ON THE PREPROCESSING OF PHYSICS-INFORMED NEURAL NETWORKS: HOW TO BETTER UTILIZE DATA IN FLUIDMECHANICS

Z X Sun[1], S F Xu[1], D L Guo[1], G W Yang[1]
[1] Institute of Mechanics, Chinese Academy of Sciences, Beijing 100190, China

Abstract. Physics-Informed Neural Networks (PINNs) serve as a flexible alternative for tackling forward and inverse problems in differential equations, displaying impressive advancements in diverse areas of applied mathematics. Despite integrating both data and underlying physics to enrich the neural network's understanding, concerns regarding the effectiveness and practicality of PINNs persist. Over the past few years, extensive efforts in the current literature have been made to enhance this evolving method, by drawing inspiration from both machine learning algorithms and numerical methods. Despite notable progressions in PINNs algorithms, the important and fundamental field of data preprocessing remain unexplored, limiting the applications of PINNs especially in solving inverse problems. Therefore in this paper, a concise yet potent data preprocessing method focusing on data normalization was proposed. By applying a linear transformation to both the data and corresponding equations concurrently, the normalized PINNs approach was evaluated on the task of reconstructing flow fields in three turbulent cases. The results illustrate that by adhering to the data preprocessing procedure, PINNs can robustly achieve higher prediction accuracy for all flow quantities under different hyperparameter setups, without incurring extra computational cost, distinctly improving the utilization of limited training data. Though only verified in Navier-Stokes (NS) equations, this method holds potential for application to various other equations.

Keywords: Physics-informed neural networks, data preprocessing, inverse problems, data normalization, flow field reconstruction