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Foundation models for black holes

Black holes represent some of the most extreme environments in the universe, spanning vast ranges in mass, size, and energy output. Observations from the Event Horizon Telescope (EHT) have provided an unprecedented opportunity to directly image black holes, with future plans aiming to create time-resolved movies of their evolution. To fully leverage these observations, we need theoretical models that can interpret them with high fidelity and within practical time constraints.

General Relativistic MagnetoHydroDynamic (GRMHD) simulations are the primary tool for modeling the plasma dynamics around accreting black holes. While these simulations provide detailed insights into accretion flows and jet formation, their extreme computational cost limits the range of black hole parameters that can be explored. In particular, variations in black hole spin and grid configurations require costly re-simulations, making it infeasible to construct fully comprehensive theoretical predictions. Within the ERC-funded Synergy project Blackholistic, we address this challenge by integrating advanced numerical simulations with cutting-edge deep learning techniques. Drawing inspiration from successful applications in atmospheric simulations (<https://arxiv.org/abs/2405.13063>), our approach aims to leverage foundation models to learn the underlying flow dynamics of accreting black hole systems, enabling rapid interpolation across simulation data. We currently base our foundation model on Universal Physics Transformers (UPTs), a type of neural operator using a uniform learning paradigm for a wide range of spatio-temporal problems where they have been shown to be applicable and well-performing (<https://arxiv.org/abs/2402.12365>).

By extending UPT architectures to curved spacetime, our framework promises a paradigm shift in GRMHD modeling, offering potential speedups of several orders of magnitude in computational efficiency while enhancing model flexibility and accuracy. Preliminary tests with transformer architectures have yielded encouraging results, and ongoing efforts are focused on scaling up model architectures, expanding training datasets, and harnessing increased computational resources. This work paves the way for real-time analysis and interpretation of observational data, marking a significant advance in the fusion of artificial intelligence with fundamental astrophysical research.

AI keywords

Universal Physics Transformers; ML-based interpolation; Foundation models for PDEs; AI-accelerated fluid dynamics; Transformers

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