Geophysical Research Abstracts
Vol. 21, EGU2019-11211, 2019
EGU General Assembly 2019

Machine Learning for Stochastic Parameterization: Generative Adversarial Networks in the Lorenz '96 Model

David Gagne (1), Hannah Christensen (2), Aneesh Subramanian (3), and Adam Monahan (4)

(1) Computational and Information Systems Lab, National Center for Atmospheric Research, Boulder, United States (dgagne@ucar.edu), (2) Atmospheric Oceanic and Planetary Physics, University of Oxford, United Kingdom (hannah.christensen@physics.ox.ac.uk), (3) Scripps Institute of Oceanography, San Diego, United States (acsubram@ucsd.edu), (4) University of Victoria, Victoria, Canada (monahana@uvic.ca)

Stochastic parameterizations perturb the tendencies of the physical processes within a numerical model in order to account for parameterization uncertainties in an ensemble prediction system. Current stochastic parameterization approaches apply some form of correlated noise directly to physics tendencies, but this requires empirical tuning of the properties of the random noise. Generative machine learning models could represent the physical process and draw stochastic samples from the parameterization conditioned on the coarse model input values. Generative Adversarial Networks (GANs) are a form of generative modeling that utilizes one neural network to generate samples from a set of conditional inputs and another neural network to act as an adaptive loss function. The Lorenz '96 model is a simple chaotic dynamical system that consists of waves propagating around a resolved slow variable (X) and a fast subgrid variable (Y) rings that are linked together. The Lorenz '96 model has served as a testbed for new data assimilation and stochastic parameterization schemes due to the simplicity and low computational requirements, and because it represents key properties of the atmosphere such as scale interaction and chaotic error growth. In this project, we developed a GAN stochastic parameterization for the Lorenz '96 model and compared it against a polynomial regression parameterization for both simulated weather and climate runs. The climate evaluation found that the GAN parameterization approximates the true distribution of X values more closely than the polynomial and matches the spatial and temporal correlations of the truth run. The weather evaluation found that GANs produce a smaller difference between spread and error than the polynomial regression and provide improved forecast skill out to 1 Lorenz model time unit ($\sim$5 atmospheric days). Hence, the GAN approach to parameterize subgrid processes in chaotic fluid flow problems shows great promise as a stochastic parameterization approach.