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DEEP LEARNING APPROACHES FOR APPLIED SCIENCES AND ENGINEERING

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ABSTRACT

Machine learning models have been used to automatically extract insight from data. Trained models are then used to make predictions, recommendations, and decisions. Deep learning has greatly advanced many tasks such as image classification, object detection, speech recognition, dimensionality reduction, prognostics, and many other applications [1]. While the solution from a physics-based simulation can be understood, many machine learning models have been labelled as black boxes which are difficult to interpret. This is in part due to the high number of parameters which can create complex and non-intuitive representations. Nevertheless, in recent years the scientific community started to work actively on incorporating deep learning into their work. Some recent advancements such as physics informed neural networks (PINN) attempt to bridge this gap between the physics we know and the complicated black box [2]. Many deep learning applications have tried to learn physical insight from data, however with PINNs partial differential equations from physics are used to write custom loss functions which penalize physically inaccurate models. Other approaches are based on transfer learning, aiming at embedding the insights from physical simulations directly into the neural networks. These combinations of continuum mechanics and deep learning may prove to be useful tools for solving complex problems such as design optimization or uncertainty quantification, because deep learning models can be orders of magnitude cheaper than high fidelity physics simulations. Further advancements of including physics as custom loss functions, weights initialization, activation functions, and others may make these models more intuitive and useful for solving such complex problems.

The goal of this mini-symposium is to discuss deep learning advancements in computational

mechanics and engineering applications. We will encourage discussion highlighting the advantages and disadvantages of these methods. Additionally, we hope to address emerging approaches at combining physics with deep learning to solve complex problems, such as optimization or uncertainty quantification problems.

REFERENCES

[1] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." *nature* 521, no. 7553 (2015): 436-444.
[2] Raissi, Maziar, Paris Perdikaris, and George E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations." *Journal of Computational Physics* 378 (2019): 686-707.

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