## ML, Microstructure, Mechanics, Design and Manufacturing

Stephen Niezgoda<sup>1</sup>, Ashley Lenau<sup>1</sup>, Simon Mason<sup>1</sup>, Dennis Dimiduk<sup>2</sup>, Mike Groeber<sup>1</sup>, Glenn Deahn<sup>1</sup>

<sup>1</sup>The University of Ohio, <sup>2</sup>Blue Quartz

## ABSTRACT

In this talk we will present an overview of how we are integrated machine learning into workflows for mechanics, design and manufacturing. The first example will be exploring the utility of machine learning for reduced order model development, specifically the creation of invertible machine learning models for crystal plasticity that allows both forward simulation, from microstructure to response, but also to "reverse" the model and predict the structure that gave rise to a particular mechanical response given a set of boundary conditions. In a second example we will look at the development of a "general purpose" microstructure AI. The development of a novel autoencoder structure, the adversarial hierarchical variational autoencoder (AHVAE) combines the benefits of the traditional VAE network, the hierarchical nature of the Nouveau VAE's latent spaces, and the improved image generation capabilities of adversarial training. Along with its use as a microstructure generator, the AHVAE can also be used as a feature extractor through the utilization of the information-dense latent space. After training the full network, the encoder can be used independently to generate low-dimensional latent space representations of microstructures. These latent spaces can then be used with separate, specifically trained decoders to extract a variety of desired material features, including physical parameter extraction, microstructure topology analysis, and material property prediction. A third example we will explore how mechanics can be used to regularize and improve the performance of deep learning frameworks. Incorporating physics-based regularization methods into deep learning algorithms can speed up the time and reduce the data needed to train a deep learning network. In the last example we will explore autonomous manufacturing via robot controlled incremental forming. The use of advanced incremental forming has been validated by blacksmiths and parts can be made that are much larger than a given available press. Systems with large robots and modestly-sized presses can develop these large forgings and in a fraction of the current time as dies do not need to be designed or built. We will present an initial robotic system - both its cyber and physical components. We will also highlight initial results in achieving required component geometries with desired microstructural characteristics. We will also present the details of the control algorithms developed for the system to operate in an autonomous manner.