Physics-Informed Neural Networks (PINNs) for solving thermal problems

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Physics-Informed neural networks (PINNs) have recently gained popularity due to their ability to solve forward and inverse problems involving partial differential equations using neural networks. Unlike conventional numerical techniques for solving PDEs, PINNs are meshless models that satisfy the prescribed initial and boundary conditions and the governing PDE. PINNs are unsupervised machine learning models as it does not require the ground truth to produce a unique solution for a well-posed PDE.

Although neural networks have been studied for a long time, it was only in the last decade they started gaining immense popularity due to the availability of open-source machine learning libraries such as PyTorch and TensorFlow. It is automatic differentiation, producing highly accurate derivatives, that enhances the accuracy of PINNs even with sparse data points.

The baseline PINN does not work well on stiff PDEs. Also, it does not scale to problems in higher dimensions. Especially, it fails to approximate the discontinuities, such as conflicting boundary conditions at adjacent corners/faces or discontinuous pressure, temperature, and density due to shockwaves. Leveraging way around from conventional numerical techniques to deal with discontinuities does not work well on PINNs. The most viable current solution is simply ignoring those points and not including them in the training dataset. Nvidia Modulus, a python library for PINNs, uses signed distance function weighting for ignoring those points with a smooth transition.

Researchers also worked to improve the accuracy of PINNs by modifying the architecture of the Neural network. Many of these architectures use Fourier transform in one way or another to remove the spectral bias. Some promising architectures are Fourier networks, Fourier neural operators and multiplicative filter networks. With these improved PINNs, many complex thermal problems can now be solved.

Currently, the computational cost of simulating physical systems using PINNs is way more compared to conventional numerical solvers. But if we can solve the complicated 3D problems in just three years after the first paper was published, maybe in the next ten years, PINNs will simulate physical systems much faster by leveraging more powerful GPUs.

It is apparent from the available literature that problems with geometrical or physics simplicity can be solved accurately with PINNs. However, many challenges exist in extending the PINNs for complex and practical issues. This lecture will discuss an overview of PINNs for solving thermal problems.