
0
2000
4000
6000
8000
10000
0
15
30
45
60
75
90
Baseline (Direct Weight Evolution)
STDP (With Developmental Activity)
STDP+NCA (Plasticity + Pattern Evolution)
STDP (No Developmental Activity)

Developmental activity is essential for plasticity



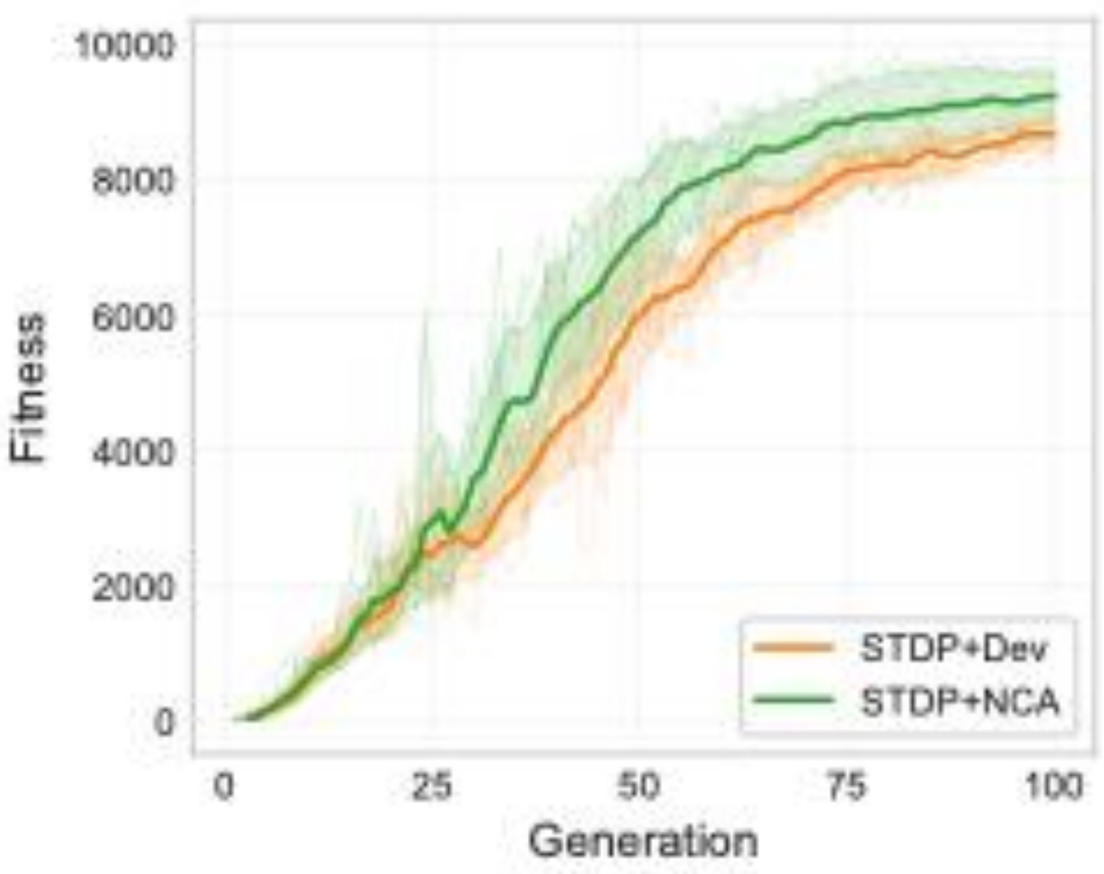
- **66% performance reduction**
  - **STDP+Dev:** 8617.1 ± 244.3
  - **STDP-NoDev:** 2858.6 ± 3524.8
  - t = 3.260, **p = 0.0307**

Plasticity rules outperform direct weight evolution



- **36% higher fitness**
  - **Direct:** 8617.1 ± 244.3
  - **STDP+Dev:** 6338.9 ± 668.0
  - t = -6.406, **p = 0.0013**

Structured patterns enhance task performance



- **7.5% improvement**
  - **STDP+NCA:** 9261.7 ± 367.3
  - **STDP+Dev:** 8617.1 ± 244.3
  - t = -2.923, **p = 0.0224**

Discussion

Key Findings and Limitations

- Spontaneous activity structures self-organization through its interaction with plasticity rules
- This lets the network avoid ruts during plastic self-organization
- Patterns encode compressed structures that help guide the network towards fit attractors

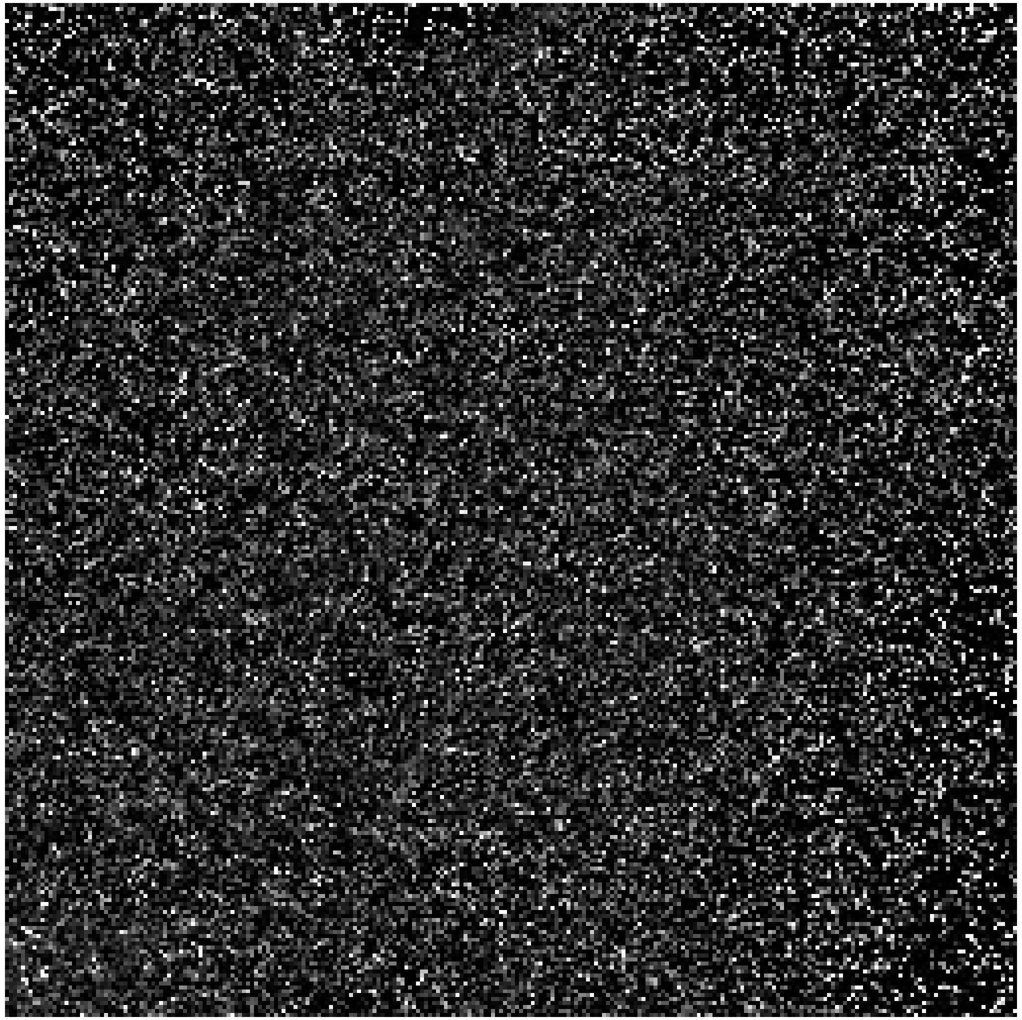
- Genome sizes are too large
  - Indirect encoding (e.g., HyperNEAT)
- Cartpole task is too limited
  - More tasks: discrete, continuous
- Hyperparameter space should be systematically explored
  - Initialization, types of randomness, sampling intervals, activity duration, NCA mapping, encoding methods, etc.
- What parts of the patterns matter?
  - Shuffling tests (Ligeralde et al., 2023)

Further Directions

- Spontaneous activity is usually not inert
  - We inject activity without effect (cf. foetal motor activity in utero)
  - This involves learning about embodiment as much as environment
- Spontaneous activity is not solely developmental
  - Neural activity is more sculpted spontaneity than input–output
  - NCAs could equally be used to generate on-line intrinsic activity
  - This may help with homeostatic criticality, motor babbling, etc.

Summary

- Spontaneous developmental activity is observed in many amniotic species
  - Best-known are retinal waves that structure the early visual system, but also sensory and motor
- We extend this thread to examine self-organizing control networks by evolving plasticity rules with random activity and then NCAs used as pattern generators
  - This confirms earlier findings on the importance of developmental activity (Plantec et al., 2024)
  - We extend these to show structured patterns can outperform random developmental activity
  - NCAs can thus serve as biologically-plausible generators for activity as well as morphogenesis



End.

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Further Slides—

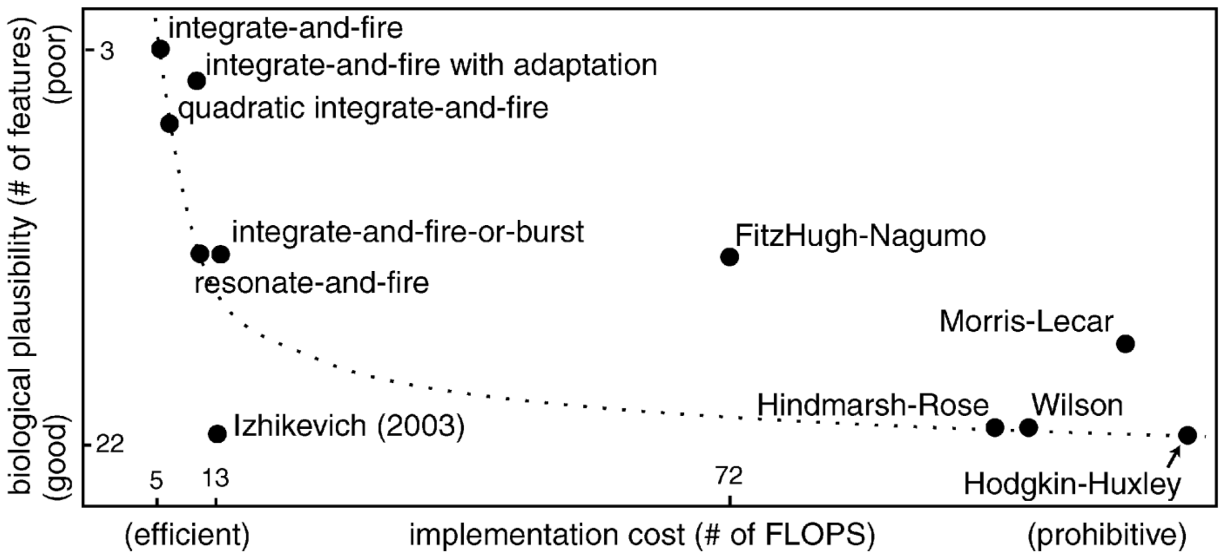
Cartpole Environment

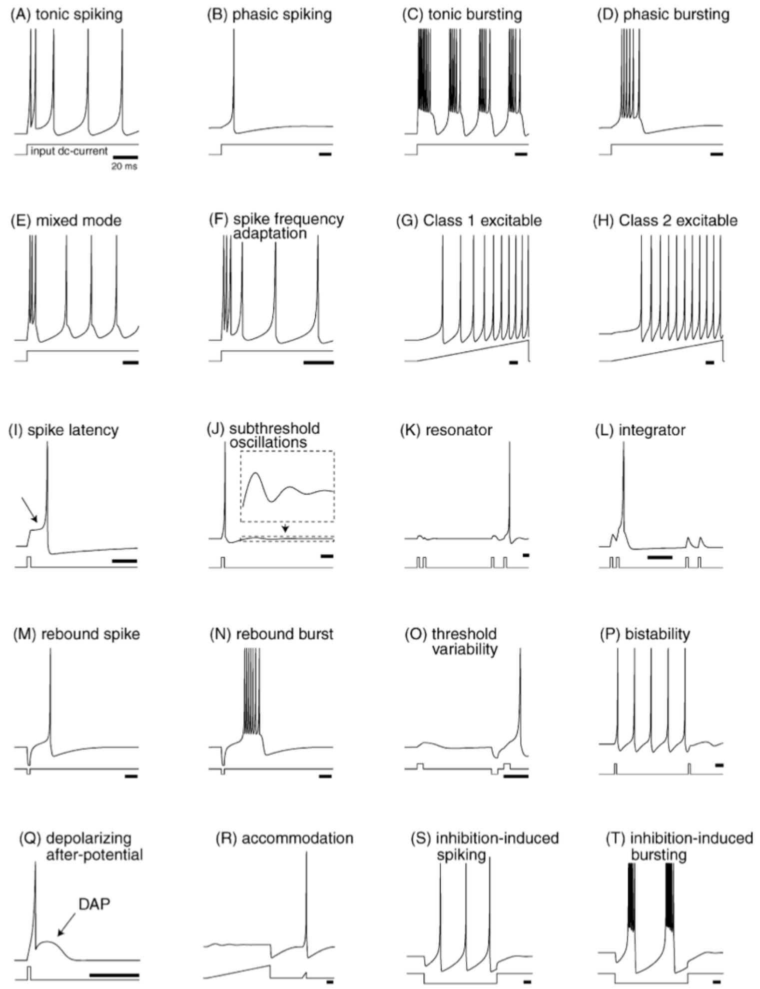
The Cart-Pole Application as a Benchmark for Neuromorphic Computing (Plank et al. 2025)

- **State Space—**
  - Four variables: cart position, cart velocity, pole angle, and pole angular velocity.
- **Action Space—**
  - The agent can apply force to the left or right (2 actions).
- **Reward Structure—**
  - Agents receive a reward of 1.0 for each timestep the pole remains upright.
- **Initial Conditions—**
  - Cart position $[-1.2, 1.2]$, pole angle $[-0.10475, 0.10475]$ radians.
- **Termination Conditions—**
  - Episodes terminate when the pole angle exceeds 12 degrees, the cart exceeds 2.4 units from centre, or 10,000 timesteps are reached.
- **Performance Metric—**
  - Fitness is measured by the average number of timesteps across 80 trials.

Neuron Model

Simple Model of Spiking Neurons (Izhikevich, 2003)





Following Izhikevich (2003), hidden layers use a **4:1 E/I ratio:**

- **Excitatory: Regular Spiking** (*a= 0.02, b = 0.2, c =−65 mV, d = 8*)
- **Inhibitory: Fast Spiking** (*a = 0.1, b = 0.2, c =−65 mV, d = 2*)

Plasticity Rule

Learning the Plasticity: Plasticity-Driven Learning Framework in Spiking Neural Networks (Shen et al., 2024)

$$\Delta w_{i,j} = \eta \left(\underbrace{A_{i,j} x_i (x_j - C_{i,j})}_{\text{Synaptic Cooperation Plasticity (SCP)}} + \underbrace{B_{i,j} x_j + D_{i,j}}_{\text{Presynaptic-Dependent Plasticity (PDP)}} \right)$$

A: Controls correlation-based strengthening

B: Regulates presynaptic influence and network stability

C: Sets threshold for postsynaptic activity effects

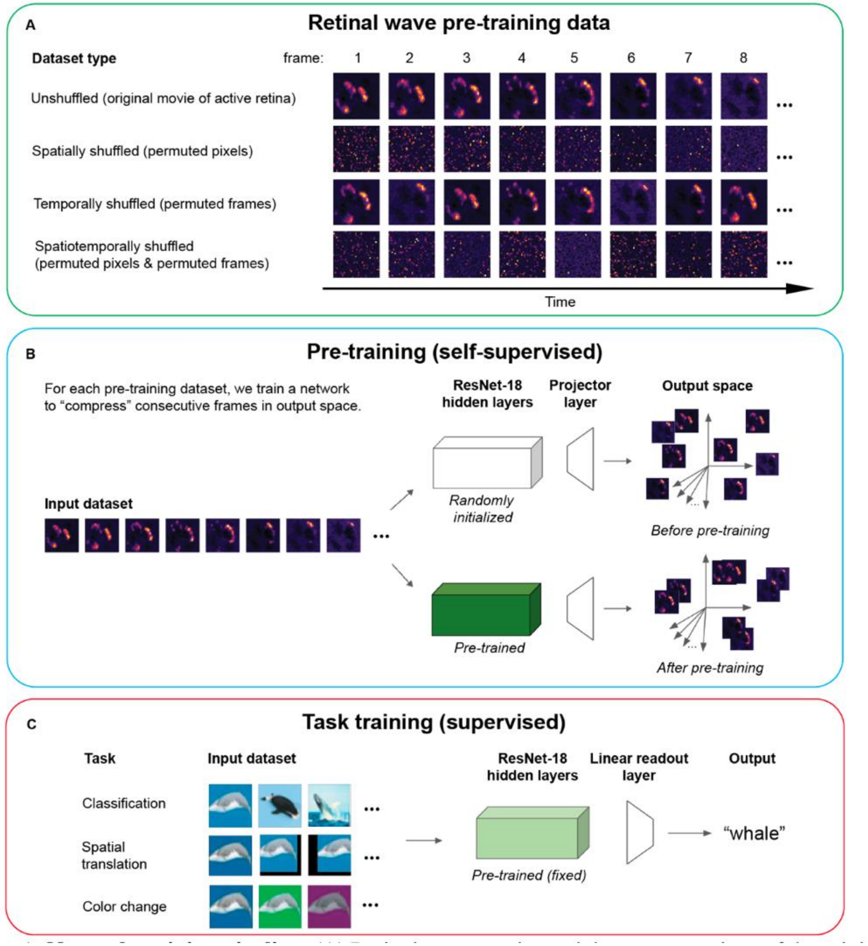
D: Provides baseline synaptic adjustment

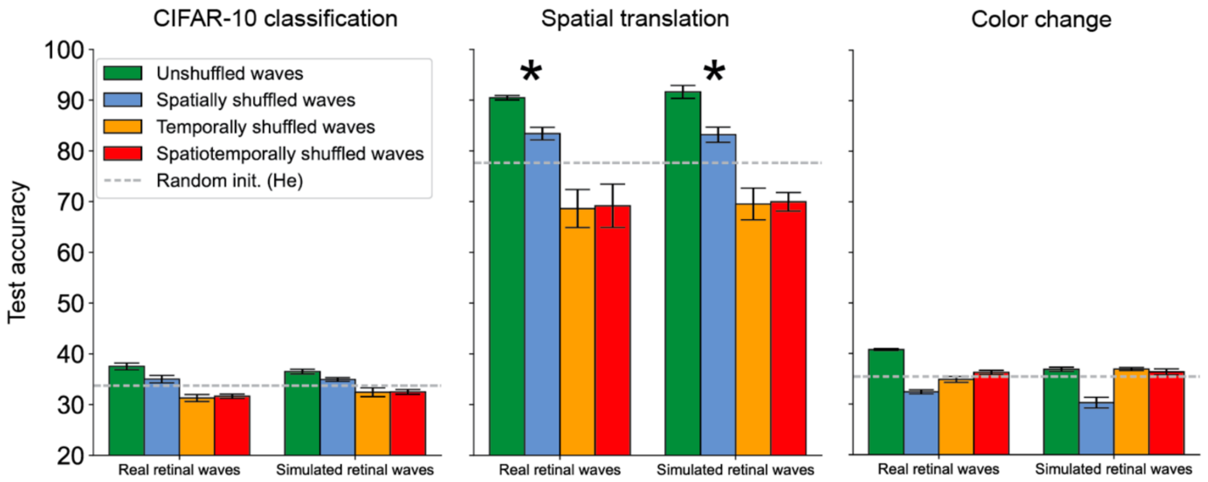
—with a fixed spike trace decay factor (0.95) and learning rate (0.01)

Per Markram et al. (1998): “Experimental evidence indicates that dynamics of neurotransmitter release under different conditions of stimulation are **potentially unique for each synapse** in an axonal tree.”

What aspects of the patterns are important?

Unsupervised learning on spontaneous retinal activity leads to efficient neural representation geometry (Ligeralde et al., 2023)





Initial results suggest it is important that patterns map regularly with the input encoding, with performance severely degraded by shuffling. Interestingly it seems that under certain conditions temporal shuffling can increase performance, but further work is needed to verify this finding.

Jean-Henri Fabre, *Souvenirs Entomologiques*

"With no one to teach him, he sets to work, exactly like his elders, to make himself a ball of food. He digs his burrow and stores it with provisions. Without ever learning it, he knows his trade to perfection."