Meta-Programming and Hybrid Parallel Strategies for Solving PDEs: An FDM and PINN Comparison ^{1 2}

Seminar Presentation III

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²repository: https://github.com/liyihai-official/Final-Project



full docs: https://livihai.com/html/index.html

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- Introduction
 - Related Work
- Problem Setups
- 3 N-Dimensional Matrix Implementation
- 4 Parallelization of Multi-dimensional Matrices on cartesian Topologies
- **S** PDE Solver Implementation
- 6 Experiments
- Discussion



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Kolmogorov PDEs

Solving
$$u(x,T)$$
, for $\mathbb{R}^1 \ni T > 0$, $x \in \mathbb{R}^d$, $t \in [0,T]$, $u(t,x) = u \in \mathbb{R}^1$, $\mu(x) \in \mathbb{R}^d$, $\sigma(x) \in \mathbb{R}^{d \times d}$,
$$u_t = \frac{1}{2} \operatorname{Trace}_{\mathbb{R}^d} \left[\sigma(x) \left[\sigma(x) \right]^* \operatorname{Hess}_x u \right] + \langle \mu(x), \nabla_x u \rangle_{\mathbb{R}^d}$$
(1)

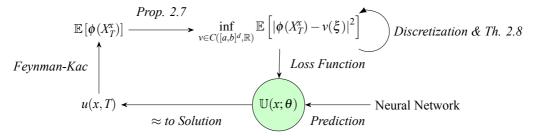


Figure: Deep Neural Network (DNN) Methodology of Solving Kolmogorov PDEs [FIRST]

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An FDM and PINN Comparison

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Introduction

Recap - Physics Informed Nerual Network

General Form of PDEs

- -u(t,x) denotes with the target function, $x \in \mathbb{R}^d$.
- $-\Gamma[\cdot;\lambda]$ is a non-linear operator parameterized by λ .

$$u_t(t,x) + \Gamma[u;\lambda] = 0 \tag{2}$$

Define f(t,x) to be given by

$$f(t,x) = u_t(t,x) + \Gamma[u;\lambda]$$
(3)

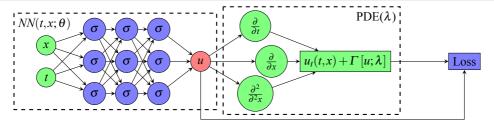


Figure: PINN, with with 3 fully connected hidden layers

Introduction Recap - Conclusion

Comparing With Finite Difference Time Domain Method (FDTD)

- Deep Neural Network [FIRST]
 - Gives lower quality approximations.
 - Takes longer time to train.
 - Possible to solve high dimension PDEs
- Physics Informed Neural Network
 - Gives higher quality approximations.
 - Takes longer time to train.
 - Has more flexible way to get results.
 - Possible to solve high dimension PDEs

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General Form of problem

The PDE parametrized by number λ and an operator $\mathcal{N}[\cdot;\lambda]$, and assume the variable x is a 2D or 3D spatio-vector which is written in

$$\begin{cases} \frac{\partial u}{\partial t}(t, \vec{x}) + \mathcal{N}[u; \lambda] = 0\\ u(0, \vec{x}) = \varphi(\vec{x}) \end{cases}$$
(4)

where φ is the initial condition, and $\vec{x} \in \Omega, t \in [0, +\infty)$.

Boundary Conditions

The Dirichlet and Von Neurmann boundary conditions are formed as

$$\begin{cases} u(t,\vec{x}) = g(t,\vec{x}) \\ \frac{\partial u}{\partial \vec{n}} = g(t,\vec{x}) \end{cases}$$
 (5)

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where \vec{n} is the normal vector on $\overline{\Omega}$ the boundary of domain Ω .

Heat Equation Specific Example

Heat Equation 2D

The function u(t,x,y) = x + y - xy, $\forall \alpha \in \mathbb{R}^1$, is the solution of 2D Heat Equation 6 below

$$\frac{\partial u}{\partial t} = \alpha \left(\frac{\partial u^2}{\partial^2 x} + \frac{\partial u^2}{\partial^2 y} \right) \qquad (x,y) \in \Omega, t \in [0, +\infty)$$

$$u(0,x,y) = \varphi(x,y) = 0 \qquad (x,y) \in \Omega \qquad (6)$$

$$u(t,x,y) = g(x,y) = \begin{cases} y, x = 0, y \in (0,1) \\ 1, x = 1, y \in (0,1) \\ x, y = 0, x \in (0,1) \\ 1, y = 1, x \in (0,1) \end{cases}$$

Heat Equation 3D

The function u(t,x,y,z) = x + y + z - 2xy - 2xz - 2yz + 4xyz, $\forall \alpha \in \mathbb{R}^1$, is the solution of 3D Heat Equation 7 below

$$\frac{\partial u}{\partial t} = \alpha \left(\frac{\partial u^2}{\partial^2 x} + \frac{\partial u^2}{\partial^2 y} + \frac{\partial u^2}{\partial^2 z} \right) \qquad (x, y, z) \in \Omega, \ t \in [0, +\infty)$$

$$u(0, x, y, z) = \varphi(x, y, z) = 0 \qquad (x, y, z) \in \Omega \qquad (7)$$

$$u(t, x, y, z) = g(x, y, z) = \begin{cases} y + z - 2yz, & x = 0, \\ 1 - y - z + 2yz, & x = 1, \\ x + z - 2xz, & y = 0, \\ 1 - x - z + 2xz, & y = 1, \\ x + y - 2xy, & z = 0, \\ 1 - x - y + 2xy, & z = 1 \end{cases}$$

$$t \in [0, +\infty)$$

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Statement Challanges & Objectives

Challanges of Nonlinear Multi-Scale Systems

- Difficulty in modeling and predicting inhomogeneous cascades of scales.
- 4 High computational costs and uncertainties in classical methods.

Project Objectives

- Implement FDTD and PINN in C++/C.
- Implement FDTD hybrid parallel version using MPI/OpenMP.
- Implement PINN GPU parallel version using Libtorch/CUDA.
- Optimize performance through parallel computing frameworks.
- Evaluate the efficiency and accuracy of FDTDs and PINNs.

Highlights

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Closing Remarks

Thank you for your attention!

Any questions?