Climate-StyleGAN : Modeling Turbulent Climate Dynamics Using Style-GAN

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Abstract

In recent years, unsupervised learning with generative adversarial networks (GANs) has been tremendously successful in computer vision applications for natural image generation. Comparatively, unsupervised learning with GANs for emulating physical systems has received less attention. Some success has been shown with physically constrained GANs but those are limited by their ability to compute constraints and to model higher resolution samples. In this work we leverage the success of StyleGANs for natural images to model complex turbulent climate data without any statistical or physical constraint. We demonstrate the use of a feature-matched and annealed LOGAN-based StyleGAN that outperforms state-of-the-art results on Rayleigh-Benard convection and successfully emulates updraft velocity fields of high-resolution climate simulations.

1 Introduction

Simulating complex multi-scale turbulent physical systems, such as Earth's climate, often involves solving coupled nonlinear partial differential equations (PDEs) across a wide range of scales, with closures (parameterizations) for the unresolved subgrid scales. Although the advancement of high performance computing has made simulating Earth's climate using high-resolution models possible, such simulations are still very expensive.

To resolve this critical challenge we propose a purely data-driven Deep Learning (DL) based approach that uses a generative model to emulate the behavior of a state-of-the-art high-resolution climate model. The proposed approach does not seek to emulate the full spatio-temporal behavior, rather, it produces realistic spatial snapshots that can be used to obtain climate statistics of interest, including extreme events (tails of the distribution). This is a first step towards building climate emulators that faithfully reproduce the dynamics of physics-based models at a significantly lower computational cost.

Deep generative modeling is a promising approach to learn the dynamics of natural systems. Recent work has shown that this approach works well in simpler dynamical systems, such as the Lorenz-96 dynamical system (1) and turbulent Rayleigh-Benard convection (2). In this work we employ Style-GAN (3), a powerful state-of-the-art generative adversarial network (GAN), that has shown success in generating realistic natural images with customized features to emulate climate data.

Previous studies (2) have incorporated physical and statistical constraints into off-the-shelf deep generative models, such as DCGAN (4), to help emulate the spatial dynamics and statistics of Rayleigh-Benard convection (RBC), a simplified model for turbulent atmospheric convection. In this study, we propose a novel purely data-driven deep generative model of much larger complexity

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[1]Work done during a NERSC Data Internship at Berkeley Lab

AI for Earth Sciences Workshop at NeurIPS 2020.

and capacity that can accurately emulate the spatial dynamics and statistics of RBC dataset and of a high-resolution climate model (CAM5.1 25-km) without any physical or statistical constraint.

To summarise we showcase how our modified Style-GAN with annealed LOGAN (5) and feature matching:

- able to outperform previously used generative models for modeling turbulent Rayleigh-Benard Convection, as in (2);
- completely self-supervised requires no additional physical or statistical constraint while training;
- able to produce on order of magnitude larger number of samples than the training dataset;
- free of the mode collapse problem, a plaguing issue in developing reliable and stable GANs;
- capable of accurately modeling the spatial dynamics and statistics of vertical velocity fields;

2 Data

In this work we test our model on two datasets of turbulent, chaotic systems of relevance to weather and climate modeling:

1. 2D turbulent Rayleigh-Benard convection (RBC) simulated using the Lattice Boltzmann Method, as in (2). We use the velocity fields of spatial resolution 1792 x 256. Each image has two channels (velocities along x and y directions). The physics parameters relevant to this simulation are: Prandtl number = 0.71, Rayleigh number = 2.5E8 and Mach number = 0.1. During training, we divide each 1792 by 256 image into 7 square sub-regions of size 256 x 256 to produce a training set with 35,000 samples.
2. Climate simulations using the Community Atmospheric Model (version CAM5.1: 25-km, 3-hourly resolution). We use vertical velocity fields at 500 hPa (ω_{500hPa}). The training dataset uses 5 years of data, with 128x128 crops centered at the equator, a total of 10568 samples.

3 Methods

GANs consist of a generator that generates an image from a latent source, and a discriminator that rates the generated image as “real" or “fake". Training GANs involves an adversarial mini-max game (6) but is often plagued by the challenging issue of mode collapse (7). We use StyleGAN (3; 8) modified by improving the efficacy of latent optimization (5). The latent-optimized StyleGAN exploits knowledge from the discriminator to refine the latent source, instead of using a randomly sampled source, and is annealed to maintain the balance between low bias and low variance.

In addition we use “feature matching”, introduced in (9), to regularize the generator’s training objective. More specifically, we train the generator to match the expected value of the features on intermediate layers of the discriminator. This is an improved choice of statistics for the generator to match, since the trained discriminator finds features that characterize the real data. A generator trained as described forces the generation of realistic data with features that are characteristic of the training dataset. We train our model for over 100k iterations in a non-progressive manner with the standard non saturating loss (6) and hyperparameters as mentioned in (3).

4 Results

4.1 Results on RBC Dataset

We first present the results of our model on RBC and compare it to recent results on constrained GANs to emulate this system (2). We calculate the ratio of energy spectra with respect to the original images and compare these with the results from (2). The energy spectra is computed by applying Fourier transforms over the mean turbulent kinetic energy (TKE) per unit mass associated with eddies in the turbulent flow over 750 randomly sampled snapshots of resolution 256 x 256. Values close to

1.0 demonstrate the ability of our model to capture the statistics of the dataset (identical with ground truth).

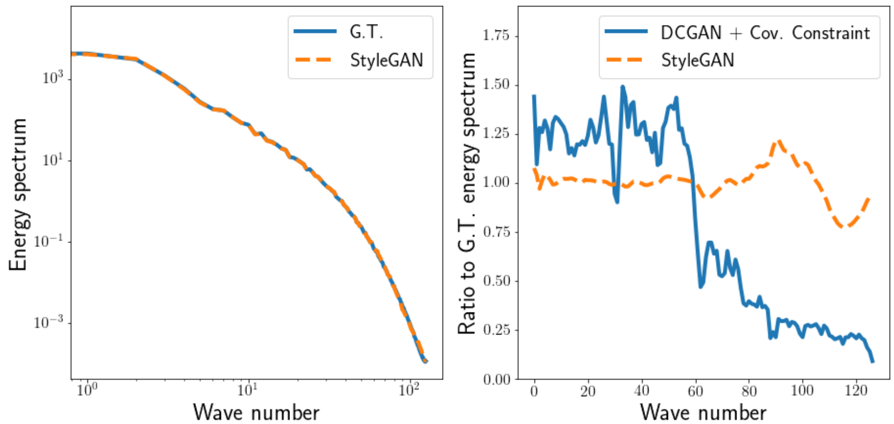

Figure 1: Comparison of Fourier spectra on TKE for our model vs RBC ground truth (on left) and vs that of (2) (on right).

4.2 Results on Climate CAM5.1 dataset

For the next set of results we train our model on ω_{500hPa}(updraft velocity) fields from a CAM5.1 dataset (10). We demonstrate that our model is not only able to capture the batch statistics but is also able to capture the extreme events (tails of the distribution) accurately. Furthermore, through the birthday paradox principle (11), we show that there are no duplicates, *i.e.* the model is free from the problem of mode collapse. Our model can generate in excess of 500,000 samples trained on just over 10,000 original samples.

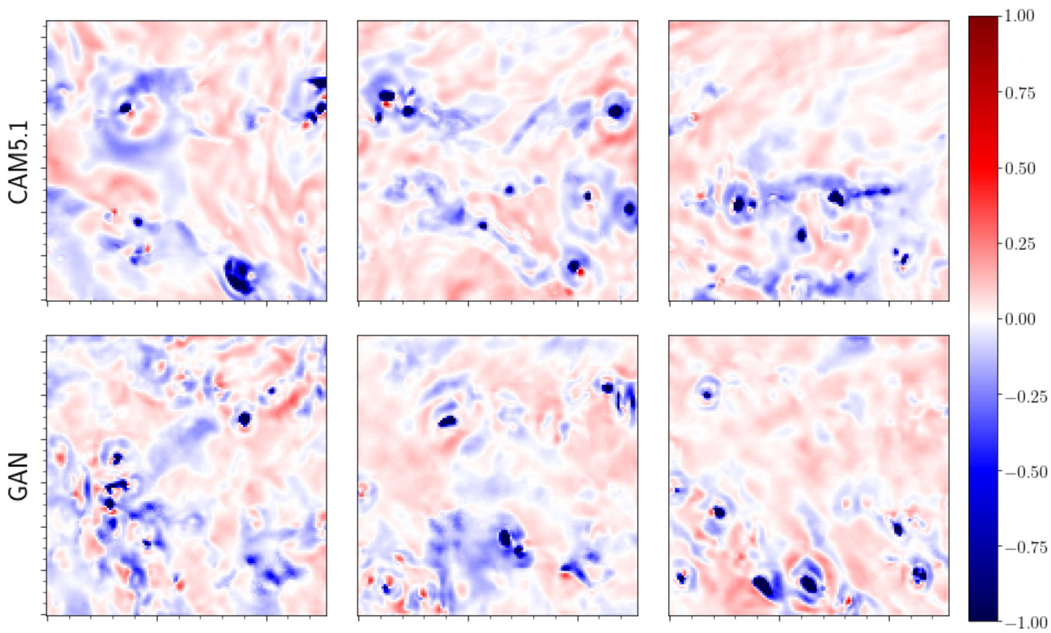

Figure 2: ω_{500hPa} samples from our model after 94,000 training iterations.

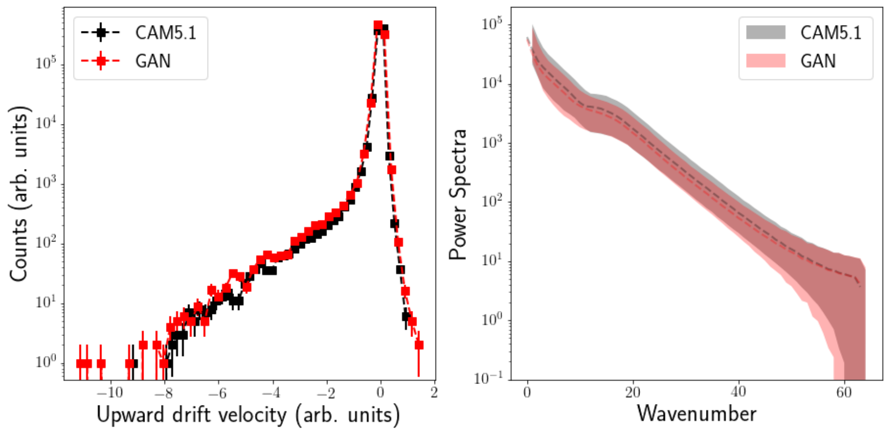

Figure 3: Histogram and spectra of generated ω_{500hPa} samples compared to the ground truth from CAM5.1 dataset. The mean and variance of the spectra over the ensemble of 750 samples are essentially identical for the GAN and the ground truth data, demonstrating the high fidelity of our results.

5 Discussions and Conclusions

We have presented a LOGAN-based StyleGAN, a novel GAN that combines an annealed optimization in the latent space with a feature matching loss that helps sample the representation space more accurately. Results on RBC show that our approach is more effective than current state-of-the-art GAN-based methods at modeling velocity fields of this system. Results on climate simulation data show that our approach can generate an order of magnitude larger high-fidelity images with accurate energy spectra while still avoiding mode collapse.

These results illustrate the feasibility of applying deep generative models to emulate the dynamics of realistic, high-resolution climate data. The key contributions of our work are as follows:

1. We develop a novel, step-annealed LOGAN (5) based StyleGAN (3) architecture that outperforms previous statistically constrained GAN models (2).
2. Our model produces order of magnitude larger high-fidelity samples of vertical velocity (ω_{500hPa}) trained on high-resolution CAM5.1 (25km) and successfully overcomes the mode-collapse problem.
3. Our model works end-to-end, without any labels or supervision, by simply utilising the highly expressive and large generative capacity of the networks. Further, it works without using any physics-based regularizers or losses while training.
4. Finally, we demonstrate that our data-driven deep generative model is capable of both matching the distribution of original data, even at the tails, and reproducing the energy spectra (power spectral density across length scales).

Future work includes: (i) training simultaneously on multiple climate variables; (ii) incorporating covariance and cross relationships between variables that maintain physical consistency; (iii) investigating the role of 'styles' in the StyleGAN to better understand what characteristics of the model can be controlled to improve emulating the wide range of scales in complex climate systems.

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