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Reinforcement Learning for Discretization-Aware LES Models

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Over the past few years, increasing efforts have been devoted to leveraging the recent advances in machine learning for the field of turbulence modeling. Most approaches in this field were based on Supervised Learning, for which artificial neural networks (ANN) are trained by means of a precomputed training dataset. However, for large eddy simulations (LES), this approach can cause instabilities in practical simulations [1], since the dynamics of the discretized equations are not captured by the training process. An approach which avoids this pitfall is the Reinforcement Learning (RL) paradigm, which, in contrast to Supervised Learning, trains ANN by interacting directly with the discretized dynamical system.

We demonstrate how the RL paradigm can be applied in the context of turbulence modeling by presenting a novel RL framework, which couples the flow solver FLEXI [2] with the machine learning library TensorFlow [3], while leveraging modern high-performance computing resources for the training process. This framework is applied to canonical flow problems, for which different ANN architectures are trained to adapt the coefficients of analytical LES models dynamically in space and time. We show that these data-driven LES models provide stable simulations, while outperforming traditional LES models in terms of accuracy. Thus, the proposed framework can provide a novel class of discretization-aware LES models, which can incorporate complex LES filter formulations and discretization effects by design.

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