



Contribution ID: 28

Type: Parallel talk

## An implementation of neural simulation-based inference for parameter estimation in ATLAS

Neural simulation-based inference is a powerful class of machine-learning-based methods for statistical inference that naturally handles high-dimensional parameter estimation without the need to bin data into low-dimensional summary histograms. Such methods are promising for a range of measurements, including at the Large Hadron Collider, where no single observable may be optimal to scan over the entire theoretical phase space under consideration, or where binning data into histograms could result in a loss of sensitivity. This work develops a neural simulation-based inference framework for statistical inference, using neural networks to estimate probability density ratios, which enables the application to a full-scale analysis. It incorporates a large number of systematic uncertainties, quantifies the uncertainty due to the finite number of events in training samples, develops a method to construct confidence intervals, and demonstrates a series of intermediate diagnostic checks that can be performed to validate the robustness of the method. A first full application of the novel techniques to an ATLAS measurement of the off-shell Higgs boson in the  $H \rightarrow ZZ \rightarrow 4\ell$  final state is also presented. This approach represents an extension to the standard statistical methodology used by the experiments at the Large Hadron Collider, and can benefit many other physics analyses as well.

### AI keywords

Simulation-Based Inference, deep neural networks, uncertainty quantification

**Primary authors:** GHOSH, Aishik (University of California Irvine); SCHAFFER, Arthur (IJCLab); ROUSSEAU, David (IJCLab-Orsay); SANDESARA, Jay (University of Wisconsin-Madison)

**Presenter:** SANDESARA, Jay (University of Wisconsin-Madison)

**Track Classification:** Inference & Uncertainty