

# Redefining Performance: New Techniques for ATLAS Jet & MET Calibration

SUSY23 Conference, Southampton

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*On behalf of the ATLAS Collaboration*

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July 17, 2023

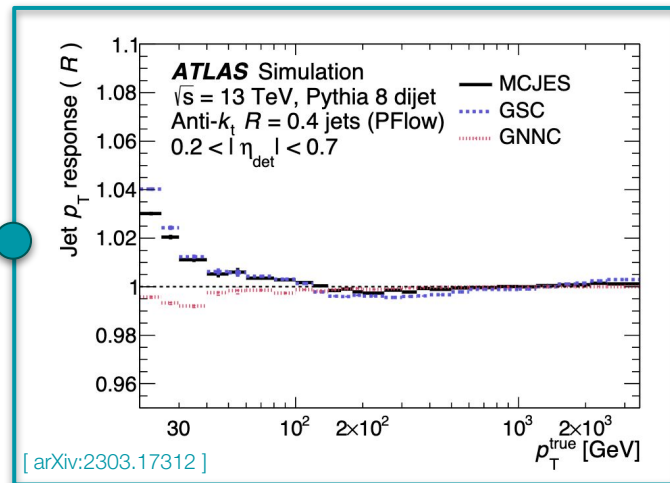
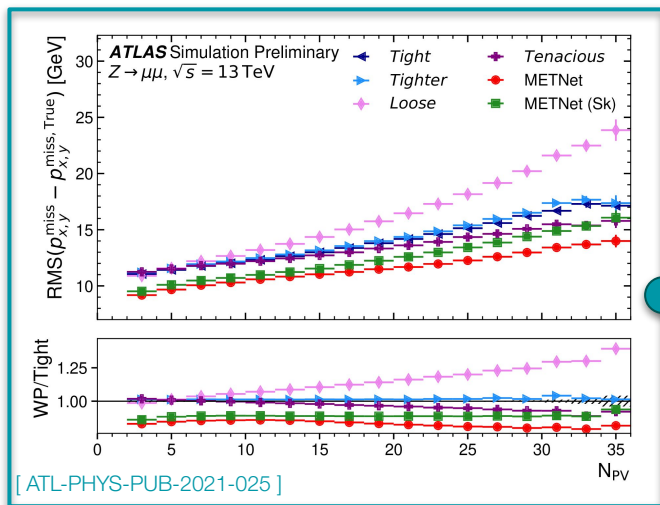


**MAX-PLANCK-INSTITUT**  
FÜR PHYSIK

# Outline

## New Techniques for Jet Calibration

- Simulation-based calibration via ML



## METNet: ML-based $p_T^{\text{miss}}$ Reconstruction

- Regression of  $p_T^{\text{miss}}$  via DNN



# Jet Reconstruction at ATLAS in Run 2

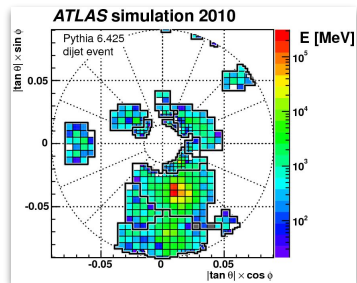
Main objective: cluster **tracks** and **calorimeter deposits** together to obtain properties of initial quark/gluon

Step 1: Create low-level cluster objects (constituents)

## Topological Clusters

[ [arXiv:1603.02934v3](https://arxiv.org/abs/1603.02934v3) ]

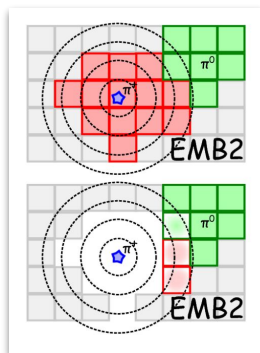
Connected groups of  
calorimeter cells



## Particle-Flow Objects (PFOs)

[ [arXiv:1703.10485v2](https://arxiv.org/abs/1703.10485v2) ]

Combine tracks and topo-clusters

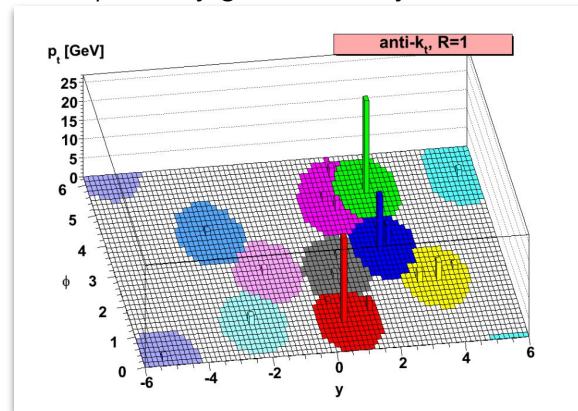


Step 2: Group clusters/PFOs into jets

## Anti- $k_T$ Algorithm

[ [arXiv:0802.1189v2](https://arxiv.org/abs/0802.1189v2) ]

Sequentially gather nearby constituents

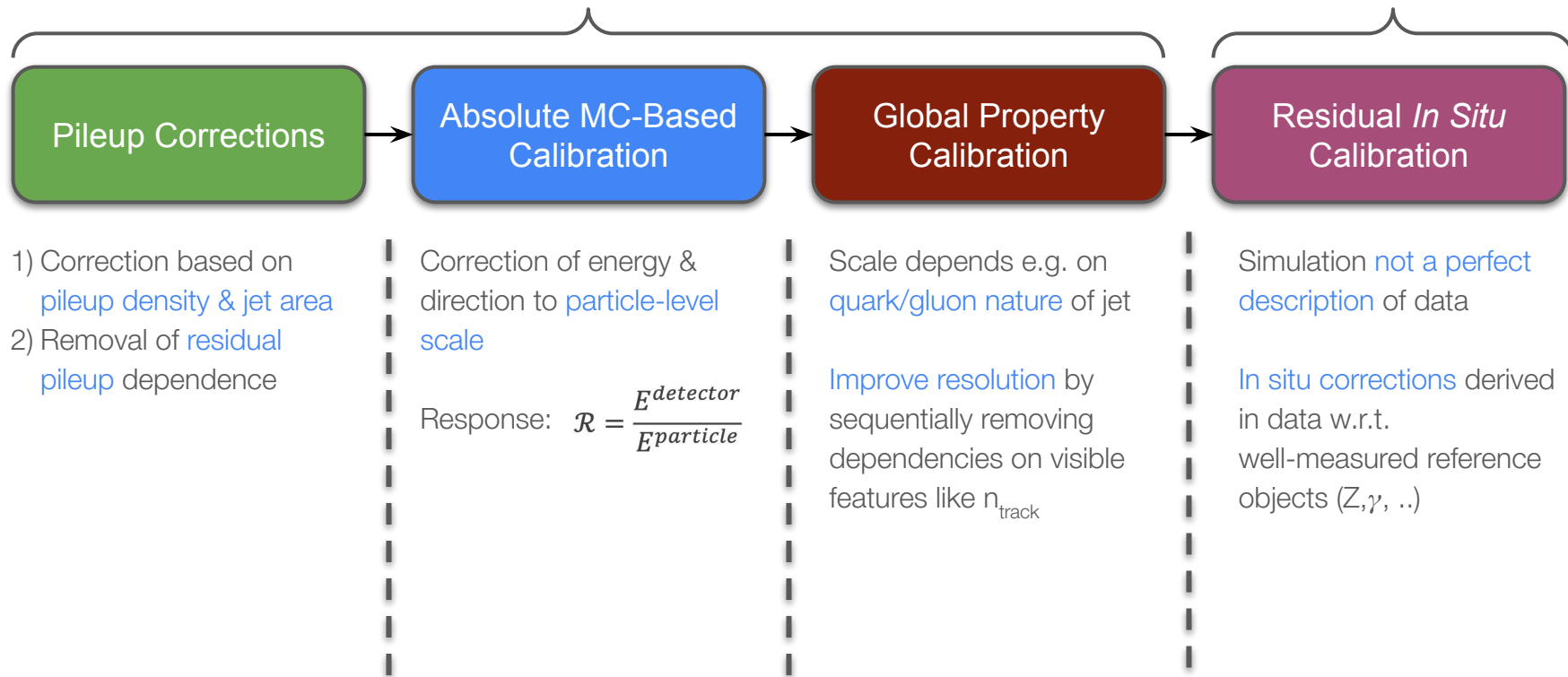


Here: focus on **small-radius jets with R=0.4**

# ATLAS Run 2 Jet Calibration Sequence

*Calibrate Jets in Simulation & Data to Particle Level*

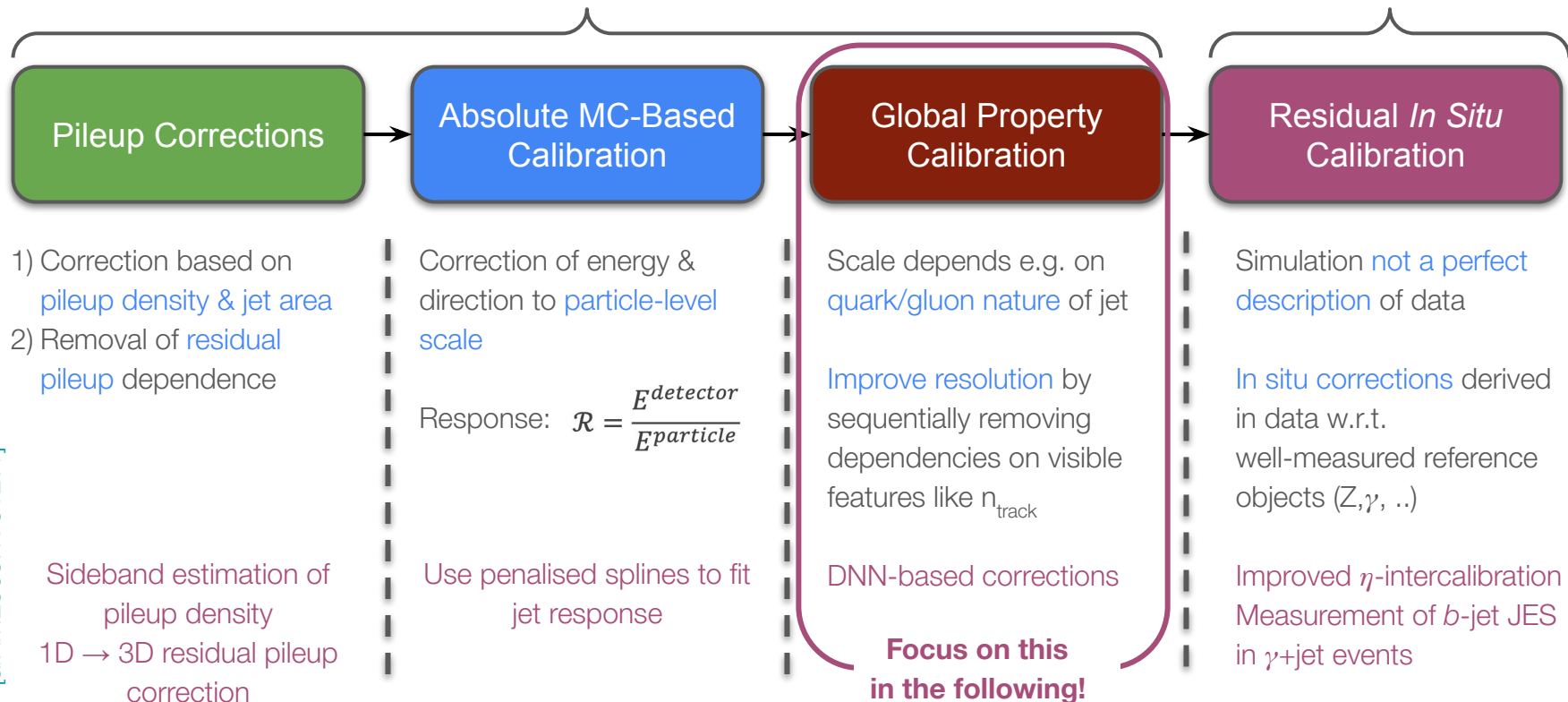
*Correct for Data/MC Discrepancies*



# ATLAS Run 2 Jet Calibration Sequence - Revised

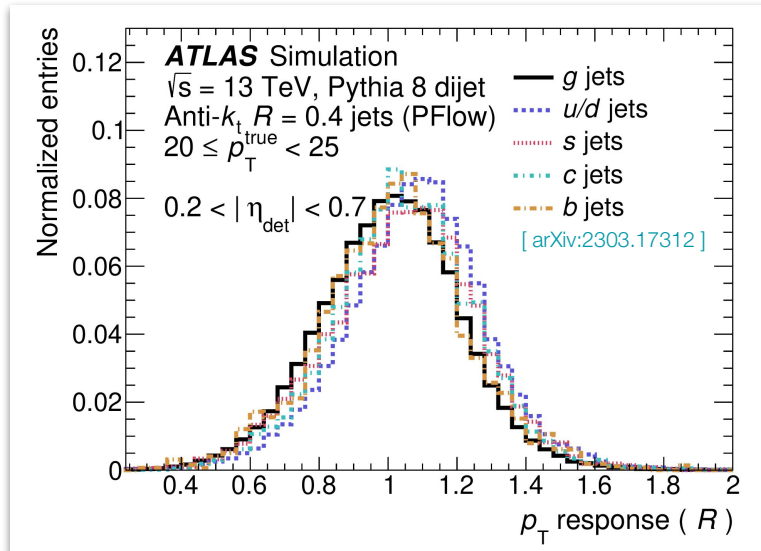
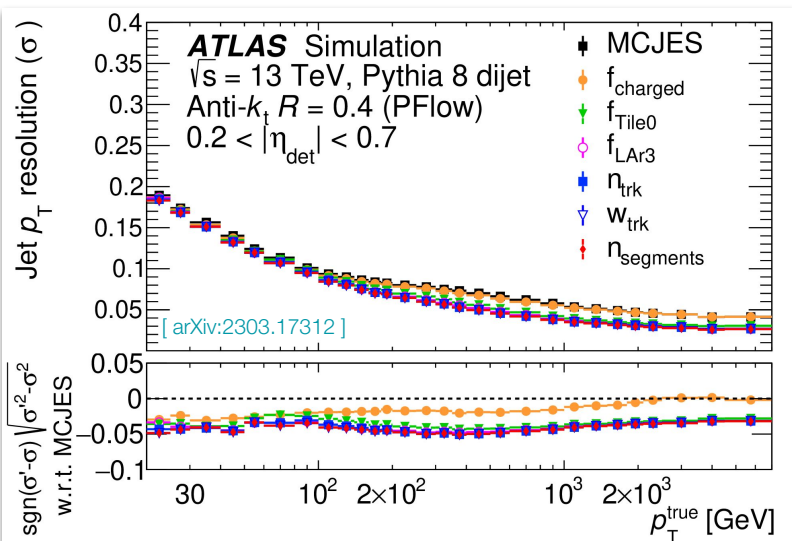
Calibrate Jets in Simulation & Data to Particle Level

Correct for Data/MC Discrepancies



# Global Jet Property Calibration

- After absolute calibration, response still **depends on characteristics of jet** (width, charged fraction, ...)
- Degrades jet energy resolution (JES)
- Mitigated by **Global Sequence Calibration (GSC)**  
→ **Series of 6 corrections** applied one after another



- Subsequent **improvement of resolution** after each step!
- Reduces also differences in MC predictions
- Limitation of GSC: variables need to be **uncorrelated**

**Simultaneous calibration** in many “dimensions” desirable  
 → **Perfect use case for Deep Neural Networks (DNNs)!**

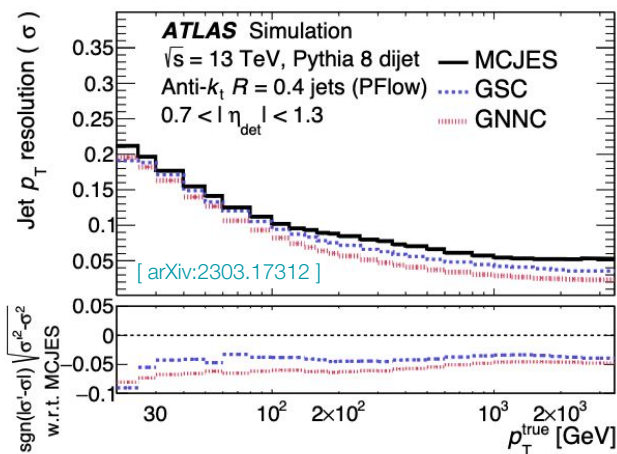
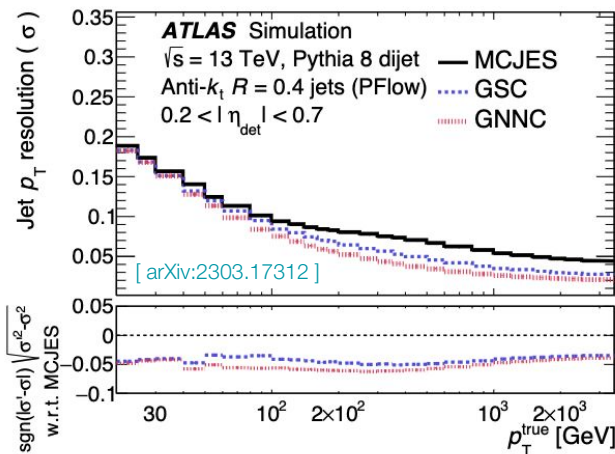
# Global Neural Network Calibration (GNNC)

- Dedicated DNN trained in each  $\eta$ -bin to accommodate detector geometry
- DNNs designed to **correct the  $p_T$  response** by minimizing a leaky Gaussian Kernel loss:

$$\text{Loss}(x^{\text{target}}, x^{\text{pred}}) = -\frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(x^{\text{target}} - x^{\text{pred}})^2}{2\alpha^2}\right) + \beta |x^{\text{target}} - x^{\text{pred}}|,$$

$\uparrow$   
 $p_T$  Response
 $\nwarrow$  Tunable Parameters

- Use **more variables than in GSC** to fully exploit potential of DNNs:  
More granular **calorimeter information, jet kinematics & pile-up** measures



Up to **30% improvement** on JES!

Smaller differences in response  
 between gluon and quark jets  
 → reduced **reduced flavour**  
**uncertainty** as well (backup)



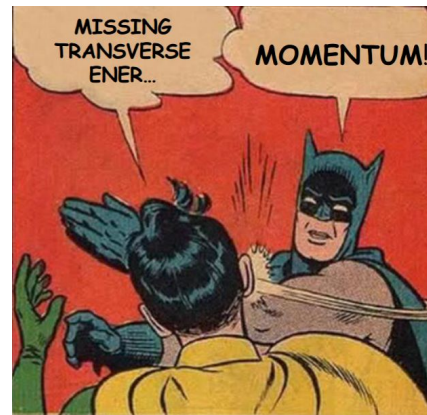
# Reminder: $p_T^{\text{miss}}$ Reconstruction

- Infer presence of “invisible” particles via momentum imbalance in transverse plane
- Basic reconstruction algorithm is taking negative vector sum:

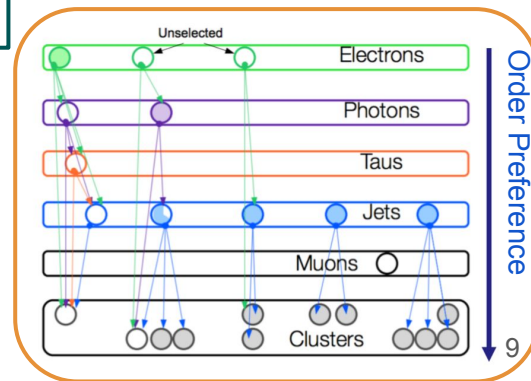
$$\vec{p}_T^{\text{miss}} = - \underbrace{\sum_{\text{selected electrons}} \vec{p}_T^e - \sum_{\text{accepted photons}} \vec{p}_T^\gamma - \sum_{\text{accepted } \tau\text{-leptons}} \vec{p}_T^{\tau\text{had}} - \sum_{\text{selected muons}} \vec{p}_T^\mu - \sum_{\text{accepted jets}} \vec{p}_T^{\text{jet}}}_{\text{hard term}} - \underbrace{\sum_{\text{unused tracks}} \vec{p}_T^{\text{track}}}_{\text{soft term}}$$

(+ internal overlap removal)

Object selection specified by Analysis (blue arrows)  
Specified by  $p_T^{\text{miss}}$  WP (red arrow)

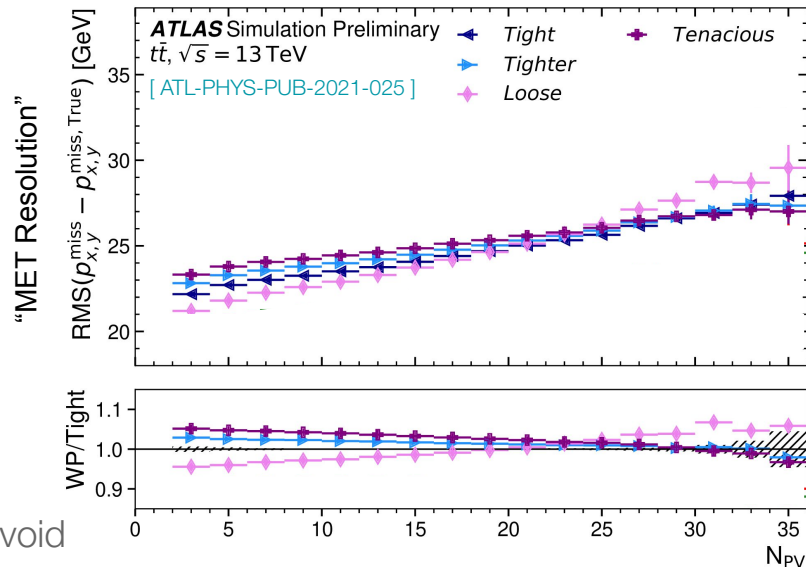


- Several  $p_T^{\text{miss}}$  WPs available (Tight, Loose, ...) balancing resolution and pile-up resilience
- **Track soft term (TST)** contains tracks associated with hard-scatter vertex but not with any hard object
- Estimate for “ $p_T^{\text{miss}}$  significance” via likelihood-based technique



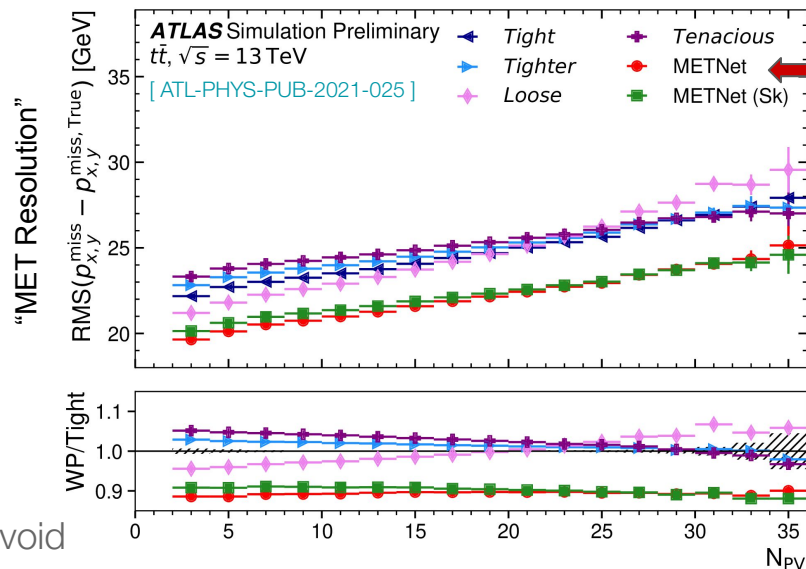
# METNet: ML-based $p_T^{\text{miss}}$ Reconstruction

- General idea: performance of  $p_T^{\text{miss}}$  WPs depend on **event topology** and **level of pile-up**
  - Let a **DNN choose optimal WP** for each event!
- **Regression-based “METNet”** trained on 60 inputs
  - Predictions of jet/soft terms of each  $p_T^{\text{miss}}$  WP
  - Lepton  $p_T^{\text{miss}}$  terms
  - Event-level pile-up quantities
- Training target:  $(p_x^{\text{miss}}, p_y^{\text{miss}})$  at particle level
- Considered two different loss functions:
  - **Huber loss** & **Huber + Sinkhorn loss**
- Network **trained on top-antitop events**, evaluated on other topologies to validate generalization
- Training sample “flattened” up to  $p_T^{\text{miss}} = 300$  GeV to avoid bias towards 0 in predictions



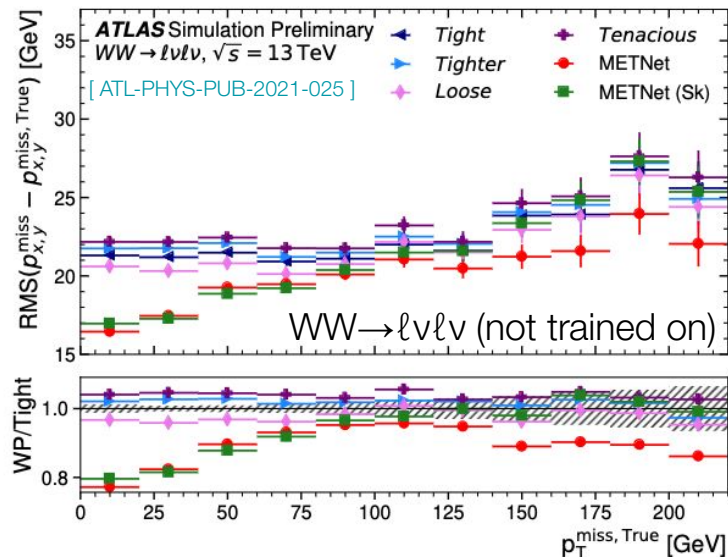
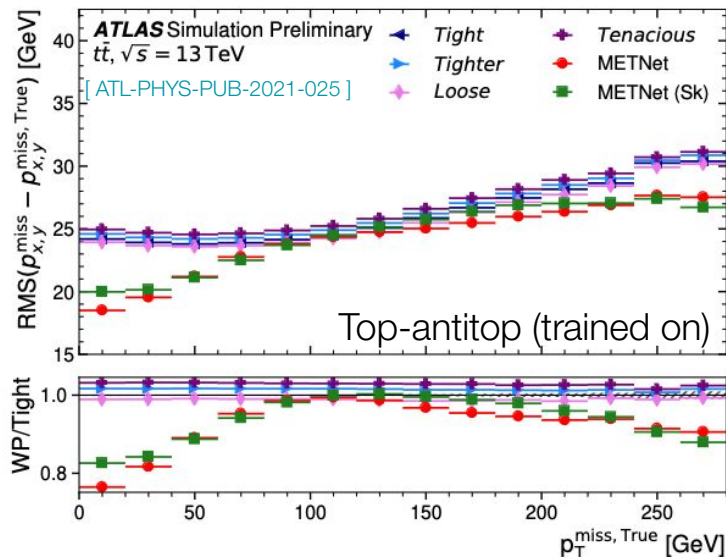
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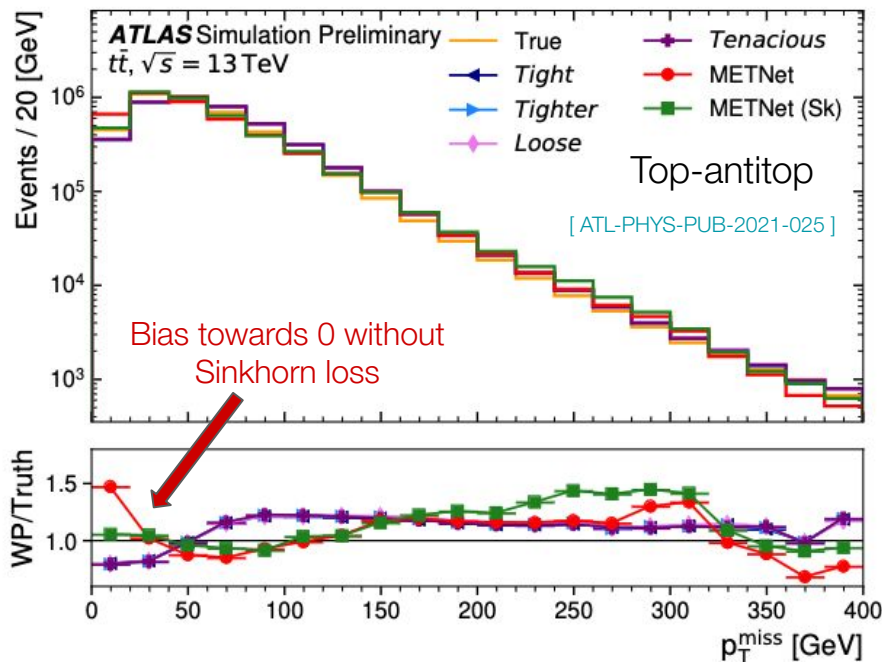
Substantial improvements in resolution by METNet!

# METNet: Generalization



- METNet has superior resolution across the  $p_T^{\text{miss}}$  range trained on
- Generalizes well to topologies not seen during training, such as  $Z \rightarrow \mu\mu$  and  $WW \rightarrow \ell \nu \ell \nu$

# METNet: Training Bias & Limitations



“Training bias”: more events with low than with high  $p_T^{\text{miss}} \rightarrow$  Challenging to tackle!

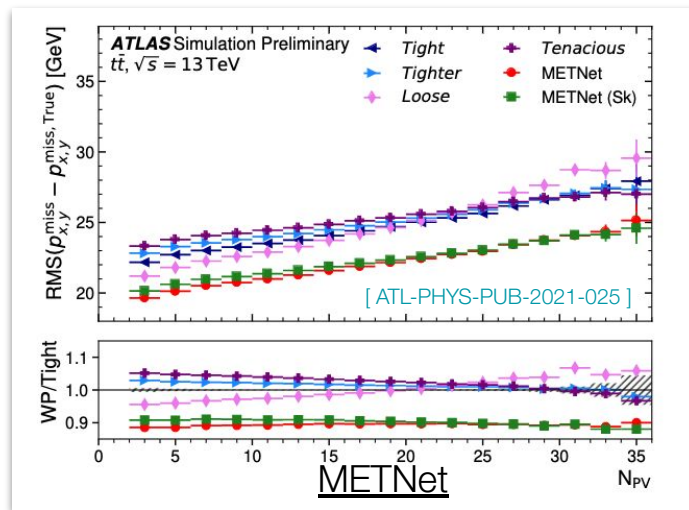
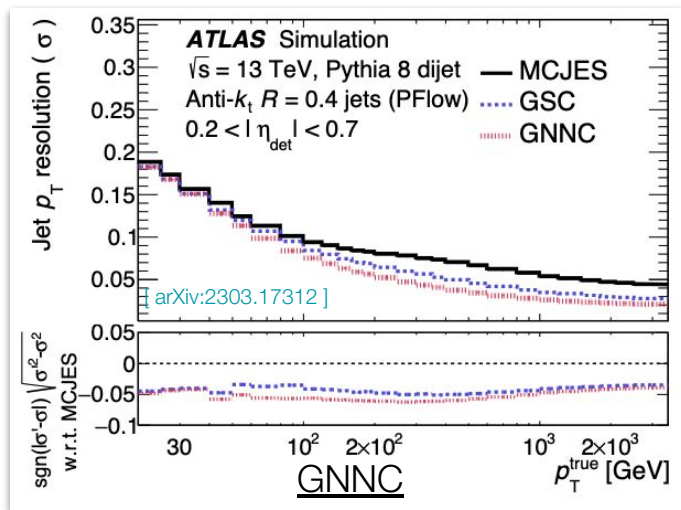
Limited performance of METNet **outside training range** (“extrapolation”)

**Classification-based METNet** approach under study

$\rightarrow$  Build weighted average of “classical”  $p_T^{\text{miss}}$  WPs

# Summary & Outlook

- Jets and missing transverse momentum essential part of nearly all ATLAS measurements & searches
- Improvements in these areas directly translate into better physics results
- Established reconstruction and calibration techniques already provide percentage-level precision
- Many ongoing efforts for further improvements to be applied in Run 3!  
→ Promising applications of ML-based techniques in jet calibration and  $p_T^{\text{miss}}$  reconstruction



Extras



# ATLAS Detector

Goal: Reconstruct products from  $pp$ -collisions: electrons, muons, jets, ..

## Inner Detector

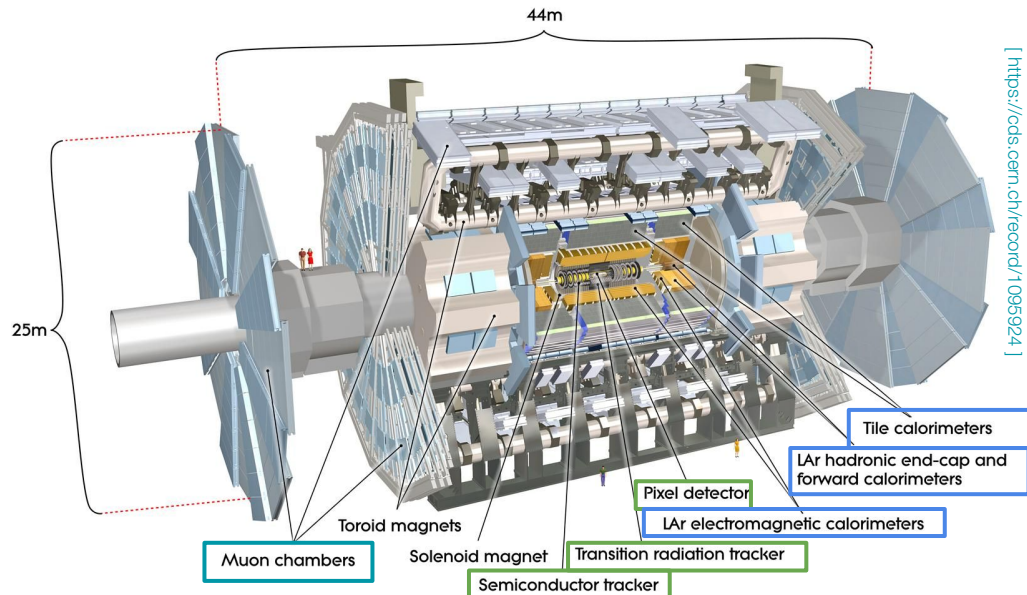
- Semiconductor & gas detectors
- Tracks and vertex reconstruction

## Calorimeters

- LAr as active material
- Contain electromagnetic and hadronic showers
- Rebuild electrons, photons & jets

## Muon Spectrometer

- Cover large area with gas detectors
- Reconstruction of muons



- Collisions occur at ~30 Mhz
- Up to ~65 simultaneous  $pp$ -interactions in Run 2



# Global Neural Network Calibration Inputs

Calorimeter	$f_{\text{LAr0-3}}^*$ $f_{\text{Tile0-2}}$ $f_{\text{HEC,0-3}}$  $f_{\text{FCAL,0-2}}$ $N_{90\%}$	<p>The <math>E_{\text{frac}}</math> measured in the 0th-3rd layer of the EM LAr calorimeter</p> <p>The <math>E_{\text{frac}}</math> measured in the 0th-2nd layer of the hadronic tile calorimeter</p> <p>The <math>E_{\text{frac}}</math> measured in the 0th-3rd layer of the hadronic end cap calorimeter</p> <p>The <math>E_{\text{frac}}</math> measured in the 0th-2nd layer of the forward calorimeter</p> <p>The minimum number of clusters containing 90% of the jet energy</p>
Jet kinematics	$p_{\text{T}}^{\text{JES}}^*$ $\eta_{\text{det}}$	<p>The jet <math>p_{\text{T}}</math> after the MCJES calibration</p> <p>The detector <math>\eta</math></p>
Tracking	$w_{\text{track}}^*$  $N_{\text{track}}^*$ $f_{\text{charged}}^*$	<p>The average <math>p_{\text{T}}</math>-weighted transverse distance in the <math>\eta</math>-<math>\phi</math> plane between the jet axis and all tracks of <math>p_{\text{T}} &gt; 1</math> GeV ghost-associated with the jet</p> <p>The number of tracks with <math>p_{\text{T}} &gt; 1</math> GeV ghost-associated with the jet</p> <p>The fraction of the jet <math>p_{\text{T}}</math> measured from ghost-associated tracks</p>
Muon segments	$N_{\text{segments}}^*$	The number of muon track segments ghost-associated with the jet
Pile-up	$\mu$ $N_{\text{PV}}$	<p>The average number of interactions per bunch crossing</p> <p>The number of reconstructed primary vertices <a href="#">[ arXiv:2303.17312 ]</a></p>

# GNNC - Flavor Uncertainties

$$\sigma_{\text{response}} = f_g (\mathcal{R}_{g,\text{PYTHIA8}} - \mathcal{R}_{g,\text{HERWIG}})$$

$$\sigma_{\text{composition}} = \sigma_g^f \frac{\mathcal{R}_q - \mathcal{R}_g}{f_g \mathcal{R}_g + (1 - f_g) \mathcal{R}_q}$$

