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Integrating Deep Learning with Plasma Physics for Accurate and Reliable Multi-Diagnostic and Time-Constrained Inverse Problem Methodologies in Nuclear Fusion

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Magnetic confinement nuclear fusion offers immense potential as a clean and sustainable energy source for the future. However, achieving net energy from fusion reactors necessitates a deeper understanding of the underlying physics and the development of efficient control strategies. Plasma diagnostics play a crucial role in these efforts, but obtaining accurate, reliable, and extensive information is challenging due to diagnostic limitations imposed by the harsh environment of nuclear fusion reactors and the complex physics governing plasma behavior [1].

Artificial intelligence (AI) methodologies have found widespread applications in plasma physics and diagnostics, including automatic diagnostic processing, information extraction, solving inverse problems, and detecting and predicting plasma instabilities. However, traditional machine and deep learning approaches, which rely solely on data, require vast amounts of training data and struggle to extrapolate beyond known cases.

In recent years, Physics-Informed Neural Networks (PINNs) have emerged as a groundbreaking solution [2]. PINNs integrate deep learning with physical equations, enabling innovative features such as meshless numerical simulations, the use of incomplete physics complemented by diagnostic constraints and noisy measurements, and physics-based regularization to mitigate data overfitting. This approach results in more robust models capable of physics-based extrapolation.

This presentation reviews the fundamental principles of PINNs and highlights the latest advancements in solving inverse problems using these neural networks. The discussion focuses on implementing time-constrained and multi-diagnostic methodologies in inverse problems, illustrated with examples from both numerical and experimental tokamak cases [3].

References

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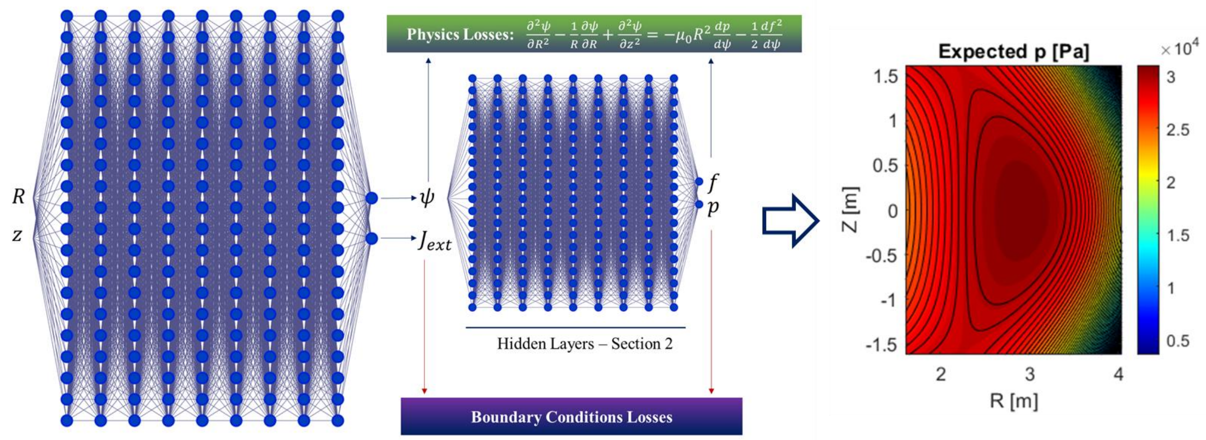

Figure 1: Schematics of one physics-informed neural network to solve the Grad-Shafranov equation, which can be used for both simulation and equilibrium reconstructions. On the right, the reconstruction of a synthetic case using the physics-informed neural network is reported as a typical example.