T 50: Data, AI, Computing, Electronics V

Time: Wednesday 16:15–18:00 Location: KH 00.024

T 50.1 Wed 16:15 KH 00.024

NEEDLE - A modern orchestration framework for Neural Simulation Based Inference tools — •Kylian Schmidt[1], Ulrich Husemann[2], Nicoló Trevisani[1], Stephen Jiggins[2], Levi Evans[2], Judith Katzy[2], Stefan Katsarov[2], Felix Kahlhöfer[3], Nino Kovačić[4], Lena Rathmann[3], and Niklas Reus[3] — [1]ETP, KIT, Karlsruhe — [2]DESY, Hamburg — [3]IAP, KIT, Karlsruhe — [4]Department of Physics, U. of Zagreb

Neural Simulation Based Inference (NSBI) is a new machine learning (ML) paradigm for statistical data analysis in high energy physics (HEP). These tools learn the underlying statistical distribution of the data using surrogate neural networks and show clear improvements over classical likelihood estimation methods. However, these methods require the training of a large number of networks in order to achieve this increase in performance while retaining robustness towards biases. It is therefore crucial to address the challenges of orchestrating many neural network trainings, alongside efficient utilization of computational resources.

The NEEDLE project aims to provide a flexible framework for distributed training together with a library of NSBI tools for deployment on High Performance Computing clusters. NEEDLE combines modern ML libraries together with commonly-used HEP data analysis tools and formats. In this talk, we present the design of the NEEDLE framework, how it handles large data streams and our integration with pytorch lightning.

T 50.2 Wed 16:30 KH 00.024

Search for keV-Scale Sterile Neutrinos with TRISTAN at KATRIN Using Neural Simulation-Based Inference — •Luca Fallböhmer for the KATRIN-Collaboration — Max-Planck-Institute for Nuclear Physics

Following the completion of its neutrino mass measurement program at the end of 2025, the KATRIN experiment aims to probe keV-scale sterile neutrinos by analyzing the full tritium beta decay spectrum with a novel detector system, TRISTAN. Leveraging KATRINs high source activity, this search is sensitive to mixing amplitudes at the parts-per-million level. However, extracting a potential sterile neutrino signature is challenging, as it relies on detailed modeling of the the observed tritium spectrum and requires computationally intensive Monte Carlo simulations. To address this challenge, we implement neural simulation-based inference using normalizing flows to approximate the underlying probability density of the physics simulation. We demonstrate that continuous normalizing flows trained via conditional flow-matching enable highly efficient modeling of experimental spectra. This approach opens up the possibility of a fast surrogate model for rapid sampling and generates a continuous, unbinned representation of the KATRIN beamline response, accelerating and enabling the analysis pipeline.

T 50.3 Wed 16:45 KH 00.024

Unbinned, High-dimensional Precision Measurements through the Lens of Deep Learning — •Jingjing Pan — Karlsruhe Institute of Technology, Karlsruhe, Germany

Unbinned, high-dimensional machine learning-based unfolding has rapidly progressed from a conceptual method to a practical analysis tool now deployed across multiple experiments, including but not limited to ATLAS, CMS, H1, LHCb, STAR and T2K. Building on the classifier-based framework of OmniFold, recent work has consolidated best practices for validation, calibration, uncertainty quantification, and data-release format, enabling robust unbinned measurements in the natural high-dimensional phase space of experimental data. Two recent analyses that highlight this progress are presented in this talk.

The recent H1 measurement performs the first OmniFold unfolding of all final-state particles in high-Q^2 events using a point-edge transformer to process variable-length event topologies. This full-phase-space result enables both re-measurements of classic DIS observables and new projections, such as simultaneous jet measurements in the laboratory and Breit frames from a single unfolded dataset. Meanwhile at the LHC, ATLAS has applied ML-assisted unfolding to extract jet track-function moments while circumventing binning artifacts that affect non-linear QCD evolution studies. These results demonstrate that modern ML-based unfolding delivers systematically controlled, fully differential data products that are broadly reusable for downstream physics.

T 50.4 Wed 17:00 KH 00.024

Unbinned Unfolding of the WWbb Analysis with OmniFold — •Josef Murnauer, Daniel Britzger, and Stefan Kluth — Max-Planck-Institute for Physics

We revisit the recently published ATLAS measurement of WWbb production and explore an alternative unfolding strategy based on OmniFold. The newly published single- and di-lepton WWbb cross-section measurements have demonstrated that this process constitutes a major new avenue for precision studies in top-quark physics at the LHC. New paradigms in data analysis for Run-III and beyond are emerging rapidly, with traditional techniques (such as cut-and-count or matrix-based unfolding) increasingly being superseded by more flexible and powerful machine-learning algorithms. We present initial results from applying an unbinned unfolding technique to the WWbb analysis in the lepton+jets channel, highlight its potential advantages over standard unfolding methods, and discuss its implications for Run-III data analyses.

T 50.5 Wed 17:15 KH 00.024

Binary Black Hole Parameter Estimation using a Conditioned Normalizing Flow — •Markus Bachlechner and Achim Stahl — III. Physikalisches Institut B, RWTH Aachen

The proposed Einstein Telescope is the first of the third-generation gravitational wave detectors. It is expected to reach a noise level at least one order of magnitude lower than current interferometers like LIGO and Virgo. Thus, the improved sensitivity increases the observable volume and extends the time window in which the inspiral phase of binary systems is measurable. To analyze the resulting vast amounts of data efficiently, Neural Networks (NNs) can be utilized. This talk presents a fast Binary Black Hole parameter reconstruction using a conventional convolutional NN, which conditions a subsequent Normalizing Flow (NF). Using the NF, an approximate posterior parameter distribution is obtained on an event-by-event basis, allowing for the estimation of uncertainties.

T 50.6 Wed 17:30 KH 00.024

Normalizing-Flow-Based Reweighting of Detector Systematics in Neutrino Telescopes — •Oliver Janik — Erlangen Centre for Astroparticle Physics (ECAP), Friedrich-Alexander-Universität Erlangen-Nürnberg

Accurate measurements of the astrophysical neutrino flux require reliable predictions of the detector response in neutrino telescopes. Because this response is highly non-analytical, such predictions rely on Monte Carlo (MC) simulations and a forward-folding approach. A key limitation is that MC simulations must assume specific detector properties. Evaluating detector systematic uncertainties therefore requires either simulating multiple MC sets with fixed detector parameters or using approaches such as SnowStorm, which sample detector parameters continuously on an event-by-event basis. In both cases, reweighting typically relies on interpolation between MC expectations, introducing an implicit dependence on an assumed flux model.We present a normalizing-flow*based approach that factorizes detector systematics into shape and yield components. A conditional normalizing flow is used to model changes in the distribution of reconstructed observables, while the overall event yield is modeled separately as a function of the relevant detector parameters. This separation enables consistent reweighting for both discrete MC sets and SnowStorm simulations, without relying on flux-dependent interpolation.In this talk, we demonstrate the application of this method to detector-systematics modeling in astrophysical neutrino flux measurements.

T 50.7 Wed 17:45 KH 00.024

Covering Unknown Correlations in Bayesian Priors by Inflating Uncertainties — •Lukas Koch — JGU Mainz

Bayesian analyses require that all variable model parameters are given a prior probability distribution. This can pose a challenge for analyses where multiple experiments are combined if these experiments use different parametrisations for their nuisance parameters. If the parameters in the two models describe exactly the same physics, they should be 100% correlated in the prior. If the parameters describe independent physics, they should be uncorrelated. But if they describe related or overlapping physics, it is not trivial to determine what the joint prior distribution should look like. Even if the priors for each experiment are well motivated, the unknown correlations between them can have unintended consequences for the posterior probability of the parameters of interest, potentially leading to underestimated uncertainties. In this presentation I will show that it is possible to choose a prior parametrisation that ensures conservative posterior uncertainties for the parameters of interest under some very general assumptions.