

Motivation

We study the paper *Mamba: Linear-Time Sequence Modeling with Selective State Spaces*. Our goal is to reimplement the core Mamba block from scratch, then extend it to spatial data using a bidirectional scan. We evaluate on datasets not used in the original paper to validate generalization. No custom CUDA kernels are used.

Contributions

Clean PyTorch reimplementation of S6 selective scan (JIT) without custom CUDA. Vision extension via bidirectional scan over patch tokens. Evaluation scripts for MNIST, CIFAR-10, TinyShakespeare, plus baselines.

Method Overview

Mamba replaces attention with a selective state space model (S6) that is input-dependent. We implement the recurrence with learned discretization Δ and depthwise causal convolution, followed by gating and projection.

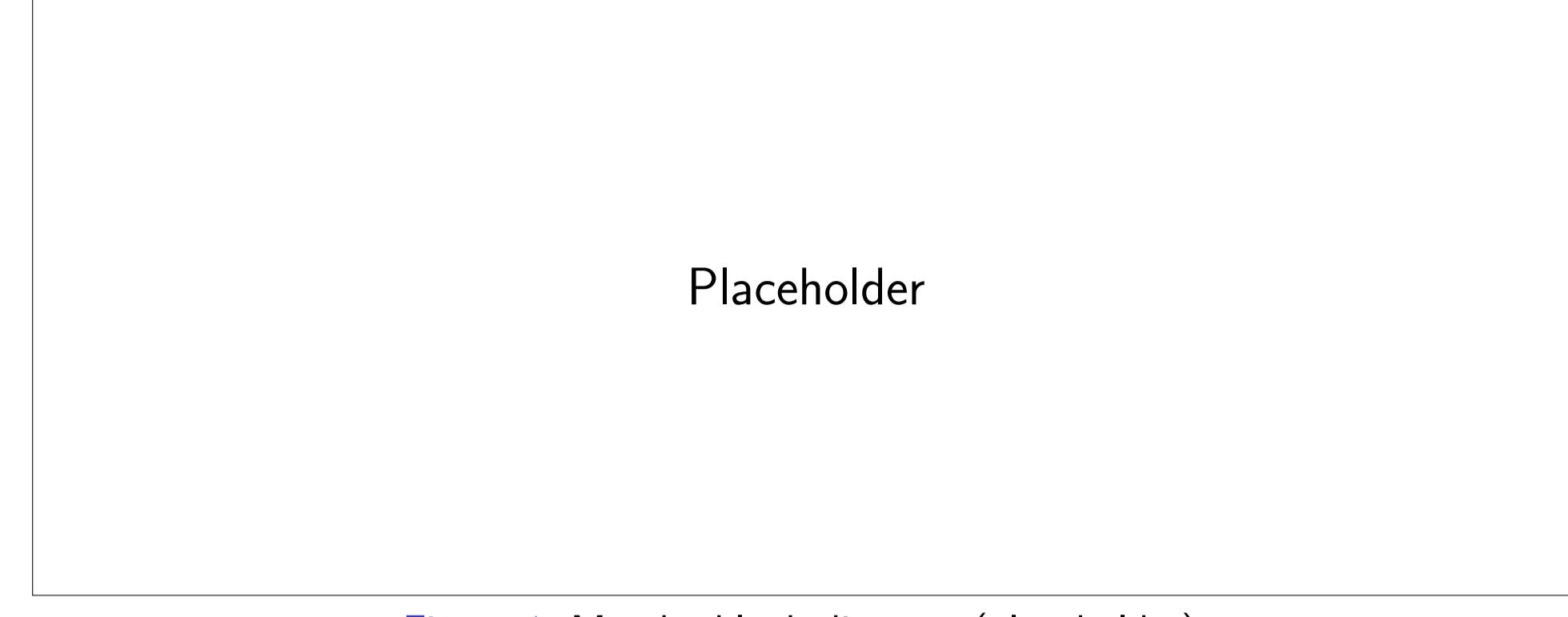


Figure 1: Mamba block diagram (placeholder).

Selective Scan (S6)

For each time step t :

$$h_t = \Delta A \odot h_{t-1} + \Delta B \odot x_t, \quad y_t = C \odot h_t + D \odot x_t$$

where Δ is input-dependent. We use a low-rank Δ projection with S4D-style initialization for stability.

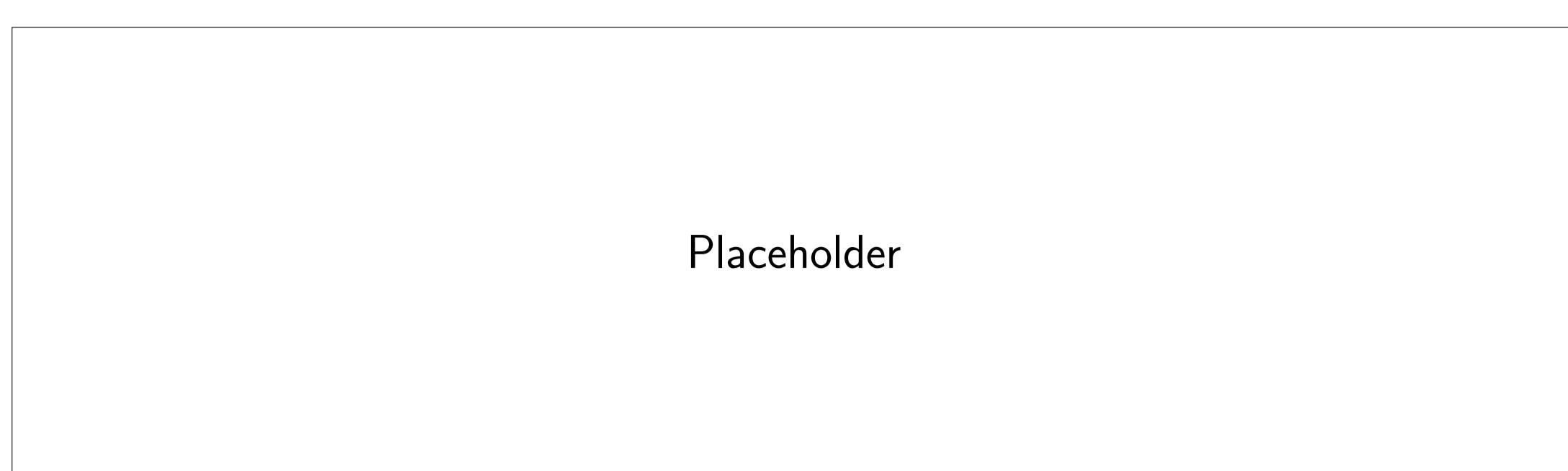


Figure 2: Selective scan illustration (placeholder).

Vision Extension

For images, a single causal scan limits spatial context. We scan sequences in both forward and backward directions, then fuse the outputs. Input images are converted into 4×4 patch tokens.

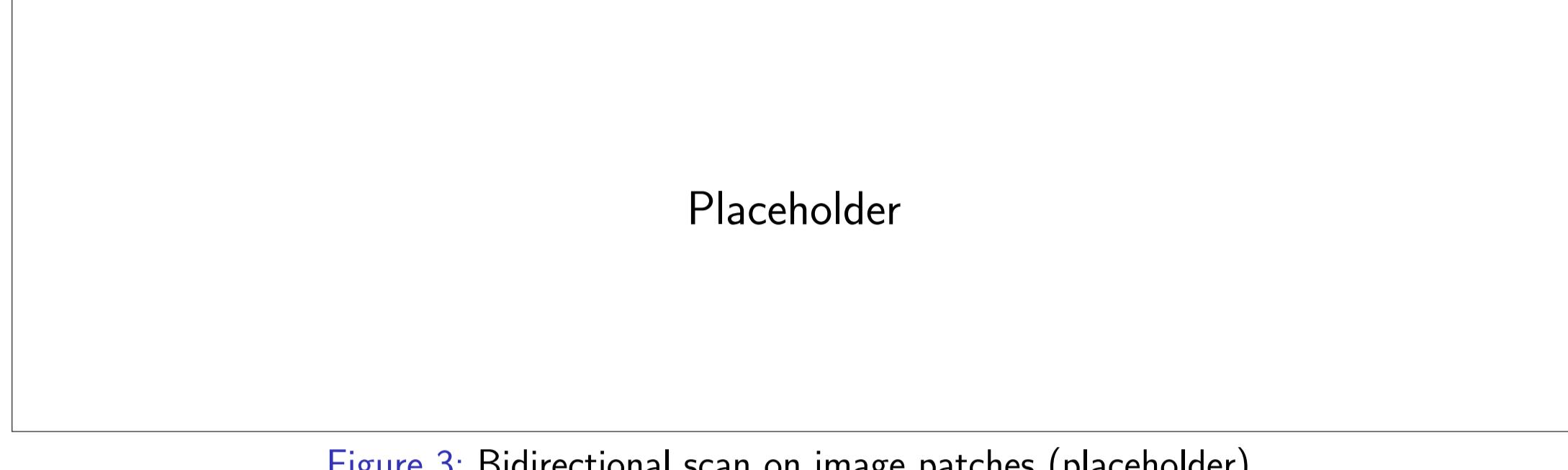


Figure 3: Bidirectional scan on image patches (placeholder).

Implementation Details

Pure PyTorch implementation using `torch.jit.script`. Depthwise 1D convolution with kernel size $d_{conv} = 4$. S6 uses input-dependent Δ with low-rank projection. RMSNorm at model output; residual connections per layer. Weight tying between token embedding and output head.

Datasets and Evaluation

MNIST: Vision Mamba, causal ablation, and vanilla RNN baseline.

CIFAR-10: patch-based image classification.

TinyShakespeare: character-level language modeling.

Dataset	Key training settings (from <code>train_*.py</code>)
MNIST (Vision)	<code>d.model=64, layers=2, batch=64, lr=1e-3, epochs=5</code>
MNIST (Causal)	<code>d.model=64, layers=2, batch=64, lr=3e-4, epochs=5</code>
MNIST (RNN)	<code>input=16, hidden=64, layers=2, batch=64, lr=1e-3, epochs=5</code>
CIFAR-10	<code>d.model=128, layers=4, batch=64, lr=1e-3, epochs=5</code>
TinyShakespeare	<code>d.model=128, layers=4, block=128, batch=32, lr=1e-3, epochs=10</code>

Table 1: Training settings summary.

Results

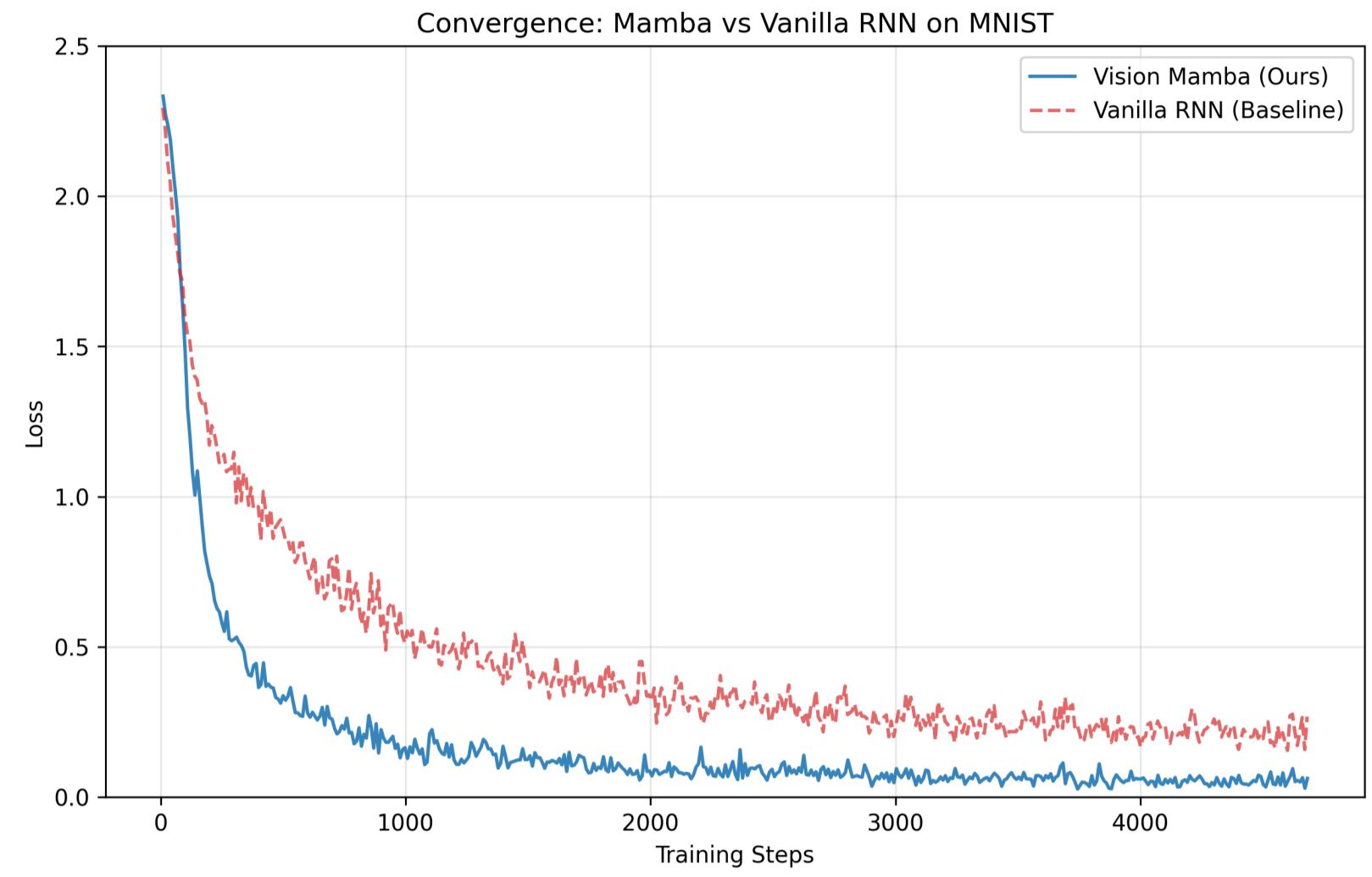


Figure 4: Vision Mamba vs RNN training loss (from outputs/figures).

Model	MNIST test accuracy (%)
Vanilla RNN (README)	94.40
Causal Vision Mamba (README)	97.00
Bi-Directional Vision Mamba (README / outputs)	97.93

Table 2: MNIST accuracy summary reported in README.md.

TinyShakespeare loss: min 1.1920 (step 5000), last 1.2393 (step 5300) from `outputs/results/shakespeare/shakespeare_results.csv`.

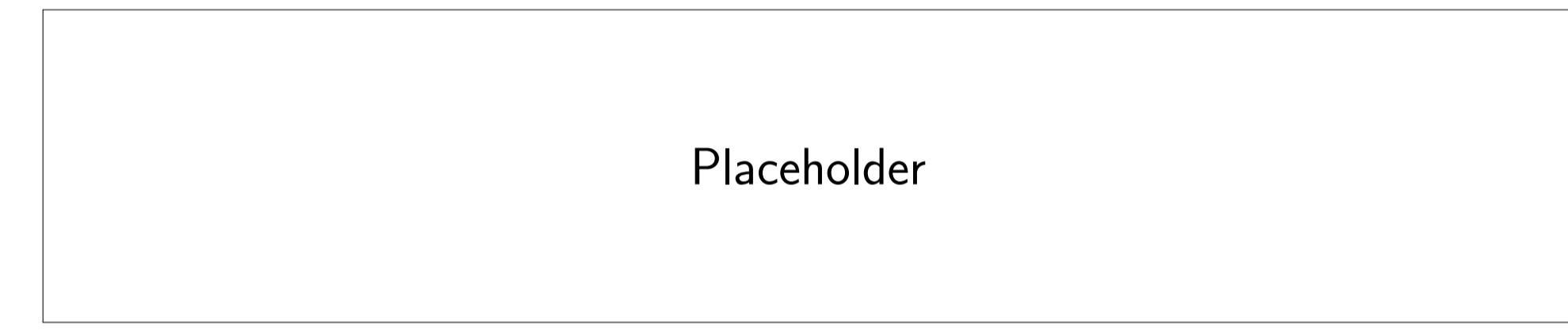


Figure 5: CIFAR-10 results (placeholder; no figure in outputs/).

Ablation and Analysis

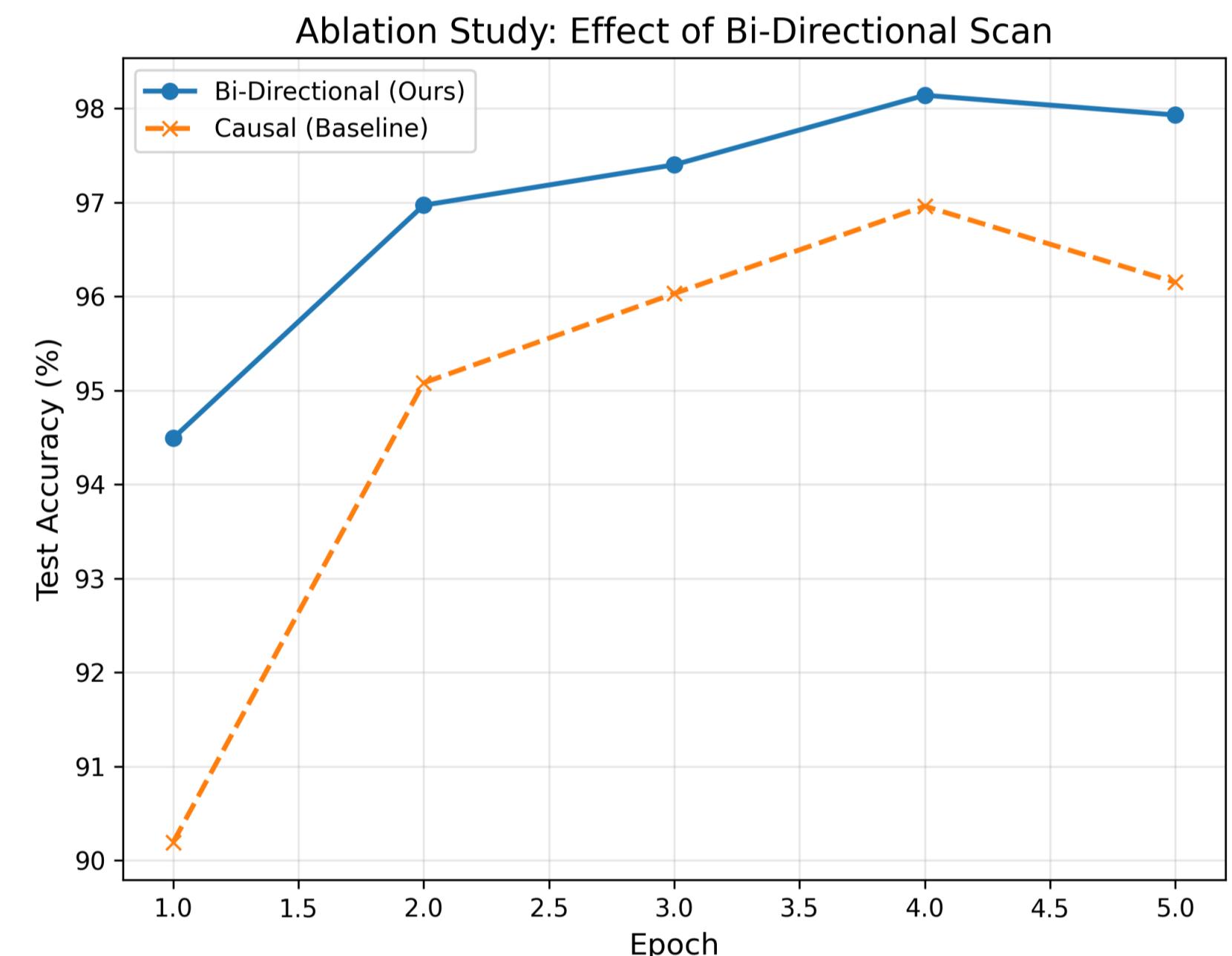


Figure 6: Ablation: causal vs bidirectional scan (from outputs/figures).

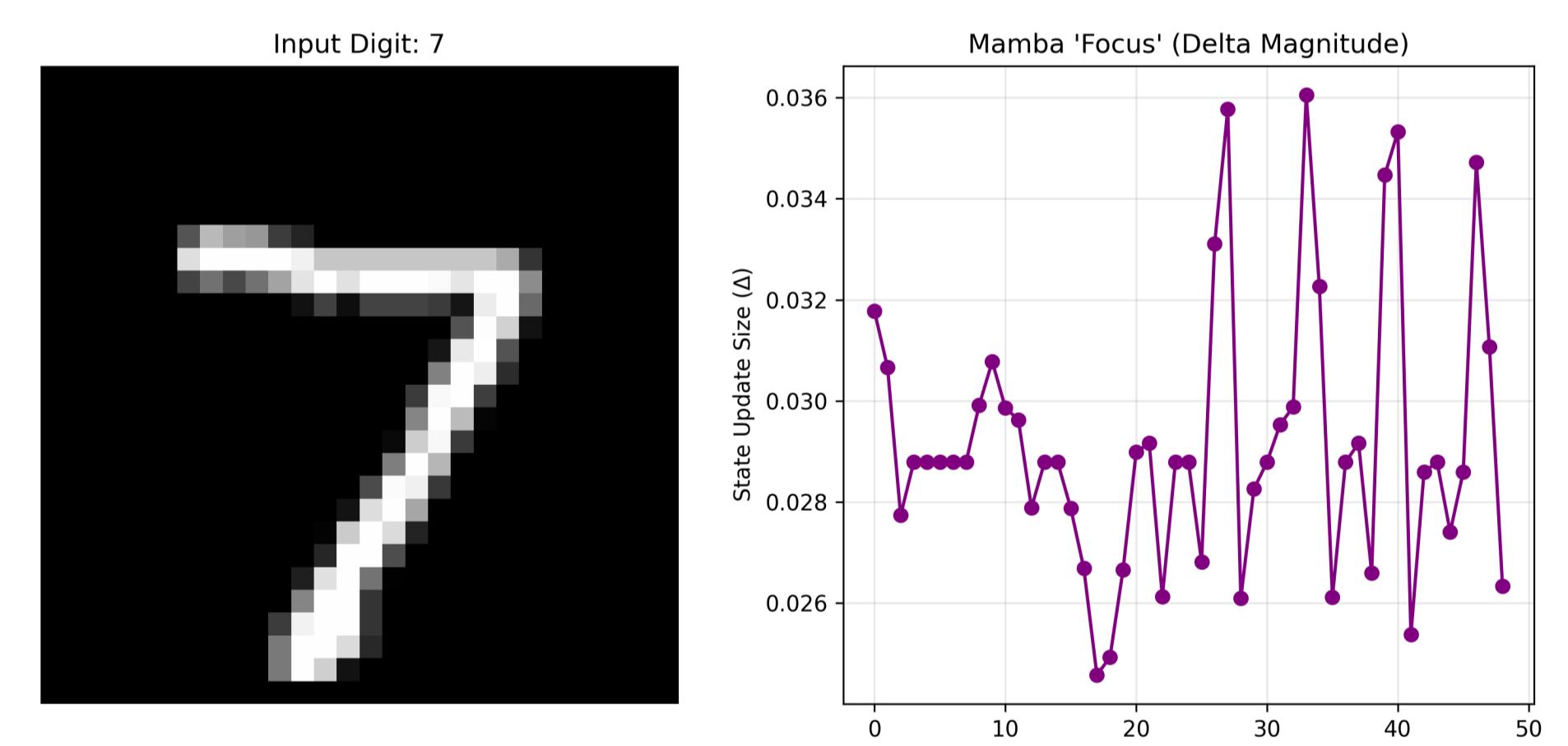


Figure 7: Visualization of Δ (from outputs/figures).

Conclusion and Future Work

Reimplemented core Mamba S6 and validated on new datasets.

Bidirectional scan improves vision tasks.

Future: larger-scale datasets and optimized kernels.

References

Gu and Dao, *Mamba: Linear-Time Sequence Modeling with Selective State Spaces*, 2023.