Regularization by architecture: Deep learning for PDE based inverse problems

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We start with an introduction of the inverse problems group at the center for industrial mathematics, University Bremen. We then give an overview and numerical comparison of neural operator concepts for PDE-based parameter identification problems. These neural operators leverage the inherent properties of PDEs, and as a result, surpass the performance of conventional deep learning architectures. While most efforts have focused on using neural operators to solve PDEs, our work extends their application to parameter identification tasks, where the goal is to infer parameters given the solution or a measurement of the solution. We present numerical results for the Poisson equation source problem and the inference of the Darcy flow diffusion term. Additionally, we explore more intricate PDEs like the Helmholtz and Navier-Stokes equations, assessing their accuracy across varying noise levels. This research broadens the scope of neural operators, showcasing their versatility and potential in diverse PDE-based applications. Finally we introduce the TorchPhysics library, which has been developed at the University of Bremen in cooperation with the Robert Bosch GmbH. It provides a user-friendly framework for implementing several Deep Learning methods - like those mentioned above - for solving differential equations, but also parameter-identification problems can be tackled. Among TorchPhysics main features is the simplicity of translating differential equations into readable code. In combination with a clean documentation and detailed tutorials, this enables a quick start for the user. Furthermore, complex or time-dependent domains can easily be realized and sampling within these domains can be done in various ways. After a broad overview about the functionalities of TorchPhysics, we will show an illustrative example and finally draw a comparison to other existing libraries.