Physics-Informed Neural Networks: Classical Demonstrations & Astrophysical Prospects

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Physics Informed Neural Network (PINN) is a training framework that incorporates governing equations through customised loss functions. The distinct advantage of PINNs lies in their ability to solve complicated partial differential equations (PDEs) continuously and mesh-free using sparse data and physical constraints.

We trained PINNs for classical fluid dynamics problems, including the Blasius boundary-layer profile and viscous Burgers equation, using collocation-based PDE residuals and boundary-condition losses with a feedforward network. These served as testbeds for learning practical PINN techniques like adaptive loss weighting, input normalization, hard boundary enforcement, and targeted collocation sampling.

In Astrophysics, such instructive PDE implementations demonstrate the potential for using PINNs in integrating heterogeneous observational data with physical constraints, allowing for parameter inference with inverse solving capabilities. The mesh-free nature is particularly suitable for producing surrogate models, enabling faster emulation.

The poster will present implementation of test cases along with limitations and steps for adapting PINNs to astrophysical problems.