

Preserving Plasticity in Continual Learning with Adaptive Linearity Injection

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CoLLAs 2025

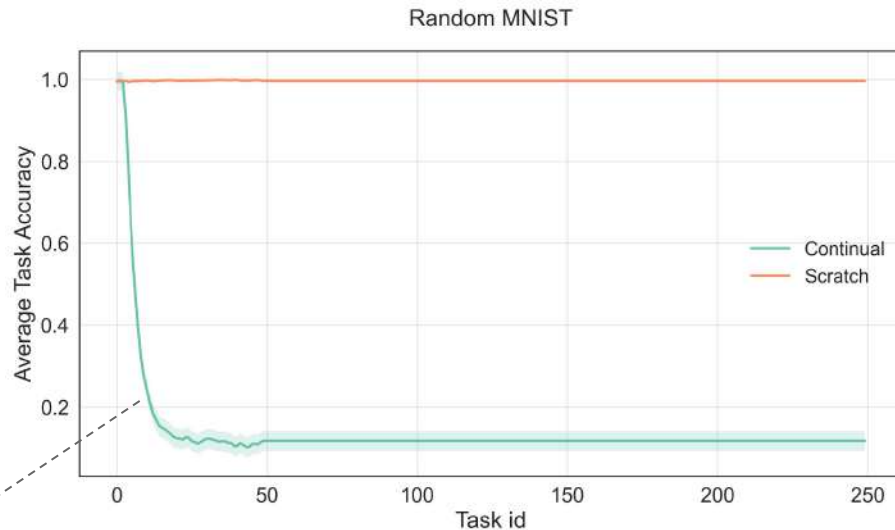
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* Equal Contribution

Loss of Plasticity: When Models Stop Learning

- **Plasticity:** the ability of a model to adapt to new data
- Important in **Continual Learning** and **Reinforcement Learning**
- **Loss of plasticity:** reduced ability to learn as training progresses

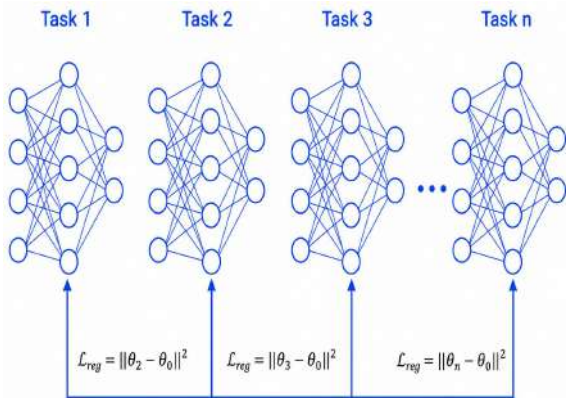


Continual training collapses, while training from scratch succeeds!

Existing Approaches and a Different Direction

Regularization

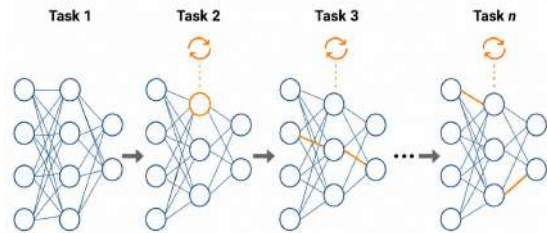
(Kumar et al., 2023, Chung et al., 2025)



Can limit expressivity

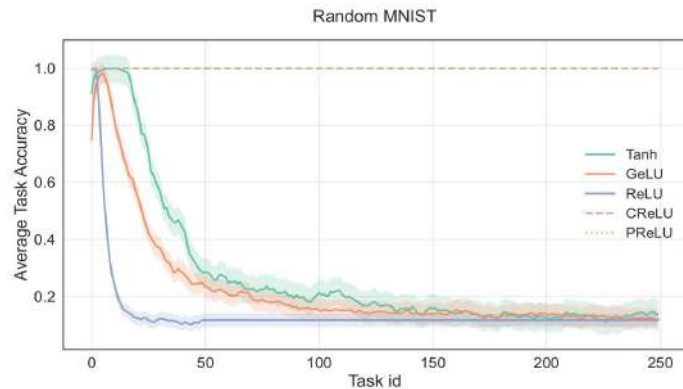
Resetting

(Dohare et al., 2024)



Requires task boundaries

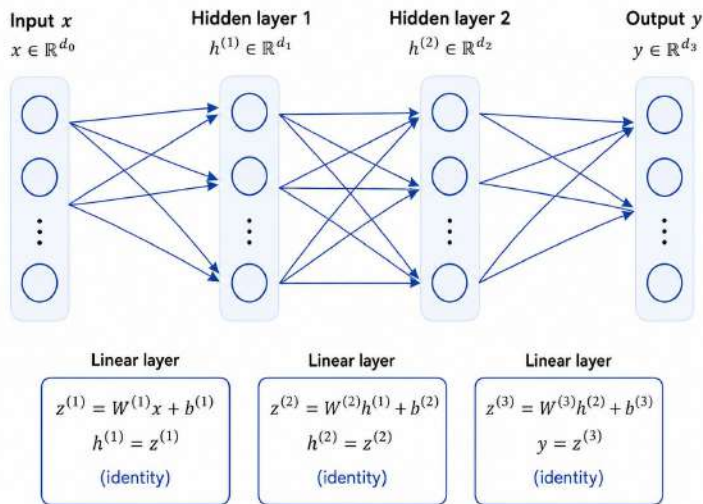
Our Direction



Some activations preserve plasticity

Motivation: Linearity Helps Plasticity

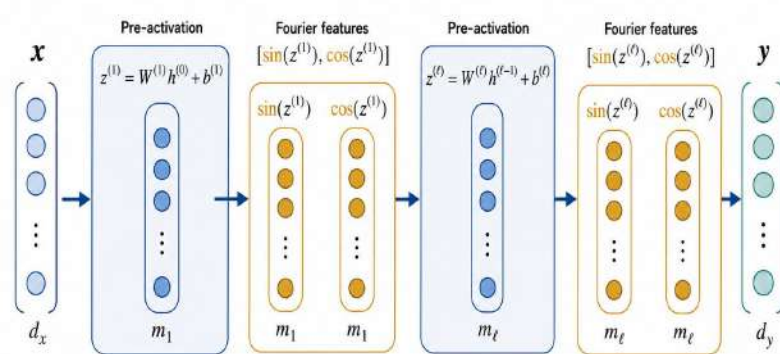
Deep Linear Networks



- ✓ preserve plasticity
- ✗ limited expressivity

Deep Fourier Features

(Lewandowski et al. 2025)



- ✓ combine linearity and nonlinearity
- ✗ fixed balance: always outputs (sine, cosine)

Can we adaptively balance linearity and nonlinearity?

For each neuron, we aim to adaptively inject linearity into its activation function

Our Approach: Adaptive Linearization (AdaLin)

We augment any non-linear activation function ϕ with a Lipschitz constant L with a **learnable linear term**:

$$f_i(x) = \phi(x) + \alpha_i \cdot x \cdot [g(x)]_{sg}$$

Diagram illustrating the components of the equation:

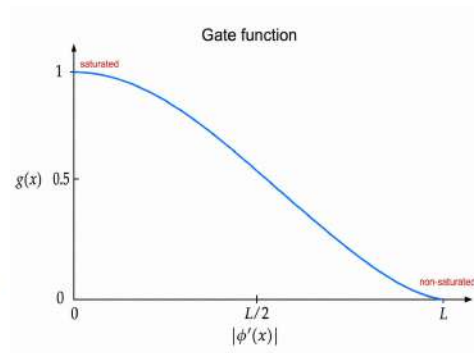
- $f_i(x)$: Output of Neuron i
- $\phi(x)$: Preactivation
- α_i : Learnable Parameter Per-neuron

where:

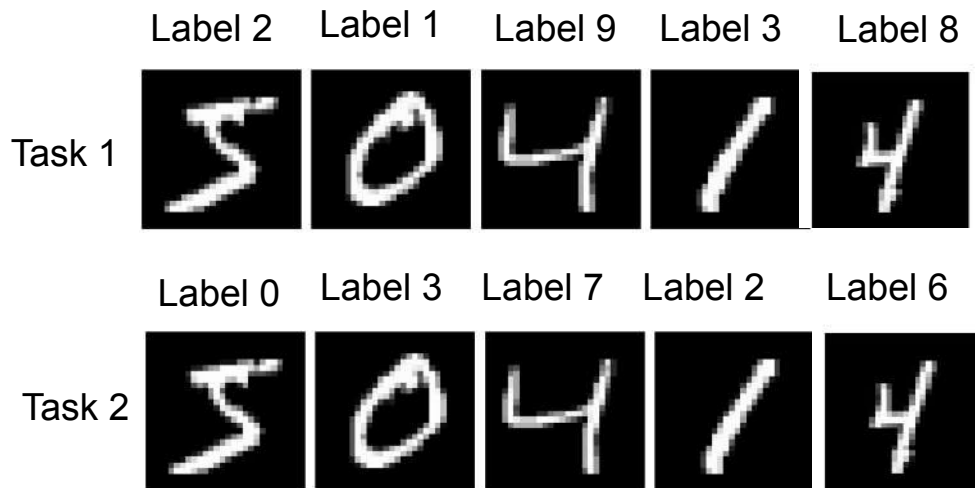
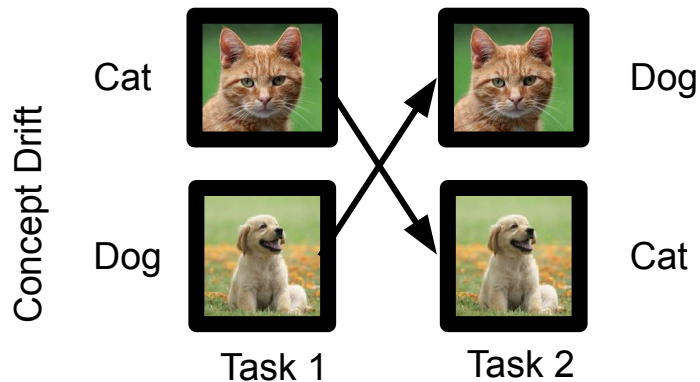
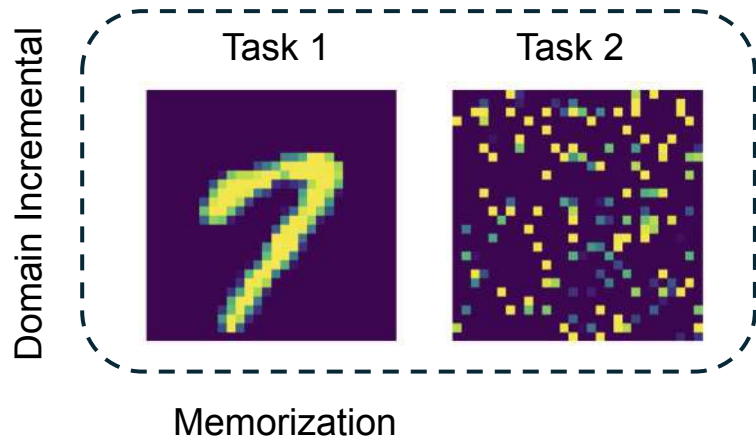
$$g(x) = \cos\left(\frac{\pi}{2} \cdot \frac{|\phi'(x)|}{L}\right)$$

Small $|\phi'(x)| \rightarrow$ Larger Gate \rightarrow More Linearity

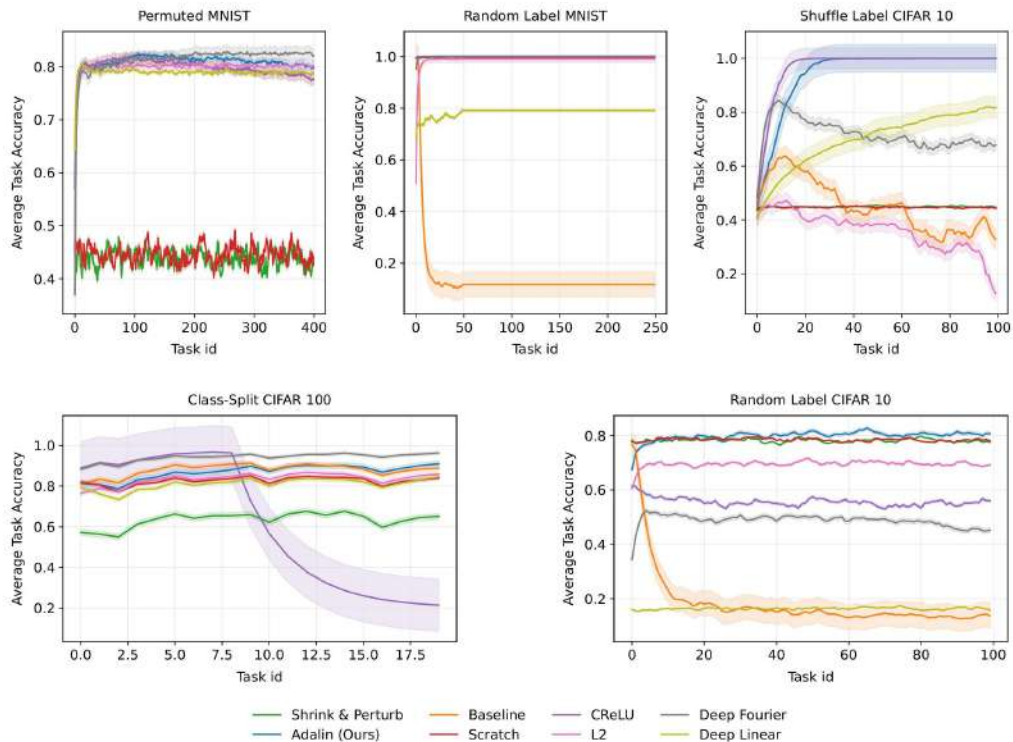
Large $|\phi'(x)| \rightarrow$ Smaller Gate \rightarrow More Non-Linearity



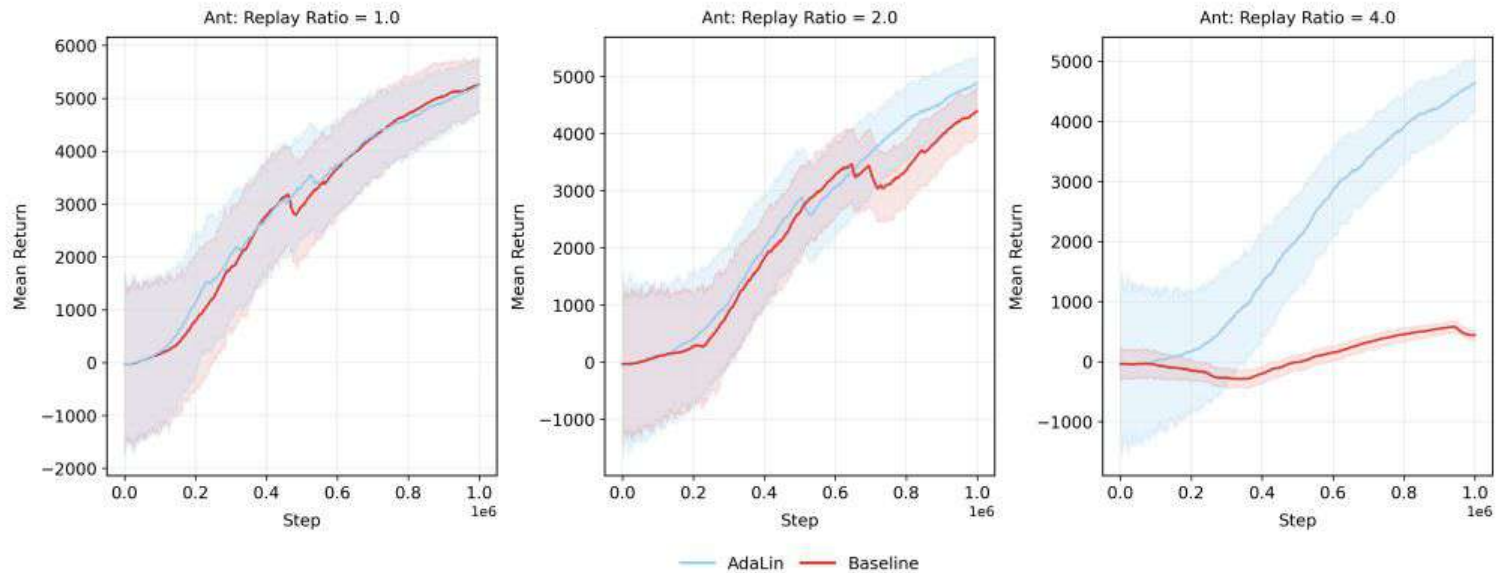
Experiments – Benchmarks



Experiments – Supervised Learning

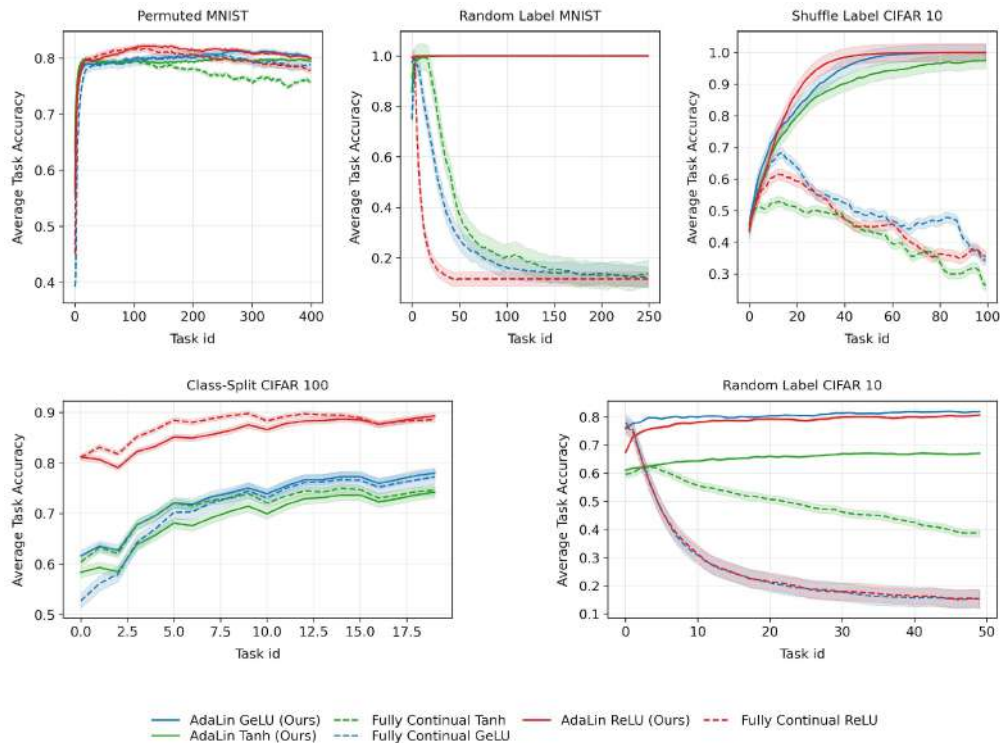


Experiments – RL



Ablations

- AdaLin can be applied to different activation functions



Thank You!