MARICELA BEST MCKAY, University of British Columbia
Approximation rates and training dynamics for Physics-informed Neural Networks

Physics-informed Neural Networks (PINNs) are an alternative to traditional numerical methods for approximating solutions to systems of Partial Differential Equations. They are especially promising for applications where it is desirable to include real-world data into a numerical model. However, PINNs can be particularly challenging to train. PINNs may fail to train altogether for multi-scale problems, or problems containing multiple frequencies. The gradient flow for PINN loss functions often exhibits characteristics of stiffness and instability. Even when PINNs are able to train, they are unable to achieve the high-order accuracy of traditional methods. Recently, theoretical guarantees for the approximation rates of continuous functions by ReLU networks have been proposed. These rates rely on the existence of an optimal network, which may or may not be findable during training. While ReLU is not a suitable choice for most PINNs, we demonstrate that ReLU like activation functions can improve PINN training dynamics. We illustrate how challenges in PINN training dynamics impact numerical error rates and explore the gaps between theory and practice for the PINN setting.