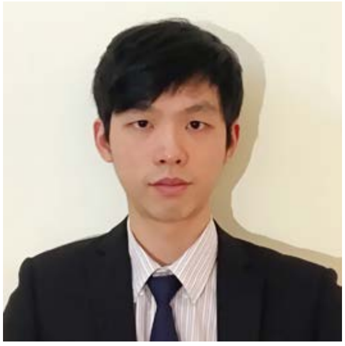
Dr. Chengping Rao



Dr. Chengping Rao is an Applied Scientist in Amazon. He received his Ph.D. in Mechanical Engineering from Northeastern University in 2021. His research lies on the interdisciplinary area of the computational physics and artificial intelligence, including the physics-informed neural network (PINN), explainable and interpretable DL for data-driven modeling of complex systems and governing partial derivative equation (PDE) discovery. He is also interested in the applications of Bayesian optimization and reinforcement learning to scientific problems. Before his Ph.D. study, he obtained B.S. and M.S. degrees in Naval Architecture and Ocean Engineering at Huazhong University of Science and Technology (2015) and Shanghai Jiao Tong University (2018) respectively.

Keynote Presentation 2:
Integrating Physics into Deep Learning for Modeling Scientific Problems

In recent years, successful applications of deep learning (DL) have inspired scientists to explore the possibilities of applying DL approaches to modeling scientific problems. Existing studies have revealed that to leverage the physics into the DL makes a good supplement to the traditional numerical methods (e.g., finite element, finite volume method) which primarily rely on partial differential equations (PDEs). While DL models are usually trained in a purely data-driven manner, integrating physics with them for simulating scientific problems could bring several benefits such as (i) physics constraints could regularize the over-parameterized model and hence mitigate the overfitting issue commonly seen in DL; (ii) physics information could also effectively reduce the amount of data needed for training the model; (iii) the resultant physics-informed DL models feature better interpretability and generalizability compared with the conventional black-box model. In this presentation, I will specifically discuss the physics-informed neural network (PINN) – one of the most prominent approaches in this area. Numerical examples would be provided to demonstrate the effectiveness of PINN on simulating a variety of physical systems, such as the laminar flow, vortex shedding and seismic wave propagation. Several applications including the data-driven simulations and solving inverse problems are presented to further exemplify the advantages of PINN over traditional numerical methods.