Using Artificial Intelligence to speed up Radiative Hydrodynamics simulations

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Radiative hydrodynamics (RHD) describes the interaction between the motion of a hypersonic, high-temperature plasma and the radiation it emits or absorbs. Most existing numerical codes rely on simplified radiation transport models that are often limited or inaccurate. To address this, the HADES 2D code was developed [1, 2, 3], offering a more realistic treatment of photon transport—particularly essential for modeling astrophysical phenomena involving optically intermediate regions, which are frequent yet poorly captured.

HADES couples hydrodynamics with the M1-gray [4] and M1-multigroup [5] radiation transfer models. The multigroup approach improves spectral resolution by discretizing the electromagnetic spectrum into frequency groups. However, RHD simulations remain extremely time-consuming, largely due to two challenges:

1. The M1-multigroup closure relation lacks an analytical form, requiring costly numerical estimations.
2. The Courant-Friedrichs-Lewy (CFL) condition constrains the explicit schemes in HADES to very small time steps.

To address these issues, we developed two AI-based strategies. First, we designed a neural network to approximate the closure relation in the M1-multigroup model, achieving high accuracy while reducing computation time by a factor of 3 000 [6], making it the most efficient method currently available.

Second, we explored the use of Physics-Informed Neural Networks (PINNs) [7] to solve the full set of RHD equations and extrapolate simulations beyond their original temporal domain. Initial tests on classical hydrodynamic shocks showed that Liu's weighting strategy [8] effectively handles discontinuities. We then applied this method to radiative shocks, where radiation shapes the shock structure, and successfully recovered key physical features, confirming PINNs' potential to accelerate and extend RHD modeling.

Keywords— Radiation hydrodynamics, Artificial Intelligence, Physics-Informed Neural Networks

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