Toward A.I.-Assisted Design of Experiments

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MOTIVATION

In 2012 we discovered the Higgs boson with machine learning tools. That marked a paradigm shift in data analysis procedures and performance.

A similar paradigm shift is offered today by Artificial Intelligence methods allowing for the end-to-end optimization of our instruments: Differentiable Programming (DP).

Detector design in HEP traditionally leverages robustness-driven paradigms
• «Track first, destroy later»;
• focus on redundancy, ensuring intercalibration;
• symmetrical layouts
→ Great, but not meant to optimize performance!

DP-based models describing all parts of an experiment, from sensor geometry to inference extraction, enable a continuous mapping of the performance, probing the result of design choices in high-dimensional spaces which we cannot explore with discrete sampling.

These models may allow the discovery of human-impervious, innovative solutions, with LARGE potential gains. E.g., see below:

Generative models for particle interactions can be used to model non-differentiable stochastic processes:

Below, left: Upgrade of LHCb EM calorimeter. Optimized significance to \( B_s \rightarrow J/\psi \pi^0 \) signal is shown given number of channels [4]. Insets show baseline PMT layout.

Below, right: Simulation of EM showers produced by GEANT4 are well reproduced by a generative adversarial network model, then used in the optimization task.

MODE [3] aims to pave the way to the full optimization of our future instruments.

By solving problems of moderate complexity, we are building a modular software library, gradually empowering the study of harder use cases [4].

Left: Encoding all system elements within a pipeline allows for the back-propagation of gradients of the objective function, and a full scanning of the parameter space of design options.

Right: Proof of optimization of a muon tomography detector.

DP software finds optimal geometry of detection panels given cost, constraints, and specified objective (e.g., power of detection of specific materials).

Case shown: detection of U blocks in scrap metal within container.

Below: Position and size of detection panels above and below the scanned volume.

Use cases currently studied include:
• Muon tomography detectors (see above)
• EM calorimeter for \( \mu \) collider detector (in progress)
• Upgrade of LHCb EM calorimeter (see left)
• Hybrid hadron calorimetry (in progress)
• SWGO Cherenkov array optimization (starting)

References