NCAR | CLIMATE & GLOBAL DYNAMICS

CGD Seminar Series

Atmospheric Physics-Guided Machine Learning: Towards Physically-Consistent, Data-Driven, and Interpretable Models of Convection

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Date: Tuesday 11 May 2021

Time: 11am – 12pm

For Zoom information, please contact Tracy Baker tbaker@ucar.edu

For live stream information, visit the CGD Seminar Webpage

ABSTRACT

Data-driven algorithms, in particular neural networks, can emulate the effect of unresolved processes in coarse-resolution climate models if trained on high-resolution simulation or observational data. However, they lack interpretability, may violate key physical constraints, and make large errors when evaluated outside of their training set. In this seminar, I will share recent progress towards overcoming these three challenges in the particular case of machine learning the effect of subgrid-scale convection and clouds on the large-scale climate. First, machine learning interpretability tools can be tailored to stabilize data-driven models of convection and confirm that they behave consistently with observations. Second, physical constraints can be enforced in neural networks, either approximately by adapting the loss function or to within machine precision by adapting the architecture. Third, as these physical constraints are insufficient to guarantee generalizability, I additionally propose to physically rescale the inputs and outputs of machine learning algorithms to help them generalize to unseen climates. Overall, these results suggest that explicitly incorporating physical knowledge into data-driven models of climate processes may improve their consistency, stability, and ability to generalize across climate regimes.