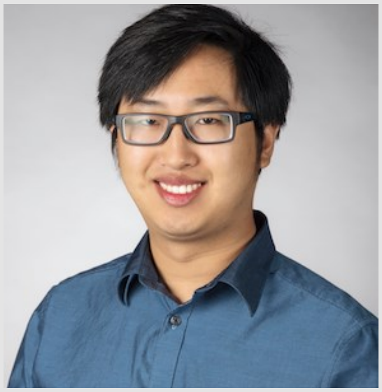
MAE *Seminar* Series

Thursday,
April 8
4:00 PM
Zoom Information
Meeting ID: 983 6137 4638
Password: MAE2021



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Physics-informed AI for Computational Fluid Mechanics with Small Data

ABSTRACT

Recent advances in data science techniques, combined with the ever-increasing availability of high-fidelity simulation/measurement data open up new opportunities for developing data-enabled computational modeling of fluid systems. However, compared to most general data science applications, the cost of data acquisition for modeling complex physical/physiological systems is usually expensive or even prohibitive, which poses challenges for directly leveraging the success of existing deep learning models. On the other hand, there is often a richness of prior knowledge, including physical laws and phenomenological principles, which can be leveraged to enable efficient learning in the “small data” regime. This talk will focus on physics-informed deep learning (PIDL), which has recently attracted increasing attention in the scientific machine learning community. The objective is to enable effective learning in a data-scarce setting by incorporating physics knowledge (e.g., conservation laws) to inform the learning architecture construction and/or constrain the training process. Novel physics-informed learning frameworks will be discussed, which enable us to solve forward and inverse problems in a unified manner, where sparse data can be naturally assimilated. Our recent developments in PIDL for, e.g., surrogate modeling, super-resolution, inverse modeling, and uncertainty quantification, will be presented. The effectiveness of the proposed methods will be demonstrated on a number of fluid problems that are relevant to hemodynamic applications.

BIO SKETCH

Dr. Jian-Xun Wang is an assistant professor of Aerospace and Mechanical Engineering at the University of Notre Dame. Dr. Wang received a Ph.D. in Aerospace Engineering from Virginia Tech in 2017 and was a postdoctoral scholar at the University of California, Berkeley before joining Notre Dame in 2018. His research focuses on developing data-driven/data-augmented computational modeling, which broadly revolves around physics-informed machine learning, Bayesian data assimilation, and uncertainty quantification. His current research interests involve surrogate modeling for fluid flows based on physics-constrained deep learning, data-augmented physiological model based on Bayesian data assimilation (e.g., assimilation of 4D flow MRI in hemodynamic modeling and data-augmented intracranial modeling).