T 67: Data, AI, Computing 5 (normalising flows)

Time: Wednesday 16:00–17:45 Location: Geb. 30.33: MTI

T 67.1 Wed 16:00 Geb. 30.33: MTI

Applications of Normalizing Flows in High-Energy Particle Physics — •Lars Sowa, Roger Wolf, Markus Klute, and Günter Quast — Institute of Experimental Particle Physics (ETP), Karlsuhe Institute of Technology (KIT)

Normalizing flows (NFs) are neural networks that preserve probability when mapping probability density distributions from a given input to an arbitrary output space. They exhibit promising capabilities both, as surrogates for the fast generation of new samples as approximators of arbitrary probability density functions. These properties make them compelling in high-energy physics (HEP) applications. This work focuses on the application of NFs for recoil calibration, specifically with LHC Run-3 data taken with the CMS detector. Additionally, an NF-based b-jet regression is introduced, enabling the estimation of the per-jet energy resolution. The proposed methods showcase the versatility of NFs in HEP, serving as effective tools.

T 67.2 Wed 16:15 Geb. 30.33: MTI

Parameter reconstruction for gravitational wave signals at the Einstein Telescope using conditional normalizing flows — Johannes Erdmann and •Tobias Reike — III. Physikalisches Institut A, RWTH Aachen University

The proposed Einstein Telescope will be a gravitational wave detector of the third generation. It will improve the sensitivity compared to the current interferometers LIGO and VIRGO by an order of magnitude, resulting in a substantial additional volume for observation. The sensitive frequency range of the Einstein Telescope will also be much larger, allowing it to observe signals earlier and for longer durations. These improvements will significantly increase the amount of incoming data compared to current experiments, so that more efficient ways of processing data are needed.

Deep learning presents a promising option for fast analysis of incoming data, handling event detection as well as reconstruction. This talk will focus on simultaneous detection and parameter estimation of gravitational wave signals from Binary Black Hole Mergers using conditional normalizing flows.

T 67.3 Wed 16:30 Geb. 30.33: MTI

Normalizing Flows to Infer Ultra-High-Energy Cosmic-Ray Source Properties from Surface Detector Measurements at the Pierre Auger Observatory — •Frederik Krieger[1], Teresa Bister[2], Martin Erdmann[1], and Josina Schulte[1] — [1]III. Physikalisches Institut A, RWTH Aachen University — [2]Institute for Mathematics, Astrophysics and Particle Physics, Radboud Universiteit Nijmegen

The energy spectrum and the depth of shower maximum $X_{\max}$ distributions of ultra-high-energy cosmic rays (UHECRs) are measured at the Pierre Auger Observatory. Since $X_{\max}$ is correlated to the mass of the primary cosmic ray, these measurements are used to constrain the astrophysical parameters of UHECR source models. These parameters include the spectral index and the maximum energy of the injected spectrum, and the initial mass composition. Owing to the stochastic nature of interactions during propagation, simple inversion of the process from source to Earth is not possible.

For parameter inference, we apply conditional invertible neural networks, a method based on normalizing flows. In comparison to the frequently used Markov Chain Monte Carlo method, they act as likelihood-free estimators. We investigate the influence of higher event statistics of the $X_{\max}$ distributions, which can now be extracted from the surface detector data of the Pierre Auger Observatory using deep learning. Our results indicate that the increased statistics lead to stronger constraints on the astrophysical parameters and to enhanced sensitivity to experimental systematic effects.

T 67.4 Wed 16:45 Geb. 30.33: MTI

Using neural networks to calculate bounce actions — •Fabio Campello[1], Georg Weiglein[2], and Thomas Biekötter[3] — [1]UHH, Hamburg, Deutschland — [2]DESY, Hamburg, Deutschland — [3]KIT, Karlsruhe, Deutschland

Computing the decay rate of a meta-stable state is a well-known problem with relevance in various areas of physics. The decay rate is dominated by an exponential factor B, called the bounce action. Determining the bounce action for a given potential and meta-stable vacuum involves solving a set of partial differential equations. Numerically solving these equations can be challenging, especially in instances where the meta-stable vacuum is nearly degenerate to the deeper vacuum, referred to as the thin-wall limit. There are several dedicated solvers available for this problem, however finding bounce actions in potentials of many variables still remains a challenge.

It is also established that neural networks can be used to solve any differential equation with fixed boundary conditions, as neural networks are general function approximators. We use a neural network to solve the partial differential equation for finding the tunneling path. Using a custom tensorflow operation for the loss function enables us to make use of the full capabilities of modern GPUs.

Subsequently, we apply this approach to analyze vacuum stability in both the Minimal Supersymmetric extension of the Standard Model (MSSM) and Next-to-MSSM (NMSSM), where we successfully determine bounce actions for the tree-level potential including all Higgs fields and 3rd generation sfermions, for a total of 22 scalar fields.

T 67.5 Wed 17:00 Geb. 30.33: MTI

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

Monte Carlo MC simulations are vital for collider experiments. They allow us to compare experimental findings with theory predictions. These simulations have a high computational demand, and future developments, such as higher event rates, are expected to push the computation needs beyond availability. Generative neuronal networks can alter MC simulations, speeding them up and mitigating the problem.

Last year, we presented a masked auto-regressive flow (MAF) based generation of particle showers. While generating highly accurate showers in highly granular calorimeters is possible, the generation on CPUs is slower than MC simulations. Also, the architecture does not scale well with input dimensions. Therefore, we change the MAF to a coupling-based flow with convolutional sub-networks. This speeds up the model by a significant factor and improves the model's accuracy further.

Lately, point-cloud-based generative models have become popular. These models represent showers as unordered sets of energy depositions characterized by their position in the detector and the amount of energy. Since fixed grid models, such as our flow, are usually trained on the irregular detector geometry, point-cloud-based models are expected to generalize better to different detector geometries. We conduct a systematic comparison between point cloud and fixed gride models.

T 67.6 Wed 17:15 Geb. 30.33: MTI

Improving MCMC sampling efficiency with normalizing flows — Michael Dudkowiak[1], Cornelius Grunwald[2], Oliver Schulz[1], and •Willy Weber[2] — [1]Max Planck Institute for Physics, Munich — [2]TU Dortmund University, Department of Physics

The Bayesian data analysis approach combines prior knowledge and observed data to derive information about the parameters of a model. Typically, numerical sampling methods are required for performing Bayesian inference due to the complexity of the models and the high-dimensional parameter spaces involved, as is usually also the case in particle physics applications. Markov Chain Monte Carlo (MCMC) methods are commonly used to generate samples that approximate the posterior distribution. Machine learning techniques have the potential to enhance MCMC methods by improving the exploration of complex parameter spaces, leading to more accurate results. This talk focuses on normalizing flow models, which allow to transform a complex distribution into a simpler one, thereby improving the sampling efficiency of MCMC algorithms. This presentation introduces an implementation of a normalizing flow enhanced MCMC ensemble algorithm currently being integrated into the Bayesian Analysis Toolkit (BAT.jl). Initial studies on the performance of this new algorithm are presented.

T 67.7 Wed 17:30 Geb. 30.33: MTI

Conditional normalizing flows for correcting simulations — •Caio Cesar Daumann[1], Mauro Donega[2], Johannes Erdmann[1], Massimiliano Galli[2], Jan Lukas Späh[1], and Davide Valsecchi[2] — [1]III. Physikalisches Institut A, RWTH Aachen University — [2]ETH

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Simulated events are key ingredients for almost all high-energy physics analyses. However, imperfections in the configuration of the simulation often result in mis-modelling and lead to discrepancies between data and simulation. Such mis-modelling often must be taken into account by correction factors accompanied by systematical uncertainties, which can compromise the sensitivity of measurements and searches. To address this issue, we propose to use normalizing flows, a powerful technique for learning the underlying distributions of input data. Where the flow is trained with both simulation and data, and is able to map betwenn the distributions.

We demonstrate that the proposed architecture can accurately correct simulation marginal distributions results in better closure with data. Additionally, we show that the flow can correct the correlations of variables, leading to significantly reduced differences in correlation matrices compared to the data.