



# Alias-Free Mamba Neural Operator

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Numerous scientific and engineering problems entail recurrently resolving intricate Partial Differential Equation (PDE) for various parameter values, including **fluid flows**, **heat transfer analysis**, and **structural deformation studies**.









- Input: initial and boundary conditions, coefficients, source terms. etc.
- Output: solution, e.g. at some given time.

Advantages: Neural operators are faster, more accurate, and more flexible than traditional methods.

## **Neural Operators**

Characteristic: Learning mappings between infinite-dimensional function spaces, ensuring discretization invariance.

Can adapt to different levels of discretization!



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Different discrete representations correspond to the same underlying continuous function.

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Existing neural operators are mainly categorized into FNO type based on frequency domain transformation, Transformer and CNN type based on spatial integration.

#### Contributions.

- A novel Mamba scanning integration is proposed as kernel integration.
- Propose MambaNO, combining global Mamba and local convolution integration.
- Prove that the proposed MambaNO is a representation-equivalent neural operator.
- Demonstrated MambaNO's outstanding performance in solving PDEs.

#### Methodologies





Our paper establishes a connection between the kernel integration formula and the statespace Model through rigorous mathematical derivation, enabling the global integration process to be implemented with linear complexity scanning!



Cross-scanning operation in Mamba integration with a computational complexity of O(N).

### MambaNO





Mamba integration, conv integration, up/downsampling, and activation function layers are all constrained within a band-limited function space to prevent aliasing.

### Experiments



• We ran fair grid search for each baseline and each benchmark.

Visualization results on the 2D Navier-Stokes equations.







### Experiments



	In/Out	GT	Unet	ResNet	DON	FNO	CNO	MambaNO
Poisson	In	4.09%	1.05%	0.63%	19.07%	7.35%	0.31%	0.17%
Equation	Out	3.47%	1.55%	1.34%	11.18%	8.62%	0.33%	0.21%
Wave	In	0.91%	0.96%	$0.70\% \\ 2.50\%$	1.43%	0.65%	0.40%	0.38%
Equation	Out	1.97%	2.24%		3.12%	1.95%	1.29%	1.22%
Smooth	In	1.18%	0.59%	0.47%	1.38%	0.34%	0.29%	0.26%
Transport	Out	666.07%	2.97%	2.73%	119.61%	1.97%	0.35%	0.34%
Discontinuous	In	1.70%	1.44%	1.41%	6.35%	1.26%	1.11%	1.08%
Transport	Out	27270.96%	1.62%	1.54%	140.73%	3.47%	1.31%	1.21%
Allen-Cahn	In	1.30%	1.38%	2.36%	22.97%	$0.87\% \\ 2.18\%$	0.91%	0.72%
Equation	Out	3.03%	3.28%	3.91%	20.75%		2.33%	2.11%
Navier-Stokes	In	4.61%	4.94%	4.10%	12.95%	3.97%	3.07%	2.74%
Equation	Out	17.23%	16.98%	15.04%	23.39%	14.89%	10.94%	5.95%
Darcy	In	0.86%	0.54%	0.42%	1.13%	0.80%	0.38%	0.33%
Flow	Out	1.17%	0.64%	0.60%	1.61%	1.11%	0.50%	0.44%
Compressible Euler	In Out	2.33% 3.14%	$0.72\% \\ 0.91\%$	1.89% 2.20%	2.15% 3.08%	$0.49\% \\ 0.74\%$	0.39% 0.63%	0.34% 0.61%

#### Table 1: Relative median $L^1$ test errors for various benchmarks and models.





• Variation in test errors across various resolutions and scaling laws.



Varying the input resolution after training.

Test error vs. Number of training samples.





## Thanks for listening

