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Towards a general limiter for systems of conservation laws: 1D scalar and system of equations

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In this work we explore the idea of a parameter free stabilisation method for hyperbolic conservation laws. It is well known that for discontinuous solutions, non-physical oscillations will develop around the discontinuity. There are different methods to control these oscillations, namely, by adding a viscous term to the PDE or to limit the solution.

In this work we use a neural network to identify cells which are in need of stabilisation with the intent to avoid fixing a parameter, which often depends on initial data.

Neural networks gained new popularity recently due to the computational tractability of the back-propagation algorithm, used for the learning of weights and biases in a deep neural network. Furthermore, it has been empirically shown to generate robust models for classification in many areas of application [1, 2] and theoretically, to generate universal classifiers and function approximators [3, 4, 5].

In this work, we adopt the following pipeline:

1. Train a neural network on labelled data run on several CFD simulations using optimally hand tuned limiters
2. Validation of model on unseen data
3. Integration of the model on a CFD code
4. Flagging cells in need of stabilisation
5. Applying a TVD limiter on flagged cells

In detail, we show how to construct a training dataset, feature selection and how to integrate this model with a CFD code. We show the performance of this trouble cell indicator for a DG scheme for scalar and systems of equations in one dimensions (namely, we focus on the Euler equations).

While this work is a proof-of-concept, it is our belief that these ideas can be applied to other problems which depend on certain local properties of the numerical solution, ultimately contributing towards CFD codes which are robust to different initial conditions and that require less parameter tuning to produce readily usable results.

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