AKPIK 3: Neural Networks I

Time: Wednesday 14:00–15:30 Location: ZEU/0118

AKPIK 3.1 Wed 14:00 ZEU/0118

"Ahead of Time compilation" of Tensorflow models — •Bogdan Wiederspan, Marcel Rieger, and Peter Schleper — University of Hamburg

In a wide range of high-energy particle physics analyses, ML methods have proven as powerful tools to enhance analysis sensitivity. In the past years, various ML applications were also integrated in central CMS workflows, leading to great improvements in reconstruction and object identification efficiencies.

However, the continuation of successful deployments might be limited due to memory and processing time constraints of more advanced models and central infrastructure. A new inference approach for models trained with Tensorflow, based on Ahead-of-time (AOT) compilation is presented that has the potential to drastically reduce memory footprints while preserving and even increasing computational performance.

AKPIK 3.2 Wed 14:15 ZEU/0118

A multi-layer approach and neural network architectures for defect detection in PBF-LB/M — •Michael Moeckel and Jorrit Voigt — TH Aschaffenburg, Würzburger Str. 45, 63743 Aschaffenburg

The substitution of expensive non-destructive material testing by data-based process monitoring is intensively explored in quality assurance for additive manufactured components. Machine learning show promising results for defect detection but require conceptual adaption to layer wise manufacturing and line scanning patterns in laser powder bed fusion. A multi-layer approach to co-register μ-computer tomography measurements with process monitoring data is developed and a workflow for automatic data set generation is implemented. The objective of this research is to benchmark the volumetric multi-layer approach and specifically selected deep learning methods for defect detection. The volumetric approach shows superior results compared to single slice monitoring. All investigated structured neural network topologies deliver similar performance.

AKPIK 3.3 Wed 14:30 ZEU/0118

Reconstructing jet characteristics using neural networks — •Arne Poggenpohl and Felix Geyer — Astroparticle Physics, TU Dortmund University, Germany

Active galactic nuclei (AGN) are among the most observed objects in the nocturnal sky. Several of these AGN have the capability to accelerate matter in their nuclei to relativistic velocities, resulting in jets. These are frequently studied sources of radio emission. Analysis of the kinematic characteristics of radio jets can provide information about physical properties of the host galaxy. Previously, this was mostly done by tracking Gaussian components of the jets manually, which is difficult to reproduce. Therefore, the goal of this work is to automatically detect Gaussian components in radio jets using a neural network and thus enable kinematic analysis. Big data sets can thereby be processed, because it is no longer necessary to concentrate on each individual image.

For the necessary object detection, an architecture based on YOLO is used. This architecture consists exclusively of convolutional layers and requires only one pass for the prediction. This allows it to be fast and accurate at the same time.

In this talk, the current state of the work is presented and improvements for the future are pointed out.

AKPIK 3.4 Wed 14:45 ZEU/0118

Deep-Learning based Estimation of the Ultra-High Energy Cosmic Ray Spectrum using the Surface Detector of the Pierre Auger Observatory — Ralph Engel, Markus Roth, Darko Veberic, Steffen Hahn, and •Fiona Ellwanger for the Pierre Auger-Collaboration — Karlsruhe Institute of Technology (IAP), Karlsruhe, Germany

To probe physics beyond the scales of human-made accelerators with cosmic rays demands an accurate knowledge of their energy. Ground-based experiments indirectly reconstruct the primary particle energy from measurements of the emitted fluorescence light or the time-dependent signal of the shower footprint.

At the Pierre Auger Observatory, the shower footprint is measured by a regular hexagonal grid of water-Cherenkov detectors. Since the shower development is a very intricate process, it non-trivial to find hidden patterns in the spatial and temporal distributions of signals. With large simulation datasets, we are able to train neural networks tackling such a problem.

In this work, we present a neural network that gives an estimate on the energy of the primary particle. The precision of the predictions is studied by evaluating the neural networks on a simulated test data set with particular regard to the mass-dependent bias. Systematic differences between simulations and measured data require special attention to possible biases, which are investigated. Methods to correct for these biases are presented. Furthermore, the energy spectrum from corrected neural network predictions is built and compared to published results.

AKPIK 3.5 Wed 15:00 ZEU/0118

Investigating Waveform Classification Using Neural Networks for the Einstein Telescope — Markus Bachlechner, •Philipp Otto, Oliver Pooth, and Achim Stahl — III. Physikalisches Institut B, RWTH Aachen

The Einstein Telescope (ET) is a proposed third-generation gravitational wave detector aiming to improve the sensitivity by more than an order of magnitude over the whole frequency band compared to the previous generation. Increased sensitivity yields a much higher event rate with overlapping signals, which will dramatically increase the computational resource requirements of conventional pattern matching methods. Neural networks are a promising approach to implement a fast and efficient waveform classification. Fast identification is also essential to allow for multi-messenger astronomy, by quickly alerting other observatories. This talk will present the investigation of a deep learning based waveform classification approach.

AKPIK 3.6 Wed 15:15 ZEU/0118

Estimating Uncertainties for Trained Neural Networks — •Sebastian Bieringer — Universität Hamburg, Hamburg, Germany

Uncertainty estimation is a crucial issue when considering the application of deep neural network to problems in high energy physics such as jet energy calibrations.

We introduce and benchmark a novel algorithm that quantifies uncertainties by Monte Carlo sampling from the models Gibbs posterior distribution. Unlike the established 'Bayes By Backpropagation' training regime, it does not rely on any approximations of the network weight posterior, is flexible to most training regimes, and can be applied after training to any network. For a one-dimensional regression task, as well as energy regression from calorimeter images, we show that this novel algorithm describes epistemic uncertainties well, including large errors for extrapolation.