Abstract Submitted
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FiniteNet: A Fully Convolutional LSTM Network Architecture for Time-Dependent Partial Differential Equations[1] BEN STEVENS, TIM COLONIUS, Caltech — In this work, we present a machine learning approach for reducing the error when numerically solving fluid mechanics problems governed by time-dependent partial differential equations (PDE). We use a fully convolutional LSTM network to exploit the spatiotemporal dynamics of PDEs. The neural network serves to enhance finite-difference and finite-volume methods (FDM/FVM) that are commonly used to solve PDEs in fluid mechanics, allowing us to maintain guarantees on the order of convergence of our method. We train the network on simulation data, and show that our network can significantly reduce error compared to the baseline algorithms. We also explore the effect of adding a temporal modeling component to the method through the LSTM, and compare the results we can achieve using this strategy to other temporal modeling techniques. We demonstrate our method on three PDEs relevant to flow problems that each feature qualitatively different dynamics: the linear advection equation, which propagates its initial conditions at a constant speed, the inviscid Burgers' equation, which develops shockwaves, and the Kuramoto-Sivashinsky (KS) equation, which is chaotic.

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Benjamin Stevens
Caltech

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