Application of Physics-Informed Neural Networks in Nonlinear Systems Identification and Parameter Estimation

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Physics-Informed Neural Networks (PINNs) represent a powerful approach for solving inverse problems, including identification and parameter estimation in nonlinear systems. The integration of physics-based knowledge into neural networks allows for more efficient and accurate learning, particularly in scenarios where limited and noisy data are available.

As a first application of the PINN idea, we introduce iNeuralSINDy as a novel approach in nonlinear system identification. SINDy is a widely adopted technique for identifying nonlinear dynamics. Despite numerous efforts, the presence of noisy and limited data continues to pose a significant hurdle to the effectiveness of the SINDy approach. We present a resilient approach for unveiling nonlinear governing equations from data characterized by noise and scarcity. Our strategy involves employing neural networks to assimilate an implicit representation based on measurement data. This representation not only generates outputs in proximity to the measurements but also encapsulates the time evolution of the output within a dynamic system. By harnessing the implicit representation through neural networks, we acquire derivative information, a prerequisite for SINDy, utilizing an automatic differentiation tool. To fortify the robustness of our methodology, we introduce an integral condition on the output of the implicit networks.

In the second application, we introduce the discrete empirical interpolation method (DEIM), specifically the QR-factorization-based variant known as Q-DEIM, as a strategic sampling technique for mitigating the computational complexities and time demands associated with parameter estimation for partial differential equations (PDEs) using PINN. Our methodology involves the judicious pre-selection of spatio-temporal data, thereby constructing a reduced dataset for training a neural network to estimate the coefficients of the underlying PDE governing the data. We establish that our proposed Q-DEIM-based sampling approach not only reduces the required training data for the neural network but also yields a commendable approximation of PDE coefficients in fewer training iterations.