Causality-Constrained Inverse PINNs: Respecting Causality for Solving Inverse Problems

Jaeseung Kim [1] and Hwijae Son [2]

1) *Department of Mathematics, Konkuk University, Seoul, KOREA*

2) *Department of Mathematics, Konkuk University, Seoul, KOREA*

Corresponding Author : Hwijae Son, hwijaeson@konkuk.ac.kr

ABSTRACT

Inverse Physics-Informed Neural Networks (Inverse PINNs) provide a promising framework for solving inverse problems governed by partial differential equations (PDEs), especially in cases with limited or noisy data. However, traditional Inverse PINNs lack mechanisms to incorporate causality, limiting the model's performance in capturing the inherent sequential dependencies of physical systems. In this study, we propose **Causal-Constrained Inverse PINNs (CC-IPINNs)**, a novel framework that integrates directional causality constraints across both time and spatial domains. By designing customized loss functions that dynamically adjust weights based on initial conditions, boundary conditions, and observed data, CC-IPINNs allow the model to align its predictions with the underlying causal structure of the system. We evaluate CC-IPINNs on three representative inverse PDE problems: the Wave equation, an inverse Mie scattering problem, and a two-dimensional PDE model, each requiring nuanced causal approaches. Results demonstrate that CC-IPINNs achieve improved accuracy and stability over conventional Inverse PINNs by progressively enforcing conditions and data consistency in a causally constrained manner. This work highlights the potential of CC-IPINNs to enhance robustness and reliability in solving complex inverse problems across various physical domains.