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A data-driven physics-informed finite-volume scheme for nonclassical undercompressive shocks

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In my PhD work, I am combining established numerical methods with machine learning techniques to build adaptive and highly accurate numerical schemes for fluid mechanics. Currently, I am interested in how neural networks can enhance the flux reconstruction process in finite-volume schemes. Most recently, I have submitted the journal paper "A data-driven physics-informed finite-volume scheme for nonclassical undercompressive shocks" to the Journal of Computational Physics. The abstract reads as follows:
„We propose a data-driven physics informed finite volume scheme for the approximation of small-scale dependent shocks. Nonlinear hyperbolic conservation laws with non-convex fluxes allow nonclassical shock wave solutions. In this work, we consider the cubic scalar conservation law as a representative of such systems. As standard numerical schemes fail to approximate nonclassical shocks, schemes with controlled dissipation and schemes with well-controlled dissipation have been introduced by LeFloch and Mohammadian and by Ernest and coworkers, respectively. Emphasis has been placed on matching the truncation error of the numerical scheme with physically relevant small-scale mechanisms. However, aforementioned schemes can introduce oscillations as well as excessive dissipation around shocks. In our approach, a convolutional neural network is used for an adaptive nonlinear flux reconstruction. Based on the local flow field, the network combines local interpolation polynomials with a regularization term to form the numerical flux. This allows to modify the discretization error by nonlinear terms. Via a supervised learning task, the model is trained to predict the time evolution of exact solutions to Riemann problems using the method of lines. The model is physics informed as it respects the underlying conservation law. Numerical experiments for the cubic scalar conservation law show that the resulting method is able to approximate nonclassical shocks very well. The adaptive reconstruction surpresses oscillations and enables sharp shock capturing. Generalization to unseen shock configurations and smooth intial value problems is robust and shows very good results."
In aforementioned work, the machine learning part is limited to the selection of local interpolation polynomials and combining them with regularization terms. This is done in order to guarantee a physically consistent numerical scheme. I am very much interested in how to relax these restrictions on the machine learning part while maintaining physical consistency in a numerical method. Therefore, in my poster I will present details on the data-driven scheme for undercompressive nonclassical shocks and possible extensions as to how the machine learning part can be further extended.

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