Biologically Plausible Learning under Non-Stationary and Sparse Regimes

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Project dataset: Microlearning

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Daniel

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- Sparse Coding
- Learning Algorithms
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Introduction to Microlearning:

Learning effectively in brain → Coordinate synaptic updates

Credit assignment problem → Synapses depend on each other

Backpropagation → Biologically implausible

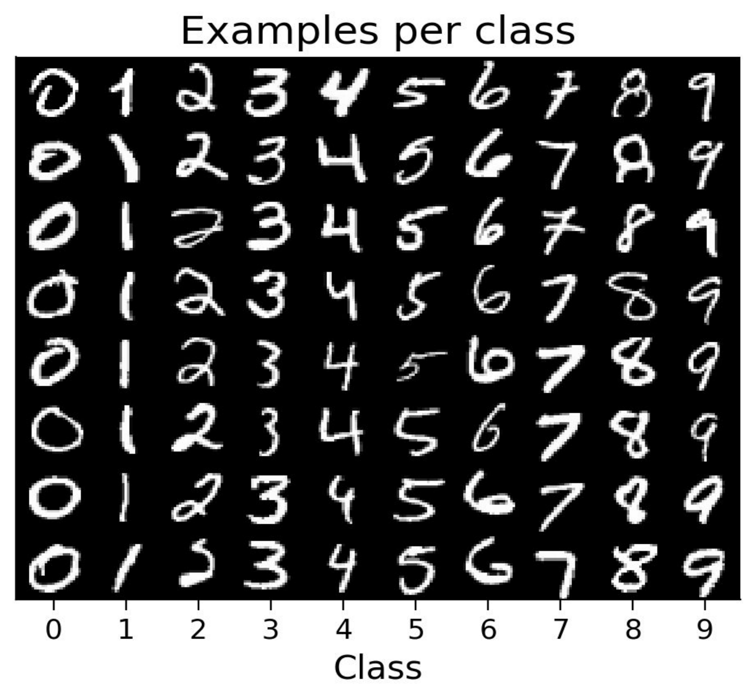
Hebbian learning → Biologically plausible

Dataset:

The MNIST Dataset

Handwritten Digit Images

10 classes



Research Questions:

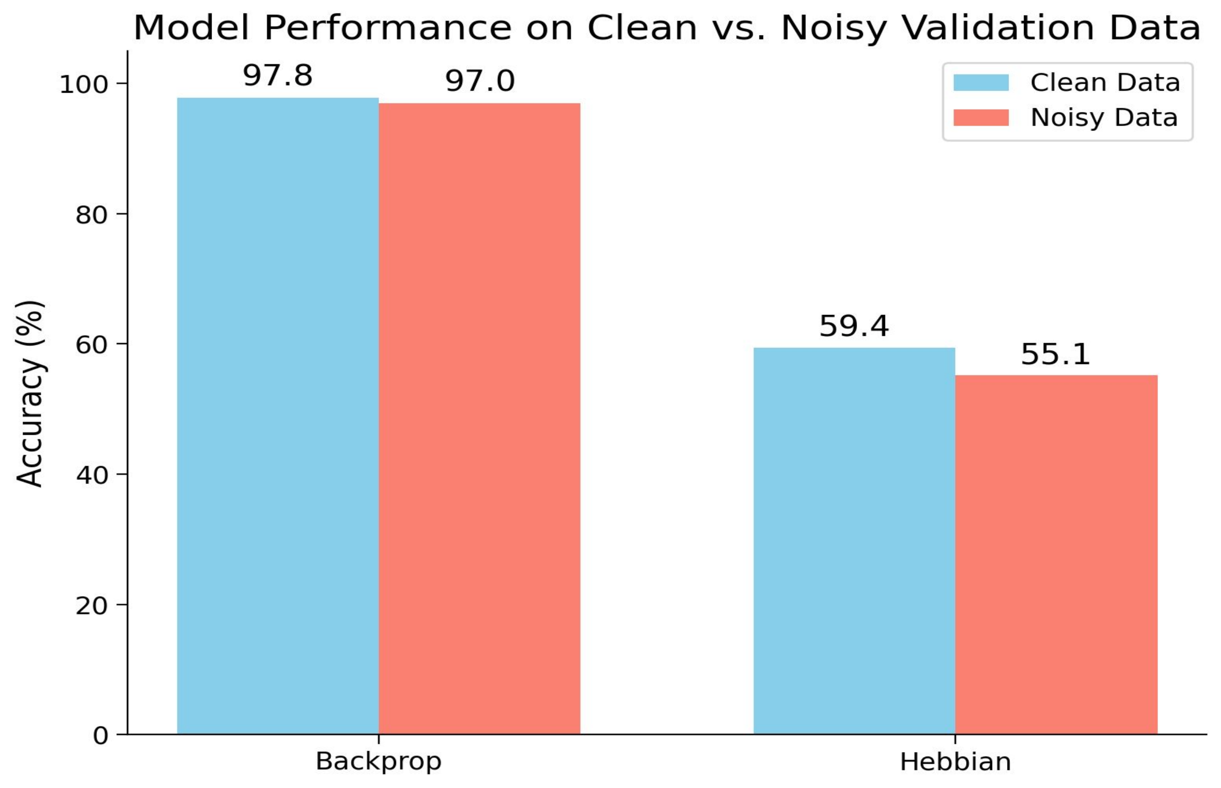
Q1. How do **biologically plausible local learning rules** (e.g., Hebbian, FA) perform in non-stationary settings **compared to BP**, considering performance degradation and forgetting as new tasks are introduced?

Q2. Can **combining Hebbian learning with sparse coding** lead to more interpretable or robust internal representations on MNIST, and how does the level of sparsity influence this?

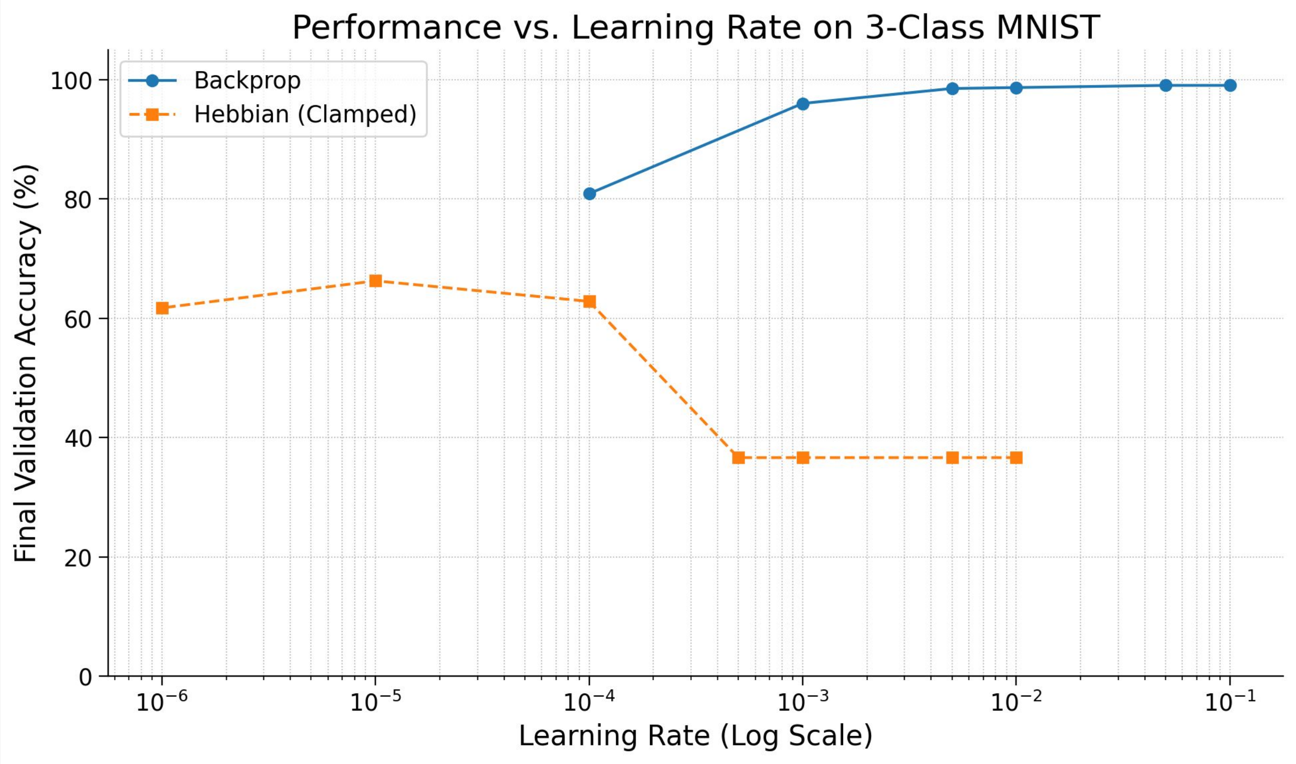
Robustness comparison:

- Adding gaussian noise to image data
- Comparing accuracy

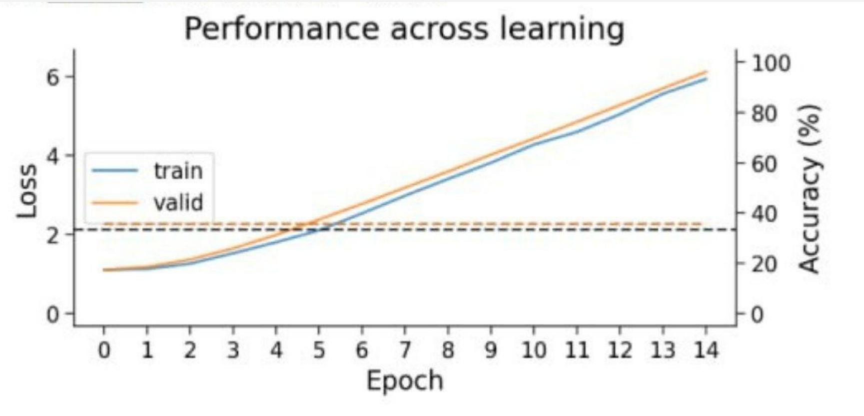
Robustness:

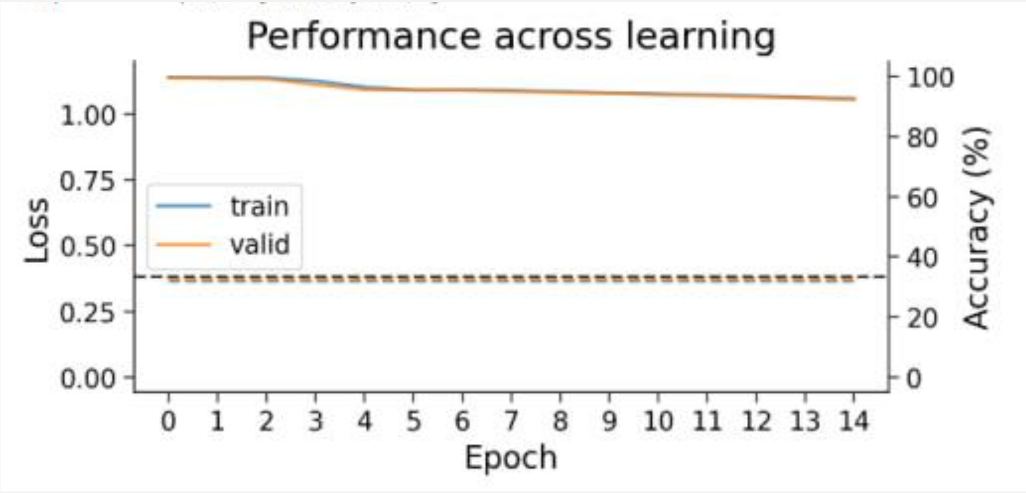

Model Performance on Clean vs. Noisy Validation Data
Clean Data
Noisy Data
Accuracy (%)
0
20
40
60
80
100
97.8
97.0
59.4
55.1
Backprop
Hebbian

Learning rate:

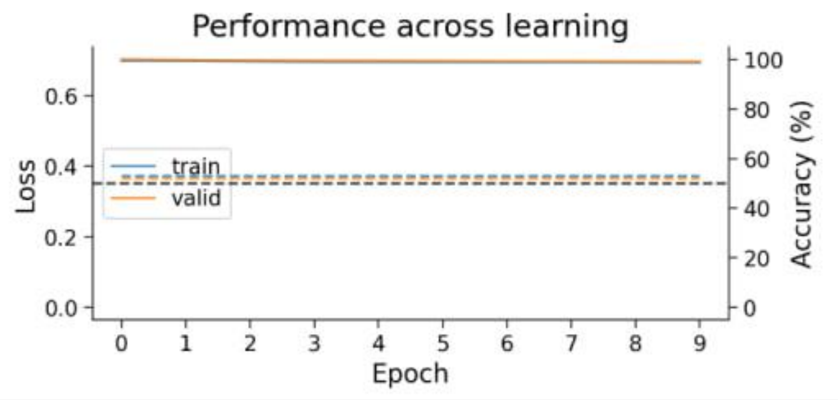


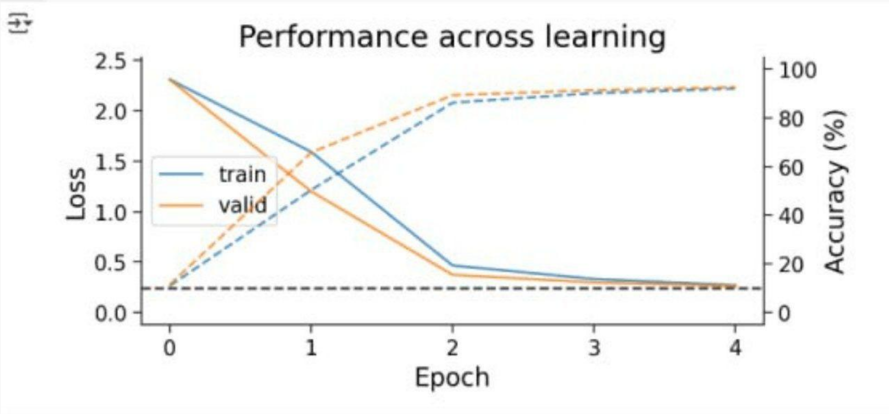
Changing Number of Layers:





Different Activation Functions:





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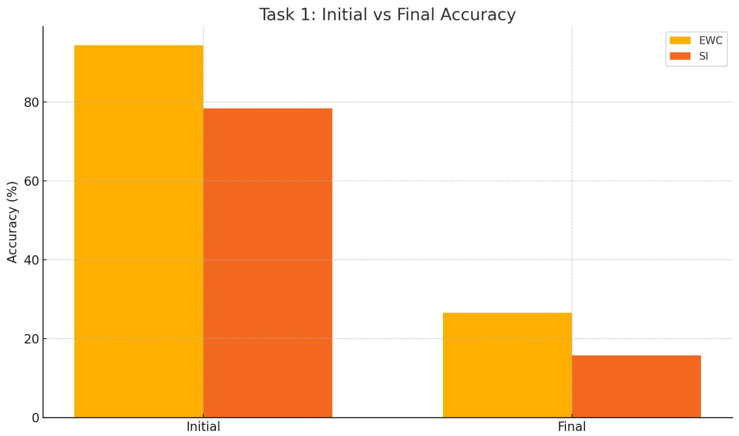
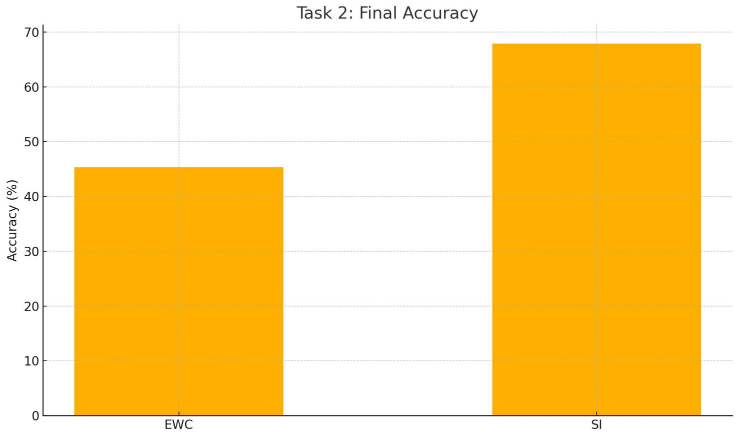
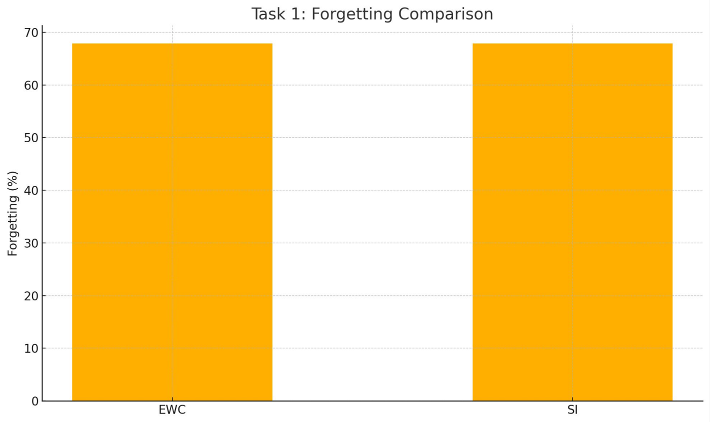
Continual Learning:

Two class MNIST: Compare ewc vs. si







Continual Learning:

Backward Transfer (BWT)

Method	Task 1 Initial (%)	Task 1 Final (%)	BWT (%)
EWC	94.42	26.52	−67.90
SI	78.41	15.79	−62.62

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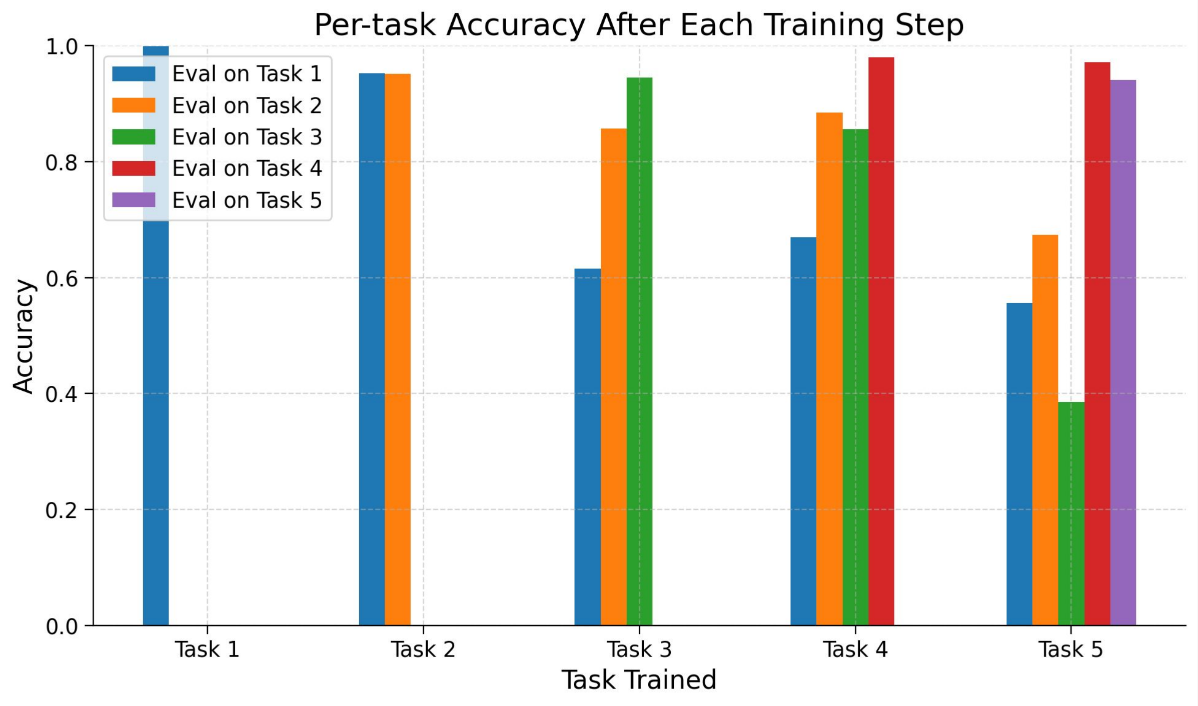
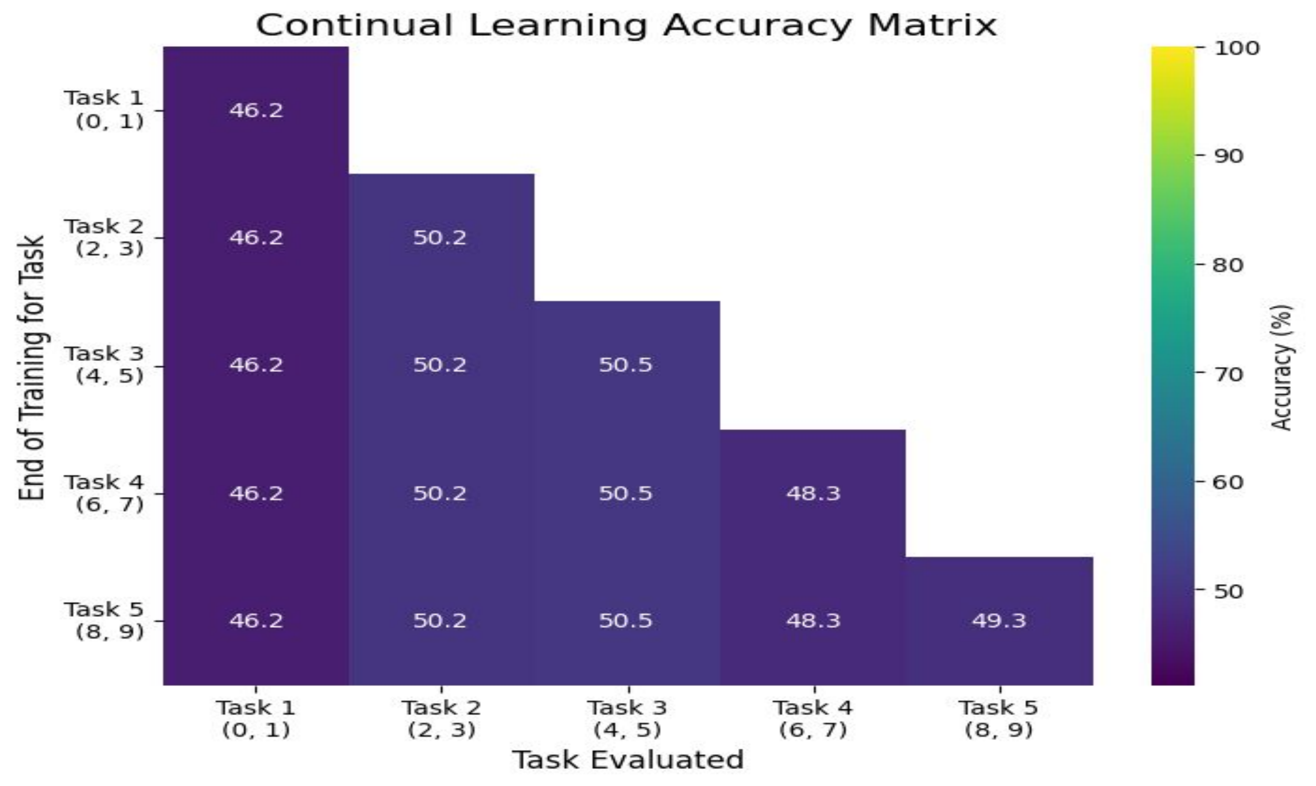
Continual Learning:

EWC MLP



Continual Learning:

Hebbian MLP



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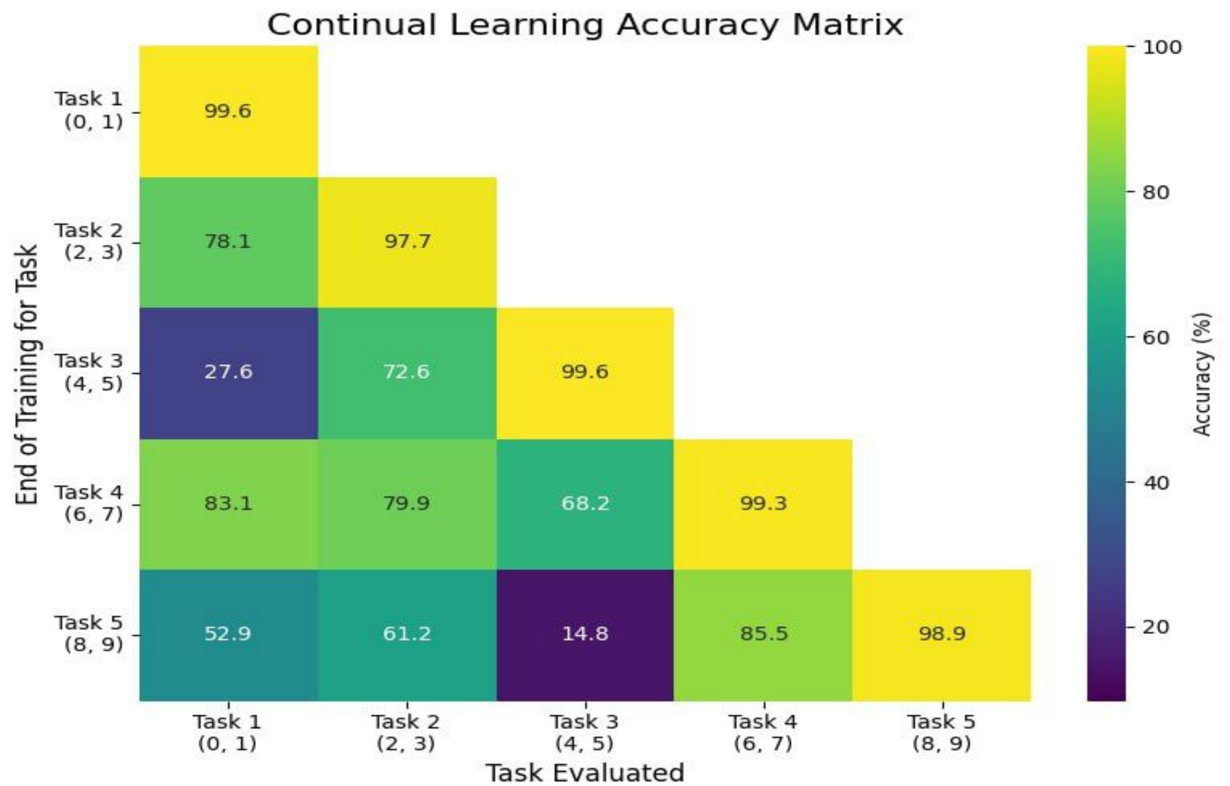
Continual Learning:

Hybrid KAN



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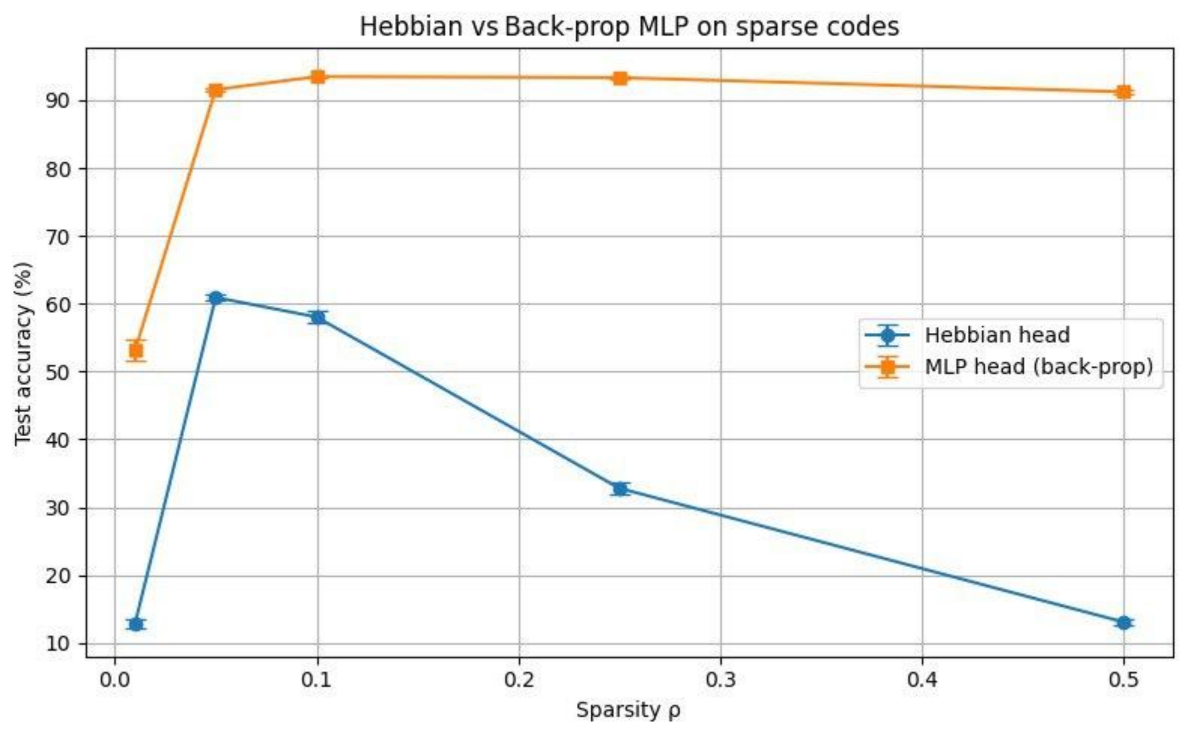
Sparse Coding:



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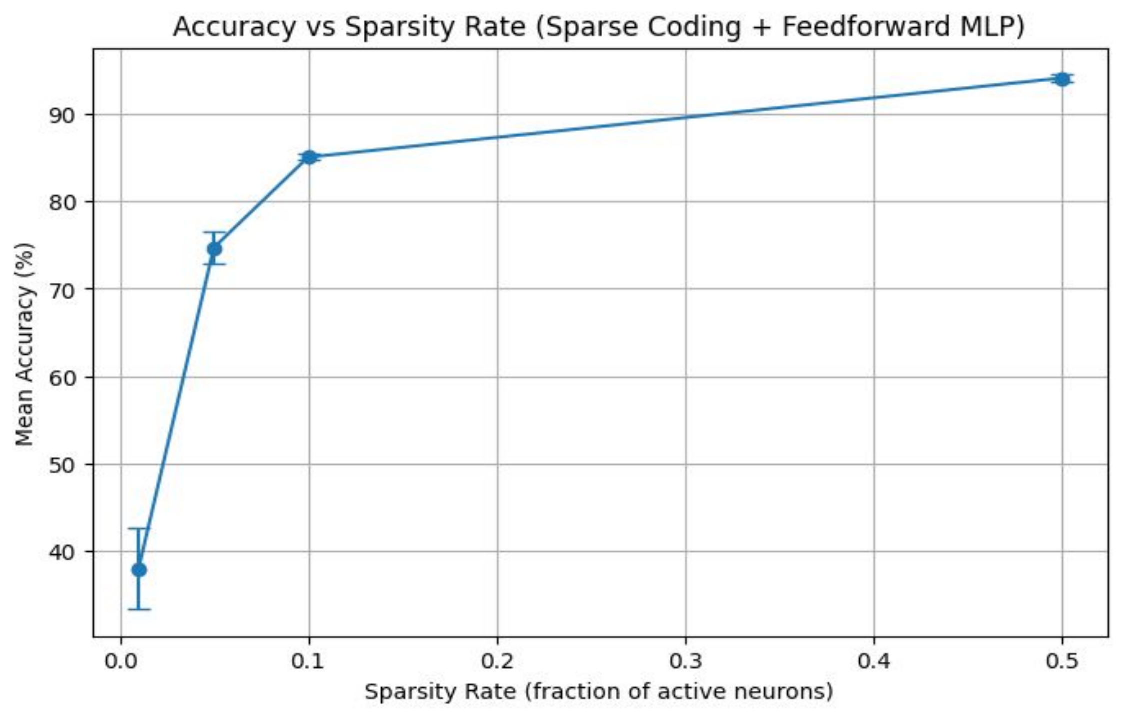
Sparse Coding:



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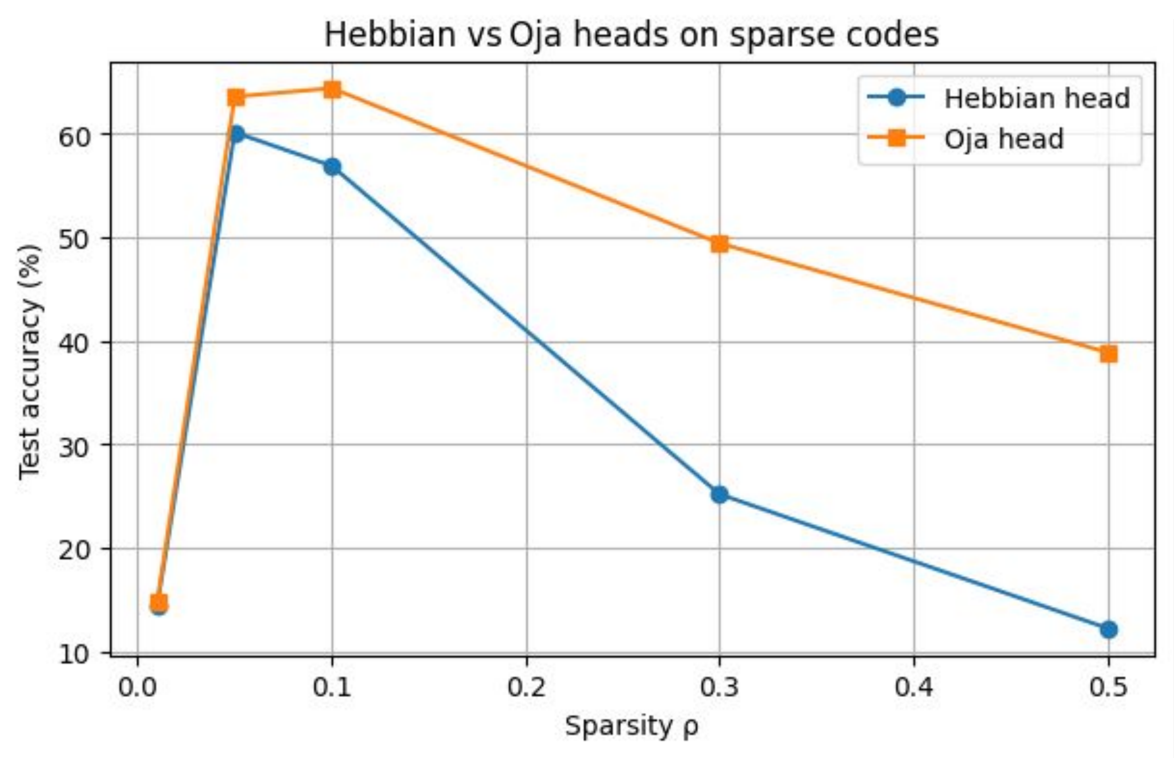
Sparse Coding:



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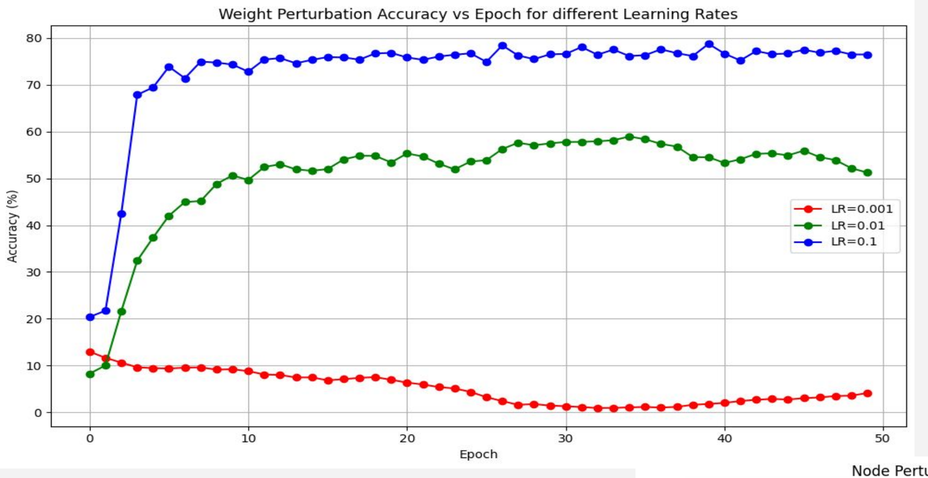
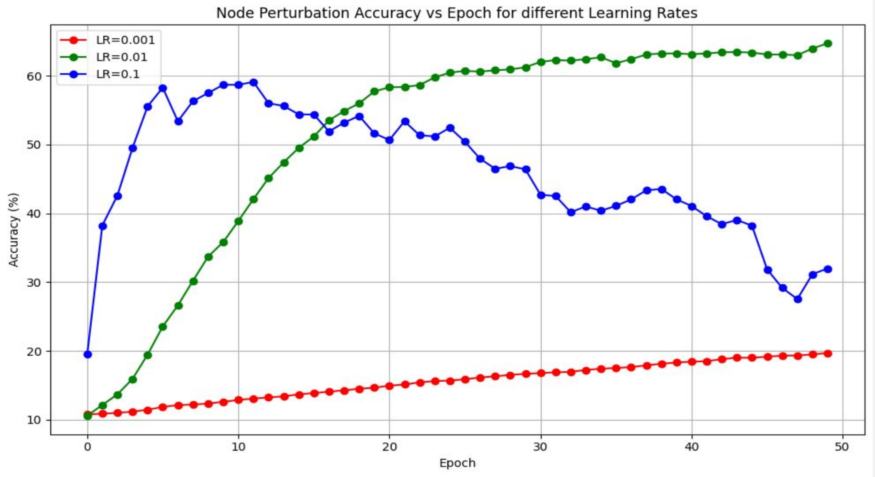
Weight and Node Perturbation:





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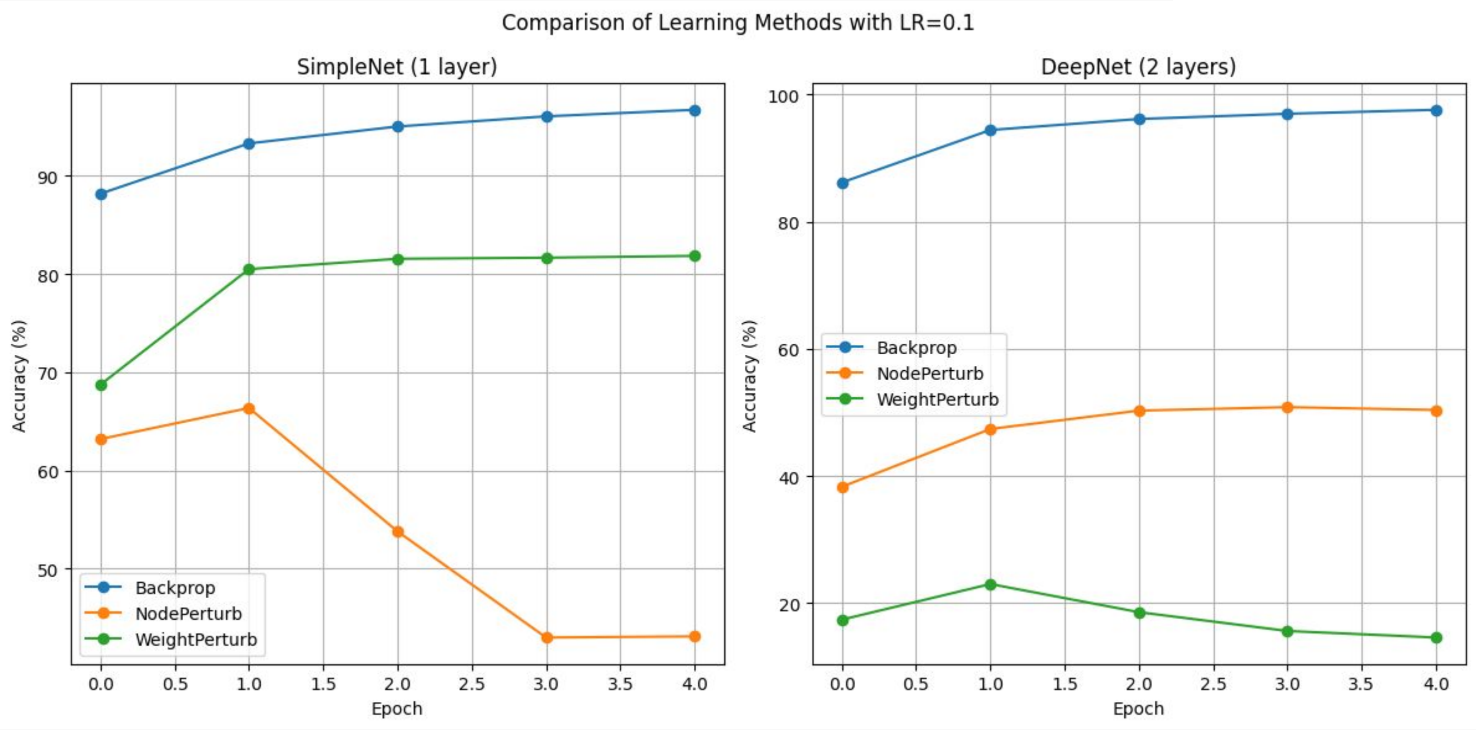

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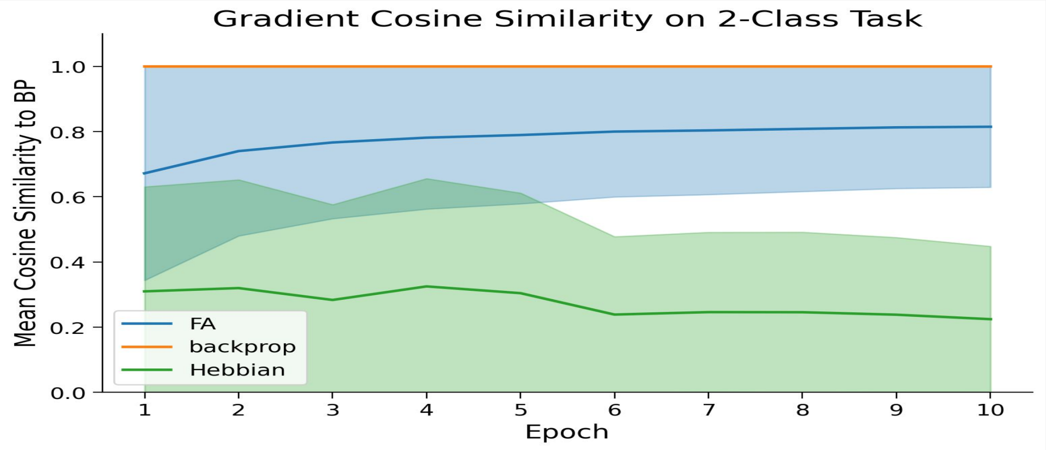
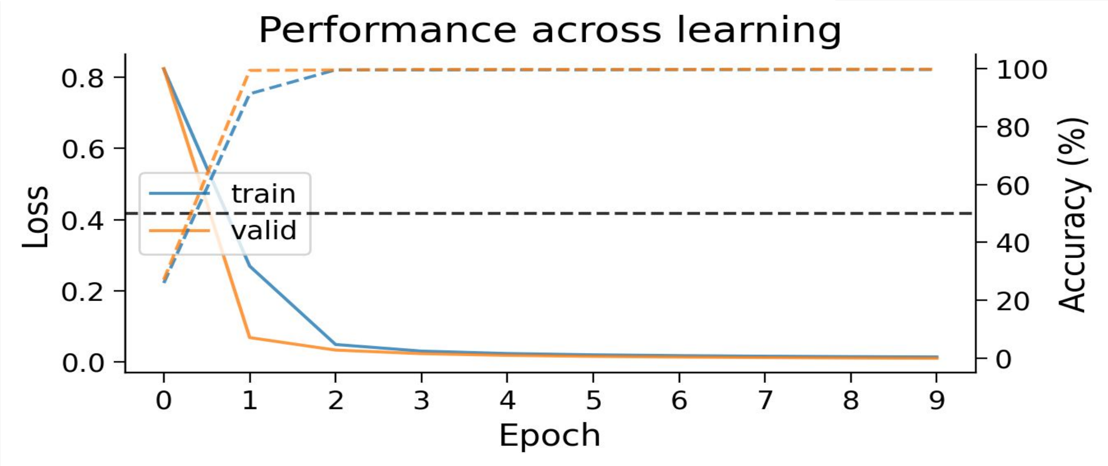
Feedback Alignment:





Conclusion and Discussion

➔ Backpropagation remains most accurate and robust, especially under noise and task switching.

➔ Hebbian learning and perturbation methods perform worse in raw accuracy, but show promise when combined with **sparse representations**.

➔ Biologically plausible methods are more sensitive to architecture choices (depth, activation) and hyperparameters.

➔ Our experiments highlight both the **limitations** and **untapped potential** of local learning rules in dynamic conditions.

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Future Work

- ➔ Hybrid Learning Architectures
- ➔ Sparse Coding & Interpretability
- ➔ Representation Analysis with RDMs
- ➔ Visualization of Learning Trajectories

THANK YOU!