Gradient-Annihilated PINNs for Solving Riemann Problems: Application to Relativistic Hydrodynamics

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Physics-Informed Neural Networks (PINNs) have gained significant attention in the field of deep learning for their ability to tackle physical scenarios, gaining significant interest since its inception in scientific literature [1]. These networks optimize neural architectures by incorporating inductive biases derived from knowledge of physics. To embed the underlying physics, a suitable loss function is defined, encompassing the necessary physical constraints. PINNs have proven versatile in comprehending and resolving diverse physical systems, resulting in their growing popularity in machine learning research and their direct application in various scientific domains [2]. However, to accurately represent and solve systems of differential equations with discontinuous solutions, modifications to the fundamental algorithms of PINNs are necessary.

We present a novel approach called Gradient-Annihilated Physics-Informed Neural Networks (GA-PINNs) [3] for solving partial differential equations with discontinuous solutions. GA-PINNs use a modified loss function and weighting function to ignore high gradients in physical variables. The method demonstrates excellent performance in solving Riemann problems in special relativistic hydrodynamics. The results obtained by GA-PINNs accurately describe the propagation speeds of discontinuities and outperform a baseline PINN algorithm. Moreover, GA-PINNs avoid the costly recovery of primitive variables, a drawback in grid-based solutions of relativistic hydrodynamics equations. This approach shows promise for modeling relativistic flows in astrophysics and particle physics with discontinuous solutions.

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