Enhancing Generalization in Physics-Informed Machine Learning with Neural Oscillators

Victor Michel-Dansac[1]

[1] Inria Strasbourg
victor.michel-dansac@inria.fr

In this talk, we delve into the challenge of generalization in physics-informed machine learning (PIML), particularly when applied to complex physical phenomena described by partial differential equations (PDEs). The primary goal of our discussion is to present a novel approach aimed at significantly improving the generalization ability of PIML for practical applications. This is achieved by integrating the causality and temporal sequential characteristics inherent in PDE solutions with recurrent neural network architectures, specifically through the concept of neural oscillators based on systems of ordinary differential equations. Our methodology addresses critical issues such as the mitigation of the exploding and vanishing gradient problem and enhances the ability of PIML models to capture long-term dependencies. The talk will provide insights into extensive experiments conducted with time-dependent nonlinear PDEs and biharmonic beam equations, showcasing the superiority of our approach over existing state-of-the-art methods in terms of generalization capabilities across various metrics. By leveraging neural oscillators, we demonstrate significant improvements in the accuracy of PIML models for extrapolation and prediction tasks beyond the scope of their training data, thereby opening new avenues for the application of machine learning in solving intricate physical problems.