

The Effect of Local Learning Rules on Memory

By: The Unsupervised Minds



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01



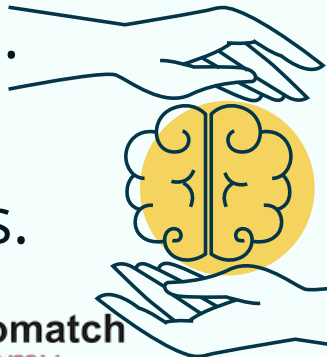
Introduction & Literature Review





Why Study Working Memory?

- Enables intelligent behaviors, like planning, reasoning, and sequencing, without explicit instruction.
- Temporarily holds and manipulates information.
- Integrates sensory, spatial, and temporal signals.



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Literature Grounding

- **Hebbian Learning**

- “Neurons that fire together, wire together” — original local plasticity rule

- **Recurrent Neural Networks (RNNs)**

- Capture sequential information
- Well-suited for modeling brain-like behavior

- **Hopfield Networks**

- Introduced attractor dynamics in RNNs
- Laid foundation for memory stability

- **Empirical Evidence**

- Primacy = long-term, Recency = short-term
- How local rules shape functionally relevant attractors

02

Question & Hypothesis



Research Question

★ Core Problem

- How does the brain learn to produce complex, organized behaviors (e.g., playing a tune, recalling an event sequence) without an external teacher?

★ Biological Basis

- Brain = vast network of interconnected neurons
- Learning → changes in synaptic strength

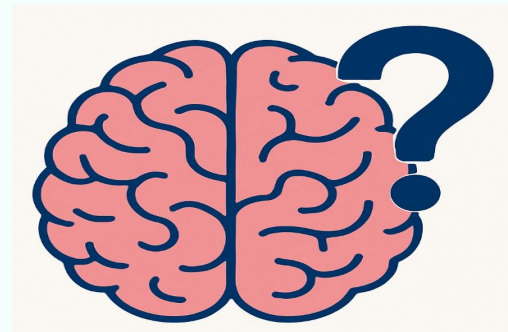
★ Computational Model

- Use Recurrent Neural Networks (RNNs) to simulate neural self-organization
- RNNs can autonomously generate sequences of activity

★ Focus of This Study

How do different local learning rules (Hebbian, anti-Hebbian) shape a network's

- **Synaptic organization**
- **Attractor landscape**



Hypotheses

01

Converging Rules

Different learning rules tend to follow a general trajectory, ultimately producing similar solutions for a given task.

02

Diverging Rules

Each learning rule follows a distinct path, resulting in different yet plausible network configurations and solutions.

03

Initial Condition Sensitive

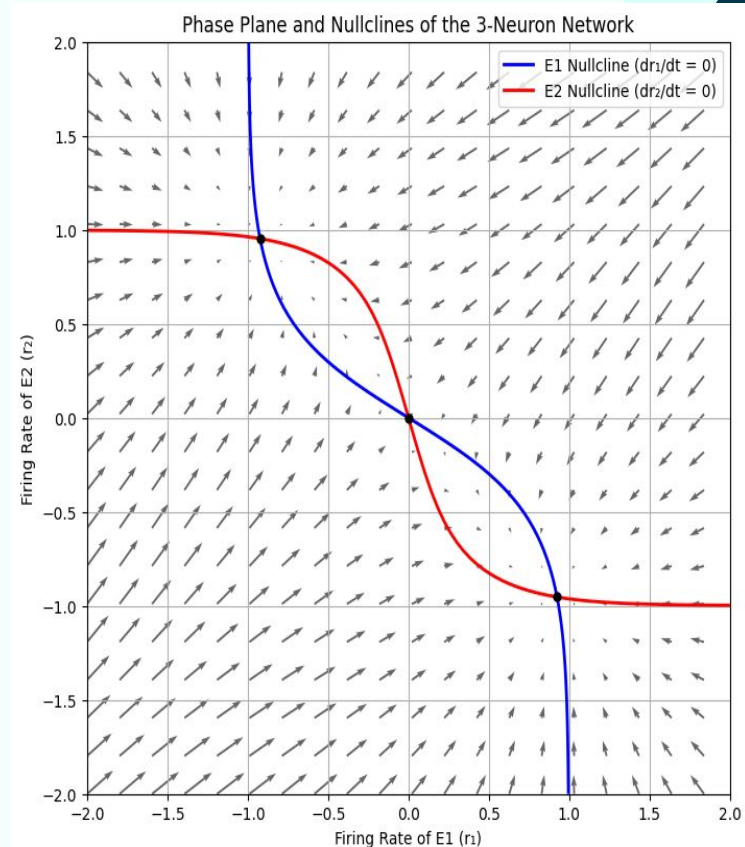
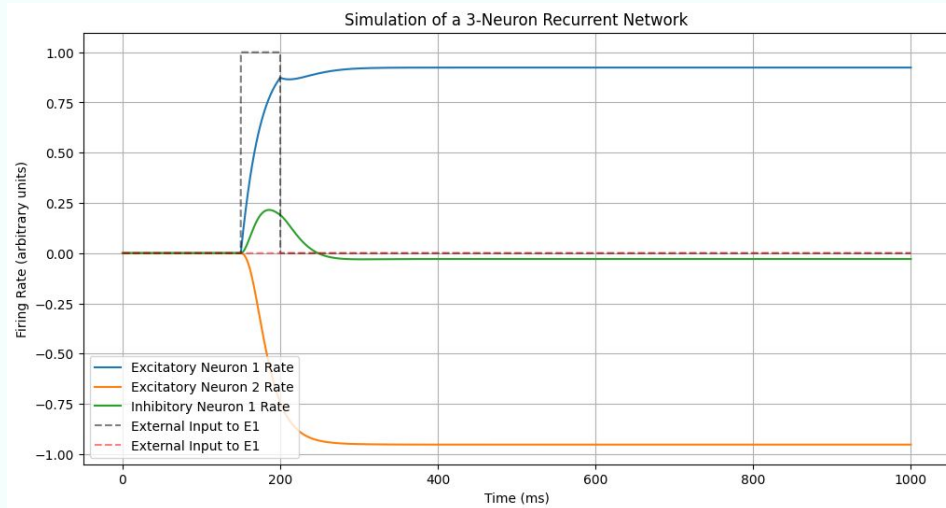
The effectiveness and outcome of a learning rule depend strongly on the initial state of the network.

03

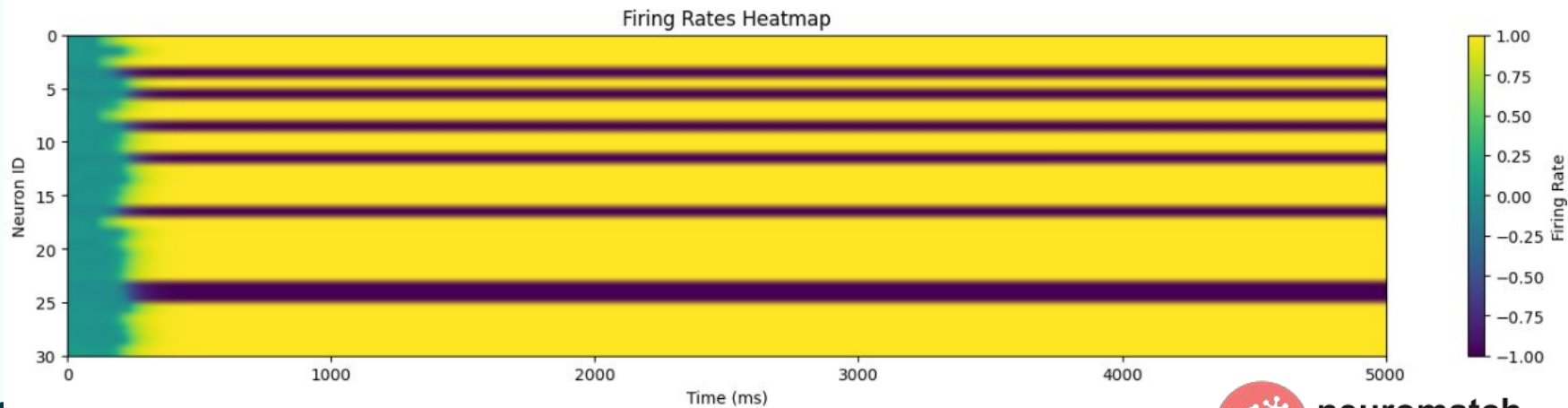
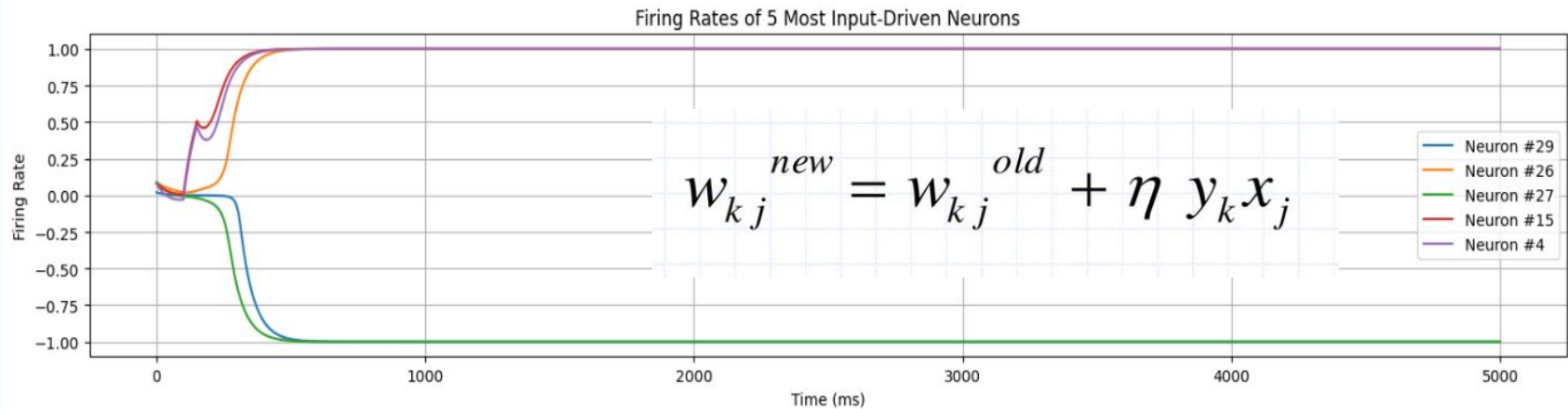
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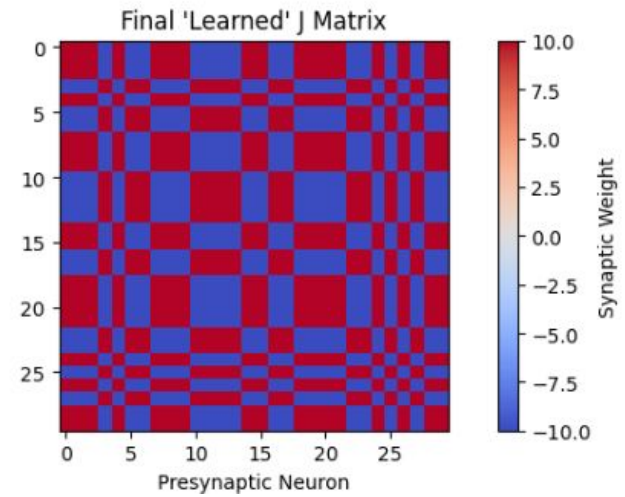
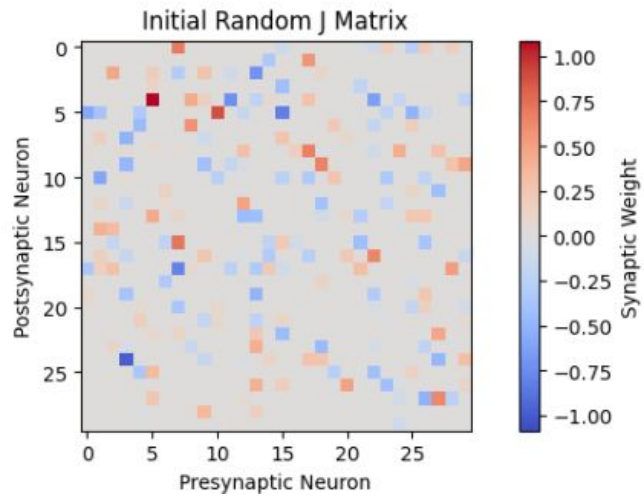
Method & Results



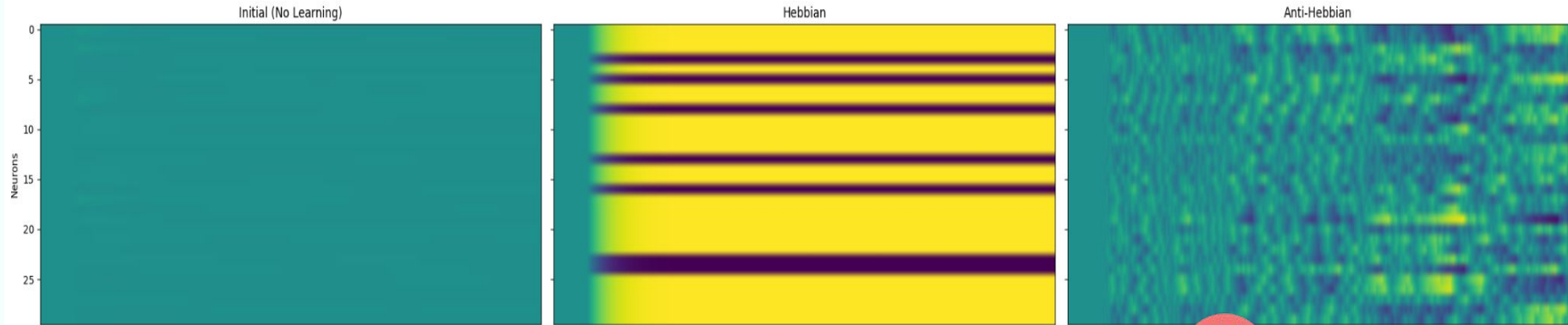


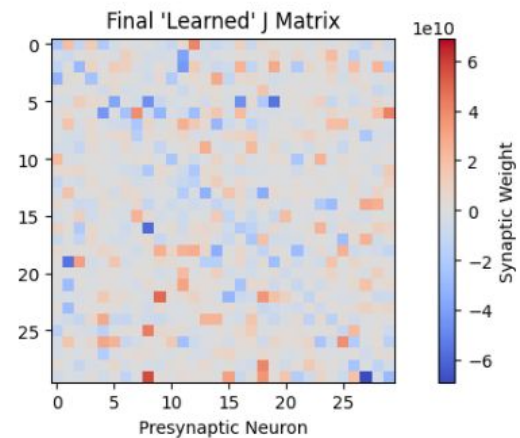
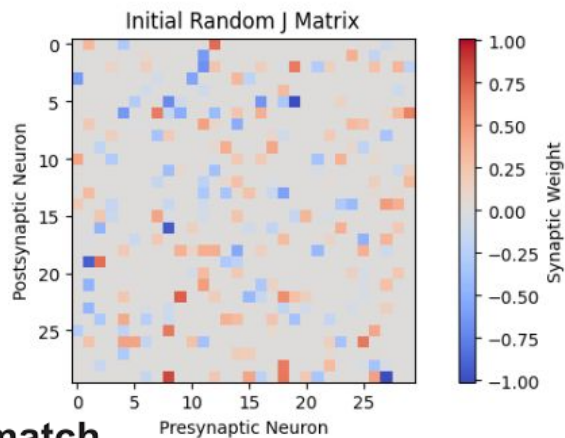
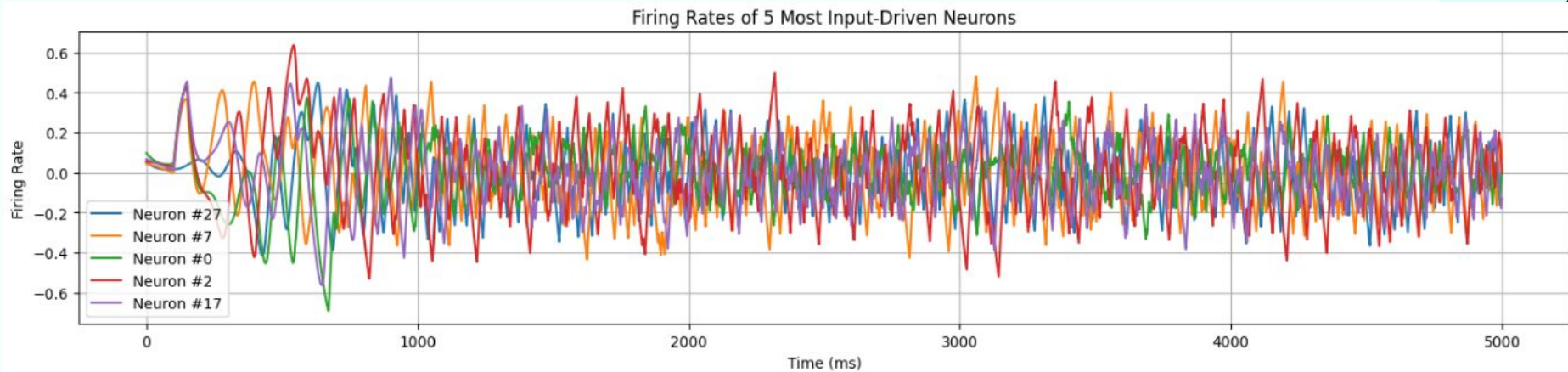
$$\tau \frac{dr}{dt} = -r + F(w \cdot r + I_{\text{ext}})$$



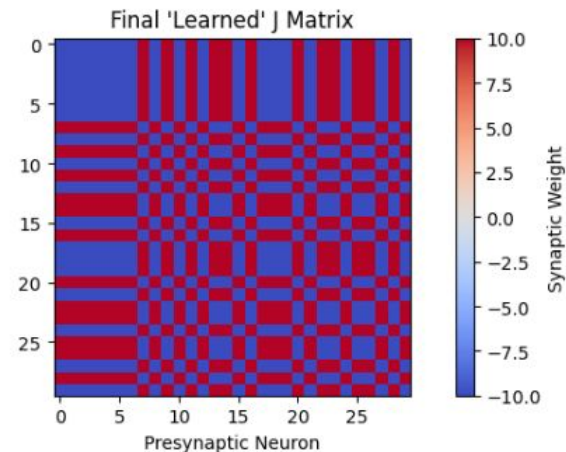
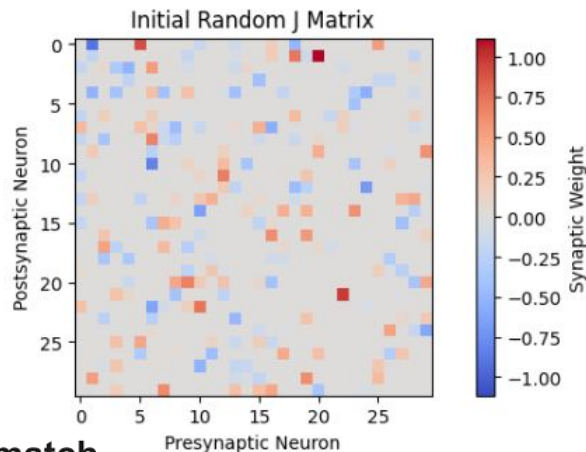
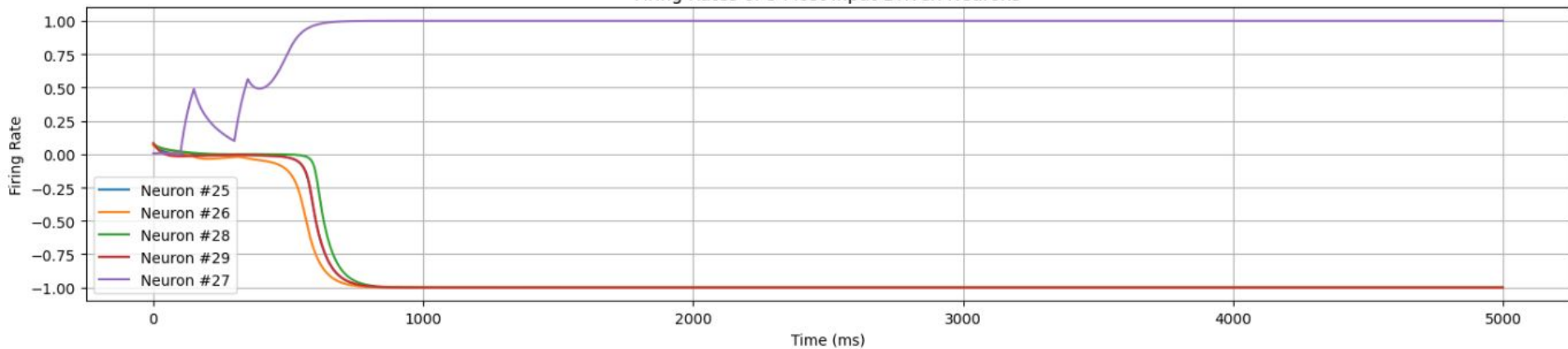


Recall Performance Comparison of Different Learning Rules





Firing Rates of 5 Most Input-Driven Neurons

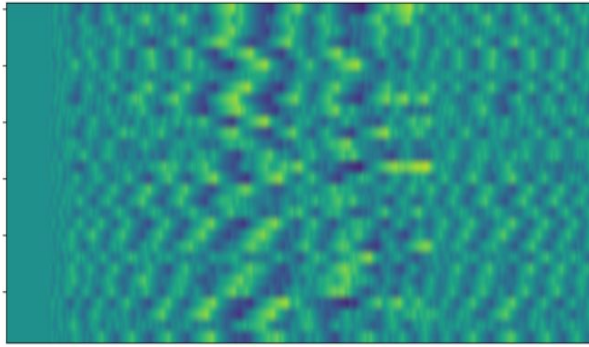


Recall Performance Comparison of Different Learning Rules

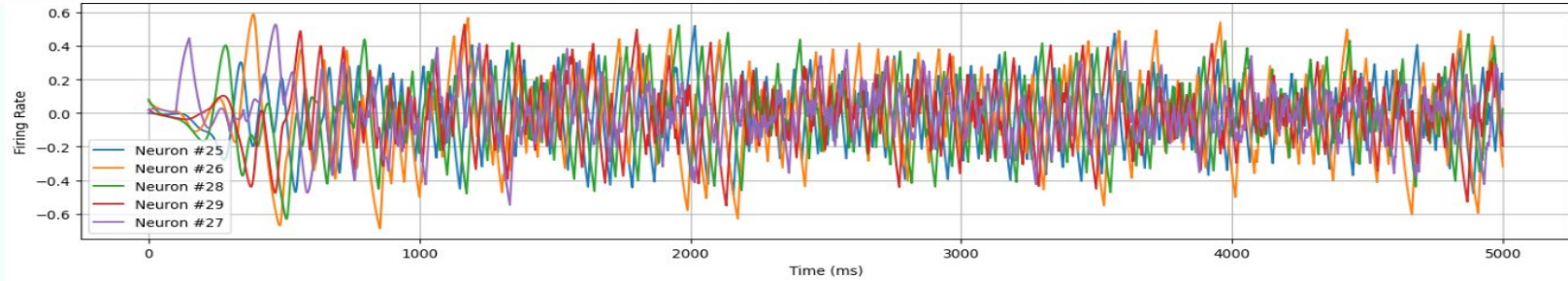
Initial (No Learning)



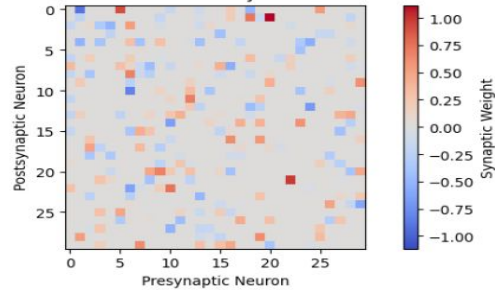
Hebbian



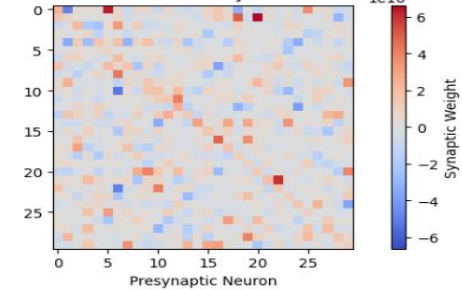
Anti-Hebbian



Initial Random J Matrix



Final 'Learned' J Matrix



04

Conclusion



What We Learned from Local Learning Rules



Local learning rules **shape neural connectivity** in distinct ways

A

How Hebbian and anti-Hebbian rules lead to different:

- Firing rate dynamics
- Final synaptic structures

B

Working
Memory

Supports **Hypothesis 2**:

- Different rules lead to different outcomes in simple memory tasks

C

Supports **Hypothesis 3**:

- The initial state of the network strongly affects memory formation
- Mirrors the primacy effect in cognitive psychology

D

Implications & Future Work



01

Biological Relevance

- Self-organizing learning can replicate **working memory effects**
- Different rules may underlie **different memory systems**

02

Computational Insight

- Design of adaptive, autonomous memory systems
- **Biologically-plausible AI**
- Pathways toward **Artificial General Intelligence (AGI)**

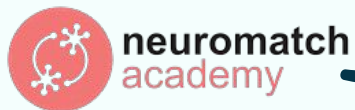
03

Future Directions

- Extend capacity to multi-pattern learning
- Explore more biologically grounded rules:
 - BCM — stability and selectivity
 - STDP — precise timing & sequence learning



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Thank you!

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