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Downscaling of surface wind speed over the North Atlantic using conditional Generative Adversarial Networks

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Accurate simulation of the physics of the Earth`s atmosphere involves solving partial differential equations with a number of closures handling subgrid processes. In some cases, the parameterizations may approximate the physics well. However, there is always room for improvement, which is often known to be computationally expensive. Thus, at the moment, modeling of the atmosphere is a theatre for a number of compromises between the accuracy of physics representation and its computational costs.

At the same time, some of the parameterizations are naturally empirical. They can be improved further based on the data-driven approach, which may provide increased approximation quality, given the same or even lower computational costs. In this perspective, a statistical model that learns a data distribution may deliver exceptional results. Recently, Generative Adversarial Networks (GANs) were shown to be a very flexible model type for approximating distributions of hidden representations in the case of two-dimensional visual scenes, a.k.a. images. The same approach may provide an opportunity for the data-driven approximation of subgrid processes in case of atmosphere modeling.

In our study, we present a novel approach for approximating subgrid processes based on conditional GANs. As proof of concept, we present the preliminary results of the downscaling of surface wind over the ocean in North Atlantic. We explore the potential of the presented approach in terms of speedup of the downscaling procedure compared to the dynamic simulations such as WRF model runs. We also study the potential of additional regularizations applied to improve the cGAN learning procedure as well as the resulting generalization ability and accuracy.