Abstract

Physics-Informed Neural Networks (PINNs) have emerged as a powerful tool for solving differential equations by embedding physical laws into the structure of deep neural networks. This report investigates the application of PINNs to a range of canonical problems, including both forward and inverse tasks. The effectiveness of PINNs is evaluated by comparing their performance against traditional numerical techniques, such as the Runge-Kutta methods. In this context the impact of grid spacing on the accuracy and convergence of the solution is systematically analyzed. The results demonstrate that PINNs offer a flexible and efficient alternative to classical methods, particularly in scenarios where data is sparse, random or noisy. Moreover, the transfer learning technique is applied to effectively solve high-frequency problems that are prone to spectral bias. However, challenges related to the optimization of the loss function are also identified, suggesting directions for future research. Consequently, the results of this study should serve as an introduction into the topic of Physics-Informed Neural Networks, paving the way for more advanced applications.