

DATA-DRIVEN METHODS FOR HYPERBOLIC CONSERVATION LAWS: NEURAL SOLVERS, DATA ASSIMILATION, AND STRUCTURE PRESERVATION

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ABSTRACT

Hyperbolic conservation laws underpin models throughout fluid dynamics, geophysics, and engineering, yet their solutions develop discontinuities that challenge classical numerical methods and modern data-driven approaches alike. Recent years have seen rapid progress in machine-learning-based techniques for these systems, including neural solvers and operator learning, surrogate models for many-query applications, and learning-augmented high-order discretizations. At the same time, discontinuous solutions, entropy conditions, and conservation constraints expose fundamental limitations of off-the-shelf learning methods, raising questions of accuracy, stability, and structure preservation that lie at the heart of the high-order methods community.

This minisymposium will highlight recent advances in data-driven methods for hyperbolic conservation laws. Topics of interest include neural solvers and operator learning for systems with discontinuous solutions; machine-learning-augmented high-order methods; structure-preserving and entropy-stable learning approaches; Bayesian and deterministic inverse problems for hyperbolic systems; and data assimilation methods that respect conservation, invariants, and solution regularity. Particular emphasis will be placed on approaches that combine the rigor of high-order discretizations with the flexibility of data-driven techniques, including hybrid solver-informed strategies and uncertainty quantification. The minisymposium aims to bring together researchers from numerical analysis, scientific machine learning, inverse problems, and data assimilation to discuss theoretical foundations, algorithms, and emerging applications, fostering exchange between the high-order methods and scientific machine learning communities.

SPEAKERS

1. Jan Giesselmann (Department of Mathematics, TU Darmstadt, Germany, giesselmann@mathematik.tu-darmstadt.de): Observer-based data assimilation for gas networks.
2. Jonathan Lindbloom (Department of Mathematics, Ohio State University, USA, jonathan@lindbloom.com): Preserving and exploiting structure in joint learning of dynamics and state.
3. Qi Tang (School of Computational Science and Engineering, Georgia Institute of Technology, USA, qtang@gatech.edu): tentative title.
4. Jan Habscheid (Department of Mathematics, Linköping University, Sweden, jan.habscheid@liu.se): Edge-preserving Bayesian neural networks with hierarchical sparsity-promoting priors.