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From bins to flows: a neural network approach to unbinned data-simulation corrections

Precise simulation-to-data corrections, encapsulated in scale factors, are crucial for achieving high precision in physics measurements at the CMS experiment. Traditional methods often rely on binned approaches, which limit the exploitation of available information and require a time-consuming fitting process repeated for each bin. This work presents a novel approach utilizing modern probabilistic machine learning techniques to compute multivariate and unbinned scale factors for CMS objects. A PyTorch-based likelihood function is developed, incorporating Normalizing Flows for signal and background distributions from simulation, and for conditional kinematic variable modeling. Neural networks are employed to parametrize data-simulation discrepancies such as detector efficiencies and variable transformations. Continuous scale factors are obtained by performing an unbinned maximum likelihood fit on data. Minimizing binning biases and improving scale factor representation, these machine learning methods exploit more observables and their correlations, with the potential to improve physics results precision.

Significance

References

Experiment context, if any

CMS experiment

Author: CMS COLLABORATION

Presenter: CMS COLLABORATION

Session Classification: Poster session with coffee break

Track Classification: Track 2: Data Analysis - Algorithms and Tools