Contribution ID: **199** Type: **Poster**

OmniFold-HI: an Advanced ML Unfolding for Heavy-Ion Data

To compare collider experiments, measured data must be corrected for detector distortions through a process known as unfolding. As measurements become more sophisticated, the need for higher-dimensional unfolding increases, but traditional techniques have limitations. To address this, machine learning-based unfolding methods were recently introduced. In this work, we introduce OmniFold-HI, an extension of OmniFold [1] to incorporate detector fakes, inefficiencies, and statistical uncertainties, enabling its application in heavy-ion collisions. By introducing auxiliary observables, we show that high-dimensional unfolding—up to 18 dimensions—significantly improves performance and reduces systematic uncertainties. We also propose a novel strategy for unfolding in the presence of large backgrounds, avoiding traditional background subtraction, and instead unifying calibration and unfolding into a single, consistent framework. Our results establish a foundation for robust, high-dimensional ML-based unfolding in complex collider environments.

[1] Andreassen et. al, Phys. Rev. Lett. 124, 182001 (2020)

Significance

This works proposes an improvement of a known machine learning unfolding algorithm (OmniFold) and its introduction to the heavy-ion physics context. The work also proposes a novel approach to jet calibration and background subtraction in heavy-ion analyses.

References

Oral presentation at ML4Jets: https://indico.cern.ch/event/1386125/contributions/6139658/
Oral presentation at Hard Probes 2024: https://indico.cern.ch/event/1339555/contributions/6040933/

Experiment context, if any

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Session Classification: Poster session with coffee break

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