Exploring machine learning methods for unbinned data analysis of Drell-Yan phase space at CMS

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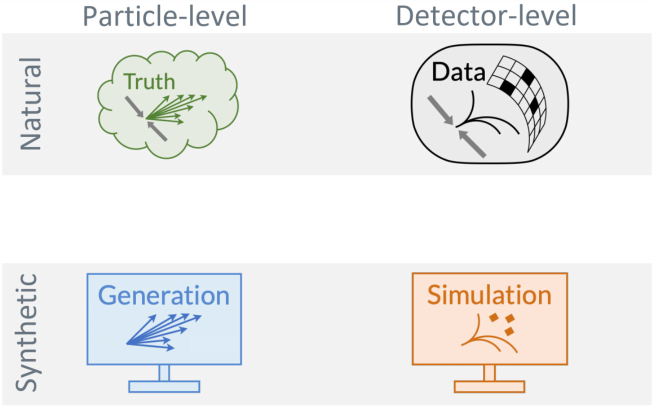
Introduction

Introduction

Particle detectors introduce smearing in measurements:

- Finite detector resolution
- Acceptance cuts (geometrical and physical)
- Binning effect in distributions

Goal: Use data (at detector level) and infer true desitributions (at particle level).

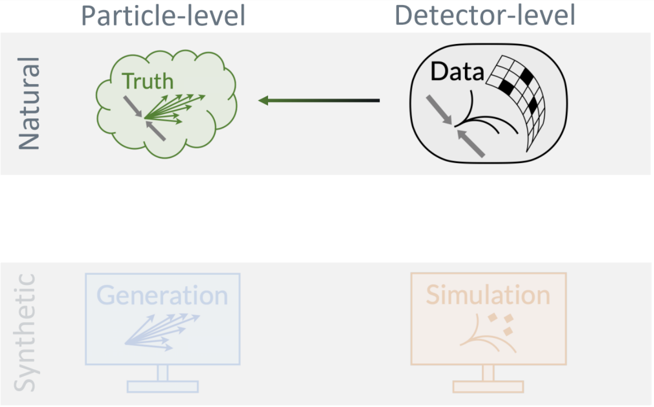


Introduction

Only then we can reliably compare the measurements against other sources:

- Semi-Inclusive theoretical predictions
- MC generator parameter tuning
- Other experiments

Unfolding (deconvolution).



Current Unfolding approach

Current Unfolding approach

Detector response can be modeled as a linear application.

$$x_{detector} = R * x_{truth} + x_{backg} \quad (1)$$

Where R represents the detector **response** as $R_{ij} = P(truthi|measurej)$.

Current Unfolding approach

Various approaches exist to unfolding:

- Naive R inversion

$$x_{truth} = R^{-1} * (x_{detector} - x_{backg}) \tag{2}$$

- Iterative Bayesian Unfolding (IBU): Given a **response** matrix and a prior distribution.

$$x_j^{(n)} = \sum_i P_{n-1}(truthi|measurej) * P(measurej) \tag{3}$$

Current Unfolding approach

Unfolding drawbacks:

- Works for binned data
- 1-dimensional by desing (very difficult to extend to higher dimensions)
- Does not account for relations between observables

Machine Learning approach

Distribution reweight.

- Using a binary classifier to distinguish between two distributions

- Likelihood ratio can be aproximated and used as weight function

$$w_{A\to B} = \frac{p_B(x)}{p_A x} \approx \frac{f(x)}{1 - f(x)} \tag{4}$$

- Distributions are binned for representation but weights are estimated per event

Machine Learning approach

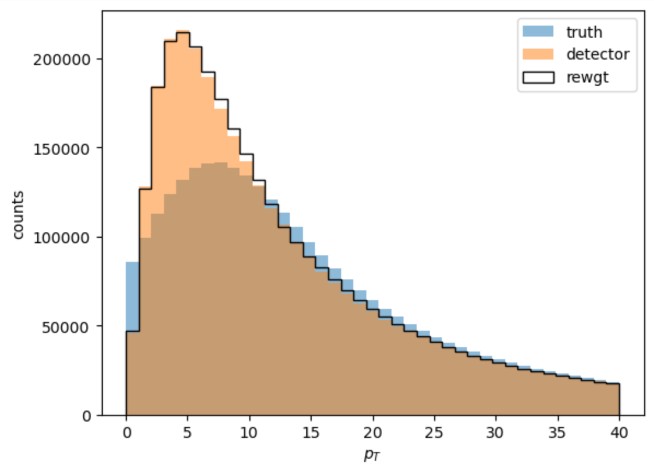


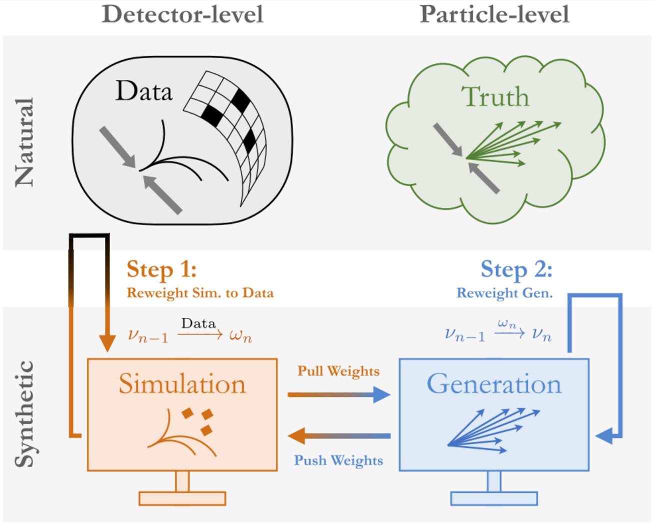
Figure 1: Transverse momentum distribution. $pp \to DY7TeV$.

Machine Learning approach

Advantages of ML reweight.

- Used for non-trivial distributions
- Easily extended to multiple dimensions
- Learns complex relations between observables

Iterative Neural Network Reweight: OmniFold.



Machine Learning approach

Iterative Neural Network Reweight: OmniFold.

- Continuous generalization of IBU
- Inherits all the advantages from ML reweight
- Unfolds experimental data using multiple dimensions (possibly full phase space)

Work in progess

Work in progess

Drell-Yan phenomenology analysis with CMS data.

- Explore HEP analysis viavility with **Python**
- Unlock ML ecosystem and methods
- Validation of NanoAODRun1 format for CMS data
- Improve accuaracy of infered distributions

Work in progess

Drell-Yan phenomenology analysis with CMS data.

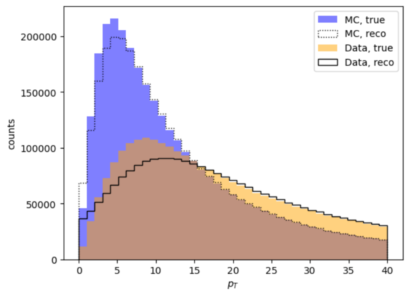


Figure 2: Syntetic and Natural distributions.

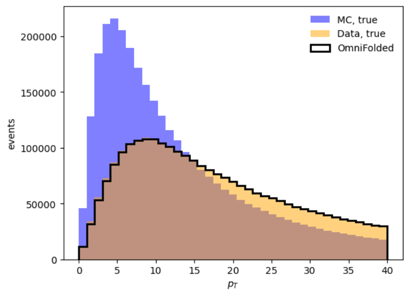


Figure 3: Result of reweighted distribution.

Work in progess

Future work.

- Full phase space unfolding
- Unbinned and data driven analysis
- Evaluate statistical and systematical uncertanties
- Search for more **robust** observables where current theoretical predictions struggle

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