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RECENT ADVANCES IN SCIENTIFIC MACHINE LEARNING FOR DIFFERENTIAL EQUATIONS AND CONTROL PROBLEMS

500 - COMPUTATIONAL APPLIED MATHEMATICS

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ABSTRACT

Machine learning has emerged as a powerful tool in the field of computational science, with plenty of applications in various domains such as fluid dynamics, materials science, and control systems. This minisymposium will explore recent trends in the realm of scientific machine learning that leverage data-driven approaches to enhance the solution of differential equations and to optimize control strategies. We aim to bring together researchers who are pushing the boundaries of how machine learning can be integrated with traditional numerical methods to solve complex scientific problems.

In the past few years, there has been a surge of interest in developing machine learning techniques that build upon or can be seamlessly integrated with classical numerical methods for solving partial differential equations or optimal control problems, see for instance [1,2]. These approaches often involve the use of neural networks or kernel methods to approximate solutions, learn operators, or even discover governing equations from data. The potential of these methods lies in their ability to handle high-dimensional problems, such as Hamilton-Jacobi-Bellman equations, and to adaptively refine solutions based on available data. Moreover, the integration of machine learning with numerical solvers can lead to significant improvements in computational efficiency and accuracy. In order to guarantee the reliability of these methods, it is of interest to investigate the theoretical foundations of machine learning techniques, including convergence properties and error estimates [3,4]. This theoretical underpinning is crucial for establishing trust in machine learning approaches when applied to scientific computing tasks.

This minisymposium will feature talks focusing on different aspects of the application of machine learning to differential equations and control problems. On the one hand, theoretical results will be presented that establish the convergence and stability of machine learning methods when applied to the numerical solution of scientific computing problems. On the other hand, practical results will be showcased, demonstrating how these methods can be effectively applied to real-world problems in various scientific domains. We will also discuss the

challenges and limitations of current approaches, as well as future directions for research in this exciting field.

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