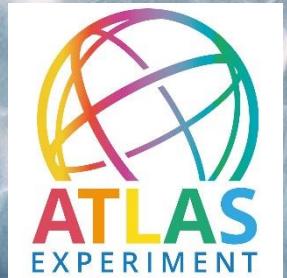




Jets & p_T^{miss} at **ATLAS**

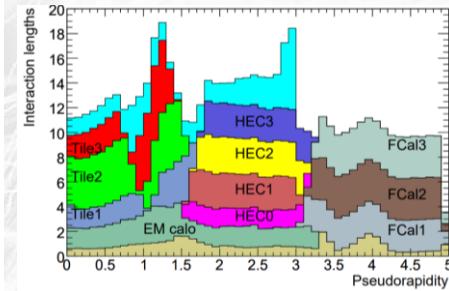
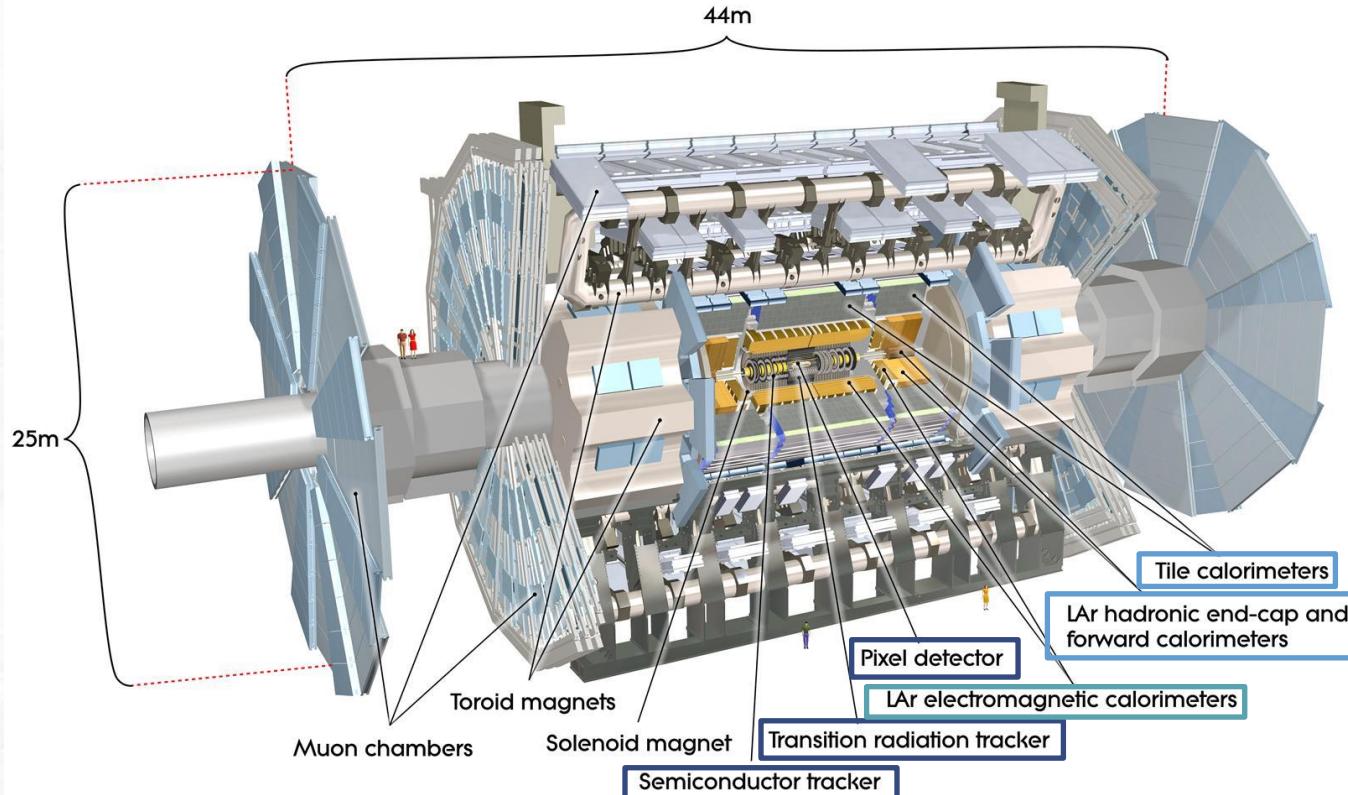
16/05/23
Holly Pacey
obo ATLAS Collaboration

CMS JetMET Workshop



ATLAS Refresher

A Toroid, Lousy Acronym & Solenoid



Each calo. Readout defines a **cell(Energy,location)**

Each shower deposits energy in many cells.

Inner Detector

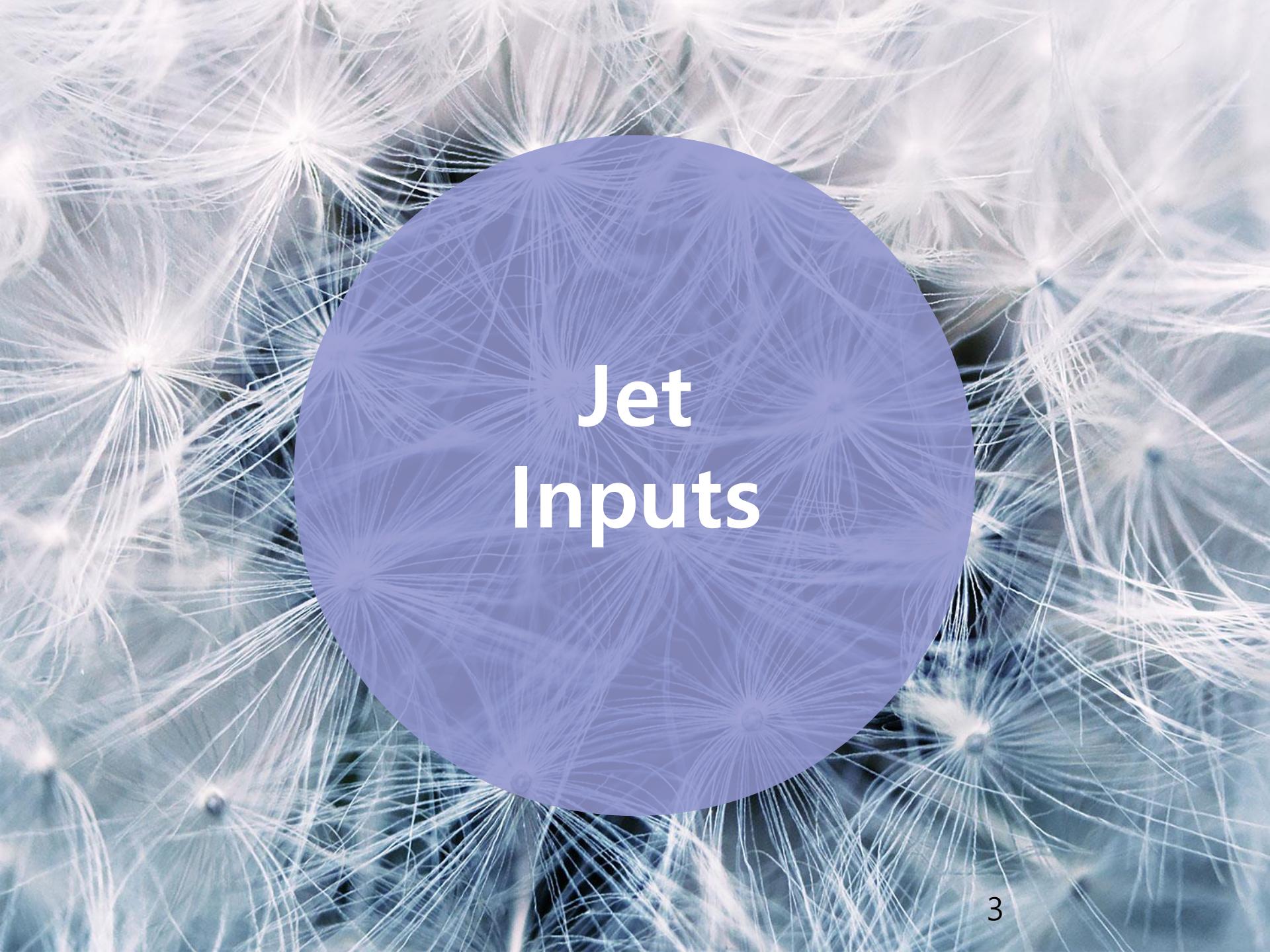
- Charged particle tracks
- Decay vertices e.g. Hard-Scatter vertex "PV"
- $|\eta| < 2.5$

EM Calorimeter

- EM Showers
- e/γ Energy & direction
- $|\eta| < 4.9$
- $\Delta\eta \times \Delta\phi = 0.025 * \pi/128$

Hadronic Calorimeter

- HAD showers
- Charged & neutral hadron Energy & direction
- $|\eta| < 4.9$

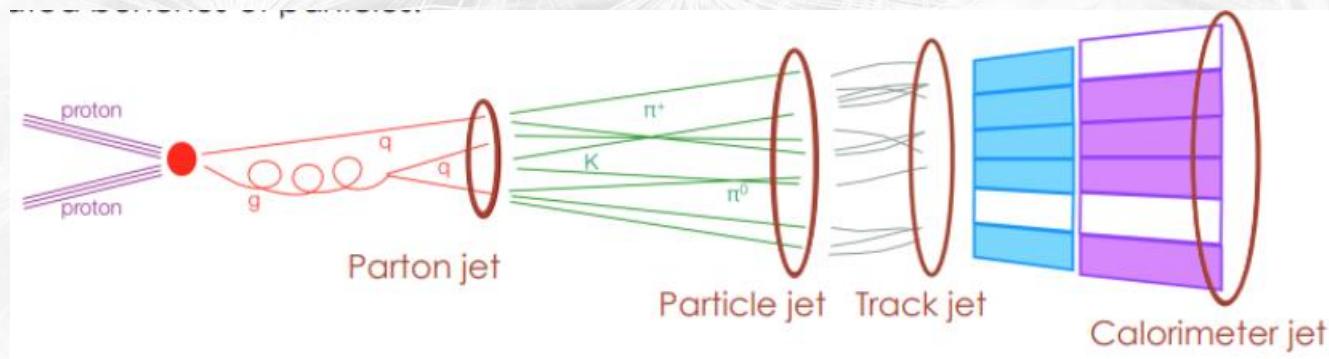


Jet Inputs

Jet Introduction

Calorimeter hits are the basis of ATLAS jet reconstruction

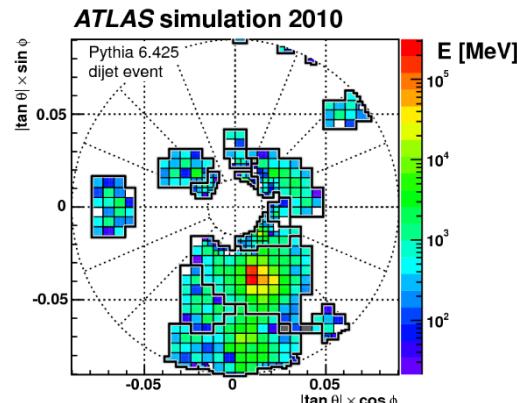
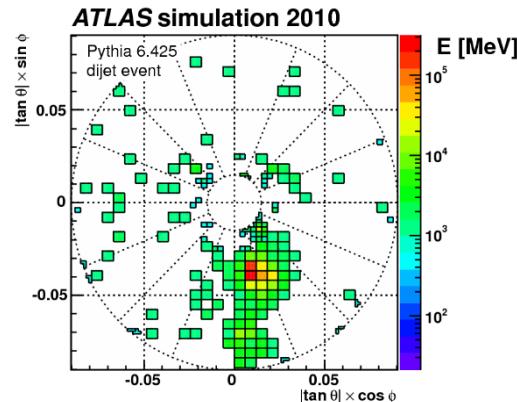
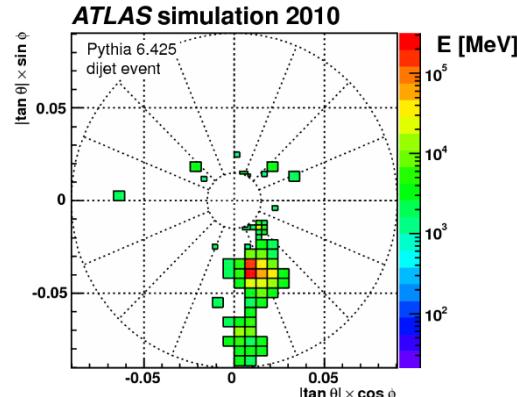
- Anti-Kt algorithm: $R=0.4$ (default “small-R”), or $R=1.0$ (“large-R”)
- Since ~2020 default Particle Flow algorithm, using both Calorimeter + Track inputs.
- Now improving PFlow reconstruction for Jet Substructure (UFOs)
- More ideas to improve calibration/tagging/... with ML

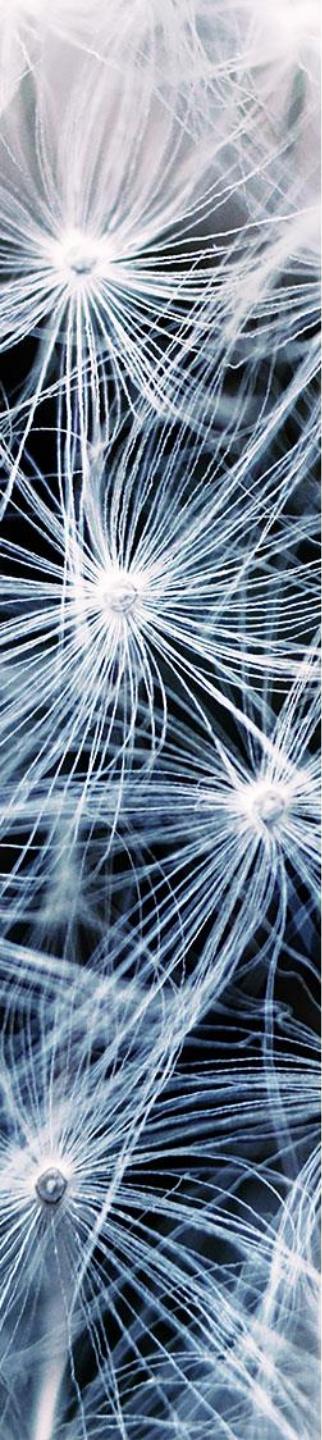


Jet Constituents

Topo-Clusters: most common jet inputs

- 3D clusters of noise-suppressed Calo. Cells
- How?
 - Define **significance** for cell: $\zeta_{cell}^{EM} = \frac{E_{cell}^{EM}}{\sigma_{noise,cell}^{EM}}$
 - Pick cells with high $\zeta_{cell}^{EM} > 4$
 - Add neighbouring cells with $\zeta_{cell}^{EM} > 2$
 - Add neighbouring cells
 - Final step breaks up large topoclusters with multiple local maxima.





Pileup Contamination

2 parts: Bias HS object energy, add PU jets to event!

PU removal at every level:

1. Whilst reconstructing jet constituents

- Noise suppression in Topoclusters
- Cut charged objects not from PV with PFlow

Pileup Contamination

2 parts: Bias HS object energy, add PU jets to event!

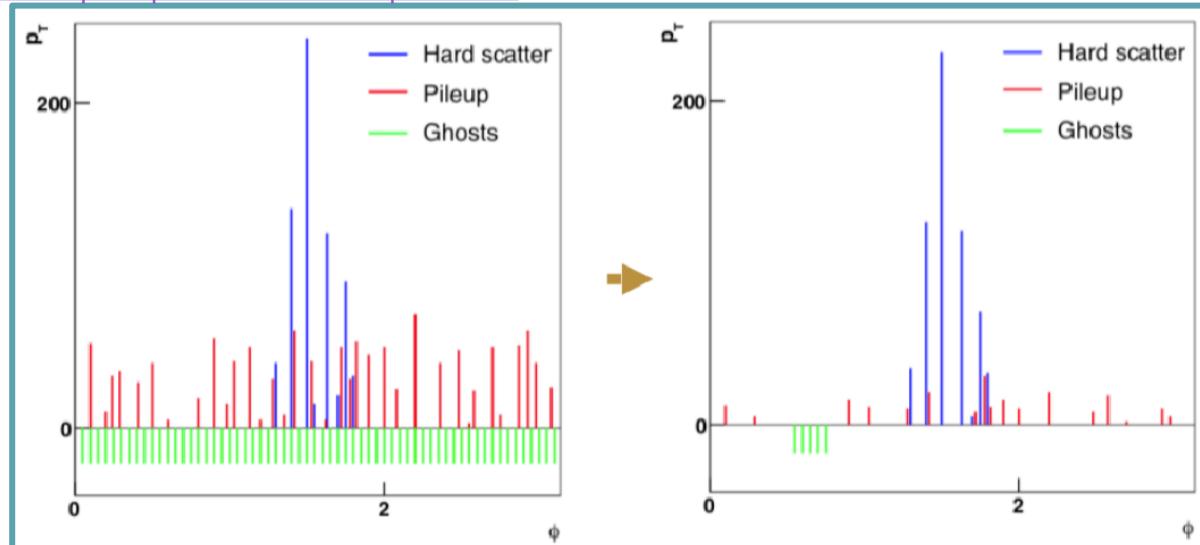
PU removal at every level:

2. On jet constituents

- PUPPI
- Voronoi Subtraction (Vor)
- **Constituent Subtraction** (CS)

[Constituent level pileup mitigation CONF 2017](#)
[Particle-level pileup subtraction Paper 2014](#)

- Constituent area subtraction
- Add 'ghosts' to event with $p_T^g = A_g \times \rho$
 - ρ Median E-density
 - A_g ghost area fixed to $\Delta\eta \times \Delta\phi = 0.1 \times 0.1$
- Subtract ghost contributions from closest constituent
 - Until $\Delta R(g, constituent) > \Delta R_{max}$
 - & never let $p_T < 0$



Pileup Contamination

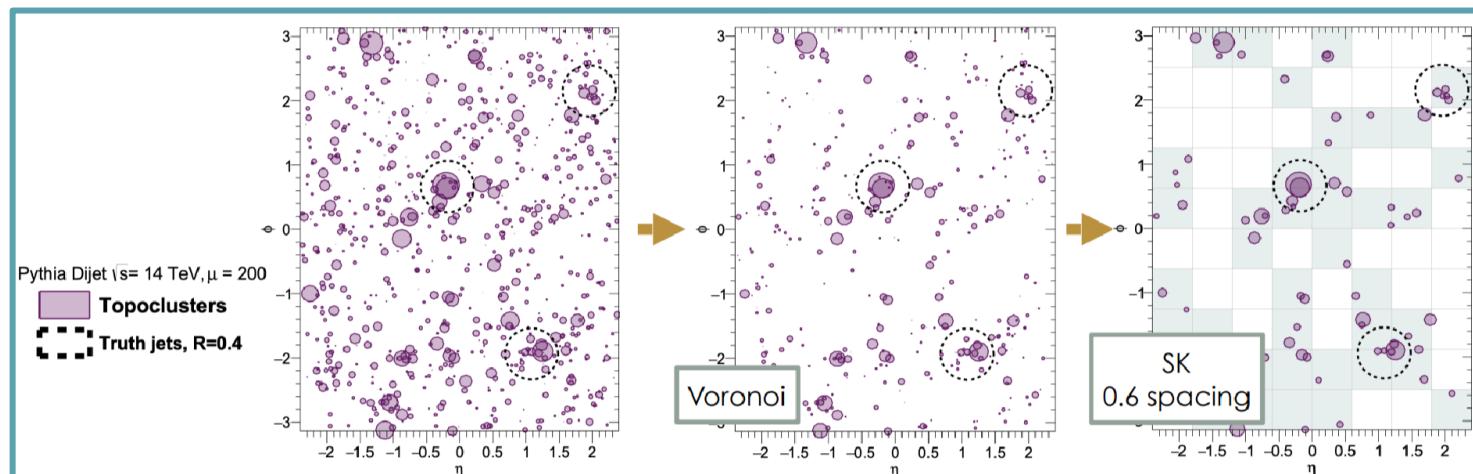
2 parts: Bias HS object energy, add PU jets to event!

PU removal at every level:

2. On jet constituents

- PUPPI
- Voronoi Subtraction (Vor)
- Constituent Subtraction (CS)
- **SoftKiller** (SK)

- Remove soft p_T constituents
- Define “soft” per-event:
 - Put constituents in $\eta - \phi$ grid
 - Require half of entries to be cut.



[Constituent level pileup mitigation CONF 2017](#)
[Particle-level pileup subtraction Paper 2014](#)

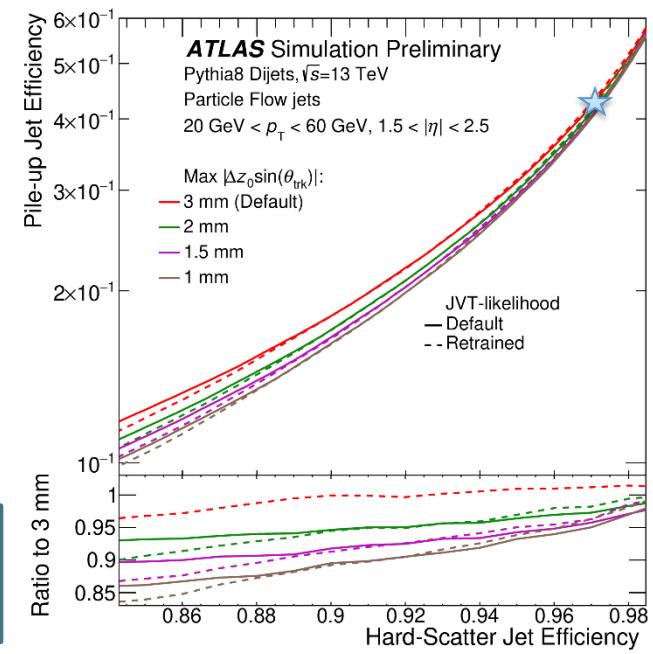
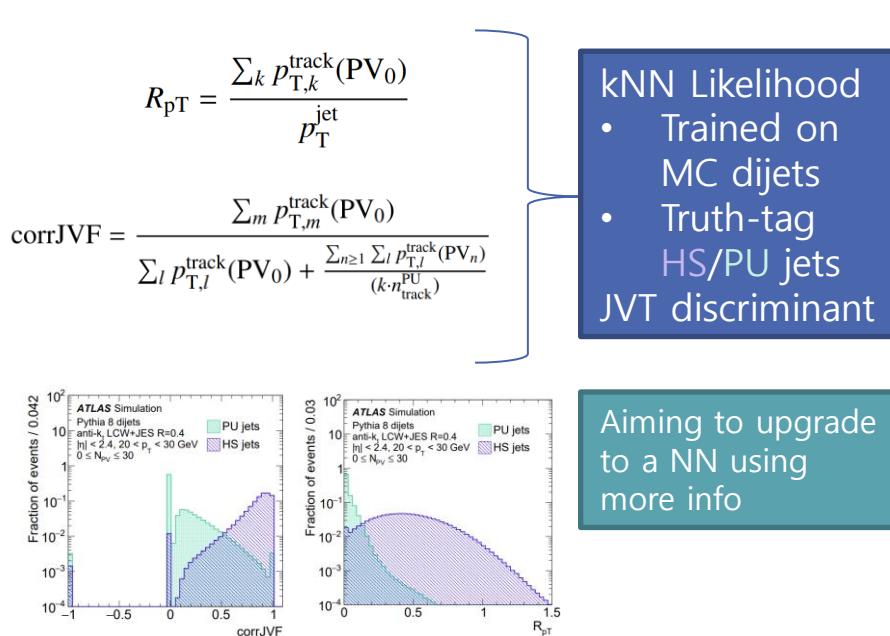
Pileup Contamination

2 parts: Bias HS object energy, add PU jets to event!

PU removal at every level:

3. On jets

- Jet Area subtraction
- Grooming (trimming, softDrop) (backup)
- Forward Jet Vertex Tagger (fJVT)
- **Jet Vertex Tagger (JVT)**

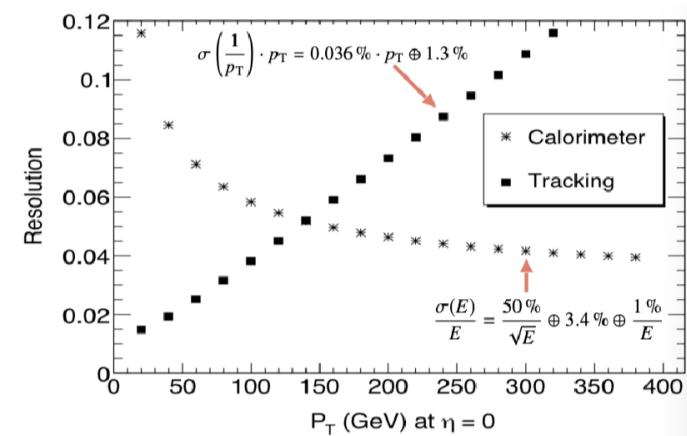


Combining with Tracks

Calorimeter & Tracker provide complementary info.

Metric	Calorimeter	Tracker
Neutral Particles	✓	✗
Charged Particles	✓	✓
PU rejection	✗	✓
Best low p_T resolution	✗	✓
Best high p_T resolution	✓	✗

- Leads to alternative jet algorithms:
 - Particle Flow (PFlow)
 - Track Calo-Clusters (TCC)
 - [Unified Flow Objects \(UFO\)](#)



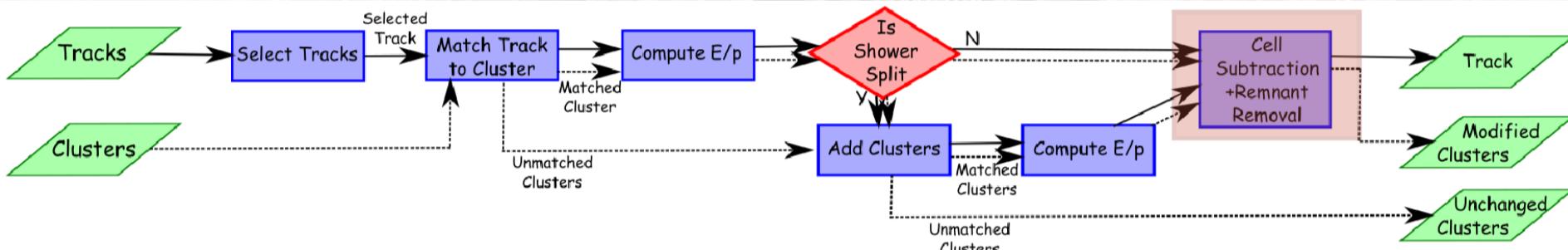
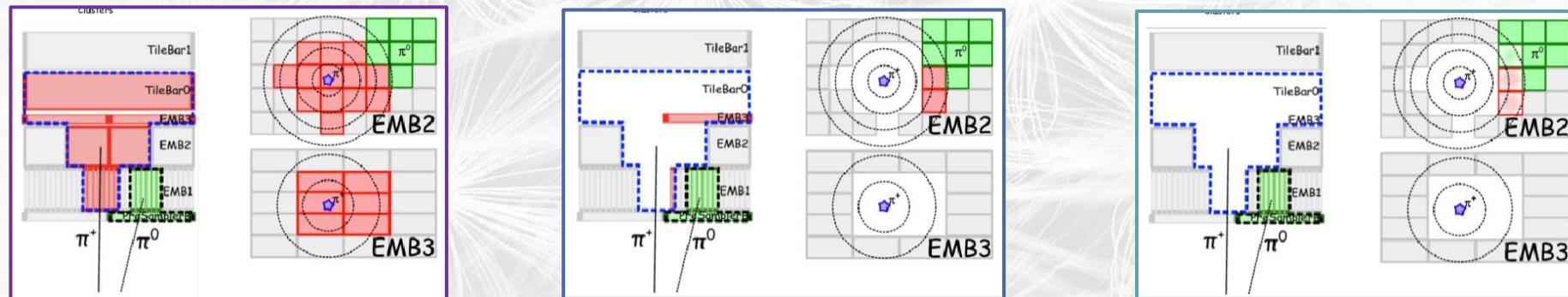
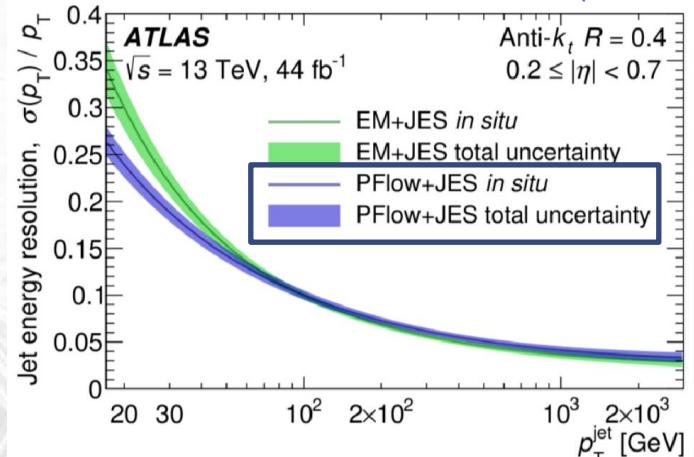


Jet Definitions

Particle Flow Jets

Combine Calo+Tracks w/o double counting

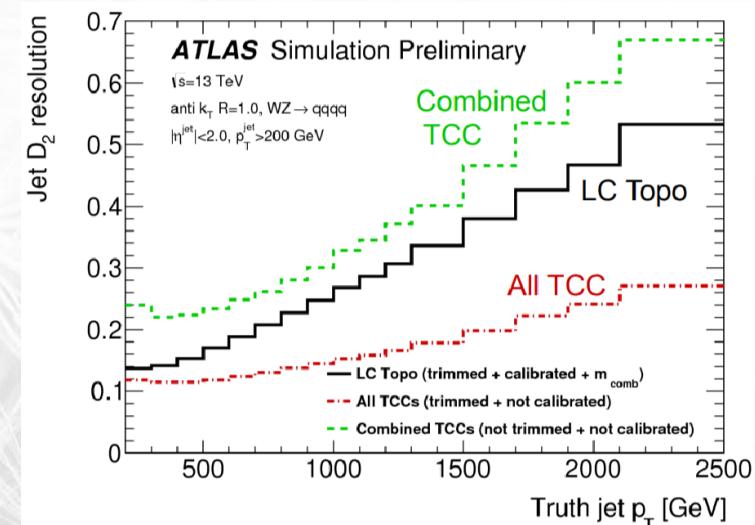
- Associate Tracks with ≥ 1 Topoclusters
- Subtract calo energy deposits matching a track.
- Remove PU tracks at the end using **Charged Hadron Subtraction (CHS)**
- Better performance/resolution at low p_T



Track Calo Clusters

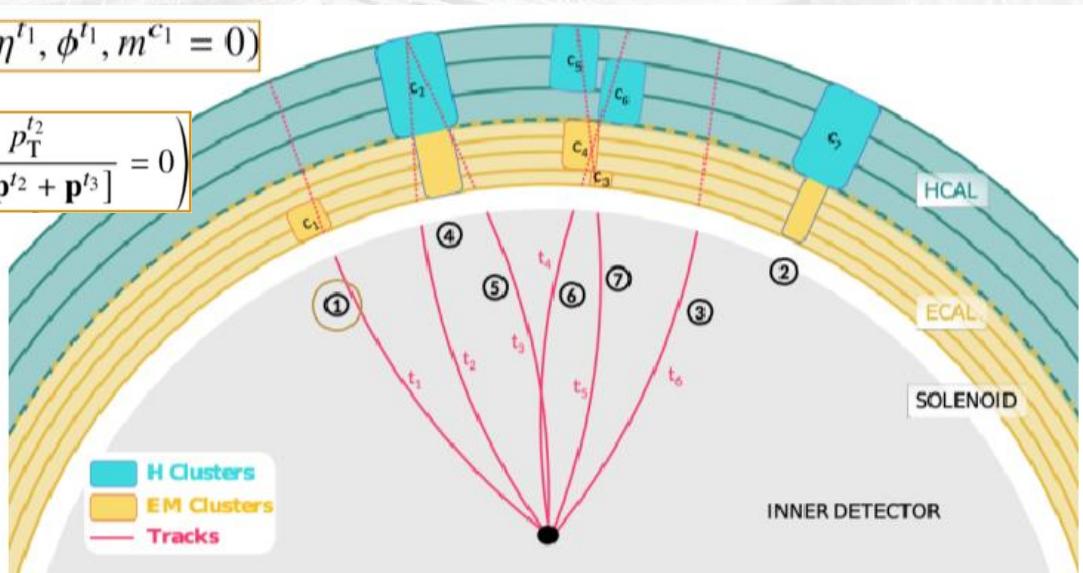
TCCs Improve angular resolution @ high p_T

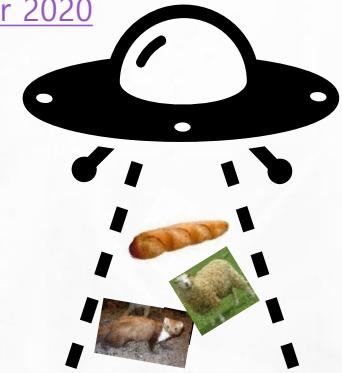
- Aim: better sub-jet definitions
- Reconstructing boosted t/W/Z/H decays
- How?
 - Match tracks to topoclusters
 - Build 4-vector from matched objects: tracker (η, ϕ) + calo (p_T, m)
 - Use track p_T to determine sharing fraction of calo energy



$$\text{TCC}_{\textcircled{1}} = (p_{\text{T}}^{c_1}, \eta^{t_1}, \phi^{t_1}, m^{c_1} = 0)$$

$$\text{TCC}_{\textcircled{4}} = \left(p_{\text{T}}^{c_2} \frac{p_{\text{T}}^{t_2}}{p_{\text{T}} [\mathbf{p}^{t_2} + \mathbf{p}^{t_3}]}, \eta^{t_2}, \phi^{t_2}, m^{c_2} \frac{p_{\text{T}}^{t_2}}{p_{\text{T}} [\mathbf{p}^{t_2} + \mathbf{p}^{t_3}]} = 0 \right)$$

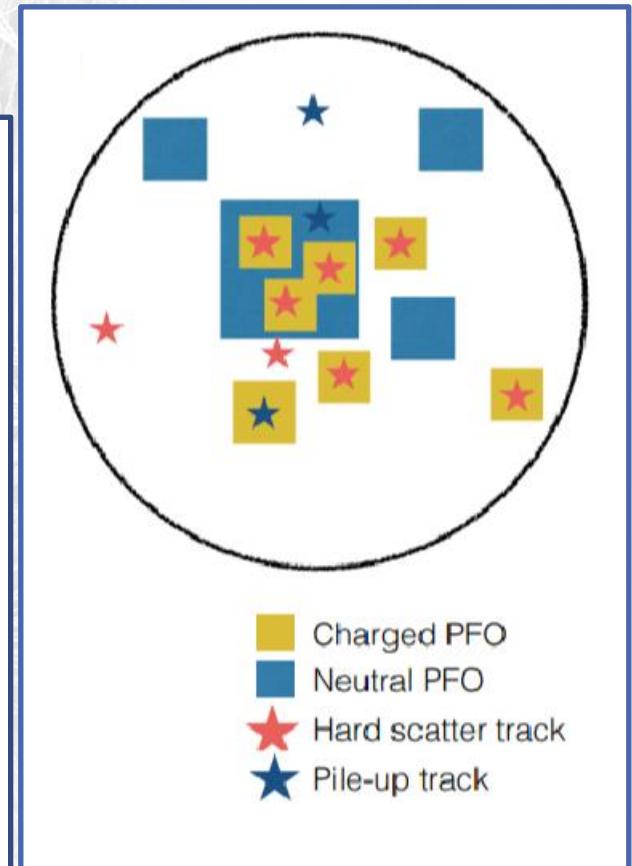
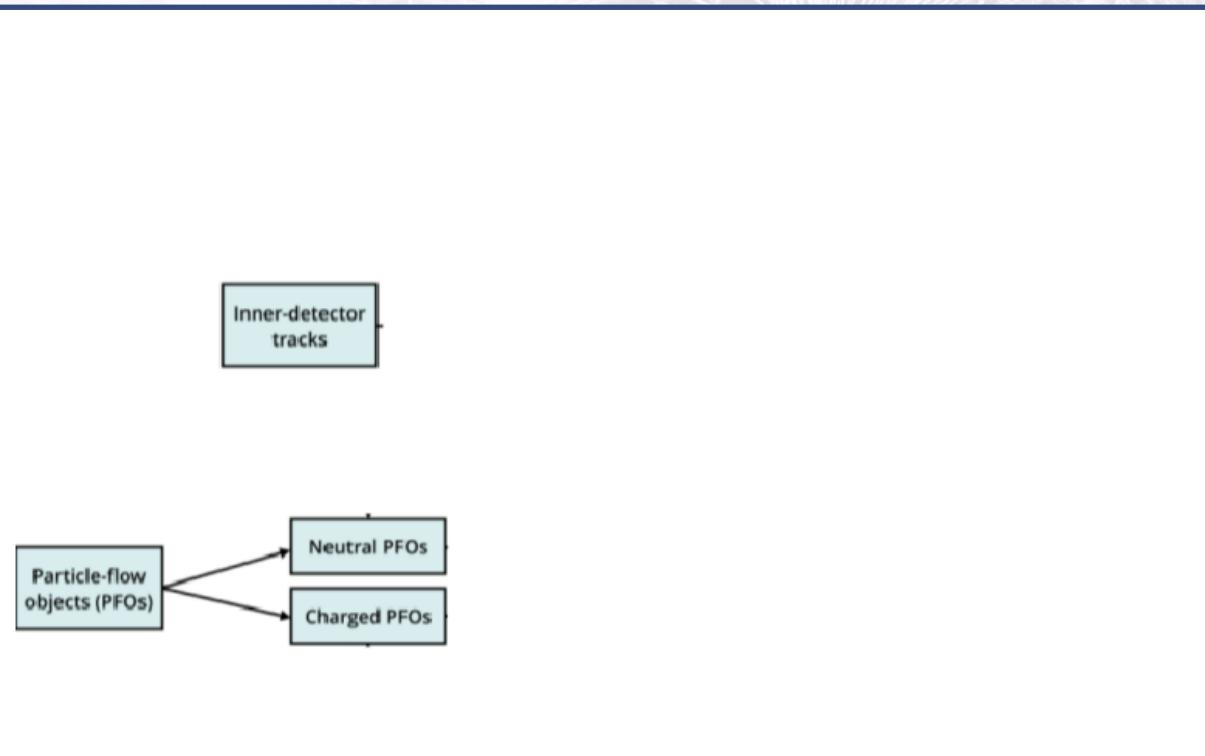


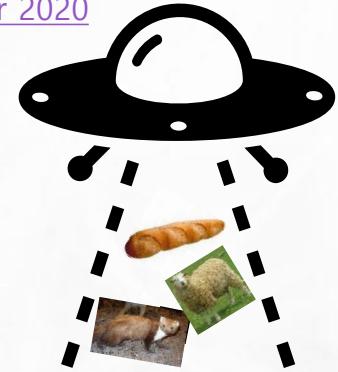


Unified Flow Objects

Combine the best of PFlow and TCC?

Start with Tracks, PFOs

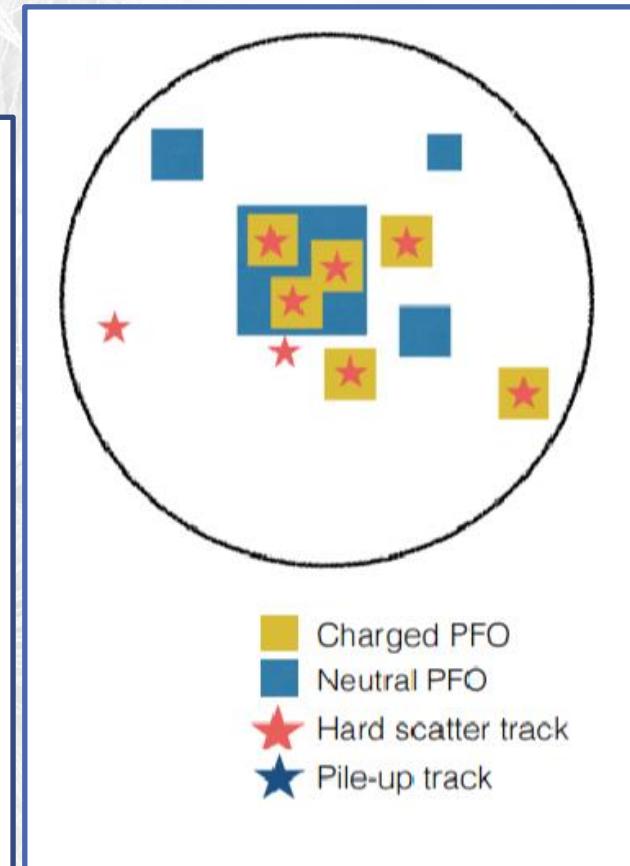
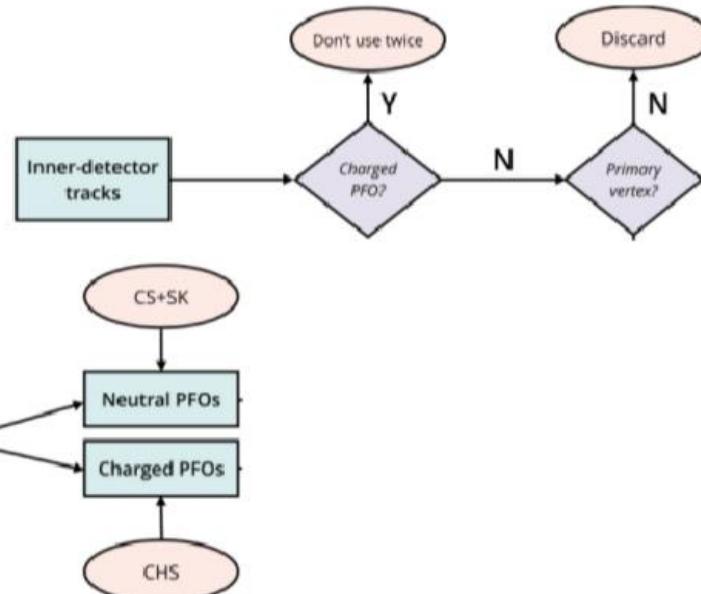


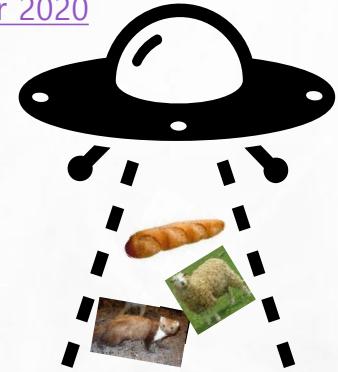


Unified Flow Objects

Combine the best of PFlow and TCC?

CHS applied, CS+SK
remove PU tracks (non-PV)

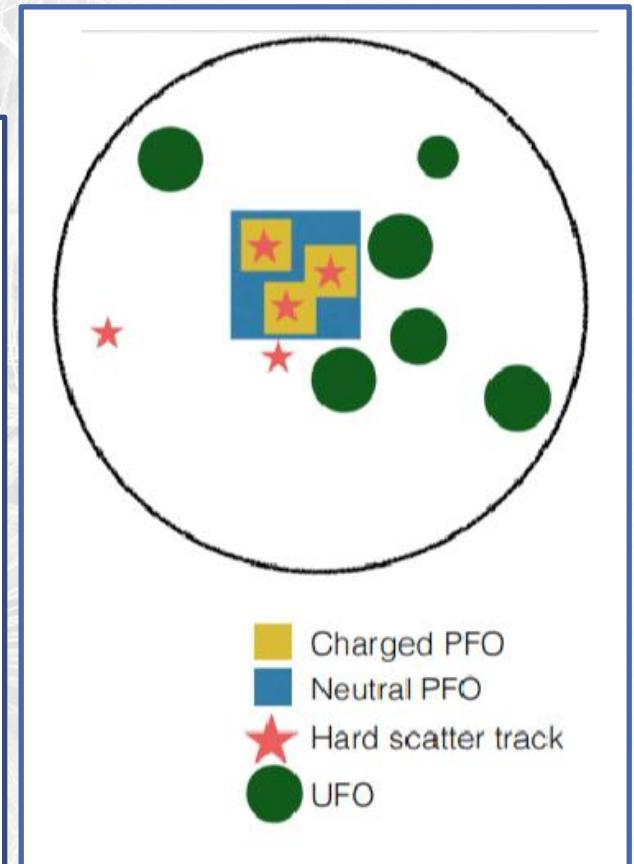
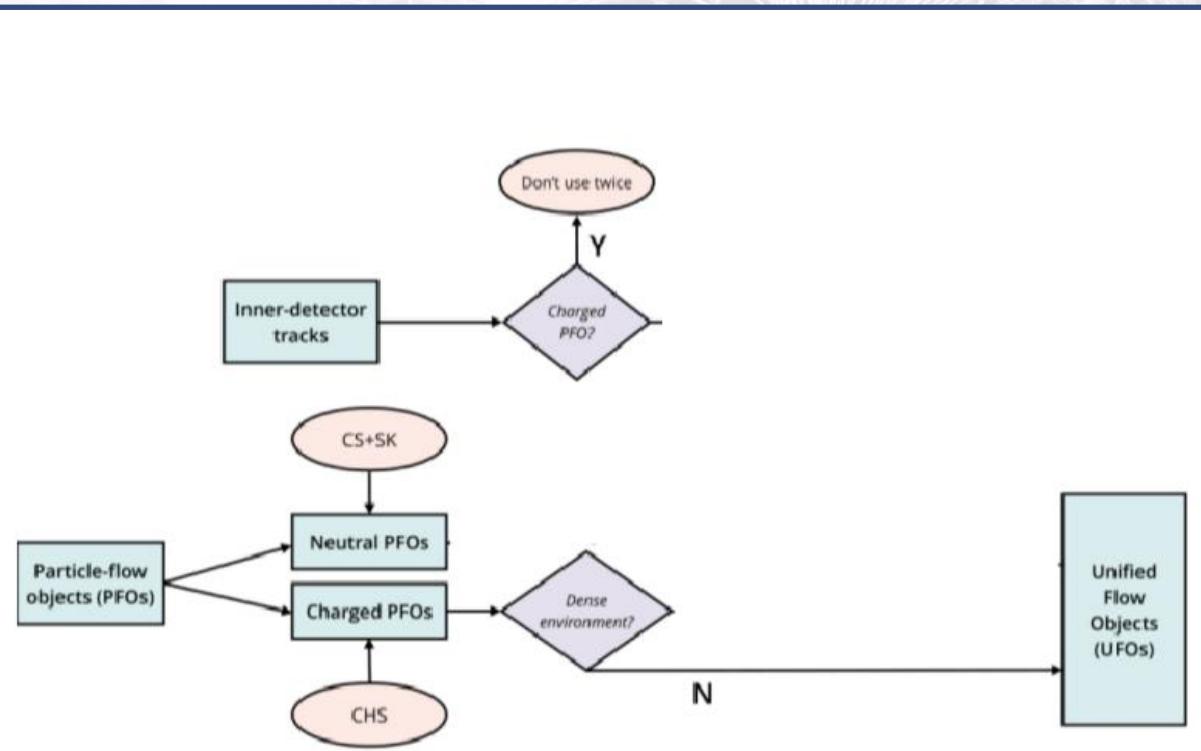




Unified Flow Objects

Combine the best of PFlow and TCC?

Charged PFOs in sparse regions become UFOs

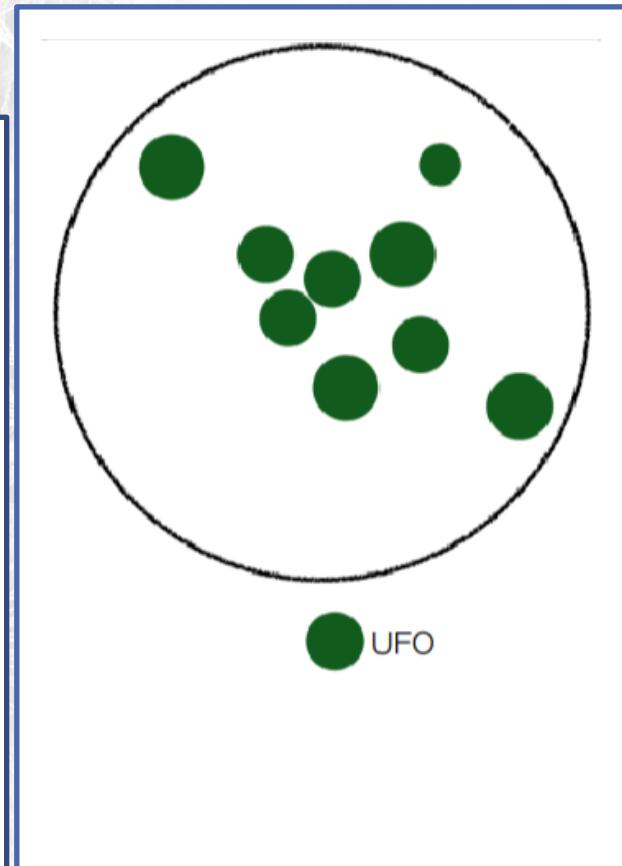
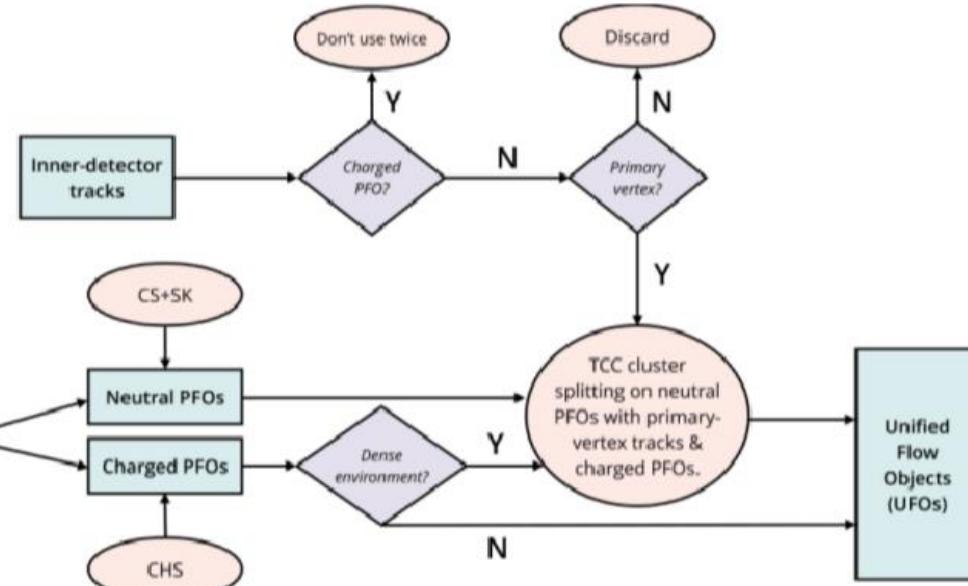


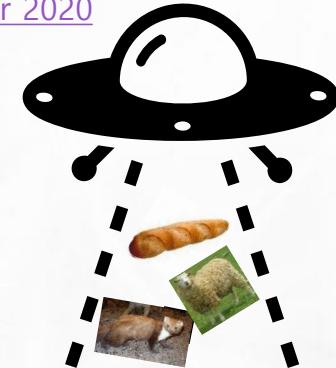


Unified Flow Objects

Combine the best of PFlow and TCC?

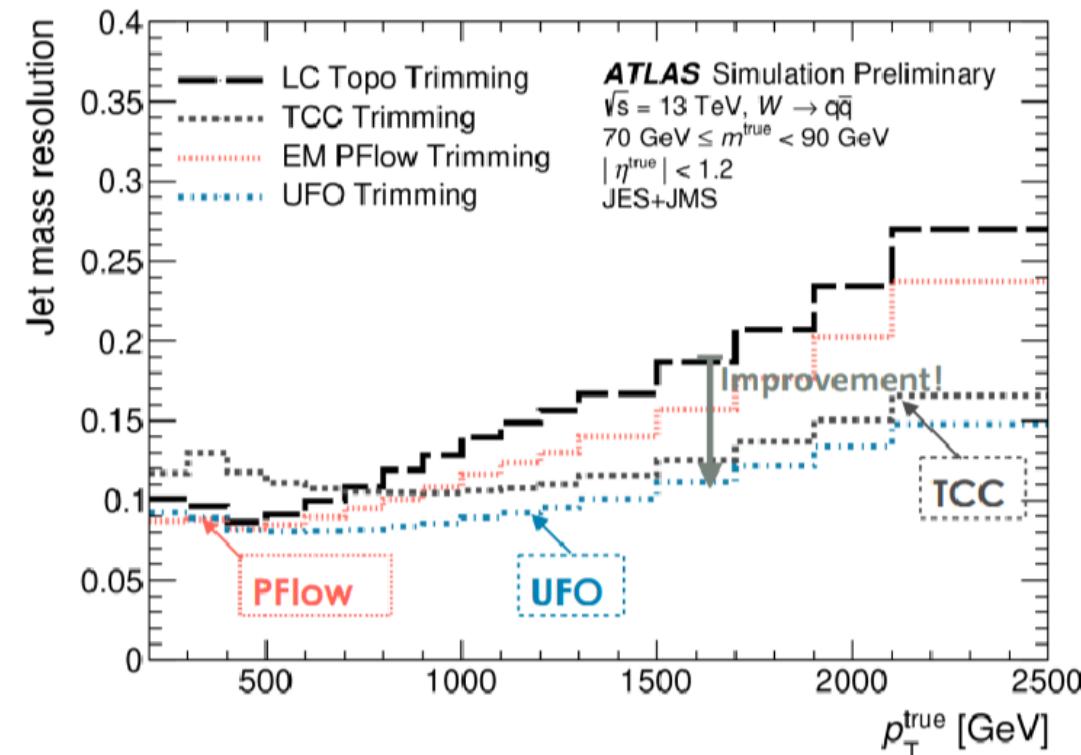
Unused tracks and neutral PFOs go through TCC split.





UFO Performance

Improves Jet Mass resolution & PU dependence





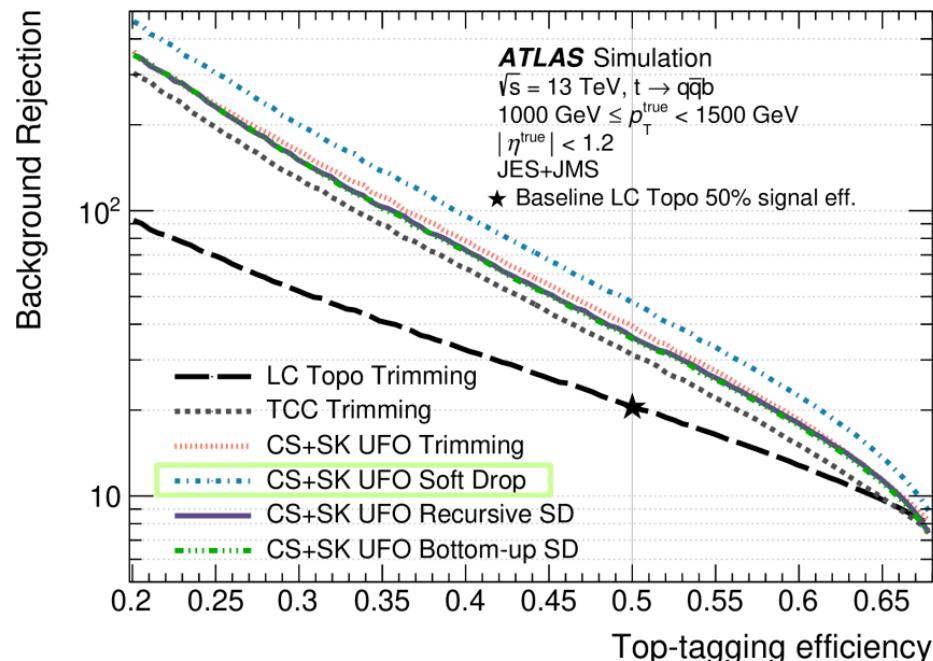
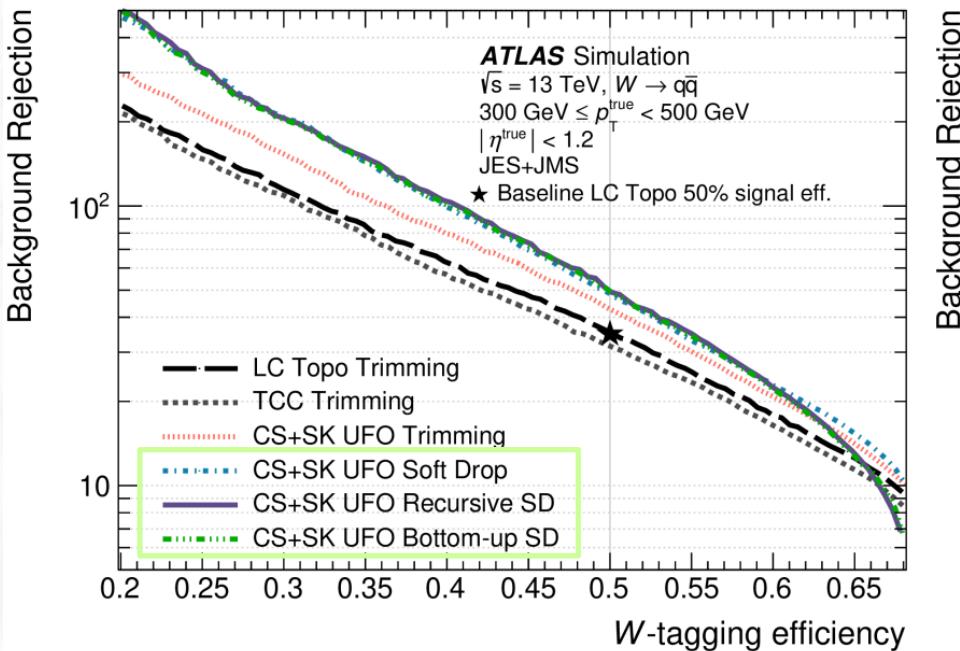
UFO Performance

UFO with CS+SK and SoftDrop default large-R jets @ Run-3

Amongst best at W-tagging

Soft-drop particularly good for top-tagging

$\geq 2x$ better rejection at 50% signal eff

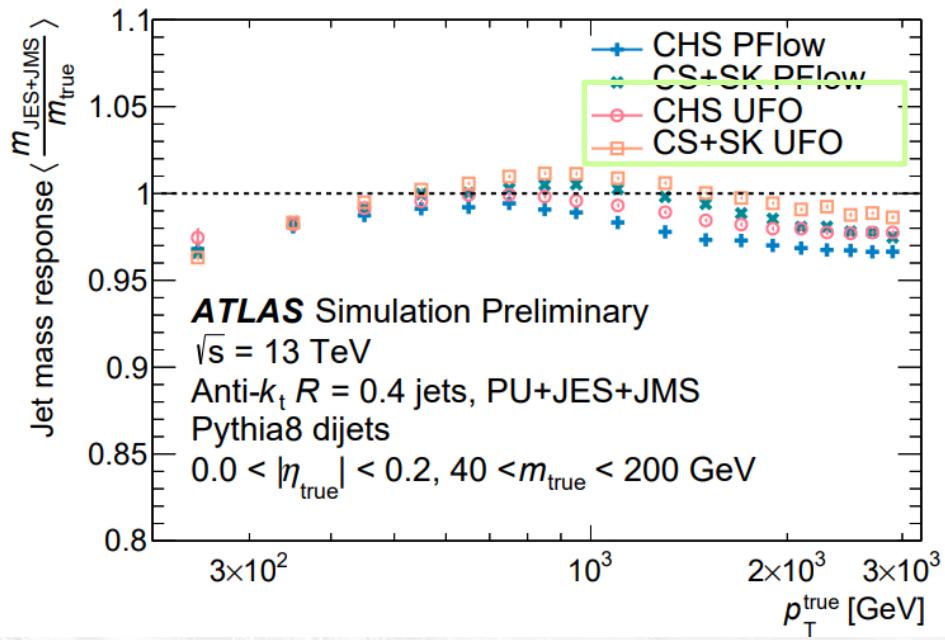
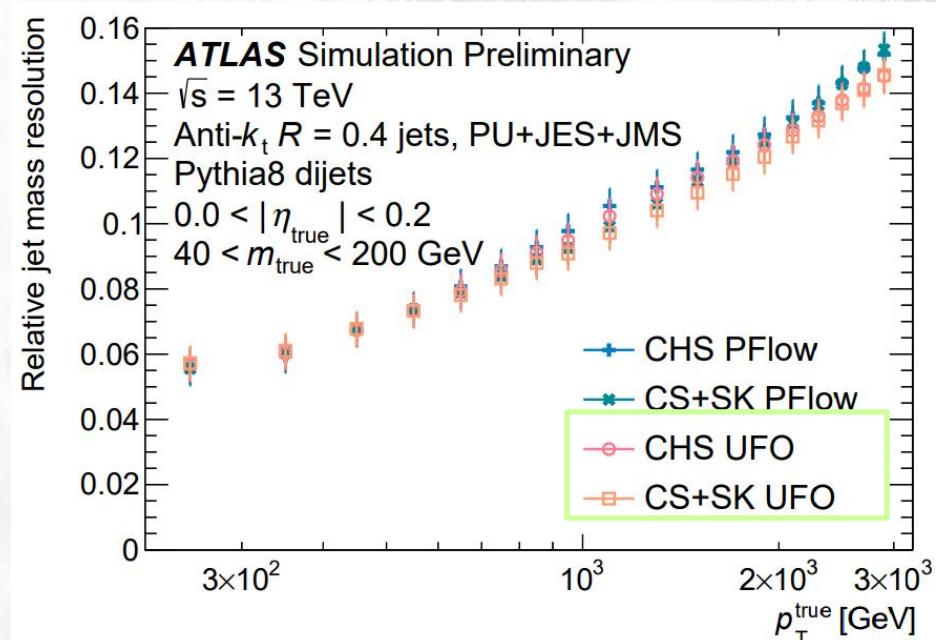


UFO for R=0.4 Jets?



New study: works as well as PFlow 😊

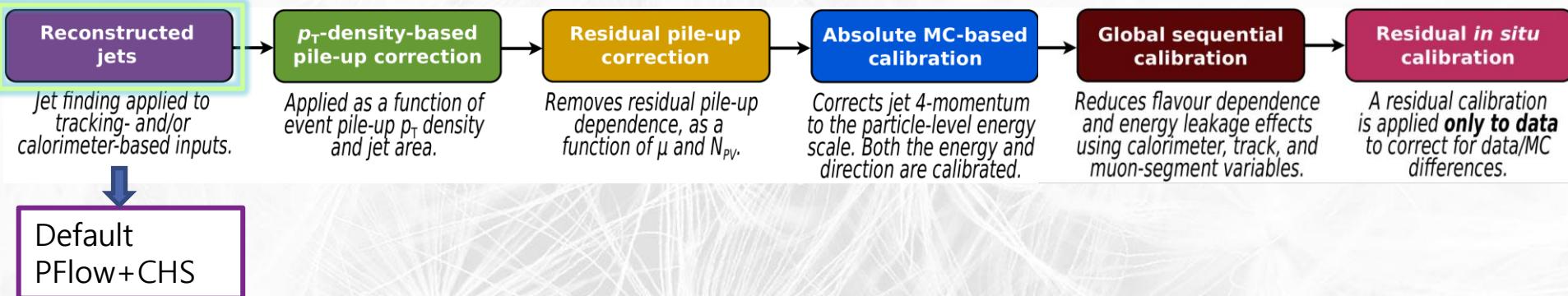
- Pythia Dijets, PU+JET+JMS Calibration
- Best Mass resolution @ high p_T & no detriment to Energy Resolution
- Best Mass response @ high p_T & good in all $|\eta|$



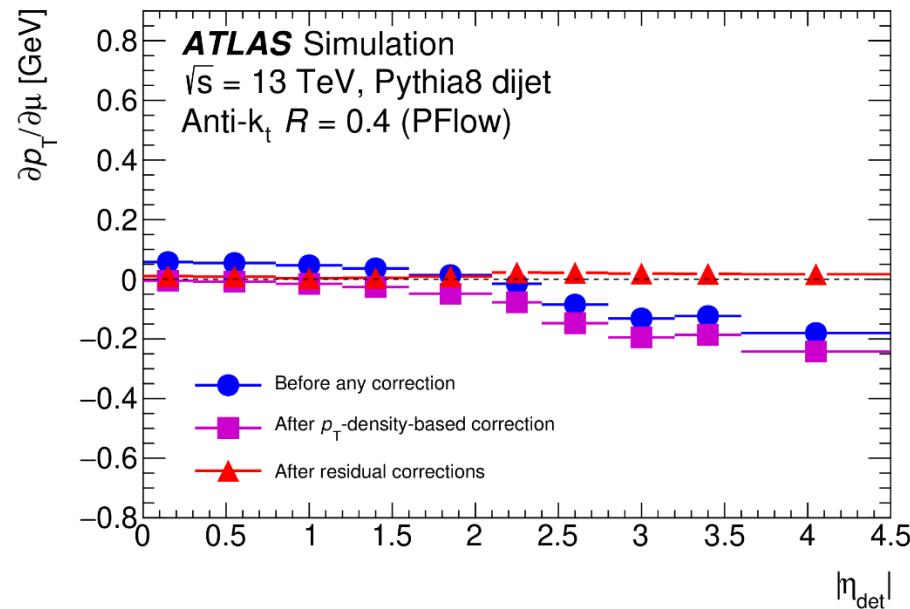
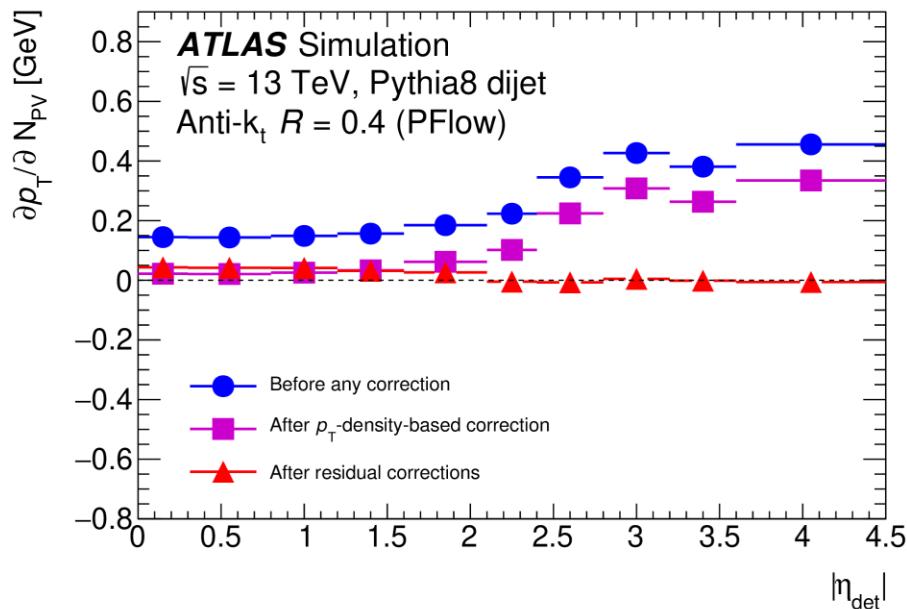
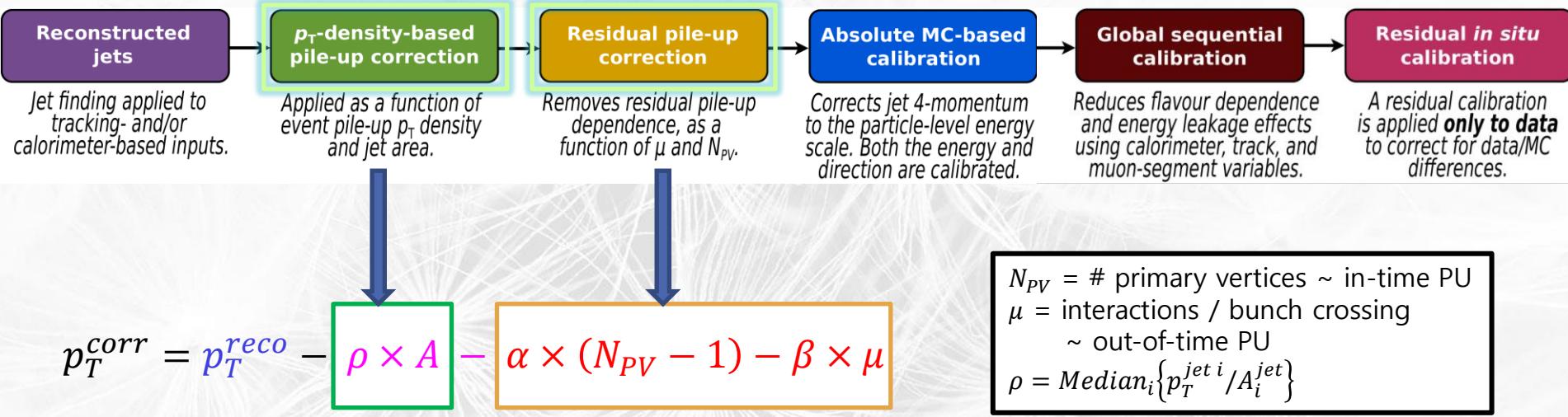


Small-R Jet Calibration

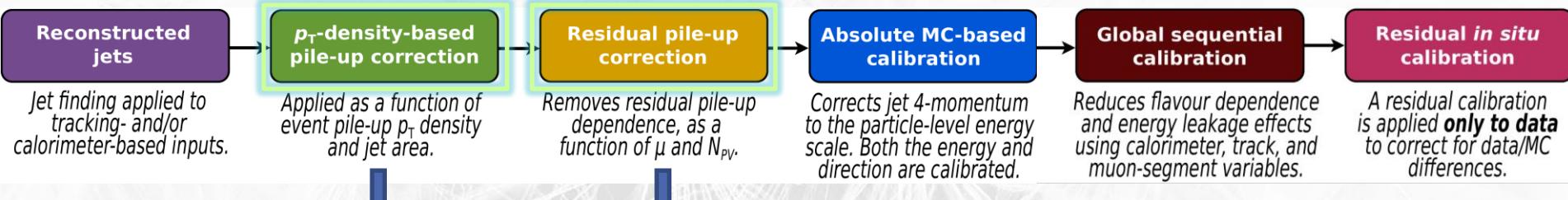
Small-R Jet Calibration



Small-R Jet Calibration



Small-R Jet Calibration

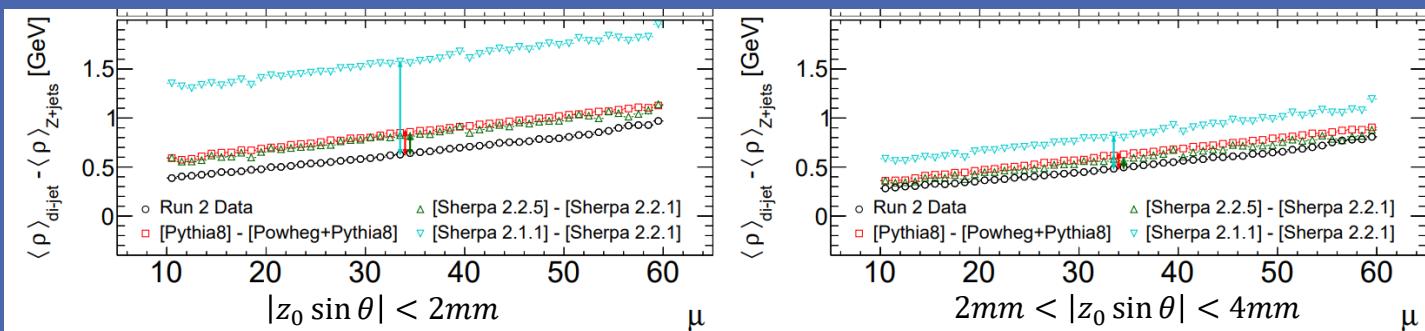


New Ideas!

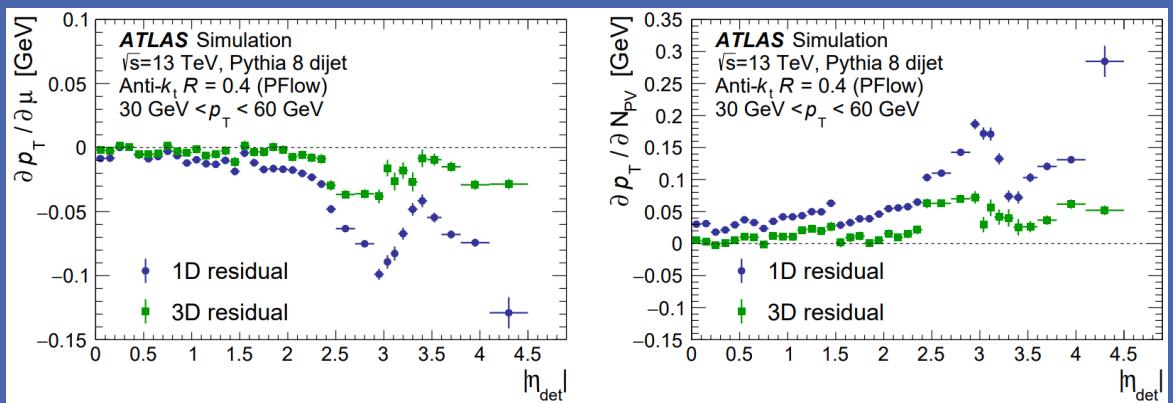
1. Alter ρ definition to reduce bias: use jets in impact-parameter sideband

- Better MC/data agreement
- More similar between topologies

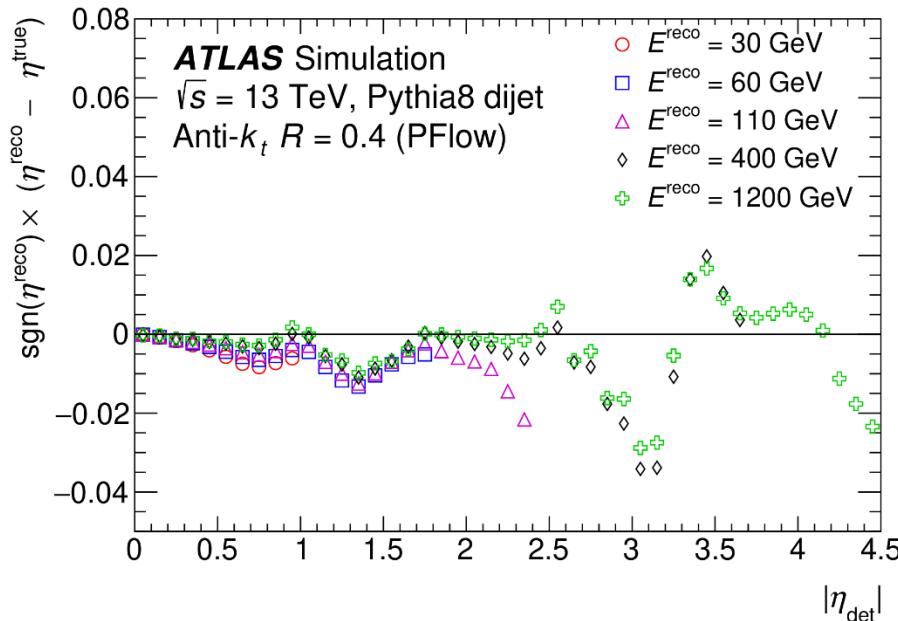
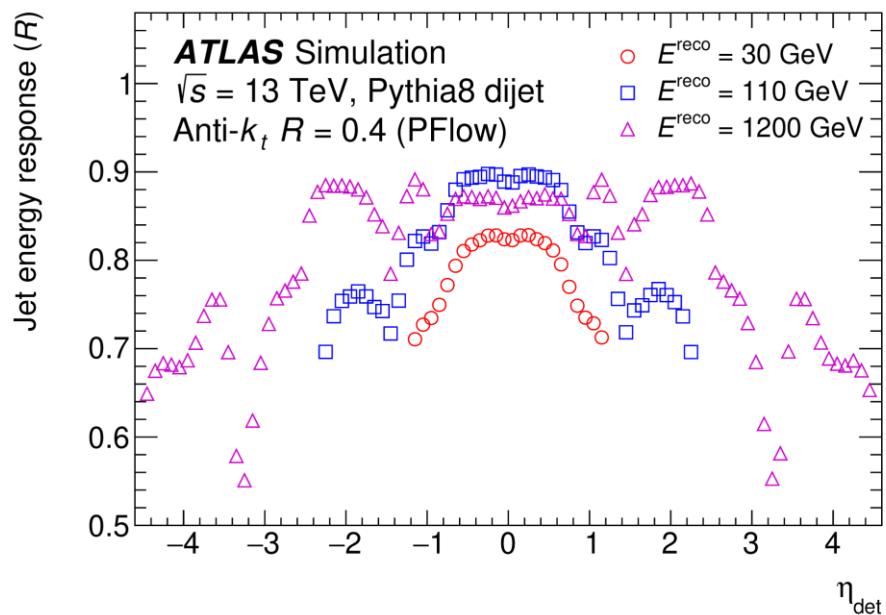
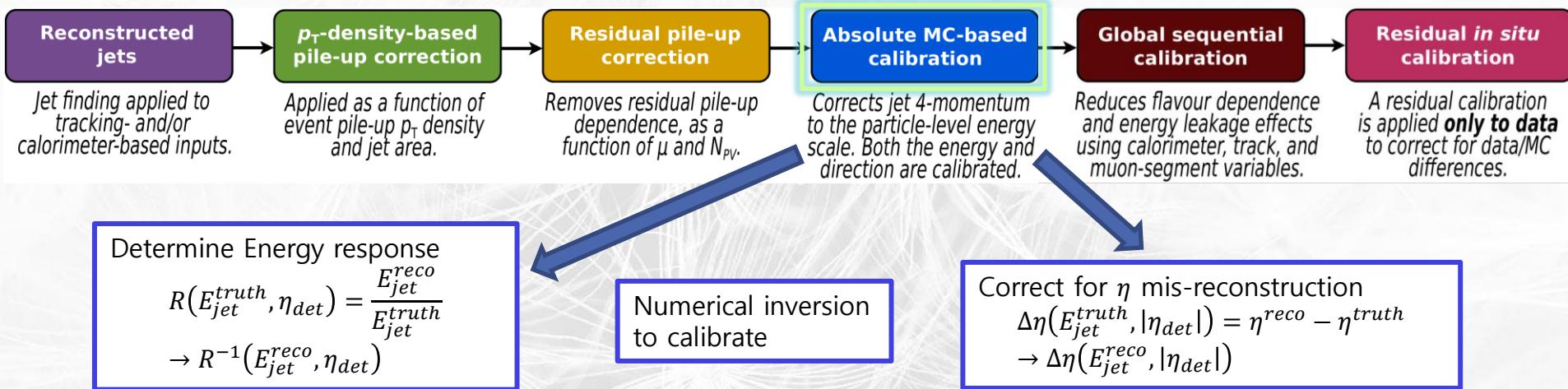
7x smaller JES unc. from ρ modelling



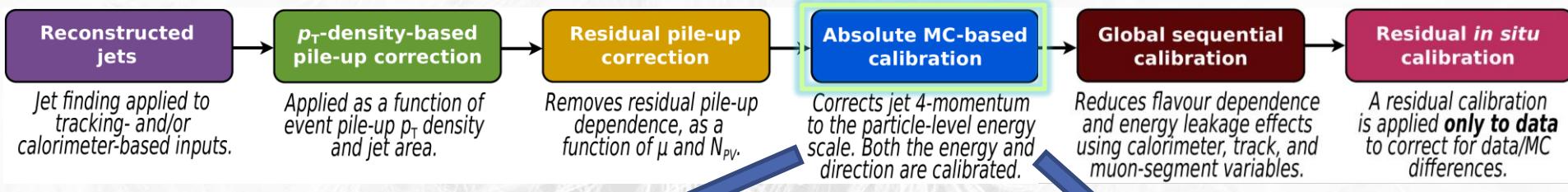
2. 1D->3D residual correction: adds correlations; corrections for extra detector effects:



Small-R Jet Calibration



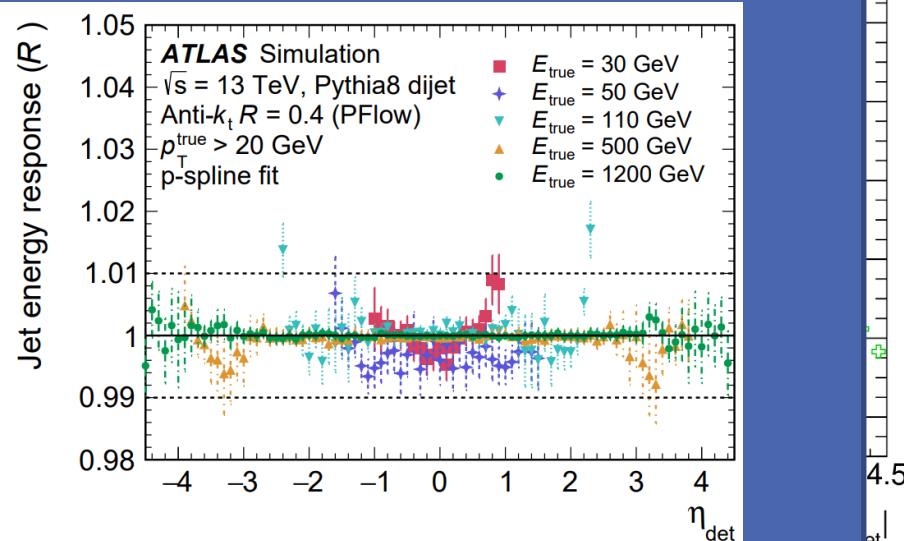
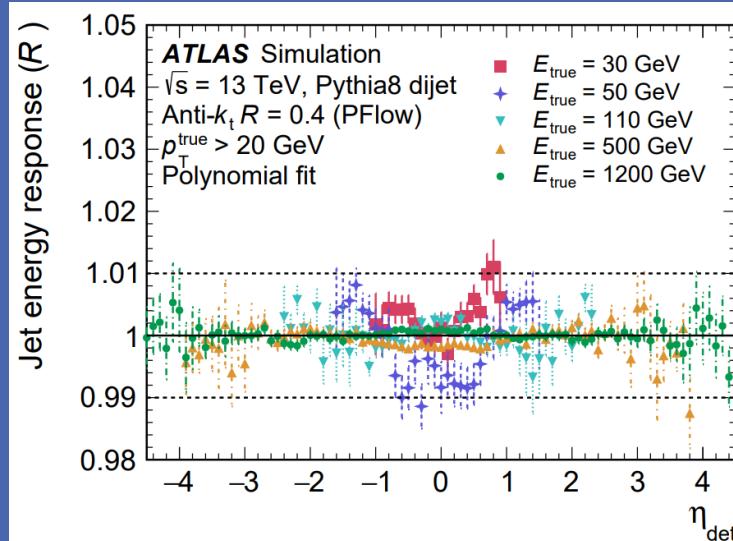
Small-R Jet Calibration



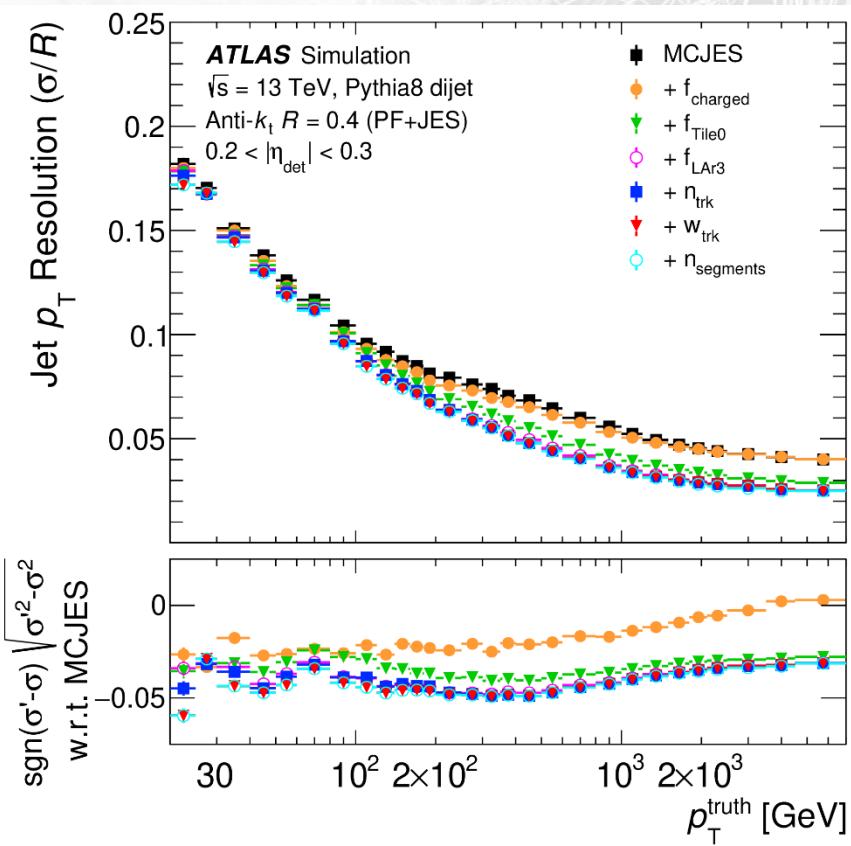
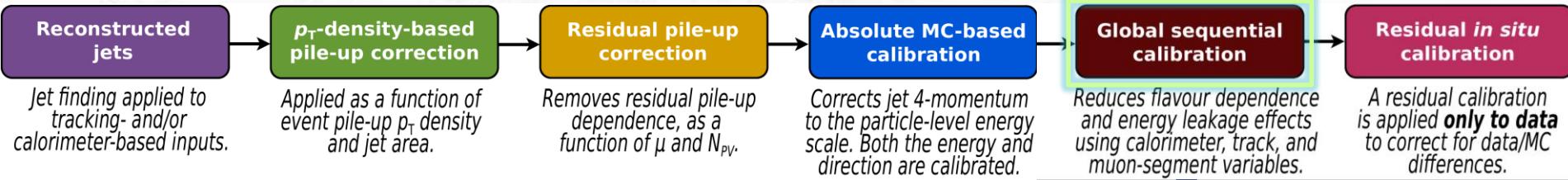
New Ideas!

Change fit used to determine $R(E_{\text{jet}}^{\text{truth}}, \eta_{\text{det}})$ function

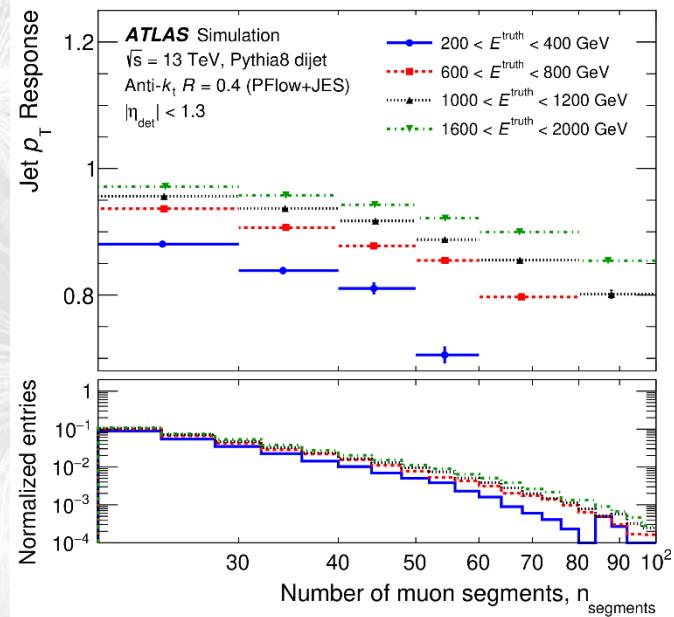
- Polynomials -> Penalised Splines
- Improves general closure
- Worse in a few η_{det} bins where response changes quickly



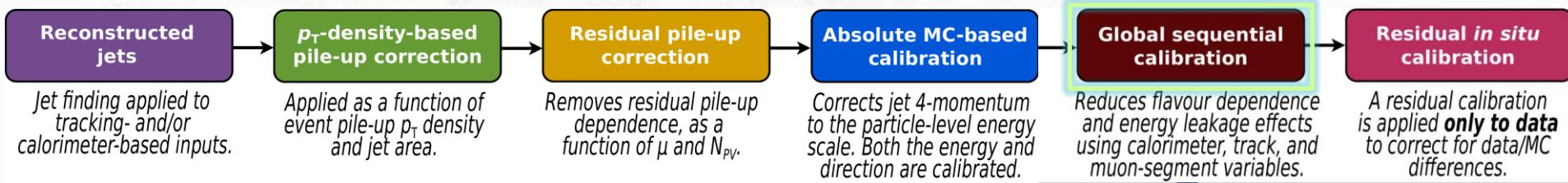
Small-R Jet Calibration



Improve JER without changing response
6 corrections (p_T, η) in sequence
e.g. punch-through from Cal. to muon system
more for high p_T and q-jets
invert jet response in Pythia8 MC.



Small-R Jet Calibration

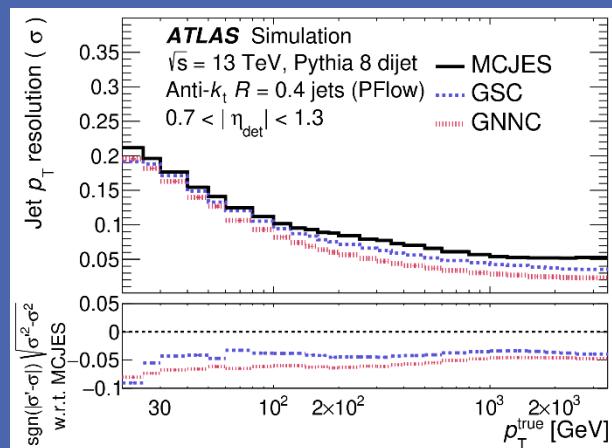
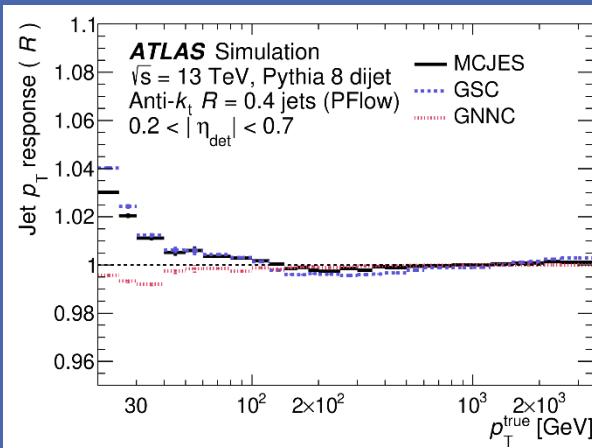
Jet p_T Resolution (σ/R)

New Ideas!

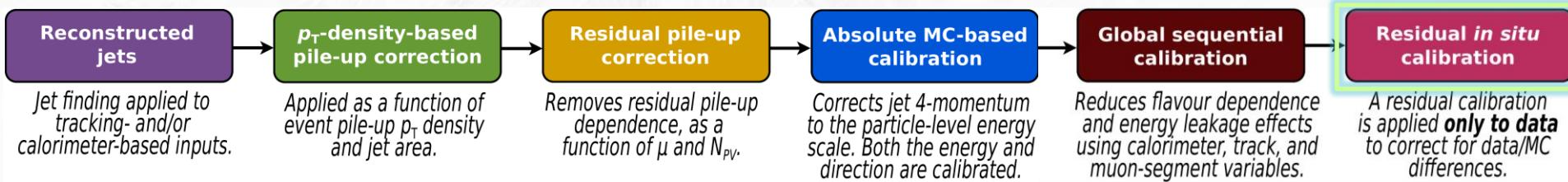
Global Sequential Calibration ->
Global Neural Network Calibration

- Add more observables
- Account for correlations

1 DNN trained in each $|\eta_{det}|$ region -> correct jet p_T
Improves Response & Resolution & JES Flavour uncs. ☺



Small-R Jet Calibration

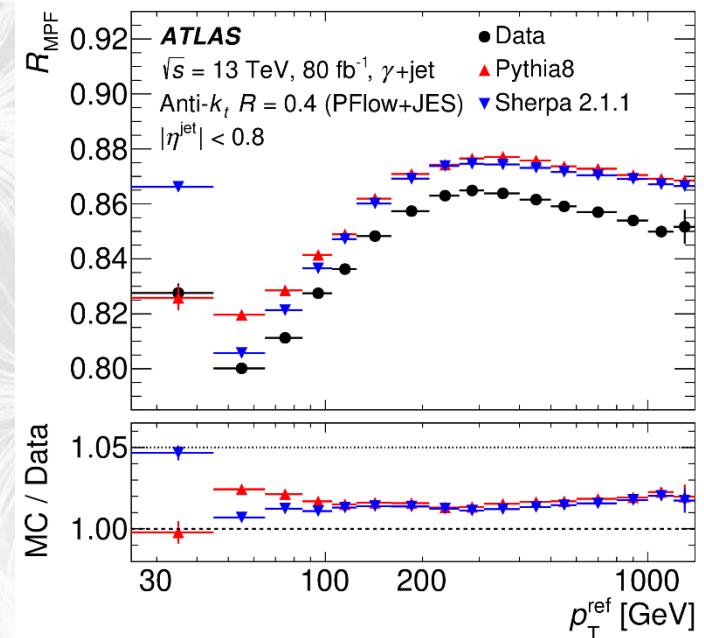
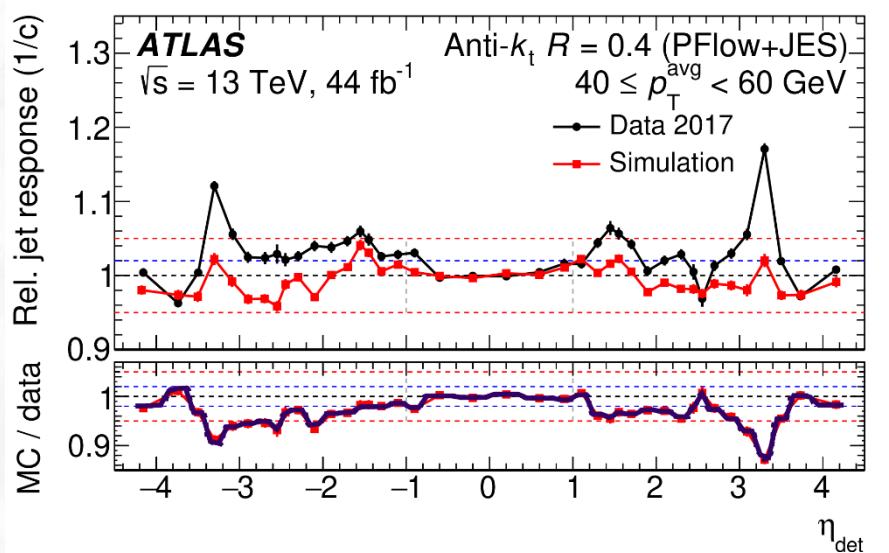


Consider p_T balance between jet and well-measured reference object: $r_{\text{in-situ}}(p_T^{\text{ref}}) = p_T^{\text{jet}} / p_T^{\text{ref}}$

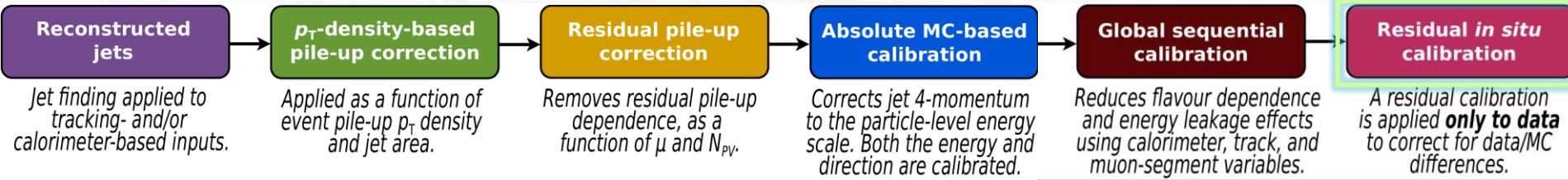
Define data-MC differences with double ratio & calibrate with inverse: $c(p_T^{\text{ref}}) = \langle r_{\text{in-situ}}^{\text{data}} / r_{\text{in-situ}}^{\text{MC}} \rangle \rightarrow c^{-1}(p_T^{\text{jet}})$

η -intercalibration to make scale same in forward region.
Compare dijet with tag-central jet and probe forward-jet

Balance for Z + jet, $\gamma + \text{jet}$, Multijet (cover full phase-space)



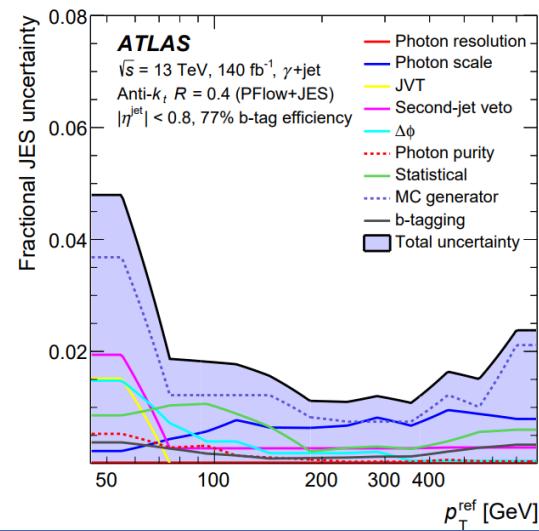
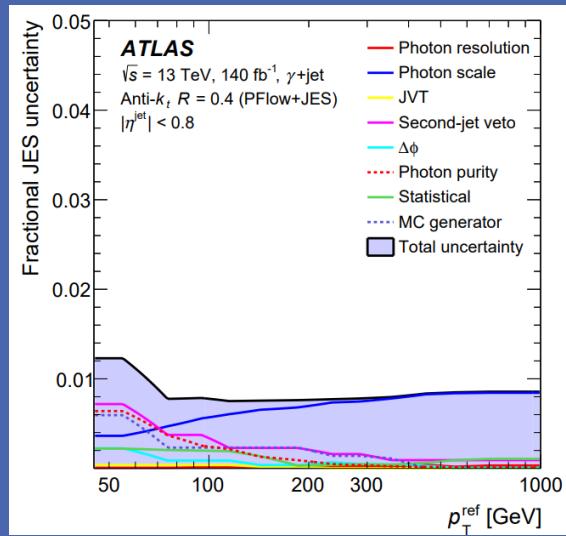
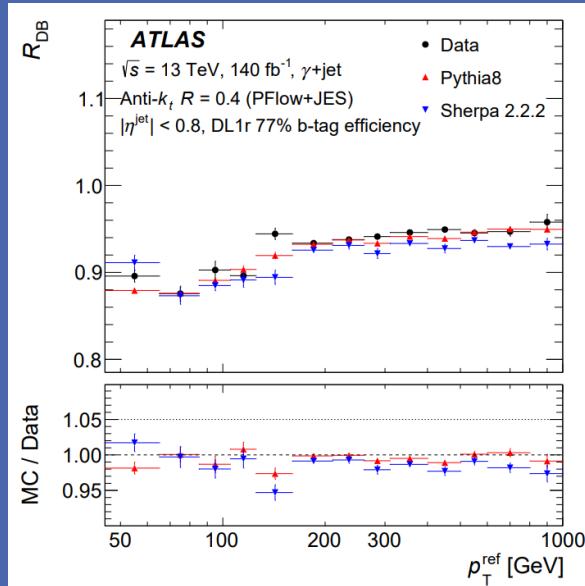
Small-R Jet Calibration



New Ideas!

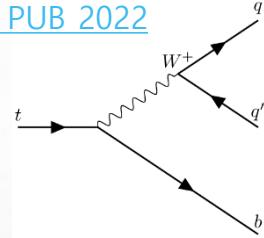
b-jet JES in PFlow jets via $\gamma + jet$

- Direct Balance method b-jet recoils photon.





New Jet Tagging



Boosted Top Tagging

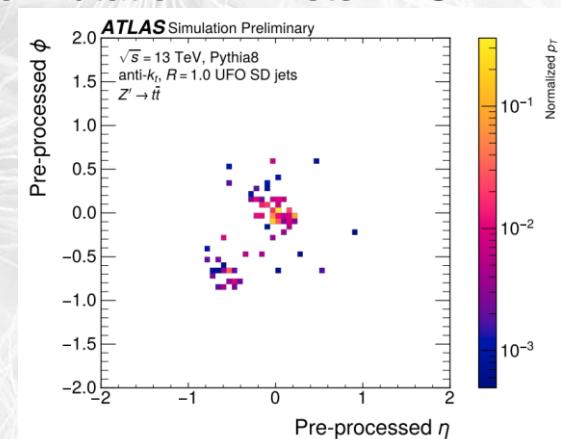
Jet constituent-based rather than high-level quantities

MC [available](#) for you to play with!

- Input Variables: constituents $\eta, \phi, R, \log(p_T), \log(En), \log\left(\frac{En}{\sum_{jet} En}\right), \log\left(\frac{p_T}{\sum_{jet} p_T}\right)$

6 Architectures:

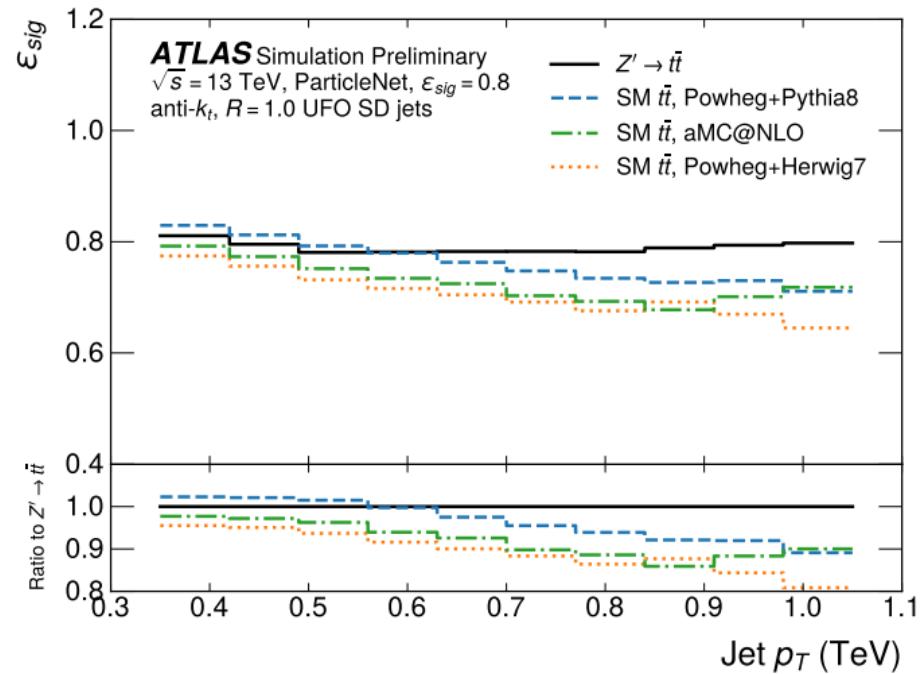
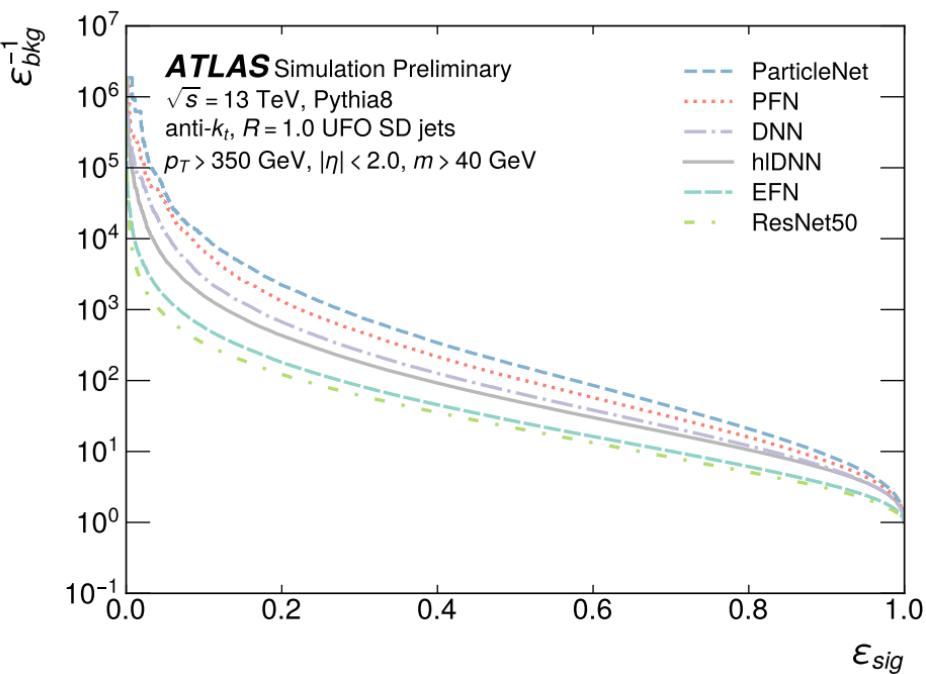
1. High-Level quantity baseline hIDNN (similar to current tagger)
2. Densely connected MLP: 0-padded p_T -ordered vectors for each variable.
3. Energy Flow Network (EFN) Deep Set: variable length, permutation inv. lists. IRC safe only – no E inputs.
4. Particle Flow Network (PFN): Like EFN but can have IRC-unsafe E inputs.
5. ResNet50 large CNN: granular η, ϕ maps of const. p_T .
6. ParticleNet GNN: const.=node, const. features = node properties, edges connect k nearest neighbours.

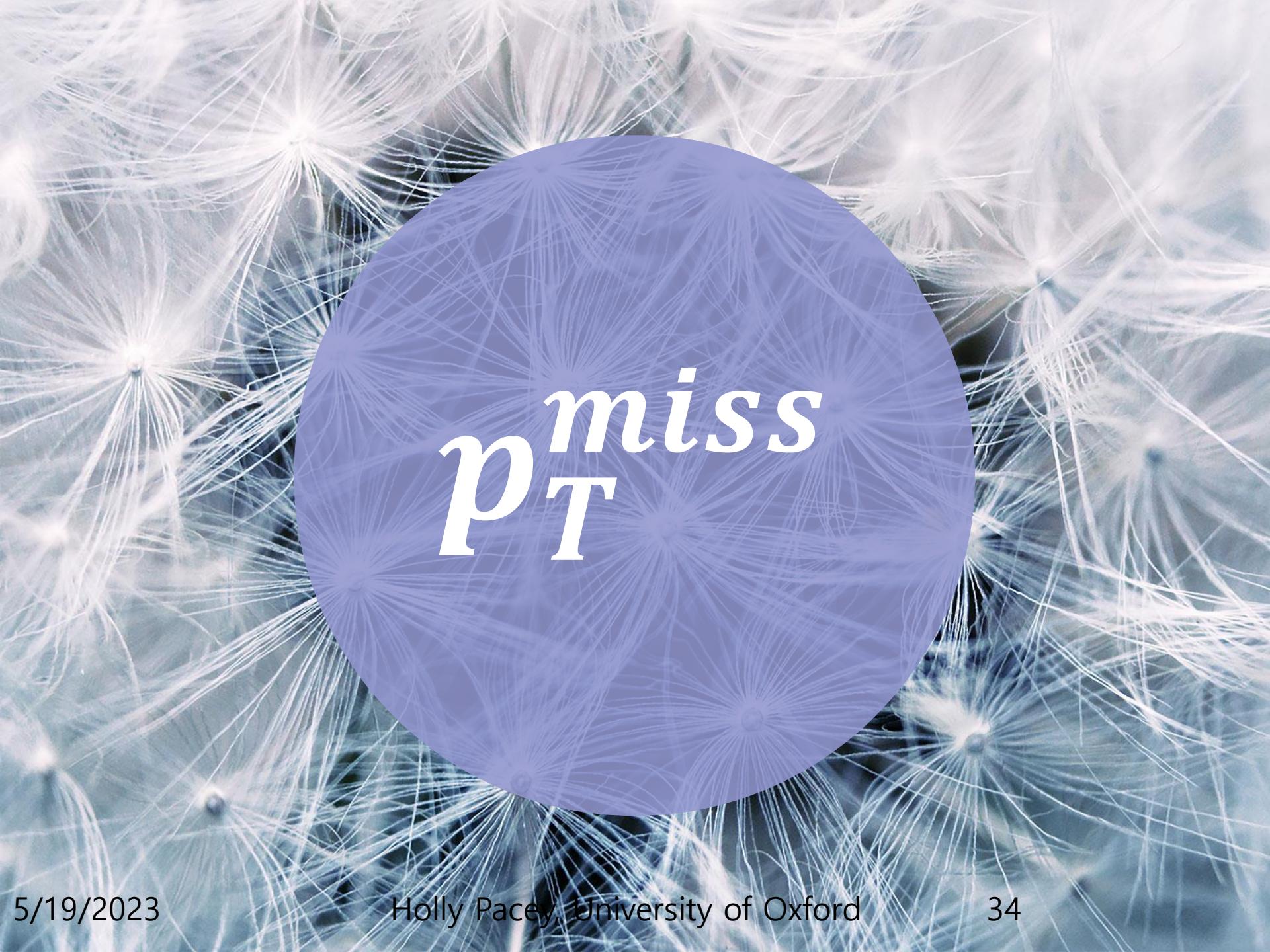


Boosted Top Tagger Performance

ParticleNet best, though some increase in modelling uncs.

2-3x better rejection @ 50-80% efficiency



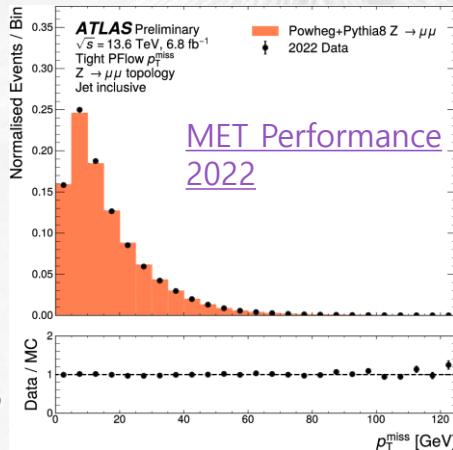


$p_{\text{T}}^{\text{miss}}$

What is p_T^{miss} ?

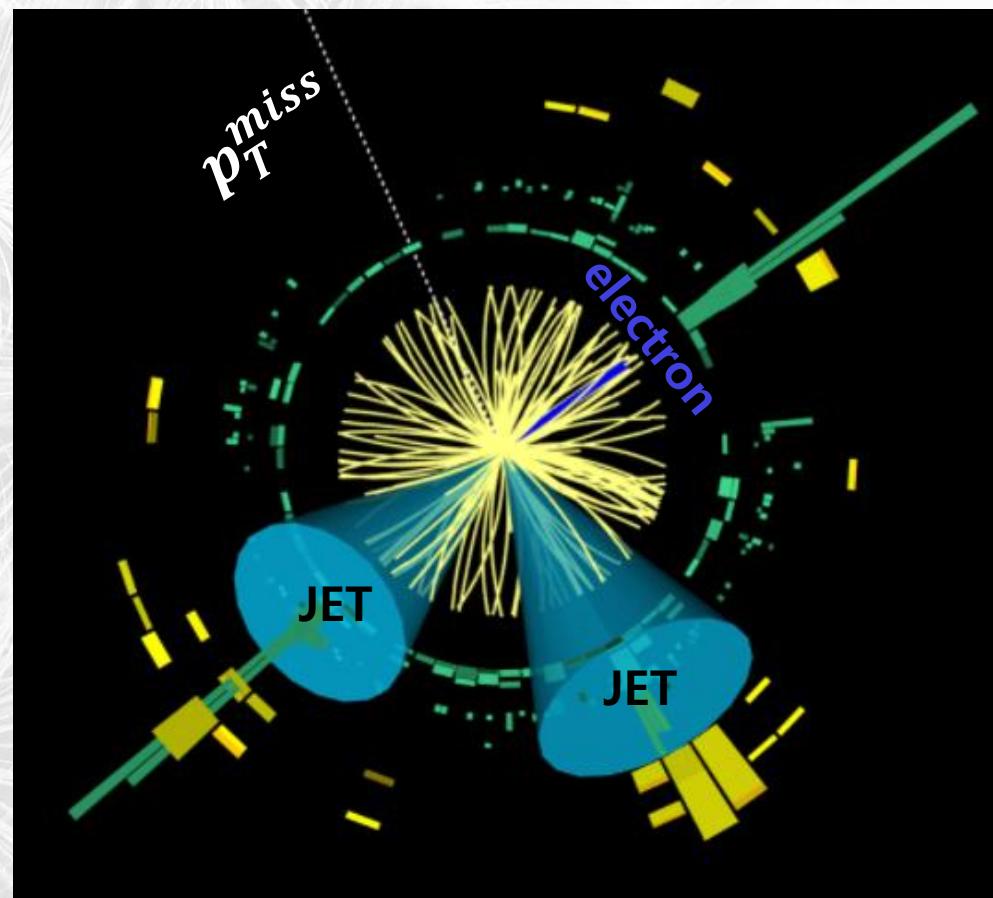
Missing transverse momentum: ‘Detector signature’ for invisible particles...

- Negative vector sum of p_T of objects in the event.
- Real p_T^{miss} :
 - neutrinos
 - stable BSM particles e.g. DM
- Or Fake p_T^{miss} :
 - Pileup (PU)
 - Detector resolution
 - Detector acceptance
- Aim: measure Real p_T^{miss} + reduce Fake p_T^{miss}



[H-c Coupling ATLAS paper](#)

Candidate event for the process $\text{WH} \rightarrow \text{e}\nu\text{cc}$



p_T^{miss} Reconstruction

$$p_T^{\text{miss}} = |\mathbf{p}_T^{\text{miss}}|$$

$$\mathbf{p}_T^{\text{miss}} = (p_x^{\text{miss}}, p_y^{\text{miss}}),$$

Object based approach built in a specific order.

- Analyses decide on what definitions to use for muons/electrons/....
- Input them to MET reconstruction algorithm
- Algorithm adds objects to \mathbf{p}_T sum in this order to use the best energy measurement/interpretations available:

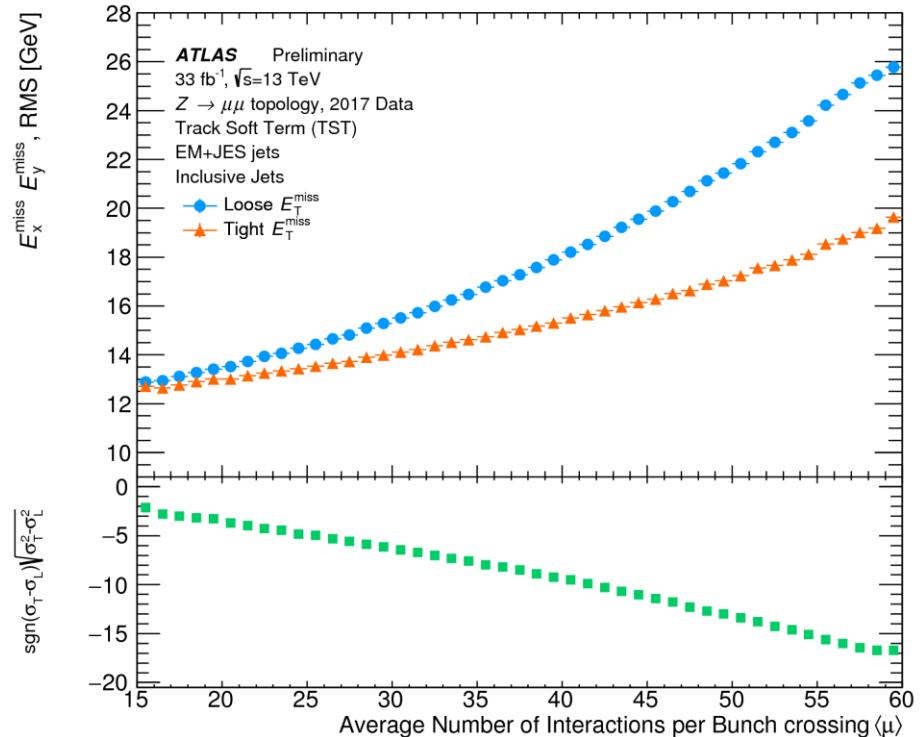
$$\mathbf{p}_T^{\text{miss}} = - \left| \underbrace{\sum_{\text{selected electrons}} \mathbf{p}_T^e + \sum_{\text{accepted photons}} \mathbf{p}_T^\gamma + \sum_{\text{accepted } \tau\text{-leptons}} \mathbf{p}_T^\tau + \sum_{\text{selected } \mu} \mathbf{p}_T^\mu + \sum_{\text{accepted jets}} \mathbf{p}_T^{\text{jet}}}_{\text{hard term}} + \underbrace{\sum_{\text{unused tracks}} \mathbf{p}_T^{\text{track}}}_{\text{soft term}} \right|$$

- Performing its own **overlap removal** on whole/*parts* of objects, removing tracks/clusters that have been used already in the \mathbf{p}_T sum.
-> **avoids double-counting!**
- Remaining unused tracks become the '**Track soft term**'.

Working Points

Multiple WPs supported to optimize performance

- Jet requirements added in addition to analysis definitions.
- Each optimal for different topologies
- Most ATLAS results use ‘Tight’
- Tighter constraints on jets improve pileup resilience, but may remove more hard-scatter jets as collateral.

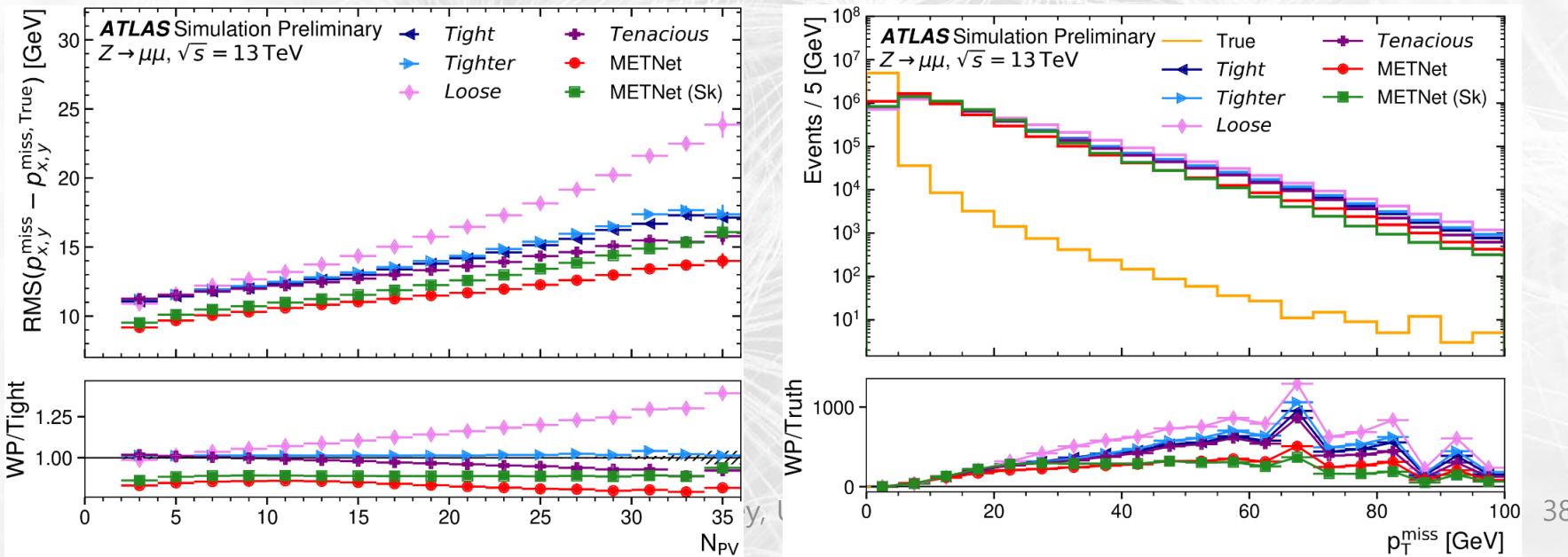


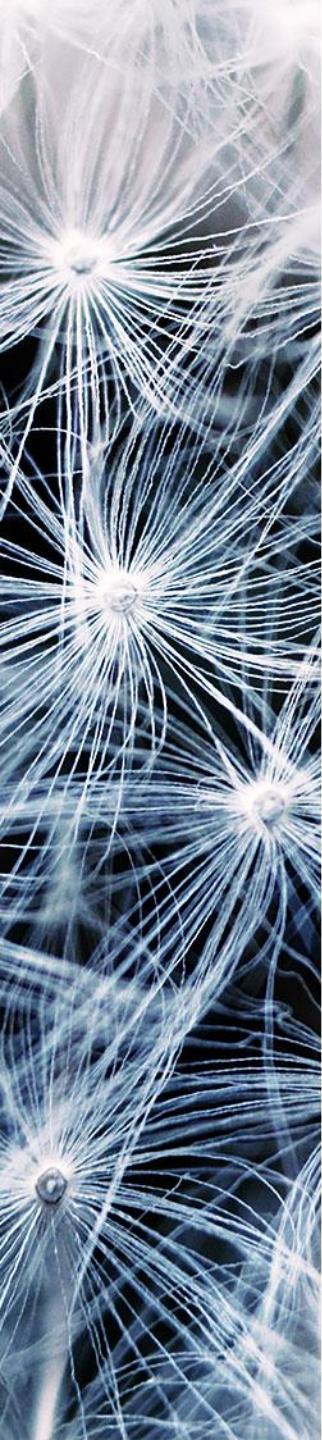
Working point	Selections		
	p_T [GeV] for jets with: $ \eta < 2.4$	$2.4 < \eta < 4.5$	JVT for jets with $ \eta < 2.4$
<i>Loose</i>	> 20	> 20	> 0.5 for $p_T < 60$ GeV jets
<i>Tight</i>	> 20	> 30	> 0.5 for $p_T < 60$ GeV jets
<i>Tighter</i>	> 20	> 35	> 0.5 for $p_T < 60$ GeV jets
<i>Tenacious</i>	> 20	> 35	> 0.91 for $20 < p_T < 40$ GeV jets > 0.59 for $40 < p_T < 60$ GeV jets > 0.11 for $60 < p_T < 120$ GeV jets

Machine Learning p_T^{miss}

Use a NN to combine the WPs optimally.

- NN inputs: different WPs p_T^{miss} , event kinematics and pileup conditions.
- NN target: $p_T^{miss, True}$, NN outputs: $p_T^{miss, NN}$ vector, $|p_T^{miss, NN}| = \text{METNet}$.
- Alternative NN option studied also adds a Sinkhorn Loss (Sk).
- Improved resolution, and reduction of fake p_T^{miss} .
- Improving issues with bias & extrapolation to v. high p_T^{miss} via Classifier combo of WPs.
- Also investigating NN MET Significance to measure real p_T^{miss} : get NN resolution output.



A close-up photograph of a dandelion seed head, showing numerous small, white, feathery seeds attached to a central stem. The background is dark, making the light-colored seeds stand out.

Conclusion

JetEtMiss @ ATLAS: a huge effort with active dev.

- Jets & p_T^{miss} ongoing improvements for Run-3
 - Modern ML based calibrations, tagging, regressions, reconstruction,
 - Use of tracks to help mitigate growing pileup via UFOs (new default large-R jet!), JVT, ...
 - ML Pion ID [via Point-Cloud representation](#)
- More improvements still to come
 - Finalising calibration improvements for PFlow/UFOs.
 - Investigating TST calibration.
 - Topo-tower inputs to improve granularity in forward region
 - Topocluster timing cut to reject pileup further
 -



BACKUP

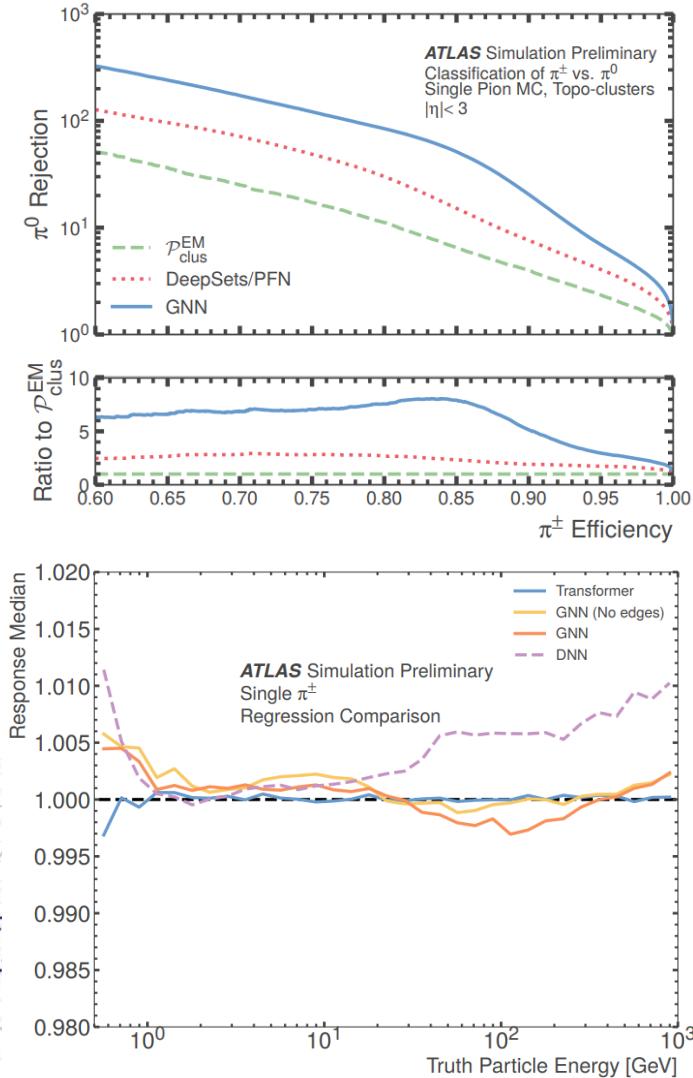
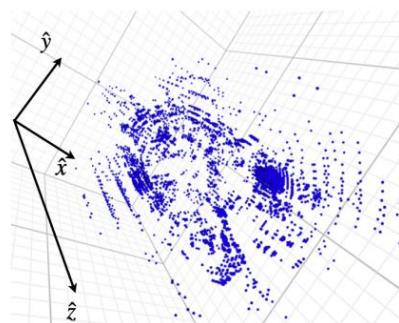
Questions & Answers

- PU subtraction Rho definition?
 - Charged PFOs passing the impact parameter requirement
 - All neutral PFOs
 - [new methods paper](#) section 4.2
- JER info: [Eur. Phys. J. C 81 \(2021\) 689](#)
- What is calo timing resolution such that a topocluster timing cut is possible?
 - [ATL-TILECAL-PROC-2021-016](#) ~0.4ns above 100GeV
- When/How is MC other than Powheg+Pythia8 used?
 - [Small-R jet Calibration Paper 2020](#), [Large-R jet Calibration Paper 2018](#) : Generator differences between Pythia/Sherpa/Herwig in In-Situ used for uncs. Pythia for nominal.
 - Impact of hadronisation model: [ATLAS-PUB-2022-021](#)
- Can/How does the 3-layer Calo. in the forward region help remove PU?
 - Can reconstruct topoclusters with noise cuts still.
 - Have [fJVT](#) to tag PU vs HS jets.
 - PU area subtraction only for central jets, but residual PU correction still applicable
- Is the particleNet version the same as the pheno paper?
 - [code available](#) no mention of mass-decorrelation in the PUB
- Why is the half-empty grid requirement chosen for softKiller?
 - [CONF](#) details. Equivalent to the lowest pT threshold that corrects the median flow density per bin to zero.
 - Related to assumption that pileup is evenly distributed over an event
- What are the penalised splines penalising?
 - [Small-R Jet Calibration New Methods Paper 2023](#) section 4.4.2. overfitting Etrue to data
- How to deal with uncertainties for METNet?
 - Inputs are e.g. the jet term of the met so we can propagate the jet uncertainties through the NN in the same way as for normal MET. Will validate the NN stability seems sensible though.

Point Clouds for Pion ID

Classifying π^0 v π^\pm key step in hadronic reconstruction

- & Regressing Energy distribution.
- Improve over previous DNN/CNN approaches:
 - Suits non-uniform 3D calo. deposit structure
- Particle Flow Network (Deep Set)**
 - perm. Invariant (not arbitrary p_T ordered cells)
 - variable length inputs (different #cells / TC)
- GNN**
 - Build a graph out of each pion topocluster
 - Nodes = cells
 - Edges = connect neighbouring cells
- Transformer (Self Attention Mechanism)**
 - For pion energy regression



Pileup Contamination

2 parts: Bias HS object energy, add PU jets to event!

PU removal at every level:

3. On jets

- Jet Area subtraction
- **Grooming** (trimming, softDrop)

Remove PU/UE wide-angle E-deposits in Large-R jets

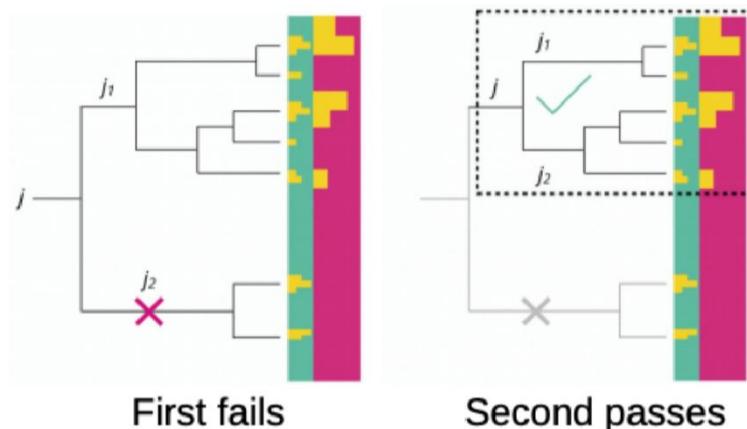
Run-2: Trimming

- Recluster sub-jets with $R=0.2$
- Keep those passing some threshold

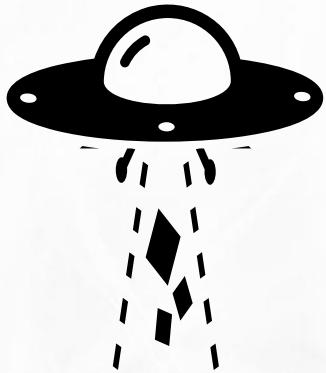
Run-3: SoftDrop

- Define sub-jet splits with Cambridge-Aachen alg (priorities closest stuff)
- Start from 1st splitting
- Reach passing condition to keep both splits, else drop constituents

$$\frac{\min(p_{T1}, p_{T2})}{p_{T1} + p_{T2}} > Z_{cut} \left(\frac{\Delta R_{12}}{R_0} \right)^\beta$$

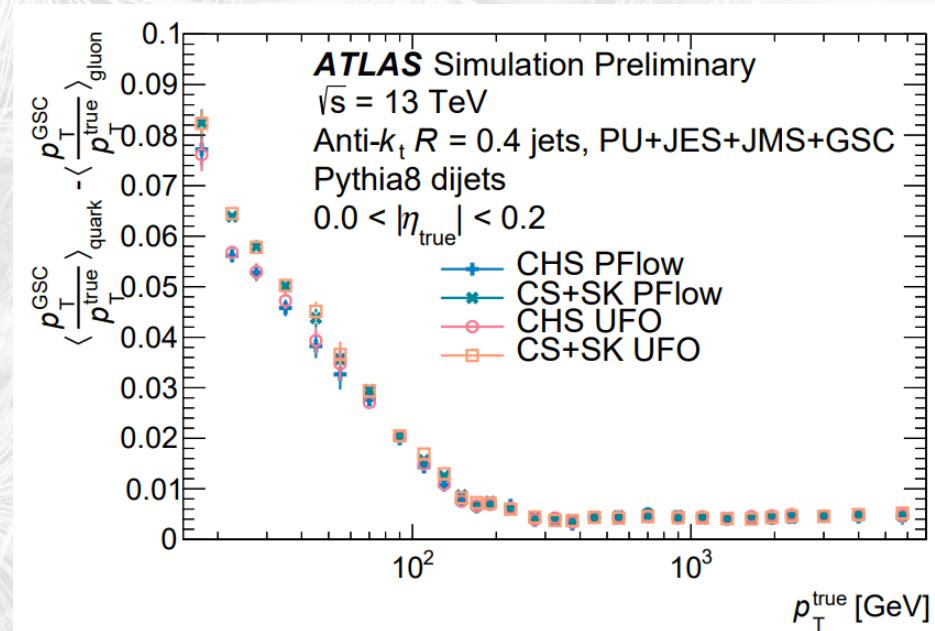


UFO for R=0.4 Jets?

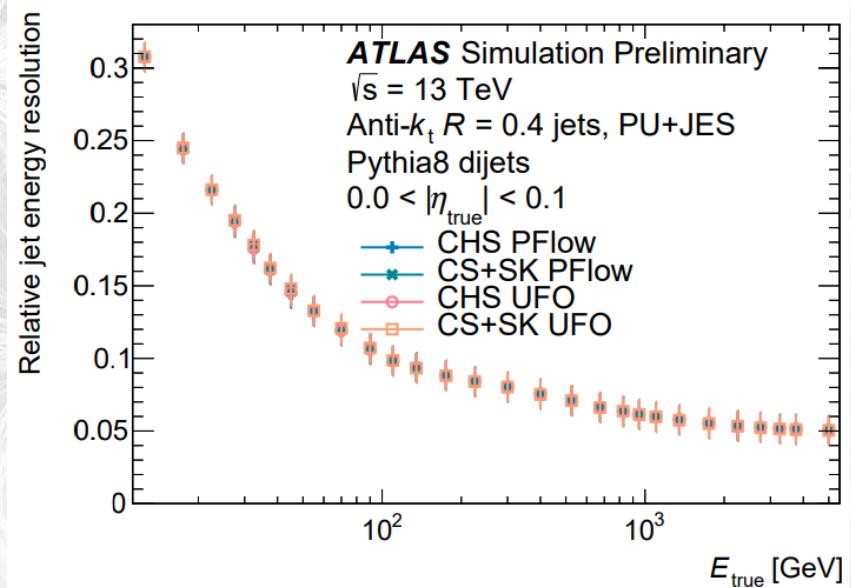
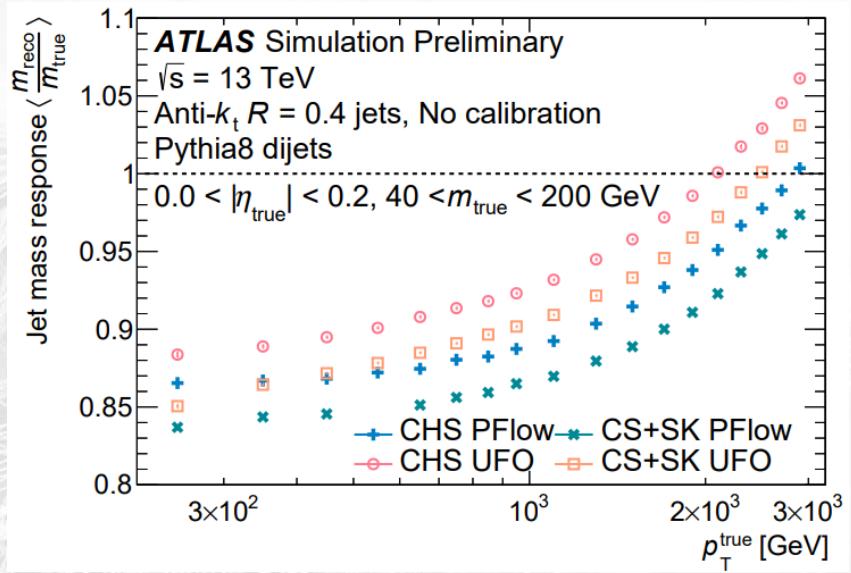
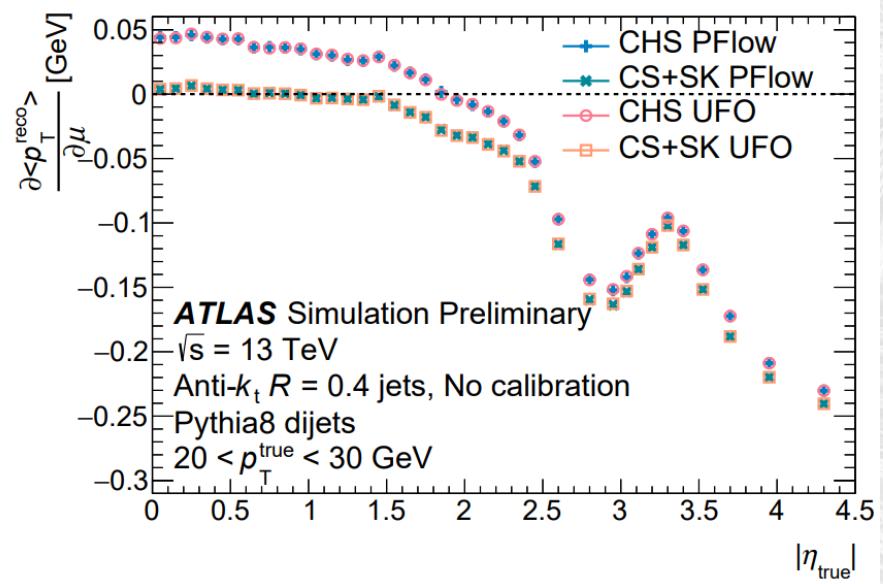


New study: works as well as PFlow ☺

- Pythia Dijets, PU+JET+JMS Calibration
- Best Mass resolution @ high p_T & no detriment to Energy Resolution
- **CS+SK more flavour diffs: soft components in jet more prevalent in g-jets (but less PU dependence)**
- May move to this for Run-3

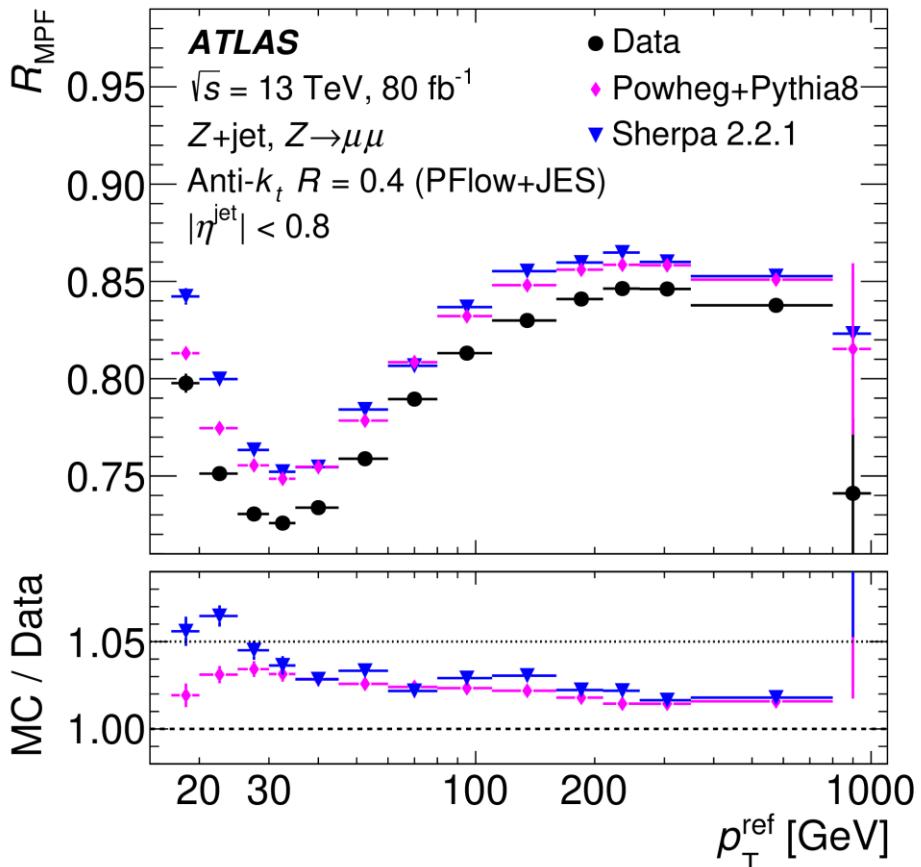
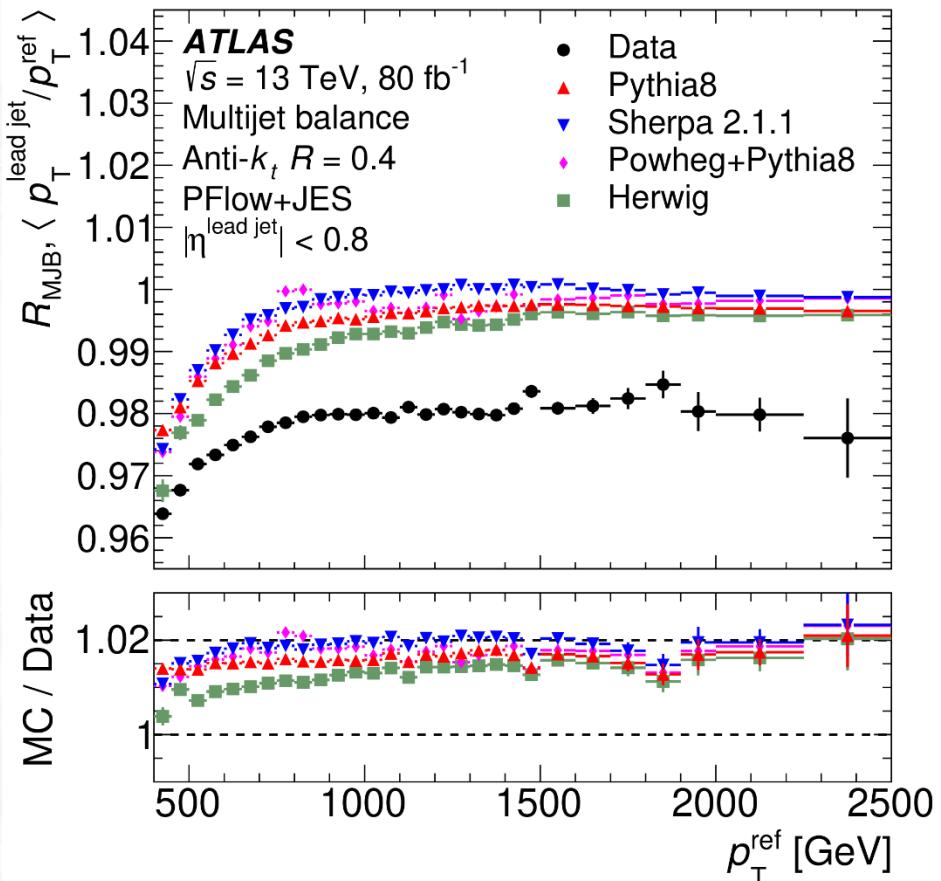


UFO for R=0.4 Jets?



In-situ

Also have dijet and Z+jet balances



GNNC Details

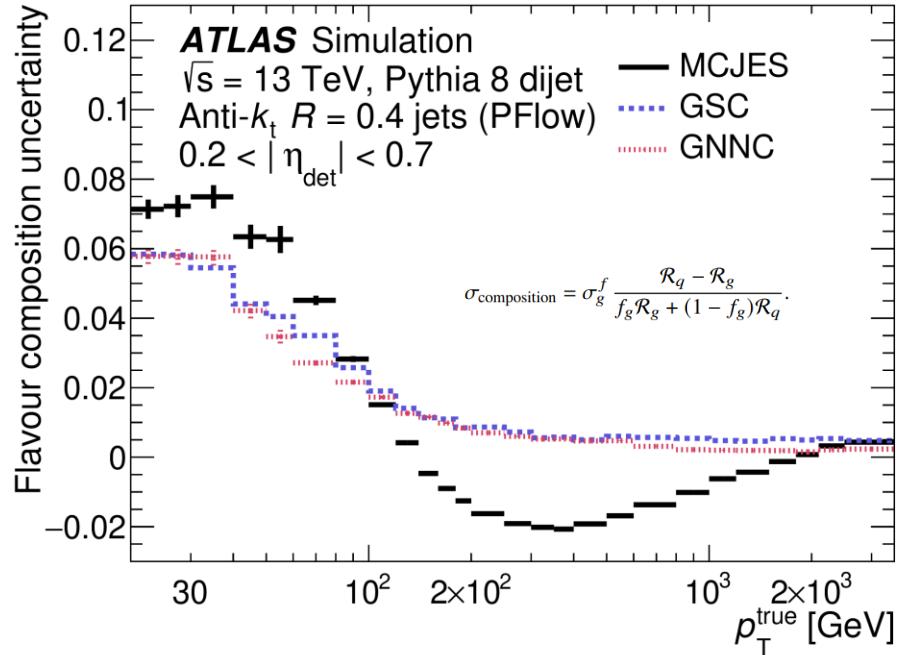
To improve the performance based on the detector geometry, a DNN is trained for each $|\eta^{\text{det}}|$ region used to derive the GSC to provide a correction to the jet p_T based on various jet- and event-level features. The DNNs are trained with Keras [55], using the Adam [56] optimisation algorithm. The network has three hidden layers with swish activation functions [57] and a single-node output layer with linear activation. The number of nodes is optimised for each $|\eta^{\text{det}}|$ bin, and ranges between 100 and 300. The network uses the leaky Gaussian kernel (LGK) loss function [58]

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

where x^{target} is the jet p_T response, x^{pred} is the corresponding NN prediction, and α and β are tunable parameters. As $\alpha \rightarrow 0$, the LGK loss learns the mode, and the second term ensures that the gradient of the error function relative to the current weight does not vanish for large $x^{\text{target}} - x^{\text{pred}}$. Learning the mode is less biased by cases where the response is not a perfect Gaussian distribution, resulting in better closure than a loss function that learns the mean of the distribution.

Calorimeter	$f_{\text{LAr}0-3*}$ $f_{\text{Tile}0*-2}$ $f_{\text{HEC},0-3}$	The E_{frac} measured in the 0th-3rd layer of the EM LAr calorimeter The E_{frac} measured in the 0th-2nd layer of the hadronic tile calorimeter The E_{frac} measured in the 0th-3rd layer of the hadronic end cap calorimeter
	$f_{\text{FCAL},0-2}$ $N_{90\%}$	The E_{frac} measured in the 0th-2nd layer of the forward calorimeter The minimum number of clusters containing 90% of the jet energy
Jet kinematics	$p_T^{\text{JES}} * \eta^{\text{det}}$	The jet p_T after the MCJES calibration The detector η
Tracking	w_{track}^* N_{track}^* f_{charged}^*	The average p_T -weighted transverse distance in the $\eta\phi$ plane between the jet axis and all tracks of $p_T > 1$ GeV ghost-associated with the jet The number of tracks with $p_T > 1$ GeV ghost-associated with the jet The fraction of the jet p_T measured from ghost-associated tracks
Muon segments	N_{segments}^*	The number of muon track segments ghost-associated with the jet
Pile-up	μ N_{PV}	The average number of interactions per bunch crossing The number of reconstructed primary vertices

Table 1: List of variables used as input to the GNNC. Variables with a * correspond to those that are also used by the GSC.



MM Eta-Intercalibration

Calibration factor R measures in bins of η_{det} , intercalibration factor c

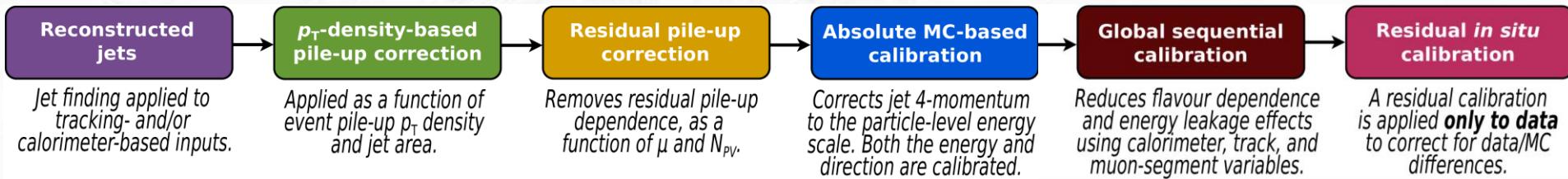
$$\mathcal{A} = \frac{p_T^{\text{left}} - p_T^{\text{right}}}{p_T^{\text{avg}}},$$

$$(p_T^{\text{avg}} = (p_T^{\text{left}} + p_T^{\text{right}})/2).$$

$$c = \frac{c^{\text{right}}}{c^{\text{left}}}$$

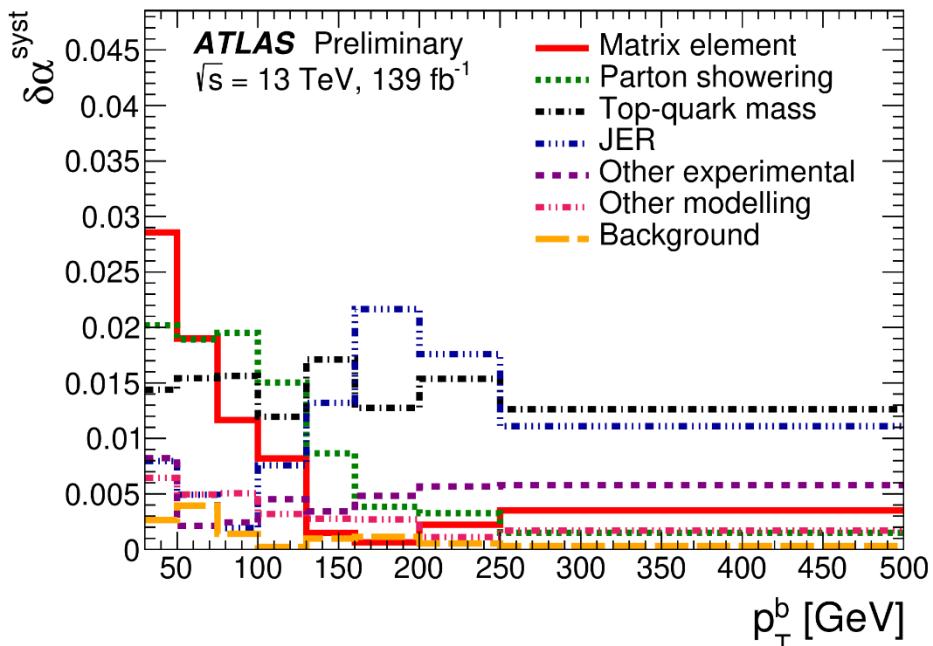
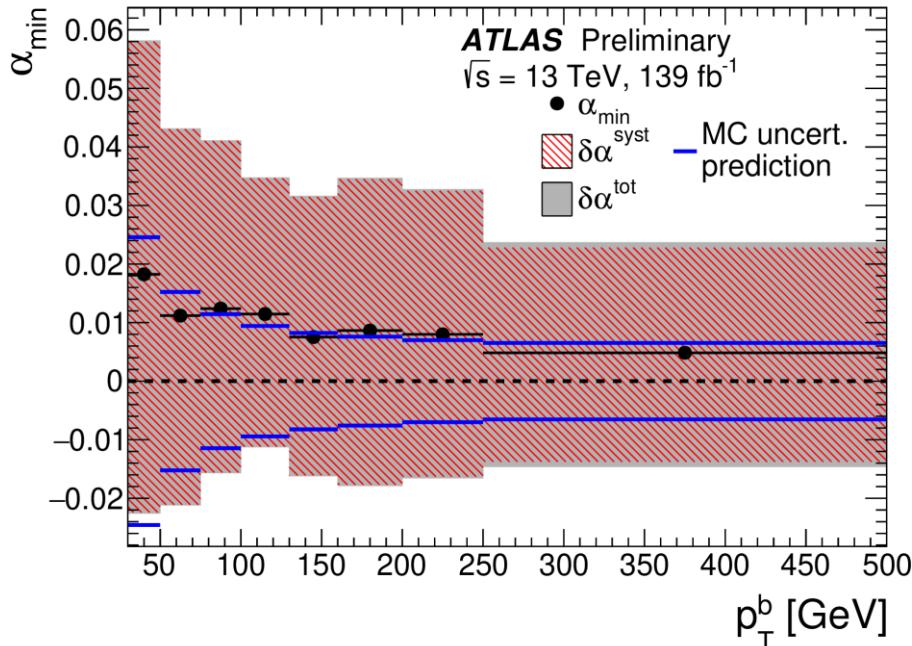
$$\mathcal{R} = \frac{c^{\text{right}}}{c^{\text{left}}} = \frac{2 + \langle \mathcal{A} \rangle}{2 - \langle \mathcal{A} \rangle} \approx \frac{\langle p_T^{\text{left}} \rangle}{\langle p_T^{\text{right}} \rangle}$$

Small-R Jet Calibration



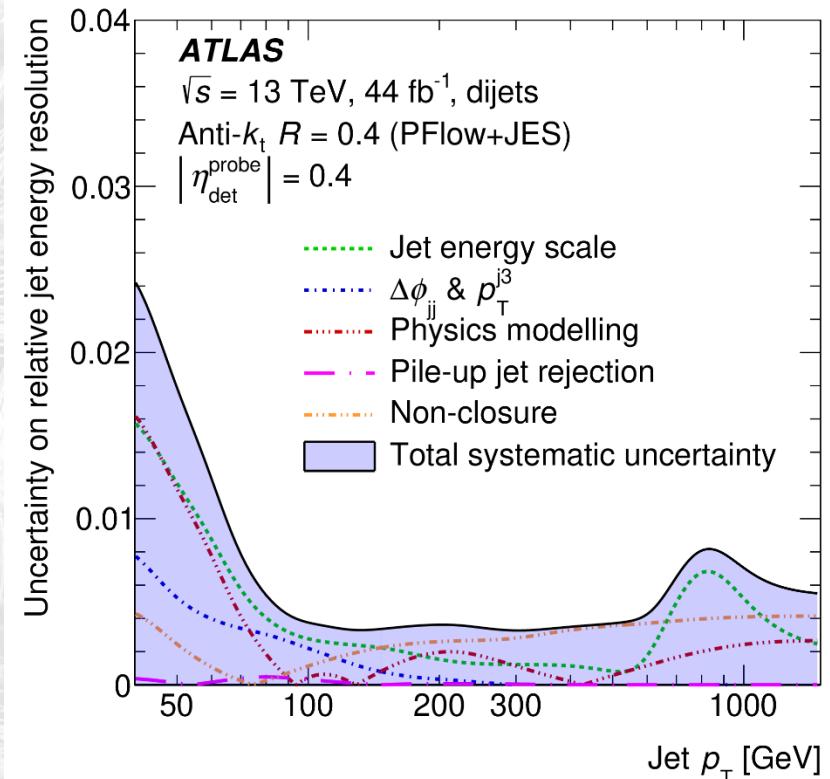
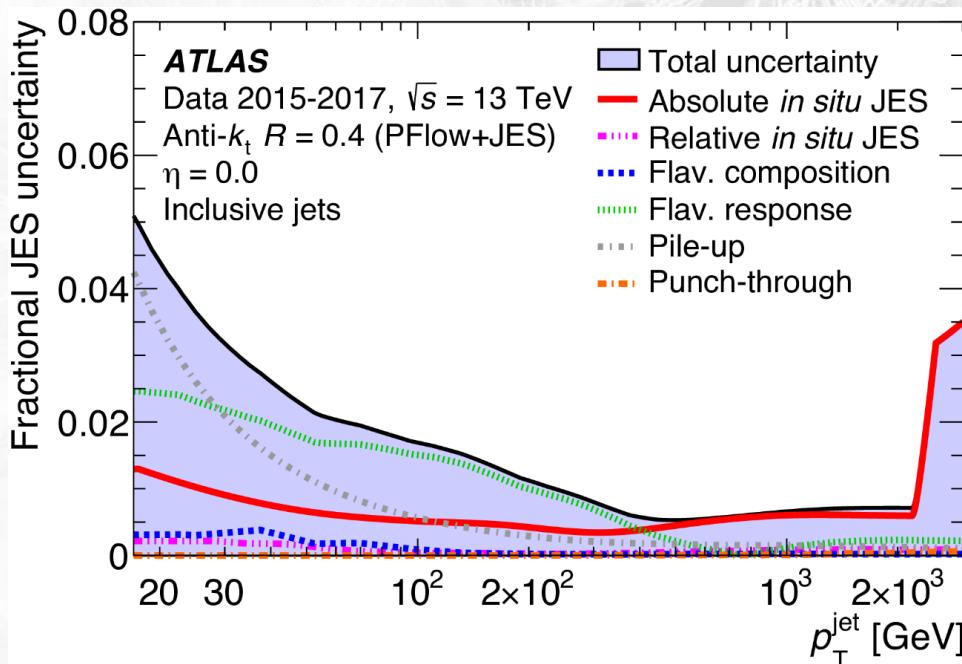
Newish study to test separate in-situ correction of b-jet energy scale "b-JES" via $t\bar{t} \rightarrow l\nu q\bar{q} b\bar{b}$

Find residual JES correction α to apply after normal calibration: $E_b^{\text{Data corrected}} = E_b^{\text{Data}} / (1 + \alpha)$, α_{\min} nominal.
(main body b-JES via photon+Jet is newer).



Small-R Jet Uncertainties

Uncertainties <2% at 200 GeV!

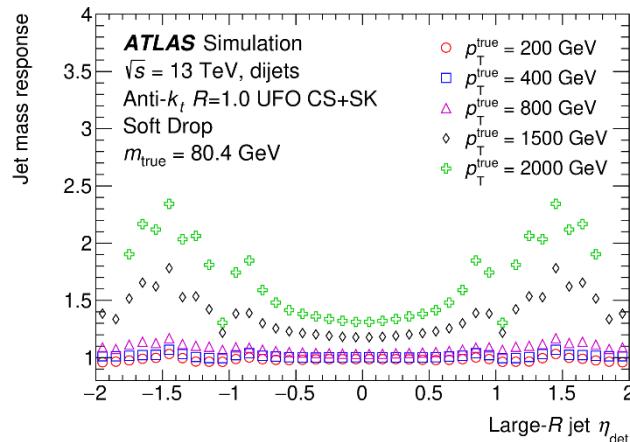
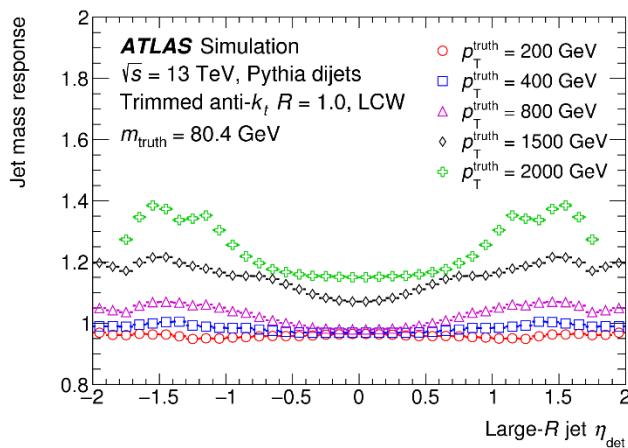


- New ρ def. for PFlow avoid Charged PFOs near PV
- New jet-by-jet flavour uncertainty
- Improving single-particle uncertainties through more measurements:
Measure response to π^\pm from $W \rightarrow \text{taunu}$

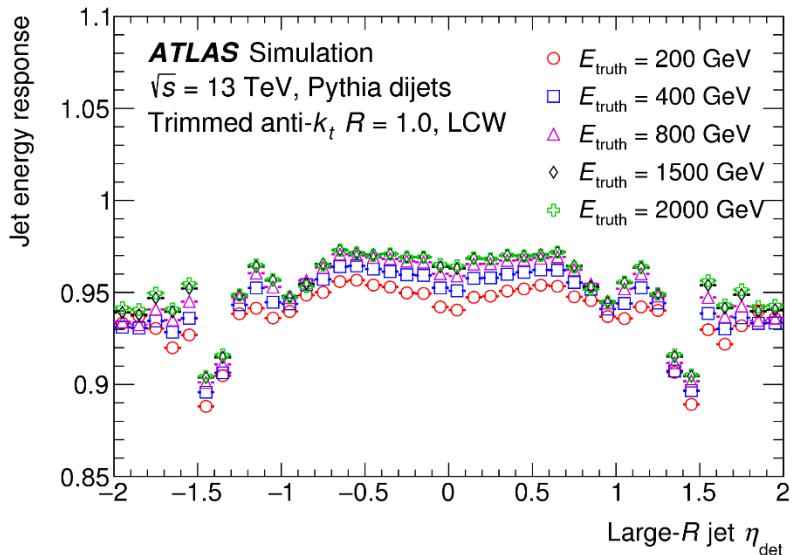
Large-R Jet Calibration



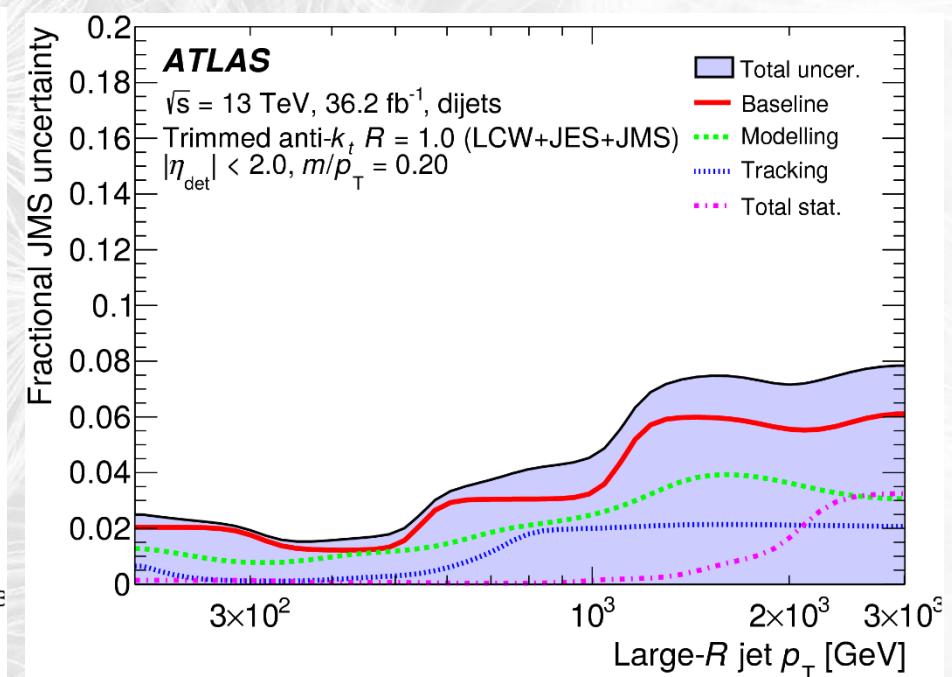
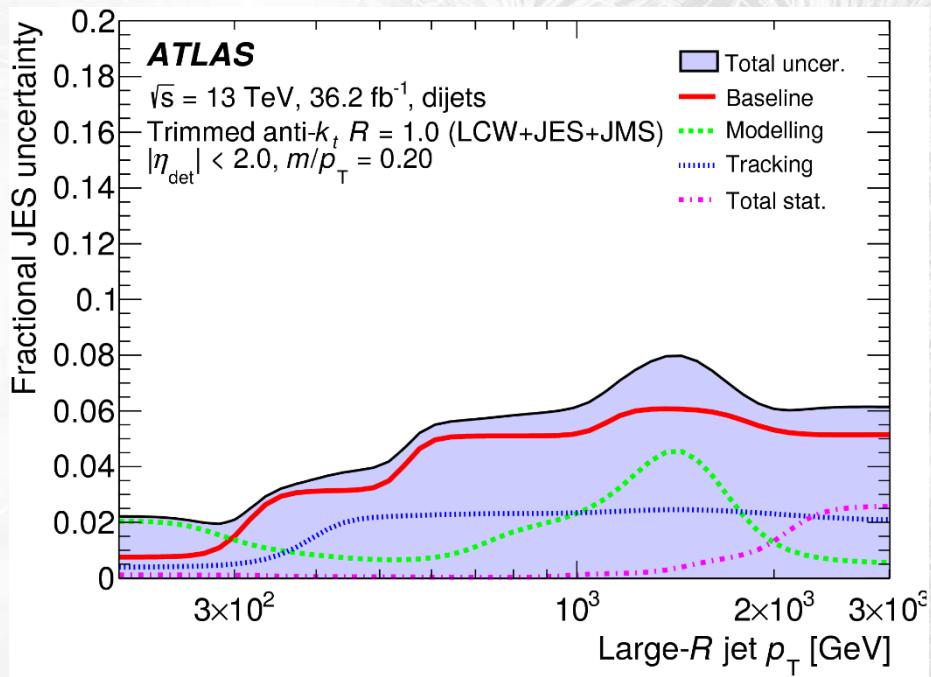
- TCs**
- Cell noise suppression
 - CS+SK
- UFOs**
- Trimming
 - SoftDrop



- Correct jet E, m, η
- Residual correction to data

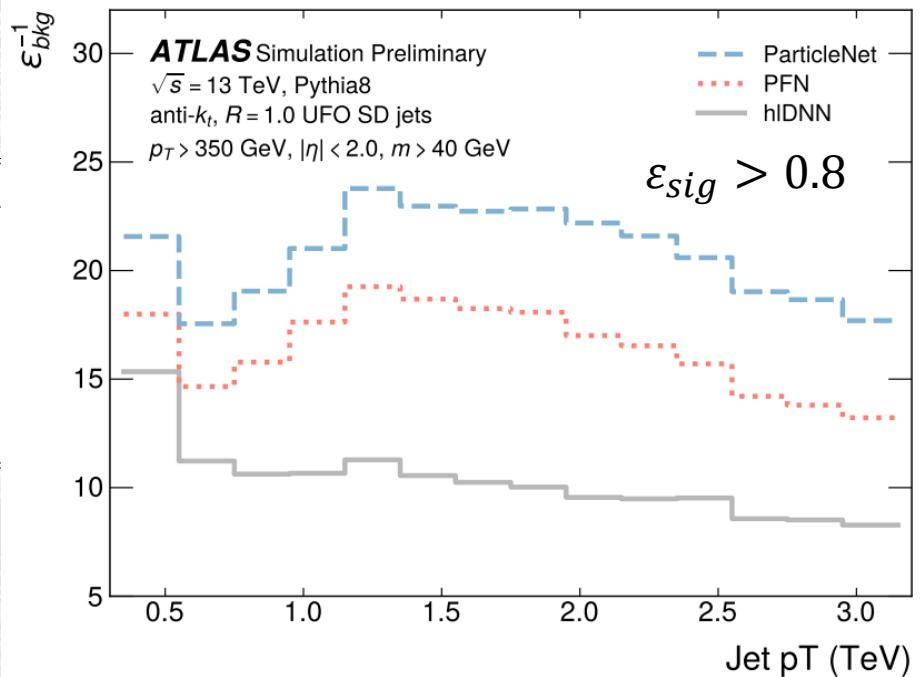


Large- r Jet uncertainties



Boosted top tagger performance

Model	AUC	ACC	ε_{bkg}^{-1} @ $\varepsilon_{sig} = 0.5$	ε_{bkg}^{-1} @ $\varepsilon_{sig} = 0.8$	# Params	Inference Time
ResNet 50	0.885	0.803	21.4	5.13	1,486,209	9 ms
EFN	0.901	0.819	26.6	6.12	1,670,451	4 ms
hDNN	0.938	0.863	51.5	10.5	93,151	3 ms
DNN	0.942	0.868	67.7	12.0	876,641	3 ms
PFN	0.954	0.882	108.0	15.9	689,801	4 ms
ParticleNet	0.961	0.894	153.7	20.4	764,887	38 ms

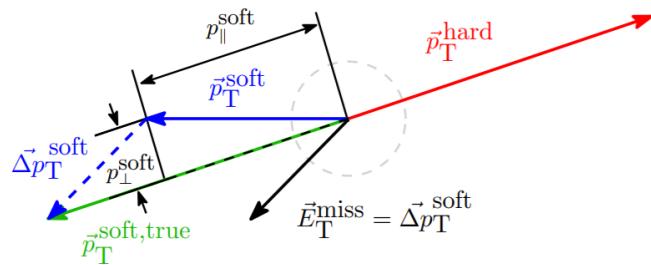


TST Uncertainties

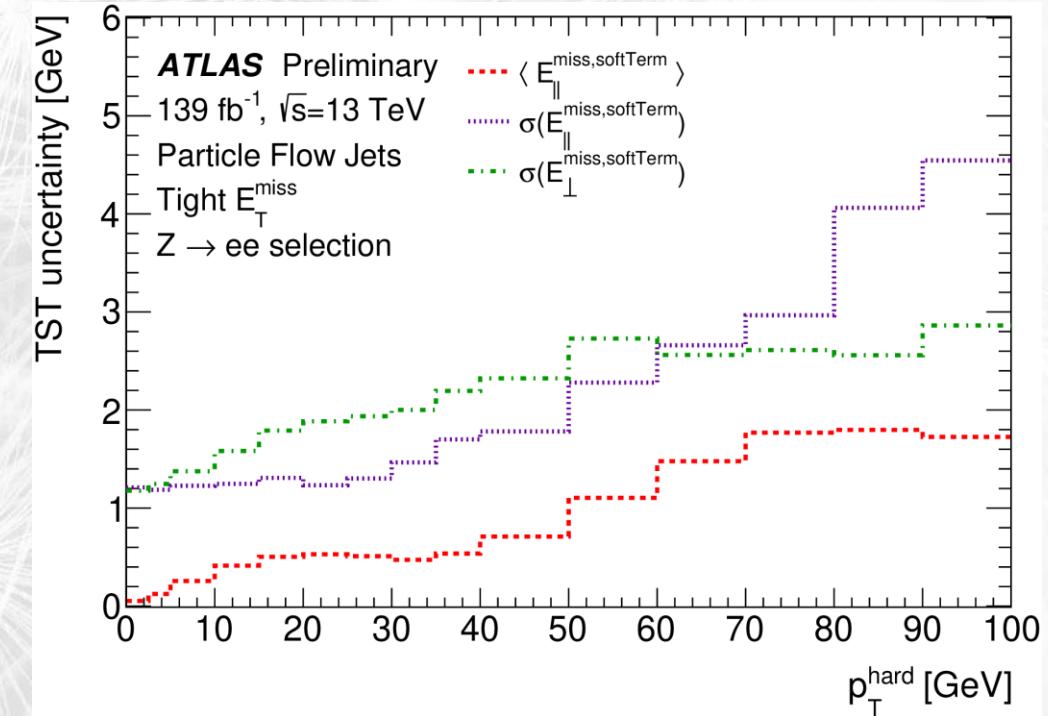
Track Soft Term uncertainties with Full Run-2

- Look at $Z \rightarrow ee$ no true p_T^{miss} : $\overrightarrow{p_T^{Hard}} = -\overrightarrow{p_T^{Soft}}$
- Binned in hard p_T , parametrised in 3 variables: soft term projection on the hard term:

- Parallel scale: $\langle p_{||}^{soft} \rangle$
- Parallel resolution: $\sigma(p_{||}^{soft})$
- Transverse resolution: $\sigma(p_{\perp}^{soft})$

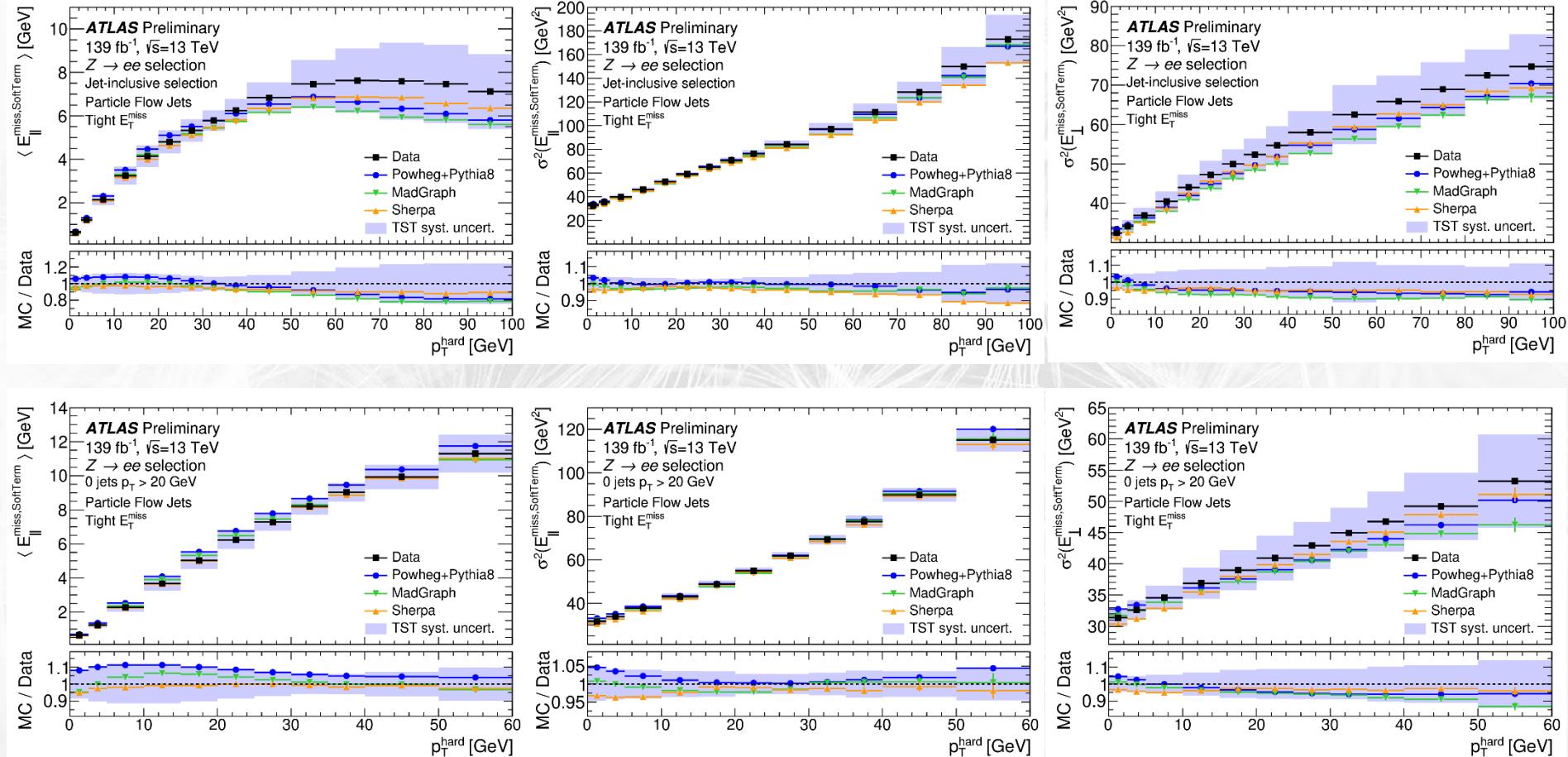


- TST uncertainties = MC/data envelope over several generators.
- Future: refined TST calibration?



TST Uncertainties

[PUBLIC PLOTS LINK](#)



p_T^{miss} Significance

Quantify confidence of real p_T^{miss} in event

- Object-based S is state-of-the-art. Considers object-resolutions used to build p_T^{miss}

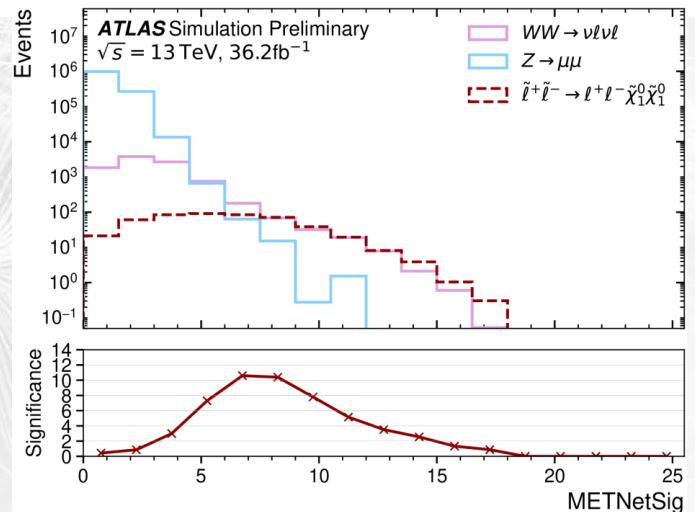
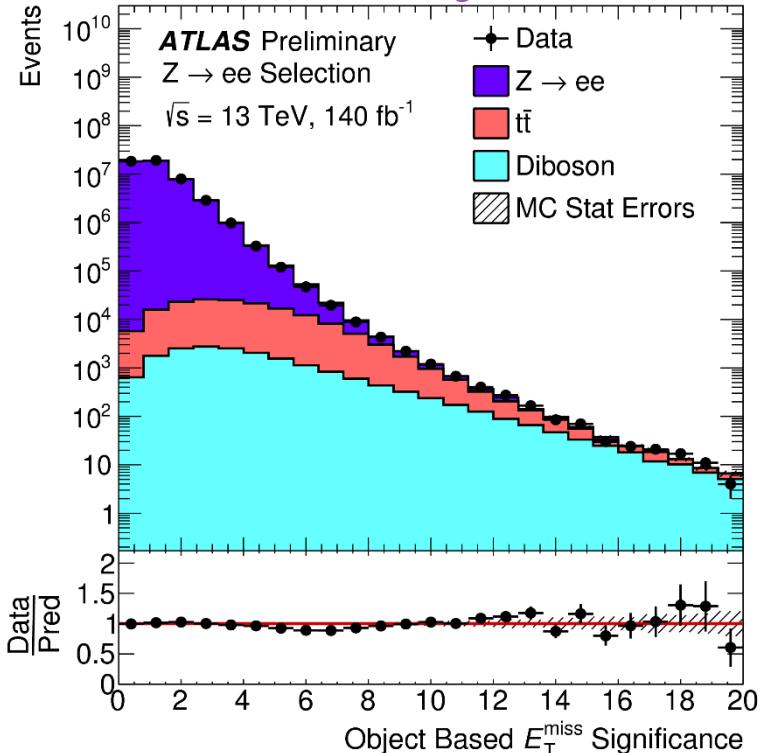
$$S^2 = \frac{|E_T^{\text{miss}}|^2}{\sigma_L^2 (1 - \rho_{LT}^2)}.$$

Variance in direction parallel to p_T^{miss}

Correlation between directions parallel and transverse to p_T^{miss} .

- Extremely useful for discriminating between BSM events with lots of real p_T^{miss} and events with only fake p_T^{miss} .
- Well-modelled in MC.

Try METNetSig too: NN outputs res/unc. in prediction.

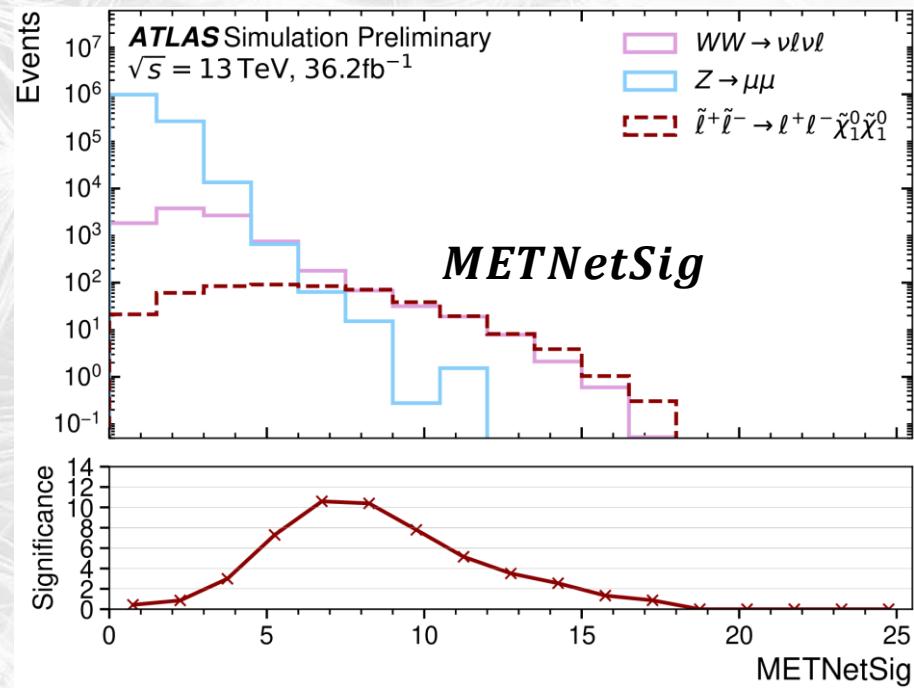
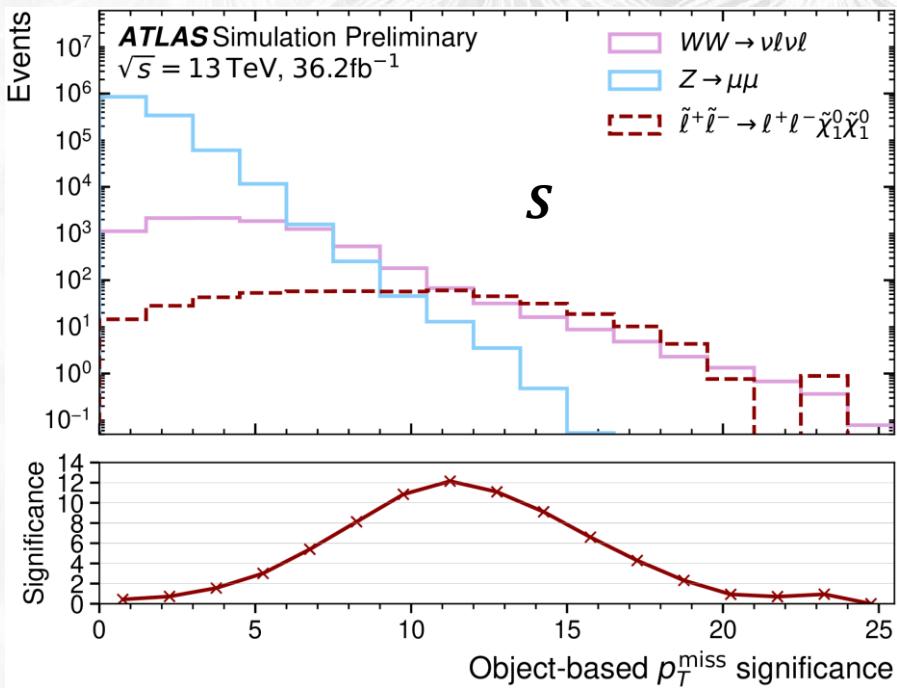


Machine Learning p_T^{miss} Significance

Inspiration Slepton search

Alternative p_T^{miss} Significance variable: ***METNetSig***

- NN outputs confidences in (p_x^{miss}, p_y^{miss})
- Verified that the correct quantiles of events appear within 1 and 2σ .
- Look at sensitivity significance for lower-bound cuts on the variables for SUSY v SM. Performs similarly to S on a **SUSY signal** – **encouraging!**



METNet Architecture

Table 6: METNet neural network architecture and hyperparameters.

Layer	Nodes	Activation	Parameters
Input	60	None	0
Hidden 1	100	SELU	6100
LayerNorm 1	100	SELU	200
Hidden 2	100	SELU	10100
LayerNorm 2	100	SELU	200
Hidden 3	100	SELU	10100
LayerNorm 3	100	SELU	200
Output	2	Linear	202
Total			27,102

(a) METNet architecture.

Hyperparameter	Value
Optimiser	Adam [67]
Weight initialization	Kaiming He [68]
Learning rate	0.001
Batch size	256
Huber loss δ	1.5

(b) METNet hyperparameters

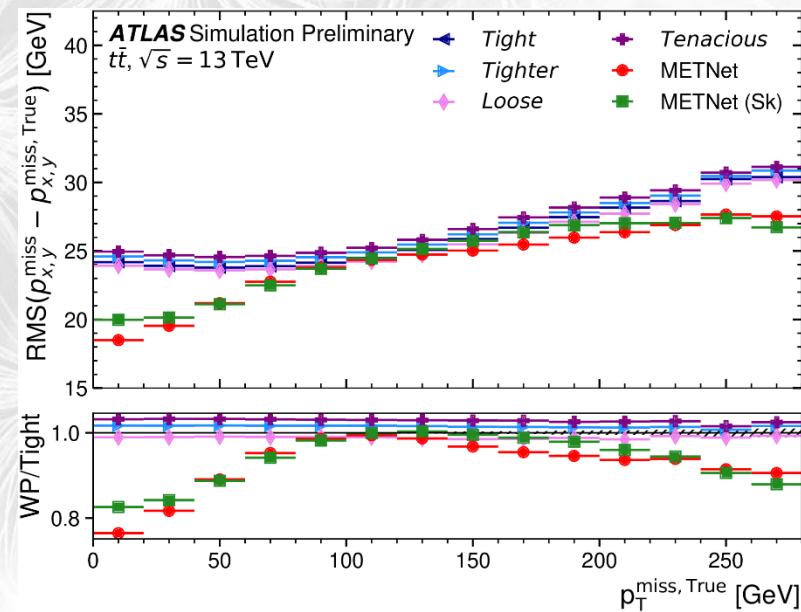
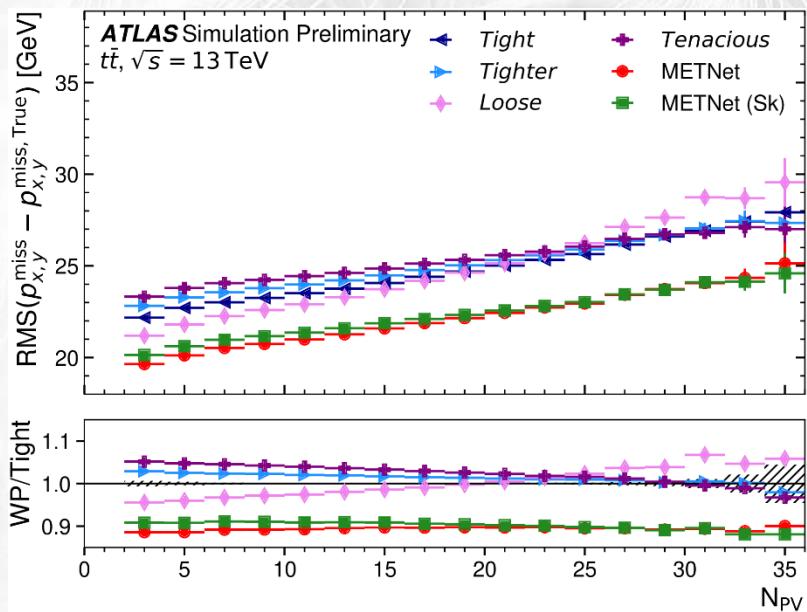
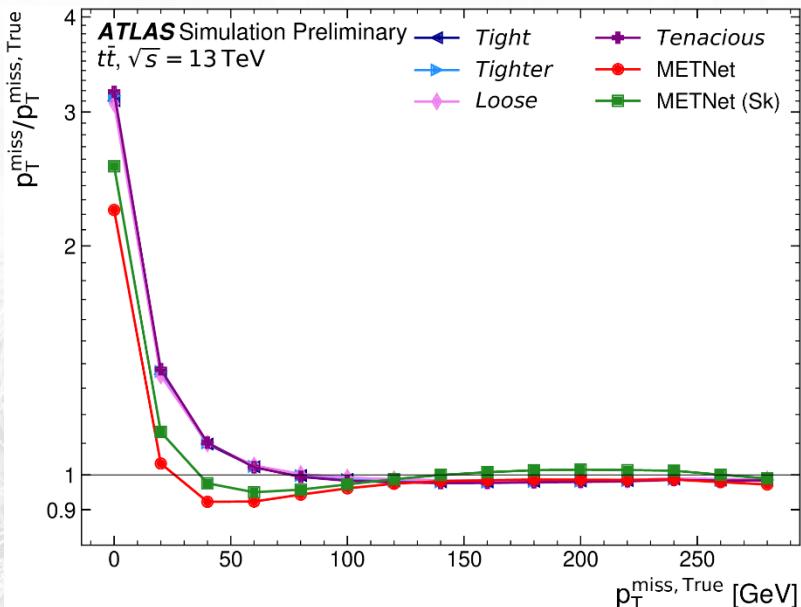
$$\mathcal{L}_{\text{Huber}} = \begin{cases} \frac{1}{2}(y - \hat{y})^2 & , \quad |y - \hat{y}| \leq \delta \\ \delta|y - \hat{y}| - \frac{1}{2}\delta^2 & , \quad \text{otherwise} \end{cases}$$

$$\mathcal{L} = \mathcal{L}_{\text{Huber}}$$

$$\mathcal{L} = \mathcal{L}_{\text{Huber}} + \mathcal{L}_{\text{Sinkhorn}}.$$

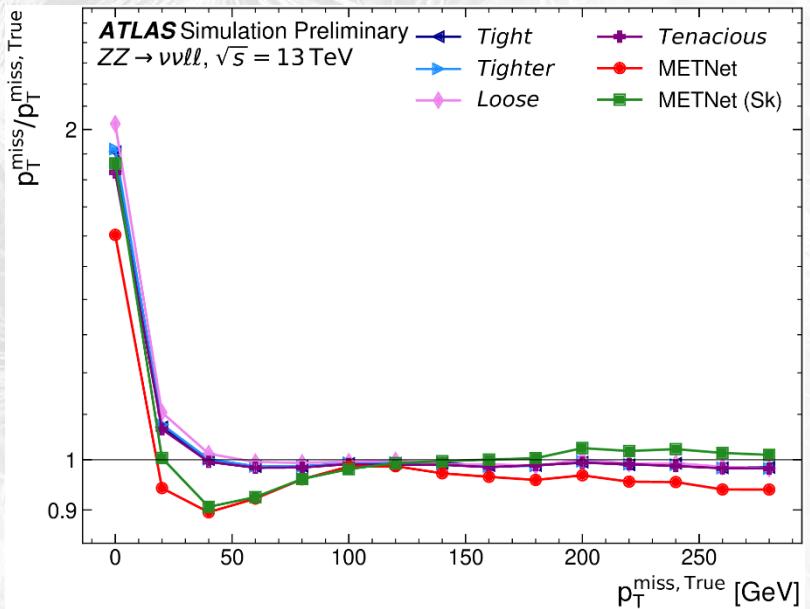
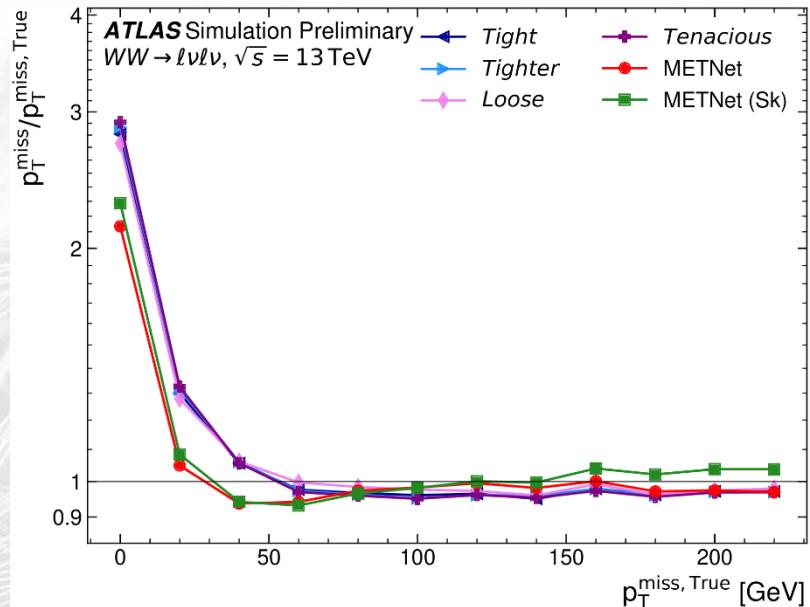
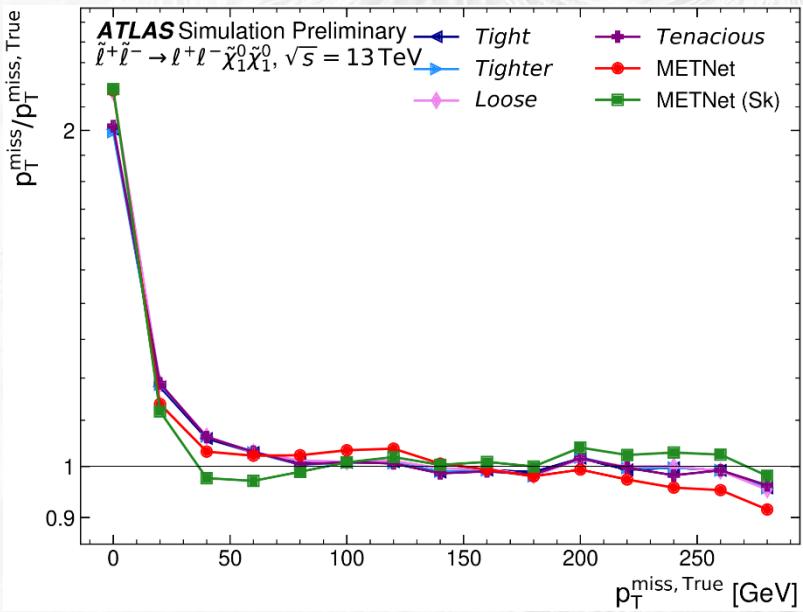
METNET plots: ttbar

METNet PUB NOTE



METNET plots: Closeness to Truth MET

METNet PUB NOTE



METNetSig Architecture

Otherwise same as METNet Architecture

$$\mathcal{L}_{GNLL} = \log \sigma + 0.5 \left(\frac{y - \hat{y}}{\sigma} \right)^2$$

$$\mathcal{L} = \mathcal{L}_{GNLL} + \mathcal{L}_{Sinkhorn}.$$

$$METNetSig = p_T^{\text{miss, NN}} / \sigma$$

$$p_T^{\text{miss, NN}} = \sqrt{(p_x^{\text{miss, NN}})^2 + (p_y^{\text{miss, NN}})^2}$$

$$\sigma = \frac{\sqrt{(p_x^{\text{miss, NN}} \sigma_x)^2 + (p_y^{\text{miss, NN}} \sigma_y)^2}}{p_T^{\text{miss, NN}}}.$$