Contribution ID: **68** Type: **Poster**

Autoencoders for Anomaly Detection and Output Reduction on the Edge (AADORE)

Detectors at next-generation high-energy physics experiments face several daunting requirements: high data rates, damaging radiation exposure, and stringent constraints on power, space, and latency. In light of this, recent detector design studies have explored the use of machine learning (ML) in readout Application-Specific Integrated Circuits (ASICs) to run intelligent inference and data reduction processes at-source. We highlight that autoencoders offer a variety of front-end benefits; an on-sensor encoder performs efficient lossy data compression and simultaneously uses the latent space representation for anomaly detection. We present results of low-latency and resource-efficient autoencoders for front-end processing, and assess the decrease in off-detector data rate compared to a similarly sized filtration approach using the Smart Pixel dataset. We also explore the use of latent space information for real-time sensor defect monitoring. This work drives forward the discussion of autoencoders for on-detector data processing; in particular, we consider future hardware targets and detector subsystem applications.

Focus areas

HEP

Author: YUE, Alexander (Stanford University/SLAC)

Co-authors: GONSKI, Julia Lynne (SLAC National Accelerator Laboratory (US)); JIA, Kenny (Stanford University/SLAC)

Presenter: YUE, Alexander (Stanford University/SLAC)