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Physics-Informed Neural Networks for Computational Fluid Dynamics Validation Using DeepXDE

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Abstract

Physics-Informed Neural Networks (PINNs) [1] have emerged as a transformative approach for solving and validating problems governed by partial differential equations, offering a novel alternative to traditional Computational Fluid Dynamics (CFD) methods. This study investigates the application of PINNs, implemented via the DeepXDE framework [2], to simulate and validate two-dimensional laminar lid-driven cavity flow, a well-established CFD benchmark. By embedding the Navier–Stokes equations into the neural network's loss function, PINNs enforce physical consistency while incorporating boundary conditions to accurately capture flow dynamics. Validating CFD simulations using conventional solvers like OpenFOAM is computationally intensive, requiring extensive meshing and discretization. In contrast, PINNs reduce reliance on these processes, potentially enhancing computational efficiency. The PINN model's results are compared with OpenFOAM simulations , demonstrating its ability to approximate velocity fields and flow patterns with reasonable accuracy. Additionally, this study explores the scalability of PINNs for more complex flow problems and their potential integration with high-performance computing environments. This work highlights PINNs as a complementary tool for CFD validation, offering insights into their efficiency and adaptability for laminar flow problems.

References

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