UNIVERSITÉ LIBRE DE BRUXELLES

Thesis update - 11/01/2024

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Outline

1. Introduction
2. Neural Operators
3. Physically Informed Neural Networks
4. What am I doing
5. What's next

Where am I

- arXiv:2305.03269 proposes to use Neural Operators to model the propagation of seismic waves
- What are Neural Operators ?
  - NN that approximates operators
  - Intended for efficiently solving PDE's
- Neural Network can use knowledge about the physics laws: PINN

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Neural Operators

- Proposed in arXiv:2108.08481 (August 2023)
- Key idea: learn the mapping between a function space to another, by using a Neural Network on the FT of the input
- Using the FT allows two main improvements:
  - To ease the manipulation of derivatives
  - To be completely independent of the input and output mesh
- Zero-shot super-resolution is proven and shown in the original paper, on various systems (*Heat diffusion, Darcy Flow, Navier Stokes, ...)*
- Only needs a few hundreds/thousands points to learn (really easy for GPU)
- Problem: only offers a solution after a determined time step t
  - Proposed solution: Markov Neural Operators

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PINN

- Proposed in arXiv:1711.10561 (November 2017)
- Key idea: Known PDE formulations can be used to express loss in NN training:
- Given $\frac{\delta f}{\delta t} = F(f)$, we want to minimize the expression $(\frac{\delta f}{\delta t} - F(f))^2$
- We can also add constraints on the boundary conditions, on the mass conservation, ...
  - Make the NN converge faster without exploring too much the solution space
  - Make the NN closer to the ground-truth operator
  - Reduces the number of data points required for learning

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Now

- Familiarizing with NO
  - On heat diffusion
  - Wave propagation
  - Other simple systems
- Dealing with (not so simple to me) calculus for expressing losses in the PINN framework
- Learning auto-differentiation tools to ease the PINN losses computations

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Directions

- Neural Operators can be used to solve PDE's (about 1000 times faster than classical numerical solver)
- They can learn at a given (sub)scale and generalize to higher scale, by the use of FT
- PINN can use physics knowledge to enhance learning and explainability
- NO have been tried (without PINN) on sismographs array data
- DAS data has a lot of advantages: better accuracy and easier installation
- No labelling is required
- Suffers from too large sampling, but NO can use higher discretization to learn
- Opens paths to apply PINO on DAS data