Topological Machine Learning for Predicting Spatiotemporal Evolution in 1D Magnetohydrodynamics

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Abstract

Magnetohydrodynamic (MHD) systems, characterized by the nonlinear interaction of fluid and magnetic field dynamics, present significant challenges for both numerical modeling and physical interpretation. In this work, we explore a hybrid and interpretable framework that integrates Topological Data Analysis (TDA) with Machine Learning (ML) to predict the temporal evolution of one-dimensional MHD configurations. Using the Brio–Wu shock tube as a benchmark, we generate high-resolution simulation data through a Finite Volume method and analyze the resulting density and pressure profiles across time. Applying delay embedding techniques, we construct phase-space reconstructions of the spatiotemporal fields, from which we compute persistent homology to extract time-resolved topological features, such as Betti curves, persistence diagrams, and landscapes. These features are employed both as descriptors of the system's dynamical structure and as regularization terms in the training of neural models for temporal extrapolation. Preliminary results show that TDA-informed neural predictors offer enhanced stability and physical consistency in forecasting, outperforming traditional black-box architectures when evaluating unseen time steps. Furthermore, the topological signatures provide interpretable indicators of shock formation, rarefaction waves, and contact discontinuities, enabling a physically meaningful assessment of the model's output. The proposed methodology opens promising avenues for using topological priors and geometric structures in the design of data-driven surrogates for hyperbolic PDE systems. This approach not only reduces computational cost but also enhances the interpretability of learned models, which is especially relevant in high-stakes applications such as plasma modeling, astrophysical flows, and geophysical simulations. We conclude by outlining generalizations of the framework to higher-dimensional MHD flows, such as the Orszag–Tang vortex and spherical blast wave, with prospects for future applications in complex dynamical systems and theoretical physics.

Keywords: Magnetohydrodynamics, Topological Data Analysis, Topological Machine Learning