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Reliable prediction of solar wind conditions is central to assessing and mitigating risks posed by space weather events to space and ground based technological systems. Traditional magnetohydrodynamic (MHD) solvers remain indispensable for simulating solar wind dynamics and are the only approach capable of providing plasma properties such as speed, density, and magnetic field. However, their high computational cost and deterministic nature limit their use in ensemble and uncertainty aware forecasting in operational settings.

In this work, we introduce a physics-informed neural operator (PINO) framework to emulate global 3D heliospheric MHD solutions with orders-of-magnitude computational acceleration. Specifically, we implement a Spherical Fourier Neural Operator (SFNO) that learns the mapping from inner-boundary solar wind conditions at 0.1 AU to the full 3D plasma state across 0.1–2.0 AU. The model is trained on global MHD simulations (AWSoM) spanning multiple solar cycle phases and predicts the full set of plasma variables (velocity, magnetic fields, density, and temperature).

To ensure physical consistency, the training objective incorporates both data-driven loss terms (from AWSoM simulations) and embedded MHD constraints, including PDE residual minimization and divergence-free magnetic field regularization. The resulting surrogate is fully differentiable, enabling gradient-based sensitivity analysis and facilitating downstream uncertainty quantification. Benchmarking demonstrates that the model accurately captures the heliospheric structures.

By reducing simulation runtimes from ~100 CPU hours to a few GPU seconds, this framework enables large-scale ensemble generation that is otherwise computationally intractable. This capability is critical for propagating uncertainties in magnetogram inputs and model assumptions, thereby supporting probabilistic forecasting of solar wind conditions. We discuss key challenges in training stability, learning sharp gradients, and generalization across solar wind regimes.
Meeting homepage
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