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COUPLING COMPUTATIONAL FLUID DYNAMICS WITH MACHINE LEARNING

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ABSTRACT

The coupling of numerical simulations for fluid dynamics with machine learning techniques, such as neural networks, reinforcement learning, autoencoders, etc. is emerging as a powerful approach for enhancing the accuracy and efficiency of computational fluid dynamics (CFD) simulations [1]. This integration leverages the strengths of both disciplines to tackle complex fluid flow problems that are difficult to solve using traditional computational methods alone.

Neural networks (and variants such as CNN, LSTM, GANs, etc.), with their ability to learn complex patterns and relationships, have been successfully employed to approximate fluid flows, model turbulence and accelerate CFD applications (e.g., [2]). Reinforcement learning, on the other hand, offers a unique framework for optimizing control strategies in fluid dynamics. Through trial and error interactions with simulated environments, reinforcement learning agents can learn optimal policies that govern fluid flow behaviors, leading to improved turbulence models [3] or new flow control paradigms [4]. This dynamic approach has the potential to revolutionize engineering design processes and enhance the performance of flow applications. Finally, autoencoders [5,6] have been employed in the context of fluid dynamics to extract meaningful low-dimensional representations of high-dimensional flow data. By encoding and decoding fluid flow variables, autoencoders can effectively compress and reconstruct flow fields, facilitating efficient data analysis, dimensionality reduction, and anomaly detection. Such techniques enable rapid exploration of large datasets, identification of flow features, and the development of reduced-order models for real-time simulations.

This mini-symposium highlights the growing importance and potential of coupling numerical simulations for fluid dynamics with machine learning techniques. The synergy between these fields promises advancements in fluid flow understanding, optimization of flow control systems, and the development of more efficient and accurate computational methods. This mini-

symposium will offer a venue for sharing leading edge research into the technical, methodological and theoretical aspects of coupling machine learning and CFD.

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