T 103: AI Topical Day – Simulation, Inverse Problems and Algorithmic Development (joint session AKPIK/T)

Time: Thursday 15:45–17:15 Location: HSZ/0004

T 103.1 Thu 15:45 HSZ/0004

Efficient Sampling from Differentiable Matrix Elements with Normalizing Flows — •Annalena Kofler[1,2], Vincent Stimper[2,3], Mikhail Mikhasenko[4], Michael Kagan[5], and Lukas Heinrich[1] — [1]Technical University Munich — [2]Max Planck Institute for Intelligent Systems, Tübingen — [3]University of Cambridge, UK — [4]ORIGINS Excellence Cluster, Munich — [5]SLAC National Accelerator Laboratory, Menlo Park, USA

The large amount of data that will be produced by the high-luminosity LHC imposes a great challenge to current data analysis and sampling techniques. As a result, new approaches that allow for faster and more efficient sampling have to be developed. Machine Learning methods such as normalizing flows, have shown great promise in related fields. There, access to not only the density function but also its gradient has proven to be helpful for training. Recently, software for accessing differentiable amplitudes, which serve as densities in particle scattering, have become available that allow us to obtain the gradients and benchmark these new methods. The described approach is demonstrated by training rational-quadratic spline flows with differentiable matrix elements of the hadronic three-body decays, $\pi(1800) \to 3\pi$ and $\Lambda_c^+ \to pK^-\pi^+$. To boost the ability to accurately learn and sample from complex densities whilst also reducing the number of training samples, we explore the use of the newly proposed method Flow Annealed Importance Sampling Bootstrap. Building on prior work, we plan to extend the approach to examples with more particles in the final state via the differentiable matrix elements provided by MadJax.

T 103.2 Thu 16:00 HSZ/0004

Generating Accurate Showers in Highly Granular Calorimeters Using Normalizing Flows — •Thorsten Buss — Institut für Experimentalphysik, Universität Hamburg, Germany

The full simulation of particle colliders incurs a significant computational cost. Among the most resource-intensive steps are detector simulations. It is expected that future developments, such as higher collider luminosities and highly granular calorimeters, will increase the computational resource requirement for simulation beyond availability. One possible solution is generative neural networks that can accelerate simulations. Normalizing flows are a promising approach in this pursuit. It has been previously demonstrated, that such flows can generate showers in low-complexity calorimeters with high accuracy. We show how normalizing flows can be improved and adapted for precise shower simulation in significantly more complex calorimeter geometries.

T 103.3 Thu 16:15 HSZ/0004

Introspection for a normalizing-flow-based recoil calibration — •Lars Sowa, Jost von den Driesch, Roger Wolf, Markus Klute, and Günter Quast — Institute of Experimental Particle Physics (ETP), Karlsruhe Institute of Technology (KIT)

Normalizing flows (NFs) are neural networks, that preserve the probability between their input and output distributions. NFs can be promising candidates either as surrogates for the fast generation of new samples or as universal approximators of arbitrary probability density functions, based on which confidence intervals may be determined, both of which are interesting properties in high-energy physics (HEP). This work presents the case study of recoil calibration on LHC Run- 3 data and Monte Carlo simulation with the goal to better understand the behavior of NFs. The result of the NF is compared to a deep ensem- ble of feed-forward neural networks created to compare the calibration results and the different coverage in the value space.

T 103.4 Thu 16:30 HSZ/0004

Normalising Flows for Parameter Estimation from Gravitational Wave Signals — Johannes Erdmann[1], •Jon Hoxha[1], and Shichao Wu[2,3] — [1]III. Physikalisches Institut A, RWTH Aachen University — [2]Max-Planck-Institut für Gravitationsphysik (Albert-Einstein-Institut) — [3]Leibniz Universität Hannover

The Einstein Telescope (ET) is a proposal for a next generation ground-based gravitational wave detector. Due to higher sensitivity, ET is expected to receive orders of magnitude more gravitational wave signals than the current 2nd generation detectors LIGO, Virgo and KAGRA. Additionally, these signals will also be in the frequency band of the detector for a longer time, which would cause overlaps of signals. The analysis methods currently in use, which are based on Markov Chain Monte Carlo (MCMC) nested sampling methods, are unsuitable for handling such data and would take up significant computing resources. Therefore, new efficient analysis methods are required. Deep learning methods form a promising approach for this task. Specifically, normalizing flows promise to provide a more efficient means for signal parameter estimation. We use mock data to estimate signal parameters through normalizing flows and compare them to the current standard approach.

T 103.5 Thu 16:45 HSZ/0004

A method for inferring signal strength modifiers by conditional invertible neural networks — •Mate Zoltan Farkas, Svenja Diekmann, Niclas Eich, and Martin Erdmann — III. Physics Institute A, RWTH Aachen

The continuous growth in model complexity in high-energy physics collider experiments demands increasingly time-consuming model fits. We show first results on the application of conditional invertible networks (cINNs) to this challenge. Specifically, we construct and train a cINN to learn the mapping from signal strength modifiers to observables and its inverse. The resulting network infers the posterior distribution of the signal strength modifiers rapidly and for low computational cost. We present performance indicators of such a setup including the treatment of systematic uncertainties. Additionally, we highlight the features of cINNs estimating the signal strength for a vector boson associated Higgs production analysis carried out at an LHC experiment on simulated data samples.

T 103.6 Thu 17:00 HSZ/0004

Reconstruction of SAXS Data using Invertible Neural Networks — •Erik Thiessenhusen[1], Melanie Rödel[1], Thomas Kluge[1], Michael Bussmann[2], Thomas Cowan[1], and Nico Hoffmann[1] — [1]HZDR, FWKT, Dresden, Germany — [2]CASUS, Görlitz, Germany

The understanding of laser-solid interactions is important to the development of future laser-driven particle and photon sources, e.g., for tumor therapy, astrophysics or fusion. Currently, these interactions can only be modeled by simulations which need verification within the scope of pump-probe experiments. This experimental setup allows us to study the laser-plasma interaction that occurs when an ultrahigh-intensity laser hits a solid density target. We employ Small-Angle X-Ray Scattering (SAXS) to image the nanometer-scale spatial- and femtosecond temporal resolution of the laser-plasma interactions. However, the analysis of the SAXS pattern is an ill-posed inverse problem meaning that multiple configurations of our target might explain the same measurement due to the loss of the phase information. We approach the ambiguities of the inverse problem by a conditional Invertible Neural Network (cINN) that is returning a probability density distribution over target parameters explaining a single SAXS pattern. We will show that the domain gap between generated training and experimental data can be approached by integrating perturbations of experimental data into the training workflow. We assess the applicability of our approach to a selected set of grating targets in terms of a comprehensive evaluation on simulation and experimental data.