Physics-informed neural networks & Domain Adaptation

Mathilde Mougeot & Thomas Alazard

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Centre Borelli, ENS Paris-Saclay,
91190 Gif, France

For decades, statistical or machine learning methods have been already applied successfully in many scientific and technical fields. However, their application to engineering science remain limited because of the lack of data and the difficulty in incorporating physical knowledge of systems into the models. Considering small data regime, researchers and engineers are turning more and more into hybrid models that combines approaches based on the knowledge of physics of the systems and also the data. Recently, there has been a growing number of researches using deep learning methods to study physical systems, which are often described by partial differential equations (PDEs), by enforcing physical constraints into models. This work focuses on Physics-informed neural networks (PINNs) [1] and their variants, which are recently proposed methods for solving forward and inverse problems involving PDEs and has gained remarkable results in different fields of research since the last two years.

The main objective is to investigate in the use of PINNs on problems with geometric variations. In the first stage, we propose to study the state-of-the-art of PINNs and existing methods concerned about domain adaptation [2-7]. In the second stage, we propose to develop appropriate approach for PINNs using domain adaptation methods to tackle the problems with geometric variations. The developed method will be applied to industrial use cases.

Required knowledge: numerical schemes for solving PDEs, deep learning (neural networks, transfer learning),.

References:

1 Raissi, Maziar, Paris Perdikaris, and George E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations." Journal of Computational Physics 378 (2019): 686-707.

2 Goswami, Somdatta, et al. "Transfer learning enhanced physics informed neural network for phase-field modeling of fracture." Theoretical and Applied Fracture Mechanics 106 (2020): 102447.

3 Psaros, A.F., Kawaguchi, K. and Karniadakis, G.E., 2021. Meta-learning PINN loss functions. arXiv preprint arXiv:2107.05544.

4 Arthurs, C.J. and King, A.P., 2021. Active training of physics-informed neural networks to aggregate and interpolate parametric solutions to the Navier-Stokes equations. Journal of Computational Physics, 438, p.110364.

5 Gao, H., Sun, L. and Wang, J.X., 2021. PhyGeoNet: physics-informed geometry-adaptive convolutional neural networks for solving parameterized steady-state PDEs on irregular domain. Journal of Computational Physics, 428, p.110079.

6 Kharazmi, E., Zhang, Z. and Karniadakis, G.E., 2021. hp-VPINNs: Variational physics-informed neural networks with domain decomposition. Computer Methods in Applied Mechanics and Engineering, 374, p.113547.

7 Jagtap, A.D. and Karniadakis, G.E., 2020. Extended physics-informed neural networks (xpinns): A generalized space-time domain decomposition based deep learning framework for nonlinear partial differential equations. Communications in Computational Physics, 28(5), pp.2002-2041.