# Tools for Precision Jet Substructure Measurements Unfolding and Tracking

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# Why precision JSS Merry monto? Why should L care about a precision $m_t$ ?





#### Stability of the Standard Model vacuum!



Butazzo, Degrassi, Giardino, Giudice, Sala

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#### SMEFI / future reinterpretation



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### **How to Get There?**





### How to Get There?

**But need** observables at generation level (for comparison with theories, new calibration routines)





## **Unfolding: An Inverse Problem**



Preserving New Physics while Simultaneously Unfolding All Observables (PRD, 2021)

# Outline

 Seeing Higher-Order QCD Effects with OmniFold

All About Precision:
 Putting JSS on Track(s)







#### Truth



Simulation





#### Generation





# Outline

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# Unfolding

Data inevitably comes with many stochastic defects:

- Acceptance & Efficiency: particles produced not measured
- Detector Noise ("fake"): particles measured not real
- Detector Bias & Resolution
- Combinatorics: detector can change the order of N particles
- Background

# Unfolding

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**Challenge:** correct all the above accurately & precisely

- $\rightarrow$  preserve higher order effects  $\rightarrow$  test improvements of jet modeling

### **A Timely Example: Testing Improvements of Jet Modeling** $\alpha_{\rm c}$ extraction from EEC

**DIRE: NLO DGLAP** added in the parton shower

(Collinear) Energy Correlators: field-theoretic, broad appeal expect better modeling by DIRE

 $\langle \mathscr{E}\mathscr{E} \rangle = \sum_{ii} \int dx'_L \frac{p_{\mathrm{T,i}} p_{\mathrm{T,j}}}{p_{\mathrm{T,iet}}^2} \,\delta(x'_L - x_L)$ 

(~4.4% NLO effects in the slope proportional to  $\alpha_{\rm s}$ )

**DIRE vs. Pythia at generation-level vs. after <b>Delphes** 





### **Testing Improvements of Jet Modeling Setup** DIRE vs. Pythia at get

Jet definition: AK4, Energy Flow algorithm from Delphes 3.5.0

Selection:  $p_{\rm T,jet} \in [500, 550]$  GeV,  $\eta < 2.5$ , the leading jet from Z+jets 1

Input: 4-vectors ( $p_{\rm T}$ ,  $\eta$ ,  $\phi$ , PID) of all the hadrons within the jet

Neural network architecture: PFN, Point Cloud Transformer (PCT) DIRE vs. Pythia at generation-level vs. after Delphes







#### **Particle-level**



#### $\omega_n$

**Detector-level** 







**Detector-level** 

#### **Particle-level**

Now with data-shaped reco-level MC  $\rightarrow$ can pull back to gen level and obtain the truth distribution!





### **Detector-level**



A. Andreassen et al., PRL 2020]

#### **Particle-level**

### Not yet... **Need 1-to-1 mapping** of gen-level kinematics

Learn another likelihood ratio  $W(gen) = \frac{p_{rw MC}(gen)}{(gen)}$ p<sub>MC</sub>(gen)  $\rightarrow$  can then apply to genlevel sample





### **Detector-level**



**Iterate the** prior dependence away

A. Andreassen et al., PRL 2020]

#### **Particle-level**

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$$\omega_n \qquad \nu_{n-1} \xrightarrow{\omega_n} \nu_n$$
(m,t)
Generation





### **Testing Improvements of Jet Modeling**



[Toolkit for Multivariate Data Analysis, A. Hoecker et al.]





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# Outline

 Seeing Higher-Order QCD effects with ML Unfolding

All About Precision:
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## **Putting JSS on Track(s) All About Precision**





## **Putting JSS on Track(s)** All About Precision



## **Putting JSS on Track(s) All About Precision**



## **Putting JSS on Track(s)** Through the Magic of Track F

### Momentum fraction of a hard parto

• Describes also correlations am



Fragmentation function only describes single identified hadron



## **Track Functions as a Probe of QCD**

Track functions will play two key roles in Jet Substructure:

- Enable precision calculations of JSS observables on charged hadrons. Provide interesting probes of QCD RG flows







Progress towards experimental studies of a new class of JSS observables **Energy Correlators** 

- Track functions are an important aspect of a precision program.
- We have shown that Omnifold can be sensitive to higher order QCD effects. Bright future for precision measurements!







# Thanks!



Backup

### **OmniFold** "Likelihood-ratio trick"

- likelihood function hard to approach in high dimensions

- the ratio of two likelihood functions can be approximated by the decision function of a binary classifier; make good use of MC

 - can process variable length, unordered input with proper neural network architecture

Neural Networks for Full Phase-space Reweighting and Parameter Tuning

Learning Likelihood Ratios with Neural Network Classifiers

$$\operatorname{argmin}_{f} L[f] = \frac{p(x \mid \theta_0)}{p(x \mid \theta_1)} = \mathcal{L}(x)$$

$$\frac{f(x)}{1-f(x)} = \frac{\frac{p(x|\theta_0)}{p(x|\theta_0)+p(x|\theta_1)}}{1-\frac{p(x|\theta_0)}{p(x|\theta_0)+p(x|\theta_1)}}$$
$$= \frac{p(x \mid \theta_0)}{\frac{p(x \mid \theta_0)}{p(x \mid \theta_0)} + p(x \mid \theta_1) - p(x \mid \theta_0)}$$
$$= \frac{p(x \mid \theta_0)}{p(x \mid \theta_1)} = \mathcal{L}(x)$$

### **OmniFold** "Likelihood-ratio trick"

Admits multiple advantages:

- Naturally unbinned & high dimensional
- Variable length, unordered sets  $\rightarrow$  full phase space unfolding
- Converges to maximum likelihood estimate of the truth distribution
- Computationally efficient (by reweighting i.e. learning small correction)
- Beyond per-event observables, readily reinterpretable



Progress towards experimental studies of a new class of JSS observables **Energy Correlators** 

 First measurement of track functions to come shortly from ATLAS! Stay Tuned!

 We have shown that Omnifold can be sensitive to higher order QCD effects. Bright future for precision measurements!



