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PINN-based Reconstruction of Particle/Density-driven Gravity Flows

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Inverse problems in fluid mechanics play an important role in science and engineering, especially when it comes to optimal design, reconstruction of biomedical and geophysical flows, parameter estimation, and more. These inverse problems are often ill-posed, thus, it is challenging or sometimes even impossible to solve them using traditional methods. Moreover, the generation of simulated data for ill-posed inverse problems can become very costly where simulation needs to be performed multiple times to either discover missing physics in the model or calibrate the free parameters in the model. One possible alternative for solving these problems is through the use of Physics-Informed Neural Networks - PINNs[1], in which we approximate the problem's solution using Neural Networks, while incorporating the known data and physical laws during the training phase, and also easily enabling us to take advantage of computational resources like GPUs without much effort. Here we show a PINN-based framework for reconstructing velocity, concentration, and pressure fields for Density/Particle-driven Gravity Flow[2] problems in which the available data can be given in two different ways: a set of scattered measurements for the concentration field, or a set of velocity and concentration measurements that follows the configurations often used in real-life experiments. We then summarize our findings by showing how PINNs can deal with flow reconstruction problems with limited observations, while we also vary systematically the amount of data that we use in order to find reasonably accurate results.

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