Investigating the Use of Omnifold in Unfolding Jet Transverse Momenta

By Simon Browning of Abilene Christian University
for the STAR Collaboration

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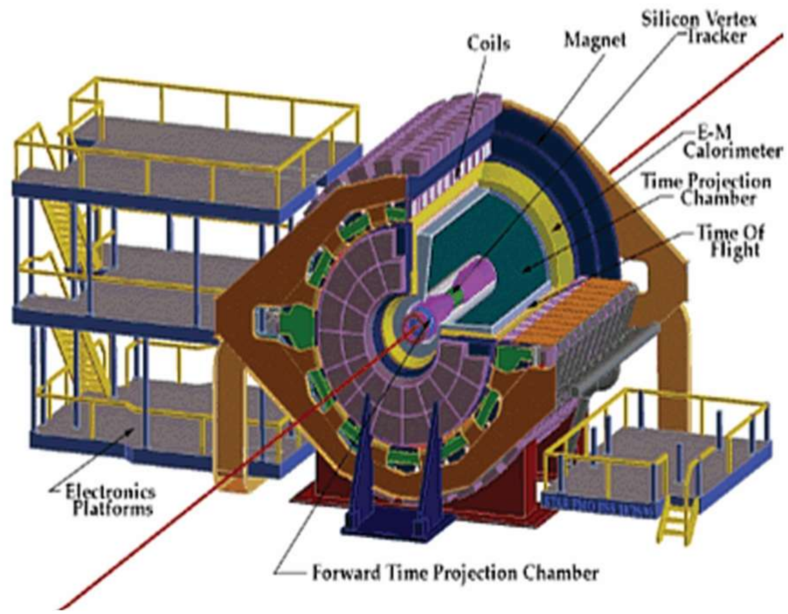
Abstract - Summary

- Detector effects distort information, requiring data to be “unfolded”.
- Correcting for effects becomes challenging with steeply-falling spectra.
- Iterative Bayesian Unfolding (IBU) is well-established but requires data to be binned.
- Omnifold is a new method that uses machine learning to unfold data event-by-event.
- Investigate Omnifold’s ability to recover true distributions.

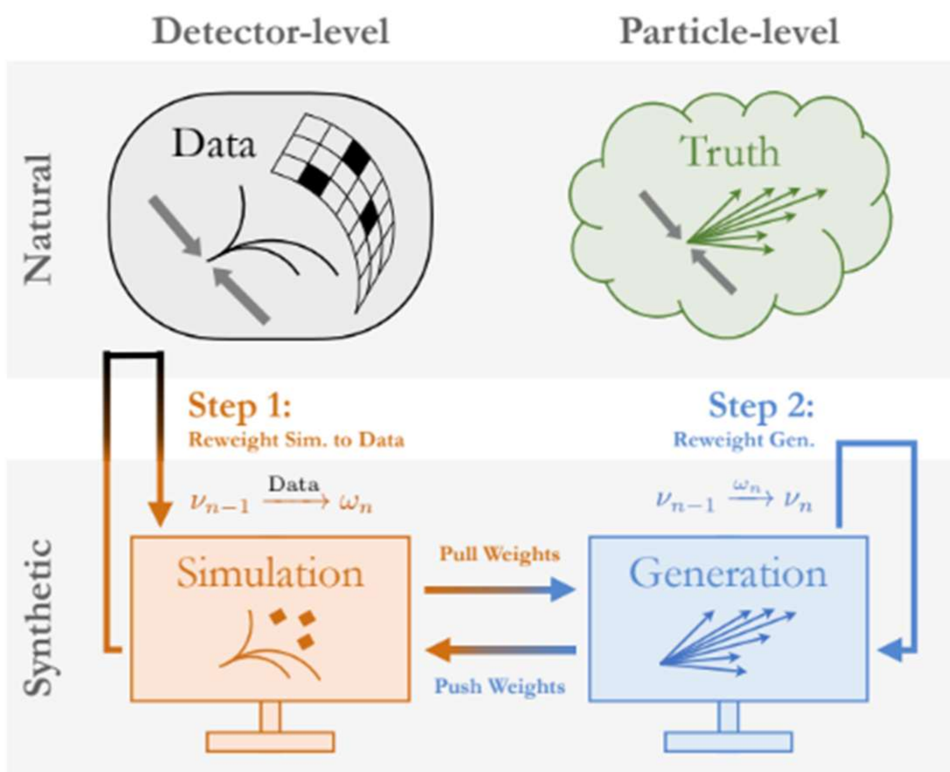
The STAR Experiment

- Studies the strong interaction between subatomic particles.
- Housed at BNL
- Focuses on studying proton spin and the quark-gluon plasma (QGP).
- Jet analysis requires the unfolding of multiple observables simultaneously.
- Difficult to do with traditional/fixed-bin unfolding techniques.



What is Omnifold?

- A machine-learning based algorithm.
- A non-fixed-bin unfolding method.
- Deals with natural and Monte Carlo synthetic data sets.
- Each data set contains detector-level and particle-level data.
- Keras neural network classifier.

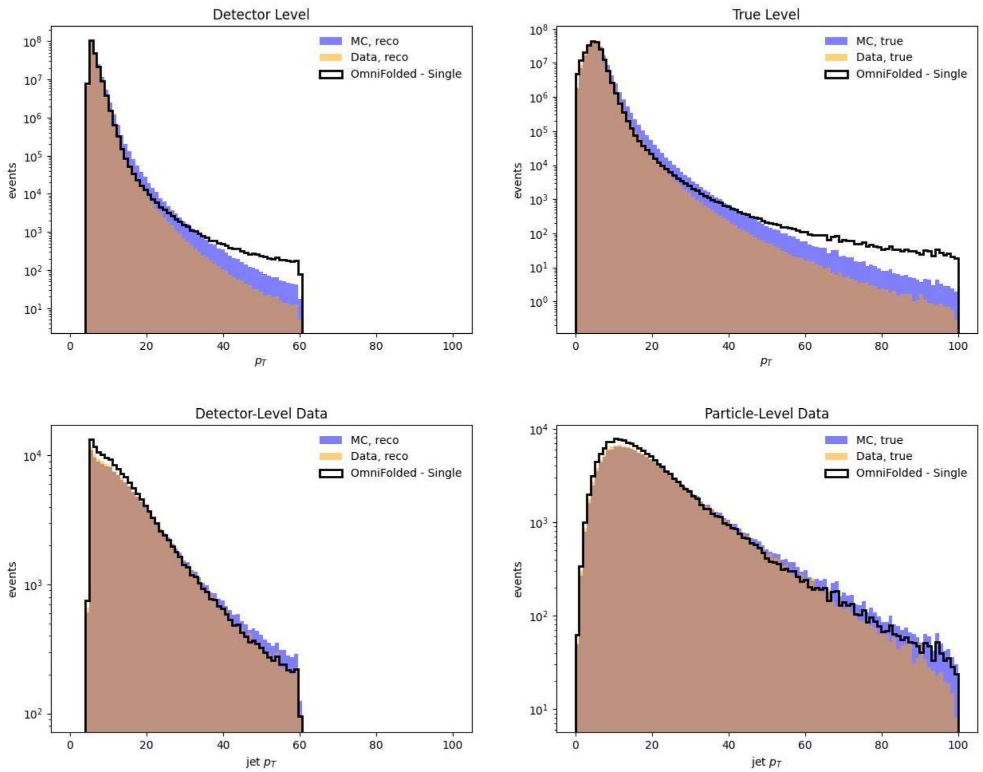


Andreassen, Anders, et al., *Omnifold: A Method to Simultaneously Unfold All Observables*, 2019.

Steeply Falling Spectra

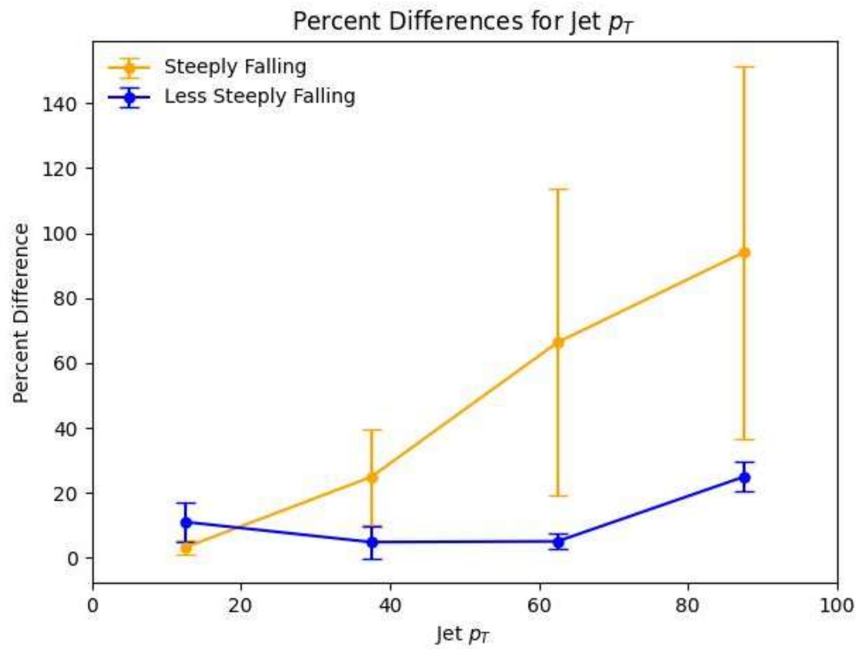
- We seek to generate data that approximates steeply-falling jet p_T spectra.
- Test data generated via fast Monte Carlo based on STAR run 11 detector simulation.
- Generating the low-statistics tails of steeply falling spectra is numerically expensive.
- We generate less steeply-falling data and then reweight to better reproduce observed jet p_T spectra.
- We apply Omnifold to each distribution to test sensitivity to steepness of the spectra.
- Better performance on less steep spectra.

Counts vs. Transverse Jet Momentum [GeV]



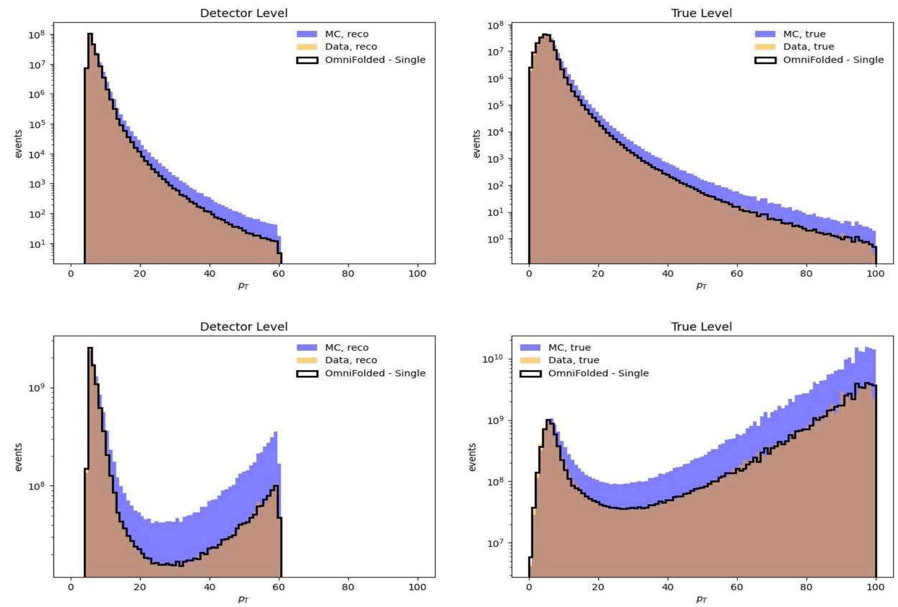
Steeply Falling Spectra

- We add all events in 25 GeV bins and compare the true spectra to the unfolding.
- Averages and standard deviations calculated from 5 tests.
- Consistently fits low momenta well.
  - High statistics/weight.
- Struggles fitting the high momenta tail.
  - Low statistics/weight.
- Better performance with less steep spectra.



Custom Weights

- Omnifold treats low momenta with more importance.
- How can we make Omnifold treat the tail with more importance?
- Give Omnifold event weights modified by a custom weighting function.
- Rescales weights to minimize the discrepancy between high and low momenta.



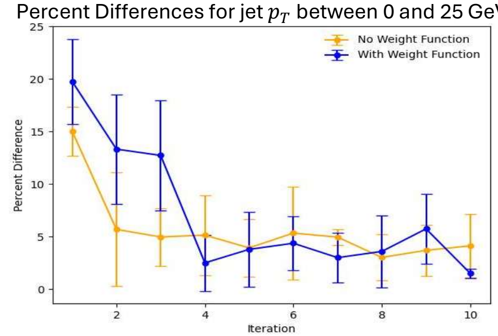
$$Weight_{new} = Weight_{old} \exp(p_T^{0.68})$$

Results

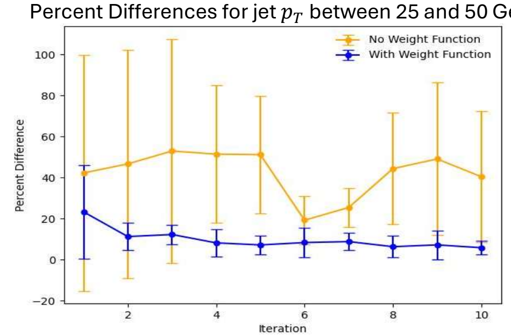
- Omnifold consistently fitted custom-weighted spectra more effectively.
- Lower average percent error and standard deviation than unaltered steeply falling spectra.

Averages and standard deviations calculated from 5 tests.

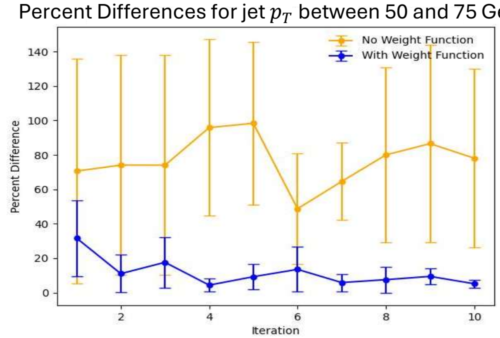
Percent Differences for jet p_T between 0 and 25 GeV



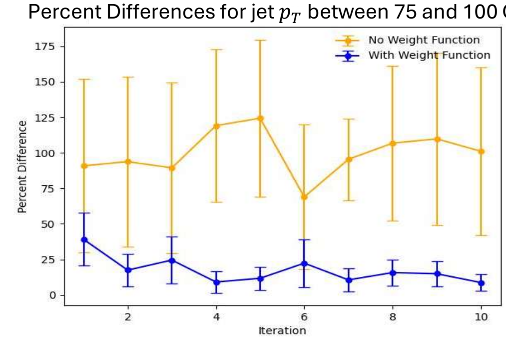
Percent Differences for jet p_T between 25 and 50 GeV



Percent Differences for jet p_T between 50 and 75 GeV



Percent Differences for jet p_T between 75 and 100 GeV



Future Work

Reweighting function must be custom made for each data set.

Find a reliable data fitting routine for steeply falling spectra.

Allows us to solve for the best reweighting function.

Investigation into uncertainty and error that this approach causes.

Acknowledgements

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Steeply Falling Spectra

$$\left(\exp(a_0 + a_1 * x) + \frac{a_2}{x^{a_3}}\right)\left(1 - \frac{1}{a_4 * x^{a_5} + 1}\right)$$

Where a_i are fit to simulate Run 11 embedding data, and can be varied to generate differing natural and synthetic distributions. Below are example parameter values for the natural distribution.

$$a_0 = 17.3, a_1 = -8.9\frac{1}{GeV}, a_2 = 2.4 * 10^{13}\ GeV^{a_3}, a_3 = 6.5, a_4 = 7.4 * 10^{-7} GeV^{-a_5}, a_5 = 8.2$$

$$\ln\left(\left(\exp(a_0 + a_1 * x) + \frac{a_2}{x^{a_3}}\right)\left(1 - \frac{1}{a_4 * x^{a_5} + 1}\right)\right)\left(\frac{x * GeV^{1.25}}{x^{2.25} + \Lambda^2}\right)^2$$

Where Λ is chosen in order to simulate Run 11 embedding data before weights are introduced.

$$\Lambda = 22\ \mathrm{Gev}^{1.125}$$