AKPIK 3: Machine Learning in Particle- and Astroparticle Physics

Time: Thursday 16:15–17:30 Location: Theo 0.134

AKPIK 3.1 Thu 16:15 Theo 0.134

A Hybrid Approach for Optimizing Background Simulations in IceCube — •Simon Koch, Christian Haack, and Benedikt Mayer — Erlangen Centre for Astroparticle Physics - ECAP, FAU Erlangen-Nürnberg

The IceCube Neutrino Observatory detects high-energy cosmic neutrinos by observing Cherenkov radiation emitted from secondary particles, such as muons, produced in neutrino interactions. A key challenge in detecting cosmic neutrinos is the large background of cosmic-ray induced muons, which has to be reduced by a factor of $\sim 10^7$.

Thus a large sample of background events has to be simulated in order to accurately estimate the background reduction efficiency. The computationally most expensive part of the simulation chain is the propagation of Cherenkov photons, induced by the muon energy losses.

In this work we develop a hybrid simulation approach that combines traditional simulation methods with a surrogate model. Our surrogate model predicts the probability of cosmic ray induced muons surviving the background reduction process based on the muon energy loss information. This approach ensures that computational resources required for the photon propagation of the background events are better spent on statistically rare events, which have a high chance of surviving the background reduction. For a given sample size of background events, we are thus able to reduce the statistical uncertainty of the estimated background reduction efficiency.

AKPIK 3.2 Thu 16:30 Theo 0.134

Searching for Ultra-High Energy Photons applying Machine Learning Methods Using the Surface Detector of the Pierre Auger Observatory — •Fiona Ellwanger for the Pierre-Auger-Collaboration — KIT, Karlsruhe, Germany

Identifying sources of cosmic rays is challenging, as the charged particles are deflected by magnetic fields and do not point back to their sources. Neutral particles, such as ultra-high energy (UHE) γ's will point directly to their sources, unless they interact in the interstellar medium or are absorbed. Cosmic ray detectors such as the $3000\,\mathrm{km}^2$ surface array of the Pierre Auger Observatory are capable of observing UHE γ's above 10^{18} eV. With increasing energy, their mean free path allows probing extragalactic sources up to a few Mpc. Unlike cosmic rays, photon-induced showers are almost purely electromagnetic. Different methods like BDTs and air-shower Universality have been previously applied to the search of γ's at different energy ranges. Although no UHE γ's have been found, the obtained bounds of the fluxes provide crucial constraints on cosmic-ray acceleration models.

Neural networks have the potential to improve discriminating variables, enhancing the sensitivity to even lower fluxes. In this work, we present a convolutional neural network designed to distinguish between simulated UHE photon and proton showers. We evaluate it on an independent test set, assessing its sensitivity and robustness to systematic uncertainties, including broken stations, detector aging, and noise. These steps aim to validate the network for application to the measured events.

AKPIK 3.3 Thu 16:45 Theo 0.134

Neural Network-Based Event-by-Event Reconstruction of Muon Number from Data of the SD-750 of the Pierre Auger Observatory — •Alina Klingel for the Pierre-Auger-Collaboration — KIT, Karlsruhe, Deutschland

Ultra-high-energy cosmic rays ($\sim$ 1 EeV) provide a unique opportunity to probe physics beyond the energies of human-made accelerators. At such extreme energies, direct detection is infeasible; instead, these cosmic rays are studied through the particle cascades, or air showers, they generate upon interacting with Earth's atmosphere. The SD-750 surface detector of the Pierre Auger Observatory records the shower footprint, the spatial distribution of particles and energy deposited on the ground, as time-resolved ground signals. The main advantage of the SD-750 lies in its proximity to the Underground Muon Detector (UMD), allowing for an independent measurement of the muon content of air showers. This setup forms an ideal testbed to develop and benchmark neural network-based estimators for the muon number, even when simulations contain discrepancies. In this contribution, we present a neural network architecture designed to predict the relative muon number in air showers. We aim to shed light on the muon puzzle by cross-calibrating with muon measurements from the UMD.

AKPIK 3.4 Thu 17:00 Theo 0.134

Advanced Northern Tracks Selection using a Graph Convolutional Neural Network for the IceCube Neutrino Observatory: Adversarial Training — •Leon Hamacher, Philipp Behrens, Jakob Böttcher, Shuyang Deng, Lasse Düser, Philipp Fürst, Philipp Soldin, and Christopher Wiebusch for the IceCube-Collaboration — RWTH Aachen

The IceCube Neutrino Observatory, located at the South Pole, detects atmospheric and astrophysical neutrinos. One important task is differentiating between these neutrinos and muons induced by air showers. The Advanced Northern Tracks Selection (ANTS) accomplishes this identification using a graph-convolutional neural network. However, neural networks can be sensitive to minor adversarial perturbations, which can significantly alter their outputs. Adversarial training is a method to include artificially perturbed data during the training process to enhance resistance to such perturbations. For this purpose, a dedicated algorithm, MiniFool, has been developed that takes experimental uncertainties into account. This talk presents the results of applying MiniFool to ANTS.

AKPIK 3.5 Thu 17:15 Theo 0.134

Adaptive Generative Modeling for Accelerated Calorimeter Simulations via Domain Transfer — •Lorenzo Valente[1], Fank Gaede[2], Gregor Kasieczka[1,3], and Anatolii Korol[2] — [1]Institut für Experimentalphysik, Universität Hamburg, Luruper Chaussee 149, 22761 Hamburg, Germany — [2]Deutsches ElektronenSynchrotron DESY, Notkestr. 85, 22607 Hamburg, Germany — [3]Center for Data and Computing in Natural Sciences CDCS, Deutsches Elektronen-Synchrotron DESY, Notkestr. 85, 22607 Hamburg, Germany

Simulating particle collider detectors presents significant computational challenges, with current methods struggling to scale with increasingly complex experimental datasets. Deep generative models offer a promising solution for dramatically reducing computational overhead, especially as upcoming particle physics experiments are expected to produce unprecedented volumes of data.

We introduce a novel domain adaptation framework that utilises state-of-the-art deep generative models to generate high-fidelity 3D point-cloud representations of particle showers. Using transfer learning techniques, our approach adapts simulations across diverse electromagnetic calorimeter geometries with exceptional data efficiency, thereby reducing training requirements and eliminating the need for a fixed-grid structure.

Preliminary results demonstrate that our method can achieve high accuracy while significantly reducing data and computational demands, offering a scalable solution for next-generation particle physics simulations.