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Adaptive Interface-PINNs (AdaI-PINNs): An Efficient Physics-Informed Neural Networks Framework for Interface Problems

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Abstract. We present an efficient physics-informed neural networks (PINNs) framework, termed Adaptive Interface-PINNs (AdaI-PINNs), to improve the modeling of interface problems with discontinuous coefficients and/or interfacial jumps. This framework is an enhanced version of its predecessor, Interface PINNs or I-PINNs (Sarma et al. [1]; https://doi.org/10.1016/j.cma.2024.117135), which involves domain decomposition and assignment of different predefined activation functions to the neural networks in each subdomain across a sharp interface, while keeping all other parameters of the neural networks identical. In AdaI-PINNs, the activation functions vary solely in their slopes, which are trained along with the other parameters of the neural networks. This makes the AdaI-PINNs framework fully automated without requiring preset activation functions. Comparative studies on one-dimensional, two-dimensional, and three-dimensional benchmark elliptic interface problems reveal that AdaI-PINNs outperform I-PINNs, reducing computational costs by 2-6 times while producing similar or better accuracy.

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Key words: PINN, I-PINNs, AdaI-PINNs, domain decomposition, interface problems, machine learning, physics-informed machine learning.

1 Introduction

In recent years, Physics-informed neural networks (PINNs) has become increasingly popular as a numerical method for solving partial differential equations (PDEs). Unlike tra-

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ditional data-driven methods that rely on large training datasets, PINNs require minimal training data because the loss functional in PINNs is constructed from the residuals of the governing equations, boundary and/or initial conditions [2, 3]. Additionally, the meshless character of PINNs makes this approach potentially suitable for solving a wide range of complex engineering problems (e.g., see [4–6]).

Despite its widespread use, the application of PINNs to interface problems is still relatively uncommon. Interfaces can cause weak or strong discontinuities in field variables, posing challenges for numerical methods that depend on underlying grids to construct approximate solutions. Grid-based methods often require conforming meshes or intrusive modifications to data structures to appropriately treat discontinuities in the field variables [7–10]. The meshless nature of PINNs makes it inherently suited for such problems. Over the past few years, notable attempts have been made to solve interface problems with PINNs [11–13]. Basir et al. [14, 15] proposed a novel framework based on constrained optimization techniques to handle non-smooth PDE solutions. Their approach employed maximum likelihood estimation to integrate noisy measurement data with the governing physics. However, all these methods involve significant modifications to the underlying PINNs architecture. Extended PINNs (XPINNs) and conservative PINNs (cPINNs) frameworks of Jagtap et al. [16, 17] provided breakthrough enhancements to the traditional PINNs framework, although still in the context of homogeneous materials, by introducing domain decomposition and prescribing flux continuity constraints at fictional interfaces. These ideas were subsequently incorporated to model fluid flow and heat conduction with discontinuous material coefficients in several follow-up studies [18, 19]. However, in these methods, the neural networks (NNs) used in each fictitious subdomain were different; therefore, the methods require significantly more trainable parameters than conventional PINNs.

Recently, Sarma et al. [1, 20] developed a novel physics-informed neural networks framework for modeling interface problems called Interface PINNs (I-PINNs). I-PINNs uses different neural networks for any two subdomains separated by a sharp interface, with the neural networks differing only in their activation functions (AFs) while sharing the same set of parameters (weights and biases). Through benchmark elliptic interface problems, it was demonstrated that I-PINNs outperformed both conventional PINNs and other domain decomposition PINNs frameworks such as multi-domain PINN (M-PINN) [18] and X-PINNs [17] in both accuracy and cost.

The key idea of the I-PINNs framework is to utilize different AFs for different subdomains. However, as the number of subdomains increases, identifying these AFs can sometimes be challenging. While using the same AFs across alternating subdomains could mitigate this issue, doing so adversely affects convergence rate of I-PINNs. The objective of this study is to address this limitation by automating the choice of AFs for each subdomain using the concept of adaptive activation functions (AAFs) [21]. The parameters for the AAFs are trained alongside the usual weights and biases to provide an optimal choice of AFs for a given problem.

The rest of the paper is structured as follows. Section 2 provides the governing equa-