

Efficient binned profile likelihood maximization with Rabbit

The High-Luminosity LHC era will deliver unprecedented data volumes, enabling measurements on fine-grained multidimensional histograms containing millions of bins with thousands of events each. Achieving ultimate precision requires modeling thousands of systematic uncertainty sources, creating computational challenges for likelihood maximization and inference. Fast optimization is crucial for efficient analysis development.

We present a novel tensorflow-based tool, Rabbit, that leverages optimized parallelization on CPUs and GPUs for this task. We utilize automatic differentiation to compute first and second-order derivatives, yielding robust and efficient results. We implement nonlinear Poisson profile likelihoods as well as Gaussian approximations including a fully linearized formalism that results analytic solutions. Our python API supports the unified histogram interface and flexible configurations with symmetrization options to establish Gaussian approximations.

Our tool distinctly focuses on measuring physical observables rather than intrinsic parameters, disentangling likelihood parameterization from quantities of interest and creating a more intuitive, less error prone user experience. Comprehensive benchmarking demonstrates excellent scaling with increased threading and reveals significant efficiency gaps when compared to commonly used frameworks in the field. These performance differences highlight the need for continued development of optimized statistical tools for high-energy physics analyses.

Authors: WALTER, David (Massachusetts Inst. of Technology (US)); BENDAVID, Josh (CERN)

Presenter: WALTER, David (Massachusetts Inst. of Technology (US))