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PDEARENA: A MODERN, SCALABLE, AND EASY TO USE PDE SURROGATE BENCHMARKING FRAMEWORK

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ABSTRACT

The field of neural PDE surrogates is still relatively new and there is currently a lack of unified and scalable frameworks available. To address this gap, we have developed PDEArena, a modern and user-friendly benchmarking framework for PDE surrogates. It contains state-of-the-art implementations of more than 20 different recently proposed PDE surrogate architectures (or combinations thereof) and is continuously updated with new architectures. The main goal of PDEArena is to enable practitioners to train PDE surrogates at scale using deep learning. Scaling up deep learning models has been immensely successful in fields such as computer vision and natural language processing, and has the potential to help overcome the computationally expensive nature of standard PDE solution techniques. However, scaling such PDE surrogate models requires a significant amount of engineering, particularly in terms of distributed training and data loading. PDEArena aims to provide a solution to these challenges and make it easier for practitioners to train and use PDE surrogates at scale. We used PDEArena in our recent paper "Towards Multi-spatiotemporal-scale Generalized PDE Modeling" [1] to compare modern UNets vs. other state of the art neural PDE surrogate learning approaches. PDEArena's simplicity and scalability allowed us to quickly iterate on different UNet variants: from the 2015 version to modern UNets [2] and our own variants thereof. Furthermore, we could easily compare various other tradeoffs like runtime and GPU memory requirements against other architectures like ResNets [3], Dilated ResNets [4], as well as various Fourier-based approaches.

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