

# Advanced Neural Ordinary Differential Equation Solver Using PETSc

**Wenjun Zhao**  
Givens Associate  
Argonne National Laboratory  
Ph.D. Candidate at New York University

**Mentor: Dr. Hong Zhang**  
Assistant Computational Mathematician  
Argonne National Laboratory

August 21<sup>st</sup>, 2020  
New York City, NY

# Introduction to Neural ODEs

- Residual networks: with  $f$  as a neural network,

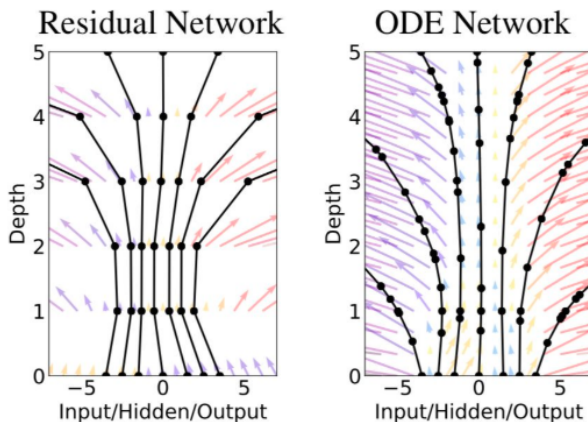
$$z_{t+1} = z_t + f(z_t, \theta_t), \quad t \in \{0, 1, \dots, T\},$$

which can be interpreted as an Euler discretization of an ODE.

- Neural ODE<sub>[1]</sub>**: in the limit of smaller time steps,

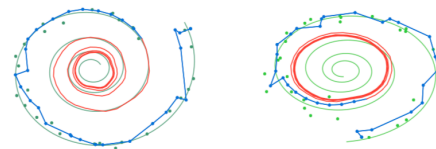
$$\frac{dz}{dt} = f(z(t), \theta(t), t), \quad z(0) = z_0,$$

and the output is defined by  $z(T)$ .



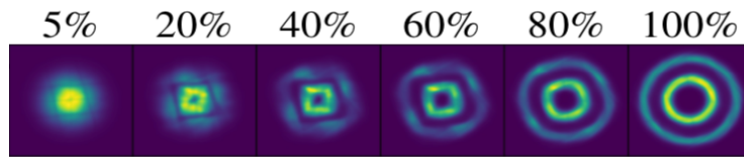
## Applications:

- Replacing residual blocks in supervised learning<sub>[1]</sub> ;
- Time series modeling<sub>[1]</sub> ;
- Density estimation through continuous normalizing flows<sub>[1][2], \dots</sub>,



(a) Recurrent Neural Network

(b) Latent Neural Ordinary Differential Equation



# Different implementations

To calculate the gradient for the loss function, the adjoint method is applied:

Forward:  $z(t_1) = z(t_0) + \int_{t_0}^{t_1} f(z, t) dt$

Backward:  $a(t_0) = a(t_1) + \int_{t_1}^{t_0} a(t)^T f_z(z, t) dt$ , where  $a(t) = L_z(z(t))$  is the adjoint state

Gradient:  $L_\theta = \int_{t_0}^{t_1} a(t)^T f_\theta(z, t) dt$

## Our approach:

We use discrete adjoint method and checkpointing strategy through PETSc TSAdjoint [6]

**We compare it with the following 3 existed implementations:**

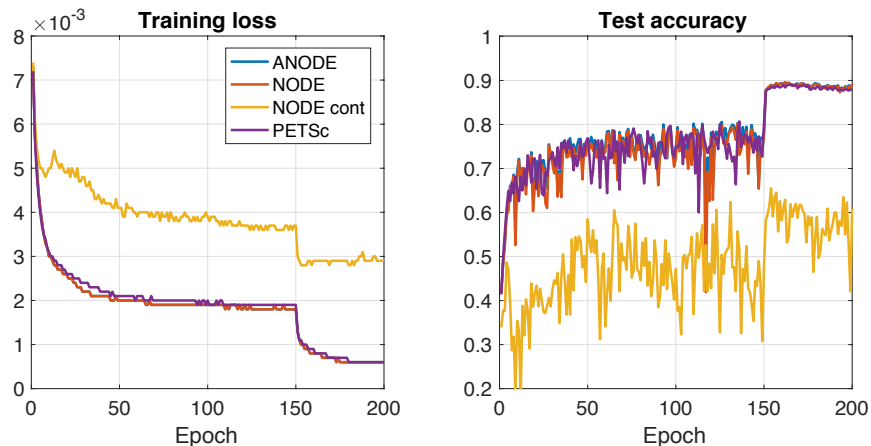
- Discrete adjoint, checkpointing everything (referred as NODE [1] )
- Continuous adjoint, no checkpointing (referred as NODE cont.[1] )
- Discrete adjoint, multi-level checkpointing (referred as ANODE [3] )

# Accuracy

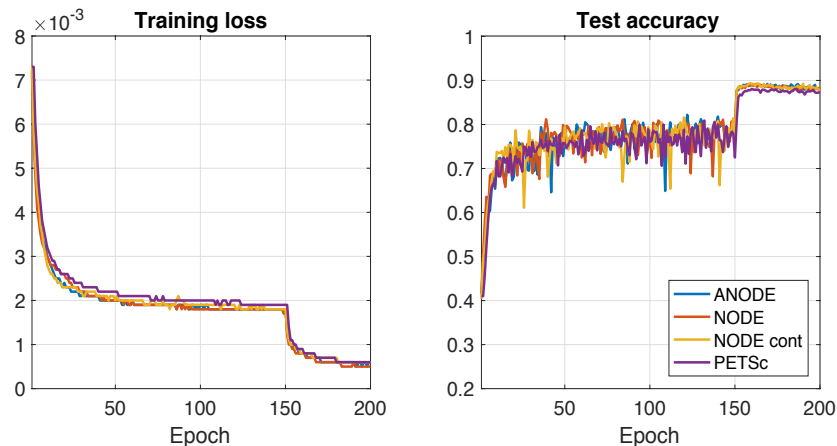
- NODE, ANODE, PETSc use discrete adjoint method, which provides exact gradients;
- NODE cont uses continuous adjoint, has large error with low accuracy time steppers.

**Example: Classification on Cifar-10 dataset, architecture with 4 ODE blocks [3]**

(1) With forward Euler method (first order):



(2) With Runge-Kutta 4 method (4-th order):



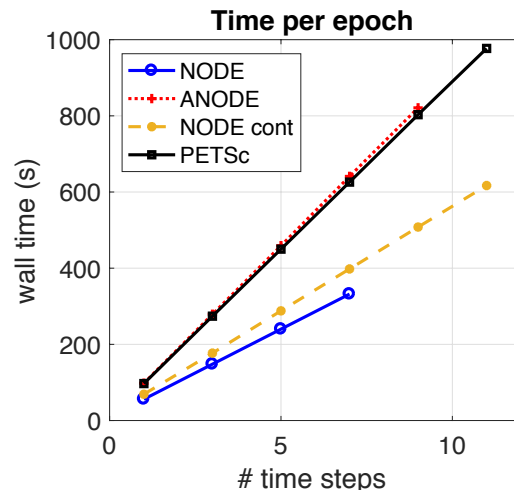
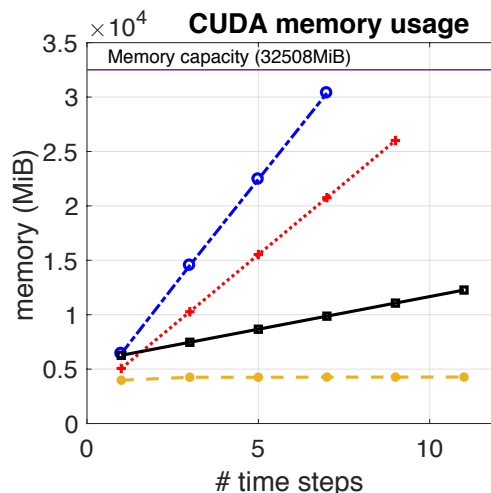
# Efficiency

- NODE **checkpoints everything** (function evaluations and trajectory) in the forward pass;
- NODE cont. reverses the ODE and **does not require checkpointing**;
- ANODE **saves only initial conditions** and recomputes from the checkpoints;
- PETSc implementation **saves the complete trajectory** but not function evaluations;

L: # ODE blocks; Nt: # time steps  
NFE: # function evaluations

	Mem	Time	NFE
NODE	$O(LNt)$	$O(LNt)$	$O(LNt)$
NODE cont.	$O(1)$	$O(2LNt)$	$O(2LNt)$
ANODE	$O(L+Nt)$	$O(2LNt)$	$O(2LNt)$
PETSc	$O(LNt)$	$O(2LNt)$	$O(2LNt)$

Example: Classification on Cifar-10 dataset,  
with 4 ODE blocks, solved through Runge-Kutta 4

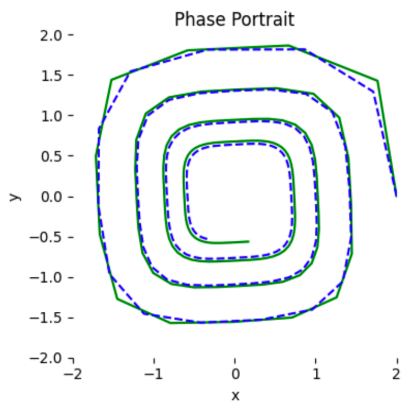


# Implicit methods for neural ODEs

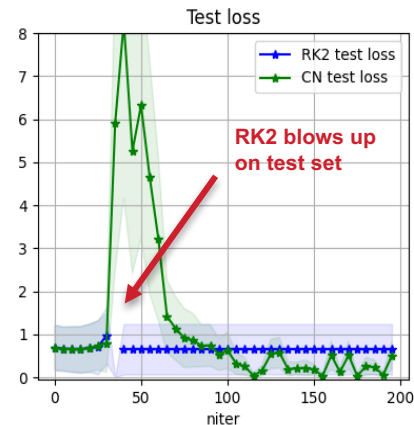
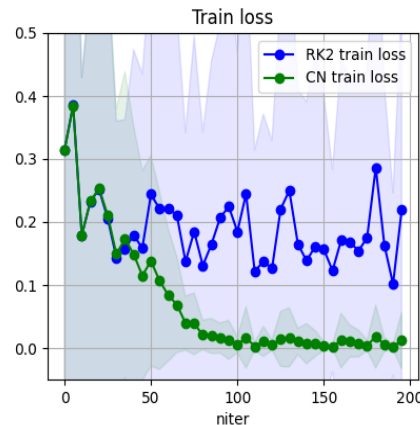
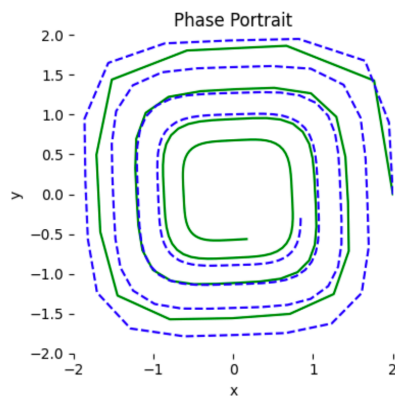
- PETSc offers sophisticated linear and nonlinear solvers that allows for implicit time stepping;
- Implicit methods are known for absolute stability with arbitrary step size, always find non-blow-up solutions during training and test.

## Example: a 2D toy model

(1) With Crank-Nicolson  
(2<sup>nd</sup> order, implicit)



(2) With Runge-Kutta 2  
(2<sup>nd</sup> order, explicit)



## References:

- [1] *Neural Ordinary Differential Equations*, Ricky T. Q. Chen, Yulia Rubanova, Jesse Bettencourt, David Duvenaud, Advances in Neural Information Processing Systems (NeurIPS), 2019
- [2] *FFJORD: Free-form Continuous Dynamics For Scalable Reversible Generative Models*, Will Grathwohl, Ricky T. Q. Chen, Jesse Bettencourt, Ilya Sutskever, David Duvenaud, International Conference On Learning Representations (ICLR), 2019
- [3] *ANODE: Unconditionally Accurate Memory-efficient Gradients For Neural Odes*, Amir Gholami, Kurt Keutzer, George Biros, International Joint Conferences On Artificial Intelligence (IJCAI'19), 2019.
- [4] *Discretize-optimize Vs. Optimize-discretize For Time-series Regression And Continuous Normalizing Flows*, Derek Onken, Lars Ruthotto, arXiv:2005.13420
- [5] *PETSc/TS: A Modern Scalable ODE/DAE Solver Library*, Shrirang Abhyankar, Jed Brown, Emil M. Constantinescu, Debojyoti Ghosh, Barry F. Smith, Hong Zhang, arXiv:1806.01437
- [6] *PETSc TSAdjoint: A Discrete Adjoint ODE Solver For First-order And Second-order Sensitivity Analysis*, Hong Zhang, Emil M. Constantinescu, Barry F. Smith, arXiv: 1912.07696

**Thank you!**