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STATE-OF-THE-ART MACHINE LEARNING TECHNIQUES FOR COMPUTATIONAL FLUID DYNAMICS

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ABSTRACT

Machine learning (ML) in scientific applications including computational fluid dynamics (CFD) is a growing field of research. The broad range of ML techniques available and their ability to learn unknown and complex correlations enable a large spectrum of applications. However, in CFD, physical constraints are invaluable to obtain reasonable predictions. Another problem is that numerical simulations, especially high-order methods, are susceptible to instabilities due to inaccurate predictions, which the learning algorithm has to account for. Moreover, the definition of a suitable input space and loss function is a crucial and difficult task due to the highly nonlinear and mostly unknown mapping which has to be learned. Thus, the ML algorithm has to be consistent to the numerical discretization used, which a supervised learning method is never fully aware of.

With these shortcomings of supervised learning techniques in mind, recently, the focus of research has concentrated on reinforcement learning (RL) or physics-informed methods applied to CFD. While state-of-the-art RL approaches are widely utilized in the ML community, their applicability to, e.g., CFD, is an ongoing research topic. The relatively slow adaptation of state-of-the-art RL techniques to CFD can be attributed to the rapid development of new RL methods and the increasing complexity of problems in CFD compared to typical applications such as game theory. Common examples for RL in CFD are flow control, turbulence modeling and shock capturing [2, 3]. An additional and continuously growing field of research which alleviates the common problems of ML in CFD are physics-informed neural networks (PINNs). In general, classical PINNs are specifically suited for smooth problems and suffer from stability problems if discontinuities are present in the solution. This is the case in many real applications such as transonic flows. Recently, modified versions of classical PINNs have been proposed to push their limitations and to enable PINNs which are more tailored to CFD [1].

With these considerations in mind, the objective of this minisymposium is to discuss the applicability, predictive performance and limitations of state-of-the-art ML methods in CFD. This can include data-enriched numerical methods based on RL such as closure models for turbulence or flow control as well as more advanced PINNs pushing the limits of their classical counterpart.

REFERENCES

[1] CHAUMET, A., GIESSELMANN, J.: *Efficient wPINN-Approximations to Entropy Solutions of Hyperbolic Conservation Laws*. 2022. `10.48550/arXiv.2211.12393`.

[2] KURZ, M., OFFENHÄUSER, P., VIOLA, D., RESCH, M., BECK, A.: *Relexi—A scalable open source reinforcement learning framework for high-performance computing*. Software Impacts, p. 100422, 2022.

[3] SCHWARZ, A., KEIM, J., CHIOCCHETTI, S., BECK, A.: *A Reinforcement Learning Based Slope Limiter for Second-Order Finite Volume Schemes*. PAMM, pp. 1–6, 2023. `10.1002/pamm.202200207`.