PROCEEDINGS OF SCIENCE

Validating the Advantage of Using Ensembles Over a Single GAN Model for Calorimeter Simulations

Kristina Jaruskova[a,b,*] **and Sofia Vallecorsa**[b]

[a] *Faculty of Nuclear Sciences and Physical Engineering, Czech Technical University in Prague, Brehova 7, 115 19 Prague 1, Czech Republic*

[b] *CERN*
Esplanade des Particules 1, 1217 Meyrin, Switzerland

E-mail: jaruskri@fjfi.cvut.cz, sofia.vallecorsa@cern.ch

The use of generative deep learning models has been of interest in the high-energy physics community intending to develop a faster alternative to the compute-intensive Monte Carlo simulations. This work focuses on evaluating an ensemble of GANs on the task of electromagnetic calorimeter simulations. We demonstrate that the diversity of samples produced by a GAN model can be significantly improved by expanding the model into a multi-generator ensemble. We present a study comparing the single-GAN model and the ensemble model using both physics-inspired and artificial features.

42nd International Conference on High Energy Physics (ICHEP2024)
18-24 July 2024
Prague, Czech Republic

*Speaker

© Copyright owned by the author(s) under the terms of the Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License (CC BY-NC-ND 4.0).

PoS(ICHEP2024)1045

1. Introduction

Detector simulations in particle physics rely on Monte Carlo-based software tools that are very accurate, but also time consuming. Deep learning (DL) models can produce high-fidelity samples for a fraction of time [1]. However, the generated sets often lack proper variability [2].

The adaGAN ensemble technique [3] promises to address the issue of mode collapse in GANs, and to increase the diversity of generated samples. We present an adaptation of the adaGAN for the use case of calorimeter simulations. We demonstrate that the ensemble outperforms a single GAN model and we point out drawbacks of this approach.

2. Ensemble model

The adaGAN model is a sequentially created ensemble of GANs. The process starts by training a vanilla GAN on the training set. Before training the next GAN, weights are assigned to the training samples based on the outputs from the trained discriminator, with high weights being assigned to samples that the discriminator does not confidently classify as training data. These weights then influence how often the next GAN is presented with each sample during the training forcing the second GAN to focus on the weak spots of the first model. This process of reweighting the training set and training a newly initialized GAN can be repeated until desired results or ensemble size are achieved.

As a baseline model for calorimeter simulation, we selected a convolutional GAN with three-branch architecture [4]. The training data represent electron showers in electromagnetic calorimeter recorded in a cube grid of $25 \times 25 \times 25$ cells and axis z aligned with the direction of the initial particle. These showers were simulated using the DD4HEP software as part of a study for the ILD detector [5]. The samples cover initial energies of the electron in the range $E_{\mathrm{p}} = 2 - 500$ GeV.

3. Results

Plots in figure 1 illustrate the dominance of the ensemble in modeling average features. The first plot depicts energy profiles along one of the axes perpendicular to the direction of the initial electron. The second plot shows ratios of energy profiles for the generated samples and training samples. It is apparent that the ensemble achieves better agreement with the training set, in particular around the edge parts of the given region.

To assess variability of the generated samples, we fitted a principal component analysis (PCA) on the training data and projected the generated samples into the same space. In figure 2, we visualize the first two principal components (PCs) in scatter plots. The first plot depicts the training samples with colors corresponding to the primary energy E_{p} of the initial electron. The plots on the right show that adding generators to the ensemble populates the space of the first two PCs. The ensemble clearly helps with variability of showers for high-energy electrons. However, the PCA projections also showed that even the ensemble of 10 generators was not able to reproduce all types of showers.

PoS(ICHEP2024)1045

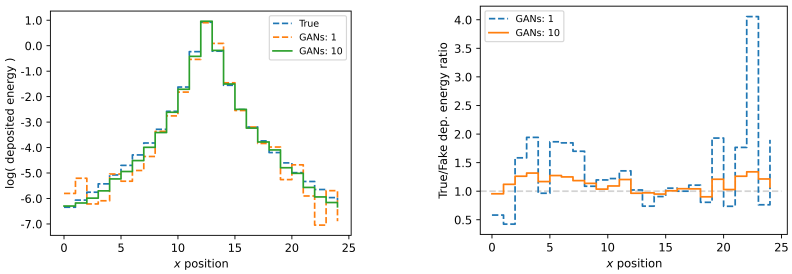

Figure 1: Comparison of the single GAN model and the ensemble of 10 GANs to the training data. (left) Average shape of deposited energy along the x axis. (right) Ratio of average energies deposited in the training samples and generated samples.

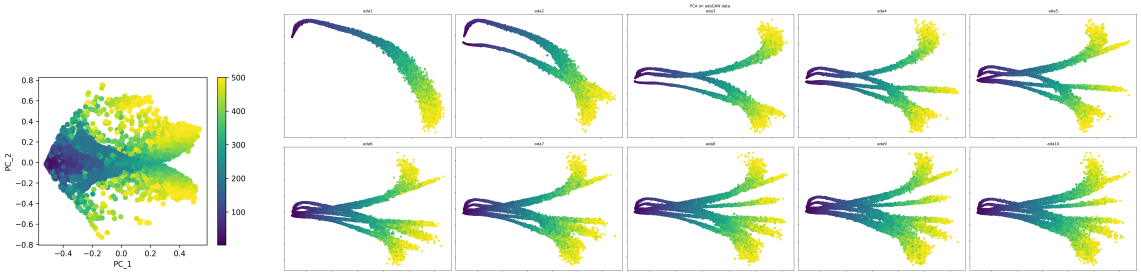

Figure 2: Scatter plots of the first two PCs. (left) Training data with points coloured by the E_{p} (in GeV). (right) Data generated by ensembles of different sizes ($1-10$ generators).

4. Conclusion

An ensemble of 10 convolutional GANs was successfully trained for the task of calorimeter shower generation. We demonstrated that performance of a single GAN model can be enhanced using the ensembling technique which helped with reproducing average quantities as well as with increasing variability of the generated showers. However, the sequential nature of the adaGAN ensemble requires training the GANs one at the time which increases the duration of the training.

References

[1] G. Aad, B. Abbott, et al. *AtlFast3: The Next Generation of Fast Simulation in ATLAS*, Comput Softw Big Sci 2022 [10.1007/s41781-021-00079-7].

[2] K. Jaruskova, S. Vallecorsa, *Estimating the Support Size of GANs for High Energy Physics Detector Simulation*. ML4PS NeurIPS 2020 (124).

[3] I. Tolstikhin et al. *AdaGAN: Boosting Generative Models*, 2017 [arXiv:1701.02386].

[4] F. Rehm, S.Vallecorsa, K. Borras, *Physics Validation of Novel Convolutional 2D Architectures for Speeding Up High Energy Physics Simulations*, CHEP 2021 (03042) [10.1051/epjconf/202125103042].

[5] M. Pierini, M. Zhang, *CLIC Calorimeter 3D images: Electron showers at Fixed Angle*, Zenogo.org 2020 [10.5281/zenodo.3603122].

PoS(ICHEP2024)1045