

Message Passing Neural PDE Solver for Fluid Dynamics

Semester / Master's Thesis

Partial Differential Equations (PDE) describe the dynamics of most physical systems. Recent advances in machine learning suggest that graph-based learned approaches, i.e. message passing neural networks, can approximate the dynamics of systems represented by particles as well as meshes. These models operate by autoregressively predicting the new state of a system given one or multiple past states, resembling a time integrator with fixed step size. Training and deploying these models has been a challenge which researchers have tried to solve in multiple ways, e.g. regularizing by injecting random noise to training inputs, or using multi-step losses.

In this work, we will explore how the latest innovations in learned PDE solvers can be applied to fluid dynamics systems. We will extend Message Passing Neural PDE Solvers (Brandstetter et al. 2022) to more complex nonlinear systems of equations like the compressible Euler or Navier-Stokes equations, and investigate the influence of different model components on performance. With our expertise in analysing PDE solvers, we will look at corner cases and discuss how well the physics are reproduced, similar to Simulating Liquids with Graph Networks.

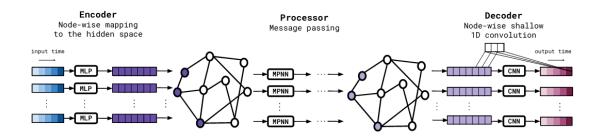


Figure 1: Schematic of MP-PDE Solver. Taken from Brandstetter et al. 2022.

Tasks

- Begin with the codebase of "Message Passing Neural PDE Solvers" and familiarize yourself with its layout and data pipeline to apply it to similar fluid dynamics problems.
- Extend the pipeline to systems of equations and apply it to the
 - 1D Euler equations for standard gas dynamics problems, e.g., SOD shock tube.
 - 2D Navier-Stokes equations for a flow past a cylinder.

Requirements

- Programming experience in Python. Experience with PyTorch is beneficial.
- Interest in (computational) fluid dynamics.
- Ability to work independently.

Contact

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