

Background: Mechanistic Neural Network (MNN)

MNN is a powerful tool.

	NeuralODE, UDE Chen et al. (2018) Rackauckas et al. (2020)	SINDy Brunton et al. (2016)	Neural Operators Li et al. (2020)	MNN Pervez et al. (2024)
Linear Discovery		✓		✓
Nonlinear Discovery				✓
Physical Parameters	✓	✓		✓
Forecasting	✓		✓	✓
Interpretability		✓		✓

Solvers

- Dense solver (dense matrices)
- Sparse solver (iterative methods conjugate gradient)

Limitations

- High computational costs in time and memory
- Inefficient GPU utilization
- Sparse solver: numerical inaccuracies in large-scale problems

Complexities for sequence length T

	Time Complexity	Space Complexity
Dense Solver	$O(T^3)$	$O(T^2)$
Sparse Solver	$O(T^2)$	$O(T^2)$



Scalable MNN (S-MNN)

Time and space complexities: O(T)

(S-)MNN = Encoders + Differentiable ODE Solver + Optional Decoders

- Encoders: learn dynamics from data
- Solver: solve linear systems for time sequence predictions
- Decoders: generate outputs for forecasting and parameter discovery

Three types of constraints

- Governing equation constraints
- Initial value constraints
- Smoothness constraints (different from the original MNN)

Forward pass (training & inference): solve linear system Ay = b in the S-MNN solver

- Under all proper use cases, the linear system is over-constrained.
- The least squares solution is $\mathbf{y} = (\mathbf{A}^{\mathsf{T}} \mathbf{A})^{-1} \mathbf{A}^{\mathsf{T}} \mathbf{b}$, denoted as $\mathbf{y} = \mathbf{M}^{-1} \boldsymbol{\beta}$.
- M is a banded symmetric matrix, so O(T) solver exists.



Backward pass (training only)

• O(T) complexity: $\frac{\partial l}{\partial \boldsymbol{\beta}} = \boldsymbol{M}^{-1} \frac{\partial l}{\partial \boldsymbol{y}}$ and $\frac{\partial l}{\partial \boldsymbol{M}} = -\frac{\partial l}{\partial \boldsymbol{\beta}} \boldsymbol{y}^{\mathsf{T}}$



Input Sequence x_1, x_2, \dots, x_T

Encoder Network

Coefficients c, d, Initial Values u, Time Intervals s

ODE Representation

Governing Equation Constraints (Same as MNN)

Linear ODE of Unknown 1D Function y(t):

$$c_0(t)y(t) + c_1(t)\frac{dy(t)}{dt} + c_2(t)\frac{d^2y(t)}{dt^2} + \dots + c_R(t)\frac{d^Ry(t)}{dt^R} + d(t) = 0$$

Initial Value Constraints (Same as MNN)

$$y(t_0) = u_0,$$
 $\frac{dy(t_0)}{dt} = u_1,$ $\frac{d^2y(t_0)}{dt^2} = u_2,$...

Smoothness Constraints Based on Taylor Expansion

(Different from MNN)

Forward:
$$y(t + s(t)) = \sum_{r=i}^{R} \frac{s(t)^r}{r!} \frac{d^r y(t)}{dt^r}, i = 0, \dots, R$$

Backward:
$$y(t) = \sum_{r=i}^{R} \frac{\left(-s(t)\right)^{r}}{r!} \frac{\mathrm{d}^{r} y(t+s(t))}{\mathrm{d}t^{r}}, \ i=0,\cdots,R$$

S-MNN Solver

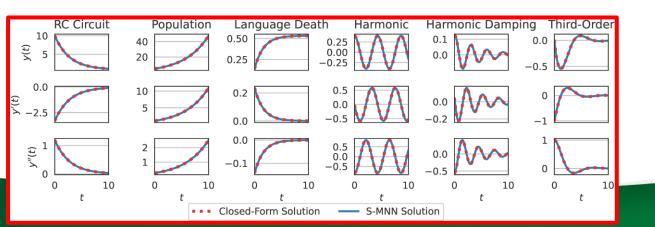
Discrete Solutions of y(t) and its Derivatives

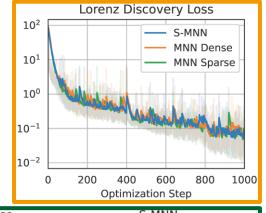
Decoder Network

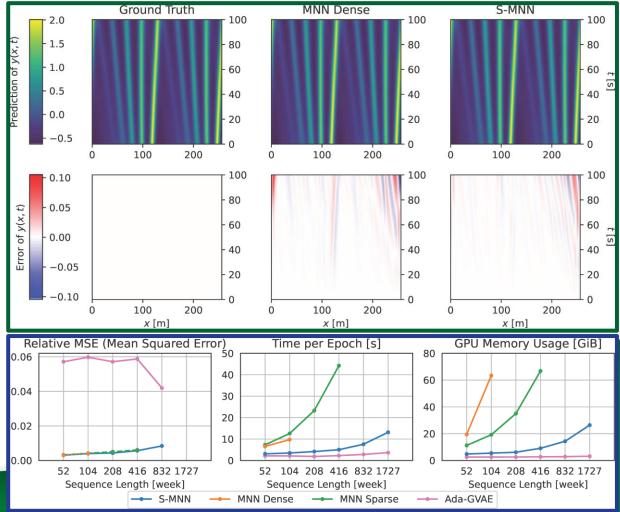
Output Sequence z_1, z_2, \dots, z_T

Evaluations

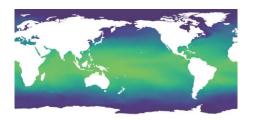
- Standalone validation [ODEs with closed-form solutions]
- Discovery of governing equations [Lorenz system]
- Solving PDEs [Korteweg-De Vries (KdV) equation]
- Real-world application [long-term sea surface temperature forecasting]







Conclusions



S-MNN overcomes the computational limitations of MNN, enabling scalable, interpretable, and efficient modeling of complex systems.

- Linear time and space complexities with respect to the sequence length
- Applications in chaotic systems, PDEs, and climate modeling
- Advances scientific machine learning

Source code is available at https://github.com/IST-DASLab/ScalableMNN



