T 10: ML Methods I

Time: Monday 16:30–18:00 Location: HSZ/0405

T 10.1 Mon 16:30 HSZ/0405

Fooling IceCube's Deep Neural Networks — •Oliver Janik, Markus Bachlechner, Thilo Birkenfeld, Philipp Soldin, Christopher Wiebusch, and Katharina Winkler for the IceCube-Collaboration — III. Physikalisches Institut B, RWTH Aachen University

Deep neural networks (DNNs) find more and more use in the data analysis of physics experiments. In IceCube, such networks are used as classifiers for particle identification or as regressors to reconstruct the direction and energy of particles. In the context of adverserial attacks, it has been observed that imperceptible changes to the input of DNNs can alter the output drastically. Algorithms like DeepFool can calculate minimal changes of the input in order to obtain a wrong output, thus fooling the network. This talk will focus on testing the robustness of IceCube's DNNs to such minimal changes.

T 10.2 Mon 16:45 HSZ/0405

Generating Calorimeter Showers as Point Clouds — •Simon Schnake[1,2], Kerstin Borras[1,2], and Dirk Krücker[1] — [1]Deutsches Elektronen-Synchrotron DESY, Hamburg, Germany — [2]RWTH Aachen, Aachen, Germany

In particle physics, precise simulations are necessary to enable scientific progress. However, accurate simulations of the interaction processes in calorimeters are complex and computationally very expensive, demanding a large fraction of the available computing resources in particle physics at present. Various generative models have been proposed to reduce this computational cost. Usually, these models interpret calorimeter showers as 3D images in which each active cell of the detector is represented as a voxel. This approach becomes difficult for high-granularity calorimeters due to the larger sparsity of the data. In this study, we use this sparseness to our advantage and interpret the calorimeter showers as point clouds. More precisely, we consider each hit as part of a hit distribution depending on a global latent calorimeter shower distribution. A first model to learn calorimeter showers as point clouds is presented. The model is evaluated on a high granular calorimeter dataset.

T 10.3 Mon 17:00 HSZ/0405

DeepTreeGAN: Fast Generation of High Dimensional Point Clouds for Calorimeter Simulation — •Moritz Scham[1,2,3], Dirk Krücker[1], and Kerstin Borras[1,2] — [1]Deutsches Elektronen-Synchrotron, Hamburg, Germany — [2]RWTH Aachen University - III. Physikalisches Institut A, Aachen, Germany — [3]Institute for Advanced Simulation - Jülich Supercomputing Centre, Juelich, Germany

In high energy physics, detailed and time-consuming simulations are used for particle interactions with detectors. To bypass these simulations with a generative model, the generation of large point clouds in a short time is required, while the complex dependencies between the particles must be correctly modeled. Particle showers are inherently tree-based processes, as each particle is produced by decays or detector interaction of a particle of the previous generation.

In this work, we present a novel GNN model that is able to generate such point clouds in a tree-based manner. We show that this model is able to reproduce complex distributions, and we evaluate its performance on the public JetNet Dataset.

T 10.4 Mon 17:15 HSZ/0405

Particle identification at Belle II using Neural Networks — •xavier simo[1,2], daniel greenwald[1], stefan wallner[2], and stephan paul[1,2] — [1]Techincal University Munich (TUM) — [2]Max Planck Institute for Physics (MPP)

We will present improvements to the charged-particle identification algorithms used by the Belle II experiment located at KEK, Japan. So far, different approaches have been used to tackle the challenge of combining the information from each subdetector into a single variable for particle identification in an optimal way. We will present evaluations of the performance of a Neural Network based approach that combines information such as the likelihood values from each subdetector and the measured momentum of the particle track.

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T 10.5 Mon 17:30 HSZ/0405

Reconstruction of Full Decays using Transformers and Hyperbolic Embedding at Belle II — •Boyang Yu, Hosein Hashemi, Nikolai Hartmann, and Thomas Kuhr — Ludwig-Maximilians-Universität München

In analyses at Belle II, it is often helpful to reconstruct the whole decay process of each electron-positron collision event using the information collected from detectors. The reconstruction is composed of several steps which require manual configurations and suffers from high uncertainty as well as low efficiency.

In this project, we are developing a software with the aim to reconstruct B decays at Belle II automatically with both high efficiency and high accuracy. The well trained models should be tolerant to rare decays that have very small branching ratio or are even unseen during the training.

To ensure high performance, the project is separated into several stages: particle level embedding, event level embedding and decay reconstruction. Inspired by the recent achievements in computer science, transformers and hyperbolic embedding are employed as building blocks with pre-training-fine-tuning framework, contrastive metric learning and knowledge transfer serving as training tools.

T 10.6 Mon 17:45 HSZ/0405

The Federation - A novel machine learning technique applied on data from the Higgs Boson Machine Learning Challenge — •Maximilian Mucha and Eckhard von Törne — Universität Bonn, Physikalisches Institut, Bonn, Germany

The Federation is a new machine learning technique for handling large amounts of data in a typical high-energy physics analysis. It utilizes Uniform Manifold Approximation and Projection (UMAP) to create an initial low-dimensional representation of a given data set, which is clustered by using Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN). These clusters can then be used for a federated learning approach, in which we separately train a classifier on the high-dimensional data of each individual cluster. By doing so, the computational resource demands for the learning process is reduced. We additionally apply an imbalanced learning method to the data in the found clusters before the training to handle high class imbalances. By using a Dynamic Classifier Selection method, the Federation can then make predictions for the whole data set.

As a proof of concept for this novel technique, open data from the Higgs Boson Machine Learning Challenge is used and comparisons to results from established methods will be presented.