CRUNCH Seminars at Brown, Division of Applied Mathematics

Friday - May 1, 2020

PhyGeoNet: Physics-Informed Geometry-Adaptive Convolutional Neural Networks for Solving Parametric PDEs on Irregular Domain

Jianxun Wang

Recently, the advent of deep learning has spurred interest in the development of physics-informed neural networks (PINN) for efficiently solving partial differential equations (PDEs), particularly in a parametric setting. Among all different classes of deep neural networks, the convolutional neural network (CNN) has attracted increasing attention in the scientific machine learning community, since the parameter-sharing feature in CNN enables efficient learning for problems with large-scale spatiotemporal fields. However, one of the biggest challenges is that CNN only can handle regular geometries with image-like format (i.e., rectangular domains with uniform grids). In this paper, we propose a novel physics-constrained CNN learning architecture, aiming to learn solutions of parametric PDEs on irregular domains without any labeled data. In order to leverage powerful classic CNN backbones, elliptic coordinate mapping is introduced to enable coordinate transforms between the irregular physical domain and regular reference domain. The proposed method has been assessed by solving a number of PDEs on irregular domains, including heat equations and steady Navier-Stokes equations with parameterized boundary conditions and varying geometries. Moreover, the proposed method has also been compared against the state-of-the-art PINN with fully-connected neural network (FC-NN) formulation. The numerical results demonstrate the effectiveness of the proposed approach and exhibit notable superiority over the FC-NN based PINN in terms of efficiency and accuracy.