Volumetric Generative Adversarial Networks

Extended Abstract

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ABSTRACT

We present the first application of Volumetric Generative Adversarial Network (VGAN) to High Energy Physics simulation. We generate three dimensional images of particles depositing energy in calorimeters. This is the first time such an approach is taken in HEP where most of data is three dimensional in nature but it is customary to convert it into two dimensional slices. The volumetric approach leads to a larger number of parameters, but two dimensional slicing loses the volumetric dependencies inherent in the dataset. The present work proves the success of handling those dependencies through VGANs. Energy showers are faithfully reproduced in all dimensions and show a reasonable agreement with standard techniques. We also demonstrate the ability to condition training on several parameters such as particle type and energy. This work aims at proving Deep Learning techniques represent a valid fast alternative to standard MonteCarlo approaches and is part of the GEANTV project.

CCS CONCEPTS

• **Computing methodologies → Feature selection**; *Scientific visualization*; • **Applied computing → Physics**;

KEYWORDS

Deep Learning, Generative Adversarial Network, High Energy Physics, simulation

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1 INTRODUCTION

Increasing need for computational resources has prompted a sustained effort to optimize High Energy Physics (HEP) software and simulation. The Large Hadron Collider (LHC) simulation demands are too high to meet the Wordlwide LHC Computing Grid (WLCG) budget estimations. The LHC experiments' expectation is that the exploitation of the LHC machine after 2018 (Run 3) will require a factor of about 100 improvement in simulation throughput with same computing resources available today [1]. A new prototype for particle transport simulation, GEANTV, is being developed to improve physics accuracy and performance on modern architectures, such as the Intel Xeon Phi and (GP) GPUs [2]. A even faster approach is to treat simulation as a black-box and replace traditional Monte Carlo simulation with a deep learning based tool. Inputs can be provided by elementary particles emerging from a collision or coming directly from a particle beam. Each particle is characterized by type, energy and direction and the position of the impact. More complex input types can also be considered such as "events", or collections of all particles emerging from a collision, including "jets" or sprays of particles moving along a cone. On the output side, there is also a large range of possibilities to consider. The most basic is the energy deposition in various parts of the detector. This approach is adopted in the present work. Three dimensional images of particles depositing energy in a calorimeter are generated. Training is conditioned using different parameters such as particle type and energy.

Section 2 provides a brief review of related work done on GAN in particular within the HEP context. The next section introduces the dataset we use, followed by an overview of the model in section 4. The adversarial training is explained in section 5 with results presented in section 6. The last section summarizes the preliminary conclusions drawn from the work.

2 RELATED WORK

Generative Adversarial Networks consist of a generator and a discriminator network competing against each other [8]. The discriminator is constantly trying to catch the fake output produced by the generator while the generator tries to fool it. GAN applications range from Multi Layer Perceptron network [8] to convolutional neural networks [6, 14]. Training can also be conditioned to a label using conditional GAN [7, 9, 15]. Calorimeter output can be interpreted as an image ans computing vision techniques can be tested as an alternative to standard Monte Carlo based detector simulation [5, 12]. The present work endeavours to step further simulating three dimensional calorimeter showers. A three dimensional approach is a recent development [16] for GANs proving that adversarial training can successfully generate complex three dimensional structures that does not only demonstrate the features of the given dataset but also make intelligent and meaningful innovations.

3 INPUT DATASET

The dataset we use for our studies is produced in the context of the CLIC detector design and it is available under the DDhep software framework [13]. It consists of energy showers generated with the Geant4 software [3] inside the Linear Collider Detector (LCD) electromagnetic calorimeter (ECAL). Individual particles are generated, they travel through the LCD tracking device and hit the inner surface of the electromagnetic calorimeter.The data set consists of energy deposits produced by the shower of particles generated by the collision of the incoming particle to the detector surface. Each cell is characterized by the energy recorded in it and three indices (iX, iY , iZ), identifying the position of the cell. For each of the 25 ECAL sensor planes, a 25x25 array of cell is identified. The energy of the incoming particle is sampled from a uniform [0-500 GeV]spectrum. Additionally 1M electrons have been simulated at different energy points: 10, 50, 100, 200, 300 GeV.

4 MODELS

Our model attempts three dimensional image reconstruction through GAN:primary particle energy is also added as class. The discriminator as well as generators exploits 3 dimensional convolutions. The image dimension for a single primary particle is 25 x 25 x 25 corresponding to the ECAL cells. Using three dimensional layer leads to a large number of training parameters, and therefore we keep the network as simple as possible. Keras [4] is used to implement three dimensional convolutional layers with three dimensional filters and padding. There are three convolutional layers in both the generator and discriminator with leaky rectified linear units activation functions. Batch normalization layers are added after the convolutional layers for improved performance [15]. The input image is mapped to two categorical outputs obtained by the final flattened layer. The first output denotes whether images are real or generated while the second output is an auxiliary condition. There were two versions of the experiment. In the first implementation the auxiliary condition is the particle class i.e electron or photon (a sigmoidal layer generated the corresponding discriminator output). In the second version the auxiliary output is the energy of the incoming particle (a rectified linear unit constitutes the discriminator output). Thus the first version corresponds to a binary classification experiments and the second to a multi-class classification. The generator uses a latent noise vector initialized to a uniform probability distribution as well as the desired class of the image to generate. We use the method described in SGAN and ACGAN [10, 11] for embedding the image class vector and the latent noise, thus conditioning image generation. Beside an initial dense layer, two up-sampling layers are also added to the generator to get the desired image dimensions, i.e 25 x 25 x 25.

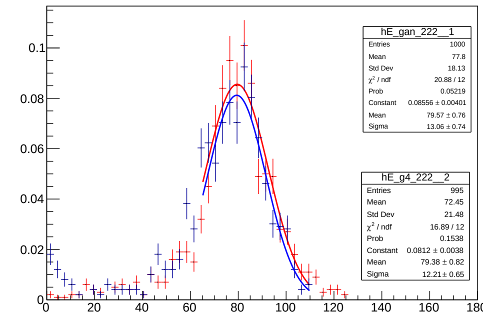

Figure 1: Energy deposited in the central calorimeter cell by a 100GeV electron generated by VGAN

5 TRAINING

The training strategy is typical of the adversarial approach setting discriminator and generator against each other[15]. Initially the generator is used to generate images using random class labels. The discriminator is then used to predict whether the images are real or fake and to predict the class of the image. The first batch of images provided to the discriminator is real images from the dataset. The discriminator is trained to make the correct prediction. Then it is trained once more on fake images. As shown in [15], training on a homogeneous batch of real images and then on a homogeneous batch of fake images provides better performance than using a batch of mixed images. We apply the same method effectively training the discriminator twice per epoch: the generator is therefore also trained twice. The loss of the generator is set equal to the the discriminator loss corresponding to the case when all the generated images are real. Training on a single GeForce GTX1080 takes aroound24 hours for 30 epochs.

6 RESULTS

The results are in good agreement with actual data. Energy showers are faithfully reproduced in all dimensions and show a reasonable agreement with standard Monte Carlo techniques. A detailed study to asses the quality of VGAN images, using typical high level calorimeter reconstruction variables is ongoing. In the meantime, we have studied the single cell energy response fitting it to a Gaussian: we obtain that the energy mean value and the standard deviation agree well within the statistical errors with the standard Monte Carlo simulation results. In particular, the standard deviations, that measure the cell energy resolution, agree within 6 percent for most of the highly populated cells (traditional fast simulation models yield typically to 10% accuracy).

7 CONCLUSIONS

Our experiment proves that GAN could be a candidate for a fast simulation tool. GAN has successfully generated images for shower energy deposition in three dimensions. The images can also be conditioned on particle class or energy. At the time of this submission, the plots and results are still preliminary. We plan to provide improved results, in particular on the energy condition, later on.

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