T 5: Machine Learning: QCD and electromagnetic showers

Time: Monday 16:30–18:00 Location: H-HS III

T 5.1 Mon 16:30 H-HS III

Deep Learning-based Air-Shower Reconstruction at the Pierre Auger Observatory — Martin Erdmann, •Jonas Glombitza, and Alexander Temme for the Pierre Auger-Collaboration — III. Institut A, RWTH AACHEN UNIVERSITY

Ultra-high energy cosmic rays are the most energetic particles found in nature and originate from extragalactic sources. When propagating within the Earth's atmosphere these particles induce extensive air showers which can be measured by cosmic-ray observatories.

The hybrid design of the Pierre Auger Observatory features a large array of surface-detector stations which is overlooked by fluorescence telescopes. The reconstruction of event-by-event information sensitive to the cosmic-ray mass is a challenging task and so far, mainly based on the fluorescence detector observations with their duty cycle of about 15%.

Recently, deep learning-based algorithms have shown to be extraordinary successful across many domains in computer vision, engineering and science. Applying these algorithms to surface-detector data opens up possibilities for improved reconstructions. In particular it allows for an event-by-event estimation of the cosmic-ray mass, exploiting the 100% duty cycle of the surface detector.

In this contribution we present our deep network, based on recurrent layers and hexagonal convolutions. We show the performance of our method and discuss solutions to systematic biases. Finally, we evaluate the performance by comparing the deep learning-based reconstruction to measurements of the fluorescence detector using Auger hybrid data.

T 5.2 Mon 16:45 H-HS III

Simulation of Extensive Air Showers with Deep Neural Networks — Steffen Hahn, •Marcel Köpke, and Markus Roth — Karlsruhe Institute of Technology, Institute for Nuclear Physics

The Pierre Auger Observatory uses CORSIKA to simulate extensive air showers. With growing incident particle energy it becomes computationally difficult to run the simulations due to increasing time complexity. Deep neural networks possess the ability to recognize patterns in an automatic way and are able to run on specialized, fast hardware like GPUs. Hence they are a good candidate to address run time issues while also offering the possibility to go beyond CORSIKA features like conditioning on meta parameters.

T 5.3 Mon 17:00 H-HS III

Generative Models for Fast Shower Simulation — •Sascha Diefenbacher[1], Erik Buhmann[1], Engin Eren[2], Frank Gaede[2], and Gregor Kasieczka[1] — [1]Universität Hamburg, Institute for Experimental Physics — [2]Deutsches Elektronen-Synchrotron DESY

In high energy physics, simulations of particle collisions play a vital role in most analysis. A significant portion of the time required for these simulations has to be allocated to modeling how highly energetic particles interact with detectors. These simulation times are bound to increase even further, as increased collider luminosities call for more generated samples and advances in detector technology require these samples to have an increasingly fine resolution. One solution is the use of so called generative machine learning models. These models can learn the properties of a calorimeter shower from a relatively small dataset, and are then able to provide new shower samples orders of magnitude faster than a state of the art, full simulation like Geant4 could. We show results of using the two main generative architectures, Generative Adversarial Networks and Variational AutoEncoders, to generate particle showers in a high granular, 5d calorimeter as proposed by the ILD project.

T 5.4 Mon 17:15 H-HS III

Understanding Generative Neural Networks for Fast Simulation of High-Granular Calorimeters — •Erik Buhmann[1], Gregor Kasieczka[1], Sascha Diefenbacher[1], Engin Eren[2], and Frank Gaede[2] — [1]Universität Hamburg, Institut für Experimentalphysik — [2]Deutsches Elektronen-Synchrotron DESY

High-granular calorimeters are necessary for the application of particle flow algorithms in detectors for future collider projects, such as the ILD calorimeters or the CMS-HGCAL. Accurate Monte Carlo (MC) simulations of such calorimeter events demand significant computing resources. An alternative to MC is fast simulation based on generative neural networks that allow event production orders of magnitude faster than traditional MC. We are using generative adverserial network (GAN) and variational autoencoder (VAE) architectures for generating electromagnetic and hadronic calorimeter events.

Determining when the training weights converge to an optimal physics representation of the generated sampels poses a challenge when training generative models. Additionally, increasing our confidence into the accuracy of the sample generation can to be achieved by understanding the latence space represenation of physics observables. In this talk we discuss both challenges and introduce methods on how to interprete the VAE latence space in view of our physics understanding of the underlying training sample distributions.

T 5.5 Mon 17:30 H-HS III

Studies on using Generative Adversarial Networks to simulate parton showers — Johannes Erdmann, •Alexander Froch, and Olaf Nackenhorst — TU Dortmund, Lehrstuhl für Experimentelle Physik IV

Monte Carlo (MC) simulations are one of the basic instruments in data analysis of high energy physics experiments. The three main parts that need to be simulated are the hard scattering process, the parton shower + hadronisation and the detector simulation. Although MC simulations bring great benefits for the data analysis of high energy physics experiments, the costs and time needed to produce them are significantly high. Generative Adversarial Networks (GANs) can be trained with samples from MC simulations to be used for fast MC simulations due to their characteristic as a much less computing-intensive model. It has been shown that GANs are capable to simulate the hard scattering process or imitate even the whole MC simulation process. They were also used as a fast detector simulation trained on samples generated with the GEANT4 detector simulation. Significantly reduced computing times for the event generation were accomplished in comparison to the GEANT4 detector simulation. Motivated by these results we examine the feasibility of generating key features of the parton shower with GANs. In this presentation the latest status of our studies is shown.

T 5.6 Mon 17:45 H-HS III

Towards a Data-Driven Simulation of QCD Radiation with Generative Models — André Schöning, •Christof Sauer, and Danilo Enoque Ferreira de Lima — Physikalisches Institut, Heidelberg, Germany

Recent developments in the field of machine learning open a new window on the simulation of events in high-energy particle physics through Generative Adversarial Networks (GANs) inspired by the pioneering work of Goodfellow *et al* in 2015. This presentation shows a potential application of GANs in terms of solely data-driven event generation with a focus on parton shower simulation. The method could be applied in analyses that are sensitive to the parton shower modelling of the background and hence rely on an accurate background estimate.

The results shown in this talk have been generated using state-of-the-art (conditional) Wasserstein GANs based on the Earth Mover's metric. Furthermore, a comparison is made with (Gaussian) Variational Auto-Encoders (VAEs) – another avenue to generative models –, whereby the latter one shows a significantly worse performance compared to the adversarial approach. All networks presented were trained on dijet samples and W jets obtained from $t\bar{t}$ events produced with MadGraph5_aMC@NLO at LO and further processed by Pythia8.2, which serve as a surrogate to examine the applicability of the methods under well-controlled conditions. The transition to real data would be a possible next step.